AN INTEGRATED MARKETING AND ENGINEERING APPROACH TO PRODUCT LINE DESIGN WITH CONSIDERATION OF REMANUFACTURED PRODUCTS

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An Integrated Marketing and Engineering Approach to Product Line Design with Consideration of Remanufactured Products

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Certificate of Originality

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

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Dated: 24/05/2016

Abstract

To satisfy the increasingly diversified customer needs, many companies have adopted the product line design (PLD) approach to provide a variety of products for customers. In the PLD approach, both marketing and engineering issues need to be considered. In recent years, an increasing number of companies have offered remanufactured products to customers by remanufacturing their end-of-life and returned products in response to social concerns, the enforcement of regulations on environmental protection, and the increasing potential of green markets. This research aims to investigate the integrated marketing and engineering approach to PLD with consideration of remanufactured products.

Remanufactured products are normally produced from returned new products and quite often launched in markets where the new products exist. However, the simultaneous consideration of new and remanufactured products in PLD was not found in previous studies. In addition, the coordination of supply chain parties in performing PLD with consideration of remanufactured products was not addressed. PLD quite often involves market surveys, demand estimation, market segmentation, and market potential estimation. Its solutions can be largely affected by various

uncertainties. Two types of uncertainties are studied in this research. The first is the uncertainties associated with market potential estimation and survey data in the development of market demand models that were not properly addressed in previous studies. The second type is the uncertainties about the quantity, timing, and quality of returned products. Determining the optimal quantity and quality of product returns for remanufacturing under uncertain quality and multi-period of returns was likewise not properly addressed in earlier studies.

In this research, a methodology for optimal PLD with consideration of remanufactured products is proposed based on an integrated marketing and engineering approach. The proposed methodology can address the abovementioned problems by (1) considering the fuzziness associated with survey data and market potential estimation in the development of market demand models using fuzzy regression and fuzzy estimate generation of market potential, (2) simultaneous consideration of new and remanufactured products in a PLD in centralized and decentralized supply chain networks, and (3) determining the optimal quantity and quality of product returns for remanufacturing under multi-period and uncertain quality of the returns. The proposed methodology mainly involves conducting conjoint surveys, generation of fuzzy market demand models, generation of dynamic demand models for simultaneous consideration of new and remanufactured products in PLD, coordination of closed-loop supply chain for PLD, formulation of multi-objective optimization models and their solutions, as well as determining optimal product returns for remanufacturing.

A case study on the PLD of tablet PCs based on the proposed methodology was conducted to illustrate the applicability of the proposed methodology. Three validation tests were performed to evaluate the effectiveness of the proposed methodology. Results of the first test indicated that the profit and market share of a PLD for the maximum profit scenario estimated based on the proposed methodology was better than those estimated based on the methodology with separate consideration of new and remanufactured products. Results of the second test showed that estimated market demand for the normal scenario based on the proposed fuzzy demand model was very close to that based on the multinomial logit model. The third validation test was about the quantity and quality grades of product returns for remanufacturing. The test results indicated that the inventory cost of the returned tablet PCs would cause a 0.5%–1.1% increase in the total cost of the remanufactured tablet PCs, while the uncertainty in the quality of returns would result in 4%–6% change in the total cost.

Publications Arising from the Thesis

Journal Papers:

[1] Aydin, R., Kwong, C. K., Ji, P., and Law, H. M. C. (2014). Market demand estimation for new product development by using fuzzy modeling and discrete choice analysis. *Neurocomputing*. Vol. 142, 136-146.

[2] Deng, S., Aydin, R., Kwong, C. K., and Huang, Y. (2014). Integrated product line design and supplier selection: a multi-objective optimization paradigm. *Computers and Industrial Engineering*, Vol. 70, 150-158.

[3] Aydin, R., Kwong, C. K., and Ji, P. (2015). A novel methodology for simultaneous consideration of remanufactured and new products in optimal product line design. *International Journal of Production Economics*, Vol. 169, 127-140.

[4] Aydin, R., Kwong, C. K., and Ji, P. (2015). Coordination of the closed-loop supply chain for product line design with consideration of remanufactured products. *Journal of Cleaner Production*, 1-13.

[5] Aydin, R., Kwong, C. K., and Okudan Kremer, G. (2016). Determining the optimal quantity and quality levels of used product returns for remanufacturing under multi-period and uncertain quality of returns. *International Journal of*

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Conference Papers:

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[7] Aydin, R., Kwong, C. K., and Ji, P. (2015). Coordination of a manufacturer and supply chain partners for product line design with consideration of remanufactured products. *The 22nd CIRP Conference on Life Cycle Engineering*, Sydney, Australia, Apr 2015.

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List of Abbreviations

CLSC	Closed-loop supply chain
DCA	Discrete choice analysis
DLM	Distributed lag model
EoL	End-of-life
EoU	End-of-use
EV1	Extreme value type 1
FOC	First-order condition
GA	Genetic algorithm
HFISP	Hierarchical fuzzy integral stated preference
IIA	Independently from irrelevant alternatives
IID	Independent and identically distributed
MNL	Multinomial logit
MXL	Mixed logit
NL	Nested logit
NPD	New product development
NSGA-II	Non-dominated sorting genetic algorithm II
OEM	Original equipment manufacturer
PAES	Pareto-archived evolution strategy
PLD	Product line design
RP	Revealed preference

SBX	Simulated binary crossover
SP	Stated preference
SPEA	Strength-Pareto evolutionary algorithm
SIMOPT	Simulation optimization
TFNs	Triangular fuzzy numbers

Chapter 1 Introduction

Section 1.1 provides the background of product line design, market demand modeling, consideration of remanufactured products in product design, integrated product and closed-loop supply chain design, and managing product returns for remanufacturing. Section 1.2 defines the problem statement of the research. Section 1.3 identifies the scope and objectives of the research. Section 1.4 presents the organization of the report.

1.1 Background

In the past decade, globalization and the increasingly diversified customer needs have resulted in the dramatic increase in product variety in the marketplace. However, companies face a number of issues they have to deal with, such as tough market competition, shortening lead times, and reducing costs. Product line design (PLD) is a promising way to deal with such issues by developing product variants for different customer segments in a short time period. PLD is mainly about determining the number of product variants and their design specifications to satisfy the needs of various market segments. PLD involves a family of products considering marketing, design and manufacturing factors (Gupta and Krishnan, 1999). It has been widely adopted by companies to increase the profitability and market share of their products. To perform PLD, marketing and engineering concerns need to be considered simultaneously (Luo, 2011). In previous studies on PLD, market demand estimations, pricing, uncertainty and product line optimization were commonly focused on.

Estimation of market demands commonly involves choice modeling and market potential estimation. Choice modeling, which is a common method for understanding consumer preferences, is widely used in the demand modeling of product design (Chen *et al.*, 2013). Heterogeneous consumer preferences, market competition and dynamics, and uncertainties regarding customer preferences have been studied in the choice and/or demand modeling of product design (Train, 2009).

In recent years, numerous companies have attempted to recover their end-of-life (EoL) and/or end-of-use (EoU) products through refurbishment, remanufacturing, recycling, and/or reuse in response to the increasing global awareness on environmental protection and enforcement of environmental regulation. These recovery strategies help reduce the cost of manufacturing and disposal, promote sustainability, and boost profit by attracting environmentally friendly consumers. Remanufacturing, a popular product recovery strategy, has been considered in product design as a profitable business strategy. Quite a number of companies, such as Apple, Dell, Sony, and Fuji Xerox, have offered remanufactured (or "refurbished") products in markets. Apple sells refurbished products, such as iMacs, iPads, iPods, and Apple Tvs, and provides a 1-year warranty for them. HP launched an "HP Renew Program" to refurbish used products and sell them as remanufactured products in markets (Wu, 2012a). The Kodak sells single use cameras in which the parts can be reused for multiple times (Atasu *et al.,* 2010). In addition, used refrigerators from Europe are remanufactured and sold in Ghana (Yalabik *et al.,* 2014). Offering remanufactured products not only allows companies to address social concerns and legal regulations, but also to respond to market needs. From a business point of view, launching remanufactured products will definitely help companies gain access to green consumer markets and second markets (less developed regions), as well as improve the company image in terms of social responsibility and environmental friendliness. Consideration of remanufactured products in the product design stage, competition between new and remanufactured products, cannibalization of remanufactured products on the sales of new products, and pricing of remanufactured products have been investigated in previous studies.

To develop remanufactured products, apart from product design, the closed-loop supply chain (CLSC) of the products has to be considered. CLSC involves the collection of used products from customers. It supports remanufacturing, recycling, and reuse, as well as manages the relationship and coordination among supply chain partners, such as manufacturers, suppliers, retailers, and/or remanufacturers. Some studies have been conducted on the design of CLSC in the product design stage.

Managing product returns has been considered essential in the production planning and control of remanufacturing, as well as in the inventory control management of product returns (Guide and Wassenhove, 2001; Srivastava and Srivastava, 2006; Shaharudin *et al*., 2015). However, a high degree of uncertainty exists in the quantity, timing and quality of returned products that can highly affect the planning and control of remanufacturing.

1.2 Problem statement

Several research problems were observed. First, remanufactured products are normally reprocessed from returned new products and quite often launched in the markets where the new products exist. Thus, they should be considered together with new products in PLD in order to acquire the maximum profit and market share of the product line. However, methodologies and/or frameworks that enable the simultaneous consideration of remanufactured and new products in a PLD are lacking.

Second, the estimation of market potential for PLD is commonly performed by market experts in industries. However, the estimation is always imprecise and fuzzy because of the subjective judgments of marketing experts. On the other hand, consumer surveys are commonly used to understand consumer preferences on products and were widely adopted in PLD. However, it is widely recognized that consumer survey data contain a high degree of fuzziness because customer responses are subjective and imprecise. Ignorance of the fuzziness would lead to the under- or over-estimation of market demands.

Third, previous studies on integrated product and CLSC design mainly focused on the competition and coordination of manufacturers and supply chain partners. However, the coordination of supply chain partners in performing PLD with consideration of remanufactured products has not been addressed.

Finally, considerable uncertainties exist in the quantity, timing, and quality of the returned products that could lead to high inventory and recovery costs, loss of profits for the remanufactured products, and poor remanufacturing performance. Therefore, it is necessary to study the determination of the optimal quantity and quality of product returns under multi-period and uncertain quality of the returns.

1.3 Research scope, aim, and objectives

The scope of this research mainly involves studies on demand models for new product development (NPD) in dynamic markets, PLD with consideration of remanufactured products, CLSC coordination for PLD, and managing product returns for remanufacturing. The research aims to study PLD with simultaneous consideration of new and remanufactured products. To achieve the research aims and address the research problems stated in the previous section, the objectives of this research are as follows:

- To develop a methodology for PLD with simultaneous consideration of new and remanufactured products using an integrated marketing and engineering approach.
- To develop fuzzy market demand models for NPD which address the uncertainty associated with market potential estimation and consumer

preferences obtained from market surveys.

- To model the coordination of a manufacturer and supply chain partners using game theory in assistance of determining product line solutions (both new and remanufactured products) and product return rate for remanufacturing.
- To determine the optimal quantity and quality grades of product returns for remanufacturing under multi-period and uncertain quality of returns.

1.4 Organization of the dissertation

The organization of the dissertation is as follows:

Chapter 2 presents a comprehensive literature review on choice modeling, PLD, remanufacturing in the product design stage, integrated product and CLSC design, and collection of used products for remanufacturing. At the end of the chapter, some research gaps and problems are presented.

Chapter 3 outlines the overall research methodology proposed in this research for the simultaneous consideration of remanufactured and new products in PLD under centralized and decentralized cases, as well as the determination of optimal product returns for remanufacturing.

Chapter 4 presents the generation of fuzzy market demand models for NPD using fuzzy regression and discrete choice analysis (DCA). A case study on estimating the market demand for a new tablet PC is used to illustrate the applicability and evaluate the effectiveness of the proposed methodology.

Chapter 5 describes the proposed methodology for simultaneous consideration of remanufactured and new products in an optimal PLD under a centralized supply chain system. A case study on optimal PLD with simultaneous consideration of remanufactured and new tablet PC design based on the proposed methodology is presented to show the applicability of the proposed methodology. The validation of the proposed methodology and its results are also presented.

Chapter 6 describes the proposed methodology for the coordination of CLSC in performing PLD, which involves both new and remanufactured products, under a decentralized case. The applicability of the proposed methodology is illustrated using a case study on the coordination of a manufacturer, and supply chain partners for the PLD of tablet PCs with consideration of remanufactured tablet PCs.

Chapter 7 presents the proposed methodology for determining the optimal quantity and quality grades of product returns for remanufacturing under multi-period and uncertain quality of returns. A case study on determining the optimal quantity and quality grades of tablet PCs based on the proposed methodology is used to evaluate the effectiveness of the proposed methodology.

Chapter 8 provides a discussion on the proposed methodology and implementation results.

Chapter 9 presents the conclusions of the current PhD research and future work related to the research.

Chapter 2 Literature Review

Section 2.1 describes choice modeling and DCA. Section 2.2 outlines a review of research on PLD. Section 2.3 describes research on the consideration of uncertainty in NPD. Section 2.4 presents research on the consideration of remanufactured products in the product design stage. Section 2.5 describes previous studies on the integration of product design with CLSC design. Section 2.6 describes research on the managing product returns for remanufacturing. Finally, Section 2.7 discusses the research gaps and problems.

2.1 Choice modeling

Developed by McFadden (1974), choice modeling is a common method used in the decision-making process to understand consumer purchasing behavior and preferences. It can be used to measure tradeoffs among the attributes in a given set of product/service alternatives. Early choice modeling applications were used to solve problems in the travel, transportation, and tourism industries according to the principle of utility maximization of customers. In the last few decades, choice modeling has been widely applied in marketing research (Louviere *et al*., 2000).

Choice modeling can capture consumer preferences for a set of competitive products, making this approach suitable for integrating marketing and engineering approaches in product design (Chen *et al.*, 2013).

In recent years, choice modeling has been used to associate consumer preferences with design attributes for NPD. Choice modeling has a great capability to demonstrate a strong link between product design attributes and consumer preferences considering market competitiveness; thus, it has various applications in the demand modeling of product design (Louviere *et al.*, 2000; Train, 2009; Chen *et al.*, 2013). The outputs of choice modeling provide decision makers important information for determining the product features and settings of design variables to satisfy various customer expectations. The latest research in choice modeling aims at understanding heterogeneous consumer preferences, estimating market demand under competition and/or uncertainty, and studying uncertainties associated with customer purchasing behavior in demand modeling (Train, 2009).

2.1.1 Review of choice models

Various types of choice models have been developed in previous studies. These types can be classified according to the principal approach, data analysis, and the modeling approach.

Choice models are classified as either aggregate or disaggregate based on the principal approach. Aggregated choice modeling is an early approach that considers all consumers as a single input and usually calculates a single parameter for group averages (Small, 2006). By contrast, instead of using a group average's data, disaggregate approaches to choice modeling use individual customer preferences or choices to estimate unbiased coefficients that distinguish disaggregate approaches from aggregate ones (Chen *et al*., 2013). Disaggregate choice models, widely called discrete choice models, consider more behavioral and individual preferences and examine the discrete alternatives of individuals rather than continuous ones (Small, 2006).

Stated and revealed preference data are two types of data used in choice models. Revealed preference (RP) choice models use past market data to analyze consumer behavior. However, if previous sales data for the market or product (e.g., new/innovative product or market development) are not available, the decision makers need to develop stated preference (SP) choice models to understand possible consumer behavior for the new market or innovative product development. Hence, SP choice modeling requires ranking, rating, or choice data to interpret consumer preferences. Furthermore, survey respondents need to select an alternative from a given choice set that will provide a similar purchasing decision process to the actual one. A choice set may include a number of competing alternatives with “no choice alternative” (Chen *et al*., 2013).

RP choice modeling only includes actual choice data to examine similar products in the market. Nevertheless, RP choice models may cause biased estimation of consumer preferences because they never account for changes in the purchasing behavior of consumers and the market conditions. On the other hand, the choice set in SP choice models may not involve all alternatives or attributes. Another issue with the SP choice models is that they do not provide a realistic purchasing decision process, because the customers only make choices but do not need to pay for the decision of purchasing intent. Therefore, customers may buy different products rather than the ones they chose in the survey (Wassenaar *et al*., 2006).

Choice models can also be classified as either deterministic or probabilistic according to the modeling approach. Deterministic choice models consider that customers only choose the best alternative, which provides the highest expected utility, whereas probabilistic choice models include a random utility part together with a deterministic part. Specifically, customers may choose (purchase) a product that has a lower utility than the highest-utility one. Given that the choice of an agent (*e.g.*, a firm or a customer), apart from observed factors, is also influenced by unobserved factors, which are defined as random entities, such choice entails the inclusion of the probabilistic approach in choice models (Train, 2009).

2.1.2 Discrete choice analysis

Mc Fadden (1974) developed choice modeling theory. He was awarded the 2000 *Nobel Prize in Economic Sciences* for his development of theory and methods for analyzing discrete choice. He specified that aggregate choice usually neglects the discrete alternatives of individuals by treating choice as a continuous variable. Furthermore, only systematic variations (random errors) in aggregate choice drive individuals to make common variations in their preferences (Louviere *et al*., 2000).

DCA is a disaggregate approach to choice modeling that is based on probabilistic distribution theory, which seeks the utility fraction of a given product among a set of competitive products. DCA aims to maximize the total utility of individual consumers who respond to experiments/surveys by capturing the tradeoffs among product attributes. It uses preference data to estimate the choice probabilities of competing alternatives for individual consumers. These individual estimations are then aggregated to predict the total choice share. Various DCA models, such as multinomial logit (MNL) (Chen *et al.*, 2013), nested logit (NL) (Kumar *et al.*, 2009), and mixed logit (MXL) (Hoyle *et al.*, 2010; He *et al.*, 2011), have been applied in choice modeling. The MNL model is a highly popular choice model adopted in previous studies on decision-based design (Wassenaar and Chen, 2003).

Louviere and Hensher (1983) integrated conjoint analysis with a discrete choice econometric model to develop a multi-attribute utility function model based on the MNL model for demand estimation of an event. Michalek *et al*. (2005) adopted conjoint data within DCA to estimate the demand for a single product design. Draganska and Jain (2006) utilized an NL model to capture heterogeneous consumer behavior among different segments and gain better substitution patterns. Kumar *et al.* (2009) developed an NL demand model instead of an MNL model to determine the competition impact on different market segments within a product family design. Hoyle *et al*. (2010) developed a Bayesian hierarchical-based choice model to integrate quantitative and qualitative product attributes in engineering design, in which heterogeneous consumer preferences were captured in demand modeling. He *et al.* (2011) combined customer satisfaction indices to upgrade the MXL model in terms of qualitative (subjective) customer attributes in order to predict the choice share of individual market segments. He *et al.* (2012) introduced usage context-based design into choice modeling to examine how product performance and consumer preferences may change with respect to using conditions and the purposes of the product. This approach did not accept the term “constant performance level” of a product for each individual because of differentiated consumer demographics and behavior. Both SP and RP data were used to analyze usage context in choice modeling to link product performances with usage context and customer profile.

2.2 Product line design

PLD is about determining the number of product variants and their design specifications to satisfy the needs of different market segments, with the objective of maximizing profit and/or market share of the product line (Krishnan and Ulrich, 2001; Kuzmanovic and Martic, 2012). It involves a family of products considering marketing, design and manufacturing factors (Gupta and Krishnan, 1999). PLD is an essential decision-making process with reduced product life cycles because of the increased level of customer satisfaction, tough market competition among firms and rapid technological changes (Raman and Chhajed, 1995). Integrating marketing and engineering approaches to obtain optimal solutions for PLD is necessary because PLD usually considers consumer preferences together with engineering issues (Luo, 2011).

2.2.1 Integrated marketing and engineering approach to PLD

In the last few years, marketing research has been integrated with product development to consider the increasingly diversified needs of various customer groups in product design (Train, 2009). The transition from single product design to PLD requires examining various marketing variables to prevent cannibalization of a firm’s existing products while gaining potential customers from competitors (Kaul and Rao, 1995). Moorthy (1984) developed a market segmentation method for optimal PLD based on consumer self-selection and competition between heterogeneous markets. Jiao *et al.* (2007) reviewed literature related to the marketing approach to PLD with consideration of customer utility, production cost, market share, profit, pricing, and product positioning.

Michalek *et al.* (2005) developed an analytical target cascading model to solve marketing planning and engineering design problems concurrently for a single product design in a homogeneous market, where conjoint analysis and DCA are used in demand modeling. Michalek *et al.* (2006) extended their methodology to solve a PLD problem with a pre-determined number of products. The study was later extended to solve market positioning and engineering design problems for an optimal PLD while satisfying the needs of heterogeneous markets (Michalek *et al.*, 2011).

Draganska and Jain (2006) examined vertical and horizontal product line pricing strategies for manufacturers and retailers considering customer preferences, while Kannan *et al.* (2009) focused on optimal pricing for digital content product forms in a product line. Kumar *et al.* (2009) introduced a product line positioning decision paradigm into product family design to determine the optimal number of products and their targeted market segments, in which marketing issues, such as heterogeneous consumer preferences and competition among different segments, were considered in the demand modeling. Luo (2011) proposed a methodology for simultaneous consideration of marketing and engineering issues in PLD, in which heterogeneous consumer preferences are modeled in a competitive market while satisfying engineering feasibility and robustness criteria for maximizing the profit of

PLD. In the study, both discrete and continuous decision variables were considered in a large design space. Lin and Okudan (2013) applied dynamic variable state models to forecast the sales and determine the time of introduction of multiple-generation product lines.

2.2.2 Optimization of PLD

Green and Krieger (1985) developed three greedy heuristic optimization models to maximize the utilities of the individual buyer (employee) and the seller. Dobson and Kalish (1988) proposed a heuristic solution procedure as an extension of Green and Krieger (1985)'s model to determine the optimal pricing and positioning of a product line with the assumptions of no-competition effect and homogenous customer behavior in the market. Dobson and Kalish (1993) further improved the heuristic solution procedure to address the competition among products. Kohli and Sukumar (1990) developed a dynamic programming-based heuristic algorithm to determine the optimal PLD for maximizing share-of-choice, buyer utility, and seller's return utility. Nair *et al.* (1995) proposed a beam search-based heuristic solution method to determine near-optimal solutions of PLD in less computational time. Shi *et al.* (2001) proposed a nested partitions-based optimization method for both single product design and PLD problems where the proposed method was proved to perform better than the beam search-based optimization method. Raman and Chhajed (1995) proposed an integrated decision support algorithm to determine optimal PLD solutions for maximizing a manufacturer's profit. All the above studies involved only a single objective function in their optimization problems.

Li and Azarm (2002) developed a PLD selection model using a multi-objective optimization approach to maximize the net present value of profit and market share under three design objectives. Customer preferences, uncertainties in marketing mix variables, and competitive market conditions were incorporated in their model. Kwong *et al.* (2011) developed a multi-objective optimization model for PLD problems to maximize total market share, as well as to minimize total product development cost and total product development life cycle. In their study, both discrete and continuous decision variables (product attributes) were considered.

Balakrishnan *et al.* (2004) proposed an integrated beam search-based hybrid genetic algorithm (GA) for PLD optimization. Alexouda (2004) used conjoint analysis to estimate the part-worth utility of a product line and associate product design attributes with consumer buying preferences, in which an evolutionary algorithm was adopted to solve market share problems for PLD. Alexouda (2005) later proposed a marketing decision support system to determine the optimal PLD for maximizing market share using evolutionary algorithms. Thevenot *et al.* (2007) incorporated multiattribute utility theory into PLD optimization by considering the criteria of product line commonality index, total profit over five years, and market coverage. Belloni *et al.* (2008) analyzed nine optimization methods for PLD problems, in which some heuristic methods were found to provide better optimum solutions. Wang *et al.* (2009) proposed a branch-and-price optimization algorithm to solve market share problems for PLD. Lin *et al.* (2010) used GAs to determine the optimal PLD for maximizing market share, in which conjoint analysis was used to capture consumer preferences for green technologies and estimate the part-worth utilities of product attributes. Lin *et al.* (2011) extended the aforementioned study with a fuzzy PLD model that considers ambiguity in consumer preferences.

Tsafarakis *et al.* (2011) developed a particle swarm-based optimization algorithm to solve PLD problems for maximizing the market share, in which Nash equilibrium was adopted to examine competitor responses to the entry of new products. Additionally, Kuzmanovic and Martic (2012) used the Nash equilibrium to model PLD problems by considering the retaliatory responses of competitors. In their study, homogeneous consumer preferences were obtained using conjoint analysis to maximize PLD profit. Luo *et al.* (2012) developed a conjoint-based one-step optimization model for product line positioning, and an interval-analysis-embedded tabu search was adopted to solve the model. Kumar and Chatterjee (2013) developed an integer programming model to solve a profit maximizing PLD problem together with proper pricing using a greedy heuristic with consideration of costs assigned to each level of product attribute.

2.3 Consideration of uncertainty in NPD

Quite a number of uncertainties can significantly affect NPD performance, such as the subjective responses of respondents in market surveys, changes in consumer preferences and market conditions, and rapid technological development. These uncertainties can affect the results of choice modeling, and demand modeling for NPD. Therefore, this section reviews previous studies of dealing with the uncertainties for NPD that involve choice modeling.

Turksen and Willson (1994) introduced a fuzzy preference model to address the ambiguity in consumer demand modeling. Instead of part-worth and hybrid models, a vector model of attribute preferences, which represented a numeric value on a certain scale, was adopted in conjoint analysis. In their study, a fuzzy set was introduced to define subject ratings as linguistic ratings rather than numerical ratings. Results of the study showed that their proposed fuzzy conjoint model outperformed the crisp conjoint model in market share prediction. Given the uncertainty of consumer preferences, Lau *et al.* (1997) extended the MNL model using switching regression techniques to minimize the sum of the absolute error in market share models. Tseng and Chiu (2005) claimed that a single MNL model does not consider the correlation among product attributes. Thus, they proposed a hierarchical fuzzy integral stated preference (HFISP) method to determine the correlation among attributes that involve the Choquet integral and estimate the utility of an event under risk and uncertainty. The predictive accuracy of the HFISP method and partitioned fuzzy integral MNL was found to be better than that of a single MNL method. Luo *et al.* (2005) proposed a robust optimization process to consider the uncertainties in design parameters and estimates of preferences. Besharati *et al.* (2006) considered uncertainty in predicting design attribute levels under different usage conditions and situations. Williams *et al.* (2010) considered uncertainty in engineering design, competing product attributes, and customer preferences under an interval uncertainty. Lin *et al.* (2011) proposed the use of fuzzy part-worth utilities in conjoint analysis under crisp and fuzzy scenarios to determine the settings of an optimal product line extension scheme, and estimate the market share with consideration of the uncertainty of consumer preferences caused by new technology entries. In their study, respondents were asked to define an interval value for their preferences according to the fuzzy triangular numbers used for ranking instead of an exact choice value (score) for each attribute. The results of their study indicated that the estimated market share is lower in fuzzy scenarios than the one in crisp scenarios because of the uncertainty of consumer preference. Hoyle *et al.* (2010) proposed integrated MXL and random-effects ordered logit models to capture both systematic and random consumer heterogeneities in error mitigation with respect to combined multiple data sources by using the Bayesian hierarchical method. Resende *et al.* (2011) applied a delta method to consider the uncertainty of parameter estimation of choice models in determining the optimal setting of product design attributes. In their study, demand uncertainty was handled by a continuous probability distribution regarding the downside firm risk tolerance level of an α-profit metric. The relationship between expected profit and downside risk (α-profit level) was determined using an MNL model.

Demand uncertainty is caused by various factors, such as preference dynamics, demand model misspecification, choice context, and response variability. Xiong *et al.* (2010) integrated fuzzy set theory into demand modeling to study the uncertainty in consumer demand and solve a dynamic pricing problem. Razu and Takai (2011) attempted to model the uncertainty in market demand, where customer utility errors were estimated by adopting bootstrap and Monte Carlo simulation in choice-based conjoint analysis. Lemos *et al.* (2012) introduced an evolving fuzzy linear regression tree method to manage the risks and uncertainties associated with the sales forecasting of petroleum products. Lin *et al.* (2011) studied the uncertainty of consumer preferences caused by unfamiliarity with new technology, which can lead to the fuzziness of market potential estimation.

2.4 Consideration of remanufactured products in the product design stage

Recovering EoL and EoU products after customer use is a promising solution for manufacturers to respond to the challenges of increasing global awareness on environmental protection and enforcement of environmental regulations (Kumar and Putnam, 2008; Bernard, 2011). Various recovery strategies, such as remanufacturing, recycling, reuse, and/or refurbishment, have been incorporated in product design and/or business operations.

One strategy involves the remanufacturing of EoL and returned EoU products. Remanufacturing aims to restore the functional and aesthetic values of these products to their original condition and even to better features. Remanufactured products can be produced from EoL and returned EoU products. Products that are faulty, damaged during shipment, or returned within a few months because of customer dissatisfaction can also be utilized through remanufacturing (Vorasayan and Ryan, 2006). Ramani *et al.* (2010) reviewed more than 200 papers on sustainable product design and highlighted the importance of integrating product design and recovery in product portfolio design.

In previous studies, remanufactured products were considered in various aspects, such as product design, market positioning, product returns, pricing, and cannibalization on the sales of new products. Atasu *et al.* (2008) investigated profitable remanufacturing strategies with consideration of various factors, such as competition, cost savings, size of green segment, cannibalization, price discrimination, and market growth rate. They found that high cost savings, large size of the green segment, slow market growth rate, and stringent competition can enhance remanufacturing profitability. Ostlin *et al.* (2009) examined different life-cycle dynamics for product and component remanufacturing, as well as the cannibalization of remanufactured components on new components. They found that the demand for remanufactured products is dependent on the demand for new products, because potential remanufacturing volumes are constituted by the returns of previously sold new products. Atasu *et al.* (2010) examined the cannibalization of remanufactured products on the sales of the new products of an original equipment manufacturer (OEM). They stated that understanding customer preferences on remanufactured products and proper pricing, as well as analyzing the return rate of original products are important factors for a profitable remanufacturing strategy.

Quite a few studies have considered various recovery strategies and remanufactured products in the product design stage. Kerr and Ryan (2001) examined a way to reduce the environmental impact of a product over its life cycle through proper remanufacturing processes. Mangun and Thurston (2002) incorporated reuse, remanufacturing, and recycling into a product portfolio design to maximize the total portfolio utility while considering the trade-off among cost, reliability, and environmental impact of products. Debo *et al.* (2005) addressed the simultaneous pricing of new and remanufactured products and the selection of appropriate investment in reusability. Debo *et al.* (2006) later investigated the diffusion of new and remanufactured products in a market on the basis of a modified Bass diffusion model with consideration of repeat purchase and diffusion rates. However, product design attributes were not considered in their study. Vorasayan and Ryan (2006) developed a queuing network model to determine the optimum quantity and price of remanufactured products by maximizing the total profit. The demand functions were formulated based on the prices and quality of the remanufactured products. However, the design attribute settings of new and remanufactured products were not considered in the model and the competition between new and remanufactured products was considered in a monopolistic market only. Ferrer and Swaminathan (2010) examined and compared the optimal policies for remanufacturing and pricing new and differentiated remanufactured products and product returns in a monopolistic market. They found that the demand for remanufactured products in a monopolistic environment mainly depends on the cost savings from remanufacturing in multi-period planning horizons.

Hatcher *et al.* (2011) reviewed the literature and defined future research needs in design for remanufacture in which EoL and life-cycle considerations were stated as essential issues in product design. Galbreth *et al.* (2012) studied how the optimal amount of product reuse (remanufacturing and/or upgrading) relates to the rate of innovation. Kwak and Kim (2011) developed a mixed-integer programming model to evaluate the profitability of a product family design for selling reused products with respect to an EoL recovery approach. However, the cannibalization between new and refurbished products and the upgrading of features of refurbished products were not considered in their study. Kwak and Kim (2013) later established a market positioning model for remanufactured products to determine the optimal settings and price of a remanufactured product with consideration of product take-back and upgrading product features. However, cannibalization and competitive market conditions were not considered in their study. Kwak and Kim (2015) extended their previous work by developing a decision-support model to determine the optimal design of new and remanufactured products simultaneously and the number of returned products in which the trade-off between total profit and environmental-impact saving was examined.

