

**REPLENISHMENT POLICY FOR PERISHABLE AND
SUBSTITUTABLE PRODUCTS AT SUPPLIERS AND RETAILERS:
A MULTI-CRITERIA APPROACH**

LINH NGUYEN KHANH DUONG

A thesis submitted to
Auckland University of Technology
in fulfilment of the requirements for the degree of
Doctor of Philosophy (PhD)

2016

Faculty of Business and Law
Department of Business Information Systems

Abstract

Defining replenishment policies for perishable products is an important activity, particularly where suppliers have a range of products. As product ranges increase, consumers can substitute products if their preferred product is out of stock. Such substitution considered simultaneously as perishability makes it difficult to achieve balanced results over different departments/companies in the face of fluctuating demand. Given these circumstances, a financially calculated replenishment policy makes communicating the impact of operational changes difficult. In contrast, non-financial measures improve the communication between departments and staff (e.g., between warehousing, procurement, and sales), and allows them to set operational targets from broad corporate strategies.

The first objective is to use non-financial performance measures to define the most favourable replenishment policy in a two-echelon model with multiple perishable and substitutable products. The second objective is to evaluate and explore the importance and interactions of the input factors (i.e., consumer demand, product lifetime, and substitution) in a perishable and substitutable inventory management model with sensitivity testing using MANOVA. Developing the framework consisted of three steps. First, the discrete event simulation (DES) was built and run for each of a given set of replenishment policies. The performance of the inventory model under each replenishment policy was measured by three conflicting non-financial performance measures; specifically, average inventory, fill rate, and order rate variance ratio. Second, the analytic hierarchy process (AHP) method was used to weight the importance of each performance measure. Third, the data envelopment analysis (DEA) method was used to evaluate and rank the performance of each replenishment policy. Then, the most favourable replenishment policy, which has the lowest DEA Cook's super-efficiency score, was chosen.

The results showed that the consumer demand, product lifetime, and substitution inputs to the model have large effects on retailers' and supplier performance; however, only the interaction between consumer demand and product lifetime had a similarly large effect on firms' performance. Suppliers are more greatly affected by the bullwhip effect in the model; in contrast, the effects on the retailers is smaller. Moreover, this research also shows that, in the studied context, the most favourable replenishment policy is stable under changes in the weights of performance measures.

This study contributes to inventory management theory by being the first research to develop a non-financial framework and demonstrate that it is comparability to financial approaches for perishable and substitutable inventory. For managers, this study contributes by providing a framework (based on non-financial measures) to develop or modify replenishment policies to balance service level/cost in contexts with perishable and substitutable products. The framework is particularly relevant for suppliers, as they are more impacted by fluctuating demand. The non-financial approach also enables managers to evaluate the effectiveness of other supplementary techniques (e.g., forecasting techniques) in the inventory management when making a business case.

Table of Contents

Abstract	i
Table of Contents	iii
List of Figures	xi
List of Tables	xvi
List of Abbreviations	xviii
Attestation of Authorship.....	xx
Acknowledgment	xxi
Chapter 1 Introduction.....	1
1.1 Background and Motivation of Research	1
1.2 Positioning the Research	3
1.3 Research Objectives and Questions.....	5
1.4 Research Methodology	6
1.5 Expected Research Contributions.....	7
1.6 Research Structure	8
Chapter 2 Literature Review.....	10
2.1 Inventory Management.....	11
2.1.1 Supply chain management	12
2.1.2 Trade-off decisions in supply chain management.....	13
2.1.3 Inventory management objective	17
2.1.4 Replenishment policy.....	18
2.2 Perishable Inventory Management	24
2.2.1 Perishability	24
2.2.2 Consumer demand.....	26
2.2.3 Product lifetime.....	28

2.2.4	Stock issuing model	30
2.2.5	Lead time.....	31
2.3	Multi-echelon Inventory Management	32
2.3.1	Definition of a multi-echelon model	32
2.3.2	Bullwhip effect.....	34
2.3.3	Serial and divergent supply chain model	35
2.3.4	Centralised and decentralised supply chain models.....	38
2.3.5	Perishable inventory management for the multi-echelon model	40
2.4	Substitution.....	43
2.4.1	Excess demand.....	43
2.4.2	Classifying substitution as driven by the consumer or decision-maker.....	46
2.4.3	Perishable inventory management for substitutable products.....	47
2.5	Key Issues in Perishable Inventory Management.....	49
2.5.1	Non-financial performance measures of the multi-echelon inventory model.....	49
2.5.1.1	Why to use the performance measures in the multi-echelon model	50
2.5.1.2	Justification the performance measures adopted	55
2.5.2	Lack of knowledge of effects of consumer demand	58
2.5.3	Lack of knowledge of effects of product lifetime.....	61
2.5.4	Lack of research on substitution	62
2.5.5	Lack of knowledge of effects of substitution.....	65
2.5.6	Lack of knowledge of effects of decision-makers' opinions	66
2.5.7	Lack of research on multi-products	68
2.5.8	Lack of research on the multi-echelon model.....	68
2.6	Research Gaps, Objectives, and Questions	69
2.6.1	Research gaps.....	70

2.6.2	Research objectives and questions.....	73
Chapter 3	Research Methodology	75
3.1	Meaning of Research Methodology	77
3.1.1	Research objectives.....	78
3.2	Research Philosophy.....	80
3.3	Research Approach.....	82
3.3.1	Towards a theoretical contribution	84
3.3.2	Definition of the multi-methodological approach.....	84
3.3.3	Research methods in operations management	85
3.3.3.1	Analytical modelling.....	86
3.3.3.2	Behavioural method.....	86
3.3.3.3	Case study/ grounded theory/ action research	88
3.3.3.4	Empirical research	89
3.3.4	The application of multi-methodological approach in operations management...	90
3.3.5	Advantages of the multi-methodological approach	91
3.3.6	Disadvantages of the multi-methodological approach.....	93
3.3.7	Justification for using multi-methodology in this research.....	93
3.3.7.1	Justification for using simulation as one of two methods in this research....	95
3.3.7.2	Justification of using multi-criteria decision-making methods.....	98
3.4	Research Design	100
3.4.1	Proposed research framework.....	100
3.5	Simulation.....	103
3.5.1	Types of simulation.....	105
3.5.1.1	Spreadsheet models.....	105
3.5.1.2	System dynamics	106

3.5.1.3	Gaming.....	107
3.5.1.4	Discrete event dynamic simulation models	108
3.5.2	Justification of using discrete-event dynamic simulation models	109
3.5.3	Simulation procedure	111
3.5.3.1	Step 1: Formulate problem.....	114
3.5.3.2	Step 2: Specify independent and dependent variables	115
3.5.3.3	Step 3: Develop and validate the conceptual model	117
3.5.3.4	Step 4: Collect data	123
3.5.3.5	Step 5: Develop and verify the computer-based model	124
3.5.3.6	Step 6: Validate the model	125
3.5.3.7	Step 7: Perform simulations.....	130
3.5.3.8	Step 8: Analysis and document results	132
3.6	Analytic Hierarchy Process	132
3.6.1	Step 1: Decompose studied model into a hierarchy	134
3.6.2	Step 2: Create a comparison matrix	134
3.6.2.1	A case study	135
3.6.2.2	Comparison results.....	137
3.6.3	Step 3: Calculation	137
3.7	Data Envelopment Analysis	138
3.7.1	Preliminaries and basic DEA models.....	138
3.7.2	Selection of inputs and outputs	140
3.7.3	Applications of DEA.....	141
3.7.4	Advantages of DEA	141
3.7.5	Limitations of DEA.....	143
3.7.5.1	Ranking approaches in DEA.....	143

3.7.5.2	Undesirable factors	145
3.7.5.3	Weight in DEA	146
3.7.6	Integrations of AHP and DEA in this research	147
3.8	Justification of the Research Framework	150
3.9	Chapter Summary	153
Chapter 4	Results	155
4.1	Selecting the Most Favourable Replenishment Policy	157
4.1.1	Discrete-event simulation under experiment #1	157
4.1.2	Analytic hierarchy process	159
4.1.3	Data envelopment analysis under experiment #1	160
4.1.4	Discussion of the result received under experiment #1	160
4.2	Sensitivity Analysis	162
4.3	Effects of Decision-makers' Opinions on the Selected Replenishment Policy	163
4.4	Effects of Input Factors on the Performance of the Inventory Model	165
4.4.1	Overview of average inventory performance	166
4.4.2	Overview of fill rate performance	169
4.4.3	Overview of order rate variance performance	170
4.5	Result Analysis	171
4.5.1	MANOVA assumption	172
4.5.1.1	The assumption of random and independence	172
4.5.1.2	The assumption of multivariate normality	173
4.5.1.3	The assumption of homogeneity of covariance matrices	175
4.5.1.4	The assumption of linearity	176
4.5.2	Multivariate analysis result	177
4.5.2.1	Multivariate analysis result – Three-independent variables interaction	179

4.5.2.2	Multivariate analysis result – Two-independent variables interaction	179
4.5.2.3	Multivariate analysis result – Main effect	180
4.5.3	Univariate analysis result	180
4.5.3.1	Interaction of three independent variables	181
4.5.3.2	Interaction of product lifetime and lost sales probability	182
4.5.3.3	Interaction of consumer demand and lost sales probability	187
4.5.3.4	Interaction of consumer demand and product lifetime	191
4.5.3.5	Main effect of consumer demand	195
4.5.3.6	Main effect of product lifetime	198
4.5.3.7	Main effect of lost sales probability	201
4.6	Summary of Effects of Input Factors on the Model’s Performance	204
Chapter 5	Discussion and Implications	209
5.1	Overview of Results	211
5.2	Non-financial versus Financial Approach	211
5.2.1	Advantages of using non-financial performance measures	212
5.2.2	Gaps in using non-financial performance measures	214
5.2.3	Contributions relating to using non-financial performance measures	215
5.2.4	Research limitation relating to using non-financial performance measures	220
5.3	The Effects of Consumer Demand	221
5.3.1	Gaps relating to the knowledge of effects of consumer demand	222
5.3.2	Contributions to the knowledge of effects of consumer demand	223
5.3.3	Research limitations relating to the knowledge of effects of consumer demand	227
5.4	The Effects of Product Lifetime	227
5.4.1	Gaps relating to the knowledge of effects of product lifetime	228
5.4.2	Contributions to the knowledge of effects of product lifetime	229

5.4.3	Research limitation relating to the knowledge of effects of product lifetime.....	231
5.5	The Effects of Substitution or Lost Sales Probability	231
5.5.1	Gaps relating to the knowledge of effects of substitution.....	232
5.5.2	Contributions to the knowledge of effects of substitution	233
5.5.3	Research limitations relating to the knowledge of effects of substitution	237
5.6	The Effects of Decision-Makers’ Opinions.....	237
5.6.1	Gaps relating to the knowledge of effects of decision-makers’ opinions	237
5.6.2	Contributions to the knowledge of effects of decision-makers’ opinions	238
5.6.3	Research limitation relating to knowledge of effects of decision-makers’ opinions	239
5.7	Summary of Discussion and Implications	240
Chapter 6	Conclusion	242
6.1	The Research Findings	243
6.1.1	RO1 – The most favourable replenishment policy	244
6.1.2	RO2 – Effects of problem characteristics	245
6.1.2.1	Decision-makers’ opinions	245
6.1.2.2	Consumer demand	246
6.1.2.3	Product lifetime.....	247
6.1.2.4	Substitution	247
6.2	Contributions	248
6.2.1	Theoretical contributions	248
6.2.2	Methodological contribution.....	251
6.2.3	Managerial contributions	257
6.2.3.1	Effects of consumer demand.....	257
6.2.3.2	Effects of product lifetime	258

6.2.3.3	Effects of substitution	259
6.2.3.4	Effects of decision-makers' opinions.....	260
6.3	Limitations.....	266
6.4	Future Research	267
6.5	Final Remarks.....	270
Reference	272
Appendix	305

List of Figures

Figure 1.1: Structure of research proposal	9
Figure 2.1: Structure of literature review	11
Figure 2.2: Trade-off between fill rate and inventory cost (adopted from Figure 1.2 in Cachon and Terwiesch (2009, p. 5))	16
Figure 2.3: An example of a redesigned system to improve the current frontier (adopted from Figure 1.3 in Cachon and Terwiesch (2009, p. 6))	17
Figure 2.4: Consumer demand follows a normal distribution	19
Figure 2.5: The EOQ policy with optimal order quantity, constant demand rate, reorder point and lead time	22
Figure 2.6: Three types of perishable products.....	25
Figure 2.7: A basic supply chain model showing the scope of considerations for both single- and multi-echelon supply chain models.....	33
Figure 2.8: An example of the bullwhip effect phenomenon whereby order quantity becomes more variable upstream in the supply chain.....	35
Figure 2.9: Serial and divergent supply chain networks (adopted from Figure 2 in Framinan and Dominguez (2014, p. 2198))	37
Figure 3.1: Structure of Research Methodology chapter	76
Figure 3.2: Integration framework the of Simulation/ AHP/ DEA model.....	103
Figure 3.3: The simulation approach (derived from Figure 1 in Manuj et al. (2009, p. 176))	113
Figure 3.4: Overview of sequential events of the research inventory model.....	119
Figure 3.5: Welch’s graphic for identifying the warm-up period and simulation length	131
Figure 3.6: The hierarchy model of the objective of performance measures	134
Figure 3.7: DEA model with two inputs, 27 outputs, and 88 scenarios	149

Figure 4.1: Structure of Results chapter	156
Figure 4.2: Conflicting results of average inventory and fill rate of the replenishment policies (1, 26), (2, 26), (3, 26), and (4, 26)	159
Figure 4.3: Performance of average inventory at the retailer	167
Figure 4.4: Performance of average inventory at the supplier	167
Figure 4.5: Performance of fill rate at the retailer	168
Figure 4.6: Performance of fill rate at the supplier	168
Figure 4.7: Performance of order rate variance ratio at the retailer	169
Figure 4.8: Performance of order rate variance ratio at the supplier	169
Figure 4.9: Effect of lifetime and lost sales probability on AI at retailer	185
Figure 4.10: Effect of lifetime and lost sales probability on AI at supplier	185
Figure 4.11: Effect of lifetime and lost sales probability on FR at retailer	185
Figure 4.12: Effect of lifetime and lost sales probability on FR at supplier	185
Figure 4.13: Effect of lifetime and lost sales probability on ORVR at retailer	185
Figure 4.14: Effect of lifetime and lost sales probability on ORVR at supplier	185
Figure 4.15: Effect of lifetime and lost sales probability on AI at supplier under high demand	186
Figure 4.16: Effect of lifetime and lost sales probability on AI at supplier under low demand	186
Figure 4.17: Effect of lifetime and lost sales probability on FR at supplier under high demand	186
Figure 4.18: Effect of lifetime and lost sales probability on FR at supplier under low demand	186
Figure 4.19: Effect of lifetime and lost sales probability on ORVR at supplier under high demand	186

Figure 4.20: Effect of lifetime and lost sales probability on ORVR at supplier under low demand	186
Figure 4.21: Effect of consumer demand and lost sales probability on AI at retailer	189
Figure 4.22: Effect of consumer demand and lost sales probability on AI at supplier	189
Figure 4.23: Effect of consumer demand and lost sales probability on FR at retailer	189
Figure 4.24: Effect of consumer demand and lost sales probability on FR at supplier	189
Figure 4.25: Effect of consumer demand and lost sales probability on ORVR at retailer	189
Figure 4.26: Effect of consumer demand and lost sales probability on ORVR at supplier ...	189
Figure 4.27: Effect of consumer demand and lost sales probability on AI at supplier under high lifetime	190
Figure 4.28: Effect of consumer demand and lost sales probability on AI at supplier under low lifetime	190
Figure 4.29: Effect of consumer demand and lost sales probability on FR at supplier under high lifetime	190
Figure 4.30: Effect of consumer demand and lost sales probability on FR at supplier under low lifetime	190
Figure 4.31: Effect of consumer demand and lost sales probability on ORVR at supplier under high lifetime	190
Figure 4.32: Effect of consumer demand and lost sales probability on ORVR at supplier under low lifetime	190
Figure 4.33: Effect of consumer demand and product lifetime on AI at retailer	193
Figure 4.34: Effect of consumer demand and product lifetime on AI at supplier	193
Figure 4.35: Effect of consumer demand and product lifetime on FR at retailer	193
Figure 4.36: Effect of consumer demand and product lifetime on FR at supplier	193
Figure 4.37: Effect of consumer demand and product lifetime on ORVR at retailer	193

Figure 4.38: Effect of consumer demand and product lifetime on ORVR at supplier	193
Figure 4.39: Effect of consumer demand and product lifetime on AI at supplier under high lost sales probability	194
Figure 4.40: Effect of consumer demand and product lifetime on AI at supplier under low lost sales probability	194
Figure 4.41: Effect of consumer demand and product lifetime on FR at supplier under high lost sales probability	194
Figure 4.42: Effect of consumer demand and product lifetime on FR at supplier under low lost sales probability	194
Figure 4.43: Effect of consumer demand and product lifetime on ORVR at supplier under high lost sales probability.....	194
Figure 4.44: Effect of consumer demand and product lifetime on ORVR at supplier under low lost sales probability.....	194
Figure 4.45: Effect of consumer demand on AI at retailer	197
Figure 4.46: Effect of consumer demand on AI at supplier.....	197
Figure 4.47: Effect of consumer demand on FR at retailer.....	197
Figure 4.48: Effect of consumer demand on FR at supplier	197
Figure 4.49: Effect of consumer demand on ORVR at retailer	197
Figure 4.50: Effect of consumer demand on ORVR at supplier.....	197
Figure 4.51: Effect of product lifetime on AI at retailer.....	200
Figure 4.52: Effect of product lifetime on AI at supplier	200
Figure 4.53: Effect of product lifetime on FR at retailer	200
Figure 4.54: Effect of product lifetime on FR at supplier.....	200
Figure 4.55: Effect of product lifetime on ORVR at retailer.....	200
Figure 4.56: Effect of product lifetime on ORVR at supplier	200

Figure 4.57: Effect of lost sales probability on AI at retailer	203
Figure 4.58: Effect of lost sales probability on AI at supplier.....	203
Figure 4.59: Effect of lost sales probability on FR at retailer.....	203
Figure 4.60: Effect of lost sales probability on FR at supplier	203
Figure 4.61: Effect of lost sales probability on ORVR at retailer	203
Figure 4.62: Effect of lost sales probability on ORVR at supplier.....	203
Figure 5.1: Structure of Discussion chapter.....	210
Figure 6.1: Structure of Conclusion chapter	243

List of Tables

Table 2.1: Related information and cost (derived from Table 4 in Cannella et al. (2013a, p. 8))	57
Table 2.2: Use of performance measures in recent papers	58
Table 2.3: Summary of papers on inventory management for perishable and substitutable products in multi-echelon models.....	63
Table 2.4: Summary of papers in two-echelon models for single-period and substitutable products.....	64
Table 3.1: A summary of methodologies used in supply chain management research (derived from Table I in the work of Golicic and Davis (2012, p. 730)).....	82
Table 3.2: Examples of recent papers using multiple methods in OM research.....	91
Table 3.3 The high and low levels of input factors.....	128
Table 3.4 The combination of a 2 ³ factorial design.....	128
Table 3.5: Rating scale (derived from Table 1 in Saaty (2008, p. 86))	135
Table 3.6: The pairwise comparison results of three measures	137
Table 4.1: The weights along with the change of each measure and the original weight	164
Table 4.2: Kolmogorov-Smirnov Test of Normality for Dependent Variables.....	174
Table 4.3: Descriptive statistics for dependent variables.....	175
Table 4.4: Levene’s test for dependent variables.....	176
Table 4.5: Bartlett’s test of sphericity for non-linear relationships	177
Table 4.6: Multivariate result – three-independent variables interaction	179
Table 4.7: Multivariate result – Two-independent variables interaction.....	180
Table 4.8: Multivariate result – Main effect	180
Table 4.9: Univariate results – Interaction of three independent variables	181
Table 4.10: Univariate results – Interaction of product lifetime and lost sales probability...	182

Table 4.11: Univariate results – Interaction of consumer demand and lost sales probability	187
Table 4.12: Univariate results – Interaction of consumer demand and product lifetime	191
Table 4.13: Univariate results – Main effects of consumer demand	195
Table 4.14: Univariate results – Main effects of product lifetime	198
Table 4.15: Univariate results – Main effects of lost sales probability	201
Table 4.16: Summary of main and interaction effects on performance of inventory model	208
Table 5.1: Differences between this research and the researches of Pauls-Worm et al. (in press) and Xue et al. (2016)	225
Table 5.2: Comparison of this research with Kouki et al. (2014), Kouki and Jouini (2015)	230
Table 5.3: Comparison of this research and previous research	235
Table 6.1: Summary of theoretical, methodological contributions and related findings, literature	253
Table 6.2: Comparison of theoretical and methodological contributions in this research with key extant research	255
Table 6.3: Summary of managerial implications at the supplier	261
Table 6.4: Summary of managerial implications at the retailer	264

List of Abbreviations

AHP	Analytic Hierarchy Process
AI	Average Inventory
ANOVA	Univariate Analysis of Variance
BCC	Banker, Charnes, and Cooper
CCR	Charnes, Cooper, and Rhodes
CPFR	Collaborative Planning, Forecasting, and Replenishment
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DES	Discrete-Event Simulation
DMU	Decision Making Unit
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
FIFO	Fist-In First-Out
FR	Fill Rate
GSP	General Simulation Program
LIFO	Last-In First-Out
MANOVA	Multivariate Analysis of Variance
MCDM	Multi-Criteria Decision-Making
MRP	Manufacturing Resource Planning
OM	Operations Management
ORVR	Order Rate Variance Ratio
PMS	Performance Measurement Systems
SCM	Supply Chain Management

SD	Systems Dynamic
VMI	Vendor-Managed Inventory
VRS	Variable Returns to Scale
WIP	Work In Progress

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

A handwritten signature in blue ink, consisting of stylized initials 'hl' followed by a long horizontal line extending to the right.

Linh Nguyen Khanh Duong

Acknowledgment

I am very thankful for the incredible support that I have received from many individuals and institutions while working on this PhD thesis. My supervisors, Dr Lincoln Christopher Wood and Associate Professor William Yu Chung Wang, were excellent academics to work with. My first and deepest thanks go to my supervisor Dr Lincoln Christopher Wood for his continuous support and friendship. I could not have successfully completed this research without his kind advice, suggestions, great patience, and devotion. Dr Lincoln Christopher Wood is, and will always be, more than a supervisor to me.

I would also like to thank my supervisor Associate Professor William Yu Chung Wang. He has always been supportive of my work. His constructive feedback has helped me to construct a better thesis. I am very grateful for his guidance.

I would like to acknowledge the contributions from the Faculty of Business and Law, the Auckland University of Technology. I am very grateful for the Doctoral Fee Scholarship awarded to me by the Faculty of Business and Law. I must also mention the Postgraduate Office team, Dr Andy Godfrey, Eathar Abdul-Ghani, and Carole Young.

I also would like to thank Imagine That Inc. and Kathi Hansen for the Research Grant to use the ExtendSim AT simulation tool in this research.

During my time at the Auckland University of Technology, I was also lucky to have the opportunity to learn from, and work with all members at the Business Information System department. My special thanks to Dr Josephine Chong for all her support and advice. Their guidance has served me well and I owe them my heartfelt appreciation.

Throughout my time at the Auckland University of Technology, I have enjoyed the journey with my fellow PhD candidates. I would like to thank Dong-hyun (Don) Lee, Xiaowei (Jason) Wang, and Hari Srivastava. I am glad you were there with me.

Finally, my biggest appreciation belongs to my family – my sisters Quynh, Vy, and my parents. Without their continuous and unconditional support, this journey would not exist. I must thank my partner Huong for her love and support. I dedicate this thesis to them.

Chapter 1 Introduction

1.1 Background and Motivation of Research

Inventory management has emerged as an important application of operations research (Bromiley & Rau, 2016; Roh, Krause, & Swink, 2016). The supposition is that maintaining an appropriate inventory level improves companies' operational performance (Koumanakos, 2008; Shin, Ennis, & Spurlin, 2015). Inventory is a company's current asset, but it is costly to maintain, for example, inventory costs of U.S. wholesale accounts for 62.4% of total sales (Chiarello-Ebner, 2015). Though surplus inventory increases costs, a lack of inventory may lead to lost sales. Effective inventory management can cut significant costs of inventory and enhance the efficient flow of goods and services in the global economy. Extant research has focused on inventory management methods to define replenishment time and quantity, which balance inventory costs and production/sales efficiency. Many techniques have been used to deal with the inventory management problem, for example, linear and nonlinear programming (Nahmias, 2011). These techniques are based on the methodology of inventory theory (Nahmias, 2011), which addresses the specific questions of when a replenishment order should be placed and for how many.

Inventory theory was based on the economic order quantity (EOQ) formula, discovered by Ford Harris in 1913 (Harris, 1990). This simple formula is used to calculate an optimal production batch size by appropriately balancing holding and set-up costs. The disadvantage of the EOQ formula is the constant demand assumption (Battini & Persona, 2014). Following Harris's work, the inventory theory has been developed successfully. However, the traditional inventory management model is based on two main assumptions, which limit its application in reality.

The first implicit assumption in the traditional inventory model is that products have an infinite lifetime or can be kept indefinitely to meet the market demand. However, this assumption is generally unrealistic as there are many types of products with a limited lifetime, usually referred to as perishable products (e.g., foods, medicines), that lose their quality during the storage period.

Perishable products represent one of the most important areas in inventory management, especially in the grocery industry. According to *WholeFoods Magazine*, perishable products account for 38.9% of total revenue of grocery stores in the U.S. (Chiarello-Ebner, 2015). Correspondingly, the perishability or limited lifetime characteristic increases the uncertainty in supply chain management (SCM) (i.e., supply and demand uncertainties) and requires careful decisions on making replenishment policy. Failure in these decisions results in high inventory level, low customer service level, or high waste of expired products. As examples, researchers have estimated that the proportion of food waste is between 25% to 40% worldwide (Gunasekera, 2015) and have called for actions to reduce food waste and resolve the current situation of 0.9 billion hungry and 2 billion malnourished (Lang & Heasman, 2015). In New Zealand, it is estimated that NZD872 million a year is thrown away on uneaten food (WasteMinz, 2015). These numbers confirm the necessity to focus on managing inventory for perishable products, which can reduce food waste.

The second assumption is that demand is an exogenous parameter and is not impacted by the available inventory on hand. However, in many settings, for example, grocery stores, there is a phenomenon where the availability of one product may affect demand for other products that is referred as a substitution effect. The marketing literature has proved that consumers who enter a store with the purpose of buying a certain product may buy a different product if their original preferred product is out of stock (Breugelmans, Campo, & Gijbrecchts, 2006). Moreover, suppliers usually offer many ranges of products to meet the variety of

demands. These ranges provide more opportunities for consumers to choose or substitute their favourite products. Stavroulaki (2011) found that the proportion of consumers who substitute, especially for perishable products, can be significant at 60%. Thus, when making decisions on the inventory of one product, it is necessary to take into account the effect of other products with similar characteristics or substitutable products.

Despite there being a large number of perishable and substitutable products in real business, the research on inventory management for these types of product is very limited. Many works have addressed the perishable management problem. These works aim at reducing waste, improving the customer service level, and reducing the inventory level, and range from identifying the waste causes (e.g., Göbel, Langen, Blumenthal, Teitscheid, & Ritter, 2015), ordering policy (e.g., Wu, Al-khateeb, Teng, & Cárdenas-Barrón, 2016a), reducing uncertainty in consumer demand (e.g., van Donselaar, Peters, de Jong, & Broekmeulen, 2016), or designing a contract between supplier and retailer (e.g., Kouvelis & Zhao, 2016). However, the work considering both perishable and substitutable products is very limited. The short explanation for this limitation is that the problems are difficult to analyse (Nahmias, 2011).

1.2 Positioning the Research

This research focuses on the topic of replenishment policy for perishable and substitutable products. It aims at understanding how managers decide a replenishment policy for perishable products that are affected by both their demand and other products' demand. In this context, the research on perishable inventory management may reach a saturation point in single-echelon models, where all possible characteristics of a problem have been combined to reflect real situations (Alizadeh, Eskandari, & Sajadifar, 2014; Duong, Wood, & Wang, in press). The difficulties are even greater when the suppliers define the replenishment policy for their retailers. In this case, which is referred to as a multi-echelon inventory model, the suppliers need many variables to track the inventory level of each product at each retailer. For example,

Ghiami and Williams (2015) defined a replenishment policy for one perishable product for a supplier and multiple retailers, but there were no relationships between these retailers. Giri and Sarker (2016) assumed retailers compete with price and service level, and investigated a two-echelon model for a newsvendor product. In the situation of multiple products, Zhang, Wang, and You (2015) investigated a multi-product newsvendor model for one supplier and one retailer where the product could substitute each other. The common assumption in these works was that newsvendor products expire after one planning period, for example, the daily newspaper.

In contrast to the rich literature on newsvendor products, there few works addressing the situation when substitutable products have a random lifetime (Pahl & Voß, 2014). Duan and Liao (2014) considered managing inventory at a blood centre and a hospital for blood cells which could substitute each other. Duan and Liao (2014) aimed at finding a replenishment policy which minimised the outdated rate of blood cells under a given fill rate. To deal with the complexity of the mathematical calculation, Duan and Liao (2014) used the discrete-event simulation (DES) technique to select the optimal replenishment policy. Nevertheless, Duan and Liao (2014) approach does not allow consideration of more measures and the involvement of more responsible people. The many variables in a multi-echelon model for perishable and substitutable products complicate the issue and is the main reason there are so few papers on this subject, although it is a common situation in real business. This limitation confirms challenges and gaps in the research conducted for perishable and substitutable goods under the multi-echelon inventory model, and is highlighted in literature review performed by Karaesmen, Scheller-Wolf, and Deniz (2011), Bakker, Riezebos, and Teunter (2012), and Pahl and Voß (2014).

This research, therefore, focuses on perishable and substitutable inventory management under a two-echelon model with one supplier and two retailers, who are selling three perishable

and substitutable products. This research direction is relevant to the suggestion of Kouki, Jemai, Sahin, and Dallery (2014), who considered the inventory model of one product at a retailer and suggested this be extended to multi-product, multi-echelon models. This research is also an extension of the study of Duan and Liao (2014) who considered a two-echelon model for substitutable products with a fixed lifetime.

In order to assess the performance of a replenishment policy, researchers have shifted from financial to non-financial performance measures (Taticchi, Tonelli, & Cagnazzo, 2010) due to their effect on continuous improvement (de Lima, da Costa, Angelis, & Munik, 2013; Piotrowicz & Cuthbertson, 2015) or performance motivation (Malik, Butt, & Choi, 2015; Shaw & Gupta, 2015). For example, Duan and Liao (2014) used the fill rate performance measure. Kaplan and Norton (2005) and Cannella, Barbosa-Póvoa, Framinan, and Relvas (2013a) suggested the use of non-financial measures (e.g., fill rate) instead of financial measures (e.g., total costs or total profit) to evaluate the performance of systems. This research attempts to address this trend in inventory management, and apply non-financial performance measures (i.e., average inventory, fill rate, and order rate variance ratio) to define a replenishment policy for the studied model.

1.3 Research Objectives and Questions

This research aims to develop a suitable heuristic solution for managers to obtain the most favourable replenishment policy that is the best trade-off between given performance measures of a two-echelon model for perishable and substitutable products. This research aims to address these issues and find the appropriate replenishment policy by addressing the following research objectives:

- Research Objective 1 (RO1): Using non-financial performance measures to define the most favourable replenishment policy for a two-echelon model under a given context of perishable and substitutable products.

- Identify and explore characteristics that are relevant to perishable and substitutable inventory management.
 - Design and develop a verified and validated inventory model that takes into account these characteristics when deciding a favourable replenishment policy.
 - Define relevant non-financial performance measures for the given context.
 - Create a framework which uses non-financial performance measures to define the most favourable replenishment policy in a given context of perishable and substitutable products.
- Research Objective 2 (RO2): Evaluate and explore the importance and interaction of these characteristics in a perishable and substitutable inventory management model.

The relevant research questions are:

- Research Question 1 (RQ1): What is the most favourable replenishment policy in a given context of perishable and substitutable products?
- Research Question 2 (RQ2): Given the context of perishable and substitutable products, how do decision-makers' opinions affect the selection of the most favourable replenishment policy?
- Research Question 3 (RQ3): Given the most favourable replenishment policy, how do the characteristics of the inventory model influence the performance of a two-echelon inventory model for perishable and substitutable products?

1.4 Research Methodology

This research uses a multi-methodological approach due to the complexity and multi-dimensional nature of the outlined research objectives (Jayswal, Singh, & Kurdi, 2016;

Zavadskas, Turskis, & Kildienė, 2014). Multi-criteria decision-making (MCDM) techniques need to be connected with modelling activities (Choi, Cheng, & Zhao, 2016). A decision framework, which is an integration of discrete-event simulation (DES) (Tako & Robinson, 2012), analytic hierarchy process (AHP), and data envelopment analysis (DEA) (Ahn & Novoa, 2016), is developed to find the most favourable replenishment policy and provide insights about perishable and substitutable inventory management. The performance of each replenishment policy is recorded by three measures from the DES (Law, 2014); namely, average inventory, fill rate, and order rate variance ratio. The importance of each measure is weighted from decision-makers' opinions via AHP. Then, DEA is used to evaluate and rank the performance of each replenishment policy based on its relative value. The most favourable replenishment policy is the one having the lowest DEA Cook's super-efficiency score.

1.5 Expected Research Contributions

The research is motivated by the gap in studies on inventory management for perishable and substitutable products under a two-echelon model. The decision framework is developed to explore and investigate effects of problem characteristics on the inventory model. Consequently, this research has theoretical, methodological, and managerial contributions to the study of perishable inventory management, which are summarised as follows:

- This research is the first known research using three non-financial measures (i.e., average inventory, fill rate, and order rate variance ratio) to define the most favourable replenishment policy.
- This research considers perishable and substitutable products for a two-echelon model where product lifetime follows an exponential distribution.
- This research proposes a decision framework, which integrates DES, AHP, and DEA to select the most favourable replenishment policy based on non-financial performance measures.

- This research provides understandings about relationships between consumer demand, product lifetime, and substitution ratio and three performance measures of an inventory model (i.e., average inventory, fill rate, and order rate variance ratio), also between decision-makers' opinions and the selection of the most favourable replenishment policy.

1.6 Research Structure

This research aims to investigate inventory management for perishable and substitutable products. From that perspective, this research is organised into six chapters (Figure 1.1).

Chapter 1 introduces the research topic and motivation to conduct this research. The scope of research, research objectives, research questions, and expected contributions are summarised in this chapter.

Chapter 2 provides foundation knowledge with regard to inventory management for perishable and substitutable products and identifies key issues and research problems to guide this research.

Chapter 3 outlines the research objectives and customises a methodology to address these research objectives. A decision framework, which integrates DES, AHP, and DEA, is also proposed in this chapter. A research design is described as the end of this research based on the proposed framework.

Chapter 4 describes a numerical example to illustrate how to use the proposed framework. Then, sensitivity analysis is conducted to provide more insights about the studied model.

Chapter 5 provides a discussion of research results. This discussion is based on the sensitivity analysis results in Chapter 4 and reflections on the extant literature on inventory management.

Chapter 6 provides a conclusion to this research. This chapter summarises the entire research and highlights contributions and limitations, and provides future research directions.

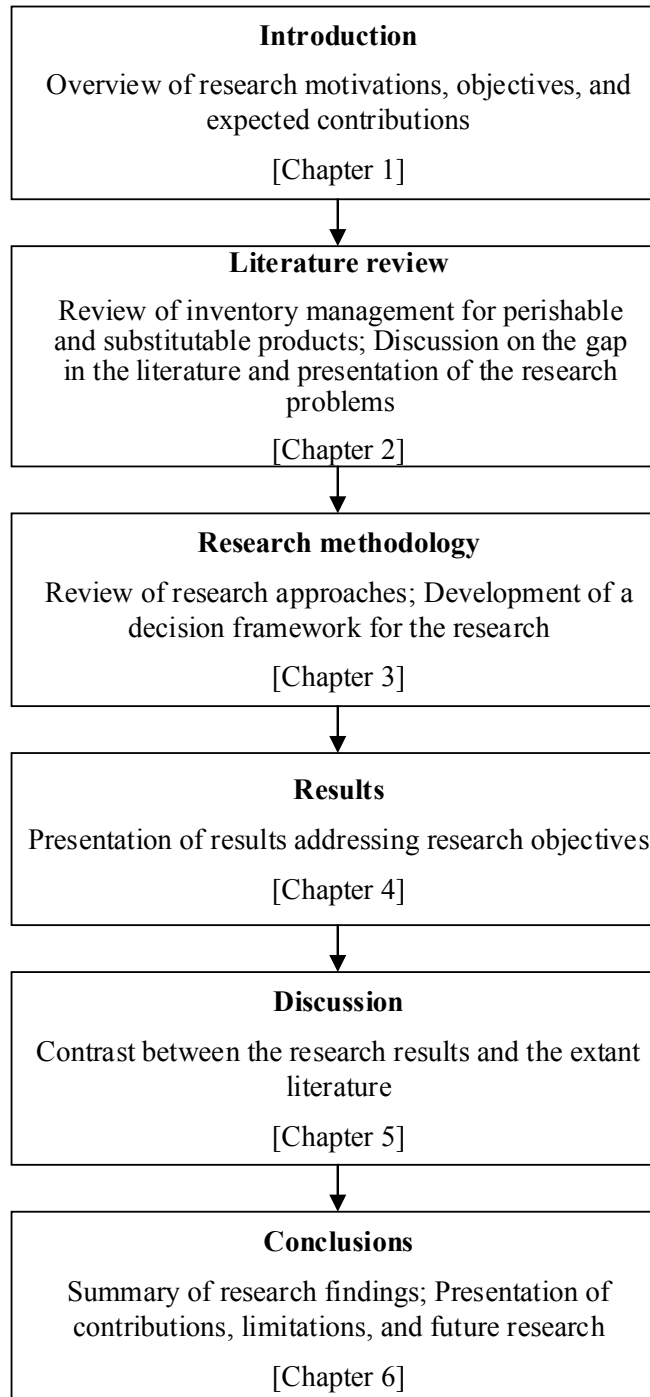


Figure 1.1: Structure of research proposal

Chapter 2 Literature Review

This section provides an overview of the literature on perishable inventory management. Concepts, summaries, and critiques of the literature define the issues, the gaps in the literature, and the research problem (Figure 2.1). To provide a broad overview, section 2.1 introduces the definitions and concepts of inventory management, whereas sections 2.2, 2.3, and 2.4 concentrate on perishability and key characteristics of perishable inventory management. Section 2.5 presents key issues relating to perishable inventory management. Then, section 2.6 specifies the gap in the literature, research objectives, and research questions.

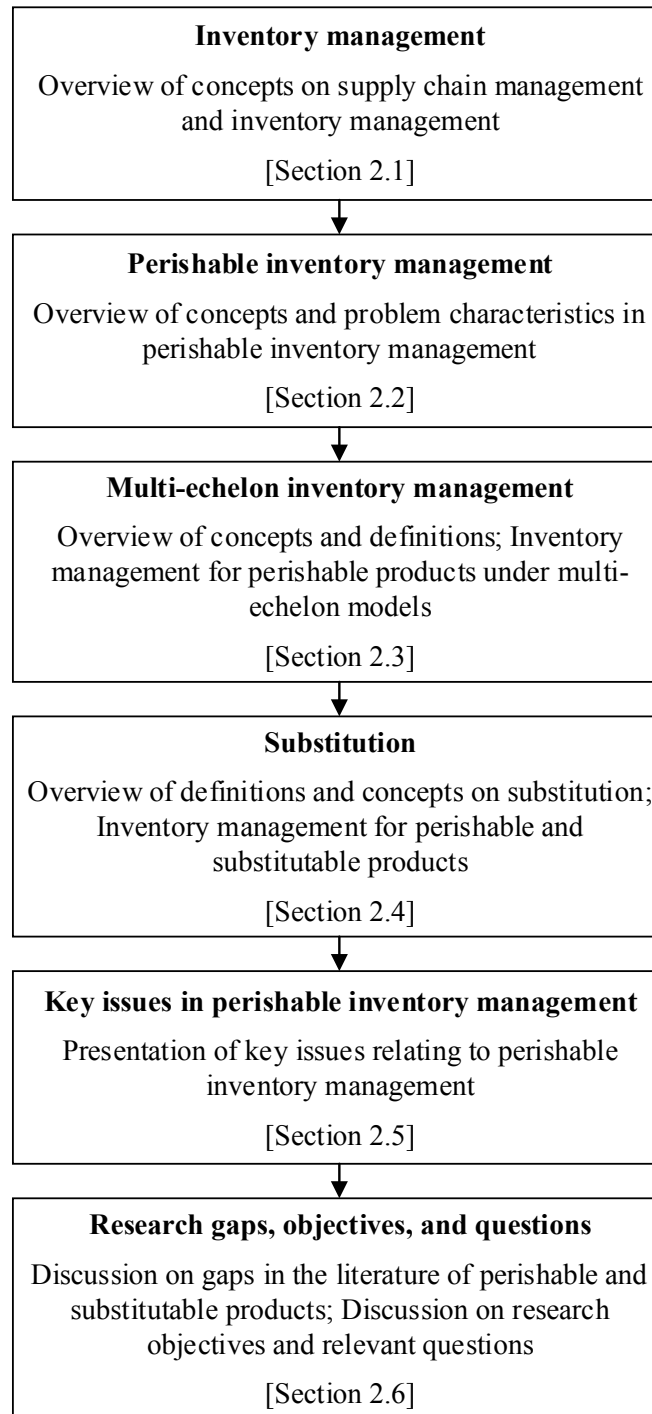


Figure 2.1: Structure of literature review

2.1 Inventory Management

In a competitive global business, most companies are competing with a high level of pressure worldwide. These companies need to develop a better method to provide high service levels

for customers at acceptable prices. Based on this strategy, the companies are now focusing on effective supply chain and inventory management. Consequently, this section provides background knowledge of supply chain and inventory management.

2.1.1 Supply chain management

In today's global market, providing products in a short time and improving customer satisfaction levels have forced companies to invest in and focus on their supply chain management (SCM) (Alftan, Kaipia, Loikkanen, & Spens, 2015). For example, a hospital needs to have enough blood to transfuse to patients as soon as possible. These things motivate companies to understand and improve supply chain management.

A supply chain model may consist of five key nodes (Govindan, Jafarian, & Nourbakhsh, 2015); namely, supplier, manufacturer, distributor, retailer, and consumer. In a typical supply chain, manufacturers buy materials from suppliers, produce finished goods from materials, and then transfer finished goods to distributors for temporary storage. The finished goods are distributed from distributors to retailers where the consumers can get what they want. The activities controlling the flow from the supplier to consumer are referred to as supply chain management.

According to Gibson, Mentzer, and Cook (2005), supply chain management is a set of activities to integrate suppliers, manufacturers, distributors, and retailers to provide the right products at the right time, to the right places with the right quantities, in order to minimise system costs with customer service level requirement.

Mentzer et al. (2001) stressed the need for coordination within the supply chain and defined supply chain management as,

the systemic, strategic *coordination* [italics added] of the traditional business functions and the tactics across these business functions within a particular company and across

businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole. (p. 18)

Supply chain management aims to maximise the overall value generated (Lee, Padmanabhan, & Whang, 1997). The value here is the difference between what the consumers pay for their products and the cost to bring these products to the consumers (Pettersson & Segerstedt, 2013). While many factors influence the performance of SCM, inventory is one of the biggest factors (Duan & Liao, 2013). Inventory management is important as it has to be kept at a trade-off level that addresses two important issues for a company (Güller, Uygun, & Noche, 2015; Gupta & Boyd, 2008):

- An inventory level must be high enough to maintain smooth production and selling activities.
- An inventory level must be low enough to minimise capital investment and enhance a company's profitability.

The next section introduces inventory management and explains how it helps to improve performance of a company's SCM.

2.1.2 Trade-off decisions in supply chain management

This research investigates inventory management – something that must satisfy two opposing objectives at the same time; that is, inventory must be high enough to cover sales activities and low enough to minimise capital investment (Güller et al., 2015; Gupta & Boyd, 2008). Thus, trade-off decisions in inventory management should be considered. This section, therefore, discusses trade-off decision making.

A trade-off can be explained as “a balance achieved between two desirable but incompatible features or as a situation where the selection of one feature results in the loss of another feature” (Luukkanen et al., 2012, p. 339). For example, maximising fill rate and minimising inventory level are two opposing objectives, as a high customer satisfaction level

requires a high inventory investment. Thus, when a decision is made based on one objective, another objective needs to be sacrificed.

Trade-off decisions have been discussed extensively in business. A company cannot often achieve two opposing objectives simultaneously. Trade-off is essential in operations and production systems, which may include production planning, impact of policies on the organisation, and supplier networks (Boyer & Lewis, 2002; Wang, Wallace, Shen, & Choi, 2015). Stevens (1989, p. 3) stated that supply chain management aims to “synchronise the requirements of the customer with the flow of material from suppliers in order to effect a balance between what are often seen as the conflicting goals of high customer service, low inventory investment and low unit cost”. The purpose of SCM is to ensure a company achieves a high customer satisfaction level at low cost. Thus, trade-off is unavoidable.

A holistic perspective, rather than optimisation in each functional area, is necessary to deal with trade-off decisions (Lambert & Cooper, 2000; Lee, 2010a), which cannot be made without information from the competitive environment and the company’s strategies (Fisher, 1997; Lee, 2002). Trade-off decisions should be assessed from strategic, tactical, and operational perspectives (Ivanov, 2010; Stevens & Johnson, 2016). The company’s objectives and policies are developed at a strategic level, which incorporates competitive priorities, and the company’s structures. Tactical decisions transform strategic objectives into specific objectives for each department and include the selection of appropriate approaches, tools, and resources. Finally, appropriate performance measures are implemented at operational levels (Stevens & Johnson, 2016).

To make trade-off decisions when having opposing objectives, decision-makers provide opinions about the weight of each objective based on information about the competitive environment and the company’s strategies (Tan & Netessine, 2014). There is a set of favourable solutions, which are non-dominated. It means no solution performs better than others in all

objectives. These solutions lie in a Pareto frontier line (Binois, Ginsbourger, & Roustant, 2015; Lou & Wang, 2016). Researchers, for example, Teimoury, Nedaei, Ansari, and Sabbaghi (2013), have suggested using multi-criteria decision-making methods (MCDM) (e.g., AHP (Saaty, 1986)) to make trade-off decisions or select the most favourable solution from the set of favourable solutions. Using these methods, decision-makers provide opinions on the importance of each objective. The objective having higher weight is more important. These weights are used to select the trade-off decision.

For example, assume that a company has to find an inventory policy satisfying two opposing objectives, namely, high customer fill rate and low inventory cost. Decision-makers need to make a trade-off decision to select the most favourable policy from five favourable policies that lie in a Pareto frontier (see Figure 2.2). Policy A has high fill rate but high inventory cost; policy E has low inventory but low fill rate. Decision-makers, based on information about the competitive environment and the company's strategies, may focus on high fill rate and put higher weight for the fill rate objective. These weights are used to select the most favourable policy.

Trade-off decisions promote a smooth flow of resources in supply chain management (Gunasekaran, Patel, & McGaughey, 2004). They minimise departmental boundaries which limit the control over the process (Leeuw, Minguela-Rata, Sabet, Boter, & Sigurðardóttir, 2016). Such decisions help in the formation of modern supply chains and improve supply chain effectiveness (Leeuw et al., 2016).

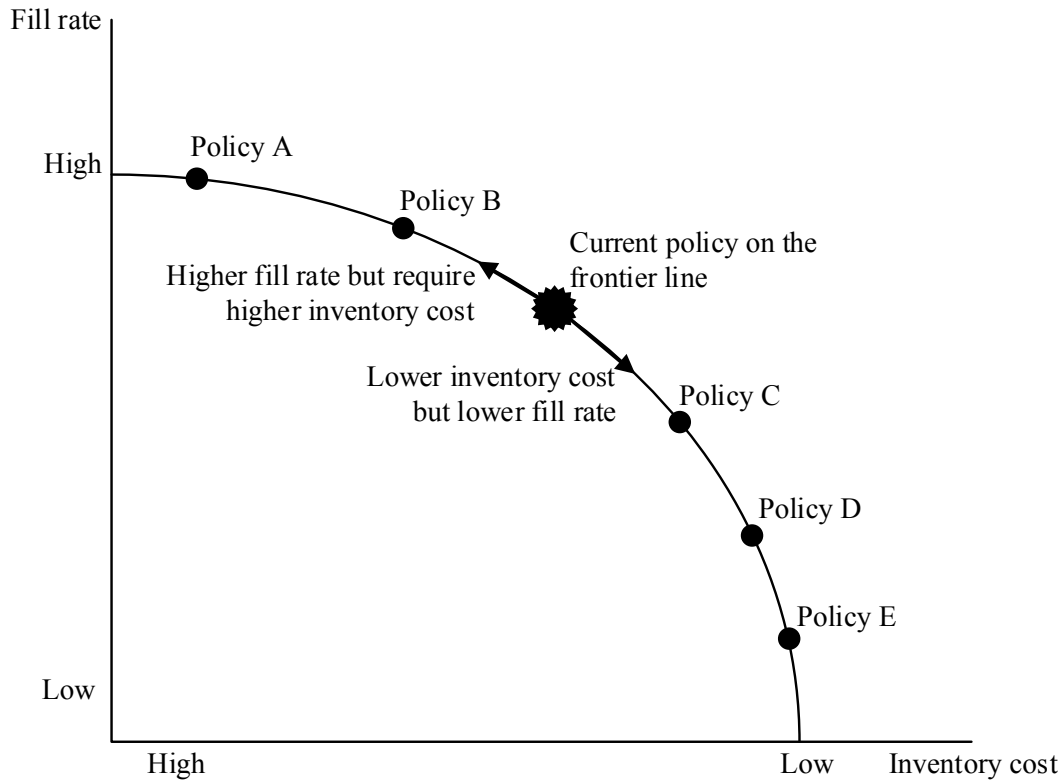


Figure 2.2: Trade-off between fill rate and inventory cost (adopted from Figure 1.2 in Cachon and Terwiesch (2009, p. 5))

Moving on the Pareto frontier to make a trade-off decision is important as it aids in evaluating compromising relationships between performance measures and provides solutions (Dixit, Seshadrinath, & Tiwari, 2016) which reflect the competitive environment and company's strategies. However, outstanding companies do not stop there. These companies may use operations management tools to redesign the current system (Gadde, 2013) and push the envelope or move the frontier to a new feasible level where performance of all objectives are better. For example, the company can invest in forecasting technology and thus improve the accuracy of forecast and fill rate (see Figure 2.3). The frontier is moved to a new level where inventory cost is lower and fill rate is higher. Unfortunately, these types of investment require time and effort (Carvalho, Barroso, Machado, Azevedo, & Cruz-Machado, 2012; Gadde, 2013). This research aims to provide more knowledge and supports managers to improve performance of inventory management.

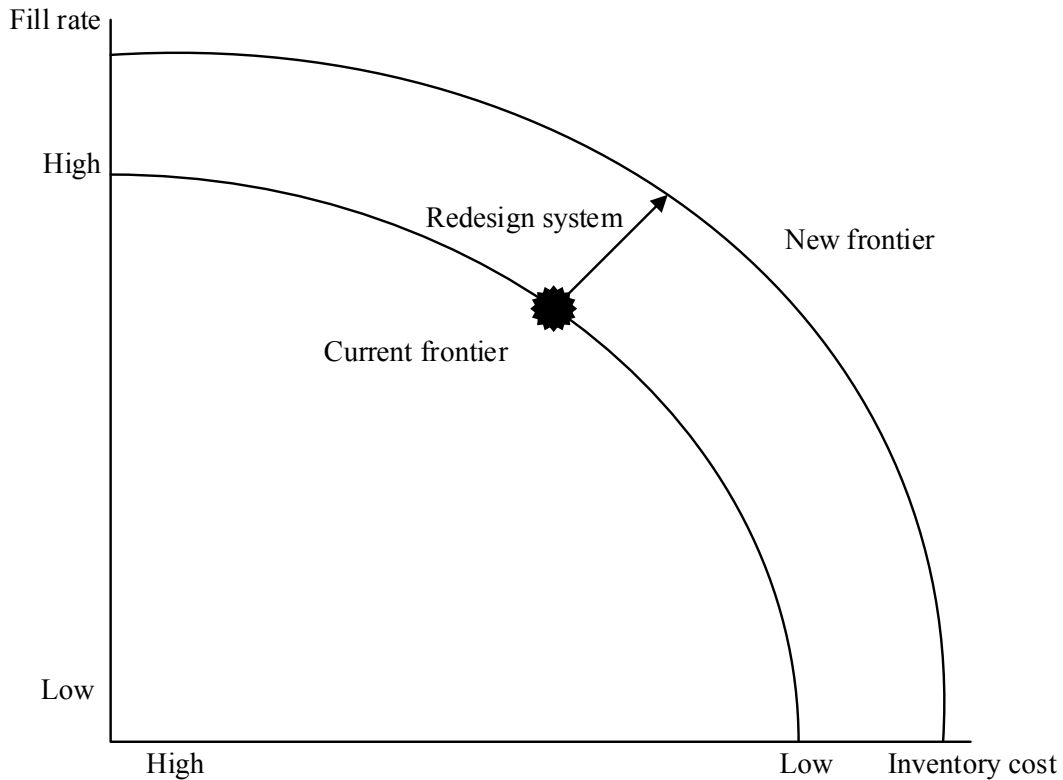


Figure 2.3: An example of a redesigned system to improve the current frontier (adopted from Figure 1.3 in Cachon and Terwiesch (2009, p. 6))

2.1.3 Inventory management objective

Inventory management happens in all nodes of the supply chain to transfer raw materials to finished products and deliver to consumers (Ventura, Valdebenito, & Golany, 2013). Inventory could be materials, work-in-process, or finished products. There are three key reasons to hold inventory. First, inventory helps to satisfy the fluctuation in consumer demand (Jung, Blau, Pekny, Reklaitis, & Eversdyk, 2004), which is affected by many factors (e.g., quality issues, natural disasters). Second, inventory helps to maintain production in case the suppliers have quality or delivery issues. Third, economic quantity in transportation encourages companies to buy more to save transportation cost.

The objective of inventory is to balance the inventory cost and the customer service level. A high inventory level easily meets customer service level requirements (Şen, 2016), but

at greater cost. For manufacturers, inventory accounts for up to 60 percent of total assets (Gümüs & Güneri, 2007). Therefore, a good replenishment policy ensures smooth production and saves costs for the companies.

2.1.4 Replenishment policy

Researchers have developed many mathematical models to find a replenishment policy, which defines time and quantity to order, to optimise the overall system value. The overall system value is usually understood as total profit (mainly in profit agencies) or total cost (mainly in non-profit agencies). These mathematical models require variables, which are the characteristics of inventory management. The main characteristics and concepts of three major replenishment policies are introduced as follows.

Consumer demand distribution: Consumer demand distribution is either deterministic or stochastic. A demand is called deterministic if it is known with certainty; for example, demand is a constant rate of time or a storeowner knows exactly how many products she sells per day. A stochastic demand is an uncertain or unknown demand; for example, a fruit storeowner does not know exactly how many oranges she sells per day. There are some main stochastic demand distributions. Researchers usually use Poisson demand distribution, which means the time interval between two demands forms a Poisson process and a demand is only a single unit per period. Figure 2.4 presents an example of statistical demand distribution which follows a normal distribution.

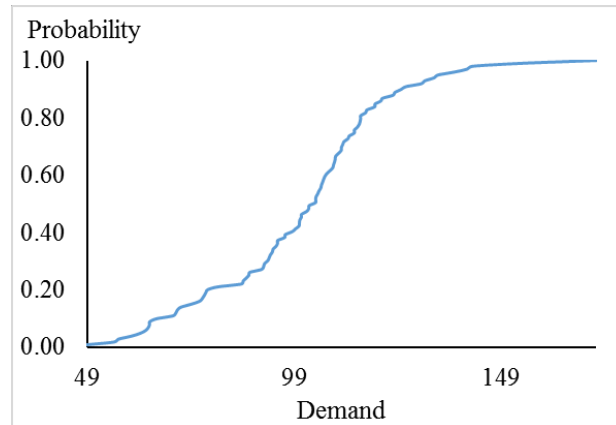


Figure 2.4: Consumer demand follows a normal distribution

Lead time: The lead time is the duration which starts at the moment a replenishment order is triggered until the moment the products arrive at the warehouse or stock point. For example, a replenishment order is triggered on 1st July and products arrive at the warehouse on 2nd July – in this case, the lead time is 1 day. Normally, for complex problems, researchers assume zero lead time. Although zero lead time is not realistic in many cases, it helps researchers understand the problems.

Stock-out situation: When the amount of stock at the warehouse does not fully meet the customer's demand, it is a stock-out or an out-of-stock situation. In this case, it is either a "lost sales" or a "back order" situation (these two terms are frequently used interchangeably). If a customer waits until she can buy the product, it is a "back order" or "back log" situation. Alternatively, if the customer does not agree to wait, it is a "lost sales" situation. For instance, a mobile phone shop runs out of iPhone 5 stock; in a back order situation, a customer waits until new iPhone 5 stock is delivered to the shop and buys it. Alternatively, in a lost sales situation, the customer can buy at another shop or buy another phone.

Inventory on hand: Inventory on hand is the stock that is currently in the warehouse and can be delivered immediately to the customers.

Stock in transit: Stock in transit is stock that has already been ordered, but has not arrived at the warehouse yet. Stock in transit means that the lead time is positive.

Inventory position or inventory level: Inventory position is the stock level, which includes the inventory on hand and stock in transit minus the back order. The inventory management system is usually based on the inventory position rather than on the inventory on hand. The reason is if a replenishment order is based on the inventory on hand, an order is placed once the inventory on hand reaches a predetermined point. Moreover, if the lead time is positive, the order takes time to arrive at the warehouse. During this period, the inventory on hand is unchanged and the replenishment order continues to trigger. This error is avoidable if the replenishment order is based on the inventory position.

Planning horizon: Planning horizon is the period of time in which inventory decisions optimise the performance of the inventory. It could be one-period, multi-period, or infinite planning.

Cost: Researchers are usually concerned about three types of cost in inventory management: holding cost, ordering cost, and back order cost.

Holding cost: Holding cost is incurred to keep the products in the warehouse. It could be assets cost (e.g., warehouse, forklift), insurance cost, and storage cost (e.g., power, labour, maintenance).

Ordering cost: Ordering cost is incurred each time an order is placed. It could be administration cost or transportation cost.

Stock-out cost: Stock-out cost is incurred in a stock-out situation. The reasons for the cost vary: in a back order situation, cost can be incurred when ordering more products, handling products, and paying for overtime labour; in a lost sales situation, costs can be incurred through loss of customers or ensuring customer satisfaction.

The next questions are when a replenishment order is triggered and how much to order. An inventory policy answers these two questions. There are three major replenishment policies: namely, economic order quantity (EOQ), periodic review, and continuous review. While EOQ

policy is usually used in problems with deterministic demand, the period review and continuous review are used in problems with a stochastic demand (Pahl & Voß, 2014). The following paragraphs introduce the formula and the usage of each policy.

Economic order quantity (EOQ) was first introduced by Ford W. Harris in 1913 (Harris, 1990). The EOQ policy minimises the total ordering cost and holding cost under a set of assumptions in order to choose an optimal order quantity. Researchers and practitioners have relaxed these assumptions to better match EOQ policy with real problems. The EOQ policy is an important part of the history of operations management. Many courses that cover inventory management introduce the EOQ policy. It is as an effective means of informing students and practitioners of the trade-off of costs in inventory management. In this research, the best trade-off replenishment policy is regarded as a policy that best balances all opposing objectives.

The assumptions underlying EOQ policy are as follows:

- Demand, D , is deterministic and constant over time.
- The unit cost of product, p , is predetermined and fixed during the planning horizon.
- Lead time, L , is known and fixed.
- The ordering cost, S , is fixed.
- The holding cost rate, h , is fixed. The total holding cost per unit, H , is calculated as $H = h \cdot p$
- No stock-out situation is allowed.
- No capacity limitation for suppliers and buyers.

From those assumptions, the EOQ policy defines the optimal order quantity, Q^* , which minimises the total ordering and holding cost. Figure 2.5 illustrates how the EOQ policy runs with optimal order quantity, constant demand rate, reorder point, and lead time.

The optimal order quantity is calculated as: $Q^* = \sqrt{\frac{2DS}{H}}$

The total cost, TC, is defined as: $TC = \frac{SD}{Q^*} + \frac{HQ^*}{2}$

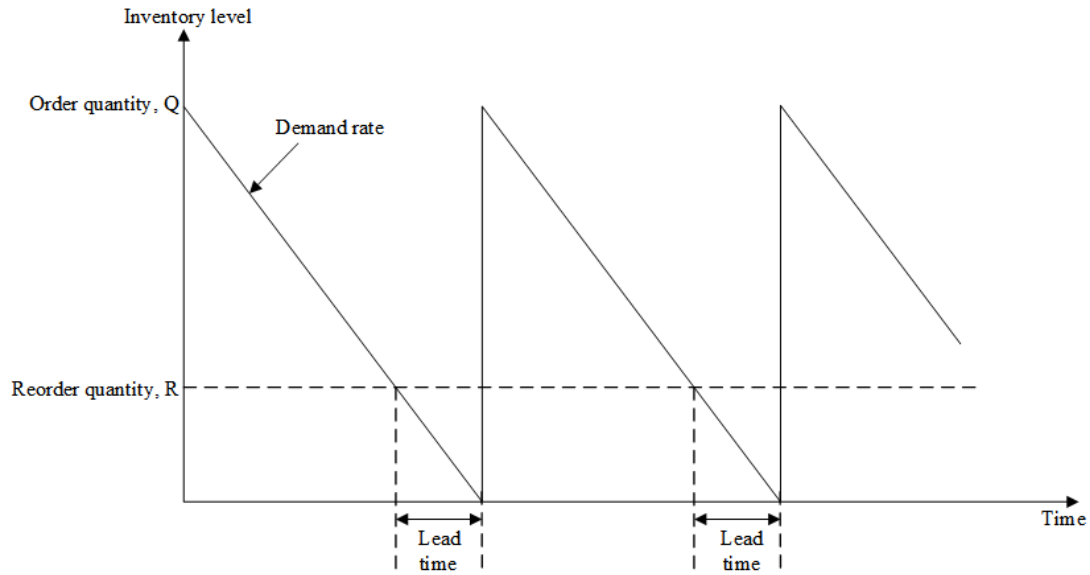


Figure 2.5: The EOQ policy with optimal order quantity, constant demand rate, reorder point and lead time

The assumptions of the EOQ policy illustrate that the policy is only used in very few cases in real business. The criticisms are because it is difficult to estimate exactly the cost and the demand in real business. EOQ policy considers items independently or there are other costs in inventory management, for example, destroyed cost.

The criticisms are right; however, EOQ policy is still often used in practice for a number of major reasons (Jaber, Zanoni, & Zavanella, 2014). First, EOQ policy provides a robust solution. The total cost function is relatively smooth nearby the optimal value. Therefore, the results from EOQ policy are acceptable. Second, not all products have the same importance level for firms. Firms can decide to apply EOQ for unimportant products and use superior policies to control important products. Third, practitioners should understand that EOQ policy provides a guideline to balance ordering cost and holding cost, it does not provide a must order quantity (Choi, 2014). Recognising the advantages and disadvantages of EOQ policy, researchers have spent a century relaxing the assumptions of EOQ policy to better address real business cases.

Continuous review: In this policy, the inventory position is checked continuously. Contemporary development of automated identification technology (e.g., Radio Frequency Identification (RFID), point of sales scanners) simplifies implementation and use of continuous review models in practice (Jones & Garza, 2011). The continuous review policy enables quick action to support the superior customer service level. van Donselaar and Broekmeulen (2014) stated that continuous review policy needs less safety stock than the other policies do, but the continuous review policy needs a complex calculation. There are some major continuous review policies that include the following:

- (s, S) : when the inventory reaches the level s (a ‘trigger’ level), an order is placed to bring the order back to the predetermined level S (the ‘target’ level); the order size is quantity $(S - s)$. This model provides significant flexibility.
- (s, nQ) or (r, nQ) : whenever the inventory reaches level s or r , an order quantity n times a predetermined Q (order quantity) is placed where n is a multiple equal to or greater than 1. This accommodates ordering in batches.
- $(S - I, S)$: in this model, whenever the inventory decreases by one unit because of the demand or because of loss of stock, an order is placed to bring the level to S . This model is preferred when lead times are zero and ordering cost is low.

Periodic review: A periodic review policy assumes that the inventory position or inventory level is checked periodically; for example, the inventory position is checked 2-day, 3-day, or weekly. Then, the order quantity varies based on the inventory position at the review time. The periodic review policy can save the administration ordering cost; however, the danger is if there is an unexpected variation in inventory position, a new replenishment quantity is only ordered at the review time. There are several main periodic review policies:

- (T, s, S) : every period T , the inventory position is checked, and an order quantity $Q = S - s$ is placed if the inventory position reaches level s . This policy is equivalent to the (s, S) policy but requires that the order quantity may vary in any amount.
- (T, s, Q) : every period T , the inventory position is checked, and a predetermined order quantity Q is placed if the inventory position reaches level s . This policy is also referred to as (T, s, nQ) where the order quantity is equal to n times a predetermined Q . This policy is equivalent to the (s, nQ) policy.
- (T, S) : every period T , the inventory position is checked and an order quantity $S -$ inventory position is placed. This policy is equivalent to the (T, s, S) policy, but it does not have the ability to skip a replenishment order in cases of low demand during the review period.

2.2 Perishable Inventory Management

One of the common assumptions of the inventory management is that product has an infinite lifetime. However, certain types of products perish in storage so that they may be partially or entirely inappropriate for consumption. For example, fresh meats become unusable after a period of time. This section focuses on the inventory management for this types of products.

2.2.1 Perishability

Products with a finite lifetime that are subject to perishability require careful management. Outdated products must be re-worked or disposed of, requiring time and cost. This problem is significant in the food or healthcare industries where the products easily lose their value during manufacturing, storage or distribution; for example, one-third of food products for humans are lost (Gustavsson, Cederberg, Sonesson, Van Otterdijk, & Meybeck, 2011). In developing countries, more than 40% of food products are lost during manufacturing and in industrialised countries, more than 40% of food products are lost by retailers and consumers (Gustavsson et

al., 2011). Perishability affects inventory management due to variation in demand distribution, lifetime, or consumer behaviour. Particularly, effective management reduces wastage and increases the opportunities to deliver the products to more customers.

Goyal and Giri (2001) classified products that decrease in value over time into two classes. First, ‘obsolescence’ refers to products that lose value because of changes in technology or the introduction of new products (e.g., high-tech products) which lessen the value of existing stock.

Second, ‘deterioration’ (e.g., meat) relates to products that lose value because of damage, spoilage, or other decreases in value over time. This classification encompasses inventories including foodstuffs and human blood supplies; these are referred to as ‘perishable’ products and have expiry dates. Other products are ‘decaying’ (e.g., gasoline) as, while having no expiration date, their quality decreases during storage. Pahl and Voß (2014) observed that most researchers use the terms deterioration and perishability interchangeably. Henceforth, to simplify discussions the term perishability is used synonymously with deterioration. Once perishable products expire, they are partially or completely without value. Figure 2.6 depicts three types of perishable products. Figure 2.6(a) shows a perishable product with a fixed expiry date – the value of product immediately becomes zero after the expiry date. Figure 2.6(b) shows a product with a discrete perished rate while Figure 2.6(c) shows a continuous perished rate.

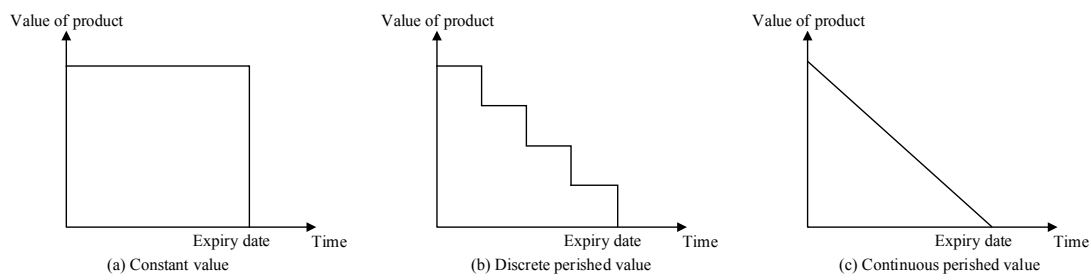


Figure 2.6: Three types of perishable products

Inventory management models for perishable products are different and affected by the characteristics of the models, for example, demand distribution, lifetime, or lead time. The

following sections review the accommodation of these characteristics of inventory management models.

2.2.2 Consumer demand

This section reviews demand distribution used in an inventory management model for perishable products. It covers both deterministic (e.g., constant rate) and stochastic demands (e.g., Poisson, compound Poisson, or renewal distribution) (O'Neil, Zhao, Sun, & Wei, 2016). The review shows that a stochastic demand is usually used as real data but is not always reliable and available (Giannoccaro, Pontrandolfo, & Scozzi, 2003) though it makes problems more complicated. Another reason for using a stochastic demand is that managers usually implement forecast techniques (e.g., Du, Leung, Zhang, & Lai, 2013) or sales plans to manage demand (e.g., Ho, Savin, & Terwiesch, 2002). Due to the complexity of a stochastic demand, the approximation approach (method to find nearby optimal solutions) is mainly used to find the inventory policy. When demand is deterministic, researchers usually use the EOQ model, while the continuous or periodic review model is often used for a stochastic demand (Pahl & Voß, 2014).

As mentioned in the discussion on demand characteristics (see section 2.1.4), the EOQ model has been used mainly when demand is deterministic. Giri, Goswami, and Chaudhuri (1996) developed an EOQ model for perishable products with a deterministic demand rate that varies with time. This type of demand is usually observed in some products like electronic components, clothes, for example, Giri et al. (1996) suggested that to relax demand rate such as demand depends on inventory level for further efforts. In fact, the assumption of deterministic demand simplifies the problem but has limited application, as it is uncommon to be able to predict exact demand in real situations.

In the case of a stochastic demand, the continuous review and periodic review model are often used (Pahl & Voß, 2014). The common assumption is demand follows a Poisson

distribution (one unit demand per time), which is suitable for a low level of demand (Cattani, Jacobs, & Schoenfelder, 2011), Kalpakam and Arivarignan (1988) proposed an approximation approach for a continuous review (s, S) inventory system. Vaughan (1994) modelled a periodic review (T, S) for perishable items with Poisson demand and a random lifetime. Kalpakam and Arivarignan (1988) and Vaughan (1994) used the approximation method to deal with the complexity of the models. The models with Poisson demand have several applications; for example, the models highlight the importance of product freshness and recognise that it is a controllable factor.

However, a company rarely faces a demand that has one unit per time only. This real business situation limits the practical utility of a model with Poisson demand and leads to the development of models with other types of demand to better describe the business reality (Nahmias, 2011). One of the other demand types is compound Poisson demand distribution, where the interval time between two demands is a Poisson distribution and the demand size is an exponential distribution. The compound Poisson demand distribution is more realistic than other types of demand distributions because in each planning period, the demand size can exceed a single unit (Matheus & Gelders, 2000); for example, it allows a description of a consumer who buys two or three bottles of water rather than one bottle per time. Baron and Berman (2010) assumed compound Poisson demand and zero lead time, and considered a continuous review (s, S) model to approximate an optimal ordering model. The compound Poisson demand type has dominated the literature due to its simplicity, its use of a standard distribution, and its ability to model fast moving products (e.g., grocery products) (Babai, Jemai, & Dallery, 2011).

Another type of demand distribution is renewal distribution which has been used when the times between two successive demands are independent and identically distributed. Kalpakam and Sapna (1996) presented the use of Markov renewal techniques to solve complex

problems relating to perishable inventory with renewal demands, exponential lead time, and a constant deterioration rate. Liu and Lian (1999) extended the works of Weiss (1980) to construct a renewal demand process. Lian, Liu, and Zhao (2009) further extended these works by incorporating a Markovian renewal demand model where the inter-demand time is generally distributed. Lian et al. (2009) concluded that an optimal ordering model is possible, although their results were achieved using approximation only.

The selection of appropriate inventory management models for perishable products depends on the demand characteristics of the problem. Nahmias (1982) observed that for perishable inventory management, the optimal ordering problem is difficult to achieve when demand is random. This observation is reconfirmed by the papers reviewed above, in which the authors only use the approximation approach to find the inventory policy. The approximation approach is used because when demand is stochastic and the product lifetime is more than one period, no replenishment model can be obtained to exclude or avoid the loss of inventory due to perishability (Nahmias, 2011). The mathematical model for this problem becomes complex because it has to contain the inventory position of each possible age group. Therefore, researchers have tended to focus on finding near optimal solutions or approximation of the optimal solution (Ardestani-Jaafari & Delage, 2016; Lowalekar, Nilakantan, & Ravichandran, 2016). Nahmias (1982) review also highlighted many assumptions that are still being extended now – for example, demand distribution, lead time and lifetime distribution, or multiple products to reflect realistic situations.

2.2.3 Product lifetime

The product lifetime is one of the major factors that impact the perishable inventory management systems (Karaesmen et al., 2011). Product lifetime can be classified into two types of product lifetime: a constant (i.e., the products can expire after a fixed period) or a stochastic lifetime (i.e., the products can expire at any time) (Kouki, Jemaï, & Minner, 2015). In a constant

lifetime, the newsvendor model (i.e., the products expire at the end of the planning period) is commonly used for its ability to simplify the problem (Nahmias, 2011). A classical newsvendor model reflects a newspaper shop where the shop owner must decide how many newspapers to order at the beginning of each day. When the product lifetime is stochastic, the problem becomes complicated as it requires many variables to track different age categories in inventory (Nahmias, 2011). In general, inventory models for perishable products are more complex than for non-perishable products because the models must be expanded with more variables (Liu & Yang, 1999).

Normally, the newsvendor problem is a basic problem and has been extended to many problems in different ways (e.g., Dai & Jerath, 2013). Pasternack and Drezner (1991) developed an order-up-to level model for two newsvendor products. The model shows that the relationship between two newsvendor products impacts on the order-up-to level received. Khouja (1999) reviewed the literature on the inventory management model for newsvendor products and suggested extending the newsvendor model to consider inventory models for multi-products and the relationship between these products.

For problems with a stochastic lifetime, the most common assumption is that the product lifetime follows an exponential distribution (Kouki & Jouini, 2015). Olsson and Tydesjö (2010) proved that a stochastic lifetime makes problems more complex because the Markovian property cannot be used to describe the stock on hand. Kouki, Sahin, Jemaï, and Dallery (2013) compared and verified the effectiveness of existing (r, Q) inventory systems for perishable items with a fixed lifetime and lead time. They also noted that the perishable problem under either the continuous or periodic review system is complex. Despite this complexity, accommodating a finite lifetime is important and Gürler and Özkaya (2008) demonstrated that accounting for a stochastic lifetime can reduce the total operations cost. Therefore, to reduce the complexity of the problem, most researchers have tended to assume

that the products have a stochastic lifetime and newly arrived products are fresh. There is a tendency towards heuristic approaches and providing approximate results as this can help overcome the problem's complexity.

2.2.4 Stock issuing model

The products are kept in the warehouse until they are issued to the customers. The way that the products are picked up and issued to customers is called stock issuing policy (Haijema, 2014; Lowalekar et al., 2016). Two major stock issuing policies in inventory management are First-In-First-Out (FIFO) and Last-In-First-Out (LIFO). In FIFO, the product that arrives in the warehouse first is then delivered to customers in the order of arrival; in LIFO, the product that has most recently arrived in the warehouse is delivered to customers first.

Haijema (2014) compared the FIFO versus LIFO issuing policies for perishable products. Assume that the lifetime of a product starts only when the product arrives in the warehouse or the products that are produced first, are delivered to the warehouse first. If consumers select products themselves, LIFO is a common example of consumer behaviour, in that most consumers prefer the freshest products that have the longest use-by-date. Store managers may put the oldest product upfront to change this selection behaviour. If consumers do not select products themselves, managers usually issue products following FIFO policy as it decreases the amount of expired products. However, although the FIFO policy seems to minimise inventory cost, when considering other factors such as pricing for fresh products or discount price for old products, the FIFO policy may not be cost beneficial (Haijema, 2014). Parlar, Perry, and Stadje (2011) conducted a comprehensive comparison between FIFO and LIFO for perishable products. They found that FIFO policy dominates LIFO policy in most situations. However, when the unit revenue increases, the difference between FIFO and LIFO decreases. Moreover, when the holding cost is high or the ordering cost is low, the LIFO policy dominates the FIFO policy.

2.2.5 Lead time

Incorporation of lead time in the inventory management models for perishable products makes the problem difficult as products age when in stock or while on order (Haijema & Minner, in press). The other difficulty is the outstanding number of orders during lead time (de Treville et al., 2014). The researchers assume lead time is zero (i.e., products are delivered immediately on order) to remove these challenges. Examples of problems with zero lead time are found in Liu (1990) who considered a Poisson demand process and exponential lifetime, zero lead time and minimised the total cost function under a (s, S) system. The assumption of zero lead time simplifies the problem. However, zero lead time does not usually happen in real business. Therefore, researchers tend to study problems with positive lead time.

Zero lead time is usually assumed to make the models more tractable and easier to examine, for example, to examine a new distribution of demand. When lead time is zero, the inventory position is added immediately whenever an order is placed, and there is no outstanding order during the review period. Later on, the assumption of zero lead time is relaxed to make the problem more realistic (Alizadeh et al., 2014; Schildbach & Morari, 2016). For example, Pauls-Worm, Hendrix, Haijema, and van der Vorst (2014) assumed zero lead time to examine replenishment policy for perishable products with non-stationary demand and service level constraints. Later, Pauls-Worm, Hendrix, Alcoba, and Haijema (in press) extended their previous work and studied a practical problem with long lead time. To overcome the complexities of positive lead time, Pauls-Worm et al. (in press) selected a different replenishment policy from Pauls-Worm et al. (2014).

