INTEGRATED PRODUCT DESIGN WITH CONSIDERATION OF REMANUFACTURED PRODUCTS AND RETURN UNCERTAINTIES

MOHAMMED WOYESO GEDA

PhD

The Hong Kong Polytechnic University

2022

The Hong Kong Polytechnic University

Department of Industrial and Systems Engineering

Integrated Product Design with Consideration of Remanufactured Products and Return Uncertainties

Mohammed Woyeso Geda

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

March 2021

CERTIFICATE OF ORIGINALITY

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____ (Signed)

__Mohammed Woyeso GEDA____________________(Name of Student)

Abstract

Remanufacturing has gained growing attention as a product recovery strategy over the past few years due to stricter product take-back legislation, customers' awareness of environmental and health concerns of used product disposals, and economic reasons. Several multinational companies currently offer remanufactured products, often branded as 'refurbished,' alongside brand-new products. Nevertheless, previous studies have identified the design of products and the timing, quantity, and quality uncertainty of used product returns as major challenges of the remanufacturing industry. This research proposes an integrated methodology framework to address product design concerns and the uncertainty of used product returns from a remanufacturing perspective.

Under this research framework, four core methodologies are proposed in this research for: i) the simultaneous consideration of assembly and disassembly concerns for the selection of fastening methods; ii) the development of a hierarchical optimisation model for the joint optimisation of configuration for new and remanufactured products with the consideration of upgrading decisions for used product returns; iii) the forecasting of used product returns for remanufacturing; and iv) the modelling of customers' preferences of product attributes and the estimation of market demands for brand-new and remanufacturing products under uncertainty

For the i) aspect, fastening methods affect both the assembly of new/remanufactured products and the disassembly of products during remanufacturing. Therefore, assembly and disassembly concerns must be addressed simultaneously for fastening methods selections, which has been little studied previously from a remanufacturing perspective holistically. In this research, a methodology for fastening methods selection from a remanufacturing perspective known as FMSRem is proposed. The proposed FMSRem considers design factors that facilitate the assembly of new products during initial manufacturing and the disassembly/re-assembly processes during the remanufacturing of used products. A mathematical optimisation model is presented with an objective function to minimise the product assembly and disassembly cost. The genetic algorithm (GA) heuristic is proposed to solve the

model. A laptop design case study is presented to demonstrate the effectiveness of the proposed methodology. Different scenarios regarding the degree of disassembly required and the volume of used product returns was run to validate the proposed methodology. The result has shown that the proposed methodology offers significant product assembly and disassembly cost savings.

For the ii) aspect, a bilevel programming model is proposed for the joint optimisation of design configurations of new and remanufactured products considering specification upgrading for remanufactured products. The joint optimisation model involves two-level decision makings. The upper-level handles the configuration of new product variants to maximise the shared surplus of new product offerings. The lower-level deals with configuration and specification upgrading of remanufactured product variants to maximise the shared surplus of remanufactured product offerings. A non-linear integer bilevel programming (NLIBP) is proposed to model the hierarchical optimisation problem. A nested bilevel genetic algorithm (NBGA) is proposed to solve the NLIBP. Furthermore, a case study involving configuration design for new and remanufactured mobile phone variants is conducted to validate the proposed model. Four scenarios are investigated to examine the effects of model parameters on the optimal solutions with the simulation result given at last.

For the iii) aspect, as remanufactured products are made from parts/modules recovered from used products, knowledge of the available quantity, timing, and quality of used product returns is crucial for successfully implementing remanufacturing. However, the uncertainty associated with the quantity, timing and quality of used product returns makes forecasting in remanufacturing a complex task. In this research, a distributed lag model (DLM) is proposed to forecast used products under uncertainty accurately. DLM’s forecasting accuracy is primarily influenced by the lag function parameters' estimates, which has not been addressed in previous studies. To address this issue, a novel approach based on Markov Chain Monte Carlo (MCMC) and Bayesian inference is proposed, which can handle parameter estimations irrespective of the type and complexity of the lag function. A numerical case study is undertaken to demonstrate the proposed forecasting model and the parameter estimation methodology. Validation tests are conducted by comparing forecasting errors of the proposed parameter estimation approach with the maximum likelihood estimate (MLE) method. The result reveals that the proposed DLM based forecasting method can lead to an improved forecasting accuracy when the proposed MCMC based Bayesian approach is used for parameter estimation.

For the iv) aspect, fuzzy regression (FR) and rating-based conjoint analysis are proposed for modelling customers' preferences for new and remanufactured product profiles. A multinomial logit model (MNL) is proposed, which uses FR and conjoint analysis results as inputs to estimate the demand for product profiles under uncertainties. A case study involving the design of new and refurbished laptop computers is further conducted to demonstrate the proposed approaches. Fuzzy utilities are determined for both the new and remanufactured product profiles, which are then used to estimate the market demands under three scenarios, including 'worst,' 'normal', and 'best' cases.

It is envisioned that the design methodologies, approaches, and insights provided in this thesis can serve as a decision support tool during the early-stage product design processes. Furthermore, the forecasting methodology proposed can enable firms to manage the uncertainties associated with used product returns in a remanufacturing context.

Publications Arising from the Thesis

Journal papers

1. Geda, M. W., Kwong, C. K., & Jiang, H. (2019). Fastening method selection with simultaneous consideration of product assembly and disassembly from a remanufacturing perspective. The International Journal of Advanced Manufacturing Technology, 101(5-8), 1481-1493. https://doi.org/10.1007/s00170-018-3027-1
2. Geda, M., & Kwong, C. K. (2021). An MCMC based Bayesian inference approach to parameter estimation of distributed lag models for forecasting used product returns for remanufacturing. Journal of Remanufacturing, 1-20. https://doi.org/10.1007/s13243-020-00099-3
3. Geda, M., P Zheng, and Kwong, C. K. A bilevel programming model for optimum design configuration of new and remanufactured products considering specification upgrading of used products. International Journal of Production Research (Under review)

Conference papers:

4. Geda, M. W., & Kwong, C. K. (2018). Simultaneous consideration of assemblability and disassemblability for fastening method selection. 8th International Conference on Industrial Engineering and Operations Management, IEOM 2018; Bandung, Indonesia; 6-8 March 2018, pp. 1616-1624.
5. M. W. Geda and C. K. Kwong, "Forecasting of Used Product Returns for Remanufacturing," 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bangkok, Thailand, 2018, pp. 889-893, https://doi.org/10.1109/IEEM.2018.8607362.

Acknowledgements

First, I would like to express my deepest gratitude to my former Chief supervisor Dr. C.K Kwong for his support, guidance, and mentorship during my PhD study. I am indebted for all his constructive advice, valuable suggestions, and provision of useful materials, which have helped me understand my studies' domain and improve my research skills.

Second, my sincere gratitude also goes to Dr Pai Zheng and Dr Carman Lee who have been assigned as my Chief supervisor and Co-Supervisor respectively since September 2020, for their advice and guidance through the accomplishment of my PhD study.

Third, I would like to thank Dr. Huimin Jiang for her encouragement and insightful suggestions during the implementation of my research. I would like to also thank my friends at PolyU who have encouraged me during my studies.

Finally, special thanks go to my parents, beloved wife Hasna, and my sons Ihsan and Khalid. Their love, understanding, and patience during my PhD study have always been sources of my strength.

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List of Abbreviations

ANP	Analytic network process
DEM	Disassemblability evaluation method
DFA	Design for assembly
DFD	Design for disassembly
DLM	Distributed lag model
DP	Design parameter
DPFO	Discounted penalty cost of forecast overestimation
DPFU	Discounted penalty cost of forecast underestimation
ELDA	End-of-life design advisor
ELV	End of life vehicle
EoL	End-of-life
EoU	End-of use
FR	Functional requirement
GA	Genetic algorithm
IC	Index of confidence
LP	Linear programming
MAPE	Mean absolute percent error
MCMC	Markov-chain Monte-carlo
MH	Metropolis Hasting
MMSE	Minimum mean-squared error
MNL	Multinomial logit
MOST	Maynard operation sequence technique
NBGA	Nested bilevel genetic algorithm
PDC	Product design configuration

PDD	Product design and development
SSE	Sum of squared error
SST	Sum of squared total
TFN	Triangular fuzzy number
TOPSIS	Order preference by similarity to ideal solution
VoE	Variance of errors
WEE	Waste from electrical and electronic equipment

Chapter 1 Introduction

Due to the rapid technological advancements, the frequently changing customer preferences, and the shortening lifespan of products, consumer products become obsolete more quickly than ever. This phenomenon has resulted in an increase in waste disposal from electronic and electrical products (WEE) and end-of-life vehicles (ELVs), which have become a growing concern globally. A study conducted by Li et al. (2015) shows that more than 5.5 million tonnes of WEEE, mainly from discarded air conditioners, refrigerators, washing machines, televisions, and computers, were generated in China alone in 2013. The amount was projected to increase to 11.7 million tonnes and 20 million tonnes in 2020 and 2040, respectively. The severe environmental and health risks associated with the disposal of WEE and ELV have led many countries to enact legislation that mandate companies to bear responsibility for the collection, disposal, and reprocessing of end-of-life (EoL) and end-of-use (EoU) products. For instances, the European Union's "Directive 2000/53/ EC" and "Directive 2002/95/EC" imposes targets on the amount of ELV and WEEE waste, respectively, that must be recovered by companies (European Commission, 2000; European Parliament & Council of the European Union, 2000). The Chinese government passed similar regulations for the take-back, recycling, and disposal of WEE for pollution control (Hatcher et al., 2013).

More and more companies have been adopting product recovery strategies in recent years to respond to legislative pressures, increasing consumer awareness of environmental and health concerns and economic justifications. Product recovery involves the harvesting of components from EoL and EoU products for subsequent reprocessing to extend the useful lives of products. Components reuse, remanufacturing, reconditioning, repairing, and recycling are some of the product recovery strategies currently being implemented by a range of manufacturers worldwide. Figure 1.1 depicts the material flow and commonly implemented product recovery options.

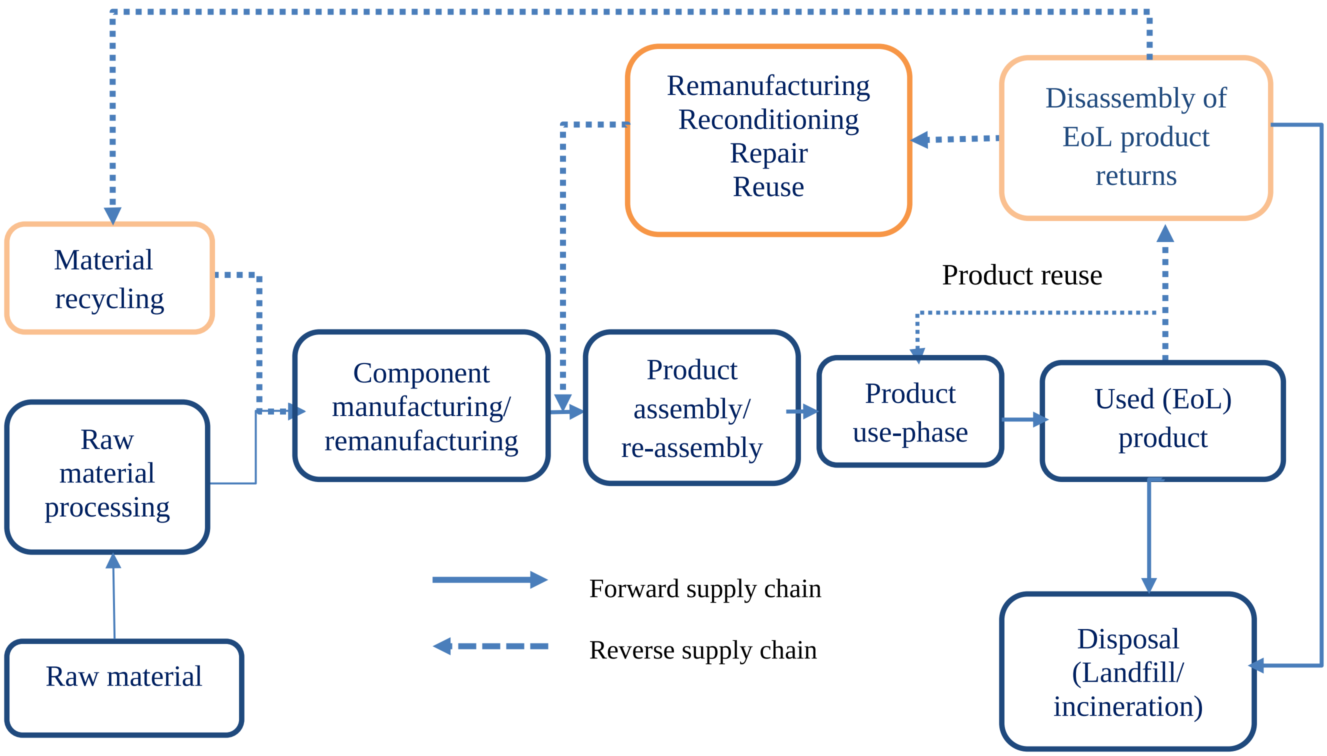


Figure 1.1 Material flow and product recovery strategy options

Product recovery options differ from each other depending on the nature of operations done on a used part and the resultant condition of products. Component reuse entails reusing parts/modules without modification. Product recondition involves repairing major parts/modules (regardless of their condition) to bring a product to a satisfactory working condition. Refurbishing differs from repair in that repairing focuses on fixing faulty/broken parts/modules, while refurbishing focuses on aesthetic improvement with a little improvement to its functionality (Benoy et al., 2014). According to Ijomah et al. (2004), remanufacturing is defined as a process whereby a used product is returned to a “like-new” condition and offered a warranty identical to that of a brand new version. In remanufacturing, components harvested from used products are inspected for subsequent reuse, refurbishment or replacement (Ismail et al., 2014; Östlin et al., 2009).

1.1 Background of the study

Over the past few decades, remanufacturing has received increasing attention from manufacturers and researchers as a profitable and environmentally sound product recovery strategy (Umeda et al., 2017). Remanufacturing conserves virgin material, which would have otherwise extracted for the manufacturing of new products, leading to significant savings in manufacturing costs and a reduction in environmental impacts. Recent studies estimated the energy, labour, and material cost savings of a remanufacturing at 50%, 33% and 80%, respectively, when compared with new product manufacturing (Li et al., 2019; Van Nguyen et al., 2020). Furthermore, Cao et al. (2020) estimated the retail price of a remanufactured product to be about 50-70% of a brand new product. Heavy duty and off-road equipment manufacturers (e.g., Caterpillar) and electronic manufacturers (e.g., Xerox, Apple, HP, and Sony) are some of the multinational companies offering remanufactured products (also marketed as "refurbished"). Products widely remanufactured include consumer electronics, car engines, automotive components, tires (retreading), aircraft components, furniture, and printing equipment. Although remanufacturing is recognized for its environmental friendliness and profitability, its adoption in developing countries is limited. Previous research has shown that the major challenges for the low adoption of remanufacturing are related to the remanufacturability of product designs and the uncertainty regarding the quantity, the quality, and the timing of used product returns (Matsumoto et al., 2016; A. Raihanian Mashhadi et al., 2015). This research focuses on product design issues and production planning uncertainties in a hybrid manufacturing and remanufacturing industry to address the research gap.

The product design and development (PDD) process can be represented using four domains: customer domain, functional domain, physical domain, and process domain (Jiao et al., 2007; Kuo & Wang, 2019). Figure 1.2 shows the interrelationship among the domains. Customer domain is where customer needs (CNs) in specific market segments are defined and synthesized. Each CN is translated into the product's functional requirements (FRs) in the functional domain. In the physical domain, FRs are converted to corresponding design parameters (DPs). DPs are critical parameters that are specified by designers for the fulfillment of FRs. Finally, the DPs are converted into process variables (PVs) to produce the resultant product design (Wang & Lu, 2018).

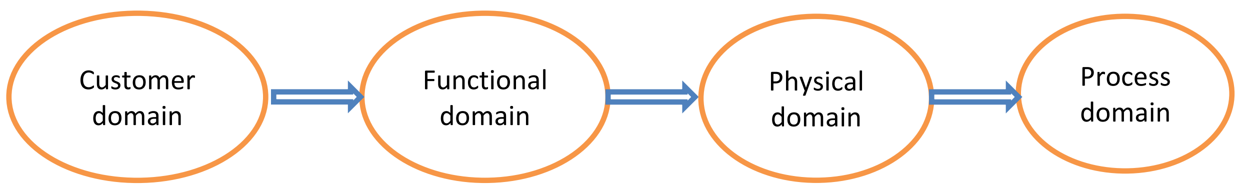


Figure 1.2 Four domains of PDD process

Unlike the traditional PDD process, in remanufacturing, early-stage design decisions need to consider factors that affect the remanufacturability of products. In this research, early-stage design refers to a stage when the design problems are defined, concepts are generated and design specifications are determined (Ahmad et al., 2018). One of the early-stage design decisions that can affect the remanufacturability of a product design is related to the selection of fastening methods. The choice of appropriate fastening methods can help facilitate the assemblability of new products during initial manufacturing as well as the disassemblability of used products during subsequent remanufacturing. Therefore, a methodology for the optimum selection of fastening methods is required during early-stage design.

