Optimisation of a two-echelon production-inventory model for food products considering quality and perceived value loss

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Abstract

Issues regarding food losses across supply chains require significant attention. It has been reported that one-third of food worldwide is wasted annually. A mismatch between supply and demand is identified as one of the main causes; therefore, efficiently managing the material flow through the whole supply chain level is necessary to reduce food waste and loss. A widely known approach that can be used to streamline the material flow is the integrated production-inventory policy. However, this current method still ignores the perishable characteristics of food products. To overcome the deficiencies, a new approach to the integrated production-inventory policy is proposed.

Unlike the majority of existing research, this study develops the production-inventory policy within the supply chain by taking into account the quality changes of food, either as raw materials or as finished goods. To describe the quality degradation of raw material, a kinetic model is applied. Whereas to characterise the perceived value loss of finished goods, a shelf-life based price function is utilised. In addition, to leverage the model performance, a synchronised approach is applied for streamlining the flow of food inventories through a single-vendor multi-buyer (SVMB) supply chain system. Those problems are formulated in a mathematical model using a mixed integer nonlinear programming (MINLP) with a combinatorial decision variable. The objective function of this model is to maximise the profit by determining four decision variables, i.e. the length of the production cycle, the number of raw material replenishment, the sequence of the product shipment and the delivery frequencies of finished goods over the production cycle.

MINLP itself can be categorised into NP-hard problem, and involving the combinatorial decision variable elevates the complexity of finding the model solution. Dealing with this issue, a biased random-key genetic algorithm (BRKGA) combined with local procedures is proposed. The hybridised BRKGA yields a better quality regarding the fitness value, the robustness and the speed to converge compared to the original BRKGA in a reasonable computation time.

Further, using the hybridised BRKGA, the performance and behaviour of the developed model are examined by employing some numerical tests. From the observed scenarios in the numerical tests, some significant findings are highlighted: (i) incorporating the quality aspects into the production-inventory policy returns a potential saving of up to 8.6% compared to that of when these aspects are neglected; (ii) the proposed synchronised method of production-inventory policy could further increase the total profit up to 1.4%; and (iii) when the demand rate is fixed, adjusting the rate of production close to the rate of demand can significantly increase the total profit of the supply chain.

Lastly, a case study in a noodle industry is carried out. It is followed by the sensitivity and error analyses to evaluate the model robustness. The case study shows that the application of this research could potentially improve the profit of the industry up to 6.9%. The resultant decision is insensitive to the changes in most parameters indicating the robustness of the proposed model. Only the change in demand causes a fair change to the total profit. Thus, this research recommends the industry to pay attention to the accuracy of the demand forecasting to make sure that the overall supply chain operates in its best performance.

Declaration

I declare that this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any University and that to the best of my knowledge it does not contain any materials previously published or written by another person except where due reference is made in the text.

Gusti Fauza

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List of Publications

Journal Papers

1. Fauza, G, Amer, Y & Lee, SH 2013, 'Model of an integrated procurement-production system for food products incorporating quality loss during storage time', *International Journal of Materials, Mechanics and Manufacturing*, vol. 1, no. 1, pp. 17-21.
2. Fauza, G, Amer, Y, Lee, SH & Prasetyo, H 2015, 'A vendor-buyer inventory model for food products based on shelf-life pricing', *Operations and Supply Chain Management: an International Journal*, vol. 8, no. 2, pp. 67-73.
3. Fauza, G, Amer, Y, Lee, SH & Prasetyo, H, 'An integrated single-vendor multi-buyer production-inventory policy for food products incorporating quality degradation', *International Journal of Production and Economics*, under second round review
4. Fauza, G, Amer, Y, Lee, SH & Prasetyo, H, 'A synchronised production and delivery cycles approach in a single vendor multi-buyer system accommodating quality and perceived value loss', *International Journal of Production and Economics*, under preparation.

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Abbreviations

2D-SPP	Two dimensional strip packing problem
ARPA	Area partitioning
AS	Autonomous system
BB	Branch and bound
BC	Branch and cut
BIP	Binary integer programming
BSCP	Blood sample collection problem
BRKGA	Biased random key genetic algorithm
CAPEX	Capital expenditure
CRMP	Cloud resource management problem
DEFT	Distributed exponential weighted flow splitting
EOQ	Economic ordering quantity
EPQ	Economic production quantity
FTL	Full-truckload shipment
GA	Genetic algorithm
GRASP	Greedy randomised adaptive search procedure
GRASP+PR	Greedy randomised adaptive search procedure with path-relinking
HBRKGA	Hybrid biased random key genetic algorithm
IP	Internet protocol
IPPP	Integrated procurement-production planning
JELS	Joint economic lot size
LP	Linear programming
LSP	Local search procedure
LTL	Less-truckload shipment
MICLSP	Multi-item capacitated lot sizing problem
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
MOSP	Minimisation and open stacks problem
MPX	Maximal preservative crossover
MPLS	Multi-protocol label switching

MST	Minimum spanning tree
NPVL	Non-perceived value loss
NLP	Nonlinear programming
OCC	Overlapping correlation clustering
OSPF	Open shortest path first
PQD	Physical quantity depletion
PVL	Perceived value loss
QL	Quality loss
RKGA	Random key genetic algorithm
RLP	Regenerator location problem
RPD	Regenerator placement and dimensioning
RWA	Routing and wavelength assignment
SCM	Supply chain management
SGS	Schedule generation scheme
SVMB	Single vendor multi buyer
TBAP	Tactical berth allocation problem
TSP	Travelling salesman problem
VRP	Vehicle routing problem
VND	Variable neighbourhood descend
WSON	Wavelength switched optical network
WTP	Willingness to pay

Nomenclature

Parameters (in the model)

A_m	:	setup cost
A_{rj}	:	finished goods transportation cost (at retailer j)
A_s	:	raw material transportation cost
C_m	:	finished goods processing cost per unit
C_r	:	finished goods purchasing cost per unit
C_s	:	raw material purchasing cost per unit
C_{Qs}	:	raw material quality loss cost per unit per time
C_{Es}	:	raw material energy cost per time
Ct_{rj}	:	the ordering cycle of retailer j
D_r	:	total demand of finished goods $D_r=\Sigma d_{rj}$
E_a	:	activation energy
$E_{Cs}(\tau)$	:	cost of energy for changing the temperature per unit time
E_{ij}	:	the age of ith batch of retailer j
Tp	:	the length of production run (on), $Tp= (D/P)T$
H_m	:	finished goods holding cost at manufacturer system
H_{rj}	:	finished goods holding cost at retailer j system
H_s	:	raw material holding cost
I	:	the average of finished goods inventory in the whole system
I_{m0}	:	dead stock of finished goods in the manufacturer
I_m	:	the average of finished goods inventory in the manufacturer
I_r	:	the average of finished goods in the retailers
I_s	:	the average of raw material inventory
$L(n_s, T)$	:	total quality loss per unit time
LT_{rj}	:	lead time of retailer j
P	:	production rate
Q_{max}	:	quality maximum status of raw material
Q_{min}	:	quality minimum status of raw material
$Q(t)$	:	remaining quality status of raw material
$Rrev(n_{rj}, T, Z)$	:	revenue in retailers (Model P)

$Rrev_1(n_{rj}, T)$	:	revenue in retailers (Model C)
$Rrev_2(n_r, T)$	:	revenue in retailers (Model SC)
$TC_m(n_s, n_{rj}, T, Z)$	:	finished goods total cost of manufacturer per unit time (Model P)
$TC_{m1}(n_s, n_{rj}, T)$	:	finished goods total cost of manufacturer per unit time (Model C)
$TC_{m2}(n_s, n_{rj}, T)$	:	finished goods total cost of manufacturer per unit time (Model SC)
$TC_r(n_{rj}, T)$	:	finished goods total cost of retailers per unit time (Model P)
$TC_{r1}(n_{rj}, T)$	:	finished goods total cost of retailers per unit time (Model C)
$TC_{r2}(n_{rj}, T)$	:	finished goods total cost of retailers per unit time (Model SC)
$TC_s(n_s, T)$	:	raw material total cost per unit time
T_{start}	:	time when the value of product starts decreasing
T_{sl}	:	product shelf-life
$TP(n_s, n_{rj}, T, Z)$	:	total profit of the synchronised cycle model (Model P)
$TP_1(n_{s,} n_r, T)$	:	total profit of the common cycle model (Model C)
$TP_2(n_{s,} n_r, T)$	:	total profit of the common cycle model (Model SC)
d_s	:	demand for the raw material
d_{rj}	:	demand for finished goods from retailer j
k_0	:	constant deterioration rate in Arrhenius equation
m	:	the power factor of the kinetic modelling
p_{max}	:	price maximum
p_{min}	:	price minimum
q	:	the size of order
q_s	:	the size of raw material order
q_{rj}	:	the size of finished goods order
ts_j	:	time between
θ	:	the rate of deterioration
β	:	gas constant
λ	:	shape parameter
ε	:	conversion factor (raw material usage to produce one unit finished goods)
τ	:	temperature
τ^*	:	ambient temperature
α	:	ratio between demand and production, $\alpha = D/P$

Parameters (in GAs)

p	:	size of population
p_e	:	size of elite population
p_m	:	size of mutant population
ρe	:	elite allele inheritance probability

Decision variables

T	:	the length of the production cycle
Z	:	delivery schedule
n_{rj}	:	the number of ordering frequencies of finished goods at retailer j
n_s	:	the number of replenishment frequencies of the raw material

Chapter 1

An introduction to inventory management for deteriorating items from the perspective of supply chain management

This chapter highlights issues in managing deteriorating inventories across a supply chain. Firstly, the importance of viewing inventory from the perspective of supply chain management (SCM) is explained to emphasise the benefit of this approach. Later, some important issues in managing deteriorating inventories are identified and briefly discussed. The aim of the identifying stage is limited only to underline some essential gaps found in literature while a more extensive literature review and discussion of the gaps is presented in Chapter 2. Further, the research aims, research objectives and research plan to achieve the aims are defined while at the end of this chapter, the structure describing the flow of this thesis is also presented.

1.1 The importance of managing inventory from the perspective of SCM

In today's competitive market, the scope of the rivalry has been escalating from just between enterprises to between supply chains (Croom, Romano & Giannakis 2000; Tan, Kannan & Handfield 1998). A traditional approach, where companies typically focus on their internal improvements and view the outside entities as business adversaries, is therefore no longer sufficient. It is simply due to the fact that the value of a product received by the end customers is an accumulative effort of several organisations that are involved in transforming raw materials into finished products. In other words, to ensure that the best value product is delivered, a firm should be able to collaborate with other partners across its supply chain. Good and effective collaboration returns a cost saving and leads to an improved competitive position for the company. For this reason,

companies increasingly realise that supply chain management (SCM) is a critical issue to be well implemented in their businesses.

SCM is concerned with managing flows of materials, money and information from suppliers, manufacturers and retailers to end customers, to create the best value product at a reduced cost (Cooper & Ellram 1993; Mentzer et al. 2001). In a SCM, all members have to work collaboratively to improve three key processes, i.e. procurement, production and distribution (Beamon 1998; Narasimhan & Carter 1998; Thomas & Griffin 1996). For instance, Wal-Mart, a giant US retailer, collaborated successfully with its partners by implementing information sharing technology in 1985. It resulted in not only a reduced cost of supply chain up to 20% but also an improved demand estimation, increased consistency, a sped up order and an enhanced stock level performance at Wal-Mart stores (Young 2002).

Among the three types of flows in a SCM (material, money and information), material flow is likely to be the most essential part to be managed to improve the overall SCM performance. Holding materials as an inventory is economically beneficial for a company since it increases business responsiveness, especially under uncertain environments (Axsäter 2006; Muller 2011; Tersine 1994). However, keeping too much stock leads to a higher operational cost for handling material (Kerber & Dreckshage 2011). The data shows that United States of America (USA) spent up to $1.21 trillion on logistics in 2010, a 10% increase from 2009 (Wilson 2011). In addition, Tersine (1994) reported that 20-40% of a company's total assets is invested in inventory in any form (i.e. raw materials, work in process items and finished goods). These facts demonstrate that inventory could reduce the enterprise's benefit significantly since it ties up financially without adding value to the final products. Therefore, a good inventory management is crucial in SCM. It is concerned with managing the flow of materials properly across a supply chain to reduce the total operational cost without sacrificing the customer's service level.

1.2 Managing deteriorating inventory across a supply chain: Some important issues

One type of material that is very critical and complicated to handle is a perishable item such as food. This material has a finite lifetime as its quality, quantity and safety deteriorate easily over time. Recent research by Gustavsson et al. (2011) reported that

approximately 1.3 billion tonnes of food for human consumption (one-third of food manufactured) is wasted per year worldwide. This food loss is defined as the loss or waste of edible products for human consumption at each stage in a supply chain. In developing countries, the majority of food losses occur during the production to retailing stage, prior to being received by the end consumer (see Figure 1.1). It was also identified that poor inventory coordination across the supply chain was the primary cause of mismatch between supply and demand leading to wasted products.

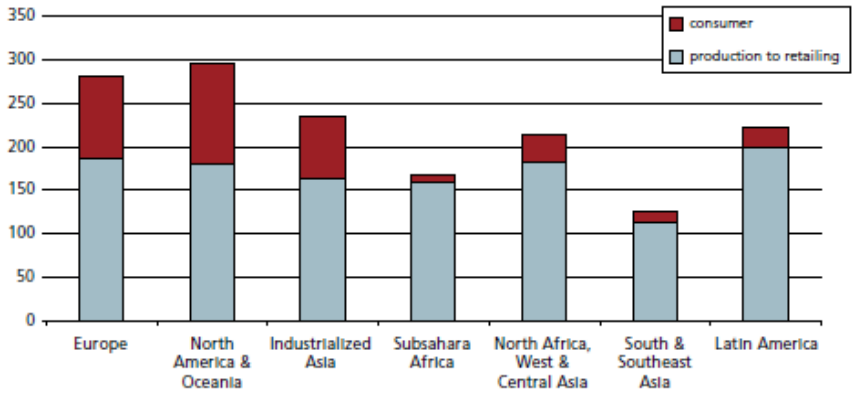


Figure 1.1 Food loss and waste (in kg/year per capita) at consumption and pre-consumption stages in different regions (Gustavsson et al. 2011)

An efficient inventory management for food products in SCM perspective is required to minimise the food losses. Unfortunately, only a minimal amount of research has been conducted addressing this issue. Therefore, it impels research on integrated inventory management for food products. From a business standpoint, such a research is beneficial for maintaining companies' competitiveness. More importantly, in a broader scope, the research is necessary to reduce food losses worldwide.

There has been extensive research dealing with inventory problems found in the literature. Most of them, however, assume that the considered items can be stored for an infinite period; in other words, the quantity and/or the values of those items are constant over time, also known as non-perishable items. In fact, certain types of products, for instance, foodstuffs, fruits, vegetables, meat, perfumes, blood *etc.*, are noted because their quantity, quality and safety deteriorate over time.

Ghare and Schrader (1963) are believed to be the first researchers to address an economic order quantity model for deteriorating items. They developed a mathematical function representing physical quantity depletion of inventory over time. During the storage time,

the inventory level is depleted not only by demand but also by some deteriorated items. Since then, this area has received considerable attention from many researchers which resulted in a significant increase in studies. Readers may refer to some extensive literature review for research in this field (to name a few: Bakker, Riezebos & Teunter 2012; Goyal & Giri 2001; Li, Lan & Mawhinney 2010; Nahmias 1982; Pahl & Voß 2014; Raafat 1991)

Despite its popularity in literature, an instantaneous physical depletion for depicting deteriorating inventory is hardly suitable for representing food deteriorating characteristics (Nahmias 2011). Such a physical depletion approach may be appropriate for alcohol or radioactive materials while for food products, e.g. apples or tomatoes, though their freshness declines over time, their quantity does not decrease instantaneously (Maihami & Nakhai Kamalabadi 2012). Even for manufactured products such as bread, milk, noodles *etc*., the quantity remains the same over their shelf-life. Therefore, developing a new inventory model for deteriorating products is required due to a need for a more representative model of more practical cases to manage food inventories across a supply chain.

In food products, the quality over time is complicated since it involves not only a physical change but also chemical, biochemical and microbial changes that are influenced by the environment. For an illustration, the duration of storage time affects amino acids activity in lemon, which causes browning and colour deterioration of the product (Sharma, Kausha & Sharma 2004). This natural phenomenon is frequently found in practical business and can be explained by a mathematical model known as a kinetic model for food quality (Van Boekel 2008). Unfortunately, the majority of existing inventory management studies for deteriorating items seems to overlook the quality degradation phenomena represented by the kinetic model.

In addition, the deterioration characteristics of food products, which become a concern in food inventory management, may be different depending on the food forms, e.g. raw material or finished goods, in the supply chain system. For example, consider wheat flour in a manufacturing system producing noodles or bread; as a raw material, wheat flour experiences a decrease in wet gluten quantity during the storage time (Miœ 2003). The deterioration could affect the quality of final products (e.g. noodles or bread). On the other hand, after transforming the wheat flour into noodles or bread and delivering them

to a retailer, the product quality behaves differently. At a retailer, the finished food products may suffer from a customer's quality perception leading to a decreased value over their shelf-life; in this study, a term of *perceived value loss* introduced by Pahl and Voß (2014) is used to describe this phenomenon.

A fully packaged manufacturing product such as noodles or bread is usually delivered with expiration date information imprinted on its label indicating the remaining shelf-life of the food product. Referring to Labuza (1999, p.1), shelf-life represents the period where food 'will retain an acceptable level of eating quality from a safety and organoleptic point of view'. It means that during its shelf-life, food should be able to fulfil the demand. However, at retailers, for this typical food, customers perceive the quality or value of the product by observing their residual shelf-life. Customers tend to select a product with a longer remaining lifetime due to several reasons such as freshness, low consumption rate, buying for stock *etc*. A study of customers' perception of expiration dates by Tsiros and Heilman (2005) demonstrates that customers' willingness to pay (WTP) significantly decreases when a product is approaching its expiration date. Consequently, during the WTP decreasing period the rate of demand becomes slower and without any action, it may lead to outdated items. Dealing with the situation, a retail manager usually applies a markdown policy to maintain the rate of demand and avoid food loss (Nijs et al. 2001). This typical deterioration commonly occurs in the grocery food business and can cause a grocery retailer a loss of up to 15% of its margin (Ferguson & Ketzenberg 2005). Despite its significant impact on the food business, unfortunately, less research on an integrated inventory management field has addressed this lifetime restriction issue (Pahl & Voß 2014).

Apart from the deficiencies of existing research regarding the approach used to represent food characteristics, the majority of deteriorating inventory studies typically deal with a single echelon system and a simple supply chain structure i.e. dyadic configuration (Bakker, Riezebos & Teunter 2012; Li, Lan & Mawhinney 2010). The dyadic configuration studies focus on the relationship of a single vendor delivering the finished goods to a single buyer (Banerjee, Kim & Burton 2007). In such a configuration, the procurement of raw material tends to be overlooked, i.e. the procurement planning is decided separately from the production and delivery planning. Consequently, this approach will lead to a sub-optimal solution rather than global optima. Some researchers

(to name a few: Banerjee, Kim & Burton 2007; Chen & Chen 2005) reported that an integrated approach to managing inventory across the supply chain potentially reduces the cost and increases the profit of the whole system. Such an integrated approach would be more significant to be applied for managing deteriorating items due to their lifetime restriction. Synchronisation and optimisation of production and inventory policies across the supply chain, covering from raw material procurement to finished goods production and delivery, are expected to be able to reduce wasted foods across the supply chain and at the same time increase the total profit of all parties in the supply chain.

Identifying and discussing shortcomings of the existing studies on deteriorating inventory models, particularly the deficiencies in representing the characteristics of food products, naturally leads to further research in this area. For this reason, the proposed research is intended to fill the gap by developing an integrated production-inventory model for managing food products in a SCM perspective considering the quality loss of raw materials and the perceived value loss of finished goods.

1.3 Research aim, objectives and significance

This research is aimed at optimising an integrated production-inventory model for perishable items that is well-suited for managing food products from the perspective of supply chain management. The model considers the quality and perceived value losses of food products. A kinetic model is proposed for representing the quality loss of raw materials while a shelf-life based price function is offered for depicting the perceived value loss of finished goods. In addition, the supply chain system considered in the proposed research involves a two-stage supply chain structure comprising a single vendor (manufacturer) and multiple buyers (distributors/retailers). The flow of material across the supply chain is streamlined and optimised by synchronising the manufacturer's inbound and outbound flows of material such that the total profit of the entire supply chain is maximised.

To accomplish the aforementioned aim, this research will be broken down into some measurable and achievable activities. These activities form the research objectives and are considered as important milestones in this research. They are summarised as follows:

a. To develop a new mathematical model of an integrated production-inventory policy for food products in a single-vendor multi-buyer supply network that maximises the total profit of the supply chain.

b. To design an effective and efficient optimisation approach that is able to find the best decision variables of the established model that leads to an optimal solution, i.e. a solution that gives the highest profit to the supply chain.

c. To investigate the performance of the model in comparison to the benchmark model and to analyse the behaviour of the model through extensive numerical tests to obtain essential insights of the problem.

d. To examine the application of the developed algorithm and the performance of the proposed model in solving a case study inspired by a real food company.

This research is expected to have a number of significant contributions to the body of knowledge, industries and society in general. To the body of knowledge, the direct outputs of this research, particularly the mathematical model, would significantly extend the existing literature on inventory model for perishable items better suited to food products. In addition, the single-vendor multi-buyer framework proposed in this research would bring the current research, which mostly deals with either single echelon or simple two-echelon framework, to the next level of integration. Similarly, the new and flexible optimisation tool designed to solve the combinatorial problem resulted from the established model would further leverage the significance of this research. To food industries, the application of both the model and optimisation tool would be expected to improve the total profit of the industries significantly. Hence, the competitiveness of the industries is enhanced. Lastly, to the society, the synchronised approach proposed in this research to streamline the flow of materials across the supply chain would minimise discrepancy between supply and demand. Thus, outdated foods across the supply chain can be reduced or minimised. It is a part of social responsibility of all societies to ensure that no food is wasted as in another part of the world there are still a lot of people that suffer from hunger and malnutrition.

1.4 Research Plan

In this research, five important steps are conducted to ensure that the set objectives can be achieved. The brief description and output of each step are summarised as follows:

Step 1: Reviewing the literature

The goal of the literature survey phase is to discuss and to review critically the existing research on models of inventory for perishable items and then to identify the potential gaps that will be addressed by this research. The output of this stage is a formal statement of the research question/problem.

Step 2: Selecting the mathematical representation and the optimisation tool

Based on the defined research problem, a survey of the existing modelling approaches is conducted to find the most appropriate mathematical representation to be adopted to model the problem. Further, some potential optimisation tools are examined and then the most appropriate tool to the problem is proposed. Thus, the outputs of this stage are the proposed mathematical representation and the optimisation tool.

Step 3: Developing the model and designing the optimisation approach

In this stage, a step by step procedure to develop a mathematical model representing the problem is conducted. An optimisation tool is designed to solve the proposed mathematical model. In addition, the optimisation tool is tested through extensive numerical tests to ensure that it works effectively and efficiently. The outputs of this stage are a mathematical model and an optimisation tool.

Step 4: Evaluating and benchmarking the developed model

In this stage, some numerical tests are conducted to evaluate the behaviour of the model. Benchmarking to the existing model is also carried out to measure the performance, in terms of the gained profit, of the proposed model in comparison to the current model. The model behaviour and benchmarking results are then analysed and discussed. Finally, some important findings are summarised in this stage.

Step 5: Applying the model and optimisation tool to a case study

To see the possibility of the model being used in real life, both the model and optimisation tool are applied to solve a practical problem based on a case study in a food industry

business. Using input parameter from the field, the problem is solved by using the proposed model and optimisation tool. The gained profit is then compared to the existing practice. Thus, the potential saving can be presented. In addition, sensitivity and error analyses are conducted to examine the robustness of the proposed model. Finally, the significant findings are highlighted.

1.5 Thesis structure

Based on the research plan, this thesis is organised into eight topics each of which is presented in a chapter as described in Figure 1.2.

Chapter 1: An introduction to inventory management for deteriorating items from the perspective of supply chain management

This chapter presents a brief explanation of the research background and motivation. It highlights some identified deficiencies of existing studies in the area of inventory management for perishable items, especially for food products, and clarifies why this research is important in this field. Further, this chapter also contains research aim, research objectives and significance, research plan and organisation of the report. The main purpose of this chapter is to present justification to conduct this research.

Chapter 2: Inventory management for deteriorating items from a supply chain management perspective: A literature review

Chapter 2 presents a thorough literature review on inventory management for perishable items. It starts with a brief introduction to the development of models for handling deteriorating inventory, and it continues with mapping these models according to their supply chain structure to see how far the issues of perishable inventories have been addressed. The established research map is then evaluated and discussed to identify the gaps and justify why these gaps are urgent to address. The main purpose of this chapter is to demonstrate the state-of-the-art of research on inventory management for food products and show the contributions of this research.

Chapter 3: Model representation and optimisation of an integrated production-inventory model for deteriorating items

This section contains a review of modelling approaches that have been used in literature to represent the defined problem leading to justification of using a combinatorial mixed-integer nonlinear programming (MINLP) as the most appropriate representation of the

addressed problem. After that, some optimisation tools that are commonly used to deal with combinatorial MINLP problems are discussed, including exact algorithm, heuristics and meta-heuristics. By examining the advantages and disadvantages of each algorithm, the genetic algorithm is chosen due to its potential performance in solving combinatorial problems. Particularly, a Biased-Random Key Genetic Algorithm (BRKGA) will be further developed to tackle the defined problem. The objective of this chapter is to explain the rationale for the most suited modelling approach and optimisation tool to be used in this research.

Chapter 4: Development of an integrated production-inventory model for food products in a two-echelon supply chain

Detailed procedures on how the integrated production-inventory model for foodstuffs is developed will be presented in Chapter 4. It begins with system characterisation demonstrating the big picture of the addressed system. Then, model notation, as well as model assumptions, is outlined. Further, a comprehensive step-by-step procedure of the mathematical model development is established and discussed. Special cases of the proposed model are also presented to demonstrate the application of the models in some particular circumstances. The main output of this chapter is a new mathematical model of an integrated production-inventory policy for food products in a single-vendor multi-buyer environment.

Chapter 5: A BRKGA for optimising the integrated production-inventory model for food products

This chapter discusses the process of designing a bias-random key genetic algorithm (BRKGA) as an optimisation tool for optimising the mathematical model developed in Chapter 4. This chapter begins with a brief introduction to BRKGAs and then a review of the existing applications of the algorithms to solve different areas of optimisation problems. Both the applications and modifications of the algorithms are then summarised. The information is then used to develop a BRKGA hybridised with local search procedures. An extensive numerical test is used to find the best setting for the parameter of the algorithm and the performance of the algorithm in comparison to the traditional BRKGA. The contribution of this chapter is to establish an efficient biased-random key genetic algorithm hybridised with local procedures to solve the defined problem.

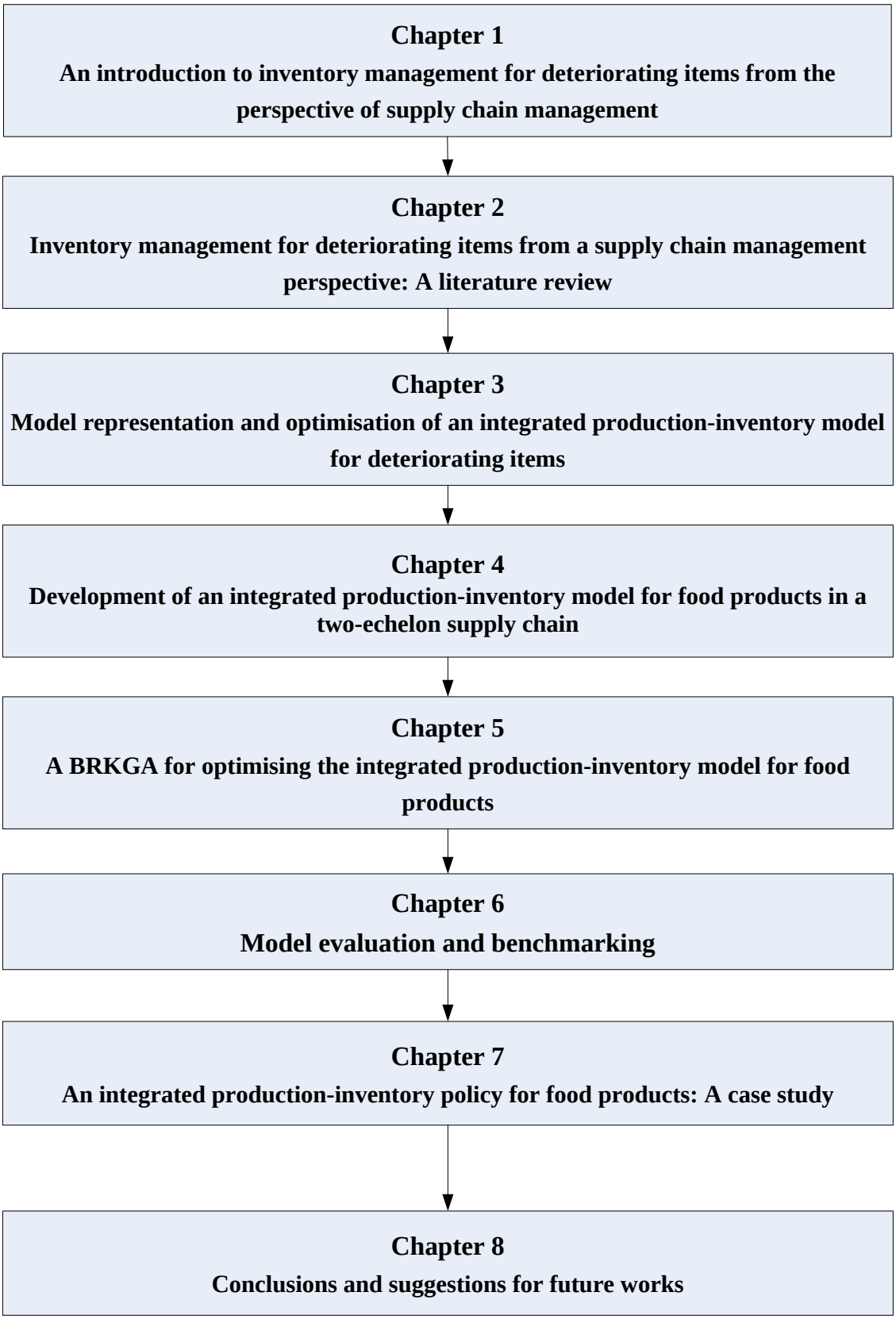


Figure 1.2 Thesis structure

Chapter 6: Model evaluation and benchmarking

Chapter 6 presents an extensive numerical test to investigate the performance and the behaviour of the proposed model. Three test scenarios are respectively used to (i) examine the performance of the algorithm compared to the benchmark model, (ii) analyse the effect of different coordination mechanisms on the model performance, and (iii) investigate the behaviour of the model in terms of output sensitivity in response to changes in some input parameters. The main objective of this chapter is to evaluate the performance of the proposed model through numerical experimentations.

Chapter 7: An integrated production-inventory policy for food products: A case study

In Chapter 7 the application of the proposed model to solve a case study in a food industry business which produces noodles will be presented. In this chapter, a brief company profile is presented to provide an overview to the problem. Then, based on the gathered data, the problem is solved using a BRKGA hybridised with local procedures. The performance of the integrated approach is then examined and compared to the existing policy in the company. In addition, the sensitivity and error analyses are conducted to show the robustness of the model. This chapter demonstrates in a practical case how the new integrated production-inventory model can be used to improve the performance of the entire supply chain.

Chapter 8: Conclusions and suggestions for future works

The final chapter summarises the results of this research as well as its contributions. At the end, research limitations are outlined and potential research avenues for the future are also recommended.

Chapter 2

Inventory management for deteriorating items from a supply chain management perspective: A literature review

2.1 Introduction

In recent years, SCM issues have been receiving much attention from practitioners and researchers. Studies in this area have been significantly increased since being introduced in the 1980s (Burgess, Singh & Koroglu 2006). SCM is concerned with the integration and collaboration on managing the flows of materials, information and money across the supply chain to achieve ultimate customers' satisfaction (Beamon 1998; Mentzer et al. 2001; Narasimhan & Carter 1998; Thomas & Griffin 1996).

Inventory management plays an important role in enhancing the performance of a supply chain since it aims to streamline the material flows across any parties in the supply chain (Meindl 2013, p.47). Unfortunately, conventional inventory management approaches, such as Economic Order Quantity (EOQ) and Economic Production Quantity (EPQ), ignore the interdependence between parties in a supply chain e.g. between manufacturer and retailer or between supplier and buyer. It often leads to a mismatch between supply and demand across the supply chain. As a result, the performance of the entire supply chain, in terms of operational cost and service level, becomes worse. Therefore, an integrated strategy is needed to manage the inventory across a supply chain.

Further, in industries, the characteristic of inventoried items can be categorised into two main groups, namely perishable items and non-perishable items. The former group is more difficult to manage than the latter due to the lifetime constraint. It has a great impact on inventory management policy since items that deteriorate over time are forced to wait to fulfil the demand (Pahl, Voss & Woodruff 2007). Therefore, it should be worth investigation to know how far studies in the integrated inventory policy have accommodated the perishable issues.

To cover the issue above, the remaining sections of this chapter are organised as follows. Section 2.2 represents exploration and elaboration of research for deteriorating items including a map of SCM-deteriorating inventory studies representing what have been done and what can be done. Based on the map and some essential issues in food SCM, gaps are identified and discussed in Section 2.3. Further, the research problems are defined in Section 2.4, and finally, Section 2.5 summarises this chapter.

2.2 Research in managing deteriorating inventories

Research in the deteriorating inventory field has received increasing attention from scholars. However, the definition and classification of the deteriorating inventories vary among authors. Ghare and Schrader (1963) defined the deteriorating inventory based on the phenomenon that the inventory level of deteriorating items is not only depleted by demand but also by some decayed items, named as *inventory decay*. Raafat (1991) distinguished the obsolete inventories (such as fashionable items, electronic devices *etc*.) from the deteriorating inventories. The last category is divided into two groups, namely, fixed shelf-life inventories, e.g. blood, packaged food, and continuous decay inventories, e.g. radioactive materials. In addition, Raafat (1991) also classified the deteriorating inventories based on their utility, i.e. constant utility (such as in drugs) and non-constant utility inventories (such as in food products). Goyal and Giri (2001) differentiated the deteriorating items based on shelf-life; a perishable product is a product with a maximum usable lifetime such as blood, vegetables, foodstuffs *etc*. while a decay product is a product which has no shelf-life but a fraction of this item evaporates over time such as alcohol, radioactive materials *etc*. Recently, Pahl and Voß (2014) categorised the deteriorating inventory based on three different phenomena observed during the warehousing time, namely physical depletion, loss of efficacy or quality and perceived value loss. The physical depletion directly affects the availability of inventory, in terms of quantity, to fulfil demand during the horizon planning such as in alcohol, gasoline or radio-active materials. Meanwhile, a loss efficacy inventory may still be able to fulfil the demand but, the advantage of consuming it is reduced e.g. vitamin C losses in orange or gluten content decreases in wheat flour during storage time. On the other hand, the perceived value loss is related to the customer perception of a product. Even though a product has a constant utility or functionality during the storage time, the demand for the product is not constant since customers perceive its utility has decreased as in fashion products, electronic devices *etc*.

In this literature review, studies in this field are divided into two main groups; 1) research which focuses on managing inventories that deteriorate over time which can be divided into quantity depletion and/or quality loss; 2) research which is concerned with managing inventories with a fixed lifetime or shelf-life that can be categorised into accommodating vs. unaccommodating the perceived value loss research. The discussion of each group is presented in the following subsection.

2.2.1 Managing continuously deteriorating inventories

In this research group, the characteristics of the continuously deteriorating items are divided into physical quantity depletion and quality or efficacy loss. Studies concerned with these issues and their approaches are presented and discussed in the following section.

2.2.1.1 Physical quantity depletion characteristic

The majority of the research in the physical quantity depletion group applied a mathematical function that was first introduced by Ghare and Schrader (1963). The mathematical model was developed based on the assumption that a fraction of inventories is spoilage, damage or vanishes over time. Hence, the quantity of inventory during the ordering cycle is depleted not only by demand but also by some deteriorated items (as illustrated in Figure 2.1).

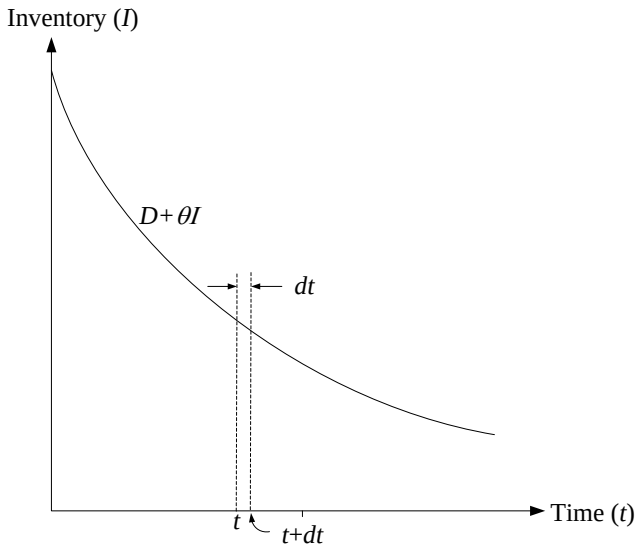


Figure 2.1 Inventory depleted by demand and some deteriorated inventories (Ghare & Schrader 1963)

As seen in Figure 2.1, during the interval (t, $t+dt$), the inventory (I) is depleted due to demand (D) and some deteriorated inventories (θI). The mathematical function of this physical quantity depletion inventory is shown in Eq. 2.1:

$$\frac{dI(t)}{dt} + \theta I(t) = -D(t) \tag{2.1}$$

where $I(t)$ and $D(t)$ refer to the inventory level and the demand rate at time t, respectively, while θ is the deteriorating rate of the item (Ghare & Schrader 1963).

This approach is used to decide the replenishment strategy or EOQ for deteriorating items. The number of items procured during the ordering cycle is higher than the demand to anticipate some deteriorated items that cannot be used to fulfil the demand due to, for example, spoilage for food or evaporation for alcohol and gasoline.

Since the first model was introduced, many developments have been extensively done to bring it closer to real life problems. Covert and Philip (1973) developed the model into EOQ for deteriorating items with Weibull distribution while Tadikamalla (1978) incorporated the Weibull and Gamma distribution. Later, Misra (1975) relaxed the assumption by considering a finite rate of replenishment, but no shortage is allowed. Shah (1977) extended Misra (1975) by developing the Exponential and Weibull distribution model allowing backorders. These studies focused on finding the optimal ordering lot size of the deteriorating items. At a manufacturing level, however, deciding the ordering strategy of raw materials separately from the production planning may lead to a sub-optimal solution rather than global optimal (Goyal 1977). Therefore, an integrated approach to the production plan and raw material procurement is essential to reduce the costs incurred by mismatching between the production needs and the supply of raw material.

Park (1983) extended the EOQ deteriorating model into an integrated procurement and production plan (IPPP) model. He considered a situation where a production produced one unit of non-perishable finished product which required one unit of deteriorating raw material. Later, Raafat (1985, 1988) advanced the model to consider the circumstance where the finished product had deteriorated as well (as illustrated in Figure 2.2). As seen in Figure 2.2, two types of raw materials (raw material 1 and raw material 2) are procured to fulfil the demand of a finished product produced during the production runtime (Tp).

A lot for lot policy was used, i.e. one ordering lot of raw material to fulfil the demand of one production cycle (*T*). The aim of the research was to find the best production policy which involved the ordering strategy of the deteriorating raw materials.

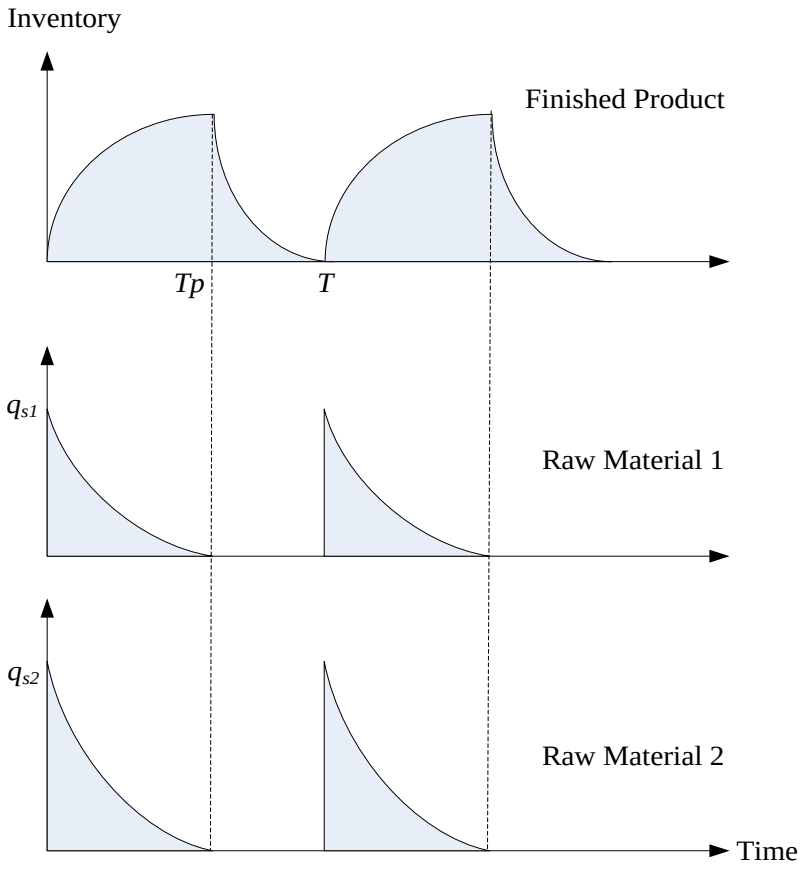


Figure 2.2. An integrated procurement and production plan (IPPP) for deteriorating inventories (Raafat 1985)

The IPPP approach is able to reduce the total cost for the manufacturer. Howeveras the market becomes more competitive, approaches that only focus on the internal improvement are no longer sufficient. More practitioners and researchers realise that a better coordination between parties in a supply chain to efficiently manage the flow of inventory across the supply chain is necessary to reduce the cost and improve the profit (Ben-Daya, Darwish & Ertogral 2008). It shows by the increase in the number of studies addressing issues of joint economic lot size (JELS) between two or more parties in a supply chain. Unlike the IPPP models which focus on the internal improvement, e.g. only in a manufacturer, in JELS approach, the production and inventory activities between parties in a supply chain is synchronised to improve the entire supply chain performance. A vendor and a buyer, for instance, collaboratively decide the best inventory strategy which minimises the joint costs and maximises the joint profit of the systems. In regards

to the quantity depletion inventory research, this issue has been addressed by some authors such as Rau, Wu and Wee (2003); Rau, Wu and Wee (2004); Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015); Yang and Wee (2003); Yang and Wee (2002); Yu, Wang and Liang (2012)

Yang and Wee (2002) developed the inventory model for deteriorating items which considered multiple delivery shipments of finished goods to the buyer over a manufacturer's production cycle, T (as illustrated in Figure 2.3). As seen in Figure 2.3, the number of batches (with size of q_r) delivered to the retailer (n_{ri}) is synchronised with the length of production cycle in the manufacturer (T) using a single setup multi delivery (SSMD) policy. The aim of the model is to minimise the joint total cost of the manufacturer and retailer by collaboratively determining the best inventory strategy for the whole system.

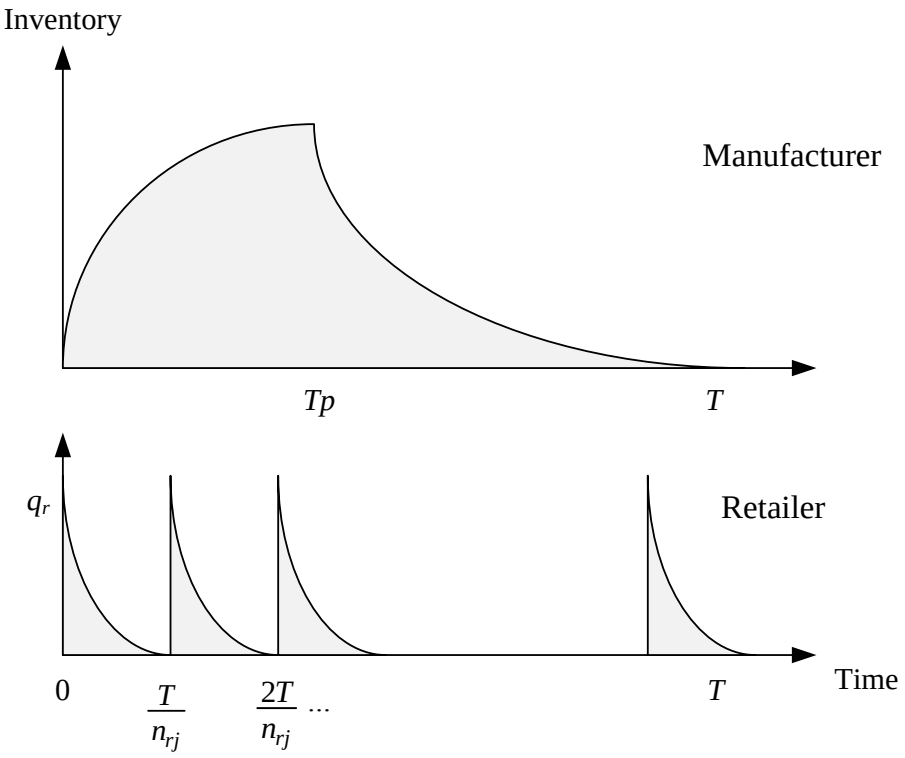


Figure 2.3 Inventory profile of an integrated production-inventory system (Yang & Wee 2002)

Even though the model in Yang and Wee (2002) has synchronised the production and delivery of finished goods between parties leading to a better inventory performance, it still, however, ignores the dependency of finished goods which require raw materials. To

fill this shortcoming, Rau, Wu and Wee (2003); Rau, Wu and Wee (2004); Yang and Wee (2003) developed an integrated model which accommodated the raw material procurement into the integrated production-delivery policy. All costs related to managing raw materials and finished goods become the performance of the whole system. The procurement strategy, production schedule and delivery plan are simultaneously determined due to costs reduction of the integrated system.

A synchronised approach from raw material procurement to production and delivery of finished goods leads to a better system performance compared to the independent policy in terms of the joint total cost (Banerjee, Kim & Burton 2007). The complexity of accommodating issues in this integrated approach, such as different characteristics of the raw material and finished goods, is a significant challenge that is worthy of investigation. Aforementioned studies still simplify the approach by assuming the same deterioration characteristic between raw materials and finished goods. More recently, Yu, Wang and Liang (2012) and Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015) relaxed this assumption and proposed an integrated model with different deterioration characteristics of the raw material and finished goods.

Figure 2.4 represents the inventory profile of parties in a supply chain in a single vendor multiple buyer (SVMB) environment proposed by Yu, Wang and Liang (2012) and Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015). A vendor or a manufacturer procures a deteriorating raw material from a supplier with ordering size of q_s. The raw material is required by production which produces a perishable finished product during production run length Tp. After one lot of finished goods (with size of q_1) is completely produced (during the production period of tp_1), it is delivered to the first retailer. Similarly, the next order (j^{th} order) is produced during tp_j with size of q_j and delivered to the jth retailer (note that a lot for lot policy or single setup-single delivery policy is applied). In addition, during the length of the production cycle (T) the inventory level of either raw materials or finished goods is depleted not only by demand but also by some deteriorated items. Unlike Rau, Wu and Wee (2003); Rau, Wu and Wee (2004); Yang and Wee (2003), in Yu, Wang and Liang (2012) and Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015) the deterioration characteristic in raw material is distinguished from that in finished goods.

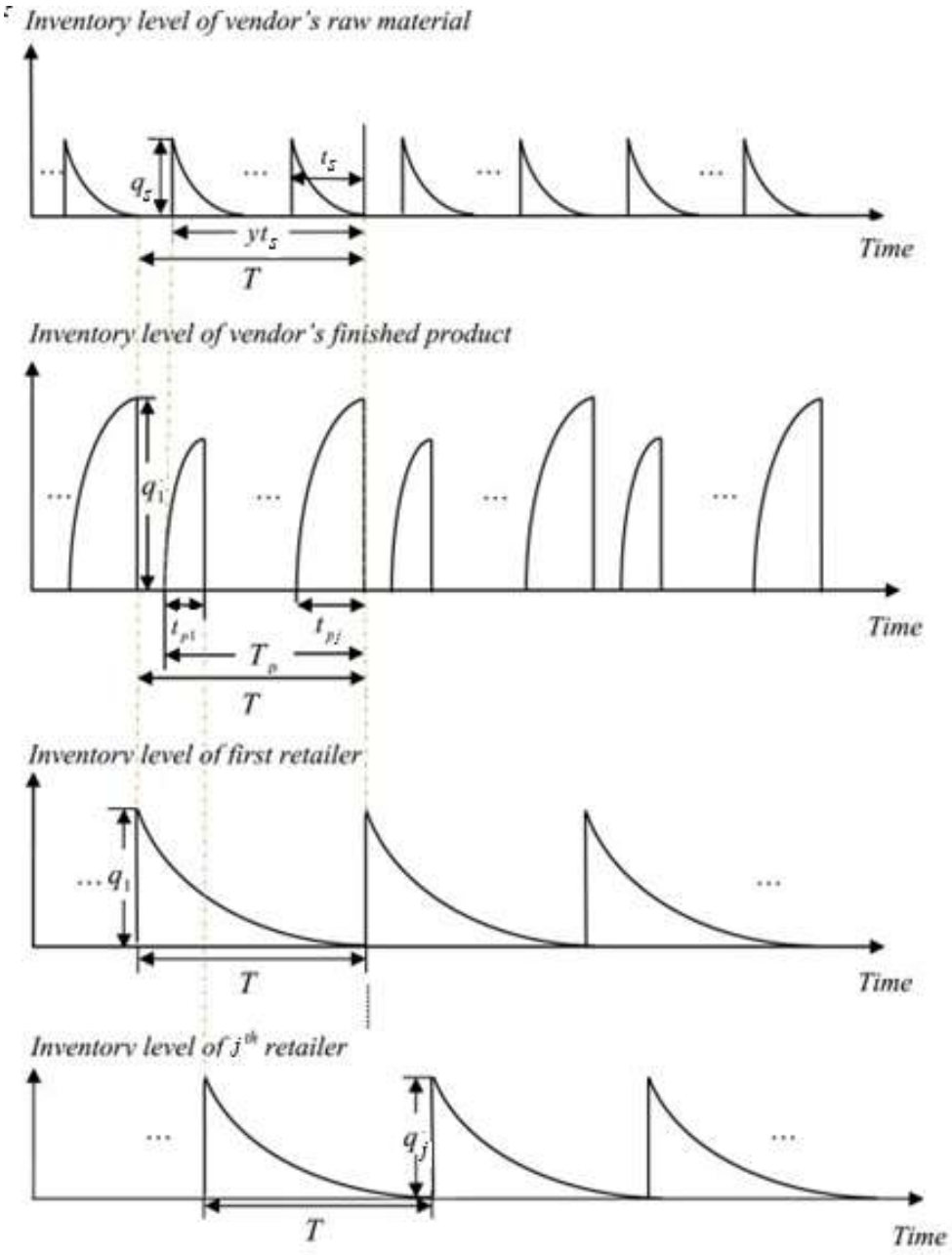


Figure 2.4 Inventory profile of the integrated production-inventory system with different deteriorating characteristics (Taleizadeh, Noori-daryan & Cárdenas-Barrón 2015)

In Yu, Wang and Liang (2012), the raw material deteriorates at a fast rate such as in raw milk, fruits and vegetables. The raw material is required by a slow rate deterioration finished goods, e.g. milk powder, pasta and cheeses. The objective function is to minimise the total cost by determining the replenishment cycle for raw materials and finished goods. Later, Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015) took into account a situation where the demand of the finished goods is price sensitive, i.e. demand is a function of the product price in retailers. Maximising the total profit is the purpose

of the model where some variables, namely, retailers' price, replenishment cycle of finished product and raw materials as well as production rate, need to be optimised.

The majority of studies in deteriorating inventory models based on the Ghare and Schrader (1963) approach, i.e. inventory decay, assumed an instantaneous physical depletion once a product is received. Wu, Ouyang and Yang (2006) and Ouyang, Wu and Yang (2006) argued that the majority of foods such as vegetables, fruit, fish and meat are not immediately deteriorated at the beginning of the arrival time. The deterioration occurs after a certain period and they called this phenomenon *non-instantaneous deterioration* (as illustrated in Figure 2.5).

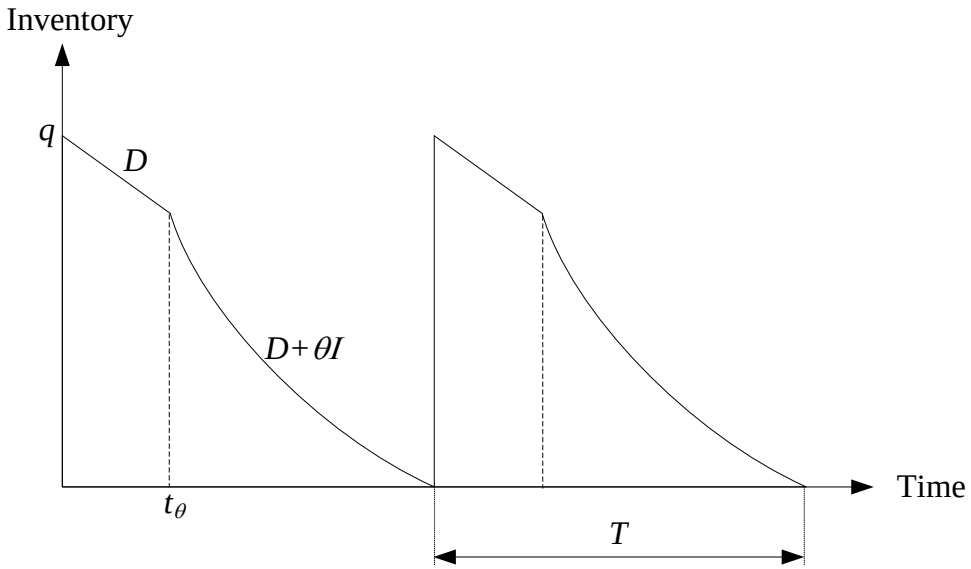


Figure 2.5 Inventory profile of non-instantaneous deteriorating items (adapted from Ouyang, Wu & Yang 2006)

As shown in Figure 2.5, at the beginning of the replenishment cycle (T), the inventory level is only depleted by demand (D). By the time, after t_θ some inventories are deteriorated with the value of θI till the end of the replenishment cycle. Thus, during $T - t_\theta$, the inventory is depleted not only by demand but also by some deteriorated items ($D + \theta I$). The objective function is to minimise the total cost by optimising the replenishment policy. This non-instantaneous approach becomes the new research mainstream in the physical quantity depletion field.

Later, Wu, Ouyang and Yang (2006)'s model was developed by Chang, Teng and Goyal (2010) and Geetha and Uthayakumar (2010). Chang, Teng and Goyal (2010) changed the objective function to the profit maximisation. The maximum inventory level is restricted,

reflecting the condition where retailers have limited shelf-life space. Further, the assumption related to zero ending inventory is relaxed. Geetha and Uthayakumar (2010) considered a permissible delay in payment in the non-instantaneous model in which shortages are allowed with partial backorders. The rate of backorder is varied depending on the waiting time of the next procurement. An algorithm to find the optimal solutions, i.e. the length of the ordering cycle and the ordering quantity per cycle has been established to minimise the total cost. More recent studies accommodating the non-instantaneous depletion approach can be found in Maihami and Abadi (2011), Shah, Soni and Patel, Soni (2013), Chung, Cárdenas-Barrón and Ting (2014) and Wu et al. (2014).

The quantity depletion studies of either instantaneous or non-instantaneous deteriorating items are popular in deteriorating inventory literature which are reflected by several review papers in this area (to name a few: Bakker, Riezebos & Teunter 2012; Goyal & Giri 2001; Li, Lan & Mawhinney 2010; Nahmias 1982; Pahl & Voß 2014; Raafat 1991). Despite its popularity in literature, very few perishable products, especially food, are deteriorated in this way (Nahmias 2011, p.55). For example, consider one lot of bananas received by a grocery retailer. At the beginning of the procurement cycle, all bananas are eligible to fulfil the demand and are sold at a normal price since they are still fresh and are at their best quality. During the replenishment cycle, some of them may be ripe but still eligible to fulfil the demand. However, since the quality e.g. freshness is degraded, the grocery manager may need to reduce the price of ripe bananas to retain the demand. It means that, even though the price is reduced during the deteriorating time, the inventory level of bananas is still only depleted by demand. At the end, once the bananas are overripe they are discarded, and the inventory level turns to zero. The example indicates that the physical quantity depletion model may not be suitable for representing this type of typical case since the quantity of inventory remains the same during a certain period while the quality, e.g. freshness, does degrade over time.

2.2.1.2 Quality or efficacy loss

Unlike research in the previous category, in this research group, the quantity of inventory during the horizon plan remains the same, i.e. there is no physical quantity depletion during the period of planning. However, the quality or efficacy of the product decreases over time, hence, although they are eligible to fulfil the demand during the replenishment cycle, benefits or advantages of using or consuming these typical items are not constant

over time. Research in this group is based on the assumption that in a perishable item, the quality or efficacy does degrade over time while the quantity remains the same.

Weiss (1982) accommodates this typical deterioration issue by applying a non-linear holding cost function into an EOQ model. This approach is different from the conventional EOQ, which assumes that the holding cost is a linear function of time, i.e. the cost of items held in storage is expressed by ht, where h is the holding cost and t is the length of time items stored in the warehouse. In the model of Weiss (1982), since the efficacy of the items is lost over time, the longer an item is stored in the warehouse its handling costs will non-linearly increase, i.e. the total holding cost is given by ht^r where r is an integer number which is greater than one (note that if r is equal to one then the model will be back to the classical EOQ). Later, Ferguson, Jayaraman and Souza (2007) showed that the non-linear holding cost function can be used as an approximation to manage perishable products such as milk in grocery stores. They conducted a numerical study which demonstrated 40% improvement in average compared to the classical EOQ.

In the same essence, Fujiwara and Perera (1993) introduced deteriorating EOQ models which considered utility degradation of the stored items. An exponential penalty cost function is applied to the inventory since its utility is degraded over time (as shown in Figure 2.6). As seen in Figure 2.6, since the utility of the deteriorating items decreases over time, the items delivered to fulfil demand (D) during a period of t, t+dt incur a penalty cost of π (i.e. the perishability cost during the period is expressed by πDt dt). Hence, the total deterioration cost is derived from $\int_0^T \pi D t \, \mathrm{d}t$, where T is the length of the replenishment cycle of the deteriorating items.

Note that these efficacy loss studies (Ferguson, Jayaraman & Souza 2007; Fujiwara & Perera 1993; Weiss 1982) focus on managing the perishable items in a single stage (in a manufacturer or a retailer) while it is essential to manage the deteriorating inventories from the perspective of SCM. In addition, the studies focus on the cost incurred because the system holds the perishable items, e.g. penalty cost in Fujiwara and Perera (1993) or non-linear holding cost in Weiss (1982) and Ferguson, Jayaraman and Souza (2007). In some cases, however, the deterioration may directly influence the quality of the product. This commonly occurs in fresh produce, e.g. vitamin C losses in oranges or browning in cutting potatoes *etc*. This deterioration causes the inventory system to bear the quality

costs because of keeping the inventory where its quality is lost over time. Some authors (to name a few: Blackburn & Scudder 2009; Rong, Akkerman & Grunow 2011; Zanoni & Zavanella 2012) examine the quality that naturally degrades in food products such as fruit and vegetables. In their model, the cost caused by quality loss is included.

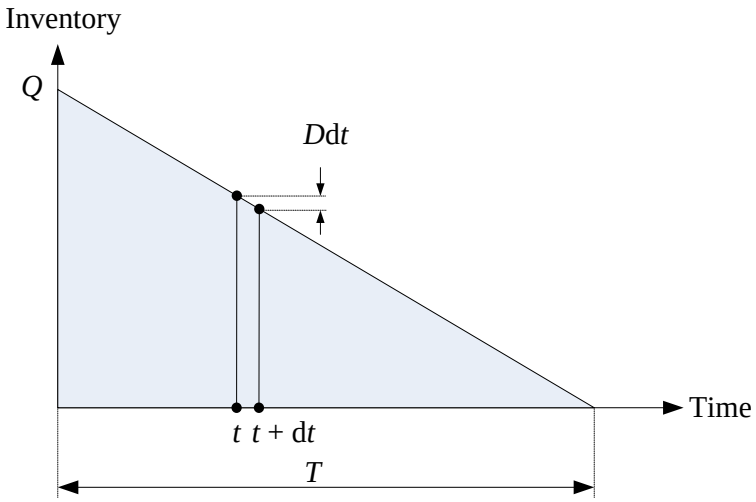


Figure 2.6 Penalty cost on the inventory with utility decrease (Fujiwara & Perera 1993)

Blackburn and Scudder (2009) investigated an appropriate strategy to minimise the loss of the product's value, e.g. sweetness level of melon and sweet corn, across a supply chain. The product's marginal value of time (MVT), i.e. the value change per unit time of one unit product through a supply chain, is used to design the strategy. The product flows across a supply chain which has non-cold and cold chains as illustrated in Figure 2.7. The variable of t_0 represents the picking time, t_1 is the starting time of cold-chain and t_2 is the end of the cold chain period. Based on the product characteristics, during the non-cold chain, the degradation rate of the product value is higher compared to that of the cold chain. To reduce the loss before the cold-chain period (t_0 - t_1) or called *responsive* segment, an approach to managing the picking rate (P) and the size of the transfer batch (q) of the products from the harvesting area to the cooling facility is proposed. Once the product enters the cooling facility, i.e. the cold-chain phase (t_1-t_2) or *efficient* segment, the rate of the value loss becomes slower. Noting that the transportation mode used for delivering the products from the cooling facility to end customers insignificantly affects the value loss, the selection of transportation mode is merely based on efficiency in the transportation cost.

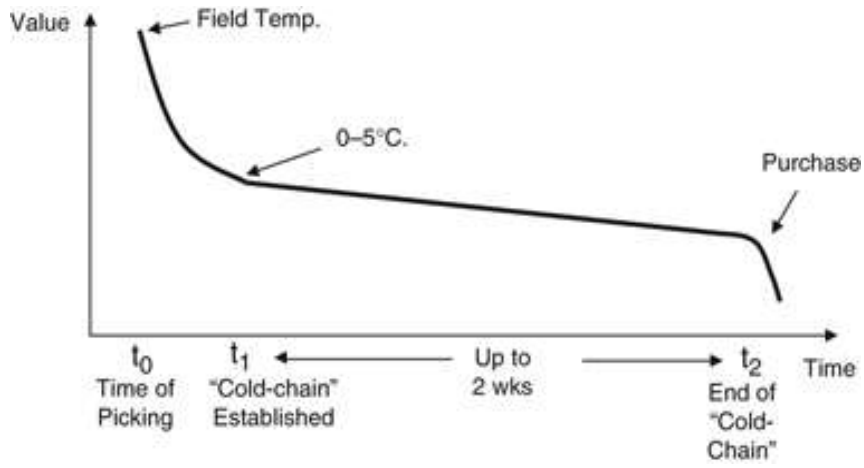


Figure 2.7 Value of a product decreases over time (Blackburn & Scudder 2009)

In a similar essence, Rong, Akkerman and Grunow (2011) proposed the strategy for managing the quality of fresh food across the supply chain. An integrated approach to production and distribution planning to control the quality of food is developed in which the kinetic model is applied to represent the quality change in food. The research focuses on controlling the quality of the fresh produce, e.g. firmness and colour of bell peppers, throughout the supply chain within production site (P), distribution centre (D) and retailer (R) as illustrated in Figure 2.8.

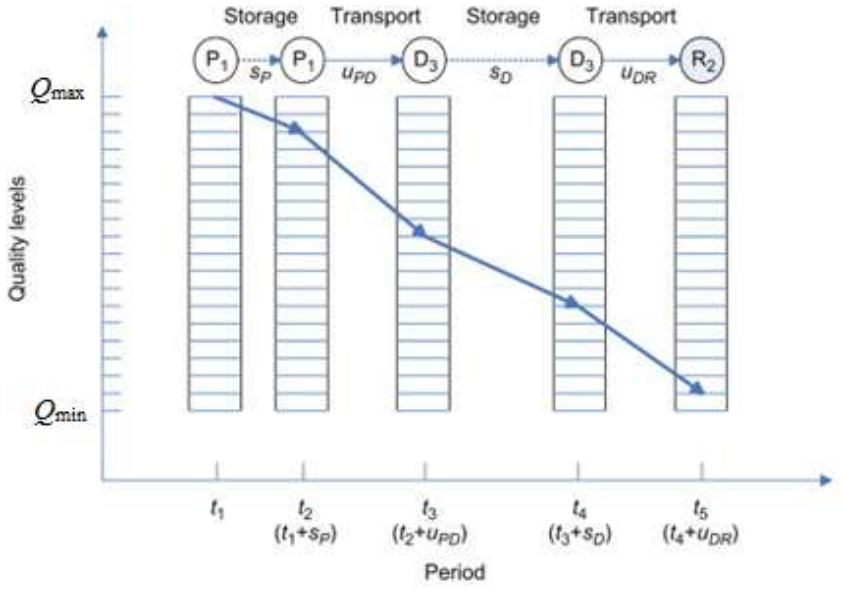


Figure 2.8 Quality loss throughout the supply chain at a given temperature (Rong, Akkerman & Grunow 2011)

It is assumed that the quality of the product is maximum (Q_{max}) at the beginning of arrival time and continues decreasing within facilities until its minimum quality (Q_{min}). In their study the quality degradation is a linear function of time at a certain temperature, hence,

besides the temperature of the facility, the storage time (S_P) and transportation time (U_{PD}) are parameters that influence the remaining quality of the product in every period of time (t). Using a mixed integer linear programming, the integrated approach is formulated where the objective function is to minimise the total cost of the whole system.

Further, Zanoni and Zavanella (2012) investigated the role of energy within the food supply chain. The research was motivated by the fact that the same type of food may require different amounts of energy when delivered across a supply chain. Hence, the economics aspect is considered representing energy used to preserve the quality of food products. A mathematical model is developed to find the best strategy for managing food products considering energy effort used for controlling the temperature. The aim is to minimise the total cost of producer and distribution centre where the transfer batch (q), the temperature at the producer site (τ_P) and temperature at the distribution centre (τ_D) are the decision variables. The study showed the relationships between time, temperature, energy and quality which influence the total cost of the system as illustrated in Figure 2.9(a) and (b).

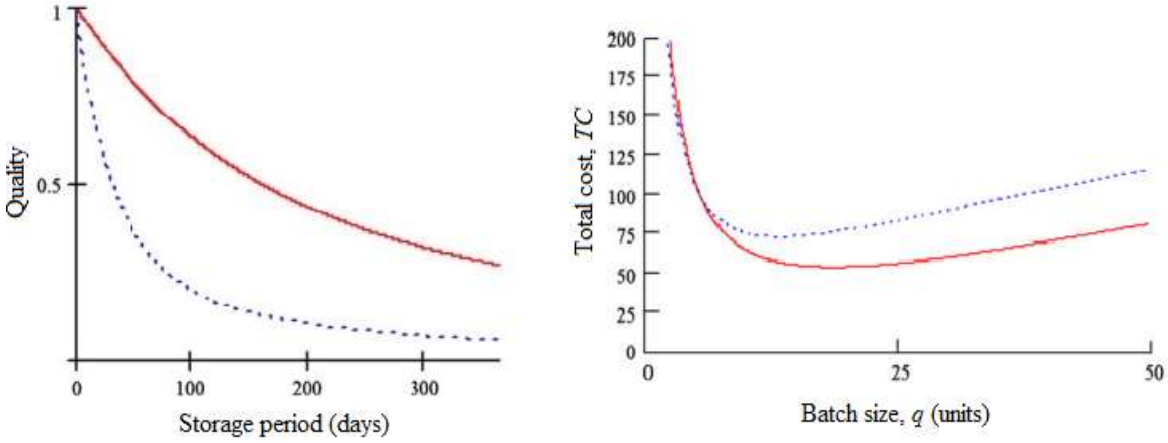


Figure 2.9 (a) quality loss during the storage period for two different temperatures and (b) total cost functions of various size of transfer batch for two different temperatures (Zanoni & Zavanella 2012)

As shown in Figure 2.9(a), temperature influences the rate of quality degradation leading to cost reduction as illustrated in Figure 2.9(b). It means that energy effort used for temperature is economically beneficial for the system. In addition, the batch size (q) is also affected by temperature. Different temperature results in the different optimal size of the transfer batch as presented in Figure 2.9(b).

2.2.1.3 Quantity and quality loss

Studies in the first group (Subsection 2.2.1.1) focus on inventory strategy for deteriorating items with physical quantity depletion while research in the second group (Subsection 2.2.1.2) is concerned with managing the efficacy or quality loss of the deteriorating inventories. Some authors in the deteriorating inventory field are interested in considering both phenomena while managing the perishable inventory across a supply chain.

Cai et al. (2010) considered both the quality drops, e.g. freshness and quantity loss, e.g. spoilage, when managing a fresh product such as flowers, which undergoes a long-distance distribution. The supply chain structure consists of a distributor and a producer. The producer supplies a batch of fresh products while, during the transportation lead time, a proper freshness-keeping effort is utilised to preserve the quality and quantity of the fresh product. The objective function is to maximise the profit by determining the order quantity, the level of freshness-keeping effort and selling price (distributor) and the wholesale price (producer). The optimal decision of each party is viewed from the decentralised and centralised approach. In addition, to facilitate supply chain collaboration between two parties, the scenario for the incentive is proposed. Later, Cai et al. (2013) extended the supply chain structure by taking into account a third-party logistics (3PL) into the observed system. The research revealed the existence of the 3PL provider and considering its transportation fee, it has a significant impact on the supply chain performance.

Recently, Qin, Wang and Wei (2014) studied joint pricing and inventory policy for fresh produce such as vegetables, strawberries and litchi where the quality, as well as quantity of the products, deteriorate simultaneously. The demand is deterministic but dependent on some variables, i.e. the quality, the selling price and the on-display stock level of the fresh produce. The objective function of the model is to maximise the profit by determining the selling price and the length of the replenishment cycle. An algorithm to find the optimal value revealed that if the demand is not too sensitive to price, then the selling price and the number of replenishment cycles can be increased to raise the profit. In addition, the seller can lengthen the replenishment period if the quality of the product deteriorates at a small rate.

Studies in the last two categories (Subsection 2.2.1.2 and 2.2.1.3) may be suitable for representing the deterioration characteristics in fresh produce. They focus on natural deteriorating characteristics in the perishable products, e.g. sweetness level decrease in melon and sweet corn (Blackburn & Scudder 2009), firmness or colour degradation in bell peppers (Rong, Akkerman & Grunow 2011), quality drops as well as physical quantity depletes in flowers (Cai et al. 2010) or vegetables, strawberries and litchi (Qin, Wang & Wei 2014). However, for some perishable items, their utilities are actually fixed or constant during their lifetime (Nahmias 2011, p.viii), e.g. fully packaged foods, usually known as fixed shelf-life products. The utility or functionality of these typical products is the same during their shelf-life. It is also interesting to note that for some perishable products, even though their utility is actually constant during their lifetime, external factors like customer perception may cause the product's value decreasing. Pahl and Voß (2014) named this phenomenon as perceived value loss problem, and this issue lifts the complexity of managing perishable items in retailers.