While using a positive lead time increases the relevance of the perishable inventory model, it also becomes complex (Sazvar, Baboli, & Akbari Jokar, 2013). Early studies included the examination by Ravichandran (1995) of a single perishable item with Poisson demand, and deterministic positive lead time and lifetime under the (s, S) continuous review system. This

case demonstrates that when realistic assumptions (e.g., positive lead time and deterministic lifetime) are used, the model becomes difficult to solve. Kalpakam and Sapna (1994), followed by Liu and Yang (1999), analysed an (s, S) perishable system with Poisson demands and exponentially distribution lead time for items with exponential lifetimes. Williams and Patuwo (2004) analysed the relationship amongst positive lead time, ordering cost, holding cost, and the ordering quantity for products with a two-period lifetime. Kouki et al. (2014) considered a periodic review (T, S) for perishable products with exponential distribution lifetime and constant lead time. Because of the complexity of these problems, Kalpakam and Sapna (1994) and Kouki et al. (2014) conducted extensive numerical computations and suggested using simulation to study the impact of lead time. It is clear that perishable inventory systems with positive lead time are complex problems when stochastic elements are introduced; this has led to most researchers using approximation of optimal results or simulation.

2.3 Multi-echelon Inventory Management

A supply chain model involves many firms at different levels or stages (i.e., echelons or nodes) of the chain; namely, suppliers, manufacturers, distributors, retailers, or consumers (Govindan et al., 2015). Some of these nodes may share a common ownership and have a relationship in making decisions. Understanding the relationship in calculating inventory policy is the essence of studying a multi-echelon model.

2.3.1 Definition of a multi-echelon model

Supply chain management activities are often considered as either a single-echelon or a multi-echelon model (Figure 2.7), each of which is distinctly different. The single-echelon model is defined as the case in which the inventory management model at a node is decided independently at each node or ignores the interrelationship among nodes; for example, in

Figure 2.7, the single-echelon is the case in which retailers decide their inventory management model independently with distributors and customers.

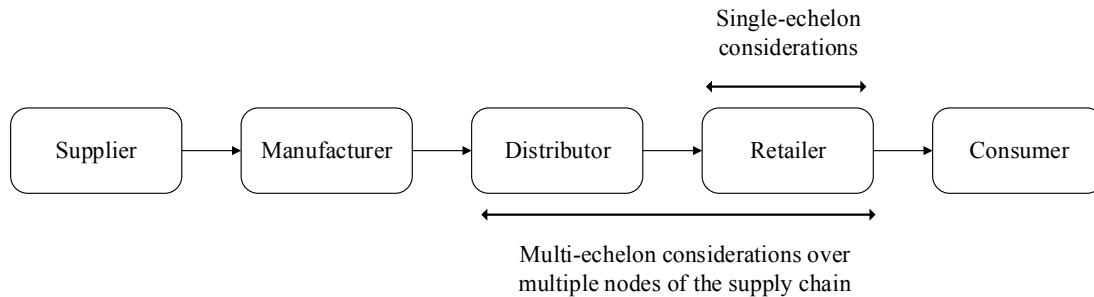


Figure 2.7: A basic supply chain model showing the scope of considerations for both single- and multi-echelon supply chain models

The multi-echelon model is where supply chain decisions are made for outcomes over multiple echelons of the supply chain simultaneously. In this model, the supply chain is considered as a system, with the results based on optimisation of system performance rather than for a specific echelon. The integrated inventory policy in a multi-echelon model reduces the cost compared with policies based on single-echelons (Yang & Wee, 2002).

A multi-echelon model increases significantly the complexity of the inventory management (Arts & Kiesmüller, 2013). In a single-echelon, all the inventory management decisions are under the control of a single node such as the manufacturer or distributor. Instead of considering inventory level on its own, in a multi-echelon model, the control nodes must pay attention to the inventory at other nodes. To simplify and standardise procedures in a complex model, it is advisable to adopt the same inventory policy for all products and all members in supply chain network if that is possible (Nenes, Panagiotidou, & Tagaras, 2010).

The market today is more competitive than ever before. The changes such as technological changes or globalisation push the companies' performance. To help companies succeed in today's market, managers must focus on the integration/coordination of activities between echelons along the supply chain (Fawcett & Magnan, 2002). Recent research from Flynn, Huo, and Zhao (2010) empirically demonstrated that supply chain integration positively

relates to operational performance. Therefore, it is necessary to pay attention to integration in supply chain management.

The purpose of the multi-echelon model is to deliver products to the end users with the highest customer service level at minimum total network inventory cost (Bushuev, Guiffrida, Jaber, & Khan, 2015). There are two major questions to consider in a multi-echelon model: how much should be kept and how to replenish at each node to minimise the total cost with a predetermined customer service level (Pazhani, Ventura, & Mendoza, 2016). The following sections review common phenomena in the multi-echelon model and state-of-the-art inventory management under a multi-echelon model for perishable products.

2.3.2 Bullwhip effect

The bullwhip effect is one of most commonly investigated phenomena in the multi-echelon supply chain model (Nepal, Murat, & Chinnam, 2012). The bullwhip effect phenomenon is defined as the amplification of demand variation in the supply chain model (Lee et al., 1997). It can be understood as an increasing trend in the replenishment quantities reflecting true demand (Nepal et al., 2012) when moving upstream in the supply chain network. Figure 2.8 shows an example where the demand variability amplifies from the lowest node (i.e., the consumer) to the highest node (i.e., the supplier). Consequently, ordered quantities placed by an upstream node have a higher variability comparing to ordered quantities placed by a downstream node (Chatfield, 2013), which causes undesirable effects – for example, stock-outs and high inventory costs (Adenso-Díaz, Moreno, Gutiérrez, & Lozano, 2012; Chatfield & Pritchard, 2013).

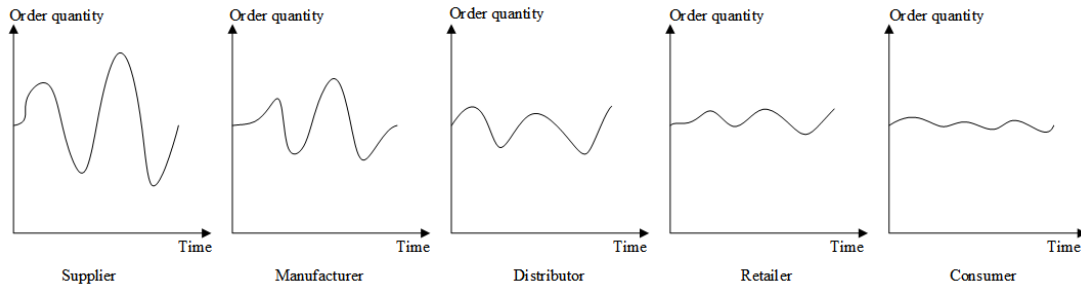


Figure 2.8: An example of the bullwhip effect phenomenon whereby order quantity becomes more variable upstream in the supply chain

The bullwhip effect is applicable for individual companies facing demand uncertainty and for the entire supply chain network (Zotteri, 2013). The global economic recession of 2008 created a bullwhip effect around the world (Cannella, Ashayeri, Miranda, & Bruccoleri, 2014; Lee, 2010b). For example, consumer demand decreased 8% while product shipment declined 10% and chip sales declined 20% in the last quarter of the recession in the US. These data proved that retailers, wholesalers, and manufacturers responded differently to the falloff in consumer demand (Dooley, Yan, Mohan, & Gopalakrishnan, 2010).

The bullwhip effect is a common phenomenon as uncertainty is ever-present in supply chains; it may be initiated due to variance in material quality or delivery dates. It also originates due to lack of information from consumers to suppliers. The uncertainty is important, as uncertainty does not exist in isolation. When a given echelon faces uncertainty, the uncertainty facing other echelons may be amplified or lessened based on the supply chain structure (Flynn, Koufteros, & Lu, 2016). The following sections review different types of supply chain structures.

2.3.3 Serial and divergent supply chain model

As the bullwhip effect is one of the main problems in improving the performance of a supply chain model. It has been received a great deal of attention from researchers and practitioners to better understand causes, consequences, and solutions to the bullwhip effect (Li, 2013). Several assumptions have been made in order to analyse the bullwhip effect due to complexities

under a real business environment (Chatfield & Pritchard, 2013). As well as assumptions concerning the number of products, lead times, capacity constraints and so on, the structure of the supply chain model is another important assumption.

The serial structure is one of the most common assumptions to simplify the real problems (Chatfield & Pritchard, 2013). This means that each node in the model has a single successor and a single predecessor node. Although the serial structure model is rarely verified in real business, it provides a powerful technique to study the bullwhip effect (Bhattacharya & Bandyopadhyay, 2011; Nienhaus, Ziegenbein, & Schoensleben, 2006). The main reason for the dominance of the serial structure model is perhaps due to the complexities and mathematical intractability of multi-echelon models (Hwarng, Chong, Xie, & Burgess, 2005; Long, Lin, & Sun, 2011).

Nowadays, the challenges in supply chain management are rising, including visibility risk and turbulence (Butner, 2010; Christopher & Holweg, 2011; Stank, Dittmann, & Autry, 2011). These challenges call for more realistic models to analyse the complexities of the supply chain networks. Thus, it is necessary to study supply chain structures where one echelon has more than one member (Ma, Wang, Che, Huang, & Xu, 2013).

The divergent structure model considers more than one member at one echelon (Beamon & Chen, 2001). This structure is similar to a tree-like structure where every member in the model receives supply from exactly one member at a higher echelon but can supply to more than one member at a lower echelon (Hwarng et al., 2005). Figure 2.9 presents examples of serial and divergent supply chain networks with four nodes: supplier, manufacturer, distributor, and retailer.

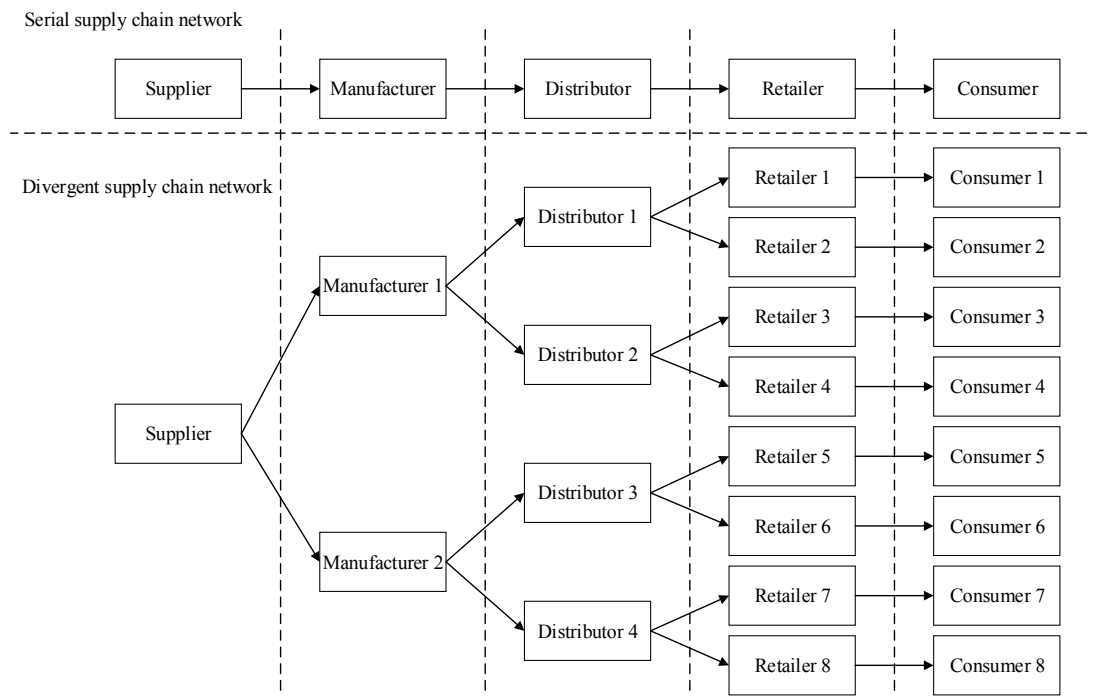


Figure 2.9: Serial and divergent supply chain networks (adopted from Figure 2 in Framinan and Dominguez (2014, p. 2198))

Framinan and Dominguez (2014) compared the bullwhip effect under serial and divergent structures. The results showed that the bullwhip effect is similar under these two structures. The main reason for the lack of research on divergent structure is its complexity. However, this may be overcome by using advanced operational research tools such as simulation (Chan & Prakash, 2012). Considering that divergent structure is commonly adopted in the real business environment, it is worth undertaking more research on this structure.

There are three other supply chain structures besides serial and divergent structures as mentioned in Huang, Lau, and Mak (2003). The convergent structure represents a situation where components provided by suppliers are assembled by a manufacturer. The dyadic structure considers two members, while the network structure combines the convergent and divergent structures.

Huang et al. (2003) reviewed research in all these five supply chain structures. The dyadic structure is often investigated by mathematical modelling (Fattahi, Mahootchi, Moattar

Husseini, Keyvanshokoo, & Alborzi, 2014). The works related to convergent and network structures are fewer, due to the complex characteristics of these two structures. Additionally, as the dyadic structure is easily extended to the divergent supply chain model (Soosay & Hyland, 2015), the number of works related to the divergent structure have started to increase (Montoya-Torres & Ortiz-Vargas, 2014).

2.3.4 Centralised and decentralised supply chain models

Bhattacharya and Bandyopadhyay (2011) identified a total of 19 operational and behavioural causes of the bullwhip effect, and the root of all 19 causes is the lack of coordination among members in the supply chain network. A supply chain network may include suppliers, manufacturers, distributors, and retailers. Decisions or activities in a supply chain network are usually spread over multiple members and function areas (Singh & O'Keefe, 2016) and are driven by consumer demand (Beamon, 1998). Therefore, it is important to have coordination in a supply chain network (Kaur, Kanda, & Deshmukh, 2008). Simatupang and Sridharan (2002) defined coordination as two or more members working jointly towards common objectives. Lack of coordination results in poor performance (Berling & Marklund, 2014), for example, excessive inventory and a low customer satisfaction level (Ramdas & Spekman, 2000). In contrast, Stadtler (2005) showed that coordination improves efficiency and reduces cost among members of the supply chain network.

Members in a supply chain network can make decisions in a centralised or a decentralised structure. In a centralised structure, a centre takes responsibilities for making decisions, while in a decentralised structure, each member make their own decisions. The crucial and succinct distinction between these two structures is stated as follows:

Centralized control means that decisions on how much and when to produce are made centrally, based on material and demand status of the entire system. Decentralized

control, on the other hand, refers to cases where each individual unit in the supply chain makes decisions based on local information. (Lee & Billington, 1993, pp. 835-836)

The centralised structure is beneficial for whole supply chain, for example, cost reductions or service level improvements (Çelebi, 2015) or forecast accuracy improvements (Alftan et al., 2015; Parida, Kumar, Galar, & Stenström, 2015; Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). Duan and Liao (2013) studied optimal replenishment policy of capacitated supply chain models under centralised and decentralised structures. To deal with the complexity of problems, Duan and Liao (2013) used a simulation framework. The results showed that the centralised structure has more benefits to the supply chain model. Compared to the decentralised structure, the inventory cost is lower and the service level is higher under the centralised structure.

However, the centralised structure has three main challenges; namely, the structure is large and complex, it is impossible to incorporate the behaviour of independent members, and it is impossible to handle conflicting objectives of different members (Thomas, Krishnamoorthy, Venkateswaran, & Singh, 2016). The centralised structure is sometimes impossible as members could be competitors, for example, competitive retailers (Rached, Bahroun, & Campagne, in press). Therefore, the decentralised structure has been developed to overcome disadvantages of the centralised structure (Thomas et al., 2016).

Due to its simplicity, it is not unusual to study the decentralised supply chain structure (Calvete, Galé, & Iranzo, 2014). In the decentralised structure, decisions are made based on local incentives and perspectives (Geunes, Romeijn, & van den Heuvel, 2016). Thus, decisions in a decentralised structure are more flexible and support companies to react quickly to changes in the business environment (Hohenstein, Feisel, Hartmann, & Giunipero, 2015).

Nevertheless, the decentralised structure has two main effects, namely, the bullwhip effect and double marginal effects (Zhang & Chen, 2013). The bullwhip effect is the

amplification of demand variability from a low to a higher echelon in supply chain models (Lee et al., 1997). The double marginal effect means that the total profit of the whole supply chain in a decentralised structure is less than in a centralised structure (Zhang & Chen, 2013). Consequently, many techniques have been studied to improve the coordination and efficiency of the supply chain structure (Thomas et al., 2016).

Sharing information has developed as one of the most common management practices to improve the performance of supply chain models (Jain & Moinzadeh, 2005; Rached et al., in press). There are several challenges in information sharing, for example, confidentiality of information, reliability, cost, and accuracy of information (Jain & Moinzadeh, 2005). Consequently, there are various technologies to support information sharing, namely, Vendor Managed Inventory (VMI) (Coelho & Laporte, 2015), Enterprise Resource Planning (ERP) (Zeng & Skibniewski, 2013), and Collaborative Planning, Forecasting and Replenishment (CPFR) (Hollmann, Scavarda, & Thomé, 2015). These techniques help to overcome challenges in sharing information and improve the performance of supply chain models (Babai, Boylan, Syntetos, & Ali, in press) in both centralised and decentralised structures.

Rudimentary inventory management models frequently assume that products have an infinite lifetime; such assumptions create a more tractable problem. However, there are many products with strictly finite lifetimes (e.g., milk,) and their value decreases with time or they may only be stored for a limited period. Therefore, the research on inventory management for perishable products has many practical benefits. The next section reviews the literature of inventory management for perishable products under the multi-echelon model.

2.3.5 Perishable inventory management for the multi-echelon model

If the inventory management for non-perishable products in the multi-echelon model is complicated, managing the multi-echelon model for perishable products is more complex (Karaesmen et al., 2011). The reason is that in the multi-echelon model, the performance at

each node impacts on the total system performance. Therefore, managers must consider the age of each product at each node as well as the quantity to deliver for each node. Given these complexities, the research on the multi-echelon model has focused on particular applications and heuristic methods (Karaesmen et al., 2011).

In contrast to the single-echelon model, there is limited research that uses a continuous review policy in the multi-echelon model for perishable products, mainly due to the problem's complexity. The reason may be that a continuous review policy is often efficient in cases of low consumer demand (Axsäter, 2011) which are not likely for perishable products (e.g., grocery products). Another reason is the continuous review policy usually requires the advancement of information technologies (e.g., VMI) (Chen & Samroengraja, 2004; Mitra & Chatterjee, 2004) which are not always available in many companies. Therefore, the periodic review or EOQ policies are usually used in perishable inventory management under multi-echelon models.

Most research on multi-echelon perishable inventory models focuses on the two-echelon model. Yang and Wee (2000) used an EOQ policy to optimise the total cost of the single-vendor, single-buyer model with perishable products, constant demand rate, and lost sales. Cai, Chen, Xiao, and Xu (2010) studied the single-producer single-distributor system for fresh products. The study suggests that the producer and the distributor should coordinate their decision especially when freshness is important. There are only a few studies on the three-echelon model. For example, Rau, Wu, and Wee (2003) studied the three-echelon model for single perishable products with lost sales and no price discount. The research shows that coordination in the three-echelon model reduces the total cost of the system. Hasani, Zegordi, and Nikbakhsh (2012) examined the design of a supply chain network for a four-echelon model with perishable products. There is no evidence of studies for five or more than five echelons. The reason could be due to the short lifetime nature of perishable products. When dealing with

perishable products (e.g., foods), suppliers try to be closer to consumers and ensure the provision of freshest products (Chen, Hsueh, & Chang, 2009). Suppliers try to bypass traditional agents between suppliers and consumers (e.g., distributors) (Egels-Zandén, Hulthén, & Wulff, 2015; Tangpong, Hung, & Li, 2014). Consequently, there is not a high requirement to consider an inventory model with too many echelons.

In reality, there is often a situation where the supplier does not accept the EOQ suggested by the buyer and vice versa (Yi & Sarker, 2013b). Therefore, companies have focused on collaboration among business partners to improve the efficiency of the integrated supply chain systems (Cannella, 2014; Yi & Sarker, 2013a). The integrated replenishment policy in the multi-echelon model can reduce the cost compared with the independent replenishment policy in the single-echelon model (Cárdenas-Barrón, Sarkar, & Treviño-Garza, 2013; Yang & Wee, 2002). Yang and Wee (2002) developed an integrated EOQ policy for perishable products for the two-echelon model with a supplier and multi-retailers. Yang and Wee showed that the integrated EOQ policy decreases the cost for the total supply chain system. Khanlarzade, Yegane, and Nakhai (2012) developed a replenishment policy with a packaging unit for perishable products under the two-echelon model. Khanlarzade et al. (2012) showed that with the new replenishment policy, the total cost of the supply chain is improved. A common approach in these papers is the use of mathematical modelling which is difficult to apply (Martínez-Costa, Mas-Machuca, Benedito, & Corominas, 2014).

For such complex multi-echelon models, the simulation approach provides more opportunities to find the inventory policy for the model (Bisogno, Calabrese, Gastaldi, & Ghiron, 2016). van der Vorst, Beulens, and van Beek (2000) presented a DES approach to study a three-echelon food model. The paper measured the inventory level at the retailers and distributors, and checked food freshness under many scenarios. Then, the results of the simulation approach were compared with the results from a real life situation.

Another issue in multi-echelon models is the bullwhip effect. An increased demand variability upstream in the supply chain (Lee et al., 1997) has recently received attention. The bullwhip effect is found in cases of the multi-echelon model, uncertainty demand, product substitution, or a shortage situation (Geary, Disney, & Towill, 2006). These causes are common in perishable inventory management and therefore the bullwhip effect exists frequently.

A lack of information sharing among supply chain members is attributed to the bullwhip effect (Katsaliaki, Mustafee, & Kumar, 2014). Sharing information on consumer demand and inventory data has been proven to improve replenishment policy decisions in supply chain models (Lau, Xie, & Zhao, 2008). For example, Aviv (2001) showed the advantages of sharing demand forecasts. Ferguson and Ketzenberg (2006) examined the benefits of information sharing to improve the freshness of perishable products and showed that information sharing is more beneficial under the FIFO issuing policy. These papers confirm the importance of information sharing in multi-echelon models, especially for perishable products.

2.4 Substitution

This section provides an overview of the literature that considers substitution in inventory management models for perishable products.

2.4.1 Excess demand

The literature review so far has included models with single or multiple products where there is no relationship amongst these products. When dealing with multiple products, consumer behaviour during periods of product unavailability is important (Akçay, Natarajan, & Xu, 2010). When faced with an excess demand or stock-out situation, consumers may find, try or evaluate, and perhaps eventually prefer an alternative product (Mahajan & van Ryzin, 2001; Waller, Tangari, & Williams, 2008; Zinn & Liu, 2001). Therefore, the consumer that identifies a suitable substitute product may change their behaviour and future buying patterns. From

manufacturers' perspective, this consumer may be lost forever, creating a negative impact on the long-term value. A repeated stock-out situation negatively affects retailers who lose customers (Dadzie & Winston, 2007). Therefore, decisions in inventory management should avoid stock-out situations, which create negative consumer behaviours. This section reviews the integration of a stock-out situation in making inventory policy and the method used by researchers to deal with it.

Models with backorder, lost sales, or both situations have received much attention. Weiss (1980) considered the lost sales and backorder continuous review perishable inventory models and found the optimal average for total expected costs. The costs are linear ordering cost, holding cost, disposal cost, and lost sales cost and revenue, with assumptions of Poisson demand, zero lead time, and fixed lifetime. The optimal control model for a lost sales case in Weiss's work was found to be $(0, S)$ or $(-1, S)$, because of zero lead time. When extending this to a more realistic problem with a positive lead time, Archibald (1981) considered lost sales with constant lead time and discrete compound Poisson demand distribution, and showed that the cost from backorders or lost sales is the same but the inventory at the beginning of the next cycle differs. This is because in the backorder problem, the inventory position must take into account the demand during lead time while in the lost sales problem, the inventory position does not need to do that.

Verhoef and Sloot (2006) examined consumers' reaction and behaviour when faced with a stock-out situation and proved that unmet demand most commonly results in lost sales. Kouki et al. (2014) considered a periodic review model for perishable products with lost sales, Poisson distribution demand, exponential distribution lifetime, and constant lead time. The model provides insights into the effect of parameters on the performance of total cost or total profit. The inventory model for lost sales has recently received more attention, with a review by Bijvank and Vis (2011) demonstrating that little is known about optimal replenishment

models accounting for lost sales. The main reason is, in lost sales situations, formulations must be established to ensure inventory position is constant during a stock-out period (Johansen & Hill, 2000). The inventory position in a lost sales problem does not simply become ‘negative inventory’ as it does with backorders.

A further complication arises from the difficulty in defining the cost of lost sales as it includes intangible costs, for example, cost of goodwill and loyalty cost (these terms are explained in Uncles, Dowling, and Hammond (2003)). To substitute the lost sales cost, researchers tend to use the customer service level (Tan & Karabati, 2013). The service level, sometimes called ‘fill rate’, is defined as a proportion of met demand. The service level may be called a ‘ready rate’, defined by the time when stock on-hand is positive (Larsen & Thorstenson, 2014). The customer service level can be classified into two models: the mean service level constraint model (controlling the average service level over the planning horizon), and the minimal service level constraint model (controlling the minimum service level over the planning horizon) (Chen & Krass, 2001). The customer service level also can be defined in two ways. The first definition is the probability of no stock-out during the replenishment cycle. The second (useful from both an analytic and practical/management perspective) is defined as the proportion of replenishment cycles which end with all consumer demand satisfied (Estellés-Miguel, Cardós, Albarracín, & Palmer, 2014).

The approximation approaches are usually used to cover complexities in lost sales situations. Estellés-Miguel et al. (2014) suggested that finding a better approximation for customer service level calculation is important as the use of exact methods for calculating customer service requires high computation techniques. Thus, approximation methods are more commonly used.

An alternative to overcome the complexity of lost sales problems emerges from comparing the ratio of published research for lost sales and back order situations. Although it

is more difficult to find an optimal solution for the lost sales problem than for the backlog problem, the ratio of problem with lost sales and backlog is almost equal (Bakker et al., 2012). This is because the models that assume full backorder are usually less realistic than models that assume lost sales or partial backorder. Moreover, approximation results are preferred to optimal results (Estellés-Miguel et al., 2014). Introducing service level gives another approach to accommodating lost sales (Tsai & Liu, 2015). Bijvank and Vis (2011) provided an overview of using service level for lost sales cases in stochastic problems; such an approach may guide further research.

Further investigation of alternate customer behaviours during stock-out situations has been called for by Bijvank and Vis (2011), for example, substituting products or frequenting substitute stores. Such substitution has a significant influence on optimal replenishment models and requires more attention. Broekmeulen, Fransoo, Van Woensel, and van Donselaar (2007) concluded that many consumers are willing to substitute another perishable product if the preferred product is stocked out. Therefore, substitutions should be included when developing inventory management policies.

2.4.2 Classifying substitution as driven by the consumer or decision-maker

There are two ways to classify substitution. First, substitution can be divided into consumer-driven substitution and decision-maker driven substitution (Broekmeulen et al., 2007). In consumer-driven substitution, the customer's willingness to substitute during a stock out is a major factor. In contrast, decision-maker driven substitution involves a managerial decision to substitute a given product with a different variant of the product. For example, when a customer decides to buy a Royal Gala apple instead of Yummy apple because the Yummy apple is out of stock, it is consumer-driven substitution. However, when a store manager decides to replace all iPhone 3G with iPhone 4G, because iPhone 4G has just been released, it is called decision-maker-driven substitution.

Second, substitution can also be divided into downward and upward substitution (Deniz, Karaesmen, & Scheller-Wolf, 2010). In upward substitution, the excess demand for higher graded products is fulfilled by lower ones and not vice-versa; for example, a customer can decide to buy near expiry date bread instead of fresh bread because fresh bread is out of stock. In downward substitution, the excess demand for lower graded products is fulfilled by higher ones; for example, a customer can decide to buy a chip Intel core i5 instead of Intel core i3, which she would have preferred to buy but it is out of stock. Ioannidis (2013) showed that upward substitution is not always accepted and that downward substitution is preferred.

Substitution greatly affects inventory management policy and future research should pay more attention to this fact. The possibility of substitution across products affects the distributions of demand. Smith and Agrawal (2000), as in the wide marketing literature (e.g., Breugelmans et al., 2006), assumed that a customer tries to look for another product one time only. The authors defined substitution as reflecting a situation in which the first preferred product is not available and consequently a customer may purchase a substitute product. Otherwise, it becomes a lost sale. From that definition, Smith and Agrawal (2000) formulated a negative linear relationship between substitution and lost sales. All discussions in this research are also based on the assumption of a negative linear relationship between substitution and lost sales.

2.4.3 Perishable inventory management for substitutable products

Rajaram and Tang (2001) studied multiple newsvendor products based on a single-echelon supply chain model. They found that if one product is out of stock, another product can substitute it. Nagarajan and Rajagopalan (2008) studied inventory management for two products based on a multi-period model, and found that the first product could substitute the second product and vice versa. The authors showed that the inventory levels for two products could be calculated easily in a one-period model, and a heuristic performs well in a multi-

period model. Huang, Zhou, and Zhao (2011) studied multiple newsvendor products, which are substitutable, and the results showed that substitution increases the total inventory level. However, as research on a single-echelon model may have reached saturation point (Alizadeh et al., 2014; Duong et al., in press), researchers are now paying more attention to multi-echelon models.

In a multi-echelon model, substitution has been studied for newsvendor or fixed lifetime products. For example, Zhang et al. (2015) focused on the effects of consumer environmental awareness on order quantities within a two-echelon model for newsvendor products. Zhang, Zhang, Zhou, Saigal, and Wang (2014) studied a centralised model for newsvendor products and the results showed that a larger substitution ratio leads to a larger order quantity. Thus, it is recommended to adopt a centralised structure in a substitution environment.

Substitution makes the inventory management models for perishable products more complex. However, most of the studies on inventory management for perishable and substitutable products in a multi-echelon model consider that newsvendor products reduce the complexity. Huang et al. (2011) considered two competitive stores for newsvendor products and developed an iterative algorithm to receive the results. Zhang et al. (2014) developed an iterative algorithm to cope with the complexity of the problem of a centralised newsvendor model with substitution.

Substitution can create additional lost sales situations by making the demand for a product increase suddenly (Yang & Schrage, 2009). Many retailers, distributors, and supermarkets order a group of products from a supplier at the same time. Moreover, companies offer a range of products to a group of customers in the same area (Rajaram & Tang, 2001). These things save the set-up ordering cost and transportation cost, and make the procurement much easier. However, it is also a challenge for inventory management because customers can substitute their preferred product with an available product. Therefore, substitution has

received more attention in defining inventory management policy, especially in a multi-echelon model.

2.5 Key Issues in Perishable Inventory Management

The previous section reviewed research on inventory management of perishable products. It discussed single-echelon and multi-echelon models, and identified and classified important characteristics in managing inventory for perishable products. This section highlights the key issues relating to the research on perishable inventory management. Addressing these issues pushes the research closer to the real problem and simultaneously contributes to the development of perishable inventory theory that serves as the theoretical underpinning of this research.

2.5.1 Non-financial performance measures of the multi-echelon inventory model

To simplify the complexity in the multi-echelon model, researchers usually optimise only the financial measures of the model, for example, total cost or total profit. The advantages of a single-objective are clear definitions of the objective, direct solution methods, generation of a single best result, and a clearer interpretation of this result (Pintarič & Kravanja, 2015). However, optimising one financial measure ignores other important problems (Savic, 2002) that occur in multi-dimension models, for example, supply chain management (Li, Ragu-Nathan, Ragu-Nathan, & Subba Rao, 2006). Furthermore, Taticchi, Tonelli, and Pasqualino (2013) observed that companies focus on non-financial rather than financial measures. This section explains why, justifies the use of non-financial performance measures as an emerging approach, and discusses the current issues of using non-financial measures in perishable inventory management problems.

2.5.1.1 Why to use the performance measures in the multi-echelon model

Inventory policies are traditionally generated by using a single financial measure, including some or all cost factors (e.g., holding cost and ordering cost). Most multi-echelon modelling has had a single-echelon modelling focus on a single financial measure (Gutjahr & Pichler, 2013). For example, Weraikat, Zanjani, and Lehoux (2016) maximised total profit to select the best consumer incentive contract for a two-echelon pharmaceutical reverse model. Using a single measure helped the researchers quantify various elements into a single-dimensional problem, which is easy to solve.

However, supply chains are by nature multidimensional (Akyuz & Erkan, 2010); consequently, rather than optimising a financial measure (e.g., total cost or profit), a range of performance measures should be used. This section accounts for this, reiterates the key concerns in optimising a single financial measure, and outlines why this is not necessarily a good approach. It then presents performance measures as an alternative to the traditional approach of optimising the financial measures.

Careful reading of the literature indicates that there are six reasons for using non-financial measures in a multi-echelon model. First, the bullwhip effect is a common phenomenon in a multi-echelon model. Usually, a demand is enlarged from downstream to the upstream level. An example of this situation is when the unavailability of demand information creates bullwhip and a higher inventory level (Lee et al., 1997). Future demand is not known exactly. Therefore, the demand is forecasted from historical data (Barlas & Gunduz, 2011). At the beginning of planning period t , the manager looks at inventory on hand $I(t)$, outstanding replenishment quantity $O(t)$, and backorder quantity $B(t)$. The demand $D(t)$ for period t is forecasted from historical data. If $D(t) > I(t) + O(t) - B(t)$, the manager must replenish some quantity to fulfil demand $D(t)$. If $D(t) \leq I(t) + O(t) - B(t)$, the manager does not place any replenishment order. Thus, the forecast demand is important when making replenishment

decision (Goyal & Giri, 2001). A forecast of more than real demand results in higher stock and a forecast of less than real demand makes an out-of-stock situation (van Donselaar et al., 2016). The manager usually increases the forecast data to avoid any risk of an out-of-stock situation. Another example happens when a Sales Manager sets a higher target than is really required in order to push the sales force. In these two examples, the demand is unknown and enlarged downstream. This enlargement gives more buffer for downstream to take any urgent actions but it causes more problems for upstream levels and supply chain management, problems which are common to the bullwhip effect in a multi-echelon model (Cannella et al., 2013a).

The bullwhip effect is an extremely complicated phenomenon which affects the strategic, tactical, and operational performance of a company and the whole supply chain (Cannella & Ciancimino, 2010). This creates bad performance results for the whole supply chain model, for example, high holding cost (Zhou & Disney, 2006), high lost sales, low service level (Wang & Disney, 2016), and high capacity levels (Isaksson & Seifert, 2016). Geary et al. (2006) documented at least 10 causes of the bullwhip effect and stated that a strong business (i.e., good performance supply chain) imposes a smooth demand pattern and reduces bullwhip effect. Consequently, it is necessary to develop a set of non-financial measures which have the ability to analyse multi-dimensional performance at both local (single-echelon) and systemic performance levels (whole-supply chain) (Gunasekaran & Kobu, 2007; Towill, Zhou, & Disney, 2007).

Second, the multi-echelon supply chain model is multi-dimensional by nature (Akyuz & Erkan, 2010) and needs to be analysed under multiple aspects. As Kaplan and Norton (2005) stated,

What you measure is what you get: the measures you use strongly affect the behavior of your managers and employees. When building a balanced scorecard, tailor the

measures to fit your company's particular challenges. That way, you'll be more likely to get the performance you need to succeed. (p. 1)

Thus, for example, a contract which is received by maximising total profit (e.g., Giri & Sarker, 2016) may improve profit but this result is not guaranteed for a long time. The reason is that focusing on total profit only may ignore other important aspects (Savic, 2002) and reduce the performance of employees (Kaplan & Norton, 2005). Therefore, although only one financial measure has advantages, for example, clear definitions of the objective, direct solution methods, generation of the single best result, and clearer interpretation of this result (Pintarič & Kravanja, 2015), it is strongly advocated to use non-financial measures.

This advocacy is stronger under multi-echelon supply chain models (Li et al., 2006). Kaplan and Norton (1995) proposed the Balanced Scorecard method to develop performance measures for the whole system. Cannella et al. (2013a) proposed non-financial measures to measure and reduce the bullwhip effect at single-echelon and whole system levels. Both studies encourage the use of non-financial measures under multi-echelon models. To further advocate the use of multiple non-financial measures, Kaplan (2008) and Grigoroudis, Orfanoudaki, and Zopounidis (2012) suggested applying MCDM methods when dealing with multiple measures.

Third, non-financial measures support continuous improvement for companies. Baines and Langfield-Smith (2003) observed that most companies that utilise non-financial measures achieve their strategic objectives. Academics and practitioners have spent time and effort in implementing performance measurement systems (PMS), mostly focusing on measures which continuously reflect the business (Kennerley & Neely, 2003). As a result, many new measures have been introduced and companies may be drowning in data (Neely et al., 2000). This issue was raised by Kennerley and Neely (2003), who emphasised that the modern business environment is competitive and requires PMS, which continue to reflect changes in priorities and organisational contexts.

There has been a focus on revolutions in PMS for many years to ensure that it is able to reflect the business environment and a company's strategies. One response has been to include both financial and non-financial measures to align PMS and a company's strategies, the most famous example being that of the Balance Scorecard developed by Kaplan and Norton (1995). Non-financial measures have been used to complement financial measures (Díaz, Gil, & Machuca, 2005). Since then, non-financial measures have emerged as appropriate tools to transform and convey company strategies (Said, HassabElnaby, & Wier, 2003) and motivate the performance of employees (Meyer, 2007). The advantages of non-financial measures are their abilities in providing daily information, promoting improvement, reflecting changes in business environments, and supporting continuous improvement (Bhagwat & Sharma, 2007; Lehtinen & Ahola, 2010). The continuous improvement ability is a key characteristic that advocates the use of non-financial measures to refine PMS in companies (de Lima et al., 2013; Piotrowicz & Cuthbertson, 2015).

Fourth, inventory management is a part of company operations. Thus, inventory management should take an active role in improving overall company performance (Chikán, 2011). For example, Supply Chain Planners monitor inventory and the Replenishment Department is responsible for delivering products. By optimising a total function, the Planners define when and how many new products to order. This decision already takes into account the customer service costs. However, optimising a total function does not provide information on how well the Replenishment Department is serving their customers. A misunderstanding in the Replenishment Department (e.g., wrong quantity) creates more costs to satisfy customers, and the total operational costs increase. Hence, using total function is more suitable when focusing on a single department only as it may not accommodate different departments with different objectives or measures.

Fifth, the traditional approach uses the total cost or profit functions to generate the results. These functions are formulated based on a series of (most importantly) inventory costs, for example, holding cost and ordering cost. Nevertheless, in reality, it is difficult to establish holding cost for a given period or processing cost per order. For instance, it is difficult to quantify the cost of the customers' dissatisfaction in a backlogged situation. The use of financial measures has been criticised as they are too aggregate, too late, and one-dimensional in nature (Ittner & Larcker, 1998a). Moreover, the values of input parameters in these total functions are inaccurate because the business environment is changing very quickly (Bonney & Jaber, 2011; Chikán, 2007). All related performance measures that are based on contributions of inventories should be focused on improving the customer satisfaction level (Chikán, 2011). Therefore, non-financial measures have been recognised as effective alternatives (Ittner & Larcker, 1998b; Otley, 2001).

Sixth, the approximation approach has been used mostly for optimising a financial measure, in order to overcome the complexity of mathematical calculations. However, Ozer and Xiong (2008) stated that the approximation approach should meet some of the following criteria before being used:

- provides a nearly optimal result (i.e., the result from approximation is not substantially different to the optimal result);
- easy to compute (i.e., the approximation result can be generated from simple calculations);
- simple to explain and use (i.e., the formula is simple to understand and the user can describe it to other users);
- strong (i.e., accurate data that is easily acquired); and,
- used to test a system (i.e., when input variables change, the system can be tested with new input).

Concentrating on only the first measure of a nearly optimal result overlooks the other criteria. Therefore, it is necessary to understand how the approximation approach runs under these five criteria to have better results. Consequently, it is not always easy to use one financial measure.

The above reasons suggest that using a single financial measure is not a good approach and suggest that an alternative approach is found. The perishable inventory management under the multi-echelon model in this research is similar to the bullwhip effect research for two reasons. First, information on the supply chain (e.g., demand) goes through two echelons that are vulnerable to external factors (e.g., disaster), and create high demand fluctuations and the bullwhip effect. For example, the demand variability increased 231% from retailers to wholesalers during the 2008 recession in the US (Dooley et al., 2010). Second, the research studies the inventory policy, which is one of three research streams on the bullwhip effect; namely, the impact of demand forecasting techniques, information sharing, and the operation management parameters (e.g., inventory management policy) (Nepal et al., 2012). Therefore, a performance measurement is developed from the review of the literature on the bullwhip effect in a multi-echelon inventory model.

2.5.1.2 Justification the performance measures adopted

A study of the bullwhip effect should focus on multidimensional analysis (Cannella et al., 2013a). A single-dimensional analysis, such as total cost measurement, only supports minimisation rather than continuous improvement of the whole organisation (Lehtinen & Ahola, 2010). Even when only considering a single firm, Akyuz and Erkan (2010) stated that a performance measure should be exact, non-financial, actionable, simple, and in the form of ratios that allow for testing, reviewing, and revising and involve organisational learning. Even managers within a company have different measures against which their work is judged. Therefore, setting up and implementing a performance measurement is a challenging task that

requires partnership and collaboration (Holweg, Disney, Holmström, & Småros, 2005; Stank, Keller, & Daugherty, 2001).

Cannella et al. (2013a) reviewed research on the bullwhip effect and proposed a performance measurement that assesses internal process capacity and customer satisfaction at both local (single-echelon) and systemic performance levels (whole-supply chain). To measure the internal process capacity at the single-echelon level, Cannella et al. (2013a) proposed the following measures: order rate variance ratio, average inventory, inventory variance ratio, work in progress (WIP) variance ratio, and zero-replenishment. To measure the internal process capacity at the whole-supply chain level, the following measures are adopted: systemic average inventory, inventory instability slope, bullwhip slope, zero-replenishment, and WIP instability slope. Customer satisfaction is measured by backlog and fill rate. Each measure has the managerial information and relevant costs. Table 2.1 presents the information provided by each measure and the managerial implications in terms of costs.

Cannella et al. (2013a) compared the performance measures with a previous study for a traditional three-echelon supply chain model. The comparative analysis results suggest the following:

- The performance measurement should assess both internal process and customer satisfaction.
- The suggested metrics provide a general improvement of performance in the supply chain model.
- The performance measurement can summarise and present a complex system in a managerial manner, provide a quantitative overview of the whole supply chain, support the decision-making process, and identify the problem.

The non-financial performance measures in Cannella et al. (2013a) are also supported by the advocated use of non-financial measures over many years (Kaplan & Norton, 2001). In

contrast to financial measures, non-financial measures are useful for developing and maintaining a company's competitive advantages (Kaplan & Anderson, 2013). The non-financial measures also positively affect employee behaviours in a company and motivate their performance. Lau and Moser (2008) showed that using non-financial measures enhances the perception of fairness by employees, who consequently perform better. Fairness is a critical aspect of employees' wellbeing and the achievement of a company's objectives. Thus, it is useful to use non-financial instead of financial measures to improve the performance of a company.

Table 2.1: Related information and cost (derived from Table 4 in Cannella et al. (2013a, p. 8))

Metric	Information	Cost
Inventory variance ratio	Fluctuation of inventory Probability of stock-out	Inflating the average inventory cost per period Increased holding cost per unit Missing production schedules Job sequencing Resource re-allocation,
Order rate variance ratio	Magnitude of bullwhip effect Stability of orders Variations of production and distribution lead time	Procurement Ordered items Ordering/ Overtime Subcontracting
WIP variance ratio	Stability of WIP System	Production/transportation set-up Scheduling resource re-allocation Slack and extra-capacity of distribution system
Average inventory	Inventory investment Probability of obsolescence Stock capacity utilisation	Holding, handling Spoilage and obsolescence, salvage
Zero-replenishment	Inertia of the production-distribution system Operational scalability and responsiveness	Slack capacity Overtime/ Subcontracting
Fill rate	Customer service level time series	Stock-out Missed sales and loss of customer's goodwill Penalties/ Priority special order Job sequencing
Backlog	Unfulfilled production delivery plan	Resource re-allocation

Non-financial performance measures have been used more often recently. Table 2.2 below reports the using of the performance measures in recent papers.

Table 2.2: Use of performance measures in recent papers

Research	Performance measures	# of echelon	Focus of analysis
Vidalis, Vrisagotis, and Varlas (2014)	Fill rate Cycle time Average inventory	2	Express performance measures as functions of key model characteristics, and determining the inventory policy
Dominguez, Cannella, and Framinan (2014)	Order rate variance ratio Bullwhip slope	4	Use of performance measures to prove advantage of information sharing in supply chain management
Lin, Jiang, and Wang (2014)	Order rate variance ratio Inventory variance ratio Average market segment share	2	Assess the performance of the supply chain model with production capacity constraint and consumer behaviour

Because the bullwhip effect is collectively responsible for cost, profit, and service level (Lin et al., 2014), the three papers in Table 2.2 use performance measures to account for such demand fluctuation. The models are evaluated under a range of measures. The performance measures are compared to research on the effect of inventory policy and find the most favourable policy for the model. These successful adoptions of performance measures in optimising performance of the supply chain model prove the efficiency of using performance measurement, especially for multi-echelon models, where the bullwhip effect exists.

2.5.2 Lack of knowledge of effects of consumer demand

The primary purpose of inventory management is to enable the smoothing between supply and demand (Zomerdijk & de Vries, 2003), and aims to answer two questions, namely, the time and quantity needed to place a replenishment order (Beheshti, 2010). A replenishment policy is calculated based on the information of consumer demand (Gallego & Özer, 2003), which is also affected by the efforts of suppliers and retailers.

The common practices of suppliers and retailers are applying promotional efforts (e.g., media advertisements, sponsorships, customer incentives, product display, or loyal reward

programmes) (Xu, Chen, & Xu, 2010). All these efforts aim to increase consumer awareness of the products or brands and increase sales or consumer demand. As a result of these efforts, the uncertainty of consumer demand increases and creates complexities in inventory management (Kärkkäinen, 2003; Sezen, 2006), especially under multi-echelon models (Chiang, 2003). Consequently, it is interesting to understand the effects of consumer demand on the performance of suppliers and retailers (Yu, Tang, & Niederhoff, 2011).

Effects of consumer demand on total cost or profit have been investigated widely. Gupta and Maranas (2003) showed that failure to forecast demand could lead to high inventory holding cost. Wang and Chen (2015) showed that expected total profit decreases as demand uncertainty increases. Inventory management has an active role and is part of a company (Chikán, 2011) thus, focusing on only total cost or profit is not suitable (Savic, 2002). Therefore, measuring the effects of consumer demand should not only focus on financial (e.g., total cost or profit) but also non-financial performance measures to motivate improvements (Kaplan & Norton, 1995).

Fill rate is the most commonly investigated non-financial measure in terms of the effects of consumer demand (Petrovic, Roy, & Petrovic, 1998; Williams & Tokar, 2008). For example, Petrovic (2001) concluded that reduced demand uncertainty could increase the fill rate. A similar conclusion was also observed by Pauls-Worm et al. (in press) and Xue, Choi, and Ma (2016).

Despite these works, the knowledge about effects of consumer demand is still limited. This research observes that there are four issues involved in understanding the effects of consumer demand. Firstly, there is a lack of investigation on the effects of consumer demand on other non-financial measures. Effects of consumer demand have been investigated mostly in terms of fill rate (FR), total cost, or total profit of the studied models (e.g., Pauls-Worm et al., in press; Xue et al., 2016). However, information on financial measures (e.g., total cost or

profit) is suitable for strategic decisions only (Kaplan & Norton, 1995). A good measure should encourage appropriate behaviour and be multi-dimensional, which are the advantages of using non-financial measures (Kaplan & Norton, 1995; Kenyon, Meixell, & Westfall, 2016). Prior works have focused mostly on the effects of consumer demand on FR; however, there are many other important non-financial measures (e.g., AI, or ORVR). Focusing on only FR may cause inappropriate decisions; for example, managers tend to keep higher inventory to achieve high FR. Thus, it is necessary to investigate the effects of consumer demand on non-financial measures other than FR.

Secondly, there is a lack of models that evaluate the effects of consumer demand on a whole multi-echelon supply chain model. Pauls-Worm et al. (in press) investigated the effects of consumer demand in a single-product single-echelon model. Xue et al. (2016) studied a two-echelon model but focused only on total profit in terms of the manufacturer not the supplier. Neither of the models supports an investigation of the effects of consumer demand on the whole supply chain. While real business is usually involved with multiple products in collaboration with multiple parties (i.e., multi-echelon models), evaluation of the whole supply chain is important as it improves performance of the whole system (Weraikat et al., 2016). Performance evaluation of the whole system is also important and necessary as in this context (i.e., multi-echelon), the bullwhip effect exists (Wang & Disney, 2016) and causes high cost and excessive inventory for the whole supply chain (Dejonckheere, Disney, Lambrecht, & Towill, 2003; Wong, 2010).

Thirdly, insights about the effects of consumer demand for products that have a random lifetime should be enhanced. Pauls-Worm et al. (in press) considered a product with a fixed maximum lifetime and Xue et al. (2016) considered a newsvendor product. However, products with a random lifetime are more common in reality, especially in terms of grocery products (Lian, Liu, & Neuts, 2005). Moreover, research on single-products with a fixed lifetime might

reach a saturation point (Karaesmen et al., 2011). Thus, future research should consider the effects of consumer demand on the performance of the supply chain model when products have a random lifetime.

Fourth, interactive effects between consumer demand and other problem characteristics have not yet been investigated widely. A study of a model or a real situation involves many characteristics, for example, consumer demand or product lifetime. The main effects of consumer demand only have been investigated; for example, Chaturvedi and Martínez-de-Albéniz (2016) studied the effects of demand uncertainty on safety stock, production capacity, and diversifying suppliers. However, knowledge about the interactive effects of different problem characteristics is also important in order to properly benchmark the performance of a company against other companies in the industry (Hancerliogullari, Sen, & Agca, 2016). Thus, it is necessary to investigate interactive effects between consumer demand and other problem characteristics.

2.5.3 Lack of knowledge of effects of product lifetime

Product lifetime is one of the major factors which affect perishable inventory management systems (Karaesmen et al., 2011), and has received significant attention in the literature. Similar to issues of consumer demand, a large part of the literature has studied the effects of product lifetime on total cost or profit of the studied model only. For example, Kouki et al. (2014) and Kouki and Jouini (2015) studied the effects of product lifetime following an exponential distribution on total cost of a single-echelon model with a single product. This research identifies three issues relating to the knowledge of the effects of product lifetime on perishable management.

First, there is a lack of research for multiple products with random lifetime under multi-echelon models. While Nagaraju, Rao, Narayanan, and Pandian (2016) pointed out that considering multi-product, multi-echelon settings helps to reduce the total cost of the whole

supply chain, the research for multi-product, multi-echelon models is still limited. For example, Zhang et al. (2015) studied the effects of consumer environment awareness on a two-echelon model with two products but assumed they are newsvendor products. In reality, products commonly have random lifetimes; for example, fresh fruits can expire sooner or later than the expected date due to storage conditions and these types of product lifetime should receive more attention. This issue was confirmed by Kouki and Jouini (2015) who stated that a study for two-echelon models (e.g., one supplier and multiple retailers) is an ambitious future work.

Second, similar to the consumer demand characteristic, the literature has focused on the effects of product lifetime on financial measures (e.g., total cost or profit). For example, Kouki et al. (2014) and Kouki and Jouini (2015) considered the effects of product lifetime on the total costs including holding cost, purchase cost, lost sales cost, and outdated cost. Based on the advantages of non-financial measures, for example, providing information for continuous improvement, ease of communication between responsible departments or people (as mentioned in section 2.5.1), it is necessary to investigate the effects of product lifetime on non-financial measures of perishable inventory management. Third, as knowledge about the interactive effects of different problem characteristics is also important (Hancerliogullari et al., 2016) (discussed in section 2.5.2), it would also be interesting to investigate the interactive effects between product lifetime and other problem characteristics.

2.5.4 Lack of research on substitution

There are many studies that have considered inventory management for perishable products under a multi-echelon model without substitution. Ruiz-Benitez and Muriel (2014) considered a two-echelon model for a newsvendor product. The retailer can refund the consumers and the supplier can refund the retailer. Rahdar and Nookabadi (2014) developed an inventory model to study the coordination of supplier and retailer for perishable products. Rahdar and Nookabadi (2014) selected a replenishment policy to optimise the total cost of the model. Lee

and Kim (2014b) developed a two-echelon model with one vendor and one retailer for a product that is perished because of lifetime and quality issues during manufacturing. These researchers have studied and emphasised possible combinations of real business issues for perishable products in a multi-echelon model. However, studying only one product limits the application of these studies due to the fact that the supplier and retailer usually sell more than one product simultaneously. Moreover, substitution is a normal case because a customer usually substitutes the product or the supplier.

Inventory policy depends on the substitution of the available products, and being concerned with substitution inventory control could lead to a better inventory policy (Bakker et al., 2012). However, there are few articles that include substitution in the model because of the complexity of the mathematical problems (Duong, Wood, & Wang, 2015a). Table 2.3 presents a summary of studies on inventory management for perishable and substitutable products in a multi-echelon model. These studies were found by using keywords: deteriorat* (meaning deterioration/deteriorated/deteriorate), perish* (meaning perishable/perishability), substitut* (meaning substitute/substitution), and multi-echelon/two-echelon/three-echelon (meaning multi-echelon supply chain model). The studies were then classified as single-period for newsvendor products and as multi-period products.

Table 2.3: Summary of papers on inventory management for perishable and substitutable products in multi-echelon models

Lifetime	With substitution	Research
Single-period	4	4 papers in Table 2.4
Multi-period	1	Duan and Liao (2014)

Substitution is commonly practised, especially for perishable products, for example, dairy and healthcare products. There are few papers that have studied inventory management for perishable and substitutable products in a multi-echelon model. All four papers below optimise the total profit function of the two-echelon model for single-period lifetime (Table 2.4). Zhang et al. (2014) and Gürler and Yılmaz (2010) observed lost sales through the service

level; Zhang et al. (2015) and Zhang, Guo, and Zhang (2009) did not consider lost sales in the model, which limited insight into the model. While studies that omit substitution have considered the total cost function, studies that include substitution consider total profit. The reason could be that substitution improves customer satisfaction and increases sales. Therefore, it is more relevant to consider the total profit in cases with substitution.

Table 2.4: Summary of papers in two-echelon models for single-period and substitutable products

Research	# of item	Excess demand
Zhang et al. (2015)	Two	Not considered
Zhang et al. (2014)	Two *	Service level
Gürler and Yılmaz (2010)	Two	Service level
Zhang et al. (2009)	Two	Not considered

(* Zhang et al. (2014) generated three and four item examples from a two-item problem)

All papers in Table 2.4 developed mathematical functions and the inventory policies were derived from numerical studies. Zhang et al. (2014) showed that the computational time increases rapidly with the number of products, and concluded that deriving a closed-form solution for a multi-item newsvendor problem is a challenge. Zhang et al. (2014) employed an approximation of demand function and developed an algorithm for the solution. The complexity of developing mathematical functions and finding solutions could be a reason for the limited number of studies on perishable and substitutable products in a multi-echelon model.

Although perishable products with a multi-period lifetime are common, only Duan and Liao (2014) considered inventory management for perishable and substitutable products with a multi-period lifetime in a multi-echelon model. The reason for this limitation is that the inventory status (e.g., age) in a multi-period lifetime remains for many periods. The solution to the multi-period lifetime problem is more difficult than the newsvendor problem, where the inventory status renews at the beginning of each period.

Duan and Liao (2014) considered multi-period lifetime products with a study of a single-hospital, single-blood centre (two-echelon) for eight substitutable blood groups. The blood centre defined how many units of blood to produce per day (replenishment order-up-to level (t, S) policy) with the objective of minimising the system-wide expiration rate with a given shortage rate. Duan and Liao (2014) assumed that the blood centre had limited production capacity and storage capacity, and all blood organisations (i.e., products) had the same situation. This provides opportunities for extension, where these assumptions can relax, for example, when each product has a unique situation, the substitution rate is flexible.

2.5.5 Lack of knowledge of effects of substitution

As a result of a lack of research on substitution, the knowledge of effects of substitution is also limited. This research identifies two issues relating to the knowledge of the effects of substitution. First, there is a lack of research considering substitutable products with a random lifetime. Most research considers perishable and substitutable products with a fixed lifetime. Bansal and Moritz (2015) and Hübner, Kuhn, and Kühn (2016) considered newsvendor products, and Duan and Liao (2014) considered blood organisations (i.e., products) where the lifetime is fixed at three days. These types of products are not common in practice. This research is motivated by the social issue of food waste. Thus, it is necessary to consider products that have a lifetime which follows an exponential distribution, which is common in the literature on perishable inventory management (Kouki & Jouini, 2015).

Second, there is a lack of research on the effects of substitution and its effects on non-financial performance measures in the inventory model. Similar to consumer demand and product lifetime characteristics, most works have only studied the effects of substitution on total cost or profit. For example, Hübner et al. (2016) studied the effects of substitution on total profit including sales revenue, purchase cost, lost sales cost, and outdated cost. Civelek, Karaesmen, and Scheller-Wolf (2015) considered blood products with a fixed lifetime of four

days and studied the effects of substitution on total costs at a blood centre. Section 2.5.2 explained the need to study the interactive effects of different problem characteristics (Hancerliogullari et al., 2016). The section mentioned that non-financial measures have many benefits for inventory management, for example, providing information for continuous improvement and ease of communication between responsible departments or people. When having substitutable products under a multi-echelon model, using non-financial measures supports the study of the bullwhip effect (Cannella & Ciancimino, 2010; Duan, Yao, & Huo, 2015). Therefore, it is worthwhile to investigate the effects of substitution and its interactions with non-financial measures in the inventory model in this research.

2.5.6 Lack of knowledge of effects of decision-makers' opinions

Inventory management has been called a classical topic in the operations literature. As a result, many concepts and techniques are available for managing inventory (Zomerdijk & de Vries, 2003). These available concepts and techniques, for example, EOQ models (Harris, 1990), manufacturing resource planning (MRP), and enterprise resource planning (ERP) (Huang & Handfield, 2015), are based on mathematical assumptions. These tools have been very valuable in inventory management. However, more recently, researchers, (e.g., Hayes, 1998; Lovejoy, 1998; Machuca, 1998), have realised that they are insufficient to overcome modern business complexities, and favour a broader perspective on operations management issues. Zomerdijk and de Vries (2003) argued that it is important to consider organisational context in inventory management. This means decisions in inventory should be focused on not only traditional aspects (e.g., order quantities and review periods) but also contextual aspects (e.g., decision-making processes).

Moreover, inventory management has two fundamental opposing objectives; namely, inventory must be high enough to cover sales activities and low enough to minimise capital investment (Güller et al., 2015; Gupta & Boyd, 2008). Thus, trade-off decisions are

unavoidable in inventory management (see section 2.1.2). These decisions should be aligned with requirements from strategic to operational levels (Boyer & Lewis, 2002; Wang et al., 2015).

When making trade-off decisions in inventory management, managers should additionally consider decision-making processes besides traditional aspects. Wang, Gunasekaran, Ngai, and Papadopoulos (2016) suggested that understanding changes in the business environment improves supply chain efficiency. Thus, decisions in inventory management should reflect changes in the business environment, including strategic, tactical, and operational requirements. These requirements concern strategic decisions on day-to-day activities (Zomerdijk & de Vries, 2003), and reflect the priorities or opinions of decision-makers. For example, decision-makers may think the performance measure fill rate is the first priority due to changes in the business environment and that the selected replenishment policy should reflect the highest importance of the fill rate measure.

Extant literature has transformed the importance of each measure into relative cost and investigated the effects of these costs on final decisions. The measure of higher cost is more important. For example, Vidalis et al. (2014) transformed measures (i.e., fill rate, average inventory, and average cycle time) into a profit function and selected the replenishment policy that maximised total profit. As mentioned in sections 2.5.1, decision-makers can quickly change priorities based on variations in the business environment (Popovič, Hackney, Coelho, & Jaklič, 2014) and it is not always easy to transform the importance into cost factors. For these reasons, using cost transformation may not reflect all effects of decision-makers' opinions on final selection.

Thus, it is necessary to not use cost transformation in investigating how changes in decision-makers' opinions affect the selection of the most favourable replenishment policy. The investigation of decision-makers' opinions on the most favourable replenishment policy is

important for managers. Results provide insights into which situations changes in decision-makers' opinions lead to changes in the most favourable replenishment policy; In other words, results clarify in which situations decision-makers should re-evaluate the ranking of replenishment policies.

2.5.7 Lack of research on multi-products

Research on the inventory management model for multiple perishable products is limited, as opposed to the single perishable product model. This imbalance is mainly due to the complexity of multi-product models. Assume that one product has a lifetime of m period, then, to consider n products, the model must consider $n*m$ variables to track the lifetime of all products (Nahmias, 2011). This requires a highly complex model and a complicated solution as well. This is a gap in real business as the multi-product model is more realistic, since companies sell many products simultaneously. In fact, companies, retailers, and consumers usually consider joint replenishment or substitution of multi-products, and this is an area that has received very little study. This gap provides opportunities for further research to develop more realistic inventory management policies.

2.5.8 Lack of research on the multi-echelon model

The research on managing perishable inventory in single-echelon models may reach a saturation point (Alizadeh et al., 2014; Duong et al., in press). In a single-echelon model, researchers have combined all possible characteristics of a problem to make it reflect the real world. For example, Weiss (1980) studied the continuous review model for a perishable product with zero lead time and Lian and Liu (2001) extended Weiss' work to consider positive lead time. van Donselaar and Broekmeulen (2014) developed a broad model using periodic review for a perishable product at a single location. The authors provided a performance measurement of inventory management for perishable products that included inventory level,

number of destroyed products, and the number of out-of-stock situations. They then developed an approximation approach to cope with the difficulty in calculating the optimal results in the perishability inventory management. The authors suggested using their approximation approach in the case of constraints such as budget constraint and fill rate constraint.

These works have covered all possible and most common characteristics of perishable inventory management in a single-echelon model. Inventory management in multi-echelon models emerges as a potential research area with the support of computerised technology, for example, Radio Frequency Identification (RFID) (Duong, Wood, & Wang, 2015b; Kärkkäinen, 2003; Prater, Frazier, & Reyes, 2005). Many papers, which have researched inventory management for multi-echelon perishable products, are two-echelon model papers, and some are three-echelon model papers. Because of the computational complexity, most of the papers have studied the two-echelon model such as that of Lee and Kim (2014b) who studied a single-supplier, single buyer model for perishable and defective products. There have been only a few papers which have studied the three-echelon model such as that of Wang, Lin, and Yu (2011) who optimised inventory management policy for perishable products in a three-echelon supply chain model. Moreover, as discussed in section 2.3, the integration replenishment policy in the multi-echelon model reduces the total cost of the supply chain. This reconfirms the need to pay more attention to studying inventory management for the multi-echelon model.

2.6 Research Gaps, Objectives, and Questions

Previous sections summarise the state-of-the-art of the perishable inventory theory, that serves as the theoretical underpinning of this research. This included a review of the relevant literature on the selection of replenishment policies for perishable and substitutable products. The review covers key definitions used in inventory theory and addresses the factors of consumer demand, product lifetime, lead time, and substitution for both single and multi-echelon models. The review shows that inventory management for perishable products under a single-echelon model

has reached a saturation point (Alizadeh et al., 2014; Duong et al., in press). It is also noted that although substitution is a common phenomenon in consumer behaviour (Mahajan & van Ryzin, 2001; Waller et al., 2008; Zinn & Liu, 2001), the inventory theory research relating to management of substitutable products is still limited (Deniz et al., 2010). The review also shows that research on inventory management for substitutable and perishable products under a multi-echelon model is lacking due to the problem complexity (Nahmias, 2011); for example, it is difficult to determine which product substitutes which product. Based on key issues in perishable inventory management as discussed in section 2.5, this section summarises the relevant gaps in the literature of perishable inventory management, the research objectives, and the research questions.

2.6.1 Research gaps

Non-financial measures have been recognised as effective in improving the performance of the multi-echelon inventory model which is multi-dimensional by nature (Akyuz & Erkan, 2010). In addition, Chikán (2011) argued that research directions should focus on all performance measures that are based on contributions of inventory to improve the customer service level. Towill et al. (2007) emphasised the complexity of the multi-echelon inventory model and called for the creation of a set of measures to improve performance. Cannella et al. (2013a) responded to this call and proposed a set of non-financial measures which aim to improve performance at each echelon and in the whole system. However, using non-financial measures necessitates a shift from traditional methodologies in inventory management, and results in five research gaps. The first two research gaps relating to non-financial performance measures.

First, it remains unclear how to select suitable non-financial measures to define a replenishment policy. There are various non-financial measures that can be used. However, selecting an appropriate number of measures for a company is problematic (Medori & Steeples, 2000). Using too many measures may lead to fatigue (Koopman, Howe, Johnson, Tan, &

Chang, 2013), in contrast, not using enough measures may cause unfairness or game-playing behaviour (Burney, Henle, & Widener, 2009; Ittner, Larcker, & Meyer, 2003). There are a number of frameworks that help to select suitable measures, for example, the Balance Scorecard (Kaplan & Norton, 1995). The common limitation of these frameworks is a lack of guidance (Medori & Steeple, 2000) or they are too complicated (Cannella et al., 2013a). Addressing this gap promotes applications of non-financial measures in inventory management (Cannella et al., 2013a), and investigations of coordination between inventory and other research areas, for example, the location-inventory model (Zhang & Unnikrishnan, 2016).

Second, there is no unique and well-defined framework for finding a trade-off solution between non-financial measures (Mardani et al., 2015). Using non-financial measures supports managers in motivating performance and increases ease of communicate (Senot, Chandrasekaran, & Ward, 2016a). However, finding a solution as the best trade-off between non-financial measures is problematic as these measures conflict with each other; for example, there is no replenishment policy that minimises inventory and maximises fill rate simultaneously. Although, Kaplan (2008) and Grigoroudis et al. (2012) suggested the use of MCDM to deal with these problems, it is still unclear how to use these methods in inventory management (Lee & Geem, 2004; Zhang et al., 2014). Addressing this gap serves as guidance in using non-financial measures to select a replenishment policy.

The third research gap relates to the lack of knowledge of the main and interactive effects of consumer demand. Prior research has investigated effects of consumer demand on total cost or profit at each echelon (e.g., Pauls-Worm et al., in press; Xue et al., 2016). Besides this financial information, knowledge of the main and interactive effects of consumer demand on non-financial measures is also important (Kaplan & Norton, 1995; Kenyon et al., 2016). This knowledge helps managers to undertake proper activities under different demand situations.

The fourth research gap relates to the lack of knowledge of the main and interactive effects of product lifetime. Similar to issues of consumer demand characteristics, prior research has not focused on the main and interactive effects of product lifetime on non-financial measures. Knowledge of these main and interactive effects helps managers to make approximate decisions under different contexts of product lifetime (Hancerliogullari et al., 2016).

The fifth research gap relates to the lack of knowledge of the effects of decision-makers' opinions on the selection of replenishment policies. Extant literature uses cost transformation to reflect decision-makers' opinions on the importance of performance measures in inventory management. However, using cost transformation may not reflect all effects (see section 2.5.6). Thus, it is necessary to investigate the effects of decision-makers' opinions, however, not via cost transformation.

Research on these gaps has two general contributions. First, this research broadens the understanding of inventory management in a multi-echelon model for perishable and substitutable products with a multi-period lifetime. The inclusion of substitution in perishable inventory management under the multi-echelon model contributes to the extant literature. As shown in Table 2.4 above, there is only one paper under the multi-echelon model for perishable and substitutable products with a multi-period lifetime. The inclusion provides opportunities for complex inventory policies, which are analytically challenging but practically rewarding (Karaesmen et al., 2011).

Second, research on these gaps helps to solve the practical issues. In today's competitive business environment, managing a multi-echelon inventory model is receiving more attention because the integration in the supply chain is more important and has many advantages, for example, less inventory level and a higher customer service level (Bakker et al., 2012). Moreover, substitution, especially in multi-period perishable products (e.g., dairy

products), is common in daily life. Through numerical studies, Liu and Lee (2007) showed that substitution improves the performance of the system such as low inventory level and higher service level. As a result, the manufacturer and retailer are able to reduce the cost and more consumers can easily acquire the necessary products.

2.6.2 Research objectives and questions

This chapter has introduced the background of the research and identified aspects of interest in perishable inventory management. It has shown that most of the research on perishable inventory management has optimised a financial measure to define a replenishment policy. However, inventory management is a complex phenomenon and requires more than a financial measure (Zhu, 2000). Moreover, the research on managing perishable inventory in single-echelon models may reach a saturation point (Alizadeh et al., 2014; Duong et al., in press); therefore, more research on multi-echelon models is required. Furthermore, there has been a call to conduct more research on substitution, which could lead to a better replenishment policy (Bakker et al., 2012). This research aims to address these issues and find the appropriate replenishment policy by addressing the following research objectives:

- Research Objective 1 (RO1): Use non-financial performance measures to define the most favourable replenishment policy for a two-echelon model under a given context of perishable and substitutable products. This objective is divided into the following four sub-objectives:
 - Identify and explore characteristics that are relevant to perishable and substitutable inventory management.
 - Design and develop a verified and validated inventory model that takes into account these characteristics when deciding on a favourable replenishment policy.

- Define relevant non-financial performance measures for the given context.
- Create a framework that uses non-financial performance measures to define the most favourable replenishment policy in a given context of perishable and substitutable products.

Moreover, the research gaps discussed in section 2.6.1 show that there is a lack of knowledge of the effects of consumer demand, product lifetime, and substitution on the performance of perishable inventory management, and the effects of decision-makers' opinions in the selection of a replenishment policy. This research defines consumer demand, product lifetime, substitution, and decision-makers' opinions as problem characteristics. Consequently, the second objective of this research is,

- Research Objective 2 (RO2): Evaluate and explore the importance and interaction of these characteristics in a perishable and substitutable inventory management model.

The relevant research questions for these two research objectives are;

- Research Question 1 (RQ1): What is the most favourable replenishment policy in a given context of perishable and substitutable products?
- Research Question 2 (RQ2): Given the context of perishable and substitutable products, how do decision-makers' opinions affect the selection of the most favourable replenishment policy?
- Research Question 3 (RQ3): Given the most favourable replenishment policy, how do the characteristics of the inventory model influence the performance of a two-echelon inventory model for perishable and substitutable products?

Chapter 3 Research Methodology

This chapter introduces the methodological approach and proposes a research framework, which is suited to the research model. It describes and explains the applicability and validity of the chosen research framework. While the previous chapters summarised and analysed what has been studied in perishable inventory management, this chapter aims to explain how the research model is conducted. A proposed research framework helps to evaluate the findings (Peffer, Tuunanen, Rothenberger, & Chatterjee, 2007), thus, it is essential for successful research. The research objectives and associated research questions highlighted in section 3.1.1 show that a multi-methodological approach (i.e., an integration of research methods) is necessary to solve the problems. Therefore, this chapter is concerned with the development of a multi-methodological approach (i.e., integration approach). The structure of this chapter is outlined in Figure 3.1.

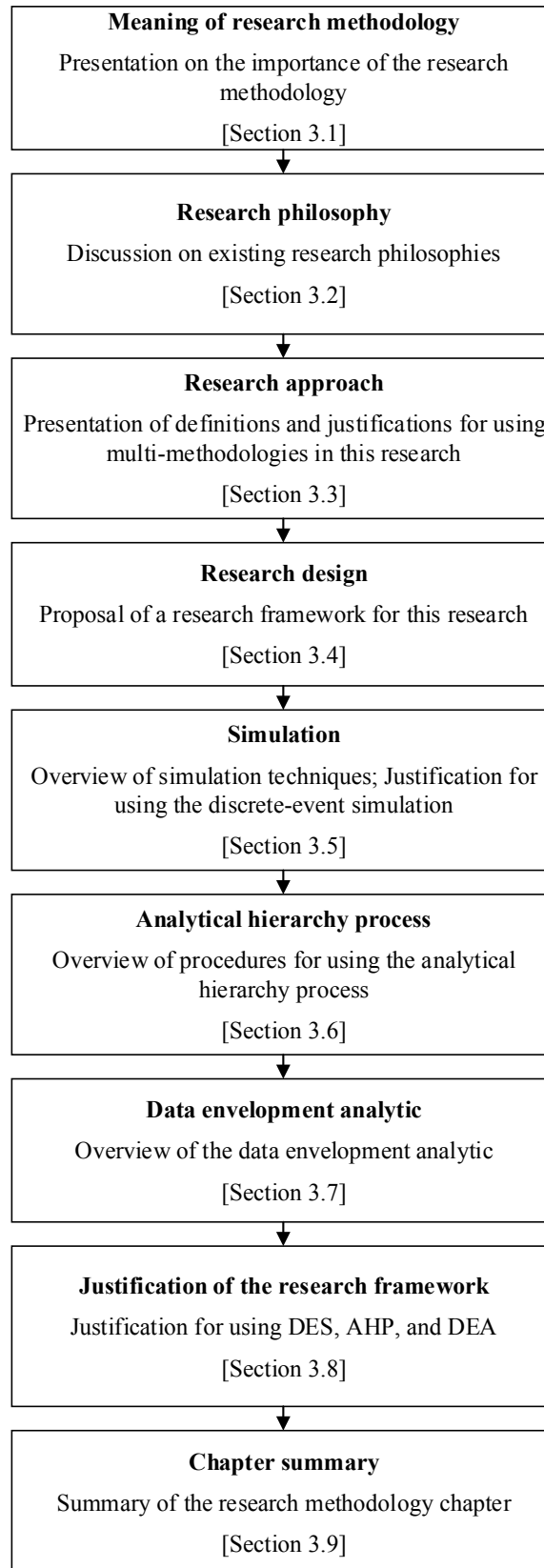


Figure 3.1: Structure of Research Methodology chapter

Section 3.1 explains the meaning of the research methodology and the essential aspects of the research methodology, and outlines the research objectives and the expected findings from this research. The research philosophy, which guides how to conduct this research, is presented in section 3.2. Section 3.3 discusses the research approach of using multiple methods to address the research objectives. Based on that discussion, section 3.4 develops a proposed research framework for this research. Details for the framework are presented in sections 3.5, 3.6, and 3.7. The proposed research framework is justified in section 3.8. All discussions in this chapter are summarised in section 3.9.

3.1 Meaning of Research Methodology

This section describes the research methodology and explains its importance in the research. The understanding of research methodology comes from two words, namely, research and methodology. Firstly, research is essential to business and academic activities (Mustak, 2014). Although there is no consensus on how a research should be defined, there is a common agreement that it should be systematic and methodical, as well as a process of inquiry and investigation. Its aim is to increase knowledge (Balaid, Abd Rozan, Hikmi, & Memon, 2016). Research must be conducted systematically with suitable methods to collect and analyse data to obtain reliable findings for exact problems (Balaid et al., 2016). Secondly, a methodology should include three fundamental elements: conceptual principles, assumptions, and procedures (Peffer et al., 2007). A methodology involves theoretical principles and a framework to guide how the research is conducted (Wilson et al., 2014). Consequently, the research methodology is an approach to systematically investigate a problem (Barnes, 2011).

A research methodology refers to research approaches, from theoretical principles to data collection and analysis (Collins, Joseph, & Bielaczyc, 2004). It is defined as a combination of tools and techniques to investigate a specific problem (Venkatesh, Brown, & Bala, 2013). Different research methodologies are suitable for different problems (Mingers & White, 2010).

A research methodology considers not only the research approach but also the logic behind the research approach, which is used in the context of the study. A researcher should explain the reasons for using a particular research approach and not using others so that the findings can be evaluated by either the researcher or other people (Scandura & Williams, 2000).

The research methodology is driven by the objective of the study. For example, the objective could be an exploratory research to produce knowledge of a phenomenon, a descriptive research to describe the characteristics of the interested phenomenon, or an explanatory research to examine relationships among variables (Yin, 2014). Supporting the study's methodology is the researcher's philosophy, which includes ontological (i.e., the nature of reality) and epistemological (i.e., knowledge of reality) assumptions and determines how to conduct the research (Fletcher, in press). These assumptions affect the selection of a research methodology which can be categorised as qualitative or quantitative, or a combination of both (Creswell, 2014). Each research methodology offers a particular research design which includes research methods for collecting and analysing the data to address the research objectives (Jogulu & Pansiri, 2011). Therefore, it is necessary to determine the research objectives, research questions, and the available data when designing a research methodology (Bono & McNamara, 2011).

The rest of this chapter reviews research objectives, research questions, and available data needed for this research. Based on that background, this chapter proposes and justifies a research framework including DES, AHP, and DEA.

3.1.1 Research objectives

As discussion in Chapter 2, this research aims to address gaps in the literature on perishable inventory management and find the appropriate replenishment policy by addressing the following research objectives:

- Research Objective 1 (RO1): Use non-financial performance measures to define the most favourable replenishment policy for a two-echelon model under a given context of perishable and substitutable products.
 - Identify and explore characteristics that are relevant to perishable and substitutable inventory management.
 - Design and develop a verified and validated inventory model that takes into account these characteristics when deciding a favourable replenishment policy.
 - Define relevant non-financial performance measures for the given context.
 - Create a framework that uses non-financial performance measures to define the most favourable replenishment policy in a given context of perishable and substitutable products.
- Research Objective 2 (RO2): Evaluate and explore the importance and interaction of these characteristics in a perishable and substitutable inventory management model.

The relevant research questions are,

- Research Question 1 (RQ1): What is the most favourable replenishment policy in a given context of perishable and substitutable products?
- Research Question 2 (RQ2): Given the context of perishable and substitutable products, how do decision-makers' opinions affect the selection of the most favourable replenishment policy?
- Research Question 3 (RQ3): Given the most favourable replenishment policy, how do the characteristics of the inventory model influence the performance of a two-echelon inventory model for perishable and substitutable products?