Some previous studies were conducted to investigate the competition between new products and remanufactured products (Vorasayan and Ryan, 2006; Atasu *et al.*, 2008; Ostlin *et al*., 2009; Guide and Li, 2010). Vorasayan and Ryan (2006) investigated the competition between new and remanufactured products in a competitive market. Guide and Li (2010) examined the cannibalization between new and remanufactured products using an empirical approach. Later on, Wu (2012b) developed a two-period game theoretical model with respect to product design and pricing decisions of new and remanufactured products. Chen and Chang (2013) then examined a dynamic pricing strategy for new and remanufactured products in a multi-period scenario considering price-dependent market demand.

Several studies investigated the cannibalization of remanufactured products on the sales of an OEM's new products because of price advantage (Debo *et al.*, 2006; Guide and Wassenhove, 2009; Ostlin *et al.*, 2009). Even if OEM does not undertake remanufacturing, some independent remanufacturers may carry out the remanufacturing of an OEM's products, an approach that would then affect the sales of the OEM's new products (Ostlin *et al.*, 2009; Atasu *et al.*, 2010). However, the cannibalization of the OEM's products caused by remanufacturing is usually stated in the conditions of a monopolistic market in previous studies. Atasu *et al.* (2008) found that remanufacturing can enhance the competitiveness of an OEM as a profitable marketing strategy in a competitive market, because remanufactured products cannibalize the product sales of competitors.

2.5 Integrated product and CLSC design

Various studies on CLSC have focused on the evolution of CLSC (Guide and Wassenhove, 2009), CLSC relationships for product remanufacturing (Ostlin *et al.*, 2008), CLSC network design and coordination of supply chain parties (Souza, 2013), and integrated sustainable product and supply chain design (Metta and Badurdeen, 2013). Guide and Wassenhove (2009) analyzed the evolution of CLSC research and pointed out that, at the beginning of the 1990s, research on remanufacturing mainly focused on reducing cost and/or increasing profit in operations. Optimization and operational research in reverse logistics became popular in the early 2000s. The coordination of reverse supply chain parties and business-driven CLSC have been conducted considering various marketing variables in the past few years. Reviews on sustainable supply chain management were conducted with respect to marketing, management, design, and modeling issues (Gupta and Palsule-Desai, 2011), and to quantitative modeling approaches in terms of economic, environmental, and/or social perspectives (Seuring, 2013).

Demirel and Gokcen (2008) proposed a mixed-integer programming model to determine the optimal reverse logistics network design for minimizing the total cost for product recovery operations. Wang *et al.* (2011a) developed a multi-objective optimization model to investigate the trade-off between environmental impact (i.e., CO_2 emissions) and total cost in a supply chain network design. Pishvaee *et al.* (2011) proposed a robust mixed-integer linear programming model to solve CLSC network design problems with consideration of uncertainty issues associated with product returns, demand for remanufactured products, and transportation costs. Shi *et al.* (2011a) established a CLSC model with a single manufacturer to determine the amount of new and remanufactured products, their selling prices, and the procurement price of used products at which remanufactured and new products are sold in the same market at the same price. Metta and Badurdeen (2013) studied the significance of integrating sustainable product and supply chain design with modeling issues for firm profitability. Huang (2013) developed an integrated product portfolio and a CLSC design model to determine configuration, remanufacturing investment decisions, and prices of products, as well as to select suppliers. In their study, Stackelberg game theory was adopted to model the coordination of multiple suppliers, a single manufacturer, and multiple retailers.

2.5.1 Coordination and competition in CLSC

CLSC activities are usually outsourced to third-party companies (Cheng and Lee, 2010), or conducted by the original manufacturer (Debo *et al.*, 2006). Savaskan *et al.* (2004), De Giovanni and Zaccour (2014) and Chuang *et al.* (2014) examined CLSC models with consideration of environmental and operational performances, in which product collection is undertaken by manufacturers, retailers, or third-party firms. Retailer collecting-based CLSC results in more demand and profits compared with the manufacturer and third-party collecting-based CLSCs because retailers are closer to customers (Savaskan *et al.*, 2004).

Some studies have investigated the competition and coordination between OEM and supply chain partners in a CLSC design. Huang *et al.* (2007) established a game theoretical model to determine the configurations of a product line and supply chain that involves a single manufacturer and multiple suppliers. Esmaeili *et al.* (2009) analyzed the competition and cooperation between an OEM and a retailer through cooperative and non-cooperative Stackelberg game models. Huang and Huang (2010) conducted a pricing analysis on a single product in a three-level supply chain model using a game theoretical approach with different power structures. Sadeghi and Zandieh (2011) formulated a game model to determine optimal product portfolio solutions considering the competition between two manufacturers. Bernard (2011) proposed a Nash equilibrium-based coordination model which involves two identical manufacturers and one remanufacturer. In his study, manufacturers need to determine the remanufacturability level of the original products under environmental regulations and/or collusion.

Wu (2012a) investigated the price and service competition in a CLSC of a manufacturer, remanufacturer, and common retailer. Wu (2012b) later established game models to examine the competition between an OEM and a remanufacturer. The price competition between an OEM and a remanufacturer was further examined by Wu (2013), in which the OEM aimed to determine the interchangeability of its new products in the design stage to maintain its competitiveness and increase the cannibalization cost of the remanufacturer. Yalabik *et al.* (2014) developed a model to compare the profitability of traditional and green companies, where the green company produces remanufacturable products for lease markets and also launches them in a secondary market.

Swami and Shah (2013) studied channel coordination between a single manufacturer and a single retailer in a sustainable supply chain, wherein the two parties aim to find optimal greening efforts in their operations to maximize their profits. Huang (2013) established a Stackelberg game model with multiple suppliers, a single manufacturer, and multiple retailers for an integrated product portfolio and

CLSC design. Qiang *et al.* (2013) investigated the competition, coordination, and uncertainties of a CLSC involving two suppliers, two manufacturers, and two retailers, in which both new and remanufactured products are launched in the same period. Ji *et al.* (2013) proposed a Stackelberg-based joint optimization model for green modular design with material reuse. Shi *et al.* (2011b) investigated optimal design and production planning of a CLSC that involved multi-products under uncertain demand and return. A similar study was conducted by Zeballos *et al.* (2014) though a multi-period scenario was considered under uncertain supply and demand.

Game theoretical models have been employed in the competition and coordination of supply chain members and in product design. Choi and Desarbo (1993) employed Nash equilibrium in conjoint analysis to model competitive reactions in an optimal product design. Luo *et al.* (2007) developed a conjoint-based game model for new product positioning and pricing in the light of the channel acceptance of the retailer. Steiner (2010) later proposed a Stackelberg-Nash game model based on conjoint data to examine the retaliatory reactions of competitors for new product design.

2.6 Managing product returns for remanufacturing

Managing product returns was treated to be essential for production planning and control for remanufacturing, as well as inventory control management of product returns (Guide and Wassenhove, 2001; Srivastava and Srivastava, 2006; Shaharudin *et al.*, 2015). Akcali and Cetinkaya (2011) conducted a review of product return models for inventory and production planning in CLSC regarding deterministic or stochastic demand. Shaharudin *et al.* (2015) conducted an empirical study to investigate the management of product returns in terms of manufacturing, distribution, and customer returns.

Leasing new products and trade-in programs are two common methods of collecting used products from customers (Aras *et al.*, 2004; Denizel *et al.*, 2010). The quantity of returns in product leasing systems can be significantly predicted. Balancing product returns with demand is noted as an important factor in managing production planning and control, as well as in inventory management for remanufacturing (Guide, 2000). Denizel *et al.* (2010) stated that the quantity of returns through a trade-in program can be correlated with the sales forecast of new products.

Quite a few previous studies forecasted the quantity and timing of product returns with consideration of the dependence of product returns on sales. Goh and Varaprasad (1986) used the Box-Jenkins transfer function model to forecast returns. However, this model requires past sales and return data to estimate the return probabilities in each period. Later on, Kelle and Silver (1989) developed a model to forecast the returns of containers. The model required less parameter estimation than that proposed by Goh and Varaprasad (1986). Toktay *et al.* (2000) established a queuing network model for the inventory management of returned and remanufactured products, in which perfect substitution between the new and remanufactured products was considered. A geometrically distributed lag model (DLM), which is a function of sales in previous periods, was used to forecast product returns. Bayesian estimation was utilized to estimate the model parameters by using sales and return data. Clottey *et al.* (2012) proposed an exponential DLM for product returns in continuous time. Sales of new products and demands for remanufactured products were modeled based on the Poisson distribution. Krapp *et al.* (2013a) proposed a Bayesian-based forecasting approach by simplifying the assumptions used in Toktay *et al.* (2000) to estimate the number of returned products. Krapp *et al.* (2013b) extended their methodology by incorporating the Kalman filter to enhance forecasting accuracy and economic value added, as well as provide discussions on forecasting decisions from an accounting approach. However, the quality of the returned products was not considered in the aforementioned studies.

Several studies have considered the quality of product returns. Guide and Wassenhove (2001) studied the importance of managing the quality and quantity of product returns to the profitability of the remanufactured products. A few studies indicated that an improved quality of returns would lead to higher profitability of the remanufactured products because of cost savings in the recovery process (Aras *et al.*, 2004; Ferguson *et al.*, 2009; Denizel *et al.*, 2010). Aras *et al.* (2004) investigated the effects of classifying returned products as low- and high-quality returns on cost savings in hybrid systems (i.e., both manufacturing and remanufacturing). Returns with higher quality were considered to have less remanufacturing cost than the ones with lower quality; however, the acquisition cost was not considered in the aforementioned study. Srivastava and Srivastava (2006) developed a system dynamics model to estimate product returns with consideration of product grading in reverse logistics network design. Zikopoulos and Tagaras (2007) proposed a profit-maximization model to investigate the profitability of a single-period reverse supply chain network regarding uncertainty in the quality of product returns, in which optimal procurement and production quantities could be determined. Zeballos *et al.* (2012) extended the aforementioned model to examine uncertainty in the quality and quantity of returns with simultaneous consideration of forward and reverse supply chain networks design. The value of grading product returns into different quality levels in a product leasing system, where both demand and number of returns are deterministic, was examined by Ferguson *et al.* (2009). They found that an average of 4% profit increase could be achieved through a grading system (up to five levels) depending on the quantity of available returns and demand for remanufactured products. Denizel *et al.* (2010) extended the study of Ferguson *et al.* (2009) with a stochastic programming model to determine the quantity and quality of the return cores for a multiperiod remanufacturing planning under uncertain quality of returns. Galbreth and Blackburn (2010) examined the optimal acquisition quantities for both uniformly distributed continuous and discrete quality conditions. Binomial distribution was used to determine the fraction of two quality categories in the discrete condition model because such distribution is validated to represent the uncertainty of the two items. Guide *et al.* (2003) proposed a profit-maximization model to determine the quantity, quality, and acquisition prices of returns, as well as the price of remanufactured products, in a single period where remanufacturing costs are quality dependent. However, the demand and product return rates in the study of

Guide *et al.* (2003) were assumed to be known and the product returns were independent of sales. Teunter and Flapper (2011) examined the optimal acquisition price of returns with different quality grades and remanufacturing policies for both deterministic and uncertain demands. Both Guide *et al.* (2003) and Teunter and Flapper (2011) assumed the qualities of returns to be independent from one another and then adopted a multinomial distribution to determine the fraction of multiple quality grades of returns. Liang *et al.* (2014) adopted a convolution-based method to forecast the quantity and quality of electrical vehicle battery returns based on sales, product life expectancy, and customer return behavior information. However, these returns were limited to failure-induced and EoL factors. Niknejad and Petrovic (2014) established a fuzzy mixed integer algorithm to optimize the reverse logistics network with consideration of uncertain demand and uncertainty in the quantity and quality levels of returned products. Most of the studies ignored the effect of the quality of returns on the take-back and remanufacturing costs. However, both acquisition price and remanufacturing cost are highly dependent on the quality of returns.

Several previous studies considered the perfect substitution of new and remanufactured products in their hybrid manufacturing/remanufacturing models. Mukhopadhyay and Ma (2009) developed a model to determine the optimal procurement and production quantities for a hybrid system, which considers the uncertainty associated with both quality of returns and demand. El Saadany and Jaber (2010) proposed a hybrid inventory model to determine the product return rate, which considers acquisition price and quality of returns with constant demand. Wang *et al.* (2011b) established a model to determine an optimal policy on the remanufacture of returned products in a hybrid system. Remanufactured products can be differentiated from manufactured ones through upgrading or positioning in competitive markets; thus, perfect substitution may not be suitable, particularly for consumer products where demand is highly dependent on customer utilities.

2.7 Discussion

This chapter presents a discussion on previous studies related to market uncertainty issues in NPD, PLD with consideration of remanufactured products, coordination of the CLSC, and managing product returns for remanufacturing.

Market demand estimation plays an important role in assessing the financial feasibility of NPD projects. Numerous studies have been conducted to consider the market uncertainties in NPD. Uncertainties, such as subjective responses in survey data, dynamic market conditions, and rapid technological development, can significantly affect the prediction accuracy of developed market demand models. Therefore, uncertainties should be considered in the development of market demand models to improve the estimation accuracy of market demand. The development of models for market demand estimation based on DCA commonly involves market potential estimation and choice modeling. Consumer survey data, which are used to develop choice models, contain a high degree of fuzziness because customer responses are always subjective and imprecise. Although fuzziness in market share estimation was considered in previous studies, no study addressed the fuzziness of survey data that were used to develop market demand models. The fuzziness of market potential estimation because of the subjective judgments of experts was also not properly addressed in previous studies. Ignorance of the fuzziness would lead to the over- or under-estimation of market demands.

Remanufactured products are normally reprocessed from returned new products and quite often launched in markets where the new products exist. Given that remanufactured products could cannibalize the sales of new products because of price advantages (Debo *et al.*, 2006), they should be considered together with new products in PLD to obtain the maximum profit and market share of the product line. Although some previous studies attempted to consider remanufactured products in the product design stage, the simultaneous consideration of new and remanufactured products in product line/family design has not been considered. In addition, the following research issues were not considered nor well addressed in previous studies: (1) consumer preferences on remanufactured products and the competition between remanufactured and new products in markets, (2) demand estimation of remanufactured products in markets, (3) downgrading and upgrading the features of remanufactured products, and (4) the time of launching remanufactured products in markets.

Quite a number of previous studies were conducted to investigate the coordination of manufacturers and various supply chain parties in product development and CLSC. However, two issues were not addressed in these studies while considering remanufactured products in PLD: (1) the coordination of supply chain partners in performing PLD with consideration of remanufactured products in competitive markets, and (2) the joint effect of new and remanufactured product design and their pricing on the estimation of market demands. Moreover, no published literature has been found thus far regarding product design with consideration of CLSC and product life-cycle dynamics.

Considerable uncertainties have been discovered in the quantity, timing and quality of returned products (Wang *et al*., 2011b; Souza, 2013) that could lead to high inventory and recovery costs, loss of profits for the remanufactured products and poor remanufacturing performance. However, determining the optimal quantity and quality of product returns under uncertain quality and multi-period of returns has not been properly addressed in previous studies. When the available number of returns is more than the demand for remanufactured products, companies need to determine the optimal quantity and timing with consideration of the supply of product returns, demand for remanufactured products, and take-back and inventory costs. Variations and uncertainty in the quality of product returns would also affect remanufacturing cost. Most of the previous studies modeled product returns and demand for remanufactured and new products separately based on stochastic distribution theory. However, the demand for remanufactured and new products may not follow a random distribution model. The following research issues were also not addressed in the determination of optimal product returns in previous studies: (1) the effect of quality of returns on the take-back and remanufacturing costs, and (2) the inventory cost of remanufactured products.

Chapter 3 Methodology

In this research, a methodology for PLD with consideration of remanufactured products based on an integrated marketing and engineering approach is proposed to determine optimal product line solutions that contain both new and remanufactured products. In the proposed methodology, optimal product line solutions for simultaneous consideration of new and remanufactured products can be obtained under centralized and decentralized supply chain networks. In the centralized case, the manufacturer undertakes collection and remanufacturing of used products, and determination of the product return rate as well as the costs associated with the remanufacture of used products. In the decentralized case, some remanufacturers collect used products from retailers, remanufacture the used products, and set the prices of remanufactured products. The remanufactured products are then delivered to the manufacturer.

The determination of the optimal product returns for remanufacturing is also addressed in the proposed methodology. The proposed methodology mainly involves the conduct of conjoint surveys, generation of fuzzy market demand models, generation of dynamic demand models for simultaneous consideration of new and remanufactured products in PLD, coordination of the CLSC for the PLD, and determination of optimal product returns for remanufacturing. Figure 3.1 shows a flowchart of the proposed methodology. Details of the proposed methodology are described in the following sub-sections.

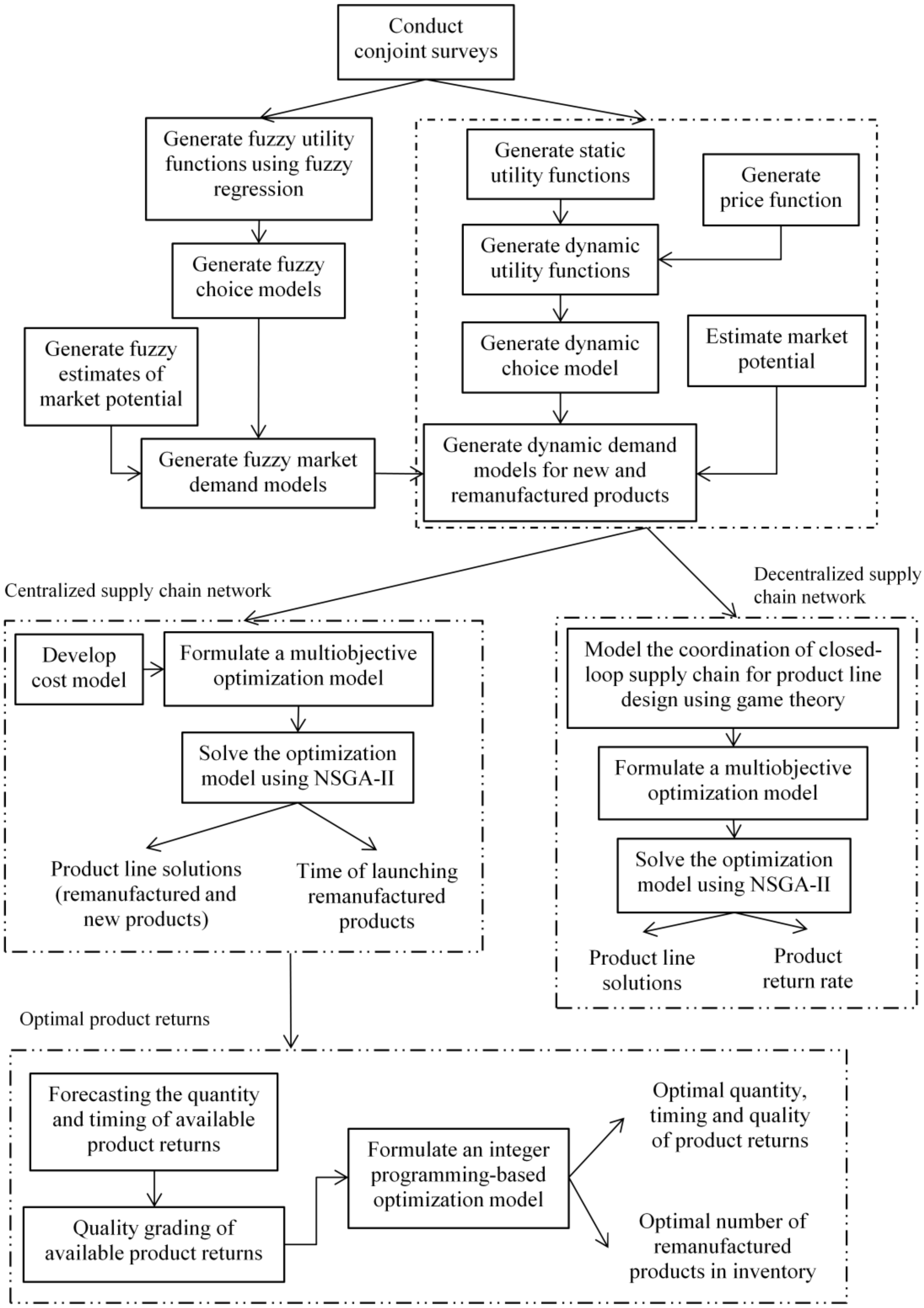


Figure 3.1 Proposed methodology

3.1 Conjoint survey design

Conjoint analysis is conducted to capture customer preferences on products by estimating consumer part-worth utilities for each level of product attribute (Chen *et al.*, 2013). There are three common types of conjoint survey designs which are rating- (Kazemzadeh *et al.*, 2009; Lin *et al.*, 2010), ranking- (Lin *et al.*, 2011), and choice-based (Razu and Takai, 2011). Rating-based conjoint survey is adopted in this research because it is more suitable to extract utility differences among alternatives compared with ranking-based ones (Louviere *et al.*, 2010). The rating-based conjoint survey was widely used in previous studies and required a set of product profiles with respect to pre-defined attributes and attribute levels (Kazemzadeh *et al.*, 2009). To reduce the time for conducting a survey, rating-based conjoint surveys are commonly designed based on orthogonal arrays (Louviere *et al.*, 2000). Consumers are asked to rate various product profiles for conjoint analysis. The survey data are analyzed to generate the following utility functions:

$$U_{ij} = \sum_{k=1}^{M} \sum_{l=1}^{N_k} u_{ikl} x_{jkl} \tag{3.1}$$

where U_{ij} represents the utility of the *j*-th product profile in the *i*-th segment; u_{ikl} is the part-worth utility of the *l*-th level of the *k*-th attribute in the *i*-th segment; *M* and N_k represent the number of attributes and number of attribute levels in the k-th attribute, respectively; and x_{jkl} denotes a dummy variable equal to 1 if the l-th level of the k-th attribute is selected for the product profile j and 0 otherwise. Hence, the total number of dummy variables is $(\sum_{k=1}^{K} N_k) - M$.

3.2 Generation of fuzzy market demand models

The development of market demand models involves choice modeling and market potential estimation. Previous studies commonly used conjoint analysis to develop utility functions, which were then used to generate market share models based on discrete choice models (Kwong *et al.*, 2011; Kuzmanovic and Martic, 2012). However, in previous studies, the fuzziness of conjoint survey data because of subjective judgment of respondents was not addressed. On the other hand, the jury of executive opinion method is commonly used in industries to estimate market potential wherein a number of experts and/or consultants are always involved. The estimation inevitably involves fuzziness because of the subjective judgment of the experts/consultants. To address the fuzziness associated with market potential estimation and survey data used in the development of market demand models, a novel approach of developing fuzzy market demand models for NPD is proposed in this research. The proposed approach allows estimation of market demand for the worst, normal, and best scenarios. It involves fuzzy choice modeling based on fuzzy regression and DCA and fuzzy estimate generation of market potential. Details of the proposed approach to the development of fuzzy market demand models and its application are presented in Chapter 4.

3.3 Generation of dynamic market demand models and formulation of a multi-objective optimization model for optimal PLD in a centralized supply chain network

In the centralized supply chain network, the generation of dynamic market demand models and formulation of multi-objective optimization models are utilized to consider new and remanufactured products simultaneously in a PLD. Dynamic market demand models are developed based on dynamic choice models, the Bass diffusion model, and market potential estimates. Dynamic choice models are generated based on developed dynamic utility functions and the MNL model of DCA. The developed dynamic demand models and cost models are used to formulate a multi-objective optimization model, which determines the optimal PLD for maximizing the total market share and profit of the product line. The model is solved using a non-dominated sorting genetic algorithm II (NSGA-II) to obtain the Pareto optimal solutions of PLD that include the number and specifications of both remanufactured and new products, and the time of launching remanufactured products. Details of the proposed methodology for simultaneous consideration of new and remanufactured products in PLD and its application are presented in Chapter 5.

3.4 Formulation of multi-objective optimization models for the coordination of CLSC in performing PLD

In the decentralized supply chain network, multi-objective optimization models are formulated based on Stackelberg game theory to model the coordination of a manufacturer and supply chain parties in performing PLD with consideration of remanufactured products. A two-period Stackelberg game theoretical model is formulated to examine the competition between the OEM and chain retailers in the first period, and the competition between the OEM and remanufacturer in the second period. Multi-objective optimization models are then formulated to determine product line solutions for both new and remanufactured products, pricing decisions of supply chain parties, and product return rate for remanufacturing by maximizing the total market share of the product line and profit of the OEM. The models are solved using NSGA-II to obtain the Pareto optimal solutions of PLD, which include the number and specifications of the new and remanufactured products, wholesale and retail prices of the new products, wholesale and selling prices of the remanufactured products, and product return rate. Details of the proposed methodology for the coordination of the CLSC for PLD and its application are presented in Chapter 6.

3.5 Determination of optimal product returns for remanufacturing

A novel approach is proposed in this research to determine the optimal quantity and quality grades of product returns for remanufacturing under multi-period and uncertain quality of returns. The effects of new product sales and demand for remanufactured products on product returns are modeled using a geometrical DLM.

Quality grading of available product returns is performed using a multinomial distribution. Sales of new products and demands for remanufactured products are estimated based on the developed dynamic market demand models. The cost model for producing remanufactured products mainly consists of take-back, remanufacturing, and inventory costs. An integer programming-based optimization model is formulated to determine optimal quantity and quality grades of product returns and inventory level of the remanufactured products for minimizing the total cost of producing remanufactured products. Post-optimality analyses are conducted to study the effects of the quality and inventory cost of product returns on the total cost of producing remanufactured products. Details of the proposed approach to determining the optimal product returns for remanufacturing and its application are presented in Chapter 7.

Chapter 4 Market Demand Estimation Using Fuzzy Modeling and Discrete Choice Analysis

This chapter first describes a proposed approach for generating fuzzy market demand models for NPD. Then, an application of the proposed approach on generating a fuzzy demand model to estimate the market demand for a new tablet PC is presented. Thereafter, validation of the proposed approach is shown in Section 4.3 Finally, a summary is given in Section 4.4.

4.1 Proposed approach for fuzzy market demand modeling

To address the fuzziness of the survey data, a fuzzy regression method is introduced into DCA to develop choice models. Fuzzy estimates of market potential, which are represented as triangular fuzzy numbers (TFNs), are generated by the jury of executive opinion method. Figure 4.1 shows a flowchart for generating fuzzy market demand models.

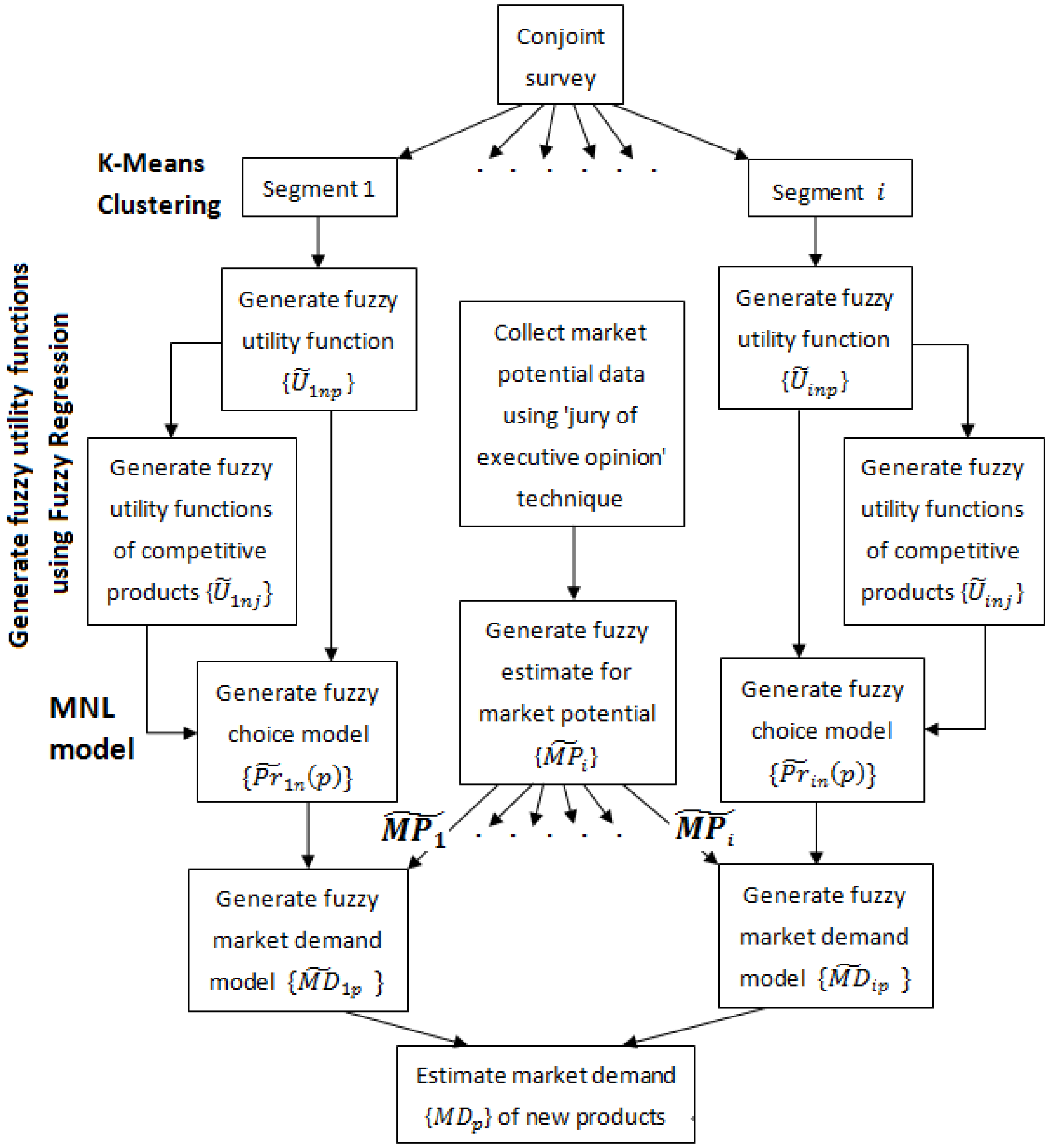


Figure 4.1 Generation of fuzzy market demand models

First, a conjoint survey is conducted to collect customer preferences on products. Survey respondents are classified into a number of individual segments through a K-means clustering technique, which is widely used in clustering. The technique is not only easy to implement, but also provides accurate clustering results

(De la Torre and Kanade, 2009). Thereafter, fuzzy regression is used to generate the fuzzy utility functions of individual segments. Fuzzy choice (or market share) models are developed based on the developed fuzzy utility functions and MNL model of DCA. Once the choice models are developed and the fuzzy estimates are obtained, fuzzy market demand models can be developed. Finally, a defuzzification method is introduced to estimate the market demand for new products.

4.1.1 Determination of the coefficients of fuzzy utility functions by using fuzzy regression

In this research, fuzzy linear regression is used to estimate the coefficients of fuzzy utility functions. The independent variables are the levels of product attributes, whereas the dependent variables are the ratings of respondents on the product profiles obtained from surveys. Dummy variables are introduced to generate the utility functions. To improve the modeling of the preferences of heterogeneous customers, individual rating data are used to generate individual fuzzy utility functions, that is, a unique fuzzy utility function is generated for each customer.

Given that human judgment and predictions are involved in the data set, uncertainty occurs in a system with respect to the relationship between dependent and independent variables. Tanaka *et al.* (1982) developed a fuzzy linear regression model as an extension of statistical linear regression analysis by relaxing the strict assumption of statistical models regarding possibility distributions rather than probabilistic distributions (Peters, 1994). The fundamental difference between statistical regression models and fuzzy regression models is the deviations between the observed and estimated values (Tanaka and Ishibuchi, 1992). In statistical regression, data variation is explained in terms of an estimated variance of measurement errors, whereas fuzzy regression variation hinges on the vagueness or impreciseness of the system structure. Therefore, fuzzy coefficients are determined by these deviations. Fuzzy regression models can be applied to find the relationship between dependent and independent variables, which are denoted by a fuzzy function (Peters, 1994; Tanaka and Ishibuchi, 1992). The parameters are commonly denoted by fuzzy numbers (Kahraman *et al.*, 2006). A fuzzy regression model can be expressed as follows:

$$\tilde{Y} = \tilde{A}_0 + \tilde{A}_1 x_1 + \cdots + \tilde{A}_j x_j + \cdots + \tilde{A}_n x_n, \quad j=1,2,\ldots,n, \tag{4.1}$$

where $\tilde{Y}$ is the estimated fuzzy output, $\tilde{A}_j$ is the fuzzy coefficient of the j-th independent variable, and x_j is the non-fuzzy vector of the *j*-th inputs (independent variable). Fuzzy coefficients are commonly expressed as TFNs, which can be either symmetric or asymmetric (Tanaka, 1987).