2.2.2 Managing fixed lifetime inventories

In this section, issues in regards to managing the fixed lifetime inventories are presented. Nahmias (2011, p.viii) defines "a perishable item is one that has constant utility up until an expiration date (which may be known or uncertain), at which point the utility drops to zero". This definition reflects the perishable items with fixed lifetime. Further, inspired by Pahl and Voß (2014), in this literature review, research on managing fixed lifetime inventories is divided into two groups, inventories with non-perceived value loss (NPVL) and inventories with perceived value loss (PVL).

The term PVL is believed to have been introduced by Pahl and Voß (2014). It appears as a result of customers perceiving the value of perishable items decreased after a certain period. This phenomenon is similar to obsolescence in electronic devices or fashionable items. Once an electronic device with new technology enters the market, then the previous device becomes old fashion. In a similar essence, in food groceries, customers prefer to choose a perishable product with longer residual shelf-life. Hence, once a "new" food with a longer residual shelf-life is displayed on the shelves, they will feel reluctant to buy the "old" food with the same price. Purchasing foods and storing them for the future consumption is one of the reasons why customers prefer to choose products with longer lifetime while freshness consideration can be the other.

The main difference between food products and electronic devices is the value at the end of a lifetime. For a fully packed food, after its lifetime period (shown by the expiration date imprinted on its label), the utility drops to zero and it must be discarded otherwise it can cause health issues. On the other hand, for an electronic device, its utility is actually still the same though it "seems" decreased once the new product with new technology is released. Unlike the food product, after its life cycle, the old fashioned electronic product still can be sold at a discounted price.

2.2.2.1 Inventories with non-perceived value loss (NPVL)

Research in managing fixed lifetime inventories without perceived value loss in a single echelon is quite straightforward when demand is deterministic; hence the majority of research for this type of perishable product focused on stochastic demand (Nahmias 2011, pp.1-2). However, managing perishable items in multi echelon can be very challenging as it is related to replenishment and allocation issues, logistic strategy and centralised vs. decentralised policy (Karaesmen, Scheller–Wolf & Deniz 2011). Issues in replenishment and allocation plans are related to the age-composition of inventories in the downstream-upstream parties as the lifetime of the product is limited, hence the best strategy is needed. Further, transhipment, distribution and collection are issues that need to be addressed in logistic strategy as the decision influences the remaining lifetime of the products. Finally, conflict of interest between two or more parties who have different strategies for managing the inventories is part of the centralised vs. decentralised problem.

Kanchanasuntorn and Techanitisawad (2006) proposed a periodic review model for fixed life inventory in a multi-echelon system which consists of a single distributor and multi retailers. The research investigated how the perishability phenomenon in the products influences the stock out policy where profit, total cost, inventory and service level are the system measurement scales. The illustration of this policy can be seen in Figure 2.10.

As shown in Figure 2.10, an instantaneous replenishment is applied to the inventory system. In Figure 2.10(a), at the central warehouse, the size of ordering quantity or q is replenished with maximum level of inventory S, the reorder point s and during the reorder cycle T. In Figure 2.10(b) and (c), at retailer 1 and 2, the ordering size q_1 and q_2 are requested from the central warehouse with identical review interval R but different levels of maximum inventory (S_1 and S_2). The product lifetime l is equal to four interval review ($l = 4R$) while the transportation lead time L from outside supplier to warehouse is equal

to two interval review (L=2R) and the internal transportation lead time (from central warehouse to each retailer) is identical and equal to the review interval ($L_2 = L_1 = R$). At the end of products' lifetime or l, all products left in the system are outdated and have to be discarded (O_1 and O_2). Consequently, the inventory level is turned to zero, and since backlog is not accommodated, then any shortages in the system are considered as lost sales.

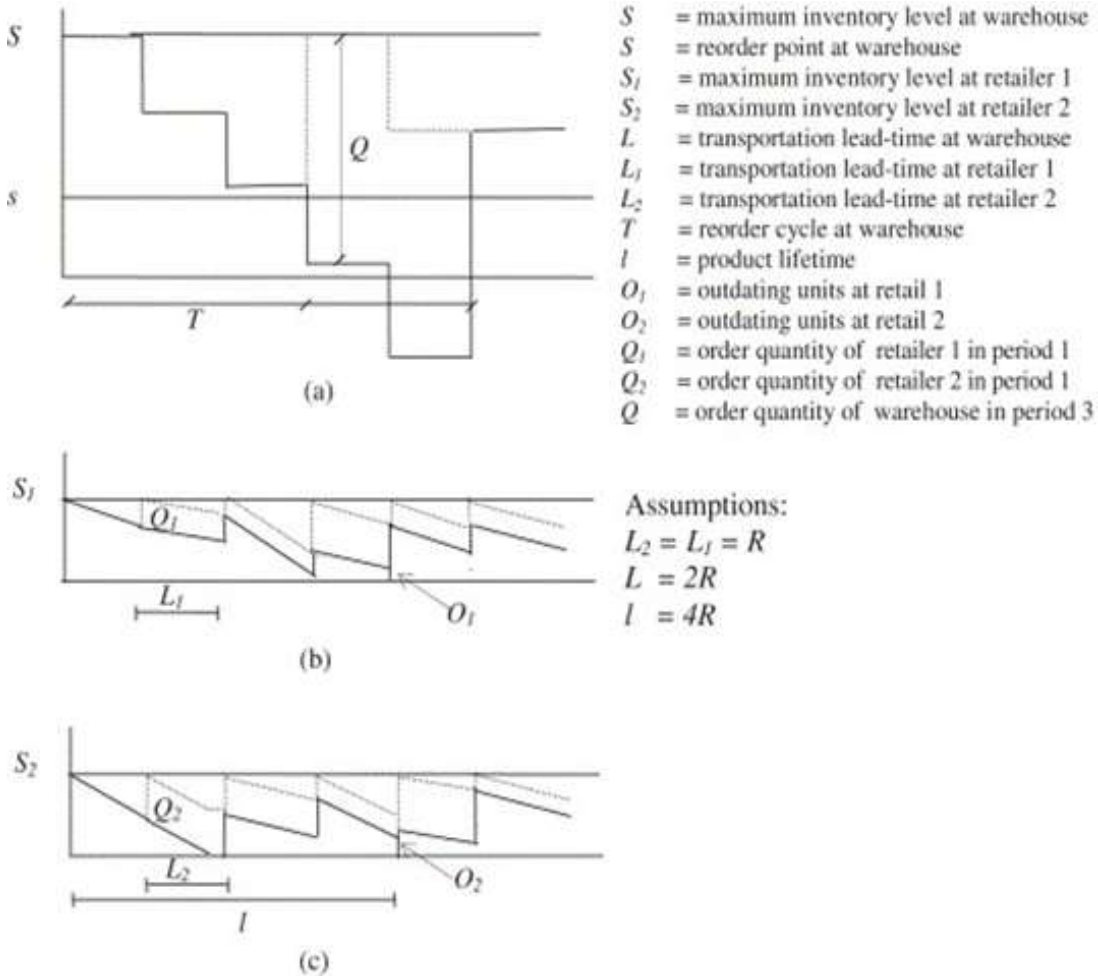


Figure 2.10 Inventory profile of fixed life items in two-echelon system a) Central warehouse; b) Retailer 1; c) Retailer 2 (Kanchanasuntorn & Techanitisawad 2006)

The total relevant cost (*TRC)* of the system is composed by purchasing cost (*UC*), outdating cost (*OC*), ordering cost (*AC*), inventory holding cost at the central warehouse (*IC*), inventory holding cost at the retailer (IC_i) and shortage cost at retailer (SC_i) as shown in Eq. 2.2;

$$TRC = E(UC) + E(OC) + E(AC) + E(IC) + \sum_{i=1}^{n} E(IC_i) + \sum_{i=1}^{n} E(SC_i) \qquad (2.2)$$

where i refers to the retailer and $i = 1, 2, \ldots, n$. To analyse the proposed model, a simulation experiment is conducted. The simulation output demonstrates that the inventory management strategy which ignores perishability results in negative impacts on the system performances. Meanwhile, addressing the perishability in the inventory management approach leads to cost reduction and improvement of the overall performances.

On the other hand, Ketzenberg and Ferguson (2008) differentiated the perishable items in grocery industry into two categories, fast moving and slow moving perishable items and then focused on discussing the latter category. For fast moving perishables, spoilage occurring to unwrapped products may be one of the challenges in managing these typical items (Tortola 2005). For slow moving perishables, however, the challenge is how to manage the inventory so the products can be sold before their expiration dates (Falck 2005). Two approaches in supply chain structures which share the information are investigated as well. The first refers to a decentralised policy, in which the parties in the chain share the information, e.g. demand, inventory and ordering policy, but the policy is decided by each party. The second is a centralised policy where those parties share the information and collaboratively decide the replenishment policy. The value of information (VOI) and value of centralised control (VCC) are then evaluated. The numerical result in Ketzenberg and Ferguson (2008) demonstrates that the total profits of the supply chain system increase 4.2% for the first policy and 5.6% for the second policy compared to a previous study which ignored the perishability behaviour of the product. They noticed that these values are relatively small and two restrictions in the model are identified as the main causes. The first restriction is the fixed revenue per unit ignoring the fact that the level of product freshness may influence the price per unit product, i.e. suppliers providing a fresher product should gain more benefit since the price of their product is higher than the suppliers with the older product. Meanwhile, the second is related to the remaining shelf-life of the perishable product, i.e. the retailers may reject products with short remaining shelf-lives. The first issue is addressed by Cai et al. (2010) and Cai et al. (2013) and has been presented in Subsection 2.2.1.3 while the second issue is discussed in the following subsection.

2.2.2.2 Inventories with perceived value loss (PVL)

Unlike fixed lifetime inventory studies in NPVL group which assume a fixed value of inventories during their shelf-lives, in this PVL group, the product value is not constant. The decrease in product value is represented by its price which is reduced once the product is near to the end of its lifetime. A fully packed food product with the expiration date imprinted on its label fits with this condition.

Entrup et al. (2005) introduced a shelf-life dependent pricing where the residual shelf-life of a perishables product (e.g. yoghurt) influences the purchasing decision of end-customers (as shown in Figure 2.11). The variable sl_j in Figure 2.11 refers to the maximum possible shelf-life of product j and ben_j denotes maximum benefit when a product meets its maximum shelf-life. The variables d and s represent the demand and production days while cr_j is the customer requirement for the minimum shelf-life of the product j and being the fraction of maximum shelf-life, i.e. minimum shelf-life required by the customer for a product is $cr_j \times sl_j$. The financial benefit for retailer grows linearly once the length of residual shelf-life increases. If a product is produced and sold on the same day ($d = s$), the benefit will be maximum (ben_j). It is obvious from Figure 2.11 that a product with a longer residual shelf-life has more financial benefit. Therefore, the manufacturer manages the production schedule which enables delivery of younger and fresher products to the retailers to maximise the benefit.

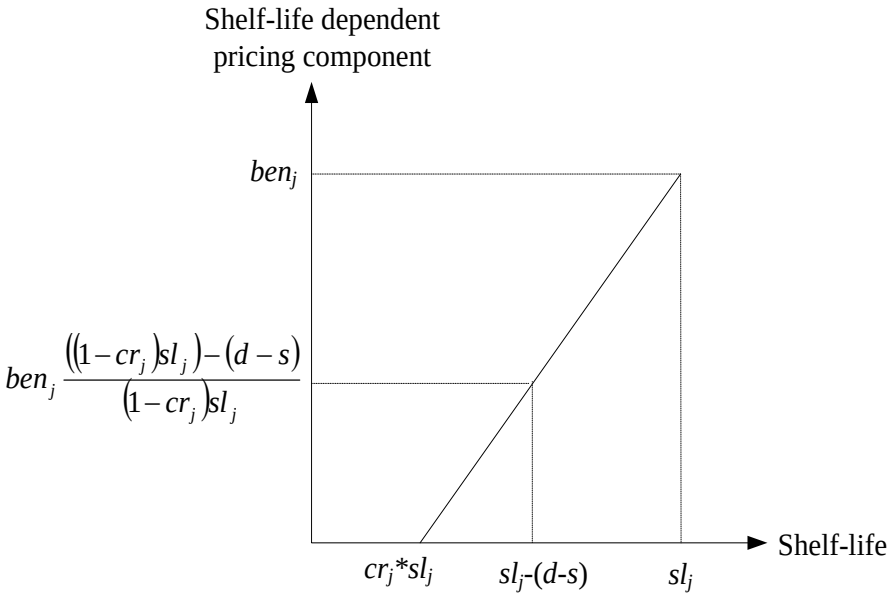


Figure 2.11 Shelf-life dependent price (Entrup et al. 2005)

Jia and Hu (2011) introduced an approach to managing perishable products in a multi-period. The aim is to find the optimal pricing strategy and the optimal ordering quantity of the products in each period. The observed system consists of one supplier and one retailer. The product is divided into two categories, the fresh product called product 2, is a product that has a lifetime of two days. Another product called product 1 can only be sold for one day. The supplier produces product 2 with a constant unit cost and daily delivery order and then determines the wholesale price. Meanwhile, the retailer only orders product 2 and determines the quantity order. If there still are some products 2 left at the first period, then they will be stored and lead to carrying cost. On the other hand, since some unsold products 1 at the next period are discarded, no holding cost is incurred but a penalty cost is charged. In this research, the demand is random and price sensitive, and the problems that need to be answered are how to find the optimal ordering cost for the retailer and how to determine the optimal wholesale price for a supplier which maximises the total expected profits.

Wang and Li (2012) proposed multiple pricing strategies to deal with issues of managing perishable products in grocery retailers. The aim is to minimise the waste and maximise the profit. In this case, the demand is not constant during the selling period. The demand rate changes once the quality of the product deteriorates. Dealing with this condition, the retailer applies multiple price strategy. The price of the perishable product changes during the selling period. The effect of the multiple price strategy to the demand is illustrated in Figure 2.12.

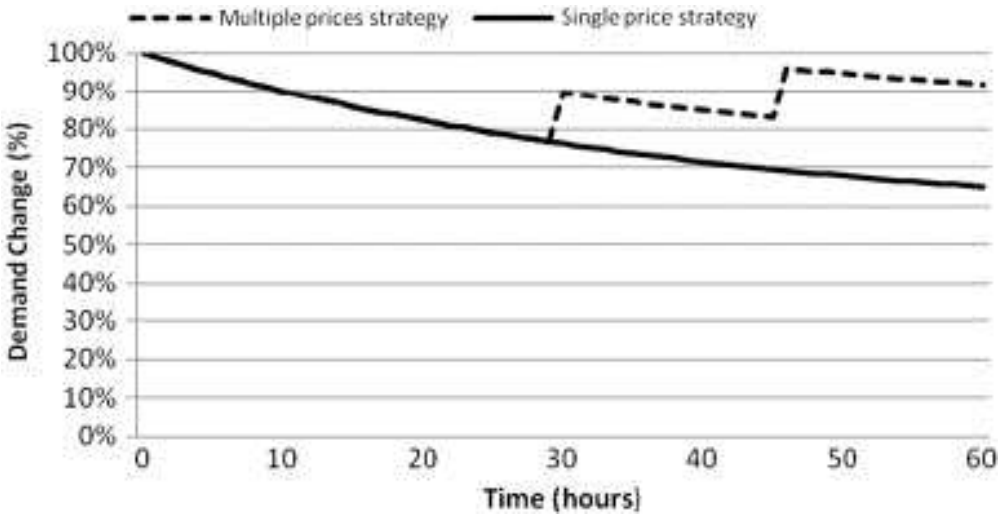


Figure 2.12 Multiple pricing strategies influences demand with exponential quality degradation (Wang & Li 2012)

As shown in Figure 2.12, in the single price strategy (represented by the solid line), the rate of demand decreases during the selling period. Since there is no intervention applied to the decrease in the demand rate, after 60 hours the demand is reduced by 40%. On the other hand, in the multiple price strategy (represented by the dashed line), a markdown strategy is applied twice during the period. This strategy successfully reduces the percentage decrease in the demand rate: hence, after 60 hours the decline in demand is only 10%. It appears that, compared to the single price approach, the multiple price strategy would have more potential to reduce waste and maximise profit.

Jia and Hu (2011) and Wang and Li (2012) focused on pricing and replenishment strategy of the perishable products. They answer the questions of how many quantities should be replenished and at what price they will be sold. A production plan issue such as when the items will be produced and delivered is not considered while, in some cases, the production plan needs to be carefully managed since it affects the age of products received by the retailers. Entrup et al. (2005) considered this issue. In their approach, the product's shelf-life is included in the production plan. The shelf-life becomes a constraint that influences the production policy. However, they only focused on issues of producing finished goods in a single echelon system (i.e. manufacturer). Raw material procurement strategy and retailers' condition are not considered in their model while it may be beneficial to integrate those plans due to cost reduction and higher benefits.

2.2.3 A map of research for deteriorating items from the SCM perspective

The research mapping aims to see the current state of the art of research in the SCM-deteriorating inventory field, to find gaps in the existing research. At the first stage, the existing research in deteriorating inventory model is collected from three recognised databases, SCOPUS, EBSCO, and Web of Science. Some keywords in Bakker, Riezebos and Teunter (2012) were used, i.e. *inventory* OR *deterioration* OR *perish* OR *decay* OR *shelf-life* OR *shelf life* OR *lifetime* combined (AND) with various words related to supply chain, such as *supply chain* OR *multi-stage* OR *multi stage* OR *three stage*. The wildcard symbol (*) was applied as well, e.g. perish*. After the collection stage, the collected research publications are filtered and only papers which contained deteriorating inventory model using the SCM perspective are selected for mapping. Further, the selected papers are divided into several groups based on four main criteria, namely, supply chain

structure, type of inventory, products' deterioration characteristics and coordination approach. A framework to categorise the existing studies is illustrated in Figure 2.13.

As shown in Figure 2.13, in regards to the supply chain configurations, Huang, Lau and Mak (2003) classified it into five groups, namely dyadic, serial, divergent, convergent and network structures. The dyadic structure is composed of two supply chain members, e.g. a supplier and a producer. The serial structure is an extension of a dyadic structure which contains more than two business entities in a supply chain. Divergent and convergent structures are actually the modification of serial structure which is used to represent more realistic problems in the supply chain system. The former basically represents a manufacturer that distributes the products to many downstream members, e.g. a manufacturer and many retailers, while the latter appears as a manufacturer that receives various assembly items from upstream members in the supply chain, e.g. many suppliers and a manufacturer. Finally, the network structure, which is the most complex structure in the supply chain, is the combination of divergent and convergent structures.

In terms of the inventory level in a manufacturing system, the category is differentiated based on two forms of inventory, namely raw materials and finished goods. The raw material inventories are the basic or unprocessed materials stocked in the manufacturer's warehouse that are required by the production line to produce goods. The finished goods inventories are products that are produced and ready to be delivered to the next level in a supply chain, e.g. distributors or retailers (Silver, Pyke & Peterson 1998, p.10).

Further, regarding the products' deterioration behaviour during the storage time, as discussed earlier, two main types of inventories are addressed, i.e. inventory with functionalities (quantity and/or quality) decrease and inventory with constant functionalities. The former group can be divided into physical quantity depletion (consisting of instantaneous, non-instantaneous depletion) and quality or efficacy loss. Meanwhile, the latter group can be categorised into fixed shelf-life product with no perceived value loss (NPVL) and fixed shelf-life product with perceived value loss (PVL).

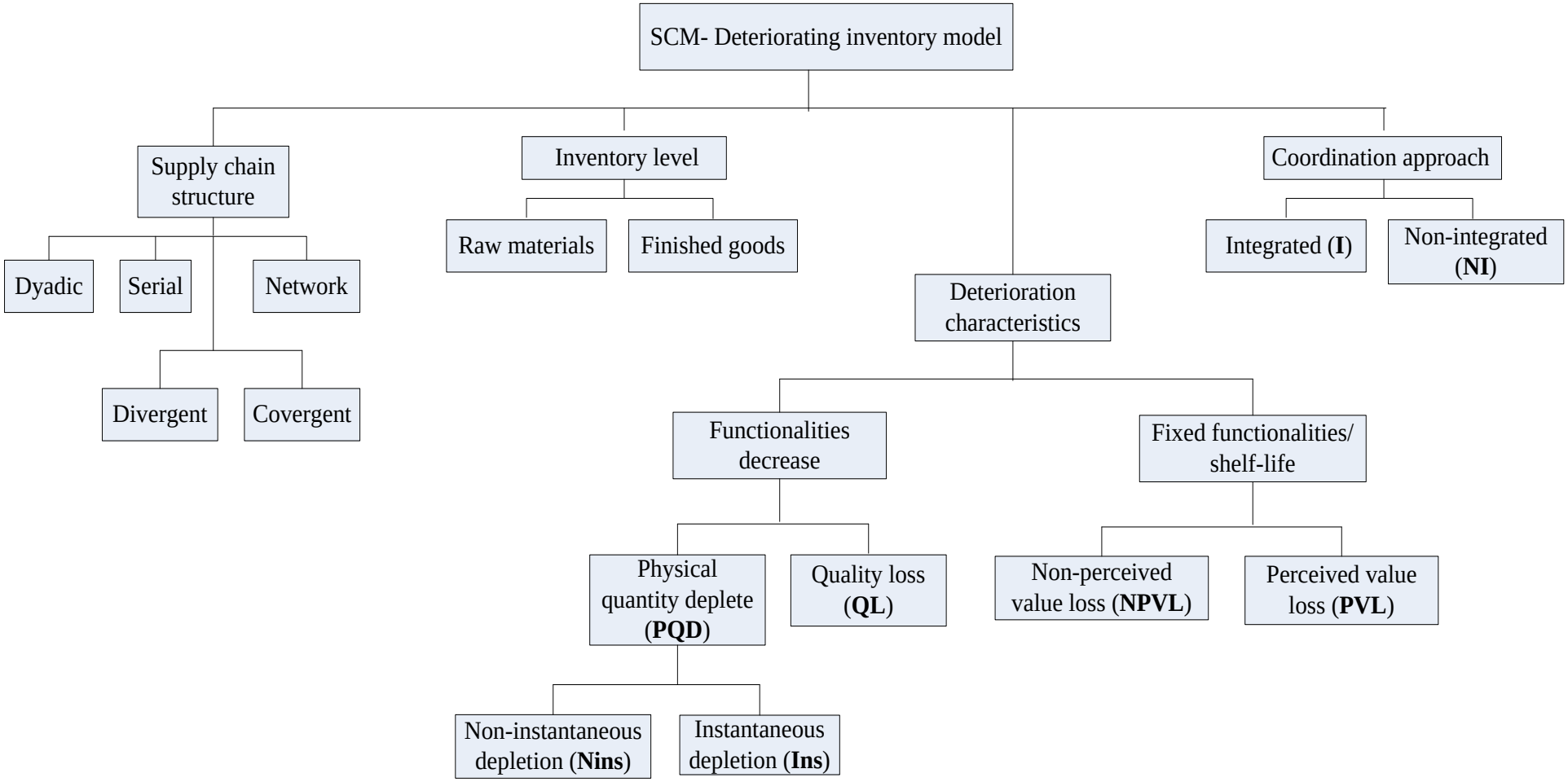


Figure 2.13 Framework used for mapping studies of deteriorating inventory models from SCM perspective

Finally, the last aspect to categorise research in this area is the coordination approach. Yu (2010) classified four types of policies for managing the inventory between suppliers and buyers. This classification is based on the bargaining power of the constituents in the supply chain as illustrated in Figure 2.14. Basically, Figure 2.14 demonstrates that there are two models of inventory policy, individual policy (Policy I, II and III) and integrated policy (Policy IV). As decribed in Figure 2.14, Policy I or completely individual policy exists in the system where a supplier and a buyer are equally dominant in the system. Thus they decide their inventory policy independently i.e. no coordination inventory policy. Policy II is from a dominant retailer who has more power to lead the coordination; Wal-Mart is a typical example. Policy III is from a supplier's perspective where a supplier usually becomes the leader of the supply chain and drives the policy; INTEL is a typical example. The last one is Policy IV or usually called coordination policy. In this case, although suppliers and buyers have equal bargaining power, they prefer to collaborate and decide inventory policies together (integrated policy). Several studies compared those policies and found that the Policy IV gives the lowest total cost of the integrated system (Chen & Chen 2005; Huang, Su & Lin 2011; Lin, Lin & Lin 2010; Yu 2010). Therefore, in this literature review, the existing studies are grouped into integrated (I) and non-integrated (NI) policy research. Studies which adopted Policies I, II and III are placed in Group NI while studies that applied Policy IV are allocated in Group I.

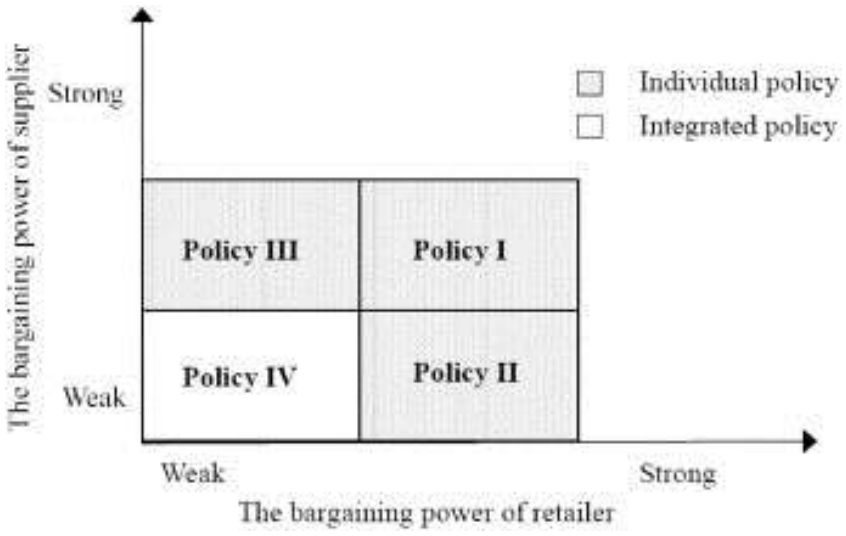


Figure 2.14 Inventory policies based on supplier-retailer bargaining power (Jonas, Wee & Wang 2008)

The initial stage of the mapping process was collecting the related papers which totalled more than two hundred. Those papers were selected based on the criteria, i.e. deteriorating inventory model and using SCM perspective. Papers that addressed issues in modelling the deteriorating inventory but in the single stage were not included and vice versa. This stage results in seventy-three papers. The selected papers are then grouped based on the framework shown in Figure 2.13 and the result is summarised in Table 2.1.

As shown in Table 2.1, seventy-three papers are selected and accordingly arranged in the table, based on the criteria. The table shows that the majority SCM-deteriorating inventory studies focused on managing items with functionalities decreasing over time (sixty-three papers). It is interesting to note that "inventory decay" models dominate studies in this area (forty-seven instantaneous physical depletion papers and seven non-instantaneous physical depletion papers). Still, from the functionalities decrease group, four papers are related to the quality loss and five papers discuss the quantity decrease and quality drop which occur simultaneously with the items. Fewer SCM-deteriorating studies have been completed to deal with fixed lifetime items (seven papers related to managing items with fixed lifetime and four papers addressed the perceived value loss issue). This finding is in line with the fact revealed by Pahl and Voß (2014) that lifetime constraint is rarely considered while managing perishable products.

Table 2.1 Map of SCM-deteriorating inventory studies

SCM-deteriorating inventory research	Type of products based on deterioration phenomena				Inventory level		Policy	SCM Structure
	Functionality decrease		Fixed shelf-life					
	PQD	QL	NPVL	PVL	RM	FG		
Chung (2011); Chung and Lin (2011)	Ins					√	NI	NA**
Wang and Lin (2012)	Ins					√	NI	Dyadic
Chen and Chen (2005); Huang, Su and Lin (2011); Lin, Lin and Lin (2010); Mahapatra, Das and Maiti (2007)	Ins					√	I & NI*	Dyadic
Battini et al. (2009); Chung and Wee (2007, 2010); Chung and Wee (2008); Das, Roy and Maiti (2004); Giri and Bardhan (2012); Giri and Maiti (2012); Jong and Wee (2008); Law and Wee (2006); Lin and Lin (2007); Lin, Yu and Wang (2009); Lo, Wee and Huang (2007); Rongwu (2007); Sarkar (2013); Shah (2011); Tsai (2010); Yang (2004)	Ins					√	I	Dyadic

Table 2.1 Map of SCM-deteriorating inventory studies (continued)

SCM-deteriorating inventory research	Type of products based on deterioration phenomena				Inventory level		Policy	SCM Structure
	Functionalities decrease		Fixed shelf-life					
	PQD	QL	NPVL	PVL	RM	FG		
Uthayakumar and Parvathi (2011); Wang, Lee and Chang (2012); Wee (1998); Wee, Jong and Yang (2006); Yan, Banerjee and Yang (2011); Yang and Wee (2000); Yang and Wee (2006); Zhou and Wang (2007)	Ins					√	I	Dyadic
Wang, Lin and Yu (2011); Yu (2010)	Ins					√	I	Serial
Chung (2009); Geetha and Uthayakumar (2010); Kun-Jen (2010); Maihami and Abadi (2011); Ouyang, Wu and Yang (2006); Soni (2013); Wu et al. (2014)	NIns					√	NI	NA**
Battini et al. (2009); Chen and Chang (2010); Yang et al. (2013); Yang et al. (2010)	Ins					√	I	Div.
He, Wang and Lai (2010)	Ins				√	√	NI	Div.
Chen and Chen (2007)	Ins				√	√	I & NI*	Dyadic
Chung and Wee (2008)	Ins				√	√	I	Dyadic
Rau, Wu and Wee (2003); Rau, Wu and Wee (2004)	Ins				√	√	I	Serial
Huang and Yao (2006); Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015); Yang and Wee (2003); Yu, Wang and Liang (2012)	Ins				√	√	I	Div.
Blackburn and Scudder (2009); Zanoni and Zavanella (2012)		√				√	I	Dyadic
Lin and Chen (2003); Rong, Akkerman and Grunow (2011)		√				√	I	Network
Qin, Wang and Wei (2014)	Ins	√				√	NI	NA**
Cai et al. (2010); Xiao, Chen and Xu (2008); Xiao and Chen (2012)	Ins	√				√	I & NI*	Dyadic
Cai et al. (2013)	Ins	√				√	I & NI*	Serial
Bakthavachalam, Navaneethakrishnan and Elango (2012); Duan et al. (2012); Duan, Luo and Huo (2010); Ketzenberg and Ferguson (2008); Zanoni and Zavanella (2007)			√			√	I	Dyadic
Kanchanasuntorn and Techanitisawad (2006); Zhao and Yang (2006)			√			√	I	Div.
Hu et al. (2010); Jia and Hu (2011)				√		√	I	Dyadic
Entrup et al. (2005); Wang and Li (2012)				√		√	NI	NA**

*the two approaches are compared

**the approaches consider another party perspective but there is no definite SCM structure and also the structure of the total cost or profit only involves single player e.g. a retailer or a manufacturer

PQL = physical quantity depletion, **QL** = quality loss, **RM** = raw materials, **FG** = finished goods, **Ins** = instantaneous deteriorating items, **Nins** = non-instantaneous deteriorating items, **I** = integrated approach, **NI** = non-integrated approach, **NA** = not available, **Div** = divergent, **NPVL** = non-perceived value loss, **PVL** = perceived value loss

In regards to the inventory form, the majority of studies are focused on managing a single type of inventory, i.e. finished goods, while only nine papers considered two inventory forms (raw material and finished goods). It appears that the majority of the research overlooked the interdependencies between these inventories. On the other hand, enough attention has been given to coordination between two parties in a supply chain, e.g. a supplier and a buyer or a manufacturer and a retailer. Only thirteen studies still used unintegrated or individual inventory policy (e.g. a permissible delay payment strategy to increase the performance of the supply chain).

Finally, based on the supply chain structure, it was identified that the majority of the deteriorating inventory studies adopted the dyadic structure. From seventy-three selected papers, forty-four papers represent the dyadic structure, five and eleven papers appear as serial and divergent structure respectively and only two papers represent network configuration. It is interesting to note that no research in this area addresses the convergent structure. The level of complexity of the model might be the main reason (Huang, Lau & Mak 2003).

2.3 Issues in food supply chain management: Major finding and discussion

Food has different deteriorating characteristics compared to other perishable items such as alcohol, gasoline, electronic products *etc*. In alcohol or gasoline, deteriorating phenomenon can be represented by a physical depletion of the products in units over time, while, for electronic products, such as mobile phones, the deterioration in the product's value occurs when a newer model enters the market. On the other hand, in food, the deterioration behaviour can change during the stages of harvesting and retailing (Heldman 2011), i.e. the deterioration properties of food as a raw material would be different from that of finished food products. Consequently, the strategy to manage food products through each level of the supply chain should be different because of the various characters of the food deterioration.

In this study, two types of food products in a supply chain system, food as raw materials and food as fully packed finished goods, are investigated. The deterioration characteristics and their effects on the strategy of managing perishable items across a supply chain are discussed and elaborated in this section.

For illustration purposes, consider a food industry system in a supply chain; at the manufacturing level, the natural quality losses in food as raw materials before being processed may affect the quality of its derivative products, e.g. the decrease in wet gluten content of wheat flour may affect the quality of noodles. To reduce the effect and maintain the quality of the next product, an additional process might be needed and it requires more cost. On the other hand, a different situation occurs when the food raw material has been transformed into a fully packed finished product and is being delivered to the retailers. For some reason, before deciding to buy a food product, consumers look at the residual shelf-life of the product. They tend to choose a product with a longer residual shelf-life. It means that, once a product is approaching its expiration date, the customer's willingness to pay for the product decreases (Tsiros & Heilman 2005). Consequently, the demand rate becomes slower which may lead to outdated items. This situation increases the complexities and difficulties of managing perishable foods by retailers. Lowering the inventory level will reduce the service level, but increasing the stock level may lead to quality, carrying and disposal costs. The following sub-sections elaborate these typical deteriorations and how they may influence the inventory strategy.

2.3.1 Quality loss in raw food products

Naturally, the quality of food products degrades over time. A kinetic modelling study is a quantitative approach that is typically used for describing the quality degradation (Van Boekel 2008). The kinetic model is represented by a mathematical expression as shown in Eq. 2.3;

$$\frac{dQ}{dt} = -\theta Q^m \tag{2.3}$$

where Q refers to the measured quality performance such as colour, texture, sensory attribute *etc*., t represents time, while θ denotes the deterioration rate depending on environment, such as temperature, and m is the order of reaction or a power factor. The value of power factor represents the quality degradation rate, for instance, $m = 0$ refers to zero order reaction leading to a linear quality decrease (see Figure 2.15, line A), while $m = 1$ means the first order reaction representing an exponential quality decay (see Figure 2.15, line B).

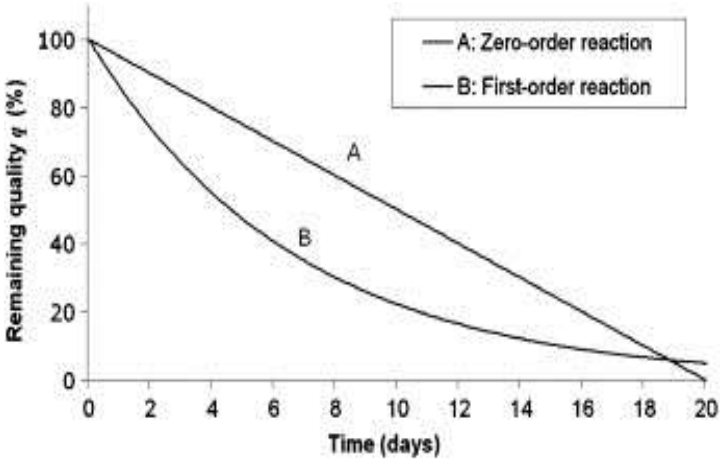


Figure 2.15 Food quality degradation illustration (Rong, Akkerman & Grunow 2011)

Managing food quality is a very complex and difficult task. It is because of the dynamic characteristics of food and its environment factors, such as temperature, humidity *etc*. Among those factors, the temperature is the most common factor used to control the deterioration rate. The Arrhenius equation, a formula that is based on a temperature-dependent chemical reaction, is commonly used to depict the deterioration rate as expressed in Eq. 2.4:

$$\theta = k_0 . e^{-E_a/\beta\tau} \tag{2.4}$$

where k_0 is a constant, E_a refers to the activation energy, while τ and β represent the temperature and universal gas constant, respectively.

It is important to note that, currently, the majority of research in food quality is separated from the inventory theory. The research is typically focused on optimising the parameters that directly influence the quality degradation in food, such as temperature. In reality, however, the total quality loss in food can be affected by the inventory plan and strategy (Rong, Akkerman & Grunow 2011; Zanoni & Zavanella 2012). Rong, Akkerman and Grunow (2011) developed a production and planning model to manage the quality loss of fresh produce across a supply chain. The quality loss over time is described by Eq. 2.5 showing that the quality loss or ΔQ depends on the temperature storage (τ) and the length of the storage time (t). It appears that the low rate of inventory turn-over leads to an increase in the total of the quality loss:

$$\Delta Q(t,\tau) = k_0 t e^{-E_a/\beta\tau} \tag{2.5}$$

Further, Zanoni and Zavanella (2012) investigated the role of temperature in a food supply chain system regarding its relations to energy effort for reducing the quality loss. A mathematical model accommodating the preservation effort is established as shown in Eqs. 2.6 and 2.7:

$$TC_p(q,\tau_p)=\left(SECecd+K_p\frac{d}{q}\right)\rho_{\tau_p} \tag{2.6}$$

The total cost in the producer facility is represented by $TC_P\ (q,\tau_P)$. It can be minimised by controlling the batch size or q and the temperature or τ_P. The variables of *SEC* and *ec* respectively refer to the Specific Energy Consumption [kWh/kg] and the cost of cooling energy [$/kWh]. The variable d denotes the demand rate, K_p is the setup cost while ρ_{τ_P} represents the ratio between cooling temperature and coefficients of performance or COP (readers may refer to Rong, Akkerman and Grunow (2011) for further explanation of COP):

$$TC_D(q,\tau_D)=K_D\frac{d}{q}+\frac{q}{2}h_s\rho_{\tau_D}+\frac{d}{q}p\left(q-\frac{d}{b(\tau_D)}\left(1-e^{-((b(\tau_D)q/d)}\right)\right) \tag{2.7}$$

As shown in Eq. 2.7, the total cost of the distribution is symbolised by $TC_D\,(q,\tau_D)$ which is respectively composed by setup cost, holding cost and the cost because of value loss in q. The variable h_s is the holding cost, p refers to the product selling price while $b(\tau_D)$ represents the temperature-dependent coefficient such as in Peleg et al. (2002).

Rong's model successfully demonstrated that there is a relationship between inventory turn-over and quality loss. Meanwhile Zanoni's model revealed the relationship between batch size (q), storage period and its temperature (τ). These models, however, consider only managing a single form of inventory, e.g. the finished goods. It appears that these approaches would be suitable for managing fresh products from producer to retailer but need to be extended for covering issues of managing food in an integrated production-inventory system. The integrated system involves the raw food material procurement strategy and finished goods production and delivery plan that are decided simultaneously due to the global optimal solution for the whole integrated supply chain system.

2.3.2 Customers' perception of the open-dating food products

It is common in the food system that a fully packaged food product is labelled with a clearly readable date indicating when the products were packed or the last date they should be sold, i.e. open-dating food products (Labuza & Szybist 2008, p.1). On the other hand, nowadays, more consumers have a good education and knowledge of the quality of food products. In regards to open-dating products, it is often found that consumers look at their residual lifetime to convince themselves about the quality. And mostly, customers have different preferences on seeing this issue, i.e. one may feel reluctant to buy a product if it only has two weeks left before being expired while another may have no problem with that. This customer's behaviour elevates the complexity of managing open dating food products in grocery retailers.

At grocery retailers, open dating food product worldwide sales in 2006 exceeded $300 billion (Li, Cheang & Lim 2012). Unfortunately, other data show that up to 15% of food losses are due to spoilage and damage in developed Western grocery retailers (Ferguson & Koenigsberg 2007). It is also reported from the grocery sector in Europe that billions of dollars are spent annually as the result of unsold products before their expiration date (Kärkkäinen 2003). Excessive inventories and/or improper quality control are the main causes of food waste which leads to severe financial consequences. If food loss can cost a grocery store from $70,000 - $340,000 a year depending on its size (Supermarket News, 1997), reducing the loss may lead to an increase in profit of a grocery store up to 15% (Hennessy 1998). Therefore, products with restricted lifetime need to be managed carefully as overstocking leads to a loss while low stocking reduces service level.

In food system, shelf-life is the most important factor in managing food inventories across a supply chain. According to Labuza (1999, p.1), shelf-life refers to the period where food 'will retain an acceptable level of eating quality from a safety and organoleptic point of view'. However, when it comes to the end customers in food grocery retailers, the "acceptable level" is not fixed or constant during shelf-life. It is shown by the customers' willingness to pay (WTP) for a product decreases when the product is approaching the end of its shelf-life (Tsiros & Heilman 2005). Since customers are free to choose the product they want to buy, mostly they will pick the fresher one (a product with a longer residual shelf-life).

Tsiros and Heilman (2005) investigated customers' behaviour with regards to perishable products in the grocery store. Six perishable products: beef, chicken, yoghurt, milk, prewashed/pre-cut carrots and pre-washed/pre-cut lettuce with printed expiration dates on their packaging were observed. Three hundred consumers from two large metropolitan areas participated in the study. The research revealed that in general, customers WTP decreases when the product is approaching its expiration date as shown in Figure 2.16. The decrease can be linear as shown in lettuce, carrots, milk and yoghurt or non-linear as in chicken and beef.

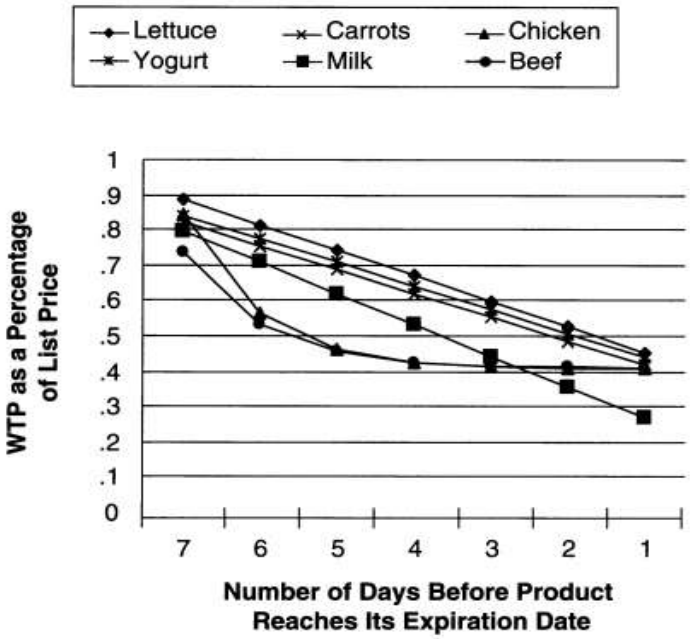


Figure 2.16 WTP throughout a perishable's shelf-life (Tsiros & Heilman 2005)

This customer behaviour research is beneficial for the retailer to make a decision regarding discounting. Nijs et al. (2001) proposed that one effective way to reduce product waste while it nearly reaches its expiration date is by promoting a significant price discount. This policy enables customers to make a trade-off between purchasing fresher items which are more expensive, and buying the discounted one with lower freshness level but still within an acceptable quality range to consume (Tsiros & Heilman 2005). Despite the fact that the discounting price policy could reduce the quantities of outdated items, this policy actually reduces retailer's margin. Therefore, a product with a longer lifetime is preferable as it gives more benefits to the business.

In practice, extending the product shelf-life can be managed in four ways: improving the process, modifying the ingredient, improving the product packaging and storage

condition (Entrup 2005, p.118). However, these might not be a preferable choice for a number of reasons, e.g. costs or health. Thus, the only option that the manufacturer can try is to manage the production and distribution of the products from the manufacturer to the retailers as soon as possible. Hence, the product remaining lifetime will be longer, and both manufacturer and retailer can get more financial benefits from it.

Entrup et al. (2005), Wang and Li (2012) and Jia and Hu (2011) consider a non-constant price of food products. Entrup et al. (2005) integrated product shelf-life into the production planning and introduced a shelf-life dependent price function. Wang and Li (2012) introduced multiple pricing strategies as demand is non-constant, i.e. influenced by quality degradation. Jia and Hu (2011) proposed an approach for managing products in multi-period and multi-price involving one supplier and one retailer system. All models are suitable for managing inventory with customers' perception loss, i.e. open dating food products, but the former two approaches are in single-echelon perspective (manufacturer or retailer). Jia and Hu (2011) as well as Wang and Li (2012) deal with a multi-echelon system but the production plan is disregarded in their approaches.

Across a supply chain, some typical foods may transform into many forms and functions such as food raw materials, work in process products or finished goods. Interestingly, its quality also behaves differently depending on its form and function. Consequently, the way food products are managed through each level of the supply chain will not be the same because of the various characteristics of the food deterioration. This increases the complexity of managing perishable inventories. Further, to avoid a mismatch between supply and demand, an integrated approach to the supply chain members is needed. Hence, the impact of the various deteriorations on inventory can be managed and excessive or shortage inventories can be avoided across a supply chain for profit maximisation.

In SCM-non-deteriorating inventory area, integrated approach research has been extensively developed. Banerjee, Kim and Burton (2007) introduced an inventory model where the procurement of raw material is decided simultaneously with production and finished goods delivery. They also compared the cost of independent approach and integrated approach and revealed that the integrated approach leads to a lower joint total cost. However, the model uses a common cycle approach which disadvantages players with small demand. Later, Chan and Kingsman (2007); Hoque (2008, 2011) relaxed this

assumption and introduced a synchronised cycle approach. In the synchronised model, retailers have their own cycle and this is more realistic in the food industry since the delivery cycle influences the residual shelf-life of the product when entering the retailers. However, the synchronised models still ignore perishability. Therefore, a new approach which implements a synchronised cycle mechanism and considers the perishability is needed to reflect a more practical application of managing food inventory across a supply chain.

2.3.3 Finding and discussion: A summary

From the literature review on SCM-deteriorating inventory studies, several research gaps are identified as follows:

1. Based on supply chain structure, the majority of research addresses a manufacturer and a buyer problem or from a dyadic structure point of view. There was limited research in serial and divergent structure and no research found in the convergent structure. These issues still have the potential to be explored since, in real life, coordination between players appears in more complex supply chain structure.
2. In terms of deterioration characteristic, the majority of studies addressed physical quantity depletion problems. In food products, however, during a certain period, the quantity may remain the same while the quality does degrade leading to the restricted lifetime of food products. Therefore, studies addressing quality degradation and restricted shelf-life problems are more suitable for representing perishability in food products. Unfortunately, from the research map, these issues still need more attention from scholars.
3. In addition, the perishable nature of food is unique and different from other perishable items. The quality behaviour changes through different levels of a supply chain depending on its form as raw material or finished goods. To reduce food waste and increase profit, it is essential to manage food in an integrated system where the raw material procurement strategy is decided simultaneously with the production plan. This leads to research which considers deterioration not only in raw material but also in finished goods. Unfortunately, from the research map in Table 2.1, the majority of SCM-deteriorating items only focus on a single form of inventory, e.g. finished goods, and limited research addressing problems in managing both the raw materials and finished goods. Therefore, accommodating deterioration issues in both

inventory forms will give significant contributions to food supply chain management studies.

4. Finally, in regard to coordination mechanism, the majority of research focuses on the dyadic relationship between two players in a supply chain, e.g. a manufacturer and retailer. Less research investigated the effect of synchronising the procurement-production-delivery plan. In the non-perishable inventory area, this issue has been addressed well and it has been revealed that the synchronisation leads to a better SCM performance. Therefore, addressing the synchronisation issue will enhance the contribution in SCM-deteriorating inventory field.

2.4 Research problem definition

Through the major finding and discussion section, the shortcomings of the existing research in this area have been identified. To make the research problem clear and manageable, the next step is to define the research problem.

Referring to the summary of finding and discussion in Section 2.3, problems considered in this research are defined as follows:

1. Due to a more representative and suitable approach for managing food inventory across a supply chain, the deterioration in raw material is differentiated from that in finished goods. A kinetic model is utilised to represent the quality loss in raw materials while the shelf-life based price function is established to represent the perceived value loss in finished goods.
2. Regarding the supply chain configuration, this research deals with a single vendor multi-buyer problem (SVMB). Unlike majority research in the SCM-deteriorating inventories, the raw material procurement strategy is simultaneously determined with the production and delivery schedule of finished goods.
3. In terms of the coordination mechanism, a synchronisation approach of the procurement-production-delivery plan is applied. Two improvements are made including:

    - **A general replenishment approach**

      The majority research procures raw material to fulfil the demand of at least one production cycle. In this approach, however, once replenishment can be used for

covering more than one production cycle. This method is more realistic to represent food raw material with seasonal pattern i.e. the supply fluctuates and relies on the season; hence, the manufacturers are allowed to replenish the material in higher quantity for covering more than one production cycle.

- **A synchronised production and multi shipments factor**

  Majority research used a common cycle approach which means that regardless the retailers' demand, all of them will have the same delivery cycle. As mentioned previously, this approach may be disadvantageous for some players, therefore, in this study a multiplier factor is used to synchronise the delivery frequencies over the production cycle, hence each retailer has its own delivery cycle.

2.5 Chapter summary

In this chapter, the literature review of research in SCM with deteriorating inventory has been completed. Studies in this area are categorised based on a framework which consists of several factors, namely, SCM configuration, deterioration characteristics, inventory form and coordination approach. It is revealed that the majority of study in this area addressed problems in the simplest SCM structure (dyadic configuration) and concern for quantity depletion problems of a single inventory form (raw material or finished goods). In addition, less research addressed an integrated approach issue (i.e. raw material replenishment is simultaneously determined with finished goods production and delivery).

For a food product, the non-quantity depletion problems such as quality decrease and perceived value loss are more often found in practical life. These typical deteriorations lift the complexity of managing food product across a supply chain. In addition, a synchronised approach between deteriorating raw material replenishment strategy and perishable finished goods production and delivery schedule is essential in food supply chain for minimising food loss and improving the supply chain profitability. Therefore, the research is aimed at filling this gap by proposing an integrated production-inventory model of food products from the perspective of SCM. Unlike the majority of research, deterioration in food raw material is distinguished from that in finished goods.

After finding the gaps, defining the problems of this research, the next stage is to select the appropriate mathematical function to model the research problem as well as to examine the most potential optimisation method to obtain the solution. These two important issues are discussed in the next chapter (Chapter 3).

Chapter 3

Model representation and optimisation of an integrated production-inventory model for deteriorating items

3.1 Introduction

In Chapter 2, an extensive literature review in SCM with deteriorating inventory has been presented and the research gaps in the existing literature have been identified, which leads to the research questions and a proposed model.

A model or an idealised representation of the system is a part of daily life, e.g. model aeroplanes, physical models, globes, portraits *etc*. (Hillier & Lieberman 2005, p.12). It plays an important role as it abstracts the essence of the observed system and demonstrates the relationship between variables and parameters leading to a facilitation to analyse the system. In this study, a mathematical model is developed to represent the problem of interest. A mathematical model is also an idealised representation which is represented by mathematical symbols and expression. Compared to a verbal model, a mathematical model more concisely describes the problems and is able to reveal the essential cause and effect relationships between elements in the model (Hillier & Lieberman 2005, p.13). However, it is important to ensure that a mathematical expression is suitable or appropriate for representing the subject of enquiry since the incorrect representation will lead to a wrong conclusion or result. Further, once the mathematical model is established, an appropriate and efficient tool to find the model's solution is needed. If the incorrect model leads to a wrong solution, the inappropriate tool results in a poor solution or output. These two issues are essential to be addressed in this study.

This chapter is aimed at determining the most appropriate mathematical approach to represent the proposed models as well as to select the most suitable optimisation methods to obtain a good output in terms of quality and efficiency, e.g. performance measurement and time computation. For the first purpose, identifying and examining the mathematical

representation of the current related models would be beneficial for ensuring that the correct approach is used. A survey related to the mathematical model used by related research is conducted and the result is then used as a rationale to justify the selected mathematical model. Similarly, optimisation methods that have been used to find the solution in the existing models are examined and the most suitable one is selected to optimise the developed model. A step by step procedure to develop the model is presented in Chapter 4 while the design of the selected optimisation tool to find the optimal solution of the developed model is demonstrated and discussed in Chapter 5.

For the rest of this chapter, the term of quality degradation will be used to represent deterioration in raw material while the phrase of perceived value loss (PVL) will be used to describe perishability in finished goods. In regards to the coordination mechanism, instead of using the common cycle approach, the synchronised cycle method, is used to synchronise the production plan and the delivery strategy (i.e. a multiplier factor of the delivery frequency over the length of the production cycle). The proposed mechanism is expected to reduce waste and improve profit.

The remaining sections of this chapter are organised as follows: identification and discussion of the mathematical representation of the existing research is presented in Section 3.2. The rationale of the selected mathematical representation (i.e. why the chosen mathematical expression is most appropriate to represent the problem) is discussed and justified in Section 3.3. Section 3.4 identifies and evaluates the optimisation approaches used by current related studies and then selects a preferable approach for obtaining the solutions of the mathematical representation of the proposed model. Section 3.5 briefly describes the selected optimisation tool while Section 3.6 summarises this chapter.

3.2 Mathematical model representation in current research: A survey

An extensive review of research in this area has been completed in Chapter 2. Further, in this section, the mathematical approaches used by selected studies are identified and discussed.

According to Hillier and Lieberman (2005, p.12), a mathematical model is an idealised representation of an integral part of daily life which is expressed in mathematical symbols to describe the essence of the problems. Hence, it generally contains decision variables

(quantifiable decisions to be determined, e.g. x_1, x_2, …, x_n), the objective function (a measure of performance, e.g. the total cost, the total profit *etc*.), constraint (the mathematical expression to show the restriction), and parameters in the objective function and constraints.

Fundamentally, based on the relations between variables and parameters within the model's objective function and constraint, there are two mathematical approaches that are widely applied in literature, namely linear programming (LP) and nonlinear programming (NLP) models. If all of the relations are linear, then the LP can be used for representing the model (Hillier & Lieberman 2005, p.25; Mishra & Agarwal 2009, p.13). Otherwise, if some or all of the relations are not linear, then the NLP is a preferable representation (Hillier & Lieberman 2005, p.547).

LP is widely used in transportation and assignment problems. However, it is hardly implemented in inventory management studies since a nonlinear function is used to represent the total cost that consists of the ordering cost and the holding cost (as illustrated in Figure 3.1).

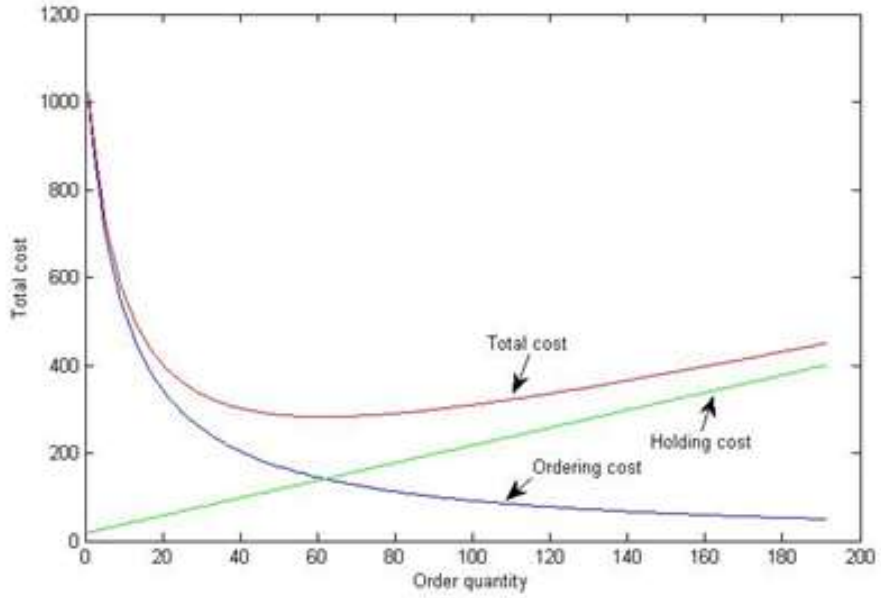


Figure 3.1 Total cost composed by ordering cost and holding cost

As seen in Figure 3.1, the number of ordering quantities influences the total cost of the inventory system. The minimum total cost is obtained when the size of the quantity order is equal to 60. Ordering a quantity less than 60 will reduce the holding cost but will increase the cost to order or procure the raw material. On the other hand, the size of order

greater than 60 will reduce the ordering cost but will increase the holding cost. Therefore, the ordering size of 60 is the best trade-off between the holding and ordering cost since it leads to the minimum total cost. The mathematical expression to describe this situation is presented in Eq. 3.1;

$$TC(q) = h\frac{q}{2} + A\frac{D}{q} \tag{3.1}$$

where $TC(q)$ represents the total cost, h denotes the cost of holding an item while A symbolises the ordering cost per one order. The variables D and q refer to the demand and the size of order respectively. This NLP model shown in Eq. 3.1 becomes one of the fundamental approaches in the inventory management theories.

Further, referring to an integrated production model in the multi-echelon system, commonly two different types of values of the decision variables are involved: a continuous value (the length of production cycle) and an integer value (the number of delivery frequencies). If a model with a linear relation has an integer and continuous unit solution, then a mixed integer linear programming (MILP) approach is used. However, if the relation is nonlinear, then a mixed integer nonlinear programming (MINLP) is applied (Hillier & Lieberman 2005, p.478). The latter form is commonly used for representing an integrated production-inventory model. For more elaboration regarding this issue, a review of mathematical model attributes, e.g. objective function, decision variables that are used by the related research, is conducted and the summary is presented in Table 3.1.

As predicted, Table 3.1 demonstrates that the majority of the observed studies used NLP approach for representing the inventory model. Exceptions are two studies by Rong, Akkerman and Grunow (2011) and Entrup et al. (2005). In their models, the inventory built up during the production length is disregarded. These typical problems are usually categorised into production-allocation problems and in most cases a LP can be used for mathematically representing them. However, in an integrated production-inventory system, the inventory built up (by production) and depleted (by demand) during the length of the production cycle is one of the important issues that cannot be disregarded. Meanwhile, obviously considering those issues leads to the NLP problems. Therefore, the MILP seems to be an inappropriate mathematical approach to representing the integrated policy.

Table 3.1 Identification of mathematical representation and solution methods that are used by existing and relating studies

Research	Objective function	Decision variables	Mathematical representation	Solution Method	Issues addressed
Ghare and Schrader (1963)	Minimise cost	Ordering size (q)	Nonlinear Programming (NLP)	Analytical and heuristic procedure	- EOQ - Single echelon - Deteriorating items (physical quantity depletion)
Raafat (1985)	Minimise cost	Length of production cycle (T)	Nonlinear Programming (NLP)	Analytical	- IPPP - Single echelon - Deteriorating raw materials (physical quantity depletion) - Perishable finished goods (physical quantity depletion)
Chang, Teng and Goyal (2010); Soni (2013)	Maximise Profit	The ending inventory level (E) or the duration of a replenishment	Nonlinear Programming (NLP)	Analytical and Heuristic procedure	- Non-instantaneous quantity depletion - Non-integrated inventory policy
Blackburn and Scudder (2009)	Minimise cost	- Transfer batch (q) - Production rate (p)	Nonlinear Programming (NLP)	Analytical	- Supplier-Buyer - Quality loss of a single fresh food
Qin, Wang and Wei (2014)	Maximise profit	- Price (p) - Replenishment period (T)	Nonlinear Programming (NLP)	Analytical and Heuristic procedure	- Quality loss and quantity depletion of a single item - Non-integrated
Cai et al. (2010); Cai et al. (2013)	Maximise profit	- Retailer price (p) - Shipping quantity (q) - Producer's wholesale price (w) - Distributor purchasing quantity ($\hat{q}$)	Nonlinear Programming (NLP)	Analytical	- Supplier-Buyer+3rdPL - Quality and quantity loss
Entrup et al. (2005)	Maximise Profit	Scheduling	Mixed integer linear programming (MILP)	ILOG's OPL Studio 3.6.1 and CPLEX 8.1	- Single echelon - Shelf-life dependent pricing

Table 3.1 Identification of mathematical representation and solution methods that are used by existing and relating studies (continued)

Research	Objective function	Decision variables	Mathematical representation	Solution Method	Issues addressed
Rong, Akkerman and Grunow (2011)	Minimise cost	- The quality level of inventory - quantity flows	Mixed integer linear programming (MILP)	ILOG's OPL studio combined with CPLEX 10.2 software	- Network - Quality loss of a single fresh food
Yang and Wee (2002)	Minimise cost	- The length of the production cycle (*T*) - Number of finished goods deliveries (*n*)	Mixed integer nonlinear programming (MINLP)	Analytical using Spiegel & Taylor's series expansion	- Single vendor multi-buyer - Perishable finished goods (physical quantity depletion)
Rau, Wu and Wee (2003)	Minimise cost	- Replenishment frequencies of raw materials (*m*) - The length of the production cycle (*T*) - Number of finished goods deliveries (*n*)	Mixed integer nonlinear programming (MINLP)	Analytic and Heuristic Procedure	- Single vendor multi-buyer (lot for lot) - Deteriorating raw materials (physical quantity depletion) - Perishable finished goods (physical quantity depletion)
Yang and Wee (2003)	Minimise cost	- Replenishment frequencies of raw materials (*m*) - The length of the production cycle (*T*) - Number of finished goods	Mixed integer nonlinear programming (MINLP)	Analytic and Heuristic Procedure	- Single vendor multi-buyer (multiple deliveries) - Deteriorating raw materials (physical quantity depletion) - Perishable finished goods (physical quantity depletion)
Chan and Kingsman (2007)	Minimise cost	- The length of the production cycle (*T*) - Number of finished goods deliveries (*n*)	Mixed integer nonlinear programming (MINLP)	Genetic Algorithm	- Single vendor multi-buyer (JELS-synchronized cycle) - Non-perishable finished goods

Table 3.1 Identification of mathematical representation and solution methods that are used by existing and relating studies (continued)

Research	Objective function	Decision variables	Mathematical representation	Solution Method	Issues addressed
Banerjee, Kim and Burton (2007)	Minimise cost	- Replenishment frequencies of raw materials (*m*) - The length of the production cycle (*T*) - Number of finished goods deliveries (*n*)	Mixed integer nonlinear programming (MINLP)	Analytic and Heuristic procedure	- Single vendor multi-buyer (JELS-common cycle) - A multiplier integer over the length of production cycle - Non-deteriorating raw material and non-perishable finished goods
Chan and Kingsman (2007)	Minimise cost	- The length of the production cycle (*T*) - Number of finished goods deliveries (*n*)	Mixed integer nonlinear programming (MINLP)	Genetic Algorithm	- Single vendor multi-buyer (JELS-synchronized cycle) - Non-perishable finished goods
Yu, Wang and Liang (2012)	Minimise cost	- Common replenishment cycle (*C*) - Raw material replenishment frequencies (*m*)	Mixed integer nonlinear programming (MINLP)	Analytical and Heuristic procedure	- Single vendor multi-buyer (JELS-lot for lot) - Deteriorating raw materials (physical quantity depletion) - Slow rate deterioration of perishable finished goods (physical quantity depletion)
Taleizadeh, Noori-daryan and Cárdenas-Barrón (2015)	Maximise profit	- Replenishment cycle (*T*) - Production rate (*P*) - Price (*p*) - Raw material ordering frequencies (*m*)	Mixed integer nonlinear programming (MINLP)	Analytical and Heuristic procedure	- Single vendor multi-buyer (JELS-lot for lot) - Deteriorating raw materials (physical quantity depletion) - Slow rate deterioration of perishable finished goods (physical quantity depletion)

Table 3.1 also indicates that physical quantity depletion models disregarding integrated inventory used NLP (the value of the decision variables is in continuous form, e.g. the length of the production cycle, the size of order). Similarly, the inventory models

considering quality loss (Blackburn & Scudder 2009; Cai et al. 2010; Cai et al. 2013; Qin, Wang & Wei 2014) also applied NLP where the decision variables are also represented by the continuous values such as price, replenishment period, production rate, size of order *etc*. Further, the integrated production-inventory approaches which involved a mixed type of values (integer and continuous) of decision variables used MINLP in their models (to name a few: Banerjee, Kim & Burton 2007; Taleizadeh, Noori-daryan & Cárdenas-Barrón 2015; and Yu, Wang & Liang 2012). Most of the inventory models with integrated policy aim to find the best values of the length of the production cycle (a continuous value) and the number of delivery frequencies (an integer value) over the production cycle. Therefore, clearly, MINLP is a more suitable approach for representing the integrated production-inventory models.

3.3 The proposed model

As discussed in the previous section, MINLP is a preferable mathematical approach to model the problems considered in this research. More elaboration and justification of using MINLP to represent the proposed model is discussed in this section. One of the aims of the proposed research is to find the best approach for the integrated production-inventory policy for perishable items, particularly food products, from the perspective of SCM. A more representative mathematical model of the inventory system is developed to cover the problems of interest. Note that, the proposed model focuses only on a single vendor multi-buyer (SVMB) supply chain system and it is formulated to represent a condition which deals with the following four essential issues:

First issue:

What is the best procurement strategy for the deteriorating raw materials, e.g. the number of replenishment frequencies over the length of the production cycle to prevent more quality loss in the raw material as well as to minimise the relevant inventory costs?

Second issue:

What is the best length of the production cycle to prevent outdated finished goods as well as to reduce the related inventory costs so that the total profit of the supply chain can be maximised?

Third issue:

What is the best number of delivery frequencies of the perishable finished goods from a manufacturer to retailers over the production cycle to minimise the relevant inventory costs and maximise the profit?

Fourth issue:

What is the best sequence of shipments from manufacturer to retailers that minimises the relevant inventory cost and maximises the whole profit?

In general, the total profit of the SVMB system is the performance measurement of the developed model. Hence, maximising the total profit of manufacturer and retailers is the objective function of the developing mathematical model. Since the inventory related costs are involved when maximising the profit, the relations between some components in the objective function are obviously nonlinear. Therefore, a nonlinear programming approach seems to be appropriately used.

Further, the first and third issues are respectively related to the number of replenishment (for raw materials) and the shipment frequencies (for finished goods) and obviously, the unit solutions should be an integer. Meanwhile, the second issue is to answer the question of how long the production will be run and what the length of the production cycle is. This is related to a unit time solution which is usually in a continuous value. It means that the solutions or the decision variables of the proposed model are the combination of integer and continuous values. Therefore, MINLP is the most suitable approach to representing the model.

In addition, the supply chain configuration considered in this research consists of a single manufacturer and multiple buyers. Each retailer (R) has its optimal ordering numbers and the sequence of the deliveries, e.g. R_1-R_3-R_1 or R_2-R_3-R_1 affects the revenue. The best sequence of shipments (the fourth issue) will lead to a maximum profit. Therefore, in this study, it is also essential to determine the shipment schedule of each retailer for the maximum profit. Accommodating this issue, a MINLP with the combinatorial solution is most likely the most appropriate mathematical approach to representing the model. The combinatorial issue not only increases the complexity of the process of developing the model but also lifts the difficulty of the optimisation approach.

3.4 Optimisation approaches for the combinatorial problems: An evaluation

As discussed in the previous chapter, a MINLP with the combinatorial solution is the most appropriate mathematical approach for representing the proposed model. Dealing with the MINLP problem (generally categorised into a Nondeterministic Polynomial (NP)-Hard problem) is quite complicated since it combines the difficulty of handling the nonlinear problem with optimising the integer variables (Bonami, Kilinç & Linderoth 2012). In addition, a combinatorial decision variable is also involved in the model leading to a combinatorial optimisation issue. Based on review summarised in Table 3.1, in deteriorating inventory research, none of the models has a combinatorial decision variable. Further, still from the same table, the majority deteriorating models use an analytical approach to prove the convexity on the model and then a step by step procedure is created to obtain the optimal solution (see the solution method column). On the other hand, a non-deteriorating model by Chan and Kingsman (2007) applied a genetic algorithm to find the solution of a synchronised cycle problem. Unlike other studies (to name a few: Banerjee, Kim & Burton 2007; Rau, Wu & Wee 2003; Rau, Wu & Wee 2004), they applied multiple integers of the basic cycle where each retailer had its own delivery cycle. The result obtained in their research provides a more flexible delivery mechanism and leads to a better performance compared to a common cycle approach such as in Banerjee, Kim and Burton (2007). Subsequently, a synchronised cycle approach is adopted in this research and additionally a shelf-life based price function is considered.

It appears that implementing the synchronised cycle approach and the shelf-life based price function, means the sequence of batches delivered to the retailers becomes essential since it affects the profit of each retailer. Therefore, an appropriate combinatorial optimisation approach is needed to optimise the total profit. This section evaluates and discusses three combinatorial optimisation methods, namely, exact algorithm, heuristics and meta-heuristics approaches. At the end of this section, the most suitable approach for the proposed research is selected.

3.4.1 Exact algorithm

An exact algorithm is an algorithm to find the optimal solution of the observed problem. The solution obtained by this approach is guaranteed to be the optimum solution of all

feasible solutions. The branch and bound (BB) algorithm and the branch and cut (BC) technique are examples of exact algorithms that are widely used to solve the optimality problems (Hillier & Lieberman 2005, pp.505-521).

Basically, *divide* and *conquer* are the concepts that underline the BB technique leading to three essential stages, namely *branching* (to divide), *bounding* and *fathoming* (to conquer) (Hillier & Lieberman 2005, pp.505-508). In the branching step, the problem is divided into smaller sub-problems. A bound is then obtained from each sub-problem to show how well its best feasible solution can be. Finally, in the fathoming step, a sub-problem is dismissed (conquered) from further consideration.

Principally, BC algorithm combines three techniques, namely, *automatic problem pre-processing*, the *generation of cutting planes* and *branch and bound* approach (Hillier & Lieberman 2005, p.522). The '*cutting planes*' is added so as not to remove any feasible solutions; it is a functional constraint used for reducing the feasible region instead (Hillier & Lieberman 2005, p.526). Combining the '*cutting planes*' with BB can improve the quality of solution and may lead to a powerful algorithm to solve the problem especially when dealing with a binary integer programming (BIP) problem.

Typically, the exact algorithm can guarantee an optimum solution will be obtained (Martí & Reinelt 2011, p.17). The method, however, depends on a fully comprehensive search to the possible solutions (Winston & Goldberg 2004) which are most likely inapplicable for a very complex and difficult problem since tremendous computation time to find the solution is required. Therefore, a heuristic approach is used to solve the problems within a reasonable time.

3.4.2 Heuristics

Unlike the exact algorithms where obtaining the optimum solution is guaranteed, the heuristic approaches only enable researchers to generate a good result which is "nearly optimum" or not necessarily optimum (Martí & Reinelt 2011, p.17). However, a well-designed approach is able to obtain a very good solution (close enough to the optimum solution) of a very complex and large problem within a reasonable time (Hillier & Lieberman 2005, p.617). In other words, when dealing with a very complex mathematical model that seems impossible to solve with any optimisation approach,

seeking a good and nearly optimal solution using a well-designed heuristic approach, can be a reasonable alternative due to efficiency and computational time- saving.