These research objectives are interrelated, and findings help to gain a deeper understanding of perishable inventory management. This research aims to understand the effects of a problem characteristic and its interactions with others in system performance under different given contexts. The model is not designed to reflect any specific set of circumstances (e.g., at a supermarket chain), but to provide a theoretical understanding of the interactions between variables. Selecting the appropriate research methodology and philosophy contributes to addressing these research objectives.

3.2 Research Philosophy

A research study in any area is influenced by a research philosophy or a research paradigm which includes a specific research strategy and research method (Näslund, 2002). A research paradigm is considered as “fundamental assumptions about the nature of phenomena (ontology), the nature of knowledge about those phenomena (epistemology), and the nature of ways of studying those phenomena (methodology)” (Gioia & Pitre, 1990, p. 585). Thus, the research paradigm should be developed to reflect the nature of the research and to address limitations and potential future research (Näslund, 2002).

There are two groups of paradigm traditionalists: post-positivists and constructivists. While a constructivist paradigm supports qualitative methods, the post-positivist paradigm advocates quantitative research methods (Creswell, 2014). The post-positivist paradigm supposes that the world is objective and external, and the researcher should centre on realities and look for causation (Mangan, Lalwani, & Gardner, 2004). In contrast, the constructivist paradigm is based on the assumption that “knowledge is in the meanings people make of it” and “is gained through people talking about their meanings” (Creswell, 1998, p. 19).

It has been argued that these two paradigms are incommensurable (Golicic & Davis, 2012). However, Hudson and Ozanne (1988) declared that “incommensurability does not mean the two approaches cannot peacefully coexist or that other middle-ground approaches cannot

or should not be developed” (p. 508). Numerous philosophical approaches are offered to settle the incommensurability debate. Researchers have observed that some data are exact demonstrations of external objects while others are socially constructed perceptions (Golicic & Davis, 2012). Correspondingly, the transformative paradigm believes that there are multiple and socially constructed viewpoints of reality (Mertens, 2010).

Traditionally, operations and supply chain management research has focused mainly on designs using quantitative methods, for example, mathematical models (Boyer & Swink, 2008). This research on operations and supply chain phenomena, including purchasing, logistics, operations, transportation, and marketing, follows a post-positivist paradigm (Davis, Golicic, & Boerstler, 2011). As research in this area has grown, researchers have examined the effect of methodology on the theory development. The reliance on quantitative methods has called for studies that investigate using qualitative methods in these areas to advocate for a better balanced approach (Näslund, 2002) and/or multiple methods (Taylor & Taylor, 2009). However, the combination of quantitative and qualitative methods within a single study (i.e. mixed or multiple methods research) is unusual (Golicic & Davis, 2012) as shown in Table 3.1.

The dominance of single-method quantitative studies weakens the robustness of operations and supply chain research in two ways (Spens & Kovács, 2006). First, each method can address only a limited number of research questions. Second, dependence on only a few research methods leads to certain biases in the development of theory and threatens the evolution of a research area.

In conclusion, all research methods have advantages and disadvantages (Boyer & Swink, 2008). The fact is that operations and supply chain management is a complex area and it is necessary to utilise more than one type of research method to understand completely the research problem (Frankel, Naslund, & Bolumole, 2005). Thus, it is advised to “use multiple methods, selected from different classes of methods with different vulnerabilities” (McGrath,

1981, p. 207) to assure the trustworthiness of the results. Using multiple methods helps to generate multiple perspectives on the studied problem and to reduce the risk of method bias.

Table 3.1: A summary of methodologies used in supply chain management research (derived from Table I in the work of Golicic and Davis (2012, p. 730))

Research	Papers reviewed	Review period	Methodology ^a
Davis et al. (2011)	3,289	1990-2008	81% quantitative 15.5% qualitative 4% multiple methods
Taylor and Taylor (2009)	310	2004-2009	46% quantitative 38% qualitative 10.5% multiple methods
Frankel et al. (2005)	108	1999-2004	63.0% quantitative 12.0% qualitative 4.6% multiple methods

Note: ^aPercentages are calculated based on the empirical papers and exclude conceptual papers and literature reviews.

Multi-method research is described as a type of research in which quantitative and qualitative research approaches are integrated within single or closely related studies (Franco & Lord, 2011; Williams & Gemperle, in press). Golicic and Davis (2012) investigated all of the published research methods in supply chain management-related disciplines to verify the coverage to which multiple methods approaches are applied in the field. The review confirms that the majority of empirical research papers are based on quantitative methods, and multi-methods have been used increasingly in recent years. This increase may be because of the expansion in the number of empirical studies and the application of qualitative methods. Hence, a selection of suitable methodologies is motivated and discussed in this chapter. The next section evaluates the applicability of the multi-methodological approach.

3.3 Research Approach

Operations management (OM) is a dynamic field that has grown with the escalating importance and complexity of business. Research has focused on using analytical and empirical methods to solve the problem in OM (Choi et al., 2016). However, researchers have raised the issue that there is a lack of advancing theory and practice in OM. In a recent study, Sodhi and Tang

(2014) pointed out two critical problems in the OM research stream, namely “isolation of methodology” and “disconnection from practice”. This section provides an overview of research approaches to OM and justifies the current trend of using multiple methods to enhance the relevance of OM research.

Many suggestions have been proposed to enhance the relevance of operations research. For example, Singhal and Singhal (2012a) suggested that instead of just working on developing the theory and mathematical modelling, researchers should include qualitative exploratory research. Sodhi and Tang (2014) proposed utilising many research methodologies to enhance research integrity and link research with practice. Thus, using multiple methodologies is feasible and desirable in OM research.

The multi-methodological approach has been accepted and become popular in operations research (Molina-Azorín, 2011). The term ‘multi-methodological approach’ might be new, but it was mentioned in the 1950s by Ackoff (1956). Since then, the use of multi-methodological approaches has been advocated because of the flexibility and benefits that they provide (Mingers, 2001). Research frameworks which support the use of multi-methodological approaches have been developed by Mingers and Brocklesby (1997) and Munro and Mingers (2002).

This section considers the benefits and appropriateness of the multi-methodological approach for an OM research. In particular, this approach increases the scientific merit of research on inventory management (Choi et al., 2016). This observation is true because there are many unknown factors (e.g., consumer demand) that affect the performance of an inventory policy in the real world (Singhal & Singhal, 2012a). The next sections discuss the meaning, the importance, and the justifications of using the multi-methodological approach in this research.

3.3.1 Towards a theoretical contribution

Creating a theoretical contribution is essential in academic research (Bergh, 2003; Colquitt & Zapata-Phelan, 2007; Corley & Gioia, 2011). Theory is the currency of the academic empire (Hambrick, 2007). A theoretical contribution is required in every top-tier journal (Corley & Gioia, 2011). However, defining what constitutes a theoretical contribution is the subject of debate amongst researchers (Maanen, Sørensen, & Mitchell, 2007). Corley and Gioia (2011) described a theoretical contribution as “a significant theoretical (as opposed to an empirical or a methodological) advancement in our understanding of a phenomenon” (p. 12). Colquitt and Zapata-Phelan (2007) and Malhotra and Grover (1998) argued that a deductive or axiomatic approach, which is adopted in this research, can be used to make theoretical contributions.

There are three criteria, which are regarded as common factors that confirm a sufficient theoretical contribution. The most widely used measure is originality (Bergh, 2003; Corley & Gioia, 2011). A theoretical contribution should expose “what we otherwise had not seen, known, or conceived” (Corley & Gioia, 2011, p. 17). The second measure is its utility; that is, a theoretical contribution must be useful in either a practical or scientific journal (Corley & Gioia, 2011). The final measure is the ability to stimulate future research (Hambrick, 2007; Kilduff, 2006), for example, by “alerting us to research opportunities hitherto unanticipated” (Kilduff, 2006, p. 252). The contribution of this research is discussed in section 6.2 in line with these three criteria.

3.3.2 Definition of the multi-methodological approach

There are different research methods in OM (Taylor & Taylor, 2009) with different implications. Sodhi and Tang (2014) listed four broad research categories for OM: analytical modelling, behavioural research, case study/ grounded theory/ action research, and empirical research. Definitions of these four categories are presented in section 3.3.3. From these categories, Choi et al. (2016) defined the multi-methodological approach for OM research as

follows: “Multi-methodological OM research is an approach for OM research in which at least two distinct OM research methods are employed non-trivially to meet the research goals” (p. 2).

Based on this definition, the multi-methodological approach is simply the application of multiple methods for an OM research. Choi et al. (2016) noted that by using the multi-methodological approach, researchers can apply different methods to examine different perspectives on an OM issue or study the same issue from different perspectives. Researchers also can apply different methods for the same or different sets of data to verify and validate research findings.

Although the multi-methodological approach was mentioned in the 1950s (Ackoff, 1956), OM researchers have over time focused on one method and applied it to specific problems. Choi et al. (2016) discussed five possible reasons for this phenomenon: the difficulty to master multiple methods; the limitation of time and resource; the lack of need to use multiple methods; the bias of using the single method; and the paradigm shift (Carter, Sanders, & Dong, 2008). However, with the advantages of technology, collaborations amongst researchers are much easier. Researchers with different backgrounds and research methodologies can easily work together. Thus, the trend of using multi-methodological approaches in OM research is increasing (Choi et al., 2016).

Before the use of multiple methods in OM research is presented, section 3.3.3 reviews the definition with some references as examples for each of four research methods.

3.3.3 Research methods in operations management

The research on OM has changed rapidly from simple mathematical techniques for a particular process (e.g., job shop scheduling) to more complicated techniques for optimising a flow of processes (Craighead & Meredith, 2008). There has been a movement towards the use of an empirical and interpretive framework and a change in the data collection techniques (Craighead

& Meredith, 2008). Sodhi and Tang (2014) summarised the research methods and pointed out that there are four broad research method categories in OM as follows.

3.3.3.1 Analytical modelling

Analytical modelling is an approach where the results are calculated using computer science or mathematics methods (Sodhi & Tang, 2014). This approach is based on a set of variables and equations to explain or predict the performance of an operations problem, and is oriented to solve real and complex OM problems (e.g., Alaei & Setak, 2015). The principle of OM is the analysis of actual operations problems, based on systematic observations and measurements to improve performance (Craighead & Meredith, 2008). This approach has developed a model, which simulates the operations of a real problem by using mathematical methods (e.g., stochastic programming) or simulation techniques (e.g., DES).

These models, however, are an abstraction from the reality and are not part of real operations problems (Martínez-Costa et al., 2014). These models are formulated independently of any example of real problems and consider just some aspects of problems. The reason is some aspects are not relevant to the method used. Practitioners use their knowledge of reality to include these aspects in the solutions later. Nevertheless, an operations problem is complicated and difficult to study from a performance point of view (Craighead & Meredith, 2008). There are many elements (e.g., human, cost, environment) that affect the performance of a problem. As a result, the analytical modelling may be based on contextual details and turn out to be tedious.

3.3.3.2 Behavioural method

The second method in OM research is the behavioural method, which is defined by Bendoly and Wezel (2015) as follows:

Behavioral operations management explores the interaction of human behaviors and operational systems and processes. Specifically, the study of behavioral operations management has the goal of identifying ways in which human psychology and sociological phenomena impact operational performance, as well as identifying the ways in which operations policies impact such behaviour. (p. ix)

Historically, the research on OM has experienced a disconnection with practice (Sodhi & Tang, 2014). Many mathematical models have not been applied in practice, mostly because of either the lack of applicable tools or the lack of knowledge of decision-makers (Bendoly, Donohue, & Schultz, 2006). Mathematical models usually ignore the characteristics of a real problem and are difficult to apply. Also, methods are difficult to implement due to lack of information or trust (Bendoly et al., 2006).

A common cause of these issues is human (Croson, Schultz, Siemsen, & Yeo, 2013). There are managers to make decisions, employees to work and improve the operations processes, and customer to buy products. In theory, many consider only the financial measure (e.g., customers purchase the product having the lowest price) (Hendricks & Singhal, 2005). However, in reality, customers may prioritise non-monetary criteria (e.g., natural products or brand reputation) to purchase a product. Therefore, when it comes to implementation, the success of OM models relies on the understanding of human behaviour.

The need to integrate behavioural factors into OM research was firstly stressed by Powell and Johnson (1980). Recently, Hopp (2004) also emphasised that the understanding of an operations problem “does not just require a theory of human motivation and a theory of material flow; it also requires a means for describing the interaction between the two” (p. 5). Since then, the integration of behavioural factors into OM research has increased.

A review of behavioural OM research can be found in the work of Croson et al. (2013). There are many behavioural factors (e.g., nature of humans, incentives), and integrations of

behavioural and technological factors that dominate in operations research (Powell & Johnson, 1980). There are three main questions, which need to be addressed when considering interactions between behavioural and technological factors. They are, “1. Which technological and behavioural variables influence productive system performance? 2. How do behavioural and technological variables interact? 3. Which variables are most important under different circumstances in determining performance?” (Powell & Johnson, 1980, p. 47).

Croson et al. (2013) pointed to the increasing number of papers in behavioural OM research since 2006. The scope of behavioural operations is widening, and usually relates to the research on ordering policy in inventory management and settings in supply chain management (Bendoly et al., 2006). Croson et al. (2013) observed that researchers have started to analyse the practice of ordering policy under different decision contexts. This observation is aligned with the recommendations of Shepherd, Williams, and Patzelt (2015), who encouraged the investigation of the intelligence of processes in which decisions are made and executed.

3.3.3.3 Case study/ grounded theory/ action research

There are numerous calls for case research in OM (Ketokivi & Choi, 2014). These calls stem from gaps between what academics have assumed and the real conditions of OM problems.

The case research is one of the most powerful methods of OM through which to develop a new theory (Voss, Tsikriktsis, & Frohlich, 2002). This method is based on social sciences where findings are generalised from observations of practice. It is an appropriate method for examining why and how questions on OM research because of its ability to deal with complex operations problems (Voss et al., 2002). The case research uses quantitative and qualitative methods to collect data, and investigates a contemporary phenomenon where the investigator has little control over events (Yin, 2014).

Despite the need for case research in OM and the success of some studies such as those in lean production (Voss et al., 2002), there has been a limited number of case studies published

in top-tier OM research journals. The reason may be that case research is perceived as lacking in rigour or less structured than analytical modelling or empirical research (Barratt, Choi, & Li, 2011). Typically, criticisms of case research point to the entire process of conducting a research. The case research paper summarises observations and impressions. These papers are weak on discussing related work, the protocol, data collection, data analysis, and findings validation (Stuart, McCutcheon, Handfield, McLachlin, & Samson, 2002). Moreover, another reason is that there are many challenges to conducting a case research: it is time-consuming, it requires interview skills, and it is difficult to generalise conclusions (Voss et al., 2002).

Meredith (1998) and Seuring (2008) discussed ways to increase rigour in case research. These include using grounded theory (Randall & Mello, 2012) or action research (Coughlan & Coughlan, 2002). A step-by-step method to conduct a case research in OM was introduced in the study by Voss et al. (2002). This extant literature can help to make case research a powerful method in OM research.

3.3.3.4 Empirical research

The gap between OM theory and practice was criticised many decades ago (Foropon & McLachlin, 2013; Singhal, Sodhi, & Tang, 2014). Flynn, Sakakibara, Schroeder, Bates, and Flynn (1990) argued that by using purely deductive techniques such as mathematical modelling, operations research cannot entirely explain the operations problem.

This gap has called for the use of empirical methods, which help to provide information from actual practices. Using empirical data contributes to building OM theory and verification (Flynn et al., 1990). To guide the researchers, Flynn et al. (1990) provided a systematic approach for conducting empirical research in OM with various types of statistical analysis.

There have been a significant number of published OM papers based on empirical data (Gupta, Verma, & Victorino, 2006). The empirical method helps to fill the gap in the understanding of analytical modelling. For example, DeHoratius and Raman (2008) used the

empirical method to study inaccuracy in inventory management, which is ignored in analytical modelling. Although accessing data is a challenge in empirical methods (Fisher, 2007), the future of conducting empirical OM research is promising, especially with the increasing role of services (Gupta et al., 2006).

There are many research methods with different implications for performing OM research. Sodhi and Tang (2014) summarised the differences in purposes and contributions of each research method in OM research. MacCarthy, Lewis, Voss, and Narasimhan (2013) discussed current challenges in the OM field, a range of methods in OM, and how researchers use these methods. OM research should be driven by needs not by methodological convenience. Thus, a variety of research methods can provide a strengthening cycle to conduct relevant, interesting and exciting research (MacCarthy et al., 2013). Considering the multi-perspective of OM (Singhal & Singhal, 2012a, 2012b), the following section discusses the integration of multiple research methods in OM.

3.3.4 The application of multi-methodological approach in operations management

Over the decades, there have been many calls and discussions concerning the use of multi-methodological research approaches. The multi-methodological approach has been accepted and applied widely to provide a better understanding of operations problems (Franco & Lord, 2011). However, there is a lack of consensus on the definition and research procedure of the multi-methodological approach (Choi et al., 2016). These issues have called for studies using multi-methodological approaches in operations and management science, for example, the call by Choi et al. (2016).

Motivated by these calls, many papers have used multiple methods in OM research. Table 3.2 presents recent papers that have used multiple methods in OM research. These papers have integrated analytical modelling, empirical research, and case study. These examples prove

that using the multi-methodological research approach is now a commonly adopted approach in OM research (Choi et al., 2016).

Table 3.2: Examples of recent papers using multiple methods in OM research

Paper	Methods used	Relationship between methods
Li, Li, Cai, and Shan (2016)	Analytical method and empirical survey	The analytical method generates theoretical insights about an OM service problem. The empirical survey supports and validates these insight findings.
Zhao, Zhao, He, and Yang (2016)	Analytical method and case study	A state-feedback model is developed to adjust the order quantity. A case study is conducted to test the effectiveness and applicability of the model.
Senot, Chandrasekaran, and Ward (2016b)	Empirical research and case study	Qualitative data are used to develop hypotheses about decision processes. Secondary data are used to test these hypotheses.

Sodhi and Tang (2014) and Choi et al. (2016) identified the multi-methodological approach framework. Different research methods have different important roles in different studies. The same research method can be applied for different purposes. Although using multiple methods is one of the primary characteristics of published papers (Choi et al., 2016), there are still some pros and cons related to this approach. The following section discusses the advantages and disadvantages of using the multi-methodological approach in OM research.

3.3.5 Advantages of the multi-methodological approach

There are four major advantages in using the multi-methodological approach in OM research. First, OM is complex and closely relates to all aspects of management in business organisations (Buhman, Kekre, & Singhal, 2005). Therefore, OM needs to be studied from multiple perspectives, which calls for the integration of multiple research methods (Singhal & Singhal, 2012a, 2012b). For example, there are many factors, including unknown factors (e.g., decision-makers' behaviour, customers' behaviour, inventory accuracy), that affect the performance of an inventory policy in a company. Using only the single method (e.g., analytical modelling) can provide various "optimal" inventory policies (Choi et al., 2016). However, there could be

inventory inaccuracy in a real company, which leads to the poor performance of those “optimal” inventory policies.

Second, there are four stages of a general OM research: awareness, framing, modelling, and validation (Sodhi & Tang, 2014). A single method is not always relevant to all four stages. Thus, it is important to choose the right method for each stage. Sodhi and Tang (2014) provided an example by investigating the supply contract for the fashion industry. In the awareness stage, the case study explored the industrial features and applications of supply contract. A taxonomy and descriptive framework for supply contracts were formed in the framing stage. The managerial insights were derived from the analytical models in the modelling stage. Finally, empirical research was conducted to validate the managerial insights in the validation stage. Therefore, it is beneficial to apply multiple methods in different stages and obtain multi-perspective solutions for an OM problem (Singhal & Singhal, 2012a).

Third, OM is an important field of study but its relevance to the real world has been debated. There are significant gaps and interests among three groups involved in OM, namely, researchers, practitioners, and educators (Sodhi & Tang, 2008). Research papers in OM-related journals have simplified the problem so it becomes solvable; however, the derived solutions do not fulfil real problems (Sodhi & Tang, 2014). Tang (2016) encouraged fine-tuned OM research and proposed to involve practitioners and the use of multiple methods to increase the relevance of operations research to the real world.

Fourth, OM research-related journals have focused on research rigour. However, over time, each method reaches a maturity point and it is hard to develop new research based on a single research method (Choi et al., 2016). For example, it is not always possible to optimise an OM problem by using the analytical modelling method because of the complexity of the problem. As a result, using multiple methods increases research value and leads to multiple

perspectives. Thus, the multi-methodological approach is considered as a feasible way to develop publishable OM research.

3.3.6 Disadvantages of the multi-methodological approach

The above section discussed the multi-methodological approach as a powerful research method for OM research. However, it has some weaknesses, a detailed discussion of which was provided by Choi et al. (2016). These weaknesses are presented as follows.

First, the multi-methodological approach consumes a great deal of time and resources. The approach needs more data collection and technical analysis. It can take more time and require more resources to complete the research, and may be unaffordable for many researchers. Second, there is no rule to decide how many methods should be employed for an OM research. Third, using one method can reduce the bias in decision-making. Using the multi-methodological approach may provide many inconsistent findings. Fourth, it is not always easy to publish a paper using the multi-methodological approach. Most journals limit the number of pages, and it is a challenge for the authors to find a balance between information and page limit.

In summary, the multi-methodological approach has many inherent advantages, contributes to strengthening the OM research, and makes the research more rigorous and practically relevant. Using multiple methods helps to explore the research topic from multiple perspectives and to obtain comprehensive findings. The following section justifies the use of the multi-methodological approach and decides which research methods are to be used in this research.

3.3.7 Justification for using multi-methodology in this research

The previous section presented benefits of using the multi-methodological approach in OM research, especially for inventory management, a traditional OM topic (Midgley et al., 2013),

as this is a multi-perspective problem (Choi et al., 2016). This research is about inventory management for perishable and substitutable products. Therefore, the multi-methodological approach is suitable for this research. This section justifies the use of two-method simulation and multi-criteria decision-making (MCDM) in this research.

In the context of a two-echelon inventory model for perishable and substitutable products, this research aims to find an inventory policy which best performs over three objectives of a perishable inventory management model. As shown in the literature review chapter, many factors affect the performance of perishable inventory management. Moreover, three objectives of the inventory problem conflict with each other. Deciding which objective should be prioritised depends on the opinions of decision-makers (Fernandez & Olmedo, 2013; Ho, Lim, & Cui, 2010), and leads to calls for using MCDM techniques. Therefore, this research selects research methods which satisfy two tasks: to calculate the performance of each inventory policy and to rank these performances for selecting the most favourable policy.

Inventory management is a traditional and key field to improve the efficiency of a company, and often requires the using of a simulation method to deal with the complexity of real problems. There are many uncertain factors, such as demand distribution or lost sales probability, that affect the performance of an inventory policy. The issue is more difficult in the perishable inventory management model where the lifetime of a product also affects the model (Nahmias, 2011). There are three main related research streams for uncertainty demand in an inventory model (Zhao et al., 2016). These models may consider demand with an exponentially smooth and Bayesian approach (e.g., Saghafian & Tomlin, 2016), a Markov demand process (e.g., Kouki, Babai, Jemai, & Minner, in press), or a stochastic demand following a forecast process (e.g., Saghafian & Tomlin, 2016). The common approach of these research streams is that the inventory policy is derived from a simulation model, for example, formulating a total cost function for multiple perishable products with a random lifetime. The

inventory policy is based on minimising the total cost function in a simulation model. Similar observations appear in the related research stream concerning customer's buying decisions and product lifetime. Wu et al. (2016a) formulated the present value of a retailer's annual total profit for perishable products. Then, the authors used a simulation model to analyse the interactions of model factors and derived managerial insights. The methodology employed in these researches is consistent with the findings of Bertrand and Fransoo (2002), Sodhi and Tang (2014), and discussions in section 3.3.3.1. These researches show that the simulation model has been used widely for solving complex OM problems in general, and perishable inventory management in particular. Motivated by these observations, this research also uses the simulation method for the studied perishable inventory model.

3.3.7.1 Justification for using simulation as one of two methods in this research

This section discusses and justifies the use of the simulation method for the studied inventory management model. The use of simulation in this research is justified by the theoretical suitability and characteristics of the studied problem, and is based on the relevant papers on OM in general, and inventory policy in particular.

Bertrand and Fransoo (2002) classified operations research into axiomatic and empirical classes. First, according to Bertrand and Fransoo (2002, p. 249), "axiomatic research produces knowledge about the behavior of certain variables in the model, based on assumptions about the behavior of other variables in the model". The main concern of axiomatic research is to achieve solutions for defined models and gain understandings of the defined models. The axiomatic model has been used productively in manufacturing systems, production and inventory management, plant, supply chain management, and optimisation problems. Typically, axiomatic research "is primarily interested in developing policies, strategies, and actions, to improve over the results available in the existing literature, to find an optimal solution for a newly defined problem, or to compare various strategies for addressing a specific

problem” (Bertrand & Fransoo, 2002, p. 250). Second, the empirical class aims “to ensure that there is a model fit between observations and actions in reality and the model made of that reality [...] is primarily interested in creating a model that adequately describes the causal relationships” (Bertrand & Fransoo, 2002, p. 250).

Craighead and Meredith (2008) produced a similar classification and observed that the research framework is one of two major dimensions in the philosophy of research. The research framework ranges from ‘rational’ (i.e., deductive or axiomatic) to ‘existential’ (i.e., inductive or interpretive). Axiomatic research “represents the theorem-proof world of research, as well as reasoning and logic models. Also, normative (e.g. mathematical programming) and descriptive (e.g. queuing) models tend to fall in this category” (Craighead & Meredith, 2008, p. 714). Interpretive research focuses “on people, context, and concepts rather than objects, with an emphasis on meanings and interpretations rather than behavior” (Craighead & Meredith, 2008, p. 714).

This research aims at finding the most favourable replenishment policies for a perishable inventory management model. According to the classification in the works of Bertrand and Fransoo (2002) and Craighead and Meredith (2008), this research falls into the axiomatic research class. Therefore, this research selects a research method used in the axiomatic class.

Bertrand and Fransoo (2002) stated that computer simulation is used for a problem that is too complex for mathematic analysis. This computer simulation method increases the scientific relevance of the problem and the contribution of the research which has been distinguished as a study of new variants of the model or a study providing new solutions to an existing model (Bertrand & Fransoo, 2002). In a similar but more specific observation, Craighead and Meredith (2008) stated that simulation is a powerful tool to solve problems in the inventory management system.

The use of simulation in this research also aids in building theoretical contributions. Simulation is useful for the development of simple theories when there are many interacting processes (Davis, Eisenhardt, & Bingham, 2007). A simple theory may include basic concepts and processes from well-known theories; for example, perishable inventory theory has been studied for many decades, especially following the work of Nahmias in 1973 (Nahmias, 1982). This research focuses on the perishable inventory theory and the interactions of problem characteristics. Thus, simulation is useful for this research (Davis et al., 2007).

Recall that the model in this research is complicated and integrates new characteristics to provide a better understanding of inventory management. Therefore, consistent with the findings of Bertrand and Fransoo (2002), Davis et al. (2007), and Craighead and Meredith (2008), the simulation method is regarded as suitable for this research.

Other observations about the relevance of the simulation method for perishable inventory management are also noted. For the perishable inventory management problems under the multi-echelon model, simulation supports a better representation of practical problems and provides more opportunities to deal with their complexity (Bakker et al., 2012; Duong & Wood, 2015). The simulation model easily allows researchers to test the system's performance and the impacts and the correlations of factors in the system (van Donselaar & Broekmeulen, 2012). Simulation is the appropriate modelling method for perishable inventory problems where the system is complex (especially with substitution), the time demand and review are discrete, and the demand is stochastic (Duan & Liao, 2014).

Carefully considering the relevance of the above findings to the studied model, this research selects simulation as a method for the studied two-echelon inventory management model of perishable and substitutable products.

3.3.7.2 Justification of using multi-criteria decision-making methods

In the studied model, three performance measures conflict with each other, and the importance of each measure is different from department to department. For instance, the sales department aims to acquire high inventory to satisfy a customer's demand at any time and achieve a high fill rate level (Jung et al., 2004). However, the operations and finance departments prefer to keep inventory level as low as possible to reduce operational costs or risks in warehouses. Therefore, the fill rate and the average inventory conflict with each other. Hence, it is impossible to have a replenishment policy that optimises all performance measures at the same time (Dächert, Klamroth, Lacour, & Vanderpooten, in press). In other words, there is no inventory policy that simultaneously provides the lowest average inventory, the highest fill rate, and the lowest order rate variance ratio. This difficulty may be a reason for the lack of research on multi-criteria in perishable inventory management, and has led to calls for using MCDM techniques. This call is supported by Xu, Moon, and Baek (2011) who stated that simulation and MCDM methods should be combined when there are various performance measures.

MCDM is the part of OM research that aims to find the best solution within a given set of solutions and a set of decision measures. This method has been commonly used because real-world problems are often complex and consist of many conflicting measures. The core decision of this method is the performance of a set of solutions is evaluated and ranked when all decision criteria are considered simultaneously (Jayswal et al., 2016).

Over the decades, many papers have reviewed the methodology used to investigate MCDM problems (Yadav & Sharma, 2015). In an early review, Korhonen, Moskowitz, and Wallenius (1992) defined common terms and solution principles used in MCDM and classified MCDM problems as discrete and continuous. According to Korhonen et al. (1992), MCDM techniques have two key development phases:

- Before the 1980s, researchers emphasised using mathematical programming and algorithm procedures for solving MCDM.
- Since the 1980s, researchers have shifted towards providing support for decision-makers and practitioners when dealing with MCDM problems.

This shift suggests that researchers should focus on decision-makers' behaviour and associated areas, for example, the promotion of communication facilities amongst decision-makers, and a consideration of problems in the organisation context. These calls have been supported by the research on behavioural operations, which has had a wide focus from the individual to the organisational level (Hämäläinen, Luoma, & Saarinen, 2013). Understanding behavioural issues provides insights into how decision-makers approach decisions and sheds light on biases which may influence decision-makers' opinions (Morton & Fasolo, 2008).

Within the MCDM field, the analytic hierarchy process (AHP) and hybrid MCDM are the first and second most common research techniques (Mardani et al., 2015). MCDM is a managerial task, and the objective of any MCDM technique is to help and guide decision-makers to find the most desired or favourable solution to the studied problem (Zavadskas et al., 2014). Mardani et al. (2015) systematically reviewed the methodologies and applications of MCDM techniques and attempted to identify which MCDM techniques have been used. The review showed that AHP was ranked as the most common method used in MCDM, with hybrid MCDM (i.e., integrations of well-known techniques such as AHP and DEA) as the second most common method. These findings are explainable as techniques such as AHP or DEA consider decision-makers' opinions when making decisions (Ahn & Novoa, 2016). This research adopts a hybrid MCDM method including AHP and DEA because of the generalisability and the ability to capture decision-makers' opinions of these two methods.

3.4 Research Design

Each research methodology leads to a particular research design, which involves a particular method for collecting and analysing the data to address research objectives. As mentioned in section 3.1.1, this research has two primary objectives: define the most favourable replenishment policy and evaluate the influence of inputs to the system's performance. These objectives call for integrating multiple methods in the research as justified in section 3.3.7.

These use of the three research methods mentioned above helps to address the research objectives because "one model can be combined with other techniques in order to improve the quality of the tools" (Ha & Krishnan, 2008, p. 1305). Given a range of replenishment policies for a complicated perishable and substitutable inventory model, simulation is suitable for evaluating the performance of each policy. The performance was measured using three different criteria, which calls for the use of AHP, the most common MCDM technique, to rank the performance of each policy (Saaty, 2008). However, AHP itself cannot rank an overly large number of policies (Falsini, Fondi, & Schiraldi, 2012), which therefore calls for the integration of DEA and AHP (Yang & Kuo, 2003). AHP was used to rank the importance of each measure and DEA ranked the performance of each policy based on these weights.

The following sections present a research framework for the studied problem. The simulation model is developed in section 3.5 to evaluate the performance of a given set of replenishment policies. The importance of each performance measure is derived via the AHP method as presented in section 3.6. The DEA method is used in section 3.7 to find the most favourable replenishment policy based on the performance and importance of each measure.

3.4.1 Proposed research framework

Simulation is a valuable method to evaluate multiple performance measures in a complicated system (Jahangirian, Eldabi, Naseer, Stergioulas, & Young, 2010). These performance measures reflect different dimensions of an OM problem and include customer satisfaction,

work in process (WIP), and average inventory level. Based on the many dimensions of performance measures, these measures usually conflict with each other. Furthermore, the knowledge, understanding, and preference for performance measures differ from person to person. When conflicting performance measures are considered simultaneously, a flexible method for decision-making is required, which has called for the combination of simulation and MCDM methods (Xu et al., 2011).

The AHP method developed by Saaty (Saaty, 1986) has been applied in many studies related to the MCDM problem over many years (Ho, 2008). Such application domains may include business, management, education, engineering, manufacturing, and industry (Subramanian & Ramanathan, 2012). The AHP method can be used alone; however, Falsini et al. (2012) identified the following practical problems in the AHP method:

- It needs a large number ($n(n - 1)/2$) of pairwise comparisons for n elements;
- It requires a high consistency index; and
- It entails the replication of the procedure when there is a variation in the number of alternatives and/or criteria.

Therefore, to improve the accuracy of decisions, researchers have recently focused on the integration of AHP with other techniques (e.g., DEA, mathematical programming) (Ho, 2008). Integration has been used mostly in logistics and manufacturing (Ho, 2008; Yang & Kuo, 2003).

On the other hand, DEA was initially developed as the CCR model by Charnes, Cooper, and Rhodes (1978) and the BCC model by Banker, Charnes, and Cooper (1984). It has been applied in many domains to evaluate the relative efficiency of DMUs. Consequently, some alternative DEA models that are customised for specific applications have been proposed. A critical feature of DEA is its high flexibility that can cover serious inefficiencies (Pedraja-Chaparro, Salinas-Jiménez, & Smith, 1999). However, Ho, Xu, and Dey (2010) pointed out

two specific limitations of DEA. First, the decision-makers can be overwhelmed by a large number of input and output criteria. Secondly, there is a risk that it fails to consider the inconsistencies of proposed ranking scales.

All three methods (i.e., simulation, AHP, and DEA) have different advantages and disadvantages. An integration of these methods appears to be the right solution to manipulate the positive aspects (Choi et al., 2016) and to overcome the negative aspects of simulation, DEA, and AHP methods. The advantages of the integration of simulation, AHP, and DEA are discussed in section 3.3.7.

Together with the integration of simulation and MCDM methods and AHP and other MCDM methods (Mardani et al., 2015), researchers have paid attention to the integration of DEA and MCDM methods for a number of decades (Carrillo & Jorge, 2016; Lee & Kim, 2014a; Toloo, 2014). A ‘methodological connection’ between MCDM and DEA methods is that if all criteria in an MCDM problem are categorised as either benefit or cost criteria, then DEA is comparable to MCDM (Sarkis, 2000; Wallenius et al., 2008).

Recall that this research aims at finding the most favourable replenishment policy for perishable and substitutable products under a two-echelon inventory model. The perishable inventory model in this research is complex due to the stochastic variables (i.e., demand, lifetime, and substitution). There was a given range of replenishment policies (suggested from other studies), and the performance of each policy was measured by three performance measures. This research endeavours to evaluate and find the most favourable replenishment policy to help companies most successfully perform in all three performance measures.

Considering the characteristics of the research objectives, and the advantages and disadvantages of simulation, AHP, and DEA, this research proposed to integrate these three methods to define the most favourable replenishment policy. This framework was developed

based on the general decision support framework for complex systems, suggested by Bonney and Jaber (2014).

The integrated framework has three steps as shown in Figure 3.2. First, the simulation model was built and run for each scenario of the replenishment policy. The performance for each measure is extracted from the simulation running for each scenario. Second, the AHP method was used to weight the importance of each performance measure. Third, the DEA method was used to rank and evaluate the scenarios. Then, the most favourable scenario or replenishment policy, which has the lowest DEA efficiency score, was chosen. This proposed framework is similar to that of Azadeh, Ghaderi, and Izadbakhsh (2008), in which computer simulation was used to verify and validate the alternatives of the railway system. The AHP method was used to weight the qualitative output criteria. Then, the DEA method ranked and selected the best railway system.

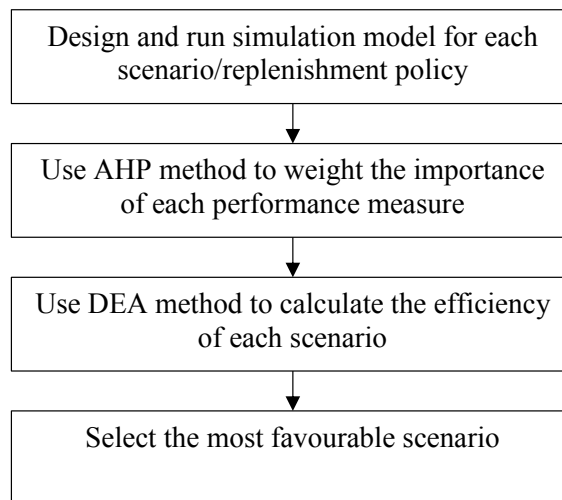


Figure 3.2: Integration framework the of Simulation/ AHP/ DEA model

3.5 Simulation

A real-world facility or process performs one or many functions. These functions can be procurement, production planning, or distribution. To study these facilities or processes, research is usually based on assumptions concerning how they work. These assumptions form

mathematical or logical relationships that provide insights into the behaviour of a facility or process (Law, 2014).

If the relationships are simple, mathematical methods can be used to obtain an understanding of these relationships. However, most real-world facilities or processes, especially in OM problems, are too complex to describe in mathematical equations, or even to obtain a solution to these equations (Lucas, Kelton, Sánchez, Sanchez, & Anderson, 2015). Therefore, these complicated facilities or processes have been studied by using simulation techniques.

Simulation imitates the operations of the studied models on a computer. The data received after the imitation are recorded and used to evaluate the performance of the models. Law (2014) defined simulation as a process of designing and creating a computerised model for a real or proposed model in order to conduct numerical experiments to better understand the behaviour of the model under a set of given parameters. Simulation is the appropriate method for models that are difficult to formulate (Law, 2014) and a good tool to emulate a real complex system to investigate and provide approximations with relevant performance measures. Simulation is well-known as a technique which can handle uncertainty and complexity easily (Tako & Robinson, 2012).

Simulation has been used widely in OM research (Bisogno et al., 2016). The main reason is it describes complex problems and can experiment with non-existing processes or existing processes without altering them. Simulation can provide valuable insights into the interaction between input and output factors. It can be used to experiment with scenarios with little or no available information, to check and make decisions before jeopardising experiments with real processes.

3.5.1 Types of simulation

Kleijnen and Smits (2003) classified four main simulation types for OM: spreadsheet, systems dynamics, gaming, and discrete-event simulation. The simulation type in this research is selected based on the studied model. The following sections introduce the main characteristics of each simulation type.

3.5.1.1 Spreadsheet models

Spreadsheet simulation simply uses a spreadsheet to do the sampling, calculating, and reporting. The spreadsheet remains popular and the most dominant spreadsheet today is Microsoft Excel (Seila, 2004). Most of the popular spreadsheets meet the minimal requirements of a simulation programme such as the abilities to represent mathematical and logical relationships, generate distributed pseudorandom numbers, and repeat a series of computations (Seila, 2004).

Spreadsheet simulation is appropriate for stochastic models or when performing any sensitivity analysis (Seila, 2004). In some cases, for example, in finance or logistics models, the parameters are stochastic or random with unpredictable values. Spreadsheet simulation allows the sampling of these parameters' values for each simulation experiment. The simulated results are observed to evaluate the performance of each experiment.

The spreadsheet is a simple and powerful simulation technique. However, it has four main drawbacks that limit the widespread use of spreadsheet simulation (Seila, 2004). First, the spreadsheet is suitable for only a simple data structure. Second, it is difficult to use a spreadsheet for complex algorithms. Third, it is slower than other simulation techniques. Fourth, the data storage is restricted. Considering these four drawbacks and the complexity of real world problems, researchers may think of alternative techniques to perform a simulation.

3.5.1.2 System dynamics

All processes or systems have echelons and flows of information within processes. It is necessary to understand why a system works the way it does. Forrester (1997) proposed a simulation methodology for dynamics models, which is considered to be the origin of system dynamics (Lane, 2008; Rahmandad & Sterman, 2012). A system dynamics model “facilitates the representation, both graphically and mathematically, of the interactions governing the dynamic behavior of the studied system or process, as well as the analysis of the interactions and their emergent effects” (Aslam & Ng, 2016, p. 292).

The basic objective of system dynamics is to provide insights on structural causes that initiate system performance (Thompson, Howick, & Belton, 2016). System dynamics is a rigorous method to explore operations and supply chain management. The method is based on the feedback basis; that is, a decision maker compares the actual performance of a measure and the target value to take corrective actions. It focuses on the dynamic performance of the model and does not require comprehensive information on relationships between input and output factors.

Since the work of Forrester (1997), researchers have used system dynamics in studies ranging from inventory management to integrated global supply chains. Recently, system dynamics has been recognised as the second most used simulation technique in manufacturing and business (Jahangirian et al., 2010). It focuses on areas such as the strategic decision-making level, the high perspective level, and knowledge management.

There are a number of advantages that explain the recent widespread use of system dynamics. First, it is a useful technique to improve system understandings, system thinking skills, and integration knowledge. Second, the development of dynamic modelling software helps researchers to utilise this technique more easily. Third, the system dynamic literature has contributed many approaches in the modelling process (Luna-Reyes & Andersen, 2003).

Despite these advantages, there are also several disadvantages in using system dynamics. First, the studied process can quickly become bigger and more complex. It creates an imbalance between data availability and accuracy in the process. Second, the inclusion of uncertain feedback loops makes the model behaviour more complicated and may not reflect real world behaviour. It is also difficult to verify and validate.

3.5.1.3 Gaming

OM aims to manage the process of creating goods and services. It involves managing technologies, information, people, and all other resources needed in the process. While it is easy to simulate the technological process, simulating human behaviour is very difficult. Therefore, it is more practical to let decision-makers operate within a simulated environment (Kleijnen & Smits, 2003). This interactive simulation is called a business game.

Business games involve a batch process (Lainema & Hilmola, 2005). This means that game participants generate business plans for their companies for a certain interval of time (e.g., months). After the game participants have completed these plans (e.g., sales plan), the plans are put in the simulation model. The simulation model calculates and generates the results from these plans. Thus, the game participants do not have internal understandings of the simulation model. In other words, the results from the business game do not provide explicit cause and effect relationships. The game participants actively join in the simulated environment and therefore business games are used mostly for training and education (Kleijnen & Smits, 2003).

A business game is usually simplified with respect to the number of participants and the number of decision variables. This is necessary as business game models are run mainly on personal computers or hand scored (Fritzsche & Burns, 2001). Running the game on personal computers allows quick and easy entering input, an easily changing business environment, and a graphical display of the simulated results (Faria, Hutchinson, Wellington, & Gold, 2009).

Today, business game simulation remains a powerful method for instruction. The development of technology and the internet has allowed more interactions for game participants and provided more opportunities for strategy formulation. As a result, this advantage enables an external evaluation of decision-making skills (Faria et al., 2009).

3.5.1.4 Discrete event dynamic simulation models

Discrete-event simulation (DES) began in 1957 with the creation of the General Simulation Program (GSP) by Tocher and Owen (Tocher & Owen, 2008). In a DES model, the behaviour of the studied system is mimicked in a computer programme (Law, 2014). It aims to investigate the dynamics of the systems and identify strategies that maximise the system's efficiencies (Terzi & Cavalieri, 2004).

The fundamental factor that distinguishes DES and other types of simulation models is the time taken for the system to change its state. In a DES model, the system changes its state at an instant or a discrete time (Viana, Brailsford, Harindra, & Harper, 2014). These time instants are referred to as events (Hoad, Monks, & O'Brien, 2015). It is an extremely flexible method, which can code and model almost any process.

DES has advantages over other analytical methods based on the growing complexity of OM (van der Zee & van der Vorst, 2005), and it is now seen as the main simulation approach in OM research (Baril, Gascon, Miller, & Côté, 2016). It can capture system dynamics and detail complexity and uncertainty (Jain, Workman, Collins, Ervin, & Lathrop, 2001) in the system behaviour resulting from the combination of random processes. Moreover, it can couple with the system structure and interconnection effects (Law, 2014). DES is computationally efficient and easy to understand (Fernandes, Land, & Carmo-Silva, 2016), and it supports the evaluation of system performance (Jeon & Kim, 2016).

Over the years, DES has been applied in many research areas. These research areas include a queue system, manufacturing, and inventory systems. Most of these works have

concentrated on improving the system's performance and aiding strategic decision making (Baril et al., 2016).

3.5.2 Justification of using discrete-event dynamic simulation models

This section justifies the using of DES for the research, which intends to find the most favourable inventory policy and understand the interaction of input factors in a two-echelon perishable and substitutable product inventory model. Therefore, the justification is based on the relevant literature on the research of inventory management for perishable and substitutable products. The justification is also based on the comprehensive review of the use of simulation techniques by Jahangirian et al. (2010).

The findings from the comprehensive review by Jahangirian et al. (2010) are interesting. While the spreadsheet is a simple technique that is easy to use on personal computers, it was not included in the final 281 papers of the authors' review. The reason may be the review work focused on high-quality papers (Jahangirian et al., 2010), which usually apply to real and complex problems. These findings are relevant to the limitations of the spreadsheet technique mentioned by Kleijnen and Smits (2003) and Seila (2004). Because of the complexity of perishable and substitutable inventory management, this research did not consider the spreadsheet as a useful simulation technique for the studied model.

The business game is a special technique that is mainly focused on education and training areas. Jahangirian et al. (2010) summarised eight papers on the business game technique and stated that this research technique has been mainly used as decision-makers want to be involved in the interactive and game-like techniques. This research does not aim to provide education or training; therefore, the business game is not considered as a simulation technique for the studied model.

Jahangirian et al. (2010) showed that the DES technique is the most common technique with over 40% of total reviewed papers focusing on it. It is appropriate for strategic and

operational decision-making levels in many industries. The dominance of DES is associated with the continuous growth of DES software (Dagkakis & Heavey, in press). Although DES has been used mostly to solve real problems, gathering data is the most difficult task when using this technique. In fact, only half of the reviewed papers in the study of Jahangirian et al. (2010) used real data; however, this is acceptable as using simulation in OM research is regarded as practical and efficient (Jahangirian et al., 2010).

System dynamics is the second most common technique with over 15% of papers reviewed by Jahangirian et al. (2010) using it. It has been used mostly on the high perspective level, the strategic decision-making level, and qualitative analysis, mainly in domains such as project management, policy and strategy development, and knowledge management. The system dynamics technique can accommodate qualitative information, which allows the decision-makers to increase their holistic perspective of the system (Jahangirian et al., 2010).

One of the main differences between discrete-event and system dynamics techniques is the effects of decisions. DES focuses on the effects of short-term decisions (e.g., daily and weekly decisions) while system dynamics simulation focuses on long-term decisions (e.g., monthly decisions). Recall that this research concentrates on inventory management and aims to find the best replenishment policy for perishable and substitutable products. This research area is classified as a short-term decision in supply chain management (Farahani, Rezapour, Drezner, & Fallah, 2014). Consequently, DES was selected as the simulation technique for this research.

The selection of DES is supported by studies on perishable and substitutable products. Brailsford (2014) observed that in contrast to other techniques, DES is powerful and allows researchers to observe, analyse, and optimise complex problems such as perishable and substitutable products under the multi-echelon model. In fact, many researchers have used the discrete-event technique to simulate the inventory management model of perishable products

(de Keizer, Haijema, Bloemhof, & van der Vorst, 2015) because DES could explicitly model inventory level, actual real-time demand, or quality loss (Cannella, Bruccoleri, Barbosa-Póvoa, & Relvas, 2013b).

In conclusion, this section selected and justified the use of the DES technique for the research model. This section reviewed the application areas of spreadsheet and business gaming simulation techniques and concluded these two simulation techniques are not relevant to the research. In the comparison between the discrete-event and the system dynamics techniques, the discrete-event emerged as the most relevant simulation technique for this research. This technique is also relevant to the knowledge of the researcher, and is supported by the simulation software ExtendSim. The next section presents the procedure for implementing DES in this research.

3.5.3 Simulation procedure

The simulation technique has been used widely in the OM research. However, Manuj, Mentzer, and Bowers (2009) observed that efforts to preserve the rigour of simulation research have not been addressed reasonably. This limitation raises doubts about the simulation technique's credibility and creates challenges in terms of the understanding of the research. One of the main reasons for this limitation is the lack of guidance for conducting a rigorous simulation research on OM (Manuj et al., 2009).

To address this limitation, Manuj et al. (2009) compiled knowledge from multiple sources and provided guidelines for developing simulation models. The process includes eight steps with detailed criteria for each step to develop a simulation model to design, implement, and evaluate logistics and supply chain models. This process also serves as a checklist to validate simulation models before they are used in practice.

Considering that the process developed by Manuj et al. (2009) has been applied successfully in recent papers on inventory management, this research applied that process for

the research model. An example of these recent papers includes the work of Cigolini, Pero, Rossi, and Sianesi (2014) who used this process to develop a simulation model for analysing the dependencies between supply chain performance. These papers confirm the usefulness of Manuj et al. (2009) process for multi-echelon and complicated models and therefore, for this research model.

The simulation model development process created by Manuj et al. (2009) includes eight steps for specific applications in supply chain management. These eight steps are summarised in Figure 3.3 and explained below.

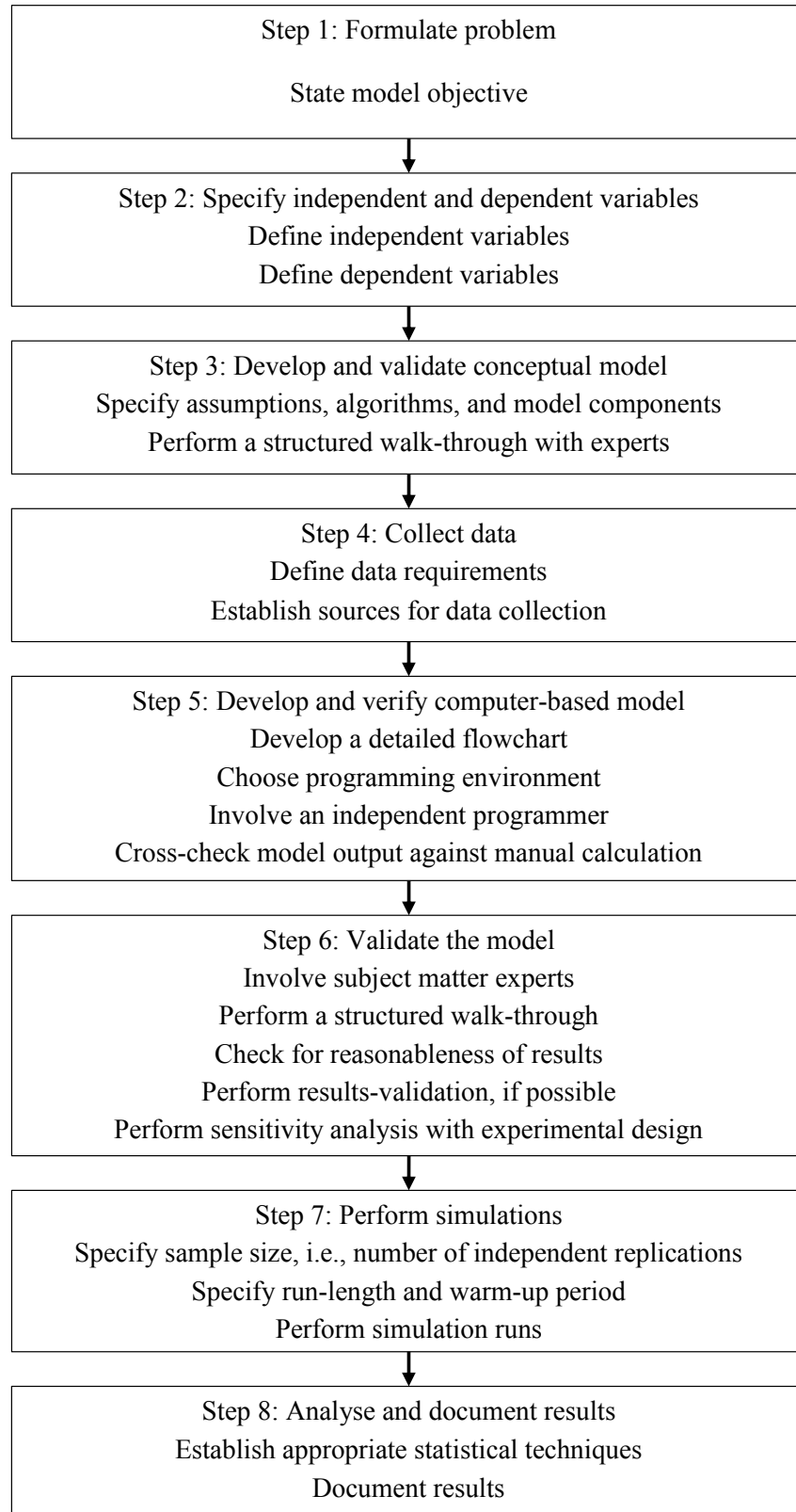


Figure 3.3: The simulation approach (derived from Figure 1 in Manuj et al. (2009, p. 176))

3.5.3.1 Step 1: Formulate problem

Step 1 involves defining research objectives and research questions, which are answered by the simulation model. The initial problem may not be stated clearly or in measurable terms. For example, while Shang, Li, and Tadikamalla (2004) clearly stated that they aimed to optimise performance in a supply chain, Zhang and Zhang (2007) merely aimed to evaluate business models and information sharing strategies.

The literature review chapter highlights the need to conduct research on inventory management for perishable and substitutable products under the two-echelon model. The research model includes:

- A two-echelon model with one supplier and two retailers (divergent structure as defined in section 2.3.3)
- Three perishable products, each of which can substitute for the others
- Products sold to a customer under the first in first out rule.
- An unmet demand that is lost with a given lost sales probability
- A lead time that is positive and fixed
- A product lifetime that follows an exponential distribution
- Consumer demand that follows a Poisson distribution
- A periodic review inventory policy (T, S).

As explained in section 2.3.4, the centralised structure helps to reduce total inventory cost and improve customer service level. This research, therefore, applied the centralised structure for the studied inventory model. All three products at the supplier and two retailers have the same replenishment policy to simplify and standardise business procedures (as explained in section 2.3.1). This assumption was used successfully by Costantino, Di Gravio, Shaban, and Tronci (2015) and Lee, Cho, and Paik (2016). In addition, the bullwhip effect is reduced when all retailers have the same order interval (Cachon, 1999).

Within that above context, the research objectives (i.e., RO1, RO2) and research questions (i.e., RQ1, RQ2, RQ3) were discussed in section 3.1.1.

3.5.3.2 Step 2: Specify independent and dependent variables

Step 2 defines dependent and independent variables. Independent variables are the system parameters, and dependent variables are the performance measures. The research objectives and research questions defined in step 1 guide the selection of dependent and independent variables. These variables may be selected based on several sources. They could be from similar studies or derived after consultation with experts and managers within the studied areas. Then, in a simulation model, independent variables are controlled, and their influences on dependent variables are analysed. This research aims to investigate the effects of consumer demand, substitution, and product lifetime on performance of the inventory model.

In the created simulation model, the daily consumer demands at two retailers affect the performance of retailers (e.g., high or low inventory level) and aggregate to affects the performance of supplier. The substitution is reflected in the lost sales probability with a negative linear relationship (see section 2.4.3), and a low lost sales probability creates a high substitution ratio, and vice versa. The substitution ratio affects the demand and the performance of the inventory model. The product lifetime influences the product availability or the ability to satisfy the customer's demand of the inventory model. Therefore, the independent variables of the research model are:

- Consumer demand,
- Lost sales probability (which has a negative linear relationship with substitution as explained in section 2.4.3), and
- Product lifetime

The dependent variables of the simulation model are the three performance measures of the research problem, which simulates daily operations of one supplier and two retailers for

perishable and substitutable products. This research aims to develop a new decision framework that uses non-financial measures to define the most favourable replenishment policy. Therefore, it is necessary to compare the result received from this non-financial approach and the financial approach. This research extends and compares the results with the work of Kouki et al. (2014). In such context, this research considers all cost factors in Kouki et al. (2014). These cost factors include ordering cost, holding cost, outdated cost, and all costs relating to the importance of customer satisfaction during a stock-out situation of perishable products. These costs are common in perishable inventory management as they are used in recent works, for example, Zhang, Wei, Zhang, and Tang (2016). Therefore, the performance measures, which consider and cover these costs, are proposed. These non-financial measures are also common and easy to apply in practice (Lin et al., 2014). The proposed performance measures that are order rate variance ratio, average inventory, and fill rate are converted from these common costs by using the guidelines in Table 2.1.

The Average Inventory (AI) is the mean of the inventory level during an inspection time, for example, a week, month, or year. It is frequently used in production and distribution systems to assess inventory investment and is treated as representative of internal process efficiency. This measure provides information on inventory investment, probability of expiration, stock capacity utilisation, and relates to holding and outdated cost.

The Fill Rate (FR) is the percentage of orders delivered on time and is representative of other customer satisfaction measures. This measure relates to the customer service level and stock-out cost.

The Order Rate Variance Ratio (ORVR), defined as the ratio of the order variance at an echelon to the order variance of the consumer (or market demand), is the most common measure to identify the bullwhip effect. A value more than one means the bullwhip exists. A

value smaller than one means the orders are smoothed (Bernstein & Federgruen, 2005; Tang, 2006). This measure provides information for the cost of procurement, and subcontracting.

Therefore, the dependent variables are:

- Average inventory (AI),
- Fill rate (FR), and
- Order rate variance ratio (ORVR)

3.5.3.3 Step 3: Develop and validate the conceptual model

Step 3 develops and validates a conceptual model which is an abstraction of a real problem by using logical and mathematical relationships. Assumptions and descriptions of relationships in the studied model are also stated explicitly in this step. This research uses mathematical formulas to form logical relationships regarding the factors and structure of the studied system. The formulas are developed based on the literature review, and they are relevant to research objectives and research questions. The system description is used to validate the outcome of a simulation model. Therefore, it is important to verify a conceptual model before developing a computer model.

One common technique to verify a conceptual model is to conduct a structural walk-through of the assumptions and description in front of experts and managers (Law, 2014). This step increases the validity and credibility (e.g., research objectives, model relationships, data, and components) of the simulation model. Performing conceptual model validation in this step increases the credibility of researchers and practitioners (Law, 2014). However, this research, as most other research, performs the conceptual model validation during the simulation model validation step (i.e., step 6 in Figure 3.3) (Manuj et al., 2009).

The objective of this research is to find the most favourable replenishment policy for a two-echelon inventory management model of three perishable and substitutable products. These three products have random lifetime, and the replenishment order is received after a

fixed lead time. The inventory position is checked and replenished at each T units of time and a replenishment quantity is ordered to bring the inventory position to the given level S . The demand follows a Poisson distribution and the unfulfilled demand is lost. On arrival, a customer is satisfied by one available product. If the preferred product is out of stock, the customer can substitute with other products. If other products are out of stock, or the customer does not want to substitute, this is a lost sale. The products are sold under the first in, first out (FIFO) rule; that is, products stocked first are sold first. The assumption of the FIFO rule comes from a real practice in supermarkets (Tekin, Gürler, & Berk, 2001). The performance of the inventory management model is measured by three measures: Order Rate Variance Ratio, Average Inventory, and Fill Rate.

The research model is similar to the model in the work of Duan and Liao (2014), which mimics the daily operations of one supplier and two retailers for perishable products. The research model includes five main events:

- (1) perished products are discarded,
- (2) a replenishment order arrives and is updated to inventory,
- (3) consumer demand is observed and satisfied,
- (4) the inventory level is reviewed if it is a review period,
- (5) a replenishment order is triggered.

These events are summarised in the flow chart, presented in Figure 3.4.

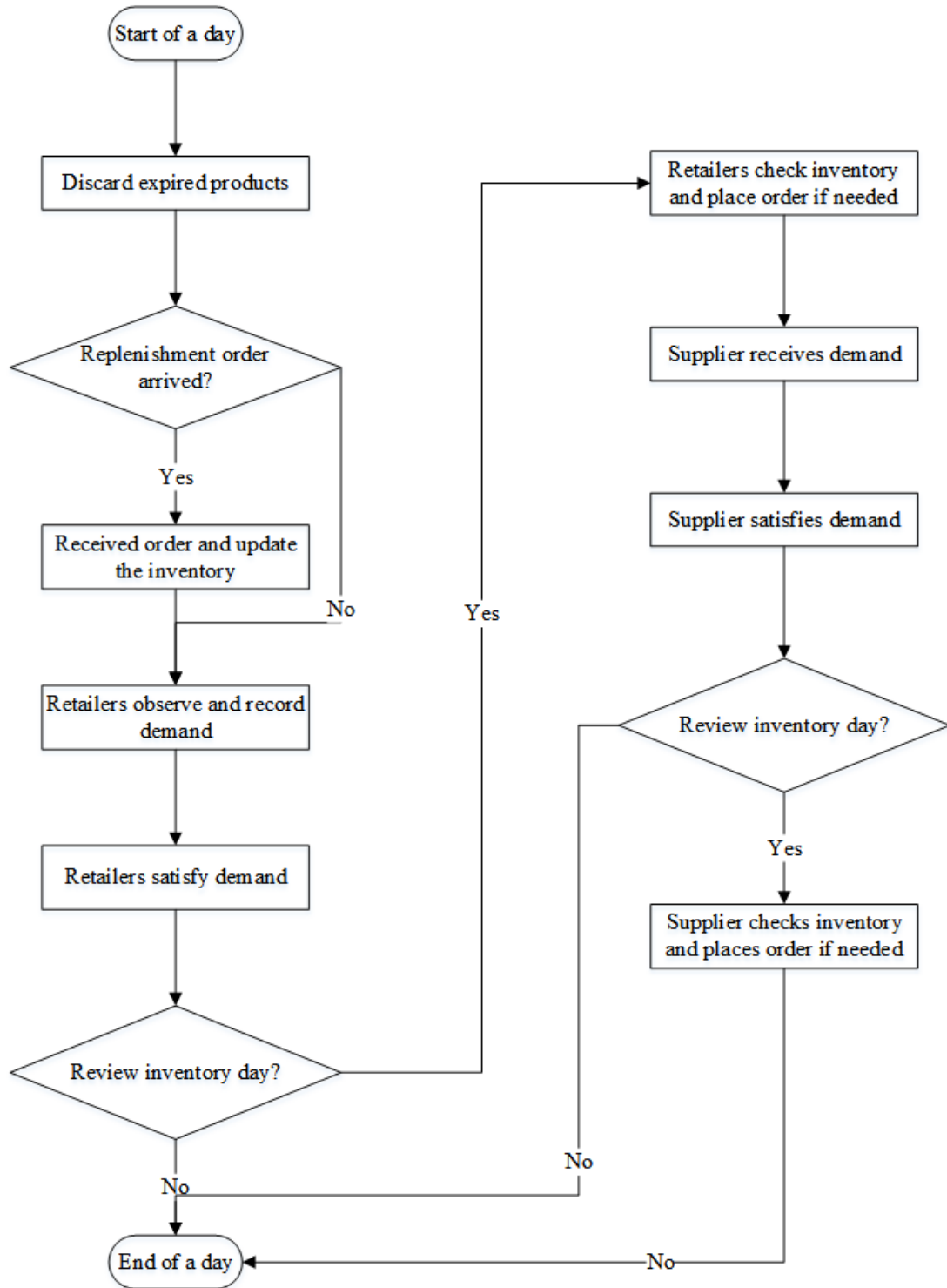


Figure 3.4: Overview of sequential events of the research inventory model

On a typical day, the following event sequence occurs at the supplier and retailers.

- The supplier and retailers check and discard the expired products.

- If any replenishment order arrives today, the supplier and retailers update the quantity and expiry date of the newly arrived products in the inventory system.
- Retailers observe and record consumer demand of today.
- Retailers satisfy today's demand.
- If today is a day to review the inventory position, retailers review the inventory position. If the inventory position is less than the inventory target, retailers place a replenishment order to bring it back to the inventory target.
- The supplier receives the replenishment order from retailers.
- The supplier satisfies the replenishment order.
- If today is a day to review the inventory position, the supplier reviews the inventory position. If the inventory position is less than the inventory target, the supplier places a replenishment order to bring it back to the inventory target.

Based on these events, the notations and formulas are formed and presented as follows:

i	The number of retailers $i = 0, 1, 2$ $i = 0$ means the supplier
j	The number of products $j = 1, 2, 3$
t	The number of period in model $t = 1 \dots T$
β	The required customer service level
S_j^i	Maximum inventory level of product j th at i th the supplier and retailers
$I(t)_j^i$	The inventory level of product j at the retailer i at the beginning of period t
$D(t)_j^i$	The demand of product j at the retailer i for the period t
$p_{jj'}^i$	The probability that a customer substitutes the product j with the product j' at the retailer i if the product j is out of stock at the retailer i
$DE(t)_j^i$	The effective demand of product j at the retailer i for the period t

$DO(t)_j^i$	The delivered quantity of product j at the retailer i for the period t
I	The lost sales probability
λ	Rate of Poisson distribution of demand
$1/\delta$	Rate of exponential distribution of lifetime
L	Replenishment lead time
T	Review period
S	Order-up-to level or inventory target
$s_{or(t)_j}^2$	The order variance of product j th at the vendor and retailer i th
$s_{DE(t)_j}^2$	The variance of demand of product j th at the vendor and retailer i th

The replenishment lead time L , $L \leq T$ to ensure there is at most one outstanding order at any time and to reduce the complexity of the model (Kouki et al., 2014).

In the inventory management problem, the demand function is first defined. The demand in the inventory management for substitutable products includes the original demand and the demand because of substitution from other products. Duan and Liao (2014) stated that the substitution demand is a fraction of the excess demand multiplied by the substitution ratio, the effective demand in the substitution problem is a total of the original demand and the substitutable demand. Hence, the effective demand function is defined as:

$$DE(t)_j^i = D(t)_j^i + \sum p_{j',j}^i (D(t)_{j'}^i - I(t)_{j'}^i)^+, x^+ = \max(x, 0) \quad (1)$$

The substitution ratio is calculated by the random substitution matrix method proposed by Smith and Agrawal (2000). This method is equivalent to the brand preference situation where all products have an equal market share, and the substitution ratio is proportional to its original market share. This paper considers a two-echelon model where a supplier manages inventory of two retailers so that the random substitution matrix method is suitable.

The substitution ratio formula is:

$$p_{jj'}^i = \frac{1-l}{j-1} = \frac{1-l}{2} \quad (2)$$

Then, the inventory level, outdated quantity, and shortage quantity is calculated based on the effective demand function. The inventory level in a period is calculated from the target inventory level, demand quantity, outdated quantity, and shortage quantity as suggested by Kouki et al. (2014):

$$I(t)_j^i = (S_j^i - DE(t)_j^i - O(t)_j^i + SE(t)_j^i)^+ \quad (3)$$

Where the shortage quantity of product jth at the supplier and retailer ith , which includes the shortage because of substitution with other products, is

$$SE(t)_j^i = (DE(t)_j^i - I(t)_j^i)^+ \quad (4)$$

Moreover, the outdated quantity of product jth at the supplier and retailer ith is

$$O(t)_j^i = \delta * I(t)_j^i \quad (5)$$

The order quantity of product jth at the supplier and retailer ith is

$$Or(t)_j^i = S_j^i - I(t)_j^i \quad (6)$$

The performance measures for the inventory management model is calculated below using the formulas presented in the work of Cannella et al. (2013a).

The Order Rate Variance Ratio (ORVR) at the supplier and retailer ith for product jth is

$$ORVR_j^i = \frac{s_{Or^i}^2}{s_{DE_j^i}^2} \quad (7)$$

The Average Inventory (AI) of the product jth at the supplier and retailer ith is

$$AI_j^i = E[I(t)_j^i] \quad (8)$$

The Fill Rate (FR) of the product j th at the supplier and retailer i th is

$$FR_j^i = \frac{DO(t)_j^i}{DE(t)_j^i} = \frac{I(t)_j^i - SE(t)_j^i}{DE(t)_j^i} \quad (9)$$

3.5.3.4 Step 4: Collect data

Data for the simulation model are collected in step 4. This is difficult as data may not be available in the required detailed levels or formats. Data can be established by using one of three approaches (Barlas & Heavey, 2016): deterministic in nature, operationalised by fitting a probability distribution, or operationalised with an empirical distribution.

Much operations research literature includes axiomatic studies that either use empirical data derived from real-world settings or rely on artificial reconstruction data (i.e., published parameters) from other research (Craighead & Meredith, 2008). Craighead and Meredith (2008) asserted that the use of axiomatic research with computer simulation built on published parameters from prior models (rather than the use of empirical data) is appropriate when extending the existing approach; for example, Duan and Liao (2014) extended their study of 2013 to investigate inventory management for red blood cells with substitution.

As this research extends the work of Kouki et al. (2014) by relating closely to real-world problems (i.e., a two-echelon model), the use of these published parameters is acceptable and reliable. This research reused the parameters in the studies of Kouki et al. (2014) (i.e., consumer demand and product lifetime) and Smith and Agrawal (2000) (i.e., lost sales probability). This research defined the replenishment policy by considering three performance non-financial measures rather than financial measures as other researches have used. Therefore, reusing parameters is acceptable as it allows a comparison of these two approaches.

The simulation model processes experimental inputs to examine changes in outputs (Law, 2014). In this research, various combinations of consumer demand, product lifetime, and lost sales probability are modelled as the stochastic inputs. The supply chain structure based

on fixed parameters (e.g., lead time) acts as fixed inputs. The values of these variables are presented in section 3.5.3.6. The outputs (i.e., average inventory, fill rate, and order rate variance ratio) are dependent variables that enable conclusions to be drawn about the performance of the inventory model.

3.5.3.5 Step 5: Develop and verify the computer-based model

The simulation model is developed and verified in step 5. Several programming software packages are used to simulate operations and supply chain management problems, including Excel, ARENA, ExtendSim, and Simio (Schriber, Brunner, & Smith, 2013). Manuj et al. (2009) observed that there is no preferential or outperforming software.

This research used ExtendSim to model the problem. ExtendSim can model many system settings using blocks, if needed, and the internal ModL language can be coded to customise existing blocks or create new ones (Law, 2014). ExtendSim's 'Scenario Manager' block provides the ability to study the variances of the model's responses from one scenario to another scenario (Law, 2014), which is useful when studying the effects of different models' settings.

Then, it is necessary to verify the computer-based model developed. The model verification is regarded as "ensuring that the computer program of the computerized model and its implementation are correct" (Sargent, 2013, p. 12). It ensures that the programme and implementation of the conceptual model are correct.

The main technique to determine if the model has been programmed correctly is the trace technique (Sargent, 2013). The outputs of the model parts are traced to verify if the model's logic is correct and if the system behaviour is acceptable (Sargent, 2013). The outputs of simulation sub-models and the whole model are compared with manual calculations to check the information passes through the simulation sub-models and the whole model as intended (Law, 2014). Reports with outputs of each simulation experiment performed (e.g., average

inventory) are created to evaluate and fix any error in the model. If the trace technique for the model has no significant variations from expected outputs, the computer-based model is verified. In addition to the trace technique, a detailed flowchart, comprehensive documents of the simulation model, and animation are useful tools for the verification process (Sargent, 2013).

The animation and report features were used in the ExtendSim software to develop a detailed flowchart of a simulated sequence of events. The simulation model used random number blocks with Poisson and exponential distributions for consumer demand and product lifetime, which ensured the inputs (i.e., consumer demand, product lifetime) had the intended values. The animation feature and detailed flowchart helped to check the simulation runs as intended. Moreover, the report function made it possible to trace the performance of the simulation model. For example, the sales report on retailer #1, product #1 (in Appendix 1) made it possible to trace the daily information on retailer #1, products #1 such as original demand, inventory on hand, effective demand, sales quantity, lost sales quantity, replenished quantity. Then, the calculation of the simulation model, and finally, the computer-based model were verified.

3.5.3.6 Step 6: Validate the model

Step 6 validates the model developed in step 5. Model validation is understood as “the substantiation that a model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” (Sargent, 2013, p. 12). To decide if a simulation model is verified and valid, Sargent (2013) suggested three approaches: model developers decide by themselves, users of a simulation decide, and a third party decides. Although letting users of a simulation model and a third party decide whether a simulation model is verified and valid are two good approaches, researchers usually make decisions by themselves due to the time and budget of the research (Sargent, 2013).

The main technique used to check the validation of the model is face validation (Sargent, 2013). This step was performed by reviewing the existing papers using simulation for perishable and substitutable products. These papers (i.e., Kouki et al. (2014); Duan and Liao (2014); Cannella et al. (2013a); Smith and Agrawal (2000) – as mentioned in step 3) provide the guidelines to calculate the effective demand, the substitution ratio, expiry quantity, lost sales quantity, average inventory, fill rate, and order rate variance ratio. Reusing the formulas in these papers confirms the validation of the model.

The sensitivity analysis is performed to “gain essential insights on model behavior, on its structure and on its response to changes in the model inputs” (Borgonovo & Plischke, 2016, p. 869). It is a crucial step in simulation-based decision-making as uncertainties may misrepresent results (Chetouane, Barker, & Viacaba Oropeza, 2012). The sensitivity analysis helps to improve the decision-making progress, including identifying important model factors, developing flexible suggestions under different contexts, understanding the robustness of an optimal solution, and investigating sub-optimal solutions (Chang, Wu, Lin, & Chen, 2007; Pannell, 1997). The sensitivity analysis in the simulation is conducted via a number of experiments. Carefully designed, the experiments are more efficient than just simply performing a series of unsystematic experiments.

The 2^k factorial experimental design technique is useful when it is unclear which factors are important and how they affect the simulation results (Law, 2014). The 2^k factorial experimental design is an economical strategy to determine the effects of input factors on the outputs. According to Sanchez, Moeeni, and Sanchez (2006), the 2^k factorial experimental design has been used frequently in operational research due to its simplicity and its ability to analyse interactions between factors and their main effects. This technique requires choosing two levels for each factor and running simulation at each of the 2^k factor-level combinations. Usually, the researchers choose the high and low levels of each factor. These two levels are far

enough apart to observe the difference in the outputs. For example, Lin, Sir, and Pasupathy (2013) examined high and low levels of resource, waiting time, and completion time to analyse the effects of these factors on surgical service.

This research assumed that consumer demand follows a Poisson distribution, product lifetime follows an exponential distribution, and there is a probability that the unmet demand is lost without substitution. These are stochastic input factors and are examined for their effects on the simulation results (i.e., AI, FR, and ORVR). It is noted that the lead time and the supply chain structure (i.e., one supplier, two retailers, three products, replenishment policies) are not stochastic and are not contained in the sensitivity analysis.

This research used two levels for each factor; thus, it was necessary to check if the outputs (i.e., AI, FR, and ORVR) were monotonic over the range of the changed input factors (i.e., demand, lifetime, and lost sales probability). Otherwise, it may be wrong to conclude that the input factors have no effect on the performance measures. It was observed that the demand and the lost sales probability correlate with the effective demand (Duan & Liao, 2014; Smith & Agrawal, 2000). If the lost sales probability is high, the substitution ratio is low and thus the effective demand is low and vice versa (Smith & Agrawal, 2000). If the demand is high, the effective demand is high and vice versa (Duan & Liao, 2014). In a research on the bullwhip effect of a four-echelon model, Cannella, Framinan, and Barbosa-Póvoa (2014) observed the monotonous change between the demand (or the effective demand) and the AI, FR, and ORVR. Therefore, these three performance measures are monotonic with the demand and the lost sales probability.

To check if the performance measures are monotonic with the product lifetime, it is assumed that other input factors are fixed. If the product lifetime is short, the products deteriorate and can be rapidly out of stock. Then, the inventory level and the fill rate are low. This explanation is relevant to the findings of van Donselaar and Broekmeulen (2012).

Consequently, the findings on the bullwhip effect show that out-of-stock situations occur frequently and this increases demand on suppliers (Costantino et al., 2015). In other words, as the product lifetime is low, the inventory level is low and leads to out-of-stock situations, Consequently, a low product lifetime increases the order variance or ORVR. If the product lifetime is long, the explanation is in reverse. In conclusion, the three performance measures AI, FR, and ORVR, are monotonic with the changed input factors. Therefore, this research applied the 2^k factor-level design technique with high confidence.

This research used the parameters in the research of Kouki et al. (2014) and Smith and Agrawal (2000). Therefore, the high and low levels of the input factors were extracted from these two papers. Table 3.3 presents the high and low level of each factor. Table 3.4 presents the experiments or the design points that are used to run the simulation.

Table 3.3 The high and low levels of input factors

	Mean of demand	Mean of lifetime	Lost sales probability
High	15	6	0.9
Low	5	2	0.1
Source	Kouki et al. (2014)	Kouki et al. (2014)	Smith and Agrawal (2000)

Table 3.4 The combination of a 2^3 factorial design

Experiment	Mean of demand	Mean of lifetime	Lost sales probability
1	15	6	0.9
2	5	6	0.9
3	15	2	0.9
4	5	2	0.9
5	15	6	0.1
6	5	6	0.1
7	15	2	0.1
8	5	2	0.1

These eight experiments were performed under the assumptions of lead time and replenishment policy as:

- A replenishment order is received after a fixed lead time $L = I$.
- According to the theorem 1 and 2 of Kouki et al. (2014), there are 88 possible replenishment policies with the range of T and S as follows:

- $T \geq T_{min} = L = 1$
- $T \leq Tc = 4$, Tc : review period in case the product has an infinite lifetime
- $26 \leq S \leq 47$,

The simulation model was then performed based on these experiments. The results from these experiments were then analysed for a variety of purposes (Montevechi, de Almeida Filho, Paiva, Costa, & Medeiros, 2010). There are many methods to analyse results from a factorial experiment and they can be classified in three main ways: statistical, mathematical, and graphical techniques (Frey & Patil, 2002). Out of these methods, statistical techniques (e.g., multivariate analysis of variance (MANOVA) and univariate analysis of variance (ANOVA) (Field, 2013; Hair, Black, Babin, & Anderson, 2010)) have been used widely (Sanchez et al., 2006). These statistical techniques have the ability to provide knowledge of system behaviour, to improve system performance, and to investigate the main effect of each input factor and interactive effect for the interaction between input factors (Frey & Patil, 2002; Sanchez et al., 2006). Statistical techniques are suitable when a simulation has input factors that follow probability distributions and aim at assessing the effects of input factors on system performance (Frey & Patil, 2002). For example, Closs, Nyaga, and Voss (2010) performed a simulation model and used MANOVA and ANOVA to examine the effects of configuration capacity, complexity, and inventory level on unit and order fill rate in a configure-to-order environment. Results suggest the main and interactive effects of input factors on unit and order fill rate, and prove the efficiency of MANOVA and ANOVA techniques.