The upper and lower intervals of a fuzzy linear regression model are constructed based on outliers, and model generation depends on the interval estimation (Figure 4.2).

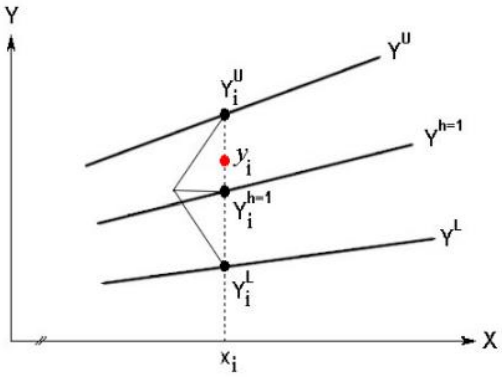


Figure 4.2 Fuzzy regression intervals (Shapiro, 2005)

For symmetrical TFNs $\tilde{A}_j$, the membership functions of $\tilde{A}_j = (\alpha_j, c_j)$ can be expressed as follows:

$$\mu_{\widetilde{A_j}}(a_j) \quad \begin{cases} 1 - \frac{|\alpha_j - a_j|}{c_j}, & \alpha_j - c_j \leq a_j \leq \alpha_j + c_j \\ 0, & \text{otherwise,} \end{cases} \tag{4.2}$$

where α_j is the center value of the fuzzy number, and c_j is the spread value of the fuzzy number. Thereafter, a fuzzy linear regression function can be written as follows:

$$\tilde{Y} = (\alpha_0, c_0) + (\alpha_1, c_1)x_1 + \cdots + (\alpha_j, c_j)x_j + \cdots + (\alpha_n, c_n)x_n. \tag{4.3}$$

Thus, the membership function can be written as follows:

$$\mu_{\tilde{Y}}(y) = \begin{cases} 1 - \frac{|y - x^t\alpha|}{c^t|x|}, & x \neq 0 \\ 1, & x = 0,\ y = 0 \\ 0, & x = 0,\ y \neq 0, \end{cases} \tag{4.4}$$

where $|x| = (|x_1|, \dots, |x_n|)^t$, $x^t\alpha$ is the central value of $\tilde{Y}$, $c^t|x|$ is the spread value, and $\mu_{\tilde{Y}}(y) = 0$ when $c^t|x| \leq |\bar{y} - x^t\alpha|$.

Tanaka *et al*. (1982) determined the objective function as minimizing the total spread of the fuzzy coefficients. The purpose of the following model is to determine the central and spread values of the coefficients with respect to the intervals supported by the *h* value.

$$Min \sum_{j=0}^{N} c_j, \tag{4.5}$$

which is subject to

$$\sum_{j=0}^{N} \alpha_j x_{ij} + (1-h) \sum_{j=0}^{N} c_j |x_{ij}| \geq \bar{y}_i + (1-h)e_i, \tag{4.6}$$

$$\sum_{j=0}^{N} \alpha_j x_{ij} - (1-h) \sum_{j=0}^{N} c_j |x_{ij}| \leq \bar{y}_i - (1-h)e_i, \tag{4.7}$$

$$c_j \geq 0, \qquad x_{i0} = 1, \qquad 0 \leq h \leq 1, \tag{4.8}$$

$$\alpha \in R, \qquad i = 1,2, \dots, M, \qquad j = 0, 1, 2, \dots, N.$$

where $\bar{y}_i$ is the central value and e_i is the spread value of the *i*-th observed fuzzy data; α_j and c_j are the center and spread values of the fuzzy coefficient of the *j*-th independent variables respectively; x_{ij} is the variable for the *j*-th independent variable of the *i*-th experimental data set; *M* is the number of experiment data sets; and *N* is the number of independent variables. Eqs. (4.6) and (4.7) set the upper and lower boundaries of the estimated data, respectively.

The *h* value is used to extend the support of the membership function (confidence interval) (Figure 4.3), which is defined as the degree of fitting of the fuzzy linear model. The increase in *h* value leads to a decrease in spread values of the fuzzy coefficients.

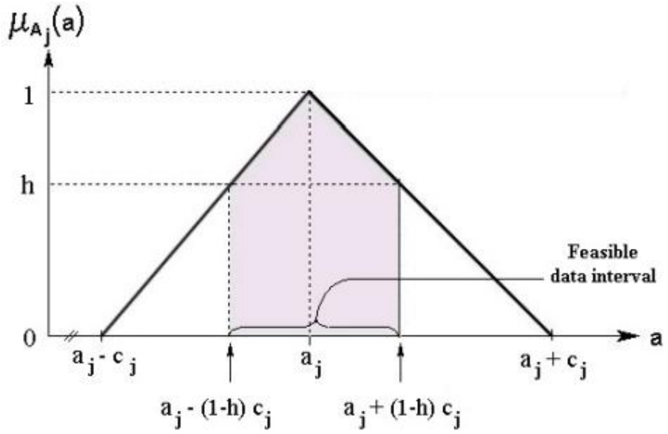


Figure 4.3 Supports of membership function with h value (Shapiro, 2005)

Tanaka *et al.* (1987) revised the objective function of the fuzzy linear regression model as minimizing the total fuzziness of the regression model by minimizing the total support of the fuzzy outputs:

$$Min \quad \sum_{j=0}^{N}\left(c_j \sum_{i=1}^{M} |x_{ij}|\right). \tag{4.9}$$

4.1.2 Fuzzy estimates of market potential

Dalrymple (1987) discussed the different types of sales forecasting methods, such as subjective, extrapolation, and quantitative sales forecasting methods, used by companies in terms of usage intention, effectiveness, and accuracy. The survey results indicate that the jury of executive opinion (subjective), sales force composite (subjective), and naive methods are the most common forecasting methods used in the industry.

The jury of executive opinion, which is also known as "expert judgment," involves a collection of forecasts or estimations from executives, experts, and/or consultants. The estimations are always subjective. The final estimation is determined by using simple average and weighted average methods.

To address the fuzziness of market potential estimation based on the jury of executive opinion method, the fuzzy estimates of market potential, represented as TFNs, are introduced. A fuzzy estimate of the market potential of market segment i, $\widetilde{MP}_i$, can be expressed as (l_i, α_i, r_i), where α_i is the center value of the market potential of the market segment i; and l_i and r_i are the left and right spread values, respectively. l_i and r_i can be determined using Eqs. (4.10) and (4.11), respectively.

$$l_i = \alpha_i - \min_{k=1,\cdots,K} \alpha_{ik}, \tag{4.10}$$

$$r_i = \max_{k=1,\cdots,K} \alpha_{ik} - \alpha_i, \tag{4.11}$$

where α_{ik} is the market potential of segment i estimated by the k-th marketing personnel.

First, data on the market potential estimated by marketing executives and/or consultants are collected. Second, the mean value of the fuzzy estimate of market potential is determined. Finally, the spread values of the fuzzy estimate of market potential can be determined by using Eqs. (4.10) and (4.11).

4.1.3 Development of fuzzy market demand models

Fuzzy market demand models can be developed using the fuzzy estimates of the market potential and fuzzy choice models. This section describes the development of fuzzy choice models based on the developed fuzzy utility functions and MNL model of DCA. The development of fuzzy market demand models is also illustrated.

A utility function contains two parts, namely, a deterministic part U and a random disturbance ε. Eq. (4.12) shows a utility function of a product profile, while

Eq. (4.13) shows the deterministic part of the deterministic part of Eq. (4.12).

$$UT_{inj} = U_{inj} + \varepsilon_{inj}, \tag{4.12}$$

$$U_{inj} = \beta_{in0} + \beta_{in11}x_{j11} + \beta_{in12}x_{j12} + \cdots + \beta_{inkl}x_{jkl}, \tag{4.13}$$

where UT_{inj} represents the total utility of the j-th product profile for respondent *n* in segment i, U_{inj} is the deterministic utility function of the observable independent variables of the *j*-th product profile for respondent *n* in segment *i*, and ε_{inj} is the random error of the *j*-th product profile for respondent *n* in segment *i*. β_{in0} is defined as the alternative-specific constant for respondent *n* in segment *i* to capture the average effect of all unobserved factors in the utility function. β_{inkl} is the utility coefficient of the *l*-th level of the *k*-th attribute for respondent *n* in segment *i*, and x_{jkl} is the dummy variable of the *l*-th level of the *k*-th attribute for product profile *j*. x_{jkl} equals 1 if the *l*-th level of the *k*-th attribute is chosen for the product profile *j*, and 0 otherwise (Train, 2009).

All model coefficients (βs) are assumed identical across all respondents and are linear within the observed (deterministic) part of the utility function. Random error terms ε are combined with the systematic part of the choice models by considering unobserved factors in choice decisions. Random error terms are assumed to be independent and identically distributed (IID) across respondent choices to reduce computation difficulty. Stochastic distribution is assigned to estimate the unmeasured or unobserved behavior of the sampled group according to assumptions made by decision makers (Chen *et al.*, 2013).

The choice probabilities in DCA are constructed independently from irrelevant alternatives (IIA), which imply that the ratio of the probabilities of choosing one alternative over another one is independent of the choice set. IIA brings proportional substitution among alternatives and ignores the correlation among alternatives. Thus, the introduction or exclusion of an alternative will result in an equal percentage decrease or increase in choice probabilities of all other alternatives in the choice set. This property provides a computational advantage in terms of adding or extracting alternatives in a choice set (Train, 2009). The IIA property assumes that error terms are IID for the extreme value type 1 (EV1) distribution, which is also called Gumbel or double-exponential distribution (Louviere *et al.*, 2000). The mean and variance of an EV1 distributed random variable are stated as $Mean = \eta + 0.577\mu$ and Variance $= \frac{\pi^2}{6}\mu^2$, where η is the mode parameter, and $1/\mu$ is the scale parameter. After a series of derivations and integrations of the EV1 distribution regarding error terms, as well as the formulation of the pure closed-form MNL model, the probability estimate of choosing the *p*-th product among the company's existing and competitive products by respondent n in segment i denoted by $Pr_{in}(p)$ can be obtained as follows (Chen *et al.*, 2013):

$$Pr_{in}(p) = \frac{e^{U_{inp}}}{\sum_{j=1}^{J} e^{U_{inj}} + \sum_{k=1}^{K} e^{U_{ink}} + e^{U_{inp}}}, \tag{4.14}$$

where U_{inp} is the utility of the *p*-th product for respondent *n* in segment *i*, U_{ink} is the utility of the *k*-th company's existing product for respondent *n* in segment *i*, and U_{inj} is the utility of the *j*-th competitive product for respondent *n* in segment *i*.

After introducing the developed fuzzy utility functions into the MNL model, a fuzzy choice model can be obtained and expressed as follows:

$$\widetilde{Pr}_{in}(p) = \frac{e^{\widetilde{U}_{inp}}}{\sum_{j=1}^{J} e^{\widetilde{U}_{inj}} + \sum_{k=1}^{K} e^{\widetilde{U}_{ink}} + e^{\widetilde{U}_{inp}}}, \tag{4.15}$$

where $\widetilde{Pr}_{in}(p)$ is the fuzzy probability of choosing the *p*-th product among the company's existing and competitive products by respondent *n* in segment *i*, $\widetilde{U}_{inp}$ is the fuzzy utility of the *p*-th product for respondent *n* in segment *i*, $\widetilde{U}_{ink}$ is the fuzzy utility of the *k*-th company's existing product for respondent *n* in segment *i*, and $\widetilde{U}_{inj}$ is the fuzzy utility of the *j*-th competitive product for respondent *n* in segment *i*.

Hence, a fuzzy market demand model can be obtained as follows:

$$\widetilde{MD}_{ip} = \frac{e^{\widetilde{U}_{ip}}}{\sum_{j=1}^{J} e^{\widetilde{U}_{ij}} + \sum_{k=1}^{K} e^{\widetilde{U}_{ik}} + e^{\widetilde{U}_{ip}}} x\ (l_i, \alpha_i, r_i), \tag{4.16}$$

where $\widetilde{MD}_{ip}$ is the fuzzy market demand for the *p*-th product in segment *i*, $\widetilde{U}_{ip}$ is the fuzzy utility of the *p*-th product in segment *i*, $\widetilde{U}_{ij}$ is the fuzzy utility of the *j*-th competitive product in segment *i*, and $\widetilde{U}_{ik}$ is the fuzzy utility of the *k*-th company's existing product in segment *i*.

The worst, normal and best scenarios of market demand can be estimated by the developed fuzzy market demand models via Eqs. (4.17), (4.18), and (4.19), respectively:

$$\widetilde{MD}_{ip}^{w} = \Pr(p)_i^w \; x \; \widetilde{MP}_i = \frac{e^{U_{ip}^w}}{\sum_{j=1}^{J} e^{U_{ij}^b} + \sum_{k=1}^{K} e^{U_{ik}^b} + e^{U_{ip}^w}} \; x \; (l_i, \alpha_i, r_i), \tag{4.17}$$

$$\widetilde{MD}_{ip}^{n} = \Pr(p)_i^n \; x \; \widetilde{MP}_i = \frac{e^{U_{ip}^n}}{\sum_{j=1}^{J} e^{U_{ij}^n} + \sum_{k=1}^{K} e^{U_{ik}^n} + e^{U_{ip}^n}} \; x \; (l_i, \alpha_i, r_i), \tag{4.18}$$

$$\widetilde{MD}_{ip}^{b} = \Pr(p)_i^b \; x \; \widetilde{MP}_i = \frac{e^{U_{ip}^b}}{\sum_{j=1}^{J} e^{U_{ij}^w} + \sum_{k=1}^{K} e^{U_{ik}^w} + e^{U_{ip}^b}} \; x \; (l_i, \alpha_i, r_i), \tag{4.19}$$

where $\widetilde{MD}_{ip}^{w}$, $\widetilde{MD}_{ip}^{n}$, and $\widetilde{MD}_{ip}^{b}$ are the fuzzy market demands for the *p*-th product in segment *i* for the worst, normal, and best scenarios, respectively. $\Pr(p)_i^w$, $\Pr(p)_i^n$, and $\Pr(p)_i^b$ are the probabilities of choosing the *p*-th product in segment *i* for the worst, normal, and best scenarios, respectively. U_{ip}^w, U_{ip}^n, and U_{ip}^b are the utilities of the *p*-th product in segment *i* for the worst, normal, and best scenarios, respectively. U_{ij}^w, U_{ij}^n, and U_{ij}^b are the utilities of the *j*-th competitive product in segment *i* for the worst, normal, and best scenarios, respectively. U_{ik}^w, U_{ik}^n, and U_{ik}^b are the utilities of the *k*-th company's existing product in segment *i* for the worst, normal, and best scenarios, respectively.

4.1.4 Estimation of market demands for new products using centroid defuzzification method

After the fuzzy market demand models for a new product are generated, the market demands for the new product in the fuzzy number can be estimated corresponding to the worst, normal, and best scenarios. To obtain the crisp estimated values of the market demand, a centroid defuzzification method is adopted as follows (Leekwijck and Kerre, 1999):

$$x^* = \frac{\int_a^b \mu_A(x)\, x\, dx}{\int_a^b \mu_A(x)\, dx}, \tag{4.20}$$

where x^* denotes the defuzzification (crisp) value, a and b are the minimum and maximum values of x, respectively.

4.2 Implementation

To illustrate the applicability of the proposed approach, a case study of the market demand estimation of a new tablet PC on the proposed approach is presented. A computer product manufacturer is planning to develop a new tablet PC for a particular market. Eight important product attributes were defined based on market information and a lead user survey. To design a conjoint survey, the company also defined the levels and settings for individual attributes. Table 4.1 shows the eight product attributes and their corresponding levels. The green index was considered because of the increasing environmental concerns of consumers in the market. Green index “1” denotes that the materials and components used in production are new. Green index “2” implies that 30% of the materials used in production are recycled and the price of the product is 15% cheaper than that of the products with green index “1.” Green index “3” indicates that 50% of the materials used in production are recycled and the price of the product is 25% cheaper than that of the products with green index “1.”

Table 4.1 Product attributes and attribute levels of tablet PCs

Index	Attributes	Attribute levels
1	CPU (Processor)	1/1.4/1.8 GHz
2	Memory (RAM)	512 MB/1 GB/2 GB
3	Hard disk	16/32/64 GB
4	Screen size	7/10 in
5	Screen resolution	1024×768/1280×800/2048×1536
6	Battery life	8/10/12 hrs
7	Connectivity	Wi-Fi/Wi-Fi + 3G/Wi-Fi + 4 G
8	Green index	1/2/3

The design of the survey and generation of product profiles for the survey are based on an L18 orthogonal array (Mori, 2011). Table 4.2 shows a part of the survey questionnaire in which 18 product profiles are generated. The conjoint survey was conducted in a university. All the respondents were university students in their early 20s and experienced users of tablet PCs. The students were invited to assess the 18 product profiles by filling out the survey questionnaires using the scales "1" to "5", which denote the linguistic variables "very bad," "bad," "moderate," "good," and "very good," respectively. About 48% of the respondents were female. Some outliers were noted and removed from the data sets for data analysis and modeling.

Table 4.2 Survey questionnaire for tablet PCs

Product profiles	CPU	RAM	Hard disk	Screen size	Screen resolution	Battery life	Connectivity	Green index	Rating (1 – 5)
1	1 GHz	512 MB	16 GB	7 in	1024 × 768	8 hrs	Wi-Fi	1	
2	1 GHz	1 GB	32 GB	7 in	1280 × 800	10 hrs	Wi-Fi + 3G	2	
3	1 GHz	2 GB	64 GB	7 in	2048 × 1536	12 hrs	Wi-Fi + 4G	3	
4	1.4 GHz	512 MB	16 GB	7 in	1280 × 800	10 hrs	Wi-Fi + 4G	3	
5	1.4 GHz	1 GB	32 GB	7 in	2048 × 1536	12 hrs	Wi-Fi	1	
6	1.4 GHz	2 GB	64 GB	7 in	1024 × 768	8 hrs	Wi-Fi + 3G	2	
7	1.8 GHz	512 MB	32 GB	7 in	1024 × 768	12 hrs	Wi-Fi + 3G	3	
8	1.8 GHz	1 GB	64 GB	7 in	1280 × 800	8 hrs	Wi-Fi + 4G	1	
9	1.8 GHz	2 GB	16 GB	7 in	2048 × 1536	10 hrs	Wi-Fi	2	
10	1 GHz	512 MB	64 GB	10 in	2048 × 1536	10 hrs	Wi-Fi + 3G	1	
11	1 GHz	1 GB	16 GB	10 in	1024 × 768	12 hrs	Wi-Fi + 4G	2	
12	1 GHz	2 GB	32 GB	10 in	1280 × 800	8 hrs	Wi-Fi	3	
13	1.4 GHz	512 MB	32 GB	10 in	2048 × 1536	8 hrs	Wi-Fi + 4G	2	
14	1.4 GHz	1 GB	64 GB	10 in	1024 × 768	10 hrs	Wi-Fi	3	
15	1.4 GHz	2 GB	16 GB	10 in	1280 × 800	12 hrs	Wi-Fi + 3G	1	
16	1.8 GHz	512 MB	64 GB	10 in	1280 × 800	12 hrs	Wi-Fi	2	
17	1.8 GHz	1 GB	16 GB	10 in	2048 × 1536	8 hrs	Wi-Fi + 3G	3	
18	1.8 GHz	2 GB	32 GB	10 in	1024 × 768	10 hrs	Wi-Fi + 4G	1	

Once the survey data were collected, a K-means clustering technique based on SPSS software package was employed to identify consumer segments. In this case study, two segments were identified. Thereafter, the ratings were converted to TFNs, where the neighbor functions intersected at the membership value of 0.5. Thus, when the membership value of a function is 1, the membership value of the neighbor function(s) is 0 or vice versa. Figure 4.4 shows the membership functions of the linguistic variables used in the survey. The ratings of “1” to “5” are converted into TFNs as follows:

“1” (very bad) = (0.83, 0.83); “2” (bad) = (1.67, 0.83); “3” (moderate) = (2.50, 0.83); “4” (good) = (3.34, 0.83); “5” (very good) = (4.17, 0.83).

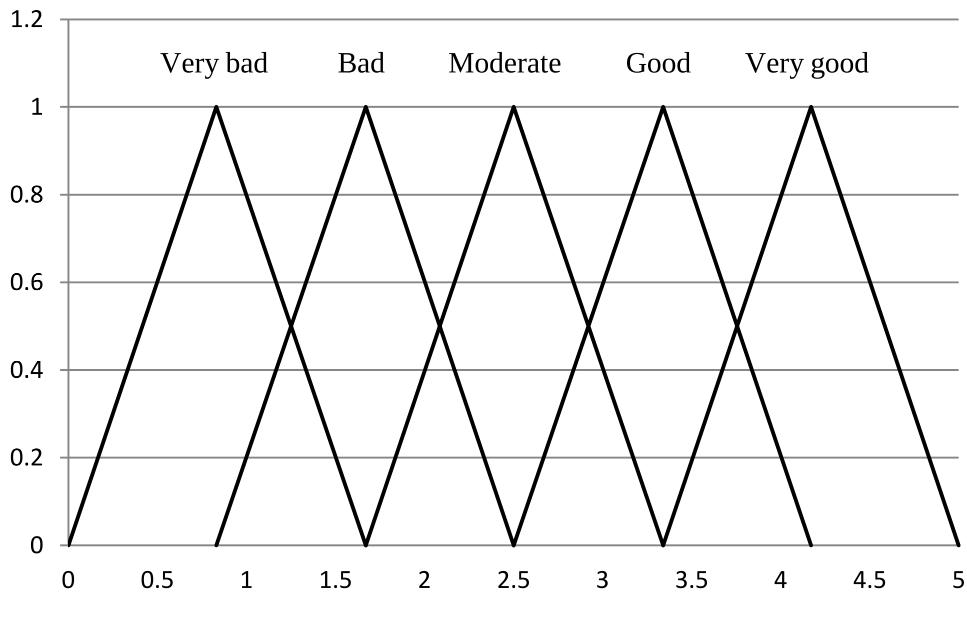


Figure 4.4 Membership function for linguistic variables

In conjoint analysis, a dummy variable regression method is commonly used to generate utility functions. This method is adopted in this research, where each product attribute consists of dummy variables for the attribute levels. If an attribute has k_i levels, it is coded in terms of $k_i - 1$ dummy variables. The value of a dummy variable is either 1 or 0. Taking the attribute CPU as an example, its levels were coded as follows:

	x_{11}	x_{12}
1 GHz	1	0
1.4 GHz	0	1
1.8 GHz	0	0

Table 4.3 shows the defined dummy variables and coded product profiles.

Table 4.3 Coded product profiles with dummy variables

Profile	x_{11}	x_{12}	x_{21}	x_{22}	x_{31}	x_{32}	x_4	x_{51}	x_{52}	x_{61}	x_{62}	x_{71}	x_{72}	x_{81}	x_{82}
1	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0
2	1	0	0	1	0	1	1	0	1	0	1	0	1	0	1
3	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	0	1	1	0	1	0	1	0	1	0	1	0	0	0	0
5	0	1	0	1	0	1	1	0	0	0	0	1	0	1	0
6	0	1	0	0	0	0	1	1	0	1	0	0	1	0	1
7	0	0	1	0	0	1	1	1	0	0	0	0	1	0	0
8	0	0	0	1	0	0	1	0	1	1	0	0	0	1	0
9	0	0	0	0	1	0	1	0	0	0	1	1	0	0	1
10	1	0	1	0	0	0	0	0	0	0	1	0	1	1	0
11	1	0	0	1	1	0	0	1	0	0	0	0	0	0	1
12	1	0	0	0	0	1	0	0	1	1	0	1	0	0	0
13	0	1	1	0	0	1	0	0	1	1	0	0	0	0	1
14	0	1	0	1	0	0	0	1	0	0	1	1	0	0	0
15	0	1	0	0	1	0	0	0	0	0	0	0	1	1	0
16	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1
17	0	0	0	1	1	0	0	0	1	1	0	0	1	0	0
18	0	0	0	0	0	1	0	1	0	0	1	0	0	1	0

Note: x_{11} and x_{12} are the dummy variables for CPU; x_{21} and x_{22} are the dummy variables for memory; x_{31} and x_{32} are the dummy variables for hard disk; x_4 is a dummy variable for screen size; x_{51} and x_{52} are the dummy variables for screen resolution; x_{61} and x_{62} are the dummy variables for battery life; x_{71} and x_{72} are the dummy variables for connectivity; and x_{81} and x_{82} are the dummy variables for green index.

After defining the dummy variables and coding the product profiles, fuzzy regression analysis was introduced to determine the fuzzy coefficients of the regression models. The development of fuzzy utility functions was implemented using Matlab software. The fuzzy utility functions for individual respondents in Segments 1 and 2 were generated. The generated fuzzy utility functions for the first respondent of Segments 1 and 2, denoted as $\widetilde{U}_{11}$ and $\widetilde{U}_{21}$, respectively, are shown as follows:

$$\begin{aligned}\widetilde{U}_{11} = (4.00, 0.06) + (0.35, 0)x_{11} + (0.07, 0.56)x_{12} + (0.59, 0.21)x_{21} \\ + (0.59, 0.21)x_{22} + (-0.38, 0.21)x_{31} + (-0.11, 0.21)x_{32} \\ + (0.14, 0.14)x_{41} + (-0.11, 0.21)x_{51} + (-0.39, 0.21)x_{52} \\ + (0.17, 0.21)x_{61} + (-0.25, 0.21)x_{62} + (-2.33, 0.21)x_{71} \\ + (-1.08, 0.21)x_{72} + (0.59, 0.21)x_{81} + (0.59, 0.21)x_{82}\end{aligned}$$

$$\begin{aligned}\widetilde{U}_{21} = (5.70, 0) + (-0.98, 1.39)x_{11} + (-1.25, 0.28)x_{12} + (0.14, 0)x_{21} \\ + (-0.28, 0)x_{22} + (-0.42, 0)x_{31} + (-0.56, 0)x_{32} + (0.56, 0)x_{41} \\ + (-0.83, 0)x_{51} + (-0.55, 0)x_{52} + (0, 0)x_{61} + (-0.56, 0)x_{62} \\ + (-0.56, 0)x_{71} + (-0.42, 0)x_{72} + (-1.67, 0)x_{81} \\ + (-0.98, 0)x_{82}\end{aligned}$$

Five marketing executives were invited to estimate the market potential of the two segments. Their estimations are shown in Table 4.4.

Table 4.4 Market potentials of two segments estimated by marketing executives

Marketing Executive	Estimated Potential of Segment 1 (×1000)	Estimated Potential of Segment 2 (×1000)
A	76.8	163.2
B	83.2	176.8
C	90.2	191.8
D	84.8	180.2
E	89.6	190.4

The mean value of the fuzzy estimate of the market potential of Segment 1, α_1, can be determined using Eq. (4.10) as shown below.

$$\alpha_1 = \frac{76.8 + 83.2 + 90.2 + 84.8 + 89.6}{5} = 84.9.$$

The left and right spread values of the fuzzy estimate are calculated as 8.1 and 5.3 using Eqs. (4.12) and (4.13), respectively. Thus, $\widetilde{MP}_1 = (l_1, \alpha_1, r_1) = (8.1, 84.9, 5.3)$. By following the same procedures, the fuzzy estimate of the market potential of Segment 2, $\widetilde{MP}_2$, was estimated as $(17.3, 180.5, 11.3)$.

The NPD team of the company preliminarily defined the specifications of a new tablet PC as shown in Table 4.5.

Table 4.5 Specifications of a new tablet PC

Attribute	Settings
CPU (Processor)	1.8 GHz
Memory (RAM)	2 GB
Storage	32 GB
Screen size	10 in
Display resolution	1280 × 800
Battery life	12 hrs

Connectivity	Wi-Fi + 4G
Green index	3

Four major competitive tablet PCs, denoted by A, B, C, and D, were identified in the target market. Specifications of the competitive products are shown in Table 4.6.

Table 4.6 Specifications of competitive products

Product	CPU	Memory (RAM)	Hard disk	Screen size	Screen resolution	Battery life	Connectivity	Green index
A	1 GHz	1 GB	16 GB	7 in	1024 × 768	10 hrs	Wi-Fi + 3G	1
B	1 GHz	512 MB	16 GB	7 in	1024 × 768	10 hrs	Wi-Fi	1
C	1.4 GHz	2 GB	32 GB	10 in	1280 × 800	10 hrs	Wi-Fi + 3G	1
D	1.4 GHz	1 GB	64 GB	10 in	2048 × 1536	10 hrs	Wi-Fi + 4G	2

The fuzzy utilities of the new product and four competitive products for each respondent in Segments 1 and 2 were calculated based on the generated fuzzy utility functions. Tables 4.7 and 4.8 show the fuzzy utilities of the first five respondents in Segments 1 and 2, respectively.

Table 4.7 Fuzzy utilities of the first five respondents in Segment 1

New		A		B		C		D	
Center	Spread	Center	Spread	Center	Spread	Center	Spread	Center	Spread
3.51	0.48	3.86	1.47	2.60	1.47	2.85	1.68	5.00	1.25
2.19	0.20	4.20	0.63	4.35	0.63	1.79	1.31	2.82	1.13
4.31	0.00	3.19	0.27	2.64	0.27	4.45	0.00	4.31	0.00
4.28	0.07	2.68	0.21	2.40	0.21	3.80	0.15	3.83	0.10
3.86	0.07	3.37	0.21	2.67	0.21	3.95	0.15	4.11	0.09

Table 4.8 Fuzzy utilities of the first five respondents in Segment 2

New		A		B		C		D	
Center	Spread	Center	Spread	Center	Spread	Center	Spread	Center	Spread
4.59	0.00	1.10	1.39	1.39	1.39	0.69	0.28	2.64	0.28
2.33	0.07	3.79	0.49	2.95	0.49	2.13	0.16	-0.06	0.10
3.47	0.00	1.52	0.83	1.10	0.83	2.50	0.00	2.64	0.00
3.33	0.00	1.39	0.28	0.83	0.28	5.28	0.28	3.20	0.28
4.97	0.07	2.81	0.21	2.54	0.21	2.83	0.16	2.30	0.10

The choice probabilities of individuals in Segments 1 and 2 for the worst, normal, and best scenarios were calculated using Eq. (4.16). Tables 4.9 and 4.10 show the choice probabilities of the first five respondents in Segments 1 and 2, respectively.

Table 4.9 Choice probabilities of the first five respondents for Segment 1

	Worst Scenario					Normal Scenario					Best Scenario				
	New	A	B	C	D	New	A	B	C	D	New	A	B	C	D
1	0.023	0.229	0.065	0.103	0.580	0.128	0.181	0.052	0.066	0.572	0.474	0.095	0.027	0.028	0.375
2	0.021	0.357	0.411	0.063	0.148	0.051	0.381	0.439	0.034	0.096	0.115	0.376	0.434	0.017	0.057
3	0.261	0.112	0.065	0.300	0.262	0.273	0.089	0.051	0.313	0.273	0.282	0.070	0.040	0.324	0.283
4	0.334	0.089	0.067	0.259	0.251	0.383	0.077	0.058	0.238	0.244	0.433	0.066	0.050	0.216	0.235
5	0.197	0.159	0.079	0.268	0.297	0.233	0.143	0.071	0.254	0.299	0.273	0.127	0.063	0.239	0.298

Table 4.10 Choice probabilities of the first five respondents for Segment 2

	Worst Scenario					Normal Scenario					Best Scenario				
	New	A	B	C	D	New	A	B	C	D	New	A	B	C	D
1	0.666	0.082	0.109	0.018	0.125	0.810	0.025	0.033	0.016	0.115	0.875	0.009	0.009	0.013	0.094
2	0.077	0.583	0.252	0.080	0.008	0.124	0.533	0.230	0.102	0.011	0.190	0.467	0.202	0.124	0.017
3	0.425	0.139	0.091	0.160	0.185	0.489	0.070	0.046	0.184	0.212	0.524	0.032	0.021	0.196	0.226
4	0.085	0.016	0.009	0.791	0.099	0.110	0.016	0.009	0.770	0.096	0.141	0.015	0.009	0.743	0.093
5	0.668	0.102	0.077	0.098	0.055	0.719	0.083	0.063	0.084	0.050	0.765	0.067	0.051	0.072	0.045

The individual choice probabilities of the new product and the competitive products were then aggregated to estimate the market shares for each market segment corresponding to the worst, normal, and best scenarios (Table 4.11).