During the past few decades, firms have transitioned from traditional mass production to a more diversified portfolio planning to satisfy the changing demands and maintain their competitiveness. Product design configuration (PDC) is a design paradigm that allows firms to introduce product variants to different market segments to satisfy their diverse needs (Hvam et al., 2013). PDC involves determining optimal levels for a set of attributes that characterises a product. The products' performances vary depending on the configuration of attribute levels of parts/modules, such that different levels of an attribute have similar functionalities but different performances (Kwong et al., 2011). The main goal of a PDC is to determine optimal attribute levels for parts/modules to satisfy specific objectives such as total profit, market share, and customer satisfaction, subject to constraints such as performance requirements (Wang et al., 2009; Wu et al., 2016).

In addition to determining attribute levels, PDC decisions involve specification upgrading for parts recovered from used product returns for firms that offer lines of both the new and remanufactured product variants. When new products previously sold return at the end of their useful period, the original specification of parts/modules incorporated in new products can become technologically obsolete (Kwak & Kim, 2013). In such a scenario, parts/modules recovered from used product returns often require upgrading with a better or cutting-edge specification to improve its functionality. However, replacements with higher specifications often lead to higher costs of remanufacturing. The upgrade level required for a used part/module largely depends on the original specification of a part/module and the timing of used product returns. Hence, the PDC during the early-stage design should consider specification upgrading of used products.

The uncertainty of used product returns is another major challenge that affects the profitability of remanufacturing. Two categories of uncertainty are involved. The first is related to the quantity and timing uncertainty of used product returns. This uncertainty emanates from the lack of information regarding the proportion of previously sold new products which will become available for returns and the timing of returns. The underestimation and overestimation of used product returns can significantly affect remanufacturing profitability. For instance, when the demand for a remanufactured product exceeds the number of used product returns, companies often expedite orders of used products from the secondary market at a higher cost to offset the deficit. However, this leads to an increase in the remanufacturing cost. On the other hand, the quality of used product returns can vary significantly from minor repair issues to total damage. The inaccurate prediction of the quality of used returns can also lead to variations in remanufacturing costs. Hence, for the effective planning of remanufacturing activities, the uncertainties regarding the quantity, timing, and quality of product returns must be addressed holistically.

1.2 Problem statement

Four sets of problems that affect the profitability of companies that offer both the new and remanufactured products are considered in this research, including i) the selection of fastening methods to facilitate the manufacturability of new products and the remanufacturability of used products; ii) product design configuration and the consideration of specification upgrading decision for used product returns; iii) the uncertainties associated with the available quantity and timing of used product returns; and iii) the modelling of customer preferences and the estimation of demands for the new and remanufactured product profiles under uncertainty.

The first problem concerns selecting appropriate fastening methods during the early design stage to facilitate the manufacturing of new products and the remanufacturing of used product returns. Early-stage design decisions regarding the selection of fastening methods affect both the assembly of new products and the disassembly of used products. Fastening methods selected to facilitate new products' assembly can become unsuitable for the disassembly of EoL products and vice versa. For instance, fasteners such as snap-fits and adhesives often require little effort to fasten during the assembly of new products.

However, they are often challenging to disassemble during the remanufacturing of used products. Therefore, decisions regarding fastening methods must consider assemblability and disassemblability concerns simultaneously during early-stage design from a remanufacturing perspective, which was not addressed in previous studies.

The second problem concerns determining optimal design configurations (PDC) and upgrading plans for remanufactured products during the early design stage. Traditionally, PDC involves determining optimal design configurations for new product profiles, which entails choosing optimal specifications for new parts. However, for firms that offer remanufactured products, early-stage product design must also plan upgrade decisions for parts recovered from used product returns. Thus, PDC decision-making entails a hierarchical framework that can be dealt with using a leader-follower optimisation paradigm. However, previous studies on PDC have not addressed the hierarchical optimisation considering upgrade decision-making for used parts.

The third research problem concerns the forecasting of the quantity and timing of EoL product returns. The widely used conventional time series-based forecasting methods cannot capture the relationship between the number of new products sold in previous periods and the available number of used product returns. Few previous studies have proposed the distributed lag model (DLM) given in Equation (1.1) to capture the relationship between the sales of new products and the available quantity of used product returns (Aydin et al., 2018a; Clottey et al., 2012; Krapp et al., 2013a).

$$m_t^{ret} = \sum_{k=1}^{t-1} \beta_k n_{t-k} + \varepsilon_{t\,;}\ \forall t = 1,23,..T \qquad (1.1)$$

Where β_k in Equation (1.1) denotes the delay function, i.e., the proportion of new products sold during $(t - k)^{th}$ period, i.e., n_{t-k}that is available for return in period t (i.e., m_t^{ret}). Previous studies have used statistical distributions such as negative binomial, exponential, geometric, and gamma distributions to model the delay function (Clottey et al., 2012; Clottey & Benton, 2014; Toktay et al., 2000). However, DLM has some limitations. First, due to the assumption of a specific distribution for the lag function, an inappropriate distribution assumption can lead to inaccurate forecasting. Second, previously proposed methods that used geometric, exponential, and gamma distributions work only for a case of product returns with short lags and therefore do not accurately forecast used product returns with longer lags (Clottey & Benton, 2014).

Negative binomial distribution, which is given in Equation (1.2), was proposed in the past to model the delay function with longer lags (Toktay et al., 2000).

$$\beta_k = \mathrm{p}\binom{k+r-1}{r} q^r (1-q)^k \tag{1.2}$$

However, the negative binomial delay function often results in over-estimating the return quantities (Clottey & Benton, 2014). Besides, the difficulty of estimating the parameter r, which represents the lag with the largest β_k, poses another challenge. Toktay et al. (2000) conducted hypothesis tests to choose appropriate values for the r parameter, which involves quite a tedious procedure.

The fourth problem concerns customers' preference modelling and the estimation of market shares for new and remanufactured product profiles under uncertainty. The conventional conjoint analysis, which is widely used in market research for modelling customers' preferences, cannot handle the imprecision of survey data that results from the subjective rating of survey responses. Such an imprecision leads to inaccurate estimates of the products' utilities and hence their market share estimates. Therefore, survey data's imprecision should be addressed to accurately determine the utilities and market shares of new and remanufactured products under uncertainty.

1.3 Research hypotheses and objectives

This research has the following hypotheses, which were formulated based on an extensive review of related literature.

- Hypothesis 1: A methodology that will help design engineers to select fastening methods during the early design stage to facilitate the assembly of new products and the disassembly of used products can be developed. The fastening methods selection methodology can improve assembly and disassembly times and the overall assembly and disassembly cost of a product.
- Hypothesis 2: A joint optimization of product design configurations for both new and remanufactured products can be obtained during the early design stage, considering specification upgrading decisions for used parts/modules.
- Hypothesis 3: It is possible to estimate the parameters of the distributed lag model (DLM) regardless of the types of lag function assumed for subsequent use in a DLM to forecast used product returns for remanufacturing based on sales in previous periods.

In order to test and validate the proposed hypotheses, this research has defined the following objectives:

- To develop a methodology for the selection of fastening methods through the simultaneous consideration of product assembly and disassembly concerns to facilitate the manufacturing of new products and the remanufacturing of used products.
- To develop a hierarchical optimisation model for optimal product design configuration for new and remanufactured products considering specification upgrading of used parts/modules.
- To develop a methodology for forecasting the quantity and timing of used product returns from a remanufacturing perspective.
- To model customers' satisfaction and estimate market demands for new and remanufactured products under uncertainty.

1.4 Scope and assumptions

This research addresses two main issues in a hybrid manufacturing/remanufacturing system: product design and development and the uncertainty of used product return. On product design and development, this thesis concentrates on three aspects. The first aspect deals with selecting optimal fastening methods during the early design stage of product development to facilitate the assembly and disassembly of products. More specifically, the main focus is to determine optimal fastening methods that will minimise the overall assembly and disassembly cost. The second aspect deals with optimising product design configuration for both new and remanufactured products, considering specification upgrading for used parts. The third aspect concerns the estimation of customers' satisfaction and market shares for new and remanufactured products under uncertainty. Moreover, to address the uncertainty issues regarding used product returns, this research focuses on forecasting the available quantity of used products in future periods and the timing of their returns based on information regarding the sales of new products in previous periods. A major assumption this research makes is that original equipment manufacturers (OEMs) design new products using a configurable modular design approach, and subsequently remanufacture used product returns. Furthermore, new product sales pattern and the condition of used product returns were assumed to follow a determinist distribution.

1.5 Organization of the thesis

Figure 1.2 outlines the thesis's roadmap, which depicts each chapter's relationship with the research framework.

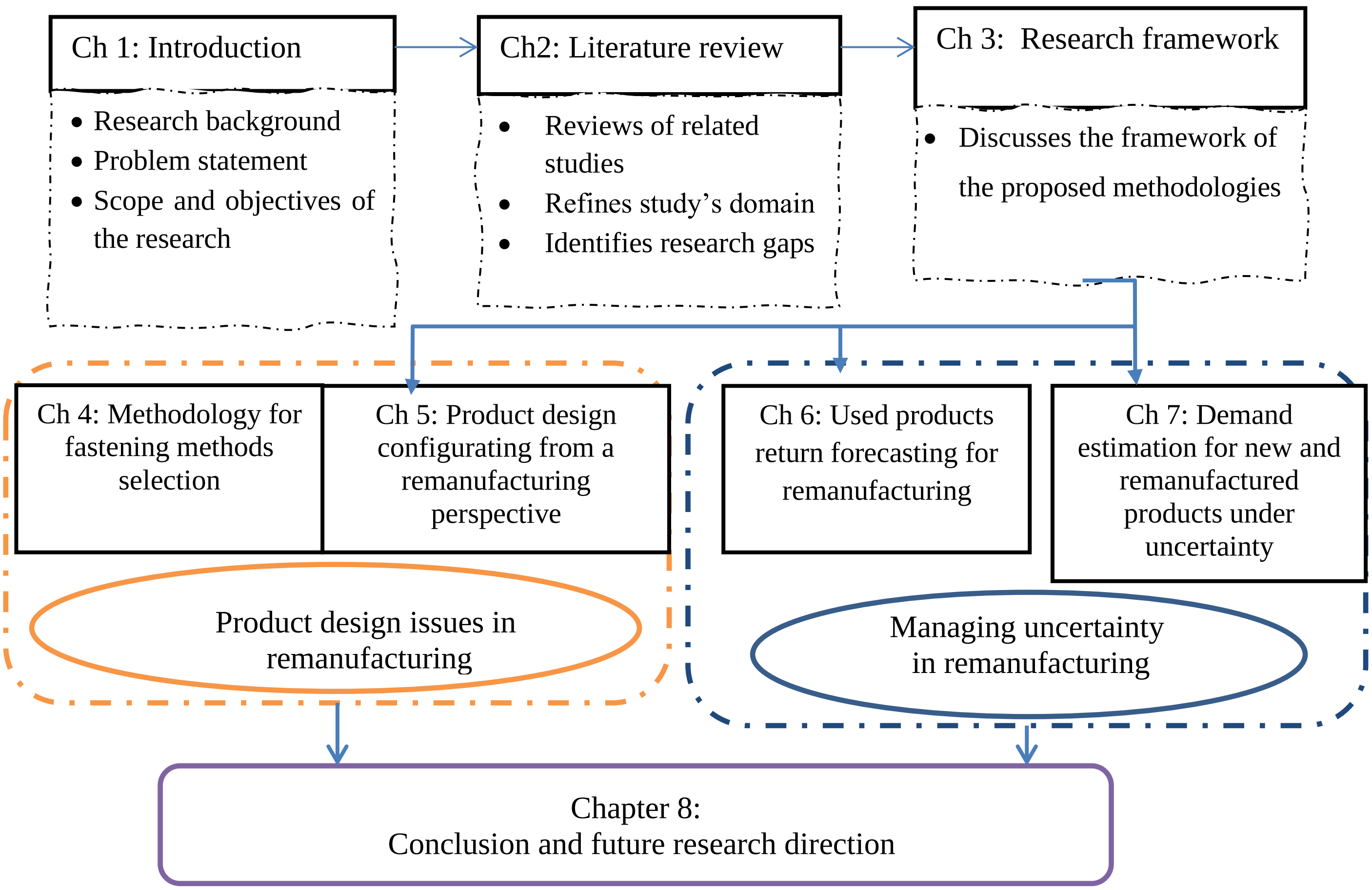


Figure 1.3 Overall study roadmap

The research's background, problem statement, hypotheses, objectives, and scope were discussed in chapter 1. The rest of the thesis is organised as follows. Chapter 2 presents a comprehensive review of previous studies related to the scope of this research. Chapter 3 discusses the overall research framework, which includes 1) the methodology for fastening methods selection during the early design stage with consideration of product assembly and disassembly; 2) the methodology for joint optimisation of product design configurations for new and remanufactured products considering specification upgrading for remanufactured products; 3) the methodology for forecasting the quantity and timing of used product returns; 3) methodology for modelling customer preferences and determining the market demand for both new and remanufactured product.

Chapters 4 and 5 deal with design concerns that affect remanufacturing profitability. Chapter 4 presents the proposed methodology for fastening methods selection to facilitate the manufacturability of new products and the remanufacturability of used products. A mathematical optimisation model and the GA solving approach are also presented. Chapter 5 presents the proposed model to determine optimal design configurations for new and remanufactured products considering specification upgrading of used products. Chapters 6 and 7 deal with the uncertainty issues that affect the production planning and control of remanufacturing operations. Chapter 6 presents the proposed DLM based forecasting model for the forecasting of used product returns for remanufacturing. The proposed MCMC based Bayesian approach for the estimation of parameters of the DLM is also described. Chapter 7 presents the methodology for modelling customers' preferences and estimating the demands for new and remanufactured products under uncertainty. Application of the rating-based conjoint analysis and the fuzzy regression model to estimate market demands for the new and remanufactured products are presented. Chapter 8 discusses the conclusion, findings, and contributions from the study. Future work is also suggested.

Chapter 2 Literature Review

A comprehensive review of previous studies related to the proposed research framework was conducted to identify potential research gaps and refine the study's focus. Two streams of literature have been identified as relevant to the proposed research framework. The first stream concerns the design methodologies, guidelines & tools developed by previous studies to facilitate the remanufacturability of a product design. Under the first stream, the following topics were reviewed. 1) Design methodologies proposed in previous studies to facilitate the selection of fastening methods during the early-stage design; 2) previous studies on product design configuration that considered both new and remanufactured products. Besides, studies on used product upgrading decision-making are also reviewed from a PDC perspective. 3) review of previous studies on the application of bilevel optimisation for product design configurations 4) managing uncertainty in product design and development. Potential research gaps have been identified.

The second stream of literature reviewed in this research concerns previous studies on the forecasting of used products from a remanufacturing perspective and the estimation of demands for remanufactured products under uncertainty. To this end, previous studies on the management of quantity and timing uncertainty of used product returns and the forecasting methodologies proposed in previous studies was reviewed.

2.1 Product design for remanufacturing

Early-stage design decisions can affect not only the functional performances of new products but also the remanufacturability of EoL products. Some previous studies have investigated design factors that affect the remanufacturability of products. Sundin (2004) studied several remanufactured products to identify product properties that facilitate the remanufacturability of product designs. The study led to the development of the “RemPro matrix,” a design methodology that guides designers to inculcate design attributes such as “ease of access,” “ease of handling,” and “wear resistance” to facilitate the remanufacturability of products. Zwolinski & Brissaud (2008) investigated several remanufactured products to identify 11 product profiles that enhance products' remanufacturability. Their investigation led to the development of “Repro2,” a tool used to evaluate products' remanufacturability based on the identified ‘remanufacturable’ profiles. Du et al. (2012) also proposed integrated remanufacturability assessment metrics based on three aspects: i) technological feasibility, which evaluates the feasibility of remanufacturing steps such as disassembly, cleaning, and reconditioning; ii) economic feasibility, and iii) environmental feasibility. Fang et al. (2016) proposed an integrated tool for evaluating the remanufacturability of a product design based on four metrics: i) disassembly complexity, ii) fastener accessibility, iii) disassemblability, and iv) recoverability. The metrics are aggregated to compute the overall remanufacturability metrics of a product design. Similarly, Yang et al. (2016) presented a Fuzzy TOPSIS approach for evaluating the remanufacturability of product designs based on four factors: i) material selection, ii) material joining methods, iii) structure design and iv) surface coating methods.

2.1.1 Product design for disassembly methods

In remanufacturing, the complete disassembly of used products is rarely undertaken due to the high costs associated. Partial disassembly is often required depending on the quality of product returns. Some previous studies have proposed design for disassembly (DFD) tools to evaluate disassemblability during the early design stage. Some of the notable contributions include tools for evaluating a product's disassembly difficulty based on work measurement analysis proposed by (Kroll, 1996; Kroll & Carver, 1999; Kroll & Hanft, 1998). Das et al. (2000) proposed an index for measuring the disassembly effort during the early design stage considering five factors: i) time, ii) force, iii) tool requirement, iv) accessibility and v) hazard. Simiarly, Desai & Mital (2005) presented a method for calculating the disassemblability score considering five factors: i) accessibility, ii) force requirement, iii) tool and positioning, and iv) material handling. Sabaghi et al. (2016) presented a similar method for evaluating the disassemblability of products based on five factors: i) accessibility, ii) the relative position of components, iii) tool requirement, iv) fasteners type, and v) the number of fasteners. On the other hand, methods for evaluating the disassembly index were also proposed in previous studies. Soh et al. (2016) investigated the disassembly complexity and the accessibility of parts to compute the disassembly index of alternative disassembly routes. Several disassemblability and accessibility constraints, including “part handling difficulty,” “fastener removal difficulty,” and “directional constraints” were considered. The Hitachi company also developed the Disassemblability Evaluation Method (DEM), a quantitative method for evaluating the disassemblability of product designs (Go et al., 2011). Bras & Hammond (1996) proposed metrics for evaluating the overall product’s remanufacturability based on the disassemblability, cleaning difficulty, damage correction, and quality assurance factors. They implemented the inverse weighted addition method to combine individual metrics into global remanufacturability metrics.