This research also used MANOVA and ANOVA techniques, via the IBM SPSS statistic software, version 23 (IBM SPSS, 2016) to analyse results from the sensitivity analysis as this research aims at gaining insights into perishable and substitutable inventory management models. The selection of these two techniques is based on the research objectives, namely, finding the most favourable replenishment policy and providing knowledge of the effects of

input factors (i.e., consumer demand, product lifetime, and substitution) on the performance of the inventory model. In addition, this research assumed consumer demand and product lifetime follow Poisson and exponential distributions respectively. These research objectives and assumptions confirm the rationale of using MANOVA and ANOVA techniques in this research (Frey & Patil, 2002; Sanchez et al., 2006).

As this research integrates simulation and AHP, the results of sensitivity analysis will be presented in the next chapter with the sensitivity analysis of AHP to report smoothly (e.g., an example of sensitivity analysis in AHP is found in Yakovleva, Sarkis, and Sloan (2012)).

3.5.3.7 Step 7: Perform simulations

At step 7, the modellers have to decide on the number of replications (i.e., sample size), the length of run, and the warm-up period for each completed experiment before performing a simulation. These are key simulation parameters, and are calculated according to Welch's procedure (Law, 2014). A large number of replications and a long length of run reduce the standard deviation of the sampling distribution and increase the absolute precision of the simulation results (Law, 2014). The warm-up period is important to the simulation results. A warm-up period "is a pre-specified length of simulation time during which data are not collected. The purpose of the warm-up period is to reduce bias in the statistical estimates by eliminating the data during the initial period of the simulation" (Shell & Hall, 2000, p. 328).

Assume that the unit of time is a day, there are seven working days in a week and no holidays, which are typical of a grocery store and a dairy manufacturing plant.

The warm-up period can be determined by using Welch's graphical procedure (Law, 2014). Without loss of generalisation, the average inventory of retailer #1, product #1 of experiment number 1 was used for the procedure to calculate the warm-up period. The selected replenishment policy is (4, 47), meaning the inventory level is reviewed every four days to bring it back to 47. The average inventory was recorded at the end of each day for 200,000

days and the procedure was repeated 10 times. Figure 3.5 below shows the time-series of the mean average inventory at each day. Based on the graph, a warm-up period of 5000 days was selected. It is a sensible period where the average inventory seems to reach a steady state (i.e., consistency in the pattern). Therefore, data for the first 5000 days were discarded when calculating the system’s performance.

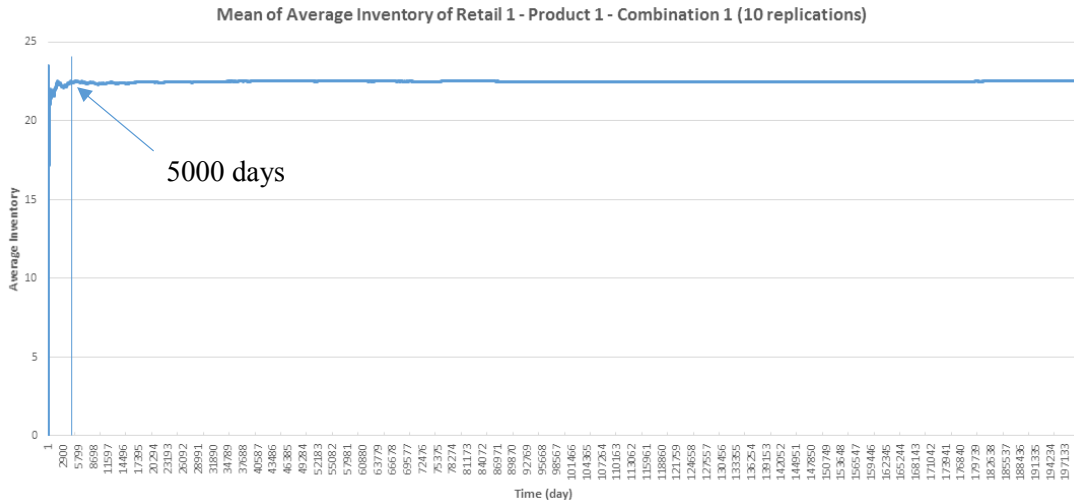


Figure 3.5: Welch’s graphic for identifying the warm-up period and simulation length

The next issue in the simulation run is the choice of run-length. Welch’s procedure was used to determine the run-length. The above graph shows that the average inventory was stable until the point of 200,000 days. The net simulation run-length with respect to the warm-up period becomes 150,000 days.

The other issue is the choice of numbers of replication for each simulation run. The number of replications represents sample size, which defines the accuracy of stochastic variables (Law, 2014). According to Law (2014, p. 504), an approximation of the number of replication $n_a^*(\beta)$, required to obtain an absolute error of β is given by:

$$n_a^*(\beta) = \min \left\{ i \geq n: t_{i-1, 1-\alpha/2} \sqrt{\frac{S^2(n)}{i}} \leq \beta \right\}$$

The value of $n_a^*(\beta)$ is defined by interactively increasing i by one until a value of i is obtained for which $t_{i-1, 1-\alpha/2} \sqrt{\frac{S^2(n)}{i}} \leq \beta$. Continuing with the average inventory of retailer #1, product #1 of the experiment number 1 under replenishment policy (4, 47), the pilot run provided the sample variance $S^2(n) = 0.00095$. For example, this research wanted to estimate average inventory with an absolute error of 0.05 and a confidence level of 99%. From the equation above, the minimum number of replication was 7. This research reused the parameters created by Kouki et al. (2014) and thus, this research also used 10 replication as in that work.

In summary, the simulation model was used to evaluate the performance of each of eight experiments. Each experiment was simulated under each of a total of 88 replenishment policies for each pair of T and S. Each simulation replicates 10 times, the length of each simulation was 200,000 units of time (i.e., days), and the first 5,000 data was discarded from calculating the system's performance.

3.5.3.8 Step 8: Analysis and document results

Finally, step 8 analyses and documents the results. The performance of each experiment under each replenishment policy was measured and recorded by three measures: average inventory, fill rate, and order rate variance ratio. For each experiment, the decision-makers would like to define the most favourable out of 88 replenishment policies. The following sections explain how the decision-makers apply AHP and DEA to find the most favourable replenishment policy.

3.6 Analytic Hierarchy Process

As the OM research area has developed over years, making a decision in OM has become more complex for managers of companies, government offices, and policy makers. Over the years, decisions in OM have shifted from single measures with cost minimisation to multiple measures (Radnor & Barnes, 2007). For example, this research selects the replenishment policy

outperforming simultaneously in three measures. This change has required the use of particular MCDM techniques which take into account inputs or judgements from decision-makers or experts for making and analysing decisions (Sodenkamp, Tavana, & Di Caprio, 2016). In this context, the analytic hierarchy process (AHP) has become an effective tool, and was used to calculate the importance of each performance measure in the studied model.

AHP was proposed by Saaty (Saaty, 1986), and has become one of the popular optimisation approaches used in MCDM problems (Subramanian & Ramanathan, 2012). It is a methodology and theory to measure proportion relatives between quantities (Bruno, Esposito, Genovese, & Simpson, 2016). For example, consider a pair of trees – AHP is not interested in knowing the exact heights of the two trees but how much taller each tree is compared to another. This is similar to the case of the OM problem; decision-makers just need to know which solution is better and are not interested in the score for each solution. The core concept of AHP is using pairwise comparisons among alternatives to construct a rating of alternatives (Bruno et al., 2016).

Since its inception, numerous fields have applied AHP methods, especially in the OM field (Wang, Huang, & Dismukes, 2004). Subramanian and Ramanathan (2012) provided a comprehensive review of AHP applications in the OM area. Based on the review, they showed a large number of AHP applications in OM and suggested that there is a significant gap in the application of AHP in several areas such as managing inventory.

The inventory model was evaluated by three conflicting performance measures: average inventory, fill rate, and order rate variance ratio. Each decision-maker or department manager has a different point of view on the importance of each measure. Therefore, it is necessary to synthesise these opinions to determine the overall importance for the performance measures, which calls for the application of AHP as explain in section 3.3.7.2. This section,

based on the procedure of (Saaty, 2008), presents how AHP was used to create the importance of each performance measure.

3.6.1 Step 1: Decompose studied model into a hierarchy

At this step, the studied model was decomposed into a hierarchy model including goal and measures. This research used AHP to evaluate the importance of each measure. Thus, the hierarchy model does not need to include the alternatives. The goal of the studied model is to find the most favourable replenishment policy. The measures are average inventory, fill rate, and order rate variance ratio. The hierarchy model is depicted in Figure 3.6.

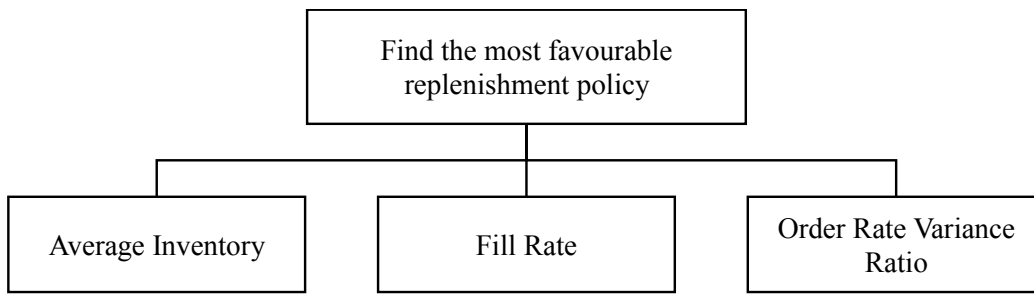


Figure 3.6: The hierarchy model of the objective of performance measures

3.6.2 Step 2: Create a comparison matrix

From the hierarchy, the decision-makers perform a pairwise comparison of the measures with respect to the goal of finding the most favourable replenishment policy. The comparisons are made for each element according to a 1 - 9 rating scale (Saaty, 2008). This rating scale is shown in Table 3.5 below.

This research built the inventory model based on published data in Kouki et al. (2014) and Smith and Agrawal (2000). Therefore, it is impossible to obtain the opinion of real decision-makers. Moreover, this research serves as a guideline, provides a demonstration of using the proposed framework, and defines the most favourable replenishment policy. Thus, the pairwise comparison data to calculate the importance of measures were drawn from a practical case study according to the researcher's experience in supply chain management (i.e.,

the researcher has worked seven years in the supply chain department for dairy and pharmaceutical companies).

Table 3.5: Rating scale (derived from Table 1 in Saaty (2008, p. 86))

Rating	Definition	Explanation
1	Equal importance	Two measures contribute equally to the goal
2	Weak	
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong importance	An activity is favoured very strongly over another; its dominance is demonstrated in practice
8	Very, very strong importance	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation

3.6.2.1 A case study

The following case study is developed from the researcher's working experience in order to illustrate the use of AHP (in section 3.4.1).

Consider a case study with a supplier who distributes a milk product brand to two retailers within its business area. These milk products are substitutable and have a random lifetime due to the storage conditions at each retailer. Like many dairy or fast moving consumer goods companies, the supplier has the power to define the replenishment policy for retailers. The retailers are referred as a selling point for the supplier. The supplier wants to define a replenishment policy for the supplier and retailers, which performs best simultaneously in three performance measures (i.e., AI, FR, and ORVR). For dairy products, suppliers print fixed expiry date for each item. However, suppliers usually recall items before that expiry date as it reduces the risk that retailers will sell expired items to consumers, or that consumers will use expired items. Therefore, the earlier recall of items ensures that consumers experience the food product in the best condition possible. Suppliers base the recall decisions on materials quality,

storage conditions, or production quality to define the recall time for each item. In such condition, the product lifetime is stochastic and the use of exponential distribution for product lifetime is reasonable.

As this milk product brand competes strongly with two other brands, it is important to have a high consumer satisfaction level. The supplier realises that in a stock-out situation, the consumers easily buys another milk brand. The substitution creates sudden demand for other products, and consequently, stock-out situation happens easily with other products. If this stock-out situation happens frequently, consumers change their tastes, and the supplier loses the market share. Therefore, FR was the most important measure for both supplier and retailers. Moreover, as the substitution accelerates the effect of stock-out, it is important to consider substitution in this case study.

The supplier and retailers also want to reduce expired products or reduce average inventory. Keeping inventory at a suitable level helps the supplier and retailers to reduce cost. Consequently, it helps suppliers to increase investment in other business activities, for example, Research and Development and Sales and Marketing. It also helps retailers to easily manage warehouse and increase investment in other businesses, for example, increasing display space for other types of products. The supplier and retailers expect to gain market share. Thus, AI can be sacrificed to achieve a high FR level.

Since the supplier and the two retailers are within a business area, the ordering and procurement costs are not problematic. As these costs are relevant to ORVR, the ORVR is not problematic in this case study.

The researcher used this case study to perform pairwise comparisons for the AHP. As mentioned in the case study, fill rate was the most important measure, followed by the average inventory and order rate variance ratio. Consequently, it was reasonable to say that compared to AI, FR was moderate plus important for the supplier and retailers. Compared to ORVR, FR

was extremely important for supplier and retailers. Finally, compared to ORVR, AI was moderate plus important for the supplier and retailers. These comparisons were converted to the rating scale in Table 3.5 and presented in the next section.

3.6.2.2 Comparison results

Table 3.6 exhibits the pairwise comparison of three performance measures with respect to the objective of the studied problem. For example, a value of 4 in the cell (fill rate, average inventory) means that the fill rate had four times the importance for the objective than the average inventory. It is noted that a value of 1/4 is entered in the cell (average inventory, fill rate).

Table 3.6: The pairwise comparison results of three measures

Measures	Average inventory	Fill rate	Order rate variance ratio
Average inventory	1	1/4	4
Fill rate	4	1	9
Order rate variance ratio	1/4	1/9	1

It is also noted that, the decision-makers only need to do three pairwise comparisons for three performance measures. If the AHP technique is used for ranking 88 alternatives (i.e., 88 replenishment policies as defined in section 3.5.3), the number of pairwise comparisons is $88 \times 87 / 2 = 3,828$. It is almost impossible to ask decision-makers to undertake such a large number of pairwise comparisons as it takes a long time and decision-makers easily lose consistency due to too many comparisons (Falsini et al., 2012). This suggests that decision-makers should integrate DEA into the proposed framework. The next step calculates the consistency of the comparison and the importance of each measure.

3.6.3 Step 3: Calculation

The consistency and the importance of each measure are calculated by using the R package 'pmr' (Lee & Yu, 2013), with calculation syntax as shown in Appendix 2. The consistency ratio is calculated to assure the consistency and appropriateness of comparison. The results

showed that the consistency ratio was 3.9%, less than the critical value 10%; therefore, there was no evidence of inconsistency (Saaty & Ozdemir, 2003). Therefore, the pairwise comparisons can be used to calculate the importance of each measure. If the consistency ratio is over 10%, the decision-makers are required to amend the comparison (Saaty & Ozdemir, 2003).

The weighting results for AI, FR, and ORVR were $w_1 = 21.7\%$, $w_2 = 71.7\%$, and $w_3 = 6.6\%$, respectively. The next section uses these values to rank the performance of each replenishment policy by using the DEA method.

3.7 Data Envelopment Analysis

Data envelopment analysis (DEA) is a well-known technique and was introduced in 1978 by Charnes, Cooper, and Rhodes (Charnes et al., 1978). The DEA technique does not need to know the relationship between inputs and outputs; it only requires the value of inputs and outputs (Wu, Chu, Sun, & Zhu, 2016b). In DEA, each scenario is referred to as a *decision-making unit (DMU)*. For each DMU, DEA examines whether there is another DMU that produces more outputs with similar inputs, or uses fewer inputs with similar outputs. If such a DMU exists, the evaluated DMU is inefficient. If there is no such DMU, the evaluated DMU is efficient. The advantages of the DEA technique in defining the efficiency for many DMUs have motivated the use of this technique in contemporary research.

3.7.1 Preliminaries and basic DEA models

The concept of efficiency is a foundation for the development of DEA. The efficiency of a DMU usually means it is successful in converting a set of inputs to a set of outputs. When the price information of inputs and outputs are unavailable (e.g., price information of customer satisfaction), the efficiency evaluation is turned into the production process itself, or *technical efficiency*. It is also difficult to evaluate the absolute performance of a DMU without any

benchmarking DMU; therefore, the terms *relative efficiency* or *relative technical efficiency* are used. The concept of relative efficiency is to find whether there is a comparable DMU that produces more outputs with similar usage of inputs, or produces similar outputs with less usage of inputs. Because the terms ‘technical efficiency’ and ‘relative technical efficiency’ are interchangeable (Lindlbauer, Schreyögg, & Winter, 2016), this research uses the term technical efficiency to refer to relative technical efficiency.

The information on the performance of each DMU allows DEA to indicate the *efficient frontier*. If DEA evaluates how a DMU consumes an amount of inputs to produce a given amount of output, the approach is called input oriented. Otherwise, if DEA evaluates how a DMU produces an amount of outputs with a given amount of input, the approach is called output oriented. If a DMU lies on the frontier, it is referred to as an *efficient DMU*, otherwise *inefficient*. The degree of efficiency for each DMU, or the distance between a DMU and the frontier line, is called *efficiency score*. DEA searches for *ideal DMU* for each inefficient DMU. The input and output values of an ideal DMU are referred to as *ideal values* for the inefficient DMUs. The decreasing inputs or increasing outputs proportionally project a DMU onto the frontier line, which is called *radial projection*. However, there is a possibility that an inefficient DMU cannot improve all inputs and outputs simultaneously; this DMU is called *weakly efficient*. The differences between input or output of a weakly efficient DMU and that of an efficient DMU are defined as input or output *slack*.

Another important preliminary in the DEA method is a *return to scale*. When a DMU changes its inputs or outputs to the ideal values and these changes have the same proportion, it is called a *constant return to scale (CRS)*; otherwise, it is a *variable return to scale (VRS)*.

The DEA method evaluates the relative efficiency of a particular DMU relative to other DMUs. The relative efficiency of each DEA is measured by the ratio of outputs to inputs. There are four basic DEA models, which are introduced in detail in the next section.

3.7.2 Selection of inputs and outputs

Typically, the selection of the number of inputs, outputs, and DMUs determines how good the discrimination is between an efficient and inefficient DMU. There are some conflicts when considering the size of the data set for DEA. A large data set improves the probability of capturing a better efficiency frontier and better discrimination power. However, a large data set may reduce the homogeneity of data, and may have some exogenous factors that affect the results. Moreover, the computational ability is required for a large data set.

To ensure the homogeneity of data, researchers have applied the rule of data set size. There is a minimal requirement of the number of DMUs to get good discrimination power. The rule of thumb is that the number of DMUs should be three times more than the total number of inputs and outputs (Lee, Park, & Choi, 2009).

Another issue is while the inputs should be characterised by a “larger is better”, at times we want to manage situations where smaller outputs are considered better (i.e., as they are undesirable factors that should be minimised) (Liu, Zhou, Ma, Liu, & Shen, 2015). For example, pollution or wastewater are undesirable outputs in the real operations process because the less there are of such outputs, the better the performance is. One method to deal with undesirable inputs/outputs is to treat them as outputs/inputs (Guo & Wu, 2013). This method follows the argument that undesirable outputs incur a cost as inputs, and the DMUs want to reduce the undesirable outputs. Proposing another method, Li, Liang, Cook, and Zhu (2016) recommended taking the inverse of these inputs and outputs. As this effectively makes an undesirable input become a smaller value as there is more of it. As an example, if we consider pollution, as pollution increases in amount, the inverse of pollution becomes smaller as the denominator becomes larger. Therefore, the relationship holds true if the inverse is used.

3.7.3 Applications of DEA

The worth of DEA rests in its ability to evaluate the efficiency or performance of a DMU within a group of interested DMUs that operates in a specific application domain such as the banking, healthcare, agriculture, or transportation industry (Liu, Lu, Lu, & Lin, 2013). These industries adopt DEA for many reasons. It can be applied to define sources of inefficiency, rank the DMUs, evaluate management, evaluate the efficiency of programmes or policies, and generate a quantitative basis for reallocating resources (Golany & Roll, 1989).

Liu et al. (2013) investigated the applications of DEA and identified five major application domains: banking, health care, agriculture and farm, transportation, and education. These domains account for a total of 41.09% of all application-embedded papers. Among all the application domains, the most recent highest growth impetus has been in energy, environment, and finance. In a given context, DEA is used to select the most favourable solution. For example, Lin et al. (2013) used DEA to evaluate and rank the efficiency of all design points in surgical services, which are the results of the simulation process. The review also shows that one-third of total papers focuses purely on methodology and two-thirds focus on application research.

3.7.4 Advantages of DEA

Wong and Wong (2008) reviewed benchmarking tools (i.e., tools to evaluate and improve an organisation's performance (Talluri & Sarkis, 2002)) used in supply chain management. DEA possesses some advantages over these tools, which makes it the most appropriate tool for evaluating and improving organisation performance (Wong & Wong, 2008). These advantages are presented as follows:

- DEA is an effective tool to evaluate the relative efficiency of DMUs in the presence of multiple performance measures.

- DEA does not need to identify the relationships of performance measures to evaluate the efficiency. This characteristic allows managers and researchers to calculate efficiently any measures, as they do not need to find any relationships.
- DEA has the ability to address the complexity resulting from the lack of a common measurement scale. Any OM processes often include quantitative measures (i.e., money, staff) as well as qualitative measures (i.e., customer satisfaction, employee commitment). DEA inherits the attribute that allows the presence of qualitative data in performance analysis. Moreover, it allows the simultaneous analyses of a relatively large number of inputs and outputs, which are measured on different scales.
- In DEA, it is not necessary to presume a priori the presence of a precise production function for weighting and aggregating inputs or outputs.
- The objectiveness arising from DEA weighting variables during the optimisation procedure releases the analysis from estimations and randomness. This objectiveness increases the acceptability of DEA results by involved parties.
- DEA can provide understanding on the most efficient DMU and analyse inefficient DMUs. It provides accurate quantification while specifying starting points to determine inefficiency causes and eliminate them.
- DEA distinguishes proper reference DMUs and involves interpretable efficiency parameters. These efficiency parameters are useful in setting realistic and achievable standards or benchmarks.
- DEA is very flexible and able to integrate with other analytical methods easily to create more significant and effective methods of evaluating performances. Many researchers have studied the extensions of DEA models in calculating

performances, for example, combining with statistical analysis, and other MCDM techniques (Olesen & Petersen, 2016).

3.7.5 Limitations of DEA

Although DEA has been used in the literature for many years, it has been criticised mostly in three points, which are presented as follows.

3.7.5.1 Ranking approaches in DEA

The concept of DEA involves computing the efficiency score to indicate how efficiently a DMU performs compared with other DMUs to convert inputs into outputs. One of the limitations of this method is the failure to rank all DMUs when DMUs have the same efficiency score (Wu et al., 2016b). To eliminate this limitation, researchers have adjusted or modified the initial DEA model to achieve a reasonable ranking of DMUs.

Adler, Friedman, and Sinuany-Stern (2002) stated that DEA ranking methods could be divided into six groups. The first group is the cross-efficiency technique, which was first developed by Sexton, Silkman, and Hogan (1986), where DMUs are both self and peer evaluated. In reality, as Lee and Kim (2014a) discussed, decision-makers do not always have a logical mechanism to select warrant boundaries. Thus, they suggested the cross-evaluation matrix for ranking DMUs. Cross-efficiency is valid for constant return to scale and not valid for variable return to scale (Lim & Zhu, 2015).

The second group is the super-efficiency method where the efficient DMUs have an equal score of unity because of small sample size or the curse of dimensionality. In these situations, it is not reasonable to declare that all efficient DMUs have the same performance. Thus, other techniques are required for ranking these efficient DMUs. Andersen and Petersen (1993) developed a new technique for ranking efficient units. The technique allows an extremely efficient DMU k to attain an efficiency score greater than one (in the case of input-

oriented, and less than one in the case of output-oriented) by removing the k th constraint in the primal formulation. However, there are three problems with this technique. First, Andersen and Petersen use a DEA objective formula value as a rank score for all DMUs, regardless that each DMU is evaluated by a different set of weights. Therefore, if the weights reflect prices, then each DMU has different prices for the same sets of inputs and outputs. Second, this technique can give special DMUs an excessively high ranking score, which has called for some development in techniques; for example, Podinovski (2016) used specific bounds on weights. The third problem is related to the infeasibility issue where the super-efficiency technique does not provide a complete ranking for all DMUs. Thrall (1996) identified extremely efficient DMUs and showed that the super-efficiency CCR model might be impossible. Researchers have suggested some modifications to the original super-efficiency CCR model. For example, Lin and Chen (2015) developed a modification based on the directional distance function to tackle the infeasibility issue. Cook, Liang, Zha, and Zhu (2009) offered an alternative technique to solve the infeasibility issue in the VRS super-efficiency model.

The third group is the benchmark ranking method, where a DMU is highly ranked if it is a reference unit for others. In DEA, a set of empirical production possibilities is formed from the observations according to several technological assumptions. The envelopment of such technology identifies an efficient frontier constructed by the efficient DMUs, which is used as a reference for the evaluation of the remaining DMUs. As stated by Cook, Tone, and Zhu (2014), “In the circumstance of benchmarking, the efficient DMUs, as defined by DEA, may not necessarily form a ‘production frontier’, but rather lead to a ‘best-practice frontier’” (p. 2). Specifically, the DMUs on the best practice frontier are potential benchmarks for the inefficient DMUs, while the targets are the coordination of these benchmarks and represent operation levels for the inefficient DMUs that would make them perform efficiently.

The fourth group utilises a multivariate statistical technique to create a complete ranking for all DMUs. The main objective of this technique is to close the gap between DEA and classical statistical approaches. DEA is a method that leads to frontiers rather than central tendencies. Instead of fitting regression planes through the centre of the data, DEA proposes an efficient frontier that rests on top of the observations. The DEA technique optimises and focuses on each DMU individually, while regression is a parametric technique that fits a single function to the data collected on the basis of average behaviour that requires the functional form to be pre-specified.

The fifth group ranks inefficiency units. The mainstream of techniques so far has not considered ranking the inefficient DMUs beyond the efficiency scores received from the DEA models. However, as mentioned in Cooper and Tone (1997), the original efficiency value can “generally be determined from different facets, which means these values are being derived from comparisons involving performances of different sets of DMUs” (p. 78).

The sixth group claims a given problem requires more additional information, and combines with multi-criteria decision methods to provide a good ranking (Golany & Roll, 1993). While the MCDM literature does not provide a complete ranking, it is useful for gaining preference information to better improve the discriminatory power of the DEA models. In this way, the decision-makers can identify which inputs and outputs have greater importance in the model solution. However, this approach requires additional knowledge and information from the decision-makers.

3.7.5.2 Undesirable factors

Another issue includes undesirable outputs. In real operations processes, there are many undesirable outputs such as pollution or wastewater. These are undesirable outputs because better performance implies there is less of these outputs. One method to deal with undesirable outputs is to treat them as inputs (Guo & Wu, 2013). This method is under the argument that

undesirable outputs incur a cost, and the DMUs want to reduce the undesirable outputs. However, this method does not reflect the true operations process (Seiford & Zhu, 2002). Another method is the use of DEA classification invariance under which classifications of efficiencies and inefficiencies are invariant to the data transformation (Seiford & Zhu, 2002). Färe, Grosskopf, Lovell, and Pasurka (1989) introduced a non-linear programming problem. Scheel (2001) proposed some radial measures, which assume that any change of the output level will involve both undesirable and desirable outputs. Jahanshahloo, Lotfi, Shoja, Tohidi, and Razavyan (2005) presented an approach to treating both undesirable inputs and outputs simultaneously in non-radial DEA models. Another approach is the use of inverse values as mentioned in section 3.7.2.

3.7.5.3 Weight in DEA

The DEA model uses the value of inputs and outputs of each DMU to evaluate the DMU's efficiency, but it ignores the information about the weights to be assigned to each input and output for each DMU. These weights – variables u_r , and v_i – are determined from the data by the DEA formulations. The DEA methodology provides the flexibility in determining the weights of each input and output; it is an attractive aspect of DEA. However, this flexibility may provide unreasonable results because the assigned weights are inconsistent with the prior knowledge of the DMU.

Another weakness of DEA, which is identified in the work of Cooper, Seiford, and Zhu (2011) is the differences in the weights that DEA assigns to different DMUs. In some situations, some DMUs take advantages by highly weighting a few inputs and outputs and the remaining factors have zero weight. When evaluating a group of DMUs, it is also unacceptable that different DMUs assign different weights to a given factor. These disadvantages led to the development of concepts of value judgement, defined as “logical constructs, incorporated within an

efficiency assessment study, reflecting the Decision Makers' (DM) preferences in the process of assessing efficiency" (Allen, Athanassopoulos, Dyson, & Thanassoulis, 1997, p. 14).

There a body of research that has focused on the use of DEA weights and how to make specific choices of weights to provide suitable evaluations for DMUs. The methods used differ primarily as some methods require prior information and some do not. A general approach in cases of having prior information is based on the weights restriction, where it defined upper and lower bound for inputs and outputs (e.g., Pedraja-Chaparro, Salinas-Jimenez, & Smith, 1997). It is not easy to define the range of inputs and outputs; and, the expert opinion and the historical data are usually combined to define the range. Sometimes, the experts quantify the value of factors and directly used to the model (e.g., Paradi & Schaffnit, 2004). Another approach is the use of a common set of weights introduced by Roll, Cook, and Golany (1991). This approach uses a multi-criteria model to define common set of weights for all DMUs using a non-linear transformation; this approach has been developed recently in the works of Hatami-Marbini, Tavana, Agrell, Farhad, and Beigi (2015) and Omrani (2013). Pakkar (2015) also used Analytic hierarchy process (AHP) technique (Saaty, 1986) to define the values of inputs and outputs in the DEA model.

3.7.6 Integrations of AHP and DEA in this research

So far, this chapter has reviewed the literature on AHP and DEA methods. Both AHP and DEA methods have some issues. One of the major issues of AHP is that humans provide information and have the main role in ranking. Another issue is that the comparison in AHP is a lengthy task due to a large number of pairwise comparisons (Falsini et al., 2012) which usually leads to inconsistency in the comparison. Likewise, the common issue of DEA is that it does not always provide a good discrimination among DMUs, especially when there are many efficient DMUs.

To utilise the advantages and eliminate the disadvantages of both AHP and DEA methods, researchers have integrated these two methods in making a decision. The integration of DEA and AHP has emerged in many categories, for example, using the AHP method to rank efficiency and inefficiency units in the DEA model (Jablonsky, 2011), using AHP to weight the efficiency score obtained from DEA (Chen, 2002), and weighting the importance of each input and output factor in the supply chain structure (Cai & Wu, 2001). These integrations avoid biased selections and behaviour from the decision-maker and provide the most favourable solution to the problem. A comprehensive review of the integration of DEA and AHP can be found in the study by Pakkar (2015). This section considers the advantages of integrating AHP and DEA and explains the application of AHP and DEA in this research.

AHP and DEA were integrated to rank the simulation outputs of replenishment policies discussed in section 3.5.3. Before conducting the DEA, Sarkis (2007) suggested to check the property of inputs and outputs. The principal assumption is that the outputs are better when larger and the inputs are better when smaller. In this research, each replenishment policy was evaluated by three performance measures or dependent variables (i.e., AI, FR, and ORVR). Before being used in the DEA method, these outputs were rescaled by multiplying each AHP weight and the simulation outputs (similar to the work of Tofallis (2014)). It is important to note that the objectives of the problem are to increase FR and decrease AI and ORVR. These outputs have different directions and are undesirable outputs. Therefore, this paper used multiplicative inverse transformation by using the reciprocal of the value of AI and ORVR. The reciprocal of value was recommended by Gomes and Lins (2008) so that these outputs have the same direction (i.e., increasing direction). The adjusted outputs are w_1/AI , w_2*FR , and $w_3/ORVR$, which satisfy the property “the larger the better” and address the undesirable issues discussed in section 3.7.2.

Regarding the inputs, this research relies on the assumption that companies prefer low review period to quickly response to market demand. The companies also prefer to low order level to reduce the quantity of expired products. This assumption is relevant to the situation of dairy products or fast moving consumer goods; for example, milk or fresh foods. In such assumption, the review period T and Order-up-to level S satisfy the property “the smaller the better” and were selected as two inputs for the DEA model.

An application of a DEA models should be followed by a procedure with three main steps: checking the homogeneity of data, defining the model’s dimension (i.e., CRS or VRS, and input or output oriented), and applying the DEA model (Golany & Roll, 1989). Therefore, in this research, firstly, the homogeneity of data is checked according to the rule of thumb discussed by Lee et al. (2009); that is, the number of DMUs should be three times more than the total number of inputs and outputs. The DEA model is presented in Figure 3.7. The model has two inputs (i.e., T , S), and 27 outputs (i.e., w_1/AI , w_2*FR , $w_3/ORVR$ for one supplier and two retailers with three products). There are in total 88 DMUs or experiments of review period and order-up-to level (explained in section 3.5.3). The total number of DMUs was over three times the total number of inputs and outputs (i.e., $88 > 3*(2+27) = 87$). Thus, the data is homogenous and allows the use of DEA (Cooper et al., 2001; Lee et al., 2009).

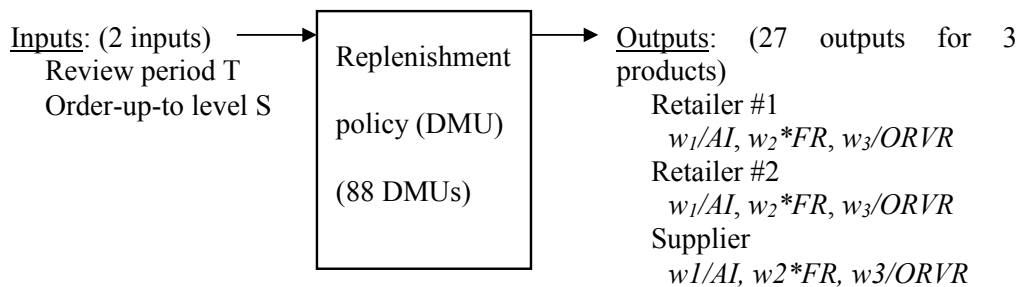


Figure 3.7: DEA model with two inputs, 27 outputs, and 88 scenarios

Secondly, the return to scale and dimension (i.e., CRS or VRS, and input or output-oriented) are examined. A portion of the report on the average inventory level at retailer #1 under experiment #1 (in Appendix 3) shows that doubling the review period from 1 to 2 (e.g.,

(1, 27) to (2, 27)) does not lead to a 50% decrease of average inventory at retailer #1 for product #1. Therefore, this research used the models based on the assumption of VRS. Moreover, this research aims at improving the model's performance; the output-orientation is suitable for the model as recommended by Golany and Roll (1989).

Finally, the DEA calculation starts with the basic BCC model (i.e., model 4 in Appendix 4). The efficiency scores were calculated by using an R package 'TFDEA' (Shott & Lim, 2015), (syntax in Appendix 5 is for experiment #1). The efficiency scores showed that most of the DMUs had a score of 1 (e.g., the efficiency scores of 88 policies under experiment #1 in Appendix 6), meaning the basic model cannot discriminate the best performing DMU. This calls for the use of alternative ranking methods.

Considering the advantages of the super-efficiency method presented in section 3.7.5, this research applied the super-efficiency method developed by Cook et al. (2009) which is output oriented. This ranking method produces the highest efficiency scenario with the lowest super-efficiency value. The super-efficiency scores were calculated by using the R package 'TFDEA' (Shott & Lim, 2015) (syntax in Appendix 7). The results of super-efficiency scores are presented and discussed in the next chapter.

3.8 Justification of the Research Framework

Based on the research objectives and chosen multi-methodological approach, this chapter proposed a research framework (i.e., integration of DES, AHP, and DEA) which was used to address the research objectives presented in section 3.1.1. This research aims to define the most favourable replenishment policy under a given context, and provide understanding of the effects of demand, lifetime, and lost sales probability as part of the inventory management problem. The research framework, therefore, needs to support performance ranking of all replenishment policies and provide insights into performance in the studied model.

The framework starts with the running of a DES model for each of the 88 replenishment policies per each of the eight experiments. The results or performances of each policy per experiment are recorded by three measures: AI, FR, and ORVR. The weight of each performance measure is calculated by using the AHP method. Finally, the DEA method is used to evaluate and rank the performance of 88 policies for each DES experiment.

This proposed framework is motivated by two integrations, namely, the integration of simulation and AHP, and the integration of AHP and DEA. DES is a useful tool to evaluate the multiple performance measures of a complex problem. However, when there are many conflicting performance measures, the DES should be integrated with other MCDM methods, such as AHP (Xu et al., 2011). The power of AHP is its ability to organise a complex, and multi-criteria problem hierarchically, and then to examine each level of the hierarchy separately. By including both qualitative and quantitative information, AHP uses the pairwise comparison to extract a relative ordering of subjective preferences.

Examples of integration simulation and AHP include the work of Xi and Poh (2015), who investigated how to reduce the risks of city flooding and expand Singapore's sources of water supply. First, the authors took real data and simulated effects of alternatives under various scenarios of population growth. Second, AHP was applied to compare alternatives based on their performance as revealed by the simulation and the judgment of decision-makers. Bamakan and Dehghanimohammadabadi (2015) proposed the use of AHP and simulation to analyse security risk for an information security system. Using this method, AHP was used to weight for security characteristic of any information asset, including Confidentiality, Integrity, and Availability. The simulation was utilised to manage the stochastic nature of risk assessment.

The AHP also has been used to weight multiple criteria for the studied system. For example, Brust and Clark (2014) examined the selection of computing infrastructure

architectures in a healthcare company. They used AHP to weight the measures of an alternative. Then, a simulation model was used to evaluate alternatives based on the weighted measures. Azadeh, Asadzadeh, Mehrangohar, and Fathi (2014) aimed to optimise the operator allocation in cellular manufacturing systems. A simulation model for various operators' layout was developed and performed. AHP was utilised to weight the measures, and the genetic algorithm was used to find the optimal solution. Another example is the work of Varthanan, Murugan, Kumar, and Parameswaran (2011) The authors developed a simulation – AHP – discrete particle swarm optimisation. AHP was used to calculate the weights of two objectives of the problem, which were then used to find the optimal solution by using discrete particle swarm optimisation. These observations support the integration of simulation and AHP in this research, where the simulation runs for various experiments and the AHP calculate the weights of performance measures of the studied model.

The second integration in the proposed framework is between AHP and DEA. Pakkar (2015) classified the integrations of AHP and DEA into a number of categories:

1. Using AHP to transform qualitative data in DEA to quantitative data (e.g, Ertay, Ruan, & Tuzkaya, 2006)
2. Using AHP to weight the efficiency scores received from DEA (e.g., Chen, 2002)
3. Using AHP to rank the efficiency or inefficiency of DMUs (e.g., Ho & Oh, 2010)
4. Using AHP to weight the inputs and outputs in the DEA model (e.g., Cai & Wu, 2001)
5. Weighing the changes in the inputs and outputs in the DEA model (e.g., Lozano & Villa, 2009)
6. Restricting the weights of inputs and outputs used in the DEA model (e.g., Takamura & Tone, 2003)
7. Restricting the weights of virtual inputs and outputs (e.g., Podinovski, 2016)

8. Estimating the missing data (e.g., Saen, Memariani, & Lotfi, 2005)
9. Constructing a combination of weights (e.g., Liu & Chen, 2004)

From these categories and referring to real business situations, where the decision-makers usually prioritise the performance measures, this study chose to use AHP to generate the weight of each performance measure (e.g., #4 in the previous example list). Setting the priorities of performance criteria or performance measures is one of five key steps to identifying the desired performance of a company (Epstein & Roy, 2001). Moreover, AHP, which uses a process of pairwise comparison, is a common method to identify the priority or relative importance of performance measures (Askariazad & Wanous, 2009).

Furthermore, DEA has also been used to rank multi-criteria alternatives in the literature (Köksalan & Tuncer, 2009). Ranking is a popular problem in MCDM literature, especially when there are a list of alternatives with single or multiple criteria to measure the performance (Sinuany-Stern, Mehrez, & Hadad, 2000). DEA is used to establish a group of efficient DMUs and has been studied to discriminate or rank between efficient DMUs (Akbarian, 2015). Researchers have successfully applied DEA and MCDM methods in the field of performance evaluation. This study concentrated on this point, and integrated AHP and DEA for the studied inventory management problem.

3.9 Chapter Summary

This chapter started by discussing the meaning of research methodology to define the study's objective. The research objectives were stated in section 3.1.1, followed by a discussion on the philosophical background of this research in section 3.2. A research method, which uses multiple methods to achieve the research objectives, was presented in section 3.3. Section 3.4 proposed to integrate simulation, AHP, and DEA to study the research problem. The simulation approach was suitable for a complex problem and provides multiple performance measures of each alternative for the studied problem. The AHP approach was used to rank the importance

of each performance measure, and the DEA approach evaluated and ranked the efficiency of each alternative. The proposed research framework was justified in section 3.8.

Chapter 4 Results

This chapter reports, analyses, and discusses results received utilising the research methodology outlined in section 3.4. These results addressed research objectives RO1 and RO2, and research questions RQ1, RQ2, and RQ3, which were developed, presented, and formulated in section 3.1.1. In line with these research objectives and research questions, this chapter illustrates how to find the most favourable replenishment policy under a given context in section 4.1. Then, the sensitivity analysis investigates the effects of decision-makers' opinions on the selection of the best replenishment policy in section 4.3. In section 4.5, the sensitivity analysis is also conducted to investigate the effects of consumer demand, product lifetime, and lost sales probability on the performance of the inventory model (i.e., average inventory, fill rate, and order rate variance ratio). The statistical MANOVA and ANOVA techniques are performed in section 4.5 to test the effects of input factors on the performance of the inventory model. The chapter structure is summarised in Figure 4.1.

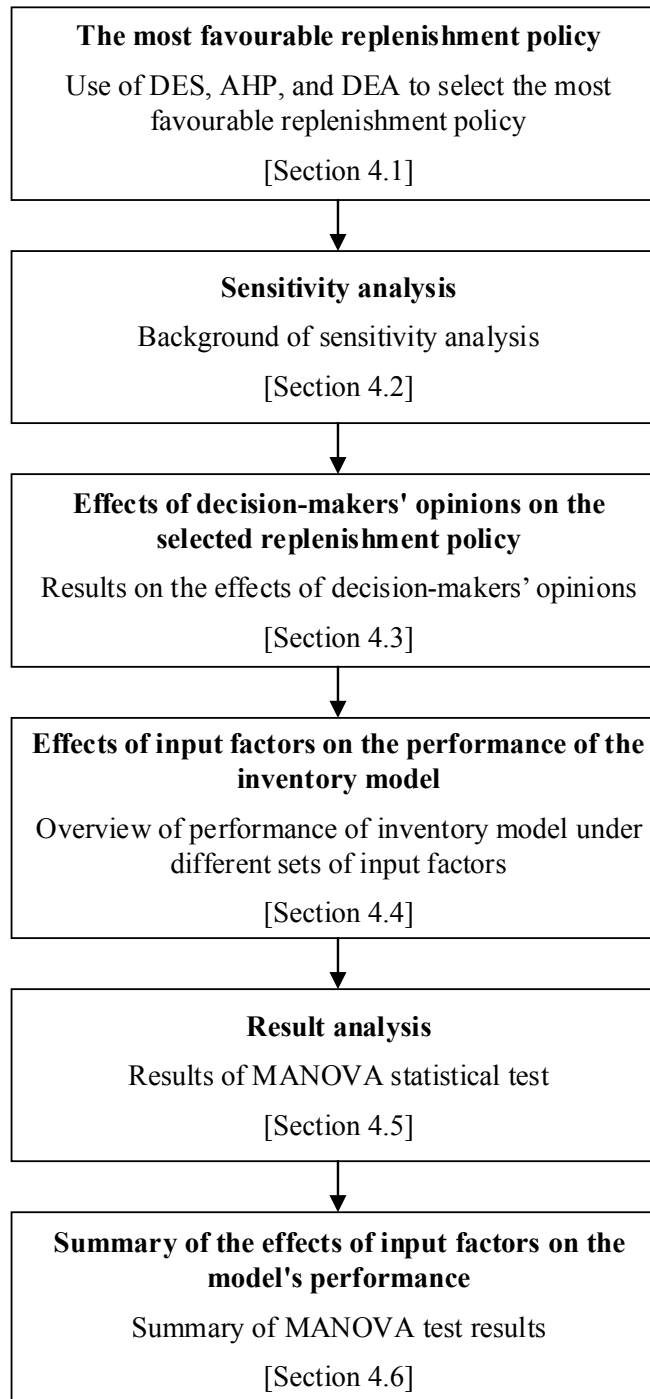


Figure 4.1: Structure of Results chapter

4.1 Selecting the Most Favourable Replenishment Policy

This section answers RQ1: What is the most favourable replenishment policy for a two-echelon model under a given context of perishable and substitutable products. This research considered eight contexts or experiments with respect to eight combinations of consumer demand, product lifetime, and lost sales probability defined in section 3.5.3.

Without loss of generalisation, this section applied the framework developed in section 3.4.1 and selected the most favourable replenishment policy under the experiment #1 in section 3.5.3. This application serves as a numerical example and an illustration of how to use the proposed framework. The most favourable replenishment policies under the other seven experiments are selected in a similar manner. There were three key steps in this framework: the simulation mimicked the operations of the inventory model under each of the 88 alternatives or replenishment policies; and three performance measures of each policy (i.e., AI, FR, and ORVR) were recorded at the end of each simulation run. The AHP was used to calculate the weight of each measure. The DEA combined simulation and AHP results, evaluated the performance of each replenishment policy, and suggested the most favourable replenishment policy by using the DEA Cook's super-efficiency method. Details of these steps are presented as follows.

4.1.1 Discrete-event simulation under experiment #1

Under experiment #1, the consumer demand follows a Poisson distribution with a mean of 15, the product lifetime follows an exponential distribution with a mean of 6, and lost sales probability is 0.9 (as explained in section 3.5.3).

There are 88 possible replenishment policies with the range of T and S as follows:

- $T \geq T_{min} = L = 1$
- $T \leq T_c = 4$, T_c : review period in case the product has an infinite lifetime
- $26 \leq S \leq 47$,

This research used ExtendSim's 'Scenario Manager' block to easily evaluate and explored the performance of different model configuration (i.e., automatically changing from one replenishment policy to another). Appendix 9 shows the input parameters of the review period and order-up-to level, and Appendix 10 shows possible replenishment policies in the 'Scenario Manager' block. This block also allows a recording of the performance of the model, which in this research is average inventory AI, fill rate FR, and order rate variance ratio ORVR.

As explained in section 3.5.3, each replenishment policy was replicated 10 times, the length of each simulation was 200,000 units of time (i.e., days), and the first 5,000 data were discarded from calculating the system's performance because of the warm up period.

Three performance measures were recorded by the mean value of 10 replications. These values were exported into an Excel file for further analysis. The settings on the 'Scenario Manager' block for recording the model's performance and exporting to the Excel file are in Appendix 11. The model's performance (i.e., simulation results) were stored in an Excel file for further analysis.

As this research's inventory model was evaluated by three conflicting performance measures, it is impossible to find one policy to simultaneously satisfy the three measures. For example, as shown in Figure 4.2 below, replenishment policy (1, 26) had a higher fill rate than policy (4, 26) did. However, policy (1, 26) also needed higher average inventory than policy (4, 26) did. These conflicting measures confirm the need to use the multi-criteria decision-making (MCDM) methods, which are AHP and DEA in this research (see section 3.3.7).

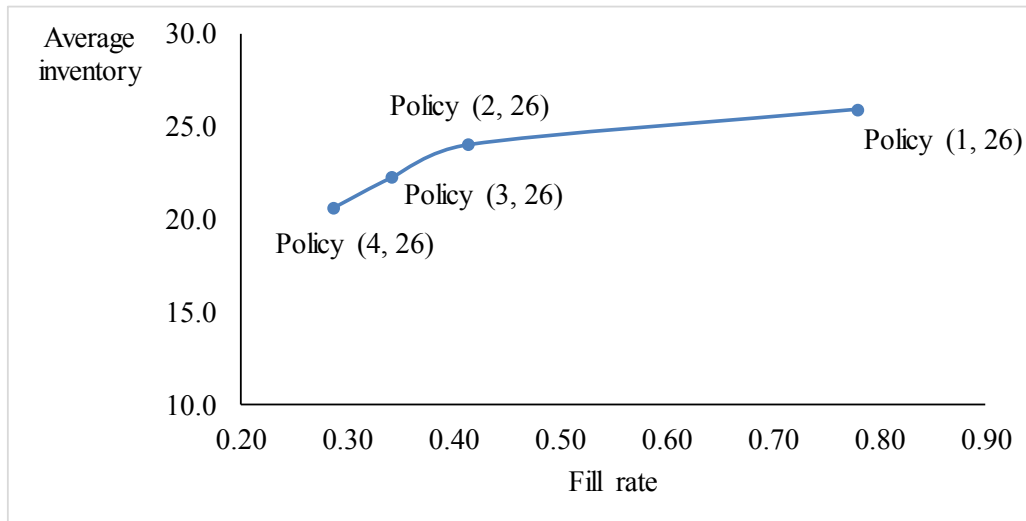


Figure 4.2: Conflicting results of average inventory and fill rate of the replenishment policies (1, 26), (2, 26), (3, 26), and (4, 26)

The next section presents how the weight of each measure is received from the AHP method. The AHP procedure to identify the weight of each measure was explained in section 3.6.

4.1.2 Analytic hierarchy process

As presented in section 3.6, the AHP method was used to calculate the weight or importance of each measure. The AHP method has three main steps (see section 3.6) (i.e., creating a hierarchy, creating a comparison matrix, and calculating the weight). The decision-makers, based on business requirement and experience, provide opinions on how important a measure is compared to another with respect to the business goal.

This research aims at providing an example of the proposed framework in use to find the most favourable replenishment policy. The researcher utilised working experience in the supply chain (i.e., the researcher has worked seven years as a supply chain leader and manager for dairy and pharmaceutical companies) to create the comparison matrix presented in Table 3.6, which was based on a case study presented in section 3.6.2.

In this research, the consistency and the importance of each measure were calculated by using the R package ‘pmr’ (Lee & Yu, 2013). The syntaxes of calculation are in Appendix

2. The results showed that the consistency ratio was 3.9%, less than the critical value of 10%. Thus, there was no evidence of inconsistency (Saaty & Ozdemir, 2003). The weighting results for AI, FR, and ORVR are $w_1 = 21.7\%$, $w_2 = 71.7\%$, and $w_3 = 6.6\%$, respectively. The next section uses these values to rank the performance of each replenishment policy by applying the DEA method.

4.1.3 Data envelopment analysis under experiment #1

As explained in the framework described in section 3.4.1, the DEA method helps to evaluate and rank the performance of replenishment policies. The DEA model in this research is presented in Figure 3.7 and has two inputs (i.e., T, S), and 27 outputs (i.e., w_1/AI , w_2*FR , and $w_3/ORVR$ for one supplier, two retailers, and three products). There is a total of 88 DMUs or replenishment policies which are combinations of the review period and order-up-to level (explained in section 3.5.3).

This research applied the super-efficiency method developed by Cook et al. (2009) and was output oriented (explained in section 3.7.6). The results in Appendix 8 showed that replenishment policy (1, 26) had the lowest super-efficiency score at 0.45147. Therefore, policy (1, 26) was the most favourable replenishment policy. In the given context of experiment #1 and given a range of policies, this replenishment policy best balances the three performance measures – AI, FR, and ORVR.

4.1.4 Discussion of the result received under experiment #1

In this research, a framework for selecting the most favourable replenishment policy was introduced in section 3.4.1, and was applied as an example (i.e., experiment #1) in Section 4.1 to illustrate how the framework is conducted. Under experiment #1, the simulation model was performed for a given set of 88 replenishment policies. The performance of 88 policies was recorded by three measures: AI, FR, and ORVR. To reflect a real business situation, where

each measure has a different weight, AHP is conducted to weight the importance of each measure. Finally, the DEA Cook's super-efficiency method evaluated and ranked the performance of 88 replenishment policies based on the simulation results and weights of the three measures. Over 88 given policies, policy (1, 26) (i.e., review inventory at the end of each day and order to bring the inventory level back to 26) had the lowest super-efficiency score and was selected as the most favourable one.

The selected policy (1, 26) was comparable to the findings from Kouki et al. (2014). The AHP method conducted in this research showed that FR was the most important measure (71.7%), followed by AI (21.7%) and ORVR (6.6%). In this context, it was preferable to have a policy that has high fill rate or low lost sales quantity. Kouki et al. (2014) showed that for a given S , the longer T is, the more quantity of expired products and lost sales quantity there is. Moreover, the short T decreases the variation of order quantity and thus, ORVR. The short T and S also reduce the daily inventory level and the average inventory level. Therefore, the selected replenishment policy (1, 26) was reasonable and comparable with Kouki et al. (2014) findings.

Thus, the proposed non-financial framework is comparable to the financial approach usually used in previous research. In addition to the advantages of the non-financial framework as explained in section 2.5.6, the proposed framework is an alternative for decision-makers to select the replenishment policy in a company.

However, many uncertainties can affect the results from the proposed framework. This research discusses the performance of the proposed framework, where the DEA technique selects the most favourable replenishment policy based on the results from the DES and AHP methods. Thus, the uncertainties in the DES and AHP results can affect the final selection and the performance of the selected policy. Firstly, this research extended and reused the parameters in the work of Kouki et al. (2014). Under this given context, the DES model was

performed for 88 replenishment policies, which were extracted from Kouki et al. (2014) work. These given policies are based on the assumption of the convexity of the total operating cost. Therefore, the most favourable replenishment policy was selected from the 88 given policies. This range of given policies could be a limitation of the research.

Second, the AHP method used in section 4.1.2 is based on the case study and experience of the researcher, who has worked seven years in the supply chain management field for dairy and pharmaceutical companies (as explained in section 3.6.2). Under different contexts, for example, different markets, financial statuses, or marketing strategies, the importance of each measure may be different. For example, a company that has a strong market share, may focus on controlling average inventory. In this case, the weight of average inventory is highest and may lead to a different replenishment policy.

In conclusion, the uncertainties in the simulation and AHP results can affect the selection of the most favourable replenishment policy and its performance. The sensitivity analysis conducted in the next sections provides an understanding of these effects.

4.2 Sensitivity Analysis

Apart from finding the most favourable replenishment policy, this chapter aims at answering research questions RQ2, and RQ3 which focus on investigating the effects of decision-makers' opinions on the selection of the most favourable replenishment policy and input factors (i.e., consumer demand, product lifetime, and lost sales probability) and on the performance of this chosen policy. The knowledge of these effects helps decision-makers anticipate and respond better to future issues. This section employs sensitivity analysis, an important technique for determining the effect of one input factor on the model performance (Law, 2014).

The performance measures of replenishment policies (viz., AI, FR, and ORVR) are received via a simulation model, and these measures are weighted by the decision-makers' opinions via the AHP method before ranking by the DEA method, which means these results

are stochastic. Therefore, decision-makers need to consider uncertainty when selecting the most favourable replenishment policy and understanding its performance.

A sensitivity analysis is conducted to determine the effects of changes in decision-makers' opinions on the policy selection and the changes in input factors on the performance of this selected replenishment policy. While the changes in the input factors affect the DES results, the changes in decision-makers' opinions affect the importance of each measure, and finally the selection of the most favourable replenishment policy. This section, consequently, conducts sensitivity analysis for decision-makers' opinions in section 4.3 and the DES model in section 4.4.

4.3 Effects of Decision-makers' Opinions on the Selected Replenishment Policy

This section answers RQ2 to understand how the changes in decision-makers' opinions affect the selection of the most favourable replenishment policy. Decision-makers' opinions were used to weight the importance of measures by the AHP method. These weights were combined with the performance of each measure received from the DES model for selecting the policy. Recall that the AHP method was based on decision-makers' opinions, which were stochastic. If decision-makers have other opinions, the weights of the three measures are changed. Thus, it is necessary to know how these changes affect the selection of the replenishment policy. To demonstrate these effects, this section performs sensitivity analysis on the importance of three performance measures: average inventory, fill rate, and order rate variance ratio. In other words, this section determines how the selected replenishment policy changes if the importance of each performance measure is changed.

This section applied the sensitivity analysis technique in the AHP method used in the work of Yakovleva et al. (2012). Yakovleva et al. (2012) performed sensitivity analysis for three dimensions in order to understand how sensitive the sustainability index was to changes

in the importance of one dimension. They varied this importance from low to high while keeping the ratio of the other two dimensions.

Applying sensitivity analysis, this research wants to understand how AI affects the replenishment policy. The weight of AI was varied from low (10%) to high (90%), while the ratio of FR and ORVR is kept the same. This procedure was repeated for FR and ORVR. Based on the results discussed in section 3.6, the weights for AI, FR, and ORVR are $w_1 = 21.7\%$, $w_2 = 71.7\%$, and $w_3 = 6.6\%$, respectively. The ratio of FR to ORVR was $71.7\% / (71.7\% + 6.6\%) = 0.92$, and the ratio of ORVR to FR is $6.6\% / (71.7\% + 6.6\%) = 0.08$. If the AI had a weight of 10%, the weight of FR was $(1 - 10\%) * 0.92 = 82.4\%$ and the weight of ORVR was $(1 - 10\%) * 0.08 = 7.6\%$. Table 4.1 presents six sets of weights associated with the change of each performance measure. These six sets of weights are the analysed effects of the decision-makers' opinions on determining the most favourable replenishment policy.

Table 4.1: The weights along with the change of each measure and the original weight

Testing number	Testing measure	AI (21.7%)	FR (71.7%)	ORVR (6.6%)
a	AI	10.0%	82.4%	7.6%
b	AI	90.0%	9.2%	0.8%
c	FR	69.0%	10.0%	21.0%
d	FR	7.7%	90.0%	2.3%
e	ORVR	20.9%	69.1%	10.0%
f	ORVR	2.3%	7.7%	90.0%

The results from each of eight simulation experiments (see Table 3.4) were analysed according to these six sets of weights. In total, there are $6 * 8 = 48$ situations that the decision-makers must consider under the uncertainty of input factors and decision-makers' opinions, as presented in Appendix 12. These 48 situations are combinations of eight simulation experiments and six sets of weights of performance measures.

Under each of the 48 situations, the performances of 88 replenishment policies were ranked and evaluated by using the DEA Cook's super-efficiency output-oriented method (Cook et al., 2009) (similar to section 4.1.3). The policy having the lowest score was selected as the most favourable replenishment policy.

The DEA results showed that policy (1, 26) had the lowest score in all 48 situations, meaning the policy (1, 26) was the most favourable replenishment policy under all 48 studied situations. This finding indicates the selection of the most favourable replenishment policy is stable under the studied context.

4.4 Effects of Input Factors on the Performance of the Inventory Model

This section answers RQ3 to investigate the effects of input factors (i.e., consumer demand, product lifetime, lost sales probability) on the performance of the selected replenishment policy. The knowledge of these effects helps decision-makers anticipate and respond better to future issues. This section employs sensitivity analysis, an important technique for determining the effect of one input factor on the model performance (Law, 2014).

The sensitivity analysis in the simulation was conducted via a number of experiments. As explained in section 3.5.3, this research applied the 2^k factorial experimental design technique for the sensitivity analysis. There were eight experiments relating to combinations of the high and low level of consumer demand, product lifetime, and lost sales probability, which are presented in Table 3.4.

Under each experiment, the selected replenishment policy was replicated 10 times; each replication ran 200,000 units of time (i.e., days). The first 5,000 data were discarded from calculating the system's performance because of the warm-up period (explained in section 3.5.3.7). The performance of this policy was recorded by three measures: AI, FR, and ORVR. As this research assumed three products and two retailers have similar characteristics, without loss of generalisation, this section only discusses the performance of each replenishment policy for the supplier, retailer #1, and product #1.

This section firstly provides an overview of the performance of all 88 replenishment policies under eight experiments. Figure 4.3 to Figure 4.8 summarise the performance of 88 policies under eight experiments for supplier, retailer #1, and product #1. These figures were

drawn from the IBM SPSS, version 23 (IBM SPSS, 2016), with the average values after 10 replications times of each policy under each experiment. The overview serves as a general understanding of the performance of the inventory model and can be used to shortlist the range of alternatives quickly. For example, if the supplier has a policy that a selected replenishment policy should bring a fill rate of over 90%, then, from Figure 4.6, it can be concluded that just policies having a review period as of 1 are analysed further.

4.4.1 Overview of average inventory performance

The simulation results showed that the higher the order-up-to level, the higher the average inventory. This is because a high order-up-to level creates a high available inventory. This result validates and verifies the studied simulation model.

The average inventory level has a decreasing trend from a short to a long review period at both the supplier and retailer sides. This is because the longer a review period is, the greater the number of expired products. Therefore, in this case, both average inventory and fill rate level are low. This calls for a trade-off decision (see section 2.1.2), or a multi-criteria decision-making solution, where the average inventory should be low enough and the fill rate level should be high enough.

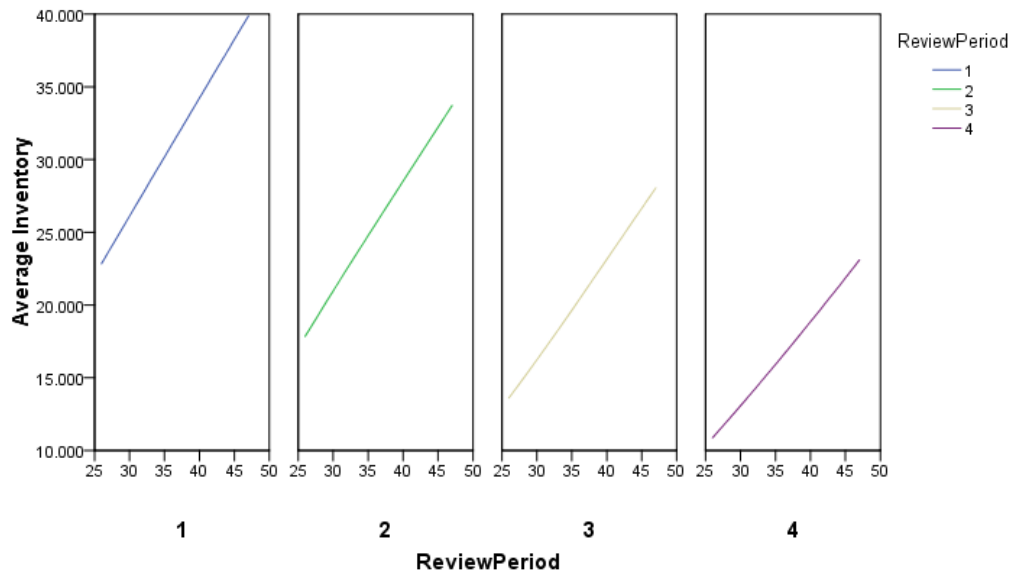


Figure 4.3: Performance of average inventory at the retailer

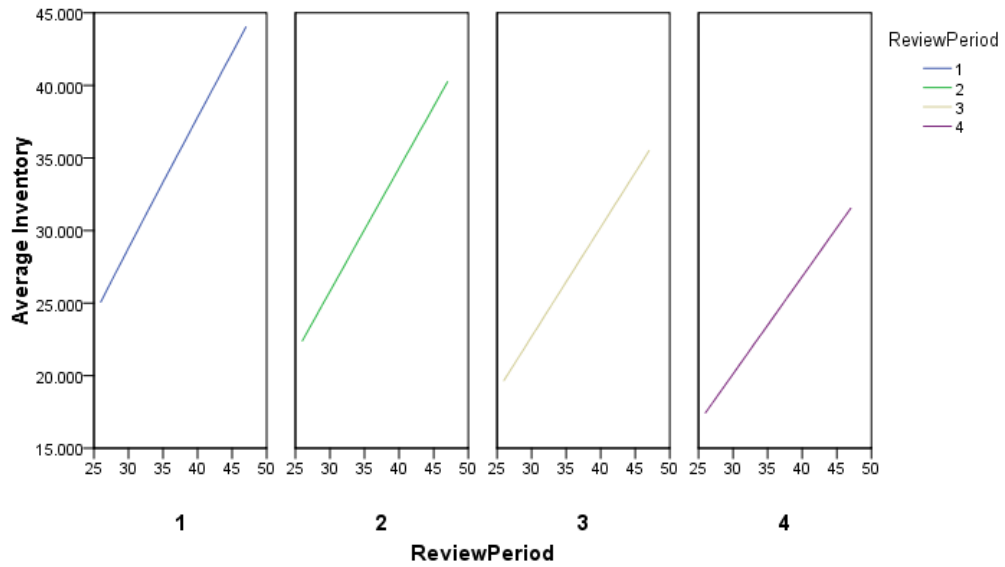


Figure 4.4: Performance of average inventory at the supplier

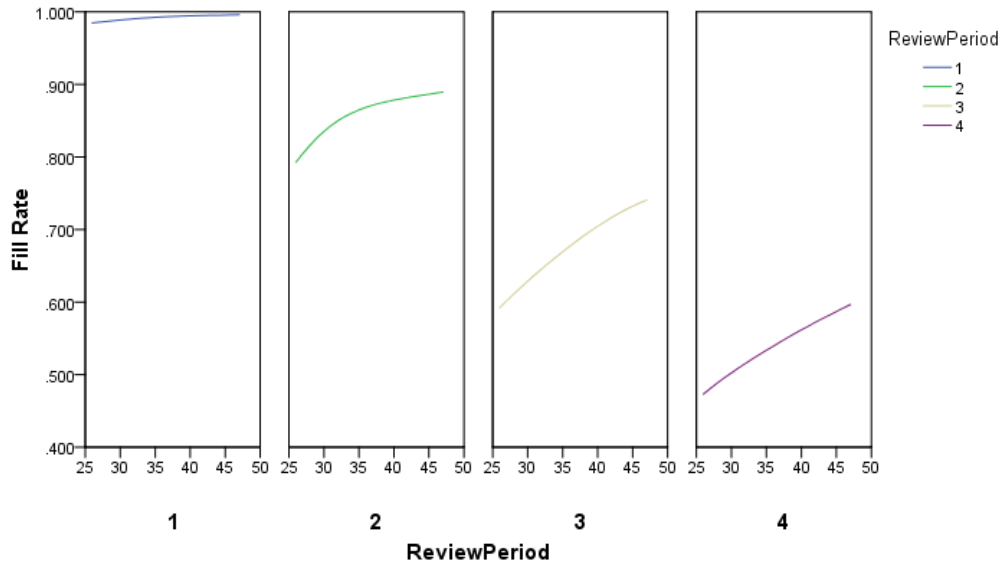


Figure 4.5: Performance of fill rate at the retailer

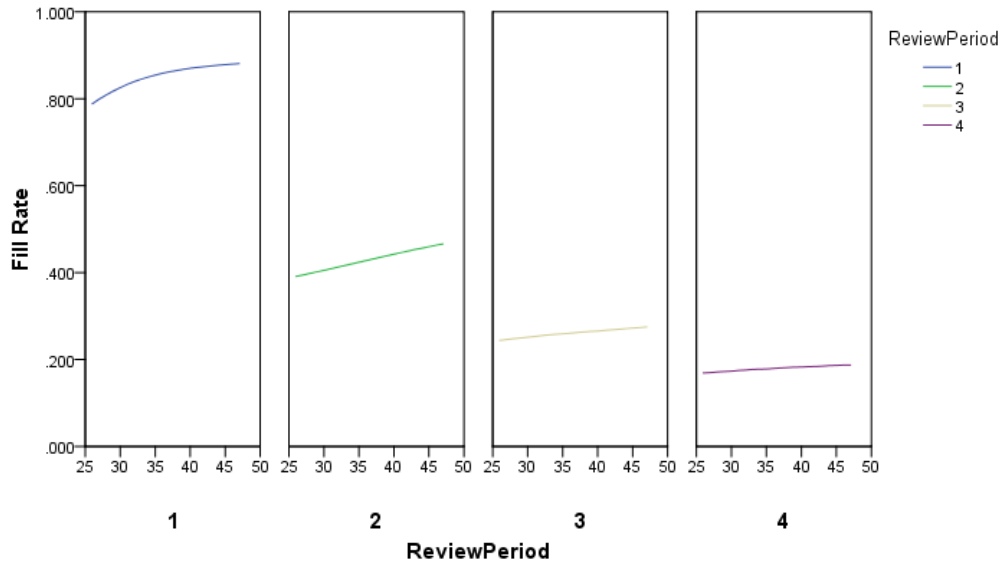


Figure 4.6: Performance of fill rate at the supplier

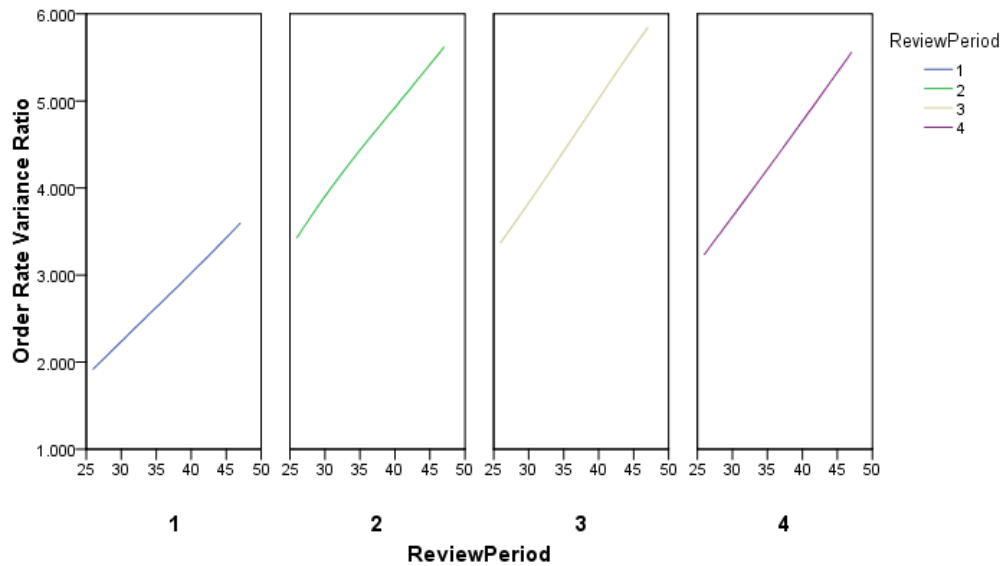


Figure 4.7: Performance of order rate variance ratio at the retailer

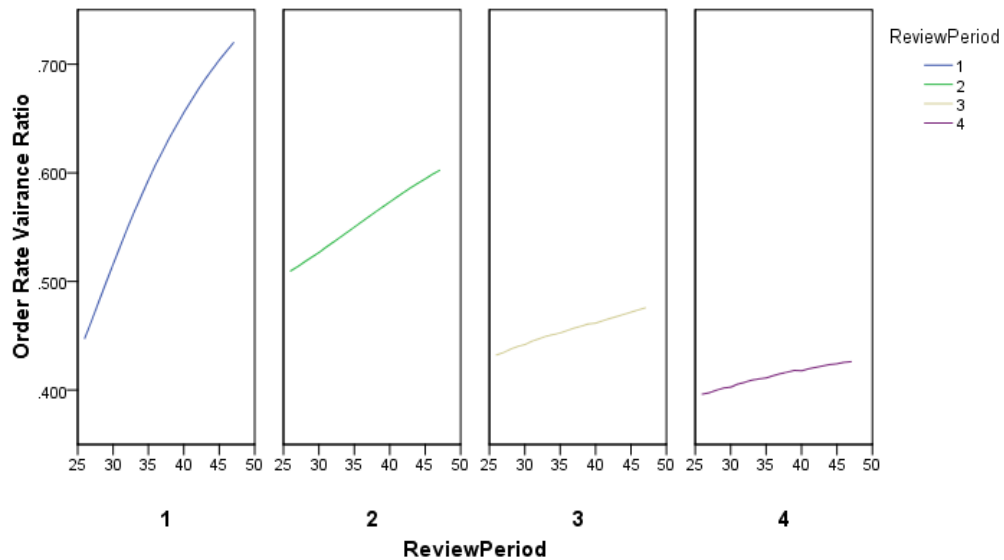


Figure 4.8: Performance of order rate variance ratio at the supplier

4.4.2 Overview of fill rate performance

The fill rate had a decreasing trend from a low to a high review period (i.e., review period from 1 to 4). This was because the studied model considered stochastic consumer demand and a product's lifetime. Thus, the longer the review period was, the more uncertain the model was.

Moreover, the fill rate had an increasing trend from left to right within each review period block (i.e., order-up-to level increases). This means that under the same review period, the higher the order-up-to level, the higher the fill rate is. For example, the policy (2, 47) had a higher fill rate level than policy (2, 26) does. These two observations are relevant to the findings of Petrovic et al. (1998); that is, the external uncertainty adversely affects the fill rate, and this negative effect can be compensated by increasing the inventory level.

Moreover, the supplier had low fill rate under replenishment policies with review periods of 2, 3, and 4 (i.e., fill rate is under 80%), and a lower fill rate in all experiments than the retailers have. Recall that this research assumed the supplier and retailers had the same replenishment policy (see section 2.3.1), and the review period at the supplier and retailers was synchronised (as in Costantino et al. (2015) and Lee et al. (2016)). It is a divergent supply chain model without sharing information; that is, the supplier receives demand from retailers and does not know the retailer's inventory level and sales data. Because of the limited product lifetime, the longer a review period is, the more the number of expired products is. Therefore, at the time retailers place an order (i.e., at the review period), the supplier has low inventory level. Thus, the supplier satisfies retailers' demand with a low level or low fill rate. This observation confirms the disadvantages of inventory models where there is no or partial information sharing (Babai et al., in press). Further research can extend to the information sharing inventory model for analysing the advantages of sharing information under the context of perishable and substitutable products.

4.4.3 Overview of order rate variance performance

The performance of order rate variance ratio at both the supplier and retailers' sides were correlated with previous bullwhip effect research, and validated and verified the simulation model. ORVR at retailers was over one because retailers tend to order over the actual demand to cover the uncertainties in operations such as uncertainties in consumer demand, or product

lifetime (Bernstein & Federgruen, 2005; Tang, 2006). ORVR at the supplier is almost stable and reduced when the review period was increased. This is because the research assumed two retailers place orders in the same periods. This assumption is similar to the scheduling ordering policy when the order interval at retailers is the same. This situation dampens the supplier's demand variance (Cachon, 1999).

Sections 4.4.1, 4.4.2, and 4.4.3 provide overviews of the performance of fill rate, average inventory, and order rate variance ratio of the studied model. The following sections investigate and report the effects of the input factor on each performance measure.

Given the most favourable replenishment policy, knowledge of the effects of input factors (i.e., consumer demand, product lifetime, and lost sales probability) on the performance of the inventory model helps decision-makers anticipate and respond better to any change in input factors. The numerical example in section 4.1 selected the replenishment policy (1, 26) as the most favourable one and suggested applying this policy. Thus, the sensitivity analysis in this research was based on the policy (1, 26). This is explainable as decision-makers normally focus on the policy being applied. Moreover, the same procedure can be used for sensitivity analysis for other policies if needed. As explained earlier, the simulation model was run under eight experiments. The statistical tests (i.e., MANOVA and ANOVA tests) were performed on the results to investigate the effects of input factors on the model's performance.

4.5 Result Analysis

This section determines the differences between experiments to test the effects of input factors on the model's performance. This section applies two statistical techniques, namely, multivariate analysis of variance (MANOVA) and univariate analysis of variance (ANOVA), to test the interactive effects of independent variables on dependent variables. According to Field (2013), ANOVA is used in a situation with one dependent variable (or output) and is

known as a univariate test. MANOVA extends the ANOVA to measure differences in two or more outputs simultaneously and is known as a multivariate test.

Before performing MANOVA and ANOVA, four assumptions need to be tested (Hair et al., 2010). These assumptions are listed below and are tested in section 4.5.1. The MANOVA and ANOVA results are presented in sections 4.5.2 and 4.5.3. All statistical tests are performed by using IBM SPSS Statistical, version 23 (IBM SPSS, 2016).

4.5.1 MANOVA assumption

Four assumptions of MANOVA are as follows. Note that MANOVA has similar assumptions to ANOVA but they are extended to the multivariate case. Therefore, this section tests the assumptions of MANOVA only.

- **Independence and random:** Observations are statistically independent and data are randomly sampled from a population.
- **Multivariate normality:** The dependent variables (or outputs) should follow a multivariate normal distribution within groups.
- **Homogeneity of covariance matrices:** The variances in each group should be roughly equal (homogeneity of variance) and the correlation between any two dependent variables is the same in all groups.
- **Linearity:** Each pair of dependent variables has a linear relationship for all groups of independent variables.

4.5.1.1 The assumption of random and independence

The violation of independence among observations is the most important MANOVA assumption (Hair et al., 2010). This violation may be caused by collecting data within group configurations. In this research, the data are collected from all experiments generated from a full factorial design of the input factors or independent variables. A total of eight experiments

was run with 10 replications per experiment. This produced a total sample size of 80. The experimental design used independent experiment replications with random seeds for data generation (Schriber et al., 2013). This ensured that data for each replication were not related to each other. Thus, the assumptions of statistical independence between experiments and random sampling from the population were met.