Table 4.11 Market share estimations in Segments 1 and 2

	Worst scenario		Normal scenario		Best scenario	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
New	0.194	0.403	0.278	0.470	0.381	0.525
A	0.167	0.152	0.169	0.112	0.163	0.086
B	0.131	0.109	0.133	0.084	0.130	0.067
C	0.227	0.185	0.177	0.176	0.134	0.164
D	0.281	0.151	0.244	0.158	0.192	0.159

The estimated market shares were combined with the fuzzy estimates of market potential to estimate the fuzzy market demands for Segments 1 and 2 (Table 4.12). Table 4.13 shows the total fuzzy market demand estimations.

Table 4.12 Fuzzy market demand estimations in Segments 1 and 2

	Worst scenario		Normal scenario		Best scenario	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
New	(1.6, 16.5, 1.0)	(7.0, 72.8, 4.6)	(2.2, 23.6, 1.5)	(8.1, 84.9, 5.3)	(3.1, 32.4, 2.0)	(9.1, 94.8, 5.9)
A	(1.4, 14.2, 0.9)	(2.6, 27.5, 1.7)	(1.4, 14.3, 0.9)	(1.9, 20.2, 1.3)	(1.3, 13.8, 0.9)	(1.5, 15.5, 1.0)
B	(1.1, 11.1, 0.7)	(1.9, 19.6, 1.2)	(1.1, 11.3, 0.7)	(1.4, 15.1, 0.9)	(1.1, 11.0, 0.7)	(1.2, 12.0, 0.8)
C	(1.8, 19.2, 1.2)	(3.2, 33.3, 2.1)	(1.4, 15.0, 0.9)	(3.0, 31.7, 2.0)	(1.1, 11.4, 0.7)	(2.8, 29.5, 1.8)
D	(2.3, 23.8, 1.5)	(2.6, 27.3, 1.7)	(2.0, 20.7, 1.3)	(2.7, 28.6, 1.8)	(1.6, 16.3, 1.0)	(2.7, 28.7, 1.8)

Table 4.13 Total fuzzy market demand estimations

	Worst scenario	Normal scenario	Best scenario
New	(8.6, 89.3, 5.6)	(10.3, 108.5, 6.8)	(12.2, 127.2, 7.9)
A	(4.0, 41.7, 2.6)	(3.3, 34.5, 2.2)	(2.8, 29.3, 1.9)

B	(3.0, 30.7, 1.9)	(2.5, 26.4, 1.6)	(2.3, 23.0, 1.5)
C	(5.0, 52.5, 3.3)	(4.4, 46.7, 2.9)	(3.9, 40.9, 2.5)
D	(4.9, 51.1, 3.2)	(4.7, 49.3, 3.1)	(4.3, 45.0, 2.8)

To estimate the crisp estimated values of the market demand for the new tablet PC, the centroid defuzzification method was applied for the worst, normal, and best scenarios as shown below:

$$MD_w^* = \frac{\left(\int_{80.7}^{89.3}(x-80.7)x\,dx\right)+\left(\int_{89.3}^{94.9}(94.9-x)x\,dx\right)}{\left(\int_{80.7}^{89.3}(x-80.7)\,dx\right)+\left(\int_{89.3}^{94.9}(94.9-x)\,dx\right)} = 87.9\;K$$

$$MD_n^* = \frac{\left(\int_{98.2}^{108.5}(x-98.2)x\,dx\right)+\left(\int_{108.5}^{115.3}(115.3-x)x\,dx\right)}{\left(\int_{98.2}^{108.5}(x-98.2)\,dx\right)+\left(\int_{108.5}^{115.3}(115.3-x)\,dx\right)} = 107\;K$$

$$MD_b^* = \frac{\left(\int_{115}^{127.2}(x-115)x\,dx\right)+\left(\int_{127.2}^{135.1}(135.1-x)x\,dx\right)}{\left(\int_{115.2}^{127.4}(x-115.2)\,dx\right)+\left(\int_{127.2}^{135.1}(135.1-x)\,dx\right)} = 126.1\;K$$

where MD_w^*, MD_n^*, and MD_b^* are the market demands for the new tablet PC for the worst, normal, and best scenarios in crisp values, respectively.

4.3 Validation

To evaluate the effectiveness of the proposed approach and estimate the market demands using the same survey data sets, an MNL-based demand model (Kwong *et al.*, 2011; *Lin et al.*, 2011) as shown in Eq. (4.21) was employed in this research. The model was widely used in previous studies to estimate market demands. The estimation results based on the MNL-based demand model were compared with those based on the proposed fuzzy demand model.

$$MD^*(p) = \sum_{i=1}^{I} Q_i \times \left[\frac{1}{\mathrm{N_i}} \times \sum\nolimits_{\mathrm{n=1}}^{\mathrm{N_i}} \frac{e^{U_{inp}}}{\sum_{j=1}^{J} e^{U_{inj}} + \sum_{k=1}^{K} e^{U_{ink}} + e^{U_{inp}}}\right] \tag{4.21}$$

where $MD^*(p)$ is the estimated total market demand and Q_i is the market potential of segment *i*. N_i is the number of respondents in segment *i*. The market share of segment *i* is estimated by taking the average of the market share estimations of N_i respondents in segment *i*.

With the use of the same survey data, the utility functions of the MNL-based demand model were generated based on a multiple linear regression method with dummy variables. The following shows the utility functions generated for the first respondent for Segments 1 and 2, denoted as U_{11} and U_{21}, respectively.

$$\begin{aligned} U_{11} = 3.44 &+ 0.5x_{11} + 0.17x_{12} + 0.83x_{21} + 0.83x_{22} - 0.33x_{31} + 0x_{32} + 0.78x_{41} \\ &+ 0x_{51} - 0.33x_{52} + 0.33x_{61} - 0.17x_{62} - 2.67x_{71} - 1.17x_{72} \\ &+ 0.83x_{81} + 0.83x_{82} \end{aligned}$$

$$\begin{aligned} U_{21} = 6.56 &- 1.17x_{11} - 1.5x_{12} + 0.17x_{21} - 0.33x_{22} - 0.5x_{31} - 0.67x_{32} \\ &+ 0.22x_{41} - 1.0x_{51} - 0.67x_{52} + 0x_{61} - 0.67x_{62} - 0.67x_{71} \\ &- 0.5x_{72} - 2.0x_{81} - 1.17x_{82} \end{aligned}$$

The utilities of the new product and four competitive products for each respondent in Segments 1 and 2 were estimated based on the generated utility functions. Table 4.14 shows the utilities of the new product and the four competitive products of the first five respondents in Segments 1 and 2.

Table 4.14 Utilities of the first five respondents in Segments 1 and 2

	Segment 1					Segment 2				
	New	A	B	C	D	New	A	B	C	D
1	3.11	4.72	3.22	2.78	5.11	5.22	0.61	0.94	0.56	2.89
2	2.50	4.17	4.33	1.83	3.17	2.17	4.17	3.17	2.00	-0.67
3	4.61	3.39	2.72	4.78	4.61	3.50	1.50	1.00	2.33	2.50
4	4.56	2.78	2.44	4.06	4.06	3.50	1.17	0.50	5.83	3.33
5	4.06	3.61	2.78	4.22	4.39	5.39	2.94	2.61	2.89	2.22

The choice probabilities of individuals in Segments 1 and 2 were calculated. Table 4.15 shows the choice probabilities of the first five respondents in Segments 1 and 2.

Table 4.15 Choice probabilities of the first five respondents for Segments 1 and 2

	Segment 1					Segment 2				
	New	A	B	C	D	New	A	B	C	D
1	0.066	0.329	0.073	0.047	0.485	0.885	0.009	0.012	0.008	0.086
2	0.067	0.353	0.417	0.034	0.130	0.083	0.615	0.226	0.070	0.005
3	0.276	0.081	0.042	0.326	0.276	0.527	0.071	0.043	0.164	0.194
4	0.399	0.068	0.048	0.242	0.242	0.081	0.008	0.004	0.838	0.069
5	0.222	0.143	0.062	0.263	0.310	0.785	0.068	0.049	0.064	0.033

The individual choice probabilities of the new product and the competitive products were then aggregated to estimate the market shares of each market segment (Table 4.16).

Table 4.16 Market share estimations in Segments 1 and 2

	Segment 1	Segment 2
New	0.274	0.499
A	0.187	0.108
B	0.133	0.079
C	0.172	0.165
D	0.234	0.148

Figure 4.5 compares the market share of the new product estimated based on the proposed model and the MNL-based model.

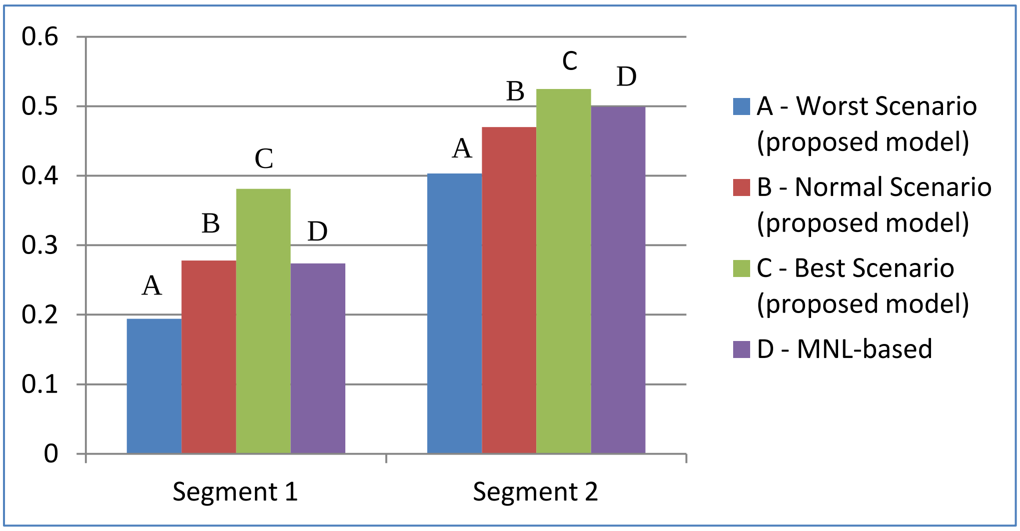


Figure 4.5 Comparison of the market share estimation of the new product

The market potential Q_i can be estimated by taking the average of those estimated by marketing executives. For this case, the market potentials of Segment 1 and 2 were calculated as 84.9 and 180.5 K, respectively. Thus, the market demand for the new product was estimated as 113.3 K based on the MNL-based demand model. It can be noted that the estimated market demand based on the MNL-based model was very close to that of the normal scenario based on the proposed model, which was 107 K. Hence, the MNL-based demand model cannot provide market demand estimations for other scenarios that companies may need to consider in the risk assessment of NPD projects, whereas the proposed model can provide the estimated market demands for both worst and best scenarios. Figure 4.6 compares the total market demands for the new product based on the proposed model and the MNL-based model.

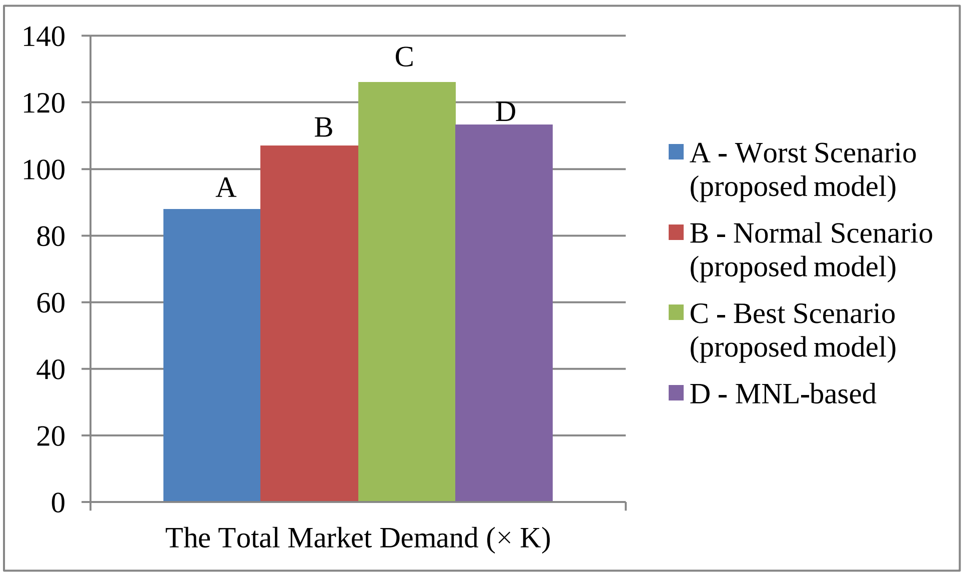


Figure 4.6 Comparison of the total market demands for the new product

The price of tablet PCs which has similar specifications as the new tablet PC proposed by the NPD team in this case is around USD 513. Since the green index of the proposed new tablet PC is 3, the price of the new tablet PC could be set to around USD 385. If the profit margin without considering the expenses of R&D, product development and marketing is 25%, then the profit per tablet PC is about USD 96. Therefore, the total profits are around USD 8.4M, USD 10.3M, and USD 12.1M for the worst, normal, and best scenarios, respectively. However, it is common for a company to invest millions of US dollars on R&D, product development, and marketing for the development and marketing of a new tablet PC. Thus, the senior management of the company may think that the profit generated from the NPD project in the worst scenario may not be good enough for the company to take the risk of undertaking the NPD project, though it may seem to be quite profitable in the normal scenario.

4.4 Summary

Market demand estimation involves various uncertainties, such as inconsistent customer behavior, subjective responses of respondents in surveys, unstable market conditions, and technological change. Two uncertainties are addressed in this research. One is the subjective judgment of respondents on product profiles in conjoint surveys, which can lead to a high degree of fuzziness of survey data. Another is the group estimation of market potential based on a jury of executive opinion method. The two uncertainties were not considered in previous studies regarding the development of market demand models. In this research, a novel approach to develop fuzzy market demand models for NPD is proposed to address the fuzziness by which market demands can be estimated for the worst, normal, and best scenarios. In the proposed approach, fuzzy regression is introduced into DCA to address the fuzziness of survey data and fuzzy estimates are generated to address the fuzziness of the market potential estimation. A case study of market demand estimation of a new tablet PC was conducted based on the proposed approach to illustrate the applicability and evaluate the effectiveness of the approach. The results of the case study were compared with those based on a popular MNL based demand model. The comparison shows that the estimated market demand based on the MNL-model was very close to that of the normal scenario based on the proposed fuzzy demand model. However, the MNL model cannot provide estimates for different scenarios, whereas the proposed model can provide estimated market demands for both the worst and best scenarios.

Chapter 5 Simultaneous Consideration of Remanufactured and New Products in Optimal Product Line Design

A proposed methodology for the simultaneous consideration of remanufactured and new products in the optimal PLD is described in Section 5.1. A case study of simultaneous consideration of remanufactured and new tablet PC design in optimal PLD based on the proposed methodology is provided in Section 5.2. Validation of the proposed methodology is then presented in Section 5.3. Finally, a summary is given in Section 5.4.

5.1 Proposed methodology for simultaneous consideration of remanufactured and new products in PLD

Remanufacturing involves collecting back of used products, testing, disassembling, reconditioning, replacing some parts, reassembling, and final testing. Remanufactured products are assumed to have a like-new condition and are launched in both first and second markets. The first market refers to a developed region where consumers are generally more interested in and willing to pay for brand-new products than remanufactured products. However, some consumers in the first market who are environmentalists and/or highly sensitive to price may be interested in remanufactured products. The second market is normally a relatively less developed region where consumers are generally unable to afford brand-new products and may be interested in lower-priced remanufactured products. Given that remanufactured and new products are launched at different times, two periods are specified in which new and remanufactured products are launched in the markets at the beginning of the first and second periods, respectively.

Figure 5.1 shows the proposed methodology, which mainly involves conjoint analysis, generation of dynamic demand models, formulation of the multi-objective optimization problem, and solving the multi-objective optimization problem by using NSGA-II. First, conjoint surveys are conducted to obtain customer preferences on products in the first and second markets. Based on the survey data, segments of individual markets can be determined using a K-means clustering technique. Thereafter, static utility functions of individual segments are generated using statistical regression. Price functions, which estimate the changing prices of product variants, are combined with the static utility functions to generate dynamic utility functions. Dynamic choice models are then developed based on the generated dynamic utility functions and the MNL model of DCA. The estimates of market potential are generated based on the jury of executive opinion method. Once the dynamic choice models are developed and the market potential estimates are obtained, dynamic market demand models can be developed for both the first and second markets. Remanufactured products are also launched in the first market, thus they would compete with the new products. Once the dynamic market demand and cost models are generated for the remanufactured and new products, a multi-objective optimization model can be formulated. NSGA-II is adopted to solve the optimization problem. With the solving algorithm for maximizing the total market share and profit of the product line, Pareto optimal PLD solutions can be obtained. These solutions include the numbers and specifications of remanufactured and new products, the time of launching remanufactured products in markets, and the market shares and profits of the PLD. Details of the proposed methodology are described in the following subsections.

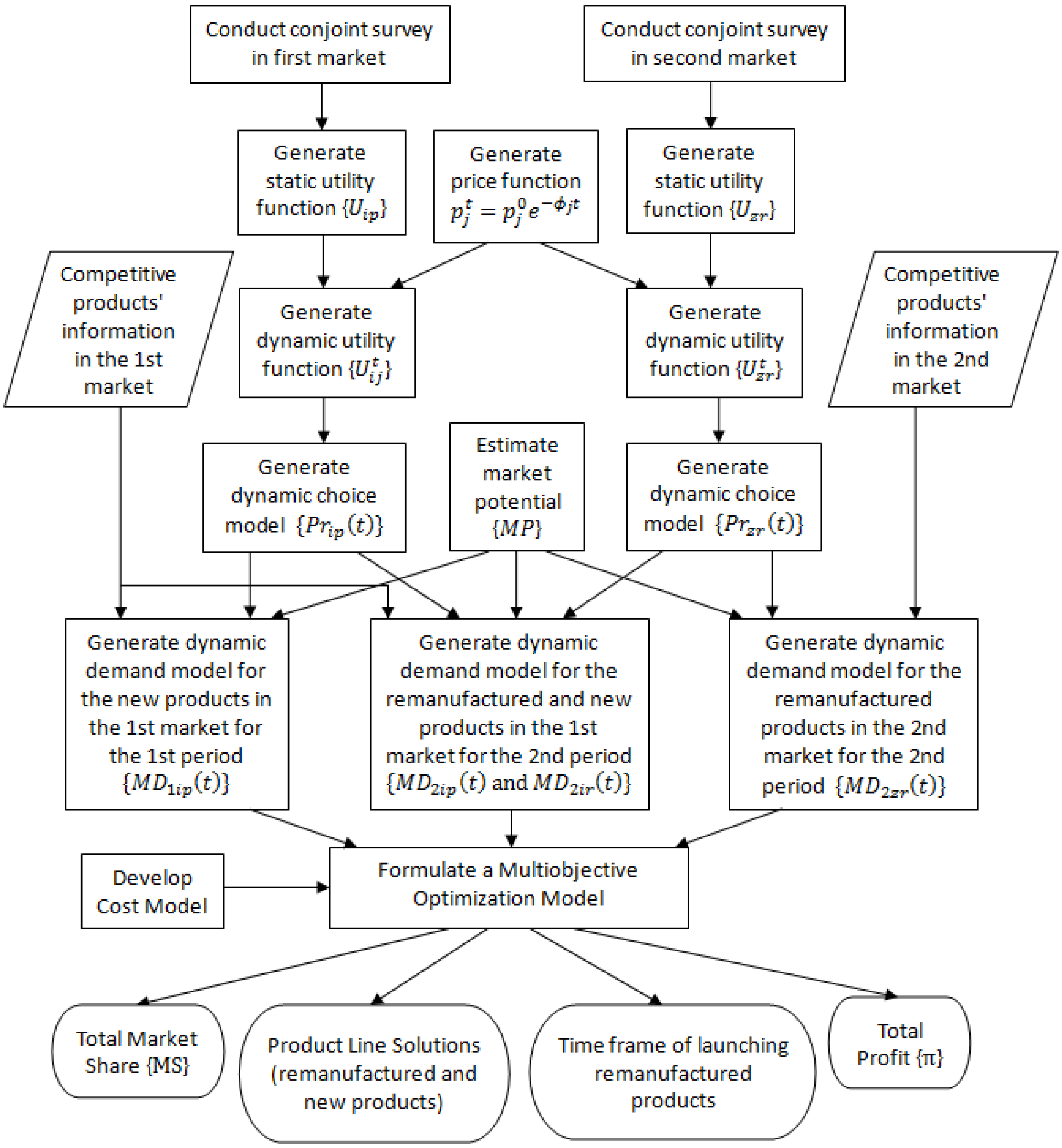


Figure 5.1 Methodology for simultaneous consideration of remanufactured and new products in PLD

5.1.1 Development of dynamic choice models

Once new products are launched in the markets, their price would always decrease over time especially for consumer products, such as smartphones and computers. Thus, in this study, the price of products is defined as a continuous-value decision variable, and a curve-fitting method is introduced to generate the utility functions of the variable. To determine the changing prices over time, an exponential price function, as shown in Eq. (5.1), is adopted (Bayus, 1993).

$$p_j^t = p_j^0 e^{-\phi_j t} \tag{5.1}$$

where p_j^0 represents the initial price of the *j*-th product, p_j^t is the price of the *j*-th product at time *t*, and the coefficient ϕ_j is the degree to which the price of the *j*-th product decreases over time.

The estimated prices based on the exponential price function are used to estimate the utility of price by using the utility functions generated based on the curve-fitting method. The following equation shows an example of the utility functions of price:

$$f_{ijt}^{price} = a_{i0} + a_{i1} p_j^t + a_{i2} \left(p_j^t\right)^2 \tag{5.2}$$

where f_{ijt}^{price} is the utility of price of the *j*-th product in the *i*-th segment at time *t*, and a_{i0}, a_{i1}, and a_{i2} are the coefficients of the quadratic polynomial function in the *i*-th segment.

Hence, the dynamic utility function with consideration of the change of product price over time can be expressed as follows:

$$U_{ij}^{t} = \sum_{k=1}^{m}\sum_{l=1}^{n_k} u_{ikl}x_{jkl} + f_{ijt}^{price} \tag{5.3}$$

where U_{ij}^{t} represents the utility of the *j*-th product profile in the *i*-th segment at time *t*; u_{ikl} is the part-worth utility of the *l*-th level of the *k*-th attribute in the *i*-th segment; *m* and n_k denote the number of attributes and number of attribute levels in the *k*-th attribute, respectively; and x_{jkl} denotes a dummy variable equal to 1 if the *l*-th level of the *k*-th attribute is selected for the product profile *j* and 0 otherwise.

Dynamic choice models can be generated by integrating the dynamic utility function (Eq. 5.3) into the MNL-based discrete choice models as shown below:

$$Pr_{ip}(t) = \frac{e^{U_{ip}^{t}}}{\sum_{j=1}^{J} e^{U_{ij}^{t}} + \sum_{k=1}^{K} e^{U_{ik}^{t}} + e^{U_{ip}^{t}}} \tag{5.4}$$

where $Pr_{ip}(t)$ is the probability of choosing the *p*-th product at time *t* among the company's existing and competitive products in the *i*-th segment; U_{ip}^{t} is the utility of the *p*-th product in segment *i* at time *t*; U_{ik}^{t} is the utility of the *k*-th company's existing product in segment *i* at time *t*; and U_{ij}^{t} is the utility of the *j*-th competitive product in segment *i* at time *t*.

5.1.2 Development of dynamic market demand models

Bass diffusion model, as shown in (Eq. 5.5), is adopted in this research to forecast the demands for new products and examine their diffusion patterns in a market with respect to innovation and imitation effects as well as market potential (Bass, 1969).

$$S(t) = [m - N(t)]\left[p + q\frac{N(t)}{m}\right] \tag{5.5}$$

where $S(t)$ is the estimated sales at time *t*, $N(t)$ is the cumulative sales until time *t*, *p* is the innovation coefficient, *q* is the imitation coefficient, and *m* is the market potential.

Bass *et al.* (1994) later developed a generalized Bass model by introducing pricing and advertising decision variables into the aforementioned model. However, the generalized Bass model cannot provide the effects of product attribute setting on the product diffusion and does not consider competition in the markets (Mahajan and Muller, 1996). Some studies have been conducted to address the issue. Mahajan and Muller (1996) extended the Bass diffusion model to perform multigenerational product diffusion, in which diffusion and substitution patterns could be captured simultaneously. Jun and Park (1999) developed a discrete choice-based multigenerational product diffusion model to capture consumer behavior in product diffusion. Kim *et al.* (2005) extended the model of Jun and Park (1999) by involving product characteristics in the choice model to forecast demand and determine the optimum introduction time of products for each successive generation. Lee *et al.* (2006) developed an extended Bass model by integrating a choice model. In this study, dynamic market demand models are mainly developed based on the dynamic choice models and the Bass diffusion model. Two periods, the first and second periods, are defined in the demands for new and remanufactured products (Figure 5.2) because remanufactured and new products are launched at different times and remanufactured products are assumed to be launched in the first market. The first period is the time frame where only new products are in the market, while the second period is the time frame where both new and remanufactured products are in the markets. The second period begins with the launch of remanufactured products.

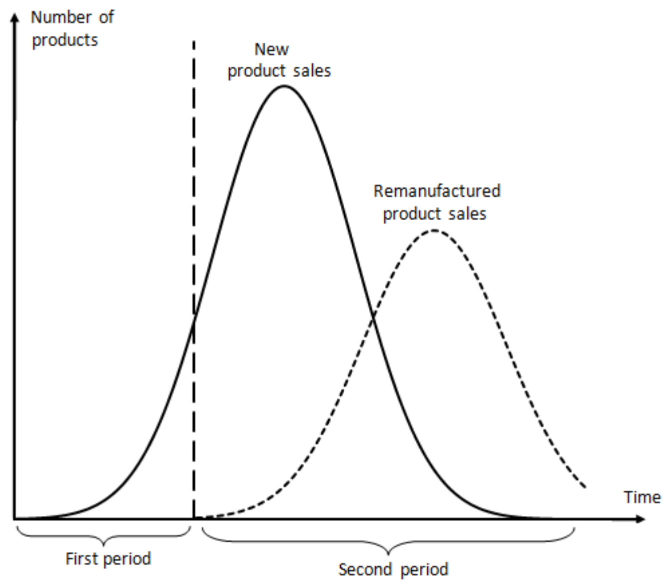


Figure 5.2 Relation between new and remanufactured product sales

5.1.2.1 Dynamic market demand modeling for new product(s) in the first and second periods

The market potential of the *p*-th new product in segment *i* at time *t* for the first period can be estimated as follows:

$$Pr_{1ip}(t)MP_{1i} \tag{5.6}$$

where MP_{1i} is the estimated market potential of segment *i* in the first market.

The market demand for new product(s) in the first period can be estimated by integrating the corresponding dynamic choice models (Eq. 5.4) and market potential estimate for the first period (Eq. 5.6) into the Bass diffusion model. Thus, the dynamic market demand for new product(s) for the first period can be expressed as follows:

$$n_{11ip}(t) = \alpha_p \left[Pr_{1ip}(t)MP_{1i} - \sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{11ip}(t) \right] \left[p_1 + q_1 \frac{\sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{11ip}(t)}{Pr_{1ip}(t)MP_{1i}} \right] \tag{5.7}$$

where $n_{11ip}(t)$ is the market demand for the *p*-th new product in segment *i* at time *t* in the first market for the first period; $Pr_{1ip}(t)$ is the probability of choosing the *p*-th new product among the new and existing products of a company and the competitive products in segment *i* at time *t* for the first period; p_1 and q_1 are the innovation and imitation coefficients of the new product, respectively; and α_p equals 1 if the *p*-th new product is selected, and 0 otherwise.

The dynamic market demand model of new product(s) for the second period can be expressed as follows:

$$n_{21ip}(t) = \alpha_p \left[Pr_{2ip}(t) MP_{1i} - \sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{21ip}(t) \right] \left[p_1 + q_1 \frac{\sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{21ip}(t)}{Pr_{2ip}(t) MP_{1i}} \right] \tag{5.8}$$

where $n_{21ip}(t)$ is the market demand for the *p*-th new product in segment *i* at time *t* in the first market for the second period, and $Pr_{2ip}(t)$ is the probability of choosing the *p*-th new product at time *t* among the existing and remanufactured product(s) of the company, and competitive products in segment *i* in the second period.

Hence, the total demand for new product(s) can be estimated as follows:

$$\sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{t_k - 1} n_{11ip}(t) + \sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=t_k}^{Tn} n_{21ip}(t) \tag{5.9}$$

where t_k is the time of launching remanufactured product(s) in the market Thus, $t_k - 1$ is the end of the first period.

5.1.2.2 Dynamic market demand modeling for remanufactured product(s) in the first and second markets

The market potential of the remanufactured product(s) in the first market for the second period is estimated by subtracting the estimated total sales of the company's existing and competitive products in the first period from the market potential of the corresponding segment in the first market that can be expressed as follows:

$$MP_{1i} - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=0}^{t_k-1} n_{11ij}(t) \tag{5.10}$$

Integrating the dynamic choice models of remanufactured product(s) and the market potential estimates of the first market in the second period (Eq. 5.10) into a Bass diffusion model can help estimate the dynamic market demand for remanufactured product(s) in the first market as follows:

$$\begin{aligned} n_{1ir}(t) = \delta_r \left[Pr_{ir1}(t) \left(MP_{1i} - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=0}^{t_k-1} n_{11ij}(t) \right) - \sum_{i=1}^{I} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{1ir}(t) \right] \Bigg[p_2 \\ + q_2 \frac{\sum_{i=1}^{I} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{1ir}(t)}{Pr_{ir1}(t) \left(MP_{1i} - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=0}^{t_k-1} n_{11ij}(t) \right)} \Bigg] \end{aligned} \tag{5.11}$$

where $n_{1ir}(t)$ is the market demand for the *r*-th remanufactured product in segment *i* for the first market at time *t*; $Pr_{ir1}(t)$ is the probability of choosing the *r*-th remanufactured product at time *t* among the existing and remanufactured product(s) of the company, and the competitive products in segment *i* in the first market; p_2 and q_2 are the innovation and imitation coefficients for the remanufactured product(s), respectively; and δ_r is equal to 1 if the *r*-th remanufactured product is selected, and 0 otherwise.

The dynamic market demand for the remanufactured product(s) in the second market can be developed similarly and expressed as follows:

$$n_{2zr}(t) = \delta_r \left[Pr_{zr2}(t)MP_{2i} - \sum_{z=1}^{Z}\sum_{r=1}^{P}\sum_{t=t_k}^{Tn} n_{2zr}(t) \right] \left[p_2 + q_2 \frac{\sum_{z=1}^{Z}\sum_{r=1}^{P}\sum_{t=t_k}^{Tn} n_{2zr}(t)}{Pr_{zr2}(t)MP_{2z}} \right] \quad (5.12)$$

where $n_{2zr}(t)$ is the market demand for the *r*-th remanufactured product in segment *z* for the second market at time *t*; $Pr_{zr2}(t)$ is the probability of choosing the *r*-th remanufactured product at time *t* among the remanufactured product(s) of the company and the competitive products in segment *z* in the second market; and MP_{2z} is the estimated market potential of segment *z* in the second market.

5.1.3 Development of cost models

The cost model for new product variants is developed based on simulation optimization (SIMOPT) models (Green and Kriger, 1992; Kwong *et al.*, 2011), which estimate the part-worth cost for each level of product attribute. Two cost components are involved: fix cost (c_p^{fix}) and variable cost (c_p^{var}). Fixed cost is the cost element not affected by or not sensitive to the profiles of product variants, such as project setup cost and administrative cost. Variable cost is defined as the cost element affected by the level setting of product attributes, which can be expressed as follows:

$$c_p^{var} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} x_{pkl} c_{pkl} \tag{5.13}$$

$$\sum_{l=1}^{L_k} x_{pkl} = 1 \tag{5.14}$$

where x_{pkl} is the binary variable and is equal to 1 if the *p*-th new product has the *l*-th level of the *k*-th attribute, and otherwise equals 0; c_{pkl} is the cost assigned to the *l*-th level of the *k*-th attribute of the *p*-th new product; and Eq. (5.14) ensures that only one level from each product attribute is chosen.

The cost of producing remanufactured products mainly consists of take-back cost, remanufacturing cost, and the cost of component change. Take-back cost refers to the sum of the average costs of collecting used products from customers and the transportation cost. Remanufacturing cost is the sum of the average costs of disassembling, inspecting, reconditioning, cleaning, assembling some modules and/or components of reused products, and testing the reused products. Cost of component change refers to the cost associated with the change of components because of product downgrade or upgrade, as well as the replacement of unsatisfactory components with new ones.