Some previous studies have also proposed disassembly evaluation methodologies based on disassembly time. Unlike other subjective metrics, disassembly time provides an objective measure of the disassemblability of a product and helps designers conduct feasibility studies of disassembly operations. Some previous studies have proposed methods to estimate the disassembly time based on the MOST work-measurement system (Kroll & Carver, 1999) and the work factor method (Yi et al., 2003). According to their method, total disassembly time is calculated by adding individual time estimates for preparation, movement, disassembly, and post-processing operations. Similarly, Desai & Mital, (2005) presented a methodology for estimating the disassembly time based on difficulty scores of factors such as i) force, ii) material handling and tools requirement, iii) accessibility, and iv) tool positioning. Germani et al. (2014)

proposed quantitative metrics to evaluate the disassemblability of product designs based on information on joining methods. The disassemblability of a target component is evaluated based on the estimate of disassembly time and cost, wherein components with the most extended disassembly times are considered for a redesign.

The impact of a product's design on remanufacturing profitability was also addressed in previous studies. Zhao & Thurston (2010) developed a mathematical model to maximise the overall profit from the sales of new products and product recovery operations. Kwong et al. (2011) proposed a profit maximisation model for product line design considering both new and remanufactured products. Kwak & Kim (2015) proposed a decision support tool based on a nonlinear mixed-integer programming model to determine whether a part should be reused or upgraded to maximise the overall profit and environmental impact saving. Similarly, Kwak & Kim (2017) presented a mixed-integer model for joint optimisation of the profit and environmental impact saving considering new and remanufactured products.

2.1.2 Fastening methods selection for product assembly and disassembly

The assembly of new products and the disassembly of used products during remanufacturing are affected by the types of fasteners used in products. Some fastening methods are suitable for product assembly but are challenging to disassemble during the remanufacturing of used products and vice-versa. Therefore, the selection of fastening methods should consider the assemblability and disassemblability issues simultaneously. Quite a few studies have considered fastening methods selection during the early design stage. Shu & Flowers (1999) proposed a method to select fasteners based on the probabilities of fasteners' failure during the disassembly process and reassembly process. Sodhi et al. (2004) proposed the unfastening effort (U-effort) model, a methodology for estimating the unfastening time. The U-effort score is determined by measuring causal attributes like the size, the shape, and the operational characteristics of commonly used fastening methods. However, the U-effort model can only be used to estimate the unfastening efforts for a limited number of fastener types. Besides, they did not consider the unfastening time required for identifying joints, tool changing requirement, and positioning requirements. Güngör (2006) also proposed a methodology to select fastener types based on the analytic network process (ANP) approach to facilitate the disassembly of products. Factors related to the assembly, usage, disassembly were considered. However, the ANP involves running several scenarios that take time to setup. Ghazilla et al. (2014) proposed the PROMETHEE, a multi-criteria decision model for selecting fasteners considering the qualitative and quantitative disassembly parameters. Kobayashi et al. (2015) presented an optimisation model to select fastening methods with an objective function of maximizing the volume of high-value components to be recovered from used products constrained with minimising the fastener removal time. The fastener removal time is computed by aggregating unfastening time and tool preparation time. de Aguiar et al. (2017) proposed a diagnostic tool for early design stage disassembly analysis and presented indices for the quantity of fasteners, types of fasteners, and accessibility of fasteners. Sabbaghi & Behdad (2017) presented a non-linear integer optimisation to minimise the mean-time-to-repair of products based on the type of fasteners used, the repair requirement, and the disassembly sequences involved.

2.2 Determining optimal configurations for new and remanufactured products

Product design configuration (PDC) is one of the critical decisions of product development during the early-stage design, which deals with determining optimal configurations for products to satisfy customers' diverse needs (C. Zhou et al., 2008). Parts/modules in different product profiles often have similar functionality/structure but different attribute levels (performances). A part/module's attributes can be measured using either a continuous scale or discrete levels (Kwong et al., 2011). For instance, a power tool can come with a design option of either a 100-120V or 220-240V power source module representing a discrete attribute level. In contrast, the attribute for the length of the power tool's handle can be measured on a continuous scale. A large volume of previous studies on PDC focused on determining optimal configurations for products' attributes to meet specific objectives. A PDC's objective often involves determining optimal configurations for product profiles to maximise the total profit, market share, customer satisfaction etc., subject to certain constraints such as performance requirements, reliability, etc. Many of the previous studies on PDC proposed multi-objective optimisation with two or more objectives (Aydin et al., 2015; Goswami et al., 2017; Kwong et al., 2011; Wang et al., 2009; Wu et al., 2016). Various solving techniques were proposed for solving PDC problems, many of which involve the aggregation of multiple objectives into a single optimisation problem (Q. Wang et al., 2018; G. Du et al., 2014; Wu et al., 2016).

While some previous studies focused on marketing and engineering concerns separately, integrating both concerns was a commonly considered approach in recent studies (Goswami et al., 2017). The market-driven approach mainly focuses on product positioning, price competition, customer satisfaction models, etc. It also involves conjoint analysis and single-stage optimisation models to determine optimal design configurations for product variants. McBride and Zufryden (1988) proposed integer programming and conjoint analysis to select product variants from a predefined candidate set. Li and Azarm (2002) investigated uncertainties regarding customers' preferences, market competitions, and multiple business goals for the optimal PDC. Kumar et al. (2009) developed a market-driven methodology to determine the appropriate positioning for product variants (i.e., determining market niches for each of the product variants) and explored the corresponding cost savings. Recently, Bechler et al. (2021) proposed a mixed-integer linear programming model for PDC, incorporating "compromise" variables into a multinomial logit model. In their study, "compromise" variables are defined as attribute levels that can take an intermediate value that are unknown a priori; for example, "medium price".

On the other hand, the engineering-driven PDC approach focuses on striking a balance between product commonality and performance targets and often neglects marketing aspects of product variants. During the past few decades, extensive studies were conducted on methods and tools for optimal product family design, platform-based product family designs. Two approaches were reported in the literature: module-based (Gauss et al., 2021) and scale-based (Simpson et al., 2001) product family designs. A comprehensive literature review can be found in (Jiao et al., 2007; Pirmoradi et al., 2014).

An integrated marketing-engineering approach provides a more profitable product line solution than when the two approaches are implemented separately (Lan, 2011). Jiao and Zhang (2005) developed a model for maximising shared surplus, which involves marketing-engineering interactions for the optimal PDC. Michalek et al. (2006) presented a methodology for quantitative evaluation of the complex trade-offs among functionality, market performance, and PDC costs for profit maximisation. Michalek et al. (2011) proposed a methodology that integrates market positioning with product line design to maximise profit and market shares. In their study, continuous realisations for attribute levels are considered. Kwong et al. (2016) proposed a multi-objective optimisation model that integrates affective design, engineering, and marketing issues to optimise new product lines. More and more studies have focused on applying machine learning /data analytics, such as opinion mining/sentiment analysis for PDC in recent years. Zhou et al. (2017) presented sentiment analysis based on affective lexicons and rough-set techniques to predict customer sentiments towards individual product features. Ireland and Liu (2018) presented a framework for integrating various machine learning algorithms and design theories to evaluate customers' sentiments towards product features. Chan et al. (2020) discussed the prospect of integrating social media data with traditional conjoint survey data for affective product design. Although several previous studies have dealt with engineering-marketing interactions for a single-stage PDC during the early design stage, consideration of used parts upgrading from a remanufacturing perspective was not addressed.

The importance of upgrading used products for extending their useful life has been recognised in previous studies (Shafiee & Chukova, 2013). Shafiee et al. (2011) and Shafiee and Chukova (2013) presented a mathematical optimisation model based on failure rate function to determine the optimal upgrade strategy for second-hand products for profit maximisation. Chung et al. (2017) proposed a dynamic programming model which integrates forecasts of technological advancements into upgrade decision making for modules of a high-cost and complex system. Quite a few previous studies have dealt with determining optimal upgrade levels for used products from a remanufacturing perspective. Kwak and Kim (2015a) proposed a mixed-integer non-linear model for the simultaneous optimisation of new product designs and design upgrades for an EOL product. However, these studies considered single-stage optimisations for used product upgrading decisions and ignored the conflicting trade-offs between the PDC of new and remanufactured products in a hierarchical framework.

2.2.1 Application of bilevel optimisation for product line design

The application of a bi-level (BL) optimisation for the product configuration design problem has received considerable attention in recent years. BL programming is used to solve hierarchical optimisation problems, which involves two sequential and non-cooperative decision-makers, the upper level & the lower level (Bard, 1998). BL optimisation follows a leader-follower type Stackelberg game where the leader (upper-level decision-maker) makes his/her decision first and passes it to the follower (lower-level decision-maker) who uses it to solve its optimisation problem. The follower responds to the leader's optimal solution to optimise his/her objective function (Colson et al., 2007; Kalashnikov et al., 2015; Sinha et al., 2018). Thus, the lower-level optimisation serves as constraint to the upper-level optimisation. The general mathematical representation of a BL optimisation takes the form shown in Equation (2.1) (Sinha et al., 2018).

$$\min_{x_u \in X_U,\, x_l \in X_L} \quad F(x_u, x_l)$$

subject to (2.1)

$$G_j(x_u, x_l) \leq 0, \quad \text{j = 1,}\cdots\text{, J}$$

$$x_l \in \underset{x_l \in X_L}{\operatorname{argmin}} \quad f(x_u, x_l)$$

subject to

$$g_k(x_u, x_l) \leq 0, \text{ k = 1,}\cdots, K$$

Where $F(x_u, x_l)$ and $f(x_u, x_l)$, respectively, denote the upper-level and lower-level objective functions; G_j and g_k, respectively, denote the upper and lower-level constraints. Variables, x_u and x_l denote decision variables while x_u and x_l denote the decision space.

The bilevel problems are often characterized as non-convex and non-differentiable (i.e., NP-hard), making them difficult to solve using conventional analytical algorithms. Classical techniques proposed in previous studies for solving bi-level problems follow simplified assumptions such as linearity, convexity, and differentiability (Sinha et al., 2018). Li and Wang (2008) proposed a method to convert a bi-level optimisation into a single level using KTT condition, which replaces lower-level problems by systems of equations and inequalities. However, the KTT condition assumes a convex & regular form for the lower level problem (Colson et al., 2005). Fliege and Vicente (2006) proposed a multi-criteria method to solve bi-level programming, which assumes convexity and continuous differentiability for the lower-level problem. Although several exact techniques are available to solve bi-level problems, they often make assumptions regarding the underlining objective functions/constraints.

In recent years, metaheuristic approaches have been demonstrated to be advantageous for solving NP-hard and large combinatorial optimisations such as product family configuration problems (Oliveto et al., 2007). Two types of metaheuristic approaches were reported in previous studies for solving bi-level optimisation problems: the nested and single-level transformation approaches (Talbi, 2013). The single-level transformation converts the bi-level optimisation into a single-level optimisation and uses classical heuristic approaches to solve it. It also assumes convex form and differentiability for the lower-level problems and constraints. On the other hand, in a nested approach, the lower-level problems are solved in a nested and sequential manner until an optimal overall solution is obtained (X. Liu et al., 2018; Singh et al., 2019).

2.3 Managing design uncertainty during early-stage product development

Design complexity and functional coupling were reported in the literature as the two main sources of uncertainties in engineering design that can affect the cost and lead time of product design and development (Alkan et al., 2017; C. Y. Wang & Lu, 2018). Suh (1998) defined design complexity as uncertainty that is caused by couplings between functional requirements (FRs) and design parameters (DPs). FRs are technical characteristics of a product, i.e., the functions a product performs. Functional coupling occurs when an FR is satisfied by one or more DPs. The axiomatic design principle which was first introduced by Suh (1998) was widely used for the objective evaluation of design complexity and functional coupling of several types of designs including hardware, software, and a combination of hardware and software. Axiomatic design principle states that good designs are designs that satisfy two design axioms, the independence axiom, and the information axiom.

The purpose of the independence axiom is to ensure the independence of functional elements. In other words, it aims to minimise the effect of changes in design parameters on functional requirements, ideally maintaining a one-to-one relationship between FRs and corresponding DPs (Villecco & Pellegrino, 2017). Failure to satisfy independence axiom leads to functional coupling, which can cause poor control and adjustability issues (Marchesi & Matt, 2017). On the other hand, addressing design complexity issues allows designers to select less coupled (modular) product designs during early-stage design (Ameri et al., 2008). The vector representation given in Equation (2.2) defines the relationship between FRs and DPs.

$$\begin{Bmatrix} FR_1 \\ \vdots \\ FR_n \end{Bmatrix} = [X] \begin{Bmatrix} DP_1 \\ \vdots \\ DP_n \end{Bmatrix} \tag{2.2}$$

Where X is a design matrix that captures the relationship between FRs and DPs. The elements of the design matrix are determined by solving the partial derivatives of FRs with respect to DPs as given in Equation (2.3).

$$X_{ij} = \frac{\partial FR_i}{\partial DP_j} \tag{2.3}$$

Accordingly, an uncoupled design is expressed as a diagonal matrix whose non-diagonal entries are zero. For instance, an uncoupled design solution with three FRs and three DPs can be represented using a diagonal design matrix as given in Equation (2.4).

$$[\mathrm{X}]= \begin{bmatrix} X_{11} & 0 & 0 \\ 0 & X_{22} & 0 \\ 0 & 0 & X_{33} \end{bmatrix} \tag{2.4}$$

Similarly, a decoupled design solution is expressed using a triangular matrix given in Equation (2.5). An independence axiom is thus satisfied when the relationship matrix results in either a coupled or decoupled design matrix. Any other matrix representation results in a coupled design.

$$[\mathrm{X}]= \begin{bmatrix} X_{11} & 0 & 0 \\ X_{21} & X_{22} & 0 \\ X_{31} & X_{32} & X_{33} \end{bmatrix} \tag{2.5}$$

The second design axiom, the information axiom, is used to ensure design simplicity through minimisation information content. Information content is inversely related to the probability of the design solution satisfying intended FRs. For a design consisting n functional requirements, the information content of a design system (I_{sys}) is computed according to Equation (2.6).

$$I_{sys} = -\sum_{i=1}^{n} \ln(p_i) \tag{2.5}$$

Where n denotes the total number of functional requirements, and p_i denotes the probability of a design solution satisfying the i^{th} functional requirement. Thus, the information axiom provides quantity metrics for the evaluation of design alternatives. According to information axiom, design solutions with the greatest probability of success ($i.e., I_{sys}$) are selected.

Measuring design complexity is essential to simplifying an engineering design, thereby reducing design uncertainty. Several previous studies have investigated methods to measure design complexities in engineering design (Ameri et al., 2008; Alkan et al., 2017; Pimapunsri & Srimuang, 2019; Shamsuzzoha et al., 2020; Villecco & Pellegrino, 2017; Wang & Lu, 2018). Much of the previous studies focused on methods for measuring the complexity of a design based on the level of entropy (information content) embedded in a product design (Ameri et al., 2008; Kim et al., 2016; Martínez-Olvera, 2020; Modrak & Bednar, 2015). Previous studies that addressed couping complexity focused on investigating the interconnectedness between various components and subassemblies in a product (Ameri et al., 2008; Wang & Lu , 2018).