4.5.1.2 The assumption of multivariate normality

Multivariate normality assumed that the effect of two or more variables followed a normal distribution. However, because there was no direct test of multivariate normality, the univariate normality of each variable was tested by using statistical techniques (Hair et al., 2010). The significant values shown in Table 4.2 taken from the Kolmogorov-Smirnov (K-S) tests of normality showed that there was a significant deviation between the dependent variables and the standard normal distributions (*Sig.* less than 0.05). However, in large samples, such as in this research, these tests can be significant for only a slight deviation from normal (Field, 2013). Therefore, the K-S test was interpreted in conjunction with skew and kurtosis information to check the data's deviation from normality.

Table 4.2: Kolmogorov-Smirnov Test of Normality for Dependent Variables

Dependent variable ¹	Tests of Normality		
	Kolmogorov-Smirnov ^a		
	Statistic	df	Sig.
AI1-1	.256	80	.000
AI1-2	.256	80	.000
AI1-3	.257	80	.000
AI2-1	.257	80	.000
AI2-2	.255	80	.000
AI2-3	.258	80	.000
AI3-1	.312	80	.000
AI3-2	.312	80	.000
AI3-3	.312	80	.000
FR1-1	.209	80	.000
FR1-2	.214	80	.000
FR1-3	.212	80	.000
FR2-1	.207	80	.000
FR2-2	.214	80	.000
FR2-3	.212	80	.000
FR3-1	.150	80	.000
FR3-2	.150	80	.000
FR3-3	.149	80	.000
OR1-1	.288	80	.000
OR1-2	.288	80	.000
OR1-3	.288	80	.000
OR2-1	.288	80	.000
OR2-2	.289	80	.000
OR2-3	.289	80	.000
OR3-1	.253	80	.000
OR3-2	.253	80	.000
OR3-3	.253	80	.000

a. Lilliefors Significance Correction

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

Descriptive statistics in Table 4.3 provided skew and kurtosis information of the data. If the value is further from zero, the data are more likely normally distributed (Field, 2013). Hair et al. (2010) suggested that skew statistics outside the range of negative one to one are substantially skewed. Although the acceptable range of kurtosis depends on the actual skewness's value, Bai and Ng (2005) suggested a range of +/-3 for kurtosis. The skew and kurtosis information in this research showed that all skewness and kurtosis values of the dependent variable were within recommended guidelines and thus, the assumption of multivariate normality was met.

Table 4.3: Descriptive statistics for dependent variables

Dependent variable ¹	N	Mean	Descriptive Statistics				
			Std. Deviation	Skewness		Kurtosis	
				Statistic	Std. Error	Statistic	Std. Error
AI1-1	80	22.851	1.440	-.526	.269	-.956	.532
AI1-2	80	22.851	1.442	-.521	.269	-.958	.532
AI1-3	80	22.851	1.441	-.522	.269	-.957	.532
AI2-1	80	22.851	1.440	-.524	.269	-.957	.532
AI2-2	80	22.852	1.441	-.520	.269	-.958	.532
AI2-3	80	22.851	1.442	-.520	.269	-.957	.532
AI3-1	80	25.083	0.911	-.268	.269	-1.644	.532
AI3-2	80	25.083	0.911	-.272	.269	-1.638	.532
AI3-3	80	25.083	0.911	-.268	.269	-1.644	.532
FR1-1	80	0.985	0.012	-.621	.269	-1.030	.532
FR1-2	80	0.985	0.012	-.627	.269	-1.025	.532
FR1-3	80	0.985	0.012	-.624	.269	-1.028	.532
FR2-1	80	0.985	0.012	-.619	.269	-1.032	.532
FR2-2	80	0.985	0.012	-.632	.269	-1.020	.532
FR2-3	80	0.985	0.012	-.626	.269	-1.021	.532
FR3-1	80	0.789	0.119	-.182	.269	-1.063	.532
FR3-2	80	0.789	0.119	-.182	.269	-1.063	.532
FR3-3	80	0.789	0.119	-.183	.269	-1.062	.532
OR1-1	80	1.920	0.686	.336	.269	-1.568	.532
OR1-2	80	1.921	0.687	.338	.269	-1.566	.532
OR1-3	80	1.921	0.687	.338	.269	-1.565	.532
OR2-1	80	1.922	0.687	.336	.269	-1.569	.532
OR2-2	80	1.920	0.686	.333	.269	-1.572	.532
OR2-3	80	1.921	0.686	.337	.269	-1.567	.532
OR3-1	80	0.448	0.343	.169	.269	-1.706	.532
OR3-2	80	0.448	0.344	.169	.269	-1.706	.532
OR3-3	80	0.447	0.344	.169	.269	-1.706	.532

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

4.5.1.3 The assumption of homogeneity of covariance matrices

This assumption indicates that the variance of dependent variables should be the same in each group of independent variables. The Levene's test was used to check this assumption. Results in Table 4.4 showed that Levene's test was non-significant in seven variables (*Sig.* value is over 0.05). The Levene's test was significant (*Sig.* value is under 0.05) for the other 20 dependent variables meaning the assumption of homogeneity of covariance matrices had failed.

Table 4.4: Levene's test for dependent variables
Test of Homogeneity of Variance

Dependent variable ¹	Levene Statistic	df1	df2	Sig.
AI1-1	.859	7	72	.543
AI1-2	1.092	7	72	.378
AI1-3	.570	7	72	.778
AI2-1	.834	7	72	.562
AI2-2	1.625	7	72	.142
AI2-3	1.154	7	72	.340
AI3-1	10.379	7	72	.000
AI3-2	12.180	7	72	.000
AI3-3	11.373	7	72	.000
FR1-1	2.790	7	72	.013
FR1-2	4.152	7	72	.001
FR1-3	2.255	7	72	.039
FR2-1	3.612	7	72	.002
FR2-2	3.852	7	72	.001
FR2-3	3.307	7	72	.004
FR3-1	2.753	7	72	.014
FR3-2	3.072	7	72	.007
FR3-3	2.358	7	72	.032
OR1-1	5.122	7	72	.000
OR1-2	4.591	7	72	.000
OR1-3	9.054	7	72	.000
OR2-1	6.649	7	72	.000
OR2-2	4.305	7	72	.001
OR2-3	7.524	7	72	.000
OR3-1	2.496	7	72	.024
OR3-2	2.505	7	72	.023
OR3-3	.901	7	72	.511

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

Therefore, in this case, the Levene's test is usually undertaken in conjunction with the variance ratio to check the assumption (Field, 2013). In this research, eight experiments had 10 equal replications, meaning each group had an equal sample size. Thus, the homogeneity of covariance matrices in this research was assumed (Hair et al., 2010).

4.5.1.4 The assumption of linearity

The assumption of linearity of all multivariate techniques is based on correlational measures of association such as MANOVA (Hair et al., 2010). Bartlett's test of sphericity was used to

test for non-linear relationships. The test indicated that significant inter-correlations exist (*Chi-Square* = 4613.337 *df* = 377, $p < 0.001$) (Table 4.5), justifying the using of MANOVA.

Table 4.5: Bartlett's test of sphericity for non-linear relationships

Bartlett's Test of Sphericity ^a	
Likelihood Ratio	0.000
Approx. Chi-Square	4613.337
df	377
Sig.	0.000

Tests the null hypothesis that the residual covariance matrix is proportional to an identity matrix.

a. Design: Intercept + Demand + Lifetime + Lost sales + Demand * Lifetime + Demand * Lost sales + Lifetime * Lost sales + Demand * Lifetime * Lost sales

4.5.2 Multivariate analysis result

This research used multivariate analysis (MANOVA) for several reasons. First, the most important assumption for using MANOVA was met. This was because eight experiments were generated by the experimental design and each independent replication in the simulation model used random seeds to generate data. Second, while the K-S test exhibited non-normality in the data, this violation of assumption was acceptable since the skewness and kurtosis values were within recommended ranges. Third, while Levene's tests showed that the data did not meet the assumption of homogeneity of covariance matrices, this violation was also mitigated because eight experiments (or groups) in this research had equal sample sizes (10 replications). Finally, the assumption of linearity in this research was met. Overall, the violations of assumptions were mitigated and the data conforms to the most important requirement of MANOVA. Therefore, it was appropriate to use MANOVA in this research.

In this research, three independent variables (or input factors) were tested across eight experiments. These independent variables were consumer demand, product lifetime, and lost sales probability and were tested under two levels of high and low value for each variable (2^k factorial design as explained in section 3.5.3). Each experiment was replicated 10 times, leading to a total sample size of 80 observations. There were 27 dependent variables and three

performance measures (Average Inventory (AI), Fill Rate (FR), and Order Rate Variance Ratio (ORVR)) for each product at each retailer/supplier.

MANOVA tests were run on IBM SPSS Statistics, version 23 (IBM SPSS, 2016). This research reported the MANOVA tests based on Pillai's trace statistics, which was the sum of the variance that can be understood as the calculation of discriminate variables (Hair et al., 2010). In comparison with Wilke's Lambda, Hotelling's trace, and Roy's Largest Root MANOVA tests, Pillai's trace was the most robust test when the sample sizes are equal (Field, 2013).

MANOVA results were reported in Tables 4-5 to 4-10, separated by main effects and each group of two-independent variables, and three-independent variables interactions. Each table had six columns. The first column, "Effect", showed the independent variables and the interactions between independent variables. The second column listed four multivariate tests and their corresponding values. The column "F-ratio" showed the significant effect of each independent variable on the multivariate. A larger F-ratio value indicated that differences are likely because of something other than chance. The most important column, "Significance", reported the significant p-value (*Sig.* value) of the F-ratio. If this *Sig.* value was less than 0.05, the interactions of independent variables differed significantly with respect to the dependent variables (Field, 2013). The column "Partial ETA Squared", represented by "Partial η^2 ", reported the effect size of the observed relationships between variables, with values ranging from zero to one. A common guideline from Cohen (1988) is that "Partial ETA Squared" value cut-offs of 0.2 for small effects, 0.5 for medium effects, 0.8 for large effects, and a value less than 0.2 indicated a negligible effect.

There were three main effects, three two-independent variable interactions, and one three-independent variable interaction. In MANOVA, interaction terms represent the

interactive effect and must be examined before interpreting the main effect (Hair et al., 2010).

Following are the multivariate interactions and the main effects.

4.5.2.1 Multivariate analysis result – Three-independent variables interaction

Using Pillai's trace, there was a significant effect of consumer demand, product lifetime, and lost sales probability on the performance of the studied inventory model, $V = 0.999$, $F(27, 46) = 1353.574$, $p < 0.001$ (Table 4.6). The effect size was large (Partial $\eta^2 = 0.999$).

Table 4.6: Multivariate result – three-independent variables interaction
Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.	Partial η^2
Demand * Lifetime * Lost sales	.999	1353.574 ^b	27.000	46.000	.000	.999 ^c

a. Design: Demand * Lifetime * Lost sales

b. Exact statistic

c. Partial η^2 : Large effect size

4.5.2.2 Multivariate analysis result – Two-independent variables interaction

There were three sets of two-independent variables interaction: consumer demand and product lifetime, consumer demand and lost sales probability, and product lifetime and lost sales probability. Using Pillai's trace, these three sets had significant effects on the studied inventory model (Table 4.7). The effect sizes were large in all three sets (Partial $\eta^2 = 1.000$).

The interaction of consumer demand and product lifetime had $V = 1.000$, $F(27, 46) = 71941.619$, $p < 0.001$.

The interaction of consumer demand and lost sales probability had $V = 1.000$, $F(27, 46) = 63363.439$, $p < 0.001$.

The interaction of product lifetime and lost sales probability had $V = 1.000$, $F(27, 46) = 6003.494$, $p < 0.001$.

Table 4.7: Multivariate result – Two-independent variables interaction
Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.	Partial η^2
Demand * Lifetime	1.000	71941.619 ^b	27.000	46.000	.000	1.000 ^c
Demand * Lost sales	1.000	63363.439 ^b	27.000	46.000	.000	1.000 ^c
Lifetime * Lost sales	1.000	6003.494 ^b	27.000	46.000	.000	1.000 ^c

a. Design: Demand * Lifetime * Lost sales

b. Exact statistic

c. Partial η^2 : Large effect size

4.5.2.3 Multivariate analysis result – Main effect

All of the three main effects were significant at $p < 0.001$, and the effect size of the three main effects were large (Partial $\eta^2 = 1.000$) as reported in Table 4.8 below.

Table 4.8: Multivariate result – Main effect
Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.	Partial η^2
Demand	1.000	4325365.881 ^b	27.000	46.000	.000	1.000 ^c
Lifetime	1.000	365920.119 ^b	27.000	46.000	.000	1.000 ^c
Lost sales	1.000	135578.830 ^b	27.000	46.000	.000	1.000 ^c

a. Design: Demand * Lifetime * Lost sales

b. Exact statistic

c. Partial η^2 : Large effect size

4.5.3 Univariate analysis result

Next, separate ANOVA tests are performed on each dependent variable. Field (2013) stated that the univariate test is not useful for interpretation unless a Bonferroni correction is chosen. Since this research considered only two response values (i.e., High and Low) for each independent variable, and applied a strict $\alpha = 0.05$ test (Field, 2013), a univariate test is significant if the p-value is under a Bonferroni correction $\alpha/1 = 0.05$ (as there is only one comparison for two groups of response value) (Field, 2013).

4.5.3.1 Interaction of three independent variables

As shown in Table 4.9, the three-way interaction, consumer demand, product lifetime, and lost sales probability, had a significant effect on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model. This interaction had large effects on AI and ORVR (partial $\eta^2 > 0.8$), small or negligible effects on FR at the supplier, medium effects on FR, and small or negligible effects on AI, ORVR at retailer 1 and 2.

Table 4.9: Univariate results – Interaction of three independent variables
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	29.038	.000	.287	small
AI1-2	1	17.647	.000	.197	negligible
AI1-3	1	37.068	.000	.340	small
AI2-1	1	44.520	.000	.382	small
AI2-2	1	23.586	.000	.247	small
AI2-3	1	11.089	.001	.133	negligible
AI3-1	1	2232.744	.000	.969	large
AI3-2	1	2098.244	.000	.967	large
AI3-3	1	2562.790	.000	.973	large
FR1-1	1	110.935	.000	.606	medium
FR1-2	1	100.822	.000	.583	medium
FR1-3	1	61.649	.000	.461	small
FR2-1	1	106.324	.000	.596	medium
FR2-2	1	54.396	.000	.430	small
FR2-3	1	85.548	.000	.543	medium
FR3-1	1	14.999	.000	.172	negligible
FR3-2	1	49.139	.000	.406	small
FR3-3	1	28.466	.000	.283	small
OR1-1	1	65.007	.000	.474	small
OR1-2	1	26.520	.000	.269	small
OR1-3	1	43.946	.000	.379	small
OR2-1	1	29.768	.000	.293	small
OR2-2	1	38.149	.000	.346	small
OR2-3	1	12.387	.001	.147	negligible
OR3-1	1	12307.759	.000	.994	large
OR3-2	1	8314.796	.000	.991	large
OR3-3	1	11477.748	.000	.994	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

4.5.3.2 Interaction of product lifetime and lost sales probability

The two-way interaction, product lifetime and lost sales probability, as shown in Table 4.10, had significant effects on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model. It had large effects on AI, FR, and ORVR (partial $\eta^2 > 0.8$) at the supplier, small effects on AI, and small and medium effects on FR and ORVR at retailer 1, and 2.

Table 4.10: Univariate results – Interaction of product lifetime and lost sales probability
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	31.324	.000	.303	small
AI1-2	1	44.353	.000	.381	small
AI1-3	1	18.490	.000	.204	small
AI2-1	1	44.159	.000	.380	small
AI2-2	1	24.959	.000	.257	small
AI2-3	1	44.193	.000	.380	small
AI3-1	1	3696.243	.000	.981	large
AI3-2	1	3518.565	.000	.980	large
AI3-3	1	4191.648	.000	.983	large
FR1-1	1	132.005	.000	.647	medium
FR1-2	1	113.941	.000	.613	medium
FR1-3	1	110.727	.000	.606	medium
FR2-1	1	101.850	.000	.586	medium
FR2-2	1	85.774	.000	.544	medium
FR2-3	1	101.723	.000	.586	medium
FR3-1	1	15650.109	.000	.995	large
FR3-2	1	16887.078	.000	.996	large
FR3-3	1	16795.416	.000	.996	large
OR1-1	1	63.279	.000	.468	small
OR1-2	1	99.063	.000	.579	medium
OR1-3	1	84.262	.000	.539	medium
OR2-1	1	86.421	.000	.546	medium
OR2-2	1	82.257	.000	.533	medium
OR2-3	1	41.708	.000	.367	small
OR3-1	1	2967.121	.000	.976	large
OR3-2	1	1953.215	.000	.964	large
OR3-3	1	2649.886	.000	.974	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

The profile plots were used to illustrate effects of the interactions in this research. As noted earlier in section 4.3, without loss of generalisation, this section showed the figures for product #1 at retailer #1 and supplier only.

Figure 4.9 to Figure 4.14 showed the effects of the interaction of product lifetime and lost sales probability on average inventory, fill rate, and order rate variance ratio at the retailer and supplier. The figures and the Partial η^2 values showed that this interaction had large effects on the performance of the supplier.

This large effect was mainly because when the product lifetime was low, the product expired soon and the product availability was low. In this situation, when the lost sales probability is low, or the customer is willing to substitute the preferred product with another available product, the demand for other products increases substantially. Therefore, it creates a high uncertainty in demand, and retailers tend to order un-smoothly (ORVR at a retailer is high as shown in Figure 4.13). This causes low FR at the supplier (Figure 4.12), therefore the supplier has to order more and inventory increases (Figure 4.10). Note that the inventory on hand is recorded at the beginning of every day after discarding the expired items and receiving a replenishment quantity.

This finding confirms the negative effects of substitution on the performance of the inventory model. When the lost sales probability is low, or the substitution ratio is high, the studied model has low fill rate and high average inventory. This negative effect is stronger under a high demand situation as shown in Figure 4.15 to Figure 4.20. It is a situation when a customer needs a type of product, for example in a sudden stock-out situation. Then, the nature of human behaviour amplifies the bullwhip effect and creates a negative effect on the performance of the inventory model (Nienhaus et al., 2006). This finding is also relevant to the work of Smith and Agrawal (2000), who studied the inventory model at a retailer and stated

that the substitution ratio has a negative effect on the performance of the inventory management at the retailer.

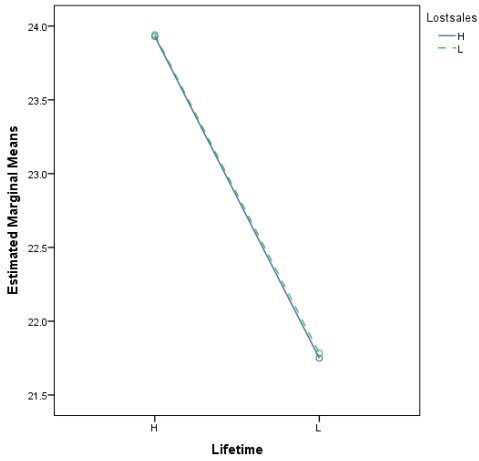


Figure 4.9: Effect of lifetime and lost sales probability on AI at retailer

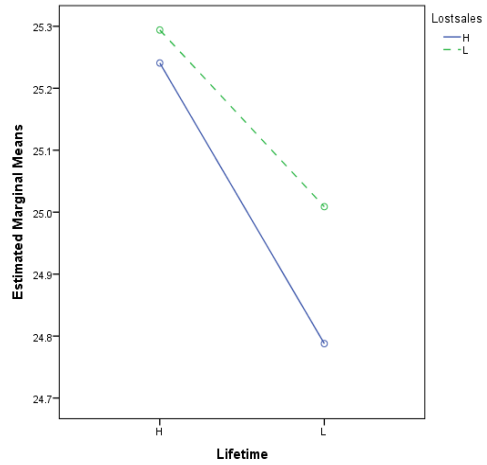


Figure 4.10: Effect of lifetime and lost sales probability on AI at supplier

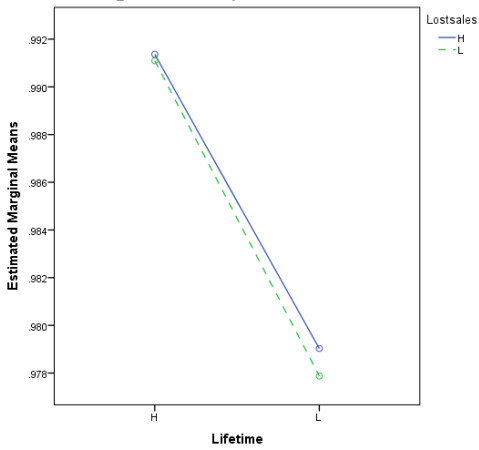


Figure 4.11: Effect of lifetime and lost sales probability on FR at retailer

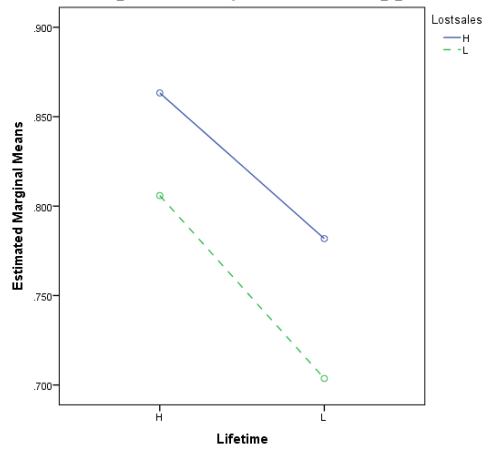


Figure 4.12: Effect of lifetime and lost sales probability on FR at supplier

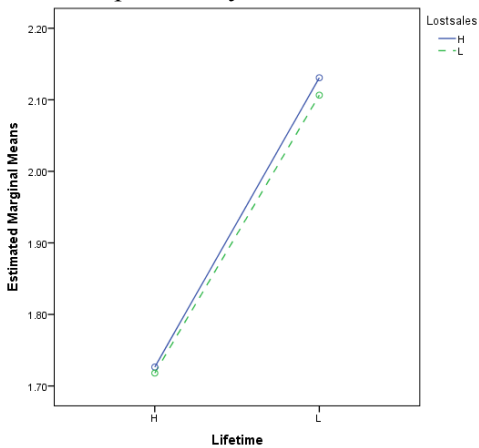


Figure 4.13: Effect of lifetime and lost sales probability on ORVR at retailer

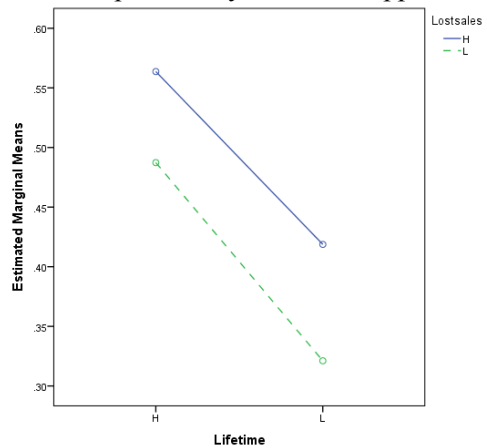


Figure 4.14: Effect of lifetime and lost sales probability on ORVR at supplier

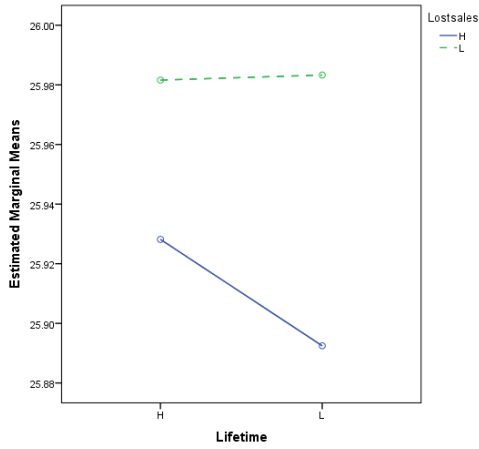


Figure 4.15: Effect of lifetime and lost sales probability on AI at supplier under high demand

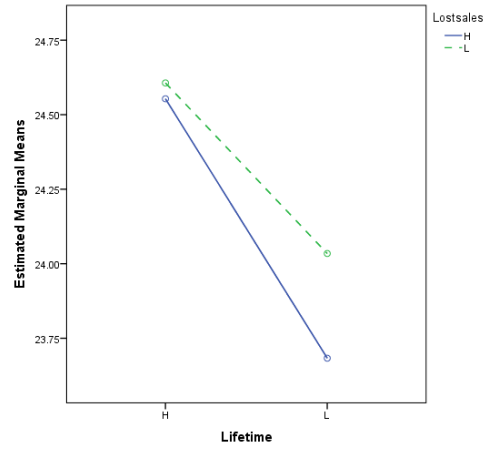


Figure 4.16: Effect of lifetime and lost sales probability on AI at supplier under low demand

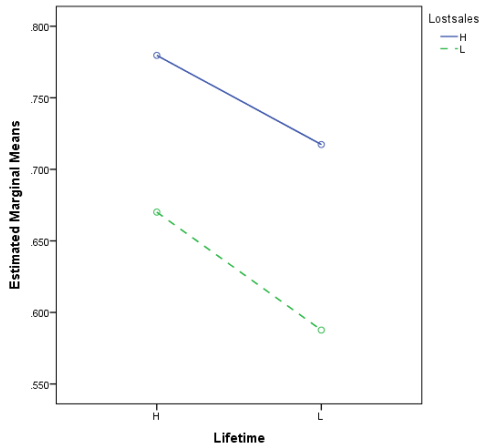


Figure 4.17: Effect of lifetime and lost sales probability on FR at supplier under high demand

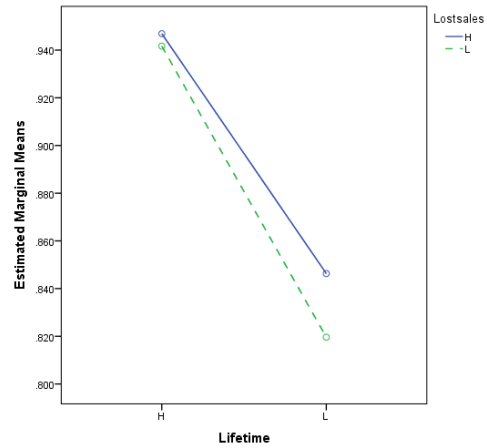


Figure 4.18: Effect of lifetime and lost sales probability on FR at supplier under low demand

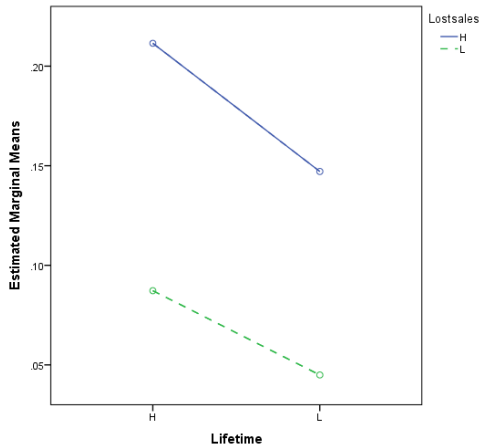


Figure 4.19: Effect of lifetime and lost sales probability on ORVR at supplier under high demand

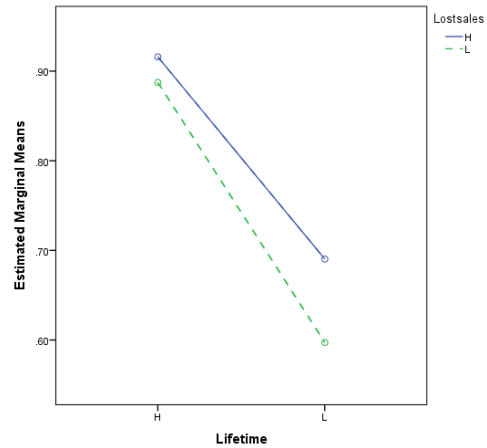


Figure 4.20: Effect of lifetime and lost sales probability on ORVR at supplier under low demand

4.5.3.3 Interaction of consumer demand and lost sales probability

The two-way interaction, consumer demand and lost sales probability, as shown in, Table 4.11, had significant effects on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model. This interaction had large effects on AI, FR, and ORVR (partial $\eta^2 > 0.8$) at the supplier and small and medium effects on AI, FR, and ORVR at retailer 1, and 2.

Table 4.11: Univariate results – Interaction of consumer demand and lost sales probability
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	71.822	.000	.499	small
AI1-2	1	84.468	.000	.540	medium
AI1-3	1	83.944	.000	.538	medium
AI2-1	1	96.382	.000	.572	medium
AI2-2	1	66.466	.000	.480	small
AI2-3	1	73.879	.000	.506	medium
AI3-1	1	2219.389	.000	.969	large
AI3-2	1	2360.941	.000	.970	large
AI3-3	1	2785.510	.000	.975	large
FR1-1	1	304.085	.000	.809	large
FR1-2	1	223.965	.000	.757	medium
FR1-3	1	238.717	.000	.768	medium
FR2-1	1	250.035	.000	.776	medium
FR2-2	1	193.495	.000	.729	medium
FR2-3	1	234.548	.000	.765	medium
FR3-1	1	388241.676	.000	1.000	large
FR3-2	1	416345.849	.000	1.000	large
FR3-3	1	417326.814	.000	1.000	large
OR1-1	1	212.855	.000	.747	medium
OR1-2	1	196.810	.000	.732	medium
OR1-3	1	166.773	.000	.698	medium
OR2-1	1	138.069	.000	.657	medium
OR2-2	1	122.297	.000	.629	medium
OR2-3	1	79.910	.000	.526	medium
OR3-1	1	18028.499	.000	.996	large
OR3-2	1	12027.632	.000	.994	large
OR3-3	1	16342.886	.000	.996	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

The profile plots, as in Figure 4.21 to Figure 4.26, show the effects of the interaction of consumer demand and lost sales probability on average inventory, fill rate, and order rate variance ratio at the retailer and supplier. The figures and the Partial η^2 values showed that this

interaction has large effects on the performance of the supplier. A low lost sales probability, meaning high substitution ratio, creates a low fill rate. Therefore, the supplier has to order more to cover the high uncertainty in consumer demand. Moreover, comparing high and low lifetime situations, these effects were larger in the low lifetime situation, or when the product was expiring soon as shown in Figure 4.27 to Figure 4.32. The effect of this interaction on fill rate is the greatest when the product has a high lifetime.

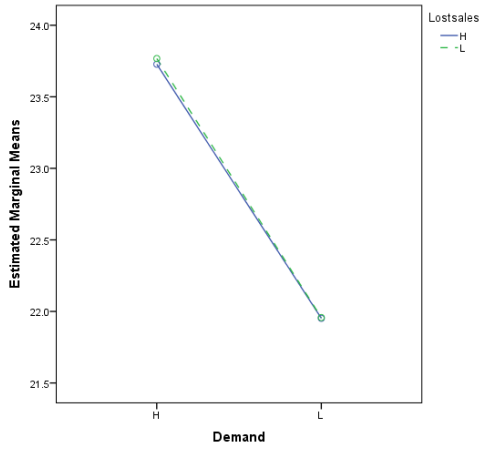


Figure 4.21: Effect of consumer demand and lost sales probability on AI at retailer

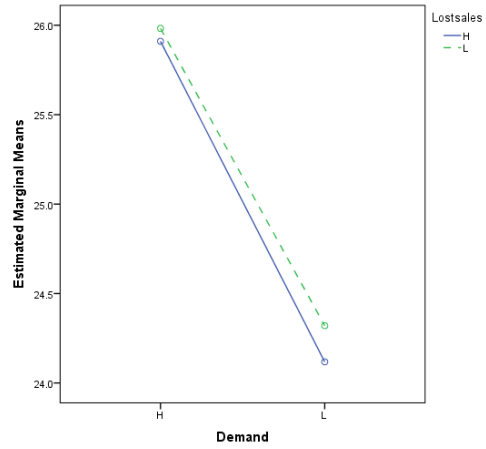


Figure 4.22: Effect of consumer demand and lost sales probability on AI at supplier

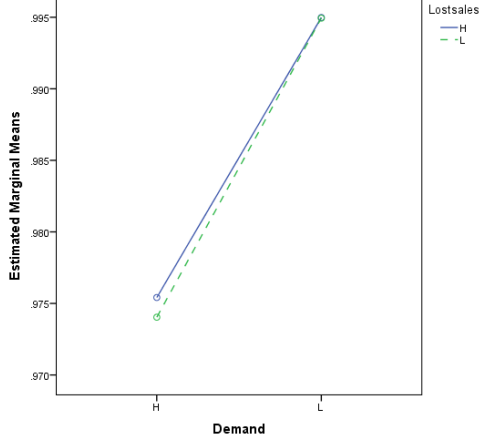


Figure 4.23: Effect of consumer demand and lost sales probability on FR at retailer

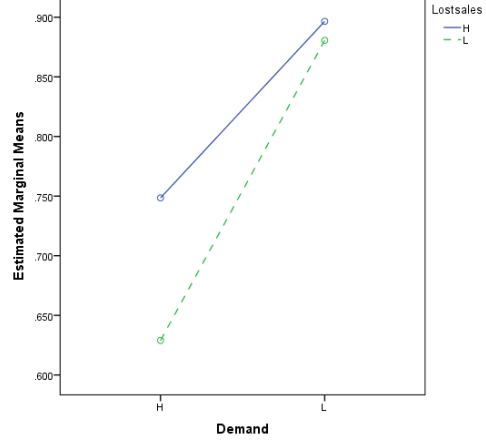


Figure 4.24: Effect of consumer demand and lost sales probability on FR at supplier

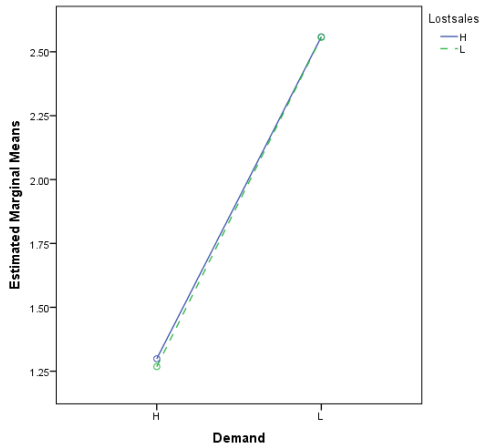


Figure 4.25: Effect of consumer demand and lost sales probability on ORVR at retailer

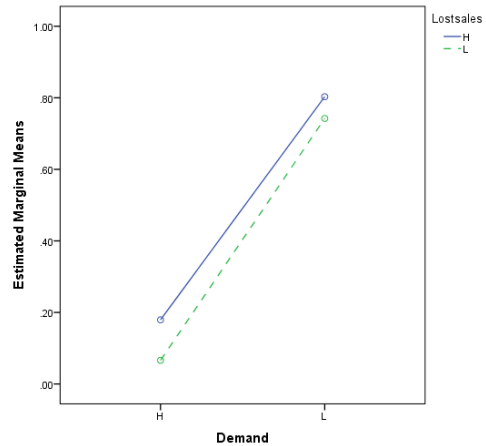


Figure 4.26: Effect of consumer demand and lost sales probability on ORVR at supplier

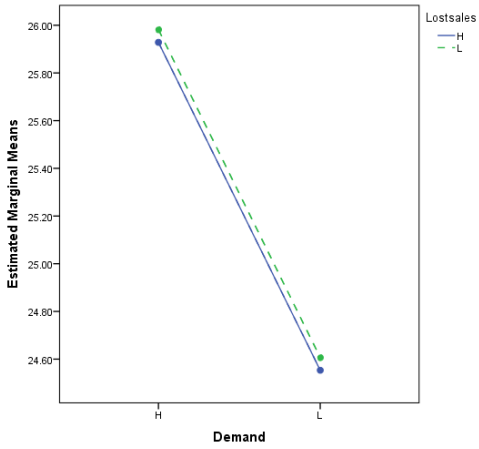


Figure 4.27: Effect of consumer demand and lost sales probability on AI at supplier under high lifetime

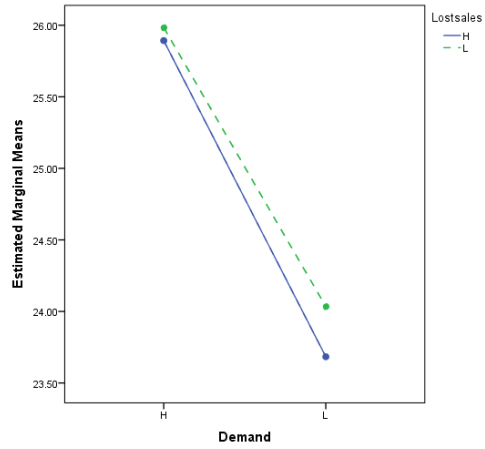


Figure 4.28: Effect of consumer demand and lost sales probability on AI at supplier under low lifetime

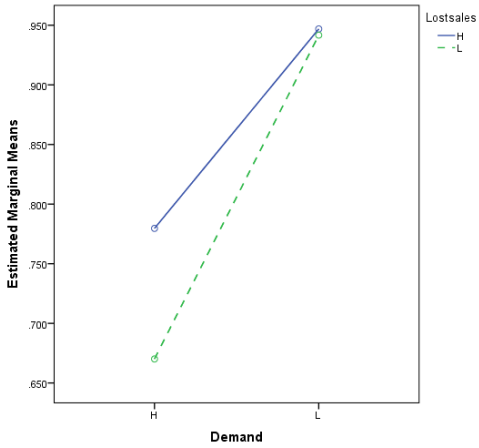


Figure 4.29: Effect of consumer demand and lost sales probability on FR at supplier under high lifetime

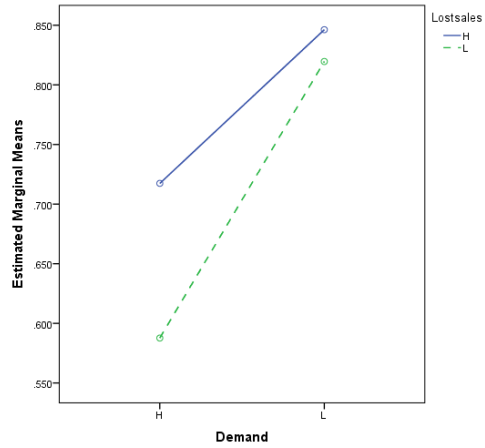


Figure 4.30: Effect of consumer demand and lost sales probability on FR at supplier under low lifetime

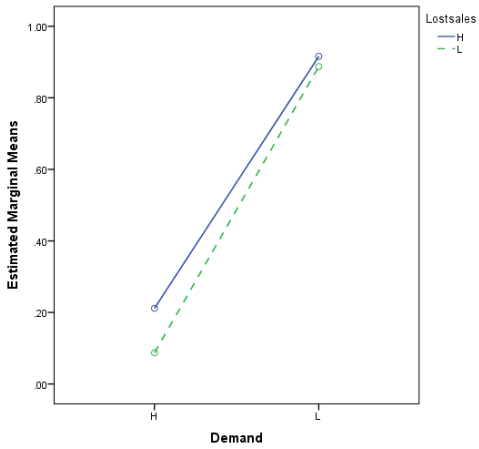


Figure 4.31: Effect of consumer demand and lost sales probability on ORVR at supplier under high lifetime

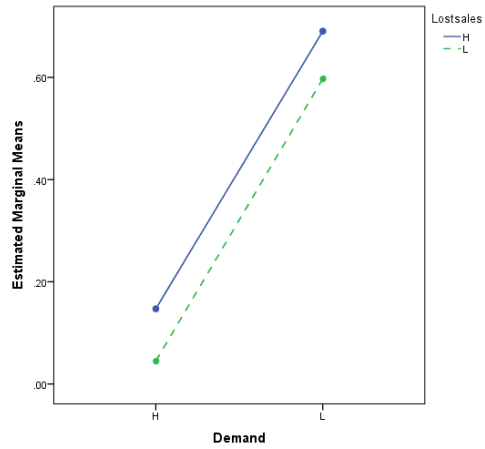


Figure 4.32: Effect of consumer demand and lost sales probability on ORVR at supplier under low lifetime

4.5.3.4 Interaction of consumer demand and product lifetime

The two-way interaction, consumer demand and product lifetime, had a significant effect on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model. This interaction had large effects on AI, FR, and ORVR (partial $\eta^2 > 0.8$) at the supplier and retailer 1, and 2 as shown in Table 4.12.

Table 4.12: Univariate results – Interaction of consumer demand and product lifetime
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	66295.566	.000	.999	large
AI1-2	1	61030.325	.000	.999	large
AI1-3	1	67188.704	.000	.999	large
AI2-1	1	79541.411	.000	.999	large
AI2-2	1	54011.667	.000	.999	large
AI2-3	1	67028.477	.000	.999	large
AI3-1	1	65114.087	.000	.999	large
AI3-2	1	64223.872	.000	.999	large
AI3-3	1	75085.680	.000	.999	large
FR1-1	1	22840.964	.000	.997	large
FR1-2	1	24649.503	.000	.997	large
FR1-3	1	23878.378	.000	.997	large
FR2-1	1	23166.074	.000	.997	large
FR2-2	1	19595.598	.000	.996	large
FR2-3	1	18432.567	.000	.996	large
FR3-1	1	54882.205	.000	.999	large
FR3-2	1	58381.155	.000	.999	large
FR3-3	1	58135.097	.000	.999	large
OR1-1	1	75693.576	.000	.999	large
OR1-2	1	75992.575	.000	.999	large
OR1-3	1	75440.788	.000	.999	large
OR2-1	1	61759.294	.000	.999	large
OR2-2	1	72611.120	.000	.999	large
OR2-3	1	37836.188	.000	.998	large
OR3-1	1	274522.408	.000	1.000	large
OR3-2	1	182568.425	.000	1.000	large
OR3-3	1	247546.636	.000	1.000	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

The profile plots, as presented in Figure 4.33 to Figure 4.38, show the effects of the interaction of consumer demand and product lifetime on average inventory, fill rate, and order rate variance ratio at the retailer and supplier.

The figures and the Partial η^2 values showed that this interaction had large effects on the performance of the supplier when the demand was low. At the supplier in particular, effects of this interaction on the performance measures are the greatest under a low lost sales probability, or high substitution ratio. In this situation, the customer tends to replace the stock-out product, and the demand is more uncertain.

At the retailer, a high demand had a greater effect on the fill rate. The reason is when demand is high and the product is expiring soon, the amount of available product is low, and the fill rate is consequently also low. Moreover, a low demand has a greater effect on the average inventory and order rate variance ratio. The reason is in a low demand situation, if a product lifetime is low, or a product is expiring soon, it creates a low average inventory and un-smooth replenishment orders.

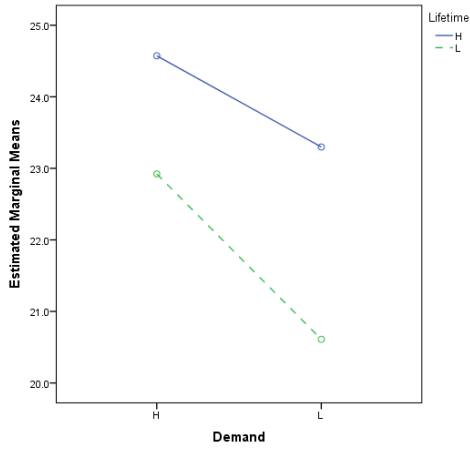


Figure 4.33: Effect of consumer demand and product lifetime on AI at retailer

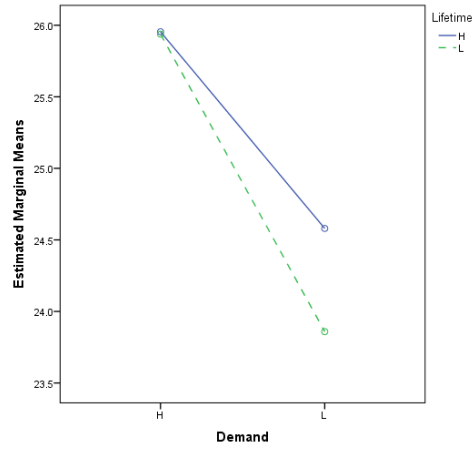


Figure 4.34: Effect of consumer demand and product lifetime on AI at supplier

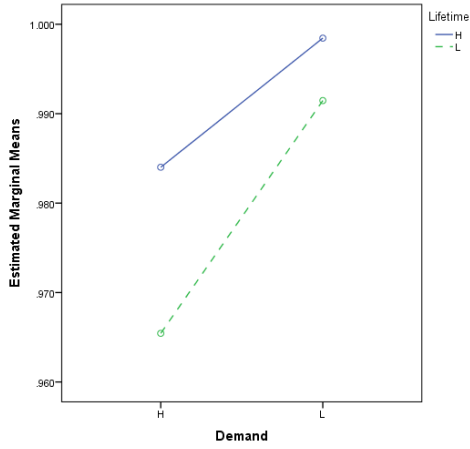


Figure 4.35: Effect of consumer demand and product lifetime on FR at retailer

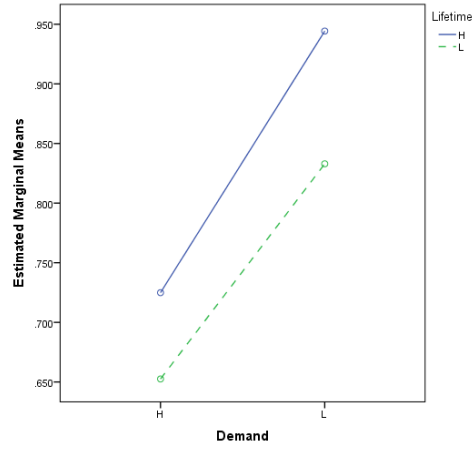


Figure 4.36: Effect of consumer demand and product lifetime on FR at supplier

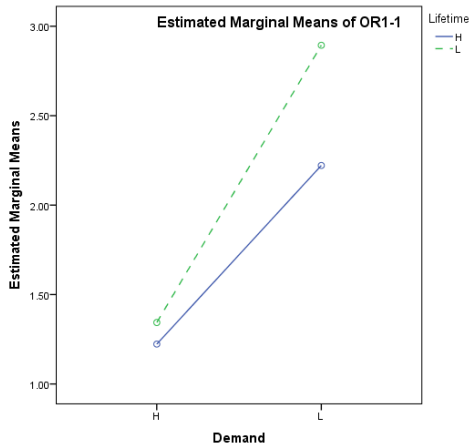


Figure 4.37: Effect of consumer demand and product lifetime on ORVR at retailer

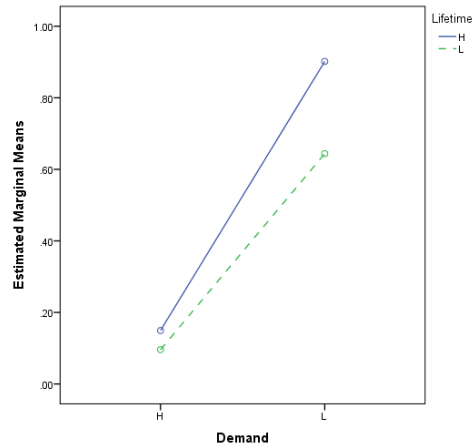


Figure 4.38: Effect of consumer demand and product lifetime on ORVR at supplier

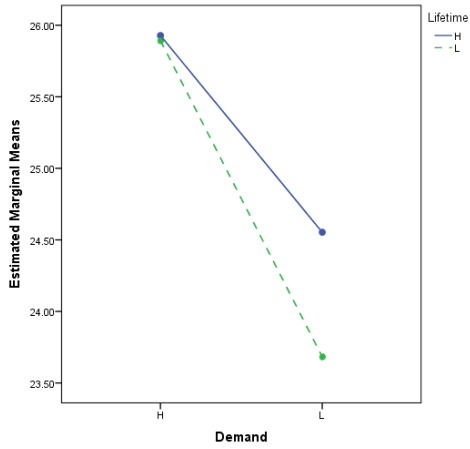


Figure 4.39: Effect of consumer demand and product lifetime on AI at supplier under high lost sales probability

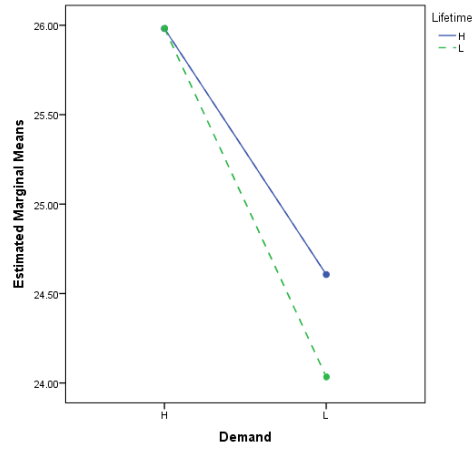


Figure 4.40: Effect of consumer demand and product lifetime on AI at supplier under low lost sales probability

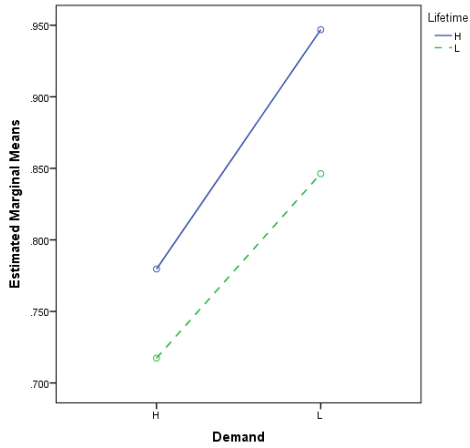


Figure 4.41: Effect of consumer demand and product lifetime on FR at supplier under high lost sales probability

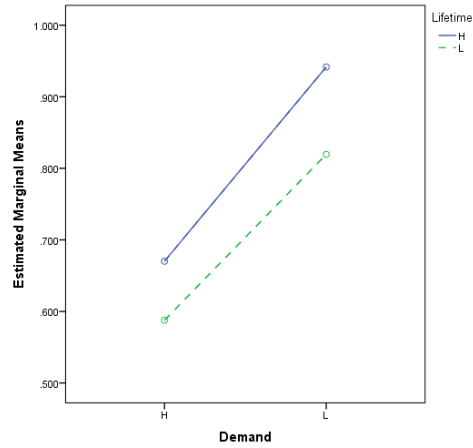


Figure 4.42: Effect of consumer demand and product lifetime on FR at supplier under low lost sales probability

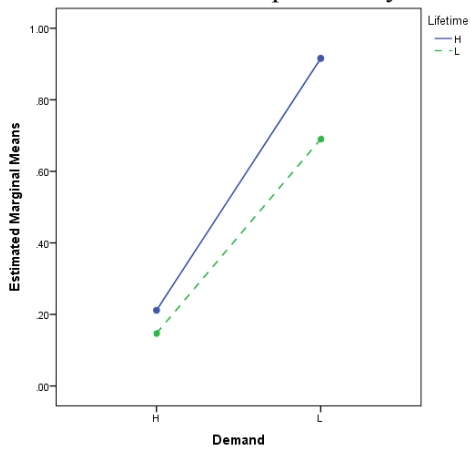


Figure 4.43: Effect of consumer demand and product lifetime on ORVR at supplier under high lost sales probability

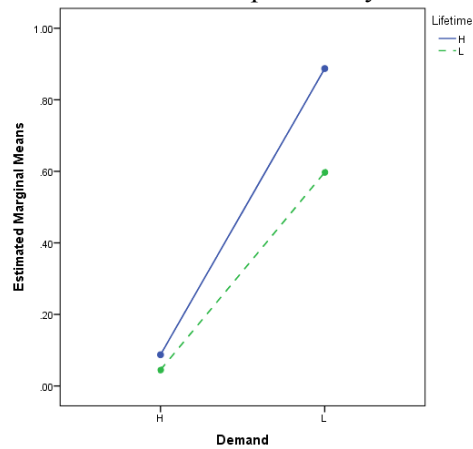


Figure 4.44: Effect of consumer demand and product lifetime on ORVR at supplier under low lost sales probability

4.5.3.5 Main effect of consumer demand

Consumer demand had a significant effect on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model as shown in Table 4.13. Partial η^2 indicated that consumer demand had large effects on all performance measures (Partial $\eta^2 = 1.000$).

Table 4.13: Univariate results – Main effects of consumer demand
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	792821.898	.000	1.000	large
AI1-2	1	743725.940	.000	1.000	large
AI1-3	1	814052.291	.000	1.000	large
AI2-1	1	958870.473	.000	1.000	large
AI2-2	1	659459.124	.000	1.000	large
AI2-3	1	822382.660	.000	1.000	large
AI3-1	1	1567213.085	.000	1.000	large
AI3-2	1	1527095.278	.000	1.000	large
AI3-3	1	1817039.330	.000	1.000	large
FR1-1	1	278787.369	.000	1.000	large
FR1-2	1	293331.239	.000	1.000	large
FR1-3	1	287808.564	.000	1.000	large
FR2-1	1	284659.200	.000	1.000	large
FR2-2	1	230050.186	.000	1.000	large
FR2-3	1	221653.781	.000	1.000	large
FR3-1	1	5777185.718	.000	1.000	large
FR3-2	1	6172582.746	.000	1.000	large
FR3-3	1	6177244.413	.000	1.000	large
OR1-1	1	1615851.798	.000	1.000	large
OR1-2	1	1606176.810	.000	1.000	large
OR1-3	1	1594596.971	.000	1.000	large
OR2-1	1	1314812.064	.000	1.000	large
OR2-2	1	1565875.786	.000	1.000	large
OR2-3	1	807719.873	.000	1.000	large
OR3-1	1	11100809.123	.000	1.000	large
OR3-2	1	7407673.533	.000	1.000	large
OR3-3	1	10011275.540	.000	1.000	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

The profile plots, as in shown in Figure 4.45 to Figure 4.50, show the effects of consumer demand on average inventory, fill rate, and order rate variance ratio at retailers and supplier. The plots show that compared to high demand, low demand results in lower average

inventory, higher fill rate, and higher order rate variance ratio at both the retailer and supplier sides.

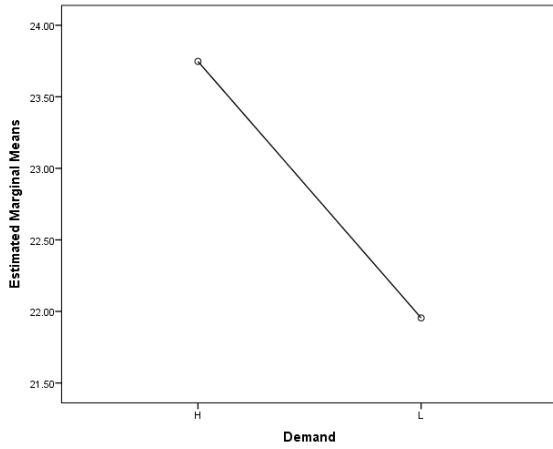


Figure 4.45: Effect of consumer demand on AI at retailer

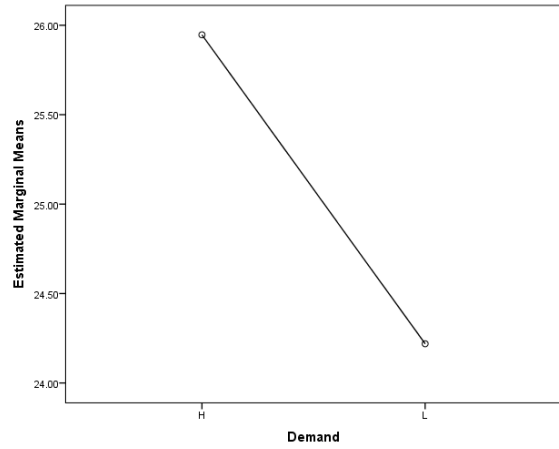


Figure 4.46: Effect of consumer demand on AI at supplier

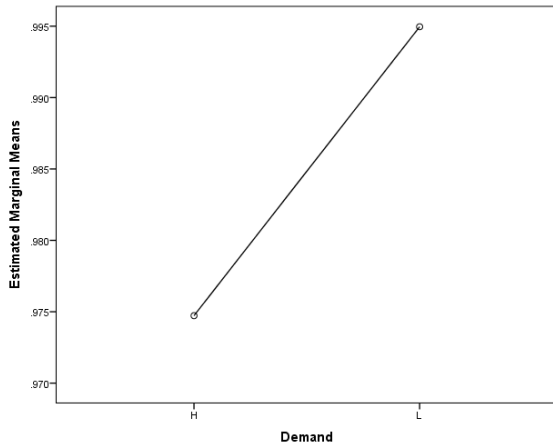


Figure 4.47: Effect of consumer demand on FR at retailer

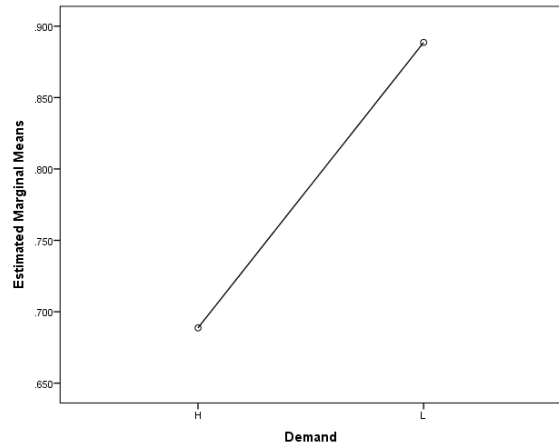


Figure 4.48: Effect of consumer demand on FR at supplier

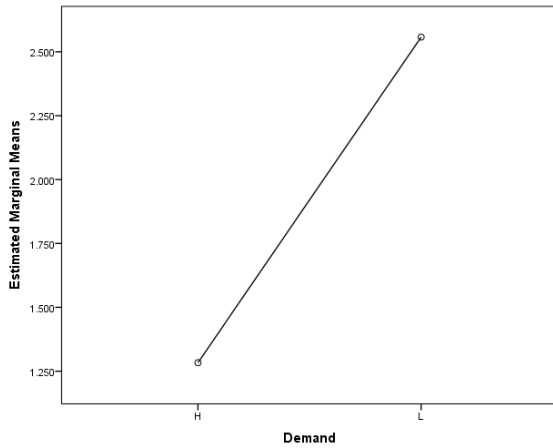


Figure 4.49: Effect of consumer demand on ORVR at retailer

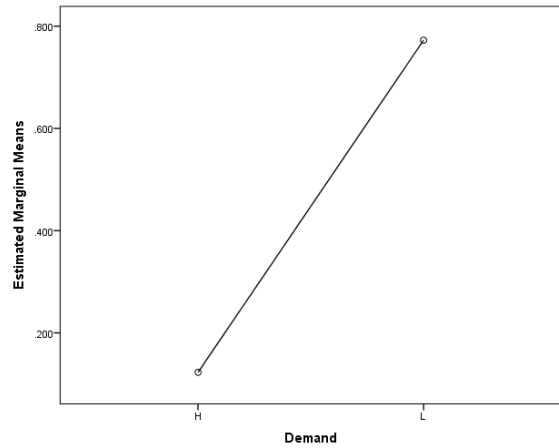


Figure 4.50: Effect of consumer demand on ORVR at supplier

4.5.3.6 Main effect of product lifetime

Product lifetime had a significant effect on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model as shown in Table 4.14. Partial η^2 indicated that product lifetime had large effects on all performance measures (Partial $\eta^2 \geq 0.999$).

Table 4.14: Univariate results – Main effects of product lifetime
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	1160483.794	.000	1.000	large
AI1-2	1	1094917.174	.000	1.000	large
AI1-3	1	1196644.547	.000	1.000	large
AI2-1	1	1406518.147	.000	1.000	large
AI2-2	1	970104.740	.000	1.000	large
AI2-3	1	1203156.149	.000	1.000	large
AI3-1	1	71551.923	.000	.999	large
AI3-2	1	70530.914	.000	.999	large
AI3-3	1	82309.651	.000	.999	large
FR1-1	1	111207.196	.000	.999	large
FR1-2	1	120534.764	.000	.999	large
FR1-3	1	117598.009	.000	.999	large
FR2-1	1	114871.095	.000	.999	large
FR2-2	1	95397.932	.000	.999	large
FR2-3	1	91110.889	.000	.999	large
FR3-1	1	1219508.132	.000	1.000	large
FR3-2	1	1306659.534	.000	1.000	large
FR3-3	1	1306673.397	.000	1.000	large
OR1-1	1	156378.342	.000	1.000	large
OR1-2	1	156277.188	.000	1.000	large
OR1-3	1	155417.900	.000	1.000	large
OR2-1	1	126986.890	.000	.999	large
OR2-2	1	150287.352	.000	1.000	large
OR2-3	1	78588.197	.000	.999	large
OR3-1	1	635819.423	.000	1.000	large
OR3-2	1	424789.412	.000	1.000	large
OR3-3	1	574228.433	.000	1.000	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on.
Retailer 3 means Supplier.

The profile plots, as presented in Figure 4.51 to Figure 4.56, show the effects of product lifetime on average inventory, fill rate, and order rate variance ratio at retailers and supplier. The plots show that compared to a high product lifetime, a low product lifetime results in lower average inventory and lower fill rate at both retailer and supplier sides. In the low product

lifetime, the amount of expired quantity is uncertain, the amount of available product is uncertain, and the replenishment order is un-smooth to cover this uncertainty; therefore, the order rate variance ratio at the retailer is increased. While the order rate variance ratio at the supplier is decreased, its values in high and low product lifetime are always less than one, meaning a smooth order; therefore, this does not need to be discussed.

Overall, if a company focuses on a high fill rate, or a high customer service level, it should consider product lifetime carefully as it has large and positive effects on the fill rate. If a company focuses on average inventory, the low product lifetime situation is beneficial. However, this situation is a trade-off with the unexpected effects of fill rate and order rate variance ratio.

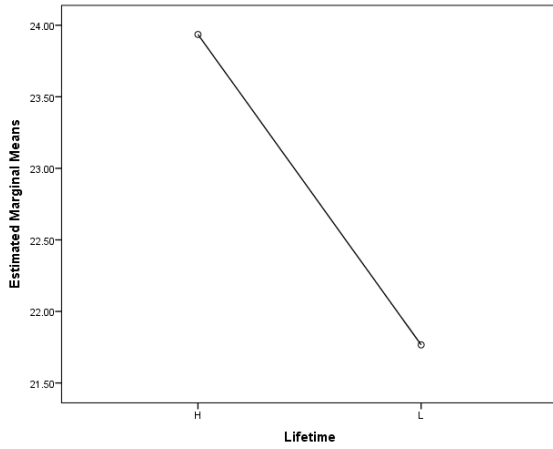


Figure 4.51: Effect of product lifetime on AI at retailer

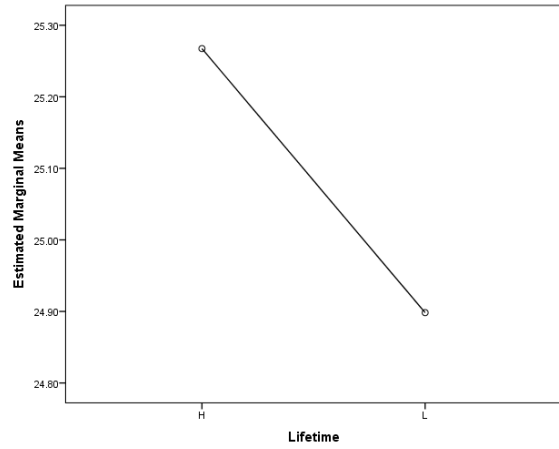


Figure 4.52: Effect of product lifetime on AI at supplier

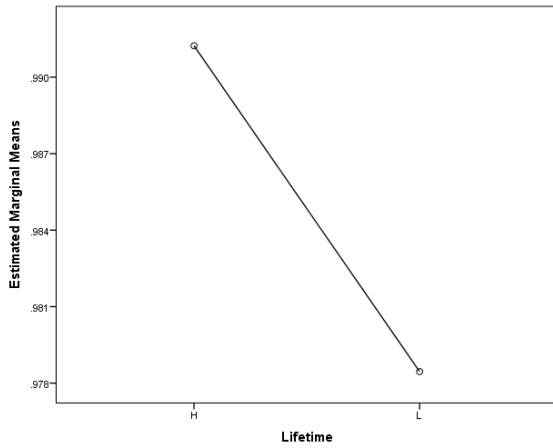


Figure 4.53: Effect of product lifetime on FR at retailer

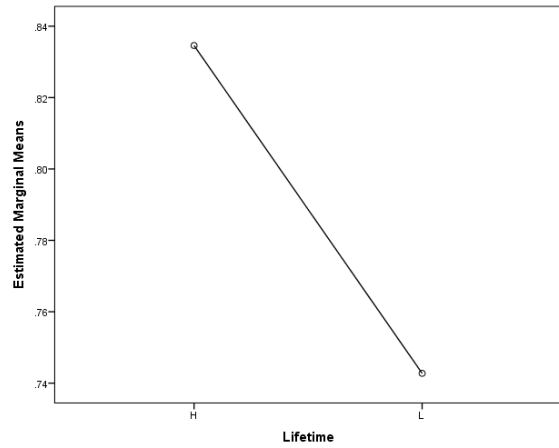


Figure 4.54: Effect of product lifetime on FR at supplier

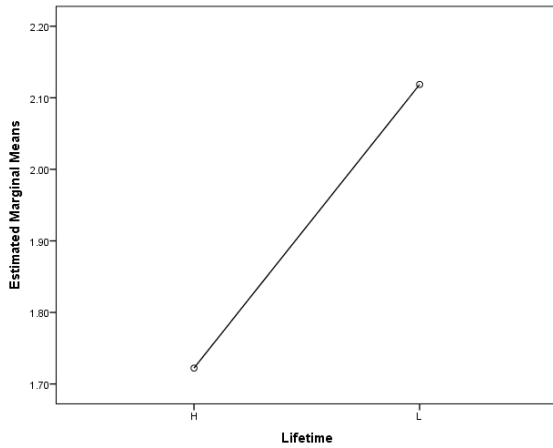


Figure 4.55: Effect of product lifetime on ORVR at retailer

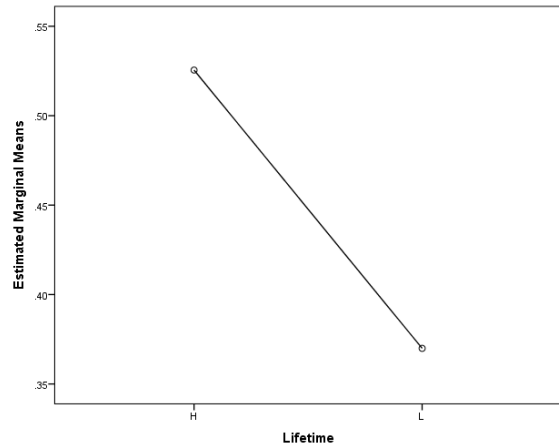


Figure 4.56: Effect of product lifetime on ORVR at supplier

4.5.3.7 Main effect of lost sales probability

Lost sales probability had a significant effect on all dependent variables ($p < 0.05$), or performance measures of the studied inventory model as shown in Table 4.15. Partial η^2 indicated that lost sales probability had large effects on all performance measures at the supplier (Partial $\eta^2 \geq 0.990$) and mostly medium effects on performance measures at the retailers, except OR1-2, OR1-3, and OR2-2. These exceptions were mainly due to the nature of the stochastic values as this research assumed two retailers and three products had the same characteristics.

Table 4.15: Univariate results – Main effects of lost sales probability
Tests of Between-Subjects Effects

Dependent variable ¹	df	F	Sig.	Partial η^2	Effect size
AI1-1	1	125.793	.000	.636	medium
AI1-2	1	109.784	.000	.604	medium
AI1-3	1	120.850	.000	.627	medium
AI2-1	1	167.122	.000	.699	medium
AI2-2	1	83.731	.000	.538	medium
AI2-3	1	93.652	.000	.565	medium
AI3-1	1	9879.349	.000	.993	large
AI3-2	1	10120.507	.000	.993	large
AI3-3	1	11819.755	.000	.994	large
FR1-1	1	344.696	.000	.827	large
FR1-2	1	206.104	.000	.741	medium
FR1-3	1	273.630	.000	.792	medium
FR2-1	1	269.033	.000	.789	medium
FR2-2	1	218.248	.000	.752	medium
FR2-3	1	237.239	.000	.767	medium
FR3-1	1	664051.361	.000	1.000	large
FR3-2	1	709602.007	.000	1.000	large
FR3-3	1	710005.749	.000	1.000	large
OR1-1	1	266.181	.000	.787	medium
OR1-2	1	310.304	.000	.812	large
OR1-3	1	322.789	.000	.818	large
OR2-1	1	250.024	.000	.776	medium
OR2-2	1	367.317	.000	.836	large
OR2-3	1	153.082	.000	.680	medium
OR3-1	1	198866.684	.000	1.000	large
OR3-2	1	133285.617	.000	.999	large
OR3-3	1	179015.700	.000	1.000	large

1. AI1-1 means Average Inventory at Retailer 1, product 1, and so on. Retailer 3 means Supplier.

The profile plots, as depicted in Figure 4.57 to Figure 4.62, show the effects of lost sales probability on average inventory, fill rate, and order rate variance ratio at retailers and supplier. The plots show that, compared to a high lost sales probability, a low lost sales probability results in higher average inventory, lower fill rate, and lower order rate variance ratio at both retailer and supplier sides. This is because low lost sales probability means a high substitution ratio. In this situation, the consumer demand is higher. Thus, low lost sales probability has similar effects as high consumer demand. Overall, lost sales probability has the reverse effect of consumer demand as discussed in section 4.5.3.5.

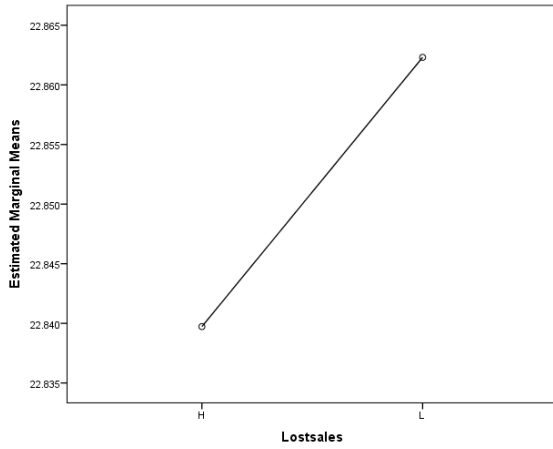


Figure 4.57: Effect of lost sales probability on AI at retailer

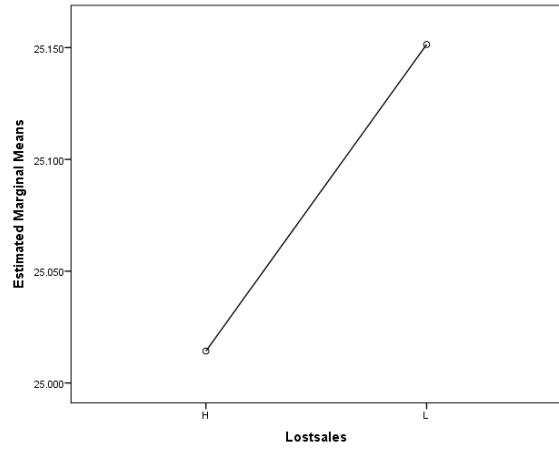


Figure 4.58: Effect of lost sales probability on AI at supplier

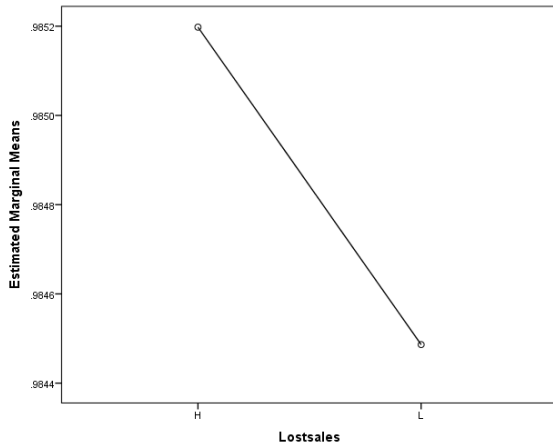


Figure 4.59: Effect of lost sales probability on FR at retailer

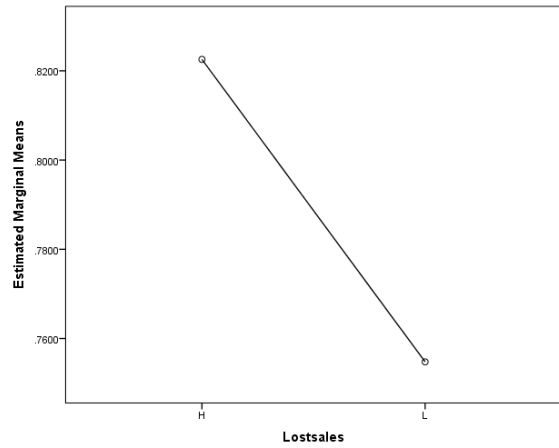


Figure 4.60: Effect of lost sales probability on FR at supplier

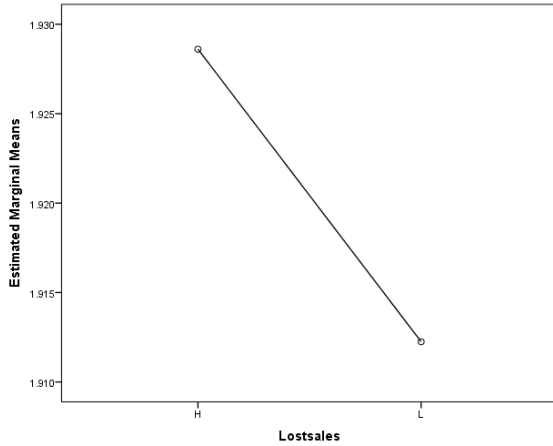


Figure 4.61: Effect of lost sales probability on ORVR at retailer

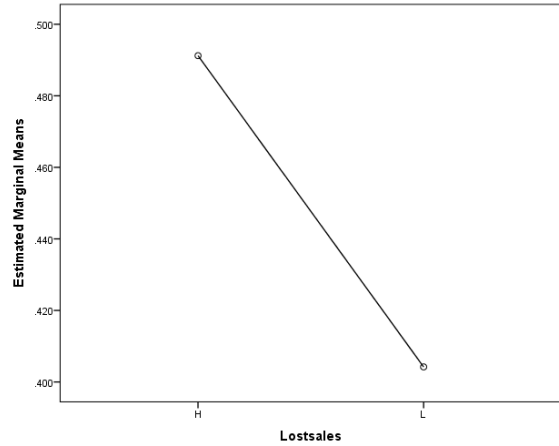


Figure 4.62: Effect of lost sales probability on ORVR at supplier

4.6 Summary of Effects of Input Factors on the Model's Performance

In conclusion, the MANOVA tests were used to test the effects of three independent variables (i.e., consumer demand, product lifetime, and lost sales probability) on all 27 dependent variables (i.e., average inventory, fill rate, and order rate variance ratio measured for each of three products at two retailers and one supplier). In total, one three-way interaction, three two-way interactions, and three main effects were tested. The MANOVA results showed that all the tests were significant, meaning they all had effects on the performance of the studied inventory model. These effects are summarised in Table 4.16 below.

First, all tests indicated that consumer demand had significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects are strong. A high consumer demand results in a high average inventory, low fill rate, and low order rate variance ratio. The reason is that a high demand results in a low inventory level at the end of each day, and a large replenishment quantity. On the next day (note that this research considered replenishment policy (1, 26) and the lead time is 1), when the expired products are discarded, and the replenishment quantity arrives, the inventory on hand at the beginning of each day is recorded and is used to calculate the average inventory level. Thus, a high demand results in a high average inventory. For example, consider a high demand of 21. The beginning inventory at the first day is 26, and the inventory at the end of the first day is 5. A replenishment order of 21 is placed and arrives the next day. At the beginning of the second day, all inventory from the first day is expired, the inventory on hand is 21. Now, consider a low demand of 11. The inventory level at the end of the first day is 15, a replenishment order of 11 is placed. At the beginning of the second day, the inventory on hand is only 11. A newsvendor-type model (e.g., Dai & Jerath, 2013) is a representation of this situation. Moreover, a high demand also leads to a high uncertainty in demand (due to the assumption of Poisson distribution). Thus, there is a high probability that demand suddenly

increases and leads to a stock-out situation. Consequently, the fill rate is low in a high uncertainty situation.

This finding means a company can try to lead consumer demand to an acceptable level by applying for sales and marketing programs. This also means a company can reduce the demand for increasing fill rate and decrease average inventory to acceptable levels. Alternatively, a company can accept to increase the inventory level to increase the fill rate.

Second, all tests indicated that the product lifetime had significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects are strong. Products with a high lifetime results in high average inventory, high fill rate, and low order rate variance ratio. This is due to a high lifetime increase in the availability level of a product, and a consequent increase in the fill rate. As a high fill rate and a low order rate variance ratio are preferred, a company might apply technology advantages to manage the disadvantages of having a high average inventory. This could be Radio Frequency Identification (RFID) technology with advantages for perishable products such as reducing labour and spoilage quantity (Duong et al., 2015b; Kärkkäinen, 2003; Prater et al., 2005).

Third, all tests indicated that the lost sales probability has significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects are strong at the supplier and mostly medium at the retailer side. A high lost sales probability means a customer does not want to substitute their preferred product with other products, and demand does not increase too much. Thus, a high lost sales probability results in a low average inventory, high fill rate, and high order rate variance ratio. Therefore, a company should improve the forecast and avoid the sudden demand from substitution. This can contribute to reducing the negative effect of substitution. Recent research on forecast techniques, especially in regards to the demand of perishable products (see van Donselaar et al., 2016), can be applied to improve the forecast demand of perishable products.

Fourth, all tests indicated that the interaction of consumer demand and product lifetime had significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects are strong and even stronger under low consumer demand. Under this interaction, the profiles plots show there is no difference when the lost sales probability is high or low.

Fifth, all tests indicate that the interaction of consumer demand and lost sales probability has significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots show that these effects are strong at the supplier and mostly medium at the retailer side. These effects are larger if a product has a low lifetime.

Sixth, all tests indicated that the interaction of product lifetime and lost sales probability has significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects are strong at the supplier, and have small effects on the average inventory, medium effects on the fill rate, and medium and small effects on the order rate variance ratio at the retailer side. At the supplier, these effects are larger if consumer demand is low.

Seventh, all tests indicated that the interaction of consumer demand, product lifetime, and lost sales probability had significant effects on all 27 performance measures of the studied model. The partial η^2 values and the profile plots showed that these effects on average inventory and order rate variance ratio at the supplier are strong, and negligible and small on fill rate. At the retailer, these effects are negligible and small on average inventory and order rate variance ratio, and small and medium on fill rate.