5.1.4 Formulation of multi-objective optimization model

The multi-objective optimization problem is formulated to determine the setting of the following decision variables:

- Number of remanufactured and new products
- Product attribute settings of the remanufactured and new products
- Prices of the remanufactured and new products
- Time of launching remanufactured products

The objectives of maximizing profits and maximizing market share are considered in this study because these are the prime objectives of most companies in their product design (Jiao *et al.*, 2007). Thus, the optimization problem is a multi-objective one that can deal with a number of objectives to be optimized simultaneously. Other objectives, such as minimizing development time and minimizing product cost, can be added without substantial modification of the model.

The first objective function aims to maximize the total market share of the product line, which is formulated by dividing the sum of the total demand for the new product(s) during the first and second periods, and the total demand for the remanufactured product(s) in the first and second markets by the sum of the market potential of individual segments of the first and second markets. The second objective function aims to maximize the profit of the product line. The unit profit of the *p*-th new product at time *t* can be estimated by subtracting the total cost of the *p*-th new product (c_p^{tot}) from the price of the corresponding new product at time *t* (p_p^t). Thus, the total profit of the new products at time *t* can be estimated by multiplying the market demand for the new products at time *t* and the unit profit of the corresponding new product at time *t*. The unit profit of the *r*-th remanufactured product at time *t* can be estimated by subtracting the total cost of the *r*-th remanufactured product (c_r^{tot}) from the price of the corresponding remanufactured product at time *t* (p_r^t). The total profit of the remanufactured products at time *t* can be estimated by multiplying the market demand for the remanufactured products at time *t* and the unit profit of the corresponding remanufactured product at time *t*. Hence, the second objective function for maximizing the profit of the product line (*x*) can be formulated as follows:

$$x = \left(\sum_{i=1}^{I} \sum_{p=1}^{P} \left(\sum_{t=0}^{t_k - 1} n_{11ip}(t) \left(p_p^t - c_p^{tot}\right) + \sum_{t=t_k}^{Tn} n_{21ip}(t) \left(p_p^t - c_p^{tot}\right) \right) \right)$$

$$+ \left(\sum_{i=1}^{I} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{1ir}(t) \left(p_r^t - c_r^{tot}\right) \right.$$

$$\left. + \sum_{z=1}^{Z} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{2zr}(t) \left(p_r^t - c_r^{tot}\right) \right) \quad (5.15)$$

In addition, the following constraints are required in the formulation of the optimization model:

$$t_k^{low} \leq t_k \leq t_k^{up} \quad (5.16)$$

$$\gamma\phi \left(\sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{t_k - 1} n_{11ip}(t) + \sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=t_k}^{Tn} n_{21ip}(t) \right)$$

$$\geq \sum_{i=1}^{I} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{1ir}(t) + \sum_{z=1}^{Z} \sum_{r=1}^{R} \sum_{t=t_k}^{Tn} n_{2zr}(t) \quad (5.17)$$

$$p_{p,low}^0 \leq p_p^0 \leq p_{p,up}^0 \quad (5.18)$$

$$p_{r,low}^{t_k} \leq p_r^{t_k} \leq p_{r,up}^{t_k} \quad (5.19)$$

Eq. (5.16) is a period of time, in which remanufactured product(s) are launched in the markets. Eq. (5.17) ensures that the total demand for the remanufactured product(s) in the second period is less than the volume of collected products in the first and second periods that can be used for remanufacturing, where γ is the collection rate, and ϕ is the passing rate of collected products for remanufacture. Eq. (5.18) is the range of the initial prices of new product(s), and Eq. (5.19) is the range of the initial prices of remanufactured product(s).

5.1.5 Solving the optimization model using NSGA-II

To solve multi-objective optimization problems, evolutionary algorithms, such as multi-objective optimization GA (Fonseca and Fleming, 1993), Pareto-archived evolution strategy (PAES) (Knowles and Come, 2000), strength-Pareto evolutionary algorithm (SPEA) (Zitzler and Thiele, 1999), and NSGA-II (Deb *et al.*, 2002), were commonly employed in previous studies. NSGA-II adopts a fast non-dominated sorting approach and crowded comparison without any need for user-defined parameters. This algorithm was shown to provide better diversified solution sets than PAES and SPEA (Deb *et al.*, 2002). NSGA-II is highly capable of reducing computational complexity and providing a fast and effective constraint-handling strategy, which makes it one of the most efficient algorithms to solve multi-objective optimization problems (Murugan *et al.*, 2009). The computational complexity is reduced by adopting fast non-dominated sorting for fitness assignment. The quality of solutions and performance of the GA have been improved using elitism preservation strategy. Diversity ensuring mechanism has been enhanced by eliminating the parameter need (Deb *et al.*, 2002). NSGA-II has been successfully applied to solve various multi-objective optimization problems, such as PLD (Kwong *et al.*, 2011), integrated PLD and supplier selection (Deng *et al.*, 2014), and product platform design (Wei *et al.*, 2009). In this study, the NSGA-II is introduced to solve the formulated multi-objective optimization problem. A flowchart of NSGA-II is shown in Appendix A.

Figure 5.3 shows the chromosome design of decision variables for this study. The variables include the time of launching remanufactured products (t_k), binary variable for the state of the *p*-th new product (α_p), product attribute settings of the *p*-th new product (x_{pkl}), initial price of the *p*-th new product (p_p^0), binary variable for the state of the *r*-th remanufactured product (δ_r), product attribute settings of the *r*-th remanufactured products (x_{rkl}), and initial price of the *r*-th remanufactured product ($p_r^{t_k}$).

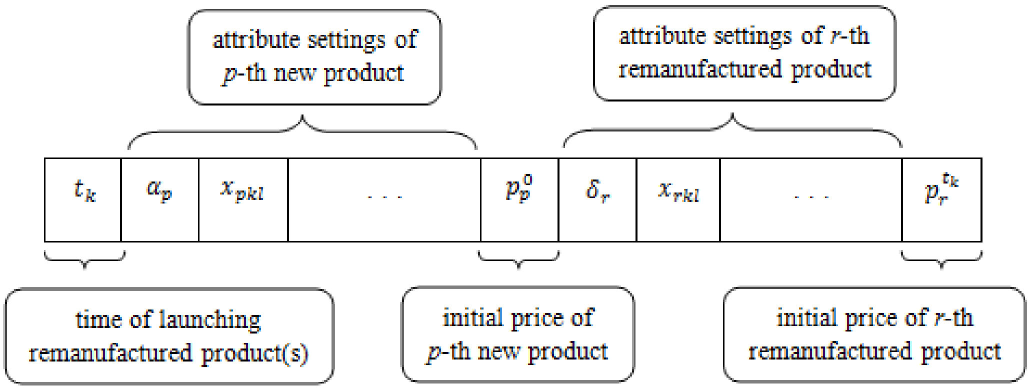


Figure 5.3 Chromosome design of decision variables

Rank and crowded distance are used as a binary tournament selection process to select parent chromosomes for the mating pool in NSGA-II. The size of the mating pool is commonly equal to one half of the population size. Once adequate parents are selected for the mating pool, crossover and mutation operations are performed to generate the child chromosomes. Real-coded GA, which uses simulated binary crossover (SBX) and polynomial mutation (Deb and Agarwal, 1995), is adopted in this study. Crossover refers to the exchange of genes between randomly selected parent chromosomes from the mating pool, in which excellent fitness value chromosomes can possibly be generated. The crossover probability, pc, is set as 0.9. Mutation refers to the change in value of randomly selected genes to search for a better fitness value for each population. Mutation probability, pm, is set as 1/n, where n is the number of decision variables (66 in this study). While two child chromosomes are generated through crossover, only one child is generated through mutation. When both crossover and mutation operations are completed, the fitness values are calculated. The chromosomes with better fitness values are selected for the solution of the population. After the maximum number of generation is reached, NSGA-II operations are terminated.

5.2 Implementation

The proposed methodology was applied to the PLD of tablet PCs. Suppose a computer product manufacturer is planning to develop a product line of tablet PCs that includes remanufactured and new products. Table 5.1 shows eight product attributes and their corresponding levels, which were defined based on the analysis of the existing tablet PCs. The first seven attributes are discrete-value attributes, and the eighth attribute (price) is a continuous-value attribute. The attribute “product condition” is used to measure consumer preferences on new and remanufactured products. To design a conjoint survey, the company defined the levels and their settings for individual attributes.

Table 5.1 Product attributes and attribute levels of tablet PCs

Index	Attributes	Attribute levels
1	Product condition	New/ remanufactured
2	Screen size	7/10 in
3	Hard disk	16/32/64 GB
4	Memory (RAM)	512 MB/1 GB/2 GB
5	CPU (Processor)	1/1.4/1.6 GHz
6	Screen resolution	1024×768/1280×800/2048×1536
7	Connectivity	Wi-Fi/Wi-Fi + 3G/Wi-Fi + 4G
8	Price	250/450/700 USD

Table 5.2 shows a part of the survey questionnaire in which 18 product profiles are indicated. Consumers from the first and second markets were invited to assess 18

product profiles by filling out the survey questionnaires using the scales “1” to “5”, which denoted the linguistic descriptors, “very bad,” “bad,” “moderate,” “good,” and “very good,” respectively.

Table 5.2 Survey questionnaire for tablet PCs

Profiles	Product Condition	Screen Size	Hard Disk	RAM	Dual CPU	Screen Resolution	Connectivity	Price (USD)	Rate (1–5)
1	New	7 in	16 GB	512 MB	1 GHz	1024 × 768	Wi-Fi	250	
2	New	7 in	32 GB	1 GB	1.4 GHz	1280 × 800	Wi-Fi + 3G	450	
3	New	7 in	64 GB	2 GB	1.6 GHz	2048 × 1536	Wi-Fi + 4G	700	
4	New	10 in	16 GB	512 MB	1.4 GHz	1280 × 800	Wi-Fi + 4G	700	
5	New	10 in	32 GB	1 GB	1.6 GHz	2048 × 1536	Wi-Fi	250	
6	New	10 in	64 GB	2 GB	1 GHz	1024 × 768	Wi-Fi + 3G	450	
7	New	7 in	16 GB	1 GB	1 GHz	2048 × 1536	Wi-Fi + 3G	700	
8	New	7 in	32 GB	2 GB	1.4 GHz	1024 × 768	Wi-Fi + 4G	250	
9	New	7 in	64 GB	512 MB	1.6 GHz	1280 × 800	Wi-Fi	450	
10	Remanufactured	7 in	16 GB	2 GB	1.6 GHz	1280 × 800	Wi-Fi + 3G	250	
11	Remanufactured	7 in	32 GB	512 MB	1 GHz	2048 × 1536	Wi-Fi + 4G	450	
12	Remanufactured	7 in	64 GB	1 GB	1.4 GHz	1024 × 768	Wi-Fi	700	
13	Remanufactured	10 in	16 GB	1 GB	1.6 GHz	1024 × 768	Wi-Fi + 4G	450	
14	Remanufactured	10 in	32 GB	2 GB	1 GHz	1280 × 800	Wi-Fi	700	
15	Remanufactured	10 in	64 GB	512 MB	1.4 GHz	2048 × 1536	Wi-Fi + 3G	250	
16	Remanufactured	7 in	16 GB	2 GB	1.4 GHz	2048 × 1536	Wi-Fi	450	
17	Remanufactured	7 in	32 GB	512 MB	1.6 GHz	1024 × 768	Wi-Fi + 3G	700	
18	Remanufactured	7 in	64 GB	1 GB	1 GHz	1280 × 800	Wi-Fi + 4G	250	

Once the survey data were collected from the first and second markets, the K-means clustering technique based on SPSS software package was employed to identify consumer segments for individual markets. In this case study, three segments were identified for the first market, and two segments were identified for the second market. Then, a dummy variable regression method was used to generate the utility functions. Table 5.3 shows the dummy variables and coded product profiles for this case study.

Table 5.3 Coded product profiles with dummy variables.

Profile	x_1	x_2	x_{31}	x_{32}	x_{41}	x_{42}	x_{51}	x_{52}	x_{61}	x_{62}	x_{71}	x_{72}	x_{81}	x_{82}
1	1	0	1	0	1	0	1	0	1	0	1	0	1	0
2	1	0	0	1	0	1	0	1	0	1	0	1	0	1
3	1	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	1	0	1	0	0	1	0	1	0	0	0	0
5	1	1	0	1	0	1	0	0	0	0	1	0	1	0
6	1	1	0	0	0	0	1	0	1	0	0	1	0	1
7	1	0	1	0	0	1	1	0	0	0	0	1	0	0
8	1	0	0	1	0	0	0	1	1	0	0	0	1	0
9	1	0	0	0	1	0	0	0	0	1	1	0	0	1
10	0	0	1	0	0	0	0	0	0	1	0	1	1	0
11	0	0	0	1	1	0	1	0	0	0	0	0	0	1
12	0	0	0	0	0	1	0	1	1	0	1	0	0	0
13	0	1	1	0	0	1	0	0	1	0	0	0	0	1
14	0	1	0	1	0	0	1	0	0	1	1	0	0	0
15	0	1	0	0	1	0	0	1	0	0	0	1	1	0
16	0	0	1	0	0	0	0	1	0	0	1	0	0	1
17	0	0	0	1	1	0	0	0	1	0	0	1	0	0
18	0	0	0	0	0	1	1	0	0	1	0	0	1	0

Note: x_1 is the dummy variable for product condition; x_2 is the dummy variable for screen size; x_{31} and x_{32} are the dummy variables for hard disk; x_{41} and x_{42} are the dummy variables for RAM; x_{51} and x_{52} are the dummy variables for dual CPU; x_{61} and x_{62} are the dummy variables for screen resolution; x_{71} and x_{72} are the dummy variables for connectivity; and x_{81} and x_{82} are the dummy variables for price.

After the product profiles were coded with the dummy variables, multiple regression analysis was applied to estimate the coefficients of the utility functions for the first and second markets (Table 5.4).

Table 5.4 Coefficients of the utility functions for the first and second markets

Market	Segment	x_1	x_2	x_{31}	x_{32}	x_{41}	x_{42}	x_{51}	x_{52}	x_{61}	x_{62}	x_{71}	x_{72}	x_{81}	x_{82}	Constant
First	1	0.67	0.17	-0.30	-0.09	-0.48	-0.09	-0.10	-0.0	-0.39	-0.40	-0.58	-0.17	0.99	0.66	3.07
	2	0.48	-0.26	-0.19	-0.53	-0.33	-0.31	-0.03	0.39	-0.44	-0.19	-1.08	-0.31	-0.25	-0.22	3.44
	3	0.48	0.07	-0.43	-0.14	-0.62	-0.13	-0.44	0.01	-0.29	-0.18	-0.14	-0.07	2.13	1.01	2.21
Second	1	-0.3	0.45	0	0.02	-1.05	0	0.21	0.02	-0.14	-0.40	-0.40	-0.21	0.38	0.43	3.63
	2	-0.3	0.10	-0.11	0.13	-0.21	-0.32	-0.08	-0.1	-0.13	0.01	-0.64	-0.10	1.33	0.64	3.08

A curve-fitting method was applied using the estimated coefficients of x_{81} and x_{82} to generate the utility functions for the continuous-value prices for each segment of the corresponding market and estimate the utility of continuous-value prices. The results are shown as follows:

$$f_{1pt}^{price} = 1.16 - 1.1 \times 10^{-4} p_p^t - 2.2 \times 10^{-6} \left(p_p^t\right)^2$$

$$f_{2pt}^{price} = -0.11 - 9.8 \times 10^{-4} p_p^t + 1.62 \times 10^{-6} \left(p_p^t\right)^2$$

$$f_{3pt}^{price} = 3.92 - 8 \times 10^{-3} p_p^t + 3.47 \times 10^{-6} \left(p_p^t\right)^2$$

$$f_{1rt}^{price} = -0.18 + 3.3 \times 10^{-3} p_r^t - 4.4 \times 10^{-6} (p_r^t)^2$$

$$f_{2rt}^{price} = 2.42 - 4.8 \times 10^{-3} p_r^t + 1.98 \times 10^{-6} (p_r^t)^2$$

where f_{mpt}^{price} is the utility function of price for the *p*-th new product in segment *m* at time *t* and *m* is equal to 1, 2 and 3; and f_{nrt}^{price} is the utility function of price for the *r*-th remanufactured product in segment *n* at time *t* and *n* is equal to 1 and 2.

In this case study, five major competitive tablet PCs in the first market and seven major competitive tablet PCs in the second market were identified. The specifications and prices of these tablet PCs can be found in Tables B.1 and B.2 of Appendix B respectively. The market potentials of individual segments for the first and second markets were estimated by marketing personnel as shown in Table 5.5.

Table 5.5 Market potentials for the first and second markets

Segment	Market potential for the first market	Market potential for the second market
1	50 000	8 000
2	20 000	12 000
3	30 000	N/A
Total	100 000	20 000

The time of launching the remanufactured tablet PCs in markets is considered between the 13th and 24th month after launching the new product(s).

5.2.1 Results

The formulated multi-objective optimization problem with the objectives of maximizing total profit and maximizing total market share of a product line was coded using Matlab software and solved using the NSGA-II algorithm. The population size of the NSGA-II was set to 100, and the maximum number of generation was set to 500. Owing to the heuristic nature of NSGA-II, the developed Matlab program was run dozens of times to obtain the average numerical results. Figure 5.4 shows the Pareto front of the multi-objective optimization problem for PLD of tablet PCs. In the multi-objective design optimization, decision making is required to select the final solution among a set of optimum solutions on the Pareto frontier. A number of decision-making techniques can be applied to determine the final optimal solution, such as Shannon Entropy and TOPSIS methods (Liu, 2014). However, in a real-world setting, different companies may have different competitive strategies and business objectives for their new product development projects. For example, company A may wish to develop a new product line with the prime objective of maximizing its profit, whereas company B may aim to develop a new product line to achieve at least 10% growth of profit in comparison with the profit gained from an existing product line and maximize its share in particular markets. Thus, the final optimum solution obtained based on the decision-making techniques may not be the most desirable one for the companies. In this study, companies are required to perform a tradeoff among various objectives and select the most preferable one with reference to their business objectives and competitive strategies.

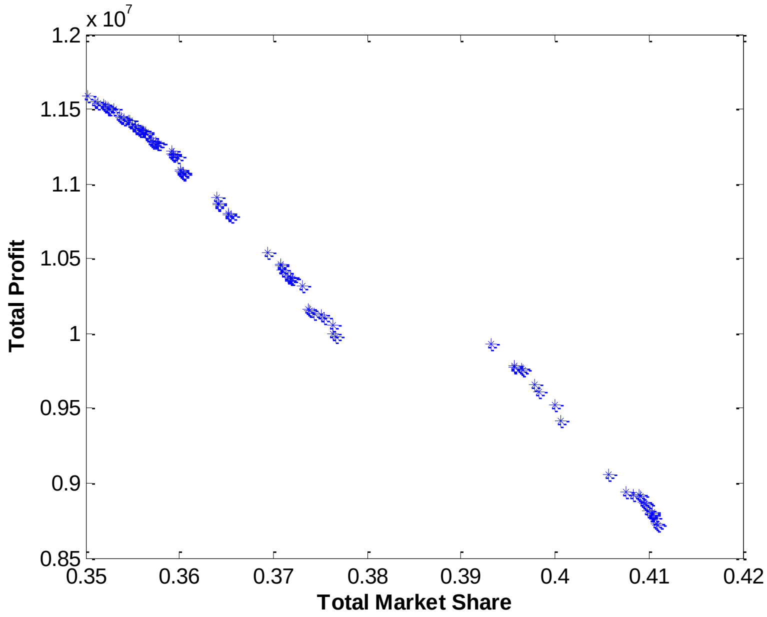


Figure 5.4 Pareto solutions

In Figure 5.4, a gap can be noted between the market share values 0.378 and 0.392. This gap may be attributed to the dramatic changes during the launching of remanufactured products. Figures 5.5 and 5.6 show the respective changes of fitness values of the first and second objective functions over 500 generations.

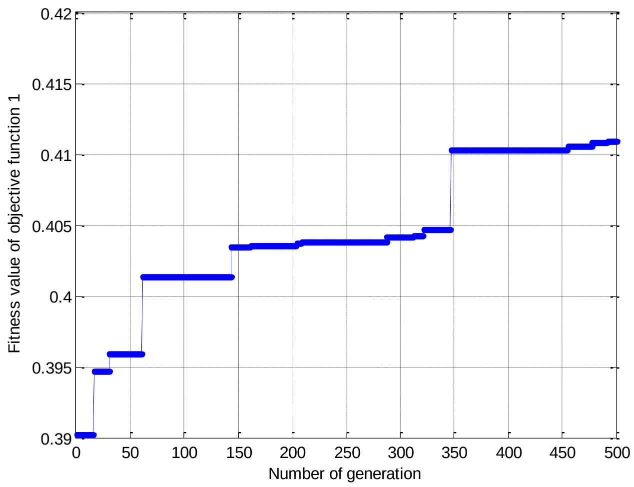


Figure 5.5 Change of fitness values of objective function 1

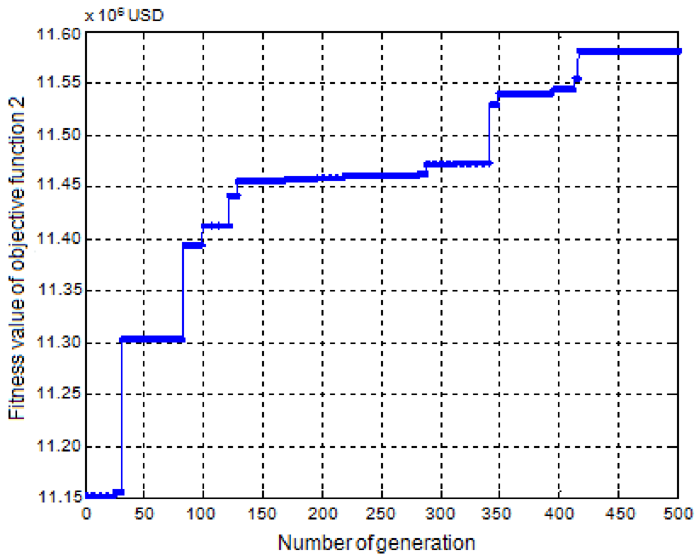


Figure 5.6 Change of fitness values of objective function 2

For illustrative purpose, we present the product line solutions under two scenarios, namely, maximum profit and maximum market share, in the proceeding sub-sections.

5.2.1.1 Maximum profit scenario

Table 5.6 shows a product line solution that leads to the maximum profit of the product line. The product line contains three new products and one remanufactured product. The estimated maximum profit and total market share of the product line are USD 11.58×10^6 and 35.03%, respectively. The suggested time of launching the remanufactured product is on the 22nd month.

Table 5.6 Product line solution for the maximum profit scenario

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)
New Product 1	10 in	32 GB	2 GB	1.4 GHz	1024×768	Wi-Fi	473
New Product 2	10 in	64 GB	2 GB	1.4 GHz	2048×1536	Wi-Fi + 4G	707
New Product 3	7 in	64 GB	2 GB	1 GHz	1024×768	Wi-Fi + 3G	532
Remanufactured Product 1	10 in	32 GB	1 GB	1.4 GHz	1024×768	Wi-Fi + 4G	403

Figure 5.7 shows the demands for the three new products. It can be noted that the demands for new products dropped a little on the 22nd month because of the launch of the remanufactured product in the markets. Although the price of New Product 2 is higher, its estimated demand is much higher than those of New Products 1 and 3 because design specification of New Product 2 is better compared with those of New Products 1 and 3. Figure 5.8 shows the demands for the remanufactured products during the period from the 22nd to the 36th month. It can be noted that the demand for remanufactured products is much higher in the second market than that in the first market.

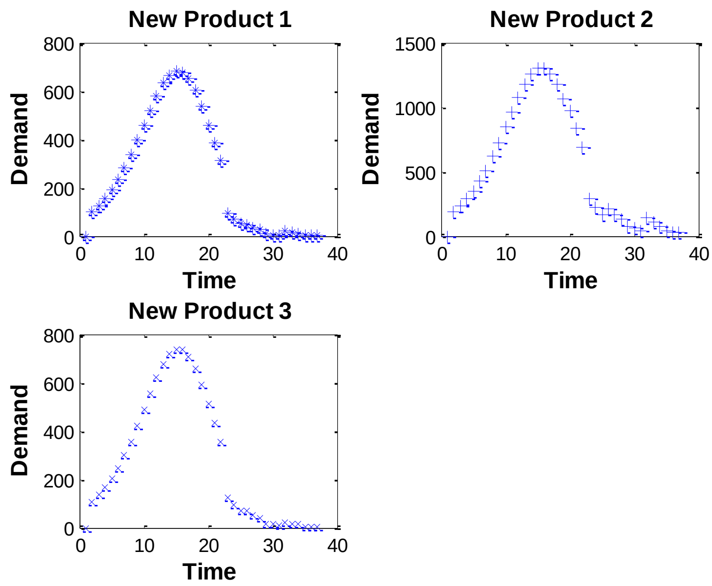


Figure 5.7 Demands for new products for the maximum profit scenario

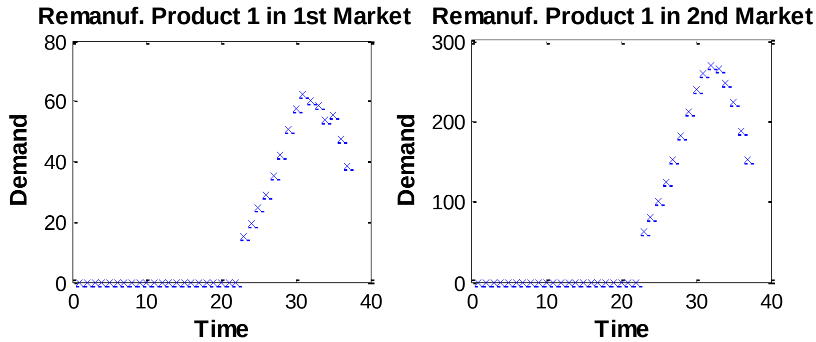


Figure 5.8 Demands for remanufactured products for the maximum profit scenario

5.2.1.2 Maximum market share scenario

Table 5.7 shows the product line solution that leads to the maximum market share of the product line. The product line contains three new products and two remanufactured products. The total market share and profit of the product line are

41.09% and USD 8.72×10^{6}, respectively. The suggested time of launching the remanufactured products is on the 14th month.

Table 5.7 Product line solution for the maximum market share scenario

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)
New Product 1	7 in	16 GB	2 GB	1.6 GHz	2048×1536	Wi-Fi + 3G	698
New Product 2	7 in	32 GB	2 GB	1.4 GHz	1024×768	Wi-Fi + 3G	323
New Product 3	10 in	32 GB	1 GB	1 GHz	2048×1536	Wi-Fi + 3G	547
Remanufactured Product 1	10 in	32 GB	1 GB	1.4 GHz	1024×768	Wi-Fi + 4G	307
Remanufactured Product 2	10 in	32 GB	512 MB	1 GHz	1024×768	Wi-Fi + 3G	203

Figures 5.9 and 5.10 show the demands for new and remanufactured products for the maximum market share scenario, respectively. It can be noted that the demands for new products under the maximum market share scenario are quite close to those under the maximum profit scenario. However, the demands for remanufactured products under the maximum market share scenario are much higher than those for remanufactured products under the maximum profit scenario, especially in the first market. It is because the prices of remanufactured products under the maximum market share scenario are lower than those under the maximum

profit scenario.

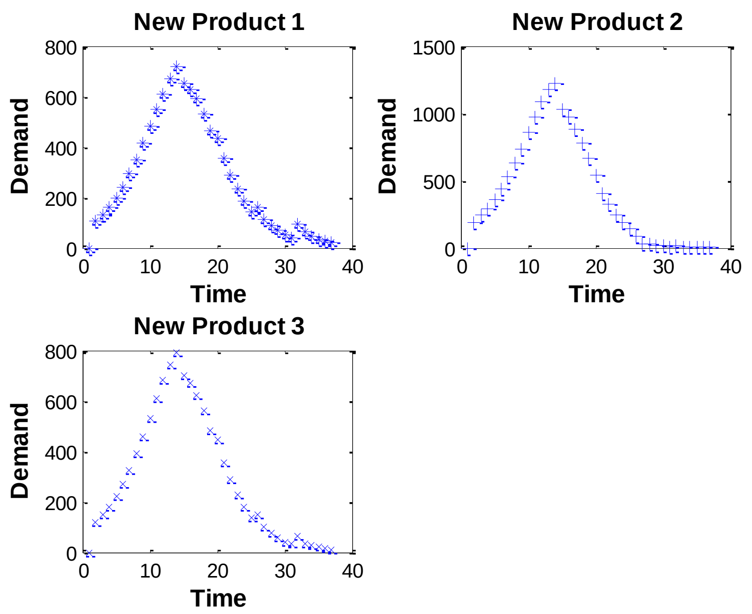


Figure 5.9 Demands for new products for the maximum market share scenario

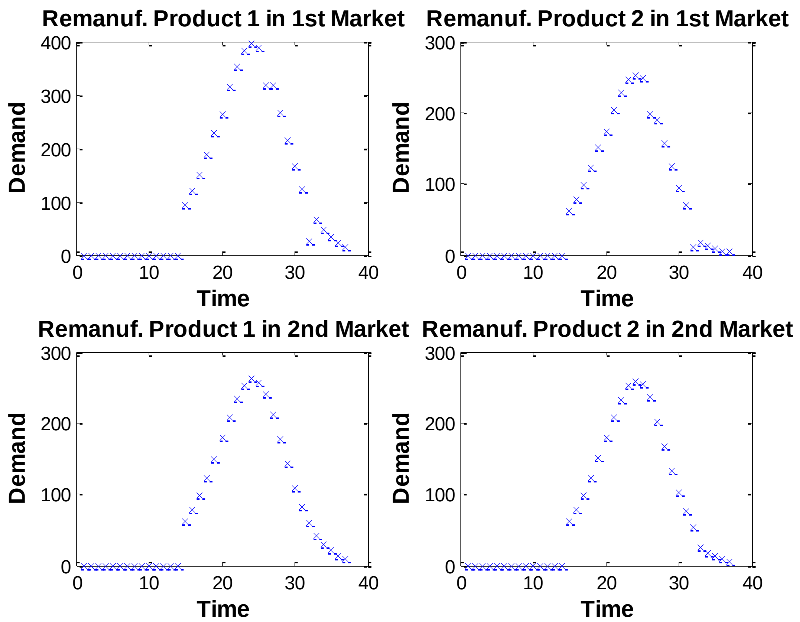


Figure 5.10 Demands for remanufactured products for the maximum market share scenario

5.3 Validation

To evaluate the effectiveness of the proposed approach, the PLD of tablet PCs was conducted based on the current method, where new and remanufactured products were considered separately in PLD. The results generated based on the current method were compared with those generated based on the proposed approach. In the current method, a product line of new products is determined first. Then, another product line of remanufactured products is generated some time later after the launch of the new products, and the time of launching the remanufactured products in the markets is commonly determined based on the judgment of marketing personnel. In this validation, the PLD for the maximum profit scenario was adopted for the comparison of the results. First, a product line solution for new products only, which leads to the maximum profit of the product line, was determined for the first market using the same survey and competitive product data sets. For the PLD for remanufactured products, another optimization model was formulated and then solved to determine an optimal product line solution that only contains remanufactured products. The two optimization models formulated for the new and remanufactured products were solved using NSGA-II with the same parameter settings adopted in Section 5.2. Tables 5.8 and 5.9 show the two product line solutions respectively for the new products and remanufactured products based on the current methodology for the maximum profit scenario.

Table 5.8 Product line solution for new products based on the current method

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)

New Product 1	10 in	32 GB	2 GB	1.6 GHz	1280×800	Wi-Fi	492
New Product 2	10 in	32 GB	2 GB	1.4 GHz	2048×1536	Wi-Fi + 3G	686
New Product 3	7 in	16 GB	1 GB	1.6 GHz	1280×800	Wi-Fi + 3G	580

Table 5.9 Product line solution for remanufactured products based on the current method

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)
Remanufactured Product 1	10 in	32 GB	2 GB	1.4 GHz	2048×1536	Wi-Fi + 3G	452
Remanufactured Product 2	7 in	16 GB	1 GB	1.6 GHz	1280×800	Wi-Fi + 3G	387

The total profit and total market share of the two product line solutions generated based on the current method are estimated as USD 10.63×10^6 and 30.84%, respectively. Figures 5.11 and 5.12 show the respective demands for the new and remanufactured products based on the current method. Section 5.2.1.1 reveals that the total profit and total market share of the product line based on the proposed approach are 9% and 13.5% respectively, higher than those based on the current method. Although the demands for remanufactured products obtained based on the current method are higher than those obtained based on the proposed methodology under the maximum profit scenario, the total demands for products obtained based on the current method are substantially lower (13.5%) than those obtained based on the proposed methodology under the maximum profit scenario.