An earlier generation of the heuristic algorithm is based on local search procedure, also known as *greedy* heuristic (Taha 2011, p.352). The algorithm starts from a randomly selected feasible solution and then iteratively moves to a better subsequent solution in the neighbourhood. If no further improvement was made by the subsequent solution, the iteration is then terminated and the solution from the last iteration is chosen as the algorithm result.

In integrated production inventory field studies, the MINLP approach is commonly used for representing the problems. As shown in Table 3.1, in most cases, the convexity of the objective function can be proved analytically to guarantee the existence of a unique solution. However, since the mathematical model is quite complicated, the closed form function of the solution is very difficult to obtain and an exact algorithm would lead to an enormous computation time. Thus, a simple heuristic procedure is often utilised to solve the problems.

As mentioned previously in this study, a MINLP with the combinatorial solution is used to represent problems in the proposed model. A combinatorial problem is commonly represented by a model with integer variables and has a finite set of feasible solutions which are more complicated compared to the integer programming (Hillier & Lieberman 2005, p.504). Principally, two main issues in combinatorial optimisation problems are how to deal with the combinatorial explosion (Gen et al. 1997, p.97) and the multiple local optima (Hillier & Lieberman 2005, pp.618-621). The disadvantage of a well-designed heuristic procedure is when it deals with problems which have multiple local optima. Once the solution becomes convergent at one local optimum and no further improvement is made, then the search will be terminated regardless, even when the local optimum may not be the global optimum. In other words, the procedure allows the solution to be trapped in the local optima. To escape from these traps, a meta-heuristic approach is used when dealing with multiple local optima problems.

3.4.3 Meta-heuristics

The meta-heuristic approach is developed to overcome the drawback of the local improvement procedure. Therefore, an essential key feature of a meta-heuristic approach

is its ability to escape from the local optima. According to Hillier and Lieberman (2005, p.617)

> A meta-heuristic is a general kind of solution method that orchestrates the interaction between local improvement procedures and higher level strategies to create a process that is capable of escaping from local optima and performing a robust search of a feasible region.

The meta-heuristics advance the heuristic procedure by designing strategies to improve the search flexibility for a better solution within a reasonable time. The approach is also more applicable to any real problems since it can be defined in general terms and no prior condition is required to formulate the problems. Three meta-heuristic approaches that are commonly used are tabu search, simulated annealing and genetic algorithms (Hillier & Lieberman 2005, p.617).

3.4.3.1 Tabu search (TS)

Tabu search (TS) is basically a local search procedure which works quite similar to the local improvement procedure; the approach is firstly presented by Glover (1986) and further explanation is discussed in Glover (1989, 1990). The key feature which differentiates TS from the local improvement procedure is by allowing *non-improving moves* rather than terminating the search. The feature would prevent TS from the local optima entrapment, but it may lead to a cycle where the search is back to the same local optimum after successfully moving away from it. Dealing with this issue, another important feature called *tabu list* is created to record the prohibited moves (Hillier & Lieberman 2005, p.625). The tabu list can guide the search using its current history which is stored in *memory*. Principally, the existence of tabu list can improve the search movement. However, it may also result in a computational time issue for a very large problem where an extra memory will be required to store the recent history of the search. Akrami, Karimi and Moattar Hosseini (2006) compared TS and genetic algorithms (GAs) to solve the integrated production-inventory problem and it was revealed that even though the quality of solutions in both methods was insignificantly different, the computation times of TS was longer than GAs and the gap generally become greater when the scale of problems was larger. In addition, as a point-based search, the initial solution affects the end solution performance and it may become one of its drawbacks as mentioned in Hillier and Lieberman (2005, p.635) and Gendron, Potvin and Soriano (2003).

3.4.3.2 Simulated annealing algorithm

The process of finding the optimum solution can be analogous to the activity of finding the tallest hill (for a maximisation problem). It starts by climbing the hill step by step until one reaches the top. The problem becomes complicated if there are too many hills. We need to make sure that we are not climbing the incorrect hill. Similar to tabu search, simulated annealing is also a point-based search (one searcher is released to find the top of the tallest hill). However, unlike tabu search which spends a lot of time to search each encountered hill, the simulated annealing focuses only on finding the tallest hill, i.e. the hill where its top is the global optimum.

Simulated annealing which was first introduced by Kirkpatrick, Gelatt and Vecchi (1983) is the analogy to a physical annealing process. It is the process of melting and cooling a metal or glass at any given temperature or *T*. During the process to reach a low-energy stable state, even though it tends to decrease, the atoms' energy levels during the process fluctuate. It is described by a mathematical model assuming that the fluctuations occur randomly, however, no increase change will always be accepted. The acceptance's probability of accepting or rejecting the increase is adopted by simulated annealing for the move selection rule.

In tabu search, *non-improving moves* are always allowed to the next solution, however, in simulated annealing no *non-improving moves* are always accepted (Hillier & Lieberman 2005, pp.635-636). A move selection rule is designed to reject some of the downward movement. By selecting the moves, the search is expected to explore the feasible region as much as possible. It is most likely that the search will slowly move towards a feasible region with the tallest hill since the majority of accepted moves are upward. In this way, the searching process will finally reach the top of the tallest hill, i.e. the global optimum. However, the process to find the tallest hill can be more challenging if the landscape of the feasible solution is very complex. It may take much more time for a single point based search to find the tallest hill in a very complex landscape of the feasible solution. It is indicated by Yao, cited in Akararungruangkul (2006, p.37) that the simulated annealing approach can result in a long computational time when it is applied to combinatorial problems.

3.4.3.3 Genetic algorithm

Genetic algorithms work in a different way from the previous methods. It is a population-based search method, i.e. rather than work with a single point solution (such as in tabu search and simulated annealing), the entire populations of trial solutions are deployed to search the global optimal at the same time. The population-based search strategy is mostly effective for exploring the feasible region which has numerous parts with very complex landscapes (Hillier & Lieberman 2005, p.644).

Genetic algorithms have been widely used to deal with complex problems including issues in lot sizing (Goren, Tunali & Jans 2010). A comparison among some meta-heuristic methods by Akrami, Karimi and Moattar-Hosseini (2006) revealed that in the integrated production-inventory issues, the quality of solutions obtained by GAs is better than others. In addition, Aytug, Khouja and Vergara (2003) showed that in production and management areas, for the majority of cases GAs is able to outperform the other meta-heuristic approaches.

Further, Siradej (2008) highlights the advantages of using genetic algorithm as follows:

a. Instead of using a single point based solution, genetic algorithms work with a set of solutions that operate at the same time (also known as population-based). This population-based strategy could effectively minimise the chance of being trapped in the local optima; therefore, an optimal (or nearly optimal) solution can be obtained.

b. Since the parallel search is applied, GAs are well-suited especially when dealing with complex objective functions with complicated landscapes, e.g. noisy, discontinuous, change over time or has many local optima.

c. Each generation in GAs provides several quality solutions; hence, the user has more alternatives to select from due to practical reasons.

d. Generally, genetic algorithms work with encoded variables and less mathematics is required to solve the problem.

e. Genetic algorithms are able to deal with any kind of objective function or any type of constraint since no auxiliary information is needed. As a result, the algorithms

are able to work in various search spaces (continuous, discrete or combination) as long as a proper decoding function is specified.

f. The majority of conventional methods use the deterministic moving procedure that needs certain convexity properties to guarantee that any solution is global optima. Contrarily, a probabilistic moving procedure is applied in genetic algorithms; hence, a global search to various types of problems can be performed effectively.

g. GAs are also flexible and can be easily hybridised with other methods due to efficiency when dealing with some specific issues.

To summarise, after evaluating the optimisation approaches, based on the characteristic of the proposed model, the meta-heuristics are more suitable tools for solving problems. In addition, three meta-heuristic methods have been evaluated and compared. Based on some advantages of using GAs and the typical problem considered in this study, it concludes that GAs are most likely a more appropriate tool to solve the problem compared to the two other methods (tabu search and simulated annealing). It is not guaranteed that GAs will lead to an optimum solution. They are, however, generally powerful enough to find "acceptable good" solutions "acceptably quickly" (Kazerooni 1997). Further description of the GAs is presented in section 3.5.

3.5 Genetic algorithms as optimisation tools: A brief description

Genetic algorithms are suitable for solving complex problems faced by industries in many areas such as production scheduling, vehicle routeing and scheduling, reliability design, and facility location and layout (Gen et al. 1997, p.2). It is an extensive stochastic search technique which mimics the evolution process mechanism. It starts with an initial set of random solutions called *population* (Goldberg, 1989). Each individual solution, called *chromosome,* is usually coded using a binary or float number. New generations are developed from the population through iterations in which new chromosomes are produced by modifying those using genetic operations (*crossover* and *mutation*). New chromosomes resulting from genetic operations are then evaluated based on a certain measure of *fitness*. Figure 3.2 illustrates the general construction of a genetic algorithm and further explanation regarding the essential properties of GAs as seen in that figure is presented in the next subsection.

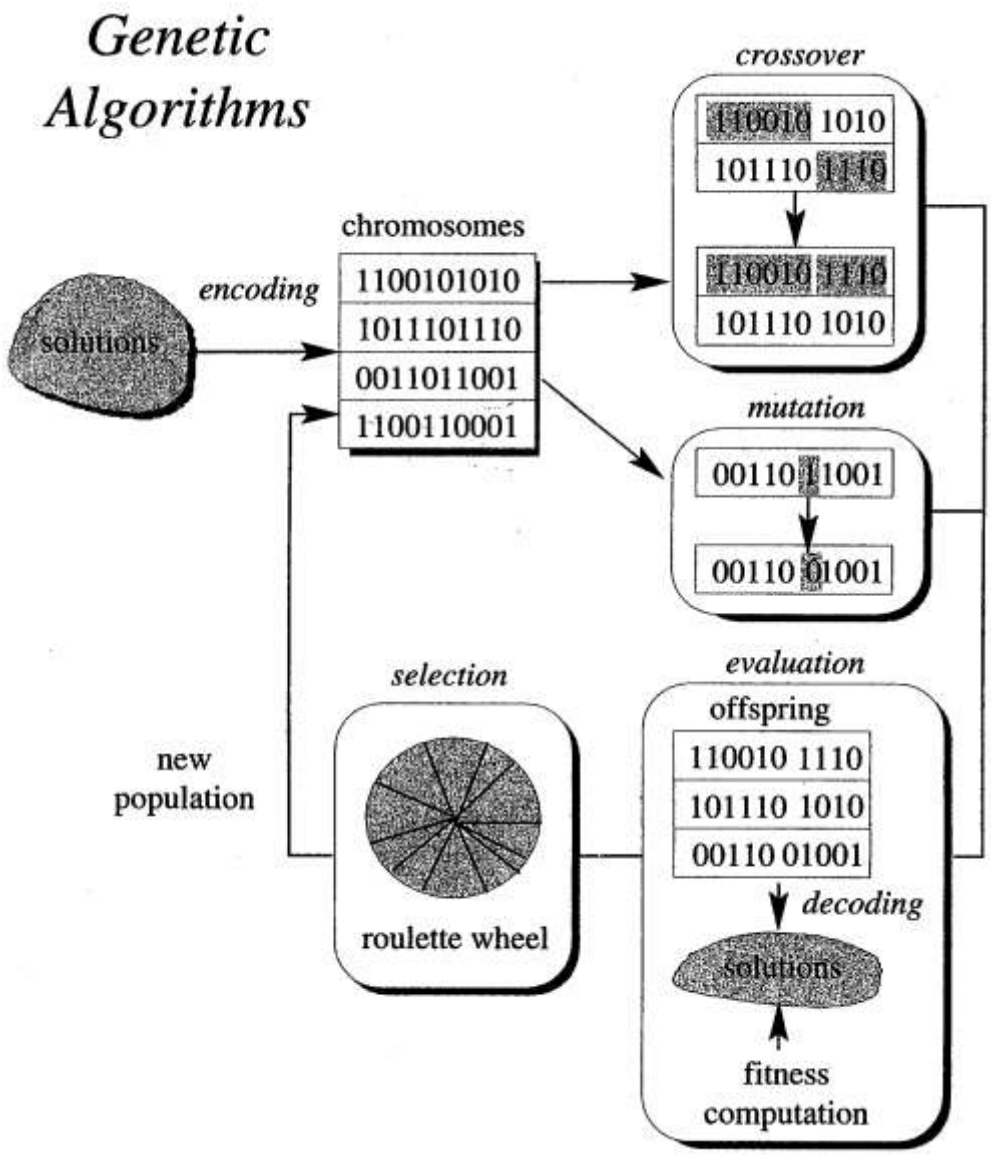


Figure 3.2 Genetic Algorithms Construction (Gen et al. 1997, p.3)

3.5.1 Chromosome representative

In GAs, a structure that represents a construction of each individual solution is called a chromosome (Gen et al. 1997, p.7). Each chromosome is composed of genes where alleles represent the values of a gene. As shown in Figure 3.2, after an initial set of solutions (called population) is established, the solutions are encoded into chromosomes. At the earlier stage of GAs research, binary encoding was widely used to represent the chromosomes (Herrera, Lozano & Verdegay 1998), i.e. the decision variables are encoded in a binary string where its length depends on the precision (Gen et al. 1997, p.8) as shown in Eq. 3.2;

$$2^{m-1} < (b-a)\times 10^{n} \le 2^{m} - 1 \qquad (3.2)$$

where *m* refers to the required bits, *n* denotes the required precision while *b* and *a* respectively represent the upper and lower bounds. This binary approach, however, has some disadvantages when used to solve problems which require a high precision solution. Therefore, for such cases the real number coding is preferable (Michalewicz & SpringerLink 1996, p.95). In the real-coded technique, a vector with floating point numbers having the same length with each chromosome is coded where the values of each element are moderated within the desired range.

As shown in Table 3.1, the majority research in integrated production-inventory policy contained different types of decision variables, e.g. discrete, continuous variables, while in the proposed model, a permutation is also involved. Using current techniques (e.g. binary or real coded) leads to inflexibility as each problem variation needs a specialised representation. To overcome this problem, Bean (1994) introduced a new approach for representing the solution called *random keys* where the solution is encoded by random numbers between [0,1). The random key technique showed promising results when dealing with problems where a sequencing or permutation solution was involved. In this study, as the problem in the proposed model also deals with a permutation solution, the random keys method is applied and will be discussed later in Chapter 5.

3.5.2 Crossover operator

In GAs, to generate the next generation or offspring, the genetic operator called crossover is set up. The crossover operator combines the chromosomes of the previous generation. A random cut point is a simple crossover technique to obtain the new chromosomes by merging the chromosome segment of one parent or V_1 (on the left side of the cut point) with the chromosome segment of the other parent or V_2 (on the right side of the cut point); using this way two new chromosomes or offspring (V_1' and V_2') are generated (as illustrated in Figure 3.3). This technique is appropriate with bit string chromosomes. Further, one cut crossover are further extended into two-cut, multi-cut and uniform crossover (Gen et al. 1997, p.60).

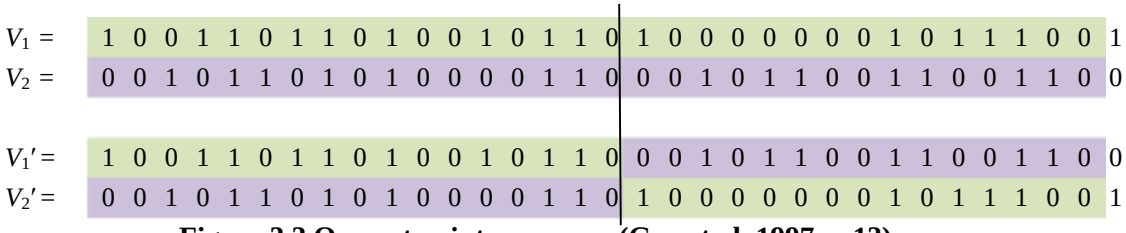


Figure 3.3 One cut point crossover (Gen et al. 1997, p.13)

The performance of crossover operator essentially affects the performance of GAs. Beside crossover mechanism, another important property of crossover is the "crossover rate" representing the offspring's proportion of the population size (*pop_size*) created in each generation. The value of 0.7 of crossover rate means that each chromosome has 0.7 chance to undergo the crossover operation hence the expected number of new chromosomes produced is equal to 0.7×*pop_size*. This value influences the quality of solution; a too high rate results in efficiency since a lot of time is spent to exploit unpromising solution space, while a very low rate may deteriorate the performance as the chances of obtaining the false optimum increase (Gen et al. 1997, p.3).

As mentioned in subsection 3.5.1, in this study, a random key technique is applied to encode the problem's solution. The main difference between this approach and the real-coded or binary chromosome is that instead of working with the derived solutions, all crossovers are operated by the random keys where the sorted values of the random keys are used to decode the solution. This technique is able to maintain producing feasible offspring in each generation. In addition, instead of using one-point or two-point crossover the parameterised uniform crossovers are used to generate the subsequent generation. Further detail regarding this mechanism is explained later in Chapter 5.

3.5.3 Mutation operator

As well as a crossover, mutation is another genetic operator in GAs where the new chromosomes are produced with spontaneously random change. It plays important roles in GAs, i.e. to replace the genetic material lost during the process of evolution and to provide the genes which were missing in the initial population (Gen et al. 1997, p.4). If crossover operator is responsible for convergence, the mutation operator opposes the convergence (Bean 1994). Mutation operation is essential to prevent the search from the premature convergence which leads to local optima.

For bit-string chromosomes, mutation operation is simply done by flipping the values of one or more selected genes. As illustrated in Figure 3.4, the gene number 18th of a parent (V_1) is randomly selected to undergo mutation operation, hence, the chromosome structure after mutation is changed into V_1' by flipping the value of the 18th gene from 1 to 0.

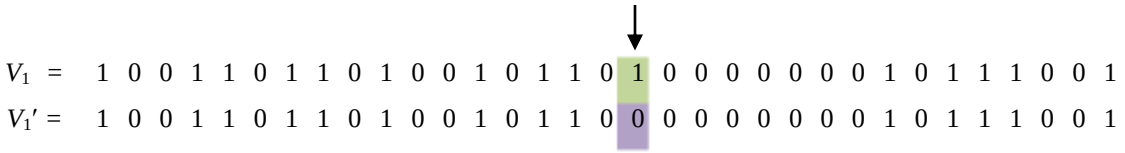


Figure 3.4 Mutation operation (Gen et al. 1997, p.14)

The rate that control the number of new genes introduced into the population is called mutation rate (p_m). A very high mutation rate means a lot of random search leading to a situation where offspring can lose their similarity to the parents and consequently the ability of the algorithm to learn from the search history is perished (Gen et al. 1997, p.4). Genetic algorithms combine operations that can make a balanced stochastic search between exploitation of the promising solution and exploration of more solution space. Therefore, setting an appropriate value for the mutation rate as well as the crossover rate is essential.

This study applies random keys technique where an elitist strategy, i.e. preserve the best chromosome (Goldberg 1989), is used to reproduce offspring. One potential drawback of this strategy is a premature convergence. To overcome this problem, a high mutation rate is suggested (Bean 1994). Issues in regards to determining some important parameters in GAs, e.g. mutation rate, crossover rate *etc*., are addressed and discussed later in Chapter 5.

3.5.4 Fitness function

In the theory of evolution, a stronger individual has a higher probability to survive. Adopting this philosophy in GAs, a process for evaluating the "strength" called *fitness evaluation* is established. Based on a “fitness” level, the quality of each individual solution represented by chromosomes is evaluated. The evaluation aims to see how close the solution is to the main goal. The goal is represented by an objective function where the solution is involved. In other words, the objective function is used to measure the fitness level or quality of each individual solution where a fitter individual is selected as one of the new population for the next generation (Michalewicz & SpringerLink 1996, p.1).

In this study, maximising the total profit is the main goal and the decision variables (i.e. the best solution) need to be determined to achieve the goal. Hence, the total profit is the

objective function where the decision variables are the production cycle, the number of replenishment frequencies, the number of shipments, and the sequence of delivery (as defined in Section 3.3). In other words, the total profit value is used to measure the fitness level to justify whether a solution is more "fit" than others. Since the desired goal is the maximum total profit, thus a higher total profit indicates a more fit solution.

3.5.5 Selection

GAs imitate Darwin's theory of evolution where the natural selection process in each generation is essential. The selection process leads the algorithm to search in the direction of the promising regions. In this stage, selective pressure is a critical issue; at one side, strong selective pressure can cause the search to be prematurely terminated while, at the other side, weak selective pressure can lead to ineffective search (Gen et al. 1997, p.56; Michalewicz & SpringerLink 1996). Basically, there are three important issues which influence the selection pressure namely: sampling space, sampling mechanism and selection probability.

One important issue in the selection process is the source of the new generation known as the sampling space. Two factors that characterise the sampling space are sampling size and sampling composition, e.g. composition of parents or offspring (Gen et al. 1997, p.20). Regarding these, there are two types of sampling space i.e. regular sampling space and enlarged sampling space. Referring to Holland (1975), in regular sampling space, a generational replacement method is applied. It means that after giving birth, the parents will be replaced by their offspring. Hence, the size of sampling space is equal to the size of the new population and composed by all offspring and some parents (as illustrated in Figure 3.5).

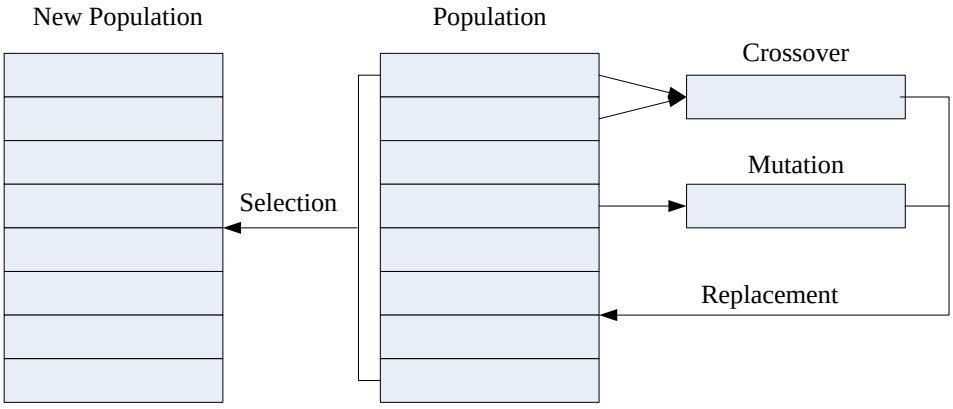


Figure 3.5 Selection operated on regular sampling space (Gen et al. 1997, p.21)

This mechanism, however, is disadvantageous if the offspring is worse than their parents (there is no mechanism to guarantee that the offspring is always better than their parents). To overcome this problem some replacement strategies have been proposed, e.g. using *crowding strategy* (once an offspring is born, a parent that most resembles the new-born offspring is selected to die) proposed by De Jong (1975) or operating *roulette wheel selection* such as in Michalewicz and SpringerLink (1996, p.32).

In enlarged sampling space, all parents and offspring have the same opportunity to compete in the selection process (Gen et al. 1997, p.21). Hence, the size of the sampling space is equal to the number of parents combined with the number of offspring and its composition contains all parents and offspring as illustrated in Figure 3.6.

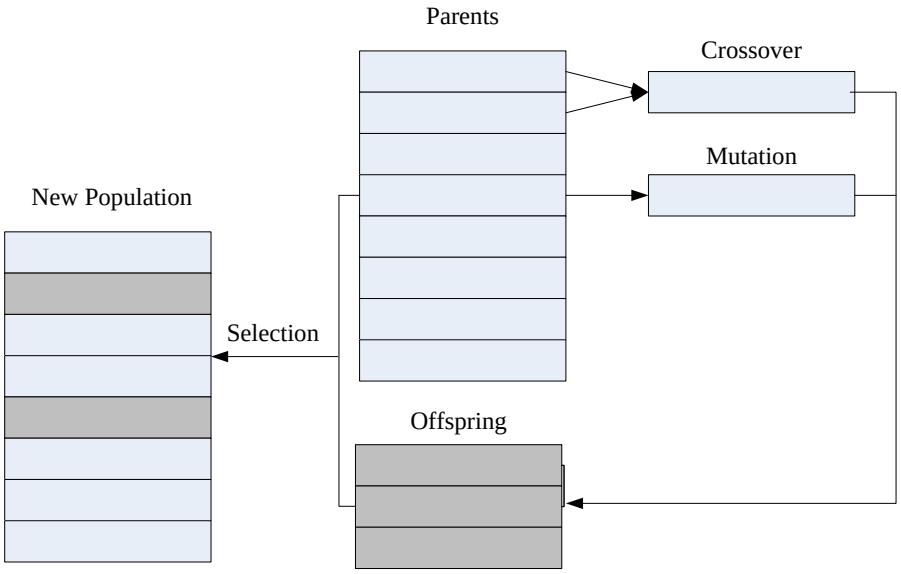


Figure 3.6 Selection operated on enlarged sampling space (Gen et al. 1997, p.22)

The way to select a chromosome from a sampling space is the main issue that the sampling mechanism deals with. Basically, there are three techniques for sampling the chromosomes, namely, stochastic sampling, deterministic sampling and mixed sampling (Gen et al. 1997, p.22). In stochastic sampling, a chromosome in the sampling space is randomly selected. The chance of a chromosome being selected depends on its survival probability which is proportional to the fitness value such as the proportionate selection in Holland (1975). Alternatively, Baker (1985) introduced a stochastic universal sampling using a single roulette wheel where the number of the equally spaced markers is the same as the population size. This technique aims to control the rapid convergence caused by super chromosomes dominating the population as well as to keep the diversity

of the population. Unlike stochastic sampling, in deterministic sampling, the best chromosome is selected from the sampling space such as in truncation selection and block selection. In these approaches, all chromosomes are ranked based on their fitness values and the top chromosomes are selected as parents (Thierens & Goldberg 1994). Another version of the deterministic sampling is an elitist selection which ensures the existence of the best chromosome in each generation (Gen et al. 1997, p.24; Michalewicz & SpringerLink 1996, p.57). The last selection mechanism is mixed sampling containing stochastic and deterministic features such as tournament selection in Goldberg, Korb and Deb (1989), stochastic tournament selection in Wetzel (1983) and remainder stochastic sampling in Brindle (1980).

The last issue in the selection phase is related to an appropriate method to determine the selection probability for each chromosome. The proportionate chromosome is one of the examples. This simple method, however, may have some disadvantageous properties such as super chromosomes which dominate the population. To overcome this problem, scaling and ranking techniques are proposed (Gen et al. 1997, p.25). In scaling approach, the selection probability is determined based on mapping relationships between the raw fitness values and some positive real values. Meanwhile in the ranking approach, the selection probability is determined based on the chromosomes' rank and disregards the objective function values.

GA is not the only population-based evolutionary algorithms (EAs). There are other EAs, e.g. particle swarm optimisation (PSO), artificial bee colony (ABC) and memetic algorithm (MA). Each algorithm has been developed from its original form to further improve the performance. It is quite difficult to claim which optimisation approach that is best suited for all optimisation problems because solving different problems may lead to different conclusions. However, in general, these evolutionary algorithms are able to solve the combinatorial problems with relatively similar results such as shown in some studies (to name a few: Muthiah & Rajkumar 2014; Ahamed, Rangajanardhana & Nagesh 2013; Panda & Padhy 2011).

In this study, the genetic algorithm is used as an optimisation tool. To improve the flexibility and the performance of the algorithm, a vector of random value generated between interval [0,1) is adopted to represent the chromosome. In addition, the process of forming the new generation is performed by (i) grouping the current population into

elite and non-elite population based on the fitness value, (ii) copying all members of elite group into the new population, (iii) mating the elite and non-elite chromosome to produce one offspring, (iv) inserting a number of mutant chromosomes into the new population. This modified GA is known as the biased random key genetic algorithm (BRKGA). This research contributes in further improving the BKRGA by combining this algorithm with local procedures. Detailed discussion regarding the hybrid BRKGA is presented in Chapter 5.

3.6 Concluding remarks

The proposed model addressed problems in an integrated production-inventory policy considering perishable characteristics of food products in the single vendor multi-buyer environment. A synchronised cycle approach, i.e. the length of manufacturer's production cycle is a multiple integers of ordering cycle, is used to organise the delivery of finished goods from the manufacturer to retailers. The coordination mechanism lifts the complexity of solving the problems since it leads to a mixed integer nonlinear programming (MINLP) approach with a combinatorial decision variable.

The MINLP itself is a NP hard problem where obtaining a close form function of the solution is almost impossible. Further, since the sequence of deliveries needs to be optimised, which results in the combinatorial explosion issues, it may not be possible to use an exact algorithm. In some cases, heuristic methods can be applicable, however for a problem with many local optima, e.g. MINLP with a combinatorial solution, the heuristic approach would cause the solution to be trapped in the local optima. Therefore, a meta-heuristic method is used to find the optimum solution for the proposed model.

There are many meta-heuristic approaches used to solve large and very complex problems. In this chapter the three most commonly used methods, namely tabu search, simulated annealing and genetics algorithm, have been discussed and evaluated. It is concluded that, in terms of efficiency (the computation time) and the quality of the result, the genetic algorithm is selected to solve the problem in the proposed model and the biased random key genetic algorithm (BRKGA) seems to be a more suitable tool to solve the proposed problem.

Chapter 4

Development of an integrated production-inventory model for food products in a two-echelon supply chain

4.1 Introduction

In Chapter 3, a MINLP with a combinatorial variable was selected as the most appropriate mathematical expression for representing the problem defined in this research. Therefore, this chapter is devoted to comprehensively explain a step-by-step procedure for formulating the mathematical model of an integrated production-inventory policy for food products in a single-vendor multi-buyer environment.

The model development comprises of three stages. The first stage is system characterisation. It aims to provide a detailed description on the addressed system, the relevant variables and the boundary of the system. This stage is essential for a clear definition of the problem and a solution that can be offered to solve the problems. The relations among variables and input parameters in forming the output (i.e. the performance of the system based on the solution) are presented by an influence diagram. Thus, the formal definition of the addressed problem can be clearly stated.

The second stage presents a list of notations denoting the parameters and decision variables in the influence diagram which resulted from the first stage. The symbolisation of involved parameters and variables is required to conveniently represent the addressed problem in a more accurate and consistent way. Apart from that, at this stage, the assumptions underlying the addressed problem are outlined and justified. These assumptions demonstrate restrictions to the proposed model, while ensuring that the problem is manageable to solve.

Finally, the last stage provides steps of the mathematical formulation depicting the relations among the parameters and variables in shaping the output as shown in the influence diagram. Thus the final representation of the proposed mathematical model,

demonstrating the objective function of the addressed problem, is established at this stage. In addition, a number of constraints are also formulated. Moreover, this stage discusses special cases of the problem and how the established model can be adjusted to handle such problems.

The remaining sections of this chapter are therefore organised based on the following structure. Section 4.2 discusses the system characterisation while in Section 4.3 the notation and assumptions are presented. Finally, in Section 4.4 the MINLP model, representing the addressed problem is developed, while the last section summarises this chapter.

4.2 System characterisation

In this section a detailed description of the addressed system as discussed in Chapter 2 is presented before defining the problem. The considered system consists of a manufacturer with multiple distributors/retailers or commonly known as single-vendor multi-buyer (SVMB) system, as shown in Figure 4-1;

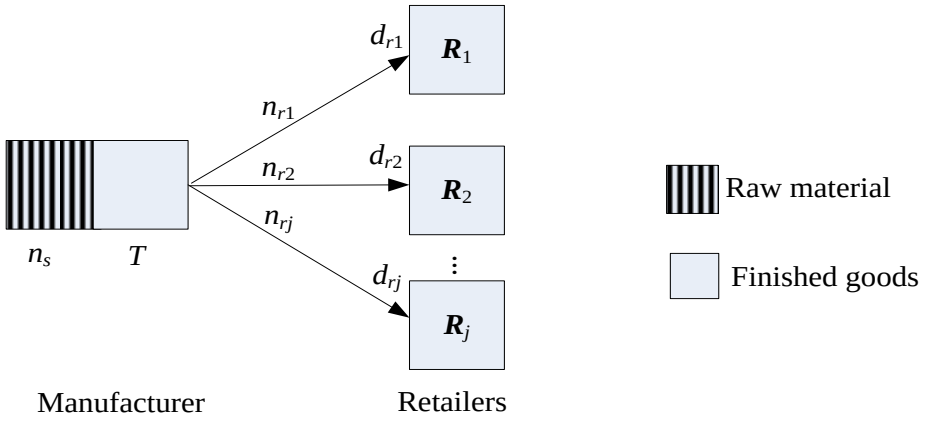


Figure 4.1 Illustration of an integrated production-inventory model in SVMB (adapted from Waters 2009)

As seen in Figure 4.1, the manufacturer produces a food product to meet a known demand from the retailers (d_{rj}). This product is made from a single main raw material. The quality and value of the raw material and finished goods respectively decline over time. The members of the supply chain are concerned with streamlining the material flow across the supply chain. The retailers deal with the ordering policy to minimise their inventory and outdated items, while the manufacturer is responsible for the production and procurement policies to reduce both inventories, i.e. raw material and finished goods.

These policies are addressed in an integrated and synchronised approach by using the integer multiplier mechanism. As depicted in Figure 4.1, the manufacturer is required to determine the production cycle (T), during which the finished goods are shipped to retailer j (R_j) in n_{rj} number of deliveries and the raw material is procured in n_s shipments.

In terms of the supply chain structure and the scope of integration, the system described above has a similarity to that discussed in Banerjee, Kim and Burton (2007). However, it has three significant differences namely, the raw material procurement strategy, the shipment policy of finished goods and more importantly the characteristics of products handled in the supply chain.

In regards to the procurement strategy, in Banerjee, Kim and Burton (2007), the minimum replenishment frequency during a production cycle is equal to one ($n_s \geq 1$). In contrast, in this study, a single lot of raw material can also be supplied to fulfil demand for more than one production cycle (or n_s can be less than 1). This approach is more realistic in practical businesses, especially in the food industry, where a manufacturer in some cases needs to procure the raw material in a greater quantity to cope with supply uncertainties.

The next difference is in the shipment strategy, i.e. how to distribute the finished goods from the manufacturer to the retailers. Banerjee, Kim and Burton (2007) used a common cycle approach where the manufacturer delivers the finished goods to all retailers in the same interval and at the same time ($n_{ri} = n_{r2} = n_{r3} = \ldots = n_{rj}$). It means that one transferred batch contains accumulated orders from all retailers over the ordering cycle (known as a full truckload system). On the other hand, in this study, a synchronised delivery cycle method is used. It means that the length of manufacturer's production cycle is equal to the multiple integer of the ordering cycle of each retailer. In other words, each retailer is allowed to have their own ordering frequency and this practice is more common in real business.

Most importantly, in terms of the inventory characteristics, Banerjee, Kim and Burton (2007) dealt with managing items with infinite lifetime, i.e. non-perishable products. In contrast, in this research, both the raw material and finished goods perish over time. As raw material, the quality degrades during its storage time, while as finished goods, the perceived value of the product declines as the remaining shelf-life of the product

approaches its expiration date. The detailed discussion on these deteriorating characteristics is presented in the following subsections.

4.2.1 Raw material quality loss during storage time

As mentioned in Chapter 2, the deterioration in a food inventory and its effect on the whole inventory system is complex. The deteriorating characteristics of the product may behave differently depending on its form, for instance as raw materials or finished goods. The raw material of food products suffers from a natural quality loss during the storage time. The loss rate is typically affected by warehouse conditions such as temperature, humidity or activation energy of the material. This quality loss can be a change in the chemical composition or a decline in physical appearance. This decreasing rate of the quality can be linear over time such as in vegetables, or exponential such as found in meat or milk (Labuza, cited in Rong, Akkerman & Grunow 2011). In a kinetic model, these linear and exponential decreasing rates are represented by zero and first order reactions, respectively.

To illustrate, the two figures in the upper part of Figure 4.2 depict the quality degradation of a raw material over t_Q, while t_Q refers to an interval in which the quality of raw material is within the control limit, i.e. still acceptable to meet the production demand (d_s). The quality is at its maximum level (Q_{max}) at the beginning of the period, then declines over time, either linearly (line A) or exponentially (line B), reaching its minimum level (Q_{min}) at t_Q. Here, Q_{min} is the minimum quality requirement of the raw material. Once the raw food quality level is below Q_{min}, then it is not eligible to be used for production and should be discarded with a salvage value.

The two figures in the lower part of Figure 4.2 show the inventory profile of a raw material projected to its corresponding quality level. Note that q_s denotes the lot size of raw material replenishment, t_s represents the length of the last raw material being stored in the warehouse. Based on the values of t_s and t_Q, there are two possible conditions, (i) $t_s \geq t_Q$ as demonstrated by Figure 4.2(a) or (ii) $t_s \leq t_Q$ such as in Figure 4.2(b). In Figure 4.2(a), since t_s is longer than t_Q, some units of q_s which are in storage for more than t_Q are not able to meet the production requirement as their quality is below Q_{min}. Consequently, shortage occurs during t_s - t_Q. On the other hand, in Figure 4.2b, as t_s is shorter than t_Q, all units of q_s can be used to fulfil the demand. In this study, it is assumed that there is no shortage allowed during the replenishment cycle. Therefore, t_s is maintained to be shorter

than t_Q ($t_s < t_Q$). This assumption is realistic as in common practices, manufacturers usually arrange the raw food replenishment cycle to be shorter than the products' usable period to avoid waste.

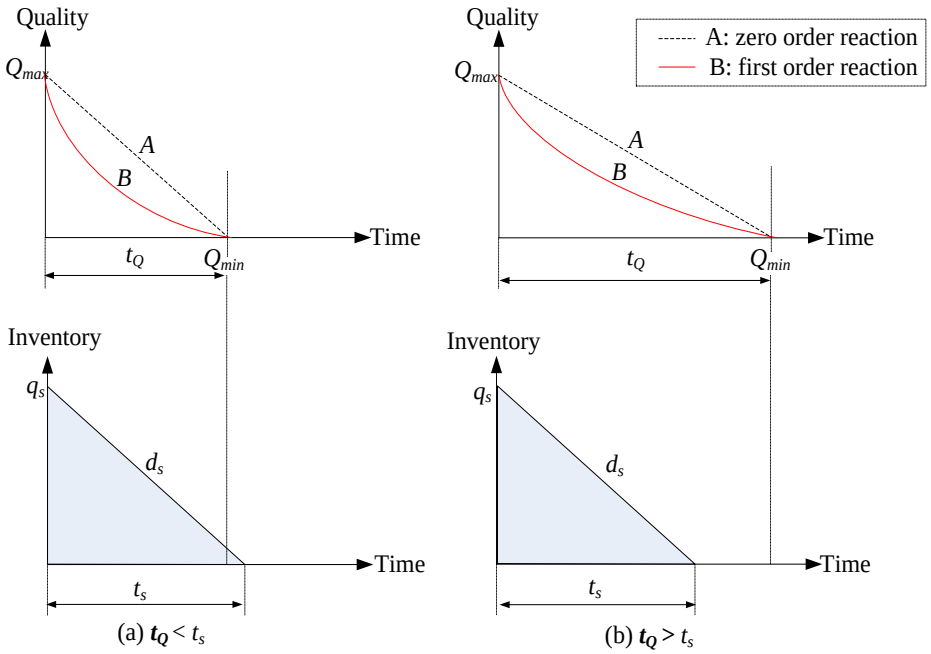


Figure 4.2 Quality loss of raw materials during storage time at manufacturer

Further, food is a unique system. The quality degradation characteristic of each food may be different to another. As mentioned in Chapter 2, generally there are two common quality degradation types, a linear degradation (represented by line A in Figure 4.2) and a nonlinear degradation (illustrated by line B in Figure 4.2). In this study both situations are accommodated to include the majority of foods.

4.2.2 Finished goods perceived value loss

Unlike the decrease in the quality of raw material, deterioration in the quality of finished goods is typically related to the customer's willingness to pay (WTP) for the product. The quality of finished goods is perceived by a customer from the information on expiration date of the products. The customer's WTP decreases once the product's shelf-life is approaching its expiration date. As illustrated in Figure 4.3, during the deterioration period, from T_{start} to T_{sl}, the product value decreases linearly (represented by line A) such as in carrots and lettuce, or exponentially (represented by line B) such as in beef and chicken (Tsiros & Heilman 2005). Note that T_{start} is the beginning of the perceived value

loss since at this point of time the customer's WTP starts decreasing, while T_{sl} is the product shelf-life.

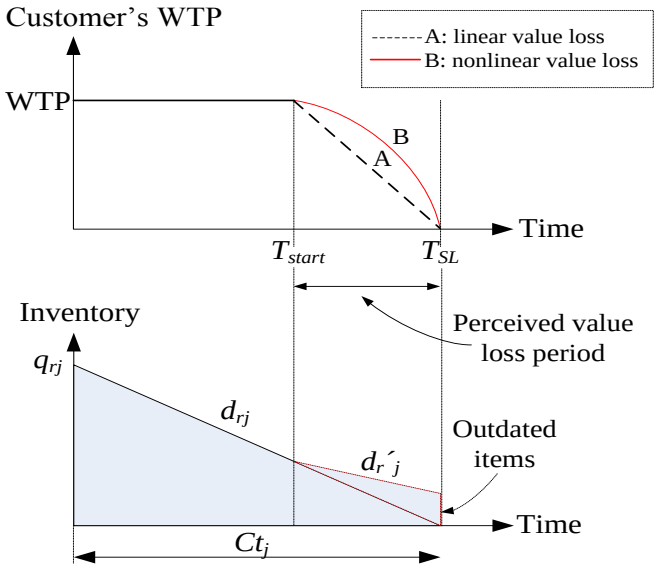


Figure 4.3 Perceived value loss (decreasing WTP) of finished goods in retailer *j*

The lower figure in Figure 4.3 shows the inventory profile of finished goods at a retailer projected to its corresponding customer's WTP. Retailer *j* receives a batch with the size of q_{rj} of finished goods to be used to fulfil the demand (d_{rj}) during the ordering cycle (Ct_j). If all units of q_{rj} are sold before T_{start} then the revenue will be at its maximum level as no product suffers from declining customers' WTP. On the other hand, if some products are unsold before T_{start}, their values will be degraded as customers would prefer to buy another product with a longer residual shelf-life. As a result, the demand rate (d_{rj}) of the product will be slower, as indicated by $d_r'_j$. Without any action, the retailer will suffer from outdated items. Dealing with this situation, the retailers typically apply a markdown strategy to maintain the demand and hence the outdated items can be minimised. The strategy may sustain the demand rate or even improve it, however the profit margin of the total sales is actually reduced. In this research the decreasing price of finished goods is represented by a shelf-life based price function which can be linear or nonlinear. Further explanation about the function is presented in Section 4.4.

4.2.3 Influence diagram for an integrated production-inventory policy

In modelling system, it is essential to clearly define the system boundary due to clarity and feasibility of finding the solutions. In this research, the subject of interest has been

generally discussed in Chapter 2 and now further detail is elaborated in this segment using an influence diagram to delineate the system boundary and its relevant environment.

Daellenbach and McNickle (2005, p.578) defined an influence diagram as 'a formal version of a causal loop diagram that shows the system transformation process from uncontrollable and controllable inputs to system output, via system variables'. Uncontrollable inputs are parameters where their values are given while the controllable inputs (also known as decision variables) are parameters where their best values need to be determined to maximise the performance of output. Figure 4.4 presents an influence diagram of the observed system which demonstrates the transformation of uncontrollable inputs (represented by clouds) and controllable inputs (illustrated by rectangles) into output (embodied by ellipse) through system variables (denoted by circles).

As shown in Figure 4.4, the system has four controllable inputs or decision variables and nineteen uncontrollable inputs. The interactions of those inputs influence nine units of variables (costs and revenue) which finally affect the output or the performance measurement of the observed system. Generally, the nine variables in the system can be divided into three categories: the manufacturer's cost, the retailers' cost and the revenue. The following parts further explain each of these categories, including the controllable inputs (CI) and uncontrollable inputs (UI).

- Total cost of the manufacturer's system

  In the manufacturer's system, the costs are related to managing two types of inventories: the raw material and finished goods. For managing the raw material inventory, three variable costs are involved: holding costs, transportation costs and costs related to the quality loss. These costs depend on the values of some controllable inputs (i.e. the number of raw material shipments and the length of production cycle) and uncontrollable inputs (i.e. the raw material holding cost per unit per time, the transportation cost per delivery, the demand of raw material and finished goods, the production rate, the cost of energy, the cost of quality and the rate of quality loss and its related parameters). On the other hand, for managing the finished goods inventory, there are two variable costs involved: the setup cost and the holding cost. The costs rely on the values of the length of production cycle, the number of shipments and the shipment schedule (as the controllable inputs) as well as the finished goods holding

cost per unit per time, the setup cost per one setup, the production rate and the demand of finished goods (as the uncontrollable inputs).

- Total cost of the retailers' system

  Retailers also bear costs because of ordering and handling the finished goods i.e. transportation costs and holding costs. The total cost depends on two controllable inputs, namely the length of production cycle and the number of finished goods shipments, and some uncontrollable inputs, including the transportation cost per delivery, the holding cost per retailer per unit per time, the production rate, the demand rate and some relevant costs.

- Revenue of the whole system

  The system's revenue depends on the product's residual shelf-life or product's age when it is received by retailers, and the product price. The controllable inputs which affect the values of those variables are the length of production cycle, the number of shipments and the shipment schedule, while the influential uncontrollable inputs are the production rate, the demand rate, the transportation lead time, the time when the customers' WTP decreases or the time to deteriorate, the shelf-life and the product price.

Finally, based on the influence diagram presented in this section, the problem of production-inventory policy for food products in a single-vendor multi-buyer environment can be defined as how to maximise the total profit of the entire supply chain. It is achieved by determining the optimal values of the identified four controllable inputs (also called decision variables), namely the production cycle length, the number of raw material shipments over one production cycle, the sequence of deliveries to the retailers and the number of finished goods deliveries to the retailers over one production cycle.

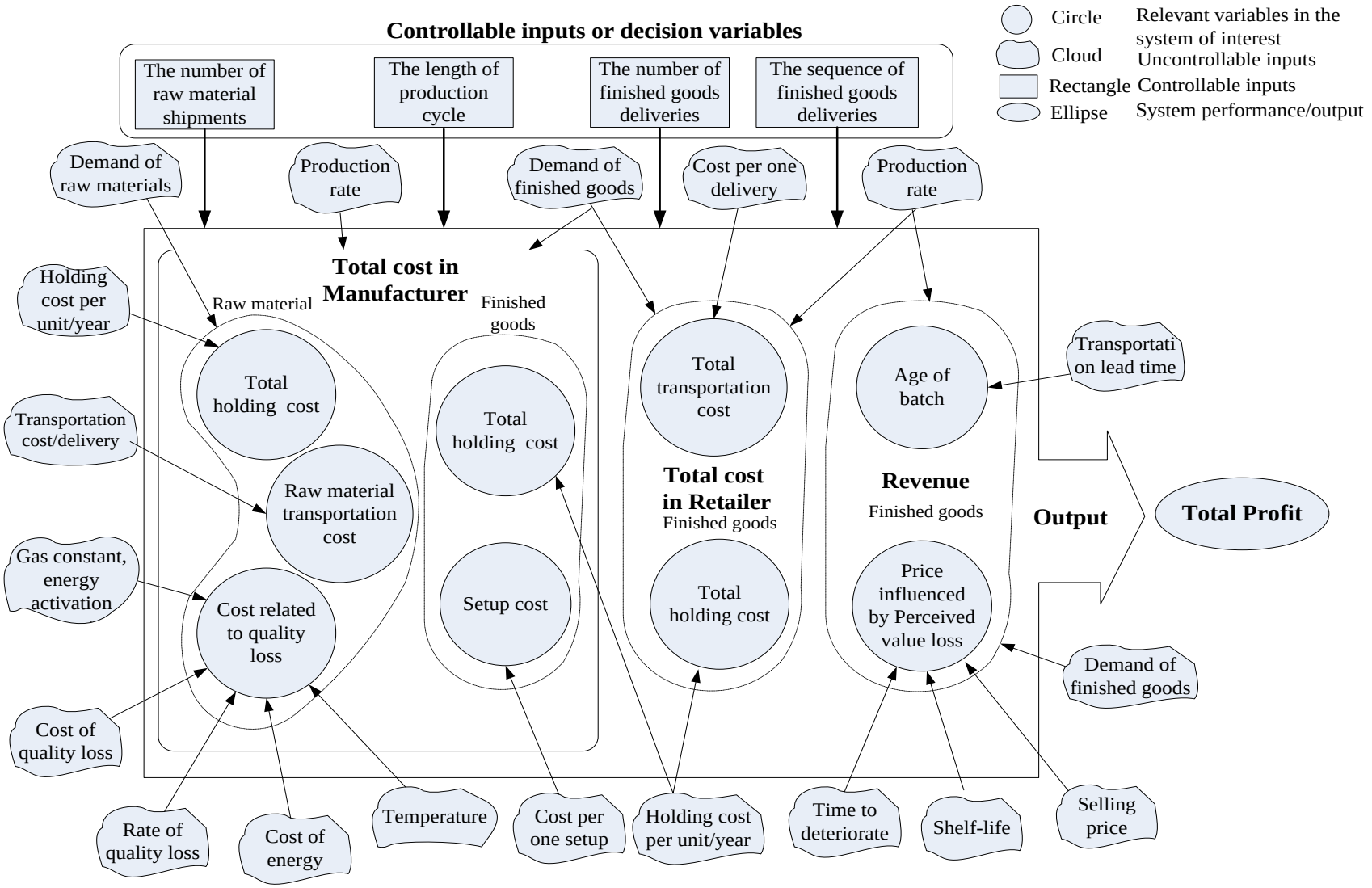


Figure 4.4 Influence diagram of an integrated production-inventory system considering quality loss and perceived value loss

4.3 Model notation and assumptions

In the previous section the parameters and variables, as well as their relationships which influence the output, have been clearly characterised and identified. Before transforming them into a mathematical model, the notation representing each of them is termed in this section.

Notation:

C_s	:	raw material price per unit ($/unit)
C_m	:	manufacturing cost of finished goods ($/unit)
C_r	:	finished goods selling price per unit ($/unit)
C_{Qs}	:	cost because of quality loss ($/unit quality loss/year)
A_s	:	raw material replenishment cost ($/one replenishment)
A_m	:	setup cost ($/one setup)
A_{rj}	:	ordering cost of finished goods at retailer j ($/one order)
H_s	:	raw material holding cost ($/unit/year)
H_m	:	finished goods holding cost at manufacturer ($/unit/year)
H_{rj}	:	finished goods holding cost at retailer j ($/unit/year)
τ	:	temperature (K)
τ^*	:	reference temperature (K)
k_0	:	constant deteriorating rate
E_a	:	activation energy (kJ/mole)
β	:	gas constant (kJ/mole K)
$Q_{\max}$	:	quality maximum of status raw material
$Q(t)$	:	remaining quality status of raw material
C_{Es}	:	cost of energy ($/year)
λ	:	shape parameter
d_s	:	demand rate of the raw material (unit/year)
d_{rj}	:	demand of retailer j (unit/year)
P	:	production rate (unit/year)
D	:	total demand of finished goods where $D = \sum d_{rj}$ (unit/year)
n_s	:	the number of replenishment frequencies of raw material
n_{rj}	:	the number of ordering frequency of finished goods at retailer j

T	:	production cycle (year)
Tp	:	the production run length (year)
q_s	:	the lot size of raw material procurement (unit)
q_{rj}	:	the transfer batch of retailer j (unit)
$p(t)$	:	shelf-life based price ($)
p_{max}	:	maximum price of the finished goods ($)
p_{min}	:	minimum price of the finished goods ($)
T_{start}	:	time when the value of products start decreasing (year)
T_{sl}	:	product shelf-life (year)
LT_{rj}	:	transportation lead time
E_{ij}	:	the age of ith batch of retailer j (year)
Ct_j	:	the ordering cycle of retailer j
$Rrev_{ij}$	:	the revenue of the ith batch of retailer j ($/year)
Z	:	delivery schedule
x_{ij}	:	the shipping time of ith batch of retailer j
ts_j	:	time between the production starting time and the 1st batch dispatched to retailer j
E_{Cs}	:	cost of energy for changing the temperature per unit time ($/year)
$L(n_s, T)$	:	total quality loss per unit time ($/year)
$TC_s(n_s, T)$	:	raw material total cost per unit time ($/year)
$TC_m(n_{rj}, T, Z)$	:	finished goods total cost of manufacturer per unit time ($/year)
$TP_m(n_s, n_{rj}, T, Z)$	:	total profit of manufacturer per unit time ($/year)
$TC_r(n_{rj}, T, Z)$	:	finished goods total cost at retailers' system per unit time ($/year)
$TP_r(n_{rj}, T, Z)$	:	total profit of retailers ($/year)
$TP(n_s, n_{rj}, T, Z)$	:	joint total profit ($/year)

Indexing

i	:	batch i^{th} delivered from manufacturer to retailer j (where i=1,2,..., n_{rj})
j	:	retailer j (where j=1,2,..., N)
k	:	the sequence of batch i delivered from the manufacturer to retailer j (where k=1, 2, …, $\sum_{j=1}^{N} n_{rj}$)

Further, some important assumptions underlying the formulation of mathematical model representing the addressed problem are given below.

- The system operates in a deterministic environment, meaning that all uncontrollable inputs are known and constant over the planning horizon. In some cases, the values of these inputs might vary, however the model established in a deterministic environment can still be applied as a basis for developing a stochastic model. In addition, the sensitivity analysis complementing the deterministic model can be used to measure the effect of input changes to the optimal decision.
- The production rate is greater than the total demand of all retailers ($P \geq D$). This assumption is required to ensure that all demand can be met and to avoid a trivial solution to the problem.
- The raw material is at maximum quality level or $Q_{\max}$ when entering the manufacturer's warehouse. It might be difficult to ensure that every incoming raw material has the same quality level, however in many practices manufacturers have set a targeted quality level for their raw material leading to relatively uniform quality level of incoming raw material.
- The value of finished goods losses mainly occur because customers' WTP starts decreasing once the product gets closer to its expiration date. Thus, any loss due to early damage, markdown pricing for promotion strategy and/or other factors is neglected.
- All raw materials should be able to meet the production need. In other words, no outdated raw material is allowed during the planning horizon. This assumption is rational as the manufacturer has full control of their procurement cycle.
- The age of products in a batch received by the retailers is smaller than T_{start}. This is to ensure that the retailers are always able to sell the product at normal price. It is very common in reality for the retailers to request the manufacturer deliver fresher products to minimise the risk of keeping outdated items.
- No shortage or backlog is allowed. Since the system is assumed to operate in a deterministic environment, any shortage/backlog is assumed to be easily anticipated.

The assumptions are practical and necessary to represent the observed system, i.e. food inventory flows through a supply chain system.

4.4 Model development of an integrated production-inventory policy for food products

In this section, a step-by step procedure for developing a model of an integrated production-inventory policy for food products is conducted. The first step focuses on the formulation of loss in the quality of raw food inventories (Sub-section 4.4.1) while the second step explains how the shelf-life based price function is defined to represent the loss in perceived value of finished goods (Sub-section 4.4.2). The next stage discusses how the whole mathematical model is established, i.e. an integrated SVMB model accommodating the deterioration in quality of both the raw material and the finished goods (Sub-section 4.4.3). Finally, special cases of the mathematical model are presented in Sub-section 4.4.4.

4.4.1 Model of loss in quality of raw materials

Deteriorating quality of raw materials is approached by using a kinetic model function. In contrast to the existing perishable inventory models, the deteriorating raw material is viewed as quality losses instead of the quantity depletion over time. It means that all inventories (q_s) during the procurement cycle (Tp/n_s) are only depleted by production needs (P). No item is instantly diminished due to the decaying process, as can be seen from the raw material inventory profile depicted in the upper side of Figure 4.5.

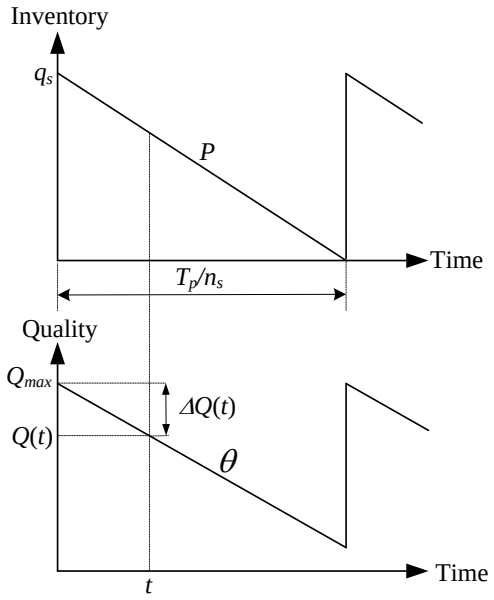


Figure 4.5 Relations between inventory and quality loss

As described in Figure 4.5, at the beginning of the replenishment cycle, the incoming raw material is at its maximum quality level (Q_{max}), then the quality naturally degrades over time with a rate of θ following the kinetic model function (Labuza, cited in Rong, Akkerman & Grunow 2011) as shown in Eq. 2.3. Based on this equation, the state of the remaining quality at time t or $Q(t)$ is therefore expressed by Eq. 4.1 and Eq. 4.2 for linear decreasing rate (m = 0) and exponential decreasing rate (m = 1) cases, respectively.

$$Q(t) = Q_{\max} - \theta t \tag{4.1}$$

$$Q(t) = Q_{\max} e^{-\theta t} \tag{4.2}$$

As the state of raw material quality degrades over time, the quality loss for an item that is consumed for production at time t or $\Delta Q(t)$ can be obtained by subtracting $Q(t)$ from $Q_{\max}$ as expressed in Eq. 4.3.

$$\Delta Q(t) = Q_{\max} - Q(t) \tag{4.3}$$

Hence, the quality loss $\Delta Q(t)$ for the different values of m (0 and 1) is respectively represented by Eqs. 4.4 and 4.5.

$$\Delta Q(t) = \theta t \qquad \text{for } m=0 \tag{4.4}$$

$$\Delta Q(t) = Q_{\max}(1 - e^{-\theta t}) \qquad \text{for } m=1 \tag{4.5}$$

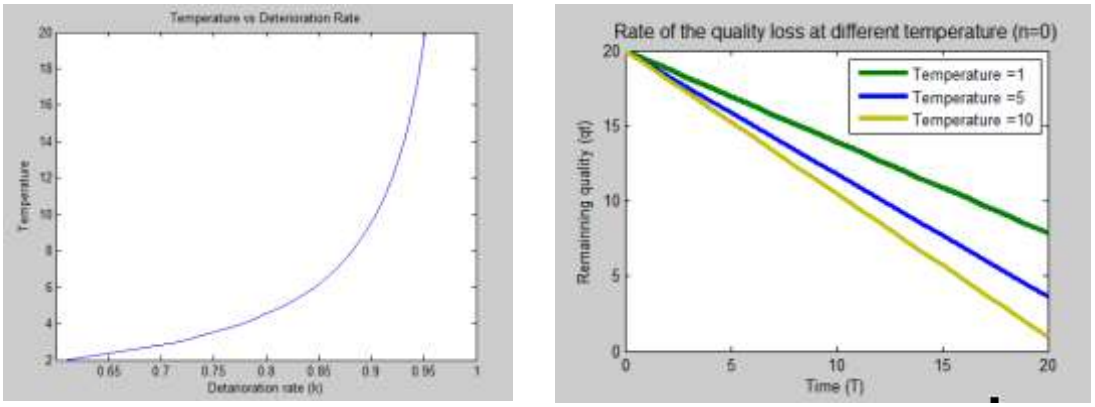
Assuming that a single unit end product requires a single unit raw material then the raw material is consumed at the rate P during the production run time (Tp), where $Tp=DT/P$. Note that the usable period of the raw material is set longer than the length of the replenishment cycle, hence there is no stock out during the replenishment cycle.

In food preservation technology, temperature (τ) plays an important role in affecting the rate of quality degradation (θ). The relation between τ and θ is expressed by Arrhenius Equation as shown in Eq. 4.6

$$\theta = k_0 e^{-(Ea/\beta\tau)} \tag{4.6}$$

where k_0 is the Arrhenius constant, E_a denotes the activation energy and β represents the universal gas constant. Eq. 4.6 shows that increasing the temperature could accelerate θ

as depicted by Figure 4.6(a) while decreasing the temperature will reduce the deterioration rate as illustrated in Figure 4.6(b). Thus, the remaining quality or $Q(t)$ over time can be maintained at a high level when the temperature is lower. Substituting Eq. 4.6 into Eqs. 4.4 and 4.5 results in Eqs. 4.7 and 4.8 respectively. These equations represent the mathematical expression of the quality loss when the temperature or τ is taken into account.



(a) Deterioration rate vs. temperature (m=0) (b) Quality loss vs. time at different temperature (m=0)

Figure 4.6 Relation between deterioration rate, quality loss and temperature

$$\Delta Q(t) = k_0 e^{-E_a/\beta\tau} t \tag{4.7}$$

$$\Delta Q(t) = Q_{\max}\left(1 - e^{-t\left(k_0 e^{-E_a/\beta\tau}\right)}\right) \tag{4.8}$$

As seen in Figure 4.6 and Eqs. 4.6, 4.7 and 4.8, the rate of the quality loss can be reduced by decreasing the temperature. However, keeping the temperature at a lower level will increase energy consumption, leading to a higher energy cost. Therefore, a trade-off between energy cost spent and benefit from reducing the rate of quality loss needs to be carefully examined. Assuming an exponential relationship between energy cost per unit time and the temperature change, Eq. 4.9 represents the mathematical expression for calculating the energy cost,

$$E_{Cs}(\tau) = C_{Es} e^{\lambda\Delta\tau} \tag{4.9}$$

where $E_{Cs}(\tau)$ is the total cost of energy required for lowering the temperature per unit time, C_E denotes a constant cost value, λ is the shaping parameters (usually based on the empirical data showing the relation between temperature change and energy used) and

$\Delta\tau$ represents the temperature change which is derived by subtracting the reduced temperature from the ambient temperature (τ^*-τ), where τ^* denotes the ambient temperature. In this study, temperature (τ) is given or $E_{Cs}(\tau)$ can be expressed as E_{Cs}. However, the effect of the temperature change ($\Delta\tau$) on the total profit will be investigated in Chapter 6.

Apart from the energy cost, as depicted from Figure 4.5, as quality of raw material at the warehouse naturally degrades over time from its maximum quality, adjustments in the production stage are required to maintain the quality of final products leading to an extra cost. If each level of quality loss incurs a cost of C_{Qs}, then given a procurement batch, raw material consumed at time t with the speed of P would suffer from an extra cost of $PC_{Qs}\Delta Q(t)$, where $\Delta Q(t) = Q_{\max} - Q(t)$. For the whole batch, this cost should be integrated from zero to Tp/n_s (Figure 4.5), where Tp is equal to DT/P. Next, as there are n_s deliveries (here, $n_s \geq 1$) over one production cycle, the total cost of quality loss per unit time should be multiplied by n_s and divided by T. Finally, the total cost related to the quality problem in raw material or $L(n_s,T)$ is the sum of energy cost and the quality loss cost as defined by Eq. 4.10

$$L(n_s,T) = E_{Cs} + C_{Qs}\frac{n_s P}{T}\int_0^{\frac{DT}{n_s P}} \Delta Q(t)dt \tag{4.10}$$

Subject to

$$t_Q > \frac{DT}{n_s P} \tag{4.11}$$

$$n_s \geq 1 \tag{4.12}$$

The constraint in Eq. 4.11 ensures that the raw material kept in the warehouse never reaches its outdated time as assumed in this research, while Eq. 4.12 demonstrates that Eq. 4.10 applies in a situation where the raw material is replenished at least once over the production cycle. In some conditions, e.g. due to fluctuation, seasonal products, discounted price *etc*., a manufacturer may have benefitted from purchasing the raw material in a greater ordering lot. If so, then Eq. 4.10 needs to be modified, and the manufacturer will have more alternatives depending on the situation.

Consider a circumstance where one replenishment cycle of raw material is used to fulfil demand for two production cycles as demonstrated in Figure 4.7. Hence, the value of n_s is equal to ½. During the first production run length (Tp_1), the quantity of raw material is depleted by production demand or P (note that in this case one unit of finished goods requires one unit of raw material) and remains the same during the off-production period (T_1-Tp_1). Further, at the next cycle it is continuously depleted until the end of Tp_2. Similar to the previous formulation method for calculating the cost of quality loss, the total relevant cost per unit time is represented by Eq. 4.13. This formula complements Eq. 4.10 for the case n_s less than one.

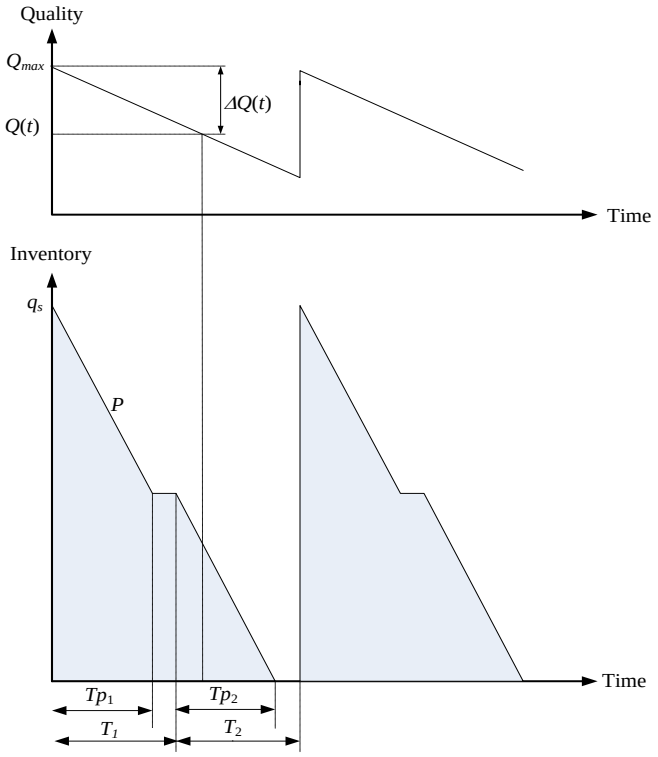


Figure 4.7 Raw material procurements n_s = ½

$$L(n_s,T) = E_{Cs}(\tau) + C_{Qs}\frac{n_s P}{T}\sum_{i=1}^{1/n_s}\int_{(i-1)T}^{(i-1)T+DT/P}\Delta Q(t)dt \tag{4.13}$$

Subject to

$$t_Q > \left(\frac{1}{n_s}-1\right)T + \frac{DT}{P} \tag{4.14}$$

$$n_s < 1 \tag{4.15}$$

Eqs. 4.14 and 4.15 can be interpreted similarly as Eqs. 4.11 and 4.12.

4.4.2 Model of loss in perceived value of finished goods

As clearly mentioned in the system description, deterioration in quality of finished goods is approached differently from that of raw materials. A shelf-life based price function is used to represent the perceived quality loss, i.e. value loss because of customers' perception. Since at a certain point of time the value of products starts decreasing, a mark down price policy is utilised to prevent the system having more outdated items. It means that the price of the product is not constant during the ordering or consuming cycle. In this study, the price during the ordering cycle of the retailer j (Ct_j) is divided into three regions, namely, Region I (p_{max} or maximum price), Region II (discounting price) and Region III (p_{min} or minimum price) as shown in Figure 4.8.

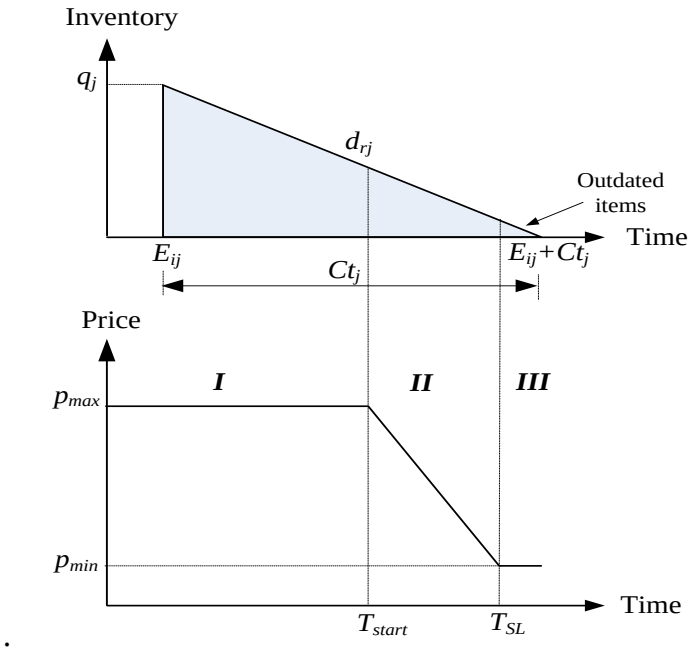


Figure 4.8 Shelf-life based price function

Over one production cycle, retailer j receives n_{rj} deliveries of finished goods. As illustrated by Figure 4.8, the ith batch for retailer j with a size q_{rj} is transferred and arrives at the retailer's warehouse having age E_{ij} counted from when it is produced until received by the retailer. The batch is then depleted by demand at retailer j (d_{rj}) during its ordering cycle (Ct_j). Here, i refers to batch delivery numbers (i = 1, 2… n_{rj}) while j denotes the order number of retailers. Since the price during product shelf-life is not constant then the selling price of each item in one transfer batch may differ depending on the age of the batch (E_{ij}) and its sold out or completion time ($CompTime$) where $CompTime_{ij} = E_{ij} + Ct_j$.

If q_{rj} has run out before T_{start} (note that T_{start} is the time when the perceived value starts decreasing) then all products are sold at the maximum price (Region I). But, if q_{rj} is sold out after T_{start} then some products are sold at the maximum price (Region I) while some others need to be discounted (Region II). Finally, if some products in q_{rj} are still unsold after the product's shelf-life (T_{sl}) then the products in this batch are sold at three different prices, the maximum price (Region I), discounted price (Region II) and minimum price (Region III). In a case when the expired products have no value and must be discarded, the minimum price is equal to zero.

Based on the above mentioned scenario, there are three possible product prices in each batch for a retailer. Noting that $p(0) = p_{max}$ and $p(T_{sl}) = p_{min}$, hence the general mathematical expression of a linear shelf-life based price function is given by:

$$p(t) = \begin{cases} p_{\max} & 0 \le t < T_{start} \\ p_{\min} + \dfrac{p_{\max} - p_{\min}}{T_{sl} - T_{start}}\left(T_{sl} - t\right) & T_{start} \le t < T_{sl} \\ p_{\min} & t \ge T_{sl} \end{cases} \tag{4.16}$$

If it is a nonlinear shelf-life based function, the expression will be:

$$p(t) = \begin{cases} p_{\max} & 0 \le t < T_{start} \\ p_{\max} - \dfrac{(p_{\max} - p_{\min})}{(e^{T_{sl} - T_{start}} - 1)}(e^{t - T_{start}} - 1) & T_{start} \le t < T_{sl} \\ p_{\min} & t \ge T_{sl} \end{cases} \tag{4.17}$$

Thus, according to the shelf-life based price function, the structure of the retailers' revenue per unit time ($Rrev_{ij}$) for each batch can be defined as the followings:

Case 1: If $CompTime_{ij} < T_{start}$ then the revenue of the batch ($Rrev_{ij}$) is maximum as all products are sold with p_{max} as defined by Eq. 4.18:

$$Rrev_{ij}(n_{rj}, T) = \frac{d_{rj}\, p_{\max}\, Ct_j}{T} \tag{4.18}$$

Case 2: If $T_{start} \le CompTime_{ij}$ then $Rrev_{ij}$ is defined by Eq. 4.19:

$$Rrev_{ij}(n_{rj}, T) = \frac{d_{rj}}{T}\left[p_{\max}(T_{start} - E_{ij}) + \int_{T_{start}}^{E_{ij} + Ct_j} p(t)dt \right] \tag{4.19}$$

Case 3: If $T_{sl} < CompTime_{ij}$ then $Rrev_{ij}$ is represented by Eq. 4.20:

$$Rrev_{ij}(n_{rj},T)=\frac{d_{rj}}{T}\left[\begin{array}{l} p_{\max}(T_{start}-E_{ij})+\int_{T_{start}}^{T_{sl}}p(t)dt \\ +\,p_{\min}(E_{ij}+Ct_j-T_{sl}) \end{array}\right] \quad (4.20)$$

As shown in Eqs. 4.18, 4.19 and 4.20, the age of batch E_{ij} at the retailers, influences the retailers' revenue.