Eighth, all three input factors and the interactions of the three input factors had large effects on three performance measures at the supplier side; however, the interaction of consumer demand, lifetime, and lost sales probability had small and negligible effects on fill rate at the supplier side. This is because the supplier is easily impacted by the bullwhip effect

phenomenon. In contrast, at the retailer side, only the interaction of consumer demand and product lifetime has a large effect on performance. Thus, these results provided implications for management as addressing large effects quickly improves performance.

Table 4.16: Summary of main and interaction effects on performance of inventory model

Source of variation	Supplier side						Retailer side					
	AI		FR		ORVR		AI		FR		ORVR	
	Effect	Size	Effect	Size	Effect	Size	Effect	Size	Effect	Size	Effect	Size
DM	P	L	N	L	N	L	P	L	N	L	N	L
LF	P	L	P	L	P	L	P	L	P	L	N	L
LS	N	L	P	L	P	L	N	M	P	M	P	M & L
DM x LF	P	L	N	L	N	L	P	L	N	L	N	L
DM x LS	P	L	N	L	N	L	P	S & M	N	M & L	N	M
LF x LS	P	L	P	L	P	L	P	S	P	M	N	S & M
DM x LF x LS		L		S & N		L		S & N		S & M		S & N

Note: DM: Consumer demand; LF: Product lifetime; LS: Lost sales probability

P: Positive effect; N: Negative effect

S: Small effect size; N: Negligible effect size; M: Medium effect size; L: Large effect size

Chapter 5 Discussion and Implications

This chapter discusses the research results in relation to the extant literature, the limitations of the research, recommendations for further research, and managerial implications. This research aims at achieving two research objectives and answering the three corresponding research questions mentioned in section 3.1.1. Section 5.2 firstly presents the use of non-financial performance measures to find the most favourable replenishment policy. Then, sections 5.3, 5.4, and 5.5 present the effects of the input factors on the performance of the studied inventory model. Section 5.6 presents the effects of decision-makers' opinions on the selection of replenishment policies. The results or the answers of these three research questions were presented in Chapter 4. Figure 5.1 below summarises the chapter structure.

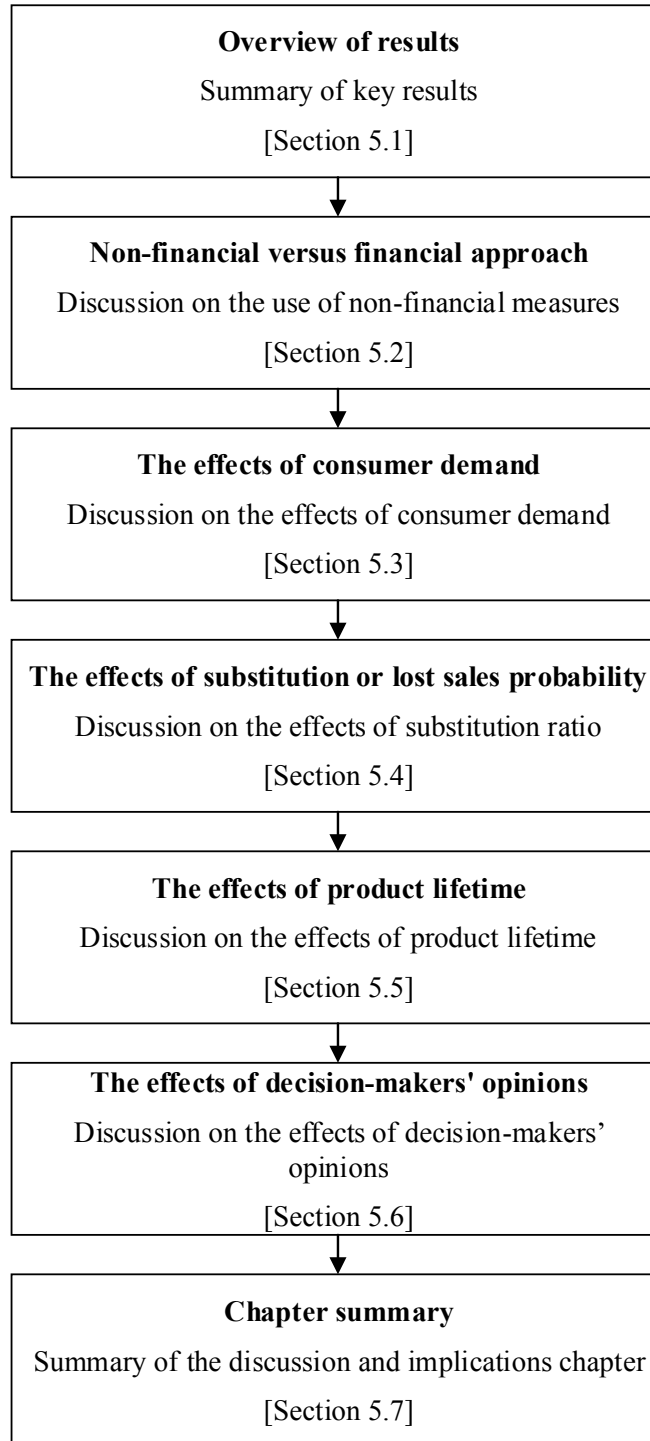


Figure 5.1: Structure of Discussion chapter

5.1 Overview of Results

The studied inventory model and the results of this research have two important purposes. First, they answer the three research questions of this research. For RQ1, section 4.1 provided an example of finding the most favourable replenishment policy by using simulation, AHP, and DEA techniques. The policy (1, 26) (i.e., review inventory daily to bring the inventory level back to 26) was selected as the most favourable replenishment policy. For RQ2, section 4.3 showed that the variation in decision-makers' opinions changes the ranking of policies; however, this does not affect the selection of the most favourable policy. For RQ3, section 4.4 performed the MANOVA test and showed that each input factor (i.e., consumer demand, product lifetime, and lost sales probability), and the interaction of these input factors have significant effects on the performance of the studied inventory model. These results are discussed further in the following sections.

Second, this research also addresses six key issues in perishable inventory management as discussed in section 2.5. The studied inventory model considered a two-echelon model, including one supplier and two retailers for three perishable products. This model replies to the calls for research on the multi-echelon model (section 2.5.8) for multiple perishable products (section 2.5.7). The model assumed the lead time is fixed at 1 day as a response to the call for using non-zero lead time (section 2.2.5). The other three issues of using service level, incorporating substitution ratio, and using multiple performance measures are addressed and discussed in the following sections.

5.2 Non-financial versus Financial Approach

Traditional performance measurement systems (PMS) have been based on financial measures, but in the last decades, non-financial performance measures have been recognised as effective measurement tools and an important research topic (Ittner & Larcker, 1998b; Otley, 2001). Proper PMS should incorporate relatively non-financial measures, apply the measures

consistently, and compensate people according to these responsible measures (Meyer, 2007). Taticchi et al. (2010) showed that PMS has shifted from financial to non-financial measures. Non-financial measures have been emphasised as an important part of the Balanced Scorecard – a comprehensive management system that motivates improvements for companies and organisations (Kaplan & Norton, 1995).

In general, non-financial measures complement financial measures in a performance measurement system (Díaz et al., 2005). Non-financial measures transform and convey a company's strategies and visions to communicate strategic objectives and motivate performance (Said et al., 2003). Further, Baines and Langfield-Smith (2003) observed that most companies that track non-financial measures achieve their strategic objectives. Therefore, non-financial measures are used primarily in modern PMS (Piotrowicz & Cuthbertson, 2015).

5.2.1 Advantages of using non-financial performance measures

In the context of multi-echelon inventory management, researchers have emphasised the need to use non-financial performance measures for four main reasons. Firstly, the bullwhip effect is a common phenomenon in a multi-echelon model, which leads to many detrimental and multi-dimensional consequences on performance (Cannella & Ciancimino, 2010), for example, high holding cost (Zhou & Disney, 2006), high lost sales, low service level (Wang & Disney, 2016), and high capacity levels (Isaksson & Seifert, 2016). Cannella et al. (2013a) designed a non-financial PMS that assesses internal process efficiency and customer satisfaction at both local (single-echelon) and systemic performance (whole supply chain) levels, as a response to strong recommendations to analyse the bullwhip effect in a multi-echelon model.

The second reason is based on the multi-dimensional nature of the multi-echelon model. Most research on perishable inventory management has selected a replenishment policy that optimises the total cost or total profit function. For example, Giri and Sarker (2016) selected a replenishment policy that maximised the total profit of the supply chain with one supplier and

two retailers. Using financial measures is common in inventory models due to their advantages, for example, clear definitions of the objective, direct solution methods, single best result generated, and clearer interpretation of this result (Pintarič & Kravanja, 2015). However, optimising one measure ignores other important measures (Savic, 2002), which can be overcome by using multi-criteria decision-making methods (Grigoroudis et al., 2012; Kaplan, 2008), especially when supply chain management is faced with multi-dimensional problems (Li et al., 2006). Kaplan and Norton (2005) suggested shifting from financial measures to non-financial measures and proposed the Balanced Scorecard method, which uses multiple measures instead of one measure to evaluate performance of systems. In a similar call, Cannella et al. (2013a) considered the bullwhip effect phenomenon under the multi-echelon supply chain model, and proposed non-financial measures that assess the performance of each echelon and the whole supply chain model. Since then, there has been a growing number of studies using non-financial measures in supply chain management. For example, Duan and Liao (2014) studied a two-echelon model and used two non-financial measures (i.e., outdated rate and fill rate) to select the replenishment policy which minimises outdated rate under a given service level.

Thirdly, non-financial measures support continuous improvement for companies. Modern and competitive business environments require innovation and new perspectives on managing PMS, which must continuously reflect changes in priorities and organisational contexts as the business environments change (Kennerley & Neely, 2003). Non-financial measures have been discussed as appropriate systems as they provide information for daily decision-making, foster improvement, reflect changes in business environments, and support continuous improvement (Lehtinen & Ahola, 2010).

Finally, inventory management has an active role in the modern business environment. Mathematical inventory models with cost variables have been criticised because business

environments have been changing quickly and this impacts on the accuracy of input parameters for these models (Bonney & Jaber, 2011; Chikán, 2007). Hence, researchers have suggested that inventory management should have an active, not a passive role. Conceptually, inventory is an integrated part of the supply chain and serves as a strategic tool in achieving customer satisfaction; thus performance measures which are based on the contribution of inventory should be focused on improving customer satisfaction (Chikán, 2011). Therefore, researchers have proposed the use of non-financial measures, which help managers understand the effects of managing inventory on the performance of a company (Bonney & Jaber, 2011).

5.2.2 Gaps in using non-financial performance measures

Despite the advantages of using non-financial performance measures, there are two disadvantages that limit the number of researches applying these measures to select the most favourable replenishment policy (Lehtinen & Ahola, 2010). First, there are various non-financial measures that can be used and a problem occurs in selecting which measures are suitable for a company (Medori & Steeple, 2000). For example, a company may select a wide range of measures from quality, delivery in-time, and delivery on-time. Cannella et al. (2013a) proposed a selected range of measures for a multi-echelon model; however, one of the research limitations, as already mentioned in Cannella et al. (2013a), is that the complexity of the system limits its practical applications.

Second, non-financial measures conflict with each other and there is no unique and well-defined framework that can be followed step-by-step for a decision-making process (Mardani et al., 2015). Using non-financial measures helps managers to easily communicate strategy objectives and motivate the performance of people and departments (Senot et al., 2016a). However, this also makes the problem more complicated due to the nature of multi-criteria problems. Researchers, (e.g., Vidalis et al., 2014), have transformed non-financial measures (i.e., fill rate, average inventory, and average cycle time) into a profit function and

selected the replenishment policy that maximises total profit. Alternatively, Duan and Liao (2014) selected a replenishment policy by minimising the outdated rate under a predetermined shortage level.

The works of Vidalis et al. (2014) and Duan and Liao (2014) have overcome the complexities of conflicting performance measures and have provided some directions for improvements. First, it is not always easy to transform correctly all non-financial measures into a profit function, as in the study of Vidalis et al. (2014), due to the delay or inaccuracy of information in supply chain management (Cannella, 2014). Second, inventory management is a part of a company. Minimising the outdated rate under a given shortage level, as in the study of Duan and Liao (2014), does not provide a performance target for other departments (e.g., procurement) or correlation between departments.

This research extended the work of Vidalis et al. (2014) and Duan and Liao (2014), and used three non-financial performance measures (i.e., AI, FR, and ORVR) in perishable inventory management. Results in section 4.1 provided evidence that in the given context of the perishable inventory model, the non-financial approach is comparable to the financial approach. This is because, in a similar context, the most favourable replenishment policy as shown in section 4.1, is reasonable and comparable to the results received from the financial approach (as explained in section 4.1.4).

5.2.3 Contributions relating to using non-financial performance measures

The comparability of the non-financial measures approach addresses the issue of using multiple performance measures, as discussed in section 2.5.6, and contributes to the inventory management theory in two ways. First, this research selected a set of three non-financial measures, which are the most common factors for perishable inventory management. Cannella et al. (2013a) proposed a set of non-financial measures for a whole supply chain; however, Cannella et al. (2013a) also stated that this set is complex and difficult for practical

applications. This research considered common factors in a total cost function drawing on previous research in perishable inventory management, namely, holding cost, purchase cost, lost sales cost, and outdated cost (Kouki et al., 2014). These costs are translated into non-financial measures including AI, FR, and ORVR by using the definition put forward by Cannella et al. (2013a). Then, instead of selecting a replenishment policy, which minimised the total cost, this research selected a replenishment policy, which was the best trade-off in all three non-financial measures (i.e., AI, FR, and ORVR). These three measures cover all common cost factors in perishable inventory management; thus, they are relevant to the non-financial measures in this problem.

Second, this research proposed a decision framework that integrates DES, AHP, and DEA to select the most favourable replenishment policy. When considering a multi-objective for the perishable inventory management problem, researchers have usually used mathematical algorithms to select the best trade-off among conflicting objectives. For example, Alaei and Setak (2015) used a harmony search algorithm to select ordering and routing decisions for the supplier facing a newsvendor problem, which are the best trade-off among three objectives, namely, supplier's profit, supplier's routing cost, and supplier's service level. However, using a mathematical algorithm has been criticised due to the complexity of calculation (Zhang et al., 2014), the large amount of enumeration memory required, and sensitivity to input values (Lee & Geem, 2004).

This research considered the disadvantages of using mathematical algorithms and proposed a framework that includes three steps. In the first step, the simulation model was built and run for each scenario of the replenishment policy or each pair-review period and order-up-to level. The performance of each replenishment policy was measured by three non-financial measures (i.e., AI, FR, and ORVR). In perishable inventory management, DES is a valuable method to evaluate multiple performance measures (Brailsford, 2014). In contrast to single-

objective problems where the performance of one measure is commensurable and easily ranked to select the optimal solution (Gutjahr & Pichler, 2013), this research considered three measures which conflict with each other. However, it is impossible to find a replenishment policy which optimises all three measures simultaneously (Dächert et al., in press). Furthermore, the knowledge, understanding, and choice of each performance measure differ from person to person. Therefore, it is necessary to integrate multi-criteria decision-making methods into the simulation method when conflicting performance measures are considered simultaneously (Xu et al., 2011).

Numerous MCDM methods have been suggested in the literature of operations management. Among MCDM methods, AHP and DEA are the two most commonly used methods (Yadav & Sharma, 2016) as they can be integrated individually or together with the simulation method. For example, Azadeh, Zarrin, and Salehi (2016) used simulation to determine the performance of suppliers. DEA was then applied to evaluate the relative performance of supplies. Bamakan and Dehghanimohammadabadi (2015) used AHP to weight security characteristics of an information asset then simulation was utilised to analyse information security risks for an organisation. Azadeh et al. (2008) used simulation to verify and validate a railway system, AHP to determine the qualitative criteria, and DEA to identify the best configuration for the railway system. Despite vast research on using simulation, AHP, and DEA, there is no evidence of any research that integrates simulation, AHP, and DEA to deal with the perishable inventory management problem. The reason is that most research on perishable inventory management focuses on optimising one objective only. This research considered a trade-off solution between three measures (i.e., AI, FR, and ORVR) thus, the integrations of simulation with AHP and DEA was reasonable.

In the second step, the AHP method was used to weight the importance of each performance measure. The weight of each measure was then multiplied by the values received

from the DES model to identify the relative value of each measure. In the third step, the DEA Cook's super-efficiency method was performed to evaluate and rank the performance of each replenishment policy based on relative values. The policy with the lowest DEA super-efficiency score was selected as the most favourable replenishment policy.

The integration framework in this research, including DES, AHP, and DEA, performed well as illustrated in section 4.1. The policy (1, 26) (meaning the inventory level is reviewed every day and a replenishment order is placed to bring it back to 26) was selected as the most favourable replenishment policy. The chosen policy is comparable with the result of Kouki et al. (2014), and confirms the efficiency of the framework. In different contexts, the framework can be performed as illustrated in section 4.1 to select the most favourable replenishment policy.

In contrast to the findings of Vidalis et al. (2014) and Duan and Liao (2014), this research has two advantages. It firstly showed that multiple non-financial measures could be used to select the most favourable replenishment policy without transforming them into a profit function and avoiding related issues. In contrast to Vidalis et al. (2014), this research did not transform three non-financial measures (i.e., AI, FR, and ORVR) into a profit function. It integrated AHP after the simulation step to weight the importance of each measure and used DEA to rank the performances of policies. This approach employs the opinions of decision-makers and avoids one of the biggest difficulties in performance measurement, which is not having relevant or accurate information (Parida et al., 2015) when transforming non-financial measures to costs. Also, using non-financial measures indicates how managers can improve performance, while financial measures only report what happened in the last period (Kaplan & Norton, 2005). For example, by measuring cycle time, delays in paperwork, machine idle time, and check-in time can be identified and eliminated (Bhagwat & Sharma, 2007).

Secondly, this research allowed consideration of more measures and encouraged more departments or responsible people to become involved. This research is similar to that of Duan and Liao (2014) in terms of using non-financial measures to select the most favourable replenishment policy. Duan and Liao (2014) predetermined a shortage level and selected the policy minimising the outdated level. However, the approach in Duan and Liao (2014) does not allow consideration of one more measure and does not support the involvement of related departments or responsible people. Also, predetermining a shortage level may impact negatively on the perception of fairness, which is a critical aspect of employee satisfaction and the achievement of company objectives (Lau & Moser, 2008). In Duan and Liao (2014), a responsible person was given a service level and had to make a decision based on that service level. That person may not have understood how that given service level was calculated and may have thought that the given service level was too high to achieve. That person would have perceived unfairness, which would have negatively impacted on their performance. In contrast to Duan and Liao (2014), this research considered more measures and did not predetermine the constraint level of any measure. AHP in this research enables decision-makers to have flexibility in defining the relative importance of each measure. Related decision-makers, based on strategic objectives and the current business environment, negotiate and define the importance of measures. This decision-making process in supply chain management that involves related decision-makers is referred to as supply chain collaboration (Stank et al., 2001) and has been advocated for a number of decades (Holweg et al., 2005). The collaboration enables sharing of information and creates a transparent demand pattern for enhancing the entire supply chain performance while reducing the bullwhip effect (Cannella, 2014). The collaboration also provides performance targets and correlation information for all related departments (Senot et al., 2016a). This approach has the ability to transform and convey strategic objectives to all related departments (Kaplan & Norton, 2005). Managers can easily

communicate strategy objectives and motivate people and departments with regards to their performance (Senot et al., 2016a).

The comparable results of this research with those of Kouki et al. (2014) confirm the contribution of this research to the literature. This is the first known research to integrate DES, AHP, and DEA into perishable inventory management problems. In contrast to Alaei and Setak (2015), this research did not use a mathematical algorithm, which is complicated for managers. Instead, this research integrated and took advantage of the DES, AHP, and DEA methods. DES helps to evaluate the performance of a model with multiple performance measures. AHP allows managers to easily weight the importance of each measure based on strategic objectives and the current business environment. DEA supports the evaluation and selection of the most favourable policy when there are many alternatives, inputs and outputs (e.g., this research considered 88 possible policies, 2 inputs, and 27 outputs). The framework also used two free R packages (i.e., 'pmr' and "TFDEA") to weight the importance of measures and rank the policy. These free R packages together with free computer simulation software versions (e.g., student versions of the ARENA software (Kleijnen & Wan, 2007)) help to promote the use of the framework in a real business environment.

5.2.4 Research limitation relating to using non-financial performance measures

One limitation of this research is the range of performance measures, which may not involve all related responsible people. This research extended the work of Kouki et al. (2014) which considered a total cost function, formulated from ordering cost, holding cost, purchase cost, lost sales cost, and outdated cost. These are common costs in perishable inventory management (an example can be found in the recent work of Zhang et al. (2016)), and are translated to relevant non-financial performance measures according to the guideline for adopting measures in Cannella et al. (2013a). However, using just three non-financial measures (i.e., AI, FR, and ORVR) may not cover all dimensions of a company and may produce game-playing behaviours

(i.e., overachievement on only some measures and underachievement on others) (Ittner et al., 2003). On the hand, using just three non-financial measures may involve a limited number of responsible people and departments and cause a perception of unfairness and thus reduce performance results (Burney et al., 2009). Therefore, future research may consider more non-financial measures (e.g., as listed in Table 2.1) to reflect the multidimensional nature of the operations and supply chain management. Future research may, for example, consider overtime costs via a zero-replenishment measure.

5.3 The Effects of Consumer Demand

Inventory management aims at determining a favourable replenishment policy, which answers two questions: when and how much should be ordered to hold an appropriate quantity of products and satisfy consumer demand (Beheshti, 2010). A replenishment policy is determined based on an assumption or the forecast of demand (Gallego & Özer, 2003). It is one of the uncontrollable factors that create complexities in determining a favourable replenishment policy (Sezen, 2006). Specifically, the uncertainty of demand impacts directly on the performance of a supply chain network (Chiang, 2003). Underestimating demand uncertainty and its effects can lead to replenishment policies that cannot protect a company against the risks (e.g., substitution, disaster). For instance, failures to forecast demand could either lead to low fill rate translating to a loss of market share or unexpectedly high inventory holding costs (Gupta & Maranas, 2003). Both are undesirable situations in the current business environment where the profit margins are very strict. The former situation links to a failure in taking the opportunity to gain additional market share while the later links to a failure in effectively managing the inventory of the company (Kärkkäinen, 2003). Inventory models, which recognise the demand uncertainty in the future, are expected to result in outstanding replenishment policies.

Effects of consumer demand on the performance of supply chain management have received attention, especially in terms of the most common non-financial measure fill rate (Williams & Tokar, 2008). Petrovic (2001) studied simulation results in fuzzy conditions and concluded that the fill rate decreases as the uncertainty of demand increases. Petrovic's model is envisaged as a first step towards the development a decision support system to assist decision-making on different supply chain contexts (Petrovic, 2001). Xue et al. (2016) considered an inventory model for a manufacturer with an unreliable supplier and uncertain demand. Pauls-Worm et al. (in press) considered a replenishment decision problem of fresh food that minimises total cost with uncertain demand. Similar to the findings of Petrovic (2001), the simulation experiments conducted by Pauls-Worm et al. (in press) and Xue et al. (2016) also showed that the fill rate decreases as demand uncertainty increases.

5.3.1 Gaps relating to the knowledge of effects of consumer demand

Despite all of the prior works, there are currently four gaps regarding the knowledge of effects of consumer demand on perishable inventory management. Firstly, there is a lack of investigation on effects of consumer demand on other non-financial measures. Prior works (e.g., Pauls-Worm et al., in press; Xue et al., 2016) have illustrated the effects of uncertain demand on FR and total costs of the inventory model. However, information on financial measures (e.g., total costs) is suitable for strategic decisions only and non-financial measures have been emphasised to motivate improvements for companies and organisations (Kaplan & Norton, 1995). Thus, a replenishment policy should illustrate effects of demand on non-financial measures other than FR.

Secondly, there is a lack of models that evaluate effects of consumer demand on a whole multi-echelon supply chain model. Pauls-Worm et al. (in press) only considered a single-product single-echelon model, which limits the applications of the model as real business usually deals with multi-products under collaboration with external parties (i.e., multi-echelon)

to improve performance (Weraikat et al., 2016). Xue et al. (2016) studied a two-echelon model for a general newsvendor product with uncertainties in demand and supply. Nevertheless, the authors were unable to evaluate the performance of the entire supply chain network, which is an important aspect in the context of a multi-echelon model where the bullwhip effect phenomenon exists (Wang & Disney, 2016).

Thirdly, insights about the effects of consumer demand for products with a random lifetime should be enhanced. Both Pauls-Worm et al. (in press) and Xue et al. (2016) assumed the product has a fixed lifetime which provides directions for future research. As research under single-product having a fixed lifetime might reach a saturation point, potential extensions would allow multiple products to have a random lifetime (Karaesmen et al., 2011).

Finally, there are other problem characteristics that affect the performance of inventory models. Prior research has investigated the main effects of consumer demand only. Thus, it is necessary to investigate interactive effects between consumer demand and other problem characteristics.

5.3.2 Contributions to the knowledge of effects of consumer demand

This research provided four complements to the studies of Pauls-Worm et al. (in press) and Xue et al. (2016). The comparison between this research and the works of Pauls-Worm et al. (in press) and Xue et al. (2016) are summarised in Table 5.1. First, the model considered three products with random lifetime, which correspond to two importance characteristics in perishable inventory management, namely, the uncertainties in product lifetime, and consumer demand due to substitution between three products (Nahmias, 2011). Within a review period, there is an unknown quantity of expired and discarded products due to the uncertainty of product lifetime (Pauls-Worm et al., in press). The substitution also amplifies the uncertainty of demand as customers tend to substitute another product when their preferred product is out of stock (Zinn & Liu, 2001). These two characteristics cause uncertainties in the availability of

stock and managers tend to increase the inventory level (Şen, 2016) as they do not know the quantity of discarded products and substitution demand beforehand. This research used DES, which enables these uncertainties to be covered (Duan & Liao, 2014). Through the DES approach, this research extended the assumptions of a single-product with a fixed lifetime in the studies of Pauls-Worm et al. (in press) and Xue et al. (2016), and addresses the gap in the research on inventory management for perishable and substitutable products (as mentioned in section 2.6).

Second, this research considered a two-echelon model with one supplier and two retailers. Whereas Pauls-Worm et al. (in press) defined a replenishment policy for a retailer only, this research defined a replenishment policy for a supplier and two retailers, which aligned with the call for more research on a multi-echelon model (Karaesmen et al., 2011). Based on the literature, considering a multi-echelon model or coordination among different levels or stages (i.e., echelon) of the supply chain provides many benefits (Nagaraju et al., 2016). For example, Berling and Marklund (2014) proved that considering coordination between suppliers and retailers brings the fill rate closer to the target and reduces total inventory costs by over 30%. This research considered one supplier and two retailers, thus extending the work of Pauls-Worm et al. (in press) to fill the gap in the research on a multi-echelon model of perishable inventory management.

Third, the proposed framework in this research is able to evaluate a wider range number of performance measures in the supply chain model. This research considered not only the FR, as in the studies of Pauls-Worm et al. (in press) and Xue et al. (2016), but also two other performance measures, that was, AI and ORVR, for supplier and retailers. Researchers have emphasised that tracking the performance of the entire supply chain is necessary as it maximises the efficiency of systems (Gunasekaran et al., 2004). Specifically, this framework has the ability to evaluate the effects of uncertain demand on not only FR but also AI and

ORVR at the supplier and retailers. Given the intense business environment, FR has become an important factor in enhancing competitiveness and continuous development in the supply chain. Although FR improves the level of customer satisfaction for the entire supply chain, it may cause ineffective operations for upstream echelons, which is a serious problem under demand uncertainties (Yin & Ma, 2015). This observation stems from a practice where retailers want to achieve a high fill rate and therefore replenish more often and keep a high inventory level, which causes high waste of expired products and capital investment. Therefore, the replenishment policy should emphasise the importance of not only FR but also the inventory level (e.g., AI measure) and procurement activities (e.g., ORVR). In contrast to the studies of Pauls-Worm et al. (in press) and Xue et al. (2016), this research did not translate the effect of uncertain demand on AR and ORVR into total costs. This approach has the advantage of using non-financial measures (as discussed in section 5.2) to improve performance of the studied model.

Fourth, besides the main effects of consumer demand, this research also investigated the effects of its interactions with product lifetime and substitution. The use of DES and statistical tests allows this research to investigate these interactive effects. Insights on interactive effects serve as guidelines for managerial implications.

Table 5.1: Differences between this research and the researches of Pauls-Worm et al. (in press) and Xue et al. (2016)

Research	No. of product	No. of echelon	Lifetime	Studied effect
Xue et al. (2016)	1	2	Newsvendor	Demand on FR
Pauls-Worm et al. (in press)	1	1	Fixed	Demand on FR
This research	3	2	Exponential	Demand on FR, AI, and ORVR

The MANOVA test results discussed in section 4.5.3.5 showed that consumer demand has large effects on all performance at the supplier and retailers. This research assumed that consumer demand follows a Poisson distribution, and analyses under two situations both the

high and low mean of demand, or the high and low variance of demand (as the characteristics of Poisson distribution (Cattani et al., 2011)). The sensitivity analysis results showed that as consumer demand changes from a high to a low situation, the AI decreases and FR increases. Since a company prefers to have a high average of consumer demand, any activities to reduce average consumer demand then reduces AI and increases FR and may not be appropriate. Instead, this result should be understood as reduced uncertainty in that consumer demand can be used to reduce AI and increase FR. This is because the inventory level at the beginning of each day was recorded to calculate the AI (as explained in section 4.6), and was also relevant to the observation that managers tend to keep higher inventory to cover high uncertainty in demand (Jung et al., 2004). This result is similar to the findings of Pauls-Worm et al. (in press) and Xue et al. (2016), where the researchers show that as the uncertainty in demand decreases, the FR increases.

Also, this research indicates that ORVR increases as the demand decreases. This is because ORVR is defined as the ratio of the order variance at an echelon to the order variance of the consumer (or market demand). As the demand decreases, the uncertainty of demand decreases and thus ORVR increases.

Besides these main effects, there are several interactive effects that could be considered to enhance the performance of the inventory model. The interaction between consumer demand and product lifetime has large effects on AI, FR, and ORVR at both the supplier and retailer sides. The interaction of consumer demand and substitution has large effects on AI, FR, and ORVR at the supplier side and mostly small and medium effects on retailer side.

From the managerial perspective, the low uncertain demand situation is preferred if the effect of ORVR is low or costs relating to ORVR are low. In this situation, AI is low and FR is high, which are preferred for business. However, ORVR is high, which is not good for business. The decision-makers, therefore, may reduce costs related to ORVR (e.g.,

procurement cost and ordering cost as listed in Table 2.1) to deal with the high ORVR in the low demand situation. They may apply advantages of technologies (e.g., enterprise resource planning (Huang & Handfield, 2015)), or improve the procurement contracts (Li, Ryan, & Sun, 2015). These solutions if approved can reduce the procurement cost, and thus, the effects of high ORVR. Another implication is to work toward reducing the uncertainty of demand when a company prioritises AI and FR, as these two measures perform well in this situation. The uncertainty of demand is reduced when the variation between actual and forecasted demand decreases. This requires the application of forecasting techniques, for example, the forecasting algorithm presented in the study of Du et al. (2013) or other techniques presented in the study of Syntetos et al. (2016).

5.3.3 Research limitations relating to the knowledge of effects of consumer demand

This research assumed that consumer demand follows a Poisson distribution with a known mean as this is a common assumption in many other works (e.g., Alizadeh et al., 2014). This assumption is suitable for a low level of demand (Cattani et al., 2011). However, researchers have stated that using a probability theory is not suitable for market demand as the data are not always reliable and available (Giannoccaro et al., 2003). Future research may relax this assumption to consider other types of demand distribution (e.g., fuzzy theory) or unknown demand distribution. This relaxation covers more realistic situations and the two branches of known and unknown demand distribution in inventory management literature (O'Neil et al., 2016).

5.4 The Effects of Product Lifetime

The literature on perishable inventory management can be classified depending on the type of review (i.e., continuous or periodic) and whether a product lifetime is constant or stochastic (Kouki et al., 2015). This research considered a product lifetime following an exponential

distribution (or stochastic lifetime), which is commonly studied with a periodic review policy, especially when having multi-products and multi-echelons (Kouki & Jouini, 2015). Therefore, this research focused on the literature on perishable inventory management with periodic review and stochastic product lifetime.

5.4.1 Gaps relating to the knowledge of effects of product lifetime

The perishability or the random lifetime of a product is one of major factors that impacts perishable inventory management systems (Karaesmen et al., 2011) and has received significant attention in the literature. However, despite the growing number of researches on perishable inventory management, the randomness lifetime problem remains complex (Nahmias, 1982). The reason is that determining the replenishment policy for perishable products requires many variables to track different age categories in inventory (Nahmias, 2011).

A large part of the literature has studied the effects of product lifetime on the performance of perishable inventory management. This research is close to two studies, that is, Kouki et al. (2014) and Kouki and Jouini (2015). Kouki et al. (2014) studied a (T, S) perishable inventory model for a product lifetime following an exponential distribution lifetime. The inventory level was observed at every T interval and a replenishment order was placed to bring the inventory position to the order-up-to-level S . Kouki and Jouini (2015) assumed a product lifetime follows an Erlang distribution, and considered a periodic review (T, r, Q) policy. The inventory level was checked at every T interval, and if it was below the reorder point r , a replenishment order with quantity Q was placed. Both of these researches concluded that the randomness of product lifetime has a significant effect on the total cost; that is, the smaller the randomness, the lower the total cost. However, both of these two researches considered the effect of product lifetime on total cost under the assumption of a single-echelon model with a single product, and this is extended in this research.

5.4.2 Contributions to the knowledge of effects of product lifetime

This research extended the works of Kouki et al. (2014) and Kouki and Jouini (2015) as was shown in Table 5.2 and had two contributions to perishable inventory management. First, this research considered three products with a random lifetime (i.e., following an exponential distribution) for a two-echelon model (i.e., one supplier and two retailers). This extension is already indicated in Kouki and Jouini (2015) who stated that a study for one supplier and multiple retailers is an ambitious future work. This extension is also important considering the benefits of research on the multi-echelon and multi-product model (e.g., reduce the total cost of the whole supply chain model) (Nagaraju et al., 2016), and fill the gap in the research on perishable inventory management for the multi-echelon multi-product model.

Second, this research studied the effects of product lifetime, specifically on each element of the total cost. While Kouki et al. (2014) and Kouki and Jouini (2015) considered the effects of product lifetime on the total cost including holding cost, purchase cost, lost sales cost, and outdated cost, this research translated these cost factors into non-financial measures (i.e., AI, FR, and ORVR) by using the description in the study of Cannella et al. (2013a). These non-financial measures bring many benefits to the inventory management; for example, they provide information for continuous improvement and ease of communication between responsible departments or people (as mentioned in section 5.2). Understanding the effects of product lifetime on AI, FR, and ORVR supports managers in making operational decisions, for example, defining business activities which are relevant to the uncertainty of a product lifetime to improve the FR for that product.

Table 5.2: Comparison of this research with Kouki et al. (2014), Kouki and Jouini (2015)

Research	Replenishment policy	Lifetime distribution	No. of Product	No. of echelon	Effect of lifetime
Kouki et al. (2014)	(T, S)	Exponential	1	1	Total cost
Kouki and Jouini (2015)	(T, r, Q)	Erlang	1	1	Total cost
This research	(T, S)	Exponential	3	2	Non-financial

Specifically, the MANOVA test results in section 4.5.3 showed that product lifetime has large effects on all performance measures at the supplier and retailers. Compared to a high product lifetime situation, in a low product lifetime situation, the AI is lower, FR is lower at both the supplier and retailer sides, and ORVR is higher at the retailer side and lower at the supplier side. Note that this research assumed a product lifetime follows an exponential distribution, meaning in a high product lifetime situation, that product has a high average lifetime but also a highly uncertain lifetime. Since a product with a long lifetime is preferable in reality, any activities to reduce the average lifetime in order to reduce AI may be not appropriate. Instead, this result should be understood as reduced uncertainty in product lifetime can be used to reduce AI. An increased average of product lifetime can be used to increase FR at both the supplier and retailer sides.

Besides the main effects of product lifetime, results also provide interactive effects of product lifetime and consumer demand, and the effects of product lifetime and substitution on AI, FR, and ORVR. The interaction of product lifetime and consumer demand has large effects on AI, FR, and ORVR at supplier and retailer sides (presented in section 5.3). The interaction of product lifetime and substitution has large effects on AI, FR, and ORVR at the supplier side, and small and medium effects on the retailer side. The bullwhip effect phenomenon can be used to explain the interactive effects of product lifetime and substitution at the supplier and retailer sides. When facing a stock-out situation at a retailer, customers substitute their preferred products with a probability. The demand with and without substitution may not be

too different at the retailers. However, at the supplier, differences at the two retailers accumulate. Therefore, the demand with and without substitution is too different and causes large effects.

This result has some managerial implications. A high lifetime situation is preferred as it results in high FR and low ORVR at the retailer. The only drawback is the unexpected high AI. (Although ORVR is high at the supplier, its value is under 1. This is considered as smoothing, and not a critical point.) Therefore, managers could invest in equipment and techniques that increase product lifetime. Examples include food irradiation, storage equipment, or chemical treatments (Ferguson & Ketzenberg, 2006). To deal with high AI, managers could implement sales dynamic plans to delay demand (Ho et al., 2002), which can better manage, predict, or drive demand and reduce the AI.

5.4.3 Research limitation relating to the knowledge of effects of product lifetime

One limitation of this research is the assumption of an exponential distribution of product lifetime. Future research can relax this assumption, and consider other types of distribution for product lifetimes such as Weibull distribution or constant rate. This relaxation covers other types of products and reflects more realistic problems.

5.5 The Effects of Substitution or Lost Sales Probability

Supply chains are usually faced with uncertainties in the business environment, and managers must make decisions on capital investment or inventory before the final market is observed. To respond to uncertainties, managers frequently employ operational flexibility. This flexibility could be flexible capacity (i.e., able to produce more than one product with shared investment) or flexible product attributes such that similar products can be substituted for each other (Bansal & Moritz, 2015).

Managers also want to compete for market share and expand ranges of products by offering more products to retailers and consumers (Rajaram & Tang, 2001). When selling substitutable products, demand for a product is not only based on its characteristics, but also on other products with similar characteristics. If a product is out of stock, customers may substitute with a similar product. Field studies of customer behaviour in stock-out situations show that customers tend to substitute with another product for the desired product (Waller et al., 2008).

5.5.1 Gaps relating to the knowledge of effects of substitution

Consequently, substitution increases uncertainties of demand and managers must consider the effects of substitution on demand to determine suitable replenishment policies. An example is in the study of Tan and Karabati (2013), who considered a retailer that sells substitutable products. They found that if customers cannot find their desired product, they substitute another product with a given possibility; otherwise, it is a lost sales situation. The retailer selects a fixed review period and order-up-to level replenishment policy, which maximises the total profit at the retailer. The results showed that by accounting for the substitution, the profit of the retailer is improved, especially when the required service level is low.

In the context of perishable products, Bansal and Moritz (2015) studied inventory management for two newsvendor products at a retailer. The authors also observed that substitution has a positive effect on the total profit at the retailer. However, they studied a problem in an industry context and assumed unidirectional substitution where one product can substitute for the other but not vice versa, for example, a “free upgrade” situation in car rental. This assumption limits the application of the model in other situations, for example, grocery stores where customers can substitute their preferred products with any product. Recently, Hübner et al. (2016) studied performance at a retailer who sells substitutable and newsvendor products. They found that substitution is flexible, meaning that one product can substitute for

the other. The results also show that the substitution has a significant effect on total profit at the retailer. Nevertheless, one common limitation of these works is the assumption of newsvendor product, as it is a basic model to find the policy maximising total profits (Hübner et al., 2016).

Research has called to relax the single-period lifetime assumption for other types of product lifetime (Shin, Park, Lee, & Benton, 2015). For example, Civelek et al. (2015) considered blood products with a fixed lifetime of four days and studied the effects of substitution on total costs at a blood centre. However, similar to the studies of Bansal and Moritz (2015) and Hübner et al. (2016), Civelek et al. (2015) only considered the effects of substitution at one echelon.

Five papers considered substitution for perishable products at two-echelon models (see Table 2.4). Four of these considered newsvendor products. The closest work to this research is that of Duan and Liao (2014), who considered a two-echelon model with blood products at a hospital and blood centre. However, the authors still assumed that blood products have a fixed lifetime of three days. As these extant works consider the effects of substitution on the single-echelon model with newsvendor products or the two-echelon model with fixed product lifetime, one of the objectives of this research is to better understand the effects of substitution in a two-echelon model with products that have random lifetime. Table 5.3 presents a comparison of this research and extant works.

5.5.2 Contributions to the knowledge of effects of substitution

This research made two contributions to the literature on inventory management for perishable and substitutable products. First, this research considered products with a lifetime following an exponential distribution, which is a common assumption in the literature of perishable inventory management (Kouki & Jouini, 2015). While Bansal and Moritz (2015) and Hübner et al. (2016) considered newsvendor products, or Duan and Liao (2014) considered products

with a fixed three days lifetime, these types of products are not common in practice. This research considered the random lifetime of dairy products (e.g., milk) and used the exponential distribution, which is relevant to real problems, where products have a random lifetime.

Second, this research investigated the main and interactive effects of substitution on non-financial measures of a two-echelon model. Duan and Liao (2014) considered a two-echelon model and studied the effect of substitution on only the outdated rate. Civelek et al. (2015) and Hübner et al. (2016) studied other effects of substitution but in the form of total cost or profit. For example, Hübner et al. (2016) studied the effects of substitution on total profit including sales revenue, purchase cost, lost sales cost, and outdated cost. However, Hübner et al. (2016) did not illustrate the effect of substitution on each factor of total profit. This research specified common factors in total profit and cost functions and studies the effects of substitution on each factor. The factors in total profit or cost function are translated into non-financial measures (i.e., AI, FR, and ORVR) by using the description in the study of Cannella et al. (2013a). Moreover, this research also considered the importance of interactive effects (Hancerliogullari et al., 2016), and investigated the effects of interactions between substitution and consumer demand, and the effects of product lifetime on the performance of an inventory model.

Using non-financial measures, ORVR also allows the study of the effect of substitution on the bullwhip effect, which is a common phenomenon in a two-echelon model (Cannella & Ciancimino, 2010), especially when having substitutable products (Duan et al., 2015). Using non-financial measures has many benefits for inventory management; for example, it provides information for continuous improvement and eases communicate between responsible departments or people (as mentioned in section 5.2). With these two contributions, this research filled the gap in the research on perishable and substitutable inventory management under a multi-echelon model. Furthermore, the substitution in this research was calculated from the

lost sales probability by the formulation in the study of Smith and Agrawal (2000). Therefore, this research also addressed the lost sales problem, which is a common problem in practice.

Table 5.3: Comparison of this research and previous research

Research	No. echelon	Lifetime	Substitution behaviour	Effects of substitution
Zhang et al. (2009)	Two-echelon	Newsvendor	Flexible	Total profit
Gürler and Yılmaz (2010)	Two-echelon	Newsvendor	Flexible	Total profit
Tan and Karabati (2013)	Single-echelon	Infinite	Flexible	Total profit
Zhang et al. (2015)	Two-echelon	Newsvendor	Flexible	Total profit
Zhang et al. (2014)	Two-echelon	Newsvendor	Flexible	Total profit
Duan and Liao (2014)	Two-echelon	Fixed	Flexible	Outdated rate
Bansal and Moritz (2015)	Single-echelon	Newsvendor	Uni-direction	Total profit
Civelek et al. (2015)	Single-echelon	Fixed	Flexible	Total cost
Hübner et al. (2016)	Single-echelon	Newsvendor	Flexible	Total profit
This research	Two-echelon	Exponential	Flexible	Non-financial

The MANOVA test results in section 4.5.3 showed that the lost sales probability has significant effects on all performance at the supplier and retailers. Recall that lost sales probability and the substitution ratio have a negative linear relationship as mentioned in section 3.5.3. This research therefore used substitution and lost sales probability with reverse meaning. This means the substitution ratio also has significant effects on all performance at the supplier and retailers. Specifically, compared to a low substitution ratio (high lost sales probability), a high substitution ratio (low lost sales probability) has higher AI, lower FR, and lower ORVR.

Besides the main effects of substitution, this research also reported interactive effects of substitution on consumer demand and product lifetime. These interactive effects also were reported in sections 5.3 and 5.4. The interaction of substitution and consumer demand had large

effects on AI, FR, and ORVR at the supplier side and mostly small and medium effects on the retailer side. The interaction of substitution and product lifetime had large effects on AI, FR, and ORVR at the supplier side, and small and medium effects on the retailer side.

The significant effects of substitution found in this research are relevant to other literature. For example, researchers have shown the positive effects of substitution on total profit (Hübner et al., 2016). Besides that, this research has shown that the substitution ratio has large effects on the supplier, which is consistent with prior research on the bullwhip effect under substitution (Duan et al., 2015). This research also found that under the context of perishable products, substitution has a significant effect on FR, which is relevant to the finding in the study of Tan and Karabati (2013) under the context of non-perishable products.

The findings on effects of substitution have several managerial implications. First, decision-makers, especially at the supplier, should consider substitution when making decisions because it has significant effects on the performance of the whole system. Second, the low substitution ratio is preferred, as in this situation, the FR is high, and the AI is low. Then, managers can focus on product design or product differentiation strategies, which result in a low substitution ratio for each product. The only drawback in a low substitution ratio is high ORVR or a high bullwhip effect; however these effects can be reduced by recent techniques such as demand management and forecasting methods (Wang & Disney, 2016). In the case of high lost sales probability, other strategies to control consumer demand may be considered. For example, managers can implement dynamic sales plans to delay demand (Ho et al., 2002), which can direct demand to a period where the availability of products is ensured. Another implication comes from the observation that ORVR reduces as lost sales probability reduces. Managers, therefore, can use consumer loyalty programmes (e.g., Uncles et al., 2003) to increase consumer loyalty to a brand or product and reduce lost sales probability.

5.5.3 Research limitations relating to the knowledge of effects of substitution

It is worthwhile to consider other types of substitution ratio in future research. Estimating substitution ratio is not an easy task. This research applied the random substitution matrix; two other matrices (i.e., adjacent substitution and one-item substitution matrices) suggested by Smith and Agrawal (2000) could be used in future research to reflect more customer choices.

5.6 The Effects of Decision-Makers' Opinions

This section discusses the effects of decision-makers' opinions on the selection of the most favourable replenishment policy. According to the proposed framework, the performance of each replenishment policy was recorded by three measures which are weighted by decision-makers' opinions via the AHP technique. The DEA technique evaluated and ranked replenishment policies based on these performance measures and their weights. Therefore, the final selection of the most favourable replenishment policy depends on the weight of each performance measure. With regards to decision-makers' responsibilities, company strategies, and business environment, decision-makers can have various opinions on the importance of each performance measure and these opinions can change across time. For example, a company may pay more attention on fill rate when it penetrates a new market. After generating a sustainable market share, that company may pay more attention to reducing average inventory to reduce operational costs. Consequently, the company may select a replenishment policy that performs better on fill rate or average inventory, respectively.

5.6.1 Gaps relating to the knowledge of effects of decision-makers' opinions

Extant literature has transformed the importance of each measure into the relative cost and used sensitivity analysis to investigate effects of these costs on final decisions. For example, Vidalis et al. (2014) transformed non-financial measures (i.e., fill rate, average inventory, and average cycle time) into a profit function and selected the replenishment policy maximising total profit.

As mentioned in sections 2.5.1 and 5.2, transforming these measures into cost factors is not always easy. In contrast, decision-makers can quickly change priorities based on variations in the business environment (Popović et al., 2014).

Thus, the investigation of decision-makers' opinions on the most favourable replenishment policy is important for managers. Results provided insights into which situations decision-makers' opinions change the most favourable replenishment policy – in other words, in which situations decision-makers should re-evaluate the ranking of replenishment policies. This research conducted sensitivity analysis to explore how changes in decision-makers' opinions affect the selection of the most favourable replenishment policy.

5.6.2 Contributions to the knowledge of effects of decision-makers' opinions

Sensitivity analysis provides information on the stability of ranking through analysis variations on the decision-makers' opinions, the changes of the weight of performance measures, and the ranking of replenishment policies. If the ranking is sensitive to small changes in the measured weights, a careful review of the decision-makers' opinions is recommended or additional performance measures should be considered to improve the discrimination of the present set of measures (Chang et al., 2007).

Surprisingly, the sensitivity analysis performed in section 4.3 showed that the final selection of the most favourable replenishment policy is stable to changes in the decision-makers' opinions. The weights of performance measures were varied separately between 10% and 90%; the weights of other measures changed accordingly, and the total weight was 100%. In all 48 situations (i.e., combinations of eight simulation experiments and six sets of weights), the (1, 26) policy was selected as the most favourable replenishment policy.

The robustness of the selection replenishment policy was surprising given that it was chosen based on the importance of three non-financial measures (i.e., AI, FR, and ORVR). It is supposed that when the most important measure is different, the selected replenishment

policy is different. For example, assume that cost unit value is the importance of each measure, then the replenishment policy minimising total costs as in Kouki et al. (2014), is also the policy performing best under the given set of importance of non-financial measures. The results in Kouki et al. (2014) showed that the most favourable replenishment policy might change under some sets of cost values.

The surprising robustness of the selected replenishment policy may be explained because of the 'start' weight of each non-financial measure, which is evaluated based on the experiment of this researcher. Although this evaluation meets the consistency ratio requirement for the AHP technique (as explained in section 3.6), it may not have strong enough distinction to discriminate the selected replenishment policy. This research also notes that weak discrimination is common in the literature. For example, the selected replenishment policy does not change under some sets of cost values in the study of Kouki et al. (2014). Another example is the study of Temur (2016) where the ranking of warehouse location does not change when the importance of each measure of warehouse location changes.

The robustness or stability in selecting the most favourable replenishment policy is important. It means managers do not have to perform the AHP technique again if they change their opinions on the importance of measures. Then, the manager can focus more on other business strategies (e.g., Research and Development or Sales and Marketing strategy).

5.6.3 Research limitation relating to knowledge of effects of decision-makers' opinions

One limitation of this research is the 'start' weight of each performance measure. The researcher bases these weights on seven years' experience working in supply chain departments for dairy and pharmaceutical companies (as explained in section 3.6.2). These weights may be different under different companies, managers, or business situations, and this is an area for future research.

5.7 Summary of Discussion and Implications

This chapter discussed the research' results and implications from the results. This research extended the knowledge inventory management for perishable and substitutable products. The research's results addressed six key issues in perishable inventory management as discussed in section 2.5 and answered the three research questions of this research as mentioned in section 2.6.

This research proved that non-financial performance measures could be used to select the most favourable replenishment policy without transforming them into total profit or cost functions. This research considered the advantages of using non-financial performance measures in the inventory management (see section 5.2.1) and selected three non-financial measures, namely, AI, FR, and ORVR. Then, this research proposed a decision framework that integrated DES, AHP, and DEA to select the most favourable replenishment policy. The integration framework performed well in as illustrated in section 4.1. The framework also allows consideration of more performance measures and encourages more departments or responsible people to become involved. The chosen policy in the illustration is comparable with the result of Kouki et al. (2014) and confirm the efficiency of the framework.

Insights into the effects of decision-makers' opinions in the selection of the most favourable replenishment policy have been developed using sensitivity analysis in the AHP step. Surprisingly, the sensitivity analysis result showed that the selection of the most favourable replenishment policy is stable to changes in the decision-makers' opinions. This finding means that the managers can focus more on other business strategies and do not need to perform the AHP again if the importance of measures is change.

The main and interaction effects of the input factors (i.e., consumer demand, product lifetime, and lost sales probability) on the performance of the inventory model have been established using sensitivity analysis and MANOVA test. This is the first known research that

shows these effects on non-financial performance measures, namely, AI, FR, and ORVR, in the context of perishable and substitutable products. The research's results showed that the supplier's performance is affected largely due to the existence of the bullwhip effect in the model. The retailers are affected mostly in medium and small effect sizes.

Chapter 6 Conclusion

This research aims at closing the gaps in the literature of inventory management for perishable and substitutable products (as mentioned in section 2.6.1). This research used non-financial performance measures to define the most favourable replenishment policy for one supplier and two retailers in the given context of three perishable and substitutable products. It also seeks to understand the effects of decision-makers' opinions on the selection of policy and input factors (i.e., consumer demand, product lifetime, and substitution ratio) and on the performance of the studied model. This research proposed a decision framework that integrates DES, AHP, and DEA to select the most favourable replenishment policy, and provided insights into the given model. Section 6.1 addresses the research objectives, while section 6.2 outlines the contributions and section 6.3 summarises the limitations of this research. Section 6.4 suggests potential future research directions to extend the research findings. Final remarks in section 6.5 conclude the research. Figure 6.1 summarises the structure of this chapter.

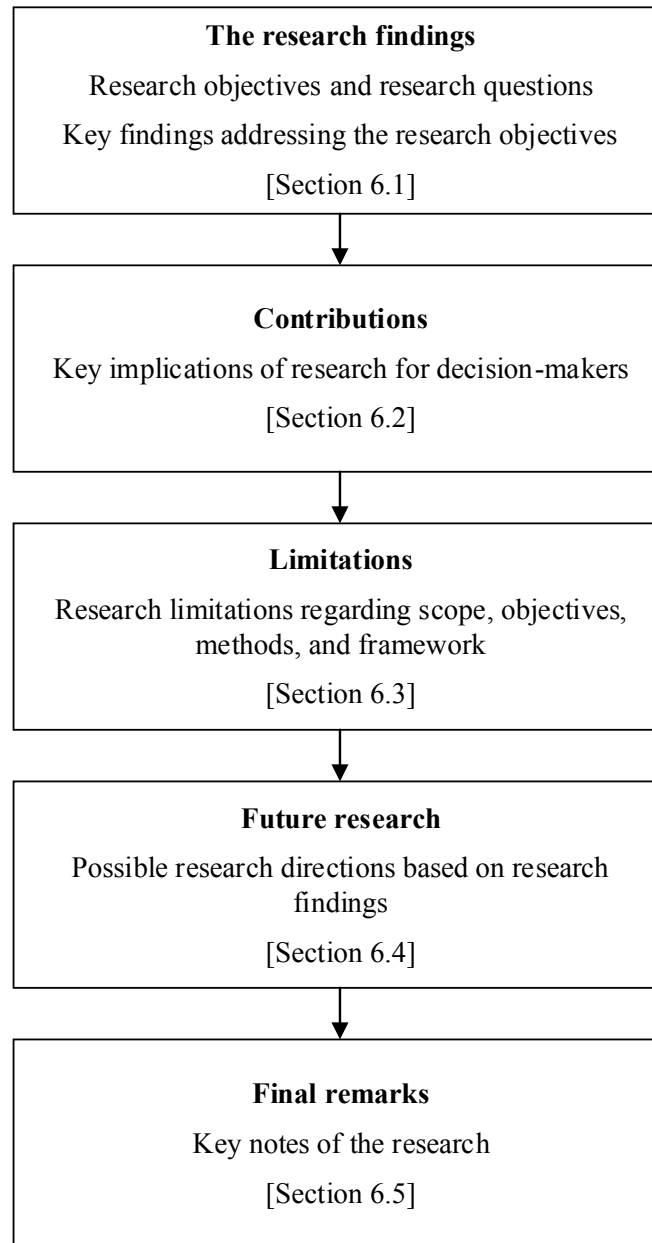


Figure 6.1: Structure of Conclusion chapter

6.1 The Research Findings

This section is structured to reflect results and findings related to two research objectives and three relevant research questions established in Chapter 1.

- Research Objective 1 (RO1): Use non-financial performance measures to define the most favourable replenishment policy for a two-echelon model under a given context of perishable and substitutable products.
- Research Objective 2 (RO2): Evaluate and explore the importance and interaction of these characteristics in a perishable and substitutable inventory management model.
- Research Question 1 (RQ1): What is the most favourable replenishment policy in a given context of perishable and substitutable products?
- Research Question 2 (RQ2): Given the context of perishable and substitutable products, how do decision-makers' opinions affect the selection of the most favourable replenishment policy?
- Research Question 3 (RQ3): Given the most favourable replenishment policy, how do the characteristics of the inventory model influence the performance of a two-echelon inventory model for perishable and substitutable products?

6.1.1 RO1 – The most favourable replenishment policy

This research studied a two-echelon model with one supplier and two retailers dealing three perishable and substitutable products. The product lifetime follows an exponential distribution. The consumer demand follows a Poisson distribution; excess demand is either lost or substituted by another available product with a given probability. The supplier and retailers follow a periodic review replenishment policy (T, S) with a lead time of 1 day.

Results showed that the most favourable replenishment policy is (1, 26), meaning the replenishment policy is reviewed at the end of each day, and a replenishment order is placed to bring the inventory level back to 26. Prior research has usually selected a replenishment policy that minimises total costs or maximises total profit. This research considered the disadvantages of using one single financial objective and the advantages of using multiple non-financial

objectives, and uses a set of three measures (i.e., AI, FR, and ORVR) (as explained in section 2.5.6) to evaluate and rank the performance of possible replenishment policies. The result indicated that policy (1, 26), which was the best trade-off between three measures (i.e., AI, FR, and ORVR), was the most favourable policy. Although this research takes a different approach (non-financial instead of financial), the result is most closely aligned with the work of Kouki et al. (2014), who focused on a retailer with one product only.

6.1.2 RO2 – Effects of problem characteristics

A carefully designed decision framework, which integrates DES, AHP, and DEA, enables further analysis of problem characteristics in an inventory model. Specifically, this research investigated and provided insights into the effects of decision-makers' opinions on the selection of the most favourable replenishment policy and input factors (i.e., consumer demand, product lifetime, substitution) and on model performance.

6.1.2.1 Decision-makers' opinions

Surprisingly, this research showed that the selection of the most favourable replenishment policy is stable to changes in decision-makers' opinions (section 4.3). This research selected a policy that is the best trade-off between three measures (i.e., AI, FR, and ORVR). Thus, when the importance of one measure is high, a policy, which performs best on that measure, has a high possibility of being selected. The selected policy is likely different when the most important measure or the decision-makers' opinion changes. In contrast to that assumption, this result showed that changes in decision-makers' opinions do not affect the selection of the most favourable replenishment policy.

This research's finding is important as it means managers do not have to perform the AHP technique again if they change their opinions on the importance of measures. Instead, the

manager could focus more on other business activities (e.g., Research and Development or Sales and Marketing strategy).

6.1.2.2 Consumer demand

Consumer demand has large effects on all performance (i.e., AI, FR, and ORVR) at the supplier and retailers (see section 4.5). Specifically, the sensitivity analysis results showed that as the average of consumer demand increases, the AI increases and the FR and ORVR decrease. When consumer demand interacts with product lifetime, this interaction has a large effect on all performance (i.e., AI, FR, and ORVR) at the supplier and retailers. When consumer demand interacts with substitution, this interaction has large effects on all performance (i.e., AI, FR, and ORVR) at the supplier and AI at retailer. When consumer demand interacts with product lifetime and substitution, this interaction has large effects on AI and ORVR at the supplier. These results suggested that consumer demand has stronger effects on the supplier than at the retailers. Managers can reduce uncertainty in demand or increase demand to improve performance of the inventory model.

Consumer demand is an uncontrollable factor that creates complexity when determining a favourable replenishment policy and its uncertainty impacts directly on the performance of a supply chain network. Underestimating demand can lead to replenishment policies that cannot protect a company against the risks (e.g., substitution, disaster); overestimating demand, however, can lead to loss of opportunity costs due to unnecessary capital investment. Most research has focused on the effect of consumer demand on fill rate. However, supply chain is multi-dimensional by nature and it is necessary to study the effect of consumer demand on other measures besides fill rate. This research selected three measures (i.e., AI, FR, and ORVR) (as explained in section 3.5.3) to evaluate the performance of replenishment policies and the effects of consumer demand. This research studied consumer demand following a Poisson distribution, in which the average is equal to the uncertainty.

Consequently, this research showed that AI increases and FR decreases as uncertainty of consumer demand increases. Future research should now focus on recognising and managing uncertainty in consumer demand.

6.1.2.3 Product lifetime

This research showed that the product lifetime has large effects on all performance measures (i.e., AI, FR, and ORVR) at the supplier and retailers (see section 4.5). The sensitivity analysis shows that when the product lifetime increases, the AI and FR increases at both the supplier and retailer side and the ORVR decreases at the retailer and increases at supplier side. When product lifetime interacts with substitution, this interaction has large effects on all performance measures (i.e., AI, FR, and ORVR) at the supplier.

The perishability or the random lifetime of products is one of major factors that affects perishable inventory management systems. Prior research has mostly studied the effect of product lifetime on total costs or total profit of the inventory model. By extending the work of Kouki et al. (2014) to a two-echelon model for perishable and substitutable products, this research also assumed product lifetime follows an exponential distribution and studies its effects on three performance measures of the model (i.e., AI, FR, and ORVR), which are translated from common cost elements in a total cost function (as explained in section 3.5.3). The results showed that high AI is the only unexpected performance when product lifetime is high. Future research, therefore, can focus on sales plans that can drive demand and reduce AI.

6.1.2.4 Substitution

This research showed that substitution has significant effects on all performance at the supplier and retailers (see section 4.5). As the substitution ratio decreases, the AI decreases and the FR and ORVR increase. Substitution occurs because managers usually offer ranges of products that have similar characteristics and can be substituted for each other to respond to uncertainties

in the business environment and compete for market share. When facing a stock-out situation, a customer may either substitute with a similar product or decide not to buy anything. In a substitution situation, demand for a product is not only by its characteristics, but also by other products with similar characteristics. Consequently, substitution increases the uncertainties of demand and managers must consider the effects of substitution on demand to determine suitable replenishment policies. This research showed that ORVR is the only drawback performance when the substitution ratio is low. Future research can focus on sharing information between echelons to reduce the bullwhip effect or ORVR.

6.2 Contributions

This research integrated DES, AHP, and DEA to address the research gap on inventory management for perishable and substitutable products under a two-echelon model (one supplier and two retailers). From that, effects of problem characteristics on the inventory model are explored and investigated. Consequently, this research has theoretical, methodological, and managerial contributions to perishable inventory management that are discussed follows. Theoretical and methodological contributions, which are summarised in Table 6.1, are discussed based on related extant literature and findings in the Discussion chapter. Table 6.2 compares theoretical and methodological contributions of this research and key extant research.

6.2.1 Theoretical contributions

This research has six theoretical contributions that are based on the studied two-echelon model (one supplier and two retailers) for perishable and substitutable products. These contributions fulfil the purpose of a theory as mention in section 3.3.1, which includes three criteria: originality, utility (practically or scientifically useful) (Corley & Gioia, 2011), and the ability to stimulate future research (Hambrick, 2007; Kilduff, 2006). The findings of this research are original because the selection of the most favourable replenishment policy and effects of

problem characteristics are linked to research gaps and un-investigated context mentioned in section 2.6.1. The findings are seen as useful as they have the ability to improve managerial practice in managing perishable and substitutable products (see section 6.2.3). Section 6.4 suggests future research directions, thereby proving the ability to stimulate future research as a last criterion that indicates the presence of theoretical contributions.

For the first theoretical contribution, this research selected AI, FR, and ORVR as three non-financial measures, which are suitable for defining the most favourable replenishment policy. Most of the literature on perishable inventory management has optimised one financial measure to select the optimal replenishment policy. The financial measure is used commonly due to its advantages, e.g., clear definitions of objective, direct solution methods, the single best result generated, and clearer interpretation of this result. However, supply chains are by nature multi-dimensional; optimising one measure ignores other important measures. Therefore, multiple non-financial performance measures have been used in operations and supply chain management. There are many non-financial measures available but selecting relevant measures for a company is problematic. This research considered the advantages of non-financial measures, the bullwhip effect phenomenon under a two-echelon model and common cost factors in inventory management, and selected three measures (i.e., AI, FR, and ORVR) to define replenishment policy (as discussed in section 5.2). Three measures, AI, FR, and ORVR, are relevant for a two-echelon inventory model as they cover all common cost factors and reflect the multi-dimensional nature of SMC.

Second, this research provided insights on the effects of consumer demand and its interactions with production lifetime and substitution on the performance of the inventory model. In contrast to prior works which have shown the effects of consumer demand on total cost or profit, this research provided knowledge of the effects of consumer demand on specific performance measures. Results showed that reduced uncertainty in consumer demand could be

used to reduce AI and increase FR, while increase in the average of consumer demand increases ORVR at the supplier and retailer sides.

Third, this research provided more knowledge of the effects of product lifetime and its interactions with consumer demand and substitution on the performance of the inventory model. Similar to the consumer demand characteristic, this research investigated these effects on non-financial measures, namely, AI, FR, and ORVR. Results showed that product lifetime has large effects on AI, FR, and ORVR at the supplier and retailer sides. As the uncertainty in product lifetime reduces, the AI reduces. As the average of product lifetime increases, the FR increases.

Fourth, this research provided knowledge of the effects of substitution and its interactions with consumer demand and product lifetime on the performance of the inventory model (i.e., non-financial measures, AI, FR, and ORVR). Results showed that substitution has large effects on AI, FR, and ORVR at the supplier side, which is mainly due to the bullwhip effect phenomenon. As the substitution ratio decreases, the AI decreases and the FR and ORVR increase at the supplier side.

Fifth, this research considered perishable and substitutable products for a two-echelon model where product lifetime follows an exponential distribution. This is an extension of the work of Duan and Liao (2014), who only considered products with a fixed lifetime. It is also an extension of the work of Kouki et al. (2014), who focused on total costs at a retailer only. This extension is important as it is more realistic and fills the gap in the research on perishable and substitutable products under a multi-echelon model.

Sixth, this research provided insights on the effects of decision-makers' opinions on the selection of the most favourable replenishment policy. Surprisingly, the selection of the most favourable replenishment policy is stable to changes in the decision-makers' opinions. The robustness in selection of the most favourable replenishment policy means that managers do

not have to re-evaluate replenishment policies if they change their opinions on the importance of measures. This allows managers to focus more on other business strategies (e.g., Research and Development or Sales and Marketing strategy).

6.2.2 Methodological contribution

This research further provided a methodological contribution. This research proposed a decision framework for using non-financial measures to select the most favourable replenishment policy. The framework integrates DES, AHP, and DEA and is robust as it has the ability to consider more responsible departments and people. This framework also does not need to transform non-financial measures into cost factors, thus, it is easy to use and communicate. This framework is the result of original research; that is, it is the first known work to define the most favourable replenishment policy based on trade-offs between non-financial measures. Moreover, this approach helps in the exploration of all unknown relationships between problem characteristics (i.e., decision-makers' opinions, consumer demand, product lifetime, and substitution ratio) and model performance.

Most research on perishable inventory management has selected a replenishment policy that optimises the total cost or total profit function. This research considered the advantages of using non-financial measures and selected three non-financial measures that are relevant to the most common cost factors in the literature on perishable inventory management. In perishable inventory management, DES is a valuable method to evaluate the multiple performance measures. As the three measures in this research conflict with each other, it is impossible to find a replenishment policy that optimises all three measures simultaneously. Furthermore, the knowledge, understanding, and choice of each performance measure differ from person to person. Therefore, it is necessary to integrate MCDM methods into the simulation method when conflicting performance measures are considered simultaneously (Xu et al., 2011).

The proposed framework integrates DES, AHP, and DEA to select the most favourable replenishment policy. First, the simulation model was built and run for each scenario of a replenishment policy or each pair-review period and order-up-to level. The performance of each replenishment policy is measured by three non-financial measures (i.e., AI, FR, and ORVR). Second, the AHP method was used to weight the importance of each performance measure. The weight of each measure is then multiplied with the values received from the DES model to form the relative value of each measure. Third, the super-efficiency DEA method was performed to evaluate and rank the performance of each replenishment policy based on relative values. The policy with the least DEA super-efficiency score was selected as the most favourable replenishment policy.

The proposed framework performs well as illustrated in section 4.1. The policy (1, 26) (meaning the inventory level is reviewed every day and a replenishment order is placed to bring it back to 26) was selected as the most favourable replenishment policy. The chosen policy is comparable with the result in the study of Kouki et al. (2014), and confirms the efficiency of the framework. Under different contexts, the framework can be used, as illustrated in section 4.1, to select the most favourable replenishment policy.

Table 6.1: Summary of theoretical, methodological contributions and related findings, literature

Contributions	Related implications	Related gaps	Related literature
Select a range of non-financial measures to find the most favourable replenishment policy for a two-echelon model (section 5.2.3 and 6.2.1)	Easy to use and communicate, motivate performance, easy to modify (section 5.2.1)	Problematic in selecting which measures are suitable for a company (section 2.5.1 and 5.2.2)	The advantages of using non-financial measures (section 2.5.1 and 5.2.1)
Propose a decision framework, which uses non-financial measures to find the most favourable replenishment policy (section 5.2.3 and 6.2.2)	Can be applied to a model with a greater number of non-financial measures (section 5.2.1)	No unique and well-defined framework that can be followed step-by-step for a decision-making process (section 2.5.1 and 5.2.2)	The advantages of using the multi-methodology approach, or an integration of DES, AHP, and DEA (section 2.5.1, 3.4, 3.8, and 5.2.1)
Provide effects of consumer demand and its interactions with product lifetime, and effects of substitution on performance measures (section 5.3.2 and 6.2.1)	Can define activities based on company's objectives (section 6.2.3.1)	Lack of knowledge of effects of consumer demand on non-financial measures for perishable inventory management (section 5.3.1)	Effects of consumer demand are mostly shown in financial functions (section 2.5.2)
Provide effects of product lifetime and its interactions with consumer demand, and effects of substitution on performance measures (section 5.4.2 and 6.2.1)	Can define activities based on company's objectives (section 6.2.3.2)	Lack of knowledge of effects of product lifetime on non-financial measures for perishable inventory management (section 5.4.1)	Effects of product lifetime are mostly shown in financial functions (section 2.5.3)
Provide effects of substitution and its interactions with product lifetime and consumer demand on performance measures (section 5.5.2 and 6.2.1)	Can define activities based on company's objectives (section 6.2.3.3)	Lack of knowledge of effects of substitution on non-financial measures for perishable inventory management (section 5.5.1)	Effects of substitution is mostly shown in financial functions (section 2.5.4 and 2.5.5)

Table 6.1: Summary of theoretical, methodological contributions and related findings, literature (continued)

Contributions	Related implications	Related gaps	Related literature
Provide effects of decision-makers' opinion (section 5.6.2 and 6.2.1)	Managers can focus on other business activities (section 6.2.3.4)	Lack of knowledge of effects of decision-makers' opinion on selecting the most favourable replenishment policy (section 5.6.1)	Good decisions cannot be achieved from incomplete information, which is common issues in financial measures approach (section 2.5.6)
Study products with random lifetime under the two-echelon model and substitution model (section 5.5.2 and 6.2.1)	Extension to a more realistic problem (section 6.2.1)	Lack of research on perishable and substitutable products with random lifetime (section 2.5.7 and 2.5.8)	Perishable inventory management with substitutable and multi-echelon models (section 2.5.7 and 2.5.8)

Table 6.2: Comparison of theoretical and methodological contributions in this research with key extant research

Research	# product	# echelon	Method	Rep. policy	Dem	Exc.	Lifetime	Substitution	Demand effect on	Substitution effect on	Lifetime effect on	Performance measures
Tan and Karabati (2013)	2	1	Sim	(T, S)	P	Lost	Inf.	Flexible	N/A	Total profit	N/A	Total profit
Vidalis et al. (2014)	1	2	Sim	(S, s)	P	Lost	Inf.	N/A	N/A	N/A	N/A	Total profit
Duan and Liao (2014)	8	2	Sim	(T, S)	sto	No	Fixed	Flexible	N/A	Outdated rate	N/A	Outdated rate
Kouki et al. (2014)	1	1	Sim	(T, S)	P	Lost	Exp.	N/A	N/A	N/A	Total cost	Total cost
Kouki and Jouini (2015)	1	1	Sim	(T, r, Q)	P	Lost	Erlang	N/A	N/A	N/A	Total cost	Total cost
Civelek et al. (2015)	2	1	Sim	(T, S)	sto	No	Fixed	Flexible	N/A	Total cost	N/A	Total cost
Bansal and Moritz (2015)	2	1	Sim	(r, Q)	sto	No	new.	Uni-direction	N/A	Total profit	N/A	Total profit
Alaei and Setak (2015)	1	2	Sim	(r, Q)	sto	Lost	new.	N/A	N/A	N/A	N/A	Firm's profit, Vendor's routing cost, and Service level

Table 6.2: Comparison of theoretical and methodological contributions in this research with key extant research (continued)

Research	# product	# echelon	Method	Rep. policy	Dem	Exc.	Lifetime	Substitution	Demand effect on	Substitution effect on	Lifetime effect on	Performance measures
Xue et al. (2016)	1	2	Sim	(r, Q)	sto	Lost	new.	N/A	FR	N/A	N/A	Total profit
Hübner et al. (2016)	2	1	Sim	(r, Q)	sto	Lost	new.	Flexible	N/A	Total profit	N/A	Total profit
Giri and Sarker (2016)	1	1	Sim	(r, Q)	sto	Lost	new.	N/A	N/A	N/A	N/A	Total profit
Pauls-Worm et al. (in press)	1	1	Sim	(Y, Q)	sto	Lost	Fixed	N/A	FR	N/A	N/A	Total cost
This research	3	2	DES, AHP, DEA	(T, S)	P	Lost	Exp.	Flexible	FR, AI, and ORVR	FR, AI, and ORVR	FR, AI, and ORVR	FR, AI, and ORVR

Note: Rep. policy: Replenishment policy;

Sim.: Simulation; DES: Discrete-event simulation; AHP: Analytic Hierarchy Process; DEA: Data Envelopment Analysis

Dem.: Consumer demand; P.: Poisson distribution; sto.: Stochastic distribution

Exc.: Excess demand; Lost: Lost sales; No: No lost sales or back order

Inf.: Infinite lifetime; new.: Newsvendor product; Exp.: Exponential distribution

N/A: Not applicable

FR: Fill rate; AI: Average inventory; ORVR: Order rate variant ratio

6.2.3 Managerial contributions

In addition to theoretical and methodological contributions, this research also provided a number of managerial implications, which are based on the understanding of the problem characteristics of the performance of the inventory model and are discussed subsequently. Through sensitivity analysis, this research provided understandings about the relationships between consumer demand, product lifetime, and substitution ratio and three performance measures of an inventory model (i.e., AI, FR, and ORVR), and also between decision-makers' opinions and the selection of the most favourable replenishment policy. These understandings help managers to understand the effects of problem characteristics on the performance of the inventory model and to take relevant actions based on their objective or priority. These managerial implications focus on large effect relationships as they quickly provide results. Results showed that input factors have larger effects on the supplier than on the retailer. Consequently, the supplier should focus more on the effects of input factors on its performance. Table 6.3 and Table 6.4 summarise all managerial implications for the supplier and retailer.

6.2.3.1 Effects of consumer demand

Results showed that compared to a high demand situation, AI is lower and FR and ORVR are higher at both the supplier and retailer sides under a low demand situation, which suggest five implications as follows:

- If managers at both the supplier and retailer side primarily focus on reducing AI and increasing FR, they are able to focus on reducing uncertainty in consumer demand, which can be achieved with forecast techniques. Note that AI covers expired products or food waste (see section 2.5.6). Reducing AI also reduces food waste, which addresses a global social issue as mentioned in section 1.1.

- When demand uncertainty is high, if suppliers want to reduce AI and increase FR, they should reduce the substitution ratio, which may be done via demand-driven techniques, for example, product differentiation strategy.
- When demand uncertainty is high, if suppliers primarily focus on increasing FR, they can increase product lifetime without substantial change in AI and ORVR.
- When demand uncertainty is high, if retailers primarily focus on reducing AI and increasing FR, they should also focus on reducing uncertainty in product lifetime and increasing product lifetime. It is interesting to note that product lifetime mainly depends on suppliers (e.g., manufacturing technology); however, retailers can also apply techniques (e.g., information sharing, storage condition) to better maintain and inform product freshness.
- If managers at both the supplier and retailer side primarily focus on reducing ORVR, they should also focus on increasing consumer demand, which can be done with other sales and marketing activities.

6.2.3.2 Effects of product lifetime

Results showed that compared to a high product lifetime situation, AI and FR are lower at both the supplier and retailer sides, ORVR is lower at supplier and higher at retailer side under low product lifetime situation, which suggest four implications as follows:

- If managers at both the supplier and retailer sides primarily focus on reducing AI, they should also focus on reducing uncertainty in product lifetime, for example, information sharing and storage conditions.
- When product lifetime uncertainty is high, if suppliers primarily focus on increasing FR, they should also focus on reducing substitution ratio, for example, product differentiation strategy.

- When product lifetime uncertainty is high, if suppliers and retailers primarily focus on reducing AI or increasing FR, they should also focus on reducing demand uncertainty, for example, forecast techniques.
- If managers primarily focus on reducing ORVR at the supplier side, they should also focus on reducing uncertainty in product lifetime.

6.2.3.3 Effects of substitution

Results showed that compared to a high substitution ratio situation, the AI is lower and FR and ORVR are higher at both the supplier and retailer sides under a low substitution ratio situation. The substitution ratio and its interaction with consumer demand and product lifetime have mostly a small and medium effect on performance at the retailer, in contrast to all large effects on the supplier side. These findings suggest four implications as follows:

- If managers at the supplier side primarily focus on reducing AI and increasing FR, they should also focus on reducing substitution ratio, which can be achieved by product differentiation or product design activities.
- When the substitution ratio is high, if suppliers primarily focus on increasing FR, they should also focus on reducing uncertainty in consumer demand or increasing product lifetime.
- When the substitution ratio is high, if suppliers primarily focus on reducing AI or increasing FR, they should also focus on reducing uncertainty in consumer demand.
- If managers at the supplier side primarily focus on reducing ORVR, they should also focus on increasing the substitution ratio, which can be achieved by consumer loyalty programmes.