2.4 Product recovery decision making

Product recovery options such as reuse, recycling, and remanufacturing are considered environmentally friendly and economically viable options compared to direct disposal. Product recovery strategies refer to options for recovering value from used product returns. Quite a few previous studies have proposed methods for product recovery decision-making during the early-stage design. Ziout et al. (2014) proposed a framework based on AHP to identify factors that affect product recovery decision-making. King et al. (2006) compared four product recovery strategies: repairing, reconditioning, remanufacturing, and recycling, and concluded that remanufacturing outperforms the others in terms of economics and environmental benefits (i.e., waste reduction and conservation of embodied energy). Rose (2000) developed a software known as “end-of-life design advisor” (ELDA), which determines appropriate recovery strategies based on products’ technical characteristics. The software uses the classification and regression tree (CART) technique to predict products' EoL strategy. Mangun & Thurston (2002) proposed a methodology to evaluate the cost effectiveness and the environmental impact of various product recovery strategies, including reuse, recycling, and disposal. Similarly, Zhao & Thurston (2010) developed product recovery decision-making considering consumer preference, the cost of processing, and environmental impact saving. Kwak & Kim (2010) developed an optimisation model for evaluating alternative product designs based on expected recovery profit. They demonstrated the model through a case study on three cell phone handset designs. Mazhar et al. (2007) presented a model which allows designers to conduct a technical evaluation of a component’s remaining life for reusing. Remery et al. (2012) presented a method to determine recovery scenarios for components during the design stage based on fuzzy order preference by similarity to ideal solution (TOPSIS) technique. They considered six recovery options in their study: reuse, recycling with and without disassembly, remanufacturing, incineration for energy recovery, and disposal. Cheung et al. (2015)presented guidelines for selecting a recovery strategy from recycling, refurbishment, and remanufacturing options considering their financial impact. Ma & Okudan Kremer (2015) proposed a quantitative method for determining an appropriate product recovery option. In their method, the economic, social, and environmental impact of product recovery strategies were considered. Lee et al. (2001) proposed a multi-objective methodology to determine feasible recovery options for a product by considering the environmental impact and economic value of used components. Desai & Mital (2005) considered factors that affect a recovery strategy, such as assembly cost, disassembly costs, cleaning cost etc., for selecting an appropriate recovery option. Behdad et al. (2010) used an integer linear programming model to determine an optimal recovery strategy considering the value that remains in each component. The model was implemented to determine appropriate recovery options for the modules of two cell phone designs. H. M. Lee et al. (2014) proposed several indices to evaluate designs for improved EoL performances. The indices for disposal, disassembly, and recovery are aggregated into a single overall index to help designers select design alternatives for optimal End-of-Life option.

Product design upgradability assessment is another issue addressed in previous studies. The rapid pace of technology poses challenges in remanufacturing due to the obsolescence of parts harvested from used products. To overcome this challenge, obsolete parts are either upgraded or replaced with new parts. Upgrading obsolete parts or replacing them with new ones increase the perceived value of remanufactured products while extending their useful life (K. Xing et al., 2013). Design features such as modularity, standardization, compatibility, and interoperability can facilitate product upgradability (Chierici & Copani, 2016). However, the decision as to whether a specific part that is recovered from a used product requires an upgrade is critical. Some previous studies have proposed decision support tools for parts upgradability assessment during the early design stage. Kwak & Kim (2013) proposed a decision-making model for upgrading a product design considering customers' preferences and recovery economics. The model allows designers to determine the parts that require an upgrade during the end-of-life stage. Ke Xing et al. (2007) proposed a mathematical model to determine a product design's upgradeability potential from remanufacturing perspective. They considered three key indicators for a product design's upgradability potential: i) compatibility to generational variety, ii) fitness for extended utilization, and iii) life cycle-oriented modularity. Pialot et al. (2012) presented a design framework for determining appropriate product architecture and upgrade scenarios for parts during the design stage considering four parameters: cost, environmental impact, reliability, and obsolescence. Each upgrade scenario was evaluated in terms of the attractiveness for customers and technological uncertainties.

2.5 The impact of remanufactured products on new product sales

Remanufactured products are often offered at low prices targeted at customers who cannot afford brand new versions. However, many manufacturers believe remanufactured products can cannibalise new product sales and thus, opt to sell remanufactured products using separate sales channels (Atasu et al., 2008). Several studies have been conducted to investigate the impact remanufactured products offering has on new product sales. Agrawal et al. (2015) conducted behavioural experiments to investigate remanufactured products' impact on new products' perceived value and concluded that remanufactured products offered in the same market with new products could lower the perceived value of new products by up to 8%. Furthermore, the study revealed that when third-party-remanufacturers offer remanufactured products, the perceived value of new products can rise by up to 7%. Atasu et al. (2008) found that remanufacturing profitability can be influenced by the balance between cost savings, market segment size, and market growth rates. Ovchinnikov (2011) studied the cannibalisation effect of remanufactured products offering and the overall impact on a company's profitability. They concluded that a remanufactured product offered at a lower price could attract low-end consumers, reducing the cannibalisation effect. Guide & Li (2010) also investigated cannibalisation effect of remanufactured products based on consumers' willingness to pay and concluded that the effect is higher for commercial products than consumer products. Strategies to overcome the cannibalisation effect are also suggested. Atasu et al. (2008) proposed a pricing strategy based on the size of customers who are indifferent to both new and remanufactured products. They suggested that a remanufacturer set a higher price when the size is large and a lower price otherwise. Guide & Li (2010) also reported that cannibalisation is significant in the price-sensitive consumer segment and suggested proper pricing and segmentation for consumers.

2.6 Managing EoL product returns for remanufacturing

Firms often get used products from ‘waste-stream or ‘market-driven collection methods in remanufacturing. The ‘waste-stream collection method refers to a mechanism whereby a remanufacturer passively collects used product returns without prior inspection. On the other hand, in the market-driven approach, incentives are paid to the product owner to return used products via retailers or third-party agents (Guide & Van Wassenhove, 2001). It is often challenging to predict used product returns in remanufacturing due to the quality, quantity, and timing uncertainty of returns (Behdad et al., 2012). Such an inherent uncertainty associated with used product returns affects the remanufacturing profitability.

2.6.1 The impact of used product return uncertainty on remanufacturing profitability

Several previous studies have attempted to investigate the impact of the uncertainty of used product returns on remanufacturing profitability. Galbreth & Blackburn (2010) presented an optimisation model to determine the optimal quantity of used products required based on remanufacturing cost and product returns’ quality. They compared the optimal acquisition quantity for cases of a linear and a non-linear remanufacturing function curve and found that a quadratic remanufacturing cost curve results in a higher optimal acquisition quantity than a linear cost curve. Raihanian Mashhadi et al. (2015) proposed a stochastic optimisation model to determine the optimal upgrade levels required for used product returns and investigated the effect returns uncertainties on remanufacturing profitability. Kim & Xirouchakis (2010) proposed a stochastic inventory model to determine the optimal quantity and timing of used product returns to satisfy stochastic demand for parts. Shi et al. (2011) presented a nonlinear optimisation model to determine the optimal quantity of new and remanufactured products and the purchasing price of used products, considering the demand and return uncertainty. They used a Lagrange relaxation approach to solve the optimisation model. Denizel et al. (2010) conducted numerical experiments to study the impact of remanufacturing costs and the salvage values of components on remanufacturing profitability considering multiple quality levels of used product returns.

2.6.2 Consideration of quality uncertainty of used product returns

Sorting of product returns based on their quality affects the remanufacturing cost and, hence, its profitability (Aras et al., 2004). Loomba & Nakashima (2012) reported that the sorting of returns into discrete quality classes improves remanufacturing production planning by allowing the disassembly and remanufacturing of good quality returns during the peak demand period. In previous studies, two types of approaches for modelling product returns' quality were reported.

The first approach assumes two quality categories for used product returns: remanufacturable and non-remanufacturable units. Determining the proportion (p) of the total quantity (Q) of remanufacturable units is difficult due to the quality uncertainty of returns. Previous studies have assumed a deterministic value for p, while others proposed a stochastic value with a known distribution function. Aras et al. (2004) studied the impact of quality-based categorization of product returns on remanufacturing profitability. According to their study, product returns are categorized as high quality and low quality based on the remanufacturing effort required. The proportion of high and low quality returns were assumed to follow a Poisson distribution. Zikopoulos & Tagaras (2007) classified used product returns as "remanufacturables" and "non- remanufacturables". Pishvaee et al. (2009) categorized used product returns as recoverable and scrapped units, whereby the proportion of recoverable units are assumed to follow a stochastic distribution. Han et al. (2013) classified returns into "good" and "bad" types based on the time required to recover components from used product returns, including the time required to disassemble a product. Zikopoulos & Tagaras (2007) classified product returns into "refurbishable" and "non-refurbishable" units, whereby the proportion of "refurbishable units" is assumed to follow a continuous known statistical distribution. Panagiotidou et al. (2013) classified product returns into remanufacturable and non-remanufacturable units. In their study, the number of remanufacturable units is assumed to follow a binomial distribution with the probability of remanufacturability of each product return following a generally distributed random variable.

The second approach assumes that the quality of used products is heterogeneous that can be categorized into multiple quality levels. Under this assumption, some previous studies have considered discrete levels of the quality of used product returns and used discrete distributions such as binomial and multinomial. In contrast, others considered continuous distributions to model product returns' quality. Guide & Van Wassenhove (2001) investigated the impact of the quality uncertainty of used product returns on the remanufacturing profitability by conducting a case study on a mobile telephone remanufacturer. Six nominal categories for the quality levels were considered based on physical and functional performances. However, this approach requires each mobile phone unit to undergo inspection and testing, which is quite cumbersome due to the heterogeneous quality of returns. Behret & Korugan (2009) proposed three quality grades, “good”, “average” and “bad,” based on associated remanufacturing processing times. The remanufacturing processing time was assumed to follow exponential distribution. Ferguson et al. (2009) categorized returns into three classes as “scraps for material recovery”; “scraps for parts harvesting” and “remanufacturables” based on the ultimate destination of parts recovered from used product returns. Remanufacturable units are further classified into discrete quality grades as “worst,” “bad,” “average,” “good,” and “best” based on the cost of remanufacturing. Similarly, Teunter & Flapper (2011) implemented a multinomial distribution to rank product returns from “high quality” to “low quality” grades based on the cost of remanufacturing. Zeballos et al. (2012) classified returns into three quality grades as “good,” “medium” and “bad,” and five grading outcomes were used, each representing different combinations of the three quality grades. They assumed a deterministic probability for the distribution of each quality grade and the grading outcome. Aydin et al. (2018b) proposed three scenarios for the quality of used product returns: "good," "average" and "bad," whereby each scenario consists of four quality levels. The proportion of each quality level was modelled using a multinomial distribution. Raihanian Mashhadi et al. (2015) classified used products into discrete quality levels and investigated the best upgrade level for used product returns.

Some previous studies assumed a standard uniform distribution to model the quality of used products, whereby the lower and upper bounds represent the worst, and best possible quality, respectively (M. Ferguson et al., 2009; Galbreth & Blackburn, 2010). Denizel et al. (2010) proposed finite grades based on the remanufacturing cost to classify used product returns. They assumed a deterministic probability for the proportion of product returns under each quality grade. Mashhadi & Behdad (2017) proposed a clustering algorithm to classify returns into distinct grades based on their reusability indices. Panagiotidou et al. (2017) presented an approach for classifying product returns into multiple quality levels based on their usage information. Accordingly, the lower the value of the usage variable, the higher the returned product's quality and, hence the higher the probability that a product can be remanufactured. C. H. Yang et al. (2015) classified product returns based on estimated remanufacturing times. They assumed the estimated times for remanufacturing each returned unit is continuously distributed. The remanufacturing yield, which represents the percentage of parts that can be remanufactured, was also used in previous studies to model product returns' quality (X. Li et al., 2015; Mukhopadhyay & Ma, 2009). Previous studies have assumed remanufacturing yield as either stochastic (Ferrer, 2003; X. Li et al., 2013, 2015; Mukhopadhyay & Ma, 2009; Zikopoulos & Tagaras, 2007) or deterministic (Bakal & Akcali, 2006; M. E. Ferguson et al., 2011; Langella, 2007; Schulz & Ferretti, 2011). The stochastic approach assumes the percentage of remanufacturable returned units as a random variable. On the other hand, the deterministic approach assumes the remanufacturer knows the yield in advance. Bakal & Akcali (2006) and

Mukhopadhyay & Ma (2009) studied the effects of a partial and perfect yield rate information on remanufacturing profitability. In their study, the remanufacturing yield rate was considered deterministic first and then extended to the stochastic case whereby the yield is assumed to depend on the acquisition price of product returns.

2.6.3 Forecasting the returns of used products

The forecasting of used product returns is essential to maintaining sufficient feedstock for remanufacturing. However, unlike conventional manufacturing, forecasting in remanufacturing is a complex and difficult task due to the quantity and timing uncertainty of used product returns. Forecasting in a remanufacturing requires information on the proportion of new products' sales that can be returned in future periods. Quite a few previous studies have attempted to address product returns forecasting grounded on statistical techniques. Kelle & Silver (1989) proposed four methods for forecasting reusable containers' returns based on the number of containers sold and returned in past periods. de Brito & van der Laan (2009) investigated the impact of imperfect information on the product return process on inventory management efficiency. They found out that imperfect information leads to a compromised performances even for the most informed forecasting methods. Toktay et al. (2000) also presented a DLM with geometric lag for forecasting the returns of disposable cameras based on a discrete-time lag model with dynamic information updating. Bayesian statistics were used in their study to estimate the parameters of lag functions. On the other hand, Marx-Gómez et al. (2002) proposed a simulation and fuzzy reasoning approaches for forecasting the returns of scrapped products, considering the usage, failure, sales, and return quota information. They conducted a simulation to generate the data for each factor, and a neuro-fuzzy technique was used to address the vagueness in the data. Similarly, Hanafi et al. (2007) proposed a fuzzy coloured Petri net forecasting model to predict product returns at different geographical locations, considering product type, historical sales data, and demographic information.

However, the technique to estimate the parameters of the distribution was not included in their methodology. Clottey et al. (2012) compared the forecasting accuracy of both discrete and continuous DLM and found that DLM with a negative exponential delay function offered a better accuracy. However, Toktay et al. (2000) and Clottey et al. (2012) assumed the monthly return lag periods, which limited their methods to cases of more extended return periods. Clottey & Benton (2014) proposed a forecasting method that deals with a more extended return lags considering the gamma delay function to overcome this limitation. They conducted a simulation experiment to compare gamma delay functions against geometric, negative binomial, and exponential delay functions proposed in earlier studies. They concluded that the proposed forecasting method can result in a significant cost savings. Krapp et al. (2013b) also criticized the methods proposed by (Toktay et al., 2000) stating that the predetermined probability distributions for used product returns and sometimes the assumption of a normal distribution for the error terms of the DLM cannot reflect the general case. They presented a generic model for product returns forecasting considering a case where the return distribution and the error term followed a general distribution. However, the model relies on assumptions regarding the return time distribution. They also implemented Bayesian statistics to estimate parameters of return distribution as in previous approaches.

2.7 Discussion

In this chapter, a literature review of topics related to the research has been conducted. The research gaps identified from the literature review are discussed as follows.

Firstly, it can be observed that most previous studies that have dealt with “design for remanufacturing” focused on identifying design features to facilitate the remanufacturability of product designs. The main issues addressed in previous studies include metrics for assessing the remanufacturability and disassemblability of product designs, and design guidelines for selecting appropriate product recovery strategies. However, the issue of fastening methods selection during the early design stage has not been properly addressed. Besides, the simultaneous consideration of assembly and disassembly concerns for fastening methods selection during the early design stage from a remanufacturing perspective was not addressed.

Secondly, several previous studies on a PDC focused on the aggregation of multiple objective functions into a single objective function. However, aggregation ignores the hierarchical nature of decision-making at distinct stages, which often involves complex trade-offs. One of such decision-making includes the upgrading of parts recovered from used product returns due to technological obsolesce. A few previous studies have proposed a hierarchical optimisation that considers two-level decision-making. Nevertheless, the consideration of specification upgrading for used parts/modules in a PDC was little studied in previous research. Specifically, the simultaneous consideration of new and remanufactured PDC and specification upgrading of recovered used parts/modules was not addressed in previous studies. The summary of previous studies on PDC is presented in Table 2.1.

Table 2.1 Summary of studies on PDC

Study	Objective function	Formulation of optimisation model and Solving approach		Consideration of reman. products	Consideration of upgrading option
		Optimisation model	Solving approach		
Wu et al.(2016)	Min. Total cost Max. market share	Hierarchical	NSGA-II	Yes	No
Badurdeen et al. (2018)	Max. Life cycle cost Min.GHG emission Min. Water usage	Single level	NSGA-II	No	No
Wang et al.(2018)	Max. Profit Min GHG emission	Single level	Weighted sum solved using GA	No	No
Wang et al. (2019)	Max. Profit Min GHG emission	Single level	Weighted sum solved using GA	Yes	No

Kwak (2018)	Max. Profit Max. Market share	Hierarchical	Epsilon constraint method	Yes	Yes
Ma (2016)	Max. Shared surplus	Hierarchical	NBGA	No	No
Kwak & Kim (2015)	Max. Total life-cycle profit	Single level	GRG	Yes	Yes
Aydin et al. (2015)	Max. Profit Max. Market share	Single level	NSGA-II	Yes	Yes
Du et al. (2014)	Max. Shared surplus	Hierarchical	Stackelberg game	No	No
This research	Max. Profit Max. Shared surplus	Hierarchical	NBGA	Yes	Yes

Lastly, quite a few previous studies have addressed the uncertainty regarding used product returns in remanufacturing. Statistical approaches, such as the distributed lag model (DLM) were used in previous studies to forecast the quantity and timing of used product returns based on the sales of new products. Various statistical distributions such as negative binomial, gamma, geometric, and exponential distributions were used to model the lag function of the DLM. However, the estimation of parameters of a DLM forecasting model, which can affect the forecasting accuracy, has not been sufficiently addressed in previous studies. Few studies have proposed Bayesian statistical techniques for the parameter estimation. However, in a Bayesian inference approach, depending on the choice of conjugate priors for the distribution of the lag function of a DLM, the resulting posterior probability can become challenging to solve. Therefore, an alternative and efficient approach for solving the posterior probability is required.