4.4.3 Integrated model of production-inventory policy accommodating quality loss and shelf-life based function

In this study an integrated approach is proposed to deal with a production-inventory policy in a single-vendor multi-buyer (SVMB) environment. The manufacturer's policy is concerned with determining the length of the production cycle (T) and the amount of incoming raw material over one production cycle (n_s), while the retailers' policy is related to specifying the number of finished goods deliveries to each retailer (n_{rj}) over the production cycle. An integrated approach adopted in this research means that all these decision variables should be determined simultaneously. As previously discussed, in contrast to the coordinated shipment policy proposed in Banerjee, Kim and Burton (2007), in this study, each retailer is allowed to have its own delivery cycles. In addition, the manufacturer can also procure the raw material in a lot size that covers manufacturing demand for a number of production cycles. These new policies increase the complexity of the model and lead to two significant challenges, i.e. how to calculate the age of each batch received by each retailer or $E_{ij,}$ and how to calculate the average inventory of the raw material at the manufacturer. These are discussed in the following subsections.

4.4.3.1 Formulation of batch age received by retailers

To simplify the explanation, consider a situation where a manufacturer delivers the finished goods to three retailers with different frequencies of deliveries, such as n_{rj} = [4, 2, 4] and different sizes of the transfer batches (q_{rj}) over the production cycle (T). Thus, the inventory profile at the manufacturer and retailers for this case can be depicted by Figure 4.9. In this study, the age of the ith batch sent to retailer j or E_{ij} is defined by the length between the time when the first product in this batch is produced and the time when this batch is received by retailer j. In other words, E_{ij} is calculated by adding the time of the batch in the manufacturer system and the time to deliver the batch from the manufacturer to the retailers (or called transportation lead time or LT_{rj}). However, to

simplify the illustration, in Figure 4.9, LT_{rj} is set to be zero but it will be included in the algorithm while calculating the final E_{ij}. As the cycle time of each retailer varies calculating E_{ij} becomes an important issue.

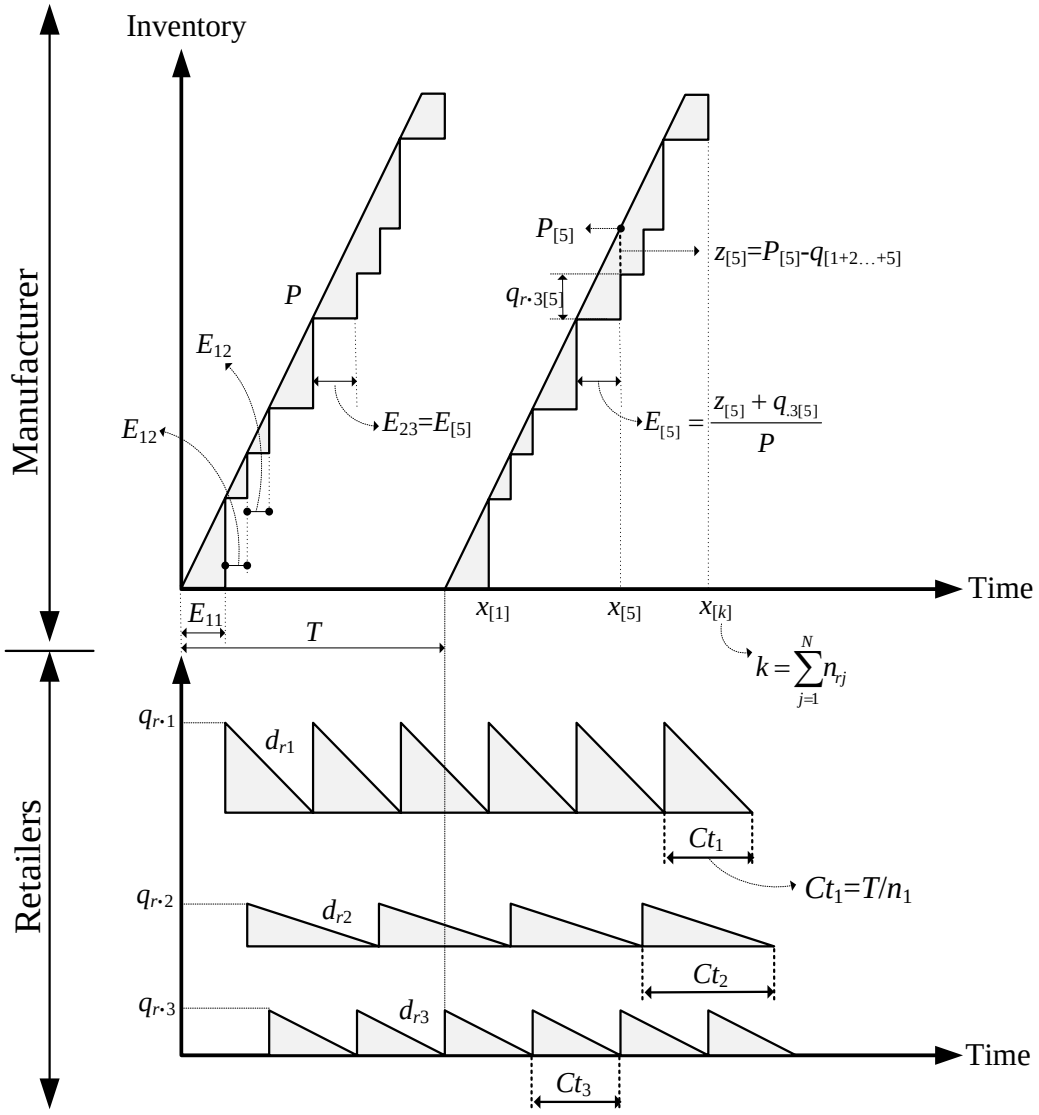


Figure 4.9 The inventory profile of the finished goods in manufacturer and retailers using synchronised cycle

Still from Figure 4.9, during the length of manufacturer's production cycle (T), the finished goods are delivered to three retailers, namely Retailer 1 (R_1), Retailer 2 (R_2) and Retailer 3 (R_3). The order of deliveries is arranged by R_1-R_2-R_3 with the quantity of each transfer batch q_1, q_2, q_3 and number of deliveries (n_{rj}), 3, 2, 3, respectively.. From Figure 4.9, let x denote the times of product deliveries from the manufacturer to retailers. Then, x_k represents the time when the kth deliveries of finished goods is executed, where $k = 1,2, \dots, \sum_{j=1}^{N} n_{rj}$. Meanwhile, z_k shows the discrepancy between the total number of items

produced and the total number of items being shipped to all retailers at time x_k. Thus, if q_r^k demonstrates the batch size of the kth shipment and E^k is the age of the batch delivered at time x_k, then E^k is equal to $(z_k + q_r^k)/P$.

To illustrate, given a production sequence Z = 1-2-3, quantity and number of deliveries of respectively q_{r1}, q_{r2}, q_{r3} (or $q_{[1]} = q_{r1,}$ $q_{[2]} = q_{r2,}$ and $q_{[3]} = q_{r3}$) and, 3, 2, 3, as shown in Figure 4.9, then total frequency of outbound shipment over one production cycle is 8 deliveries (maximum value of k). The first deliveries to all retailers (the first three batches) have no discrepancy between the item produced and shipped or $z_k = 0$ for k = 1, 2, 3. Then, E^1, E^2 and E^3 which is associated with E_{11}, E_{12} and E_{13} are respectively $q_{[1]}/P$, $q_{[2]}/P$ and $q_{[3]}/P$. Another example, at time x_5, the E^5 is derived from $(z_5+q_r^5)/P$. As can be seen from the figure q_r^5 and E^5 are respectively associated with $q_{[3]} = q_3$ and E_{23}. Note that z_k can be calculated by subtracting $\sum_{l=1}^{k} q_r^l$ from Px_k. The problem is how to find the associated value of q_r^k and to obtain E_{ij}. Therefore, the following procedure (called *Algorithm* 1) is proposed.

Algorithm 1

***Step 1*: Calculating time of delivery for each batch**

a. Given Z, label each retailer and its corresponding parameter based on its delivery schedule (Z), i.e. 1stR, 2ndR, …, N^{th}R with order quantity q_{r1}, q_{r2}, …, q_{rN}.

b. Given n_{rj}, establish table of x_{ij} indicating the time when the ith batch (row) for the jth retailer (column) is shipped, where i = 1, 2 … n_{rj} and j = 1, 2 … N.

1stR	2ndR	…	N^{th}R	
x_{11}	x_{12}	…	x_{1N}	1st batch
x_{21}	x_{22}	…	x_{2N}	2nd batch
x_{31}	x_{32}	…	x_{3N}	3rd batch
⋮	⋮		⋮	
$x_{n_1 1}$	$x_{n_2 2}$	…	$x_{n_N N}$	n_{rj}^{th} batch

c. Calculate the values of x_{ij} using formula below

$$
\begin{array}{cccc}
1^{st}\text{R} & 2^{nd}\text{R} & \dots & N^{th}\text{R} & \\
\left[\begin{array}{cccc}
ts_1 & ts_2 & \dots & ts_N \\
ts_1+Ct_1 & ts_2+Ct_2 & \dots & ts_N+Ct_N \\
ts_1+2Ct_1 & ts_2+2Ct_2 & \dots & ts_N+2Ct_N \\
\vdots & \vdots & & \vdots \\
ts_1+(n_1\text{-}1)Ct_1 & ts_2+(n_2\text{-}1)Ct_2 & \dots & ts_N+(n_N\text{-}1)Ct_N
\end{array}\right] & \begin{array}{c} 1^{st}\text{ batch} \\ 2^{nd}\text{ batch} \\ 3^{rd}\text{ batch} \\ \\ n_{rj}{}^{th}\text{ batch} \end{array}
\end{array}
$$

where ts_j is the interval time between the production starting time and the dispatching time of the 1st batch for retailer j. It is calculated using Eq. 4.21.

$$ts_j = \frac{\sum_{l=1}^{j} q_l}{P} \tag{4.21}$$

***Step 2*: Calculating the ordered times to deliver all batches (x_k)**

Sort the values of x_{ij} in an increasing order to create vector x representing the times each delivery is executed, [x_1 x_2 x_3 … x_k], while keeping their corresponding value of i and j in tables x_{ij} and q_{rj}.

***Step 3*: Calculating the age of batch E_{ij}**

a. For every x_k compute $z_k = Px_k - \sum_{l=1}^{k} q_r{}^l$

b. Determine E^k by (z_k-min(z)+$q_r{}^k$)/P, where $q_r{}^k = DT/n_{rj}$.

c. Finally by retrieving the associated index of $k \rightarrow i, j$ obtained from step 2, E_{ij} can be determined. Note that the transportation lead time to retailer (LT_{rj}) can directly be added to this E_{ij} to find the final E_{ij}.

4.4.3.2 Formulation of average raw material and finished goods inventories

In this considered system, the manufacturer is allowed to procure the raw materials either with $n_s \geq 1$ as illustrated by Figure 4.10, or with $n_s < 1$ as demonstrated by Figure 4.11. As shown in Figure 4.10, the raw material is supplied two times (n_s=2) over one production cycle (T) at size of q_s. The raw material is consumed during the production run length (on-production) or Tp where $Tp = DT/P$. In addition, it is also assumed in this case that one unit end product needs one unit raw material i.e. the demand rate for raw

material (d_s) is equal to the production rate (P). Noting that $q_s = d_s Tp/n_s$, the average inventory of raw materials (I_s) is obtained by calculating the total inventory during Tp (the shaded area of inventory profile for raw material) and then dividing the result by T. The average inventory can then be represented by Eq. 4.22.

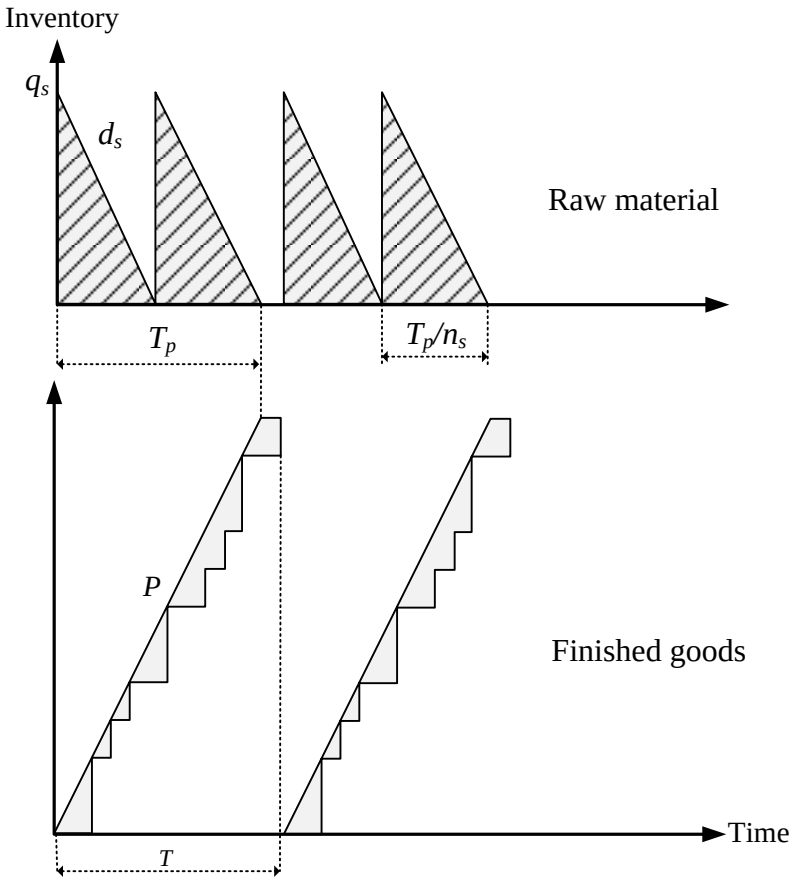


Figure 4.10 The inventory profile of the raw material and finished goods in manufacturer ($n_s \geq 1$)

$$I_s = \frac{D^2 T}{2 n_s P}, \text{ for } n_s \geq 1 \qquad (4.22)$$

Similarly, for $n_s < 1$ as illustrated by Figure 4.11 where one lot of replenished raw material (q_s) is supplied to fulfil demand for two production cycles (n_s=1/2), the average inventory can be formulated by calculating the shaded area of raw material inventory profile during T/n_s and then dividing the result by T/n_s. Hence, the average inventory of raw material (I_s) can be presented by Eq. 4.23.

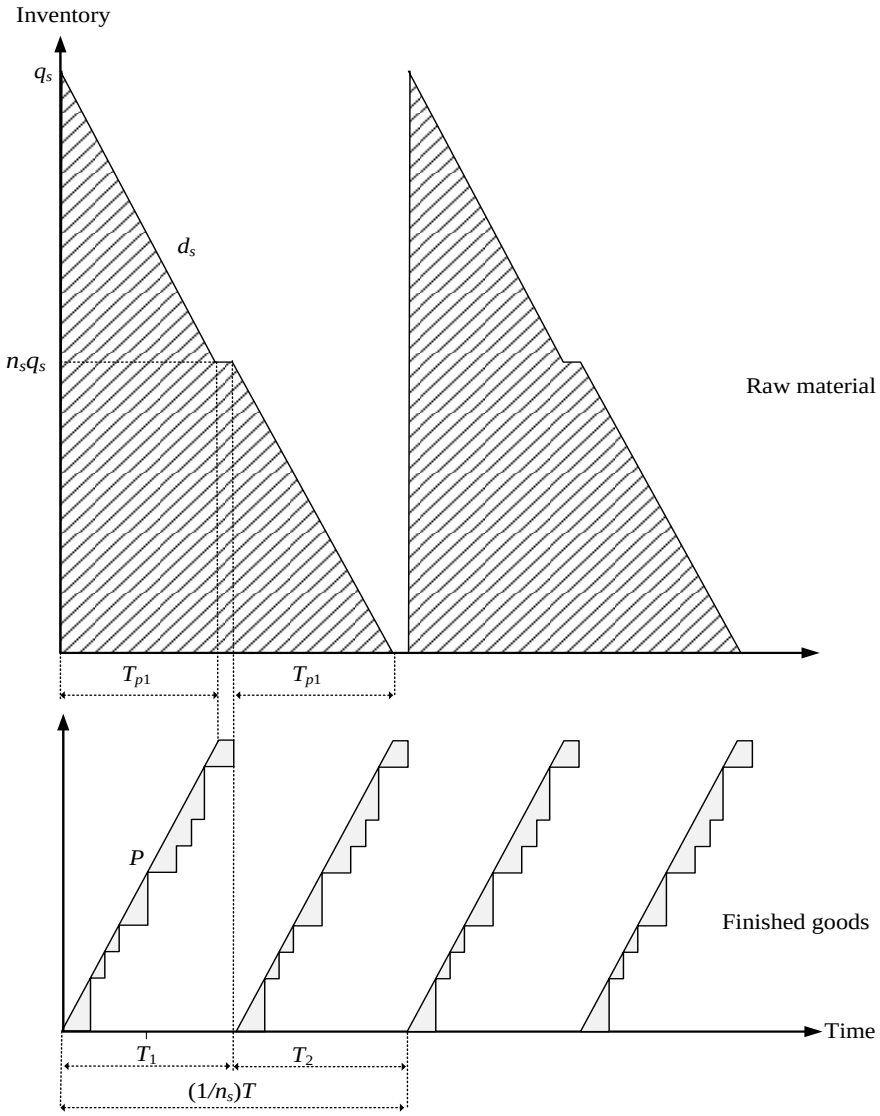


Figure 4.11 The inventory profile of the raw material and finished goods in manufacturer ($n_s < 1$)

$$I_s = n_s T\left[\frac{D^2}{2n_s P} + \sum_{i=1}^{1/n_s}(i-1)\frac{D^2 T}{P}\right], \text{ for } n_s < 1 \tag{4.23}$$

Having established mathematical models of the average raw material inventory for different cases, the next step is to develop a mathematical model for the average inventory of the finished goods in the systems of the manufacturer and retailers. In the manufacturer's system, the average inventory of finished goods can be calculated by subtracting the average retailers' inventory from the total system inventory (Prasetyo & Lee 2013). The average retailers' inventory (I_r) is calculated using Eq. 4.24,

$$I_r = 0.5\sum_{j=1}^{N} d_{rj}\frac{T}{n_{rj}} \tag{4.24}$$

while the average inventory for the whole system (I) is represented by Eq. 4.25,

$$I = I_{m0} + 0.5(1 - D/P)\sum_{j=1}^{N} d_{rj}T \tag{4.25}$$

where I_{m0}, is the dead stock in the system. It is important to note that the dead stock of the system is affected by the delivery sequence (Z). If the bracketed index indicates the sequence of the delivery, the dead stock is obtained by calculating total demand from the starting production to the first shipments of each retailer or indicated by ts_j. The result is presented in Eq. 4.26.

$$I_{m0} = \sum_{j=1}^{N} ts_{[j]} d_{r[j]} \tag{4.26}$$

Hence, the average inventory of finished goods at the manufacturer is the total system inventory deducted by the retailers' inventory and can be expressed by Eq. 4.27,

$$I_m = \sum_{j=1}^{N} ts_{[j]} d_{r[j]} + 0.5(1 - D/P)\sum_{j=1}^{N} d_{rj}T - 0.5\sum_{j=1}^{N} d_{rj}\frac{T}{n_j} \tag{4.27}$$

where ts_j is calculated using Eq. 4.21 and Z is the first batch delivery sequence of the finished goods from the manufacturer to the retailers. From, Eqs 4.26 and 4.27, it is indicated that Z affects not only the age of batch but also the manufacturer's average inventory. Having established E_{ij}, I_s and I_m, the total profit as the performance indicator of the supply chain system can now be formulated and will be discussed in the following subsection.

4.4.3.3 Formulation of total profit of the integrated system

Total profit of the supply chain is the sum of total profits of both the manufacturer and the retailers. The total profit of the manufacturer (TP_m) is achieved by subtracting the total cost of the manufacturer's system from its total revenue. As discussed in Section 4.2, the costs in the manufacturer's system can be divided into two main categories i.e. the costs related to managing the raw materials (TC_s) and the costs associated with producing and handling finished goods (TC_m). The costs related to managing the raw material consists of the purchasing cost, the procuring/transportation cost, the holding cost and the costs related to quality loss. The total cost per year is respectively represented by parts in Eq. 4.28.

$$TC_s(n_s, T) = C_s D_s + A_s\frac{n_s}{T} + H_s I_s + L(n_s, T) \tag{4.28}$$

Beside the total raw material costs, the manufacturer also bears the costs related to finished goods before delivering them to the retailers. The costs consist of the manufacturing cost, the setup cost and the holding cost. Thus, the total cost per year is represented respectively by Eq. 4.29.

$$TC_m(T,\mathbf{n},Z) = C_m D + \frac{A_m}{T} + H_m \left[\begin{array}{l} \sum_{j=1}^{N} ts_{[j]} d_{r[j]} + 0.5(1-D/P)\sum_{j=1}^{N} d_{rj} T \\ -0.5\sum_{j=1}^{N} d_{rj} \dfrac{T}{n_{rj}} \end{array} \right] \tag{4.29}$$

Note that **n** denotes a matrix-vector representing the number of shipments for all retailers (n_{r1}, $n_{r2,\ldots}$, n_{rN}).

Having formulated the costs at the manufacturer, the manufacturer's revenue is obtained by multiplying the selling price of the finished goods (C_r) with total demand (D). Finally, the total profit of the manufacturer is counted by subtracting the total cost from the revenue. Assuming that the selling price to all retailers is the same, the total profit of the manufacturer per year is then demonstrated by Eq. 4.30.

$$TP_m(n_s,T,\mathbf{n},Z) = C_r D - \left[TC_s(n_s,T) + TC_m(T,\mathbf{n},Z)\right] \tag{4.30}$$

In the considered system, the retailers also bear costs related to the finished goods, namely, the purchasing cost, the ordering cost and the holding cost. The total cost per year at the retailers is represented by Eq. 4.31.

$$TC_r(\mathbf{n},T) = C_r D + \frac{1}{T}\sum_{j=1}^{N} A_{rj} n_{rj} + 0.5 H_r \sum_{j=1}^{N} \frac{d_{rj} T}{n_{rj}} \tag{4.31}$$

Meanwhile, the total profit per year of all retailers is obtained by deducting the Eq. 4.31 from the total revenue per unit time obtained by Eqs. 4.18, 4.19 and 4.20. The result is then expressed by Eq. 4.32.

$$TP_r(\mathbf{n},T,Z) = \sum_{j=1}^{N}\sum_{i=1}^{n_j} R_{ij}(\mathbf{n},T,Z) - TC_r(\mathbf{n},T) \tag{4.32}$$

Finally, the total joint profit of the whole supply chain can be acquired by adding Eq. 4.30 to Eq. 4.32. The complete formulation of the problem can then be expressed as follows:

Maximise:

$$TP(n_s, \mathbf{n}, T, Z) = TP_m(n_s, \mathbf{n}, T, Z) + TP_r(\mathbf{n}, T, Z) \quad (4.33)$$

Subject to:

$P \geq D$;

(4.34)

$E_{ij} < T_{start}$; for $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, N$ (4.35)

$T > 0$; (4.36)

$\mathbf{n}, Z > 0$ and integer, $n_s \in \{\ldots, ¼, 1/3, ½, 1, 2, 3, 4, \ldots\}$ (4.37)

Eq. 4.33 denotes the total profit of integrated production-inventory policy addressed in this research that is going to be maximised. The optimisation has to meet some constraints. Firstly, the production rate is able to meet all demand (Eq. 4.34); secondly, no batch arrives with ages more than a point where the customer's WTP starts declining (Eq. 4.35), and lastly, the decision variables constraints (Eqs. 4.36 and 4.37). This profit maximisation is achieved by determining simultaneously the optimal four decision variables, namely n_s, $\mathbf{n}$, T and Z.

4.4.4 A special case to the model: Common cycle coordination approach

As discussed previously (Subsection 4.2) in terms of the approach for coordinating the production and inventory policies between the manufacturer and the retailers, the model established in Eq. 4.33 has extended the coordination approach proposed by Banerjee, Kim and Burton (2007), i.e. each retailer is allowed to have different ordering cycles. It is expected that this coordination mechanism would result in a better supply chain performance. In case the common cycle coordination approach is adopted in the supply chain, this subsection is devoted to formulate the total profit for such a circumstance. Hence, the performance of the integer multiplier coordination approach proposed in this research can be compared to the common cycle approach. Here, a common cycle approach means that instead of having their own ordering cycle (such as n_{rj} in the proposed model), all retailers receive the same frequency of orders (n_r) over one production cycle (T).

In the common cycle approach, models for two cases are developed. In the first model, Model C, each batch is delivered to each retailer using a single truck in the same interval

but differs in time, also known as less-truckload shipment (LTL). Meanwhile in the second model, model SC, the shipments to all retailers are consolidated and delivered to the retailers at the same time using a single truck or full-truck load shipment (FTL), assuming that transportation capacity is enough to deliver the consolidated batches. Model SC is typically applicable when the retailers are located adjacent to each other.

4.4.4.1 Model C: Common cycle approach with less-truckload shipment

In Model C, one batch is delivered to fulfil the demand of each retailer. Unlike the shipment policy in the proposed model (synchronised cycle), the length of ordering cycles for all retailers is the same as illustrated by Figure 4.12. To simplify the explanation, the transportation lead time is assumed to be zero, hence the formula to calculate E_{ij} for the first batch ($i = 1$) and the remaining batches of retailer j is expressed by Eq. 4.38 and Eq. 4.39, respectively.

$$E_{ij} = \frac{d_{rj} T}{n_r P}, \text{ for } i = 1 \tag{4.38}$$

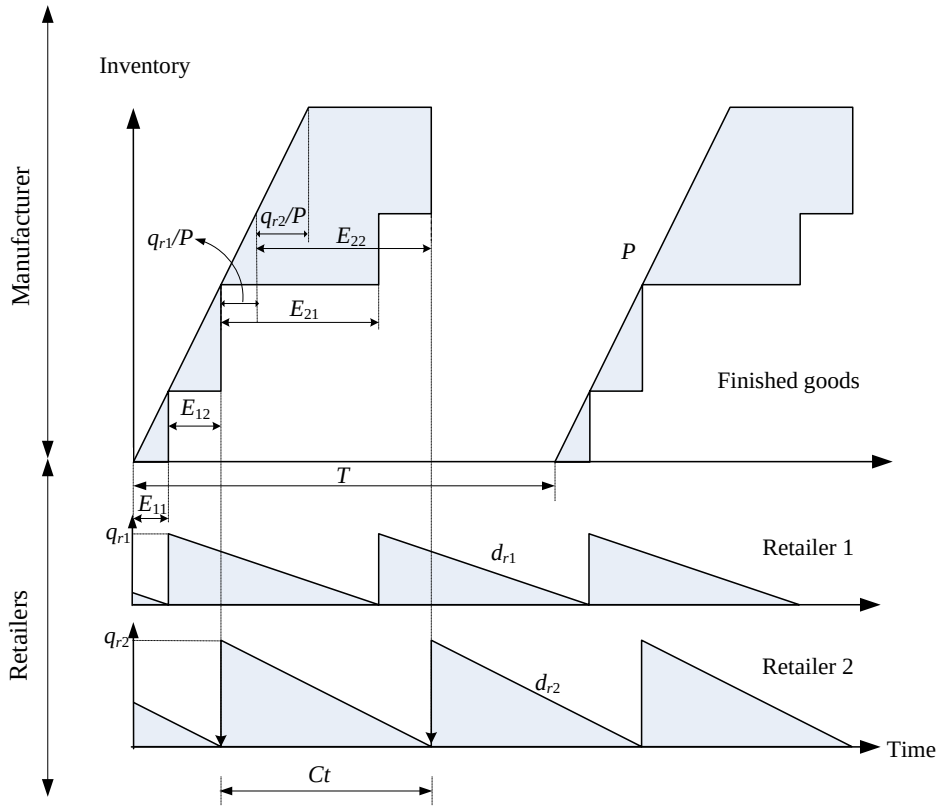


Figure 4.12 Common cycle approach: one transfer batch to each retailer

$$E_{ij} = \frac{d_{rj}T}{n_r P} + (i-1)\left[\frac{T}{n_r} - \sum_{j=1}^{N}\frac{n_r d_{rj}T}{n_r P}\right], \text{ for } \quad i = 2, 3, \ldots, n_r \tag{4.39}$$

Similar to the proposed model, Model P, an approach to calculate the average inventory of finished goods in the manufacturer refers to Prasetyo and Lee (2013). Eqs. 4.40 and 4.41 respectively represent the mathematical functions to acquire the average inventory of finished goods at the retailers (I_r) and the dead stock (I_{m0}) at manufacturer. Hence the total average inventory of finished goods at the manufacturer is obtained by subtracting I_r from the whole inventory in the system as shown in Eq. 4.42.

$$I_r = \frac{\sum_{j=1}^{N} d_{rj}\frac{T}{n_r}}{2} \tag{4.40}$$

$$I_{m0} = \sum_{j=i}^{N} d_{rj} \sum_{l=1}^{j} \frac{d_{rl}T}{n_r P} \tag{4.41}$$

$$I_m = \left[\sum_{j=1}^{N} d_{rj} \sum_{l=1}^{j} \frac{d_{rl}T}{n_r P} - \frac{T}{2}\sum_{j=1}^{N} d_{rj}\left(1 - \frac{D}{P} - \frac{1}{n_r}\right)\right] \tag{4.42}$$

Further, Eq. 4.43 is used to calculate the total cost of managing finished goods in the manufacturing system or $TC_{m1}(n, T)$ and Eq. 4.44 is applied to obtain the total cost in the retailers $TC_{r1}(n, T)$.

$$TC_{m1}(n_r, T) = C_m D + \frac{A_m}{T} + H_m\left[\begin{array}{l}\sum_{j=1}^{N} d_{rj} \sum_{l=1}^{j} \frac{d_{rl}T}{n_r P} \\ -\frac{T}{2}\sum_{j=1}^{N} d_{rj}\left(1 - \frac{D}{P} - \frac{1}{n_r}\right)\end{array}\right] \tag{4.43}$$

$$TC_{r1}(n_r, T) = C_r D + \frac{n_r}{T}\sum_{j=1}^{N} A_{rj} + H_r \sum_{j=1}^{N} \frac{d_{rj}T}{2n_r} \tag{4.44}$$

Hence, the profit of the manufacturer $TP_{m1}(n_s, n_r, T)$ and retailers $TP_{r1}(n_s, n_r, T)$ are respectively presented by Eqs. 4.45 and 4.46.

$$TP_{m1}(n_s, n_r, T) = C_r D - \left[TC_s(n_s, T) + TC_m(n_r, T)\right] \tag{4.45}$$

$$TP_{r1}(n_r,T)=\sum_{j=1}^{N}\sum_{i=1}^{n_r}Rrev_{ij}(n_r,T)-TC_{r1}(n_r,T) \tag{4.46}$$

where $Rrev_{ij}$ denotes the revenue of the ith batch of retailer j or q_{ij} based on E_{ij} function shown in Eqs. 4.38-39.

Finally, the formal formulation of the integrated production-inventory model adopting the common cycle approach with LTL can be expressed by the following equations;

Maximise:

$$TP_1(n_s,n_r,T)=TP_{m1}(n_s,n_r,T)+TP_{r1}(n_r,T) \tag{4.47}$$

Subject to:

$$P > D; \tag{4.48}$$

$$E_{ij} < T_{start}; \text{ for } i = 1, 2, \ldots, n_r \text{ and } j = 1, 2, \ldots, N \tag{4.49}$$

$$T > 0; \tag{4.50}$$

$$n > 0 \text{ and integer, } n_s \in \{\ldots, ¼, 1/3, ½, 1, 2, 3, 4, \ldots\}; \tag{4.51}$$

4.4.4.2 Model SC: Common cycle approach with full-truckload shipment

In model SC, the shipment mechanism is exactly the same as that in Banerjee, Kim and Burton (2007) as illustrated by Figure 4.13. A consolidated batch (q_B) is delivered to fulfil the demand of all retailers, i.e. q_B consists of q_1 and q_2. This strategy may reduce transportation costs, particularly if all retailers are located relatively close to each other. This approach also assumes that the transportation capacity is enough to load the consolidated batch.

Using one shipment to all retailers as shown in Figure 4.13 simplifies the formula to calculate the age of each batch since all retailers' time will receive i^{th} batch with the same age or $E_1(q_{r1}) = E_1(q_{r2})$ as demonstrated by Eq. 4.52.

$$E_i=(i-1)\frac{T}{n_r}-(i-2)\frac{\sum_{j=1}^{N}d_{rj}T}{n_rP} \tag{4.52}$$

where E_i is the age of the ith batch of all retailers and n is the number of deliveries.

This delivery shipment influences the average inventory of finished goods. To calculate the costs related to managing the finished goods either in the manufacturer's or retailers' systems, the approach in Banerjee, Kim and Burton (2007) is used. Hence, respectively, Eqs. 4.53 and 4.54 represent the total cost at the manufacturer, $TC_{m2}(n_r, T)$ and at the retailers, $TC_{r2}(n, T)$.

$$TC_{m2}(n_r,T) = C_m D + \frac{A_m}{T} + H_m \frac{DT}{2n_r}\left[\frac{D}{P}(2-n_r)+(n_r-1)\right] \tag{4.53}$$

$$TC_{r2}(n_r,T) = C_r D + \frac{A_r n_r}{T} + H_r \frac{DT}{2n_r} \tag{4.54}$$

Thus, the profit of both the manufacturer $TP_{m2}(n_s,n,T)$ and the retailers $TP_{r2}(n,T)$ is obtained by subtracting the corresponding costs from its corresponding revenue as demonstrated by Eqs. 4.55 and 4.56.

$$TP_{m2}(n_s,n_r,T) = C_r D - \left[TC_s(n_s,T) + TC_{m2}(n_r,T)\right] \tag{4.55}$$

$$TP_{r2}(n_r,T) = \sum_{i=1}^{n} Rrev_i(n_r,T) - TC_{r2}(n_r,T) \tag{4.56}$$

where R_i denotes the revenue of the ith transfer batch or q_B based on E_i function shown in Eq. 4.52.

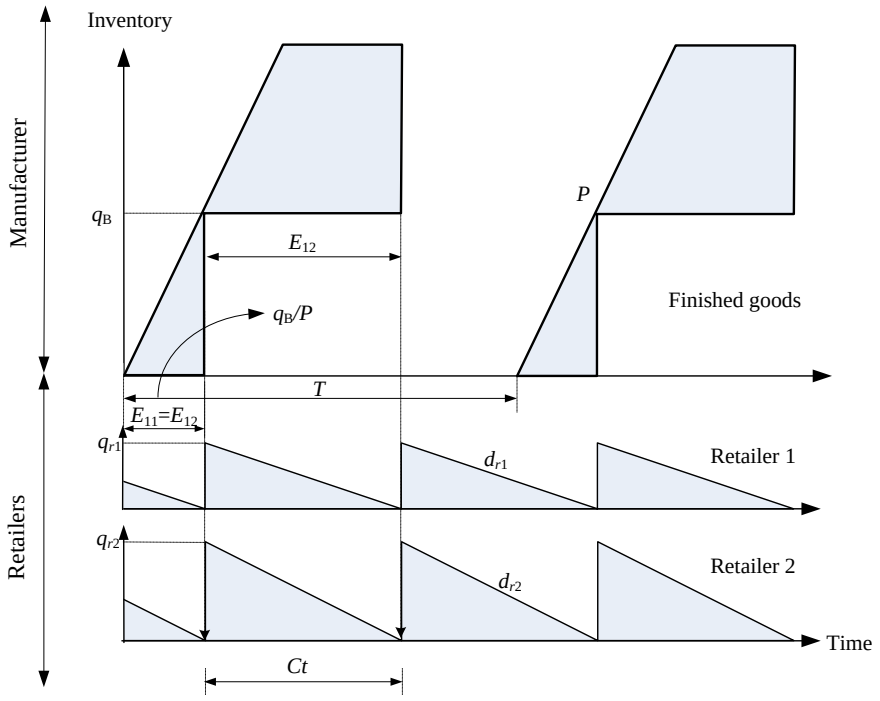


Figure 4.13 Common cycle approach: one transfer batch to all retailers

Finally, the formal formulation of the integrated production-inventory model adopting the common cycle approach with FTL can be expressed by Eqs. 4.57, 4.58, 4.59, 4.60 and 4.61.

Maximise:

$$TP_2(n_s, n_r, T) = TP_{m2}(n_s, n_r, T) + TP_{r2}(n_r, T) \tag{4.57}$$

Subject to:

$$P > D; \tag{4.58}$$

$$E_i < T_{start}; \text{ for } i = 1, 2, \ldots, n_r \tag{4.59}$$

$$T > 0; \tag{4.60}$$

$$n_r > 0 \text{ and integer, } n_s \in \{\ldots, ¼, 1/3, ½, 1, 2, 3, 4, \ldots\}; \tag{4.61}$$

As predicted, the consolidated batch shipment mechanism simplifies the formula to obtain the total profit. Apart from that, for both models with common cycle approach, it is not necessary to determine the sequence of delivery since it does not affect the dead stock and the age of the batch.

As discussed in Subsection 4.4.3, unlike the special cases, the proposed model has four decision variables, i.e. n_s, T, n_{rj} and Z, which need to be simultaneously determined. The involvement of shipment schedule (Z) escalates the complexity of finding the model solution. For illustration, consider a supply chain system consists of one manufacturer with three retailers. The input parameters are presented in Table 4.1. The total profit of the system at any given solutions can be calculated by entering the parameters in Table 4.1 into Eq. 4.33. The summary of the given solutions and their corresponding total profit is then presented in Table 4.2.

Table 4.1 The values of parameters in the manufacturer-retailer system

Manufacturer					
P	:	30000	C_s	:	10
β	:	0.0083	C_m	:	8
E_a	:	20	C_r	:	5
k_0	:	200	A_s	:	75
τ	:	300	A_m	:	750
λ	:	0.02	H_s	:	15
C_{Es}	:	1.5	H_m	:	20
C_{Qs}	:	20			

Table 4.1 The values of parameters in the manufacturer-retailer system (continued)

Retailers		
d_{rj}	:	3000;1000;15000
A_{rj}	:	30;100;20
H_{rj}	:	25;25;25
T_{sl}	:	0.1670
T_{start}	:	0.083
p_{max}	:	75
p_{min}	:	5
LT_{rj}	:	0.0137;0.0082;0.011

Table 4.2 Possible set of solutions and their corresponding total profit

No	n_s	T	n_{rj}			Z	Total Profit (TP)
			1	2	3		
1	3	0.113	3	3	3	1-2-3	1136377
2	1	0.113	3	3	3	1-2-3	1131193
3	3	0.226	3	3	3	1-2-3	655922
4	3	0.113	2	4	1	1-2-3	577361
5	3	0.113	2	4	1	1-3-2	580069
6	3	0.113	2	4	1	2-1-3	585723
7	3	0.113	2	4	1	2-3-1	582454
8	3	0.113	2	4	1	3-2-1	588869
9	3	0.113	2	4	1	3-1-2	587648
10	3	0.113	2	1	4	1-2-3	1135454
11	3	0.113	2	1	4	1-3-2	1138487
12	3	0.113	2	1	4	2-1-3	1134204
13	3	0.113	2	1	4	2-3-1	1137741
14	3	0.113	2	1	4	3-2-1	1138709
15	3	0.113	2	1	4	3-1-2	1139959

In Table 4.2, there are fifteen possible solutions or decision variables with their corresponding total profit. Note that there can be a huge number of possible solutions of the proposed model particularly due to the existence of integer variables (n_s, and n_{rj}) and a combinatorial variable (Z). For such a problem analytical solution approach is hardly implemented. Considering this situation, a meta-heuristic approach based on biased random key genetic algorithms (BRKGAs) is proposed to solve this problem. More detailed information regarding the BRKGAs is represented in Chapter 5.

4.5 Concluding remarks

A model of an integrated production-inventory policy for food products in a single-vendor multi-buyer supply chain structure has been successfully developed in this chapter. The model considers the loss in quality of raw food materials and the loss in perceived value of finished food products. A kinetic model has been applied to represent the raw material quality loss, while a shelf-life based function has been developed to accommodate the product value loss because of customers' perception. Further, a synchronised approach between procurement-production and delivery has been accommodated to find the maximum profit of the whole supply chain. Four decision variables need to be simultaneously optimised to obtain the maximum profit of the system; they are the production cycle length, the number of raw material shipments over one production cycle, the sequence of deliveries to the retailers and the number of finished goods deliveries to the retailers over one production cycle.

Two special cases to the model based on the common cycle coordination approach were also formulated in this chapter. Thus, it is worthy to examine the potential benefit of accommodating the quality and perceived value losses when managing food products in a single-vendor multi-buyer system. In addition, in terms of performance of the proposed coordination mechanism approach, a comparison to the common cycle approach as a benchmark model is important to be investigated. More importantly, the behaviour of the established model needs to be analysed and evaluated. These important issues will be addressed in Chapter 6.

Finally, the mathematical expression of the total profit is a mixed integer nonlinear programming (MINLP) involving a combinatorial variable Z. As has been discussed in Chapter 3, such a problem requires an effective and efficient optimisation tool to find the optimal decision variables. A novel variant of genetic-algorithm based approach called the biased-random key genetic algorithms (BRKGAs) is proposed in this research. The detailed explanation of the algorithm is presented in Chapter 5.

Chapter 5

A BRKGA for optimising the integrated production-inventory model for food products

5.1 Introduction

In this Chapter, an optimisation tool to find the solution of the problems in Chapter 4 is developed. In Chapter 3 it is concluded that the biased random keys genetic algorithms (BRKGAs) is a more suitable tool to optimise the proposed model. Before designing the BRKGAs, a literature survey of the applications that used BRKGAs is conducted to see how far this tool has been applied and what else can be done to improve the performance of the algorithm. The output of this chapter is a BRKGA design with its best parameter setting that will be used in Chapter 6 to evaluate the performance of the developed model.

The remaining section of this chapter is organised as follows. A brief introduction to BRKGAs is presented in Section 5.2 while the review of its current applications to solve a range of problems, and the modifications in an attempt to improve its performance is discussed in Section 5.3. Further, the development of the framework for the BRKGA proposed in this research is thoroughly discussed in Section 5.4 while the parameter setting as well as the numerical test is presented in Section 5.5. Based on the numerical test result, the performance of the proposed algorithm is analysed in Section 5.6 and finally Section 5.7 summarises this chapter.

5.2 Biased-random key genetic algorithms (BRKGAs): An introduction

Before starting the discussion on the biased random key genetic algorithms (BRKGAs), it is important to firstly introduce the concept of GAs with random numbers or random key genetic algorithms (RKGAs) introduced by Bean (1994), as BRKGAs are actually a variant of RKGAs. Bean (1994) proposed a chromosomal encoding using a vector of random keys of real numbers generated randomly in the interval [0, 1) to representing a solution. The solution to the problem is obtained by decoding the chromosome using a deterministic procedure.

In comparison to the standard representations, the random keys encoding has an advantage in terms of its flexibility as such a representation is not problem-specific. Apart from that, the offspring produced is always feasible without requiring further treatments/refinements. As standard genetic algorithms, RKGAs involve a population consisting p real n-vector of random keys that evolves over generations or iterations. In generation K, each chromosome in the population is decoded into a solution and then its fitness value is computed. After that, the solutions are then sorted in descending order based on the fitness value and partitioned into two groups of solutions, namely a smaller group of p_e elite solutions with best fitness values, and the remaining individuals of p-p_e non-elite solutions with less fitness values, as shown in Figure 5.1.

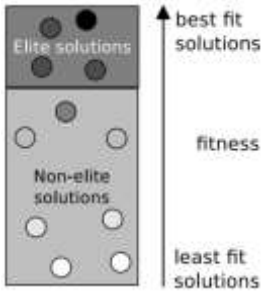


Figure 5.1 The partition of the population according to the fitness values of the solutions /individuals (Gonçalves, Resende & Toso 2014)

The number of individuals in each generation is maintained. The population of the generation $K + 1$ is created by copying all p_e elite solutions (in standard genetic algorithms it is also known as elitism strategy), and generating randomly new p_m individuals or mutant solutions (it is also referred to as migration strategy to avoid local optima), as illustrated in Figure 5.2, while the remaining individuals are formed using crossover operator.

The parameterised uniform crossover proposed by Spears and De Jong (1991) is applied to mate parents consisting of two chromosomes producing one offspring. Figure 5.3 illustrates the process of mating two random key vectors with four genes, each representing two chromosomes of parents (Chromosome 1 and Chromosome 2). A random number associated with each gene in a chromosome is generated. If the random number is less than a predetermined crossover probability or ρ_e (in this example $\rho_e = 0.7$), the corresponding gene in Chromosome 1 is inherited to the offspring chromosome, otherwise it is taken from Chromosome 2. From the example given in Figure 5.3, only random a number for the 2nd gene having value above the threshold probability

(0.89 > 0.7), thus the value of the corresponding gene in Chromosome 2 (0.15), is transferred to the offspring chromosome, while the remaining genes are obtained from Chromosome 1.

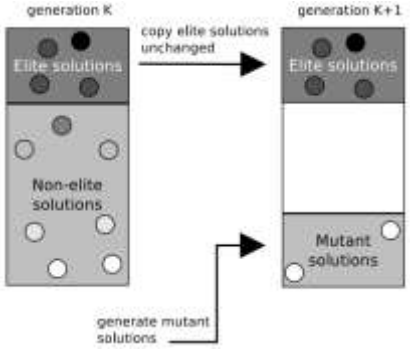


Figure 5.2 Elitism strategy and mutant generation for generation *K* + 1 (Gonçalves, Resende & Toso 2014)

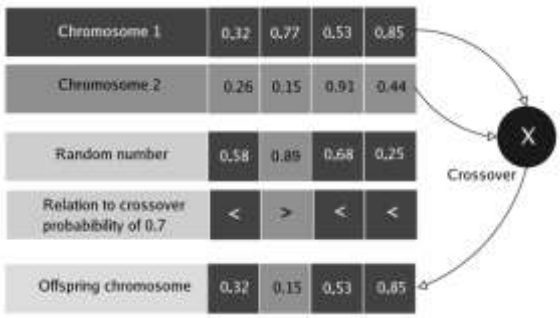


Figure 5.3 Parameterised uniform crossover (Gonçalves & Resende 2011c)

It is important to note that the RKGAs and BRKGAs differ in the method of choosing the parent for crossover operation. In the former, two parents are selected randomly from all individuals in the entire population *K*. Therefore, it is possible to obtain two individuals from one group solution, either non-elite solutions or elite solutions. In the latter, each individual of the parents must be picked randomly from different groups of solutions. Figure 5.4 illustrates these two selection strategies.

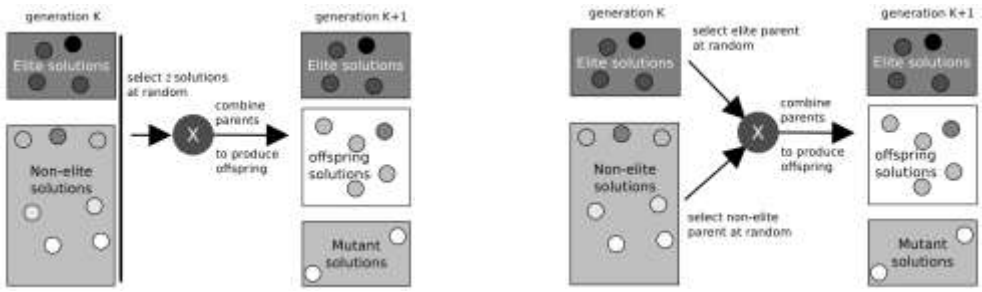


Figure 5.4 Mechanism of selecting parents in RKGAs (a) and BRKGAs (b), adapted from Gonçalves, Resende and Toso (2014)

The process of generating new population or evolution process, continues until it meets the stopping rule criteria, e.g. a maximum number of iteration is satisfied (Figure 5.5). Since RKGAs apply a vector of random keys, the representation is problem independent, thus, only the decoding process is problem dependent. As a result, the algorithms have more flexibility to any problem structure. In addition, the result of the mating process always returns a feasible solution. These become the major contributions of RKGAs over the standard genetic algorithms (GAs).

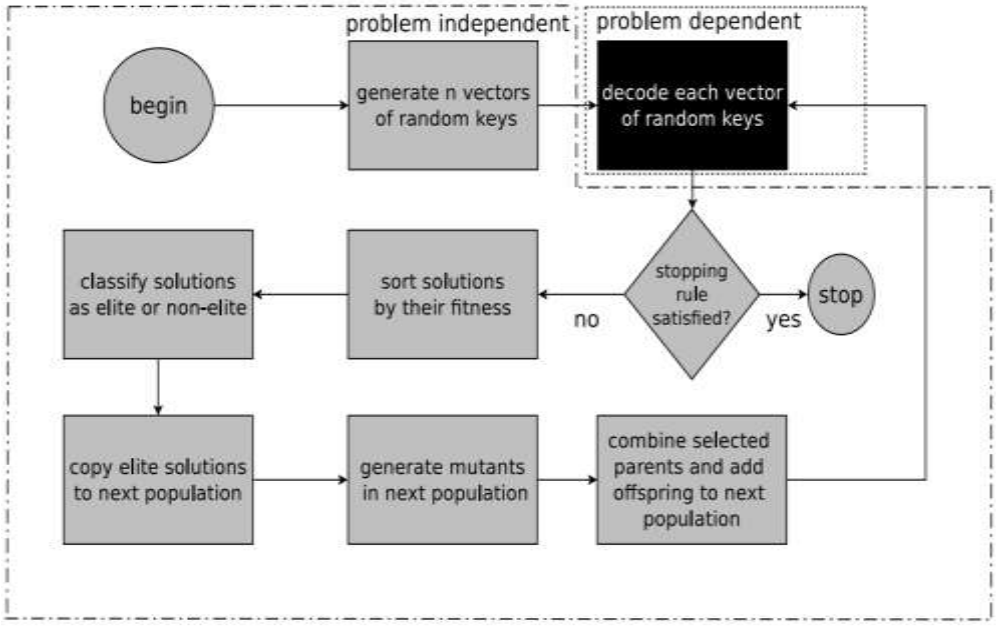


Figure 5.5 The cycle of evolution process in RKGAs/BRKGAs (Gonçalves & Resende 2011c)

As discussed above, the only difference between BRKGAs and RKGAs is at the crossover phase, namely in the procedure of selecting the parents to be mated to produce a new individual. An extensive numerical test for a number of problems conducted by Gonçalves, Resende and Toso (2012); Gonçalves, Resende and Toso (2014), showed that this slight modification could improve the performance of RKGAs. Genetic algorithms with random keys including BRKGAs involve parameters to be carefully set, namely, the number of genes in a chromosome (x), the number of individuals in the population (p), the number of elite solutions (p_e) and mutant solutions (p_m), and the inheritance probability of genes (ρ_e). The best setting of these parameters should be obtained from experiments. Gonçalves and Resende (2011c) proposed recommended parameter value settings for guidance as presented in Table 5.1.

Table 5.1 Recommended parameter value settings (Gonçalves & Resende 2011c)

Parameter	Description	Recommended value
p	size of population	$p = ax$, where $1 \leq a \in \mathbb{R}$ is a constant and x is the length of the chromosome
p_e	size of elite population	$0.10p \leq p_e \leq 0.25p$
p_m	size of mutant population	$0.10p \leq p_m \leq 0.30p$
ρ_e	elite allele inheritance probability	$0.5 \leq \rho_e \leq 0.8$

5.3 Biased-random key genetic algorithms for solving optimisation problems

Since being introduced, BRKGAs have been attracting researchers to explore its applications for dealing with numerous optimisation problems due to its advantages over the standard GAs. The section discusses this matter in detail.

5.3.1 Telecommunication problems

Numerous optimisation problems occur in telecommunications. One of them is how the traffic on the internet through the autonomous systems (AS) can be managed efficiently to maximise the utilisation of resources. Open Shortest Path First (OSPF) is one protocol commonly used for routing the traffic. The main problem is how to give weight to each link or route such that the network cost can be minimised. Ericsson, Resende and Pardalos (2002) used the BRKGA with integer number chromosome representation for setting the weight of OSPF problem to improve congestions of network traffic. Buriol et al. (2005) applied the BRKGA combined with a local search for similar problems to minimise the network cost. Reis et al. (2011) optimised the proper weights setting of two routing protocols, OSPF and Distributed Exponential-Weighted Flow Splitting (DEFT) using the BRKGA with a local search procedure. They confirm that the DEFT routing yields a less congestion compared to the OSPF routing.

Another important problem to address in telecommunications is related to the design of survivable internet protocol (IP) networks. Consider a network with given nodes, estimated traffic between nodes, a set of arcs connecting the nodes, a set of fibre link types with its capacity and cost, and a set of failure configuration. Then, the problem can be defined as how to determine the fibre units installed at each link that the traffic can be routed to the network under the no-failure and all-failure modes at a minimum cost. Buriol, Resende and Thorup (2007) solved this problem using BRKGA. The traffic is routed using OSPF with a single type of link. Ruiz et al. (2011) studied the survivable

IP/multi-protocol label switching (MPLS) over wavelength switched optical network (WSON). The objective is to design the network to meet the traffic such that the capital expenditure is minimised. The BRKGA is applied to solve the problem.

Noronha, Resende and Ribeiro (2011) discussed the BRKGA for solving routing and wavelength assignment (RWA) problems to minimise the total number of the wavelength used. This problem is also referred to as the path colouring problem. A more detailed survey of studies on the applications of the BRKGA for solving problems in the area of telecommunications up to the year 2012 can be found in Resende (2012).

More recently, Velasco et al. (2013) dealt with designing a national network by decomposing the problem into two sub-problems, namely the area partitioning (ARPA) and network design (ND) problems. The objective is to minimise the capital expenditure (CAPEX). The first sub-problem, ARPA is concerned with finding the optimal set of areas (each of which comprises a subset of locations) to maximise the total aggregated traffic to be conveyed by the core optical network. The second step, the IP/multiprotocol label switching (IP/MPLS) and core optical networks are designed given their particular traffic matrices to minimise the CAPEX. The problems are NP-hard and formulated by using Mixed-Integer Linear Programming. The BRKGA is devised to solve the problems.

Morán-Mirabal, González-Velarde and Resende (2013) adopted the BRKGA to provide automatic tuning of greedy randomised adaptive search procedure (GRASP) with path-relinking (PR). A similar method is used in Morán-Mirabal et al. (2013) to solve handover minimisation in mobility networks to minimise the dropped connections. Its application includes the controller that manages the handover of the signal of a mobile device from one tower to another tower.

Pedrola et al. (2013) were concerned with regenerator placement and dimensioning (RPD) problems in sub-wavelength switching optical networks to minimise the total number of regenerators that have to be placed on the network. The BRKGA is combined with the local search variable neighbourhood descent (VND) and path-relinking (PR). Duarte et al. (2014) applied the BRKGA for dealing with regenerator location problem (RLP) in optical telecommunication networks. It is concerned with determining paths connecting available nodes and locating regenerators for a given and undirected graph so that the signal can travel within an allowed maximum length.

5.3.2 Power plant management

Roque, Fontes and Fontes (2011) dealt with the application of BRKGA for optimising unit commitment (UC) problem which plays a significant role in planning and operating power systems. It involves the scheduling of the turn-off and turn-on of the generating units as well as the dispatch of each line unit. The decision variables include binary variables representing the state of each unit and floating numbers indicating the amount of energy produced unit per unit time. The objective is to minimise fuel costs and start-up costs. Roque, Fontes and Fontes (2014) proposed a hybrid BRKGA (HBRKGA) for solving the same problem. The decoding of the BRKGA in Roque, Fontes and Fontes (2011) is improved and incorporated with repaired mechanisms to make the algorithm applicable to work on enclosed space (consisting of only feasible solutions) and to avoid the problem of choosing penalties. This algorithm is also combined with a local search procedure.

5.3.3 Container loading problem

A container loading problem is defined by how to place a given subset of rectangular boxes in a three-dimensional container. Gonçalves and Resende (2012) dealt with this problem considering that the container utilisation is high. The BRKGA is used for setting the order of boxes to be placed in the container and then a heuristic procedure is used to determine the placement of boxes in the container. The performance of the solution is determined by the total volume packed in the container. Arefi and Rezaei (2015) extended this BRKGA by adopting the population extinction over generations from 500 to 50. The experiment shows that this extension potentially gives a better result. Further, Kirke, While and Kendall (2013) revisited Gonçalves and Resende (2012) by accommodating multiple objectives for a container loading problem, namely to maximise the volume utilisation and to maximise the accessibility of the packed objects. A similar study is conducted by Zheng, Chien and Gen (2014) where a multi-population BRKGA is utilised for solving a 3D container loading problem with multiple objectives, namely the space utilisation of the container and the total value of boxes.

Gonçalves and Resende (2013) addressed 2D and 3D bin packing problems by using the BRKGA hybridised with a placement procedure. The chromosome encodes the box packing sequence and the vector of box orientations used to pack the boxes into the bin. The approach uses a maximal-space representation to manage the free space in the bin.

The parallel implementation is used for the fitness evaluation. Thomas and Chaudhari (2014) adopted the maximal preservative crossover (MPX) in the BRKGA to solve 2D strip packing problem (2D-SPP). It deals with arranging a set of rectangular blocks in a container with a fixed width and infinite height such that the highest point of the arrangement is minimised.

5.3.4 Assembly line balancing problem

The assembly line balancing problem is concerned with assigning the assembly line workers to workstations to distribute the workload over the stations. Gonçalves and De Almeida (2002) addressed a simple assembly line balancing problem. Given the cycle time *C*, they aimed to minimise the number of workstations required. The BRKGA is used to provide a set of priorities of operations represented by the chromosome in a population. It evolves over generations. Using a heuristic station-oriented procedure, the operations are then assigned to workstations and finally a local improvement procedure was applied to improve the obtained solution.

Moreira et al. (2012) concentrated on an assembly line worker assignment and balancing problem. Given a fixed number of workstations, tasks and workers are assigned to the workstation (without violating the constraints) so that the cycle time is minimised. The BRKGA is utilised for providing the priorities of tasks and workers. In addition, a local search is applied by shifting a task from one station to another and swapping two tasks between different stations without violating the constraints. Araújo, Costa and Miralles (2013) used the BRKGA to deal with the worker assignment and balancing problem at the parallel assembly line. The objective is to minimise the combined cycle time by selecting the workers and determining the configuration of the parallel lines.

5.3.5 Job scheduling problem

The job scheduling problem is concerned with sequencing the jobs on every machine to satisfy certain objectives. Gonçalves, de Magalhães Mendes and Resende (2005) applied the BRKGA for scheduling a job shop with n-job m-machine to minimise the make-span. The algorithm is used to provide a priority rule of the sequence and then combined with a local search procedure by swapping two operations at the critical path operations. Gonçalves and Resende (2014) further improved the algorithm by combining the BRKGA with a search procedure extending two-job graphical approach by Akers (1956).

The decoder consists of three phases: (i) produces an active schedule from a given chromosome, (ii) attempts to improve the schedule with local searches based on an extension of the graphical method and the well-known tabu search based local improvement procedure, (iii) adjusts the chromosome to reflect the obtained solution.

Valente, Gonçalves and Alves (2006) used the BRKGA to solve an early/tardy scheduling problem where the algorithm was adopted to establish a possible order of the schedule while a local search procedure (job interchange) was used to improve the solution. The machine is only idle where no available jobs are waiting. Later, Valente and Gonçalves (2009) considered a single machine scheduling problem with linear earliness and quadratic tardiness penalty costs and no machine idle time. Various BRKGAs are adopted to minimise the cost, including the genuine BRKGA, the BRKGA with inserting non-random chromosome in the initial population and the BRKGA with a local improvement procedure to improve the obtained sequence.

5.3.6 Project scheduling problem

Gonçalves, Mendes and Resende (2008) applied the BRKGA to solve multi-project scheduling problems with resource and precedence constraints to maximise the performance measure which simultaneously incorporates the criteria of tardiness, earliness and flow time. The chromosome is used to represent the priorities of activities, delay times and release dates, and then the decoder is responsible for constructing a parameterised active schedule from the chromosome.

Gonçalves, Resende and Mendes (2011) dealt with the application of BRKGA to solve a resource constrained project scheduling problem. The problem is concerned with scheduling activities taking into account the resource and precedence constraints that minimise the make-span. The first step is to chromosome encode the priorities of activities, and then an active schedule can be constructed using a serial schedule generation scheme (SGS). Finally, a forward-backward improvement is proposed. A chromosome is adjusted according to a final schedule obtained from these processes.

5.3.7 Traffic congestion problem

The traffic congestion problem deals with efforts or pricing strategies to streamline traffic on the road network. Buriol et al. (2010) addressed this problem by determining the location of toll booths and the corresponding toll tariff to minimise the average trip

duration of the system. The BRKGAs, both with and without local improvement procedure, are applied to optimise the solution. Stefanello et al. (2013) implemented the BRKGA for dealing with how to assign tolls to streets and roads. The objective is to induce drivers to take alternative routes thus the traffic across the road networks can be distributed. This problem is also known as toll booth problem. More recently, Stefanello, Buriol and Resende (2013) dealt with a preliminary study on implementing the BRKGA for network pricing problem. It is concerned with defining tariffs for a given subset of the arcs, maximising revenue when users take the least cost path.

5.3.8 Assignment problem

Festa et al. (2010) used two phased hybrid heuristic to solve a generalised quadratic assignment problem. The first phase is a turning phase where the BRKGA is used to explore the GRASP+PR parameter space by running for Y1 generations while the second phase using the parameter obtained the GRASP+PR is run for Y2 generations to seek the optimal assignment of facilities to locations.

Lalla-Ruiz et al. (2014) developed the BRKGA for dealing with the tactical berth allocation problem (TBAP). The problem is concerned with allocating ships to berthing positions and assigning quay crane profiles to them to minimise housekeeping costs and to maximise the total value of the quay crane profiles assigned to the ships.

5.3.9 Layout problem

Gonçalves (2007) studies the placement of a fixed set of small rectangles on to a larger rectangle to minimise the amount of trim loss (maximise the material utilisation). The BRKGA combined with a placement strategy and is applied to solve the problem. More recently, Gonçalves and Resende (2011a) addressed a placement problem of a fixed set of small rectangles on to a larger rectangle to maximise the value of the rectangles packed. The solution is obtained using the BRKGA combined with a new placement strategy. The BRKGA adopts a multi-population strategy. In comparison to other heuristics, including population heuristics, GA, GRASP and tabu, for numerous problems, the proposed approach produces a better solution.

Gonçalves, Resende and Costa (2014) presented the implementation of the BRKGA combined with a local procedure for the minimisation of open stacks problem (MOSP). It deals with cutting smaller pieces of objects from larger pieces to minimise waste or

maximise profit and minimise the open stack on the floor through the selection of excellent cutting patterns.

Recently, Gonçalves and Resende (2015) addressed the BRKGA to solve an unequal area facility layout problem where a set of rectangular facilities with given area requirements has to be placed, without overlapping, on a rectangular floor space. The objective is to find the location and dimension of the facilities such that the sum of the weighted distances between centroids of the facilities is minimised. The decoder is composed of five phases: (a) facility placement sequence decoder, (b) facility aspect ratio decoder, (c) position of the first facility decoder, (d) placement strategy and (e) fitness evaluation.

5.3.10 Network optimisation problem

A number of researchers have applied the BRKGA to solve network optimisation problems. Fontes and Gonçalves (2007) addressed the problem of a single-source un-capacitated minimum cost network flow with general concave cost functions. The BRKGA is combined with a local search procedure using small perturbations. The algorithm is used to provide node priorities.

Resende et al. (2012) used the BRKGA with multiple populations to solve a set covering problem known as the Steiner triple covering problem while Hokama et al. (n.d.) applied the BRKGA to solve Stochastic Steiner Tree Problem. Andrade et al. (2015) designed the wireless backhaul network, a variant of the Steiner tree and Facility location problem and optimised the problem using the BRKGA. The objective is to establish routing trees that give the best trade-off between the obtained revenue from the routed traffic and the cost of the network.

Andrade, Miyazawa and Resende (2013) applied the BRKGA with a local search procedure for solving the *k*-interconnected multi-depot multi-travelling salesman problem. It can be defined by selecting *k* terminals from a given graph and then connecting these terminals with a cycle (inner cycle). For each terminal, another cycle is built covering the remaining nodes in the graphs. The objective is to minimise the sum of edge weights of the inner and outer cycles. In a similar area, Morán-Mirabal, González-Velarde and Resende (2014) introduced a variant of TSP known as family travelling salesman problem (TSP) where subsets of nodes have to be visited for each node cluster in the graph. The objective is to minimise the distance travelled. In comparison to GRASP

with evolutionary PR (GRASP+EvPR), the proposed BRKGA returns better results for small problems and equal or better solutions for large scale problems but in less time.

Coco et al. (2014) proposed exact algorithm and meta-heuristics based on BRKGAs to solve a min-max relative regret shortest path problem. Basically, it is a generalisation of the shortest path problem by addressing the uncertain arc cost (represented in an interval value). The problem is formulated in integer linear programming. Fontes and Gonçalves (2013) applied the BRKGA using a multi-population strategy and combined with a local search to deal with a communication design problem. The objective is to minimise the cost of spanning tree connecting nodes of a given network. Lately, Ruiz et al. (2015) addressed a capacitated minimum spanning tree (MST). This type of problem is common in telecommunication network design, distribution and logistics. The BRKGA is combined with local search procedures including swapping two vertices, reassigning vertices, reassigning sub-trees and merging sub-trees.

5.3.11 Continuous global optimisation problem

Since its introduction, the BRKGA is mostly used to solve discrete combinatorial optimisation problems. The continuous global optimisation problem is defined by seeking the decision variable x^* such that $f(x^*) \leq f(x)$ where x is a continuous real number. Silva et al. (2012) addressed the BRKGA to solve global optimisation subject to box constraints. A problem from robot kinematics is used to measure the performance of the proposed algorithm. It is shown that the results indicate a potential use of BRKGA for addressing global optimisation problems. More recently, this research is extended by incorporating nonlinear constraints (Silva et al. 2013a) and linear constraints (Silva et al. 2013b). The BRKGA is hybridised with a local improvement procedure. Silva, Resende and Pardalos (2014) applied the BRKGA with a local improvement procedure to find all roots of seven nonlinear equations, namely Ferraris and Tronconi problem, Robot kinematics problem, nonIsothermal CSTR problem, Automotive steering problem, Math-14706 problem, Brown's problem, and Himmelblau problem.

5.3.12 Other problems

BRKGA has also been used to solve other problems, and this section will briefly introduce some of them.

Satellite scheduling

Tangpattanakul, Jozefowiez and Lopez (2012) and Tangpattanakul, Jozefowiez and Lopez (2015) dealt with selecting and scheduling a satellite observing earth in response to the request of photographs from users managed by the ground centre. The objective is to maximise the total profit and to minimise the difference in profit between users for the fairness of the resource sharing. In these studies, the BRKGA is used to address a multiple objectives optimisation. Hybrid decoding is proposed, i.e. one chromosome encodes two solutions.

Lot sizing problem

Chan et al. (2013) and Chan et al. (2015) dealt with multi-item capacitated lot sizing problem (MICLSP) incorporating uncertain demand using the BRKGA. The objective is to minimise the total cost comprising the production, inventory, setup and penalty costs due to lost sale and insufficient resource capacity.

Data clustering

Festa (2013) used the BRKGA for clustering data. It is shown that the BRKGA is a well-suited approach for data clustering. Andrade et al. (2014) devised the BRKGA to solve overlapping correlation clustering (OCC) problem. Unlike conventional clustering where each object belongs to a single cluster, in OCC, an object might belong to two or more clusters.

Application Program Interface

Silva, Resende and Pardalos (2013) presented the coding for the BRKGA library using Python/C++ for bound constrained global optimisation while Toso and Resende (2015) developed the BRKGA application program interface (API) using C++.

Vehicle routing problem

Grasas et al. (2014) applied the BRKGA to solve logistics of blood sample collection at two clinical laboratories in Catalonia, Spain. The blood sample collection problem (BSCP) is to find the routes to collect blood samples from different locations and to deliver them to a clinical laboratory for analysis. It is a variant of vehicle routing problem (VRP) with additional constraints: routes are open and the time per route is constrained. Each vehicle is based at a single depot to meet demands for a set of geographically

dispersed customers. The problem is how to find the best sequence of the route so that all customers are served and the total distance travelled by all vehicles is minimised.

Cloud resource management problem

Heilig, Lalla-Ruiz and Voß (2015) optimised a cloud resource management problem (CRMP) from a consumer's perspective using the BRKGA. It involves a consumer selecting an appropriate configuration of cloud resources offered by multiple cloud providers with various prices and features. The objective is to minimise the costs and the total execution time.

Cellular manufacturing system problem

Gonçalves and Resende (2004) applied the BRKGA to form machine cells and production families in cellular manufacturing. The algorithm is used to establish sets of machine cells and then the solution obtained is improved by using a local search heuristic. The objective is to minimise the inter-cellular transportation and maximise utilisation of the machines within a cell.

5.3.13 Remarks on the applications and modifications of the BRKGA

As discussed in the previous subsections, BRKGAs have been devised to solve optimisation problems in various areas. The BRKGAs have been used to solve not only single objective problems but also problems with multiple objectives, such as those found in Tangpattanakul, Jozefowiez and Lopez (2012), Kirke, While and Kendall (2013), Zheng, Chien and Gen (2014), Heilig, Lalla-Ruiz and Voß (2015) and Tangpattanakul, Jozefowiez and Lopez (2015).

In the last five years, studies on the optimisation using the BRKGA algorithm have increased significantly with some modifications to further enhance its performance as summarised in Table 5.2. The algorithms have been typically hybridised with local procedures which are problem-dependent. Regarding the population, a number of studies consider the BRKGAs with a non-random initial population instead of generating all chromosomes randomly, i.e. inserting some chromosomes that are constructed by using certain procedures, such as found in Valente, Gonçalves and Alves (2006), Valente and Gonçalves (2009), and Gonçalves and Resende (2011a). Multiple population strategies where two or more populations are run simultaneously over generations and then

information exchange is performed every certain iteration by swapping some chromosomes between populations are presented in Gonçalves and Resende (2011a), Gonçalves and Resende (2012), Fontes and Gonçalves (2013), Morán-Mirabal et al. (2013) and Zheng, Chien and Gen (2014). In addition, instead of keeping the number of population constant, Arefi and Rezaei (2015) consider a decreasing number of population over the generations. To avoid local optima traps, Gonçalves, Resende and Toso (2014) reset the population every 200 generations.