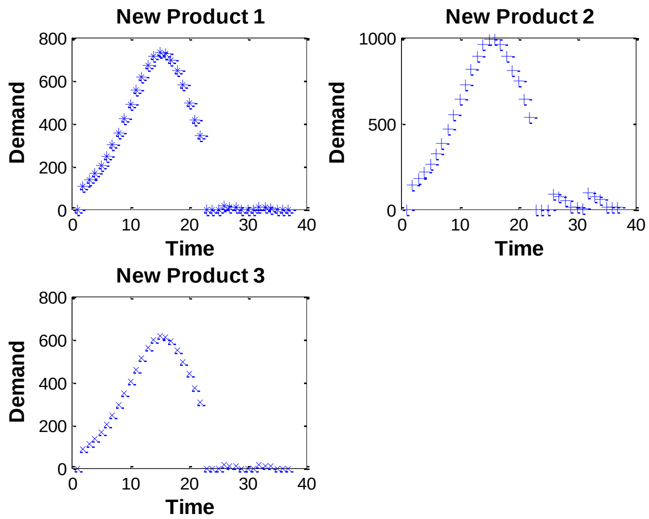


Figure 5.11 Demands for new products based on the current method

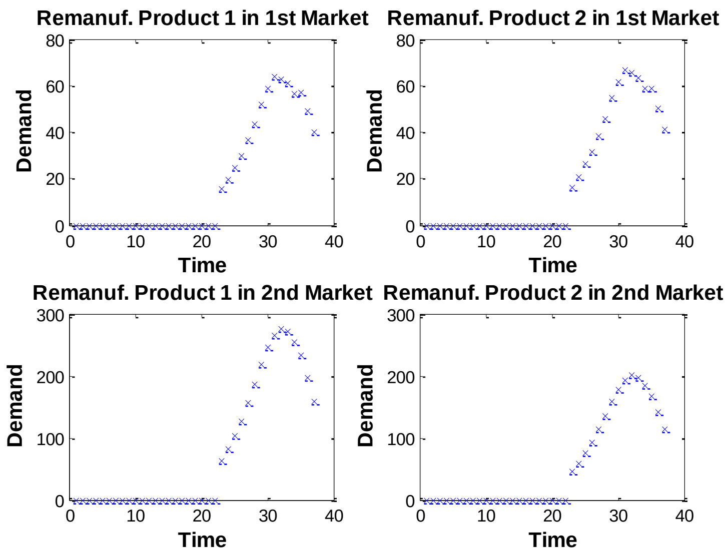


Figure 5.12 Demands for remanufactured products based on the current method

5.4 Summary

In this chapter, a methodology for simultaneous consideration of new and remanufactured products in optimal PLD is described. The methodology mainly involves the development of dynamic demand models, discrete choice analysis, formulation of a multi-objective optimization model, and generation of Pareto optimal solutions using NSGA-II. Various issues, including consumer preferences, product design attributes, change of product price over time, and cannibalization effect of remanufactured products on the sales of new products, are considered in the development of the dynamic market demands. Two common objectives of PLD, maximizing profit and market share, are considered in this research, and the tradeoff between the two objectives is realized by using a multi-objective optimization paradigm. In this research, Pareto optimal solutions are generated by solving the optimization model using NSGA-II. The solutions contain design specifications and prices of both new and remanufactured products, estimated total profits and market share of the product line and the time of launching remanufactured products in the markets. A case study on the simultaneous consideration of remanufactured and new tablet PCs in PLD was performed to illustrate the applicability of the proposed methodology. A validation test was conducted to evaluate the effectiveness of the proposed methodology in comparison with the current method.

Chapter 6 Coordination of Closed-loop Supply Chain for Product Line Design with Consideration of Remanufactured Products

This chapter first describes a proposed methodology for the coordination of a manufacturer and supply chain partners for PLD with consideration of remanufactured products. Section 6.2 presents a case study on the coordination of a manufacturer, and supply chain partners for the PLD of tablet PCs, which involves remanufactured tablet PCs based on the proposed methodology. Section 6.3 provides a summary of the study.

6.1 Proposed methodology for coordination of a manufacturer and supply chain partners for PLD with consideration of remanufactured products

Figure 6.1 shows the CLSC considered in the development of the proposed methodology. The straight-line and dashed-line arrows indicate the forward and reverse flow of the supply chain, respectively.

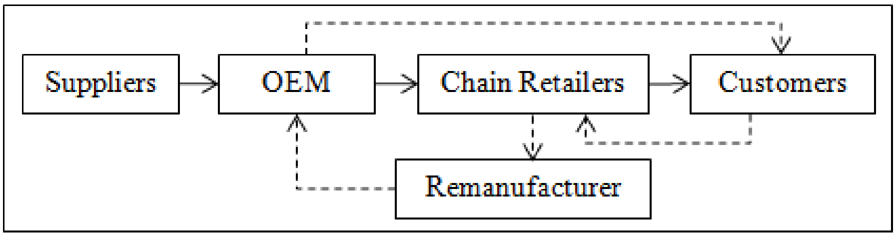


Figure 6.1 Closed-loop supply chain

Two types of markets are considered in this research: the first and second markets. New products are launched only in the first market, whereas remanufactured products are launched only in the second market. New and remanufactured products are launched at different times or in two periods, such that the new and remanufactured products are launched in the first and second periods, respectively. In the first period, new products are produced by the OEM and sold to customers by chain retailers. Used or defective products are collected by chain retailers, who have a closer relationship with customers than do the remanufacturer and OEM. Chain retailers do not gain direct profits from remanufactured products, but they may gain profits through trade-in programs. The returned products are shipped to the remanufacturer, who pays the collect-back and transportation costs. In the second period, the remanufacturer refurbishes the collected products by changing some of their components and reconditioning them. The remanufactured products are then shipped to the OEM and sold in the second market.

A two-period Stackelberg game theoretical model is formulated to determine the setting of the decision variables, including the number of new and remanufactured products to be offered, product attribute settings of the new and remanufactured products, wholesale and retail prices of the new products, wholesale and selling prices of the remanufactured products, and product return rate. Figures 6.2(a) and 6.2(b) show the proposed methodology for the first and second periods, respectively. The proposed methodology mainly involves conjoint analysis, generation of choice models, formulation of Stackelberg game and multi-objective optimization models, and solving the optimization problems using NSGA-II.

In the proposed methodology, conjoint analysis is conducted to obtain customer preferences on products in the first and second markets. Survey respondents are classified into a number of individual segments by using a K-means clustering technique. The utility functions of the individual segments are thereafter generated using statistical regression. The MNL model is used to generate choice models together with the generated utility functions. The market potential is estimated based on the jury of the executive opinion method. Once the choice models are developed and the market potential estimates are obtained, demand models can be developed for both the first and second markets.

The OEM and chain retailers compete for the prices of new products in the first period, as shown in the proposed methodology for the first period shown in Figure 6.2(a). Given that an OEM is usually a focal company in a supply chain, the Stackelberg game theoretical model is adopted and incorporated into the proposed methodology. As the leader, the OEM determines the specifications and wholesale prices of the new products with consideration of the reaction function of the chain retailers. The retail prices of the new products are determined concurrently based on the reaction function of the chain retailers and determined specifications and on the wholesale prices of the new products. Two multi-objective optimization models for the first and second periods need to be formulated. NSGA-II is adopted to solve the optimization models, in which Pareto optimal PLD solutions for the new products, market shares, and profits of the PLD can be obtained.

Figure 6.2(b) outlines the proposed methodology for the second period. In this period, the OEM and remanufacturer compete for the prices of the remanufactured products. The OEM determines the specifications and selling prices of the remanufactured products with consideration of the reaction function of the remanufacturer and the information of the new products. The wholesale prices of the remanufactured products are determined concurrently according to the remanufacturer’s reaction function and determined specifications and to the selling prices of the remanufactured products. The market shares and profits of the product line solution for the remanufactured products can be obtained. The remanufacturer determines the product return rate according to the demand for remanufactured products in the second market and the remanufacturability rate of the returned new products.

Details of the proposed methodology are described in the following sub-sections.

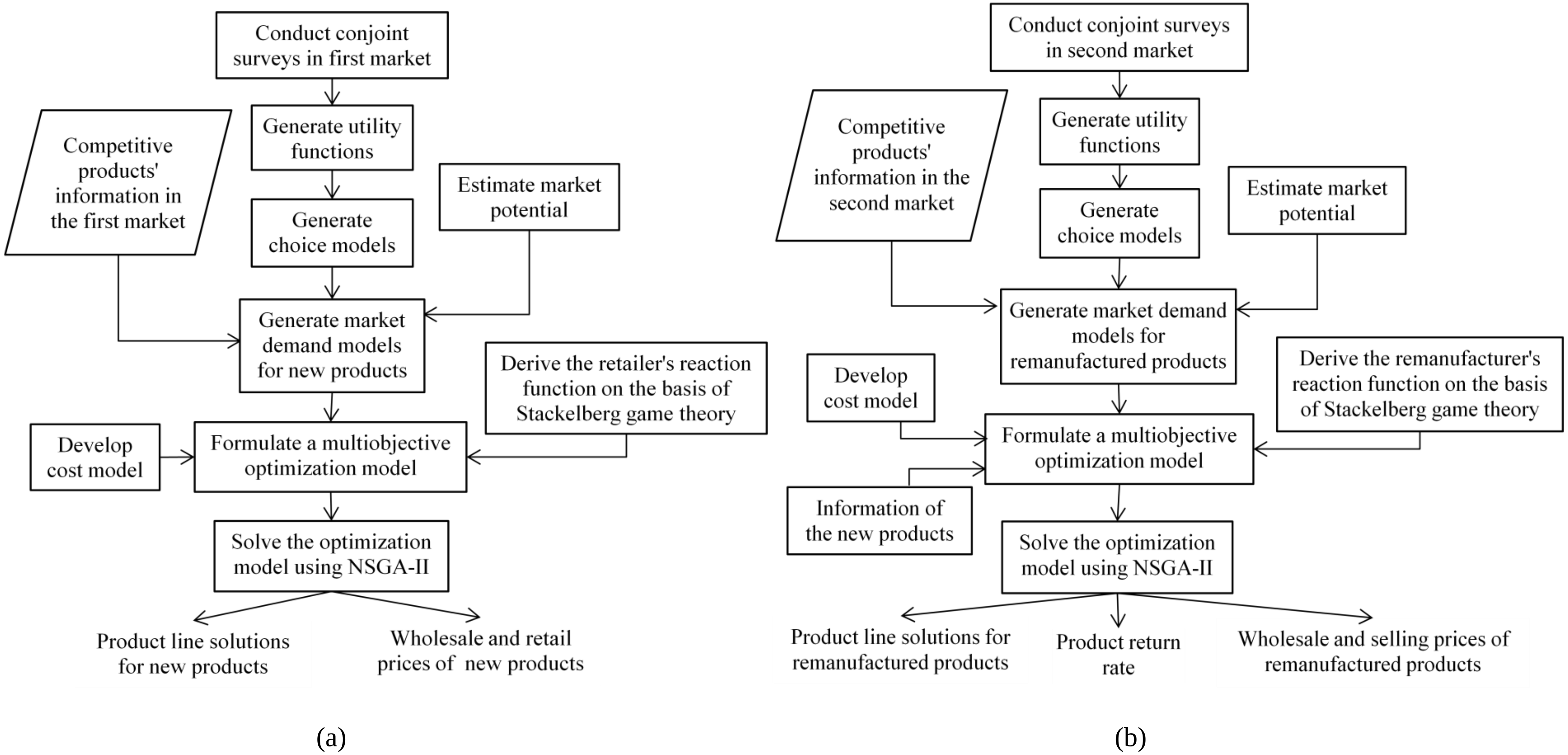


Figure 6.2 Proposed methodology for the (a) first and (b) second periods

6.1.1 Development of market share models

The utility functions of the products are generated using statistical regression based on the conjoint survey data. The processes of the generation are the same as those described in Section 3.1.

In this study, the selling prices of products are defined as continuous variables. A curve-fitting method is introduced to generate the utility functions of the variables. The following shows an example of the utility functions of prices:

$$f_{ij}^{pr} = a_{i0} + a_{i1}p_j + a_{i2}(p_j)^2 \tag{6.1}$$

where f_{ij}^{pr} is the utility of the retail price of the *j*-th product in the *i*-th segment; a_{i0}, a_{i1}, and a_{i2} are the coefficients of the quadratic polynomial function in the *i*-th segment; and p_j represents the price of the *j*-th product.

In this research, market share models are developed based on the MNL model (Eq. 4.14) and the generated utility functions.

6.1.2 Development of cost models

The approach and processes of developing the cost model for new products are the same as those described in Section 5.1.3, where two cost components are involved:

fixed cost (c_p^f) and variable cost (c_p^v). Chain retailers incur two cost components for new product sales: wholesale cost of new products (p_{pw}) and retailing cost (c_p^R). Retailing cost is the sum of the overhead, operation, and marketing costs subjected to chain retailers.

The approach and processes of developing the cost model of producing remanufactured products (c_r^T) are the same as those described in Section 5.1.3, where three cost components are involved: take-back cost (c_r^{tb}), remanufacturing cost (c_r^r), and cost of component change (c_r^{ch}). The OEM has to pay the remanufacturer for remanufactured products and bear other operational costs (c_r^M), such as transportation, holding, overhead, and remarketing costs.

6.1.3 Formulation of a multi-objective optimization model for the first period

The profit functions of both OEM and chain retailers and the reaction function of the chain retailers must first be constituted to formulate a multi-objective optimization model in the first period. The unit profit of the OEM from the *p*-th new product can be estimated by subtracting the total cost of developing the *p*-th new product from the wholesale price of the corresponding new product. The market demand for the

p-th new product in the i-th segment can be estimated by multiplying the market share of the p-th new product in the i-th segment and the market potential of the corresponding segment in the first market. Hence, the profit of the OEM from new product sales can be estimated using Eq. (6.2):

$$\pi_{ip}^{M} = \left[p_{pw} - \left(c_p^f + c_p^v\right)\right] Q_i MS_{ip} \tag{6.2}$$

where π_{ip}^{M} is the profit of the OEM from the p-th new product sales in the i-th segment; p_{pw} is the wholesale price of the p-th new product; Q_i is the estimated market potential of the i-th segment in the first market; and MS_{ip} is the market share of the p-th new product in the i-th segment.

The unit profit of the chain retailers from the p-th new product can be estimated by subtracting the wholesale price of the p-th new product from the retail price of the corresponding new product. The profit of the chain retailers from new product sales in the first period can be formulated as follows:

$$\pi_{ip}^{R} = \left[p_{pr} - p_{pw} - c_p^R\right] Q_i MS_{ip} \tag{6.3}$$

where π_{ip}^{R} is the profit of the chain retailers from the p-th new product sales in the i-th segment, and p_{pr} is the retail price of the p-th new product.

Therefore, the reaction function of the chain retailers, which is the first-order conditions (FOCs) of Eq. (6.3), can be derived as follows:

$$\frac{\partial \pi_{ip}^{R}}{\partial p_{pr}} = \frac{e^{U_{ip}}}{\sum_{j=1}^{J} e^{U_{ij}} + e^{U_{ip}}} + \left(p_{pr} - p_{pw} - c_p^R\right)\left[\frac{e^{U_{ip}}\left(\sum_{j=1}^{J} e^{U_{ij}}\right)\left(a_{i1} + 2a_{i2}p_{pr}\right)}{\left(e^{U_{ip}} + \sum_{j=1}^{J} e^{U_{ij}}\right)^2}\right]$$

$$= 0 \tag{6.4}$$

where U_{ip} is the utility of the p-th product in segment i and U_{ij} is the utility of the j-th competitive product in segment i.

The second derivative of the profit function of the chain retailers can be obtained as follows:

$$\frac{\partial^2 \pi_{ip}^{R}}{\partial {p_{pr}}^2} = \frac{(e^{U_{ip}})(\sum_{j=1}^{J} e^{U_{ij}})\left(a_{i1} + 2a_{i2}p_{pr}\right)}{\left(e^{U_{ip}} + \sum_{j=1}^{J} e^{U_{ij}}\right)^2}$$

$$+ \left[\frac{e^{U_{ip}}\left(\sum_{j=1}^{J} e^{U_{ij}}\right)\left(a_{i1} + 2a_{i2}p_{pr}\right)}{\left(e^{U_{ip}} + \sum_{j=1}^{J} e^{U_{ij}}\right)^2}\right.$$

$$- \left(p_{pr} - p_{pw}\right.$$

$$\left.\left. - c_p^R\right)\left[\frac{(\sum_{j=1}^{J} e^{U_{ij}})(e^{U_{ip}})\left(\left(a_{i1} + 2a_{i2}p_{pr}\right)^2 + 2a_{i2}\right)}{\left(e^{U_{ip}} + \sum_{j=1}^{J} e^{U_{ij}}\right)^4}\right]\right] \tag{6.5}$$

The term $a_{i1} + 2a_{i2}p_{pr}$, which denotes the first derivatives of the utility functions of prices in different markets, must be negative because $e^{U_{ip}}$ and $\sum_{j=1}^{J} e^{U_{ij}}$ are positive terms. We assume that the utility functions of prices are decreasing; hence, the first derivatives of the utility functions of prices are negative. Thus, $\frac{\partial^2 \pi_{ip}^{R}}{\partial {p_{pr}}^2} < 0$, which proves the existence of a Stackelberg equilibrium point in the first period.

The multi-objective optimization problem in the first period is formulated to determine the Pareto optimal PLD solutions of new product(s) by maximizing the total market share and profit of the product line. Decision variables involve the number and specifications of new product(s) and the wholesale and retail prices of new product(s). Two objective functions are involved in the optimization. The first objective function is maximizing the total market share of the product line in the first period (Obj_1^1), which is formulated by dividing the sum of the total demand for new product(s) by the sum of the market potential of individual segments of the first market. The following equation gives the first objective function:

$$\mathrm{Obj}_1^1 = \frac{\sum_{i=1}^{I} \sum_{p=1}^{P} Q_i MS_{ip}}{\sum_{i=1}^{I} Q_i} \tag{6.6}$$

The second objective function is maximizing the total profit of the OEM from the new products (Obj_2^1), as shown in Eq. (6.7), which can be estimated by summing the profits of the OEM from new product(s) in individual segments of the first market.

$$\mathrm{Obj}_2^1 = \sum_{i=1}^{I} \sum_{p=1}^{P} \pi_{ip}^{M} \tag{6.7}$$

6.1.4 Formulation of a multi-objective optimization model for the second period

The profit functions of both OEM and remanufacturer and the reaction function of the remanufacturer need to be constituted first in order to formulate a multi-objective optimization model for the second period. The unit profit of the OEM from the *r*-th remanufactured product can be estimated by subtracting the wholesale price of the *r*-th remanufactured product from its selling price. The market demand for the *r*-th remanufactured product in the *z*-th segment can be estimated by multiplying the market share of the *r*-th remanufactured product in the *z*-th segment with the market potential of the corresponding segment in the second market. Hence, the profit of the OEM from the remanufactured products in the second period can be estimated using Eq. (6.8):

$$\pi_{zr}^{M} = [p_{rs} - p_{rw} - c_{r}^{M}]Q_{z}MS_{zr} \tag{6.8}$$

where π_{zr}^{M} is the profit of the OEM from the *r*-th remanufactured product in the *z*-th segment; p_{rs} is the selling price of the *r*-th remanufactured product determined by the OEM; p_{rw} is the wholesale price of the *r*-th remanufactured product determined by the remanufacturer; Q_z is the market potential of the remanufactured products in the *z*-th segment; and MS_{zr} is the market share of the *r*-th remanufactured product in the z-th segment.

The unit profit of the remanufacturer from the r-th remanufactured product can be estimated by subtracting the total cost of developing the r-th remanufactured product from the wholesale price of the corresponding remanufactured product. The profit of the remanufacturer from the remanufactured products can be estimated using Eq. (6.9):

$$\pi_{zr}^{R} = [p_{rw} - (c_r^{tb} + c_r^{r} + c_r^{ch})]Q_z MS_{zr} \tag{6.9}$$

where π_{zr}^{R} is the profit of the remanufacturer from the r-th remanufactured product in the z-th segment.

Therefore, the reaction function of the remanufacturer, FOCs of Eq. (6.9), can be derived as follows:

$$\frac{\partial \pi_{zr}^{R}}{\partial p_{rw}} = \frac{e^{U_{zr}}}{\sum_{j=1}^{J} e^{U_{zj}} + e^{U_{zr}}} + [p_{rw} - c_r^{T}]\left[\frac{e^{U_{zr}}\left(\sum_{j=1}^{J} e^{U_{zj}}\right)(a_{z1} + 2a_{z2}p_{rw})}{\left(e^{U_{zr}} + \sum_{j=1}^{J} e^{U_{zj}}\right)^2}\right]$$

$$= 0 \tag{6.10}$$

where U_{zr} is the utility of the r-th remanufactured product in segment z; U_{zj} is the utility of the j-th competitive product in segment z; and a_{z1} and a_{z2} are the coefficients of the utility functions of price in the z-th segment.

The second derivative of the profit function of the remanufacturer can be obtained as follows:

$$\frac{\partial^2 \pi_{zr}^R}{\partial {p_{rw}}^2} = \frac{(e^{U_{zr}})(\sum_{j=1}^{J} e^{U_{zj}})(a_{z1} + 2a_{z2}p_{rw})}{\left(e^{U_{zr}} + \sum_{j=1}^{J} e^{U_{zj}}\right)^2} + \left[\frac{e^{U_{zr}}\left(\sum_{j=1}^{J} e^{U_{zj}}\right)(a_{z1} + 2a_{z2}p_{rw})}{\left(e^{U_{zr}} + \sum_{j=1}^{J} e^{U_{zj}}\right)^2} - (p_{rw} - c_r^T)\left[\frac{\left(\sum_{j=1}^{J} e^{U_{zj}}\right)(e^{U_{zr}})((a_{z1} + 2a_{z2}p_{rw})^2 + 2a_{z2})}{\left(e^{U_{zr}} + \sum_{j=1}^{J} e^{U_{zj}}\right)^4}\right]\right] \quad (6.11)$$

The term $a_{z1} + 2a_{z2}p_{rw}$, denotes the first derivatives of the utility functions of prices in different markets. We assume that the utility functions of prices are decreasing. Hence, the first derivatives of the utility functions of prices are negative. Thus, we obtain $\frac{\partial^2 \pi_{zr}^R}{\partial {p_{rw}}^2} < 0$, which indicates the existence of a Stackelberg equilibrium point in the second period.

Two objective functions are involved in the formulation of the multi-objective optimization model. The first objective function aims to maximize the total market share of the product line in the second period (Obj_1^2), which is formulated as follows:

$$\mathrm{Obj}_1^2 = \frac{\sum_{z=1}^{Z} \sum_{r=1}^{R} Q_z MS_{zr}}{\sum_{z=1}^{Z} Q_z} \quad (6.12)$$

The second objective function aims to maximize the total profit of the OEM obtained from the remanufactured products (Obj_2^2), which can be expressed as follows:

$$\mathrm{Obj}_2^2 = \sum_{z=1}^{Z}\sum_{r=1}^{R}\pi_{zr}^{M} \tag{6.13}$$

In addition, the following constraint is required to ensure that the total demand for the remanufactured product(s) in the second period is less than the volume of the collected products that can be remanufactured in the first periods.

$$\sum_{z=1}^{Z}\sum_{r=1}^{R} Q_{\mathrm{z}} MS_{zr} \ \leq \delta_r \phi_r \sum_{i=1}^{I}\sum_{p=1}^{P} Q_i MS_{ip} \tag{6.14}$$

where δ_r is the product return rate and ϕ_r is the remanufacturability rate.

After solving the optimization model using NSGA-II, the Pareto optimal PLD solutions of the remanufactured product(s) can be obtained. The solutions include the number and specifications of the remanufactured product(s), wholesale and selling prices of the remanufactured product(s), and product return rate.

6.2 Implementation

The proposed approach was applied to the PLD of tablet PCs, which includes both remanufactured and new products, and the CLSC, which involves a manufacturer, chain retailers, and remanufacturer. A conjoint survey was conducted to reveal the consumer preferences on tablet PCs based on the defined attributes and attribute levels shown in Table 5.1 in Section 5.1. Once the survey data were collected from the first and second markets, a K-means clustering technique based on the SPSS software package was employed to identify the consumer segments for individual markets. In this case study, three segments were identified for the first market, and two segments for the second market. A dummy variable regression method was used to generate the utility functions in this research. After the product profiles were coded with the dummy variables, multiple regression analysis was conducted to estimate the coefficients of the utility functions for the first and second markets (Table 6.1).

Table 6.1 Coefficients of the utility functions for the first and second markets

Market	Seg.	x_1	x_2	x_{31}	x_{32}	x_{41}	x_{42}	x_{51}	x_{52}	x_{61}	x_{62}	x_{71}	x_{72}	x_{81}	x_{82}	Regr.
First	1	0.67	0.17	-0.30	-0.09	-0.48	-0.09	-0.10	-0.04	-0.39	-0.40	-0.58	-0.17	0.99	0.66	3.07
	2	0.48	-0.26	-0.19	-0.53	-0.33	-0.31	-0.03	0.39	-0.44	-0.19	-1.08	-0.31	0.25	0.12	3.44
	3	0.48	0.07	-0.43	-0.14	-0.62	-0.13	-0.44	0.01	-0.29	-0.18	-0.14	-0.07	2.13	1.01	2.21
Second	1	-0.25	0.46	-0.04	0	-1.38	-0.04	0.25	-0.04	-0.21	-0.46	-0.46	-0.33	0.58	0.42	3.71
	2	-0.35	0.10	-0.11	0.13	-0.21	-0.32	-0.08	-0.11	-0.13	0.01	-0.64	-0.10	1.33	0.64	3.08

Note: x_1 is the dummy variable for product condition; x_2 is the dummy variable for screen size; x_{31} and x_{32} are the dummy variables for hard disk; x_{41} and x_{42} are the dummy variables for RAM; x_{51} and x_{52} are the dummy variables for dual CPU; x_{61} and x_{62} are the dummy variables for screen resolution; x_{71} and x_{72} are the dummy variables for connectivity; and x_{81} and x_{82} are the dummy variables for price.

To estimate the utility of continuous-value prices, a curve-fitting method was applied to generate the utility functions of the "price" for individual market segments based on the estimated coefficients of x_{81} and x_{82}. The results are shown as follows:

$$f_{1p}^{pr} = 1.155 - 1.1 \times 10^{-4} p_{pr} - 2.2 \times 10^{-6} \left(p_{pr}\right)^2$$

$$f_{2p}^{pr} = 0.455 - 9.14 \times 10^{-4} p_{pr} + 3.78 \times 10^{-7} \left(p_{pr}\right)^2$$

$$f_{3p}^{pr} = 3.92 - 8.027 \times 10^{-3} p_{pr} + 3.467 \times 10^{-6} \left(p_{pr}\right)^2$$

$$f_{1r}^{pr} = 0.56 + 5.689 \times 10^{-4} p_{rs} - 1.956 \times 10^{-6} (p_{rs})^2$$

$$f_{2r}^{pr} = 2.415 - 4.834 \times 10^{-3} p_{rs} + 1.978 \times 10^{-6} (p_{rs})^2,$$

where f_{ip}^{pr} is the utility function of price for the *p*-th new product in segment *i* (i=1, 2, and 3), and f_{zr}^{pr} is the utility function of the price for the *r*-th remanufactured product in segment *z* (z=1 and 2).

In this case study, five major competitive tablet PCs in the first market and seven major competitive tablet PCs in the second market were identified. Their respective specifications and prices are listed in Tables B.1 and B.2 of Appendix B. The market potentials of the individual segments for the first and second markets were estimated by marketing personnel, as shown in Table 6.2.

Table 6.2 Market potentials for the first and second markets

Segment	Market potential for the first market	Market potential for the second market
1	50 000	5 000
2	20 000	15 000
3	30 000	N/A
Total	100 000	20 000

6.2.1 Results

The multi-objective optimization models for the first period was formulated and coded with Matlab software. The model was solved using NSGA-II to determine the product line solutions of new tablet PCs. In this study, the population size of the NSGA-II was set to 100 and the maximum number of generation was set to 1000. Figure 6.3 shows the Pareto optimal solutions of the multi-objective optimization problem for the PLD of new tablet PCs.

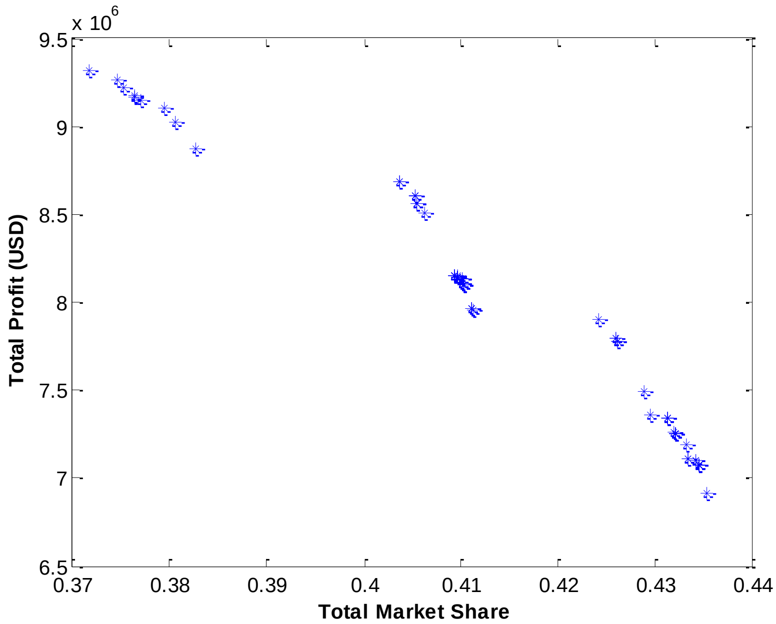


Figure 6.3 Pareto solutions for the PLD of new tablet PCs

The total profit of the OEM obtained from the PLD of new tablet PCs ranges from USD 6.9×10^6 to 9.3×10^6 depending on the total market share of the PLD they would like to obtain. Figure 6.4 shows the estimated profits of the chain retailers, ranging from USD 2.5×10^6 to 4.8×10^6 according to the OEM decisions. The total profit of the chain retailers increases as the total market share increases because the profits of the chain retailers increase as retail prices decrease, thereby leading to higher market share with reference to the reaction functions of the chain retailers. Figures 6.5 and 6.6 illustrate the changes in fitness values of the first and second objective functions over 1000 generations respectively. From the figures, the maximum profit and maximum market share from the PLD of new tablet PCs are obtained around the 910th and 975th generations, respectively.