Chapter 3 Overall Research Framework

In this research, a framework for integrated product design considering remanufactured products and used product returns uncertainty is proposed. Under the framework, which is shown in Figure 3.1, four methodologies are proposed, respectively, for: i) fastening methods selection considering both product assembly and disassembly from a remanufacturing perspective; ii) determining optimal configurations for both new and remanufactured products considering used products upgrading iii) forecasting of used product returns for remanufacturing and iv) modelling of customers' preferences and estimation of market demands for the new and remanufactured products

The methodology for the optimal selection of fastening methods addresses product assembly and disassembly concerns simultaneously during the early design stage. The proposed methodology involves an optimisation model to select fastening methods that minimise the overall product assembly and disassembly costs subject to assembly and disassembly constraints. A hierarchical optimisation model is proposed to determine optimal specifications for the new and remanufactured products, considering upgrading decisions for remanufactured products. This research proposes a methodology for forecasting used product returns based on distributed lag model (DLM) to address used product returns uncertainty. A methodology for the estimation of parameters for a DLM is also proposed. Finally, this research presents a fuzzy regression (FR) approach that involves conjoint analysis to model customers' preferences. A multinomial logit model (MNL) is used to determine market demands for new and remanufactured products under uncertainty Detailed discussions of the proposed methodologies are described in the following sub-sections.

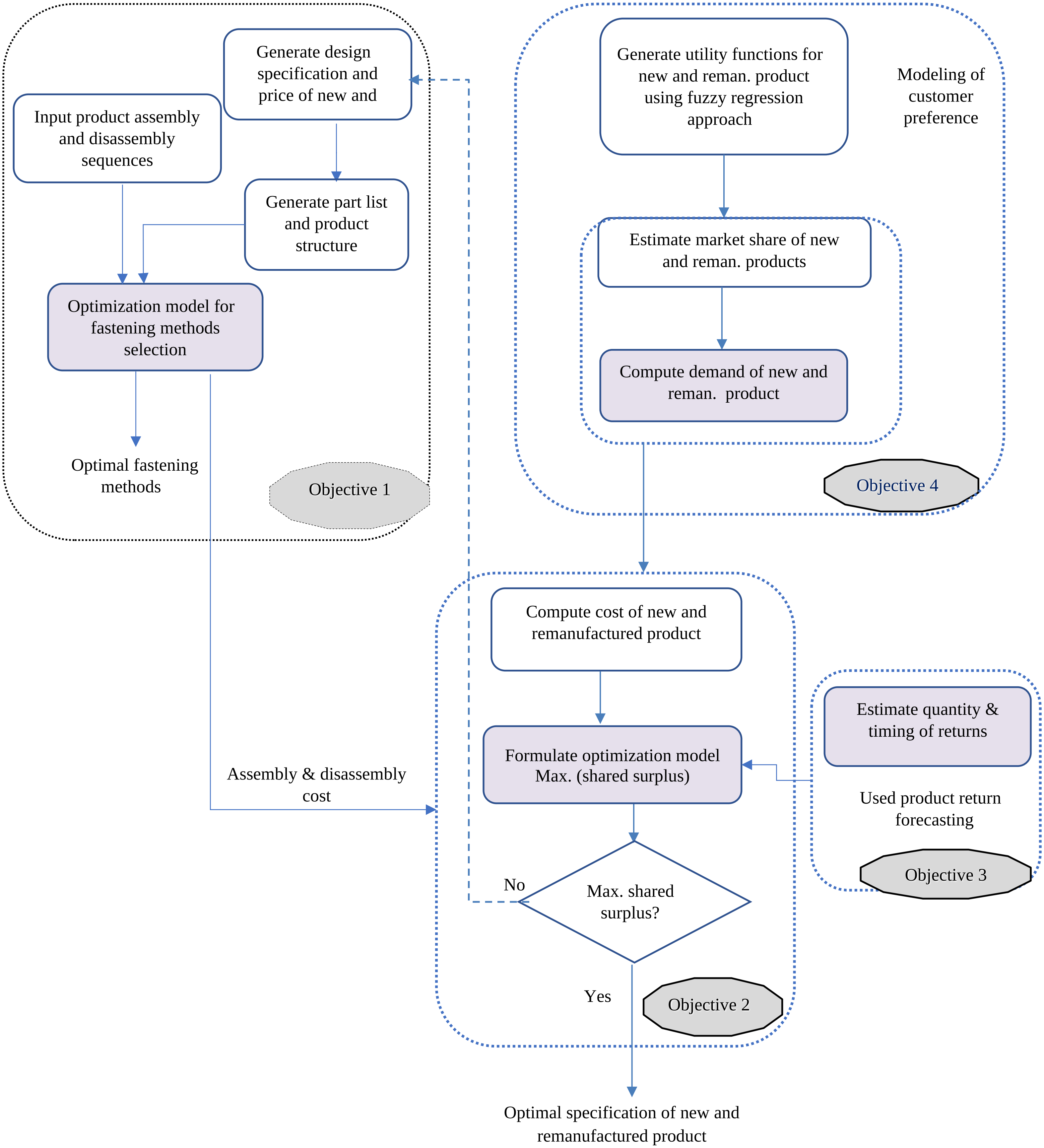


Figure 3.1 Proposed research framework

3.1 Selection of fastening methods during the early design stage

This study proposes a methodology for fastening methods selection known as FMSRem, which simultaneously considers assembly and disassembly factors. A mathematical optimisation model is formulated for the FMSRem to minimise total product assembly and disassembly cost subject to assembly and disassembly concerns. The objective function is formulated based on the assembly and disassembly time estimates. Disassembly time for a part is estimated based on Maynard Operation Sequence Technique (MOST), considering factors that affect the unfastening and part removal operations. The factors which affect the unfastening and part removal operations can be obtained from previous studies (Desai & Mital, 2003, 2005; Sabaghi et al., 2016; Sodhi et al., 2004; Yi et al., 2003). Figure 3.2 outlines the factors which affect the unfastening and part removal operations.

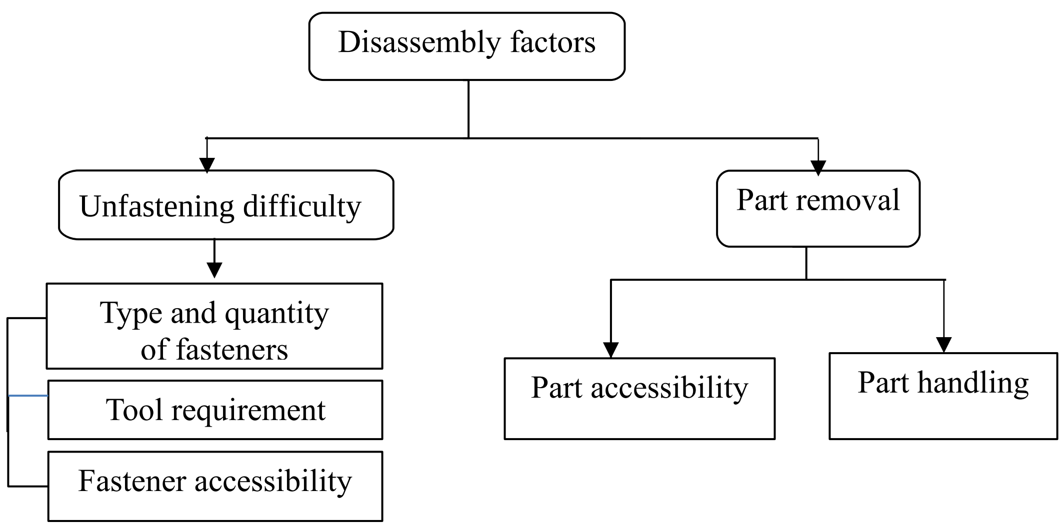


Figure 3.2 Factors affecting disassembly time

The design for assembly (DFA) method proposed by Boothroyd (1994) is used to classify assembly related parameters in terms of fastening methods complexity and component handling complexity. Figure 3.3 outlines the factors which affect assembly operations.

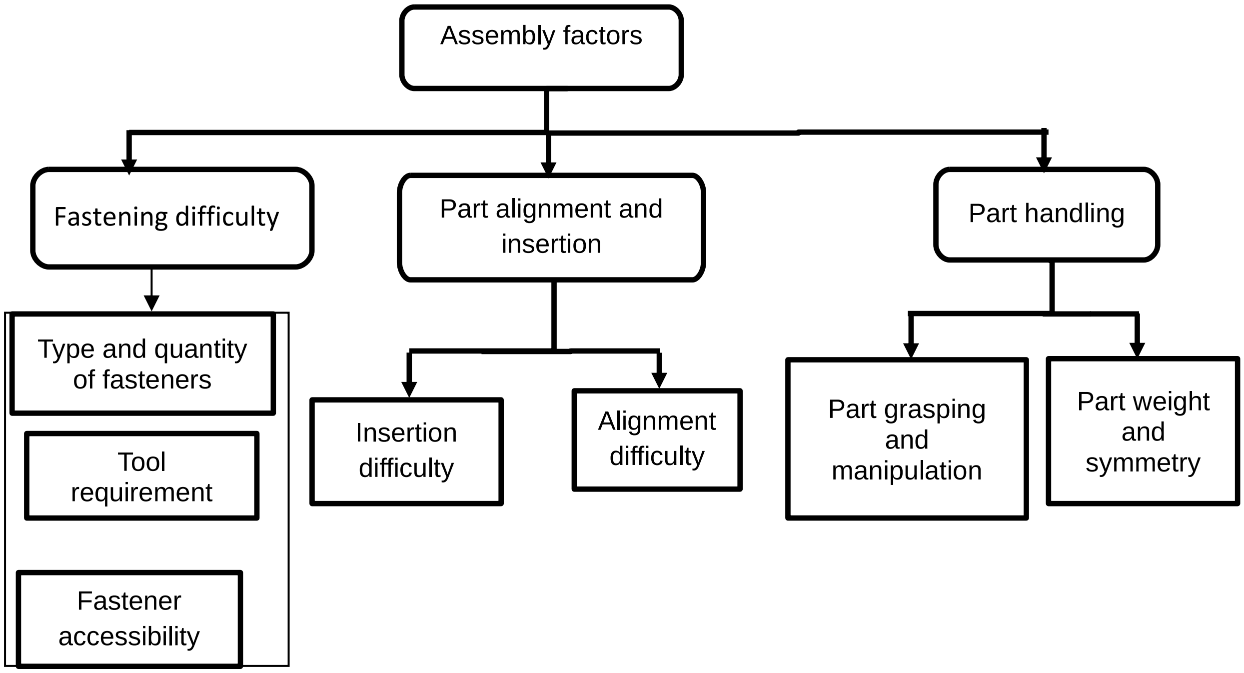


Figure 3.3 Factors affecting assembly time

Assembly times are computed based on estimated fastening time and assembly difficulty factors, while disassembly times are computed based on the estimated unfastening times and disassembly difficulty factors. The selection of fastening methods for individual parts based on assembly and disassembly concerns is formulated as combinatorial optimisation model. The Genetic algorithm (GA) heuristics is adopted in the study to solve the model. Derivations for the optimisation model and its solution are presented in Chapter 4.

3.2 Determining optimum configuration for new and remanufactured products considering upgrade decisions for used parts

This research proposes a hierarchical optimisation model to determine the optimal configurations of both new and remanufactured products considering specification upgrading for used parts. Figure 3.4 shows the framework of the proposed hierarchical optimisation.

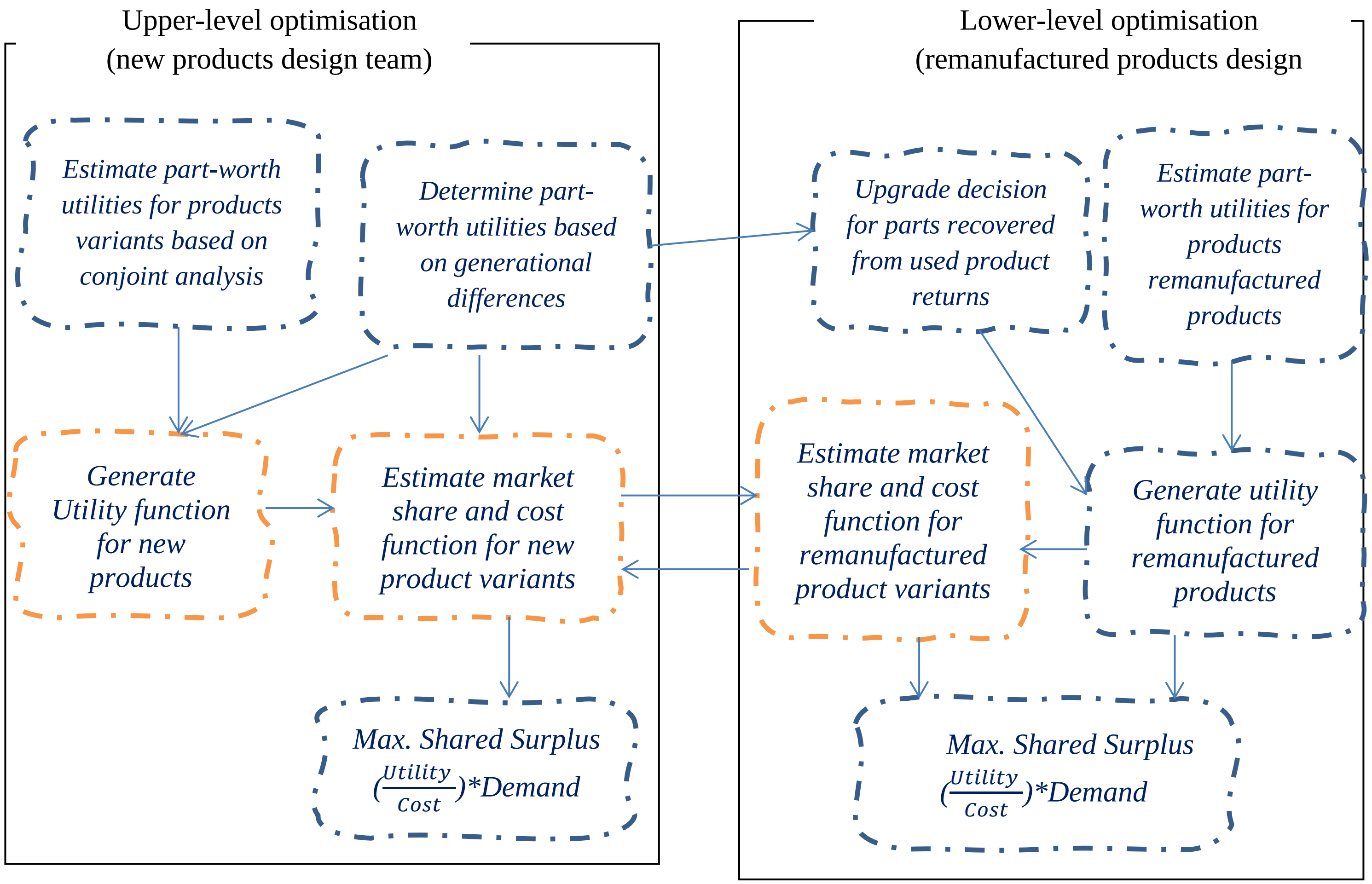


Figure 3.4 Framework of the proposed hierarchical optimisation.

The proposed methodology assumes a firm that offers new products to satisfy the demand in a primary market in the first period; remanufactures used product returns in the subsequent periods to satisfy the demand in both the primary and secondary market segments. New products are configured from sets of new parts, while remanufactured products are configured from parts recovered from used product returns. Parts in a set have similar functionality (attribute) but different performances (attribute levels) such that each product profile is a combination of various attributes, each of which has one or more attribute levels (Wu et al., 2016).

The proposed hierarchical optimisation model is implemented in a nested and sequential approach. The upper-level optimisation handles the determination of optimal product configurations for the new products. Similarly, the lower-level optimisation handles the determination of optimal configurations for the remanufactured product profiles. The upper-level optimisation involves computing utility functions that are subsequently integrated into an MNL to determine the market share and demand function for new products. Assuming both the new and remanufactured profiles are launched in the same market, the demand function for a new product is also dependent on the perceived utilities of remanufactured product profiles according to an MNL (Uncles et al., 1987).

The decision made by the upper-level optimisation regarding the configuration of attribute levels (i.e., utilities of new product profiles) is passed on to the lower-level optimisation. The shortening life cycles of consumer goods due to rapid technological advancements entails some parts recovered from used product returns can already become technologically obsolete. Therefore, the selection of attribute levels for remanufactured products depends on the condition of parts recovered from used product returns. Obsolete parts require either replacement with a cutting-edge new part or an upgraded version. Replacement with cutting-edge new parts improves the performance of products but leads to an increase in remanufacturing cost. On the other hand, using technologically obsolete parts results in an inferior product which reduces remanufactured products' market share. Hence, the determination of optimal configurations for remanufactured product profiles involves decision-making at a lower-level optimisation regarding an upgrade plan for used parts.

The NP-hard nature of a hierarchical optimisation problem renders it challenging to solve using conventional analytical techniques. Metaheuristics are suited to solve NP-hard problems involving discrete decision variables (Talbi, 2013). This research proposes a nested bilevel GA (NBGA) for solving the bilevel optimisation model to determine optimal configurations for new and remanufactured products and upgrade levels required for used parts/modules. The detailed formulation of the proposed optimisation model and the solving approach are discussed in Chapter 5. A case study to demonstrate its implementation is also presented.