Table 5.2 Summary of settings and modifications to the BRKGAs

No	Authors	Hybridised/ modifications	Coded	Parameters	Remarks
1.	Gonçalves and De Almeida (2002)	Local search procedure	Visual Basic 6.0	$p=x$| p_e= 0.15p | p_m= 0.2p | ρ_e= 0.7	
2.	Gonçalves and Resende (2004)	Local search procedure	Vis. Objects 2.0b-1	p= 3x| p_e= 0.2p| p_m= 0.3p| ρ_e= 0.7	
3.	Buriol et al. (2005), Buriol, Resende and Thorup (2007), Buriol et al. (2010)	Local search procedure	C	p= 50| p_e= 0.25p| p_m= 0.05p|ρ_e= 0.7	
4.	Gonçalves, de Magalhães Mendes and Resende (2005)	Local search procedure	Visual Basic 6.0	$p=x$| p_e= 0.1p| p_m= 0.2p| ρ_e= 0.7	
5.	Valente, Gonçalves and Alves (2006)	Local search procedure	N/A	p= 2x| p_e= 0.1p| p_m= 0.2p| ρ_e= 0.7	Two non-random initial populations
6.	Fontes and Gonçalves (2007)	Local search procedure	N/A	p= 10x| p_e= 0.15p| p_m= 0.15p| ρ_e= 0.7	
7.	Gonçalves (2007)	Local search procedure	Visual Basic 6.0	p= 10x| p_e= 0.15p| p_m= 0.15p| ρ_e= 0.7	
8.	Gonçalves, Mendes and Resende (2008)	-	Visual Basic 6.0	p= min(0.2*no of activities, 250) |p_e= 0.05p| p_m= 0.25p| ρ_e= 0.7	
9.	Valente and Gonçalves (2009)	Local search procedure	Visual C++ 6.0	p= (1, 2 & 3)x|p_e= 0.15p| p_m= 0.15p| ρ_e= 0.7	Three non-random initial populations
10.	Festa et al. (2010)	-	Java	$p=15$| p_e= 0.3p| p_m= 0.2p| ρ_e= 0.7	
11.	Gonçalves and Resende (2011b)	A local search	C++	$p=max$(100, 0.5*no of operations)|p_e= 10| p_m= 10| ρ_e= 0.85	
12.	Gonçalves and Resende (2011a)	Triple population; A placement procedure	C++	p= 15*no rectangles| p_e= 0.25p|p_m= 0.15p| ρ_e= 0.7	Four non-random initial populations; Exchange two best chroms. every 15 gens; Parallel implementation

13.	Noronha, Resende and Ribeiro (2011)	-	C++	$p=x$ | p_e= 0.25p | p_m= 0.05p | ρ_e= 0.7	
14.	Reis et al. (2011)	A local search	N/A	p=50| p_e= 0.25p | p_m= 0.05p | ρ_e= 0.7	
15.	Roque, Fontes and Fontes (2011)	-	MATLAB	p=*min*(2x, 60)| p_e= 0.2p | p_m= 0.25p | ρ_e= 0.7	
16.	Ruiz et al. (2011)	-	N/A	p=*min*(x, 50)| p_e= 0.2p | p_m= 0.2p | ρ_e= 0.7	
17.	Gonçalves and Resende (2012)	Triple population; A placement procedure	C++	p=20**no of rectangles* | p_e= 0.15p | p_m= 0.15p | ρ_e= 0.7	Exchange two best chroms. every 15 gens; Parallel implementation
18.	Moreira et al. (2012)	Local search procedure	C	*p=100* | p_e= ?| p_m= ? | ρ_e= 0.5	
19.	Resende et al. (2012)	-	C++	p= 10x| p_e= 0.15p | p_m= 0.55p | ρ_e= 0.6	Parallel implementation
20.	(Silva et al. 2012)	-	C++	p= 10x| p_e= 0.2p | p_m= 0.1p | ρ_e= 0.7	
21.	Tangpattanakul, Jozefowiez and Lopez (2012)	two selection methods for p_e	C++	p=x, 2x | p_e= 0.15p | p_m= 0.3p | ρ_e= 0.6	Multiple objectives
22.	Andrade, Miyazawa and Resende (2013)	Local search procedure	C++	p=*min*(10x, 100)| p_e= 0.3p | p_m= 0.15p ρ_e= 0.7	
23.	Araújo, Costa and Miralles (2013)	-	C++	p=100|p_e= 0.2p | p_m= 0.1p | ρ_e= 0.7	
24.	Chan et al. (2013)	-	MATLAB	p= 50| p_e= 0.3p | p_m= ?| ρ_e= 0.7	
25.	Festa (2013)	-	Java	p= 30x| p_e= 0.1p | p_m= 0.15p | ρ_e= 0.7	
26.	Fontes and Gonçalves (2013)	Triple-population + Local search	C++	p= 15* *no of vertices* | p_e= 0.25p | p_m= 0.15p | ρ_e= 0.7	Exchanging two best solutions every 15 gens.
27.	Gonçalves and Resende (2013)	Placement strategy	C++	p= 30x| p_e= 0.1p | p_m= 0.15p | ρ_e= 0.7	Parallel core implementation
28.	Kirke, While and Kendall (2013)	?	Java	?	Multiple objectives
29.	Morán-Mirabal et al. (2013)	Triple-population + Population reset every 500 gens	C++	p= 1000| p_e= 0.3p | p_m= 0.2p | ρ_e= 0.7	Exchanging two best solutions every 500 gens
30.	Pedrola et al. (2013)	Local searches	Java SE	p= 20| p_e= 0.2p | p_m= 0.2p | ρ_e= 0.7	Path relinking + variable neighbourhood descent
31.	Silva et al. (2013b)	Local search procedure	C++	p= 100| p_e= 0.2p | p_m= 0.1p | ρ_e= 0.7	
32.	Silva et al. (2013a)	Local search procedure	C++	p= 100| p_e= 0.2p | p_m= 0.1p | ρ_e= 0.7	
33.	Stefanello et al. (2013)	Local search procedure	C	p= 50| p_e= 0.25p | p_m= 0.05p | ρ_e= 0.7	
34.	Velasco et al. (2013)	N/A	N/A	N/A	

35.	Andrade et al. (2014)	Local search procedure	C++	p= 500| p_e= 0.3p | p_m= 0.15p | ρ_e= 0.7	
36.	Coco et al. (2014)	-	C++	p= 100| p_e= 0.1p*; 0.2*p | p_m= 0.2p*; 0.1*p | ρ_e= 0.7	
37.	Duarte et al. (2014)	-	Java SE 6	p= 100| p_e= 0.15p | p_m= 0.*1*p | ρ_e= 0.7	
38.	Gonçalves and Resende (2014)	Local search procedure	C++	p=*max*(100, 0.5*jobs*machines)| p_e= 10 p_m= 10| ρ_e= 0.85	
39.	Gonçalves, Resende and Costa (2014)	Local search procedure	C++	p= 10x| p_e=*min*(0.25p, 50)| p_m= 0.2p| ρ_e= 0.7	
40.	Gonçalves, Resende and Toso (2014)	Restarting population every 200 gens.	C++	*Problem I, II, III & IV* p=x;10x; 10x; 10x; | p_e= 0.2p; 0.15p; 0.2p; 0.2p; | p_m= 0.15p; 0.55p; 0.15p; | 0.15p ρ_e= 0.7; 0.65; 0.7; 0.7;	
41.	Grasas et al. (2014)	-	C	N/A	
42.	Lalla-Ruiz et al. (2014)	-	ANSI C	p= 100 | p_e= 7| p_m= 10| ρ_e= 0.7	
43.	Lucena et al. (2014)	Gender chroms. + Triple parents	C++	p= 10x| p_e= 1.5x| p_m= 5.5x| ρ_e= 0.6	
44.	Morán‐Mirabal, González‐Velarde and Resende (2014)	Local search	C++	p= 1000; 800; 600; 400| p_e= 0.15p | p_m= 0.2p | ρ_e= 0.7	
45.	Roque, Fontes and Fontes (2014)	Local search	MATLAB	p= 2x| p_e= 0.2p | p_m= 0.2p | ρ_e= 0.7	
46.	Silva, Resende and Pardalos (2014)	Local improvement	C++	p= 100| p_e= 0.2p | p_m= 0.1p | ρ_e= 0.7	
47.	Thomas and Chaudhari (2014)	-	N/A	p= 10| p_e= 0.125p | p_m= 0.3p	Two point maximal preservative crossover (MPX)
48.	Zheng, Chien and Gen (2014)	Triple population + fuzzy logics	N/A	p= 100 | p_e= 0.3p | p_m= 0.5p | ρ_e= 0.7	Exchange 3 best chroms. every 20 gens; multiple objectives
49.	Andrade et al. (2015)	-	C++	p= 500 |p_e= 0.3p | p_m= 0.15p | ρ_e= 0.7	
50	Arefi and Rezaei (2015)	Population decrease over gens.	MATLAB	p= 400-->50 | p_e= 0.2-0.25-0.3-0.25-0.2(increasing then decreasing) | p_m= 0.002	Integer-decimal encoding; Placement strategy
51.	Chan et al. (2015)	-	MATLAB	p= 100 | p_e= 15 | p_m= 10 | ρ_e= 0.7	2D chromosome
52.	Gonçalves and Resende (2015)	-	C++	p= 100x | p_e=*min*(0.25p, 50) | p_m= 0.25p | ρ_e= 0.7	Placement strategy
53.	Heilig, Lalla-Ruiz and Voß (2015)	-	Java	p= 100 | p_e= 10 | p_m= 10 | ρ_e= 0.8	Multiple objectives

54.	Ruiz et al. (2015)	Local search procedure	C++	p= 100 | p_e= 0.25p | p_m= 0.1p | ρ_e= 0.65	
55.	Tangpattanakul, Jozefowiez and Lopez (2015)	Three selection methods for p_e	C++	p=x, 2x | p_e= 0.15p | p_m= 0.3p | ρ_e= 0.6	Multiple objectives; two decoding methods

Apart from the modification regarding the population, a number of studies have modified the crossover operation of the genuine BRKGAs. Instead of pairing two-chromosome parents, in the crossover operation multiple parents mating is proposed in Gonçalves and Resende (2012), Fontes and Gonçalves (2013), Morán-Mirabal et al. (2013), Lucena et al. (2014) and Zheng, Chien and Gen (2014). In addition, Thomas and Chaudhari (2014) consider a two-point maximal preservative crossover in contrast to the original approach which is based on the parameterised uniform crossover. Lucena et al. (2014) attempt to classify the gender of chromosomes to be mated to improve the result although according to their experiment this classification gives no advantage.

It is worth noting that the algorithms are mostly coded using C++. Other languages that are used include MATLAB, Java, C, Visual Basic and Visual Objects as can be seen from Table 5.2. In addition, to speed up the computation the BRKGAs are implemented in parallel using multi cores processor as found in Gonçalves and Resende (2011a), Gonçalves and Resende (2012), Resende et al. (2012) and Gonçalves and Resende (2013).

In terms of the optimisation area, the majority studies focus on discrete combinatorial optimisation problems. Less attention has been given to addressing global optimisation problems utilising this algorithm. These limited studies include Silva et al. (2012), Silva et al. (2013a); Silva et al. (2013b) and Silva, Resende and Pardalos (2014). Further, Silva, Resende and Pardalos (2013) developed the BRKGA library for global optimisation with bounded constraints using Python. Studies in Chan et al. (2013) and Chan et al. (2015) involve a binary and a number of continuous decision variables. The chromosome is however only used to represent the binary decision variable while the remaining decision variables are calculated by using the obtained binary values. It is worth noting that the problem of the integrated production-inventory policy addressed in this research has involved continuous and discrete combinatorial variables simultaneously as discussed in Chapter 4. To the best of knowledge, no study found in literature which deals with this problem utilises the BRKGAs. Therefore, the utilisation of the BRKGAs in this research would be expected to further enrich the existing applications of the algorithm, in terms

of (i) diverse application areas, i.e. in the area of integrated production-inventory policy; and (ii) different types of decision variables involved simultaneously, i.e. continuous variables and discrete combinatorial variables.

5.4 BRKGA for integrated production and inventory policy for perishable items

From the mathematical model established in Chapter 4, the proposed model has the following decision variables: (i) n_s, the number of raw material arrivals over one production cycle; (ii) n_{rj}, the number of finished goods shipments to distributor j over one production cycle (j = 1, 2, …, N); (iii) T, the production cycle length; and (iv) $\boldsymbol{Z}$, the sequence of the first shipment to the distributors. The value of variable n_s can be …, 1/4, 1/3, 1/2, 1, 2, 3, 4, … with minimum value (min_n_s) 1/50 and maximum value 50, whereas n_{rj} is a positive integer with a minimum value (min_n) of 1 and a maximum value (max_n) of 50. Here, min_n and max_n are two N-vectors containing minimum values and maximum values, respectively, of a number of shipments to different distributors over one production cycle. Variable T is a floating number above 0 to max_T, and variable $\boldsymbol{Z}$ is an integer demonstrating a permutation of N.

5.4.1 Chromosome representation and decoding mechanism

The decision variables for the mathematical model of integrated production and inventory policy can be represented by 2(N+1)-vector of random key [0,1). Then, the first gene encodes variable n_s, the adjacent N genes represent n_{rj}, and then the following gene encrypts variable T and finally the last N genes encode $\boldsymbol{Z}$ as shown in Figure 5.6.

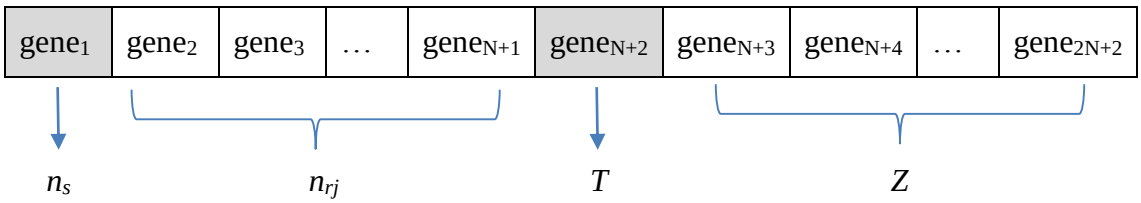


Figure 5.6 Chromosome representation

The solution to the model can be obtained by decoding the chromosome using the following procedure (*Algorithm 2*).

Algorithm 2

Step 1 : Obtain the value of n_{rj} by rounding up $((gene_1 - 0.5) \times 2 \times max_n_{rj})$ if gene$_1 \geq 0.5$, otherwise $1/\lceil |gene_1 - 0.5|/(2 \times min_n_{rj}) \rceil$.

Step 2 : Obtain the values of n_{rj} by rounding up $\left(min_n_{rj} + (gene_2 : gene_{N+1}). \times (max_n_{rj} - min_n_{rj})\right)$.
Here, symbol .× denotes a scalar operator for multiplying matrices.

Step 3 : Use $\min_T + gene_{N+2} \times (max_T - min_T)$ to obtain the value of T

Step 4 : Obtain the value of $\boldsymbol{Z}$ by sorting the last N genes in ascending order to get the sequence of the shipments.

To illustrate the decoding procedure described above, consider a chromosome of five distributors as depicted in Figure 5.7. Applying the previous procedure, the value of n_s is obtained by rounding up (0.781-0.5)×100 or equal to 29. For obtaining n_{rj}, for instance, n_{r4} is acquired by 1 + 0.916×(90-1) to get 83. The last five genes encoding $\boldsymbol{Z}$ are 0.462, 0.424, 0.461, 0.770 and 0.322. Arranging these genes in ascending order would result in 0.322, 0.424, 0.461, 0.462, 0.770 or, in terms of the location of this corresponding genes, 5th, 2nd, 3rd, 1st, and 4th, respectively. Thus, $\boldsymbol{Z}$ = 5-2-3-1-4.

Min	1/50	1	1	1	1	1	0					
Max	50	100	80	50	100	90	1					
Chrom.	0.781	0.675	0.007	0.602	0.387	0.916	0.001	0.462	0.424	0.461	0.770	0.322
	n_s	n_{r1}	n_{r2}	n_{r3}	n_{r4}	n_{r5}	T	Z				
Solution	29	68	2	30	39	83	0.001	5	2	3	1	4

Figure 5.7 Illustration of an application of the decoding procedure

5.4.2 Crossover and local search procedure

In a preliminary attempt, the arithmetical crossover operator was initially applied. However, the performance of the result in dealing with the addressed problem tends to be inferior compared to the standard crossover for BRKGA, i.e. the parameterised uniform crossover. For this reason, the parameterised uniform crossover operator as shown in Figure 5.3 is then applied to the proposed BRKGA.

The improvement of the BRKGA is made by combining this algorithm with a local search procedure. The local search procedure is applied to the elite chromosomes. Thus, instead of just copying these elite chromosomes, the elite chromosomes at generation K+1

resulted from the local search refinement to the previous (generation *K*) elite chromosomes as illustrated in Figure 5.8.

Two local search methods are applied to find the neighbour of each elite chromosome. The first method is conducted by shifting the value of a randomly selected gene by a certain portion of a predetermined grid while the second method is performed by swapping two randomly chosen genes. To illustrate, consider an example in Figure 5.9. The figure shows two neighbour chromosomes obtained from applying the first local search method (LSP 1) and the second local search method (LSP 2). For LSP 1, the 5th gene is selected and altered by adding a random number between [-0.5, 0.5] multiplied by the grid (in this example grid = 0.3 is used) to the value of this gene. Absolute value with truncated process is required to ensure that the obtained gene is always between 0 and 1. For LSP 2, genes 2 and 8 which are picked randomly are exchanged to obtain a new chromosome.

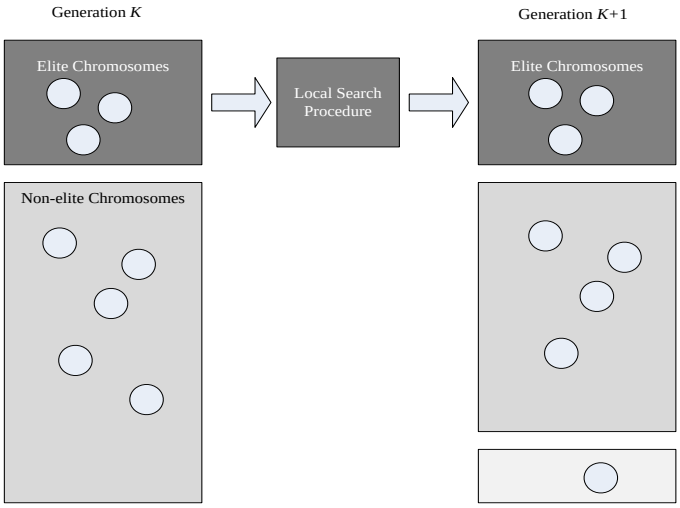


Figure 5.8 Local search improvement to elite chromosomes

LSP 1	0.781	0.675	0.007	0.602	**0.279**	0.916	0.001	0.462	0.424	0.461	0.770	0.322
					= |0.3×(-0.361) + 0.387| - TRUNC|0.3×(-0.361) + 0.387|							
Elite Chrom.	0.781	**0.675**	0.007	0.602	**0.387**	0.916	0.001	**0.462**	0.424	0.461	0.770	0.322
LSP 2	0.781	**0.462**	0.007	0.602	0.387	0.916	0.001	**0.675**	0.424	0.461	0.770	0.322

Figure 5.9 Two neighbour chromosomes resulted from LSP 1 and LSP 2

The pseudo code for the local search procedure is shown in Figure 5.10. In step 1, the inputs to the local search procedure include the elite chromosomes and their corresponding fitness values, the initial and end values of the discrete grid (*grid_start* and *grid_end*, respectively) and the total number of neighbour chromosomes to be observed (*max_points*). Then, in steps 3 to 6, an elite chromosome is picked to be improved by starting grid of *h*. Initially, the improvement state, *imp*, is set to be zero, meaning that no improvement has been made yet. In steps 8 to 21, the local improvement to each elite chromosome is conducted. Given the total number of neighbour chromosomes to be found (*max_points*), half of these neighbour chromosomes are obtained by applying LSP 1 to the elite chromosome (Step 8), while the remaining chromosomes are acquired by conducting LSP 2 to the elite chromosome (Step 9). For all neighbour chromosomes, their corresponding fitness values are computed and then the best fitness and chromosome are selected. If this best fitness is better than the fitness of the elite chromosome, replace the fitness value and its corresponding elite chromosome with this new chromosome and fitness value (Steps 14 and 15) and then the local search for this elite chromosome is stopped. A new search is started for another elite chromosome. If the best fitness is worse than the fitness of the elite chromosome, then reduce the grid by half (Step 20) and then find new neighbour chromosomes using this new grid. This process may be repeated until the grid is lower than *grid_end*. Steps 24 and 25 store the chromosomes and fitness of new elite chromosomes.

```
1.    Input ← elite_chromosomes, elite_fitness, grid_start, grid_end, max_points
2.    for i = 1 to number of elite_chromosomes do
3.    chromosome ← elite_chromosomes(i)
4.    fitness ← elite_fitness(i)
5.    h ← grid_start;
6.    imp ← 0;
7.    while h ≥ grid_end do
8.    for j = 1 to max_point/2 do
9.    neighbour(j) ← perform LSP 1 to chromosome;
10.   neighbour(max_point/2 + j) ← perform LSP 2 chromosome;
11.   temp_fitness ← calculate fitness value of neighbour chromosomes
12.   [best_fitness best_chromosome] ← select the best chromosome and its corresponding fitness;
13.   if best_fitness > fitness do
14.   chromosome ← best_chromosome;
15.   fitness ← best_fitness;
16.   imp ← 1;
17.   h ← -grid_end;
```

```
18.     end if
19.     if imp = 0 do
20.     h ← h/2;
21.     end if
22.     end for
23.     end while
24.     elite_chromosome(i) ← chromosome;
25.     elite_fitness(i) ← fitness;
26.     end for
```

Figure 5.10 Pseudo code of the proposed local search procedure

5.4.3 Procedure of the proposed BRKGA

Having discussed the methods of local improvement procedure used in this research, the complete procedure of the proposed BRKGA is outlined as represented by *Algorithm* 3.

Algorithm 3

***Step* 1** : Generate *pop_size* vectors with 2(N+1) length of random keys as the initial population and set them as old population (*old_pop*).

***Step* 2** : Decode *old_pop* using procedure explained in Section 5.4.1 to get the solutions.

***Step* 3** : Determine fitness of each solution by calculating the total profit using Eq. 4.33 in Chapter 4.

***Step* 4** : Classify the solutions into elite and non-elite solutions, with a proportion of elite ones by p_e, by sorting their corresponding fitness.

***Step* 5** : Perform local improvement procedures to the elite solutions using steps in Figure 5.10 and add the results to the next population.

***Step* 6** : Generate mutants with a proportion of p_m in the next population.

***Step* 7** : Fill the remaining next population $(1-p_e-p_m)*pop_size$, by mating parents which contain two individuals taken from elite group and non-elite group, respectively, and then add the offspring to the next population.

***Step* 8** : Set the new population as *old_pop* and repeat steps 2-7 until maximum iteration (*max_iteration*) is reached.

This procedure differs from that of the conventional BRKGA in Step 5, where local improvement procedures are proposed to further enhance the performance of the algorithm.

5.5 Parameter setting and numerical tests

The procedure of BRKGA proposed in this research is coded in MATLAB R2009a. To ensure that the total profit function gives a correct value, the code has been tested and compared with a manual calculation in Ms. Excel. It is important to note that the coded algorithm was run on a notebook with processor Intel®Core i5-480M 2.66GHz with 320GB with 320GB hard drive and 4GB RAM. In addition, to reduce the computation time the program was run using 4 cores in parallel.

The algorithm has a number of parameters that have to be properly set to achieve its optimal performance. They are the size of population, the size of the elite population, the size of the mutant population, and probability inheritance of elite allele. For the population size, Gonçalves et al. (2011c) recommended a value that is the length of the chromosome multiplied by a constant. In general, a larger population would be expected to produce better solutions. However, it will definitely increase the computation time as confirmed in the initial trials in this research. Considering this situation and benchmarking to the previous research (for instance Gonçalves and De Almeida (2002), Gonçalves, de Magalhães Mendes and Resende (2005), Noronha, Resende and Ribeiro (2011), Tangpattanakul, Jozefowiez and Lopez (2012)) as summarised in Table 5.2, in this research a population size that is equal to the length of the chromosome ($2(N+1)$) is used, while the remaining parameters are set based on the numerical tests conducted to this research. A number of different tested values of these parameters depicted in Table 5.3 are based on the recommendation in Gonçalves et al. (2011c) that has been confirmed in the majority of the existing studies (Table 5.2).

Table 5.3 Tested values of the parameters

Parameter	Description	Tested values
p_e	size of elite population	0.10; 0.15; 0.2; 0.25
p_m	size of mutant population	0.10; 0.2; 0.30
ρ_e	elite allele inheritance probability	0.5; 0.6; 0.7; 0.8

For the test purpose, the mathematical model Equation 4.33 presented in Chapter 4 with parameters given in Table 5.4 is then optimised using the proposed BRKGA with a different combination of algorithm parameters as shown in Table 5.3. Since for p_e, p_m, and ρ_e, there are 4, 3 and 4 set of values to be tested, the whole tests are then 48 different sets (combination 4, 3 and 4 of p_e, p_m, and ρ_e, respectively). Since $N = 10$, the population size is 22 from 2×(10+1), whereas for the local procedure the values of 0.3, 0.001 and 10

are respectively for *grid_start*, *grid_end* and *max_points*. Due to the natural behaviour of genetic algorithms, each operation of BRKGA will result in a slightly different value from other runs. For each set of BRKGA parameters, the run is replicated 50 times and then the average and deviation of the result are summarised as shown in Table 5.5.

Table 5.4 Parameter of the tested model

A. Distributor							
d_{rj}	:	3000; 4000; 5000; 2500; 6000; 8000; 10000; 1000;15000; 9000					unit/year
A_{rj}	:	50; 40; 30; 100; 50; 60; 30; 40; 20; 40					unit/delivered lot
H_{rj}	:	14; 14; 14; 14; 14; 14; 14; 14; 14; 14					$/unit/year
T_{sl}	:	0.1233					year
T_{start}	:	0.083					year
p_{max}	:	40					$/unit
p_{min}	:	5					$/unit
LT_{rj}	:	0.0274; 0.0164; 0.0192; 0.0082; 0.0027; 0.0192; 0.0274; 0.0164; 0.0027; 0.0110					year
B. Manufacturer							
P	:	90000	unit/year	C_s	:	10	$/unit
β	:	0.0083	kJ/mole °K	C_m	:	8	$/unit
E_a	:	20	kJ/mole	C_r	:	25	$/unit
k_0	:	500		A_s	:	50	$/delivered lot
τ	:	300	°K	A_m	:	1500	$/one-setup
λ	:	0.02		H_s	:	10	$/unit/year
C_{Es}	:	600		H_m	:	13	$/unit/year
C_{Qs}	:	10	$/unit quality loss/year				``

Table 5.5 Summary of the numerical test results

p_e	p_m	ρ_e	Avg. Elapsed time (second)	Max. ($)	Average ($)	Stdev. ($)	Stdev/Avg. (%)
0.1	0.1	0.5	39.12	577,256.11	576,956.94	244.83	0.042%
		0.6	39.84	577,298.44	576,969.03	244.04	0.042%
		0.7	42.14	577,294.88	576,874.16	395.07	0.068%
		0.8	41.83	577,244.19	576,932.21	234.58	0.041%
	0.2	0.5	38.36	577,297.70	576,963.29	216.79	0.038%
		0.6	39.88	577,275.48	576,903.98	355.38	0.062%
		0.7	40.13	577,244.41	576,974.82	245.79	0.043%
		0.8	39.88	77,272.90	576,909.89	293.96	0.051%
	0.3	0.5	36.63	577,244.41	576,873.00	256.57	0.044%
		0.6	37.84	577,297.99	576,866.93	262.55	0.046%
		0.7	39.21	577,259.60	576,899.86	287.75	0.050%
		0.8	39.20	577,256.18	576,878.54	341.98	0.059%

Table 5.5 Summary of the numerical test results (continued)

p_e	p_m	ρ_e	Avg. Elapsed time (second)	Max. ($)	Average ($)	Stdev. ($)	Stdev/Avg. (%)
0.15	0.1	0.5	50.93	577,277.65	577,018.14	190.18	0.033%
		0.6	52.04	577,276.48	576,966.30	196.20	0.034%
		0.7	52.89	577,255.90	577,029.18	186.48	0.032%
		0.8	52.84	577,256.11	576,949.39	311.80	0.054%
	0.2	0.5	50.07	577,244.40	576,903.86	296.57	0.051%
		0.6	50.90	577,251.88	577,012.68	157.39	0.027%
		0.7	52.21	577,277.68	576,981.72	258.82	0.045%
		0.8	51.96	577,276.48	576,980.29	246.39	0.043%
	0.3	0.5	47.44	577,298.66	577,047.16	221.97	0.038%
		0.6	49.00	577,244.41	576,972.80	262.20	0.045%
		0.7	51.20	577,244.37	576,987.72	207.95	0.036%
		0.8	51.07	577,244.40	576,983.20	207.76	0.036%
0.2	0.1	0.5	62.44	577,297.99	577,000.92	234.03	0.041%
		0.6	63.70	577,249.71	577,018.44	191.48	0.033%
		0.7	64.69	577,244.41	577,018.86	177.35	0.031%
		0.8	64.88	577,277.70	577,030.40	155.09	0.027%
	0.2	0.5	60.76	577,256.18	577,039.42	168.38	0.029%
		0.6	62.79	577,251.89	576,988.80	211.21	0.037%
		0.7	63.87	577,277.68	577,050.49	161.19	0.028%
		0.8	64.00	577,256.08	577,047.11	166.88	0.029%
	0.3	0.5	56.55	577,282.35	577,028.37	150.94	0.026%
		0.6	59.61	577,297.04	577,024.81	206.20	0.036%
		0.7	61.00	577,277.69	576,985.82	215.04	0.037%
		0.8	62.94	577,244.30	577,061.31	125.06	0.022%
0.25	0.1	0.5	74.09	577,277.65	577,093.20	148.45	0.026%
		0.6	74.79	577,277.70	577,062.36	183.98	0.032%
		0.7	77.28	577,298.59	577,085.02	189.34	0.033%
		0.8	77.97	577,277.21	577,065.15	162.82	0.028%
	0.2	0.5	69.86	577,276.48	577,087.78	135.46	0.023%
		0.6	73.19	577,244.38	577,026.66	179.42	0.031%
		0.7	74.52	577,244.41	577,005.39	203.46	0.035%
		0.8	76.83	577,256.18	577,016.06	197.60	0.034%
	0.3	0.5	65.25	577,269.35	577,044.76	172.14	0.030%
		0.6	69.11	577,298.69	577,079.72	143.68	0.025%
		0.7	71.94	577,255.98	577,086.79	145.09	0.025%
		0.8	73.79	577,277.38	577,032.64	151.13	0.026%

From the result shown in Table 5.5, a set of algorithm parameters with p_e, p_m, and ρ_e equal to 0.25, 0.1, and 0.5, respectively, returns the highest average of $577,093.20 with a standard deviation of 148.45. The ratio of this deviation to the average value is 0.026%. Based on this figure, this set of parameter is therefore selected to be used for the proposed BRKGA.

5.6 Performance of the proposed BRKGA

In this subsection, the performance of the proposed BRKGA applying the set of parameters chosen is further discussed.

There are a number of criteria that are commonly used to measure the performance of genetic algorithms, namely the ability to converge to optimal solutions, the quality of the obtained solution, and the computation time. Therefore, in this subsection, the profile of these criteria for the proposed BRKGA is investigated.

In terms of the ability to find optimal solutions, the proposed BRKGA which is combined with local procedures is capable of converging to an optimal solution over generations or iterations. In comparison to the genuine BRKGA (without incorporating the local search procedures), it is revealed that the proposed BRKGA yields a better performance. As shown in Figure 5.11, the algorithm produces a better solution which is indicated by a better profit obtained of around $580,365 compared to $576,569 when the conventional BRKGA is applied. In addition, the proposed BRKGA is able to converge faster than the benchmark algorithm. As shown in Figure 5.11, the algorithm starts meeting the optimal solution just after 50 iterations, while for BRKGA without applying local procedures, it starts converging to an optimal solution after reaching 150 iterations.

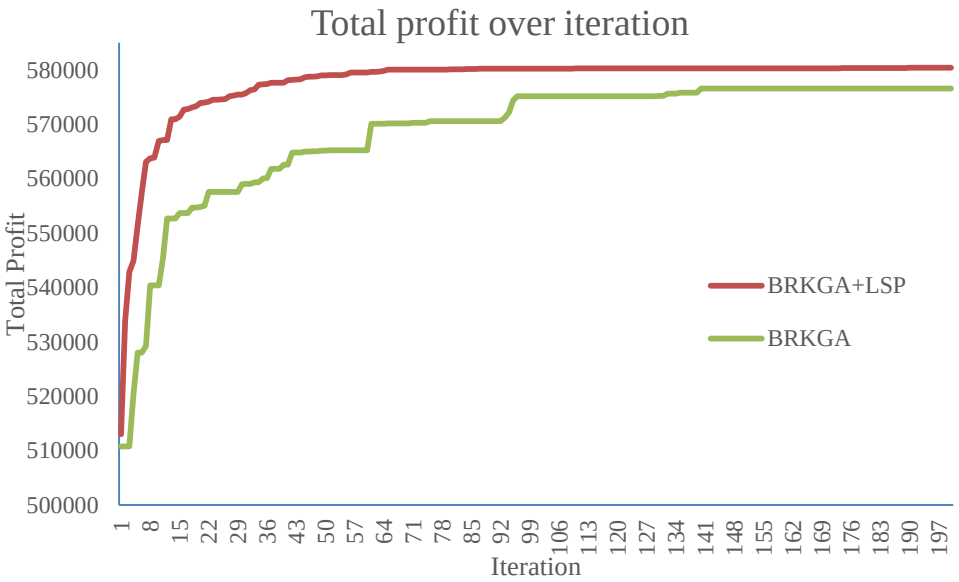


Figure 5.11 Total gained profit over iterations

In this research, the global optimal solution for the addressed problem has not been known in any literature yet. Therefore, it is not possible to claim that the proposed

algorithm has successfully found the global optimal solution. However, rather from the numerical test depicted in Figure 5.11 it has been shown that the proposed algorithm has successfully enhanced the performance of the original BRKGA, which is proven to be more effective for use for finding an optimal solution of complex problems, by approximately 0.7%. Apart from the fitness value or, in this case, the total gained profit, the quality of a solution produced by a genetic algorithm should be further measured by the standard deviation of the solutions when the process of finding optimal solutions is replicated because it is a good indicator of the robustness of the algorithm. As observed from Table 5.5, for all considered cases in 50 replications, the proposed BRKGA returns solutions with standard deviations of 395.07 at maximum or if indicated by the ratio of the deviation to the average gained profit, it is 0.068%. Meanwhile for the chosen parameter (p_e, p_m, and ρ_e equals 0.25, 0.1, and 0.5, respectively) the resulting standard deviation and its ratio to the profit give more convincing results of 148.45 and 0.026% respectively, demonstrating consistency of the algorithm for finding the optimal solution. These results indicate that the proposed BRKGA produces quite satisfying performances in terms of the solution quality.

Incorporating two local search procedures into the BRKGA will inevitably increase the elapsed time of the algorithm. Based on the numerical tests summarised in Table 5.5, the average elapsed time increases consistently along with the size of elite population; it is indicated by the value of p_e. It is because more iterations are required to search local improvements for all individuals of elite population as illustrated in Figure 5.8. For the chosen parameter (p_e, p_m, and ρ_e equals 0.25, 0.1, and 0.5, respectively), the average time for 50 trials is 74.09 seconds using parallel computation in MATLAB with four cores. Certainly, it is slower than the computation time of the original BRKGA (approximately 2.85 seconds). However, in the context of a planning horizon of the production-inventory problems addressed in this research, the elapsed time of the proposed algorithm is insignificant. Thus, it can be affirmed that this algorithm performs quite fast.

To sum up based on all indicators namely, the ability to converge to optimal solutions, the quality of the obtained solution, and the computation time, it can be asserted that the proposed BRKGA yields significantly better results. The use of the proposed algorithm for solving a mathematical model of an integrated multi-echelon production-inventory

policy considering the quality loss in food products developed in Chapter 4 can, therefore, be justified.

5.7 Concluding remarks

In this chapter, the concept of BRKGA and its applications to solve numerous optimisation problems have been reviewed and discussed. It has been revealed that the BRKGA is well-suited to be used to deal with combinatorial optimisation problems indicated by its performance in terms of the solution quality compared to other meta-heuristics algorithms. Apart from that, the BRKGA algorithm is designed to be problem independent. It is, therefore, flexible to be adopted with modifications for different problems. Considering these advantages, the BRKGA for integrated production-inventory model established in Chapter 4 is designed in this chapter. This algorithm is hybridised with two local procedures by shifting the value of a gene gradually and swapping two randomly selected genes in a chromosome. These chromosomes are incorporated into this algorithm to further improve exploitation and exploration capabilities of the algorithm, thus, the performance is improved. The algorithm was successfully coded in MATLAB and tested utilising four cores in parallel to reduce the computation time.

An extensive numerical test is conducted to observe the performance of the proposed BRKGA. Based on the result of this test, the overall performance of the proposed BRKGA indicated by several common indicators, such as the ability to converge to an optimal solution, the solution quality, the robustness and the computational time, is justified. Thus, the proposed algorithm is appropriate to be applied to solve the mathematical model representing the problem of integrated production-inventory policy considering quality and perceived value loss in multi echelon supply chains which was established in Chapter 4.

Chapter 6

Model evaluation and benchmarking

6.1 Introduction

The proposed model has been established in Chapter 4 and the hybridised BRKGA to find the optimal solution of the model has been discussed in Chapter 5. The next step is to conduct a numerical test for the model evaluation purpose. The result of the numerical tests is then examined, evaluated and discussed. Basically, there are three aims for conducting the numerical test as shown in Table 6.1. To achieve them, three scenarios are designed. The scenarios are constructed to answer questions derived from the aims of conduction of the numerical test (as seen in Table 6.1)

Table 6.1 Aims, questions and numerical test scenarios

Aim	Question/s	Scenario
To see the potential benefit of accommodating the quality degradation and perceived value loss	In terms of the total profit, does accommodating the perishable characteristics potentially improve the performance of the integrated system?	Comparing Model P with Model P′ – **scenario one**
To see whether the coordination mechanism affects the model performance	Does the coordination mechanism influence the system performance? Does the synchronised cycle approach outperform the common cycle approach?	Comparing Model P with Model C – **scenario two**
To evaluate and examine how the developed model behaves	a. How does the model behave if the rate of the quality loss in raw material is increased? b. How does the model behave if the perceived value loss (T_{start}) occurs earlier? c. How does the model behave if the shelf-life (T_{sl}) of the product is shorter? d. How does the model behave if the production rate is changed?	Changing the value of the related parameters in Model P – **scenario three**

The first numerical test scenario is designed to see the potential benefit of accommodating the quality degradation and perceived value loss while managing the deteriorating inventories. The result of the test is expected to answer the question whether the inventory

strategy addressing perishable characteristics will significantly improve the performance of the integrated system (in terms of the total profit) compared to a strategy disregarding the perishable characteristics. To this purpose, in **scenario one**, the proposed model or Model P is compared to the non-perishable model or Model P′ (note that Model P′ is the non-perishable version of the proposed model or Model P – Eq. 4.33). A more detailed description regarding this is presented in Subsection 6.3.1.

Further, still from the same table, the second aim of this numerical test is to see whether the coordination mechanism affects the system performance. When delivering the finished goods from the manufacturer to the retailers, there are two coordination mechanisms introduced in Chapter 4, i.e. synchronised cycle approach, Model P, and common cycle approach, Model C. Referring to the mathematical functions to calculate the age of the delivered batches, the coordination strategy may influence the age of each batch. In other words, a different mechanism may lead to a different average age of the delivered batches which finally affects the total profit. To prove this, a numerical test (**scenario two**) is carried out to compare the performance of the models.

Finally, the last aim is to evaluate and examine how the proposed model behaves. It is worth investigating the roles of some parameters such as the rate and the cost of quality loss, time to deteriorate, shelf-life and production rate. To achieve this aim, in the numerical test (**scenario three**), the values of those parameters are changed and the performance of the model with the new parameters is measured and discussed.

The remaining section of this chapter is organised as follows. Section 6.2 presents the parameters used in the developed models (P, C and SC) as well as parameter settings for the optimisation tool (BRKGA). Further, the numerical test results, as well as finding and discussion of each scenario (one, two and three), are respectively represented in Section 6.3. Finally, Section 6.4 summarises this chapter.

6.2 Parameter setting

In this section, the parameters used in the numerical test scenarios are presented. Firstly, since the models are optimised by GAs, it is essential to find the best parameter before running the program. This step has been completed in Chapter 5 and the parameters in Table 6.2 are the best setting parameters of the BRKGA, believed to be able to lead to a better quality of result. Further, parameters used as the inputs of scenarios one and two

are provided in Table 6.3. The input parameters are adopted from Banerjee, Kim and Burton (2007) but with some adjustment to fit the proposed model.

Table 6.2 Parameter setting in BRKGA

No	Component BRKGA	Setting value
1	Population size	22
2	Percentage elite	0.25
3	Percentage mutant	0.1
4	Percentage inheritance	0.5
5	Number of generation	200

Table 6.3 Parameters used in scenario one and two

Notation	**Value**	
P	90	1000 units/year
d_{rj}	[3 4 5 2.5 6 8 10 1 15 9]	1000 units/year
D	63.5	1000 units/year
C_{Qs}	60	$/unit-quality/year
C_{Es}	600	$
C_s	10	$/unit
C_m	10	$/unit
C_r	25	$/unit
A_s	50	$/delivered lot
A_m	1500	$/one-setup
A_{rj}	[60 50 40 100 30 20 10 110 10 10]	unit/delivered lot
H_s	10	$/unit/year
H_m	13	$/unit/year
H_{rj}	[14 14 14 14 14 14 14 14 14 14]	$/unit/year
k_0	500	unit-quality/year
β	0.0083	kJ/mole K
E_a	20	kJ/mole
τ	300	K
λ	0.02	
p_{max}	30	$/unit
p_{min}	5	$/unit
LT_{rj}	[0.0274 0.0164 0.0082 0.0027 0.0192 0.0274 0.0164 0.0027 0.0110]	year
T_{sl}	0.1233	year
T_{start}	0.083	year

Finally, at scenario three, some parameters are changed to answer some issues regarding the proposed model's performance. The first issue is to reveal the relation between the rate of quality loss (θ), the cost because of quality lost (C_{Qs}) and the total profit (TP). The second issue related to the question of how the model behaves if the value of T_{start} changed while the third issue concerns the effect of shorter T_{sl} on the model performance. The last is to investigate the role of the production rate in this system. Related to this, a parameter called α is introduced where α represents the ratio between the demand rate and the production rate ($\alpha = D/P$) and in this scenario, its value varies from 0.5 to 0.9. The changes made to those related parameters are presented in Table 6.4 and the results are discussed in Subsection 6.3.3.

Table 6.4 Parameter inputs in scenario three

Parameter	Original value	Changes
θ	0.162	[0.1 0.3 0.6 0.9]
C_{Qs}	60	[120 180 240 300]
T_{start}	0.083	[$0.25T_{sl}$ $0.5T_{sl}$ $0.75T_{sl}$]
T_{sl}	0.1233	[0.0208 0.0417 0.0833 0.0167]
α	0.53	[0.5 0.6 0.7 0.8 0.9]

6.3 Numerical test: Result, finding and discussion

In this section, the result of each scenario of the numerical test is presented. Some findings are presented and discussed.

6.3.1 Scenario one: Model benchmarking

In scenario one, the proposed model (Model P) is compared to Model P′. Parameters in Table 6.3 are used to find the solution of Model P which is based on Eq. 4.33 in Chapter 4. Similarly, to find the solution of Model P′, parameters in Table 6.2 are also used but with some changes as follows:

1. The parameter related to the quality loss, e.g. cost of quality loss (C_{Qs}) is set to zero implying that the quality loss in raw material has no effect on the model performance.

2. The values of T_{start} and T_{sl} are set to a bigger number such as nine and ten years which implicitly means that the finished goods are treated as non-perishable inventories and their price or value is constant, i.e. no perceived value loss occurs.

Further, the optimal or nearly optimal solution of both models is obtained using the BRKGA that has been developed in Chapter 5. The best setting parameters of the BRKGA presented in Table 6.2 are applied. Using MATLAB R2009a the program is run on processor Intel®Core i5-480M 2.66GHz with 320GB hard drive and 4GB RAM. The performance of both models is presented in Table 6.5 while the solutions are shown in Table 6.6.

Table 6.5 Model performance

Model P′ (non-perishable model)	Manufacturer ($/year)	Retailer ($/year)	Total ($/year)
Total Cost	1,299,700	1,610,300	2,910,000
Revenue	1,587,500	1,856,900	3,444,400
Total Profit	287,790	246,600	534,390
Model P (perishable model)	Manufacturer ($/year)	Retailer ($/year)	Total ($/year)
Total Cost	1,302,325	1,609,723	2,912,047
Revenue	1,587,500	1,904,931	3,492,431
Total Profit	285,175	295,208	580,383
Percentage of changes (P'-P)/P'*100%	Manufacturer	Retailer	Total
Total Cost	-0.2%	0.04%	-0.1%
Revenue	0.0%	2.6%	1.4%
Total Profit	-0.9%	19.7%	8.6%

As shown in Table 6.5, in terms of the total profit per year, Model P gains $580,383 total profit per year while Model P′ produces $534,390 per year. It shows that in general, accommodating the perishable characteristics, i.e. quality loss and perceived value loss, potentially improves the performance by 8.6%. However, the new approach, slightly reduces the manufacturer's profit. The total cost for the manufacturer slightly increases (0.2%) leading to a decrease in manufacturer's profit around 0.9% –note that manufacturer's revenue is fixed since it is obtained from multiplying the selling price and demand for the finished goods ($C_r \times D_r$); in other words any strategy used will not

influence the manufacturer's revenue. It appears that the proposed method is more beneficial for retailers than the manufacturer. Even though their total cost is slightly reduced (0.04%), the revenue increases (2.6%) leading to a significant increase in the profit (19.7%). Model P′ disregards the perishability, hence the strategy only focuses on minimising the cost resulting in the joint cost in Model P′ being lower (0.1%) than Model P. However, applying this approach in the system that manages perishable products would result in the loss of chance to gain more revenue (1.4%) and more profit (8.6%).

Table 6.6 Model solution

Model	n_s	T	n_{rj}										Z
			R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	
P′	8	0.1179	1	2	2	1	3	5	10	1	14	9	R_9-R_7-R_{10}-R_6-R_5-R_2-R_3-R_8-R_1-R_4
P	10	0.1119	2	2	3	2	3	4	10	2	11	7	R_9-R_7-R_{10}-R_8-R_4-R_3-R_6-R_5-R_2-R_1

In addition, regarding the procurement strategy, in Model P, the raw material is replenished more frequent than Model P′. This is because, in Model P′, the costs of quality loss in the raw material are disregarded, hence the approach only focuses on minimising the cost of holding and transferring the raw materials which leads to a higher size of raw material order (q_s) compared to that in Model P. Consequently, the average of quality loss in Model P′ is higher as the more raw materials stocked in the warehouse, the more quality loss (as shown in Table 6.7). It means that applying the approach in Model P′ to manage raw material with quality loss characteristics can lead to a decision which eradicates the chance to save the quality cost up to 24%. Further discussion of the relation between the rate of quality, cost and model performance is represented in Subsection 6.3.3.1.

Table 6.7 Relation between the size of raw material order (q_s) and the quality cost

Model	q_s (units)	unit quality loss (per year)	quality cost ($/year)
P′	1326	53.6	3215.9
P	1007	40.7	2442.6

Further, the solutions in Table 6.6 also show that the length of the production cycle (T) in Model P is 5.1% shorter than that of Model P′. The models have a different number of delivered batches (n_{rj}) as well as the sequence (Z). The decision variables affect the completion time of each batch in each retailer. As discussed in Chapter 4, batch completion time is the time where all items in a batch at a retailer are completely sold to customers (*CompTime*). It is determined by adding the age of a batch or q_{rij} received by a retailer with the ordering cycle or Ct_j ($CompTime_{ij} = E_{ij} + Ct_j$). The values of q_{rij}, E_{ij}, Ct_j and $CompTime_{ij}$ of both models are presented in Table 6.8 (for Model P′) and Table 6.9 (for Model P).

As can be seen in Table 6.8, in Model P′, four batches (i.e. q_{12}, q_{22}, q_{13} and q_{23}) have a longer completion time than T_{start} (0.083). It means that after T_{start}, there are still some items left in the batches. The value of those items, however, is perceived by customers as outdated items (i.e. customer perceives that their values are degraded), hence they will be sold at a discounted price, otherwise, the demand will decrease which may lead to outdated items. Therefore, during the period, products in q_{12}, q_{22}, q_{13} and q_{23} are sold with two prices, the maximum price and the discounted price.

Further, still in the same table, the completion time of three batches (q_{18}, q_{11} and q_{14}) is longer than shelf-life ($T_{sl} = 0.1233$). It means that the batches have some expired products as they are still unsold at the end of their expiration dates. Therefore, items in the batch will be sold with three prices, the maximum price, the discounted price and the minimum price.

On the other hand, Model P has anticipated the perceived value loss and the lifetime restriction of the products. T_{start} and T_{sl} have been accommodated in model performance (total profit). Hence, the decision variables that shorten the completion time are preferable as they will reduce the number of outdating and outdated items resulting in increasing the total profit. As can be seen in Table 6.9, Model P only has two batches (q_{28} and q_{21}) that have completion time longer than T_{start}. The table also shows that there is no batch sold after T_{sl}, i.e. no outdated item found in Model P. It appears that considering the perceived value loss and product lifetime restriction (represented by T_{start} and T_{sl}) is beneficial to prevent the retailers from having more outdating and outdated items.

Table 6.8 Ordering cycle, size of order and age and completion time of each batch in each retailer (Model P′)

Retailer	Ct_j	Age of a batch received by a retailer (E_{ij})													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
9	0.0084	0.0342	0.0339	0.0311	0.0296	0.0332	0.0376	0.0407	0.0443	0.0500	0.0464	0.0508	0.0552	0.0575	0.0619
7	0.0118	0.0232	0.0236	0.0196	0.0238	0.029	0.0333	0.0384	0.0408	0.0445	0.0515	0	0	0	0
10	0.0131	0.0259	0.0231	0.0214	0.0305	0.0335	0.0411	0.0422	0.0473	0.0529	0	0	0	0	0
6	0.0236	0.0157	0.0121	0.0215	0.0290	0.0384	0	0	0	0	0	0	0	0	0
5	0.0393	0.0108	0.0161	0.0265	0	0	0	0	0	0	0	0	0	0	0
2	0.0589	0.0258	0.0406	0	0	0	0	0	0	0	0	0	0	0	0
3	0.0589	0.0334	0.0482	0	0	0	0	0	0	0	0	0	0	0	0
8	0.1178	0.0205	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0.1178	0.0067	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0.1178	0.0142	0	0	0	0	0	0	0	0	0	0	0	0	0

Retailer	q_{rij}	Completion time each batch in each retailer ($CompTime_{ij}$)													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
9	126	0.0426	0.0423	0.0395	0.038	0.0416	0.0460	0.0491	0.0527	0.0584	0.0548	0.0592	0.0636	0.0659	0.0703
7	118	0.0350	0.0354	0.0314	0.0356	0.0408	0.0450	0.0502	0.0526	0.0563	0.0633	0	0	0	0
10	118	0.0390	0.0362	0.0345	0.0436	0.0466	0.0542	0.0553	0.0604	0.066	0	0	0	0	0
6	189	0.0393	0.0356	0.0450	0.0526	0.0620	0	0	0	0	0	0	0	0	0
5	236	0.0501	0.0554	0.0658	0	0	0	0	0	0	0	0	0	0	0
2	236	0.0847	0.0995	0	0	0	0	0	0	0	0	0	0	0	0
3	295	0.0923	0.1071	0	0	0	0	0	0	0	0	0	0	0	0
8	118	0.1383	0	0	0	0	0	0	0	0	0	0	0	0	0
1	354	0.1245	0	0	0	0	0	0	0	0	0	0	0	0	0
4	295	0.1321	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 6.9 Ordering cycle, size of order and age and completion time of each batch in each retailer (Model P)

Retailer	Ct_j	Age of a batch received by a retailer (E_{ij})										
		1	2	3	4	5	6	7	8	9	10	11
9	0.0102	0.0320	0.0309	0.0297	0.0370	0.0401	0.0412	0.0462	0.0469	0.0523	0.0534	0.0577
7	0.0112	0.0206	0.0181	0.0204	0.0270	0.0307	0.0349	0.0369	0.0407	0.0428	0.0453	0
10	0.0160	0.0237	0.0216	0.0313	0.0345	0.0396	0.0417	0.0482	0	0	0	0
8	0.0559	0.0118	0.0276	0	0	0	0	0	0	0	0	0
4	0.0559	0.0072	0.0231	0	0	0	0	0	0	0	0	0
3	0.0373	0.0242	0.0339	0.0427	0	0	0	0	0	0	0	0
6	0.0280	0.0328	0.0395	0.0490	0.0536	0	0	0	0	0	0	0
5	0.0373	0.0202	0.0328	0.0412	0	0	0	0	0	0	0	0
2	0.0559	0.0052	0.0240	0	0	0	0	0	0	0	0	0
1	0.0559	0.0128	0.0299	0	0	0	0	0	0	0	0	0

Retailer	q_{rj}	Completion time each batch in each retailer ($CompTime_{ij}$)										
		1	2	3	4	5	6	7	8	9	10	11
9	153	0.0422	0.0411	0.0399	0.0471	0.0503	0.0514	0.0564	0.0571	0.0624	0.0635	0.0679
7	112	0.0318	0.0292	0.0315	0.0382	0.0419	0.0460	0.0480	0.0519	0.0540	0.0565	0
10	144	0.0397	0.0376	0.0473	0.0505	0.0556	0.0577	0.0641	0	0	0	0
8	56	0.0677	0.0836	0	0	0	0	0	0	0	0	0
4	140	0.0632	0.0790	0	0	0	0	0	0	0	0	0
3	186	0.0615	0.0712	0.0800	0	0	0	0	0	0	0	0
6	224	0.0608	0.0674	0.0770	0.0816	0	0	0	0	0	0	0
5	224	0.0575	0.0701	0.0785	0	0	0	0	0	0	0	0
2	224	0.0612	0.0800	0	0	0	0	0	0	0	0	0
1	168	0.0688	0.0859	0	0	0	0	0	0	0	0	0

More detailed information regarding the process of calculating the number of outdating and outdated items of selected batches (e.g. q_{r18}, and q_{r21}) is illustrated in Figures 6.1 and 6.2 (note that all units are converted into days). As illustrated in Figure 6.1, the size of order q_{18} is equal to 118 units and its age is 7.5 days when received by retailer eight (R_8). Demand rate of R_8 or d_8 is 2.74 units per day, hence the ordering cycle (Ct_8) is 43 days. Assuming demand is deterministic and constant during the ordering cycle, then all units in the batch q_{18} will be sold out at day 50.5 ($CompTime_{18}$ = 50.5). Customers perceive the value of the products degrades at day 30 (T_{start} = 30) before they are expired and have no value at day 45 (T_{sl} = 45). Based on this, the number of the outdating or degrading product can be calculated by subtracting T_{start} from T_{sl} and the result is then multiplied by demand or (45-30)×2.73 = 40.3 units. Meanwhile, the number of outdated or expired products is obtained by subtracting the T_{sl} from *CompTime* and the result is then multiplied by demand or (50.3-45)×2.7=15 units.

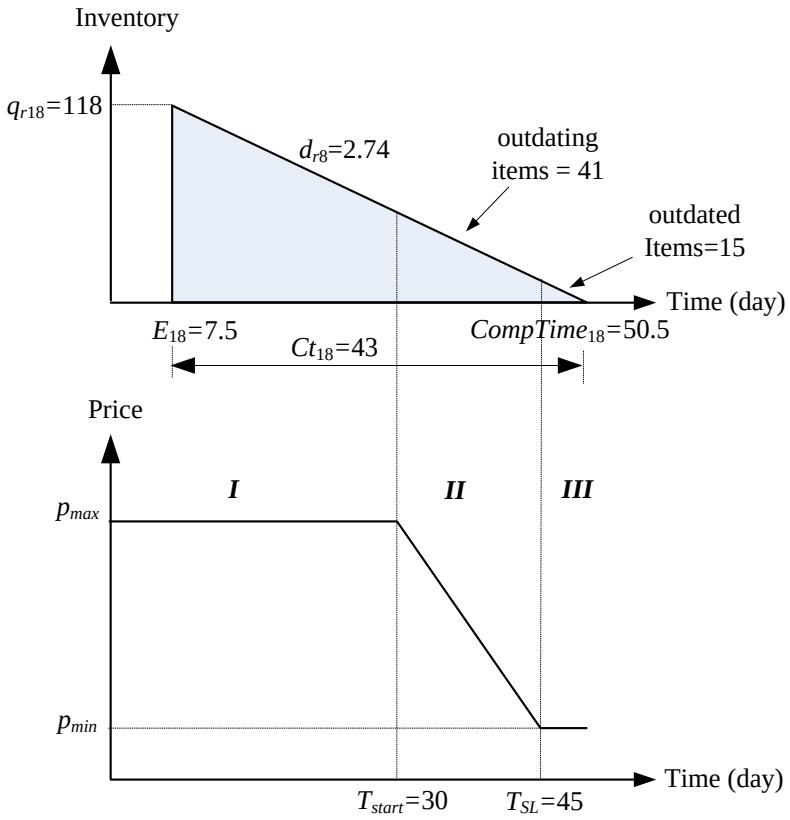


Figure 6.1 Illustration of the outdating and outdated items of the 1st batch of R_8 (Model P′)

Similarly, in Figure 6.2, 168 units of batch q_{21} is received by retailer one (R_1) when its age is equal to 11 days. Since d_1 is 8.2 units per day, Ct_1 is 20.5 days leading to 31.5 days to sell all units in the batch. It means that there are units of q_{21} sold at normal price but

there are also some discounted items as their age is higher than T_{start} (30 days) but there are no outdated items since at day 31.5 all items have been sold out. The number of the discounted items is 12.3 units obtained from (31.5-30)×8.2. The summary of these calculations is presented in Table 6.10

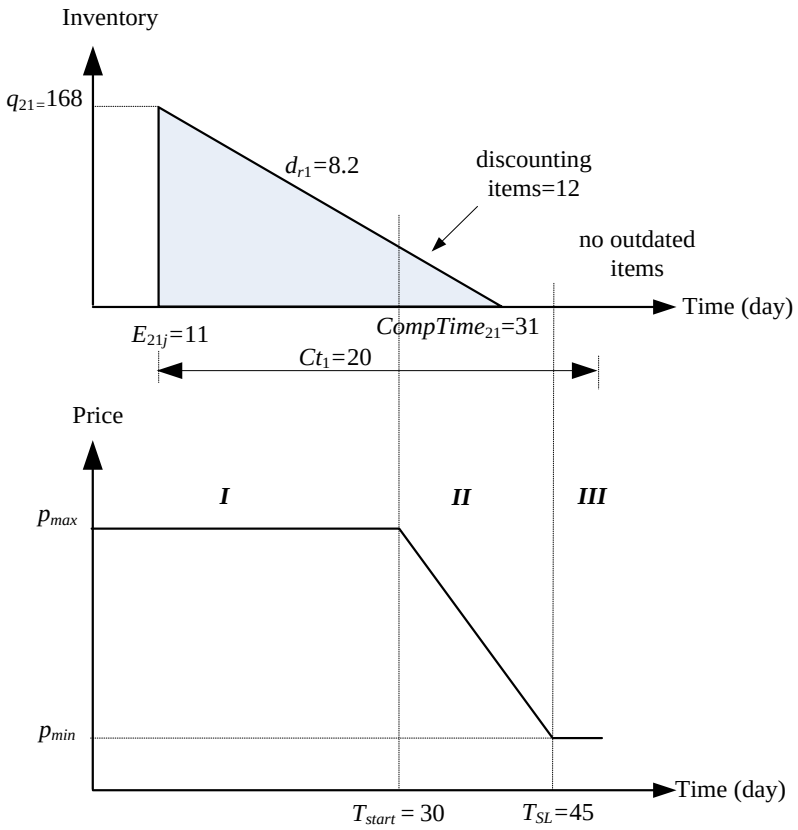


Figure 6.2 Illustration of the outdating and outdated items of the 2nd batch of R_1 (Model P)

As shown in Table 6.10, Model P has 13 products that are sold at discounted price, while Model P′ has 504 units of discounted items. In addition, Model P has no outdated items while there are 41 expired items in Model P′. It appears that considering the perceived value loss and lifetime restriction can reduce outdating and outdated products while disregarding them can lead to a decision that overlooks a chance to reduce the outdating products and eliminate outdated items.

The result in scenario one shows that when the cost of handling the quality loss is considered in the approach, the raw material is replenished more frequently to avoid the penalty due to the loss. Hence, the quality loss can be reduced. Apart from that, the scenario one results also demonstrate that while managing the perishable finished goods, the policy regarding the size of order as well as the sequence of order, influences the age

of batch which results in affecting the revenue. Therefore, it is beneficial to apply the shelf-life price function which represents the perceived value loss in the finished goods.

Table 6.10 Summary of the outdating and outdated items (in units)

Components	Model P′							Model P	
	q_{12}	q_{22}	q_{13}	q_{23}	q_{18}	q_{11}	q_{14}	q_{28}	q_{21}
Age of batch (E_{ij})	0.0258	0.0406	0.0334	0.0482	0.0205	0.0067	0.0142	0.0276	0.03
Cycle time (Ct_j)	0.059	0.059	0.059	0.059	0.118	0.118	0.118	0.0559	0.057
Completion time ($CompTime_{ij}$)	0.0848	0.0996	0.0924	0.1072	0.139	0.1247	0.1322	0.0836	0.0869
d_{rj}	4,000	4,000	5,000	5,000	1,000	3,000	2,500	1,000	3,000
Number of outdating products	7	66	47	121	41	121	101	1	12
Number of outdated products	0	0	0	0	15	4	22	0	0

6.3.2 Scenario two: Effects of coordination mechanism on the model performance

In scenario two, the coordination mechanisms are evaluated. In this case, the shipment policy in Model C, i.e. common cycle approach, is compared to that in Model P, i.e. synchronised cycle approach. The performance of total cost, revenue and profit of each party of the integrated system is shown in Table 6.11 while the solutions are presented in Table 6.12.

Table 6.11 Detail performances of each model

Coordination mechanism	Manufacturer		Retailers		Profit
	Total cost ($/year)	Total revenue ($/year)	Total cost ($/year)	Total revenue ($/year)	
Common cycle approach (Model C)	1,304,403	1,587,500	1,615,541	1,904,965	572,521
Synchronised cycle approach (Model P)	1,302,325	1,587,500	1,609,723	1,904,931	580,383
Saving (P-C)	-2,078	0	-5,818	34	7,862

Table 6.12 Solution of each strategy

Coordination mechanism	n_s	T	n_{rj}	Z
Common cycle approach (**Model C**)	10	0.10134	[3 3 3 3 3 3 3 3 3 3]	Not available
Synchronised cycle approach (**Model P**)	10	0.11188	[2 2 3 2 3 4 10 2 11 7]	R_9-R_7-R_{10}-R_6-R_5-R_2-R_3-R_8-R_1-R_4

As shown in Table 6.11, the total profit of Model P is 1.4% higher than that of Model C. Even though there is a slight decrease in total revenue ($34), the synchronised cycle approach potentially reduces the costs both in manufacturer and retailers. Compared to the common cycle approach, the costs in manufacturer and retailers (if the synchronised cycle is applied) are respectively $2078 and $5818 lower. It means that allowing retailers to have their own ordering cycle potentially decreases the cost and finally increases the total profit.

Further, as shown in Table 6.12, regarding the raw material replenishment strategy, both approaches lead to the same number of replenishment frequencies. However, the length of the production cycle (T) of the common approach is slightly shorter than that of the synchronised method, leading to a younger delivered batch and fewer outdating items. In other words, the number of discounted items in common cycle approach is lower compared to that in synchronised approach. Related parameters to the outdating and/or outdated items are illustrated in Table 6.13.

Table 6.13 Ordering cycle, size of order and age and completion time of each batch in each retailer (Model C)

Retailer	Age of a batch received by a retailer (E_{ij})			Ct_j	Completion time each batch in each retailer ($CompTime_{ij}$)			q_{rj}
	1	2	3		1	2	3	
1	0.0278	0.0377	0.0477	0.0338	0.0616	0.0715	0.0814	101
2	0.0174	0.0273	0.0373	0.0338	0.0512	0.0611	0.0710	135
3	0.0203	0.0303	0.0402	0.0338	0.0541	0.0640	0.0740	169
4	0.0097	0.0197	0.0296	0.0338	0.0435	0.0534	0.0634	84
5	0.0046	0.0146	0.0245	0.0338	0.0384	0.0483	0.0583	203
6	0.0214	0.0314	0.0413	0.0338	0.0552	0.0652	0.0751	270
7	0.0304	0.0403	0.0503	0.0338	0.0642	0.0741	0.0841	338
8	0.0198	0.0298	0.0397	0.0338	0.0536	0.0635	0.0735	34
9	0.0065	0.0164	0.0264	0.0338	0.0403	0.0502	0.0602	507
10	0.0166	0.0265	0.0365	0.0338	0.0504	0.0603	0.0703	304

As shown in Table 6.13, only one batch that has outdating items, i.e. the third batch of retailer 7 (q_{27}). From 338 units in batch q_{27}, there are 11 units that sold with a discounted price (note that d_{r7} = 10,000 units/year, T_{start} = 0.083 year, hence outdating item in batch q_{27} = 10,000×(0.0841− 0.083)). Compared to the synchronised approach (as shown in Table 6.10), the number of outdating items in the common approach is 2 units lower. It means that the common cycle strategy which has a shorter T may increase retailers' revenue. However, the strategy may be disadvantageous if the related costs increase

significantly. In this case, the increase in costs is considerably greater than the increase in revenue, leading to the total profit in Model P is $7,862 higher than that in Model C (as seen in Table 6.11).

Further, it is interesting to note that in the common cycle strategy, the sequence of delivery does not affect the retailers' revenue, i.e. any sequence will lead to the same revenue. Therefore, in common cycle approach, the retailers' order (Z) is not essential to determine. The strategy only focuses on optimising the number of replenishment cycles (n_s), the length of the production cycle (T) and the shipment frequency (n_{rj}). Though the common approach looks simpler (in terms of effort to find the optimal solution), the inflexibility in determining the ordering cycle of each retailer significantly increases some costs. Table 6.14 compares the relevant costs of two strategies.

Table 6.14 Values of the relevant costs

	Cost	Common cycle approach (**Model C**)	Synchronised cycle approach (**Model P**)	Saving
Manufacturer	Transportation cost for procuring the raw materials	4,934	4,469	465
	Holding cost of raw materials	2,270	2,506	-236
	Cost due to quality loss in raw materials	2,212	2,443	-230
	Production setup cost	14,802	13,407	1,395
	Holding cost of finished goods in manufacturer system	9,585	8,900	685
Retailers	Transportation cost for distributing the finished goods from manufacturer to retailers	13,026	10,815	2,211
	Holding cost of finished goods in manufacturer system	15,015	11,408	3,607
	Total	61,844	53,948	7,896

As shown in Table 6.14, reduction in retailers' cost because of using the synchronised approach dominates the total saving. Respectively, the holding cost and the transportation cost in retailers are reduced by 45.7% and 28%. Meanwhile, in manufacturer, the holding cost and raw material transportation cost decreased around 8.7% and 5.9% respectively. On the other hand, the costs of holding raw materials and handling the quality loss slightly increase 3% and 2.9% (in a respective order). It is because the size of raw material order (q_s) in Model P is greater than that of in Model C. The value of q_s is obtained by dividing the length of production cycle with the number of raw material replenishment or T/n_s. As

shown in Table 6.12, both models have the same value of n_s but T in Model P is longer than that of Model C. Consequently, q_s in Model P is greater leading to a slightly higher holding and quality cost.

In addition, aside from reducing the overall costs, using the synchronised cycle approach may lead to a better performance of profit distribution in each retailer. To evaluate this, the ratio between the profit gained and the costs spent by each retailer, both for common and synchronised cycle approaches, is calculated (respectively demonstrated in Tables 6.15 and 6.16). The ratio represents the rate of the investment benefit of each retailer, i.e. how much profit a retailer gains after investing some costs.

Table 6.15 Ratio between profit and cost of each retailer (Model C – common cycle)

Retailer	Demand	Revenue	Costs	Profit	Ratio (cost/profit)
1	3,000	90,000	77,486	12,514	0.16
2	4,000	120,000	102,426	17,574	0.17
3	5,000	150,000	127,366	22,634	0.18
4	2,500	75,000	66,052	8,948	0.14
5	6,000	180,000	152,307	27,693	0.18
6	8,000	240,000	202,484	37,516	0.19
7	10,000	299,965	252,661	47,304	0.19
8	1,000	30,000	28,493	1,507	0.05
9	15,000	450,000	378,843	71,157	0.19
10	9,000	270,000	227,424	42,576	0.19
Total	63,500	1,904,965	1,615,541	289,424	
Average					0.163
Standard deviation					0.042

As shown in Tables 6.15 and 6.16, the ratios in Model P are more proportionally distributed compared to that in Model C. It is indicated by the values of standard deviation of ratios in Model P (0.029) which is lower than that in Model C (0.042). In addition, the common cycle strategy seems to be undesirable for a retailer with small demand. As can be seen in Table 6.15, R_8 (the retailer with the smallest demand) has spent \$28,493 costs but only received \$1,507 profit. In other words, R_8 is disadvantaged by applying the common cycle approach.

Table 6.16 Ratio between profit and cost of each retailer (Model P – synchronised cycle)

Retailer	Demand	Revenue	Costs	Profit	Ratio (cost/profit)
1	3,000	89,932	77,247	12,684	0.16
2	4,000	120,000	102,460	17,540	0.17
3	5,000	150,000	127,378	22,622	0.18
4	2,500	75,000	65,267	9,733	0.15
5	6,000	180,000	152,371	27,629	0.18
6	8,000	240,000	202,281	37,719	0.19
7	10,000	300,000	251,677	48,323	0.19
8	1,000	29,999	27,358	2,641	0.10
9	15,000	450,000	377,051	72,949	0.19
10	9,000	270,000	226,633	43,367	0.19
Total	63,500	1,904,931	1,609,723	295,208	
Average					0.170
Standard deviation					0.029

Further, it is also interesting to investigate whether the total profit of the integrated system is proportionally distributed between the manufacturer and the retailers. To evaluate this, the ratio between the total profit gained and the cost spent by each player (manufacturer vs. retailers) is calculated and presented in Table 6.17. As shown in Table 6.17 the ratios of the total profit to the total cost for both approaches have similar proportions. However, the synchronised cycle produces a slightly better result indicated by a smaller ratio gap between the manufacturer and the retailers. The gap between ratios indicates that one player gets more benefit of investment than another player in the supply chain system. In this case, for both approaches, the rate of the investment benefit for retailers is lower compared to that in the manufacturer. It appears that in the integrated policy either the common or synchronised cycle does not advantage the retailers as much as it does the manufacturer. To rectify this condition, the manufacturer can offer a quantity discount to entice the retailers in the integrated policy. This strategy is important since it would offer a win-win solution resulting in the integrated approach being acceptable to all parties in the supply chain.