6.2.3.4 Effects of decision-makers' opinions

Results showed that changes in decision-makers' opinions do not change the most favourable replenishment policy under the studied context. This finding means that managers do not need to be concerned about the effects of changing priority or opinions. They do not need to perform the AHP technique again if they change their opinions on the importance of measures. They can focus more on other business activities (e.g., Research and Development or Sales and Marketing activities).

Table 6.3: Summary of managerial implications at the supplier

Focused measure			Controllable factor			Managerial implications	Possible techniques
AI	FR	ORVR	Demand	Lifetime	Substitution		
Yes			Yes			At a supplier, reduced uncertainty in demand can reduce AI regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
Yes				Yes		At a supplier, reduced uncertainty in product lifetime can reduce AI regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes					Yes	At a supplier, reduced substitution ratio can reduce AI regardless of consumer demand and product lifetime	Increase product differentiation (section 6.2.3.3)
	Yes		Yes			At a supplier, reduced uncertainty in demand can increase FR regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
	Yes			Yes		At a supplier, increased product lifetime can increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
	Yes				Yes	At a supplier, reduced substitution ratio can increase FR regardless of consumer demand and product lifetime	Increase product differentiation (section 6.2.3.3)
		Yes	Yes			At a supplier, increased consumer demand can reduce ORVR regardless of product lifetime and substitution ratio	Sales and Marketing (section 6.2.3.1)
		Yes		Yes		At a supplier, reduced uncertainty in product lifetime can reduce ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)

Table 6.3: Summary of managerial implications at the supplier (continued)

Focused measure			Controllable factor			Managerial implications	Possible techniques
AI	FR	ORVR	Demand	Lifetime	Substitution		
		Yes			Yes	At a supplier, increased substitution ratio can reduce ORVR regardless of consumer demand and product lifetime	Increase consumer loyalty (section 6.2.3.3)
Yes	Yes		Yes			At a supplier, reduced uncertainty in demand can reduce AI and increase FR regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
Yes	Yes			Yes		At a supplier, reduced uncertainty in product lifetime and increased product lifetime can reduce AI and increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes	Yes				Yes	At a supplier, reduced substitution ratio can reduce AI and increase FR regardless of consumer demand and product lifetime	Increase product differentiation (section 6.2.3.3)
Yes		Yes	Yes			At a supplier, increased demand and reduced uncertainty in demand can reduce AI and ORVR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)
Yes		Yes		Yes		At a supplier, reduced uncertainty in product lifetime can reduce AI and ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes		Yes			Yes	Impossible	
	Yes	Yes	Yes			At a supplier, increased demand and reduced uncertainty in demand can increase FR and reduce ORVR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)

Table 6.3: Summary of managerial implications at the supplier (continued)

Focused measure			Controllable factor			Managerial implications	Possible techniques
AI	FR	ORVR	Demand	Lifetime	Substitution		
Yes	Yes			Yes		At a supplier, increased product lifetime and reduced uncertainty in product lifetime can increase FR and reduce ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
	Yes	Yes			Yes	Impossible	
Yes	Yes	Yes	Yes			At a supplier, increased demand and reduced uncertainty in demand can reduce AI and ORVR, increase FR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)
Yes	Yes	Yes		Yes		At a supplier, reduced uncertainty in product lifetime and increased product lifetime can reduce AI and ORVR and increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes	Yes	Yes			Yes	Impossible	

Note: For the purpose of simplification, this table presents managerial implications for separate input factors only. Implications for interactions between two or three input factors can be combined from this table. For example, reduced uncertainty in demand and uncertainty in product lifetime can reduce AI at a supplier.

Table 6.4: Summary of managerial implications at the retailer

Focused measure			Controllable factor			Managerial implications	Possible techniques
AI	FR	ORVR	Demand	Lifetime	Substitution		
Yes			Yes			At a retailer, reduced uncertainty in demand can reduce AI regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
Yes				Yes		At a retailer, reduced uncertainty in product lifetime can reduce AI regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
	Yes		Yes			At a retailer, reduced uncertainty in demand can increase FR regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
	Yes			Yes		At a retailer, increased product lifetime can increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
		Yes	Yes			At a retailer, increased consumer demand can reduce ORVR regardless of product lifetime and substitution ratio	Sales and Marketing (section 6.2.3.1)
		Yes		Yes		At a retailer, increased product lifetime can reduce ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes	Yes		Yes			At a retailer, reduced uncertainty in demand can reduce AI and increase FR regardless of product lifetime and substitution ratio	Forecast (section 6.2.3.1)
Yes	Yes			Yes		At a retailer, increased product lifetime and reduced uncertainty can reduce AI and increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)

Table 6.4: Summary of managerial implications at the retailer (continued)

Focused measure			Controllable factor			Managerial implications	Possible techniques
AI	FR	ORVR	Demand	Lifetime	Substitution		
Yes		Yes	Yes			At a retailer, increased consumer demand and reduced uncertainty in demand can reduce AI and ORVR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)
Yes		Yes		Yes		At a retailer, increased product lifetime and reduced uncertainty can reduce AI and ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
	Yes	Yes	Yes			At a retailer, increased consumer demand and reduced uncertainty in demand can reduce ORVR and increase FR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)
	Yes	Yes		Yes		At a retailer, increased product lifetime can increase FR and reduced ORVR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)
Yes	Yes	Yes	Yes			At a retailer, increased consumer demand and reduced uncertainty in demand can reduce AI and ORVR and increase FR regardless of product lifetime and substitution ratio	Sales and Marketing, Forecast (section 6.2.3.1)
Yes	Yes	Yes		Yes		At a retailer, increased product lifetime and reduced uncertainty can reduce AI and ORVR and increase FR regardless of consumer demand and substitution ratio	RFID, Sharing information (section 6.2.3.2)

Note: For the purpose of simplification, this table presents managerial implications for separate input factors only. Implications for interactions between two or three input factors can be combined from this table. For example, reduced uncertainty in demand and uncertainty in product lifetime can reduce AI at a retailer.

6.3 Limitations

This section indicates three limitations of this research that relate to the scope, objectives, and research processes of this research.

First, there are many research opportunities for perishable inventory management, which become obvious through the literature review in Chapter 2, especially in section 2.5, which identifies the gap in the literature. Although there are many research questions that could be explored, this research limits the scope to a manageable work, and develops two feasible research objectives. The findings in this research provide basic insights about defining a replenishment policy for perishable and substitutable products. However, they cannot address other important research directions in supply chain management, for example, considering pricing competition in inventory management (see Şen (2016) as an example).

Second, while the decision framework is illustrated successfully in this research, its limitation relates to the AHP process. The researcher used a case study and the experience of working in a supply chain department to define weights for performance measures (see section 3.6.2). Although this is not a negative effect, it may provide biased outcomes.

The third limitation of this research relates to the data used in the simulation mode. This research was the first known work to use three non-financial measures (i.e., AI, FR, and ORVR), which extended the works of Kouki et al. (2014) and Duan and Liao (2014), to define the most favourable replenishment policy. Therefore, using published parameters from a prior model (i.e., Kouki et al. (2014)) (rather than the use of empirical data) is appropriate (Craighead & Meredith, 2008). Thus, this research also inherits limitations on data from Kouki et al. (2014); for example, Kouki and Jouini (2015) considered product lifetime follows an Erlang distribution to cover a greater range of variability, instead of exponential distribution as in the study of Kouki et al. (2014).

6.4 Future Research

This research achieves two research objectives defined in Chapter 1 and provided additional insights on perishable and substitutable inventory management. However, there are several opportunities for future research. Specifically, this research suggests future research focus on new research contexts that originate from this research. Consequently, eight future research opportunities are discussed as follows.

First, research results showed that reducing the uncertainty in consumer demand and product lifetime improves performance at the supplier and retailer sides, which include reducing average inventory, increasing fill rate, and reducing order rate variance ratio. This research suggests using techniques (e.g., forecasting and sharing information) to reduce the uncertainty in consumer demand and product lifetime. Future research can further investigate how much these possible techniques improve performance, which may serve as an analysis factor for adopting these possible techniques. For example, van Donselaar et al. (2016) built regression models to study the effects of price discounts on product sales during a promotion. The authors showed that forecast accuracy improves when there are distinct product categories. Future research can apply the regression model produced by van Donselaar et al. (2016) to generate consumer demand and examine the performance of the inventory model during a promotion. Understanding performance of the inventory model during a promotion helps companies to better prepare for a promotion campaign, for example, warehouse or transportation preparation.

Second, results showed that reducing the substitution ratio for each product can reduce average inventory and increase fill rate, especially at the supplier side. This research suggested that increasing the number of products may reduce the substitution ratio for each product, which reduces average inventory and fill rate. However, increasing the number of products increases the total average and creates difficulties in managing inventory. Therefore, future

research may study this trade-off decision and define the most suitable number of products for each brand a company can offer. For example, future research can adopt the simulation model framework proposed in this research (see sections 3.5, 3.6, and 3.7) and increase the number of products. Different situations have different number of products. Performance results (i.e., average inventory, fill rate, and order rate variance ratio) of the inventory model under different situations can then be evaluated and ranked. A situation performing best in three non-financial measures is the most suitable number of products for a company.

Third, this research showed that decision-makers' opinions do not change the most favourable replenishment policy. This result is surprising as the final decision is usually meant to change once the decision-makers' opinions change. In other contexts, decision-makers' opinions may have effects on the most favourable replenishment policy. The importance of performance measures may be different from different companies, managers, or business situations. Future research could conduct a case study to investigate the effects of decision-makers' opinions in a real problem and examine under which context decision-makers' opinions change the most favourable replenishment policy. For example, real data from a number of products under the same product brand can be used to run the simulation model (as shown in section 3.5). Responsible decision-makers can be asked to do a pairwise comparison of three performance measures (i.e., average inventory, fill rate, and order rate variance ratio), which can then be used to calculate the weight of each measure (via the AHP as explained in section 3.6). The DEA (as in section 3.7) can be used to select the most favourable replenishment policy for companies. Sensitivity analysis (as in section 4.3) can be performed to investigate which set of decision-makers' opinions change the most favourable replenishment policy. A case study can help to solve a real problem and investigate the performance of the proposed model in reality.

Future research directions also arise from the exploratory nature of this research, which aims at using non-financial measures to select the most favourable replenishment policy for perishable and substitutable products. Therefore, this research did not add excessive complexity that may disguise the understanding of the results and comes at the price of a number of limitations. This research showed that non-financial measures could be used directly to find the most favourable replenishment policy for a company. However, it is a fact that in the real business environment there are usually more than two echelons in a supply chain and a company often offers more than three products from the same brand.

Thus, the fourth future research direction can extend this research by examining a real problem. For example, future research can study a supply chain model with more than two echelons, for example, manufacturers, distributors, and retailers. Alternatively, future research can consider more than three products, for example, one type of milk with different packaging sizes. This research considered a periodic review policy (T, S) with a fixed lead time as 1 day. Other types of replenishment policy (e.g., continuous review policy) or lead time (e.g., a longer lead time or random lead time in urban areas) may be adopted to extend this research.

Fifth, future research can apply a greater number of non-financial measures. This research used three non-financial measures (i.e., AI, FR, and ORVR) which are translated from common cost factors according to the measurement adoption guideline in the work of Cannella et al. (2013a). They may not cover all dimensions of a company and may produce game-playing behaviours (Ittner et al., 2003), or create a perception of unfairness, resulting in reduced performance results (Burney et al., 2009). Therefore, future research may use a greater number of non-financial measures to overcome these disadvantages. Future research can also apply different frameworks to define the performance measures for a company, for example, Balance Scorecard (Kaplan & Norton, 1995).

Sixth, this research assumed that consumer demand follows a Poisson distribution. However this assumption may be wrong if the data are unreliable and unavailable (Giannoccaro et al., 2003). Future research may relax this assumption to consider other types of demand distribution (e.g., fuzzy theory) or unknown demand distribution, which covers more realistic situations. Future research may also want to consider the integration of techniques to reduce demand uncertainty or increase demand (e.g., forecast, sales and marketing) when defining the most favourable replenishment policy.

Seventh, future research may consider other substitution ratios besides the random substitution matrix in this research. For example, future research could use the two other matrices (i.e., adjacent substitution and one-item substitution matrices) suggested by Smith and Agrawal (2000) to reflect more customer choices. Otherwise, future research can extend to situations which have related activities to a substitution ratio (e.g., consumer loyalty programme, and product differentiation) and which may provide further insights on perishable inventory management.

Eighth, it is worthwhile to consider other types of distribution for product lifetimes such as Weibull distribution or constant rate. Future research may consider other types of products and reflect more realistic problems. Furthermore, future research can assess the benefits of using techniques to increase product lifetime and reduce uncertainty in product lifetime (e.g., RFID, sharing information, and storage conditions) in perishable inventory management.

6.5 Final Remarks

This research is motivated by the practical requirements in managing inventory for perishable and substitutable products and the lack of literature in this field. Perishable and substitutable products are very common in practice. Failure to manage these types of products results in high investment capital, waste, and low customer satisfaction level. The decision framework proposed in this research aims to define the most favourable replenishment policy based on the

specific requirements of a company. However, there are many other aspects of a company that impact on inventory management. The decision framework and findings in this research support necessary future research.

Reference

- Ackoff, R. L. (1956). The development of operations research as a science. *Operations Research*, 4(3), 265-295. doi: 10.1287/opre.4.3.265
- Adenso-Díaz, B., Moreno, P., Gutiérrez, E., & Lozano, S. (2012). An analysis of the main factors affecting bullwhip in reverse supply chains. *International Journal of Production Economics*, 135(2), 917-928. doi: 10.1016/j.ijpe.2011.11.007
- Adler, N., Friedman, L., & Sinuany-Stern, Z. (2002). Review of ranking methods in the data envelopment analysis context. *European Journal of Operational Research*, 140(2), 249-265. doi: 10.1016/s0377-2217(02)00068-1
- Ahn, H., & Novoa, N. V. (2016). The decoy effect in relative performance evaluation and the debiasing role of DEA. *European Journal of Operational Research*, 249(3), 959-967. doi: 10.1016/j.ejor.2015.07.045
- Akbarian, D. (2015). Ranking all DEA-efficient DMUs based on cross efficiency and analytic hierarchy process methods. *Journal of Optimization*, 2015, 1-10. doi: 10.1155/2015/594727
- Akçay, Y., Natarajan, H. P., & Xu, S. H. (2010). Joint dynamic pricing of multiple perishable products under consumer choice. *Management Science*, 56(8), 1345-1361. doi: 10.1287/mnsc.1100.1178
- Akyuz, G. A., & Erkan, T. E. (2010). Supply chain performance measurement: A literature review. *International Journal of Production Research*, 48(17/18), 5137-5155. doi: 10.1080/00207540903089536
- Alaei, S., & Setak, M. (2015). Multi objective coordination of a supply chain with routing and service level consideration. *International Journal of Production Economics*, 167(1), 271-281. doi: 10.1016/j.ijpe.2015.06.002
- Alftan, A., Kaipia, R., Loikkanen, L., & Spens, K. (2015). Centralised grocery supply chain planning: Improved exception management. *International Journal of Physical Distribution & Logistics Management*, 45(3), 237-259. doi: 10.1108/ijpdlm-02-2014-0017
- Alizadeh, M., Eskandari, H., & Sajadifar, S. M. (2014). A modified (S - 1, S) inventory system for deteriorating items with Poisson demand and non-zero lead time. *Applied Mathematical Modelling*, 38(2), 699-711. doi: 10.1016/j.apm.2013.07.014
- Allen, R., Athanassopoulos, A., Dyson, R. G., & Thanassoulis, E. (1997). Weights restrictions and value judgements in data envelopment analysis: Evolution, development and future directions. *Annals of Operations Research*, 73(1), 13-34. doi: 10.1023/a:1018968909638
- Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39(10), 1261-1264. doi: 10.1287/mnsc.39.10.1261
- Archibald, B. C. (1981). Continuous review (s, S) policies with lost sales. *Management Science*, 27(10), 1171-1177. doi: 10.1287/mnsc.27.10.1171
- Ardestani-Jaafari, A., & Delage, E. (2016). Robust optimization of sums of piecewise linear functions with application to inventory problems. *Operations Research*, 64(2), 474-494. doi: 10.1287/opre.2016.1483
- Arts, J., & Kiesmüller, G. P. (2013). Analysis of a two-echelon inventory system with two supply modes. *European Journal of Operational Research*, 225(2), 263-272. doi: 10.1016/j.ejor.2012.09.043

- Askariyazad, M., & Wanous, M. (2009). A proposed value model for prioritising supply chain performance measures. *International Journal of Business Performance and Supply Chain Modelling*, 1(2-3), 115-128. doi: 10.1504/ijbpscm.2009.030637
- Aslam, T., & Ng, A. H. C. (2016). Combining system dynamics and multi-objective optimization with design space reduction. *Industrial Management & Data Systems*, 116(2), 291-321. doi: 10.1108/imds-05-2015-0215
- Aviv, Y. (2001). The effect of collaborative forecasting on supply chain performance. *Management Science*, 47(10), 1326-1343. doi: 10.1287/mnsc.47.10.1326.10260
- Axsäter, S. (2011). Inventory control when the lead-time changes. *Production and Operations Management*, 20(1), 72-80. doi: 10.1111/j.1937-5956.2010.01125.x
- Azadeh, A., Asadzadeh, S. M., Mehrangohar, M., & Fathi, E. (2014). Integration of genetic algorithm, analytic hierarchy process and computer simulation for optimisation of operator allocation in manufacturing systems with weighted variables. *International Journal of Logistics Systems and Management*, 17(3), 318-339. doi: 10.1504/ijlsm.2014.059765
- Azadeh, A., Ghaderi, S. F., & Izadbakhsh, H. (2008). Integration of DEA and AHP with computer simulation for railway system improvement and optimization. *Applied Mathematics and Computation*, 195(2), 775-785. doi: 10.1016/j.amc.2007.05.023
- Azadeh, A., Zarrin, M., & Salehi, N. (2016). Supplier selection in closed loop supply chain by an integrated simulation-Taguchi-DEA approach. *Journal of Enterprise Information Management*, 29(3), 302-326. doi: 10.1108/jeim-09-2014-0089
- Babai, M. Z., Boylan, J. E., Syntetos, A. A., & Ali, M. M. (in press). Reduction of the value of information sharing as demand becomes strongly auto-correlated. *International Journal of Production Economics*. doi: 10.1016/j.ijpe.2015.05.005
- Babai, M. Z., Jemai, Z., & Dallery, Y. (2011). Analysis of order-up-to-level inventory systems with compound Poisson demand. *European Journal of Operational Research*, 210(3), 552-558. doi: 10.1016/j.ejor.2010.10.004
- Bai, J., & Ng, S. (2005). Tests for skewness, kurtosis, and normality for time series data. *Journal of Business & Economic Statistics*, 23(1), 49-60. doi: 10.1198/073500104000000271
- Baines, A., & Langfield-Smith, K. (2003). Antecedents to management accounting change: A structural equation approach. *Accounting, Organizations and Society*, 28(7-8), 675-698. doi: 10.1016/s0361-3682(02)00102-2
- Bakker, M., Riezebos, J., & Teunter, R. H. (2012). Review of inventory systems with deterioration since 2001. *European Journal of Operational Research*, 221(2), 275-284. doi: 10.1016/j.ejor.2012.03.004
- Balaid, A., Abd Rozan, M. Z., Hikmi, S. N., & Memon, J. (2016). Knowledge maps: A systematic literature review and directions for future research. *International Journal of Information Management*, 36(3), 451-475. doi: 10.1016/j.ijinfomgt.2016.02.005
- Bamakan, S. M. H., & Dehghanimohammadabadi, M. (2015). A weighted Monte Carlo simulation approach to risk assessment of information security management system. *International Journal of Enterprise Information Systems*, 11(4), 63-78. doi: 10.4018/ijeis.2015100103
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092. doi: 10.1287/mnsc.30.9.1078
- Bansal, S., & Moritz, B. (2015). Perceived versus actual value of product substitution flexibility: An experimental investigation. *Journal of Operations Management*, 38(1), 56-70. doi: 10.1016/j.jom.2015.08.001

- Baril, C., Gascon, V., Miller, J., & Côté, N. (2016). Use of a discrete-event simulation in a Kaizen event: A case study in healthcare. *European Journal of Operational Research*, 249(1), 327-339. doi: 10.1016/j.ejor.2015.08.036
- Barlas, P., & Heavey, C. (2016). Automation of input data to discrete event simulation for manufacturing: A review. *International Journal of Modeling, Simulation, and Scientific Computing*, 07(01), 1630001. doi: 10.1142/S1793962316300016
- Barlas, Y., & Gunduz, B. (2011). Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains. *Journal of the Operational Research Society*, 62(3), 458-473. doi: 10.1057/jors.2010.188
- Barnes, D. (2011). Research methods for the empirical investigation of the process of formation of operations strategy. *International Journal of Operations & Production Management*, 21(8), 1076-1095. doi: 10.1108/eum0000000005586
- Baron, O., & Berman, O. (2010). Continuous review inventory models for perishable items ordered in batches. *Mathematical Methods of Operations Research*, 72(2), 217-247. doi: 10.1007/s00186-010-0318-1
- Barratt, M., Choi, T. Y., & Li, M. (2011). Qualitative case studies in operations management: Trends, research outcomes, and future research implications. *Journal of Operations Management*, 29(4), 329-342. doi: 10.1016/j.jom.2010.06.002
- Battini, D., & Persona, A. (2014). A sustainable EOQ model: Theoretical formulation and applications. *International Journal of Production Economics*, 149(1), 145-153. doi: 10.1016/j.ijpe.2013.06.026
- Beamon, B. M. (1998). Supply chain design and analysis: Models and methods. *International Journal of Production Economics*, 55(3), 281-294. doi: 10.1016/s0925-5273(98)00079-6
- Beamon, B. M., & Chen, V. C. P. (2001). Performance analysis of conjoined supply chains. *International Journal of Production Research*, 39(14), 3195-3218. doi: 10.1080/00207540110053156
- Beheshti, H. M. (2010). A decision support system for improving performance of inventory management in a supply chain network. *International Journal of Productivity and Performance Management*, 59(5), 452-467. doi: 10.1108/17410401011052887
- Bendoly, E., Donohue, K., & Schultz, K. L. (2006). Behavior in operations management: Assessing recent findings and revisiting old assumptions. *Journal of Operations Management*, 24(6), 737-752. doi: 10.1016/j.jom.2005.10.001
- Bendoly, E., & Wezel, W. V. (2015). *The handbook of behavioral operations management: Social and psychological dynamics in production and service settings*. London, UK: Oxford University Press.
- Bergh, D. D. (2003). Thinking strategically about contribution. *Academy of Management Journal*, 46(2), 135-136. doi: 10.5465/amj.2003.17481820
- Berling, P., & Marklund, J. (2014). Multi-echelon inventory control: An adjusted normal demand model for implementation in practice. *International Journal of Production Research*, 52(11), 3331-3347. doi: 10.1080/00207543.2013.873555
- Bernstein, F., & Federgruen, A. (2005). Decentralized supply chains with competing retailers under demand uncertainty. *Management Science*, 51(1), 18-29. doi: 10.1287/mnsc.1040.0218
- Bertrand, J. W. M., & Fransoo, J. C. (2002). Operations management research methodologies using quantitative modeling. *International Journal of Operations and Production Management*, 22(2), 241-264. doi: 10.1108/01443570210414338
- Bhagwat, R., & Sharma, M. K. (2007). Performance measurement of supply chain management: A balanced scorecard approach. *Computers & Industrial Engineering*, 53(1), 43-62. doi: 10.1016/j.cie.2007.04.001

- Bhattacharya, R., & Bandyopadhyay, S. (2011). A review of the causes of bullwhip effect in a supply chain. *International Journal of Advanced Manufacturing Technology*, 54(9), 1245-1261. doi: 10.1007/s00170-010-2987-6
- Bijvank, M., & Vis, I. F. A. (2011). Lost-sales inventory theory: A review. *European Journal of Operational Research*, 215(1), 1-13. doi: 10.1016/j.ejor.2011.02.004
- Binois, M., Ginsbourger, D., & Roustant, O. (2015). Quantifying uncertainty on Pareto fronts with Gaussian process conditional simulations. *European Journal of Operational Research*, 243(2), 386-394. doi: 10.1016/j.ejor.2014.07.032
- Bisogno, S., Calabrese, A., Gastaldi, M., & Ghiron, N. L. (2016). Combining modelling and simulation approaches: How to measure performance of business processes. *Business Process Management Journal*, 22(1), 56-74. doi: 10.1108/bpmj-02-2015-0021
- Bonney, M., & Jaber, M. Y. (2011). Environmentally responsible inventory models: Non-classical models for a non-classical era. *International Journal of Production Economics*, 133(1), 43-53. doi: 10.1016/j.ijpe.2009.10.033
- Bonney, M., & Jaber, M. Y. (2014). Deriving research agendas for manufacturing and logistics systems: A methodology. *International Journal of Production Economics*, 157(1), 49-61. doi: 10.1016/j.ijpe.2013.12.007
- Bono, J. E., & McNamara, G. (2011). Publishing in AMJ - Part 2: Research design. *Academy of Management Journal*, 54(4), 657-660. doi: 10.5465/amj.2011.64869103
- Borgonovo, E., & Plischke, E. (2016). Sensitivity analysis: A review of recent advances. *European Journal of Operational Research*, 248(3), 869-887. doi: 10.1016/j.ejor.2015.06.032
- Boyer, K. K., & Lewis, M. W. (2002). Competitive priorities: Investigating the need for trade-offs in operations strategy. *Production and Operations Management*, 11(1), 9-20. doi: 10.1111/j.1937-5956.2002.tb00181.x
- Boyer, K. K., & Swink, M. L. (2008). Empirical elephants - Why multiple methods are essential to quality research in operations and supply chain management. *Journal of Operations Management*, 26(3), 338-344. doi: 10.1016/j.jom.2008.03.002
- Brailsford, S. (2014). Discrete-event simulation is alive and kicking! *Journal of Simulation*, 8(1), 1-8. doi: 10.1057/jos.2013.13
- Breugelmans, E., Campo, K., & Gijsbrechts, E. (2006). Opportunities for active stock-out management in online stores: The impact of the stock-out policy on online stock-out reactions. *Journal of Retailing*, 82(3), 215-228. doi: 10.1016/j.jretai.2006.05.001
- Broekmeulen, R. A. C. M., Fransoo, J. C., Van Woensel, T., & van Donselaar, K. H. (2007). Consumer responses to shelf-out-of-stocks of perishable products. *International Journal of Physical Distribution and Logistics Management*, 37(9), 704-718. doi: 10.1108/09600030710840822
- Bromiley, P., & Rau, D. (2016). Operations management and the resource based view: Another view. *Journal of Operations Management*, 41(1), 95-106. doi: 10.1016/j.jom.2015.11.003
- Bruno, G., Esposito, E., Genovese, A., & Simpson, M. (2016). Applying supplier selection methodologies in a multi-stakeholder environment: A case study and a critical assessment. *Expert Systems with Applications*, 43(1), 271-285. doi: 10.1016/j.eswa.2015.07.016
- Brust, C. S., & Clark, R. (2014). System simulation as decision data in healthcare it. In A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley & J. A. Miller (Eds.), *Proceeding of the 2014 winter simulation conference* (pp. 1317-1328). Savannah, GA: IEEE. doi: 10.1109/wsc.2014.7019987

- Buhman, C., Kekre, S., & Singhal, J. (2005). Interdisciplinary and interorganizational research: Establishing the science of enterprise networks. *Production and Operations Management, 14*(4), 493-513. doi: 10.1111/j.1937-5956.2005.tb00236.x
- Burney, L. L., Henle, C. A., & Widener, S. K. (2009). A path model examining the relations among strategic performance measurement system characteristics, organizational justice, and extra- and in-role performance. *Accounting, Organizations and Society, 34*(3-4), 305-321. doi: 10.1016/j.aos.2008.11.002
- Bushuev, M. A., Guiffrida, A., Jaber, M. Y., & Khan, M. (2015). A review of inventory lot sizing review papers. *Management Research Review, 38*(3), 283-298. doi: 10.1108/mrr-09-2013-0204
- Butner, K. (2010). The smarter supply chain of the future. *Strategy & Leadership, 38*(1), 22-31. doi: 10.1108/10878571011009859
- Cachon, G. P. (1999). Managing supply chain demand variability with scheduled ordering policies. *Management Science, 45*(6), 843-856. doi: 10.1287/mnsc.45.6.843
- Cachon, G. P., & Terwiesch, C. (2009). *Matching supply with demand: An introduction to operations management* (2nd ed.). New York, NY: McGraw-Hill/Irwin.
- Cai, X., Chen, J., Xiao, Y., & Xu, X. (2010). Optimization and coordination of fresh product supply chains with freshness-keeping effort: Optimization and coordination of fresh product supply chains. *Production and Operations Management, 19*(3), 261-278. doi: 10.1111/j.1937-5956.2009.01096.x
- Cai, Y., & Wu, W. (2001). Synthetic financial evaluation by a method of combining DEA with AHP. *International Transactions in Operational Research, 8*(5), 603-609. doi: 10.1111/1475-3995.00336
- Calvete, H. I., Galé, C., & Iranzo, J. A. (2014). Planning of a decentralized distribution network using bilevel optimization. *Omega, 49*(1), 30-41. doi: 10.1016/j.omega.2014.05.004
- Cannella, S. (2014). Order-up-to policies in information exchange supply chains. *Applied Mathematical Modelling, 38*(23), 5553-5561. doi: 10.1016/j.apm.2014.04.029
- Cannella, S., Ashayeri, J., Miranda, P. A., & Bruccoleri, M. (2014). Current economic downturn and supply chain: The significance of demand and inventory smoothing. *International Journal of Computer Integrated Manufacturing, 27*(3), 201-212. doi: 10.1080/0951192x.2013.812801
- Cannella, S., Barbosa-Póvoa, A. P., Framinan, J. M., & Relvas, S. (2013a). Metrics for bullwhip effect analysis. *Journal of the Operational Research Society, 64*(1), 1-16. doi: 10.1057/jors.2011.139
- Cannella, S., Bruccoleri, M., Barbosa-Póvoa, A. P., & Relvas, S. (2013b). Methodological approach to study the dynamics of production networks: Discrete-event simulation modelling. *International Journal of Logistics Systems and Management, 16*(2), 211-223. doi: 10.1504/ijlsm.2013.056174
- Cannella, S., & Ciancimino, E. (2010). On the bullwhip avoidance phase: Supply chain collaboration and order smoothing. *International Journal of Production Research, 48*(21/22), 6739-6776. doi: 10.1080/00207540903252308
- Cannella, S., Framinan, J. M., & Barbosa-Póvoa, A. P. (2014). An IT-enabled supply chain model: A simulation study. *International Journal of Systems Science, 45*(11), 2327-2341. doi: 10.1080/00207721.2013.769072
- Cárdenas-Barrón, L. E., Sarkar, B., & Treviño-Garza, G. (2013). An improved solution to the replenishment policy for the EMQ model with rework and multiple shipments. *Applied Mathematical Modelling, 37*(7), 5549-5554. doi: 10.1016/j.apm.2012.10.017
- Carrillo, M., & Jorge, J. M. (2016). A multiobjective DEA approach to ranking alternatives. *Expert Systems with Applications, 50*, 130-139. doi: 10.1016/j.eswa.2015.12.022

- Carter, C. R., Sanders, N. R., & Dong, Y. (2008). Paradigms, revolutions, and tipping points: The need for using multiple methodologies within the field of supply chain management. *Journal of Operations Management*, 26(6), 693-696. doi: 10.1016/j.jom.2008.07.002
- Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, 62(1), 329-341. doi: 10.1016/j.cie.2011.10.003
- Cattani, K. D., Jacobs, F. R., & Schoenfelder, J. (2011). Common inventory modeling assumptions that fall short: Arborescent networks, Poisson demand, and single-echelon approximations. *Journal of Operations Management*, 29(5), 488-499. doi: 10.1016/j.jom.2010.11.008
- Çelebi, D. (2015). Inventory control in a centralized distribution network using genetic algorithms: A case study. *Computers & Industrial Engineering*, 87, 532-539. doi: 10.1016/j.cie.2015.05.035
- Chan, F. T. S., & Prakash, A. (2012). Inventory management in a lateral collaborative manufacturing supply chain: A simulation study. *International Journal of Production Research*, 50(16), 4670-4685. doi: 10.1080/00207543.2011.628709
- Chang, C.-W., Wu, C.-R., Lin, C.-T., & Chen, H.-C. (2007). An application of AHP and sensitivity analysis for selecting the best slicing machine. *Computers & Industrial Engineering*, 52(2), 296-307. doi: 10.1016/j.cie.2006.11.006
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444. doi: 10.1016/0377-2217(78)90138-8
- Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow through. *Management Science*, 27(6), 668-697. doi: 10.1287/mnsc.27.6.668
- Chatfield, D. C. (2013). Underestimating the bullwhip effect: A simulation study of the decomposability assumption. *International Journal of Production Research*, 51(1), 230-244. doi: 10.1080/00207543.2012.660576
- Chatfield, D. C., & Pritchard, A. M. (2013). Returns and the bullwhip effect. *Transportation Research Part E: Logistics and Transportation Review*, 49(1), 159-175. doi: 10.1016/j.tre.2012.08.004
- Chaturvedi, A., & Martínez-de-Albéniz, V. (2016). Safety stock, excess capacity or diversification: Trade-offs under supply and demand uncertainty. *Production and Operations Management*, 25(1), 77-95. doi: 10.1111/poms.12406
- Chen, F., & Samroengraja, R. (2004). Order volatility and supply chain costs. *Operations Research*, 52(5), 707-722. doi: 10.1287/opre.1040.0132
- Chen, F. Y., & Krass, D. (2001). Inventory models with minimal service level constraints. *European Journal of Operational Research*, 134(1), 120-140. doi: 10.1016/s0377-2217(00)00243-5
- Chen, H.-K., Hsueh, C.-F., & Chang, M.-S. (2009). Production scheduling and vehicle routing with time windows for perishable food products. *Computers & Operations Research*, 36(7), 2311-2319. doi: 10.1016/j.cor.2008.09.010
- Chen, T.-Y. (2002). Measuring firm performance with DEA and prior information in Taiwan's banks. *Applied Economics Letters*, 9(3), 201-204. doi: 10.1080/13504850110057947
- Chetouane, F., Barker, K., & Viacaba Oropeza, A. S. (2012). Sensitivity analysis for simulation-based decision making: Application to a hospital emergency service design. *Simulation Modelling Practice and Theory*, 20(1), 99-111. doi: 10.1016/j.simpat.2011.09.003

- Chiang, C. (2003). Optimal replenishment for a periodic review inventory system with two supply modes. *European Journal of Operational Research*, 149(1), 229-244. doi: 10.1016/s0377-2217(02)00446-0
- Chiarello-Ebner, K. (2015, November). 2015 WholeFoods magazine retailer survey overview. *WholeFoods Magazine*, 38, 18-25.
- Chikán, A. (2007). The new role of inventories in business: Real world changes and research consequences. *International Journal of Production Economics*, 108(1–2), 54-62. doi: 10.1016/j.ijpe.2006.12.002
- Chikán, A. (2011). Managers' view of a new inventory paradigm. *International Journal of Production Economics*, 133(1), 54-59. doi: 10.1016/j.ijpe.2010.09.009
- Choi, T.-M. (Ed.). (2014). *Handbook of EOQ inventory problems: Stochastic and deterministic models and applications* (Vol. 197). New York, NY: Springer.
- Choi, T.-M., Cheng, T. C. E., & Zhao, X. (2016). Multi-methodological research in operations management. *Production and Operations Management*, 25(3), 379-389. doi: 10.1111/poms.12534
- Christopher, M., & Holweg, M. (2011). “Supply chain 2.0”: Managing supply chains in the era of turbulence. *International Journal of Physical Distribution & Logistics Management*, 41(1), 63-82. doi: 10.1108/09600031111101439
- Cigolini, R., Pero, M., Rossi, T., & Sianesi, A. (2014). Linking supply chain configuration to supply chain performance: A discrete event simulation model. *Simulation Modelling Practice and Theory*, 40(1), 1-11. doi: 10.1016/j.simpat.2013.08.002
- Civelek, I., Karaesmen, I., & Scheller-Wolf, A. (2015). Blood platelet inventory management with protection levels. *European Journal of Operational Research*, 243(3), 826-838. doi: 10.1016/j.ejor.2015.01.023
- Closs, D. J., Nyaga, G. N., & Voss, M. D. (2010). The differential impact of product complexity, inventory level, and configuration capacity on unit and order fill rate performance. *Journal of Operations Management*, 28(1), 47-57. doi: 10.1016/j.jom.2009.04.003
- Coelho, L. C., & Laporte, G. (2015). An optimised target-level inventory replenishment policy for vendor-managed inventory systems. *International Journal of Production Research*, 53(12), 3651-3660. doi: 10.1080/00207543.2014.986299
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.
- Collins, A., Joseph, D., & Bielaczyc, K. (2004). Design research: Theoretical and methodological issues. *Journal of the Learning Sciences*, 13(1), 15-42. doi: 10.1207/s15327809jls1301_2
- Colquitt, J. A., & Zapata-Phelan, C. P. (2007). Trends in theory building and theory testing: A five-decade study of the "Academy of Management Journal". *Academy of Management Journal*, 50(6), 1281-1303. doi: 10.2307/20159472
- Cook, W. D., Liang, L., Zha, Y., & Zhu, J. (2009). A modified super-efficiency DEA model for infeasibility. *Journal of the Operational Research Society*, 60(2), 276-281. doi: 10.1057/palgrave.jors.2602544
- Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega*, 44(1), 1-4. doi: 10.1016/j.omega.2013.09.004
- Cooper, W. W., Li, S., Seiford, L. M., Tone, K., Thrall, R. M., & Zhu, J. (2001). Sensitivity and stability analysis in DEA: Some recent developments. *Journal of Productivity Analysis*, 15(3), 217-246. doi: 10.1023/a:1011128409257
- Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). *Handbook on data envelopment analysis*. New York, NY: Springer.

- Cooper, W. W., & Tone, K. (1997). Measures of inefficiency in data envelopment analysis and stochastic frontier estimation. *European Journal of Operational Research*, 99(1), 72-88. doi: 10.1016/s0377-2217(96)00384-0
- Corley, K. G., & Gioia, D. A. (2011). Building theory about theory building: What constitutes a theoretical contribution? *Academy of Management Review*, 36(1), 12-32. doi: 10.5465/amr.2009.0486
- Costantino, F., Di Gravio, G., Shaban, A., & Tronci, M. (2015). The impact of information sharing on ordering policies to improve supply chain performances. *Computers & Industrial Engineering*, 82, 127-142. doi: 10.1016/j.cie.2015.01.024
- Coughlan, P., & Coughlan, D. (2002). Action research for operations management. *International Journal of Operations & Production Management*, 22(2), 220-240. doi: 10.1108/01443570210417515
- Craighead, C. W., & Meredith, J. R. (2008). Operations management research: Evolution and alternative future paths. *International Journal of Operations & Production Management*, 28(8), 710-726. doi: 10.1108/01443570810888625
- Creswell, J. W. (1998). *Qualitative inquiry and research design: Choosing among five approaches*. Thousand Oaks, CA: Sage.
- Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage.
- Croson, R., Schultz, K., Siemsen, E., & Yeo, M. L. (2013). Behavioral operations: The state of the field. *Journal of Operations Management*, 31(1-2), 1-5. doi: 10.1016/j.jom.2012.12.001
- Dächert, K., Klamroth, K., Lacour, R., & Vanderpooten, D. (in press). Efficient computation of the search region in multi-objective optimization. *European Journal of Operational Research*. doi: 10.1016/j.ejor.2016.05.029
- Dadzie, K. Q., & Winston, E. (2007). Consumer response to stock-out in the online supply chain. *International Journal of Physical Distribution & Logistics Management*, 37(1), 19-42. doi: 10.1108/09600030710723309
- Dagkakis, G., & Heavey, C. (in press). A review of open source discrete event simulation software for operations research. *Journal of Simulation*. doi: 10.1057/jos.2015.9
- Dai, T., & Jerath, K. (2013). Salesforce compensation with inventory considerations. *Management Science*, 59(11), 2490-2501. doi: 10.1287/mnsc.2013.1809
- Davis, D. F., Golicic, S. L., & Boerstler, C. N. (2011). Benefits and challenges of conducting multiple methods research in marketing. *Journal of the Academy of Marketing Science*, 39(3), 467-479. doi: 10.1007/s11747-010-0204-7
- Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review*, 32(2), 480-499. doi: 10.2307/20159312
- de Keizer, M., Haijema, R., Bloemhof, J. M., & van der Vorst, J. G. A. J. (2015). Hybrid optimization and simulation to design a logistics network for distributing perishable products. *Computers & Industrial Engineering*, 88, 26-38. doi: 10.1016/j.cie.2015.06.017
- de Lima, E. P., da Costa, S. E. G., Angelis, J. J., & Munik, J. (2013). Performance measurement systems: A consensual analysis of their roles. *International Journal of Production Economics*, 146(2), 524-542. doi: 10.1016/j.ijpe.2012.05.007
- de Treville, S., Bicer, I., Chavez-Demoulin, V., Hagspiel, V., Schürhoff, N., Tasserit, C., & Wager, S. (2014). Valuing lead time. *Journal of Operations Management*, 32(6), 337-346. doi: 10.1016/j.jom.2014.06.002
- DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: An empirical analysis. *Management Science*, 54(4), 627-641. doi: 10.1287/mnsc.1070.0789

- Dejonckheere, J., Disney, S. M., Lambrecht, M. R., & Towill, D. R. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research*, *147*(3), 567-590. doi: 10.1016/s0377-2217(02)00369-7
- Deniz, B., Karaesmen, I. Z., & Scheller-Wolf, A. (2010). Managing perishables with substitution: Inventory issuance and replenishment heuristics. *Manufacturing and Service Operations Management*, *12*(2), 319-329. doi: 10.1287/msom.1090.0276
- Díaz, M. S., Gil, M. J. Á., & Machuca, J. A. D. (2005). Performance measurement systems, competitive priorities, and advanced manufacturing technology: Some evidence from the aeronautical sector. *International Journal of Operations & Production Management*, *25*(8), 781-799. doi: 10.1108/01443570510608600
- Dixit, V., Seshadrinath, N., & Tiwari, M. K. (2016). Performance measures based optimization of supply chain network resilience: A NSGA-II + Co-Kriging approach. *Computers & Industrial Engineering*, *93*, 205-214. doi: 10.1016/j.cie.2015.12.029
- Dominguez, R., Cannella, S., & Framinan, J. M. (2014). On bullwhip-limiting strategies in divergent supply chain networks. *Computers & Industrial Engineering*, *73*, 85-95. doi: 10.1016/j.cie.2014.04.008
- Dooley, K. J., Yan, T., Mohan, S., & Gopalakrishnan, M. (2010). Inventory management and the bullwhip effect during the 2007 - 2009 recession: Evidence from the manufacturing sector. *Journal of Supply Chain Management*, *46*(1), 12-18. doi: 10.1111/j.1745-493x.2009.03183.x
- Du, X. F., Leung, S. C. H., Zhang, J. L., & Lai, K. K. (2013). Demand forecasting of perishable farm products using support vector machine. *International Journal of Systems Science*, *44*(3), 556-567. doi: 10.1080/00207721.2011.617888
- Duan, Q., & Liao, T. W. (2013). Optimization of replenishment policies for decentralized and centralized capacitated supply chains under various demands. *International Journal of Production Economics*, *142*(1), 194-204. doi: 10.1016/j.ijpe.2012.11.004
- Duan, Q., & Liao, T. W. (2014). Optimization of blood supply chain with shortened shelf lives and ABO compatibility. *International Journal of Production Economics*, *153*, 113-129. doi: 10.1016/j.ijpe.2014.02.012
- Duan, Y., Yao, Y., & Huo, J. (2015). Bullwhip effect under substitute products. *Journal of Operations Management*, *36*, 75-89. doi: 10.1016/j.jom.2015.03.002
- Duong, L. N. K., & Wood, L. C. (2015). Simulation to improve management of perishable and substitutable inventory. In M. Khosrow-Pour (Ed.), *Encyclopedia of information science and technology* (3rd ed., pp. 915-922). Hershey, PA: IGI Global.
- Duong, L. N. K., Wood, L. C., & Wang, W. Y. C. (2015a). A multi-criteria inventory management system for perishable & substitutable products. *Procedia Manufacturing*, *2*, 66-76. doi: 10.1016/j.promfg.2015.07.012
- Duong, L. N. K., Wood, L. C., & Wang, W. Y. C. (in press). A review and reflection on inventory management of perishable products in a single-echelon model. *International Journal of Operational Research*.
- Duong, L. N. K., Wood, L. C., & Wang, X. (2015b). Review of RFID applications in perishable inventory management. In B. Christiansen (Ed.), *Handbook of research on global supply chain management* (pp. 139-146). Hershey, PA: IGI Global.
- Egels-Zandén, N., Hulthén, K., & Wulff, G. (2015). Trade-offs in supply chain transparency: The case of Nudie Jeans Co. *Journal of Cleaner Production*, *107*, 95-104. doi: 10.1016/j.jclepro.2014.04.074
- Epstein, M. J., & Roy, M.-J. (2001). Sustainability in action: Identifying and measuring the key performance drivers. *Long Range Planning*, *34*(5), 585-604. doi: 10.1016/s0024-6301(01)00084-x

- Ertay, T., Ruan, D., & Tuzkaya, U. R. (2006). Integrating data envelopment analysis and analytic hierarchy for the facility layout design in manufacturing systems. *Information Sciences*, *176*(3), 237-262. doi: 10.1016/j.ins.2004.12.001
- Estellés-Miguel, S., Cardós, M., Albarraçín, J. M., & Palmer, M. E. (2014). Design of a continuous review stock policy. In J. C. Prado-Prado & J. García-Arca (Eds.), *Annals of industrial engineering* (pp. 139-146). London, UK: Springer.
- Falsini, D., Fondi, F., & Schiraldi, M. M. (2012). A logistics provider evaluation and selection methodology based on AHP, DEA and linear programming integration. *International Journal of Production Research*, *50*(17), 4822-4829. doi: 10.1080/00207543.2012.657969
- Farahani, R. Z., Rezapour, S., Drezner, T., & Fallah, S. (2014). Competitive supply chain network design: An overview of classifications, models, solution techniques and applications. *Omega*, *45*, 92-118. doi: 10.1016/j.omega.2013.08.006
- Färe, R., Grosskopf, S., Lovell, C. A. K., & Pasurka, C. (1989). Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *Review of Economics and Statistics*, *71*(1), 90-98. doi: 10.2307/1928055
- Faria, A. J., Hutchinson, D., Wellington, W. J., & Gold, S. (2009). Developments in business gaming a review of the past 40 years. *Simulation & Gaming*, *40*(4), 464-487. doi: 10.1177/1046878108327585
- Fattahi, M., Mahootchi, M., Moattar Husseini, S. M., Keyvanshokoh, E., & Alborzi, F. (2014). Investigating replenishment policies for centralised and decentralised supply chains using stochastic programming approach. *International Journal of Production Research*, *53*(1), 41-69. doi: 10.1080/00207543.2014.922710
- Fawcett, S. E., & Magnan, G. M. (2002). The rhetoric and reality of supply chain integration. *International Journal of Physical Distribution & Logistics Management*, *32*(5), 339-361. doi: 10.1108/09600030210436222
- Ferguson, M. E., & Ketzenberg, M. E. (2006). Information sharing to improve retail product freshness of perishables. *Production and Operations Management*, *15*(1), 57-73.
- Fernandes, N. O., Land, M. J., & Carmo-Silva, S. (2016). Aligning workload control theory and practice: Lot splitting and operation overlapping issues. *International Journal of Production Research*, *54*(10), 2965-2975. doi: 10.1080/00207543.2016.1143134
- Fernandez, E., & Olmedo, R. (2013). An outranking-based general approach to solving group multi-objective optimization problems. *European Journal of Operational Research*, *225*(3), 497-506. doi: 10.1016/j.ejor.2012.10.023
- Field, A. P. (2013). *Discovering statistics using IBM SPSS statistics: And sex and drugs and rock 'n' roll*. Thousand Oaks, CA: Sage.
- Fisher, M. L. (1997). What is the right supply chain for your product? *Harvard Business Review*, *75*, 105-117.
- Fisher, M. L. (2007). Strengthening the empirical base of operations management. *Manufacturing & Service Operations Management*, *9*(4), 368-382. doi: 10.1287/msom.1070.0168
- Fletcher, A. J. (in press). Applying critical realism in qualitative research: Methodology meets method. *International Journal of Social Research Methodology*. doi: 10.1080/13645579.2016.1144401
- Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, *28*(1), 58-71. doi: 10.1016/j.jom.2009.06.001
- Flynn, B. B., Koufteros, X., & Lu, G. (2016). On theory in supply chain uncertainty and its implications for supply chain integration. *Journal of Supply Chain Management*, *52*(3), 3-27. doi: 10.1111/jscm.12106

- Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A., & Flynn, E. J. (1990). Empirical research methods in operations management. *Journal of Operations Management*, 9(2), 250-284. doi: 10.1016/0272-6963(90)90098-x
- Foropon, C., & McLachlin, R. (2013). Metaphors in operations management theory building. *International Journal of Operations & Production Management*, 33(2), 181-196. doi: 10.1108/01443571311295626
- Forrester, J. W. (1997). Industrial dynamics. *Journal of the Operational Research Society*, 48(10), 1037-1041. doi: 10.1057/palgrave.jors.2600946
- Framinan, J. M., & Dominguez, R. (2014). Serial vs. divergent supply chain networks: A comparative analysis of the bullwhip effect. *International Journal of Production Research*, 52(7), 2194-2210. doi: 10.1080/00207543.2013.860495
- Franco, L. A., & Lord, E. (2011). Understanding multi-methodology: Evaluating the perceived impact of mixing methods for group budgetary decisions. *Omega*, 39(3), 362-372. doi: 10.1016/j.omega.2010.06.008
- Frankel, R., Naslund, D., & Bolumole, Y. (2005). The “white space” of logistics research: A look at the role of methods usage. *Journal of Business Logistics*, 26(2), 185-209. doi: 10.1002/j.2158-1592.2005.tb00211.x
- Frey, H. C., & Patil, S. R. (2002). Identification and review of sensitivity analysis methods. *Risk Analysis*, 22(3), 553-578. doi: 10.1111/0272-4332.00039
- Fritzsche, D. J., & Burns, A. C. (2001). The role of ABSEL in the development of marketing simulations in collegiate education. *Simulation & Gaming*, 32(1), 85-96. doi: 10.1177/104687810103200107
- Gadde, L.-E. (2013). Moving corporate boundaries: Consequences for innovative redesign. *Journal of Supply Chain Management*, 49(4), 12-26. doi: 10.1111/jscm.12027
- Gallego, G., & Özer, Ö. (2003). Optimal replenishment policies for multiechelon inventory problems under advance demand information. *Manufacturing & Service Operations Management*, 5(2), 157-175. doi: 10.1287/msom.5.2.157.16072
- Geary, S., Disney, S. M., & Towill, D. R. (2006). On bullwhip in supply chains - Historical review, present practice and expected future impact. *International Journal of Production Economics*, 101(1), 2-18. doi: 10.1016/j.ijpe.2005.05.009
- Geunes, J., Romeijn, H. E., & van den Heuvel, W. (2016). Improving the efficiency of decentralized supply chains with fixed ordering costs. *European Journal of Operational Research*, 252(3), 815-828. doi: 10.1016/j.ejor.2016.02.004
- Ghiami, Y., & Williams, T. (2015). A two-echelon production-inventory model for deteriorating items with multiple buyers. *International Journal of Production Economics*, 159(1), 233-240. doi: 10.1016/j.ijpe.2014.09.017
- Giannoccaro, I., Pontrandolfo, P., & Scozzi, B. (2003). A fuzzy echelon approach for inventory management in supply chains. *European Journal of Operational Research*, 149(1), 185-196. doi: 10.1016/s0377-2217(02)00441-1
- Gibson, B. J., Mentzer, J. T., & Cook, R. L. (2005). Supply chain management: The pursuit of a consensus definition. *Journal of Business Logistics*, 26(2), 17-25. doi: 10.1002/j.2158-1592.2005.tb00203.x
- Gioia, D. A., & Pitre, E. (1990). Multiparadigm perspectives on theory building. *Academy of Management Review*, 15(4), 584-602. doi: 10.5465/amr.1990.4310758
- Giri, B. C., Goswami, A., & Chaudhuri, K. S. (1996). An EOQ model for deteriorating items with time varying demand and costs. *Journal of the Operational Research Society*, 47(11), 1398-1405. doi: 10.1057/jors.1996.175
- Giri, B. C., & Sarker, B. R. (2016). Coordinating a two-echelon supply chain under production disruption when retailers compete with price and service level. *Operational Research*, 16(1), 71-88. doi: 10.1007/s12351-015-0187-8

- Göbel, C., Langen, N., Blumenthal, A., Teitscheid, P., & Ritter, G. (2015). Cutting food waste through cooperation along the food supply chain. *Sustainability*, 7(2), 1429-1445. doi: 10.3390/su7021429
- Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega*, 17(3), 237-250. doi: 10.1016/0305-0483(89)90029-7
- Golany, B., & Roll, Y. (1993). Some extensions of techniques to handle non-discretionary factors in data envelopment analysis. *Journal of Productivity Analysis*, 4(4), 419-432. doi: 10.1007/bf01073549
- Golicic, S. L., & Davis, D. F. (2012). Implementing mixed methods research in supply chain management. *International Journal of Physical Distribution & Logistics Management*, 42(8-9), 726-741. doi: 10.1108/09600031211269721
- Gomes, E. G., & Lins, M. P. E. (2008). Modelling undesirable outputs with zero sum gains data envelopment analysis models. *Journal of the Operational Research Society*, 59(5), 616-623. doi: 10.1057/palgrave.jors.2602384
- Govindan, K., Jafarian, A., & Nourbakhsh, V. (2015). Bi-objective integrating sustainable order allocation and sustainable supply chain network strategic design with stochastic demand using a novel robust hybrid multi-objective metaheuristic. *Computers & Operations Research*, 62, 112-130. doi: 10.1016/j.cor.2014.12.014
- Goyal, S. K., & Giri, B. C. (2001). Recent trends in modeling of deteriorating inventory. *European Journal of Operational Research*, 134(1), 1-16. doi: 10.1016/s0377-2217(00)00248-4
- Grigoroudis, E., Orfanoudaki, E., & Zopounidis, C. (2012). Strategic performance measurement in a healthcare organisation: A multiple criteria approach based on balanced scorecard. *Omega*, 40(1), 104-119. doi: 10.1016/j.omega.2011.04.001
- Güller, M., Uygun, Y., & Noche, B. (2015). Simulation-based optimization for a capacitated multi-echelon production-inventory system. *Journal of Simulation*, 9(4), 325-336. doi: 10.1057/jos.2015.5
- Gümüş, A. T., & Güneri, A. F. (2007). Multi-echelon inventory management in supply chains with uncertain demand and lead times: Literature review from an operational research perspective. *Journal of Engineering Manufacture*, 221(10), 1553-1570. doi: 10.1243/09544054jem889
- Gunasekaran, A., & Kobu, B. (2007). Performance measures and metrics in logistics and supply chain management: A review of recent literature (1995-2004) for research and applications. *International Journal of Production Research*, 45(12), 2819-2840. doi: 10.1080/00207540600806513
- Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics*, 87(3), 333-347. doi: 10.1016/j.ijpe.2003.08.003
- Gunasekera, D. (2015). Food production: Cut food waste to help feed world. *Nature*, 524(7566), 415-415. doi: 10.1038/524415a
- Guo, D., & Wu, J. (2013). A complete ranking of DMUs with undesirable outputs using restrictions in DEA models. *Mathematical and Computer Modelling*, 58(5-6), 1102-1109. doi: 10.1016/j.mcm.2011.12.044
- Gupta, A., & Maranas, C. D. (2003). Managing demand uncertainty in supply chain planning. *Computers & Chemical Engineering*, 27(8-9), 1219-1227. doi: 10.1016/s0098-1354(03)00048-6
- Gupta, M. C., & Boyd, L. H. (2008). Theory of constraints: A theory for operations management. *International Journal of Operations & Production Management*, 28(10), 991-1012. doi: 10.1108/01443570810903122

- Gupta, S., Verma, R., & Victorino, L. (2006). Empirical research published in production and operations management (1992–2005): Trends and future research directions. *Production and Operations Management*, 15(3), 432-448. doi: 10.1111/j.1937-5956.2006.tb00256.x
- Gürler, Ü., & Özkaya, B. Y. (2008). Analysis of the (s, S) policy for perishables with a random shelf life. *IIE Transactions*, 40(8), 759-781. doi: 10.1080/07408170701730792
- Gürler, Ü., & Yılmaz, A. (2010). Inventory and coordination issues with two substitutable products. *Applied Mathematical Modelling*, 34(3), 539-551. doi: 10.1016/j.apm.2009.06.030
- Gustavsson, J., Cederberg, C., Sonesson, U., Van Otterdijk, R., & Meybeck, A. (2011). *Global food losses and food waste: Extent, causes and prevention*. Retrieved from www.fao.org/docrep/014/mb060e/mb060e.pdf.
- Gutjahr, W. J., & Pichler, A. (2013). Stochastic multi-objective optimization: A survey on non-scalarizing methods. *Annals of Operations Research*, 236(2), 475-499. doi: 10.1007/s10479-013-1369-5
- Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications*, 34(2), 1303-1311. doi: 10.1016/j.eswa.2006.12.008
- Haijema, R. (2014). Optimal ordering, issuance and disposal policies for inventory management of perishable products. *International Journal of Production Economics*, 157, 158-169. doi: 10.1016/j.ijpe.2014.06.014
- Haijema, R., & Minner, S. (in press). Stock-level dependent ordering of perishables: A comparison of hybrid base-stock and constant order policies. *International Journal of Production Economics*. doi: 10.1016/j.ijpe.2015.10.013
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. New York, NY: Pearson.
- Hämäläinen, R. P., Luoma, J., & Saarinen, E. (2013). On the importance of behavioral operational research: The case of understanding and communicating about dynamic systems. *European Journal of Operational Research*, 228(3), 623-634. doi: 10.1016/j.ejor.2013.02.001
- Hambrick, D. C. (2007). The field of management's devotion to theory: Too much of a good thing? *Academy of Management Journal*, 50(6), 1346-1352. doi: 10.5465/amj.2007.28166119
- Hancerliogullari, G., Sen, A., & Agca, E. (2016). Demand uncertainty and inventory turnover performance: An empirical analysis of the US retail industry. *International Journal of Physical Distribution & Logistics Management*, 46(6/7), 681-708. doi: 10.1108/ijpdlm-12-2014-0303
- Harris, F. W. (1990). How many parts to make at once. *Operations Research*, 38(6), 947-950. doi: 10.1287/opre.38.6.947
- Hasani, A., Zegordi, S. H., & Nikbaksh, E. (2012). Robust closed-loop supply chain network design for perishable goods in agile manufacturing under uncertainty. *International Journal of Production Research*, 50(16), 4649-4669. doi: 10.1080/00207543.2011.625051
- Hatami-Marbini, A., Tavana, M., Agrell, P. J., Farhad, H. L., & Beigi, Z. G. (2015). A common-weights DEA model for centralized resource reduction and target setting. *Computers & Industrial Engineering*, 79, 195-203. doi: 10.1016/j.cie.2014.10.024
- Hayes, R. H. (1998). Developing POM faculties for the 21st century. *Production and Operations Management*, 7(2), 94-98. doi: 10.1111/j.1937-5956.1998.tb00441.x

- Hendricks, K. B., & Singhal, V. R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, 14(1), 35-52. doi: 10.1111/j.1937-5956.2005.tb00008.x
- Ho, C.-T. B., & Oh, K. B. (2010). Selecting Internet company stocks using a combined DEA and AHP approach. *International Journal of Systems Science*, 41(3), 325-336. doi: 10.1080/00207720903326902
- Ho, T.-H., Lim, N., & Cui, T. H. (2010). Reference dependence in multilocation newsvendor models: A structural analysis. *Management Science*, 56(11), 1891-1910. doi: 10.1287/mnsc.1100.1225
- Ho, T.-H., Savin, S., & Terwiesch, C. (2002). Managing demand and sales dynamics in new product diffusion under supply constraint. *Management Science*, 48(2), 187-206. doi: 10.1287/mnsc.48.2.187.257
- Ho, W. (2008). Integrated analytic hierarchy process and its applications – A literature review. *European Journal of Operational Research*, 186(1), 211-228. doi: 10.1016/j.ejor.2007.01.004
- Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1), 16-24. doi: 10.1016/j.ejor.2009.05.009
- Hoad, K., Monks, T., & O'Brien, F. (2015). The use of search experimentation in discrete-event simulation practice. *Journal of the Operational Research Society*, 66(7), 1155-1168. doi: 10.1057/jors.2014.79
- Hohenstein, N.-O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience - A systematic review and paths for further investigation. *International Journal of Physical Distribution & Logistics Management*, 45(1/2), 90-117. doi: 10.1108/ijpdlm-05-2013-0128
- Hollmann, R. L., Scavarda, L. F., & Thomé, A. M. T. (2015). Collaborative planning, forecasting and replenishment: A literature review. *International Journal of Productivity and Performance Management*, 64(7), 971-993. doi: 10.1108/ijppm-03-2014-0039
- Holweg, M., Disney, S., Holmström, J., & Småros, J. (2005). Supply chain collaboration: Making sense of the strategy continuum. *European Management Journal*, 23(2), 170-181. doi: 10.1016/j.emj.2005.02.008
- Hopp, W. J. (2004). Fifty years of management science. *Management Science*, 50(1), 1-7. doi: 10.1287/mnsc.1030.0181
- Huang, D., Zhou, H., & Zhao, Q. H. (2011). A competitive multiple-product newsboy problem with partial product substitution. *Omega*, 39(3), 302-312. doi: 10.1016/j.omega.2010.07.008
- Huang, G. Q., Lau, J. S. K., & Mak, K. L. (2003). The impacts of sharing production information on supply chain dynamics: A review of the literature. *International Journal of Production Research*, 41(7), 1483-1517. doi: 10.1080/0020754031000069625
- Huang, Y.-Y., & Handfield, R. B. (2015). Measuring the benefits of ERP on supply management maturity model: A "big data" method. *International Journal of Operations & Production Management*, 35(1), 2-25. doi: 10.1108/ijopm-07-2013-0341
- Hübner, A., Kuhn, H., & Kühn, S. (2016). An efficient algorithm for capacitated assortment planning with stochastic demand and substitution. *European Journal of Operational Research*, 250(2), 505-520. doi: 10.1016/j.ejor.2015.11.007
- Hudson, L. A., & Ozanne, J. L. (1988). Alternative ways of seeking knowledge in consumer research. *Journal of Consumer Research*, 14(4), 508-521. doi: 10.1086/209132

- Hwang, H. B., Chong, C. S. P., Xie, N., & Burgess, T. F. (2005). Modelling a complex supply chain: Understanding the effect of simplified assumptions. *International Journal of Production Research*, 43(13), 2829-2872. doi: 10.1080/00207540500066812
- IBM SPSS. (2016). IBM - Statistical analysis software package - SPSS statistics. Retrieved from www.ibm.com
- Ioannidis, S. (2013). Joint production and quality control in production systems with two customer classes and lost sales. *IIE Transactions*, 45(6), 605-616. doi: 10.1080/0740817X.2012.721948
- Isaksson, O. H. D., & Seifert, R. W. (2016). Quantifying the bullwhip effect using two-echelon data: A cross-industry empirical investigation. *International Journal of Production Economics*, 171, Part 3, 311-320. doi: 10.1016/j.ijpe.2015.08.027
- Ittner, C. D., & Larcker, D. F. (1998a). Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research*, 36(1), 1-35. doi: 10.2307/2491304
- Ittner, C. D., & Larcker, D. F. (1998b). Innovations in performance measurement: Trends and research implications. *Journal of Management Accounting Research*, 10, 205-238.
- Ittner, C. D., Larcker, D. F., & Meyer, M. W. (2003). Subjectivity and the weighting of performance measures: Evidence from a balanced scorecard. *Accounting Review*, 78(3), 725-758. doi: 10.2308/accr.2003.78.3.725
- Ivanov, D. (2010). An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations. *International Journal of Production Research*, 48(13), 3999-4017. doi: 10.1080/00207540902893417
- Jaber, M. Y., Zanoni, S., & Zavanella, L. E. (2014). Economic order quantity models for imperfect items with buy and repair options. *International Journal of Production Economics*, 155, 126-131. doi: 10.1016/j.ijpe.2013.10.014
- Jablonsky, J. (2011). Multicriteria approaches for ranking of efficient units in DEA models. *Central European Journal of Operations Research*, 20(3), 435-449. doi: 10.1007/s10100-011-0223-6
- Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., & Young, T. (2010). Simulation in manufacturing and business: A review. *European Journal of Operational Research*, 203(1), 1-13. doi: 10.1016/j.ejor.2009.06.004
- Jahanshahloo, G. R., Lotfi, F. H., Shoja, N., Tohidi, G., & Razavyan, S. (2005). Undesirable inputs and outputs in DEA models. *Applied Mathematics and Computation*, 169(2), 917-925. doi: 10.1016/j.amc.2004.09.069
- Jain, A., & Moinzadeh, K. (2005). A supply chain model with reverse information exchange. *Manufacturing & Service Operations Management*, 7(4), 360-378. doi: 10.1287/msom.1050.0084
- Jain, S., Workman, R., Collins, L., Ervin, E., & Lathrop, A. (2001). Development of a high-level supply chain simulation model. In B. A. Peters, J. S. Smith, D. J. Medeiros & M. W. Rohrer (Eds.), *Proceeding of the 2001 winter simulation conference* (pp. 1129-1137). Arlington, VA: IEEE. doi: 10.1109/wsc.2001.977425
- Jayswal, A., Singh, S., & Kurdi, A. (2016). Multitime multiobjective variational problems and vector variational-like inequalities. *European Journal of Operational Research*, 254(3), 739-745. doi: 10.1016/j.ejor.2016.05.006
- Jeon, S. M., & Kim, G. (2016). A survey of simulation modeling techniques in production planning and control (PPC). *Production Planning & Control*, 27(5), 360-377. doi: 10.1080/09537287.2015.1128010
- Jogulu, U. D., & Pansiri, J. (2011). Mixed methods: A research design for management doctoral dissertations. *Management Research Review*, 34(6), 687-701. doi: 10.1108/01409171111136211

- Johansen, S. G., & Hill, R. M. (2000). The (r, Q) control of a periodic-review inventory system with continuous demand and lost sales. *International Journal of Production Economics*, 68(3), 279-286. doi: 10.1016/s0925-5273(00)00051-7
- Jones, E. C., & Garza, A. (2011). Innovating continuous review policies with RFID to minimize obsolete inventory. In T. Doolen & E. V. Aken (Eds.), *Proceedings of the 2011 industrial engineering research conference* (pp. 1-8). Norcross, GA: Institute of Industrial Engineers. Retrieved from www.proquest.com.
- Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., & Eversdyk, D. (2004). A simulation based optimization approach to supply chain management under demand uncertainty. *Computers & Chemical Engineering*, 28(10), 2087-2106. doi: 10.1016/j.compchemeng.2004.06.006
- Kalpakam, S., & Arivarignan, G. (1988). A continuous review perishable inventory model. *Statistics*, 19(3), 389-398. doi: 10.1080/02331888808802112
- Kalpakam, S., & Sapna, K. P. (1994). Continuous review (s, S) inventory system with random lifetimes and positive leadtimes. *Operations Research Letters*, 16(2), 115-119. doi: 10.1016/0167-6377(94)90066-3
- Kalpakam, S., & Sapna, K. P. (1996). A lost sales (S - 1, S) perishable inventory system with renewal demand. *Naval Research Logistics*, 43(1), 129-142. doi: 10.1002/(sici)1520-6750(199602)43:1<129::aid-nav8>3.0.co;2-d
- Kaplan, R. S. (2008). Conceptual foundations of the balanced scorecard. In C. S. Chapman, A. G. Hopwood & M. D. Shields (Eds.), *Handbooks of management accounting research* (Vol. 3, pp. 1253-1269). Oxford, UK: Elsevier.
- Kaplan, R. S., & Anderson, S. R. (2013). *Time-driven activity-based costing: A simpler and more powerful path to higher profits*. Boston, MA: Harvard Business School.
- Kaplan, R. S., & Norton, D. P. (1995). Putting the balanced scorecard to work. In D. G. Shaw, C. E. Schneier, R. W. Beatty & L. S. Baird (Eds.), *Performance measurement, management, and appraisal sourcebook* (pp. 66-79). Amherst, MA: Human Resource Development.
- Kaplan, R. S., & Norton, D. P. (2001). Transforming the balanced scorecard from performance measurement to strategic management: Part I. *Accounting Horizons*, 15(1), 87-104. doi: 10.2308/acch.2001.15.1.87
- Kaplan, R. S., & Norton, D. P. (2005). The balanced scorecard: Measures that drive performance. *Harvard Business Review*, 83(7), 172-183.
- Karaesmen, I. Z., Scheller-Wolf, A., & Deniz, B. (2011). Managing perishable and aging inventories: Review and future research directions. In K. G. Kempf, P. Keskinocak & R. Uzsoy (Eds.), *Planning production and inventories in the extended enterprise* (Vol. 151, pp. 393-436). New York, NY: Springer.
- Kärkkäinen, M. (2003). Increasing efficiency in the supply chain for short shelf life goods using RFID tagging. *International Journal of Retail & Distribution Management*, 31(10), 529-536. doi: 10.1108/09590550310497058
- Katsaliaki, K., Mustafee, N., & Kumar, S. (2014). A game-based approach towards facilitating decision making for perishable products: An example of blood supply chain. *Expert Systems with Applications*, 41(9), 4043-4059. doi: 10.1016/j.eswa.2013.12.038
- Kaur, A., Kanda, A., & Deshmukh, S. G. (2008). Supply chain coordination: Perspectives, empirical studies and research directions. *International Journal of Production Economics*, 115(2), 316-335. doi: 10.1016/j.ijpe.2008.05.011
- Kennerley, M., & Neely, A. (2003). Measuring performance in a changing business environment. *International Journal of Operations & Production Management*, 23(2), 213-229. doi: 10.1108/01443570310458465

- Kenyon, G. N., Meixell, M. J., & Westfall, P. H. (2016). Production outsourcing and operational performance: An empirical study using secondary data. *International Journal of Production Economics*, 171, Part 3, 336-349. doi: 10.1016/j.ijpe.2015.09.017
- Ketokivi, M., & Choi, T. (2014). Renaissance of case research as a scientific method. *Journal of Operations Management*, 32(5), 232-240. doi: 10.1016/j.jom.2014.03.004
- Khanlarzade, N., Yegane, B. Y., & Nakhai, I. (2012). Genetic algorithm to optimize two-echelon inventory control system for perishable goods in terms of active packaging. *International Journal of Industrial Engineering Computations*, 3(2), 103-114. doi: 10.5267/j.ijiec.2011.10.001
- Khouja, M. (1999). The single-period (news-vendor) problem: Literature review and suggestions for future research. *Omega*, 27(5), 537-553. doi: 10.1016/s0305-0483(99)00017-1
- Kilduff, M. (2006). Editor's comments: Publishing theory. *Academy of Management Review*, 31(2), 252-255. doi: 10.5465/amr.2006.20208678
- Kleijnen, J. P. C., & Smits, M. T. (2003). Performance metrics in supply chain management. *Journal of the Operational Research Society*, 54(5), 507-514. doi: 10.1057/palgrave.jors.2601539
- Kleijnen, J. P. C., & Wan, J. (2007). Optimization of simulated systems: OptQuest and alternatives. *Simulation Modelling Practice and Theory*, 15(3), 354-362. doi: 10.1016/j.simpat.2006.11.001
- Köksalan, M., & Tuncer, C. (2009). A DEA-based approach to ranking multi-criteria alternatives. *International Journal of Information Technology & Decision Making*, 8(1), 29-54. doi: 10.1142/s0219622009003259
- Koopman, J., Howe, M., Johnson, R. E., Tan, J. A., & Chang, C.-H. (2013). A framework for developing word fragment completion tasks. *Human Resource Management Review*, 23(3), 242-253. doi: 10.1016/j.hrmr.2012.12.005
- Korhonen, P., Moskowitz, H., & Wallenius, J. (1992). Multiple criteria decision support - A review. *European Journal of Operational Research*, 63(3), 361-375. doi: 10.1016/0377-2217(92)90155-3
- Kouki, C., Babai, M. Z., Jemai, Z., & Minner, S. (in press). A coordinated multi-item inventory system for perishables with random lifetime. *International Journal of Production Economics*. doi: 10.1016/j.ijpe.2016.01.013
- Kouki, C., Jemai, Z., & Minner, S. (2015). A lost sales (r, Q) inventory control model for perishables with fixed lifetime and lead time. *International Journal of Production Economics*, 168(1), 143-157. doi: 10.1016/j.ijpe.2015.06.010
- Kouki, C., Jemai, Z., Sahin, E., & Dallery, Y. (2014). Analysis of a periodic review inventory control system with perishables having random lifetime. *International Journal of Production Research*, 52(1), 283-298. doi: 10.1080/00207543.2013.839895
- Kouki, C., & Jouini, O. (2015). On the effect of lifetime variability on the performance of inventory systems. *International Journal of Production Economics*, 167(1), 23-34. doi: 10.1016/j.ijpe.2015.05.007
- Kouki, C., Sahin, E., Jemai, Z., & Dallery, Y. (2013). *Comparison between continuous review inventory control systems for perishables with deterministic lifetime and lead time*. Paper presented at the 2013 5th International Conference on Modeling, Simulation and Applied Optimization (ICMSAO), Hammamet, Tunisia.
- Koumanakos, D. P. (2008). The effect of inventory management on firm performance. *International Journal of Productivity and Performance Management*, 57(5), 355-369. doi: 10.1108/17410400810881827

- Kouvelis, P., & Zhao, W. (2016). Supply chain contract design under financial constraints and bankruptcy costs. *Management Science*, 62(8), 2341-2357. doi: 10.1287/mnsc.2015.2248
- Lainema, T., & Hilmola, O.-P. (2005). Learn more, better and faster: Computer-based simulation gaming of production and operations. *International Journal of Business Performance Management*, 7(1), 34-59. doi: 10.1504/ijbpm.2005.006242
- Lambert, D. M., & Cooper, M. C. (2000). Issues in supply chain management. *Industrial Marketing Management*, 29(1), 65-83. doi: 10.1016/s0019-8501(99)00113-3
- Lane, D. C. (2008). The emergence and use of diagramming in system dynamics: A critical account. *Systems Research and Behavioral Science*, 25(1), 3-23. doi: 10.1002/sres.826
- Lang, T., & Heasman, M. (2015). *Food wars: The global battle for mouths, minds and markets*. Sterling, VA: Routledge.
- Larsen, C., & Thorstenson, A. (2014). The order and volume fill rates in inventory control systems. *International Journal of Production Economics*, 147(1), 13-19. doi: 10.1016/j.ijpe.2012.07.021
- Lau, C. M., & Moser, A. (2008). Behavioral effects of nonfinancial performance measures: The role of procedural fairness. *Behavioral Research in Accounting*, 20(2), 55-71. doi: 10.2308/bria.2008.20.2.55
- Lau, R. S. M., Xie, J., & Zhao, X. (2008). Effects of inventory policy on supply chain performance: A simulation study of critical decision parameters. *Computers & Industrial Engineering*, 55(3), 620-633. doi: 10.1016/j.cie.2008.02.002
- Law, A. M. (2014). *Simulation modeling and analysis*. New York, NY: McGraw-Hill Education.
- Lee, H., & Kim, C. (2014a). Benchmarking of service quality with data envelopment analysis. *Expert Systems with Applications*, 41(8), 3761-3768. doi: 10.1016/j.eswa.2013.12.008
- Lee, H., Park, Y., & Choi, H. (2009). Comparative evaluation of performance of national R&D programs with heterogeneous objectives: A DEA approach. *European Journal of Operational Research*, 196(3), 847-855. doi: 10.1016/j.ejor.2008.06.016
- Lee, H. L. (2002). Aligning supply chain strategies with product uncertainties. *California Management Review*, 44(3), 105-119. doi: 10.2307/41166135
- Lee, H. L. (2010a). Don't tweak your supply chain - Rethink it end to end. *Harvard Business Review*, 88(10), 62-69.
- Lee, H. L. (2010b). Taming the bullwhip. *Journal of Supply Chain Management*, 46(1), 7-7. doi: 10.1111/j.1745-493X.2009.03180.x
- Lee, H. L., & Billington, C. (1993). Material management in decentralized supply chains. *Operations Research*, 41(5), 835-847. doi: 10.1287/opre.41.5.835
- Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science*, 43(4), 546-558. doi: 10.2307/2634565
- Lee, J.-Y., Cho, R. K., & Paik, S.-K. (2016). Supply chain coordination in vendor-managed inventory systems with stockout-cost sharing under limited storage capacity. *European Journal of Operational Research*, 248(1), 95-106. doi: 10.1016/j.ejor.2015.06.080
- Lee, K. S., & Geem, Z. W. (2004). A new structural optimization method based on the harmony search algorithm. *Computers & Structures*, 82(9-10), 781-798. doi: 10.1016/j.compstruc.2004.01.002
- Lee, P. H., & Yu, P. L. H. (2013). An R package for analyzing and modeling ranking data. *BMC Medical Research Methodology*, 13(1), 65-76. doi: 10.1186/1471-2288-13-65
- Lee, S., & Kim, D. (2014b). An optimal policy for a single-vendor single-buyer integrated production-distribution model with both deteriorating and defective items. *International Journal of Production Economics*, 147(1), 161-170. doi: 10.1016/j.ijpe.2013.09.011

- Leeuw, S. d., Minguela-Rata, B., Sabet, E., Boter, J., & Sigurðardóttir, R. (2016). Trade-offs in managing commercial consumer returns for online apparel retail. *International Journal of Operations & Production Management*, 36(6), 710-731. doi: 10.1108/ijopm-01-2015-0010
- Lehtinen, J., & Ahola, T. (2010). Is performance measurement suitable for an extended enterprise? *International Journal of Operations & Production Management*, 30(2), 181-204. doi: 10.1108/01443571011018707
- Li, C. (2013). Controlling the bullwhip effect in a supply chain system with constrained information flows. *Applied Mathematical Modelling*, 37(4), 1897-1909. doi: 10.1016/j.apm.2012.04.020
- Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Subba Rao, S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega*, 34(2), 107-124. doi: 10.1016/j.omega.2004.08.002
- Li, W., Liang, L., Cook, W. D., & Zhu, J. (2016). DEA models for non-homogeneous DMUs with different input configurations. *European Journal of Operational Research*, 254(3), 946-956. doi: 10.1016/j.ejor.2016.04.063
- Li, X., Li, Y., Cai, X., & Shan, J. (2016). Service channel choice for supply chain: Who is better off by undertaking the service? *Production and Operations Management*, 25(3), 516-534. doi: 10.1111/poms.12392
- Li, Z., Ryan, J. K., & Sun, D. (2015). Multi-attribute procurement contracts. *International Journal of Production Economics*, 159, 137-146. doi: 10.1016/j.ijpe.2014.09.032
- Lian, Z., & Liu, L. (2001). Continuous review perishable inventory systems: Models and heuristics. *IIE Transactions*, 33(9), 809-822. doi: 10.1080/07408170108936874
- Lian, Z., Liu, L., & Neuts, M. F. (2005). A discrete-time model for common lifetime inventory systems. *Mathematics of Operations Research*, 30(3), 718-732. doi: 10.1287/moor.1040.0133
- Lian, Z., Liu, X., & Zhao, N. (2009). A perishable inventory model with Markovian renewal demands. *International Journal of Production Economics*, 121(1), 176-182. doi: 10.1016/j.ijpe.2009.04.026
- Lim, S., & Zhu, J. (2015). DEA cross-efficiency evaluation under variable returns to scale. *Journal of the Operational Research Society*, 66(3), 476-487. doi: 10.1057/jors.2014.13
- Lin, R.-C., Sir, M. Y., & Pasupathy, K. S. (2013). Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: Specific application to determining optimal resource levels in surgical services. *Omega*, 41(5), 881-892. doi: 10.1016/j.omega.2012.11.003
- Lin, R., & Chen, Z. (2015). Super-efficiency measurement under variable return to scale: An approach based on a new directional distance function. *Journal of the Operational Research Society*, 66(9), 1506-1510. doi: 10.1057/jors.2014.118
- Lin, W.-J., Jiang, Z.-B., & Wang, L. (2014). Modelling and analysis of the bullwhip effect with customers' baulking behaviours and production capacity constraint. *International Journal of Production Research*, 52(16), 4835-4852. doi: 10.1080/00207543.2014.891060
- Lindlbauer, I., Schreyögg, J., & Winter, V. (2016). Changes in technical efficiency after quality management certification: A DEA approach using difference-in-difference estimation with genetic matching in the hospital industry. *European Journal of Operational Research*, 250(3), 1026-1036. doi: 10.1016/j.ejor.2015.10.029
- Liu, C., & Chen, C. (2004). Incorporating value judgments into data envelopment analysis to improve decision quality for organization. *Journal of American Academy of Business*, 5(1/2), 423-427.