3.3 Forecasting of the quantity and timing of used product returns

The distributed lag model (DLM) shown in Equation (3.1) is proposed to model the quantity of used product returns based on the sales of new products (Clottey et al., 2012; Krapp et al., 2013b).

$$m_t^{ret} = \sum_{k=1}^{t-1} \beta_k n_{t-k} + \varepsilon_{t\,;}\ \forall t = 1,23,..T \tag{3.1}$$

$$\beta_k\text{=p}\binom{k+r-1}{r} q^r (1-q)^k \tag{3.2}$$

where m_t^{ret} and n_{t-k} represent the quantity of used product returns, and the quantity of new products sold respectively at time t. The coefficient, β_k (also known as the kth reaction coefficient) represents the contribution of sales in period t-k (i.e., n_{t-k}) for the returns in period t (i.e., m_t^{ret}). A negative binomial distribution, Equation (3.2), is used to model β_k. p denotes the return probability of a new product sold in the previous periods; q is the conditional probability of the return of a new product in the next period given p; parameter r represents the lag of the largest β_k coefficient. The Markov-chain Monte-carlo (MCMC) based Bayesian inference approach is proposed in this research to estimate the parameter r. The Bayesian inference approach for estimating the posterior probability of parameter r is given in Equation (3.3).

$$P\left({}^{r}/_{Data,\,M}\right) = \frac{P({}^{Data}/_{r})P(r/M)}{\int_{r=1}^{N} P\left({}^{Data}/_{r,\,M}\right) P(r/M)dr} \tag{3.3}$$

where P(r/M) denotes the prior (initial belief regarding the probability of parameter r); P(Data/r) is the likelihood function. The denominator represents the marginal likelihood, i.e., the probability of the observed data given the model (M). The nominator term can be solved analytically. However, the denominator (the marginal likelihood) is often difficult to solve for slightly non-trivial functions. Such difficulty is the Bayesian interference approach's limitation for estimating model parameters.

In this study, the MCMC approach is proposed for estimating the marginal likelihood of different models by directly generating samples from the posterior distribution. The workflow of the proposed is shown in Figure 3.5.

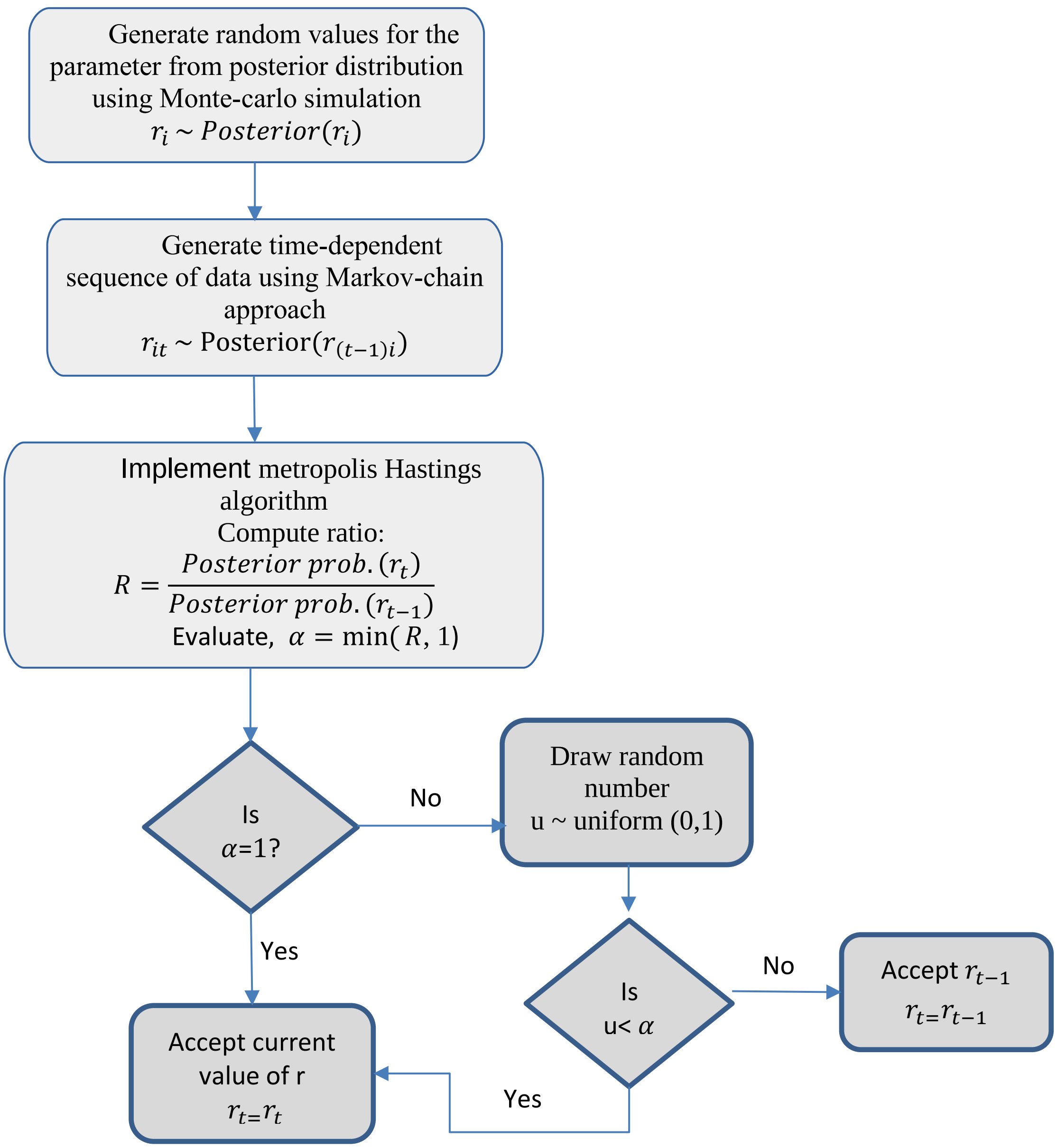


Figure 3.5 Markov chain Monte Carlo simulation for parameter estimation

The procedure involves three steps , which are: 1) generation of random samples from the posterior distribution using Monte-carlo simulation; 2)generation of a sequence of data which depends on previously generated data using Markov chain procedure; and 3) implementation of the Metropolis Hasting's (MH)) algorithm for calculating the posterior probability using the newly and previously generated value of the parameter(s) from the proposal distribution to decide whether the parameters' values should be accepted.

3.4 Modelling of customers' preferences and estimation of market shares

Modelling of customers' preferences for new and remanufactured product profiles involves conducting a conjoint analysis, which has three stages. First, the product attributes and levels are determined. Second, a questionnaire is designed. Third, the survey data is analysed to determine the utility of each attribute (also known as part-worth utilities). The conjoint survey can be designed using three types of conjoint survey techniques: rating, ranking, and choice-based types (Asioli et al., 2016; Baier et al., 2015; Green et al., 2001). The rating-based conjoint survey technique is used in this study because it can be easily interpreted using the same units as the rating scores (Asioli et al., 2016). This approach has also been widely used in previous studies (Karniouchina et al., 2009).

To design a manageable combination of potential profiles to be rated by the respondents, orthogonal designs or orthogonal arrays are commonly used (Green et al., 2001). The fuzzy regression analysis proposed by Aydin et al. (2014) and Kwong et al. (2016) is adopted in this study to address fuzziness due to subjective judgments. The product's utility is determined using the fuzzy utility function given in Equation (3.4).

$$\widetilde{U} = (a_0^c, a_0^s) + \sum_{k=1}^{M} \sum_{l=1}^{N_k} ((a_{kl}^c, a_{k1}^s) x_{kl}) \qquad (3.4)$$

where $\widetilde{U}$ denotes an independent variable that represents the ratings of respondents on the product profile; (a_0^c, a_0^s) and (a_{kl}^c, a_{k1}^s) are fuzzy coefficients in which a_{kl}^c and a_{k1}^s represent the central and spread of fuzzy numbers, respectively; x_{kl} is a decision variable that represents whether the l^{th} level of the k^{th} attribute is selected for the product profile or not; M represents the total number of attributes, and N_k represents the number of attribute levels in the k^{th} attribute. Based on the estimated utility of remanufactured products and information regarding competitive products, estimates for market share and demand for new and remanufactured products are determined using the multinomial logit (MNL) model.

Chapter 4 Fastening Methods Selection During Early-Stage Design considering Remanufactured Products

This chapter presents the proposed methodology for selecting fastening methods during early-stage design from a remanufacturing perspective. The general framework of the proposed methodology is presented in section 4.1. The mathematical formulation of the proposed optimisation model and its solution approach is discussed in section 4.2 and section 4.3. The methodology for estimating the assembly and disassembly times of fastening methods is presented in section 4.4. A case study is presented in section 4.5 to demonstrate the implementation of the proposed approach.

4.1 Framework of the proposed methodology

Figure 4.1 shows the framework of the proposed methodology for fastening method selection.

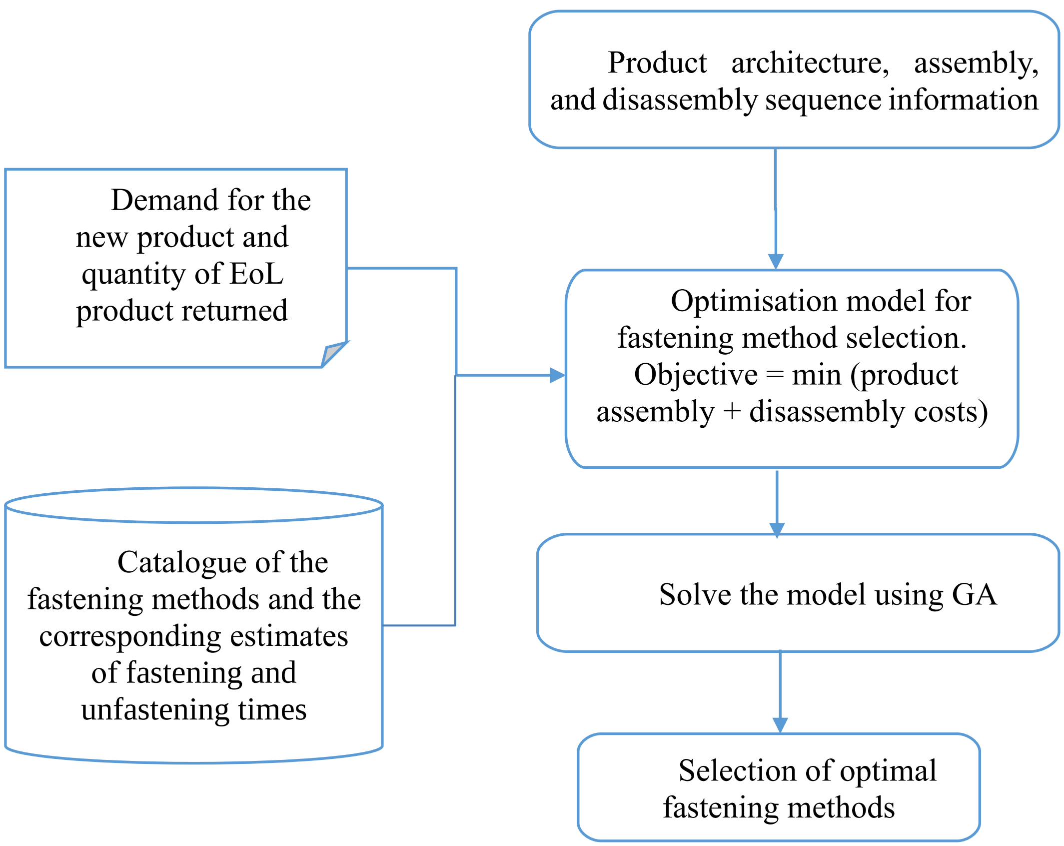


Figure 4.1 Flow chart of the FMSRem methodology

The proposed methodology, known as FMSRem, involves methods for estimating assembly and disassembly times. Several assembly and disassembly factors are considered to estimate the assembly and disassembly times. Next, a repository of fastening methods is also established, containing information regarding the fastening and unfastening times for each fastener type. A combinatorial optimisation is proposed for the selection of fastening methods with the objective of minimising the total cost of product assembly and disassembly. The optimisation model is solved using a genetic algorithm (GA) approach that is widely used to solve combinatorial optimisations. The detailed derivation of the optimisation and GA solving approaches is presented in sections 4.2-4.4.

4.2 An optimisation model for fastening methods selection

To derive the optimisation model for the proposed fastening methods selection, factors that influence the difficulty and/or the cost of assembly and disassembly tasks are considered. The factors considered include i) assembly difficulty, ii) disassembly difficulty, iii) assembly costs, and iv) disassembly costs. In the formulation, the condition of used product returns is assumed uniform, i.e., all returned units will require an identical degree of difficulty during product disassembly. On the other hand, the assembly and disassembly sequences of products are pre-determined while applying the proposed methodology. The definitions for notations used to derive the optimisation model are presented below.

Indices:

$i = \{1,2,3, \ldots N_i\}$ indices of parts, $i \in I$

$j = \{1,2,3, \ldots N_j\}$ indices of fastening methods, $j \in J$

Parameters:

t_{ij}^{a} an estimate of assembly time of the i^{th} part for the j^{th} fastener type

t_{ij}^{d} an estimate of disassembly time of the i^{th} part for the j^{th} fastener type

t_{ij}^{pre} the tool preparation time of the j^{th} fastener type selected for i^{th} part

t_{ij}^{acc} an estimated time for accessing the j^{th} fastener type selected for i^{th} part

t_{ij}^{pos} an estimated time for positioning tool against the j^{th} fastener when used in i^{th} part

t_{ij}^{f} an estimated time for fastening the j^{th} fastener as used in the i^{th} part

t_{ij}^{uf} an estimated time for unfastening the j^{th} fastener as used in the i^{th} part

t_{i}^{h} handling time for the i^{th} part

Q_n the demand for new products (i.e., quantity required to be assembled)

Q_r the number of EoL products returned and disassembled

L assembly/disassembly employee’s wage in \$/hr

W_a the number of assembly employees

W_d the number of disassembly employees

C_T the total assembly and disassembly cost

C_a the estimated assembly cost

C_d the estimated disassembly cost

q_{ij}^{f} the quantity of j^{th} fasteners needed for fastening the i^{th} part

V_{max}^{f} the maximum number of fastening method types per single part

F_{ij}^{D} the direction of fastening/unfastening given as $F_{ij}^{D} \in$ {-x, +x, -y, +y, -z, +z}

α_i the penalty for changing fastening/unfastening direction between successive parts

β_i the penalty for changing fastening/unfastening methods between successive parts

Decision variables:

s_i^j binary variable which represents the choice of j^{th} fastener for i^{th} part

$$= \begin{cases} 1 \text{ , if } j^{th} \text{fastening method is selected for } i^{th} \text{part} \\ 0, \ \& \text{ otherwise} \end{cases}$$

q_{ij}^f the maximum quantity of the j^{th} fastener selected for i^{th} part

The optimisation model for the fastening methods selection problem is given by Equations (4.1) to (4.3) as follows:

$$Min: C_T = C_a + C_d \quad (4.1)$$

$$C_a = \mathrm{Q_n W_a} L(\textstyle\sum_{\mathrm{i}} \sum_{\mathrm{j}} (\mathrm{t_{ij}^a s_i^j q_{ij}^f}\ ) + \sum_i (\alpha_i + \beta_i)) \quad (4.2)$$

$$\mathrm{C_d} = Q_r W_d \mathrm{L} \textstyle\sum_{\mathrm{i}} \sum_{\mathrm{j}} (\mathrm{t_{ij}^d s_i^j q_{ij}^f}) + \sum_i (\alpha_i + \beta_i)) \quad (4.3)$$

$$t_{ij}^a = q_{ij}^f t_{ij}^f + t_i^h \quad (4.4)$$

$$t_{ij}^d = q_{ij}^f * (t_{ij}^{acc} + t_{ij}^{pos} + t_{ij}^{uf}) + t_{ij}^{pre} + t_i^h \quad (4.5)$$

The objective function is subjected to the following constraints:

$$1 \leq \sum_j s_i^j \leq V_{max}^f, \forall\ i \in I \quad (4.6)$$

$$\sum_j s_i^j \leq q_{ij}^f, \forall\ i \in I \quad (4.7)$$

$$\alpha_i = \begin{cases} 0, & \text{if no direction change is required between } i^{th} \text{ part and a predecessor part} \\ 1 \text{ sec}, & \text{if the direction change needed is } 90^0 \text{ e.g from +x to +y} \\ 2 \text{ sec}, & \text{if the direction change needed is } 180^0, \text{ e.g from -x to +x} \end{cases} \tag{4.8}$$

$$\beta_i = \begin{cases} 2.54\, sec, & \text{if fastening method selected for } i^{th} \text{ part is different from its predecessor} \\ 0, & \text{otherwise} \end{cases} \tag{4.9}$$

$$s_i^j \in \{0,1\}, \qquad \forall\ i,j \tag{4.10}$$

$$q_{ij'}^f \geq 0 \qquad \forall\ i,j \tag{4.11}$$

The constraints in Equations (4.6) and (4.7) define the type and quantity of fasteners selected for a part. Equation (4.6) ensures the variety of fasteners selected for a part does not exceed the maximum number of different types of fasteners permissible for a single part. Equation (4.7) ensures the number of fasteners selected for a given part should not exceed the maximum number of fasteners permissible for a part. Equations (4.8) and (4.9) denote the penalty due to change of disassembly direction and fastening methods, respectively. Equation (4.10) defines a binary variable for the fastening method selection. Equation (4.11) ensures non-negativity for the decision variables.