Table 6.17 Ratio between profit and cost of players in the supply chain

Player	Model C – common cycle			Model P – synchronised cycle		
	Total cost	Total profit	Ratio	Total cost	Total profit	Ratio
Manufacturer	1,304,403	283,097	0.217	1,302,325	285,175	0.2190
Retailers	1,615,541	289,424	0.179	1,609,723	295,208	0.1834
Total	2,919,944	572,521		2,912,048	580,383	
Range			0.038			0.036

6.3.3 Scenario three: Model behaviour

In scenario three, how the proposed model or Model P behaves is evaluated and discussed. Similar to the previous scenarios, parameters in Table 6.2 are used as the inputs to BRKGA program. Meanwhile, parameters in Table 6.3 are the inputs for Model P (Equation 4.33) with modification in some related parameters as shown in Table 6.4. There are some questions that need to be answered in this scenario which are discussed in the following section.

6.3.3.1 Relation between the quality loss in raw material and model performance

Numerical test in this section is aimed at elaborating the relations between some quality parameters, e.g. the rate of quality loss (θ), the cost because of quality loss (C_{Qs}) and the total profit. It is moderated by changing the value of θ from 0.1 to 0.5 and altering the value of C_{Qs} from 10 to 300. Using the modified quality parameters, the model is optimised and the new total profit is then summarised in Table 6.16. Further, the relationship between parameter changes and total profit is represented in Figure 6.3.

Table 6.18 shows the total profit diminishes when the rate of the quality loss (θ) as well as the quality cost increases (C_{Qs}). The increase in C_{Qs} and θ also influences the replenishment strategy, i.e. the number of raw material procured during the length of production cycle becomes greater. It means that when the rate of quality loss is higher and the cost because of the quality loss is greater, the size of raw material order is smaller. This is essential to ensure that the raw material has a higher quality when it is consumed for production hence a higher cost because the quality loss can be avoided. In addition, the result in Table 6.18 also shows that the changes in C_{Qs} and θ insignificantly affect the production and distribution plan. The values of T, n_{rj} and Z, are relatively the same.

Further, Figure 6.3 demonstrates that for any value of θ, the decrease in the total profit as C_{Qs} grows following a linear trend. Similarly, for any value of C_{Qs}, the total profit decreases when θ increases. The total profit reaches its lowest level of \$563,025 when the values of the quality loss rate and the quality cost are at their highest level (θ = 0.5 and C_{Qs} = \$300). This would agree with intuition that if the quality loss and the cost of quality loss are higher, consequently, the total profit will be lower.

Table 6.18 Model performance at various rates of the quality loss and the penalty cost

θ	C_{Qs}	TP	n_s	T	n_{rj}										Z									
					R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
0.1	10	582725	8	0.1175	2	3	3	2	3	5	10	2	14	10	9	7	10	8	4	2	6	5	1	3
	60	581331	10	0.1162	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	120	579928	11	0.1127	2	2	3	2	4	4	10	2	13	7	9	7	10	8	4	6	5	3	2	1
	180	578599	13	0.1161	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	240	577466	14	0.1120	2	2	3	2	3	4	10	2	13	7	9	7	10	8	1	3	6	5	2	4
	300	576403	15	0.1155	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
0.3	10	582166	9	0.1163	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	60	578599	13	0.1161	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	120	575440	17	0.1163	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	180	572849	20	0.1162	2	3	3	2	4	6	9	2	13	10	9	10	7	6	4	2	5	3	1	8
	240	570621	22	0.1162	2	3	3	2	4	6	10	2	15	8	9	7	10	6	4	2	5	3	1	8
	300	568693	24	0.1133	2	2	3	2	4	4	10	2	13	7	9	7	10	8	4	6	5	3	2	1
0.5	10	581610	9	0.1119	2	2	3	2	3	4	10	2	13	7	9	7	10	8	1	3	6	5	2	4
	60	576403	15	0.1155	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8
	120	572107	20	0.1128	2	2	3	2	4	4	7	2	13	10	9	10	7	8	4	6	5	3	2	1
	180	568693	24	0.1133	2	2	3	2	4	4	10	2	13	7	9	7	10	8	4	6	5	3	2	1
	240	565605	28	0.1178	2	3	3	2	3	5	12	2	14	9	9	7	10	8	4	2	6	5	1	3
	300	563025	31	0.1161	2	3	3	2	4	6	10	2	13	9	9	7	10	6	4	2	5	3	1	8

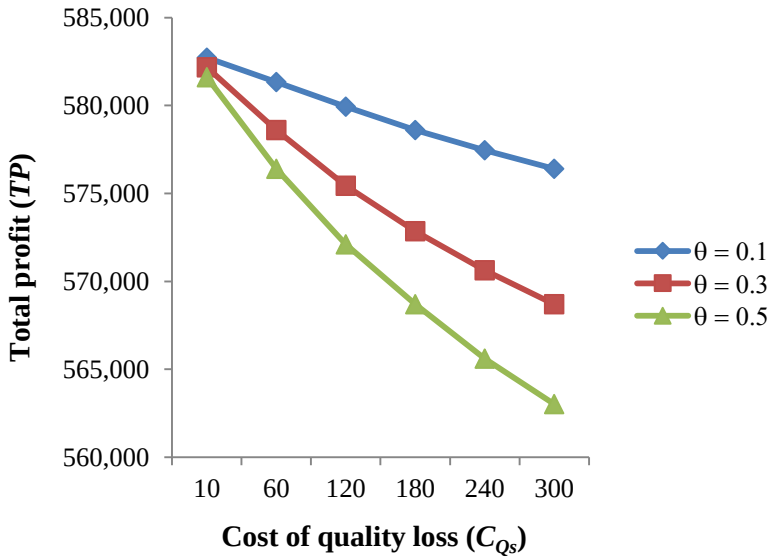


Figure 6.3 The effect of various deterioration rates and costs of quality loss on the total profit

For a situation where quality loss cost is high, reducing the temperature may be beneficial for the system as it will decrease the rate of quality deterioration or θ (Rong, Akkerman & Grunow 2011; Zanoni & Zavanella 2012). To investigate such a problem, the current temperature in Table 6.3 is changed to 290 K and 280 K. The changes in the rate of quality loss, the related costs and the total profit due to these temperature reductions are presented in Table 6.19.

Table 6.19 The values of the quality loss rate, the related costs and the total profit at different temperature

Temperature (τ)	Quality loss rate (θ)	Costs of quality loss	Costs of energy	Total profit (TP)
300 K	0.162	6,857	600	573,635
290 K	0.123	5,661	733	575,155
280 K	0.092	4,649	895	576,566

As seen from Table 6.19, when the temperature is reduced by 20 K, the rate of quality loss decreases from 0.162 to 0.092. Since the quality loss rate becomes smaller, the costs of quality loss also diminish. As predicted, the costs of energy increase as the temperature decreases. The increase in energy costs, however, is compensated by saving from the decline in quality costs. Hence, in overall the total profit increases from $573,635 to $576,566. This finding is in-line with Rong, Akkerman and Grunow (2011) and Zanoni and Zavanella (2012) demonstrating that managing the storage temperature can be beneficial for the system.

6.3.3.2 Relation between the perceived value loss in finished goods and model performance

In this numerical test, the relationship between the perceived value loss parameters (T_{start} and T_{sl}) and model performance is evaluated. The variable T_{start} represents the time when the customers' willingness to pay for the product starts decreasing as they perceive the product value is degraded. The value is based on customers' perception with various preferences. It makes deciding the exact value of T_{start} quite complicated. Contrarily, the information of T_{sl} or product shelf-life is easily found since the product expiration date is imprinted on the food label. In this numerical test some various values of T_{start} and T_{sl} such as in Table 6.4 are used as the inputs of the proposed model. The model with the various values is then optimised and the new result is presented in Table 6.20. Further, the relationship between total profit and various values of T_{start} and T_{sl} is illustrated in Figure 6.4.

As shown in Table 6.20, the change in the values of T_{start} and T_{sl} dramatically changes the strategy of managing the perishable items. Firstly, in situations where T_{start} appears earlier (i.e. the customer willingness to pay, WTP, for the product decreases early) and the product has a short shelf-life; the length of production cycle in the manufacturer or T is significantly shorter. Secondly, when T_{start} becomes shorter, the frequency of raw material replenishment and delivery of finished goods are also reduced. The strategy of shortening the T_{start} is aimed at preventing the system from having more outdating and outdated items. Though it may work, it significantly increases the setup cost. For example, the value of 0.1176 of T (T_{sl} = 0.1667, T_{start} = 0.5T_{sl}) leads to \$12,760 setup cost while T=0.0148 (T_{sl} = 0.0417, T_{start} = 0.25T_{sl}) results in \$101,163 setup cost.

Further, as seen in Figure 6.4, the decrease in the total profit is nonlinear to the changes in T_{sl} as well as T_{start}. It is indicated by widening gaps between the lines at different values of T_{sl} and T_{start} and the gap is more obvious at the smallest value of T_{sl} (0.0412). For example, from Table 6.19, at T_{sl} = 0.0412, if the value of T_{start} changes from 0.75T_{sl} to 0.50T_{sl} the total profit declines from \$503,734 to \$386,723 (gap = \$117,011). Meanwhile, varying T_{start} from 0.50T_{sl} to 0.25T_{sl} leads to a huge decrease in the total profit, i.e. from \$386,723 to \$85,794 (gap = \$300,929 – almost three times higher than the previous gap). It means that the effect of a change in T_{start} is significant to the total profit with a nonlinear pattern.

Table 6.20 Model performance due to various T_{sl} and T_{start}

T_{start}	T_{sl}	TP	n_s	T	n_{rj}										Z									
					R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
$0.25T_{sl}$	0.0412	85,794	1	0.0148	1	2	1	1	2	2	2	1	3	3	8	5	2	10	9	1	4	3	7	6
	0.0824	472,071	1	0.0285	3	4	3	2	4	2	3	1	5	4	4	5	2	9	7	1	8	3	6	10
	0.1236	539,646	4	0.0455	2	2	5	3	3	4	9	2	6	8	4	9	10	6	1	3	8	7	2	5
	0.1648	564,866	6	0.0665	4	3	3	2	4	3	6	2	6	8	1	9	7	3	4	10	8	5	6	2
$0.50T_{sl}$	0.0412	386,723	1	0.0206	3	4	3	2	4	3	2	1	3	4	4	5	2	9	6	1	8	3	7	10
	0.0824	559,936	5	0.0562	2	2	3	2	4	5	5	3	6	12	10	7	9	4	1	6	8	5	2	3
	0.1236	577,181	9	0.0909	2	3	3	2	4	4	8	2	12	7	9	2	7	8	4	5	10	6	1	3
	0.1648	580,507	11	0.1176	2	3	3	2	4	6	10	2	13	9	9	7	10	6	8	2	5	3	1	4
$0.75T_{sl}$	0.0412	503,734	1	0.0278	5	2	1	1	3	2	5	2	5	4	1	5	10	6	4	7	8	9	3	2
	0.0824	576,923	9	0.0912	2	3	4	2	4	6	8	2	15	9	9	6	7	8	4	3	10	5	1	2
	0.1236	580,884	11	0.1184	2	2	3	2	3	6	12	2	14	9	9	7	10	6	4	5	3	8	2	1
	0.1648	582,832	10	0.1102	1	2	2	1	3	5	10	1	13	9	9	10	7	6	5	2	3	8	4	1

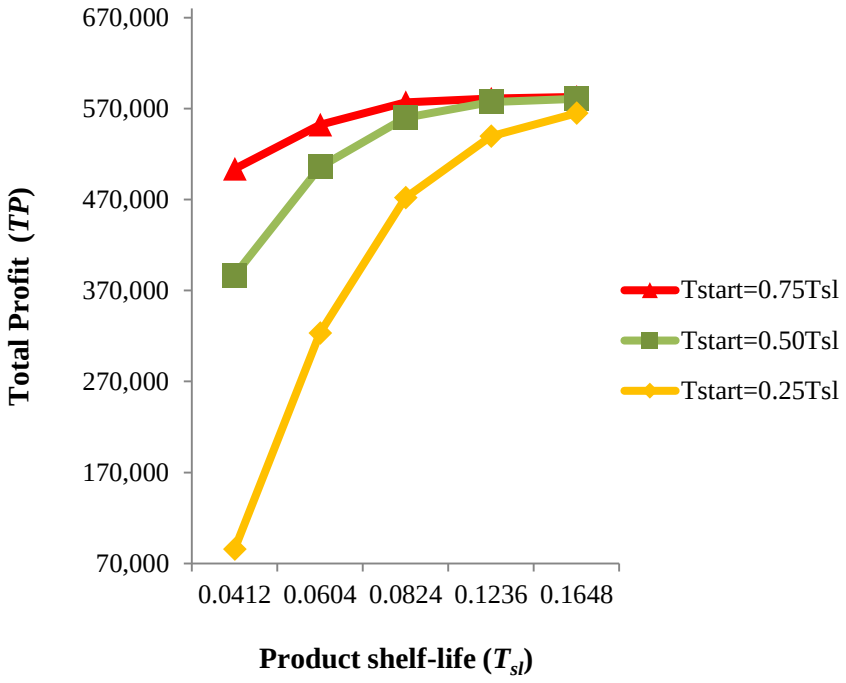


Figure 6.4 T_{sl} vs. total profit for various T_{start}

Similarly, still from Table 6.20, at the value of $T_{start} = 0.25T_{sl}$, if the shelf-life is gradually reduced at interval 0.0412, the total profit then nonlinearly declines from \$564,866 to \$85,794. The rate of decline in the total profit becomes faster when T_{sl} reaches the value of 0.0824 (as seen in Figure 6.4). The result shows that a product with short shelf-life can significantly reduce the total profit hence it needs to be carefully managed. In addition, it is also worth investigating the relationship between the investment on preservation effort and the benefit gained from prolonging product shelf-life. An investigation such as in Hsu, Wee and Teng (2010) which considered the preservation investment to reduce the rate of deterioration in quantity depletion inventory can be another alternative to improve model performance. Hence, the manufacturer and retailers have more options when deciding the strategy of managing perishable items.

6.3.3.3 Relation between the production rate and model performance

The numerical test in this section is aimed at investigating the relationship between the production rate and the total profit, i.e. how the change in production rate influences the total profit. For this purpose, the various values of α such as in Table 6.4 are used. The variable α represents the ratio between the demand rate (D) and the production rate (P). Hence, $\alpha = 1$ meaning that the demand rate is equal to the production rate. A low value of α represents a condition where the production rate is much greater than the rate of

demand, while a high value of α indicates that the production rate is slightly over the demand rate. In this numerical test, the model performance with various α is measured and the best solution is selected. The result is then presented in Table 6.21, and Figure 6.5 depicts the relationship between the value of α and the total profit.

As seen in Table 6.21, the total profit increases when α grows from 0.5 to 0.9. It appears that the closer the value of production rate to the rate of demand the higher the total profit will be. The increase of the total profit as α grows shows a nonlinear trend. Increasing α from 0.5 to 0.6 leads to a change in the total profit from $576,007 to $577,318 (gap of the profits = $1,241). Meanwhile, changing α from 0.6 to 0.7 results in an increase in the total profit from $577,318 to $580,174 (gap of the profits = $2,856 or double the previous gap).

This relation is clearly seen in Figure 6.5 that the total profit grows from around $576,000 to almost $590,000 when α is increased from 0.5 to 0.9. This indicates that if the production rate is adjustable, it would be more beneficial to set its value near to the rate of demand due to higher profit. This finding is in line with Blackburn and Scudder (2009) who found that the picking rates of melons and sweet corn need to be controlled to reduce the value loss of the products across the supply chain to ensure the profit can be maximised.

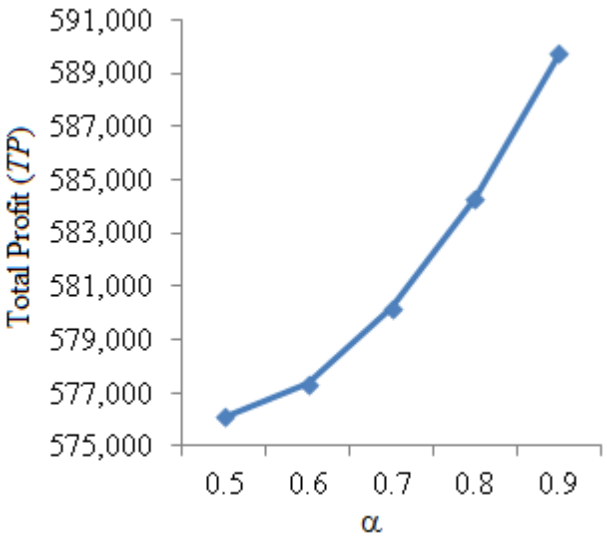


Figure 6.5 Relation between α and the total profit

Table 6.21 Model performance at difference α

D	P	α	TP	n_s	T	n_{rj}										Z									
						R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
63,500	127,000	0.5	576,077	6	0.0787	1	2	2	1	2	3	5	1	8	6	9	10	7	3	4	2	6	5	1	8
	105,833	0.6	577,318	8	0.0921	2	2	2	2	3	4	7	1	11	6	9	7	10	6	1	4	5	2	8	3
	90,714	0.7	580,174	11	0.1156	2	3	3	2	4	6	10	2	15	8	9	7	10	6	4	2	5	3	1	8
	79,375	0.8	584,286	14	0.1352	3	3	4	2	4	6	14	2	15	12	9	7	10	6	8	5	3	1	4	2
	70,556	0.9	589,728	21	0.1963	4	4	5	3	6	9	19	3	28	19	9	7	10	6	8	5	3	2	4	1

Further, still looking at Table 6.21, when the production rate is much greater than the demand rate, the length of production cycle or T tends to be shorter. Increasing the production rate from 70,556 to 79,375 units per year (around 12.5% higher) reduces T from 0.196 to 0.135 per year (around 31.1% shorter). The reduction of T is to anticipate the increase in holding costs since a high production rate potentially raises the average of the inventory. Note that a shorter T is beneficial to prevent the system from having more aging products as a high production rate may lead to a longer waiting time of items after being produced in the manufacturing system.

On the other hand, when the production rate is slightly over the demand rate, a longer T is preferable. As previously discussed, a longer T reduces the setup cost but increase the quality cost of raw material and the holding cost of inventory. To anticipate this, a more frequent raw material replenishment and finished goods deliveries during the production cycle is desirable. As shown in Table 6.21, at T = 0.135 (the length of the production cycle is equal to 0.135 year), the raw material is replenished 14 times and the finished goods are delivered 55 times (in aggregate) during the production cycle. It means that the size of raw material order (q_s) is equal to 766.7 units ($P \times T/n_s$ = 79,375×0.135/14) and the size of the delivered finished goods (in average) is equal to 143.7 units ($\overline{q_{rj}}$ = $\Sigma(T/n_{rj}) \times d_{rj}$). When T is lengthened from 0.135 to 0.196 per year, the values of n_s and n_{rj} increase (21 and 65 respectively), hence q_s is equal to 659.6 units (70,556×0.196/21) and $\overline{q_{rj}}$ = 144.1 units. Increasing the length of the production cycle around 31.1% does not raise the average inventory of raw material (as q_s decreases) though it slightly influences the inventory of finished goods (as $\overline{q_{rj}}$ slightly increases). The effect of a longer production cycle to the quality and perceived value loss still can be managed by elevating the values of n_s and n_{rj}. This strategy leads to a higher total profit as seen in Figure 6.5.

6.4 Concluding remarks

In this chapter numerical tests to benchmark and evaluate the performance and the response of the developed model are conducted and the results are analysed. The problems represented by the mathematical models presented in Chapter 4 are solved using the hybridised BRKGA developed in Chapter 5. Three scenarios of the numerical

tests which related to some questions regarding the models are carried out and the results are evaluated and discussed.

The results of the first scenario revealed a potential benefit of considering the quality and perceived value loss while managing the inventory of raw materials and finished goods across the supply chain. The result of comparing the perishable and non-perishable approach showed that overlooking the perishable items may lead to an inventory strategy which eradicates a chance to increase the profit by up to 8.6 %. It also demonstrates that the strategy has potential to minimise the number of outdating and outdated items. The numerical test results of scenario one emphasises the importance of accommodating the specific characteristic of a perishable item like food while deciding the inventory strategy.

Further, the numerical tests in scenario two confirmed the hypothesis that the coordination mechanism affects the system performance. A comparison between a synchronised cycle and common cycle policy demonstrated a potential benefit of synchronising the production cycle in manufacturer with the ordering cycle of retailers. The synchronised cycle potentially reduces some related costs. The approach is also more flexible and relatively fairer since the retailers are free to have a more desirable number of ordering cycles. Meanwhile, in the common cycle approach, all retailers are forced to have the same interval of orders which can be a disadvantage for some retailers, especially a retailer with small demand.

Finally, in the last scenario, the model behaviour according to some parameter changes has been evaluated and discussed. The first numerical test in scenario three illustrated the linear correlation between the model performance (the total profit) and the quality-related parameters in raw materials, e.g. the rate of quality loss and the cost of handling the quality loss. The results showed that the total profit linearly decreased when the rates of quality loss and cost grew. On the other hand, the second numerical result revealed a nonlinear relationship between the total profit and the perceived value loss-related parameters, e.g. time when customer willingness to pay (WTP) for the perishable finished goods starts decreasing or T_{start} and product shelf-life or T_{sl}. A product with a short shelf-life experiences an earlier decrease in customer WTP, resulting in the reduction of the total profit. The last numerical tests demonstrated a nonlinear relationship between the total profit and the production rate. The total profit increased nonlinearly when the rate of production was approaching the rate of demand. Therefore, if the production rate is

adjustable then setting its value closer to the rate of demand is more desirable for a higher profit of the integrated system.

Further, it would be interesting to discover if the developed model is able to be implemented in a real case. This will be presented and discussed in Chapter 7

Chapter 7

An integrated production-inventory policy for food products: A case study

7.1 Introduction

The numerical result in Chapter 6 shows significant potential benefits of applying the proposed model when managing perishable items across the integrated single vendor multi buyer system. It is revealed that considering the quality degradation of food products, either in raw materials or finished goods, while deciding the inventory policy would reduce the waste (outdated items) and increase the total profit.

The developed model is further validated in this chapter by conducting a case study to evaluate a possible application. A food company which produces noodles is selected as a case study. The characteristics of the company are suited to the developed model for the following reasons. Firstly, it procures deteriorating raw materials such as wheat flour where the quality is degraded over time. Secondly, the company produces fully packed perishable items (noodles) with the shelf-life information imprinted on their package. In addition, from preliminary observation, it is also indicated that customers require a longer remaining shelf-life of noodles and feel reluctant to buy them when the products approach their expiration dates. These characteristics are similar to issues that are addressed in the developed model.

Relevant information such as product profile and features, supply chain configuration, *etc*. is collected and then used as an input to the developed model. This will be described in detail later. Similar to the optimisation process in Chapter 6, the BRKGAs are utilised to find the optimal solution. The result is then evaluated, analysed and discussed. In addition, all input parameters in the case study are assumed to be constant over the planning horizon. In real life, however, some changes in input parameters may occur. Hence, sensitivity and error analyses are used to evaluate how far the changes in parameters influence the solution.

The remaining sections of this chapter, therefore, are organised as follows. Section 7.2 briefly describes the case study and Section 7.3 discusses the potential application of the developed model and proposes a production-inventory plan based on the developed model for the case study. Section 7.4 evaluates the performance of the proposed method and compares it to the current system while Section 7.5 analyses the sensitivity of the purposed model and measures error because of changes in input parameters. Finally, Section 7.6 summarises this chapter.

7.2 A brief description of the case study

The case study is inspired by an observation of a food company which produces noodles in Indonesia. The company (called Company X due to confidentiality) is an important food producer in Indonesia. Its products, especially the dried noodles, are popular in Indonesia. The observation focused on the dried noodles production since it is the company's primary product. The explanation for product profile and characteristics is presented in the following subsections.

7.2.1 Product profile and characteristics

Noodles are one of the most popular foods in Indonesia. They play a significant role in the food consumption pattern of Indonesian society. Indonesian biro statistic BPS (2015) reported that the carbohydrate intake from rice (which is the staple food in Indonesia) decreases 1.5% per year while the non-rice carbohydrate intake (especially from noodles) increases. The same source also reported that the rate of Indonesian household expenditure allocated for consuming noodles increases 5.95% per year. It confirms the fact that this kind of food is not only becoming more popular but also influences the pattern of food consumption of Indonesians.

Three types of noodles commonly consumed by Indonesians are fresh noodles, instant noodles and dried noodles. Fresh noodles are categorised as raw and wet food products. They have a moisture content ranging from 32% to 40% thus their shelf-life is quite short from one to a few days depending on the storage condition (Fu 2008). On the other hand, instant noodles are raw noodles cooked by steaming and dehydrated by frying process. They contain cooking oil around 15-22% (Fu 2008) and have longer shelf-life (6-8 months) compared to the fresh noodles. Further, dried noodles are raw noodles that have been steamed and dried at high temperature. The drying process reduces the water activity

where the considered moisture content of dried noodle is less than 14% (Hatcher 2001). The low level water activity prolongs the shelf-life of dried noodles since it stops quality deterioration and microbial growth (Crosbie & Ross 2004). The last two noodles (dried and instant noodles) are produced in Company X where the dried noodles are the company's primary product.

The growth in market value of dried noodles in Indonesia shows a significant increase as depicted in Table 7.1. Together with ice cream and cooking oil, the dried noodles lead the growth in the food market around 50%, 30% and 30% respectively. A significant growth in the dried noodle market is followed by the increase in production capacity of some important players in this sector as shown in Table 7.2. In the last few years, majority companies increased their production capacity. Also from Table 7.2, one company (Sinar Pangan Sejahtera) even doubled its production capacity, and another company (Surya Pratista Hutama) extended it up to three times. The data shown in Tables 7.1 and 7.2 confirm the potentiality of this sector since the market continuously grows (Nielsen, cited in Setiadi, 2012).

Table 7.1 Market growth of food products (Nielsen, cited in Setiadi, 2012)

Product	Growth (in percentage)
Ice cream	>50%
Cooking oil	>30
Dried noodles	>30
Chilli sauce	>20
Cheese	>20
Soya sauce	>20
Tea and ready to drink (RTD)	17.5
Milk	17.3
Chocolate	16.7
Coffee	15.8
Syrup	13.6
Gum	12.2
Margarine	10.6
Cereal	10.2

Further, regarding the flour used, the dried noodles can be categorised into rice flour noodles and wheat flour noodles, and both types are produced in Company X. However, the case study only focuses on the wheat flour noodles since the production scale is the largest and the main raw material (i.e. wheat flour) needs to be carefully managed.

Table 7.2 Production rate growth of some important players in dried noodle business (Nielsen, cited in Setiadi, 2012)

Company	Capacity growth (in percentage)
Subafood Pangan Jaya	>30
Tiga Pilar Sejahtera	>25
Indofood	>25
Heinz Suprama	>45
Sinar Pangan Sejahtera	>100
Wijaya Panca Sentosa Food	>45
Surya Pratista Hutama	>295
Kuala Pangan	>25

Using appropriate wheat flour is essential for dried noodles quality. In general, dried noodle requires wheat flour with gluten content not less than 11% (Hatcher 2001). The gluten is responsible for creating the main structure of a noodle strand (Crosbie & Ross 2004). It is also helpful in preventing noodles from breakage during the drying process (Fu 2008). Note that apart from its important role in creating noodle texture and process, the wet gluten quantity in wheat flour can decrease during storage time (Miœ 2003).

Miœ (2003) investigated the influence of storage time on the quantity of wet gluten. Two types of wheat flour (called ROMA and IGNA) with 11.5% moisture content were stored for 8 months at a temperature of 22.5°C. The result showed that the quantity of wet gluten in both wheat flours decreases during the storage period. Wet gluten quantity in ROMA decreases around 3.1% (from 22.6 to 19.5%) while, in IGNA, the quantity is reduced by 10.3% (from 25.4 to 15.1) over 32 weeks as shown in Figure 7.1. The decrease in wet gluten quantity will affect the quality of its derivative products. This phenomenon is suited for representing the quality loss model developed in this research.

As discussed earlier, handling the quality loss in wheat flour as a raw material is the main concern to avoid a higher cost due to this quality loss. However, when the wheat flour is processed and transformed into dried noodles and shipped to retailers, the problem is changed. The wheat flour-dried noodles are sold in packages with their expiration dates imprinted on their label. The shelf-life of dried noodles can reach 12 months due to their low water content level (Fu 2008). However, the consumption behaviour of dried noodles

is different from fresh noodles. For fresh noodles, the interval between "buy" and "consume" is short. The customer should buy as much fresh noodles as needed and cook them on the same day since they cannot be stored for a long time. On the other hand, for dried noodles, customers buy them in a relatively large quantity (not for the same day need) and keep them as inventory. Consequently, dried noodles with longer residual shelf-life are preferable. Customers become curious about the expiration date information and prefer to buy a product with a longer remaining lifetime. In addition, business in this sector is quite competitive and usually there is no loyal customer. Customers quickly change their decision on selecting the noodles, i.e. not loyal to just one brand. Besides price and taste, the product's residual shelf-life can be one factor that makes the customer decide to buy or not buy it. Therefore, the perceived value loss phenomenon is relevant to dried noodles. Even though the product is still eligible to be consumed, its value is degraded when customers compare its residual shelf-life with other products which have a longer remaining lifetime.

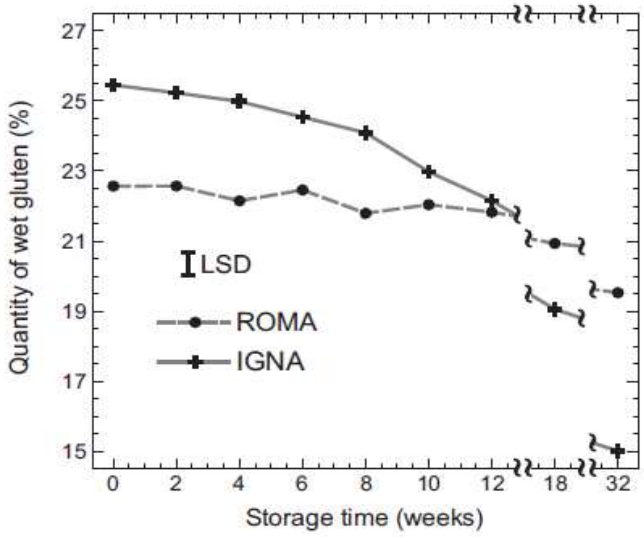


Figure 7.1 The effect of storage time wheat flour on the quantity of wet gluten (Miœ 2003)

7.2.2 Supply chain configuration of the observed system

Company X supplies its products to more than one hundred cities and thousands of outlets separated from the eastern to the western areas of Indonesia. They have twenty nine main networks at different places. The networks are the other unit business of Company X's owner. They are under the same holding company but in different unit businesses, i.e. as

a producer or a manufacturer, Company X, and as seller or distributor, the twenty nine networks. In this case study, Company X plays a role as the **manufacturer** while the networks are the **distributors** ($D_{1\text{-}29}$) which buy Company X products and sell them to the customers. In a situation where the players are from the same owner, the integrated policy is easier to execute. Even if the policy is more advantageous for one party, it may not cause a big issue since the profit can be easily shared. The position of Company X in the supply chain configuration of this business is presented in Figure 7.2.

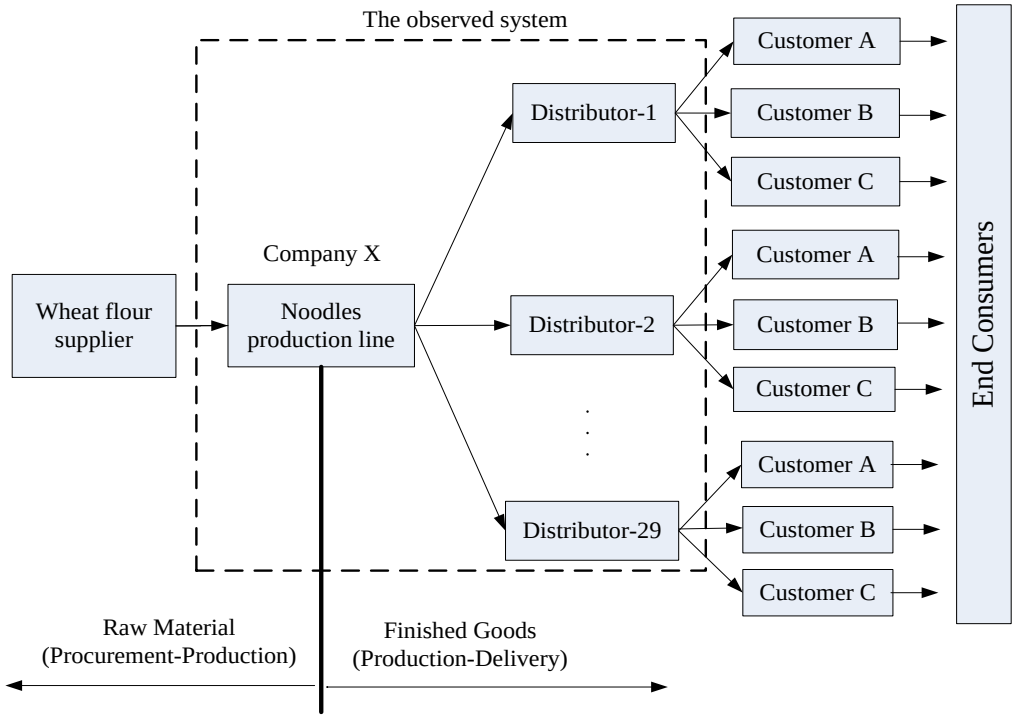


Figure 7.2 Noodles supply chain configuration

As seen in Figure 7.2, the raw material is supplied from other companies. The procurement contract is renewed every three months and the replenishment is done during the length of the production run. Company X produces the wheat flour-dried noodles and delivers them to the distributors. The distributors buy the dried noodles from Company X then sell them to customers. The customers are mainly categorised into three groups, namely A, B and C. Modern markets such as supermarkets, minimarkets *etc*. are part of customer A while traditional markets are members of customer B. Customer C consists of restaurants, catering and other food service businesses. Customers A and B supply the dried noodles from the distributor and sell them to the next buyers which are the end customers while, in the food service business group, the dried noodles are the raw materials that will be processed before selling them to the end customers.

7.2.3 Relevant data

In this case study, collecting the relevant data that can be used to measure the performance of the observed system is quite complicated due to availability and confidentiality. For the holding cost data, for instance, most of the time companies do not exactly define this type of cost thus the information regarding this cost is not available in their financial report. Dealing with these issues, some data are estimated using the relevant data available. For example, the cost of holding inventories is approached as the percentage of the product price in the market. The percentage value or *i* is set slightly higher than the Indonesian bank interest rate.

Further, to make the calculation easier, all data are converted to the same metrics. For example, the wheat flour is procured in the sack (1 sack = 25kgs) while dried noodles are sold in packages or bags (1 bag = 200gs). To simplify the calculation, kilogram will be used to represent the quantity of both items. Metrics used to represent quantity, time and currency are kilogram, year and Indonesian *rupiah* or Rp, respectively. Those data are divided into three groups, namely, data of raw material, data of finished goods in the manufacturer system and data of finished goods in the distributor system.

The data related to the raw materials are the demand, purchasing cost, the transportation cost, the holding cost, the quality loss cost and the rate of the quality loss. The demand for raw materials depends on the number of raw materials required to produce one kilogram dried noodles. To produce a kilogram of noodles 1.05 kilograms of wheat flour is needed (the conversion factor or ε is equal to 1.05). It means that if the demand for finished products is equal to 1000 kilograms then the demand of raw materials (d_s) should be 1050 kilograms (1000×1.05). Further, the transportation cost is assumed to be fixed as per size of order while the cost incurred for holding one kilogram raw material per year depends on the purchasing cost of the raw material and the value of *i*. The variable *i* represents the proportion of the raw material purchasing cost where its value is slightly higher than the Indonesian bank interest rate (i = 0.065). Finally, the cost of quality loss is decided as a fraction of the finished product selling price (0.1) during one year while the characteristic of quality loss refers to the decrease in gluten washed out quantity such as in Miœ (2003). All estimations of the values of parameters related to the input in the raw material are presented in Table 7.3.

Table 7.3 Data related to the raw materials

Parameters	Notation	Value	
Conversion factor	ε	1.05	
Demand for raw material	D_{raw}	50,400	1000 kg/year
Raw material price	C_s	9	Rp. 1000/kg
Transportation cost	A_s	5,000	Rp. 1000/replenishment
Holding cost	H_s	7.02	Rp. 1000/kg/year
Rate of quality loss	θ	0.2	
Cost because of quality loss	C_{Qs}	15	Rp. 1000/kg/year

Further, the data related to the finished goods are divided into data in the manufacturer (Company X) and the distributors (D_1-D_{29}). Data related to finished goods of the manufacturer are the production rate, the total demand, the selling price, the holding cost, the processing cost and the setup cost. Company X is able to produce 48 million kilograms of dried noodles per year while the demand of this type of noodles is 25 million kilograms per year. The price of selling dried noodles to distributors is Rp.12500/kg while 20% of this price is estimated for the manufacturing or processing costs. Further, the approach in estimating the cost of holding the finished goods is similar to the approach to obtain the raw material holding cost, i.e. it is charged proportionally from the product price (0.065×Rp.12500). The summary of these parameters is presented in Table 7.4

Table 7.4 Data related to the finished goods in manufacturer

Parameters	Notation	Value (000)	
Production rate	P	48,000	kg/year
Total demand	D	28,000	kg/year
Price for distributors	C_r	12.5	Rp/kg
Manufacturing cost	C_m	2,5	Rp/kg
Holding cost	H_m	9.75	Rp/kg/year
Setup cost	A_m	100,000	Rp/setup

Data related to the finished goods in the distributor system are the cost of purchasing dried noodles from the manufacturer, the perceived value loss parameters (i.e. time when customer's WTP starts decreasing and product shelf-life), the transportation cost of the finished goods, the holding cost, demand of each retailer, the transportation lead time and the selling price of the products to the next customers (customers A, B and C).

The purchasing cost in retailers is equal to the selling price of the manufacturer while the selling price to the next customer depends on the age of the batch ranging from maximum price to minimum price. The maximum price is the regular price before the perceived value loss occurs while the minimum price is the price when the product is expired or will not be sold to customers. Theoretically, the age of noodles is around 12 months (Fu 2008). However, in practice, products with one to three months left before their expiration dates will be recalled from the distributors. Company X will buy the products back with a reject product price (slightly lower than the raw material purchasing cost). Using this policy, the shelf-life of the products for the distributors is consequently shorter than its real shelf-life. For example, the expiration date of the dried noodles is 12 December 2016. On12 October 2016 (depending on the contract), if there are still some unsold dried noodles left with the distributors, Company X will buy them back though they are actually relatively far from expired. Considering this, in this case study, the 'buy back' time (2 months before expiration date) is set as the end of product shelf-life, i.e. T_{sl} = 10 months ≈ 0.833 year. In addition, it is also important to note that the distributors require that the products be delivered as soon as they are produced. It is expected that the distributors can receive a batch of products with age less than two months so they can sell the batch to the next customers at the maximum price. Hence, the perceived value loss is assumed to start when the products are at the age of two months (T_{start} = 2 months ≈ 0.167 year). The summary of this information is represented in Table 7.5

Table 7.5 Data related to perceived value loss parameters in distributors

Parameters	Notation	Value (000)
Maximum price	P_{max}	16
Minimum price	P_{min}	7
Time when customer's WTP decreases	T_{start}	0.167
Product shelf-life	T_{sl}	0.833

Finally, the cost of holding finished goods in the distributors is equal to the proportion of the maximum price of the products. Since the maximum price in all distributors is assumed to be the same, the holding cost in all distributors is also assumed to be the same. On the other hand, the transportation cost to each distributor is different depending on the transportation lead time. The longer the lead time, the higher the transportation cost. The

lead time value ranges from 1 to 4 weeks covering the loading, transferring and unloading time of the orders. The information related to these parameters is provided in Table 7.6

Table 7.6 Data related to the finished goods in distributors

Distributor	Demand, d_{rj} (000kg/year)	Lead time, LT_{rj} (year)	Transportation cost A_{rj} (Rp.000/shipment)	Holding cost H_{rj} (Rp.000/kg/year)
1	450	0.0411	10,000	13.65
2	1,200	0.0411	10,000	13.65
3	600	0.0274	8,000	13.65
4	600	0.0274	10,000	13.65
5	600	0.0274	8,000	13.65
6	450	0.0274	8,000	13.65
7	300	0.0274	8,000	13.65
8	600	0.0274	8,000	13.65
9	300	0.0274	8,000	13.65
10	600	0.0274	8,000	13.65
11	3,000	0.0192	5,000	13.65
12	2,400	0.0192	5,000	13.65
13	3,000	0.0192	5,000	13.65
14	3,000	0.0192	5,000	13.65
15	900	0.0274	8,000	13.65
16	600	0.0411	8,000	13.65
17	750	0.0274	12,000	13.65
18	450	0.0274	12,000	13.65
19	450	0.0274	12,500	13.65
20	600	0.0274	13,000	13.65
21	300	0.0274	15,000	13.65
22	450	0.0274	15,000	13.65
23	1,200	0.0411	15,000	13.65
24	600	0.0575	15,000	13.65
25	300	0.0384	15,000	13.65
26	300	0.0575	16,000	13.65
27	300	0.0575	16,000	13.65
28	250	0.0822	20,000	13.65
29	450	0.0822	20,000	13.65

7.3 An integrated production-inventory policy to manage the deteriorating raw materials and perishable finished goods in the integrated system

In this section, the information presented in Section 7.2 is used to formulate a production-inventory strategy to manage the deteriorating raw materials and perishable finished goods. The synchronised cycle model accommodating the deteriorating characteristics of

food product developed in Chapter 4 is utilised where the optimisation tool designed in Chapter 5 is applied to find the best decision. The result is presented in Table 7.7.

Table 7.7 Strategy proposed for the integrated production-inventory system

Decision Variables	Value														
n_s	8														
T	0.06471														
Distributor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
n_{rj}	1	2	1	1	1	1	1	1	1	1	4	3	4	4	2
Distributor	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	
n_{rj}	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
Z	**D_{13}-D_{11}-D_{14}-D_{12}-D_{15}-D_2-D_1-D_{16}-D_{21}-D_7-D_8-D_{22}-D_{17}-D_{20}-D_{29}-D_{10}-D_{23}-D_{18}-D_{19}-D_{27}-D_5-D_{26}-D_4-D_6-D_9-D_{24}-D_{28}-D_3**														

From Table 7.7, regarding the raw material procurement plan, the wheat flour will be replenished eight times ($n_s = 8$) during the production run length (Tp). Tp is calculated by multiplying the production cycle time (T) with α, or the ratio between demand and production rate ($Tp = \alpha T$). Given D_r = 25 million kg/year and P = 48 million kg/year then Tp is equal to 0.0337 year or around 12.3 days. Referring to $n_s = 8$ then the wheat flour will be replenished every 1.53 days. Further, still from Table 7.7, over the same production cycle, the finished goods, i.e. dried noodles, are delivered to the distributors where the distributors have their own ordering frequency ranging from 1 to 4 times (represented by n_{rj}). In addition, since the sequence of deliveries influences the performance of the system, the best schedule is also determined accordingly. The result is represented by Z where the first shipment is allocated for Distributor-13 and the last shipment is delivered to Distributor-3.

7.4 Evaluating the performance of the integrated policy

This section is aimed at evaluating the improvement made by the proposed production-inventory policy. A comparison study of total profit that can be gained from the proposed policy and the current policy is conducted and the result is examined and discussed. The information on the current policy is presented in Table 7.8.

As seen in Table 7.8, the current system has a shorter production cycle and fewer numbers of raw material replenishment frequencies during the production cycle compared to the data presented in Table 7.7. Meanwhile, the number of finished goods delivery of each distributor is quite similar, ranging from 1 to 4 times over the length of the production

cycle. Different from the proposed policy which optimised the delivery sequence, in the current policy, the sequence is arranged based on the transportation lead time from the longest to the shortest, i.e. the distributor with the longest transportation lead time will be scheduled at the first place. Therefore, the shipments for Distributor 28 and 29 are scheduled at the beginning while the batches delivered to Distributor 10-14 are arranged at the end as they have the shortest transportation lead time.

Table 7.8 Current strategy of the integrated production-inventory system

Decision Variables	Value														
n_s	2														
T	0.03156														
Distributor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
n_{rj}	1	2	1	1	1	1	1	1	1	1	4	4	4	4	2
Distributor	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	
n_{rj}	1	1	1	1	1	1	1	2	1	1	1	1	1	1	
Z	**D_{28}-D_{29}-D_{24}-D_{26}-D_{27}-D_{16}-D_{23}-D_1-D_2-D_{25}-D_3-D_4-D_{15}-D_{17}-D_{18}-D_{19}-D_{20}-D_{21}-D_{22}-D_5-D_6-D_7-D_8-D_9-D_{10}-D_{11}-D_{12}-D_{13}-D_{14}**														

Further, it is important to evaluate the performance of the current policy and compare it to the proposed policy. Hence, using the decision variables in Tables 7.7 and 7.8, and parameters in Tables 7.3, 7.4, 7.5 and 7.6 the performance of both systems are calculated and compared. The result is then summarised in Table 7.9.

Table 7.9 Performance of the current strategy and the proposed strategy: a comparison

Current Strategy	Manufacturer	Distributor	Total
Total Cost	305,003,763,331	328,725,907,922	633,729,671,253
Revenue	312,500,000,000	400,000,000,000	712,500,000,000
Total Profit	7,496,236,669	71,274,092,078	78,770,328,747
Proposed Strategy	Manufacturer	Distributor	Total
Total Cost	302,831,486,357	325,439,745,603	628,271,231,959
Revenue	312,500,000,000	400,000,000,000	712,500,000,000
Total Profit	9,668,513,643	74,560,254,397	84,228,768,041
Changes	Manufacturer	Distributor	Total
Total Cost	2,172,276,974	3,286,162,320	5,458,439,294
Revenue	0	0	0
Total Profit (%)	29.0%	4.6%	6.9%

As depicted in Table 7.9, with the given parameters, the proposed policy leads to a better system performance in terms of total profit. Implementing the proposed policy potentially increases the total profit by 6.9%. Both policies result in the same revenue, but the cost in the proposed policy is lower leading to the increased total profit of the system. The

proposed policy benefits the manufacturer since it leads to a total cost saving of up to 29% while the distributors are also advantaged since their total cost is reduced by 4.6%. Further detail regarding the cost saving in each item is presented in Table 7.10.

Table 7.10 Costs of the current strategy vs. the proposed strategy

Manufacturer system	Current (C)	Proposed (P)	C-P	% saving
Raw material transportation cost	316,836,702	618,140,743	- 301,304,041	
Raw material holding cost	759,201,069	389,139,150	370,061,920	
Raw material quality cost	324,444,901	166,298,782	158,146,119	
Finished goods holding cost	1,092,808,359	770,450,549	322,357,810	
Setup cost	3,168,367,024	1,545,351,858	1,623,015,165	
Total relevant cost	**5,661,658,056**	**3,489,381,082**	**2,172,276,974**	**38.4%**
Distributor system	Current (C)	Proposed (P)	C-P	% saving
Transportation cost	13,037,830,302	6,050,052,525	6,987,777,777	
Finished goods holding cost	3,188,077,620	6,889,693,078	-3,701,615,458	
Total relevant cost	**16,225,907,922**	**12,939,745,603**	**3,286,162,320**	**20.3%**

As seen in Table 7.10, in the proposed policy, the raw material transportation cost of the manufacturer and the finished goods holding cost of the distributors is almost doubled compared to those in the current policy. However, significant saving is gained from majority costs in the system where the costs are reduced by 50% (i.e. raw material holding cost, raw material quality cost, setup cost and finished goods transportation cost). Overall, the total relevant cost in manufacturer and distributor systems are reduced by 38.4% and 20.3% respectively (note that the total relevant cost is only composed of variable costs which are affected by the decision variables; some fixed costs such as raw material purchasing costs and processing costs are not included in the total relevant cost). A significant saving in the total relevant cost confirms that the proposed strategy has potential to improve the performance of the current system.

7.5 Sensitivity and error analysis

As discussed earlier, in the case study all parameters are assumed to have constant values during the planning horizon. In real life, however, the values may be fluctuated due to

uncertain factors. This fluctuation may or may not significantly influence the performance of the system. However, it would be beneficial to examine how far the changes in parameters affect the system performance to evaluate the robustness of the proposed policy. For this purpose, a sensitivity and error analysis is conducted.

The aim of carrying the sensitivity analysis is to examine the robustness of a model (Daellenbach 2004, p.148). A robust model means that a change in parameters does not affect the performance of the model due to its flexibility and ability to adapt. To examine whether the proposed model is robust, some steps for the sensitivity analysis are created. Firstly, the value of one parameter is changed from +20% to -20% while the values of the other parameters are kept the same. For example, the value of quality loss cost is changed to 18000 (+20%) and 12000 (-20%) while the values of others, holding cost, transportation cost *etc*. remain the same. Secondly, the proposed model with the new value of quality loss cost is optimised and the new performance (i.e. new total profit) is measured. Lastly, the new total profit with the new optimum solution is compared to the total profit with the current solution obtained in Section 7.3 (before the parameter changes) and the percentage of changes is analysed. The percentage indicates whether the model is robust or non-robust to the change in the cost of quality loss parameter. The same step is used for other parameters such as holding cost, transportation cost, demand, production rate *etc*., as represented in Table 7.11.

Further, the changes in the parameters will affect the related decision variables resulting in influencing the final result. Consequently, the total profit will be less. It is because the current solution (presented in Table 7.7 in Section 7.3) is not the optimum solution any more since the related parameter has changed (error in determining the decision variables or solution). To measure the potential loss, a procedure similar to the sensitivity analysis is carried out. Steps one and two of error analyses are the same as steps one and two of sensitivity analyses. But at step three, the new parameters are used to calculate the total profit of the current decision variables. Finally, at the last step, the percentage of potential loss is also calculated by comparing the total profit with the current decision variables and the total profit with the new decision variables. The summary of the sensitivity and error analyses are presented in Table 7.11.

Table 7.11 Sensitivity and error analyses

		Parameters	Parameters changes (%)	New optimised total profit (**a**)	Existing optimised total profit (**b**)	Total profit changes (a-b)/b*100% (**c**)	Total profit obtained from previous policy (**d**)	Total profit changes (a-d)/a*100% (**e**)
Manufacturer	a.	Raw material transportation cost	+20	84,118,589,501	84,228,768,052	-0.131%	84,105,139,892	0.0160%
			-20	84,352,880,127	84,228,768,052	0.147%	84,352,396,189	0.0006%
	b.	Raw material holding cost	+20	84,151,133,424	84,228,768,052	-0.092%	84,150,940,211	0.0002%
			-20	84,315,782,121	84,228,768,052	0.103%	84,306,595,870	0.0109%
	c.	Raw material quality loss	+20	84,195,543,161	84,228,768,052	-0.039%	84,195,508,284	0.0000%
			-20	84,265,142,324	84,228,768,052	0.043%	84,262,027,797	0.0037%
	d.	Raw material quality loss cost	+20	84,195,543,161	84,228,768,052	-0.039%	84,195,508,284	0.0000%
			-20	84,265,142,324	84,228,768,052	0.043%	84,262,027,797	0.0037%
	e.	Production Rate	+20	83,995,744,636	84,228,768,052	-0.277%	83,955,525,439	0.0479%
			-20	84,650,458,644	84,228,768,052	0.501%	84,638,631,943	0.0140%
	f.	Finished goods holding cost	+20	84,090,803,712	84,228,768,052	-0.164%	84,074,677,931	0.0192%
			-20	84,383,564,655	84,228,768,052	0.184%	84,382,858,150	0.0008%
	g.	Production setup cost	+20	83,922,513,912	84,228,768,052	-0.364%	83,919,697,669	0.0034%
			-20	84,545,395,998	84,228,768,052	0.376%	84,537,838,412	0.0089%
Distributors	h.	Demand	+20	103,169,888,325	84,228,768,052	22.488%	103,110,700,020	0.0574%
			-20	65,591,768,198	84,228,768,052	-22.127%	65,477,992,510	0.1735%
	i.	Finished goods holding cost	+20	82,915,160,170	84,228,768,052	-1.560%	82,850,829,425	0.0776%
			-20	85,690,213,394	84,228,768,052	1.735%	85,606,706,656	0.0975%
	j.	Transportation cost	+20	83,061,513,802	84,228,768,052	-1.386%	83,018,757,536	0.0515%
			-20	85,498,355,481	84,228,768,052	1.507%	85,438,778,546	0.0697%
	k.	Lead time	+20	84,228,768,159	84,228,768,052	0.000%	84,228,768,041	0.0000%
			-20	84,228,768,162	84,228,768,052	0.000%	84,228,768,041	0.0000%
	l.	Time to deteriorate	+20	84,228,768,179	84,228,768,052	0.000%	84,228,768,041	0.0000%
			-20	84,218,734,170	84,228,768,052	-0.012%	84,211,226,225	0.0089%

As depicted in Table 7.11, thirteen parameters are used to analyse the sensitivity and error analysis of the proposed model. The value of those parameters is changed to +20% and -20%. With the new parameters, the new optimised total profit with the new optimum solution is calculated as represented by column (**a)**. The information in column (**b)** presents the total profit of the current solution before parameter changes while data in column (**d)** demonstrate the total profit of the current solution after the parameter changes. Further, the percentage of changes in column (**c)** reflects the sensitivity of the model due to changes in parameters while the proportion of changes in column (**e**) illustrates the potential loss because of error in the decision variables.

As seen in column (**c)** of Table 7.11, the proposed model is generally robust to the changes in parameters. For majority parameters, decreasing or increasing their values by ±20% only affects less than 1% change in the total profit. Two parameters where their changes result in more than 1% change in the total profit are the holding and the transportation costs in the distributor system. However, the percentage of total profit deviation is only around 1.3-1.7% which is much lower compared to the percentage change in values of those parameters (±20%). The only parameter which has significant influences on the model performance is the demand rate. Decreasing or increasing the demand by ±20% leads to around ±22% deviation in total profit. It appears that the proposed model is not robust enough to the change in the value of demand. However, it is an expected result, since the fluctuation in demand will affect much more significantly all parameters in all members along the supply chain

Further, from column (**e)** of Table 7.11, using the same decision variables obtained before the parameter changes, insignificantly influences the total profit since the value is still relatively close to the new optimised profit indicated by the value of the percentage of changes. It means that decreasing or increasing the parameters by ±20 only causes a small decision variables error since the deviation in total profit is less than 1%.

In conclusion, from the result of sensitivity and error analyses, the developed model is confirmed to be robust to the changes in all parameters except the demand. The changes in parameters insignificantly influence the decision variables resulting in small deviation in the model performance. The result confirms the flexibility and validity of the solution. However, the proposed model is sensitive to the change in demand, therefore, the value of demand needs to be carefully estimated. Establishing a good forecasting method is

necessary to ensure that the optimised decision variables lead to the best performance of the system during the horizon planning

7.6 Concluding remarks

In this chapter, a case study in a food company has been conducted to analyse the potentiality of the developed model to be applied to solve real life problems. The proposed policy of the developed model is then compared to the existing policy. The result shows a significant improvement from the proposed policy. The decision obtained from the developed model results in significant saving, indicating the increase in the system performance.

Currently, the majority of SCM-deteriorating models apply the common cycle approach to managing the deliveries of perishable products from the manufacturer to the retailers. However, in a situation where the transportation cost and lead time between distributors are highly diverse such as in the case study, the synchronised cycle approach applied in the developed model is more applicable and more realistic. Instead of forcing all distributors to have the same ordering cycle, in the synchronised cycle they can have their own ordering cycle which is fairer for all members along the supply chain.

Chapter 8

Conclusions and suggestions for future works

8.1 Introduction

This study is aimed at filling the gaps in inventory management literature as identified by the literature survey in Chapter 2. The existing research in the area of an integrated production-inventory policy still inadequately accommodates the perishability characteristics of food inventories, i.e. the quality loss of raw food inventories and perceived value loss of end-packaging food products. To fill this gap, therefore, a new integrated production-inventory model considering those deteriorating characteristics (quality and perceived value loss) in a two echelon supply chain system was proposed. The supply chain comprises of a manufacturer and a number of distributors/retailers.

The proposed model has been completely developed and analysed. A mixed integer nonlinear programming (MINLP) approach involving a combinatorial decision variable has been established with the objective function to maximise the total profit of the whole system. To solve this problem type, a biased random key genetic algorithm (BRKGA) combined with local procedures has been designed and utilised to obtain the best solution. An extensive numerical test was conducted to find the best parameter setting of the algorithm to ensure that the proposed algorithm work effectively in finding the optimal solution to the problem. The benchmarking test demonstrates that the proposed algorithm outperforms the original BRKGA in terms of the quality and the robustness of the obtained solution. Moreover, the performance of the proposed model was evaluated through several numerical test scenarios. It was confirmed that by adopting the proposed model in dealing with integrated production-inventory policy for food products, the supply chain could significantly improve the total profit. This finding is then justified by the application of the proposed model to solve a case study in a real industry, which demonstrates that the profit of the entire supply chain could be improved by adopting the decision obtained from the proposed model and algorithm.

Based on the analysis obtained in the previous chapters, the contributions of this research are underlined and summarised in Section 8.2. Further, as there is always room for improvement, the limitations of this research and the potential future works are discussed in Section 8.3.

8.2 Research contributions

There are two main contributions of this research: the first is related to developing a more representative model for an integrated production-inventory policy when dealing with perishable products, particularly food products; the second contribution is to design a more appropriate optimisation tool to solve the developed model. Further discussion regarding these research contributions is presented in the following sections.

8.2.1 Contribution to developing an integrated production-inventory model

As discussed in the literature review in Chapter 2, the existing research in production-inventory policy inadequately represents the perishability characteristics on some deteriorating inventories such as food. To fill this gap therefore, a new and more representative mathematical model of integrated production-inventory policy especially for food products has been successfully formulated. The developed model is a mixed integer non-linear model with combinatorial decision variables. The following are several points that distinguish the developed model from the existing models.

1. Accommodating different perishability characteristics of deteriorating inventories depending on the inventory form. In this research, the deteriorating feature of raw materials is approached differently from that of finished goods as discussed in the following:

    a) Modelling the quality loss of raw materials

    The quality loss over time commonly happens in deteriorating foods, i.e. the vitamin C content in an orange is depleted over time following a kinetic model although physically the fruit is still fresh. Unfortunately, the majority of existing models of an integrated production-inventory policy for perishable items has overlooked this phenomenon as most of the models adopt an instantaneous quantity depletion of perishable items. In contrast to these models, in this research, the rate of quality loss of the raw material and

the costs related to this quality loss have been formulated and incorporated into the objective function of the established model. From the numerical tests and a case study, it is demonstrated that this strategy could reduce the total relevant costs in the manufacturer's system. It appears that the proposed model potentially retains a better quality of raw material compared to the existing models, to avoid the penalty cost in the system

b) Modelling the perceived value loss of finished goods

In the form of finished goods, a quality of food products is typically perceived by customers from the remaining shelf-life as printed on the packaging, i.e. their willingness to pay a product decreases as the product is approaching its expiration. Yet again, the existing models for perishable items typically disregard this phenomenon. In contrast to the existing models, the perceived value loss as a result of the decrease in customer willingness to pay has been considered in this research. A shelf-life based price function of finished goods has been developed to represent this value loss. In other words, the product price is not constant during the selling period. It depends on the age of products or their residual shelf-life when they are sold to customers. The fresh products with a longer residual shelf-life are sold at a regular price, but once they are aging, the discounted price is applied to attract a higher amount of sales. These characteristics have been accommodated in the objective function of the developed model. Based on both the numerical tests and the case study, it is shown that accommodating the perceived value loss to the finished goods could significantly improve the total profit of the entire system.

2. In terms of the coordination mechanism, applying the synchronised cycle approach to distribute products is another contribution of the developed model. In contrast to the majority of research in deteriorating inventory models for single vendor and multi-buyer (SVMB), the proposed model coordinates the supply chain both horizontally and vertically using an integer multiplier mechanism. The inbound and outbound logistics of the manufacturer are an integer multiplier or a fraction (for the inbound) of the production cycle. The numerical tests show that this synchronised cycle approach not only results in a better total profit compared

to both uncoordinated and common cycle approaches, but also leads to a better distribution of the profit among involved parties. It is further confirmed by the case study that this approach is best-suited for a manufacturer having downstream partners which are highly diverse in demand and geographically dispersed.

8.2.2 Contribution to the optimisation approach

Apart from its contribution to the development of a more realistic mathematical model of an integrated production-inventory for food products in a supply chain perspective, this study also offers a new genetic-algorithm based optimisation approach to solve the problem. As discussed in Chapter 3, considering the mathematical approach and the type of decision variables involved in the model, the GAs appear to be the most suitable optimisation tool to solve the proposed model. Instead of using conventional genetic algorithms, this research proposes a biased random key GA (BRKGA), a novel branch of GAs with a better flexibility and a convincing performance. In addition, to improve both exploitation and exploration capabilities of the algorithm, two local search procedures are incorporated into the BRKGA. The numerical tests demonstrate that the performance of the proposed BRKGA is satisfactory. It further enhances the solution quality, the speed to converge to an optimal solution, and the robustness of the genuine BRKGA in a reasonable.

8.3 Limitations and suggestions for future works

It has been demonstrated by both extensive numerical tests and a case study that the developed model and optimisation approach have potential applications to improve the performance of an integrated production-inventory policy for food products in a real life problem. However, from field observations, there are still some restrictions on the model that require further investigation as discussed in the following subsections.

8.3.1 Deterministic environment assumption

This research assumes a deterministic environment where all parameters are known and fixed. As shown from the numerical tests, this deterministic approach is still applicable when these parameters vary slightly however, when the parameters are uncertain and fluctuating considerably during the planning horizon, the proposed model would result in a solution that is far from its optimal solution. In that case, a probabilistic model of

integrated production-inventory policy for food products should be proposed, and this can be an important future research avenue.

From the numerical tests, fluctuating demand from the distributors/retailers may lead to reasonable changes to the total gained profit. Thus, in case this parameter is uncertain with a high variance, a probabilistic model accommodating this issue would be another significant further extension to this research. An optimal buffer stock for perishable products needs to be determined in this situation.

Further, another factor that is assumed to be fixed is the production rate and its reliability. From the numerical tests, it is revealed that a higher ratio of production rate to the demand rate would increase the costs. In a situation where the production rate is adjustable, incorporating this parameter into the decision variable of the system is expected to improve the performance of the system. This would also be another important extension of this research. Apart from that, this research assumes a steady production state during the planning horizon. In reality, however, the production state can be gradually shifting from in control to out of control states. In other words, the production process can deteriorate during the planning horizon. The proposed model does not anticipate a condition where the production line may need to be stopped due to a corrective or preventive maintenance. As this phenomenon is often found in reality, accommodating the deterioration of the production process into the production-inventory model is also suggested to be investigated in upcoming research.

8.3.2 Single item consideration

The model established in this research considers a single perishable item made from a single raw material. In reality, a manufacturer can produce multiple items to meet sophisticated demand. In addition, each item may require a number of different types of raw materials. Thus, the considered supply chain manages multiple raw material and finished goods. This multi-item problem lifts the complexity of the development of the mathematical model, but it is worth consideration in forthcoming studies since it better reflects the practical business. The proposed BRKGA is still expected to be applicable to solving the established mathematical model.

Moreover, when multi-item problems are considered, the items delivered to the distributors may need to be consolidated to reduce the transportation cost. Each truck

shipped to the distributor contains a number of different types of products with different quantities. Therefore, the production schedule has to be synchronised with this practice. Dealing with this issue would bring this research closer to real industrial practices.

8.3.3 Supply chain configuration and integration policy

This research addresses issues of managing perishable inventories across a single vendor multi buyer (SVMB) supply chain configuration. Again, in reality, the supply chain network may comprise of more complex supply chain structures. Food products pass through multiple stages each of which contains a number of players. Although this extension is challenging in terms of complexity in modelling and optimisation to the problem, incorporating more stages and more players, in general, would further enhance the performance the whole supply chain.

As demonstrated in this research, the integration proposed leads to profit elevation of the entire supply chain system. However when the cost and profit structures of each player are examined, some parties might be disadvantaged by the integrated decision. This may not be a big issue if the players are from the same holding company such as in the case study. In a decentralised supply chain environment where the players are from different companies, disadvantaged parties will be reluctant to adopt and implement the integrated strategy. For this reason, coordination mechanisms to fairly distribute the gained profit (and risks) to all parties require further investigation to ensure a win-win solution among supply chain members. This is proposed as another potential research avenue.

8.3.4 Optimisation tools

Based on literature review on optimisation approaches conducted in Chapter 3, the biased random key genetic algorithm (BRKGA) which is a population-based approach is preferred than some single point-based meta-heuristic approaches for instances tabu search and simulated annealing. In this study, the BRKGA that is hybridised with local procedures shows a better performance in terms of the quality of solution compared to the BRKGA. However, the developed algorithm cannot be claimed as the best tool to optimise the problem addressed in this research.

In literature, there are some other population-based approaches that are also potential for solving complex problems, e.g. particle swarm optimisation (PSO), artificial bee colony (ABC) and memetic algorithm (MA). Therefore, in the future research, it should be worth

of investigation to compare the performance of the other population-based algorithms such as PSO, ABC and MA to the hybrid BRKGA.

Reference

Ahamed, S, Rangajanardhana, G & Nagesh, E 2013, 'Development of Supply Chain Tools Using Genetic Algorithm and Comparison with Particle Swarm Optimization and Simulated Annealing Optimization Algorithms', *IUP Journal of Supply Chain Management*, vol. 10, no. 2, pp. 33-43.

Akararungruangkul, R 2006, 'Optimisation of distribution network design using a hybrid genetic algorithm', PhD thesis, University of South Australia, Adelaide, SA.

Akers, S 1956, 'A graphical approach to production scheduling problems', *Operations Research*, vol. 4, no. 2, pp. 244-245.

Akrami, B, Karimi, B & Moattar-Hosseini, SM 2006, 'Two metaheuristic methods for the common cycle economic lot sizing and scheduling in flexible flow shops with limited intermediate buffers: The finite horizon case', *Applied Mathematics and Computation*, vol. 183, no. 1, pp. 634-645.

Andrade, CE, Miyazawa, FK & Resende, MG 2013, 'Evolutionary algorithm for the *k*-interconnected multi-depot multi-traveling salesmen problem', *Proceedings of the 15th annual conference on Genetic and evolutionary computation*, pp. 463-470.

Andrade, CE, Resende, MG, Karloff, HJ & Miyazawa, FK 2014, 'Evolutionary algorithms for overlapping correlation clustering', *Proceedings of the 2014 conference on Genetic and evolutionary computation*, pp. 405-412.

Andrade, CE, Resende, MG, Zhang, W, Sinha, RK, Reichmann, KC, Doverspike, RD & Miyazawa, FK 2015, 'A biased random-key genetic algorithm for wireless backhaul network design', *Applied Soft Computing*, vol. 33, pp. 150-169.

Araújo, FF, Costa, AM & Miralles, C 2013, 'Balancing parallel assembly lines with disabled workers', *European Journal of Industrial Engineering*, vol. 9, no. 3, pp. 1-19.

Arefi, MS & Rezaei, H 2015, 'Problem solving of container loading using genetic algorithm based on modified random keys', *Journal of Advanced Computer Science & Technology*, vol. 4, no. 1, pp. 190-197.

Axsäter, S 2006, *Inventory control*, 2nd edn, Springer, New York.

Aytug, H, Khouja, M & Vergara, F 2003, 'Use of genetic algorithms to solve production and operations management problems: A review', *International Journal of Production Research*, vol. 41, no. 17, pp. 3955-4009.

Baker, JE 1985, 'Adaptive selection methods for genetic algorithms', *Proceedings of an International Conference on Genetic Algorithms and their applications*, pp. 101-111.

Bakker, M, Riezebos, J & Teunter, RH 2012, 'Review of inventory systems with deterioration since 2001', *European Journal of Operational Research,* vol. 221, no. 2, pp. 275-284.

Bakthavachalam, R, Navaneethakrishnan, S & Elango, C 2012, 'Stochastic perishable inventory control systems in supply chain with partial backorders', *International Journal of Mathematical Sciences and Applications,* vol. 2, no. 2, pp. 759-766.

Banerjee, A, Kim, S-L & Burton, J 2007, 'Supply chain coordination through effective multi-stage inventory linkages in a JIT environment', *International Journal of Production Economics,* vol. 108, no. 1, pp. 271-280.

Battini, D, Gunasekaran, A, Faccio, M, Persona, A & Sgarbossa, F 2009, 'Consignment stock inventory model in an integrated supply chain', *International Journal of Production Research,* vol. 48, no. 2, pp. 477-500.

Beamon, BM 1998, 'Supply chain design and analysis: Models and methods', *International Journal of Production Economics,* vol. 55, no. 3, pp. 281-294.

Bean, JC 1994, 'Genetic algorithms and random keys for sequencing and optimization', *ORSA journal on computing,* vol. 6, no. 2, pp. 154-160.

Ben-Daya, M, Darwish, M & Ertogral, K 2008, 'The joint economic lot sizing problem: Review and extensions', *European Journal of Operational Research,* vol. 185, no. 2, pp. 726-742.

Blackburn, J & Scudder, G 2009, 'Supply chain strategies for perishable products: The case of fresh produce', *Production and Operations Management,* vol. 18, no. 2, pp. 129-137.

Bonami, P, Kilinç, M & Linderoth, J 2012, 'Algorithms and software for convex mixed integer nonlinear programs', *Mixed integer nonlinear programming,* Springer, New York, pp. 1-39.

Brindle, A 1980, 'Genetic algorithms for function optimization', PhD thesis, University of Alberta, Canada.

Burgess, K, Singh, PJ & Koroglu, R 2006, 'Supply chain management: A structured literature review and implications for future research', *International Journal of Operations & Production Management,* vol. 26, no. 7, pp. 703-729.

Buriol, LS, Resende, MG, Ribeiro, CC & Thorup, M 2005, 'A hybrid genetic algorithm for the weight setting problem in OSPF/IS‐IS routing', *Networks,* vol. 46, no. 1, pp. 36-56.

Buriol, LS, Resende, MG & Thorup, M 2007, 'Survivable IP network design with OSPF routing', *Networks,* vol. 49, no. 1, pp. 51-64.

Buriol, LS, Hirsch, MJ, Pardalos, PM, Querido, T, Resende, MG & Ritt, M 2010, 'A biased random-key genetic algorithm for road congestion minimization', *Optimization Letters,* vol. 4, no. 4, pp. 619-633.

Cai, X, Chen, J, Xiao, Y & Xu, X 2010, 'Optimization and Coordination of Fresh Product Supply Chains with Freshness-Keeping Effort', *Production and Operations Management,* vol. 19, no. 3, pp. 261-278.

Cai, X, Chen, J, Xiao, Y, Xu, X & Yu, G 2013, 'Fresh-product supply chain management with logistics outsourcing', *Omega,* vol. 41, no. 4, pp. 752-765.

Chan, CK & Kingsman, BG 2007, 'Coordination in a single-vendor multi-buyer supply chain by synchronizing delivery and production cycles', *Transportation Research Part E: Logistics and Transportation Review,* vol. 43, no. 2, pp. 90-111.