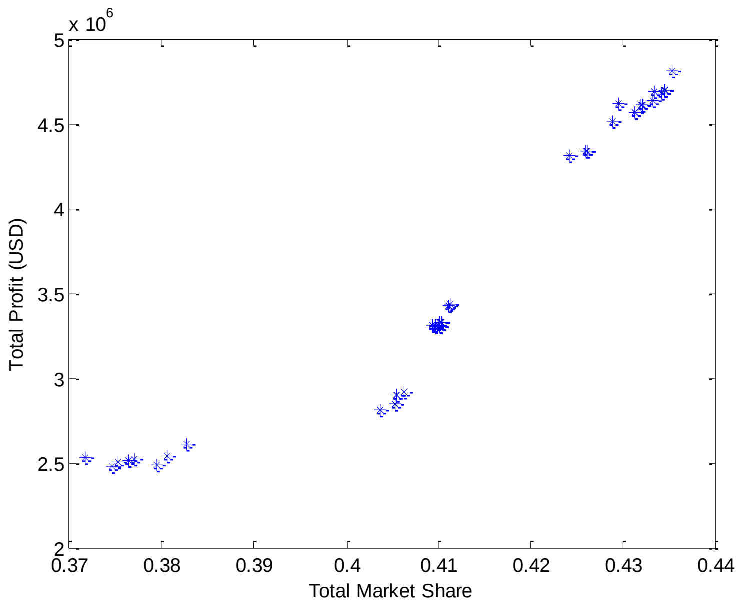


Figure 6.4 Estimated profits of the chain retailers from PLD of new tablet PCs

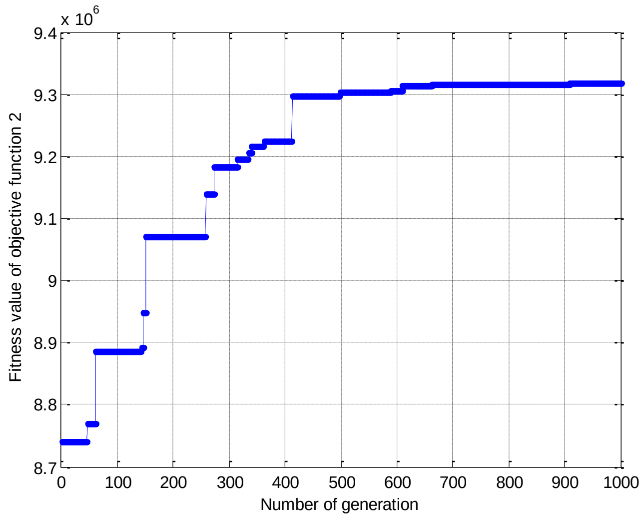


Figure 6.5 Change of fitness values of objective function 1

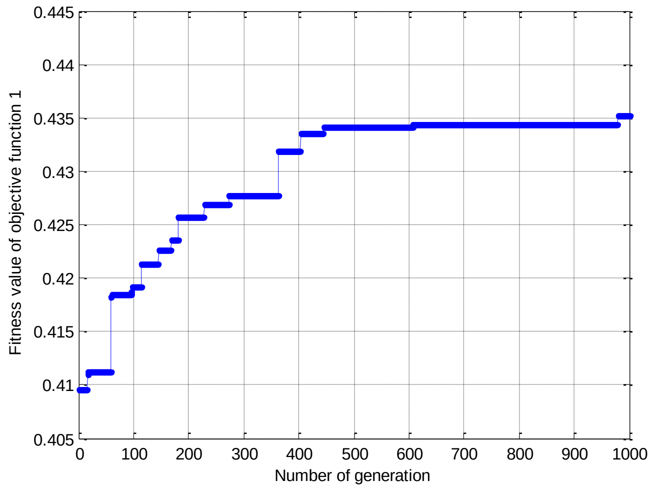


Figure 6.6 Change of fitness values of objective function 2

In simultaneously considering various objectives for a PLD, the objectives may conflict with one another. Therefore, companies need to perform a tradeoff among various objectives. In the first period, the Pareto optimal solutions are generated for the PLD of new tablet PCs. To obtain the Pareto optimal solutions for the PLD of remanufactured tablet PCs, the company can compare the solutions in the first period, perform a tradeoff between the two objectives, and select the best one with reference to their goals and business strategy. In the following sub-sections, two product line solutions are presented under two scenarios: maximum profit and maximum market share.

6.2.1.1 Maximum profit scenario of OEM

Table 6.3 shows a product line solution for new tablet PCs that leads to the maximum profit of the product line. The product line contains three new products. The estimated profit of the OEM is USD 9.3×10^6, while the total market share of the product line is 37.2%. The estimated total profit of the chain retailers is USD 2.5×10^6.

Table 6.3 Product line solution of new tablet PCs for the maximum profit scenario

Product	Screen size	Hard disk	Memory	Dual CPU	Screen resolution	Connectivity	Wholes price ($)	Retail price ($)
New product 1	10 in	32 GB	2 GB	1.4 GHz	2048×1536	Wi-Fi + 3G	531	641
New product 2	10 in	32 GB	1 GB	1.6 GHz	1280×800	Wi-Fi + 3G	499	580
New product 3	7 in	32 GB	2 GB	1.4 GHz	1280×800	Wi-Fi	350	448

After obtaining the product line solution for the PLD of new tablet PCs, the PLD of remanufactured tablet PCs based on the maximum profit scenario was then obtained by solving another multi-objective optimization problem. Figure 6.7 shows the Pareto optimal solutions for the PLD of remanufactured tablet PCs based on the maximum profit scenario of the OEM.

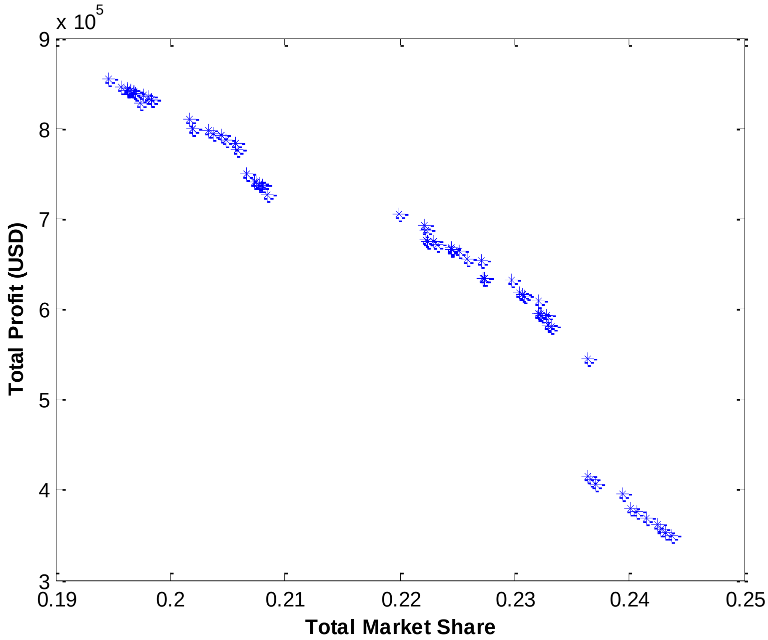


Figure 6.7 Pareto solutions for the PLD of remanufactured tablet PCs for the maximum profit scenario

Figure 6.7 shows that the estimated total profits of the OEM obtained from the PLD of remanufactured tablet PCs range from USD 3.5×10^5 to USD 8.5×10^5, while the estimated total market shares of the PLD of remanufactured tablet PCs range from 19.5% to 24.4%. Figure 6.8 shows that the estimated profits of the remanufacturer range from USD 4.9×10^5 to USD 9.9×10^5. The total profit of the remanufacturer increases as the market share increases because the remanufacturer increases the wholesale prices as selling prices decrease based on the reaction function.

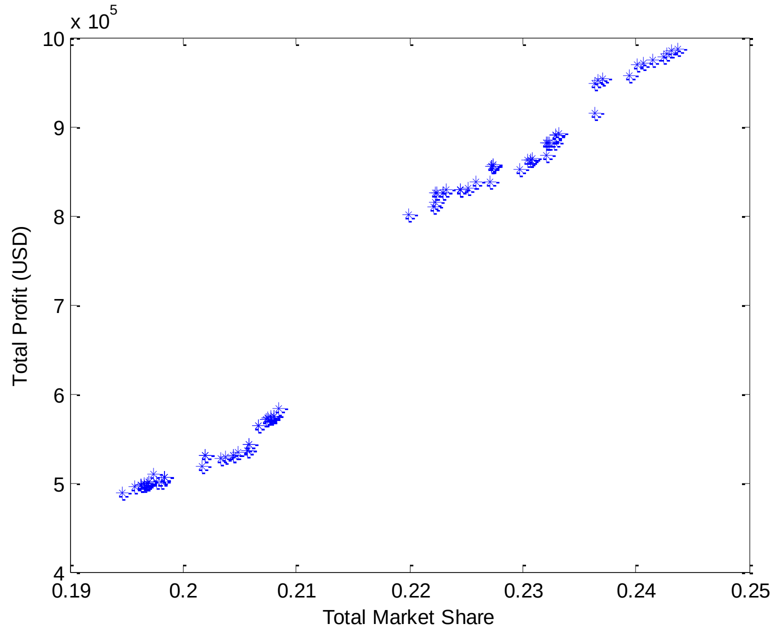


Figure 6.8 Estimated profits of the remanufacturer for the maximum profit scenario

Table 6.4 shows a product line solution of remanufactured tablet PCs, which leads to the maximum profit of the product line. The product line contains two remanufactured products. The estimated maximum profit of the OEM is USD 8.5×10^5 and the total market share of the product line is 19.5%. The estimated total profit of the remanufacturer is USD 4.9×10^5 while the product return rate is 0.15.

Table 6.4 Product line solution of remanufactured tablet PCs for the maximum profit scenario

Product	Screen size	Hard disk	Memory	Dual CPU	Screen resolution	Connectivity	Wholes price ($)	Selling price ($)
Remanufactured product 1	10 in	32 GB	1 GB	1.6 GHz	1280×800	Wi-Fi + 3G	256	490
Remanufactured product 2	7 in	32 GB	512 MB	1.4 GHz	1024×768	Wi-Fi + 3G	150	396

6.2.1.2 Maximum market share scenario of OEM

A product line solution for new tablet PCs based on the maximum market share scenario was generated, as shown in Table 6.5. The product line contains three new products. The estimated profit and the total market share of the product line are USD 6.9×10^6 and 43.5%, respectively. The estimated total profit of the chain retailers is USD 4.8×10^6.

Table 6.5 Product line solution of new tablet PCs for the maximum market share scenario

Product	Screen size	Hard disk	Memory	Dual CPU	Screen resolution	Connectivity	Wholes price ($)	Retail price ($)
New product 1	10 in	64 GB	2 GB	1.4 GHz	2048×1536	Wi-Fi + 3G	491	666
New product 2	10 in	32 GB	2 GB	1.6 GHz	1024×768	Wi-Fi + 4G	337	485
New product 3	7 in	32 GB	1 GB	1 GHz	1280×800	Wi-Fi + 3G	285	373

The product line solutions of new tablet PCs based on the maximum market share scenario above were adopted as inputs to the multi-objective optimization model for the second period. Figure 6.9 shows the Pareto optimal solutions for the PLD of remanufactured tablet PCs based on the maximum market share scenario of the OEM.

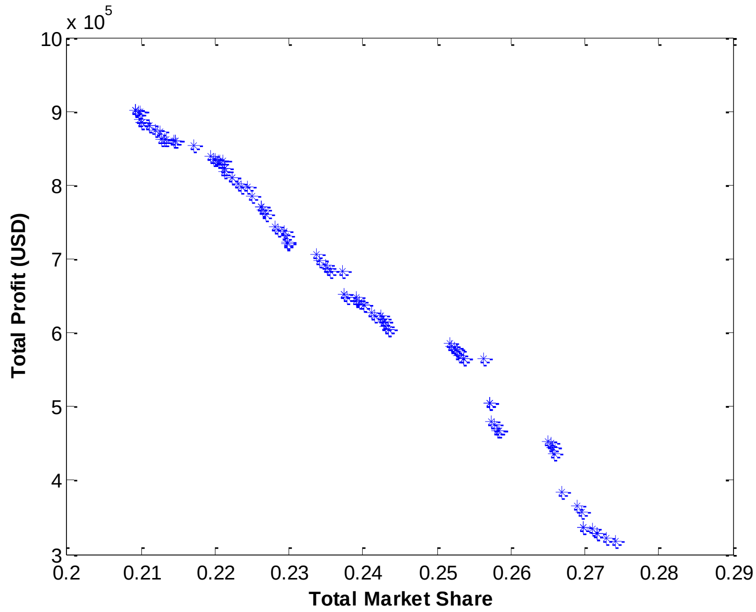


Figure 6.9 Pareto solutions for PLD of remanufactured tablet PCs for maximum market share scenario

Figure 6.9 shows that the estimated total profit of the OEM obtained from the PLD of remanufactured tablet PCs ranges from USD 3.2×10^5 to USD 9×10^5, whereas the estimated total market share of the PLD of remanufactured tablet PCs ranges from 20.9% to 27.4%. Figure 6.10 shows that the estimated profits of the remanufacturer range from USD 5.4×10^5 to USD 11.9×10^5.

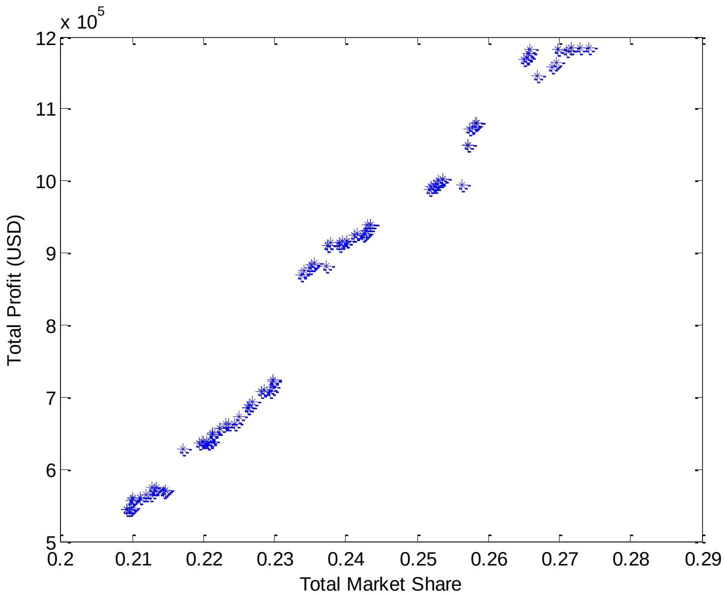


Figure 6.10 Estimated profits of the remanufacturer for the maximum market share scenario

Table 6.6 shows a product line solution of remanufactured tablet PCs, which leads to the maximum market share of the product line. The product line contains two remanufactured products. The estimated profit of the OEM is USD 3.2×10^5 and the total market share of the product line is 27.4%. The estimated total profit of the remanufacturer is USD 11.9×10^5 while the product return rate is 0.18.

Table 6.6 Product line solution of remanufactured tablet PCs for the maximum market share scenario

Product	Screen size	Hard disk	Memory	Dual CPU	Screen resolution	Connectivity	Wholesale price ($)	Selling price ($)
Remanufactured product 1	10 in	32 GB	512 MB	1 GHz	2048×1536	Wi-Fi + 4G	300	382
Remanufactured product 2	7 in	64 GB	2 GB	1.4 GHz	1280×800	Wi-Fi + 4G	279	353

6.3 Discussion of results

Researchers and companies can adopt the proposed methodology to determine product line solutions that involve both new and remanufactured products, pricing decisions of supply chain parties, and product return rate for remanufacturing. The PLD under the two distinct scenarios of maximum profit and maximum market share were examined. In the first period, the OEM obtains much higher profit than the chain retailers for both the maximum profit and maximum market share scenarios. In the maximum market share scenario, the OEM's profit generated from new products decreases by 25.8% while their market share increases by 16.9% compared to those in the maximum profit scenario. However, the total profit of the chain retailers increases as the market share increases. Both the retail and wholesale prices of new tablet PCs are lower in the maximum market share scenario than those in the maximum profit scenario because the reduction of the retail prices of new tablet PCs makes the new tablet PCs more attractive in markets, thereby increasing the market share of tablet PCs. On the other hand, the specifications of the new tablet PCs in the maximum market share scenario are better than those in the maximum profit scenario. In the second period, the profits of the OEM and the total market share obtained from the PLD of remanufactured tablet PCs for maximum profit and market share scenarios are very close because of the availability of product returns and considerable demand in the second market. In the maximum market share scenario, the OEM's profit obtained from remanufactured products decreases by 62.3% while their market share increases by 40.5% compared to those in the maximum profit scenario. However, the remanufacturer gains a much higher profit under the maximum market share scenario than under the maximum profit scenario. These results indicate that both chain retailers and remanufacturer play stronger roles in the game for the maximum market share scenario than that for the maximum profit scenario. OEM needs to increase the pay-off to chain retailers and remanufacturer to increase the market share of its products. Since the model was developed based on the OEM's perspective, the tradeoff between the two objectives, maximizing market share, and maximizing profit, can only be performed for the OEM.

The product return rate depends on a number of parameters, such as the market potential of both the first and second markets, remanufacturability rate, and production capacity of the remanufacturer. In this case study, the production capacity of the remanufacturer is assumed to be adequate to produce the required quantities of remanufactured products. Therefore, the product return rate may need to be increased to satisfy the demand for the second market and improve the profits of both the OEM and the remanufacturer. By contrast, the remanufacturability rate decreases and/or the market potential of the second market increases.

6.4 Summary

In this chapter, a methodology for the coordination of a manufacturer, chain retailers, and a remanufacturer to undertake PLD with consideration of remanufactured products is proposed to maximize the profit and market share of product lines. The methodology addresses the relationship between product returns and demand for remanufactured products and determines the return rate of new products. The methodology mainly involves conjoint analysis, generation of choice models, Stackelberg game theoretical approach, formulation of multi-objective optimization problems, and solving the multi-objective optimization problems by NSGA-II. Two multi-objective optimization models are formulated for the first and second periods using Stackelberg game theory. Product line solutions are obtained by solving the optimization models, which contain specifications of new and remanufactured products, estimated total profits and market shares of the product lines, wholesale and retail prices of new products, wholesale and selling prices of remanufactured products, and product return rate. A case study was conducted on the coordination of a manufacturer and supply chain partners for the PLD of tablet PCs with consideration of remanufactured tablet PCs to evaluate the effectiveness of the proposed methodology.

Chapter 7 Determining the Optimal Quantity and Quality Grades of Product Returns for Remanufacturing Under Multi-period and Uncertain Quality of Returns

In this chapter, a proposed methodology for determining the optimal quantity and quality grades of product returns for remanufacturing with consideration of uncertain quality and multi-period of returns is described in Section 7.1. A case study on the determination of optimal quantity and quality grades of returned tablet PCs based on the proposed methodology is presented in Section 7.2. Results of the post-optimality analyses under different quality scenarios and inventory cost considerations are discussed in Section 7.3. A summary of the study is provided in Section 7.4.

7.1 Proposed methodology for determining the quantity and quality grades of product returns for remanufacturing

Figure 7.1 shows the centralized CLSC considered in this study. The straight-line and dashed-line arrows indicate the forward and reverse flow of the supply chain, respectively. The manufacturer produces new products and delivers them to chain retailers, who then sell the products to customers in the market. Used and defective products are collected by chain retailers through trade-in programs. The returned products are categorized into different quality grades based on their condition. The manufacturer can determine the quantity and quality grades of the returned products, which will be collected in a specific period based on the estimated demand for remanufactured products. Thereafter, the manufacturer refurbishes the returned products and sells them in a secondary market.

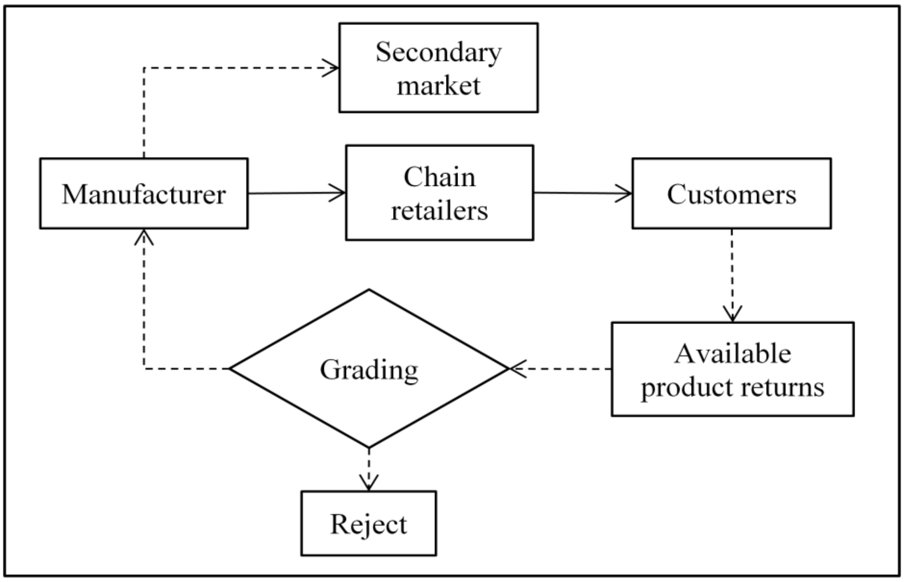


Figure 7.1 Closed-loop supply chain

A methodology for determining the optimal quantity and quality grades of product returns for remanufacturing is proposed in this research. In the proposed methodology, an integer programming-based optimization model is developed to determine the optimal quantity and quality grades of returned products for remanufacturing with consideration of the availability of the cores, demand for remanufactured products, inventory costs, and uncertainty in the quality of returns. The objective of this model is to minimize the total cost of producing remanufactured products, that is the sum of the take-back, remanufacturing, and inventory costs. The following two issues are also addressed in the proposed methodology:

- effect of sales of new products on product returns and
- effect of demand for remanufactured products on product returns.

Figure 7.2 shows a flowchart of the proposed methodology. First, the sales of new products are estimated based on a dynamic market demand model (Aydin *et al.*, 2015). Based on the sales estimates, the quantity of available product returns and the timing of collecting them are forecasted using a geometrical DLM. Thereafter, the quality grades of the available product returns are estimated using a multinomial distribution. The demand for remanufactured products is also estimated based on a dynamic market demand model. The cost model for producing remanufactured products mainly consists of take-back, remanufacturing, and inventory costs. Once the cost model is developed and the demand for remanufactured products is obtained, an integer programming-based optimization model can be formulated. The solutions include the optimal quantity and quality grades of product returns for remanufacturing and inventory level of the remanufactured products for each period. Details of the proposed methodology are described in the following sub-sections.

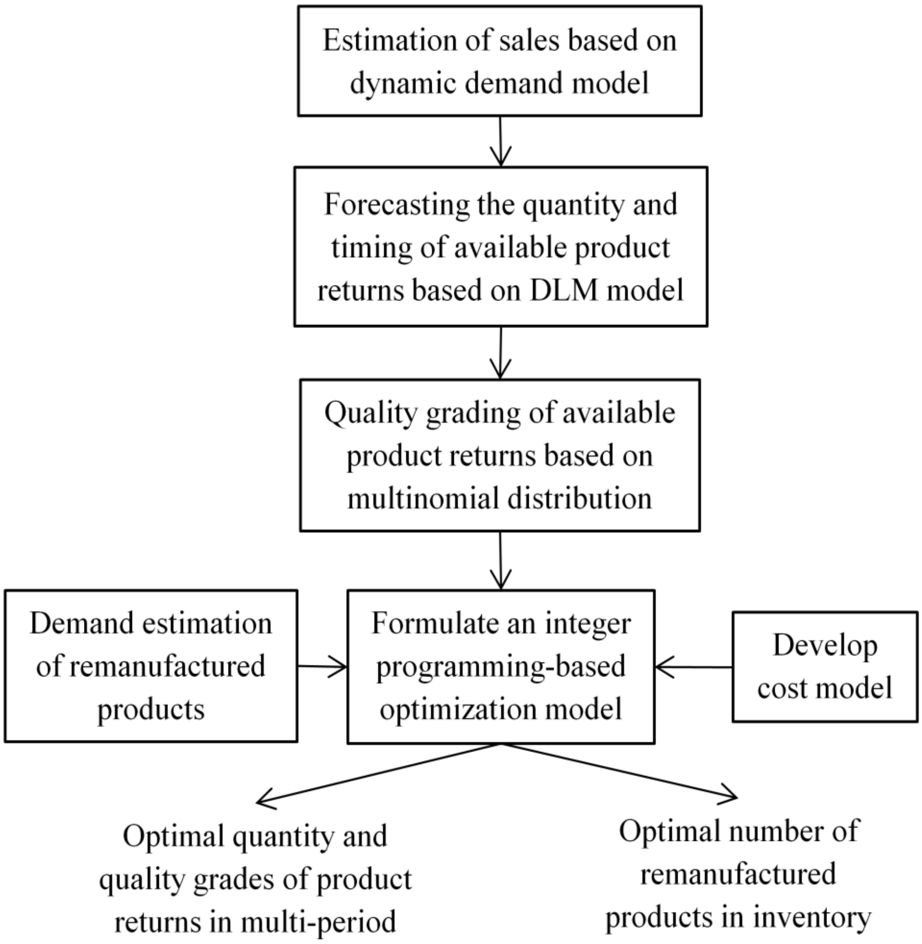


Figure 7.2 Methodology for the determination of the optimal quantity and quality grades of returned products

7.1.1 Forecasting the quantity and timing of available product returns

Traditional statistical forecasting techniques, such as time series method or exponential smoothing cannot address the correlation between sales and product returns (Clottey *et al.*, 2012). However, DLM, which had been applied successfully by Toktay *et al.* (2000), Clottey *et al.* (2012), and Krapp *et al.* (2013a), can capture the relationship between sales and product returns and can be expressed as follows:

$$m_t^{ret} = \sum_{k=1}^{t-1} \beta_k n_{t-k} + \varepsilon_t; \text{ for } t = 2, 3, \dots, T. \tag{7.1}$$

where n_t and m_t^{ret} denote the number of products sold and available returned products, respectively, at time *t*; and β_k is a geometric delay function for the returns (Toktay *et al.*, 2000; Krapp *et al.*, 2013a), which represents the return rate at a specific time. It can be expressed as follows:

$$\beta_k = pq(1-q)^{k-1} \tag{7.2}$$

where p is the probability that a sold product will ever be returned, and q is the conditional probability that a product would be returned in the next period given that it will be returned.

7.1.2 Quality grading of available product returns

The quality of product returns has significant effects on the remanufacturing cost (Akcali and Cetinkaya, 2011). As discussed in Section 2.6, grading returned products into different quality levels helps reduce the cost of producing remanufactured products. Zikopoulos and Tagaras (2007) conducted a numerical analysis to investigate the different quality levels of returns, because estimating the quality of returned products is highly complicated and ambiguous. Zeballos *et al.* (2012) modeled the uncertain quality of returns by considering five quality grades and three quality scenarios (good, medium, and bad). Multinomial distribution, a generalization of binomial distribution, has been utilized to determine the fraction of each quality grade of returned products when more than two possible quality grades are present (Guide *et al.*, 2003; Teunter and Flapper, 2011).

Four quality grades are considered in the current study. The quality of returned products is highly uncertain. Thus, post-optimality analyses (sensitivity analyses) of various quality distributions are considered in this research to provide decision-makers with alternative solutions, and investigate how the total cost of producing remanufactured products changes when the quantities and quality grades of returned products vary and the inventory cost is considered. Three quality scenarios, namely, good, average, and bad, are studied and represented as follows:

$$Q_t^s = (p_{1t}^s \ \ p_{2t}^s \ \ p_{3t}^s \ \ p_{4t}^s); \ \text{ for } s = 1, 2, 3 \text{ and } t = 2, 3, \dots, T. \tag{7.3}$$

where Q_t^s represents the quality distribution of returned products at time *t* for scenario *s* based on multinomial distributions, and p_{nt}^s is the return probability of quality grade *n* at time *t* for scenario *s*.

7.1.3 Estimation of sales of new products and demand for remanufactured products

The sales of new products and demand for remanufactured products are estimated based on the dynamic market demand model developed in our previous study, in which consumer preferences on both new and remanufactured products can be obtained using conjoint analysis (Aydin *et al.*, 2015). The model was developed by incorporating the dynamic choice models into the Bass diffusion model. The dynamic choice models, which were generated based on the MNL model and dynamic utility functions, are described in Section 5.1.1.

7.1.4 Formulation of integer programming-based optimization model

An integer programming-based optimization model is developed to determine the optimal quantity and quality grades of product returns for remanufacturing. The decision variables are the quantity of returned products for each quality grade in each period. Therefore, the number of decision variables can be calculated by multiplying the number of quality grades and the collection periods. The objective of this model is to minimize the total cost of producing remanufactured products, that is, the sum of the take-back, remanufacturing, and inventory costs. Thus, the objective function can be expressed as follows:

$$\sum_{t=2}^{T-1}\sum_{q=1}^{Q} m_{qt}^{s}\left(c_q^{col}+c_q^{rem}\right)+\left(\sum_{t=3}^{T-1} s_t^{s}\right)c^{inv} \tag{7.4}$$

where m_{qt}^{s} denotes the number of returned products with quality grade q at time t for scenario s; c_q^{col}, c_q^{rem} and c_q^{inv} are the take-back, remanufacturing, and inventory costs, respectively; and s_t^{s} is the number of remanufactured products in the inventory at the end of period t for scenario s, which can be calculated as:

$$s_t^{s}=\sum_{Q=1}^{Q} m_{qt}^{s}-d_{t+1}^{rem};\ \text{ for } t=3,4,5,\ldots T. \tag{7.5}$$

$$s_1^{s}=0;\text{ and } s_2^{s}=0. \tag{7.6}$$

where d_t^{rem} denotes the demand for remanufactured products at time t.

Eq. (7.6) means that no remanufactured products are produced in the first two periods, because product returns are only available starting from the second period, wherein the returned products are treated as work-in-process. After collection, the returned products are shipped to the manufacturer and disassembled, repaired, cleaned, and assembled again. If any returned products are sold in the coming period, they are not considered in the inventory. Otherwise, they are treated as inventory items in the coming period. The following constraints are also required in the formulation of the optimization model:

$$\sum_{t=2}^{T-1}\sum_{q=1}^{Q} m_{qt}^{s} \leq \sum_{t=2}^{T-1}\sum_{q=1}^{Q} m_{t}^{ret}.\,Q_{qt}^{s} \tag{7.7}$$

$$\sum_{t=2}^{T-1} d_{t+1}^{rem} \leq \sum_{t=2}^{T-1}\sum_{q=1}^{Q} m_{qt}^{s} \tag{7.8}$$

Eq. (7.7) ensures that the number of returned products for each quality grade in each period is less than or equal to the available number of returned products for the corresponding quality grade and period. Eq. (7.8) ensures that the total number of returned products at time t is more than or equal to the demand for the remanufactured product at a corresponding time. To study the effect of inventory cost on product returns and total cost, the inventory cost ($/unit/year) can be estimated as 15% of the take-back cost for electronic products (Hauser and Lund, 2003).

7.2 Implementation

The proposed approach was applied to determine the optimal quantity and quality grades of returned tablet PCs for remanufacturing based on the case study of new and remanufactured tablet PC design, as described in Section 5.2. In the case study, product line design solutions of tablet PCs containing both new and remanufactured products were determined. The dynamic demand models were generated to estimate the demand for new and remanufactured tablet PCs in multi-periods. The product line solution for maximum profits obtained in Section 5.2.1 is adopted here to illustrate the proposed methodology for determining the optimal quantity and quality grades of product returns. The product returns contain one 7-inch model and two different 10-inch models of new tablet PCs, as well as one 10-inch remanufactured tablet PC. The best time of launching the 10-inch remanufactured tablet PC was determined to be on the 13th month.

Time periods are specified quarterly. New tablet PCs are launched in the market from periods 1 to 12, and used tablet PCs are collected starting from period 2. Remanufactured tablet PCs are launched in the market from period 5 (i.e., approximately on the 13th month). Therefore, used tablet PCs can be collected from periods 2 to 15 because the market demand for remanufactured tablet PCs is forecasted during those periods. The sales of new tablet PCs and demand for remanufactured tablet PCs were estimated using Eqs. (5.7) to (5.12). The number of available returns for each period was estimated based on the geometrical DLM. Table 7.1 shows the sales of new products, demand for remanufactured products, and number of available returned tablet PCs in each period.

Table 7.1 Sales, demand, and number of available returned tablet PCs

Period	Sales	Demand	Available returned tablet PCs
1	1044	0	0
2	1704	0	78
3	2649	0	197
4	3742	0	371
5	4404	115	605
6	4283	276	860
7	3685	450	1073
8	2553	700	1216
9	1775	967	1255
10	983	1154	1231
11	754	1094	1151
12	376	851	1064
13	0	507	959
14	0	298	839
15	0	135	734
16	0	85	0
Total	27952	6632	11633

Multinomial distribution was used to estimate the quantity of the returned tablet PCs for individual quality grades. In this case study, the returned tablet PCs are categorized into four quality grades, namely, quality 1 to quality 4. Quality 1 is the best, whereas quality 4 is the worst. Post-optimality analyses under three quality scenarios, namely, good, average, and bad, as well as the effect of inventory cost on the cost of remanufactured tablet PCs are also examined in this case study. The following sub-sections present the implementation results under the three quality scenarios with or without inventory cost consideration.

7.2.1 Implementation results under average quality scenario

In this scenario, the distribution probabilities of the four quality grades of the returned tablet PCs are all 0.25. Table 7.2 shows the number of available returned tablet PCs for each quality grade in each period based on the average quality scenario.