4.3 Assembly and disassembly time estimation

This section discusses the procedures for estimating the assembly and disassembly times of parts considering feasible alternative fastening methods. Five types of fastener categories are considered in this study, namely: i) discrete fasteners such as screw and rivets; ii) integral fasteners (e.g., snap fits and locks); iii) adhesive bonding in which adhesive materials such as glue are used; iv) energy bonding (e.g., welding and soldering); iv) other fasteners.

Once fastening methods are determined, the database of assembly and disassembly time for each fastening method is established. Assembly time estimation methodology proposed by Boothroyd et al. (2010, pp. 83-84) is used in this study to compute estimates of assembly times. According to the methodology, assembly times are obtained from the summation of the times required for the handling and insertion tasks as given in the predefined synthetic data (Boothroyd et al., 2010). On the other hand, the disassembly time is computed based on time estimates for disassembly related tasks such as i) preparation, ii) unfastening task, iii) part removal, iv) disassembly direction change, and v) change in disassembly method. The time estimates for each factor were computed using Maynard Operation Sequence Technique (MOST) developed by (Kroll & Carver, 1999). MOST technique uses motions related to the disassembly tasks to define disassembly moves as "general," "controlled," and "tool use" (Zandin, 2002). Accordingly, the unfastening time is modelled using motion sequence |Lx| while the removal of a fastener is modelled using motion sequence |AxBxGxAxPx|. The sequence indices are computed based on MOST's synthetic data as provided in (Boothroyd et al., 2010). The MOST technique for estimating the time required to dismantle a part assembled using four units of Phillips PM2.0×3.0 fastening screws is illustrated as follows. The time estimates for various disassembly tasks are given in Table 4.1.

Table 4.1 Demonstration of MOST technique for disassembly time calculation

Time estimates for different influencing factors (sec)						
Fastener index j	Quantity of j^th fastener q_j^f	Time required to access fasteners t_{ij}^{acc}	Tool Positioning time t_{ij}^{pos}	Tool preparation time t_{ij}^{pre}	Unfastening time t_{ij}^{uf}	Part removal time t_i^h
1	4	1.08	1.4	2.52	5.04	2.88

Hence, following the MOST technique, the disassembly task's unfastening time can be modelled as |L10|+ |A1B0G1A1P1| equivalent to 140 time-measurement-units (i.e., 100+10+0+10+10+10=140

TMUs) or 140*0.036 sec=5.04 seconds. Thus, based on Equation (4.5), a part's disassembly time can be estimated as t_{ij}^{d}= 4(1.08+1.4+5.04) +2.52+2.88 = 35.5sec.

4.4 Solving the optimisation model

The optimisation model considers several factors that affect the disassemblability of products for the selection of appropriate fastening methods. Hence, the search space can become significantly large. In such cases, deterministic solving techniques are not desirable. Previous studies have implemented metaheuristic algorithms like GA, ant-colony and simulated annealing for solving combinatorial optimisations (Hoseini & Shayesteh, 2010). GA is implemented in this study to solve the proposed optimisation model. The chromosome for the decision variables is defined as shown in Figure 4.2. The arrangement of the genes in the chromosome corresponds to i) index for a part ii) the chosen fastening method, iii) the fastening/unfastening direction, iv) part's assembly time and v) part's disassembly time, respectively in a sequence.

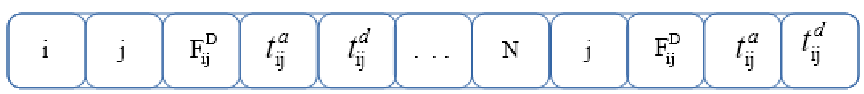


Figure 4.2 Chromosome encoding for the decision variables

Part's index is obtained from the product assembly/disassembly sequence information. The assembly and disassembly time of a given fastening method is obtained from the fastener's repository. For example, in Figure 4.3, the sequence of genes denotes respectively; the 1st part in the sequence assembled using the 2nd fastening method in the +z direction; the corresponding assembly time is 4.5sec, and the disassembly time is 5.5sec. The size of a chromosome depends on the number of parts in a product.

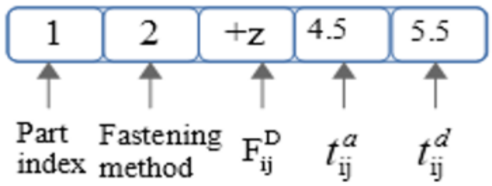
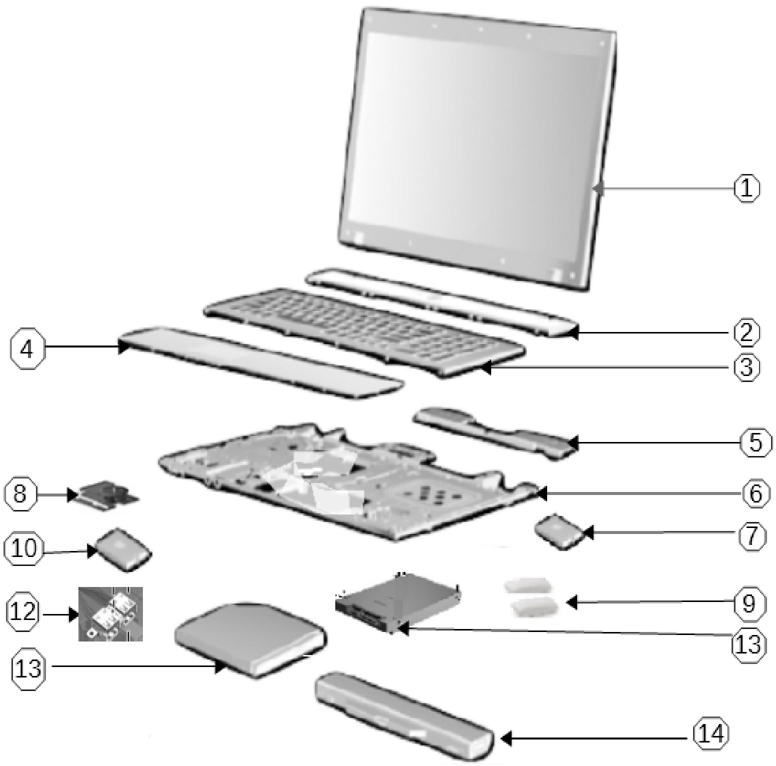


Figure 4.3 Example of chromosome encoding

The chromosomes are evaluated using the fitness function, i.e., the total assembly and disassembly cost function. The roulette wheel technique is employed for the selection of chromosomes. The crossover and the mutation operations are then applied to the selected batch of chromosomes to create a new population. For a crossover, the one-point crossover technique is implemented by interchanging the sequence of genes between the two parents, which leads to creating a new child chromosome. The mutation operation involves randomly swapping genes between parents with very low probability, which maintains genetic diversity within the population.

4.5 Implementation

In this section, a case study is presented to illustrate the proposed fastening methods selection methodology. A company that manufactures and offers new products to a primary market and remanufactures used laptops for a secondary market is considered for the case study. Due to stringent environmental regulations, the company remanufactures laptop computers from used product returns (i.e., from products sold in previous periods). The applicability and effectiveness of the proposed methodology are evaluated. The assembly schematic diagram of the product and the fourteen major components selected for the case study are shown in Figure 4.4. It is also assumed that the product's fastening methods were chosen without proper consideration of the disassembly for remanufacturing. The laptop computer was designed so that all fastening and unfastening operations are performed in +z direction, and thus no additional time is required for direction change.



Part Name

1. Display assembly
2. Switch cover
3. Keyboard module
4. Palm rest
5. Speaker
6. Top casing
7. Modem module
8. Fan Assembly
9. Memory module
10. WLAN Module
11. Hard drive
12. USB connector
13. Optical drive
14. Battery

Figure 4.4 Product assembly architecture and parts information

Table 4.2 shows the fastening methods selected in the original design and related assembly and disassembly times. The assembly and disassembly time estimates were computed using the methods described in section 4.3. For this case study, six types of assembly methods, namely: i) Philips PM2.5×3.0 ii) screws, iii) captive screws, iv) cantilever snap-fit, iv) cylindrical snap fits, v) retaining tabs, and vi) adhesives are considered. Besides, it is assumed that four workers carry out the product assembly/disassembly tasks with a pay rate of $15/hour. The goal is to determine appropriate fastening methods which can facilitate the assembly process during the manufacturing process of new laptops and the disassembly process during the remanufacturing of used laptops.

Table 4.2 Fastening methods selected for the new product design

Part Index	Part name	Fastening method	F_{ij}^{D}	q_{ij}^{f}	t_{ij}^{a} (sec)	t_{ij}^{d} (sec)	$t_{ij}^{a} + t_{ij}^{d}$ (sec)
1	Display assembly	Phillips PM2.5×4.5	-x	6	32.5	45.7	78.2
2	Switch cover	PM2.5×3.0 screws	+z	7	37.5	52.9	90.4
3	Keyboard module	Phillips PM2.5×4.5	+z	2	12.5	16.9	29.4
4	Palm rest	Phillips PM2.0×3.0	+z	3	17.5	24.1	41.6
5	Speaker	Phillips PM2.0×3.1	+z	4	22.5	31.3	53.8
6	Top cover	Torx T8M2.5×6.0	+z	22	112.5	160.9	273.4
7	Modem module	Phillips PM2.5×3.0	+z	2	12.5	16.9	29.4
8	Fan assembly	Phillips PM2.5×8.0	+z	7	37.5	72.5	110
9	Memory module	Retaining tab	-y	2	4	5.04	9.04
10	WLAN module	Phillips PM2.5×3.0	+z	2	12.5	16.9	29.4
11	Hard drive	Phillips PM2.0×4.0	+z	3	17.5	26.9	44.4
12	USB connector	Phillips PM2.5×3.0	+z	2	12.5	19.7	32.2
13	Optical drive	Phillips PM2.5×4.5	-y	1	7.5	9.7	17.2
14	Battery	Retaining tabs	-z	2	4	5.04	9.04
				Total	343	504.5	847.5

The chromosome representing the optimisation problem's decision variables is encoded, as shown in Figure 4.5. The sequence of genes represents the part index, the type of fastening method chosen, and the assembly/disassembly direction, respectively. The assembly and disassembly time estimates related to each fastening method are predetermined

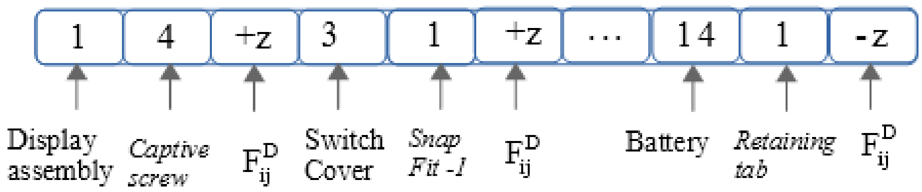


Figure 4.5 Chromosome encoding of the decision variables

The initial population of size 120 is generated at random. The GA parameters were determined through an experiment by altering the crossover, mutation rates, and population sizes. First, population sizes ranging from 40 to 180 were considered while fixing the crossover rate at 0.5 and the mutation rate at 0.01. As shown in Figure 4.6, the result indicates that a population size of 160 led to an improved convergence. Similarly, the cross-over rate ranging from 0.5 to 1.0 in the span of 0.1 was used while fixing the mutation rate and the population size at 0.01 and at 160, respectively. The experiment was repeated to obtain a mutation rate of 0.07. Hence, the crossover rate, mutation rate and population size were fixed at 0.7, 0.07, and 160, respectively. Afterward, the GA was run in a MATLAB environment.

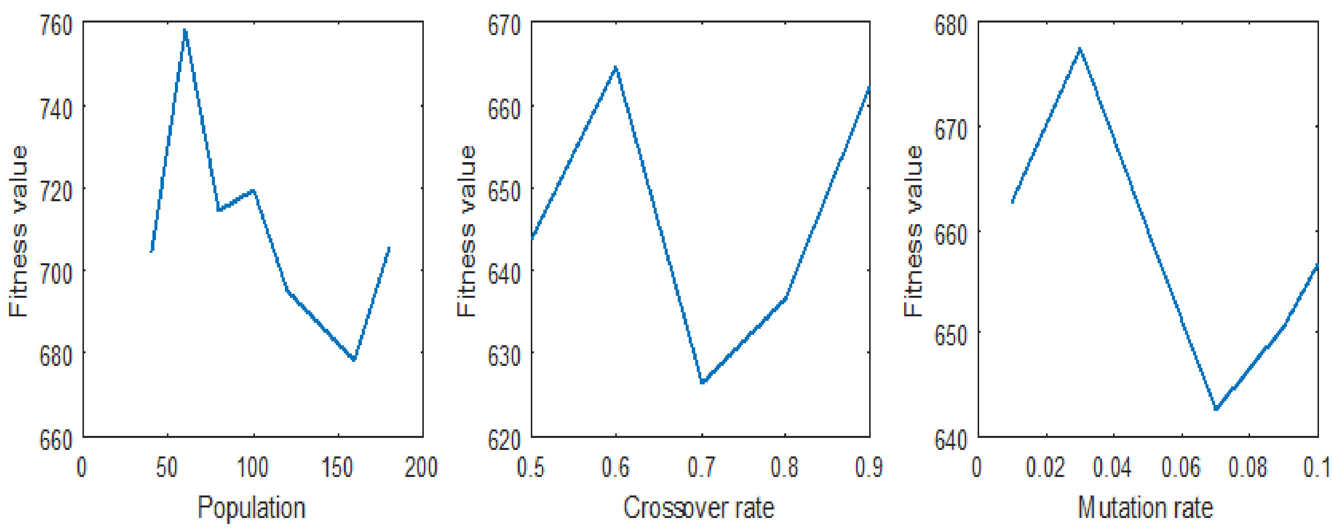


Figure 4.6 Experimental results of GA parameters

The optimal solution, shown in Figure 4.7 for 100 generations, converges after 48 generations. The GA's optimal solution corresponds to fastening methods that minimise the total assembly and disassembly costs.

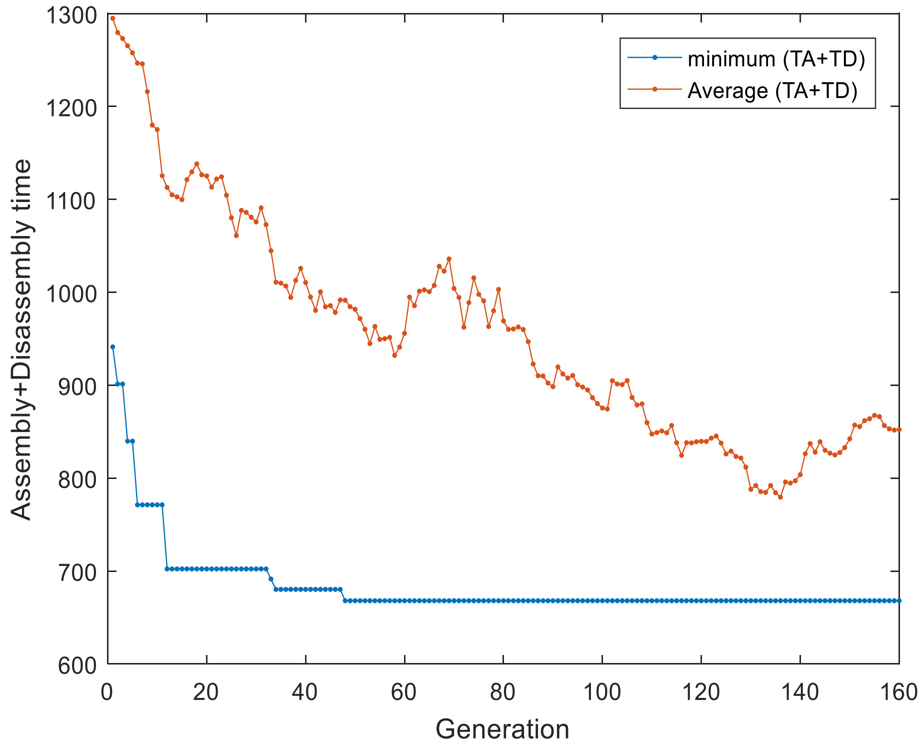


Figure 4.7 Min (Ass. and Diss. time) Vs GA iteration

Table 4.3 shows the selected fastening methods for each part, along with their assembly/disassembly times. Hence, from the results, the proposed methodology resulted in the overall reduction of assembly and disassembly times from 847.5sec. to 596.3sec i.e., a 29.6 % reduction.