Chan, F, Tibrewal, RK, Prakash, A & Tiwari, M 2015, 'A biased random key genetic algorithm approach for inventory-based multi-item lot-sizing problem', *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,* vol. 229, no. 1, pp. 157-171.

Chan, FT, Tibrewal, R, Prakash, A & Tiwari, M 2013, 'Inventory based multi-item lot-sizing problem in uncertain environment: BRKGA approach', *Advances in Sustainable and Competitive Manufacturing Systems*, Springer, pp. 1197-1206.

Chang, C-T, Teng, J-T & Goyal, SK 2010, 'Optimal replenishment policies for non-instantaneous deteriorating items with stock-dependent demand', *International Journal of Production Economics,* vol. 123, no. 1, pp. 62-68.

Chen, J-M & Chen, T-H 2007, 'The profit-maximization model for a multi-item distribution channel', *Transportation Research Part E: Logistics and Transportation Review,* vol. 43, no. 4, pp. 338-354.

Chen, JM & Chen, TH 2005, 'Effects of joint replenishment and channel coordination for managing multiple deteriorating products in a supply chain', *The Journal of the Operational Research Society,* vol. 56, no. 10, pp. 1224-1234.

Chen, T-H & Chang, H-M 2010, 'Optimal ordering and pricing policies for deteriorating items in one-vendor multi-retailer supply chain', *The International Journal of Advanced Manufacturing Technology*, vol. 49, no. 1, pp. 341-355.

Chopra, S & Meindl, P 2013, *Supply chain management: Strategy, planning, and operation*, 5th edn, Pearson, Upper Saddle River, N.J.

Chung, C-J & Wee, H-M 2007, 'Optimal replenishment policy for an integrated supplier–buyer deteriorating inventory model considering multiple JIT delivery and other cost functions', *Asia-Pacific Journal of operational research,* vol. 24, no. 1, pp. 125-145.

Chung, C-J & Wee, H-M 2010, 'Green-product-design value and information-technology investment on replenishment model with remanufacturing', *International Journal of Computer Integrated Manufacturing,* vol. 23, no. 5, pp. 466-485.

Chung, CJ & Wee, HM 2008, 'An integrated production-inventory deteriorating model for pricing policy considering imperfect production, inspection planning and warranty-period and stock-level-dependant demand', *International Journal of Systems Science,* vol. 39, no. 8, pp. 823-837.

Chung, K 2009, 'A complete proof on the solution procedure for non-instantaneous deteriorating items with permissible delay in payment', *Computers & Industrial Engineering,* vol. 56, no. 1, pp. 267-273.

Chung, K-J 2011, 'Some improved algorithms to locate the optimal solutions for exponentially deteriorating items under trade credit financing in a supply chain system', *Computers & Mathematics with Applications,* vol. 61, no. 9, pp. 2353-2361.

Chung, K-J & Lin, S-D 2011, 'The inventory model for trade credit in economic ordering policies of deteriorating items in a supply chain system', *Applied Mathematical Modelling,* vol. 35, no. 6, pp. 3111-3115.

Coco, AA, Júnior, JCA, Noronha, TF & Santos, AC 2014, 'An integer linear programming formulation and heuristics for the minmax relative regret robust shortest path problem', *Journal of Global Optimization,* vol. 60, no. 2, pp. 265-287.

Cooper, MC & Ellram, LM 1993, 'Characteristics of supply chain management and the implications for purchasing and logistics strategy', *The International Journal of Logistics Management,* vol. 4, no. 2, pp. 13-24.

Covert, RP & Philip, GC 1973, 'An EOQ model for items with Weibull distribution deterioration', *AIIE transactions,* vol. 5, no. 4, pp. 323-326.

Croom, S, Romano, P & Giannakis, M 2000, 'Supply chain management: An analytical framework for critical literature review', *European Journal of Purchasing & Supply Management,* vol. 6, no. 1, pp. 67-83.

Crosbie, GB & Ross, AS 2004, 'Asian wheat flour noodles', *The encyclopedia of grain science,* vol. 2, pp. 304-312.

Daellenbach, HG 2004, *Management Science Decision-making Through Systems Thinking,* Palgrave Macmillan Ltd., Basingstoke.

Daellenbach, HG & McNickle, DC 2005, *Management science: Decision making through systems thinking,* Palgrave Macmillan, New York.

Das, K, Roy, TK & Maiti, M 2004, 'Buyer-seller fuzzy inventory model for a deteriorating item with discount', *International Journal of Systems Science,* vol. 35, no. 8, pp. 457-466.

De Jong, KA 1975, 'Analysis of the behavior of a class of genetic adaptive systems', PhD thesis, University of Michigan.

Duan, Y, Luo, J & Huo, J 2010, 'Buyer–vendor inventory coordination with quantity discount incentive for fixed lifetime product', *International Journal of Production Economics,* vol. 128, no. 1, pp. 351-357.

Duan, Y, Huo, J, Zhang, Y & Zhang, J 2012, 'Two level supply chain coordination with delay in payments for fixed lifetime products', *Computers & Industrial Engineering,* vol. 63, no. 2, pp. 456-463.

Duarte, A, Martí, R, Resende, M & Silva, R 2014, 'Improved heuristics for the regenerator location problem', *International Transactions in Operational Research,* vol. 21, no. 4, pp. 541-558.

Entrup, ML 2005, *Advanced Planning in Fresh Food Industries Integrating Shelf Life into Production Planning,* Springer, Dordrecht, pp. 117-129.

Entrup, ML, Günther, HO, Van Beek, P, Grunow, M & Seiler, T 2005, 'Mixed-Integer Linear Programming approaches to shelf-life-integrated planning and scheduling in yoghurt production', *International Journal of Production Research,* vol. 43, no. 23, pp. 5071-5100.

Ericsson, M, Resende, MGC & Pardalos, PM 2002, 'A genetic algorithm for the weight setting problem in OSPF routing', *Journal of Combinatorial Optimization,* vol. 6, no. 3, pp. 299-333.

Falck, CM 2005, 'Efficient store ordering', PhD thesis, Helsinki University Of Technology, Espoo, Finland.

Ferguson, M, Jayaraman, V & Souza, GC 2007, 'Note: An application of the EOQ model with nonlinear holding cost to inventory management of perishables', *European Journal of Operational Research,* vol. 180, no. 1, pp. 485-490.

Ferguson, ME & Ketzenberg, ME 2005, 'Information sharing to improve retail product freshness of perishables', *Production and Operations Management,* vol. 15, no. 1, pp. 57-73.

Ferguson, ME & Koenigsberg, O 2007, 'How should a firm manage deteriorating inventory?', *Production and Operations Management,* vol. 16, no. 3, pp. 306-321.

Festa, P, Gonçalves, JF, Resende, MG & Silva, RM 2010, 'Automatic tuning of GRASP with path-relinking heuristics with a biased random-key genetic algorithm', *Experimental Algorithms,* Springer, pp. 338-349.

Festa, P 2013, 'A biased random-key genetic algorithm for data clustering', *Mathematical biosciences,* vol. 245, no. 1, pp. 76-85.

Fontes, DB & Gonçalves, JF 2007, 'Heuristic solutions for general concave minimum cost network flow problems', *Networks,* vol. 50, no. 1, pp. 67-76.

Fontes, DB & Gonçalves, JF 2013, 'A multi-population hybrid biased random key genetic algorithm for hop-constrained trees in nonlinear cost flow networks', *Optimization Letters,* vol. 7, no. 6, pp. 1303-1324.

Fu, BX 2008, 'Asian noodles: History, classification, raw materials, and processing', *Food Research International,* vol. 41, no. 9, pp. 888-902.

Fujiwara, O & Perera, ULJSR 1993, 'EOQ models for continuously deteriorating products using linear and exponential penalty costs', *European Journal of Operational Research,* vol. 70, no. 1, pp. 104-114.

Geetha, KV & Uthayakumar, R 2010, 'Economic design of an inventory policy for non-instantaneous deteriorating items under permissible delay in payments', *Journal of Computational and Applied Mathematics,* vol. 233, no. 10, pp. 2492-2505.

Gen, M, Cheng, R, Interscience, W & Sons, JW 1997, *Genetic algorithms and engineering design*, Wiley, New York.

Gendron, B, Potvin, J-Y & Soriano, P 2003, 'A tabu search with slope scaling for the multicommodity capacitated location problem with balancing requirements', *Annals of Operations Research,* vol. 122, no. 1, pp. 193-217.

Ghare, P & Schrader, G 1963, 'A model for exponentially decaying inventory', *Journal of Industrial Engineering,* vol. 14, no. 5, pp. 238-243.

Giri, B & Bardhan, S 2012, 'Supply chain coordination for a deteriorating item with stock and price-dependent demand under revenue sharing contract', *International Transactions in Operational Research,* vol. 19, no. 5, pp. 753-768.

Giri, BC & Maiti, T 2012, 'Supply chain model for a deteriorating product with time-varying demand and production rate', *Journal of the Operational Research Society,* vol. 63, no. 5, pp. 665-673.

Glover, F 1986, 'Future paths for integer programming and links to artificial intelligence', *Computers & Operations Research,* vol. 13, no. 5, pp. 533-549.

Glover, F 1989, 'Tabu search-part I', *ORSA Journal on computing,* vol. 1, no. 3, pp. 190-206.

Glover, F 1990, 'Tabu search-part II', *ORSA Journal on computing,* vol. 2, no. 1, pp. 4-32.

Goldberg, DE 1989, 'Genetic algorithm in search, optimization and machine learning', *Wesley Publishing Company, Reading, MA,* vol. 1, no. 98, p. 9.

Goldberg, DE, Korb, B & Deb, K 1989, 'Messy genetic algorithms: Motivation, analysis, and first results', *Complex Systems,* vol. 3, no. 5, pp. 493-530.

Gonçalves, JF & De Almeida, JR 2002, 'A hybrid genetic algorithm for assembly line balancing', *Journal of Heuristics,* vol. 8, no. 6, pp. 629-642.

Gonçalves, JF & Resende, MGC 2004, 'An evolutionary algorithm for manufacturing cell formation', *Computers & Industrial Engineering,* vol. 47, no. 2, pp. 247-273.

Gonçalves, JF, de Magalhães Mendes, JJ & Resende, McG 2005, 'A hybrid genetic algorithm for the job shop scheduling problem', *European Journal of Operational Research,* vol. 167, no. 1, pp. 77-95.

Gonçalves, JF 2007, 'A hybrid genetic algorithm-heuristic for a two-dimensional orthogonal packing problem', *European Journal of Operational Research,* vol. 183, no. 3, pp. 1212-1229.

Gonçalves, JF, Mendes, JJ & Resende, MG 2008, 'A genetic algorithm for the resource constrained multi-project scheduling problem', *European Journal of Operational Research,* vol. 189, no. 3, pp. 1171-1190.

Gonçalves, JF & Resende, MG 2011a, 'A parallel multi-population genetic algorithm for a constrained two-dimensional orthogonal packing problem', *Journal of Combinatorial Optimization,* vol. 22, no. 2, pp. 180-201.

Gonçalves, JF & Resende, MG 2011b, 'A biased random-key genetic algorithm for job-shop scheduling', *AT&T Labs Research Technical Report,* vol. 46, pp. 253-271.

Gonçalves, JF & Resende, MG 2011c, 'Biased random-key genetic algorithms for combinatorial optimization', *Journal of Heuristics,* vol. 17, no. 5, pp. 487-525.

Gonçalves, JF, Resende, MG & Mendes, JJ 2011, 'A biased random-key genetic algorithm with forward-backward improvement for the resource constrained project scheduling problem', *Journal of Heuristics,* vol. 17, no. 5, pp. 467-486.

Gonçalves, JF & Resende, MG 2012, 'A parallel multi-population biased random-key genetic algorithm for a container loading problem', *Computers & Operations Research,* vol. 39, no. 2, pp. 179-190.

Gonçalves, JF, Resende, MG & Toso, RF 2012, 'Biased and unbiased random-key genetic algorithms: An experimental analysis', *AT&T Labs Research, Florham Park.*

Gonçalves, JF & Resende, MG 2013, 'A biased random key genetic algorithm for 2D and 3D bin packing problems', *International Journal of Production Economics,* vol. 145, no. 2, pp. 500-510.

Gonçalves, JF & Resende, MG 2014, 'An extended Akers graphical method with a biased random-key genetic algorithm for jobshop scheduling', *International Transactions in Operational Research,* vol. 21, no. 2, pp. 215-246.

Gonçalves, JF, Resende, MG & Costa, MD 2014, 'A biased random-key genetic algorithm for the minimization of open stacks problem', *International Transactions in Operational Research,* vol. 23, no. 1-2, pp.25-46.

Gonçalves, JF, Resende, MG & Toso, RF 2014, 'An experimental comparison of biased and unbiased random-key genetic algorithms', *Pesquisa Operacional*, vol. 34, no. 2, pp. 143-164.

Gonçalves, JF & Resende, MGC 2015, 'A biased random-key genetic algorithm for the unequal area facility layout problem', *European Journal of Operational Research*, vol. 246, no. 1, pp.86-107

Goren, HG, Tunali, S & Jans, R 2010, 'A review of applications of genetic algorithms in lot sizing', *Journal of Intelligent Manufacturing*, vol. 21, no. 4, pp. 575-590.

Goyal, SK 1977, 'An integrated inventory model for a single product system', *Operational Research Quarterly*, vol. 28, no. 3, pp. 539-545.

Goyal, SK & Giri, BC 2001, 'Recent trends in modeling of deteriorating inventory', *European Journal of Operational Research*, vol. 134, no. 1, pp. 1-16.

Grasas, A, Ramalhinho, H, Pessoa, LS, Resende, MG, Caballé, I & Barba, N 2014, 'On the improvement of blood sample collection at clinical laboratories', *BMC Health Services Research*, vol. 14, no. 1, p. 12.

Gustavsson, J, Cederberg, C, Sonesson, U, van Otterdijk, R & Meybeck, A 2011, 'Global food losses and food waste', *Food and Agriculture Organization of the United Nations, Rom*.

Hatcher, DW 2001, 'Asian noodle processing', *Cereals processing technology*, pp. 131-157.

He, Y, Wang, S-Y & Lai, KK 2010, 'An optimal production-inventory model for deteriorating items with multiple-market demand', *European Journal of Operational Research*, vol. 203, no. 3, pp. 593-600.

Heilig, L, Lalla-Ruiz, E & Voß, S 2015, 'A biased random-key genetic algorithm for the cloud resource management problem', *Evolutionary Computation in Combinatorial Optimization*, Springer, pp. 1-12.

Heldman, DR 2011, '2 - Kinetic models for food systems', *Food Preservation Process Design*, Academic Press, San Diego, pp. 19-48.

Hennessy, T 1998, 'Where category management really counts', *Progressive Grocer*, vol. 77, no. 2, pp. 63-66.

Herrera, F, Lozano, M & Verdegay, JL 1998, 'Tackling real-coded genetic algorithms: Operators and tools for behavioural analysis', *Artificial Intelligence Review*, vol. 12, no. 4, pp. 265-319.

Hillier, F & Lieberman, G 2005, *Operations research concepts and cases*, Tata McGraw-Hill, New Delhi.

Hokama, P, San Felice, MC, Bracht, EC & Usberti, FL n.d. 'A heuristic approach for the stochastic steiner tree problem', University of Campinas, Brazil.

Holland, JH 1975, '*Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence*', U Michigan Press.

Hoque, M 2008, 'Synchronization in the single-manufacturer multi-buyer integrated inventory supply chain', *European Journal of Operational Research,* vol. 188, no. 3, pp. 811-825.

Hoque, M 2011, 'Generalized single-vendor multi-buyer integrated inventory supply chain models with a better synchronization', *International Journal of Production Economics,* vol. 131, no. 2, pp. 463-472.

Hsu, PH, Wee, HM & Teng, HM 2010, 'Preservation technology investment for deteriorating inventory', *International Journal of Production Economics,* vol. 124, no. 2, pp. 388-394.

Hu, J-S, Zheng, H, Xu, R-Q, Ji, Y-P & Guo, C-Y 2010, 'Supply chain coordination for fuzzy random newsboy problem with imperfect quality', *International Journal of Approximate Reasoning,* vol. 51, no. 7, pp. 771-784.

Huang, GQ, Lau, JSK & Mak, KL 2003, 'The impacts of sharing production information on supply chain dynamics: A review of the literature', *International Journal of Production Research,* vol. 41, no. 7, pp. 1483-1517.

Huang, J-Y & Yao, M-J 2006, 'A new algorithm for optimally determining lot-sizing policies for a deteriorating item in an integrated production-inventory system', *Computers and Mathematics with Applications,* vol. 51, no. 1, pp. 83-104.

Huang, Y-S, Su, W-J & Lin, Z-L 2011, 'A study on lead-time discount coordination for deteriorating products', *European Journal of Operational Research,* vol. 215, no. 2, pp. 358-366.

Jia, J & Hu, Q 2011, 'Dynamic ordering and pricing for a perishable goods supply chain', *Computers & Industrial Engineering,* vol. 60, no. 2, pp. 302-309.

Jonas, C, Wee, H & Wang, K 2008, 'Supply chain partnership for three-echelon deteriorating inventory model', *Management,* vol. 4, no. 4, pp. 827-842.

Jong, JF & Wee, HM 2008, 'A near optimal solution for integrated production inventory supplier-buyer deteriorating model considering JIT delivery batch', *International Journal of Computer Integrated Manufacturing,* vol. 21, no. 3, pp. 289-300.

Kanchanasuntorn, K & Techanitisawad, A 2006, 'An approximate periodic model for fixed-life perishable products in a two-echelon inventory–distribution system', *International Journal of Production Economics,* vol. 100, no. 1, pp. 101-115.

Karaesmen, IZ, Scheller–Wolf, A & Deniz, B 2011, 'Managing perishable and aging inventories: Review and future research directions', *Planning Production and Inventories in the Extended Enterprise*, pp. 393-436.

Kärkkäinen, M 2003, 'Increasing efficiency in the supply chain for short shelf life goods using RFID tagging', *International Journal of Retail & Distribution Management*, vol. 31, no. 10, pp. 529-536.

Kazerooni, M 1997, 'An integrated methodology for cellular manufacturing system design', PhD Thesis thesis, University of South Australia, Adelaide, SA.

Kerber, B & Dreckshage, BJ 2011, *Lean supply chain management essentials: A framework for materials managers*, CRC Press, Boca Raton, London.

Ketzenberg, M & Ferguson, ME 2008, 'Managing slow-moving perishables in the grocery industry', *Production and Operations Management*, vol. 17, no. 5, pp. 513-521.

Kirke, T, While, L & Kendall, G 2013, 'Multi-drop container loading using a multi-objective evolutionary algorithm', *Evolutionary Computation (CEC), 2013 IEEE Congress on Evolutionary Computation*, pp. 165-172.

Kirkpatrick, S, Gelatt, CD & Vecchi, MP 1983, 'Optimization by simulated annealing', *Science*, vol. 220, no. 4598, pp. 671-680.

Kun-Jen, C 2010, 'Using the convexities of total annual relevant costs to determine the optimal cycle times of inventory models for deteriorating items with permissible delay in payments', *Computers & Industrial Engineering*, vol. 58, no. 4, pp. 801-808.

Labuza, T 1999, 'Determination of the shelf life of foods', *Department of Food Science and Nutrition. University of Minnesota. St. Paul, MN*, vol. 55108.

Labuza, TP & Szybist, LM 2008, *Open dating of foods*, John Wiley & Sons,

Lalla-Ruiz, E, González-Velarde, JL, Melián-Batista, B & Moreno-Vega, JM 2014, 'Biased random key genetic algorithm for the tactical berth allocation problem', *Applied Soft Computing*, vol. 22, pp. 60-76.

Law, S-T & Wee, H-M 2006, 'An integrated production-inventory model for ameliorating and deteriorating items taking account of time discounting', *Mathematical and Computer Modelling*, vol. 43, no. 5–6, pp. 673-685.

Li, R, Lan, H & Mawhinney, JR 2010, 'A review on deteriorating inventory study', *Journal of Service Science and Management*, vol. 3, no. 1, pp. 117-117.

Li, Y, Cheang, B & Lim, A 2012, 'Grocery perishables management', *Production and Operations Management*, vol. 21, no. 3, pp. 504-517.

Lin, C-WR & Chen, H-YS 2003, 'Dynamic allocation of uncertain supply for the perishable commodity supply chain', *International Journal of Production Research*, vol. 41, no. 13, p. 3119.

Lin, C & Lin, Y 2007, 'A cooperative inventory policy with deteriorating items for a two-echelon model', *European Journal of Operational Research,* vol. 178, no. 1, pp. 92-111.

Lin, Y-H, Lin, C & Lin, B 2010, 'On conflict and cooperation in a two-echelon inventory model for deteriorating items', *Computers & Industrial Engineering,* vol. 59, no. 4, pp. 703-711.

Lin, YS, Yu, JCP & Wang, K-J 2009, 'An efficient replenishment model of deteriorating items for a supplier–buyer partnership in hi-tech industry', *Production Planning & Control,* vol. 20, no. 5, pp. 431-444.

Lo, S-T, Wee, H-M & Huang, W-C 2007, 'An integrated production-inventory model with imperfect production processes and Weibull distribution deterioration under inflation', *International Journal of Production Economics,* vol. 106, no. 1, pp. 248-260.

Lucena, ML, Andrade, CE, Resende, MG & Miyazawa, FK 2014, 'Some extensions of biased random-key genetic algorithms', *Simposio Brasileiro de Pesquisa Operacional XLVI.*

Mahapatra, N, Das, K & Maiti, M 2007, 'Production-inventory policy for a deteriorating item with a single vendor-buyer system', *Optimization and Engineering,* vol. 8, no. 4, pp. 431-448.

Maihami, R & Abadi, INK 2011, 'Joint control of inventory and its pricing for non-instantaneously deteriorating items under permissible delay in payments and partial backlogging', *Mathematical and Computer Modelling,* vol. 55, no. 5, pp. 1722-1733.

Maihami, R & Nakhai Kamalabadi, I 2012, 'Joint pricing and inventory control for non-instantaneous deteriorating items with partial backlogging and time and price dependent demand', *International Journal of Production Economics,* vol. 136, no. 1, pp. 116-122.

Martí, R & Reinelt, G 2011, *The linear ordering problem: Exact and heuristic methods in combinatorial optimization*, Springer Science & Business Media,

Mentzer, JT, DeWitt, W, Keebler, JS, Min, S, Nix, NW, D., SC & Zacharia, ZG 2001, 'Defining supply chain management', *Journal of Business Logistics,* vol. 22, no. 2, pp. 1-25.

Michalewicz, Z & SpringerLink 1996, *Genetic algorithms + data structures = evolution programs*, Springer, Berlin, Heidelberg.

Miœ, A 2003, 'Influence of the storage of wheat flour on the physical properties of gluten', *International Agrophysics,* vol. 17, pp. 71-75.

Mishra, DN & Agarwal, SK 2009, *Operation research*, Word-Press,

Misra, RB 1975, 'Optimum production lot size model for a system with deteriorating inventory', *International Journal of Production Research,* vol. 13, no. 5, p. 495.

Morán-Mirabal, L, González-Velarde, J & Resende, MG 2013, 'Automatic tuning of GRASP with evolutionary path-relinking', *Hybrid Metaheuristics*, Springer, pp. 62-77.

Morán-Mirabal, L, González-Velarde, J, Resende, MG & Silva, RM 2013, 'Randomized heuristics for handover minimization in mobility networks', *Journal of Heuristics*, vol. 19, no. 6, pp. 845-880.

Morán-Mirabal, L, González-Velarde, J & Resende, M 2014, 'Randomized heuristics for the family traveling salesperson problem', *International Transactions in Operational Research*, vol. 21, no. 1, pp. 41-57.

Moreira, MCO, Ritt, M, Costa, AM & Chaves, AA 2012, 'Simple heuristics for the assembly line worker assignment and balancing problem', *Journal of Heuristics*, vol. 18, no. 3, pp. 505-524.

Muller, M 2011, *Essentials of inventory management*, 2nd edn, Amacom, New York. <http://UNISA.eblib.com.au/patron/FullRecord.aspx?p=678727>

Muthiah, A & Rajkumar, R 2014, 'A comparison of artificial bee colony algorithm and genetic algorithm to minimize the make-span for job shop scheduling', *Procedia Engineering*, vol. 97, no. 1, pp. 1745-1754.

Nahmias, S 1982, 'Perishable inventory theory: A review', *Operations Research*, vol. 30, no. 4, pp. 680-708.

Nahmias, S 2011, *Perishable inventory systems*, Springer Science & Business Media,

Narasimhan, R & Carter, J 1998, 'Linking business unit and material sourcing strategies', *Journal of Business Logistics*, vol. 19, no. 2, pp. 155-171.

Nijs, VR, Dekimpe, MG, Steenkamp, JBEM & Hanssens, DM 2001, 'The category-demand effects of price promotions', *Marketing Science*, pp. 1-22.

Noronha, TF, Resende, MG & Ribeiro, CC 2011, 'A biased random-key genetic algorithm for routing and wavelength assignment', *Journal of Global Optimization*, vol. 50, no. 3, pp. 503-518.

Ouyang, L-Y, Wu, K-S & Yang, C-T 2006, 'A study on an inventory model for non-instantaneous deteriorating items with permissible delay in payments', *Computers & Industrial Engineering*, vol. 51, no. 4, pp. 637-651.

Pahl, J, Voss, S & Woodruff, D 2007, 'Production planning with deterioration constraints: a survey'. In *The development of collaborative production and service systems in emergent economies, proceedings of the 19th international conference on production research*, pp. 1-6.

Pahl, J & Voß, S 2014, 'Integrating deterioration and lifetime constraints in production and supply chain planning: A survey', *European Journal of Operational Research*, vol. 238, no. 3, pp. 654-674.

Panda, S & Padhy, NP 2008, 'Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design',*Applied Soft Computing Journal*, vol. 8, no. 4, pp. 1418-1427.

Park, KS 1983, 'An integrated production-inventory model for decaying raw materials', *International Journal of Systems Science*, vol. 14, no. 7, pp. 801-806.

Pedrola, O, Careglio, D, Klinkowski, M, Velasco, L, Bergman, K & Solé-Pareta, J 2013, 'Metaheuristic hybridizations for the regenerator placement and dimensioning problem in sub-wavelength switching optical networks', *European Journal of Operational Research*, vol. 224, no. 3, pp. 614-624.

Peleg, M, Engel, R, Gonzalez-Martinez, C & Corradini, MG 2002, 'Non-Arrhenius and non-WLF kinetics in food systems', *Journal of the Science of Food and Agriculture*, vol. 82, no. 12, pp. 1346-1355.

Prasetyo, H & Lee, S-H 2013, 'Comment on "Simultaneous determination of multiproduct batch and full truckload shipment schedules"', *International Journal of Production Economics*, vol. 144, no. 2, pp. 405-408.

Qin, Y, Wang, J & Wei, C 2014, 'Joint pricing and inventory control for fresh produce and foods with quality and physical quantity deteriorating simultaneously', *International Journal of Production Economics*, vol. 152, pp. 42-48.

Raafat, F 1985, 'A production-inventory model for decaying raw materials and a decaying single finished product system', *International Journal of Systems Science*, vol. 16, no. 8, pp. 1039-1044.

Raafat, F 1988, 'Inventory model for a system with monotonically increasing decay of raw materials and a decaying single finished product', *International Journal of Systems Science*, vol. 19, no. 12, pp. 2625-2629.

Raafat, F 1991, 'Survey of literature on continuously deteriorating inventory models', *The Journal of the Operational Research Society*, vol. 42, no. 1, pp. 27-37.

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*, vol. 86, no. 2, pp. 155-168.

Rau, H, Wu, MY & Wee, HM 2004, 'Deteriorating item inventory model with shortage due to supplier in an integrated supply chain', *International Journal of Systems Science*, vol. 35, no. 5, pp. 293-303.

Reis, R, Ritt, M, Buriol, LS & Resende, MG 2011, 'A biased random-key genetic algorithm for OSPF and DEFT routing to minimize network congestion', *International Transactions in Operational Research*, vol. 18, no. 3, pp. 401-423.

Resende, MG 2012, 'Biased random-key genetic algorithms with applications in telecommunications', *Top*, vol. 20, no. 1, pp. 130-153.

Resende, MG, Toso, RF, Gonçalves, JF & Silva, RM 2012, 'A biased random-key genetic algorithm for the Steiner triple covering problem', *Optimization Letters*, vol. 6, no. 4, pp. 605-619.

Rong, A, Akkerman, R & Grunow, M 2011, 'An optimization approach for managing fresh food quality throughout the supply chain', *International Journal of Production Economics*, vol. 131, no. 1, pp. 421-429.

Rongwu, L 2007, 'Deterministic deteriorating product's production-inventory model with variable productivity', *Automation and Logistics, 2007 IEEE International Conference on*, 18-21 Aug. 2007, pp. 695-699.

Roque, L, Fontes, D & Fontes, F 2014, 'A hybrid biased random key genetic algorithm approach for the unit commitment problem', *Journal of Combinatorial Optimization*, vol. 28, no. 1, pp. 140-166.

Roque, LA, Fontes, DB & Fontes, FA 2011, 'A biased random key genetic algorithm approach for unit commitment problem', *Experimental Algorithms*, Springer, pp. 327-339.

Ruiz, E, Albareda-Sambola, M, Fernández, E & Resende, MG 2015, 'A biased random-key genetic algorithm for the capacitated minimum spanning tree problem', *Computers & Operations Research*, vol. 57, pp. 95-108.

Ruiz, M, Pedrola, O, Velasco, L, Careglio, D, Fernández-Palacios, J & Junyent, G 2011, 'Survivable IP/MPLS-over-WSON multilayer network optimization', *Journal of Optical Communications and Networking*, vol. 3, no. 8, pp. 629-640.

Sarkar, B 2013, 'A production-inventory model with probabilistic deterioration in two-echelon supply chain management', *Applied Mathematical Modelling*, vol. 37, no. 5, pp. 3138-3151.

Setiadi, A 2012,'Era baru konsumen Indonesia', *Food Review*, February, viewed 8 December 2015,
< http://foodreview.co.id/preview.php?view2&id=56341#.Vs2hkvl97cc>.

Shah, N 2011, 'Single supplier–buyer integrated inventory model under multiple JIT delivery and stock-dependent demand', *Journal of Mathematical Modelling and Algorithms*, vol. 10, no. 3, pp. 293-305.

Shah, NH, Soni, HN & Patel, KA 'Optimizing inventory and marketing policy for non-instantaneous deteriorating items with generalized type deterioration and holding cost rates', *Omega*, vol. 41, no. 2, pp. 421-430.

Shah, Y 1977, 'An order-level lot-size inventory model for deteriorating items', *AIIE transactions*, vol. 9, no. 1, pp. 108-112.

Sharma, S, Kausha, B & Sharma, P 2004, 'Effect of temperature and removal of amino acids on non-enzymatic browning of lemon juice concentrates during storage', *Journal of Scientific and Industrial Research*, vol. 63, pp. 444-451.

Silva, R, Resende, M, Pardalos, P & Gonçalves, J 2012, 'Biased random-key genetic algorithm for bound-constrained global optimization', *Proceedings of the global optimization workshop*, pp. 133-136.

Silva, R, Resende, M & Pardalos, P 2013, 'A Python/C++ library for bound-constrained global optimization using a biased random-key genetic algorithm', *Journal of Combinatorial Optimization*, vol. 30, no. 3, pp. 710-728.

Silva, RM, Resende, MG, Pardalos, PM & Facó, JL 2013a, 'Biased random-key genetic algorithm for nonlinearly-constrained global optimization', *IEEE Congress on Evolutionary Computation*, pp. 2201-2206.

Silva, RM, Resende, MG & Pardalos, PM 2014, 'Finding multiple roots of a box-constrained system of nonlinear equations with a biased random-key genetic algorithm', *Journal of Global Optimization*, vol. 60, no. 2, pp. 289-306.

Silva, RMdA, Resende, MG, Pardalos, PM & Faco, JL 2013b, 'Biased random-key genetic algorithm for linearly-constrained global optimization', *Proceedings of the 15th annual conference companion on Genetic and evolutionary computation*, pp. 79-80.

Silver, E, Pyke, D & Peterson, R 1998, *Inventory management and production planning and scheduling*, 3rd edn, J. Wiley, New York.

Siradej, C 2008, 'Optimization of multiple location inventories using hybrid genetic algorithms ', PhD thesis, University of South Australia, Adelaide, SA.

Soni, HN 2013, 'Optimal replenishment policies for non-instantaneous deteriorating items with price and stock sensitive demand under permissible delay in payment', *International Journal of Production Economics*, vol. 146, no. 1, pp. 259-268.

Spears, VM & De Jong, KA 1991, 'On the virtues of parameterized uniform crossover', *In Proceedings of the Fourth International Conference on Genetic Algorithms*, pp. 230–236.

Stefanello, F, Buriol, L, Hirsch, M, Pardalos, P, Querido, T, Resende, M & Ritt, M 2013, 'On the minimization of traffic congestion in road networks with tolls', *Annals of Operations Research*, pp.1-21.

Stefanello, F, Buriol, L & Resende, MG 2013, 'A biased random-key genetic algorithm for a network pricing problem', *Brazilian Symposium on Operations Research*.

Tadikamalla, PR 1978, 'An EOQ inventory model for items with gamma distributed deterioration', *AIIE transactions*, vol. 10, no. 1, pp. 100-103.

Taha, HA 2011, *Operations research: An introduction*, 9th edn, Prentice Hall, Upper Saddle River, N.J.

Taleizadeh, AA, Noori-daryan, M & Cárdenas-Barrón, LE 2015, 'Joint optimization of price, replenishment frequency, replenishment cycle and production rate in vendor

managed inventory system with deteriorating items', *International Journal of Production Economics*, vol. 159, pp. 285-295.

Tan, KC, Kannan, VR & Handfield, RB 1998, 'Supply chain management: Supplier performance and firm performance', *International Journal of Purchasing and Materials Management*, vol. 34, no. 3, pp. 2-9.

Tangpattanakul, P, Jozefowiez, N & Lopez, P 2012, 'Multi-objective optimization for selecting and scheduling observations', *International Conference on Parallel Problem Solving From Nature (PPSN 2012)*, vol. 7492, pp. 112-121.

Tangpattanakul, P, Jozefowiez, N & Lopez, P 2015, 'Biased random key genetic algorithm for multi-user earth observation scheduling', *Recent Advances in Computational Optimization*, Springer, pp. 143-160.

Tersine, RJ 1994, *Principles of inventory and materials management*, 4th edn, Prentice Hall, Englewood Cliffs, N.J.

Thierens, D & Goldberg, D 1994, 'Convergence models of genetic algorithm selection schemes', *Parallel problem solving from nature—PPSN III*, Springer, pp. 119-129.

Thomas, DJ & Griffin, PM 1996, 'Coordinated supply chain management', *European Journal of Operational Research*, vol. 94, no. 1, pp. 1-15.

Thomas, J & Chaudhari, NS 2014, 'A new metaheuristic genetic-based placement algorithm for 2D strip packing', *Journal of Industrial Engineering International*, vol. 10, no. 1, pp. 1-16.

Tortola, J 2005, 'Loss leader', *Progressive Grocer*, vol. 84, no. 7, pp. 14-15.

Toso, RF & Resende, MG 2015, 'A C++ application programming interface for biased random-key genetic algorithms', *Optimization Methods and Software*, vol. 30, no. 1, pp. 81-93.

Tsai, D-M 2010, 'An optimal production and shipment policy for a single-vendor single-buyer integrated system with both learning effect and deteriorating items', *International Journal of Production Research*, vol. 49, no. 3, pp. 903-922.

Tsiros, M & Heilman, CM 2005, 'The effect of expiration dates and perceived risk on purchasing behavior in grocery store perishable categories', *Journal of Marketing*, pp. 114-129.

Uthayakumar, R & Parvathi, P 2011, 'A two-stage supply chain with order cost reduction and credit period incentives for deteriorating items', *The International Journal of Advanced Manufacturing Technology*, vol. 56, no. 5-8, pp. 799-807.

Valente, JM, Gonçalves, JF & Alves, RA 2006, 'A hybrid genetic algorithm for the early/tardy scheduling problem', *Asia-Pacific Journal of operational research*, vol. 23, no. 03, pp. 393-405.

Valente, JM & Gonçalves, JF 2009, 'A genetic algorithm approach for the single machine scheduling problem with linear earliness and quadratic tardiness penalties', *Computers & Operations Research,* vol. 36, no. 10, pp. 2707-2715.

Van Boekel, MAJS 2008, 'Kinetic modeling of food quality: A critical review', *Comprehensive Reviews in Food Science and Food Safety,* vol. 7, no. 1, pp. 144-158.

Velasco, L, Wright, P, Lord, A & Junyent, G 2013, 'Saving CAPEX by extending flexgrid-based core optical networks toward the edges ', *Optical Communications and Networking, IEEE/OSA Journal of,* vol. 5, no. 10, pp. A171-A183.

Wang, K-J, Lin, YS & Yu, JCP 2011, 'Optimizing inventory policy for products with time-sensitive deteriorating rates in a multi-echelon supply chain', *International Journal of Production Economics,* vol. 130, no. 1, pp. 66-76.

Wang, K-J & Lin, Y-S 2012, 'Optimal inventory replenishment strategy for deteriorating items in a demand-declining market with the retailer's price manipulation', *Annals of Operations Research,* vol. 201, no. 1, pp. 475-494.

Wang, SP, Lee, W & Chang, CY 2012, 'Modeling the consignment inventory for a deteriorating item while the buyer has warehouse capacity constraint', *International Journal of Production Economics,* vol. 138, no. 2, pp. 284-292.

Wang, X & Li, D 2012, 'A dynamic product quality evaluation based pricing model for perishable food supply chains', *Omega,* vol. 40, no. 6, pp. 906-917.

Waters, CDJ 2009, *Supply chain management: An introduction to logistics*, Palgrave Macmillan,

Wee, H-M 1998, 'Optimal buyer-seller discount pricing and ordering policy for deteriorating items', *The Engineering Economist,* vol. 43, no. 2, pp. 151-168.

Wee, H-M, Jong, JF & Yang, P-C 2006, 'A discussion on economic ordering policy of deteriorated item for vendor and buyer', *Production Planning & Control,* vol. 17, no. 8, pp. 792-795.

Weiss, HJ 1982, 'Economic order quantity models with nonlinear holding costs', *European Journal of Operational Research,* vol. 9, no. 1, pp. 56-60.

Wetzel, A 1983, 'Evaluation of the effectiveness of genetic algorithms in combinatorial optimization'.

Wilson, R 2011, '22nd annual state of logistics report', *Council of Supply Chain Management Professionals*.

Winston, WL & Goldberg, JB 2004, *Operations research: Applications and algorithms*, Duxbury press Boston,

Wu, J, Skouri, K, Teng, J-T & Ouyang, L-Y 2014, 'A note on "optimal replenishment policies for non-instantaneous deteriorating items with price and stock sensitive demand

under permissible delay in payment’", *International Journal of Production Economics*, vol. 155, pp. 324-329.

Wu, K-S, Ouyang, L-Y & Yang, C-T 2006, 'An optimal replenishment policy for non-instantaneous deteriorating items with stock-dependent demand and partial backlogging', *International Journal of Production Economics*, vol. 101, no. 2, pp. 369-384.

Xiao, Y-b, Chen, J & Xu, X-l 2008, 'Fresh product supply chain coordination under cif business model with long distance transportation', *Systems Engineering-Theory & Practice*, vol. 28, no. 2, pp. 19-34.

Xiao, Y & Chen, J 2012, 'Supply chain management of fresh products with producer transportation', *Decision Sciences*, vol. 43, no. 5, pp. 785-815.

Yan, C, Banerjee, A & Yang, L 2011, 'An integrated production–distribution model for a deteriorating inventory item', *International Journal of Production Economics*, vol. 133, no. 1, pp. 228-232.

Yang, P-C & Wee, H-M 2000, 'Economic ordering policy of deteriorated item for vendor and buyer: An integrated approach', *Production Planning & Control*, vol. 11, no. 5, pp. 474-480.

Yang, P-C & Wee, H-M 2003, 'An integrated multi-lot-size production inventory model for deteriorating item', *Computers & Operations Research*, vol. 30, no. 5, pp. 671-682.

Yang, PC & Wee, HM 2002, 'A single-vendor and multiple-buyers production–inventory policy for a deteriorating item', *European Journal of Operational Research*, vol. 143, no. 3, pp. 570-581.

Yang, PC 2004, 'Pricing strategy for deteriorating items using quantity discount when demand is price sensitive', *European Journal of Operational Research*, vol. 157, no. 2, pp. 389-397.

Yang, PC & Wee, HM 2006, 'A collaborative inventory system with permissible delay in payment for deteriorating items', *Mathematical and Computer Modelling*, vol. 43, no. 3–4, pp. 209-221.

Yang, PC, Wee, HM, Chung, SL & Ho, PC 2010, 'Sequential and global optimization for a closed-loop deteriorating inventory supply chain', *Mathematical and Computer Modelling*, vol. 52, no. 1–2, pp. 161-176.

Yang, PC, Chung, SL, Wee, HM, Zahara, E & Peng, CY 2013, 'Collaboration for a closed-loop deteriorating inventory supply chain with multi-retailer and price-sensitive demand', *International Journal of Production Economics*, vol. 143, no. 2, pp. 557-566.

Young, E 2002, *Web marketplaces that really work*, Fortune.

Yu, JCP 2010, 'Optimal deteriorating items inventory model with a three-echelon supply chain strategic alliance', *Asia-Pacific Journal of Operational Research*, vol. 27, no. 6, pp. 693-711.

Yu, Y, Wang, Z & Liang, L 2012, 'A vendor managed inventory supply chain with deteriorating raw materials and products', *International Journal of Production Economics*, vol. 136, no. 2, pp. 266-274.

Zanoni, S & Zavanella, L 2007, 'Single-vendor single-buyer with integrated transport-inventory system: Models and heuristics in the case of perishable goods', *Computers & Industrial Engineering*, vol. 52, no. 1, pp. 107-123.

Zanoni, S & Zavanella, L 2012, 'Chilled or frozen? Decision strategies for sustainable food supply chains', *International Journal of Production Economics*, vol. 140, no. 2, pp. 731-736.

Zhao, Q & Yang, J 2006, 'Optimal pricing and return policy for enterprise under supply chain management', *International Journal of Management and Enterprise Development*, vol. 4, no. 2, pp. 218-233.

Zheng, J-N, Chien, C-F & Gen, M 2014, 'Multi-objective multi-population biased random-key genetic algorithm for the 3-D container loading problem', *Computers & Industrial Engineering*, vol. 88, pp. 80-87.

Zhou, Y-W & Wang, S-D 2007, 'Optimal production and shipment models for a single-vendor single-buyer integrated system', *European Journal of Operational Research*, vol. 180, no. 1, pp. 309-328.

Appendix: Selected publications

1. Fauza, G, Amer, Y & Lee, SH 2013, 'A map of research in inventory models for perishable items from the perspective of supply chain', Refereed proceedings of IEEE Symposium on Business, Engineering and Industrial Applications (ISBEIA), pp. 330-334.
2. Fauza, G, Amer, Y & Lee, SH 2013, 'Model of an integrated procurement-production system for food products incorporating quality loss during storage time', *International Journal of Materials, Mechanics and Manufacturing*, vol. 1, no. 1, pp. 17-21.
3. Fauza, G, Amer, Y, Lee, SH & Prasetyo, H 2015, 'A vendor-buyer inventory model for food products based on shelf-life pricing', *Operations and Supply Chain Management: an International Journal*, vol. 8, no. 2, pp. 67-73.
4. Fauza, G, Amer, Y, Lee, SH & Prasetyo, H 2015, 'An Inventory Model of Production-Inventory Policy for Food Products Considering Quality Loss in Raw Materials', Refereed proceeding of the IEEE Industrial Engineering and Engineering Management (IEEM), pp. 910-914.

A map of research in inventory models for perishable items from the perspective of supply chain management

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Abstract— **This paper presents a categorization of existing studies in the area of inventory models for deteriorating items from the perspective of supply chain management (SCM). It aims to fill the gap of literature studies in this field. Existing literature studies mainly focus on deteriorating issues such as the deterioration type of inventories or characteristics of demand. This paper however, emphasizes on assessment the literature from the SCM view. In this context, three effects of the deterioration on inventory, namely, quantity, quality and value degradation of inventoried items across supply chain are discussed. Then, a new framework is introduced to map studies in this field and some potential gaps for future research are identified.**

Keywords—inventory; perishable items; SCM

I. Introduction

In today's competitive market, the scope of rivalry has been escalating from just between enterprises to between supply chains [1]. To remain competitive, companies, therefore, need to implement supply chain management (SCM) into their businesses. In SCM, inventory is one of the most essential parts to be managed to improve the overall performance of the supply chain as it ties up financially. Tersine [2] reported that 20-40% of a company's total assets are invested in inventory. This means that overstocking will increase operational costs in every stage of the supply chain, while low stocking will raise the risk of having a lower service level. Consequently, managing inventory should focus on providing an adequate number of inventories across the supply chain to significantly reduce the material handling cost without sacrificing the service level.

In managing an inventory, a perishable item is one type of material that is more complicated to handle than non-perishable item. This material has a limited life time since its quality, quantity or safety deteriorates over time, as found in food. Over production and overstocking of food may result in waste. Recent research by Gustavsson, et al. [3] reports that approximately 1.3 billion tons of food for human consumption (one-third food manufactured) is wasted per year worldwide across supply chains. This study showed that poor inventory coordination across the supply chain leading to mismatch between supply and demand is identified as the main cause. This fact signifies the importance of handling the inventory across supply chains.

The concept of inventory management for perishable items was introduced in 1963 by Ghare and Schrader [4]. Since then, extensive studies have been conducted in this area as can be seen from some review papers in this field [5-9]. Unfortunately, the majority of existing studies are in a single stage, while in fact it is important to handle deteriorating inventories by management across supply chain. It appears that the existing literature review overlooks this issue. This paper is, therefore, aimed at filling this gap by addressing an assessment to inventory models for perishable items from the SCM view. In addition, it is focused on models that adopt an integrated policy, where the inventory policies of all participants in the supply chain are collaboratively and simultaneously determined. Such policy results in the minimum total costs of supply chains [10].

The remaining sections of this paper are organized as follows. Section 2 discusses the proposed framework, and Section 3 presents the steps for assessing the existing studies. Section 4 covers results and discussion, and Section 5 is a summary.

II. Framework used for mapping the studies

The framework used for classifying and analysing the existing studies of deteriorating models in multi echelon supply chains comprises four aspects (as shown in Fig 1.): supply chain structure, deterioration effects on an inventory, demand characteristics and miscellaneous factors in inventory models Compared to the existing framework used by the previous literature surveys, this framework enriches the aspects by incorporating the supply chain structure and deterioration effects on inventory.

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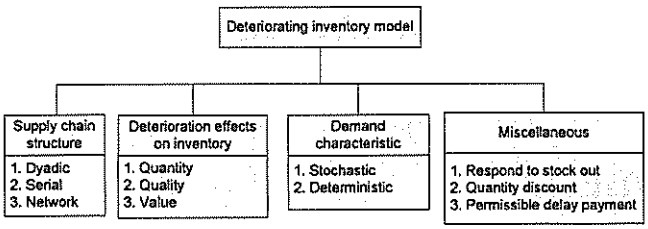

Figure 1.The framework used for mapping studies of deteriorating inventory models from SCM perspective

For supply chain structures, the categorization is adopted from Croom *et al.*[1], namely, dyadic structure, serial structure and networks structure. Dyadic structure refers to a model that only covers two-parties, supplier and buyer, or manufacturer and retailer. Meanwhile, a serial structure model extends a set of dyadic relationships such as a supplier's supplier, a manufacturer's manufacturer, etc. Further, a model which considers a group of organization in upstream and/or downstream linkage belongs to the network structure.

The next classification group in the framework is the deterioration effects on the inventory. This refers to the fact that deteriorating item can affect the inventory system in some ways. First of all, the amount of stored items deplete over time, such as found in gasoline or alcohol. Therefore, disregarding this circumstance may result in demand shortages. In this context, the deterioration affects the quantity of inventory. Secondly, some perishable items experience quality degradation over the storage time while the quantity remains the same. For example, the gluten content of wheat flour would decrease during storage time [11], hence the baking quality of end products would be affected. Thus, for this type of product the deterioration influences the quality of the stored items. Lastly, for certain items such as bread, although their quality may be within acceptable range or safe to be consumed, their value may diminish as the remaining shelf life approaches the expiration date. In this case, the deterioration results in value decrease of the product.

For demand categories, two demand approaches are used, either deterministic or stochastic. If demand is deterministic or ascertained, managing perishable items becomes relatively simple or straightforward to a problem [1], while in reality, demand is often found uncertain or stochastic. Despite of this fact, deterministic demand, however, is still important to contribute the initial development of a deteriorating inventory model [2]. Therefore, this framework still includes deterministic demand as one of the important factors in mapping research in this field.

The last group covers some additional factors in modelling the deteriorating inventory across the supply chain. These factors represent cases from real life conditions, such as (a) how to respond running out of stock, (b) quantity discount policy and (c) permissible delay payment policy.

III. Methodology of the study

There are three stages used to map the current research of deteriorating inventory models from the supply chain perspective: the initial stage, the filtering stage and the classifying stage.

In the initial stage, collections of papers from journals were sourced from three recognized databases, namely, SCOPUS, EBSCO, and Web of Sciences. Some key words in [9], such as *inventory*, *deterioration*, *perish*, *decay* and *shelf life*, combined with various key words identifying supply chain research, such as *supply chain*, *multi stage*, *three stage*, etc. were used to find the related papers. The wildcard symbol (*), and searching operators, such as AND and OR are applied as well. This stage resulted in 238 papers.

Secondly, in the filtering stage, only papers that address inventory model were chosen. Some papers dealing with supply chain and perishable items but focus on production and distribution planning, such as in [12] was discarded. Then, the remaining papers were sorted based on the integration policy. Only papers that address integrated inventory policy as referred to policy Type IV in [10] were selected. Therefore, papers that adopt the SCM perspective, but the inventory decision is made individually, were excluded. This process generated 61 papers.

Lastly, these 61 papers were categorized based on the framework in Fig. 1. The result of this classification is presented by Table 1.

IV. Result and discussion

From Table 1, it can be seen that based on supply chain management structure category, the majority research addresses the simple supply chain configurations. 45 papers are classified into the dyadic structure and 7 into the serial structure. There are 9 papers addressing a more complex supply chain configuration by covering a divergent structure. In reality, however, it is often found that the structure of a supply chain is more complex. It can be comprised of companies linked to more than one upstream partner (divergent structure) or downstream partner (convergent structure) or a combination of both. For example, a bread factory of a size supplying a supermarket typically has many suppliers who provide raw materials and many retailers who buy the finished goods. Despite this fact, no research addresses this configuration. This indicates that the existing research in terms of the supply chain structure is still inadequate to represent the real industrial problems. Thus, the application of the established models tends to be restricted. Therefore, this area is potential to be further explored in the future.

In terms of the deterioration effects on inventory, information in Table 1 shows that most of the studies (61 papers) are concerned with the quantity aspect. Interestingly, in real life, there are only limited types of perishable products that their quantity depletes instantaneously over the storage time. Therefore, the application of this approach is limited. For instance, the models are unsuitable for representing inventory for food. It is because in food, during their shelf life, the deterioration does not decrease the quantity but quality or value instead. Despite the fact that quality or value aspects is important to be considered in inventory for food, Table 1

shows that only 6 papers attempt to accommodate the quality degradation and no research considers the value loss. This fact demonstrates a significant gap in studies of inventory model for perishable items which is also potential for future research

In the demand characteristics category, the majority of existing studies assume a simple demand characteristic. Table 1 represents that more than 75% papers in this area (48 papers) address a deterministic demand in modelling the deteriorating inventory. In practical life, demand is, however, often found uncertain during the horizon planning, so stochastic approach is actually more plausible. Unfortunately, only 12 papers accommodate demand with this characteristic. Further, it is also important to point out that the majority of studies that deal with more challenging demand address the simpler supply chain structure. Thus, this presents a third potential for forthcoming research.

Table 1. Papers of studies in deteriorating inventory model from SCM perspective

SCM Structure	Research	Demand		Deterioration effects on inventory			Additional factors in managing inventory through SCM		
		Deterministic	Stochastic	Quantity	Quality	Value	Shortage	Quantity discount	Delay payment
Dyadic	[10],[13-29]	√		√					
	[30-38]	√		√			√		
	[39-41]	√		√				√	
	[42-46]	√		√					√
	[47]	√			√				
	[48]		√	√					
	[49-51]		√	√	√				
	[52-56]		√	√			√		
Serial	[57-60]	√		√					
	[61]	√		√			√		
	[62,63]		√	√	√				
Divergent	[64-70]	√		√					
	[71,72]		√	√					
Numbers		48	13	60	6	0	15	4	5

The last category in Table 1 represents some cases in reality accommodated in this field. It appears that the majority of studies tend to simplify their models by overlooking cases in managing a perishable inventory across the supply chain. First of all is the case of shortages. It is often in reality that sometimes a shortage can occur in any stage of the supply chain. This will influence the total cost of the supply chain and ignoring this possibility will make the model less readily applicable in real life. From the selected papers, only 15 accommodate this issue and majority of them assume that shortage is not allowed. Secondly, in an integrated supply chain, sometimes it is found that though the integrated decision may reduce the total cost of the whole system, it may increase costs of a participant in the system. For example, a small delivering lot size may reduce a retailer's holding cost but at the same time, it may rise the manufacturer's set up cost. So, manufacturers sometime use a strategy such as offering quantity discount or permissible delay payment scenario to retailers in order to share the benefit as they agree to increase an ordering size. Accommodating this issue in the models will enhance the model's performance in resembling the real supply chain. In fact, very few papers model this strategy, whereas 4 papers address quantity discount policy and 5 papers accommodate permissible delay payment. Further, it is interesting to notice that the more complex the configuration of the supply chain the fewer factors from real cases are accommodated by the models. Thus, this area presents a fourth potential in future research.

v. Conclusion

This paper reviews inventory models for perishable items in an integrated SCM. A new framework has been proposed to classify the studies in this field. The framework incorporates four aspects: the supply chain structure, the deterioration effects on an inventory, the demand characteristics and some miscellaneous factors which represent cases in a real situation. Based on these categories, papers related to inventory models for perishable items have been classified, analysed and discussed to identify some potential gaps for future research.

From this paper, it is revealed that some aspects, such as deterministic demand and quantity decrease, have been studied in detail in modelling inventory in this area. Other aspects which are more realistic, such as stochastic demand, quality and value loss and some real cases in the supply chain, are however still not developed. In addition, it is also interesting to point out that generally, the more complex supply chain configuration, the fewer aspects are accommodated by the models. This is a potential gap that invites future challenging research.

References

[1] S. Croom, P. Romano, and M. Giannakis, "Supply chain management: an analytical framework for critical literature review," *European Journal of Purchasing & Supply Management*, vol. 6, pp. 67-83, 3// 2000.

[2] R. J. Tersine, "Principles of inventory and materials management, PTR Prentice-Hall," *Inc., Englewood Cliffs, New Jersey,* 1994.

[3] J. Gustavsson, C. Cederberg, U. Sonesson, R. van Otterdijk, and A. Meybeck, "Global food losses and food waste," *Food and Agriculture Organization of the United Nations, Rom,* 2011.

[4] P. Ghare and G. Schrader, "A model for exponentially decaying inventory," *Journal of Industrial Engineering,* vol. 14, pp. 238-243, 1963.

[5] S. Nahmias, "Perishable Inventory Theory: A Review," *Operations Research,* vol. 30, pp. 680-708, 1982.

[6] F. Raafat, "Survey of Literature on Continuously Deteriorating Inventory Models," *The Journal of the Operational Research Society,* vol. 42, pp. 27-37, 1991.

[7] S. K. Goyal and B. C. Giri, "Recent trends in modeling of deteriorating inventory," *European Journal of Operational Research,* vol. 134, pp. 1-16, 2001.

[8] L. Ruxian, L. Hongjie, and J. R. Mawhinney, "A Review on Deteriorating Inventory Study," *Journal of Service Science & Management,* vol. 3, pp. 117-129, 2010.

[9] M. Bakker, J. Riezebos, and R. H. Teunter, "Review of inventory systems with deterioration since 2001," *European Journal of Operational Research,* vol. 221, pp. 275-284, // 2012.

[10] J. M. Chen and T. H. Chen, "Effects of joint replenishment and channel coordination for managing multiple deteriorating products in a supply chain," *Journal of the Operational Research Society,* vol. 56, pp. 1224-1234, // 2005.

[11] A. Micœ, "Influence of the storage of wheat flour on the physical properties of gluten," *Int. Agrophysics,* vol. 17, pp. 71-75, 2003.

[12] A. Rong, R. Akkerman, and M. Grunow, "An optimization approach for managing fresh food quality throughout the supply chain," *International Journal of Production Economics,* vol. 131, pp. 421-429, May 2011.

[13] P.-C. Yang and H.-M. Wee, "Economic ordering policy of deteriorated item for vendor and buyer: An integrated approach," *Production Planning & Control,* vol. 11, pp. 474-480, 2000/01/01 2000.

[14] A. Persona, A. Grassi, and M. Catena, "Consignment stock of inventories in the presence of obsolescence," *International Journal of Production Research,* vol. 43, pp. 4969-4988, // 2005.

[15] H. M. Wee, J. F. Jong, and P. C. Yang, "A discussion on economic ordering policy of deteriorated item for vendor and buyer," *Production Planning and Control,* vol. 17, pp. 792-795, // 2006.

[16] J.-M. Chen and T.-H. Chen, "The profit-maximization model for a multi-item distribution channel," *Transportation Research Part E-Logistics and Transportation Review,* vol. 43, pp. 338-354, Jul 2007.

[17] C.-J. Chung and H.-M. Wee, "Optimal replenishment policy for an integrated supplier-buyer deteriorating inventory model considering multiple JIT delivery and other cost functions," *Asia-Pacific Journal of Operational Research,* vol. 24, pp. 125-145, Feb 2007.

[18] C. J. Chung and H. M. Wee, "Scheduling and replenishment plan for an integrated deteriorating inventory model with stock-dependent selling rate," *International Journal of Advanced Manufacturing Technology,* vol. 35, pp. 665-679, // 2008.

[19] J. F. Jong and H. M. Wee, "A near optimal solution for integrated production inventory supplier-buyer deteriorating model considering JIT delivery batch," *International Journal of Computer Integrated Manufacturing,* vol. 21, pp. 289-300, 2008.

[20] Y. S. Lin, J. C. P. Yu, and K.-J. Wang, "An efficient replenishment model of deteriorating items for a supplier-buyer partnership in hi-tech industry," *Production Planning & Control,* vol. 20, pp. 431-444, 2009 2009.

[21] D. M. Tsai, "An optimal production and shipment policy for a single-vendor single-buyer integrated system with both learning effect and deteriorating items," *International Journal of Production Research,* vol. 49, pp. 903-922, // 2011.

[22] D. Battini, A. Grassi, A. Persona, and F. Sgarbossa, "Consignment stock inventory policy: Methodological framework and model," *International Journal of Production Research,* vol. 48, pp. 2055-2079, // 2010.

[23] C.-J. Chung and H.-M. Wee, "Green-product-design value and information-technology investment on replenishment model with remanufacturing," *International Journal of Computer Integrated Manufacturing,* vol. 23, pp. 466-485, 2010 2010.

[24] C. Yan, A. Banerjee, and L. Yang, "An integrated production-distribution model for a deteriorating inventory item," *International Journal of Production Economics,* vol. 133, pp. 228-232, Sep 2011.

[25] N. H. Shah, "Single Supplier-Buyer Integrated Inventory Model Under Multiple JIT Delivery and Stock-Dependent Demand," *Journal of Mathematical Modelling and Algorithms,* vol. 10, pp. 293-305, // 2011.

[26] K. J. Wang and Y. S. Lin, "Optimal inventory replenishment strategy for deteriorating items in a demand-declining market with the retailer's price manipulation," *Annals of Operations Research,* pp. 1-20, // 2012.

[27] S. P. Wang, W. Lee, and C. Y. Chang, "Modeling the consignment inventory for a deteriorating item while the buyer has warehouse capacity constraint," *International Journal of Production Economics,* vol. 138, pp. 284-292, // 2012.

[28] B. Sarkar, "A production-inventory model with probabilistic deterioration in two-echelon supply chain management," *Applied Mathematical Modelling,* // 2012.

[29] B. C. Giri and S. Bardhan, "Supply chain coordination for a deteriorating item with stock and price-dependent demand under revenue sharing contract," *International Transactions in Operational Research,* vol. 19, pp. 753-768, Sep 2012.

[30] S.-T. Law and H.-M. Wee, "An integrated production-inventory model for ameliorating and deteriorating items taking account of time discounting," *Mathematical and Computer Modelling,* vol. 43, pp. 673-685, 3// 2006.

[31] Y. W. Zhou and S. D. Wang, "Optimal production and shipment models for a single-vendor-single-buyer integrated system," *European Journal of Operational Research,* vol. 180, pp. 309-328, // 2007.

[32] C. Lin and Y. Lin, "A cooperative inventory policy with deteriorating items for a two-echelon model," *European Journal of Operational Research,* vol. 178, pp. 92-111, Apr 1 2007.

[33] S.-T. Lo, H.-M. Wee, and W.-C. Huang, "An integrated production-inventory model with imperfect production processes and Weibull distribution deterioration under inflation," *International Journal of Production Economics,* vol. 106, pp. 493-505, Apr 2007.

[34] N. Mahapatra, K. Das, and M. Maiti, "Production-inventory policy for a deteriorating item with a single vendor-buyer system," *Optimization and Engineering,* vol. 8, pp. 431-448, 2007.

[35] C. J. Chung and H. M. Wee, "An integrated production-inventory deteriorating model for pricing policy considering imperfect production, inspection planning and warranty-period- and stock-level-dependant demand," *International Journal of Systems Science,* vol. 39, pp. 823-837, 2008.

[36] Y. H. Lin, C. Lin, and B. Lin, "On conflict and cooperation in a two-echelon inventory model for deteriorating items," *Computers and Industrial Engineering,* vol. 59, pp. 703-711, // 2010.

[37] N. Khanlarzade, B. Y. Yegane, and I. Nakhai, "Genetic algorithm to optimize two-echelon inventory control system for perishable goods in terms of active packaging," *International Journal of Industrial Engineering Computations,* vol. 3, pp. 103-114, 2012.

[38] B. C. Giri and T. Maiti, "Supply chain model for a deteriorating product with time-varying demand and production rate," *Journal of the Operational Research Society,* vol. 63, pp. 665-673, // 2012.

[39] Y. Duan, J. Luo, and J. Huo, "Buyer-vendor inventory coordination with quantity discount incentive for fixed lifetime product," *International Journal of Production Economics,* vol. 128, pp. 351-357, Nov 2010.

[40] W. Hui-Ming, "Optimal buyer-seller discount pricing and ordering policy for deteriorating items," *The Engineering Economist,* vol. 43, pp. 151-168, 1998.

[41] K. Das, T. K. Roy, and M. Maiti *, "Buyer–seller fuzzy inventory model for a deteriorating item with discount," *International Journal of Systems Science,* vol. 35, pp. 457-466, 2004/07/10 2004.

[42] P. C. Yang, "Pricing strategy for deteriorating items using quantity discount when demand is price sensitive," *European Journal of Operational Research,* vol. 157, pp. 389-397, 9/1/ 2004.

[43] P. C. Yang and H. M. Wee, "A collaborative inventory system with permissible delay in payment for deteriorating items," *Mathematical and Computer Modelling*, vol. 43, pp. 209-221, 2// 2006.

[44] R. Uthayakumar and P. Parvathi, "A two-stage supply chain with order cost reduction and credit period incentives for deteriorating items," *International Journal of Advanced Manufacturing Technology*, vol. 56, pp. 799-807, // 2011.

[45] K. J. Chung, "Some improved algorithms to locate the optimal solutions for exponentially deteriorating items under trade credit financing in a supply chain system," *Computers and Mathematics with Applications*, vol. 61, pp. 2353-2361, // 2011.

[46] Y. Duan, J. Huo, Y. Zhang, and J. Zhang, "Two level supply chain coordination with delay in payments for fixed lifetime products," *Computers & Industrial Engineering*, vol. 63, pp. 456-463, Sep 2012.

[47] K. H. Widodo, H. Nagasawa, K. Morizawa, and M. Ota, "A periodical flowering-harvesting model for delivering agricultural fresh products," *European Journal of Operational Research*, vol. 170, pp. 24-43, Apr 1 2006.

[48] J. Jia and Q. Hu, "Dynamic ordering and pricing for a perishable goods supply chain," *Computers & Industrial Engineering*, vol. 60, pp. 302-309, 3// 2011.

[49] Y.-b. Xiao, J. Chen, and X.-l. Xu, "Fresh Product Supply Chain Coordination under CIF Business Model with Long Distance Transportation," *Systems Engineering - Theory & Practice*, vol. 28, pp. 19-34, 2// 2008.

[50] X. Cai, J. Chen, Y. Xiao, and X. Xu, "Optimization and Coordination of Fresh Product Supply Chains with Freshness-Keeping Effort," *Production and Operations Management*, vol. 19, pp. 261-278, May-Jun 2010.

[51] Y. Xiao and J. Chen, "Supply chain management of fresh products with producer transportation," *Decision Sciences*, vol. 43, pp. 785-815, // 2012.

[52] M. Ketzenberg and M. E. Ferguson, "Managing slow-moving perishables in the grocery industry," *Production and Operations Management*, vol. 17, pp. 513-521, // 2008.

[53] J. K. Jha and K. Shanker, "A single-vendor single-buyer production-inventory model with controllable lead time and service level constraint for decaying items," *International Journal of Production Research*, vol. 47, pp. 6875-6898, // 2009.

[54] J. S. Hu, H. Zheng, R. Q. Xu, Y. P. Ji, and C. Y. Guo, "Supply chain coordination for fuzzy random newsboy problem with imperfect quality," *International Journal of Approximate Reasoning*, vol. 51, pp. 771-784, // 2010.

[55] Y.-S. Huang, W.-J. Su, and Z.-L. Lin, "A study on lead-time discount coordination for deteriorating products," *European Journal of Operational Research*, vol. 215, pp. 358-366, Dec 1 2011.

[56] R. Bakthavachalam, S. Navaneethakrishnan, and C. Elango, "Stochastic perishable inventory control systems in supply chain with partial backorders," *Int. J. of Mathematical Sciences and Applications*, vol. 2, 2012.

[57] K.-J. Wang, Y. S. Lin, and J. C. P. Yu, "Optimizing inventory policy for products with time-sensitive deteriorating rates in a multi-echelon supply chain," *International Journal of Production Economics*, vol. 130, pp. 66-76, 2011.

[58] J. C. P. Yu, "Optimal deteriorating items inventory model with a three-echelon supply chain strategic alliance," *Asia-Pacific Journal of Operational Research*, vol. 27, pp. 693-711, // 2010.

[59] P. C. Yang, H. M. Wee, S. L. Chung, and P. C. Ho, "Sequential and global optimization for a closed-loop deteriorating inventory supply chain," *Mathematical and Computer Modelling*, vol. 52, pp. 161-176, // 2010.

[60] H. Rau, M. Y. Wu, and H. M. Wee, "Integrated inventory model for deteriorating items under a multi-echelon supply chain environment," *International Journal of Production Economics*, vol. 86, pp. 155-168, // 2003.

[61] H. Rau, M. Y. Wu, and H. M. Wee, "Deteriorating item inventory model with shortage due to supplier in an integrated supply chain," *International Journal of Systems Science*, vol. 35, pp. 293-303, // 2004.

[62] T. Xiao, J. Jin, G. Chen, J. Shi, and M. Xie, "Ordering, wholesale pricing and lead-time decisions in a three-stage supply chain under demand uncertainty," *Computers and Industrial Engineering*, vol. 59, pp. 840-852, // 2010.

[63] X. Cai, J. Chen, Y. Xiao, X. Xu, and G. Yu, "Fresh-product supply chain management with logistics outsourcing," *Omega*, vol. 41, pp. 752-765, 8// 2013.

[64] P. C. Yang, S. L. Chung, H. M. Wee, E. Zahara, and C. Y. Peng, "Collaboration for a closed-loop deteriorating inventory supply chain with multi-retailer and price-sensitive demand," *International Journal of Production Economics*, // 2012.

[65] Y. Yu, Z. Wang, and L. Liang, "A vendor managed inventory supply chain with deteriorating raw materials and products," *International Journal of Production Economics*, vol. 136, pp. 266-274, // 2012.

[66] Y. Yu, G. Q. Huang, Z. Hong, and X. Zhang, "An integrated pricing and deteriorating model and a hybrid algorithm for a VMI (vendor-managed-inventory) supply chain," *IEEE Transactions on Automation Science and Engineering*, vol. 8, pp. 673-682, // 2011.

[67] T.-H. Chen and H.-M. Chang, "Optimal ordering and pricing policies for deteriorating items in one-vendor multi-retailer supply chain," *International Journal of Advanced Manufacturing Technology*, vol. 49, pp. 341-355, Jul 2010.

[68] D. Battini, A. Gunasekaran, M. Faccio, A. Persona, and F. Sgarbossa, "Consignment stock inventory model in an integrated supply chain," *International Journal of Production Research*, vol. 48, pp. 477-500, 2010.

[69] C. Tsung-Hui and C. Hung-Ming, "Optimal ordering and pricing policies for deteriorating items in one-vendor multi-retailer supply chain," *International Journal of Advanced Manufacturing Technology*, vol. 49, pp. 341-355, 2010.

[70] P.-C. Yang and H.-M. Wee, "An integrated multi-lot-size production inventory model for deteriorating item," *Computers & Operations Research*, vol. 30, pp. 671-682, 4// 2003.

[71] Q. Zhao and J. Yang, "Optimal pricing and return policy for enterprise under supply chain management," *International Journal of Management and Enterprise Development*, vol. 4, pp. 218-233, // 2007.

[72] K. Kanchanasuntorn and A. Techanitisawad, "An approximate periodic model for fixed-life perishable products in a two-echelon inventory-distribution system," *International Journal of Production Economics*, vol. 100, pp. 101-115, // 2006

Model of an Integrated Procurement-Production System for Food Products Incorporating Quality Loss during Storage Time

Gusti Fauza, Yousef Amer, and Sang-Heon Lee

***Abstract*—Research on procurement-production systems for deteriorating items has been done. The majority of studies assume that the perishable characteristics affect only the quantity of inventoried items. For food products, however, their quantity remains constant during their shelf life period, but the quality deteriorates over time. This paper proposes a new procurement-production model incorporating this situation. The quality change behavior of food products is approached differently depending on their forms either as raw materials or finished goods. As raw materials, the kinetic model is used to represent the quality degradation during storage time, while as finished goods the shelf-life dependent pricing is utilized to describe the value loss due to the quality perception of customers. A mathematical model representing the integrated procurement-production of raw materials and finished goods at a manufacturer is established in this research. The objective is to maximize the total profit per unit time of the system by controlling a number of variables, namely the production cycle (*T*), the number of raw materials' procurement over one production cycle (*m*) and the number of finished goods delivery over one production cycle (*n*).**

***Index Terms*—Deteriorating items, food inventory, procurement-production system, quality loss, value loss.**

I. Introduction

Ever since EOQ (Economic of Quantity) inventory control has been introduced, many researchers still develop it to solve various inventory problems. Conventionally, economic lot-size of raw materials was decided separately from finished product and this may lead to sub-optimization. It is because demand for raw materials depends on production schedule of finished products. Later, Goyal [1] developed an integrated inventory model for raw material and finished product. This research gave the first contribution in the field of integrated procurement-production (IPP) systems.