Table 7.2 Number of available returned tablet PCs in each quality grade for the average quality scenario

Period	Available returned tablet PCs			
	Quality 1	Quality 2	Quality 3	Quality 4
1	0	0	0	0
2	19	21	16	22

3	53	45	46	53
4	80	105	89	97
5	154	142	146	163
6	247	208	186	219
7	273	257	275	268
8	308	302	325	281
9	308	307	324	316
10	296	313	300	322
11	269	291	281	310
12	241	286	285	252
13	226	222	250	261
14	211	195	204	229
15	159	190	201	184
16	0	0	0	0
Total	2844	2884	2928	2977

Table 7.3 shows the number of returned tablet PCs for each quality grade and the number of remanufactured products in the inventory when no inventory cost is considered based on the average quality scenario. The total cost of collecting and producing the remanufactured products is USD 1,011,685.

Table 7.3 Number and inventory levels of the returned tablet PCs with no inventory cost (Average quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality	Total	
1	0	0	0	0	0	0
2	19	21	16	0	56	0
3	53	45	0	0	98	56
4	80	105	0	0	185	154
5	154	142	0	0	296	224
6	247	208	186	0	641	244
7	273	257	275	0	805	435
8	308	302	325	0	935	540
9	308	307	324	0	939	508
10	296	313	202	0	811	293
11	269	291	281	0	841	10
12	241	286	0	0	527	0
13	226	52	0	0	278	20
14	135	0	0	0	135	0
15	85	0	0	0	85	0

16	0	0	0	0	0	0
Total	2694	2329	1609	0	6632	2484

Table 7.4 shows the number of returned tablet PCs for each quality grade and the number of remanufactured tablet PCs in the inventory when the inventory cost ($/unit/year) is set to the 15% of the take-back cost (Hauser and Lund, 2003) based on the average quality scenario. The total cost of collecting and producing the remanufactured product is USD 1,019,531.

Table 7.4 Number and inventory levels of product returns involving inventory cost (Average quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality 4	Total	
1	0	0	0	0	0	0
2	19	0	0	0	19	0
3	53	45	0	0	98	19
4	80	105	0	0	185	117
5	154	142	0	0	296	187
6	247	208	0	0	455	207
7	273	257	275	0	805	212
8	308	302	325	0	935	317
9	308	307	324	0	939	285
10	296	313	300	115	1024	70
11	269	291	281	10	851	0
12	241	266	0	0	507	0
13	226	72	0	0	298	0
14	135	0	0	0	135	0
15	85	0	0	0	85	0
16	0	0	0	0	0	0
Total	2694	2308	1505	125	6632	1414

7.2.2 Implementation results under good quality scenario

In the good quality scenario, the distribution probabilities of the quality grades are 0.40, 0.30, 0.20, and 0.10 for quality grades 1, 2, 3, and 4 of the returned tablet PCs, respectively. Table 7.5 shows the number of available returned tablet PCs for each quality grade in each period based on the good quality scenario.

Table 7.5 Number of available returned tablet PCs in each quality grade for the good quality scenario

Period	Available returned tablet PCs			
	Quality 1	Quality 2	Quality 3	Quality 4
1	0	0	0	0
2	26	16	22	14
3	84	68	31	14
4	159	102	79	31
5	238	183	120	64
6	353	252	161	94
7	412	339	207	115
8	462	378	230	146
9	492	372	249	142
10	498	355	260	118
11	452	348	222	129
12	394	329	214	127
13	399	293	182	85
14	325	234	188	92
15	286	231	144	73
16	0	0	0	0
Total	4580	3500	2309	1244

Table 7.6 shows the number of returned tablet PCs in each quality grade and the number of remanufactured tablet PCs in the inventory when no inventory cost is considered based on the good quality scenario. The estimated total cost of collecting

and producing remanufactured tablet PCs is USD 966,910.

Table 7.6 Number and inventory levels of the returned tablet PCs with no inventory cost (Good quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality 4	Total	
1	0	0	0	0	0	0
2	26	16	0	0	42	0
3	84	68	0	0	152	42
4	159	102	0	0	261	194
5	238	183	0	0	421	340
6	353	252	0	0	605	485
7	412	339	0	0	751	640
8	462	378	0	0	840	691
9	492	372	18	0	882	564
10	498	355	0	0	853	292
11	452	348	0	0	800	51
12	394	113	0	0	507	0
13	298	0	0	0	298	0
14	135	0	0	0	135	0
15	85	0	0	0	85	0
16	0	0	0	0	0	0
Total	4088	2526	18	0	6632	3299

Table 7.7 shows the number of returned tablet PCs in each quality grade and the number of remanufactured tablet PCs in the inventory when the inventory cost is involved based on the good quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 977,221.

Table 7.7 Number and inventory levels of the returned tablet PCs involving inventory cost (Good quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality 4	Total	
1	0	0	0	0	0	0
2	26	0	0	0	26	0

3	84	0	0	0	84	26
4	159	0	0	0	159	110
5	238	0	0	0	238	154
6	353	252	0	0	605	116
7	412	339	0	0	751	271
8	462	378	0	0	840	322
9	492	372	95	0	959	195
10	498	355	241	0	1094	0
11	452	348	51	0	851	0
12	394	113	0	0	507	0
13	298	0	0	0	298	0
14	135	0	0	0	135	0
15	85	0	0	0	85	0
16	0	0	0	0	0	0
Total	4088	2157	387	0	6632	1194

7.2.3 Implementation results under bad quality scenario

In the bad quality scenario, the distribution probabilities of the quality grades of returned tablet PCs are 0.10, 0.20, 0.30, and 0.40 for quality grades 1, 2, 3, and 4, respectively. Table 7.8 shows the number of available returned tablet PCs for the individual quality grades during periods 2 to 15 based on the bad quality scenario.

Table 7.8 Number of available returned tablet PCs in each quality grade for the bad quality scenario

Period	Available returned tablet PCs			
	Quality 1	Quality 2	Quality 3	Quality 4
1	0	0	0	0
2	8	7	25	38
3	15	30	68	84
4	34	75	118	144
5	61	112	200	232
6	81	145	281	353
7	109	208	328	428
8	129	249	370	468
9	120	228	386	521

10	121	251	344	515
11	100	249	332	470
12	97	218	307	442
13	64	213	291	391
14	83	177	251	328
15	74	155	213	292
16	0	0	0	0
Total	1096	2317	3514	4706

Table 7.9 shows the number of returned tablet PCs for each quality grade and the number of remanufactured tablet PCs in the inventory when no inventory cost is considered based on the bad quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 1,076,185.

Table 7.9 Number and inventory levels of returned tablet PCs with no inventory cost (Bad quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality 4	Total	
1	0	0	0	0	0	0
2	8	7	25	0	40	0
3	15	30	68	84	197	40
4	34	75	118	0	227	237
5	61	112	200	232	605	349
6	81	145	281	0	507	678
7	109	208	328	0	645	735
8	129	249	370	0	748	680
9	120	228	386	507	1241	461
10	121	251	344	0	716	548
11	100	249	332	0	681	170
12	97	218	192	0	507	0
13	64	213	21	0	298	0
14	83	52	0	0	135	0
15	74	11	0	0	85	0
16	0	0	0	0	0	0
Total	1096	2048	2665	823	6632	3898

Table 7.10 shows the number of returned tablet PCs for the individual quality grades and the number of remanufactured tablet PCs in the inventory when the inventory cost is considered based on the bad quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 1,081,914.

Table 7.10 Number and inventory levels of the returned tablet PCs involving inventory cost (Bad quality scenario)

Period	Returned tablet PCs					Inventory
	Quality 1	Quality 2	Quality 3	Quality 4	Total	
1	-	-	-	-	-	0
2	8	7	0	0	15	0
3	15	30	0	0	45	15
4	34	75	0	0	109	60
5	61	112	200	0	373	54
6	81	145	281	0	507	151
7	109	208	328	0	645	208
8	129	249	370	66	814	153
9	120	228	386	420	1154	0
10	121	251	344	378	1094	0
11	100	249	332	170	851	0
12	97	218	192	0	507	0
13	64	213	21	0	298	0
14	83	52	0	0	135	0
15	74	11	0	0	85	0
16	0	0	0	0	0	0
Total	1096	2048	2454	1034	6632	641

7.3 Discussion of results

Based on the implementation results presented in sub-sections 7.2.1 to 7.2.3, Figure 7.3 is generated to summarize the optimal quantities of returned tablet PCs for the individual quality grades under the three quality scenarios and inventory cost considerations. The number of returned tablet PCs in quality 1 and quality 2 constitute a large percentage of returns in the good and average scenarios. The number of returned tablet PCs in quality 3 and quality 4 are relatively higher in the bad scenario than the ones in the good and average scenarios. When the inventory cost is considered, the number of returns with the lower quality may increase to compensate for the incurred inventory cost.

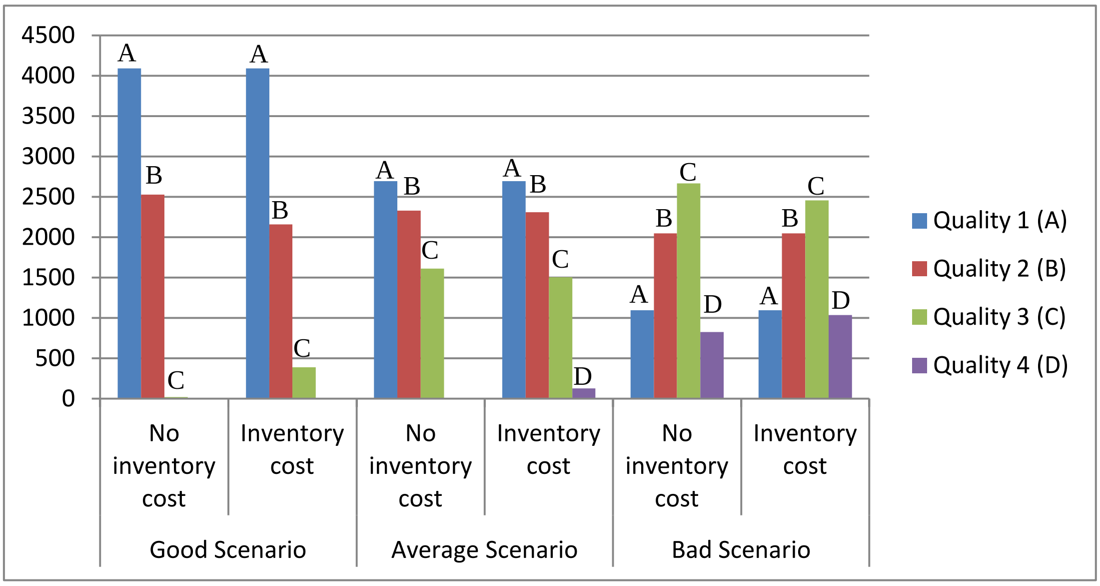


Figure 7.3 Summary of the optimal quantities of returns for the individual quality grades

Figure 7.4 summarizes the number of stocks under the three quality scenarios with or without inventory costs. Note for all the quality scenarios, the number of stocks decreases when the inventory cost is considered. Without inventory cost, the number of stocks in the bad quality scenario is relatively higher than those in the average and good quality scenarios. However, the number of stocks in the bad quality scenario is considerably lower than those in the average and good quality scenarios when the inventory cost is considered. These figures clearly indicate how the number of available returns in different quality scenarios and the inventory cost considerations would affect the number of stocks. When the inventory cost is zero, the higher quality returns are collected and kept as inventory.

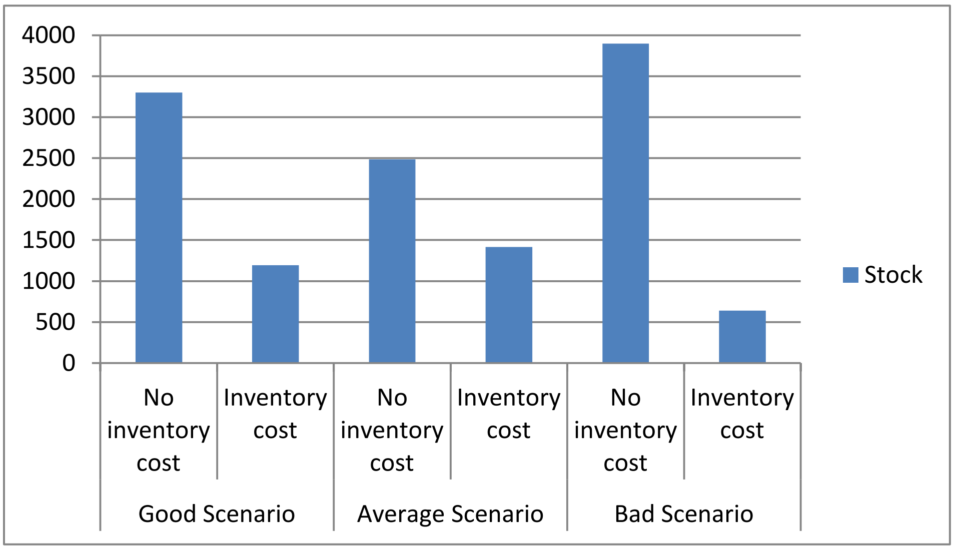


Figure 7.4 Number of stocks under different quality scenarios and inventory cost considerations

Table 7.11 illustrates the overall analysis of the total cost of collecting and producing remanufactured tablet PCs under different quality scenarios and inventory cost considerations. The total costs obtained based on the average quality scenario are used for the benchmark. The percentages shown in the brackets of Table 7.11 are the difference in percentages between the total cost obtained based on the average quality scenario and that based on the corresponding scenario. Table 7.11 also shows that the total cost obtained based on the good quality scenario is approximately 4% lower than the one based on the average scenario. However, the total cost obtained based on the bad scenario is approximately 6% higher than the one based on the average scenario. The total cost increases approximately 0.5% to 1% when the inventory cost is considered.

Table 7.11 Overall analysis of the total cost estimations

	Average Scenario	Good Scenario	Bad Scenario
No inventory cost	USD 1,011,685	USD 966,910 (-4.4%)	USD 1,076,185 (+6.4%)
Inventory cost (15% of the take-back cost)	USD 1,019,531	USD 977,221 (-4.1%)	USD 1,081,914 (+6.1%)
Difference of the total costs (with and without inventory cost)	+0.8%	+1.1%	+0.5%

The total costs obtained on the bad scenario with/without involving the inventory costs are also approximately 11% higher than the corresponding ones based on the good quality scenario. This result clearly indicates that the quality of product returns could significantly affect the cost of remanufactured products. The differences in percentages between the total costs with and without involving inventory costs for all the three scenarios are minimal. However, higher percentage differences are obtained when more used tablet PCs with good quality are collected.

7.4 Summary

Managing product returns has been found to be essential in the production planning and control for the remanufacturing and inventory control management of product returns. However, considerable uncertainties have been found in the quantity, timing, and quality of returned products. Most of the previous studies developed models for product returns and demand for remanufactured and new products separately based on stochastic distribution theory. However, the demand for remanufactured and new products may not follow a random distribution model. The effect of quality of returns on the take-back and remanufacturing costs were ignored in previous studies. However, both acquisition price and remanufacturing cost are highly dependent on the quality of returns. In this chapter, a methodology for the determination of the optimal quantity and quality grades of product returns for remanufacturing with consideration of multi-period and uncertain quality of the returns is proposed. This methodology aims to minimize the total cost of producing remanufactured products. In this study, the effects of sales of new products and demand for remanufactured products on product returns are also studied. Consumer preferences are considered in the demand estimations of remanufactured and new products, which can help improve the accuracy of the estimations. Post-optimality analyses are performed on the different quality scenarios and inventory cost considerations. The implementation results of a case study of tablet PCs indicate that the inventory cost of returned tablet PCs would lead to 0.5%–1.1% increase in the total cost of remanufactured tablet PCs, whereas uncertainty in the quality of returns would result in 4%–6% changes in the total cost.

Chapter 8 Discussion

In this chapter, some discussions on the proposed methodologies and their implementations are presented.

8.1 Discussion on the proposed methodology for PLD with consideration of remanufactured products and its implementation

In this research, a methodology for PLD with simultaneous consideration of new and remanufactured products under centralized and decentralized supply chain networks was developed to determine optimal product line solutions, and maximize profit and market share of the product lines. In the methodology, rating-based conjoint surveys are adopted because these are more suitable to extract utility differences among alternative. However, if the surveys involve a large number of product profiles, it would take a long time for respondents to fill out questionnaires and they may not be serious and willing to participate in the surveys. In this case, choice-based conjoint surveys could be considered to reduce the effect of the respondents' reluctance in filling out the questionnaires. Although sampling was not addressed in this research, it could affect the prediction accuracy of developed demand models to a certain extent. Sampling error is the deviation of selected samples from the true characteristics of the entire population, and it may occur in the survey design. In this research, sampling error may arise from both the competitive products and the respondents. Typically, survey samples are chosen through a random sampling method or statistically experimental design methods. Uneven sampling may result in some areas of the design space and may be sampled less or not at all. Outliers may also exist in survey data because of instrument errors, human errors, and so on. The existence of outliers in data sets could affect the quality of model development.

In this research, dynamic demand models are generated by incorporating generated dynamic choice models into Bass diffusion models in order to consider the effects of consumer preferences and product attribute setting on product diffusion as well as competition in markets. With the modes, the dynamic issue of product lifecycle was considered to determine the best time of launching remanufactured products and their prices. Solving the optimization model, which involves both discrete and continuous variables, for an optimal solution using deterministic optimization methods is very difficult. In this research, NSGA-II was utilized to solve the optimization model. The optimization model was run dozens of times by changing the parameter settings of NSGA-II, such as population size and maximum number of generation, in order to obtain more reliable Pareto optimal solutions. In view of the industrial practice in new product development, companies could establish some rules and/or guidelines for each new product development project to help them select their most desirable solutions because NSGA-II cannot guarantee that the obtained non-dominant solutions are Pareto ones.

The proposed methodology can also be used to determine a profitable CLSC network. However, decision makers need to consider whether third-party companies will be used or not for the collection and/or remanufacturing of used products before applying the methodology.

Although a case study on tablet PC design was conducted to show the applicability of the proposed methodology, the methodology is generic and can be applied to the design of various products, such as office equipment and automobiles, where products can be remanufactured and sold in competitive markets. This study has some limitations. First, the returned products and their components are assumed to meet the quality and reliability requirements of producing remanufactured products. Residue reliability of reused components and products could be considered in future in order to determine the degree of reliability of remanufactured products.

Second, reactions of imitation competitors are not considered.

8.2 Discussion on the developed fuzzy demand models

Fuzzy market demand models were generated based on fuzzy regression and fuzzy estimates of market potential. The estimated market demands can also be used to estimate the profits of an NPD project under the worst, normal, and best scenarios. Those estimated profits under different scenarios are useful for companies in assessing the financial viability of NPD projects. In this research, the proposed fuzzy demand model was applied on the market demand estimation of tablet PCs. In fact, the method can be applied on any type of product so long as the product does not monopolize the market.

In this research, the proposed fuzzy demand model was generated based on static utility functions and/or static choice models. However, the generated dynamic utility functions and/or dynamic choice models can be incorporated into the proposed fuzzy demand model without substantial changes. An integrated dynamic fuzzy demand model would be able to capture the fuzziness of survey data and consider various issues of market dynamics, such as price changes and addition or removal of competitors. This study has some limitations. First, the addition or removal of competitive products during the life cycles of new and remanufactured products was not considered. Second, the brand-name effect of products on market share estimation was not considered.

8.3 Discussion on the proposed methodology of coordination of the CLSC for PLD with consideration of remanufactured products

In this study, a two-period Stackelberg game theoretical model was developed to examine the competition among supply chain parties in performing PLD, which involves both new and remanufactured products. Pareto solutions of PLD can be obtained under various scenarios. Hence, supply chain parties could select their most desirable solutions with reference to their business objectives and strategies.

In this research, OEM is assumed to be the leader of the supply chain in the Stackelberg game model. However, some famous chain retailers, such as Walmart and BestBuy could have great influence on other supply chain parties. Thus, the proposed methodology could be extended by considering those chain retailers as the leader of the supply chain, and this would not cause substantial changes on the proposed model. The proposed methodology was formulated based on a two-period game model. If the PLD problem involves multi-period, the proposed methodology could be extended to deal with the problem by incorporating a multi-period game model. However, derivations of reaction functions would be very difficult because of the exponential nature of the market demand models.

This study has some assumptions and limitations. The quality of returned products was assumed to be average and the effect of product quality on the total cost was not considered. Therefore, fixed return price was considered with all returned products. The number of available returns was assumed to be larger than the demand for remanufactured products. Capacities of production and remanufacturing were also neglected in this study.

8.4 Discussion on the proposed methodology of product returns for remanufacturing

This study can provide useful information to both managers and researchers in several aspects. For the research aspect, the optimal quantity and quality grades of product returns in multi-period can be determined, particularly when numerous returns are available. For the industrial aspect, the results of this study can be used to assess the financial viability of remanufacturing projects, and support the production planning and control for remanufacturing, as well as the inventory control management for product returns and remanufactured products. Sensitivity analysis can help decision makers have a better understanding of the effects of different quality scenarios and inventory costs on the total cost. Results of this study also support previous studies, in which returns with higher quality increase the profitability of remanufactured products and provide better cost savings than returns with lower quality.

In this research, the available number of product returns was assumed to be larger than the demand for remanufactured products. Parameter setting for the DLM model was determined based on the experience gained in the case study. If past data about product returns are available, parameter setting can be estimated by using some statistical methods, such as Bayesian estimation. Capacity constraints for production and inventory were not considered in this research. In addition, lead times for returning different quality grades of products were assumed to be equal.

Chapter 9 Conclusion and Future Work

This chapter presents the conclusion and major contributions of the research. Suggestions for future work are also presented.

9.1 Conclusion

Producing remanufactured products requires the collection and recovery of EoL and returned products previously sold in markets as new products. Remanufactured products are commonly launched in markets where new products exist. Thus, they should be considered together with the new products in PLD in order to acquire the maximum profit and market share of the product line. This research aims to study PLD with simultaneous consideration of new and remanufactured products. After reviewing related research, several research gaps were found. First, there was a lack of methodologies and/or frameworks that enable simultaneous consideration of remanufactured and new products in PLD. Second, the coordination of supply chain parties in performing PLD with consideration of remanufactured products was not addressed in previous studies. Third, the determination of optimal quantity and quality of product returns for remanufacturing under uncertain quality and multi-period of returns was not properly addressed in previous studies. Finally, uncertainties associated with consumer preferences and market potential estimation were not properly addressed in the development of market demand models in previous studies.

In this research, a methodology for product line design with consideration of remanufactured products based on an integrated marketing and engineering approach is proposed and developed to determine optimal product line solutions that contain both new and remanufactured products. In the proposed methodology, product line solutions can be obtained under centralized and decentralized supply chain networks. The proposed methodology mainly involves the conduct of conjoint surveys, generation of fuzzy market demand models, generation of dynamic demand models for simultaneous consideration of new and remanufactured products in PLD coordination of CLSC for PLD, formulation of multi-objective optimization models, and determination of optimal product returns for remanufacturing. NSGA-II was adopted to solve the optimization models by which the Pareto optimal solution for PLD can be obtained.

A case study on the PLD of tablet PCs based on the proposed methodology was conducted to illustrate the proposed methodology. A validation test was conducted to evaluate the effectiveness of the proposed methodology. In the test, the PLD solutions obtained based on the proposed methodology were compared with those based on the conventional methodology (i.e., separate consideration of new and remanufactured products in PLD). The validation results indicated that the proposed methodology outperforms the conventional methodology in terms of total profit and total market share of product lines.

In the proposed methodology, fuzzy demand models were generated based on fuzzy regression and DCA to address the fuzziness of consumer survey data in the estimation of market demands under different scenarios. A validation test was conducted on the developed fuzzy demand models. Results of the test showed that the estimated market demands based on fuzzy demand models are very close to those based on MNL models. However, various scenarios of demand estimation can be obtained from the fuzzy demand models but not from the MNL-based models.

On the other hand, coordination of a manufacturer, chain retailers, and a remanufacturer in performing PLD can be realized in the proposed methodology using a two-period Stackelberg game model to determine product line solutions that involve both new and remanufactured products, pricing decisions of supply chain parties, and product return rate for remanufacturing. The methodology can be used to study the relationship between product returns and demand of remanufactured products as well as determine the return rate of new products.

To determine optimal product returns for remanufacturing, an integer programming-based optimization model was formulated to determine the optimal quantity and quality grades of product returns under multi-period and uncertain quality of the returns. The effects of sales of new products and demand for remanufactured products on product returns are also addressed in the proposed methodology. Post-optimality analyses were performed to help decision makers examine the effects of the different quality scenarios and inventory costs on the total cost of producing remanufactured products.

To facilitate the simultaneous consideration of new and remanufactured products in PLD, the development of dynamic demand models based on DCA, Bass diffusion theory, and dynamic price functions was proposed. The generated models were able to address the dynamic issues of product life cycle and determine the optimal time for launching remanufactured products and their prices. The major contributions of the research are summarized as follows:

- A novel methodology for simultaneous consideration of new and remanufactured products in PLD based on an integrated marketing and engineering approach was proposed and developed to determine product line solutions under centralized and decentralized supply chain networks. The proposed methodology showed better performance than the current methodology (separate consideration of new and remanufactured products) in terms of total profit and total market share of product lines.

- A novel methodology to generate dynamic demand models was developed in this research to address the dynamic issues of product life cycle, launching of remanufactured products, and pricing.
- A new approach to generate fuzzy market demand models was developed to address the fuzziness associated with consumer survey data and market potential estimation in the estimation of market demands under different scenarios.
- This research can be treated as a pioneer study in developing a methodology to coordinate an OEM and supply chain parties for PLD, which involves both new and remanufactured products for determining optimal PLD solutions.
- A novel methodology for the determination of optimal product returns for remanufacturing was developed to address the uncertainty in the quantity, quality, and timing of returns. The effects of sales of new products and

demand for remanufactured products on product returns were also considered in the methodology.

9.2 Future work

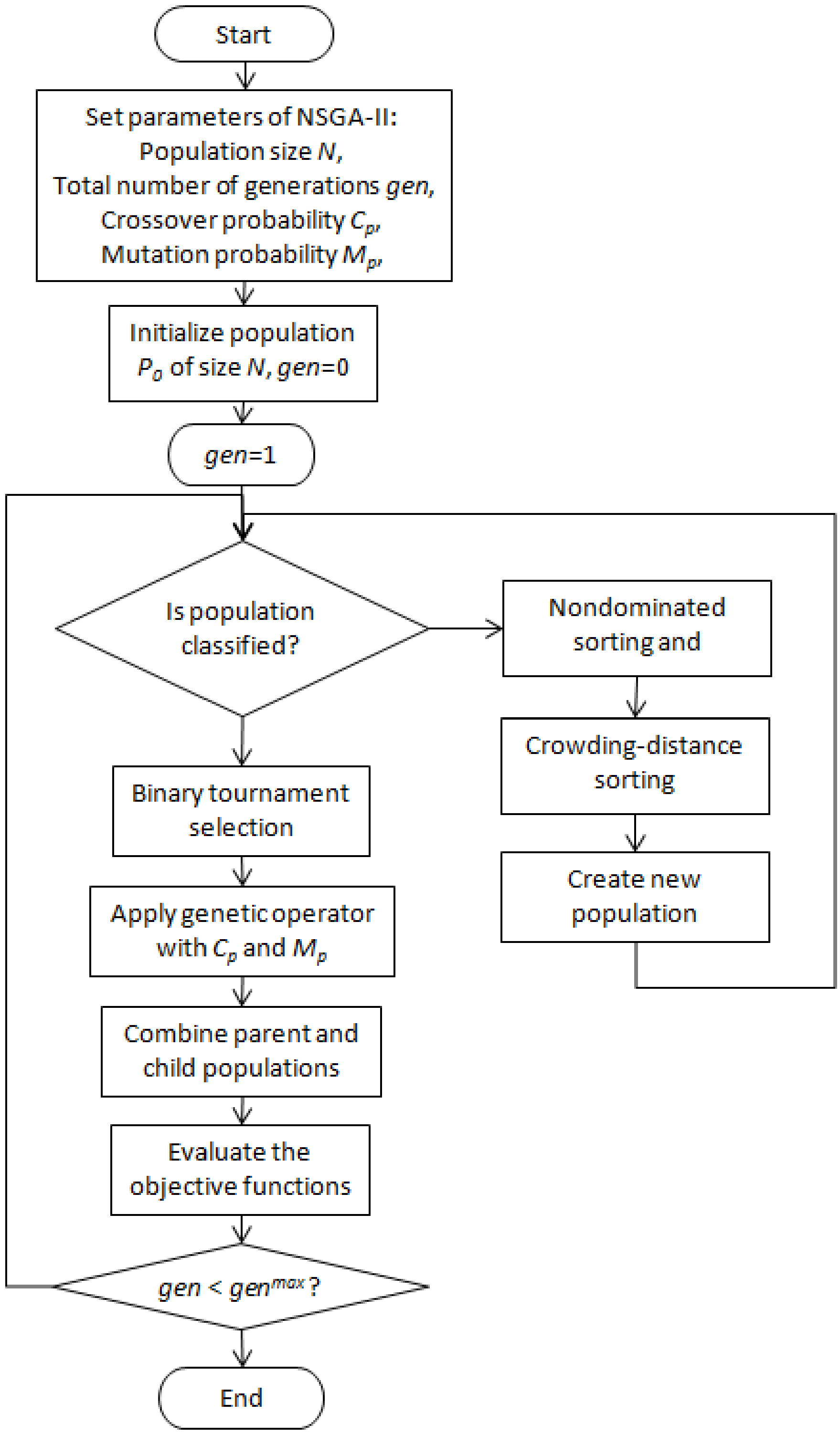
Future studies related to this research are suggested as follows:

- In the development of dynamic demand models, the Bass diffusion model was used together with discrete choice analysis and exponential price functions. In the future, changes in consumer behaviors and other market situations, such as reaction of competitors, could be considered in the development of the dynamic demand models.
- In the proposed methodology for the coordination of CLSC for PLD, a two-period static game model was introduced. To better address the market dynamics, a dynamic game model could be established in the future to determine the best time for launching remanufactured products in the markets and the periodic quantity of product returns. The study could also be extended to consider multiple supply chain parties in the coordination model.
- In the generation of fuzzy demand models, a fuzzy least square regression

method could be used in the future to generate utility functions for improving the modeling accuracy of the fuzzy utility functions, especially when survey data contain random errors.

- Dynamic utility functions and/or dynamic choice models could be incorporated into fuzzy demand models for developing fuzzy dynamic demand models, such that both the uncertainty and dynamic issues of product design and market conditions can be addressed.
- In the future, uncertainty in the demand for remanufactured products could be considered in determining optimal product returns for remanufacturing because it may largely affect the profit generated from the remanufactured products.
- Understanding consumer behavior on returning used products would help companies forecast the quantity and timing of product returns more accurately. Therefore, the effect of consumer behavior on returning used products could be studied and considered in the forecast of quantity and timing of product returns in future work.

Appendix A. Flowchart of NSGA-II



Appendix B. Specifications and prices of competitive tablet PCs in markets

Table B.1. Specifications and prices of competitive tablet PCs in the first market

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)
Product A	10 in	16 GB	2 GB	1.4 GHz	1280×800	Wi-Fi + 3G	510
Product B	10 in	32 GB	2 GB	1.6 GHz	2048×1536	Wi-Fi	440
Product C	7 in	16 GB	2 GB	1.6 GHz	1280×800	Wi-Fi	320
Product D	7 in	16 GB	512 MB	1 GHz	1024×768	Wi-Fi + 3G	450
Product E	10 in	32 GB	1 GB	1.4 GHz	2048×1536	Wi-Fi + 4G	700

Table B.2. Specifications and prices of competitive tablet PCs in the second market

Product	Screen Size	Hard Disk	Memory	Dual CPU	Screen Resolution	Connectivity	Price (USD)
Product F	10 in	16 GB	2 GB	1.4 GHz	1280×800	Wi-Fi	340
Product G	10 in	16 GB	1 GB	1 GHz	1280×800	Wi-Fi	260
Product H	10 in	16 GB	1 GB	1 GHz	1280×800	Wi-Fi	160
Product I	10 in	64 GB	1 GB	1 GHz	1024×768	Wi-Fi + 3G	500
Product J	7 in	32 GB	1 GB	1 GHz	1280×800	Wi-Fi	155
Product K	10 in	32 GB	1 GB	1.4 GHz	2048×1536	Wi-Fi + 4G	500
Product L	7 in	16 GB	512 MB	1 GHz	1024×768	Wi-Fi + 3G	360

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