- Liu, J., & Lee, C.-G. (2007). Evaluation of inventory policies with unidirectional substitutions. *European Journal of Operational Research*, 182(1), 145-163. doi: 10.1016/j.ejor.2006.06.058
- Liu, J. S., Lu, L. Y. Y., Lu, W.-M., & Lin, B. J. Y. (2013). A survey of DEA applications. *Omega*, 41(5), 893-902. doi: 10.1016/j.omega.2012.11.004
- Liu, L. (1990). (s, S) continuous review models for inventory with random lifetimes. *Operations Research Letters*, 9(3), 161-167. doi: 10.1016/0167-6377(90)90014-v
- Liu, L., & Lian, Z. (1999). (s, S) continuous review models for products with fixed lifetimes. *Operations Research*, 47(1), 150-158. doi: 10.1287/opre.47.1.150
- Liu, L., & Yang, T. (1999). An (s, S) random lifetime inventory model with a positive lead time. *European Journal of Operational Research*, 113(1), 52-63. doi: 10.1016/s0377-2217(97)00426-8
- Liu, W., Zhou, Z., Ma, C., Liu, D., & Shen, W. (2015). Two-stage DEA models with undesirable input-intermediate-outputs. *Omega*, 56, 74-87. doi: 10.1016/j.omega.2015.03.009
- Long, Q., Lin, J., & Sun, Z. (2011). Modeling and distributed simulation of supply chain with a multi-agent platform. *International Journal of Advanced Manufacturing Technology*, 55(9-12), 1241-1252. doi: 10.1007/s00170-010-3148-7
- Lou, Y., & Wang, S. (2016). Approximate representation of the Pareto frontier in multiparty negotiations: Decentralized methods and privacy preservation. *European Journal of Operational Research*, 254(3), 968-976. doi: 10.1016/j.ejor.2016.04.060
- Lovejoy, W. S. (1998). Integrated operations: A proposal for operations management teaching and research. *Production and Operations Management*, 7(2), 106-124. doi: 10.1111/j.1937-5956.1998.tb00443.x
- Lowalekar, H., Nilakantan, R., & Ravichandran, N. (2016). Analysis of an order-up-to-level policy for perishables with random issuing. *Journal of the Operational Research Society*, 67(3), 483-505. doi: 10.1057/jors.2015.59
- Lozano, S., & Villa, G. (2009). Multiobjective target setting in data envelopment analysis using AHP. *Computers & Operations Research*, 36(2), 549-564. doi: 10.1016/j.cor.2007.10.015
- Lucas, T. W., Kelton, W. D., Sánchez, P. J., Sanchez, S. M., & Anderson, B. L. (2015). Changing the paradigm: Simulation, now a method of first resort. *Naval Research Logistics*, 62(4), 293-303. doi: 10.1002/nav.21628
- Luna-Reyes, L. F., & Andersen, D. L. (2003). Collecting and analyzing qualitative data for system dynamics: Methods and models. *System Dynamics Review*, 19(4), 271-296. doi: 10.1002/sdr.280
- Luukkanen, J., Vehmas, J., Panula-Ontto, J., Allievi, F., Kaivo-oja, J., Pasanen, T., & Auffermann, B. (2012). Synergies or trade-offs? A new method to quantify synergy between different dimensions of sustainability. *Environmental Policy and Governance*, 22(5), 337-349. doi: 10.1002/eet.1598
- Ma, Y., Wang, N., Che, A., Huang, Y., & Xu, J. (2013). The bullwhip effect on product orders and inventory: A perspective of demand forecasting techniques. *International Journal of Production Research*, 51(1), 281-302. doi: 10.1080/00207543.2012.676682
- Maanen, J. V., Sørensen, J. B., & Mitchell, T. R. (2007). The interplay between theory and method. *Academy of Management Review*, 32(4), 1145-1154. doi: 10.5465/amr.2007.26586080
- MacCarthy, B. L., Lewis, M., Voss, C., & Narasimhan, R. (2013). The same old methodologies? Perspectives on OM research in the post-lean age. *International Journal of Operations & Production Management*, 33(7), 934-956. doi: 10.1108/ijopm-08-2013-0373

- Machuca, J. A. D. (1998). Improving POM learning: Systems thinking and transparent-box business simulators. *Production and Operations Management*, 7(2), 210-227. doi: 10.1111/j.1937-5956.1998.tb00453.x
- Mahajan, S., & van Ryzin, G. (2001). Inventory competition under dynamic consumer choice. *Operations Research*, 49(5), 646-657. doi: 10.1287/opre.49.5.646.10603
- Malhotra, M. K., & Grover, V. (1998). An assessment of survey research in POM: From constructs to theory. *Journal of Operations Management*, 16(4), 407-425. doi: 10.1016/s0272-6963(98)00021-7
- Malik, M. A. R., Butt, A. N., & Choi, J. N. (2015). Rewards and employee creative performance: Moderating effects of creative self-efficacy, reward importance, and locus of control. *Journal of Organizational Behavior*, 36(1), 59-74. doi: 10.1002/job.1943
- Mangan, J., Lalwani, C., & Gardner, B. (2004). Combining quantitative and qualitative methodologies in logistics research. *International Journal of Physical Distribution & Logistics Management*, 34(7), 565-578. doi: 10.1108/09600030410552258
- Manuj, I., Mentzer, J. T., & Bowers, M. R. (2009). Improving the rigor of discrete-event simulation in logistics and supply chain research. *International Journal of Physical Distribution & Logistics Management*, 39(3), 172-201. doi: 10.1108/09600030910951692
- Mardani, A., Jusoh, A., Nor, K. M. D., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications – A review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istraživanja*, 28(1), 516-571. doi: 10.1080/1331677x.2015.1075139
- Martínez-Costa, C., Mas-Machuca, M., Benedito, E., & Corominas, A. (2014). A review of mathematical programming models for strategic capacity planning in manufacturing. *International Journal of Production Economics*, 153, 66-85. doi: 10.1016/j.ijpe.2014.03.011
- Matheus, P., & Gelders, L. (2000). The (R, Q) inventory policy subject to a compound Poisson demand pattern. *International Journal of Production Economics*, 68(3), 307-317. doi: 10.1016/s0925-5273(99)00110-3
- McGrath, J. E. (1981). Dilemmatics: "The study of research choices and dilemmas". *American Behavioral Scientist*, 25(2), 179-210. doi: 10.1177/000276428102500205
- Medori, D., & Steeple, D. (2000). A framework for auditing and enhancing performance measurement systems. *International Journal of Operations & Production Management*, 20(5), 520-533. doi: 10.1108/01443570010318896
- Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics*, 22(2), 1-25. doi: 10.1002/j.2158-1592.2001.tb00001.x
- Meredith, J. (1998). Building operations management theory through case and field research. *Journal of Operations Management*, 16(4), 441-454. doi: 10.1016/s0272-6963(98)00023-0
- Mertens, D. M. (2010). Transformative mixed methods research. *Qualitative Inquiry*, 16(6), 469-474. doi: 10.1177/1077800410364612
- Meyer, M. W. (2007). Finding performance: The new discipline in management. In A. Neely (Ed.), *Business performance measurement: Unifying theories and integrating practice* (2nd ed., pp. 113-124). Cambridge, UK: Cambridge University Press.
- Midgley, G., Cavana, R. Y., Brocklesby, J., Foote, J. L., Wood, D. R. R., & Ahuriri-Driscoll, A. (2013). Towards a new framework for evaluating systemic problem structuring methods. *European Journal of Operational Research*, 229(1), 143-154. doi: 10.1016/j.ejor.2013.01.047

- Mingers, J. (2001). Combining IS research methods: Towards a pluralist methodology. *Information Systems Research*, 12(3), 240-259. doi: 10.1287/isre.12.3.240.9709
- Mingers, J., & Brocklesby, J. (1997). Multimethodology: Towards a framework for mixing methodologies. *Omega*, 25(5), 489-509. doi: 10.1016/s0305-0483(97)00018-2
- Mingers, J., & White, L. (2010). A review of the recent contribution of systems thinking to operational research and management science. *European Journal of Operational Research*, 207(3), 1147-1161. doi: 10.1016/j.ejor.2009.12.019
- Mitra, S., & Chatterjee, A. K. (2004). Echelon stock based continuous review (R,Q) policy for fast moving items. *Omega*, 32(2), 161-166. doi: 10.1016/j.omega.2003.10.003
- Molina-Azorín, J. F. (2011). The use and added value of mixed methods in management research. *Journal of Mixed Methods Research*, 5(1), 7-24. doi: 10.1177/1558689810384490
- Montevechi, J. a. B., de Almeida Filho, R. G., Paiva, A. P., Costa, R. F. S., & Medeiros, A. L. (2010). Sensitivity analysis in discrete-event simulation using fractional factorial designs. *Journal of Simulation*, 4(2), 128-142. doi: 10.1057/jos.2009.23
- Montoya-Torres, J. R., & Ortiz-Vargas, D. A. (2014). Collaboration and information sharing in dyadic supply chains: A literature review over the period 2000–2012. *Estudios Gerenciales*, 30(133), 343-354. doi: 10.1016/j.estger.2014.05.006
- Morton, A., & Fasolo, B. (2008). Behavioural decision theory for multi-criteria decision analysis: A guided tour. *Journal of the Operational Research Society*, 60(2), 268-275. doi: 10.1057/palgrave.jors.2602550
- Munro, I., & Mingers, J. (2002). The use of multimethodology in practice - Results of a survey of practitioners. *Journal of the Operational Research Society*, 53(4), 369-378. doi: 10.1057/palgrave/2601331
- Mustak, M. (2014). Service innovation in networks: A systematic review and implications for business-to-business service innovation research. *Journal of Business & Industrial Marketing*, 29(2), 151-163. doi: 10.1108/jbim-05-2013-0122
- Nagarajan, M., & Rajagopalan, S. (2008). Inventory models for substitutable products: Optimal policies and heuristics. *Management Science*, 54(8), 1453-1466. doi: 10.1287/mnsc.1080.0871
- Nagaraju, D., Rao, A. R., Narayanan, S., & Pandian, P. (2016). Optimal cycle time and inventory decisions in coordinated and non-coordinated two-echelon inventory system under inflation and time value of money. *International Journal of Production Research*, 54(9), 2709-2730. doi: 10.1080/00207543.2015.1126679
- Nahmias, S. (1982). Perishable inventory theory: A review. *Operations Research*, 30(4), 680-708. doi: 10.2307/170438
- Nahmias, S. (Ed.). (2011). *Perishable inventory systems* (Vol. 160). New York, NY: Springer.
- Näslund, D. (2002). Logistics needs qualitative research – Especially action research. *International Journal of Physical Distribution & Logistics Management*, 32(5), 321-338. doi: 10.1108/09600030210434143
- Neely, A., Mills, J., Platts, K., Richards, H., Gregory, M., Bourne, M., & Kennerley, M. (2000). Performance measurement system design: Developing and testing a process-based approach. *International Journal of Operations & Production Management*, 20(10), 1119-1145. doi: 10.1108/01443570010343708
- Nenes, G., Panagiotidou, S., & Tagaras, G. (2010). Inventory management of multiple items with irregular demand: A case study. *European Journal of Operational Research*, 205(2), 313-324. doi: 10.1016/j.ejor.2009.12.022
- Nepal, B., Murat, A., & Chinnam, R. B. (2012). The bullwhip effect in capacitated supply chains with consideration for product life-cycle aspects. *International Journal of Production Economics*, 136(2), 318-331. doi: 10.1016/j.ijpe.2011.12.018

- Nienhaus, J., Ziegenbein, A., & Schoensleben, P. (2006). How human behaviour amplifies the bullwhip effect. A study based on the beer distribution game online. *Production Planning & Control*, 17(6), 547-557. doi: 10.1080/09537280600866587
- O'Neil, S., Zhao, X., Sun, D., & Wei, J. C. (2016). Newsvendor problems with demand shocks and unknown demand distributions. *Decision Sciences*, 47(1), 125-156. doi: 10.1111/deci.12187
- Olesen, O. B., & Petersen, N. C. (2016). Stochastic data envelopment analysis - A review. *European Journal of Operational Research*, 251(1), 2-21. doi: 10.1016/j.ejor.2015.07.058
- Olsson, F., & Tydesjö, P. (2010). Inventory problems with perishable items: Fixed lifetimes and backlogging. *European Journal of Operational Research*, 202(1), 131-137. doi: 10.1016/j.ejor.2009.05.010
- Omrani, H. (2013). Common weights data envelopment analysis with uncertain data: A robust optimization approach. *Computers & Industrial Engineering*, 66(4), 1163-1170. doi: 10.1016/j.cie.2013.07.023
- Otley, D. (2001). Accounting performance measurement: A review of its purposes and practices. *International Journal of Business Performance Management*, 3(2-4), 245-260. doi: 10.1504/ijbpm.2001.000102
- Ozer, O., & Xiong, H. (2008). Stock positioning and performance estimation for distribution systems with service constraints. *IIE Transactions*, 40(12), 1141-1157. doi: 10.1080/07408170802322960
- Pahl, J., & Voß, S. (2014). Integrating deterioration and lifetime constraints in production and supply chain planning: A survey. *European Journal of Operational Research*, 238(3), 654-674. doi: 10.1016/j.ejor.2014.01.060
- Pakkar, M. S. (2015). An integrated approach based on DEA and AHP. *Computational Management Science*, 12(1), 153-169. doi: 10.1007/s10287-014-0207-9
- Pannell, D. J. (1997). Sensitivity analysis of normative economic models: Theoretical framework and practical strategies. *Agricultural Economics*, 16(2), 139-152. doi: 10.1016/s0169-5150(96)01217-0
- Paradi, J. C., & Schaffnit, C. (2004). Commercial branch performance evaluation and results communication in a Canadian bank - A DEA application. *European Journal of Operational Research*, 156(3), 719-735. doi: 10.1016/s0377-2217(03)00108-5
- Parida, A., Kumar, U., Galar, D., & Stenström, C. (2015). Performance measurement and management for maintenance: A literature review. *Journal of Quality in Maintenance Engineering*, 21(1), 2-33. doi: 10.1108/jqme-10-2013-0067
- Parlar, M., Perry, D., & Stadje, W. (2011). FIFO versus LIFO issuing policies for stochastic perishable inventory systems. *Methodology and Computing in Applied Probability*, 13(2), 405-417. doi: 10.1007/s11009-009-9162-2
- Pasternack, B. A., & Drezner, Z. (1991). Optimal inventory policies for substitutable commodities with stochastic demand. *Naval Research Logistics*, 38(2), 221-240. doi: 10.1002/1520-6750(199104)38:2<221::aid-nav3220380208>3.0.co;2-7
- Pauls-Worm, K. G. J., Hendrix, E. M. T., Alcoba, A. G., & Haijema, R. (in press). Order quantities for perishable inventory control with non-stationary demand and a fill rate constraint. *International Journal of Production Economics*. doi: 10.1016/j.ijpe.2015.10.009
- Pauls-Worm, K. G. J., Hendrix, E. M. T., Haijema, R., & van der Vorst, J. G. A. J. (2014). An MILP approximation for ordering perishable products with non-stationary demand and service level constraints. *International Journal of Production Economics*, 157, 133-146. doi: 10.1016/j.ijpe.2014.07.020

- Pazhani, S., Ventura, J. A., & Mendoza, A. (2016). A serial inventory system with supplier selection and order quantity allocation considering transportation costs. *Applied Mathematical Modelling*, 40(1), 612-634. doi: 10.1016/j.apm.2015.06.008
- Pedraja-Chaparro, F., Salinas-Jimenez, J., & Smith, P. (1997). On the role of weight restrictions in data envelopment analysis. *Journal of Productivity Analysis*, 8(2), 215-230. doi: 10.1023/a:1007715912664
- Pedraja-Chaparro, F., Salinas-Jiménez, J., & Smith, P. (1999). On the quality of the data envelopment analysis model. *Journal of the Operational Research Society*, 50(6), 636-644. doi: 10.1057/palgrave.jors.2600741
- Peffer, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, 24(3), 45-77. doi: 10.2307/40398896
- Petrovic, D. (2001). Simulation of supply chain behaviour and performance in an uncertain environment. *International Journal of Production Economics*, 71(1-3), 429-438. doi: 10.1016/s0925-5273(00)00140-7
- Petrovic, D., Roy, R., & Petrovic, R. (1998). Modelling and simulation of a supply chain in an uncertain environment. *European Journal of Operational Research*, 109(2), 299-309. doi: 10.1016/s0377-2217(98)00058-7
- Pettersson, A. I., & Segerstedt, A. (2013). Measuring supply chain cost. *International Journal of Production Economics*, 143(2), 357-363. doi: 10.1016/j.ijpe.2012.03.012
- Pintarić, Z. N., & Kravanja, Z. (2015). The importance of proper economic criteria and process modeling for single- and multi-objective optimizations. *Computers & Chemical Engineering*, 83, 35-47. doi: 10.1016/j.compchemeng.2015.02.008
- Piotrowicz, W., & Cuthbertson, R. (2015). Performance measurement and metrics in supply chains: An exploratory study. *International Journal of Productivity and Performance Management*, 64(8), 1068-1091. doi: 10.1108/ijppm-04-2014-0064
- Podinovski, V. V. (2016). Optimal weights in DEA models with weight restrictions. *European Journal of Operational Research*, 254(3), 916-924. doi: 10.1016/j.ejor.2016.04.035
- Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2014). How information-sharing values influence the use of information systems: An investigation in the business intelligence systems context. *Journal of Strategic Information Systems*, 23(4), 270-283. doi: 10.1016/j.jsis.2014.08.003
- Powell, G. N., & Johnson, G. A. (1980). An expectancy-equity model of productive system performance. *Journal of Operations Management*, 1(1), 47-56. doi: 10.1016/0272-6963(80)90011-x
- Prater, E., Frazier, G. V., & Reyes, P. M. (2005). Future impacts of RFID on e-supply chains in grocery retailing. *Supply Chain Management: An International Journal*, 10(2), 134-142. doi: 10.1108/13598540510589205
- Rached, M., Bahroun, Z., & Campagne, J.-P. (in press). Decentralised decision-making with information sharing vs. centralised decision-making in supply chains. *International Journal of Production Research*. doi: 10.1080/00207543.2016.1173255
- Radnor, Z. J., & Barnes, D. (2007). Historical analysis of performance measurement and management in operations management. *International Journal of Productivity and Performance Management*, 56(5/6), 384-396. doi: 10.1108/17410400710757105
- Rahdar, M., & Nookabadi, A. S. (2014). Coordination mechanism for a deteriorating item in a two-level supply chain system. *Applied Mathematical Modelling*, 38(11-12), 2884-2900. doi: 10.1016/j.apm.2013.11.019
- Rahmandad, H., & Sterman, J. D. (2012). Reporting guidelines for simulation-based research in social sciences. *System Dynamics Review*, 28(4), 396-411. doi: 10.1002/sdr.1481

- Rajaram, K., & Tang, C. S. (2001). The impact of product substitution on retail merchandising. *European Journal of Operational Research*, 135(3), 582-601. doi: 10.1016/s0377-2217(01)00021-2
- Ramdas, K., & Spekman, R. E. (2000). Chain or shackles: Understanding what drives supply-chain performance. *Interfaces*, 30(4), 3-21. doi: 10.1287/inte.30.4.3.11644
- Randall, W. S., & Mello, J. E. (2012). Grounded theory: An inductive method for supply chain research. *International Journal of Physical Distribution & Logistics Management*, 42(8/9), 863-880. doi: 10.1108/09600031211269794
- Rau, H., Wu, M. Y., & Wee, H. M. (2003). Integrated inventory model for deteriorating items under a multi-echelon supply chain environment. *International Journal of Production Economics*, 86(2), 155-168. doi: 10.1016/s0925-5273(03)00048-3
- Ravichandran, N. (1995). Stochastic analysis of a continuous review perishable inventory system with positive lead time and Poisson demand. *European Journal of Operational Research*, 84(2), 444-457. doi: 10.1016/0377-2217(93)e0254-u
- Roh, J., Krause, R., & Swink, M. (2016). The appointment of chief supply chain officers to top management teams: A contingency model of firm-level antecedents and consequences. *Journal of Operations Management*, 44, 48-61. doi: 10.1016/j.jom.2016.05.001
- Roll, Y., Cook, W. D., & Golany, B. (1991). Controlling factor weights in data envelopment analysis. *IIE Transactions*, 23(1), 2-9. doi: 10.1080/07408179108963835
- Ruiz-Benitez, R., & Muriel, A. (2014). Consumer returns in a decentralized supply chain. *International Journal of Production Economics*, 147(1), 573-592. doi: 10.1016/j.ijpe.2013.05.010
- Saaty, T. L. (1986). Axiomatic foundation of the analytic hierarchy process. *Management Science*, 32(7), 841-855. doi: 10.1287/mnsc.32.7.841
- Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, 1(1), 83-98. doi: 10.1504/ijssci.2008.017590
- Saaty, T. L., & Ozdemir, M. S. (2003). Why the magic number seven plus or minus two. *Mathematical and Computer Modelling*, 38(3-4), 233-244. doi: 10.1016/s0895-7177(03)90083-5
- Saen, R. F., Memariani, A., & Lotfi, F. H. (2005). Determining relative efficiency of slightly non-homogeneous decision making units by data envelopment analysis: A case study in IROST. *Applied Mathematics and Computation*, 165(2), 313-328. doi: 10.1016/j.amc.2004.04.050
- Saghafian, S., & Tomlin, B. (2016). The newsvendor under demand ambiguity: Combining data with moment and tail information. *Operations Research*, 64(1), 167-185. doi: 10.1287/opre.2015.1454
- Said, A. A., HassabElnaby, H. R., & Wier, B. (2003). An empirical investigation of the performance consequences of nonfinancial measures. *Journal of Management Accounting Research*, 15(1), 193-223. doi: 10.2308/jmar.2003.15.1.193
- Sanchez, S. M., Moeni, F., & Sanchez, P. J. (2006). So many factors, so little time...Simulation experiments in the frequency domain. *International Journal of Production Economics*, 103(1), 149-165. doi: 10.1016/j.ijpe.2005.06.007
- Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation*, 7(1), 12-24. doi: 10.1057/jos.2012.20
- Sarkis, J. (2000). A comparative analysis of DEA as a discrete alternative multiple criteria decision tool. *European Journal of Operational Research*, 123(3), 543-557. doi: 10.1016/s0377-2217(99)00099-5
- Sarkis, J. (2007). Preparing your data for DEA. In J. Zhu & W. D. Cook (Eds.), *Modeling data irregularities and structural complexities in data envelopment analysis* (pp. 305-320). New York, US: Springer.

- Savic, D. (2002). Single-objective vs. multiobjective optimisation for integrated decision support. *Integrated Assessment and Decision Support*, 1, 7-12.
- Sazvar, Z., Baboli, A., & Akbari Jokar, M. (2013). A replenishment policy for perishable products with non-linear holding cost under stochastic supply lead time. *International Journal of Advanced Manufacturing Technology*, 64(5-8), 1087-1098. doi: 10.1007/s00170-012-4042-2
- Scandura, T. A., & Williams, E. A. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management Journal*, 43(6), 1248-1264. doi: 10.2307/1556348
- Scheel, H. (2001). Undesirable outputs in efficiency valuations. *European Journal of Operational Research*, 132(2), 400-410. doi: 10.1016/s0377-2217(00)00160-0
- Schildbach, G., & Morari, M. (2016). Scenario-based model predictive control for multi-echelon supply chain management. *European Journal of Operational Research*, 252(2), 540-549. doi: 10.1016/j.ejor.2016.01.051
- Schriber, T. J., Brunner, D. T., & Smith, J. S. (2013). Inside discrete-event simulation software: How it works and why it matters. In R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill & M. E. Kuhl (Eds.), *Proceeding of the 2013 winter simulation conference* (pp. 424-438). Austin, TX: IEEE. doi: 10.1109/wsc.2013.6721439
- Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142(1), 16-20. doi: 10.1016/s0377-2217(01)00293-4
- Seila, A. F. (2004). Spreadsheet simulation. In R. G. Ingalls, M. D. Rossetti, J. S. Smith & B. A. Peters (Eds.), *Proceedings of the 2004 winter simulation conference* (pp. 41-48). Athens, GA: IEEE. Retrieved from <http://dl.acm.org/citation.cfm?id=1161734.1161746>. doi: 10.1109/wsc.2004.1371300
- Şen, A. (2016). Competitive markdown timing for perishable and substitutable products. *Omega*, 64, 24-41. doi: 10.1016/j.omega.2015.10.016
- Senot, C., Chandrasekaran, A., & Ward, P. T. (2016a). Collaboration between service professionals during the delivery of health care: Evidence from a multiple-case study in U.S. hospitals. *Journal of Operations Management*, 42-43, 62-79. doi: 10.1016/j.jom.2016.03.004
- Senot, C., Chandrasekaran, A., & Ward, P. T. (2016b). Role of bottom-up decision processes in improving the quality of health care delivery: A contingency perspective. *Production and Operations Management*, 25(3), 458-476. doi: 10.1111/poms.12404
- Seuring, S. A. A. (2008). Assessing the rigor of case study research in supply chain management. *Supply Chain Management: An International Journal*, 13(2), 128-137. doi: 10.1108/13598540810860967
- Sexton, T. R., Silkman, R. H., & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. *New Directions for Program Evaluation*, 1986(32), 73-105. doi: 10.1002/ev.1441
- Sezen, B. (2006). Changes in performance under various lengths of review periods in a periodic review inventory control system with lost sales: A simulation study. *International Journal of Physical Distribution & Logistics Management*, 36(5), 360-373. doi: 10.1108/09600030610676240
- Shang, J. S., Li, S., & Tadikamalla, P. (2004). Operational design of a supply chain system using the Taguchi method, response surface methodology, simulation, and optimization. *International Journal of Production Research*, 42(18), 3823-3849. doi: 10.1080/00207540410001704050

- Shaw, J. D., & Gupta, N. (2015). Let the evidence speak again! Financial incentives are more effective than we thought. *Human Resource Management Journal*, 25(3), 281-293. doi: 10.1111/1748-8583.12080
- Shell, R. L., & Hall, E. L. (Eds.). (2000). *Handbook of industrial automation*. New York, NY: Marcel Dekker.
- Shepherd, D. A., Williams, T. A., & Patzelt, H. (2015). Thinking about entrepreneurial decision making review and research agenda. *Journal of Management*, 41(1), 11-46. doi: 10.1177/0149206314541153
- Shin, H., Park, S., Lee, E., & Benton, W. C. (2015). A classification of the literature on the planning of substitutable products. *European Journal of Operational Research*, 246(3), 686-699. doi: 10.1016/j.ejor.2015.04.013
- Shin, S., Ennis, K. L., & Spurlin, W. P. (2015). Effect of inventory management efficiency on profitability: Current evidence from the U.S. manufacturing industry. *Journal of Economics and Economic Education Research*, 16(1), 98-106.
- Shott, T., & Lim, D.-J. (2015). TFDEA: Technology forecasting using DEA (data envelopment analysis) (Version 0.9.8.3). Retrieved from <https://cran.r-project.org/web/packages/TFDEA/index.html>
- Simatupang, T. M., & Sridharan, R. (2002). The collaborative supply chain. *International Journal of Logistics Management*, 13(1), 15-30. doi: 10.1108/09574090210806333
- Singh, G., & O'Keefe, C. M. (2016). Decentralised scheduling with confidentiality protection. *Operations Research Letters*, 44(4), 514-519. doi: 10.1016/j.orl.2016.05.004
- Singhal, K., & Singhal, J. (2012a). Imperatives of the science of operations and supply-chain management. *Journal of Operations Management*, 30(3), 237-244. doi: 10.1016/j.jom.2011.11.003
- Singhal, K., & Singhal, J. (2012b). Opportunities for developing the science of operations and supply-chain management. *Journal of Operations Management*, 30(3), 245-252. doi: 10.1016/j.jom.2011.11.002
- Singhal, K., Sodhi, M. S., & Tang, C. S. (2014). POMS initiatives for promoting practice-driven research and research-influenced practice. *Production and Operations Management*, 23(5), 725-727. doi: 10.1111/poms.12229
- Sinuany-Stern, Z., Mehrez, A., & Hadad, Y. (2000). An AHP/DEA methodology for ranking decision making units. *International Transactions in Operational Research*, 7(2), 109-124. doi: 10.1111/j.1475-3995.2000.tb00189.x
- Smith, S. A., & Agrawal, N. (2000). Management of multi-item retail inventory systems with demand substitution. *Operations Research*, 48(1), 50-64. doi: 10.1287/opre.48.1.50.12443
- Sodenkamp, M. A., Tavana, M., & Di Caprio, D. (2016). Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading. *European Journal of Operational Research*, 254(3), 859-874. doi: 10.1016/j.ejor.2016.04.015
- Sodhi, M. S., & Tang, C. S. (2008). The OR/MS ecosystem: Strengths, weaknesses, opportunities, and threats. *Operations Research*, 56(2), 267-277. doi: 10.1287/opre.1080.0519
- Sodhi, M. S., & Tang, C. S. (2014). Guiding the next generation of doctoral students in operations management. *International Journal of Production Economics*, 150(1), 28-36. doi: 10.1016/j.ijpe.2013.11.016
- Soosay, C. A., & Hyland, P. (2015). A decade of supply chain collaboration and directions for future research. *Supply Chain Management: An International Journal*, 20(6), 613-630. doi: 10.1108/scm-06-2015-0217

- Spens, K. M., & Kovács, G. (2006). A content analysis of research approaches in logistics research. *International Journal of Physical Distribution & Logistics Management*, 36(5), 374-390. doi: 10.1108/09600030610676259
- Stadtler, H. (2005). Supply chain management and advanced planning - Basics, overview and challenges. *European Journal of Operational Research*, 163(3), 575-588. doi: 10.1016/j.ejor.2004.03.001
- Stank, T. P., Dittmann, J. P., & Autry, C. W. (2011). The new supply chain agenda: A synopsis and directions for future research. *International Journal of Physical Distribution & Logistics Management*, 41(10), 940-955. doi: 10.1108/09600031111185220
- Stank, T. P., Keller, S. B., & Daugherty, P. J. (2001). Supply chain collaboration and logistical service performance. *Journal of Business Logistics*, 22(1), 29-48. doi: 10.1002/j.2158-1592.2001.tb00158.x
- Stavroulaki, E. (2011). Inventory decisions for substitutable products with stock-dependent demand. *International Journal of Production Economics*, 129(1), 65-78. doi: 10.1016/j.ijpe.2010.09.002
- Stevens, G., & Johnson, M. (2016). Integrating the supply chain... 25 years on. *International Journal of Physical Distribution & Logistics Management*, 46(1), 19-42. doi: 10.1108/ijpdlm-07-2015-0175
- Stevens, G. C. (1989). Integrating the supply chain. *International Journal of Physical Distribution & Materials Management*, 19(8), 3-8. doi: 10.1108/eum00000000000329
- Stuart, I., McCutcheon, D., Handfield, R., McLachlin, R., & Samson, D. (2002). Effective case research in operations management: A process perspective. *Journal of Operations Management*, 20(5), 419-433. doi: 10.1016/s0272-6963(02)00022-0
- Subramanian, N., & Ramanathan, R. (2012). A review of applications of analytic hierarchy process in operations management. *International Journal of Production Economics*, 138(2), 215-241. doi: 10.1016/j.ijpe.2012.03.036
- Syntetos, A. A., Babai, Z., Boylan, J. E., Kolassa, S., & Nikolopoulos, K. (2016). Supply chain forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research*, 252(1), 1-26. doi: 10.1016/j.ejor.2015.11.010
- Takamura, Y., & Tone, K. (2003). A comparative site evaluation study for relocating Japanese government agencies out of Tokyo. *Socio-Economic Planning Sciences*, 37(2), 85-102. doi: 10.1016/s0038-0121(02)00049-6
- Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, 52(4), 802-815. doi: 10.1016/j.dss.2011.11.015
- Talluri, S., & Sarkis, J. (2002). A methodology for monitoring system performance. *International Journal of Production Research*, 40(7), 1567-1582. doi: 10.1080/00207540110118659
- Tan, B., & Karabati, S. (2013). Retail inventory management with stock-out based dynamic demand substitution. *International Journal of Production Economics*, 145(1), 78-87. doi: 10.1016/j.ijpe.2012.10.002
- Tan, T. F., & Netessine, S. (2014). When does the devil make work? An empirical study of the impact of workload on worker productivity. *Management Science*, 60(6), 1574-1593. doi: 10.1287/mnsc.2014.1950
- Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451-488. doi: 10.1016/j.ijpe.2005.12.006
- Tang, C. S. (2016). OM forum - Making OM research more relevant: "Why?" and "how?". *Manufacturing & Service Operations Management*, 18(2), 178-183. doi: 10.1287/msom.2015.0553

- Tangpong, C., Hung, K.-T., & Li, J. (2014). Agent-system co-development in supply chain research: Propositions and demonstrative findings. *Journal of Operations Management*, 32(4), 154-174. doi: 10.1016/j.jom.2014.03.002
- Taticchi, P., Tonelli, F., & Cagnazzo, L. (2010). Performance measurement and management: A literature review and a research agenda. *Measuring Business Excellence*, 14(1), 4-18. doi: 10.1108/13683041011027418
- Taticchi, P., Tonelli, F., & Pasqualino, R. (2013). Performance measurement of sustainable supply chains: A literature review and a research agenda. *International Journal of Productivity and Performance Management*, 62(8), 782-804. doi: 10.1108/ijppm-03-2013-0037
- Taylor, A., & Taylor, M. (2009). Operations management research: Contemporary themes, trends and potential future directions. *International Journal of Operations & Production Management*, 29(12), 1316-1340. doi: 10.1108/01443570911006018
- Teimoury, E., Nedaei, H., Ansari, S., & Sabbaghi, M. (2013). A multi-objective analysis for import quota policy making in a perishable fruit and vegetable supply chain: A system dynamics approach. *Computers and Electronics in Agriculture*, 93(1), 37-45. doi: 10.1016/j.compag.2013.01.010
- Tekin, E., Gürler, Ü., & Berk, E. (2001). Age-based vs. stock level control policies for a perishable inventory system. *European Journal of Operational Research*, 134(2), 309-329. doi: 10.1016/s0377-2217(00)00250-2
- Temur, G. T. (2016). A novel multi attribute decision making approach for location decision under high uncertainty. *Applied Soft Computing*, 40, 674-682. doi: 10.1016/j.asoc.2015.12.027
- Terzi, S., & Cavalieri, S. (2004). Simulation in the supply chain context: A survey. *Computers in Industry*, 53(1), 3-16. doi: 10.1016/s0166-3615(03)00104-0
- Thomas, A., Krishnamoorthy, M., Venkateswaran, J., & Singh, G. (2016). Decentralised decision-making in a multi-party supply chain. *International Journal of Production Research*, 54(2), 405-425. doi: 10.1080/00207543.2015.1096977
- Thompson, J. P., Howick, S., & Belton, V. (2016). Critical learning incidents in system dynamics modelling engagements. *European Journal of Operational Research*, 249(3), 945-958. doi: 10.1016/j.ejor.2015.09.048
- Thrall, R. M. (1996). Duality, classification and slacks in DEA. *Annals of Operations Research*, 66(2), 109-138. doi: 10.1007/bf02187297
- Tocher, K. D., & Owen, D. G. (2008). The automatic programming of simulations. *Journal of Simulation*, 2(3), 143-152. doi: 10.1057/jos.2008.13
- Tofallis, C. (2014). On constructing a composite indicator with multiplicative aggregation and the avoidance of zero weights in DEA. *Journal of the Operational Research Society*, 65(5), 791-792. doi: 10.1057/jors.2013.137
- Toloo, M. (2014). Selecting and full ranking suppliers with imprecise data: A new DEA method. *International Journal of Advanced Manufacturing Technology*, 74(5-8), 1141-1148. doi: 10.1007/s00170-014-6035-9
- Towill, D. R., Zhou, L., & Disney, S. M. (2007). Reducing the bullwhip effect: Looking through the appropriate lens. *International Journal of Production Economics*, 108(1), 444-453. doi: 10.1016/j.ijpe.2006.12.024
- Tsai, S. C., & Liu, C. H. (2015). A simulation-based decision support system for a multi-echelon inventory problem with service level constraints. *Computers & Operations Research*, 53(1), 118-127. doi: 10.1016/j.cor.2014.07.018
- Uncles, M. D., Dowling, G. R., & Hammond, K. (2003). Customer loyalty and customer loyalty programs. *Journal of Consumer Marketing*, 20(4), 294-316. doi: 10.1108/07363760310483676

- van der Vorst, J. G. A. J., Beulens, A. J. M., & van Beek, P. (2000). Modelling and simulating multi-echelon food systems. *European Journal of Operational Research*, 122(2), 354-366. doi: 10.1016/s0377-2217(99)00238-6
- van der Zee, D.-J., & van der Vorst, J. G. A. J. (2005). A modeling framework for supply chain simulation: Opportunities for improved decision making. *Decision Sciences*, 36(1), 65-95. doi: 10.1111/j.1540-5915.2005.00066.x
- van Donselaar, K. H., & Broekmeulen, R. A. C. M. (2012). Approximations for the relative outdating of perishable products by combining stochastic modeling, simulation and regression modeling. *International Journal of Production Economics*, 140(2), 660-669. doi: 10.1016/j.ijpe.2012.02.023
- van Donselaar, K. H., & Broekmeulen, R. A. C. M. (2014). Stochastic inventory models for a single item at a single location. (BETA publicatie: Working papers; 447). Retrieved June 26, 2014 http://cms.ieis.tue.nl/Beta/Files/WorkingPapers/wp_447.pdf
- van Donselaar, K. H., Peters, J., de Jong, A., & Broekmeulen, R. A. C. M. (2016). Analysis and forecasting of demand during promotions for perishable items. *International Journal of Production Economics*, 172, 65-75. doi: 10.1016/j.ijpe.2015.10.022
- Varthanan, P. A., Murugan, N., Kumar, G. M., & Parameswaran, S. (2011). Development of simulation-based AHP-DPSO algorithm for generating multi-criteria production–distribution plan. *International Journal of Advanced Manufacturing Technology*, 60(1-4), 373-396. doi: 10.1007/s00170-011-3606-x
- Vaughan, T. S. (1994). A model of the perishable inventory system with reference to consumer realized product expiration. *Journal of the Operational Research Society*, 45(5), 519-528. doi: 10.2307/2584387
- Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 37(1), 21-54.
- Ventura, J. A., Valdebenito, V. A., & Golany, B. (2013). A dynamic inventory model with supplier selection in a serial supply chain structure. *European Journal of Operational Research*, 230(2), 258-271. doi: 10.1016/j.ejor.2013.03.012
- Verhoef, P. C., & Sloot, L. M. (2006). Out-of-stock: Reactions, antecedents, management solutions, and a future perspective. In M. Krafft & M. K. Mantrala (Eds.), *Retailing in the 21st century: Current and future trends* (2nd ed., pp. 285-299). Berlin, Germany: Springer.
- Viana, J., Brailsford, S. C., Harindra, V., & Harper, P. R. (2014). Combining discrete-event simulation and system dynamics in a healthcare setting: A composite model for Chlamydia infection. *European Journal of Operational Research*, 237(1), 196-206. doi: 10.1016/j.ejor.2014.02.052
- Vidalis, M., Vrisagotis, V., & Varlas, G. (2014). Performance evaluation of a two-echelon supply chain with stochastic demand, lost sales, and Coxian-2 phase replenishment times. *International Transactions in Operational Research*, 21(4), 649-671. doi: 10.1111/itor.12057
- Voss, C., Tsikriktsis, N., & Frohlich, M. (2002). Case research in operations management. *International Journal of Operations & Production Management*, 22(2), 195-219. doi: 10.1108/01443570210414329
- Wallenius, J., Dyer, J. S., Fishburn, P. C., Steuer, R. E., Zionts, S., & Deb, K. (2008). Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead. *Management Science*, 54(7), 1336-1349. doi: 10.1287/mnsc.1070.0838
- Waller, M. A., Tangari, A. H., & Williams, B. D. (2008). Case pack quantity's effect on retail market share: An examination of the backroom logistics effect and the store-level fill

- rate effect. *International Journal of Physical Distribution & Logistics Management*, 38(6), 436-451. doi: 10.1108/09600030810893508
- Wang, C., & Chen, X. (2015). Optimal ordering policy for a price-setting newsvendor with option contracts under demand uncertainty. *International Journal of Production Research*, 53(20), 6279-6293. doi: 10.1080/00207543.2015.1053577
- Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98-110. doi: 10.1016/j.ijpe.2016.03.014
- Wang, G., Huang, S. H., & Dismukes, J. P. (2004). Product-driven supply chain selection using integrated multi-criteria decision-making methodology. *International Journal of Production Economics*, 91(1), 1-15. doi: 10.1016/s0925-5273(03)00221-4
- Wang, K.-J., Lin, Y. S., & Yu, J. C. P. (2011). Optimizing inventory policy for products with time-sensitive deteriorating rates in a multi-echelon supply chain. *International Journal of Production Economics*, 130(1), 66-76. doi: 10.1016/j.ijpe.2010.11.009
- Wang, X., & Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. *European Journal of Operational Research*, 250(3), 691-701. doi: 10.1016/j.ejor.2015.07.022
- Wang, Y., Wallace, S. W., Shen, B., & Choi, T.-M. (2015). Service supply chain management: A review of operational models. *European Journal of Operational Research*, 247(3), 685-698. doi: 10.1016/j.ejor.2015.05.053
- WasteMinz. (2015). Love food hate waste NZ. Retrieved from <http://www.wasteminz.org.nz/sector-groups/behaviour-change/love-food-hate-waste/>
- Weiss, H. J. (1980). Optimal ordering policies for continuous review perishable inventory models. *Operations Research*, 28(2), 365-374. doi: 10.2307/170452
- Weraikat, D., Zanjani, M. K., & Lehoux, N. (2016). Two-echelon pharmaceutical reverse supply chain coordination with customers incentives. *International Journal of Production Economics*, 176, 41-52. doi: 10.1016/j.ijpe.2016.03.003
- Williams, B. D., & Tokar, T. (2008). A review of inventory management research in major logistics journals: Themes and future directions. *International Journal of Logistics Management*, 19(2), 212-232. doi: 10.1108/09574090810895960
- Williams, C. L., & Patuwo, E. B. (2004). Analysis of the effect of various unit costs on the optimal incoming quantity in a perishable inventory model. *European Journal of Operational Research*, 156(1), 140-147. doi: 10.1016/s0377-2217(02)00919-0
- Williams, T., & Gemperle, S. M. (in press). Sequence will tell! Integrating temporality into set-theoretic multi-method research combining comparative process tracing and qualitative comparative analysis. *International Journal of Social Research Methodology*. doi: 10.1080/13645579.2016.1149316
- Wilson, S. R., Whitmoyer, J. G., Pieper, T. M., Astrachan, J. H., Hair Jr, J. F., & Sarstedt, M. (2014). Method trends and method needs: Examining methods needed for accelerating the field. *Journal of Family Business Strategy*, 5(1), 4-14. doi: 10.1016/j.jfbs.2014.01.011
- Wong, J.-T. (2010). The distribution processing and replenishment policy of the supply chain under asymmetric information and deterioration: Insight into the information value. *Expert Systems with Applications*, 37(3), 2347-2353. doi: 10.1016/j.eswa.2009.07.040
- Wong, W. P., & Wong, K. Y. (2008). A review on benchmarking of supply chain performance measures. *Benchmarking: An International Journal*, 15(1), 25-51. doi: 10.1108/14635770810854335
- Wu, J., Al-khateeb, F. B., Teng, J.-T., & Cárdenas-Barrón, L. E. (2016a). Inventory models for deteriorating items with maximum lifetime under downstream partial trade credits to

- credit-risk customers by discounted cash-flow analysis. *International Journal of Production Economics*, 171, Part 1, 105-115. doi: 10.1016/j.ijpe.2015.10.020
- Wu, J., Chu, J., Sun, J., & Zhu, Q. (2016b). DEA cross-efficiency evaluation based on Pareto improvement. *European Journal of Operational Research*, 248(2), 571-579. doi: 10.1016/j.ejor.2015.07.042
- Xi, X., & Poh, K. L. (2015). A novel integrated decision support tool for sustainable water resources management in Singapore: Synergies between system dynamics and analytic hierarchy process. *Water Resources Management*, 29(4), 1329-1350. doi: 10.1007/s11269-014-0876-8
- Xu, M., Chen, Y., & Xu, X. (2010). The effect of demand uncertainty in a price-setting newsvendor model. *European Journal of Operational Research*, 207(2), 946-957. doi: 10.1016/j.ejor.2010.06.024
- Xu, T., Moon, D. H., & Baek, S. G. (2011). A simulation study integrated with analytic hierarchy process (AHP) in an automotive manufacturing system. *Simulation*, 88(4), 450-463. doi: 10.1177/0037549711407781
- Xue, W., Choi, T.-M., & Ma, L. (2016). Diversification strategy with random yield suppliers for a mean-variance risk-sensitive manufacturer. *Transportation Research Part E: Logistics and Transportation Review*, 90, 90-107. doi: 10.1016/j.tre.2016.01.013
- Yadav, V., & Sharma, M. K. (2015). An application of hybrid data envelopment analytical hierarchy process approach for supplier selection. *Journal of Enterprise Information Management*, 28(2), 218-242. doi: 10.1108/jeim-04-2014-0041
- Yadav, V., & Sharma, M. K. (2016). Multi-criteria supplier selection model using the analytic hierarchy process approach. *Journal of Modelling in Management*, 11(1), 326-354. doi: 10.1108/jm2-06-2014-0052
- Yakovleva, N., Sarkis, J., & Sloan, T. (2012). Sustainable benchmarking of supply chains: The case of the food industry. *International Journal of Production Research*, 50(5), 1297-1317. doi: 10.1080/00207543.2011.571926
- Yang, H., & Schrage, L. (2009). Conditions that cause risk pooling to increase inventory. *European Journal of Operational Research*, 192(3), 837-851. doi: 10.1016/j.ejor.2007.10.064
- Yang, P. C., & Wee, H. M. (2000). Economic ordering policy of deteriorated item for vendor and buyer: An integrated approach. *Production Planning & Control*, 11(5), 474-480. doi: 10.1080/09537280050051979
- Yang, P. C., & Wee, H. M. (2002). A single-vendor and multiple-buyers production-inventory policy for a deteriorating item. *European Journal of Operational Research*, 143(3), 570-581. doi: 10.1016/s0377-2217(01)00345-9
- Yang, T., & Kuo, C. (2003). A hierarchical AHP/DEA methodology for the facilities layout design problem. *European Journal of Operational Research*, 147(1), 128-136. doi: 10.1016/s0377-2217(02)00251-5
- Yi, H., & Sarker, B. R. (2013a). An operational policy for an integrated inventory system under consignment stock policy with controllable lead time and buyers' space limitation. *Computers & Operations Research*, 40(11), 2632-2645. doi: 10.1016/j.cor.2013.05.001
- Yi, H., & Sarker, B. R. (2013b). An optimal consignment stock production and replenishment policy with controllable lead time. *International Journal of Production Research*, 51(21), 6316-6335. doi: 10.1080/00207543.2013.795668
- Yin, R. K. (2014). *Case study research: Design and methods* (5th ed.). Thousand Oaks, CA: Sage.
- Yin, Z., & Ma, S. (2015). Incentives to improve the service level in a random yield supply chain: The role of bonus contracts. *European Journal of Operational Research*, 244(3), 778-791. doi: 10.1016/j.ejor.2015.02.006

- Yu, D. Z., Tang, S. Y., & Niederhoff, J. (2011). On the benefits of operational flexibility in a distribution network with transshipment. *Omega*, 39(3), 350-361. doi: 10.1016/j.omega.2010.08.004
- Zavadskas, E. K., Turskis, Z., & Kildienė, S. (2014). State of art surveys of overviews on MCDM/MADM methods. *Technological and Economic Development of Economy*, 20(1), 165-179. doi: 10.3846/20294913.2014.892037
- Zeng, Y., & Skibniewski, M. J. (2013). Risk assessment for enterprise resource planning (ERP) system implementations: A fault tree analysis approach. *Enterprise Information Systems*, 7(3), 332-353. doi: 10.1080/17517575.2012.690049
- Zhang, A., Guo, X., & Zhang, Z. (2009). Inventory decision models with competition existing between two parallel supply chains. *International Journal of Services and Operations Management*, 5(5), 717-736. doi: 10.1504/ij som.2009.025122
- Zhang, C., & Zhang, C. (2007). Design and simulation of demand information sharing in a supply chain. *Simulation Modelling Practice and Theory*, 15(1), 32-46. doi: 10.1016/j.simpat.2006.09.011
- Zhang, J., & Chen, J. (2013). Coordination of information sharing in a supply chain. *International Journal of Production Economics*, 143(1), 178-187. doi: 10.1016/j.ijpe.2013.01.005
- Zhang, J., Wei, Q., Zhang, Q., & Tang, W. (2016). Pricing, service and preservation technology investments policy for deteriorating items under common resource constraints. *Computers & Industrial Engineering*, 95, 1-9. doi: 10.1016/j.cie.2016.02.014
- Zhang, L., Wang, J., & You, J. (2015). Consumer environmental awareness and channel coordination with two substitutable products. *European Journal of Operational Research*, 241(1), 63-73. doi: 10.1016/j.ejor.2014.07.043
- Zhang, R.-Q., Zhang, L.-K., Zhou, W.-H., Saigal, R., & Wang, H.-W. (2014). The multi-item newsvendor model with cross-selling and the solution when demand is jointly normally distributed. *European Journal of Operational Research*, 236(1), 147-159. doi: 10.1016/j.ejor.2014.01.006
- Zhang, Z.-H., & Unnikrishnan, A. (2016). A coordinated location-inventory problem in closed-loop supply chain. *Transportation Research Part B: Methodological*, 89, 127-148. doi: 10.1016/j.trb.2016.04.006
- Zhao, Y., Zhao, C., He, M., & Yang, C. (2016). A state-feedback approach to inventory control: Analytical and empirical studies. *Production and Operations Management*, 25(3), 535-547. doi: 10.1111/poms.12522
- Zhou, L., & Disney, S. M. (2006). Bullwhip and inventory variance in a closed loop supply chain. *OR Spectrum*, 28(1), 123-145. doi: 10.1007/s00291-005-0009-0
- Zhu, J. (2000). Multi-factor performance measure model with an application to Fortune 500 companies. *European Journal of Operational Research*, 123(1), 105-124. doi: 10.1016/s0377-2217(99)00096-x
- Zinn, W., & Liu, P. C. (2001). Consumer response to retail stockouts. *Journal of Business Logistics*, 22(1), 49-71. doi: 10.1002/j.2158-1592.2001.tb00159.x
- Zomerdijk, L. G., & de Vries, J. (2003). An organizational perspective on inventory control: Theory and a case study. *International Journal of Production Economics*, 81-82(1), 173-183. doi: 10.1016/s0925-5273(02)00276-1
- Zotteri, G. (2013). An empirical investigation on causes and effects of the bullwhip-effect: Evidence from the personal care sector. *International Journal of Production Economics*, 143(2), 489-498. doi: 10.1016/j.ijpe.2012.06.006

Appendix

Appendix 1 Sales report of retailer #1, product #1, experiment #1, policy (4,47)

Record #	Current Date	Original Demand	Inventory Onhand	Effective Demand	Sales	Lost	Replenished Quantity	Expiry Date
1	1/1/2015 0:00:00	11	0	16	0	16	47	1/2/2015 0:00:00
2	1/2/2015 0:00:00	8	47	8	8	0	0	
3	1/3/2015 0:00:00	7	0	14	0	14	0	
4	1/4/2015 0:00:00	15	0	25	0	25	0	
5	1/5/2015 0:00:00	8	0	15	0	15	47	1/6/2015 0:00:00
6	1/6/2015 0:00:00	10	47	10	10	0	0	
7	1/7/2015 0:00:00	10	0	10	0	10	0	
8	1/8/2015 0:00:00	11	0	11	0	11	0	
9	1/9/2015 0:00:00	10	0	19	0	19	47	1/14/2015 0:00:00
10	1/10/2015 0:00:00	10	47	10	10	0	0	
11	1/11/2015 0:00:00	11	37	11	11	0	0	
12	1/12/2015 0:00:00	8	28	8	8	0	0	
13	1/13/2015 0:00:00	13	18	17	17	0	46	1/15/2015 0:00:00
14	1/14/2015 0:00:00	5	47	5	5	0	0	
15	1/15/2015 0:00:00	14	42	17	17	0	0	
16	1/16/2015 0:00:00	12	0	18	0	18	0	
17	1/17/2015 0:00:00	9	0	15	0	15	47	1/19/2015 0:00:00
18	1/18/2015 0:00:00	14	47	14	14	0	0	
19	1/19/2015 0:00:00	10	33	18	18	0	0	
20	1/20/2015 0:00:00	7	0	14	0	14	0	
21	1/21/2015 0:00:00	4	0	13	0	13	47	1/22/2015 0:00:00
22	1/22/2015 0:00:00	9	47	9	9	0	0	
23	1/23/2015 0:00:00	15	0	20	0	20	0	
24	1/24/2015 0:00:00	14	0	17	0	17	0	
25	1/25/2015 0:00:00	10	0	18	0	18	47	1/28/2015 0:00:00
26	1/26/2015 0:00:00	13	47	13	13	0	0	
27	1/27/2015 0:00:00	12	0	12	0	12	0	
28	1/28/2015 0:00:00	14	0	22	0	22	0	
29	1/29/2015 0:00:00	11	0	20	0	20	47	1/30/2015 0:00:00
30	1/30/2015 0:00:00	12	47	12	12	0	0	
31	1/31/2015 0:00:00	9	0	13	0	13	0	
32	2/1/2015 0:00:00	8	0	11	0	11	0	
33	2/2/2015 0:00:00	10	0	19	0	19	47	2/3/2015 0:00:00
34	2/3/2015 0:00:00	9	47	9	9	0	0	
35	2/4/2015 0:00:00	9	0	13	0	13	0	
36	2/5/2015 0:00:00	6	0	8	0	8	0	
37	2/6/2015 0:00:00	7	0	15	0	15	47	2/15/2015 0:00:00
38	2/7/2015 0:00:00	14	47	14	14	0	0	
39	2/8/2015 0:00:00	8	33	8	8	0	0	
40	2/9/2015 0:00:00	11	25	11	11	0	0	
41	2/10/2015 0:00:00	18	14	18	14	4	47	2/15/2015 0:00:00
42	2/11/2015 0:00:00	9	47	9	9	0	0	
43	2/12/2015 0:00:00	9	38	10	10	0	0	
44	2/13/2015 0:00:00	11	28	14	14	0	0	
45	2/14/2015 0:00:00	11	14	14	14	0	47	2/18/2015 0:00:00
46	2/15/2015 0:00:00	11	47	11	11	0	0	
47	2/16/2015 0:00:00	9	38	9	9	0	0	
48	2/17/2015 0:00:00	9	0	9	0	9	0	
49	2/18/2015 0:00:00	8	0	10	0	10	47	2/19/2015 0:00:00

**Appendix 2 Syntax and results of calculating the weight of performance measures in
'pmr' – an R package**

```
library(pmr)
```

```
Loading required package: stats4
```

```
ahp <- matrix(data = 1:9, nrow = 3, ncol = 3, byrow = TRUE)
```

```
ahp[1,1] <- 1
```

```
ahp[1,2] <- 1/4
```

```
ahp[1,3] <- 4
```

```
ahp[2,1] <- 4
```

```
ahp[2,2] <- 1
```

```
ahp[2,3] <- 9
```

```
ahp[3,1] <- 1/4
```

```
ahp[3,2] <- 1/9
```

```
ahp[3,3] <- 1
```

```
ahp(ahp)
```

```
Summary of pairwise comparison matrices:
```

```
$weighting: weights of items; $Saaty: Saaty's inconsistency; $Koczkodaj: Koczkodaj's
```

```
inconsistency
```

```
$weighting
```

```
[1] 0.21716561 0.71706504 0.06576935
```

```
$Saaty
```

```
[1] 0.0387141
```

```
$Koczkodaj
```

```
[1] 0.4375
```

Appendix 3 A portion report of average inventory at retailer #1, experiment #1

Review Period	Order-up-to level	Average Inventory Retailer 1, product 1	Average Inventory Retailer 1, product 2	Average Inventory Retailer 1, product 3
1	26	24.569	24.570	24.572
1	27	25.456	25.455	25.453
1	28	26.334	26.343	26.344
1	29	27.223	27.225	27.222
1	30	28.105	28.108	28.111
1	31	28.992	28.990	28.990
1	32	29.869	29.868	29.870
1	33	30.747	30.748	30.748
1	34	31.626	31.631	31.628
1	35	32.503	32.500	32.508
1	36	33.382	33.377	33.379
1	37	34.254	34.248	34.250
1	38	35.125	35.117	35.123
1	39	36.010	35.994	36.004
1	40	36.865	36.867	36.868
1	41	37.748	37.743	37.739
1	42	38.618	38.623	38.625
1	43	39.484	39.492	39.495
1	44	40.360	40.365	40.365
1	45	41.236	41.247	41.239
1	46	42.101	42.105	42.101
1	47	42.977	42.973	42.981
2	26	17.580	17.584	17.587
2	27	18.473	18.473	18.474
2	28	19.356	19.357	19.361
2	29	20.235	20.238	20.232
2	30	21.106	21.107	21.104
2	31	21.968	21.965	21.974
2	32	22.827	22.823	22.823
2	33	23.678	23.673	23.672
2	34	24.522	24.512	24.511
2	35	25.355	25.356	25.359
2	36	26.188	26.190	26.192
2	37	27.018	27.019	27.018
2	38	27.850	27.852	27.841
2	39	28.683	28.673	28.676
2	40	29.505	29.504	29.509
2	41	30.328	30.317	30.320
2	42	31.150	31.156	31.155
2	43	31.970	31.972	31.976
2	44	32.804	32.803	32.798
2	45	33.628	33.625	33.626

Appendix 4 Four basic DEA models

In the DEA model, the term decision-making unit (DMU) is used to refer to any entity which that evaluates its capabilities to transform inputs into outputs. Assume that there are n DMUs; each DMU consumes m inputs to produce s outputs. Particularly, DMU _{j} consumes x_{ij} amount of input i to produce y_{rj} amount of output r ; $x_{ij}, y_{rj} \geq 0$. The inputs of a firm can be the number of staff, the number of branches, the firm's space, or the firm's location. The outputs can be a number of produced products, customer satisfaction, sales volume, or revenue.

Model 1: Constant return to scale – Input-oriented model

The concept of DEA is to focus on each performance of a DMU. Charnes, Cooper, and Rhodes (1981) defined DEA as “a mathematical programming model applied to observational data and a new way of obtaining experimental estimates of relations such as the production functions and/or efficient production possibility surfaces” (p. 668). DEA evaluates the relative efficiency of a particular DMU relative to other DMUs. The relative efficiency of each DEA is measured by the ratio of outputs to inputs. The objective function of a particular DMU₀ is formed as:

$$\text{Max } h_0(u, v) = \frac{\sum_r u_r y_{r0}}{\sum_i v_i x_{i0}} \quad (1)$$

subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1, \text{ for } j = 1, \dots, n$$

$$u_r, v_i \geq 0$$

Where u_r , and v_i are the weight given to output r and input i respectively. The constraint of the upper bound of one is generalised from the engineering science definition from a single input and a single output (Cooper et al., 2011). A DMU is efficient if the efficiency score equals one.

The formulation (1) can be converted to a linear formulation as:

$$\text{Max } Z = \sum_{r=1}^s u_r y_{ro} \quad (2)$$

subject to

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0$$

$$\sum_{i=1}^m v_i x_{i0} = 1$$

$$u_r, v_i \geq 0$$

Model 2: Constant return to scale – Output-oriented model

Alternatively, one could start with the output side and consider the ratio of inputs to outputs.

In this case, it is the output-oriented DEA model. The objective of a DMU reorients from maximum to minimum.

$$\text{Min } h_0(u, v) = \frac{\sum_i v_i x_{i0}}{\sum_r u_r y_{ro}} \quad (3)$$

Subject to

$$\frac{\sum_i v_i x_{ij}}{\sum_r u_r y_{rj}} \geq 1, \text{ for } j = 1, \dots, n$$

$$u_r, v_i \geq 0$$

The formulation (3) is transformed into the linear formulation as below:

$$\text{Min } Z = \sum_{i=1}^m v_i x_{i0} \quad (4)$$

subject to

$$\sum_{i=1}^m v_i x_{ij} - \sum_{r=1}^s u_r y_{rj} \geq 0$$

$$\sum_{r=1}^s u_r y_{rj} = 1$$

$$u_r, v_i \geq 0$$

Model 2: Variable return to scale – Input-oriented model

Afterwards, Banker et al. (1984) studied the variable return to scale and developed a model called BCC. An additional variable μ is added into the model to allow the change of scale. The formulations of the input-oriented of the BCC model is presented like the CCR models.

$$\text{Max } h_0(u, v) = \frac{\sum_r u_r y_{ro} + \mu}{\sum_i v_i x_{io}} \quad (5)$$

Subject to

$$\frac{\sum_r u_r y_{rj} + \mu}{\sum_i v_i x_{ij}} \leq 1, \text{ for } j = 1, \dots, n$$

$$u_r, v_i \geq 0$$

The linear formulation is:

$$\text{Max } Z = \sum_{r=1}^s u_r y_{ro} + \mu \quad (6)$$

subject to

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} + \mu \leq 0$$

$$\sum_{i=1}^m v_i x_{i0} = 1$$

$$u_r, v_i \geq 0$$

Model 4: Variable return to scale – Output-oriented model

The output-oriented of the BCC model is presented as:

$$\text{Min } h_0(u, v) = \frac{\sum_i v_i x_{i0} + \mu}{\sum_r u_r y_{r0}} \quad (7)$$

Subject to

$$\frac{\sum_i v_i x_{ij} + \mu}{\sum_r u_r y_{rj}} \geq 1, \text{ for } j = 1, \dots, n$$

$$u_r, v_i \geq 0$$

Moreover, the linear formulation is:

$$\text{Min } Z = \sum_{i=1}^m v_i x_{i0} + \mu \quad (8)$$

subject to

$$\sum_{i=1}^m v_i x_{ij} - \sum_{r=1}^s u_r y_{rj} + \mu \geq 0$$

$$\sum_{r=1}^s u_r y_{rj} = 1$$

$$u_r, v_i \geq 0$$

Appendix 5 Syntax of calculating efficiency score for policies under experiment #1

```
library(rJava)
library(XLConnect)
library(TFDEA)
library(openxlsx)
input <- readWorksheetFromFile("Two-echelon-0.4.xlsx", sheet = "C1-base", startRow = 1,
startCol = 5, endRow = 89, endCol = 6)
cols <- (7:33)
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C1-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
basicdea <- DEA(input, output, rts="vrs", orientation="output")
eff(basicdea)
```

**Appendix 6 Efficiency score of replenishment policies under basic DEA model,
experiment #1**

Policy	Efficiency score	Policy	Efficiency score	Policy	Efficiency score	Policy	Efficiency score
(1, 26)	1.00000	(2, 26)	1.00445	(3, 26)	1.00424	(4, 26)	1.00000
(1, 27)	1.00000	(2, 27)	1.02698	(3, 27)	1.04269	(4, 27)	1.02826
(1, 28)	1.00000	(2, 28)	1.04890	(3, 28)	1.07518	(4, 28)	1.05548
(1, 29)	1.00000	(2, 29)	1.05630	(3, 29)	1.09963	(4, 29)	1.08053
(1, 30)	1.00000	(2, 30)	1.05849	(3, 30)	1.12345	(4, 30)	1.10389
(1, 31)	1.00000	(2, 31)	1.06110	(3, 31)	1.14584	(4, 31)	1.12677
(1, 32)	1.00000	(2, 32)	1.06422	(3, 32)	1.15618	(4, 32)	1.14746
(1, 33)	1.00000	(2, 33)	1.06861	(3, 33)	1.16272	(4, 33)	1.16633
(1, 34)	1.00000	(2, 34)	1.07298	(3, 34)	1.16815	(4, 34)	1.18409
(1, 35)	1.00000	(2, 35)	1.07814	(3, 35)	1.17219	(4, 35)	1.20000
(1, 36)	1.00000	(2, 36)	1.08342	(3, 36)	1.17504	(4, 36)	1.21440
(1, 37)	1.00000	(2, 37)	1.08613	(3, 37)	1.17719	(4, 37)	1.22712
(1, 38)	1.00000	(2, 38)	1.08373	(3, 38)	1.17853	(4, 38)	1.23864
(1, 39)	1.00000	(2, 39)	1.08227	(3, 39)	1.17949	(4, 39)	1.24924
(1, 40)	1.00000	(2, 40)	1.08097	(3, 40)	1.17989	(4, 40)	1.25816
(1, 41)	1.00000	(2, 41)	1.08025	(3, 41)	1.18046	(4, 41)	1.26594
(1, 42)	1.00000	(2, 42)	1.07888	(3, 42)	1.18165	(4, 42)	1.27289
(1, 43)	1.00000	(2, 43)	1.07771	(3, 43)	1.18211	(4, 43)	1.27830
(1, 44)	1.00000	(2, 44)	1.07676	(3, 44)	1.18300	(4, 44)	1.28358
(1, 45)	1.00000	(2, 45)	1.07546	(3, 45)	1.18465	(4, 45)	1.28731
(1, 46)	1.00000	(2, 46)	1.07380	(3, 46)	1.18647	(4, 46)	1.29018
(1, 47)	1.00000	(2, 47)	1.07227	(3, 47)	1.18846	(4, 47)	1.29317

Appendix 7 Syntax of calculating super-efficiency score under 8 experiments

```

library(rJava)

library(XLConnect)

library(TFDEA)

library(openxlsx)

input <- readWorksheetFromFile("Two-echelon-0.4.xlsx", sheet = "C1-a", startRow = 1,
startCol = 5, endRow = 89, endCol = 6)

cols <- (7:33)

#experiment #1

output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C1-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)

effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))

effsdeacook

#experiment #2

output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C2-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)

effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))

effsdeacook

#experiment #3

output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C3-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)

effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))

effsdeacook

#experiment #4

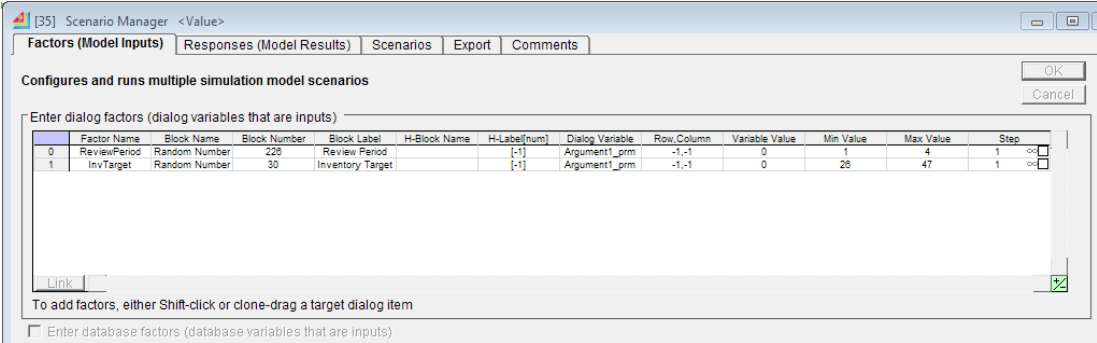
```

```
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C4-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))
effsdeacook
#experiment #5
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C5-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))
effsdeacook
#experiment #6
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C6-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))
effsdeacook
#experiment #7
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C7-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))
effsdeacook
#experiment #8
output <- read.xlsx("Two-echelon-0.4.xlsx",sheet = "C8-base",startRow = 1, colNames =
TRUE, rowNames = FALSE, rows = NULL, cols = cols)
effsdeacook <- eff(SDEA(input, output, rts = "vrs", orientation = "output", cook = TRUE))
effsdeacook
```

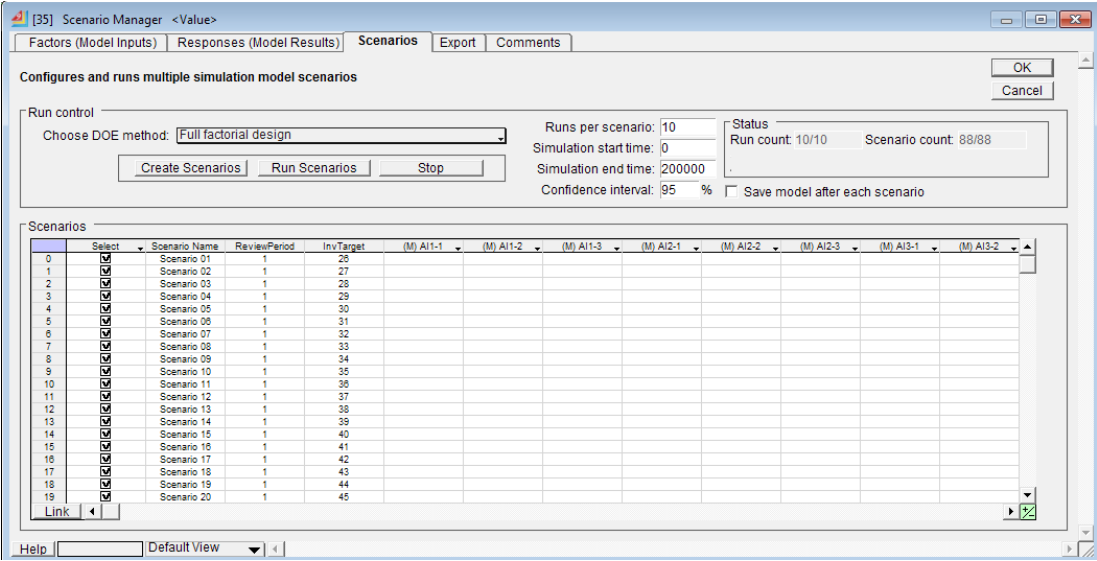
Appendix 8 Super-efficiency score of policies under experiment #1

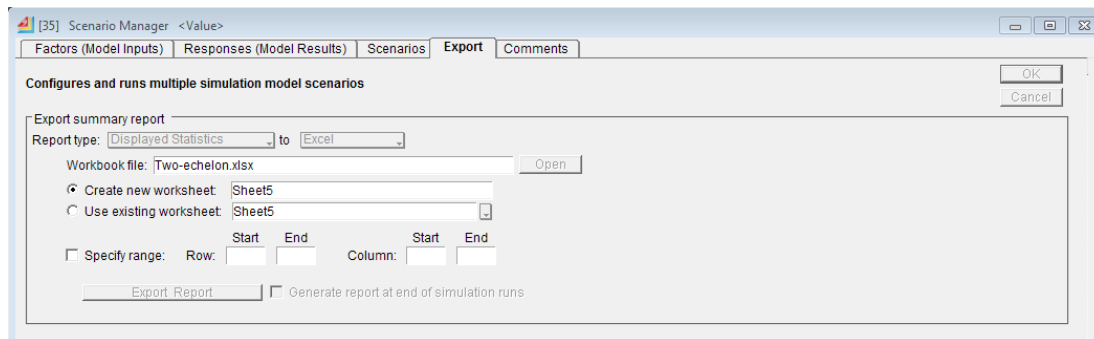
Policy	Efficiency score	Policy	Efficiency score	Policy	Efficiency score	Policy	Efficiency score
(1, 26)	0.45147	(1, 43)	0.99983	(2, 41)	1.08025	(3, 40)	1.17989
(4, 26)	0.74972	(3, 26)	1.00424	(4, 29)	1.08053	(3, 41)	1.18046
(1, 47)	0.99765	(2, 26)	1.00445	(2, 40)	1.08095	(3, 42)	1.18165
(1, 28)	0.99856	(2, 27)	1.02698	(2, 39)	1.08227	(3, 43)	1.18211
(1, 27)	0.99859	(4, 27)	1.02826	(2, 36)	1.08342	(3, 44)	1.18300
(1, 30)	0.99872	(3, 27)	1.04269	(2, 38)	1.08369	(4, 34)	1.18409
(1, 29)	0.99886	(2, 28)	1.04890	(2, 37)	1.08613	(3, 45)	1.18465
(1, 31)	0.99903	(4, 28)	1.05548	(3, 29)	1.09963	(3, 46)	1.18647
(1, 33)	0.99908	(2, 29)	1.05630	(4, 30)	1.10389	(3, 47)	1.18846
(1, 32)	0.99910	(2, 30)	1.05849	(3, 30)	1.12345	(4, 35)	1.20000
(1, 39)	0.99930	(2, 31)	1.06110	(4, 31)	1.12677	(4, 36)	1.21440
(1, 35)	0.99933	(2, 32)	1.06422	(3, 31)	1.14584	(4, 37)	1.22712
(1, 34)	0.99943	(2, 33)	1.06861	(4, 32)	1.14746	(4, 38)	1.23864
(1, 44)	0.99952	(2, 47)	1.07225	(3, 32)	1.15618	(4, 39)	1.24924
(1, 37)	0.99955	(2, 34)	1.07298	(3, 33)	1.16272	(4, 40)	1.25816
(1, 42)	0.99958	(2, 46)	1.07380	(4, 33)	1.16632	(4, 41)	1.26594
(1, 36)	0.99960	(3, 28)	1.07518	(3, 34)	1.16815	(4, 42)	1.27289
(1, 38)	0.99966	(2, 45)	1.07545	(3, 35)	1.17219	(4, 43)	1.27830
(1, 41)	0.99971	(2, 44)	1.07675	(3, 36)	1.17504	(4, 44)	1.28358
(1, 40)	0.99973	(2, 43)	1.07771	(3, 37)	1.17719	(4, 45)	1.28731
(1, 45)	0.99974	(2, 35)	1.07814	(3, 38)	1.17853	(4, 46)	1.29018
(1, 46)	0.99978	(2, 42)	1.07888	(3, 39)	1.17949	(4, 47)	1.29317

Appendix 9 Input parameters for the Scenario manager block



Appendix 10 Possible replenishment policies in the Scenario manager block



Appendix 11 Settings to export simulation results to the Excel file

Appendix 12 48 heuristics for sensitivity analysis

Heuristic name	Simulation experiment	AHP testing number	Heuristic name	Simulation experiment	AHP testing number
1-a	1	a	5-a	5	a
1-b	1	b	5-b	5	b
1-c	1	c	5-c	5	c
1-d	1	d	5-d	5	d
1-e	1	e	5-e	5	e
1-f	1	f	5-f	5	f
2-a	2	a	6-a	6	a
2-b	2	b	6-b	6	b
2-c	2	c	6-c	6	c
2-d	2	d	6-d	6	d
2-e	2	e	6-e	6	e
2-f	2	f	6-f	6	f
3-a	3	a	7-a	7	a
3-b	3	b	7-b	7	b
3-c	3	c	7-c	7	c
3-d	3	d	7-d	7	d
3-e	3	e	7-e	7	e
3-f	3	f	7-f	7	f
4-a	4	a	8-a	8	a
4-b	4	b	8-b	8	b
4-c	4	c	8-c	8	c
4-d	4	d	8-d	8	d
4-e	4	e	8-e	8	e
4-f	4	f	8-f	8	f