Recently, research in the field of IPP system receives significant attention from scholars and many inventory models has been developed to accommodate this issue [2]. Goyal and Deshmukh [3] developed a model for IPP systems in just in time JIT environment to minimize set up time. And later, Lee [4] extend the IPP to an integrated supply chain problem by integrating the economic lot size of raw material, manufacturing set up and finished products. However, those studies assume that items can be stored infinitely, while in fact, some items have limited life time.

In reality, it is often found that some particular items deteriorate over the storage period, for instance food products. For such items, the quality degradation during the storage time can lead to a significant waste or loss. To illustrate, an FAO study reported that every year 1.3 billion tones food are wasted globally [5]. The major food losses occur in producer-retailer stage and the mismatch between production and demand is identified as the main cause. Noting this situation, it is crucial to incorporate the perishability characteristics of the items while managing the inventory.

Actually, studies on integrated inventory models for perishable items have been done [6]-[8]. However, those models assume that the deterioration of the items leads to the quantity decrease, as observed in the inventory of gasoline, alcohol or radioactive materials. Certainly, these assumptions are not suitable for food products. The quantity of food typically remains the same during their shelf-life, while their quality, which can be represented by the freshness, obviously degrades. In addition, it is also assumed in the previous models that the deterioration characteristics of the raw materials and the finished goods are identical. But food is a dynamic item [9]. The perishable characteristics of food are not identical and need to be approached differently. Therefore, the existing models are inadequate for representing the inventory systems of food products.

This paper proposes a new model of food inventory in the IPP system incorporating quality loss during storage time. Unlike the previous research in this field, the proposed model approaches deteriorating characteristics for raw materials and finished goods in different ways.

The remaining sections of this paper are organized as follows: Section 2 contains a review of existing inventory models for perishable items, while Section 3 discusses the modeling of quality degradation of raw materials. Moreover, Section 4 presents model for the quality of finished goods, or called value loss model. The complete model of an integrated procurement-production system for food products is covered in Section 5, while the last section, Section 6, summarizes this paper.

II. Literature Review

In this literature review, two groups of studies on the deteriorating inventory model are discussed. The first group includes models that address quantity decay as the result of storage time, while the second one covers models that deal with value or utility decrease.

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Research in the first group is based on the assumption that during the inventory period, the inventory level is depleted by demand and deteriorated items. This deteriorating phenomenon was accommodated into an EOQ model by Ghare and Schrader [10] using a differential equation as can be seen from (1).

$$\frac{dI(t)}{dt} + \theta I(t) = -D(t) \quad (1)$$

where $I(t)$ refers to the inventory level, $D(t)$ represents the demand rate at time t, and θ is the deteriorating rate of the item. Park [6] extended the deteriorating models into an integrated procurement-production problem. He assumed that only raw materials decayed during the production cycle. Later, Raafat [11] developed it and used the more realistic assumption that the finished good deteriorated as well. Recently, other scholars [12] and [13] advanced the integrated inventory model by implementing a multi-shipment policy in a multi-echelon system.

While studies in the perishable inventory model in the first group were showing quantity decrease as the result of perishable items, research in the second group was focusing on value and utility decay instead. Weiss [14] charged a non-linear holding cost on EOQ models. A few years later, Ferguson, et al. [15] applied this model to manage perishable inventories. Similarly, Fujiwara and Perera [16] viewed this problem from a utility perspective. They used both linear and exponential penalty cost charged for every perishable item held in storage as the usability of the products decayed over time. Recently, Blackburn and Scudder [17] developed a supply chain strategy for perishable products by considering fresh produce value decrease through a supply chain.

Comparing models in those two groups, the approaches in second group are more suitable for food products. However, these models are still insufficient to represent food inventory model in an integrated procurement-production system. They still ignore the fact that the raw materials supplied for production should not be procure separately from finished goods production planning. In addition, the assumption of an identical deteriorating characteristic is still used. Therefore, there is a need to revisit those models and revise them into a new model which is more appropriate in representing inventory model for food products in the integrated procurement-production system.

III. Modeling the Quality Degradation of Raw Food Materials

As explained in Section 1, in this paper, the quality degradation in raw materials is approached differently with that in finish goods. An interesting approach on accommodating quality degradation in production has been proposed by Rong, *et al*. [18]. They employed quality loss function model to describe quality degradation of food during distribution time. A quantitative approach, called *kinetic model*, is adopted to represent the quality loss of raw food materials. In this model, the quality of the items degrades depending on environment and time of storage as illustrated by (2).

$$\frac{dq}{dt} = kq^n \quad (2)$$

q represents the quality factor measured depending food characteristics and t is time, which usually in months for more stable food and in days for more deteriorating food. Meanwhile, k is the rate of deterioration depending on storage environment (e.g. temperature, activation energy, gas constant) and n denotes a power factor or the reaction order [19]. The value of n influences the pattern of the quality loss as described by Fig. 1.

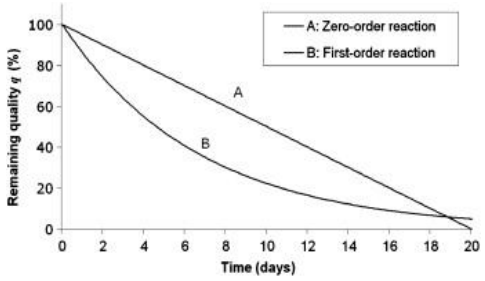

Fig. 1. Quality degradation illustration of food products [18].

For n=0, or called zero order reaction, the quality decreases linearly over time as represented by line A in Fig.1. Alternatively, for n=1, or called first-order reaction, the quality degrades exponentially as illustrated by line B at the same figure. Based on the phenomena in this figure, the inventory model of raw materials accommodating quality loss will be developed.

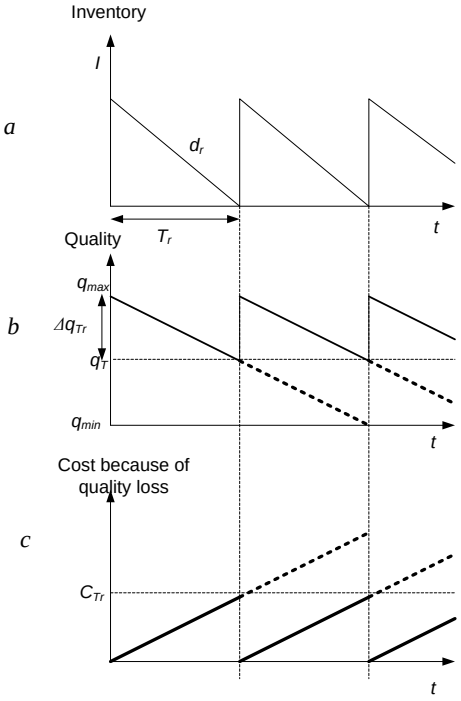

Fig. 2. The relation between inventory, quality and cost of raw food materials.

Generally, the majority research in deteriorating inventory assumed that during the shelf life period, the quality of the items is constant. This assumption, however, ignore the fact, which is shown in Fig. 1, that the food quality degrades during storage time; the longer the items are stored, the more their quality degrade. This degradation could affect the quality of final products and could lead to a higher cost for maintaining product quality. Therefore, these issues need to be addressed carefully in deteriorating inventory model to provide a more realistic model in presenting food characteristic. The relation between quality, quantity, time

and cost is illustrated by Fig. 2.

In Fig. 2*a*, inventory (*I*) is depleted only by demand (d_r). Moreover, all inventoried items are in their maximum quality (q_{max}) at the beginning of the procurement cycle (t=0). However, by the time, as can be seen from Fig. 2*b*, the quality of raw material linearly degrades during the period t, $t+d_rt$, called $\Delta q(t)$. Every single item which suffers from the quality loss will be charged by quality cost C which linearly increases over time (Fig. 2*c*). It means that, the longer items stored in the storage, the higher cost of quality. Thus, adapting Fujiwara and Perera [16] approach, the cost of the raw material quality loss (L) during one replenishment cycle (T_r) can be represented by (3).

$$L = \int_0^{T_r} C d_r \Delta q(t)\, dt \qquad (3)$$

IV. Modeling Value Deterioration of Finished Food Products

Generally, in reality, customers realize that the quality of food products deteriorates over time. Although customers may not have direct access to examine the quality of food products, they can judge them from the products' remaining lifetime by seeing the products' best before date (BBF). In this situation, customer prefer to buy products with longer remaining lifetime or later BBF which are judged as 'fresher' [20]. Tsiros and Heilman [21] reported that customers' willingness to pay (WTP) decrease as the product's lifetime gets closer to its BBF. It means that even though a product is still in its shelf-life period, the value of the product could loss. This value loss needs to be handled properly as it can influence companies' sales benefit. The relation between benefit and remaining lifetime is illustrated by Figure 3.

In Fig. 3, benefit b is a linear function of remaining lifetime t. In this case, t is come from shelf life T_{SL} minus storage time T_{ST}. If t is equal to T_{SL}, which means there is no T_{ST} or T_{ST} =0, then manufacturer will get maximum benefit (*Max b*). Otherwise, if t is equal to customers' minimum requirement of product's remaining life time T_{min}, manufacturer will gain no benefit.

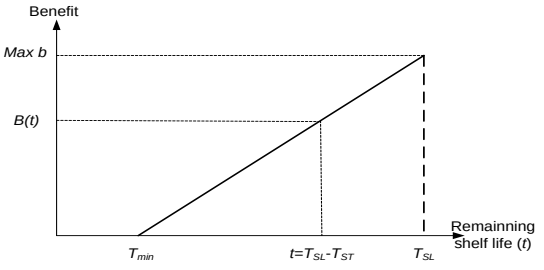

Fig. 3. The relation between shelf life, remaining shelf life and sales benefit [adapted from 20].

Equation (4) shows the linear correlation between benefit b and remaining life time t.

$$b(t) = \frac{Max\ b}{T_{SL} - T_{min}} . t + A \qquad (4)$$

If t is equal to T_{min}, then $b(T_{min})$ will be equivalent to zero. Consequently, the value of A (constant) will be equal to (5).

$$A = -\frac{Max\ b}{T_{SL} - T_{min}} . T_{min} \qquad (5)$$

substituting (5) to (4) leads to (6).

$$b(t) = \frac{Max\ b}{T_{SL} - T_{min}} . [T_{SL} - T_{min} - T_{ST}(t)] \qquad (6)$$

Equation (6) shows that since the T_{SL} and T_{min} are fixed and given, the length of storage time or T_{ST} becomes the only factor which reduces benefit b. In other words, the longer the items are stored in the storage, the more they will lessen the benefit.

V. The Proposed Model for Quality and Value Degradation in an Integrated Procurement-Production System

In this section, the quality loss of raw material and the value degradation of finished goods will be integrated into an integrated procurement-production system. The interaction between both deterioration types will affect the inventory policy, namely, the production cycle, raw material ordering and frequency of the delivery of finished goods. The best value of those decision variables will lead to the companies' maximum profit.

This proposed model will use the following notations and assumptions

Notation

d_r	:	Raw materials' demand rate ($d_r = P$)
d_p	:	Finished goods' demand rate ($d_p > P$)
P	:	Production rate
m	:	Raw materials' ordering frequency
n	:	Finished goods' delivery frequency
o	:	Ordering cost
s	:	Set up cost
a	:	Delivery cost
h_r	:	Raw materials' holding cost
h_p	:	Finished goods' holding cost
C	:	Cost of quality loss
T_r	:	Raw materials' replenishment cycle
T_p	:	Production run length
T	:	Production cycle time
T_{ST}	:	Storage time
T_{SL}	:	Product shelf life
T_{min}	:	Customers' requirement of minimum t
T_d	:	Delivery cycle of finished good
t	:	Product remaining shelf life where $t = T_{SL} - T_{ST}$
Max b	:	Company's maximum benefit when $t = T_{SL}$ or T_{ST}=0
$b(t)$	:	Company's benefit depending t
$B(T,m,n)$	:	Company's total profit

Assumptions

1) The rate of demand and production is constant during cycle time where $P>d_p$
2) The quality degradation of the raw food material is constants (n=0)
3) The deterioration of the value of the finished goods during storage time (T_{ST}) is constant
4) The shelf life of raw materials is set to be longer than the replenishment cycle ($t_{qmin} \geq t_{sl}$)
5) No shortage or backlog is allowed

The characteristic of this system is illustrated by Fig. 4.

Fig. 4a shows that the raw material fulfills the production demand d_r in batches m during the production run time T_p. The total cost per unit time for raw materials TC_r consists of ordering cost, holding cost and cost of quality loss which are then divided by production cycle T. The shaded area of the triangle figure represents the total inventory of raw materials during T, which is equal to ½q_rT_p. Since q_r is identical to d_pT/m and T_p is the same with d_pT/P, as a result the total inventory of raw material is equivalent with $\frac{1}{2}\frac{d_p^2T}{mp}$. Adjusting Eq. 3 and combining it into ordering cost and holding cost is equivalent to the total cost of raw materials per unit time (7).

$$TC_r(T,m) = \frac{1}{T}\begin{Bmatrix} om + h_r \frac{{d_p}^2}{P}\frac{T^2}{m} \\ +Cd_r \int_0^{\frac{d_p}{mp}T} \Delta q_r(t)dt \end{Bmatrix} \quad (7)$$

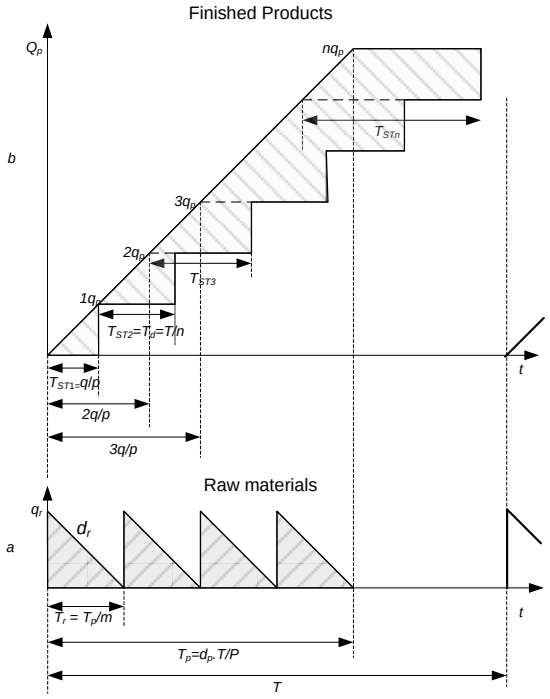

Fig. 4. The behavior of the IPP system.

On the other hand, finished products figure (Fig.4*b*) shows that the production rate is higher than customers' demand rate and causes inventory of finished goods (represented by shaded area). In addition, the finished goods deliver to retailer using multi-shipment delivery policy[18]. Hence, the total cost of finished goods (8) is composed by delivery cost per unit time, set up cost and holding cost per unit time.

$$TC_p(T,n) = \frac{an+s}{T} + h_p \frac{d_pT}{2n}\left\{\frac{(2-n)d_p}{P} + n - 1\right\} \quad (8)$$

In addition, as mentioned before in Section VI, the sales benefit depends on the product's remaining shelf life t (6). In this case, t is equal to product shelf life T_{SL} minus storage time T_{ST} (Fig.4*b*). T_{ST} is defined as completion time of the product (in batch) minus the time when the product start to be produced. For first batch or n=1, T_{ST} is equal to q_p/p and for n=2, T_{ST} is equal to T_d or T/n. The mathematical function to express the storage time for n batch is represented by (9). Substituting this function to (6), leads to total benefit b (10)

$$T_{ST_n} = (n-1)\frac{T}{n} + \frac{d_pT}{nP}(2-n) \quad (9)$$

$$b = \frac{Max\ B}{T_{SL}-T_{min}} \cdot \sum_{n=1}^{N} \begin{matrix} T_{SL} - T_{min} - (n-1)\frac{T}{n} \\ +\frac{d_pT}{nP}(2-n) \end{matrix} \quad (10)$$

Finally, the manufacturer's total profit, $B(T, m, n)$, which is equal to total benefit b minus both total cost of raw materials TC_r and finished goods TC_p is represented by (11).

$$B(T,m,n) = \frac{1}{T}\left[\left(\frac{Max\ b}{T_{SL}-T_{min}} \cdot \sum_{n=1}^{N} T_{SL} - T_{min} - (n-1)\frac{T}{n} + \frac{d_pT}{nP}(2-n)\right) - \left(om + h_r\frac{{d_p}^2}{P}\frac{T^2}{m} + mCd_r\int_0^{\frac{d_p}{mp}T}\Delta q_r(t)dt\right)\right] - \left[\frac{an+s}{T} + h_p\frac{d_pT}{2n}\left\{\frac{(2-n)d_p}{P} + n - 1\right\}\right] \quad (11)$$

Equation 11 shows that integrating the result of deterioration of raw materials and finished goods affects the value of the inventory policy (T, m, n). Therefore, ignoring these deteriorating characteristics may lead to less than best decision in managing perishable items such as food products.

VI. Conclusion

A new model for IPP system has been developed in this paper. The model is more appropriate for food products for several reasons. Quality degradation and value loss, which are the main characteristics of perishable food, have been addressed in the model. The different quality degradation impacts on the inventory of two perishable items, either raw food materials or finished food products, have been considered. Therefore, this model is more realistic in representing the food inventory in IPP system.

In addition, the mathematical model of the objective function (the company's total profit) has been developed to examine the observed system. Three decision variables, namely, the production cycle (T), raw materials ordering frequency (m) and the finished product delivery number (n) are identified and need to be optimized for the IPP's maximum profit.

However, there are some limitations in this research waiting for the future research. First, the proposed model only considers food inventory problems at manufacturing level or known as a single-stage perspective, while managing food is very complex and need to be viewed from an integrated supply chain or multi stage perspective. Second, in food preservation theory, the quality loss actually can be controlled by adjusting the temperature, so this is another important factor to be considered. Finally, a constant quality degradation (n=0) has been assumed in the model, while in fact, some food has an exponential quality degradation or n=1 [9]. Therefore, for future development, it is expected to be able to revise these limitations to a more representative food inventory model.

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REFERENCES

[1] S. K. Goyal, "An integrated inventory model for a single product system," *Operational Research Quarterly (1970-1977)*, vol. 28, pp. 539-545, 1977.
[2] S. K. Goyal and S. Deshmukh, "Integrated procurement-production systems: Areview," *European journal of operational research*, vol. 62, pp. 1-10, 1992.
[3] S. Goyal and S. Deshmukh, "Integrated procurement-production system in a just-in-time environment-modelling and analysis," *Production Planning and Control*, vol. 8, pp. 31-36, 1997.
[4] W. Lee, "A joint economic lot size model for raw material ordering, manufacturing setup, and finished goods delivering," *Omega*, vol. 33, pp. 163-174, 2005.
[5] J. Gustavsson, C. Cederberg, U. Sonesson, R. van Otterdijk, and A. Meybeck, "Global food losses and food waste," *Food and Agriculture Organization of the United Nations, Rom*, 2011.
[6] K. S. Park, "An integrated production-inventory model for decaying raw materials," *International Journal of Systems Science*, vol. 14, pp. 801-806, 1983.
[7] F. Raafat, "Inventory systems of age-independent perishable items subject to on-going deterioration," Oklahoma State University, 1982.
[8] H. Rau, M. Y. Wu, and H. M. Wee, "Integrated inventory model for deteriorating items under a multi-echelon supply chain environment," *International Journal of Production Economics*, vol. 86, pp. 155-168, 2003.
[9] D. R. Heldman, "2 - Kinetic models for food systems," in *Food Preservation Process Design*, ed San Diego: Academic Press, 2011, pp. 19-48.
[10] P. Ghare and G. Schrader, "A model for exponentially decaying inventory," *Journal of Industrial Engineering*, vol. 14, pp. 238-243, 1963.
[11] F. Raafat, "Inventory model for a system with monotonically increasing decay of raw materials and a decaying single finished product," *International Journal of Systems Science*, vol. 19, pp. 2625-2629, 1988.
[12] J. F. Jong and H. M. Wee, "A near optimal solution for integrated production inventory supplier-buyer deteriorating model considering JIT delivery batch," *International Journal of Computer Integrated Manufacturing*, vol. 21, pp. 289-300, 2008.
[13] P. C. Yang and H. M. Wee, "An integrated multi-lot-size production inventory model for deteriorating item," *Computers and amp; Operations Research*, vol. 30, pp. 671-682, 2003.
[14] H. J. Weiss, "Economic order quantity models with nonlinear holding costs," *European Journal of Operational Research*, vol. 9, pp. 56-60, 1982.
[15] M. Ferguson, V. Jayaraman, and G. C. Souza, "Note: An application of the EOQ model with nonlinear holding cost to inventory management of perishables," *European Journal of Operational Research*, vol. 180, pp. 485-490, 2007.
[16] O. Fujiwara and U. L. J. S. R. Perera, "EOQ models for continuously deteriorating products using linear and exponential penalty costs," *European Journal of Operational Research*, vol. 70, pp. 104-114, 1993.
[17] J. Blackburn and G. Scudder, "Supply chain strategies for perishable products: The case of fresh produce," *Production and Operations Management*, vol. 18, pp. 129-137, 2009.
[18] A. Rong, R. Akkerman, and M. Grunow, "An optimization approach for managing fresh food quality throughout the supply chain," *International Journal of Production Economics*, vol. 131, pp. 421-429, 2011.
[19] A. Kramer, F. E. Bender, and S. Sirivichaya, "A generalized theory on rate of quality loss in foods," *International Journal of Refrigeration*, vol. 3, pp. 353-359, 1980.
[20] M. L. Entrup, H. O. Günther, P. Van Beek, M. Grunow, and T. Seiler, "Mixed-Integer Linear Programming approaches to shelf-life-integrated planning and scheduling in yoghurt production," *International Journal of Production Research*, vol. 43, pp. 5071-5100, 2005.
[21] M. Tsiros and C. M. Heilman, "The effect of expiration dates and perceived risk on purchasing behavior in grocery store perishable categories," *Journal of Marketing*, pp. 114-129, 2005.



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A Vendor-Buyer Inventory Model for Food Products Based On Shelf-Life Pricing

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ABSTRACT

Research on coordinated inventory policy for perishable items between a manufacturer and a retailer has been extensively done. The majority studies however assumed that the stored item starts to deteriorate instantaneously once its production process completed. This may be suitable for representing the characteristic of certain perishable items such as alcohol or radioactive materials. In many cases, particularly for food products such as fruits, vegetables, meat and bakeries, over the shelf-life the quantity remains constant while the value does degrade once the product is approaching its expiration date. Despite this phenomenon, less research addresses this issue, particularly in a multi-echelon supply chain system. Therefore, this research deals with inventory policy for a manufacturer-retailer system considering value degradation for food products. A mathematical model representing the system is proposed. A shelf-life based pricing function is applied to represent the value degradation of the product. The objective function is to maximise the joint profit per unit time which is achieved by optimising the length of manufacturer's production cycle (*T*) and the ordering frequency of finished goods (*n*) over the production cycle. The numerical test for the established model demonstrates that the model outperforms the existing model in terms of its potential capability of returning a significant profit improvement.

Keywords: *deteriorating items, inventory model, value degradation, shelf-life based function*

1. INTRODUCTION

Recently, the growth of research in the supply chain management area has created a new way in managing inventories of a multi-echelon system (Ben-Daya et al., 2008). A conventional inventory management approach where a company only focuses on its own inventory, disregarding their partner's situation, may lead to sub-optimal improvement. Due to fiercer competition in the market nowadays, each company is advised to work collaboratively with their partners in managing the inventory across the supply chain (Msimangira and Venkatraman, 2014) to achieve the optimal performance of the whole system.

A collaborative approach in managing the production and inventory between two parties i.e. manufacturer and retailer, can be achieved by determining the economic production and ordering lot sizes jointly between these two parties. This concept was initially introduced by Goyal (1977). In this scenario, the production and order quantities are decided by considering the joint variable cost between the manufacturer and the retailer. The model assumed an infinite production rate and a lot-for-lot shipment policy. Later, Hill (1997) relaxed this assumption to a general shipment policy and a finite production rate. Many other studies in this field (Avijit and Seung-Lae, 1995; Ha and Kim, 1997; Kim and Ha, 2003) eradicated the limitation of the requirement to have the production lot being completed before delivering the ordering batches to the retailer. More recently, other factors such as investment to reduce some related costs, stochastic demand and three layer systems are investigated by many scholars in this area (Ben-Daya et al., 2008). All of the studies mentioned above, however, assume that the items can be stored infinitely.

In real life, it is often found that numerous items such as alcohol, food and radioactive materials perish over time. Ghare and Schrader (1963) firstly introduced a mathematical model representing the inventory profile for perishable items (Eq. 1),

$$\frac{dI(t)}{dt} + \theta I(t) = -D(t) \quad (1)$$

where $I(t)$ refers to the inventory level over t, $D(t)$ represents the demand rate at time t, and θ is the deterioration rate of the item. The equation explicitly demonstrates that an inventory for perishable items is depleted by demand rate and a fixed fraction of the inventory or $\theta I(t)$ which diminishes over time.

Since the model was introduced, it has been continuously developed to be more representative of capturing real life cases. Substantial literature reviews by Raafat (1991), Goyal and Giri (2001), Bakker et al. (2012) reveal that the majority research in deteriorating inventory areas are referred to this model, where extensive extensions have been conducted to accommodate various conditions such as, different characteristics of demand e.g. time varying demand (Goyal and Giri, 2003), stock dependent demand (Pattnaik, 2012) and price dependent demand (Maihami and Nakhai Kamalabadi, 2012) and different types of systems e.g. single echelon and multi-echelon systems.

The existing models might resemble inventory characteristics of some perishable items such as alcohol, gasoline and radio-active materials. They are however hardly applied to food (Nahmias, 2011) such as fruits, meat, milk and bakeries as for over the shelf-life, its quantity diminished only due to demand, while its quality or value is deteriorated over time. A study by Blackburn and Scudder (2009) introduced a product's marginal value of time (MVT) of a fresh product such as melon. They observed that as the sugar levels of a melon loses over time through a supply chain, controlling some variables such as picking rate and transfer batch size can be an appropriate strategy to minimize the value loss and maintain the product freshness across the supply chain. Unfortunately, this approach is not suited for managing food products which degrade in a different way, such as bakeries or noodles.

Generally customers examine the product freshness in two ways, by evaluating the physical condition of the products e.g. colour and firmness such as in fruits or simply checking the product shelf-life while they are unable to directly assess the product quality such as in bakeries, noodles, milk or other fully package products (Entrup, 2005). Regarding the former, Blackburn and Scudder (2009) strategy can be applied, for a fully packed product however a different approach is needed.

Research by Tsiros and Heilman (2005) reported that the customers perceive the quality of a fully packed food product by seeing its expiration date. The research also reveals that customer's willingness to pay (WTP) for this typical product decreases once the product's life is approaching its expiration date. Customers tend to purchase products with a longer remaining lifetime and avoid the one which is aging. Consequently, the demand rate of the products during the aging period will be slower. To manage this situation, retailers will initiate a price reduction or discount of the products to maintain the demand and prevent them being outdated. Though the mark down strategy may retain or even improve the demand rate, the margin of the products is accordingly reduced.

The issue discussed above makes the strategy to manage perishable items in retailers becomes more complicated. A coordinated inventory approach in managing food products between a manufacturer and a retailer needs to consider this situation before deciding the production and ordering lot policy. Yan et al. (2011) extended an integrated production-inventory model of Kim and Ha (2003) by considering deteriorating items. This model, however, still viewed the deterioration as a function of inventory i.e. a fraction number of inventory is instantaneously and continually lost over time. Therefore, this research proposes a new approach in managing food inventory by accommodating the degradation value of the product perceived by customers based on its remaining lifetime. The aim is to determine the manufacturer's production cycle and the number of deliveries to the retailer over the production cycle to maximize the total profit of the manufacturer-retailer system.

The remaining sections of this paper are organised as follows: Section 2 presents model assumptions and notation while Section 3 discusses the modelling formulation stages. Numerical tests explaining the behaviour of the proposed model are provided in Section 4, and the last section summarises this paper.

2. ASSUMPTIONS AND NOTATIONS

The model is developed based on these following assumptions and notation:

Assumptions

a. The manufacturers' production rate and the retailer's demand rate are constant.
b. The production rate is greater than the demand rate
c. The retailer pays transportation and order handling costs
d. Lead time is neglected and no shortage is allowed
e. Customer's willingness to buy a product decreases linearly once the product reaches time to deteriorate (Tstart)
f. Price before Tstart is maximum and price for outdated product is zero

Apart from these additions and deletions in the detentions of service quality by various scholars, there is an another group of scholars those who have derived measurement scales with an attempt to quantify the quality of service provided by a hospital (Hulka et al., 1970; and Fitzpatrick, 1991). Hulka et al. (1970) used statements based on just three dimensions: personal relationship, convenience, and professional competence. Thompson (1983) based his work on seven dimensions: tangible, communications, relationships between staff and patients, waiting time, admission and discharge procedures, visiting procedures, and religious needs while Baker (1990) concentrated on consultation time, professional care, and depth of relationship. Other researchers, Tomes and Ng (1995) conducted content analysis with a total of eight dimensions and renamed the dimension as empathy, understanding of illness, relationship of mutual respect, dignity, food, physical environment, and religious needs.

Notation

For the manufacturer

P	:	production rate
C_m	:	manufacturing cost per unit
S	:	setup cost for a production cycle
h_m	:	inventory holding cost
p_m	:	price of finished goods
$TP_m(n,T)$	:	manufacturer's profit

For the retailer

D	:	demand rate

$p_{\max}$	:	maximum price
T_{SL}	:	product shelf-life
T_{start}	:	time when customer's WTP starts decreasing
E_i	:	age of batch i when entering the retailer system
O_r	:	ordering cost
h_r	:	inventory holding cost
F	:	fixed transportation cost per delivery
V	:	unit variable cost for order handling
$R(n,T)$	:	retailer's revenue
$TP_r(n,T)$	:	retailer's profit
$TP(n,T)$	:	total profit of the integrated system (the objective function of the integrated inventory model)

Decision Variables

n	:	number of deliveries per production cycle
T	:	production cycle

3. MODEL DEVELOPMENT

This section presents the procedure for formulating a new inventory model considering food shelf-life and customers' WTP.

3.1 Revenue Model Accommodating Shelf-life Based Pricing Function

It is a common phenomenon in a retailer that customers prefer to buy a product with a longer remaining lifetime i.e. the customers' WTPs decrease once the product approaches its expiration date (Tsiros and Heilman, 2005). Consequently, to maintain the demand and avoid outdated items, the retailer offers a discount to those outdating products. It is also mentioned that the customers' WTPs over time can decrease linearly such as in pre-cut lettuce, pre-cut carrots, milk and yoghurt or exponentially such as in beef and chicken. In this research, a linear WTP decrease is assumed before establishing the model (**Figure 1**).

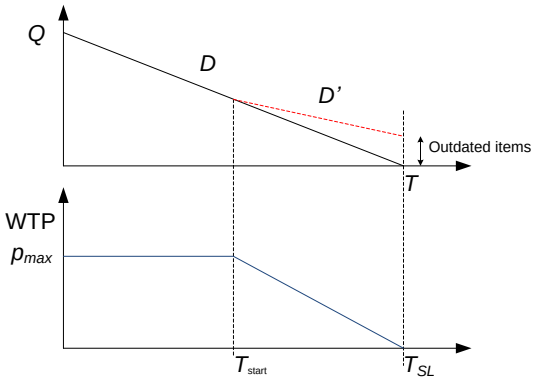

Figure 1 Customer's WTP starts decreasing at time $=T_{start}$

From **Figure 1**, customers' WTPs start decreasing at Tstart. Without any action, the demand of the product would change from D to D' (where D'< D) leading to outdated stocks at the end of the cycle. To avoid the system producing outdated items, the retailer will apply a markdown strategy to stabilize the demand. Over Tstart-TSL period, the price is reduced linearly. In other words, the price of each product depends on its age when entering the retailer. Therefore, for each batch, every product has three possible pricing conditions as defined by Equation 2,

$$p(t)=\begin{cases} p_{\max} & 0\le t<T_{start} \\ \dfrac{p_{\max}}{T_{SL}-T_{start}}\left(T_{SL}-t\right) & T_{start}\le t<T_{SL} \\ 0 & t\ge T_{SL} \end{cases} \quad (2)$$

where $p(t)$ represents the shelf-life based pricing function, p_{max} denotes to the maximum price while T_{sl} and T_{start} symbolize the shelf-life and the decreasing time respectively. After defining the price function, then the revenue of each batch can be generated as demonstrated by **Figure 2**.

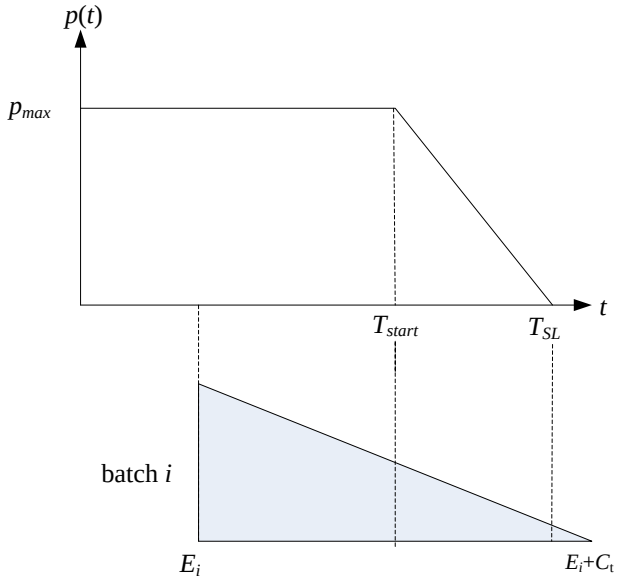

Figure 2 Shelf-life based pricing of batch i

Referring to **Figure 2**, E_i represents the age of batch i received by retailer and C_t is the ordering cycle. Noting that every batch has different age when entering the retailer then the structure of retailer's revenue for each batch per unit time can be defined as the followings:

1. Case 1: if $(E_i+C_t) < T_{start}$ then the revenue can be obtained by selling all product in batch i at maximum price as defined by Equation 3

$$R(n,T)=\frac{DC_t p_{\max}}{T} \quad (3)$$

2. Case 2: if $T_{start} \le (E_i+C_t) < T_{SL}$ then the revenue of batch i is denoted by Equation 4

$$R(n,t)=\frac{1}{T}\left[Dp_{\max}(T_{start}-E_i)+D\int_{T_{start}}^{E_i+C_t}p(t)dt\right] \quad (4)$$

3. Case 3: if $(E_i+C_t) \ge T_{SL}$ then Equation 5 represents the revenue function of this condition

$$R(n,T)=\frac{1}{T}\left[Dp_{\max}(T_{start}-E_i)+D\int_{T_{start}}^{T_{SL}}p(t)dt+D\int_{T_{SL}}^{E_i+C_t}p(t)dt\right] \quad (5)$$

Since it is assumed that the price of expired products is zero then the revenue function in Equation 5 can be represented by Equation 6.

$$R(n,T)=\frac{1}{T}\left[Dp_{\max}(T_{start}-E_i)+D\int_{T_{start}}^{T_{SL}}p(t)dt\right] \quad (6)$$

From Equation 4-6, it can be seen that revenue is influenced by C_t and E_i. The length of ordering cycle (C_t) depends on n and T where $C_t=T/n$. The age of batch i (E_i) is calculated by examining the storage time of batch i at the manufacturer (St_i) as illustrated by **Figure 3**.

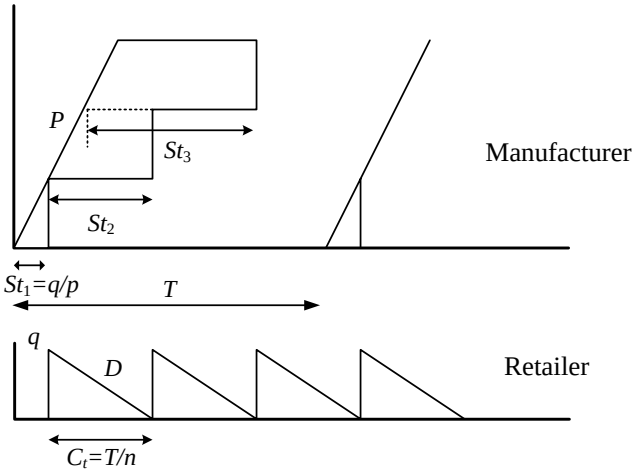

Figure 3 Inventory in a manufacturer-retailer system

Assuming that the transportation lead time is insignificant or can be considered as zero then E_i is equal to St_i. As illustrated by Figure 3, St_i starts from time when batch i is produced until time when it is received by the retailer. For instance, the storage time of batch one or St_1 is equal to q/p while the storage time of the next batch is represented by $q/p+q/d$. Since $q=DT/n$, generalizing the formula of calculating St_i or E_i leads to Equation 7.

$$E_i=(i-1)\frac{T}{n}-(i-2)\frac{DT}{nP} \quad (7)$$

3.2 An integrated production-inventory model considering shelf-life based pricing function

This research is an extension to the integrated production-inventory model by Kim and Ha (2003). A manufacturer and a retailer collaborate to decide the best production and inventory policies considering the shelf-life of the food products. The main aim is to find the maximum joint profit $TP(n,T)$ of the manufacturer and the retailer by specifying the best set value of manufacturer's production length (T) and the number of deliveries to the retailer (n) over the production length.

In the manufacturer's system the total profit, $TP_m(n,T)$, is obtained by subtracting the total cost from the revenue where the costs involved in the manufacturer's system are manufacturing, set up and carrying costs as represented by Equation 8. Similarly, the retailer's profit, $TP_r(n,T)$, is attained by deducting the costs i.e. procurement, ordering, carrying and transportation costs from retailer's revenue in which the shelf life based pricing function is considered as described by Equation 9. Further, the total profit of the system $TP(n,T)$ is achieved by combining Equation 8 and Equation 9 as symbolized by Equation 10.

$$TP_m(n,T)=Dp_m-C_mD+\frac{S}{T}+\frac{DT}{2n}\left[\frac{D}{P}(2-n)+(n-1)\right]h_m \quad (8)$$

$$TP_r(n,T)=R(n,T)-D(V+p_m)+\frac{O_r}{T}+\frac{DT}{2n}h_r+\frac{n}{T}F \quad (9)$$

$$TP(n,T)=TP_m+TP_r \quad (10)$$

As expected, the two decision variables namely n and T should be simultaneously determined to maximize the total profit in Equation 10. In this study, the optimization tool in Matlab R2014a is used to find the optimal values of both n and T.

4. NUMERICAL EXAMPLE

A numerical test is conducted in this research to examine the behaviour of the proposed model. The parameter used in the numerical test is adopted from Kim and Ha (2003) with a slight modification to suit the proposed model as shown by **Table 1**.

Table 1 Parameters in the proposed model

Notation	Value	
p_m	30	\$/unit
P	19,200	unit/year
C_m	5	\$/unit
S	600	\$/order
h_m	6	\$/unit/year
D	4,800	unit/year
$p_{\max}$	50	\$/unit
T_{SL}	0.208	year
T_{start}	0.167	year
O_r	25	\$/order
h_r	7	\$/unit/year
F	50	\$/delivery
V	1	\$/unit

The proposed model is used to solve the problem and the profit is compared to that of obtained from the established model in Kim and Ha (2003). The decision variables (n and T) and the profile of total cost, revenue and total profit for each party and each approach are then presented in **Table 2**.

As depicted in **Table 2**, the proposed model yields a better total profit of \$204,397.1per year with 3 times deliveries (n=3) over 0.1825 year where the delivery size (q) is 292 units. Contrarily, the model of Kim and Ha (2003) in which the product deteriorating value is unconsidered, results in \$171,642.9 of total profit per year with a longer T

and a higher q (0.2406 year and 385 units respectively). Hence, the total profit of the proposed model is $32,754.2 higher (19% increase) than that of Kim and Ha (2003). This indicates that the proposed model potentially yields a better performance in terms of the total gained profit.

Table 2 Total cost, revenue and profit of the proposed model and the previous model

Kim and Ha (2003)	n=3; T=0.2406 year; q=376		
	Manufacturer	Retailer	Total
Total Cost	28,514.8	150,874.7	179,389.5
Revenue	144,000.0	207,032.4	351,032.4
Total Profit	115,485.2	56,157.7	171,642.9
Outdated items	≈58 units per production cycle		
The proposed model	n=3; T=0.1825 year ; q≈292		
	Manufacturer	Retailer	Total
Total Cost	28,820.7	150,780.9	179,601.6
Revenue	144,000.0	239,998.6	383,998.6
Total Profit	115,179.3	89,217.7	204,397.1
Outdated items	0 unit per production cycle		

It is important to note from **Table 2** that the proposed model, with smaller delivery size and shorter production cycle, results in zero outdated items while its counterpart has 58 expired units. It is also found that T significantly affects the total gained profit which means that a small change of T leads to a significant profit reduction as clearly shown in **Figure 3**.

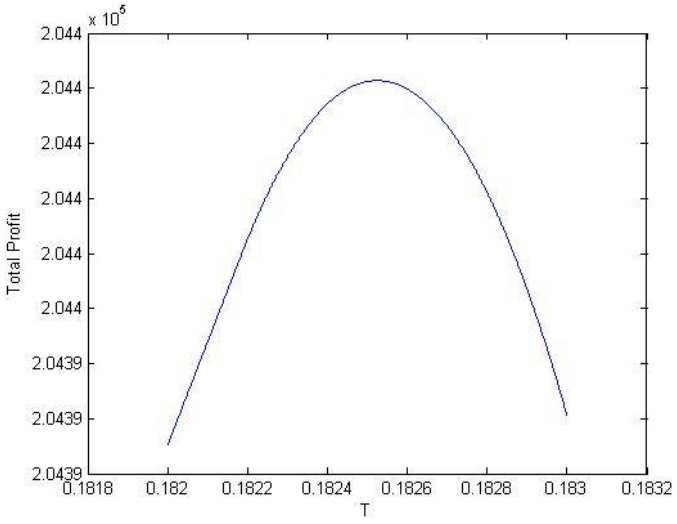

Figure 2 Correlation between T and total profit

4.1 Sensitivity and Error Analysis

As discussed earlier, the proposed model assumes that all parameters are constant over time. In reality, over the planning horizon they might change due to unmanageable factors. As a result, the performance of the model might be affected. To deal with this situation, a sensitivity analysis is applied to examine the robustness of the solution and model while the error analysis is utilised for calculating the potential loss because of changes in parameters (Daellenbach and McNickle, 2005).

In this scenario, the sensitivity analysis is conducted by changing the value of one parameter to -20% and +20% while keeping the rest parameters unchanged. Then, a new total profit is obtained by optimizing the model with the altered parameters. The percentage of change between the new and the current total profit is calculated to examine the model sensitivity to each parameter as presented in **Table 3** column a-c.

In general, result in **Table 3** Column c demonstrates that the optimal solution is relatively insensitive to the changes of majority parameters. It is indicated by fluctuating the parameters by 20% only cause changes in total profit by less than 1%. A slight change of 4.9% is observed in the total profit by the variation in T_{start}. This change, however, is still far from 20%. The demand rate and price are the only parameters that influence the total profit; 20% change in those input parameters proportionally affects the total profit.

In case that the supply chain system has adopted the optimised solution while the actual value of the parameter deviates from its expected value, it is important to investigate the potential loss caused by this decision (also known as error analysis). The error analysis is performed by calculating the difference in percentage between the profit resulted from the optimised decision (**Table 3** column a) and the actual profit when the actual parameter differs from its expected value (**Table 3** column d). It is depicted in column e that variations in majority input parameters insignificantly influence the total profit.

Either overestimating or underestimating the most of inputs by 20% only results in less than 1% variation in total profit. T_{start} is the only parameter which contributes to the benefit loss i.e. underestimating the value of this input by 20% may lead to 4.8% decrease in the total profit. T_{start} is time when customer's WTP starts decreasing and its value depends on the customer's perception on a specific food product. A careful investigation relating to the customer's behaviour is important to ensure a sufficient accuracy for this parameter.

Table 3 The summary of sensitivity and error analyses

Parameter	Parameter changes	New total profit	Current total profit	Total profit changes (a-b)/b*100%	Actual total profit	Total profit changes (a-d)/a*100%
	%	(a)	(b)	(c)	(d)	(e)
D	-20%	162491.8	204,397.1	-20.50%	162593.9	-0.06%
	+20%	246180.0		20.44%	246214.4	-0.01%
P	-20%	204453.2	204,397.1	0.03%	204509.8	-0.03%
	+20%	204233.8		-0.08%	204334.9	-0.05%
S	-20%	205054.6	204,397.1	0.32%	205054.7	0.00%
	+20%	203739.5		-0.32%	203732.8	0.00%
O_r	-20%	204424.5	204,397.1	0.01%	204424.5	0.00%
	+20%	204369.7		-0.01%	204369.7	0.00%
F	-20%	204561.4	204,397.1	0.08%	204569.1	0.00%
	+20%	204232.7		-0.08%	204232.7	0.00%
h_m	-20%	204703.7	204,397.1	0.15%	204704.3	0.00%
	+20%	204090.5		-0.15%	204090.5	0.00%
h_r	-20%	204601.5	204,397.1	0.10%	204520.6	0.04%
	+20%	204192.7		-0.10%	204199.3	0.00%
T_{start}	-20%	194366.4	204,397.1	-4.91%	203855.4	-4.88%
	+20%	204398.4		0.00%	204574.7	-0.09%
pmax	-20%	156397.3	204,397.1	-23.48%	156397.5	0.00%
	+20%	252396.8		23.48%	252396.8	0.00%

5. CONCLUSION

A production-inventory model considering a shelf-life based price function which incorporates the value loss because of customers' perception on product quality has been established. The numerical test reveals that the proposed model may lead to a reduction in the number of outdated items and increase in the total profit of the manufacturer-retailer system in comparison to the existing model. The sensitivity analysis indicates that the optimal profit is relatively steady as the majority input parameters fluctuate. From the error analysis it is further shown that this deviation insignificantly affects to the total expected profit. These results demonstrate that the proposed model not only outperforms the benchmark model but also it is robust to any parameter change.

The vendor-buyer inventory model proposed in this research has not incorporated the procurement of raw material. Thus, it is expected that the total profit could be further extended by accommodating the raw material procurement planning. In addition, noting that deterioration characteristics of raw materials may behave differently from finished goods, proposing different approaches to dealing with quality loss in raw materials can be a challenging subject for investigation. Therefore, extending this model to an integrated production-inventory system which covers a raw material procurement strategy and accommodating efforts to preserve the quality or value loss to lengthen the product shelf-life could be potential for further research avenues.

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REFERENCES

Avijit, B. and Seung-Lae, K. (1995). An integrated JIT inventory model. *International Journal of Operation & Production management* 15, pp. 237-244.

Bakker, M., Riezebos, J. and Teunter, RH. (2012). Review of inventory systems with deterioration since 2001. *European Journal of Operational Research* 221, pp. 275-284.

Ben-daya, M., Darwish, M. and Ertogral, K. (2008). The joint economic lot sizing problem: Review and extensions. *European Journal of Operational Research* 185, pp. 726-742.

Blackburn, J. and Scudder, G. (2009). Supply chain strategies for perishable products: The case of fresh produce. *Production and Operations Management* 18, pp. 129-137.

Daellenbach, HG. and Mcnickle, DC. (2005). *Management Science: decision making through systems thinking*, Palgrave Macmillan Basingstoke, Hants.

Entrup, ML. (2005). *Advanced Planning in Fresh Food Industries: Integrating Shelf Life into Production Planning*, 1 edn, Springer, Dordrecht.
<http://UNISA.eblib.com.au/patron/FullRecord.aspx?p=304796>

Ghare, P. and Schrader, G. (1963). A model for exponentially decaying inventory. *Journal of Industrial Engineering*. 14, pp. 238-243.

Goyal, SK. (1977). An Integrated Inventory Model for a Single Product System', *Operational Research Quarterly (1970-1977)* 28, pp. 539-545.

Goyal, SK. and Giri, BC. (2001). Recent trends in modeling of deteriorating inventory. *European Journal of Operational Research* 134, pp. 1-16.

Goyal, SK. and Giri, BC. (2003). The production–inventory problem of a product with time varying demand, production and deterioration rates. *European Journal of Operational Research* 147, pp. 549-557.

Ha, D. and Kim, S-L. (1997). Implementation of JIT purchasing: An integrated approach. *Production Planning & Control* 8, pp. 152-157.

Hill, RM. (1997). The single-vendor single-buyer integrated production inventory model woth a generalised policy. European Journal of Operational Research 97, pp. 493-499.

Kim, S-L. and Ha, D. (2003). A JIT lot-splitting model for supply chain management: Enhancing buyer–supplier linkage. *International Journal of Production Economics 86*, pp. 1-10.

Maihami, R. and Nakhai Kamalabadi, I. (2012) Joint pricing and inventory control for non-instantaneous deteriorating items with partial backlogging and time and price dependent demand. *International Journal of Production Economics* 136, pp. 116-122.

Msimangira, KA. and Venkatraman, S. (2014). Supply chain management integration: Critical problems and solutions. *Operations and Supply Chain Management* 7, pp. 23-31.

Nahmias, S. (2011). Perishable inventory systems. Springer

Pattnaik, M. (2012). A Note on Non-Linear Profit-Maximization Entropic Order Quantitiy (EnOQ) Model for Deteriorating Items with Stock Dependent Demand Rate. *Operations and Supply Chain Management 5*, pp. 97-102.

Raafat, F. (1991). Survey of Literature on Continuously Deteriorating Inventory Models. *The Journal of the Operational Research Society* 42, pp. 27-37.

Tsiros, M. and Heilman, CM. (2005). The effect of expiration dates and perceived risk on purchasing behavior in grocery store perishable categories. *Journal of Marketing*, pp. 114-129.

Yan, C., Banerjee, A. and Yang, L. (2011). An integrated production–distribution model for a deteriorating inventory item. *International Journal of Production Economics* 133, pp. 228-232.

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An Inventory Model of Production-Inventory Policy for Food Products Considering Quality Loss in Raw Materials

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Abstract - **The majority research on inventory model for deteriorating items in multi-echelon system assumes that a physical depletion of some inventories occurred over time. It means that the inventory is depleted not only due to the demand but also due to some deteriorated items. In food products, however, during a certain period, its quantity remains the same while its quality does degrade over time. Therefore, this study is aimed at developing a more representative inventory model in mimicking food deterioration characteristics. A mathematical model is established to represent the integrated inventory policy of procurement-production-delivery in which the total profit of the whole system is the objective function. The length of the production cycle, the frequency of raw material procurement and finished goods deliveries over the production cycle are the controlling variables. The numerical test indicates that the proposed model yields to a better profit compared to the benchmark model.**

Keywords – **perishable inventory, quality loss, value degradation**

I. INTRODUCTION

Research on the deteriorating inventory has been done extensively. A mathematical model to determine the optimum ordering lot size of the deteriorating items is firstly introduced by [1]. Park [2] then develop this model into an integrated procurement and production system (known as IPP). It is assumed that the raw materials for producing non-perishable finished goods are deteriorated during the production cycle. Raafat [3] extended this model by taking into account the condition where the finished goods are deteriorated as well. Yang and Wee [4] developed a model of an integrated production-inventory policy for perishable product in a single vendor and single buyer system. This model is extended in their next paper by taking into account the procurement strategy for the deteriorating raw materials [5]. Recently, Yu, et al. [6] developed a multi-stage deteriorating inventory where deterioration characteristic of raw materials is different from finished goods.

The models mentioned above assume that a physical depletion occurs in a fraction number of inventoried items. This means that once the inventory enters the warehouse its quantity is depleted not only by demand but also by some deteriorated items. Some typical items e.g. alcohol, gasoline and radioactive-materials may perish in this way. In many cases, however, during a certain time, the quantity of a perishable item remains constant while the quality does degrade.

Some researchers in inventory fields developed different approaches. Blackburn and Scudder [7] examined the value of melons and sweet corns losses across a supply chain since one of the quality indicators e.g. sweetness level decreases over time. To reduce the loss, they managed the picking rate and the size of the transfer batch of the food products. Rong, et al. [8] introduced an approach to maintain the quality of food products e.g. peppers across a supply chain. They utilized a kinetic model to represent the quality loss in peppers. Temperature, one of the important factors for maintaining food quality, is taken into account. Qin, et al. [9] developed a joint pricing model where the quality as well as the quantity of a fresh produces e.g. vegetables, strawberries and litchi are deteriorated over time. Recently, Fauza, et al. [10] introduced a shelf-life based price function to represent the value degradation of a fully pack food product e.g. noodles and bakeries. Studies in this group are suitable in representing deterioration characteristics of one single form of food product e.g. melons, pepper, vegetables, noodles, while during different stages of a supply chain the form of food are shifted from raw materials to finished goods.

A food product flows across different stages of supply chain with various deterioration characteristics depending on its form [11]. The decrease of gluten content in wheat flour during storage time [12] is an example of deterioration in food as raw materials. Once the wheat flour is processed and transformed to the next product, noodles for instance, its quality behaves differently. As a finished good, the quality of a food product is perceived by customers who prefer to buy a fresher product i.e. a product with longer remaining life time [13]. It means that the customer's willingness to pay (WTP) decreases when the product is getting closer to its expiration dates. Consequently, the demand rate during the decreasing period becomes slower. To maintain the demand, a marking down policy is applied, otherwise, it may increase the number of outdated items. These phenomena are often found in practical life but less attention is given. Therefore, this research is aimed at filling this gap by proposing an integrated inventory policy for managing deteriorating raw materials and perishable finished goods through a supply chain.

The remaining sections of this paper are organized based on the following structure. Section 2 presents the model development step while the numerical tests for examining

the behavior of the model are discussed in Section 3. The last section then summarizes this paper.

II. MODEL DEVELOPMENT

Consider a manufacturer (vendor) and a retailer which collaboratively decide the inventory policy. Manufacturer produces a single perishable product composed by a single deteriorating raw material. The product which has imprinted expiration dates on its package is delivered to retailers using a multi-shipment policy. The quality of raw materials losses during procurement cycle and without any adjustment it may affect the quality of its sequence product. On the other hand, when the raw material is changed into a finished good and is received by retailer, its value is suffering from a customer who perceives the product quality by seeing its expiration dates. To maintain the demand and avoid outdated items, a price reduction policy for aging product is applied. Some products such as noodles, bakeries and yoghurt are fitted with this situation.

Further, the observed system apply a coordination mechanism. The frequency of raw materials procurement or n_s is synchronized with the length of production cycle or T (at manufacturer) and finished goods delivery numbers or n (at retailer). The objective is to maximize the system performance i.e. the total profit or $TP(n_s, T, n)$ by determining the best value of n_s, T and n.

A. Assumptions and notations

The model is developed based on the following assumptions

1. The production rate and demand rate are constant
2. The quality of raw materials losses at a constant rate
3. The value of finished goods degrades linearly once it reaches its time to deteriorate or T_{start} (time when the customer's willingness to pay for the product decreases)
4. Lead time is neglected and no shortage is allowed

The following notation is used in this study

D : demand rate
P : production rate
Q : quality performance
k : deterioration rate
C_l : quality loss cost
C_s : purchasing cost of raw materials
C_m : manufacturing cost
C_r : purchasing cost of finished goods
$p_{\max}$: maximum price of the product
F_s : transportation cost of raw materials
F_r : transportation cost of finished goods
A_m : setup cost
A_r : ordering cost of finished goods
H_s : holding cost of raw materials
H_m : holding cost of finished goods (vendor)
H_r : holding cost of finished goods (retailer)
T_{start} : time to deteriorate
T_{sl} : shelf-life
E_i : the age of batch i
R_i : revenue of batch i
C_t : ordering cycle of finished goods
n_s : frequency of raw material procurement
T : the length of production cycle
n : finished good delivery numbers
L : total cost of the quality loss
R : total revenue
JTC : joint total cost
JTR : joint total revenue
JP : joint profit

B. An integrated production-inventory model

The system configuration is similar to the structure of an integrated JIT inventory model in [14] as illustrated by Figure 1. The manufacturer produces finished goods with production rate P during the production cycle (T) and then delivers the product three times (n=3) over T to fulfill the demand of the retailer (D). Since the value of the product is not constant over time, the age of a batch received by retailers or E_i (where i = 1, 2, …, n) becomes essential for retailer's revenue. Fauza, et al. [10] define E_i as the duration time between the time (t) when a batch is received by retailer and the time it is produced (a zero lead time is assumed). For examples, the first batch (q^1) is shipped once the production quantity meets the size of lot transfer (q) and is consumed during ordering cycle (C_t); it is received by retailer at $t=q/P$ and is produced at t=0 thus $E_1 = q/P$. Using the same approach, hence E_2 is equal to q/D. Since $q=DT/n$, a general formula to calculate E_i is then represented by (1)

$$E_i = (i-1)\frac{T}{n} - (i-2)\frac{DT}{nP} \quad (1)$$

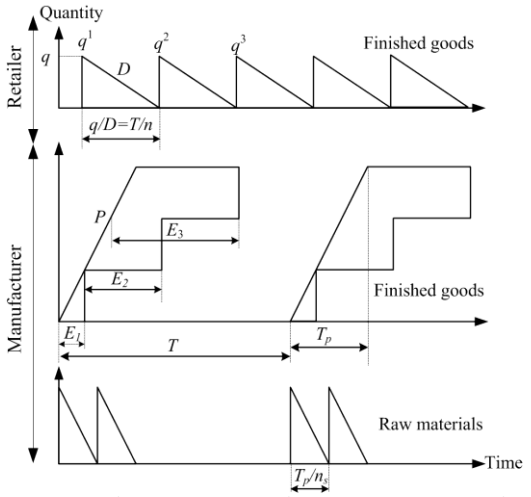

Fig. 1. Inventory of raw materials and finished goods in a manufacturer-retailer system [14]

After the age of batch i is defined, its revenue (R_i) hence can be obtained. R_i depends on the value of Ei and C_t. Fauza et al (2015) introduced a shelf-life based price function $p(t)$ which divided the price of product into three regions, namely, maximum price, decreasing price and zero price area (illustrated by Figure 2). T_{start} refers to a product's deteriorating time (the time when customer's WTP starts decreasing) while T_{sl} stands for product's shelf-life time (product's expired dates). If a product falls before T_{start} then it will be sold with maximum price (Region I) however if a product is still available after T_{start} and run out before T_{sl}, its value is decreasing, hence the price will be reduced (Region II). Finally, if any products left at T_{sl}, they will be discarded as the value is zero (Region III). Based on this approach the retailer's revenue is calculated. Further explanation for the revenue calculation of each batch can be seen at Fauza et al (2015).

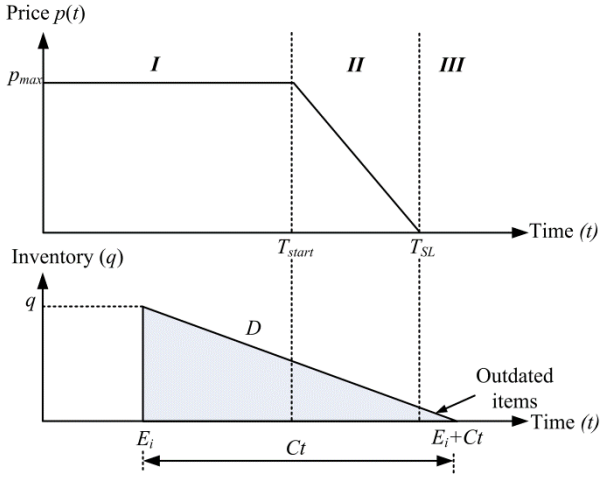

Fig. 2. Shelf-life based price function [10]

The joint total revenue of the whole system $JTR(T, n)$ is obtained from adding the revenue of retailer with the revenue of manufacturer as presented by (2)

$$JTR(T,n) = C_m D + \sum_{i=1}^{n} R_i(T,n) \tag{2}$$

This model develops Fauza et al (2015) by integrating the strategy of procuring deteriorating raw materials into the inventory policy. As can be seen at Figure 1, the raw materials are procured two times (n_s=2) to fulfill the demand of raw materials during the production time (T_p). In this case, one unit raw material is used to produce one unit finished good. Therefore, the rate of raw material demand is equal to the rate of production (P).

As mentioned previously, the quality of raw materials degrades during the storage time (demonstrated by Figure 3). A kinetic model function in (3) is used to represent the quality losses.

$$\frac{dQ}{dt} = kQ^m \tag{3}$$

Q refers to the quality performance of a food product such as gluten content in wheat flour. t stands for time, k represents the deterioration rate and m denotes to the reaction order.

At the first time a lot of raw materials (q_s) received by the manufacturer the quality is maximum (Q_{max}) and then starts decreasing linearly (a zero value of m is assumed) at the rate of deterioration k (illustrated by Figure 3). Since m=0, the quality performance of the raw materials over time or Q(t) is calculated by (4)

$$Q(t) = Q_{\max} - kt \tag{4}$$

As shown by Figure 3, at the time t, the raw material consumed for production P is suffered from a quality loss ΔQ by $Q_{\max}$-$Q(t)$ and incur a quality cost C_l. Since the quality deviates from $Q_{\max}$ at rate of k during the procurement cycle (T_p/n_s) and T_p=DT/P, thus the total cost of quality loss of raw materials per unit time is represented by (5)

$$L(n_s,T) = C_l \frac{n_s P}{T} \int_0^{\frac{DT}{n_s P}} \Delta Q(t)dt \tag{5}$$

Hence, Equation (6) represents the total cost of raw materials in manufacturing system per unit time $TRC_s(n_s, T)$ which consists of purchasing cost, ordering cost, carrying cost and quality loss cost respectively

$$TC_s(n_s,T) = C_s D + A_s \frac{n_s}{T} + H_s \frac{D^2 T}{2 n_s P} + L(n_s,T) \tag{5}$$

and the total relevant cost of finished goods in manufacturer system per unit time $TRC_m(T, n)$ configured by processing cost, setup cost and holding cost is consecutively presented by (7)

$$TC_m(T,n) = C_m D + \frac{A_m}{T} + H_m \frac{DT}{2n}\left(\frac{D}{P}(2-n) + (n-1)\right) \tag{7}$$

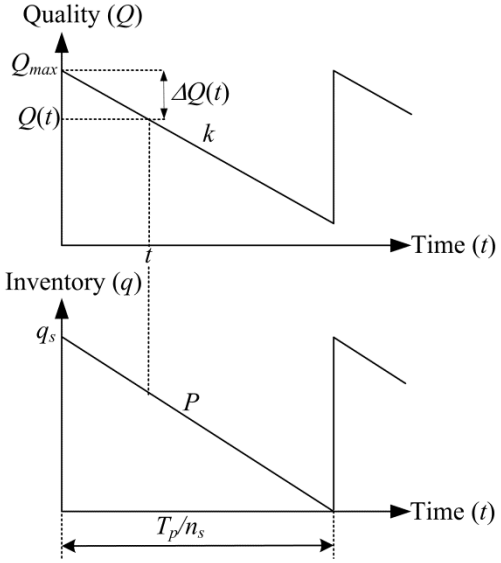

Fig. 3. Relation between quality degradation and raw material procurement cycle

while Equation (8) demonstrates the total cost of finished goods in retailer system per unit time $TC_r(T, n)$ which contains the purchasing cost, the ordering cost, the transportation cost and the holding cost respectively.

$$TC_r(T,n) = C_r D + \frac{A_r}{T} + F_r \frac{n}{T} + H_r \frac{DT}{2n} \quad (8)$$

Hence, the joint total cost of the whole system is described by (9).

$$JTC(n_s,T,n) = TC(n_s,T) + TC(T,n) + TC_r(T,n) \quad (9)$$

The joint profit, the objective function of the integrated policy $JP(n_s, T, n)$, is gained by subtracting the joint total cost from the joint total revenue as described by (10)

$$JP(n_s,T,n) = JTR(T,n) - JTC(n_s,T,n) \quad (10)$$

As expected, there decision variables, n_s, T and n need to be determined to maximize the profit of the whole system. In this case, a genetic algorithm tool in Matlab R2014a is used.

III. NUMERICAL EXAMPLE

In this numerical test two existing models are used for benchmarking. The first is a non-deteriorating integrated inventory policy such as in [14] while the second is a perishable finished good integrated model [10]. Parameter inputs in [10] is used in the numerical test with a slight adjustment to suit the model configuration as presented by Table I. The proposed model is then utilized to find solution by using the genetic algorithm tool in Matlab R2014a.

TABLE I
PARAMETERS IN THE NUMERICAL TESTS

Notation	Value	
P	19,200	unit/year
D	4,800	unit/year
C_s	5	$/unit
C_l	20	$/unit quality/year
k	0.5	unit quality/year
H_s	3	$/unit/year
F_s	45	$/frequency
C_r	30	$/unit
C_m	5	$/unit
A_m	600	$/order
H_m	6	$/unit/year
p_{max}	50	$/unit
T_{sl}	0.208	year
T_{start}	0.167	year
A_r	25	$/order
H_r	7	$/unit/year
F_r	50	$/delivery

The following setting is used in the GA
Population size : 100 individuals
Crossover rate : 0.7
Migration : every 20 generations with rate of 0.2
Stopping rule : maximum of 200 generations
The lower limit : [1 0 1]
The upper limit : [100 1 100]
The GA is run 20 times and the best value is selected and compared to the benchmarks model as can be seen at Table II

As demonstrated by Table II, the proposed model yields a better performance in terms of total profit. This approach results in $183,992.16 profit margin per year with two times raw material procurement during 0.1825 year production cycle length and three times finished goods deliveries over the same period. It is interesting to note that the production length (T) in the non-deteriorating model is the longest compared to others. It relates to the deterioration characteristics in the food products. As a finished good, a shorter T is preferable to prevent food inventory from aging and become outdated and as a raw material a shorter T would be able to maintain the quality of the stored food.

In numerical test, all input parameters are assumed to be constant over time. In fact, during the planning horizon these parameters are likely to change and it may affect the model performance. In this test, the change of two significant parameters e.g. cost of quality loss C_l and time to deteriorate or T_{start} is investigated. The first parameter is related to the quality loss in raw materials while the second parameter is the effect of value degradation in finished goods. Two scenarios are used, the first is increasing the value of C_l from 2 to 4 times of its original value while the second scenario is reducing the value of T_{start} from ½ to ¼ of its current value. The result can be seen at Table III.

TABLE II
TOTAL COST, REVENUE AND PROFIT

Non-deteriorating model	ns=2; T=0.2409 year, n=3		
	Manufacturer	Retailer	Total
Total Cost	53,827.35	146,075.59	199,902.94
Revenue	144,000.00	206,766.03	350,766.03
Total Profit	90,172.65	60,690.43	150,863.09
Deteriorating finished goods [10]	ns=1; T=0.1825 year, n=3		
	Manufacturer	Retailer	Total
Total Cost	54,490.75	145,980.90	200,471.65
Revenue	144,000.00	239,998.64	383,998.64
Total Profit	89,509.25	94,017.73	183,526.99
The proposed model	ns=2; T=0.1825 year, n=3		
	Manufacturer	Retailer	Total
Total Cost	54,025.73	145,980.90	200,006.62
Revenue	144,000.00	239,998.79	383,998.79
Total Profit	89,974.27	94,017.89	183,992.16

TABLE III
CHANGE IN TOTAL POFIT, QUALITY LOSS COST (C_l) AND TIME TO DETERIORATE (T_{start})

Parameter	Value	n_s	T	n	JP'^*	Ratio**
C_l	40	3	0.183	3	183,618	0.9980
	80	4	0.182	3	183,034	0.9948
T_{start}	0.0835	1	0.095	3	181,168	0.9846
	0.0418	1	0.058	3	174,978	0.9510

*JP'=the new optimized profit
**ratio between the new profit and the current profit

As depicted by Table III, the change in the quality loss cost influences the strategy of procuring the raw materials (as represented by n_s). The raw material is supplied more frequently to ensure the quality of raw material. Similarly, the change in time to deteriorate affects the decision of production cycle length. If the time to deteriorate occurs earlier then a shorter production cycle length is preferable.

In terms of profit, the change of the value input in T_{start} has more effect on profit compared to the change in the value of C_l. As shown by values at Ratio column in Table III, the increase in value of C_l until four times only reduce the ratio less than one percent. Meanwhile, the decline in the value of T_{start} until one fourth times reduce the ration around five percent.

IV. CONCLUSION

In this paper, an integrated production inventory model considering quality and value loss has been established. Two different approaches for representing the deterioration in raw materials and finished goods have been applied. The numerical test shows that, in term of total gained profit, the proposed model results in a better performance compared to the current models. The model however is limited to cover problems in a simple supply chain configuration therefore extending the model by addressing issues in a more complex supply chain structure is potential for the future research.

REFERENCES

[1] P. Ghare and G. Schrader, "A model for exponentially decaying inventory," *Journal of Industrial Engineering*, vol. 14, pp. 238-243, 1963.

[2] K. S. Park, "An integrated production-inventory model for decaying raw materials," *International Journal of Systems Science*, vol. 14, pp. 801-806, 1983/07/01 1983.

[3] F. Raafat, "A production-inventory model for decaying raw materials and a decaying single finished product system," *International Journal of Systems Science*, vol. 16, pp. 1039-1044, 1985.

[4] P.-C. Yang and H.-M. Wee, "Economic ordering policy of deteriorated item for vendor and buyer: An integrated approach," *Production Planning & Control*, vol. 11, pp. 474-480, 2000/01/01 2000.

[5] P.-C. Yang and H.-M. Wee, "An integrated multi-lot-size production inventory model for deteriorating item," *Computers & Operations Research*, vol. 30, pp. 671-682, 2003.

[6] Y. Yu, Z. Wang, and L. Liang, "A vendor managed inventory supply chain with deteriorating raw materials and products," *International Journal of Production Economics*, vol. 136, pp. 266-274, 2012.

[7] J. Blackburn and G. Scudder, "Supply chain strategies for perishable products: The case of fresh produce," *Production and Operations Management*, vol. 18, pp. 129-137, 2009.

[8] A. Rong, R. Akkerman, and M. Grunow, "An optimization approach for managing fresh food quality throughout the supply chain," *International Journal of Production Economics*, vol. 131, pp. 421-429, 2011.

[9] Y. Qin, J. Wang, and C. Wei, "Joint pricing and inventory control for fresh produce and foods with quality and physical quantity deteriorating simultaneously," *International Journal of Production Economics*, vol. 152, pp. 42-48, 2014.

[10] G. Fauza, Y. Amer, S.-H. Lee, and H. Prasetyo, "A Vendor-Buyer Inventory Model for Food Products Based on Shelf-Life Pricing," *Operations and Supply Chain Management* vol. 8, pp. 67-73, May 2015 2015.

[11] D. R. Heldman, "2 - Kinetic Models for Food Systems," in *Food Preservation Process Design*, ed San Diego: Academic Press, 2011, pp. 19-48.

[12] A. Miœ, "Influence of the storage of wheat flour on the physical properties of gluten," *Int. Agrophysics*, vol. 17, pp. 71-75, 2003.

[13] M. Tsiros and C. M. Heilman, "The effect of expiration dates and perceived risk on purchasing behavior in grocery store perishable categories," *Journal of Marketing*, pp. 114-129, 2005.

[14] A. Banerjee and S.-L. Kim, "An integrated JIT inventory model," *International Journal of Operations & Production Management*, vol. 15, pp. 237-244, 1995.