Table 4.3 Fastening methods selected by GA

Part Index	Part name	Fastening method	Quantity of Fasteners	t_{ij}^{a} (sec)	t_{ij}^{d} (sec)	$t_{ij}^{a}+t_{ij}^{d}$ (sec)
1	Display Assembly	Phillips PM2.5×4.5	8	32.5	45.7	78.2
2	Switch cover	Snap fit 1	2	20	38.5	58.5
3	Keyboard Module	Phillips PM2.5×4.5	4	12.5	16.9	29.4
4	Palm rest	Phillips PM2.5×4.5	4	20	20.5	40.5
5	Speaker Module	Phillips PM2.5×4.5	4	22.5	31.3	53.8
6	Top cover	Captive screw	8	40	74.5	114.5
7	Modem module	Phillips PM2.5×4.5	2	12.5	16.9	29.4
8	Fan Assembly	Snap fit 1	4	20	38.5	58.5
9	WLAN Module	Phillips PM2.5×4.5	2	12.5	16.9	29.4
10	USB Connector	Phillips PM2.5×4.5	2	12.5	16.9	29.4
11	Memory Module	Cantilever Snap fit	2	4	4	8
12	Optical	Phillips PM2.5×4.5	1	7.5	9.7	17.2
13	Battery	Retaining tabs	2	4	5.04	9.04
14	Hard drive	Phillips PM2.5×4.5	4	20	20.5	40.5
	Total			240.5	355.84	596.34

4.5.1 Investigation of the cost savings of the proposed approach

This section investigates the proposed methodology's cost savings from a remanufacturing perspective. The optimisation model was altered such that consideration of the product assembly was omitted. After solving the altered optimisation model, new sets of fastening methods were obtained respectively for the original design, the design based on DFA, and the design based on the proposed methodology. Fastening methods selected based on the DFA design and their assembly and disassembly times are shown in Table 4.4.

Table 4.4 Fastening methods selected based on the DFA

Part index	Part name	Fastening methods (based on DFA)	$\mathbf{t}_{ij}^{a}$ (secs)	t_{ij}^{d} (secs)
1	Display assembly	Phillips PM2.5×4.5	32.5	45.7
2	Switch cover	Snap fit 1	20	38.5
3	Keyboard module	Phillips PM2.5×4.5	12.5	16.9
4	Palm rest	Phillips PM2.5×4.5	14.5	100
5	Speaker module	Snap fit 1	14.5	100
6	Top cover	Adhesive	29	300
7	Modem module	Phillips PM2.5×4.5	12.5	16.9
8	Fan assembly	Snap fit 1	20	38.5
9	WLAN module	Phillips PM2.5×4.5	12.5	16.9
10	USB connector	Phillips PM2.5×4.5	12.5	16.9
11	Memory module	Snap fit 1	4	4
12	Optical drive	Captive screw	7.5	12.5
13	Battery	Retaining tab	4	5.04
14	Hard drive	Phillips PM2.5×4.5	17.5	24.1
	Total		213.5	735.94

Three scenarios were compared, considering the demand for new products and remanufactured products. The total assembly and disassembly cost of a product, CT, based on the three sets of fastening methods were computed for each scenario. The cost savings (i.e., CT computed based on the proposed methodology – CT computed based on DFA; and CT computed based on the proposed methodology - CT computed for the original design) were determined. The results are shown in Table 4.5.

Table 4.5 Cost savings for different scenario

		Scenario 1	Scenario 2	Scenario 3
Demand	New products, Q_n	40,000	40,000	40,000
	Remanufactured products, Q_r	8,000	12,000	15,000
Total cost C_T	Original design	295,930.7	329,562.7	354,786.7
	DFA	240,458.7	289,521.3	326,318.3
	Proposed methodology	219,459	244,521	263,318
Cost Saving	Proposed methodology vs Original design	76,472	85,041	91,468
	Proposed methodology vs DFA	21,000	45,000	63,000

The result shows that the total product assembly and disassembly costs obtained based on the proposed methodology is the least in all the scenarios. With the increasing demand for remanufactured products, higher cost savings based on the proposed methodology can be obtained.

4.5.2 The impact of the degree of product disassembly

In this section, the impact of the degrees of disassembly requirement of used products on cost saving is investigated. Due to the variability of the condition of used product returns, different products often require different degree of disassembly. The degrees of product disassembly in the range ‘0.1’ - ‘1.0’ were investigated such that a ‘0.1’ degree requires a slight disassembly and a ‘1.0’ degree requires complete disassembly. Figure 4.8 (a) shows the cost saving (i.e., subtracting the CT of the original design from the CT obtained based on the proposed methodology).

Under all three scenarios, the result shows that the proposed methodology led to higher cost savings for an increase in the degree of product disassembly. The cost savings obtained after subtracting the CT of the DFA methodology from the CT of the proposed methodology is shown in Figure 4.8 (b). Therefore, the fastening methods obtained using the proposed methodology result in a higher cost saving as the degree of product disassembly increases under all three scenarios.

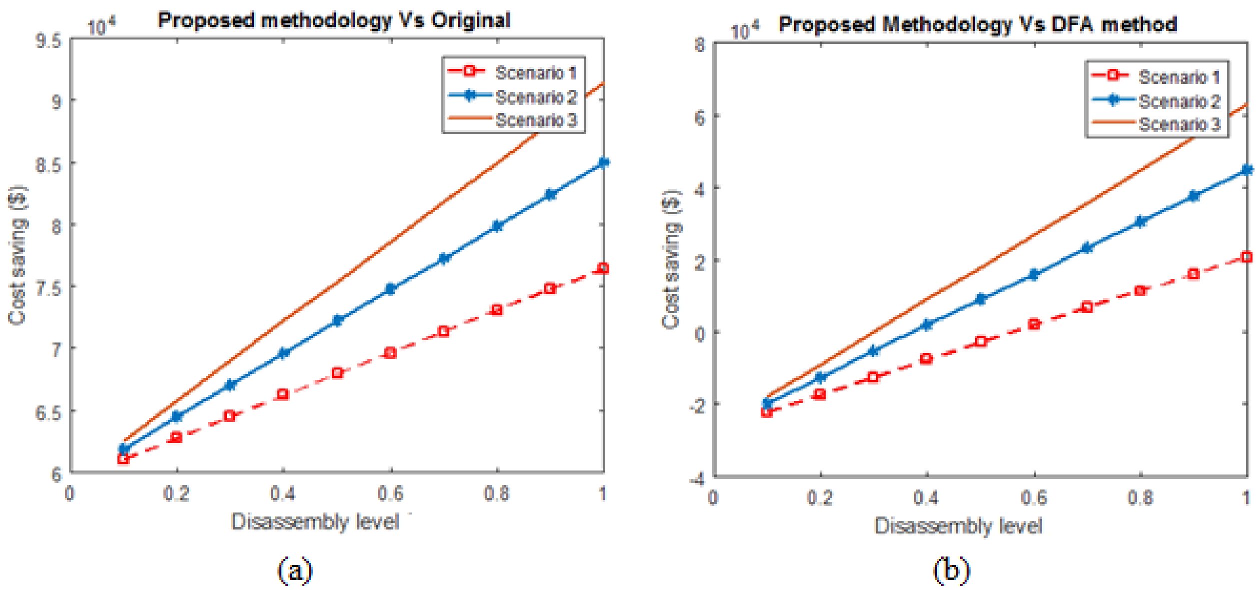


Figure 4.8 Disassembly degree Vs assembly and disassembly cost saving

4.6 Chapter Summary

This chapter proposed a methodology for fastening methods selection during the early design stage from a remanufacturing perspective. The proposed fastening methods selection methodology considers product assembly and disassembly concerns simultaneously. A mathematical optimisation model is derived for the selection of fastening methods to minimise the total product assembly and disassembly costs. The genetic algorithm is used to solve the optimisation model.

A case study on the selection of appropriate fastening methods for the new and the remanufactured laptop version laptop was conducted to illustrate the applicability of the proposed methodology. Different scenarios of return quantities and degrees of product disassembly were also investigated to validate the proposed approach. The result showed that the proposed methodology offers better cost savings under all the scenarios.

Chapter 5 A Bilevel Optimisation Model for the Design Configuration of New and Remanufactured Products Considering Specification Upgrading of Used Products

This chapter presents the proposed hierarchical model for joint optimisation of product design configurations (PDC) of new and remanufactured products considering specification upgrading of used product returns. The chapter is organized as follows: Section 5.1 describes the problem statement. Section 5.2 presents the formulation of the bilevel optimisation model. Section 5.3 discusses the methodology for solving the proposed model. An industrial case study is presented in section 5.4 to demonstrate the proposed methodology's applicability and performance. The case study results, and the sensitivity analysis are presented in sections 5.5 and 5.6, respectively. Section 5.7 presents conclusions and future research directions.

5.1 Problem description

This study concerns firms that offer lines of new product variants in period 1 and remanufacture used product returns to launch lines of remanufactured product variants in period 2 to satisfy customers' diversified needs in distinct market segments. Remanufactured products are assumed to be offered in period 2, but they are planned during the new product design stage. New products are assembled from new parts, while remanufactured products are assembled from parts recovered from used product returns. Due to technological obsolescence, recovered used parts often require specification upgrading. Hence, remanufactured product development involves critical decisions regarding specification upgrading for used parts (Kwak & Kim, 2013). We adopt the concept of generational difference introduced by Kwak and Kim (2013, 2015), which defines the relative technological obsolescence of used parts relative to the cutting-edge specification. Their generation often characterises parts/modules in consumer electronics such as computers and mobile phones. For instance, Intel's Core™ i7 processors are characterised in terms of their generations as "1st", "2nd" etc. generations with the cutting-edge specification (i.e., latest generation) having a zero generational difference. If the current cutting-edge generation is the 10th generation, a processor module with Intel® Core™ i7 6th generation would have a generational difference of four.

This study assumes that customers prefer products with the latest generation attributes (i.e., attributes with low generational differences) than similar product variants whose attribute levels are older generations. The joint optimisation of PDC aims to determine optimal attribute levels and their generational differences for new product variants and optimal attribute levels and upgrade decisions for remanufactured product variants. The joint PDC for new and remanufactured product is modelled using upper-level and lower-level optimisations, respectively. The framework depicted in Figure 5.1 and Figure 5.2 illustrate attributes and choice of attribute levels for new and remanufactured product variants. The framework outlines product variant architecture for a firm that plans to introduce new and remanufactured products.

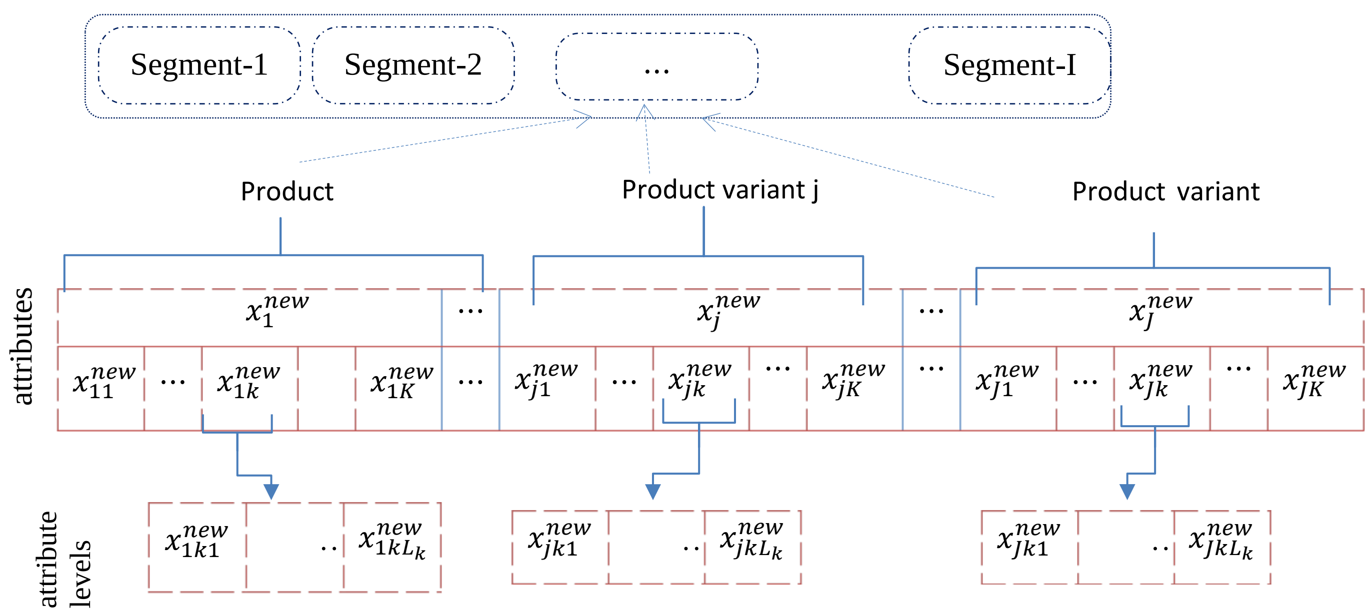


Figure 5.1 Attributes and attribute levels of new product variants

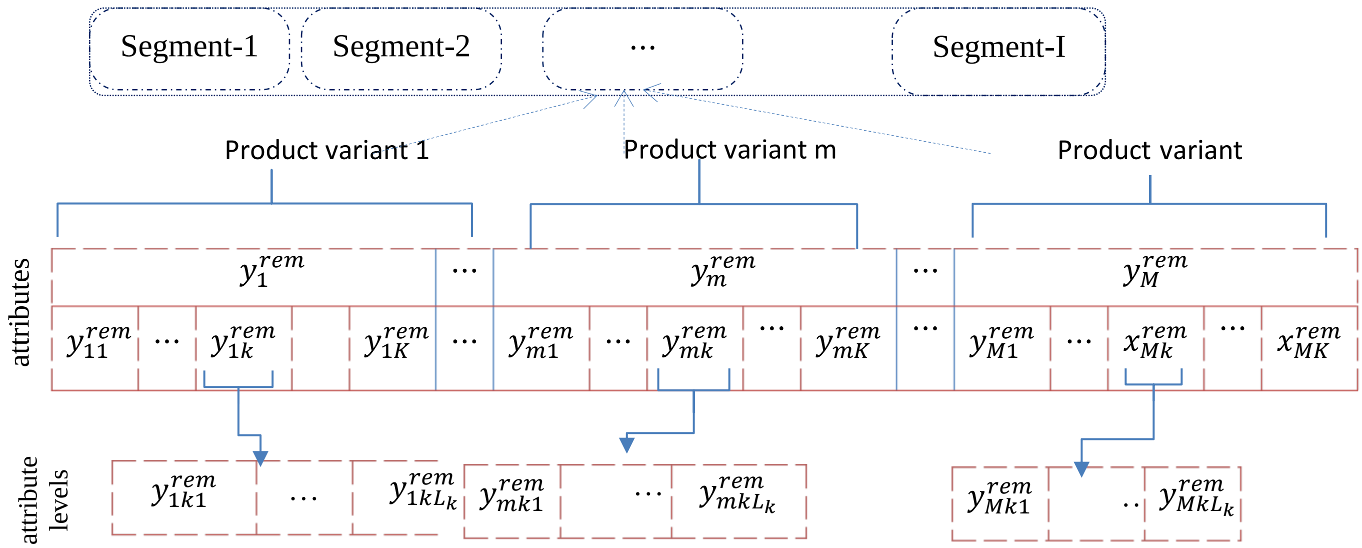


Figure 5.2 Attributes and attribute levels of new remanufactured product variants

It is assumed that the firm launches J new product variants in period 1; remanufactures used product returns to launch M remanufactured product variants along with J new product variants in period 2 to satisfy customer needs in I market segments. The x_{jkl}^{new} and y_{mkl}^{rem} denote binary decision variables for the selection of the l^{th} level of the k^{th} attribute for j^{th} new and m^{th} remanufactured product variants, respectively.

5.2 Formulation of Bilevel optimisation model for PDC

The notations and indices used in the formulation of the bilevel optimisation model are defined as follows:

Indices:

$i = 1,2,\cdots \mathrm{I}$ set of market segments where I denotes the total number of markets

$k = 1,2,\cdots K$ set of attributes where K denote the total number of attributes of a product

$l = 1,2,\cdots L_k$ denote the set of attribute levels where L_k denote the total number levels for the k$^{\text{th}}$ attribute

$j = 1,2,\cdots J$ index for a new product variant, where J denotes the total number of new product variants

$m = 1,2,\cdots M$ index for a remanufactured product variant, where J denotes the total number of remanufactured product variants

Decision variable

$$x_{ij}^{new} = \begin{cases} 1 & \text{if the } m^{\text{th}} \text{ remanufactured product variant is offered in the } i^{\text{th}} \text{ market segment} \\ 0 & \text{otherwise} \end{cases}$$

$$x_{jkl}^{new} = \begin{cases} 1 & \text{if } the\ l^{\text{th}} \text{ level is selected for } k^{\text{th}} \text{ attribute for jth new product} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{mkl}^{rem} = \begin{cases} 1 & \text{if } the\ l^{\text{th}} \text{ level is selected for } k^{\text{th}} \text{ attribute for } m^{\text{th}} \text{ remanufactured product} \\ 0 & \text{otherwise} \end{cases}$$

$$z_{mkl}^{rem} \begin{cases} 1 & \text{if the } l^{\text{th}} \text{ level of } k^{\text{th}} \text{ attribute selected for } m^{\text{th}} \text{ reman. product requires an upgrade} \\ 0 & \text{otherwise} \end{cases}$$

λ_{jkl}^{new} the generational difference of the l^{th} level of k^{th} attribute selected for the j^{th} new product

λ_{mkl}^{rem} *the* generational difference of the l^{th} level of k^{th} attribute selected for m^{th} remanufactured product

θ_{mkl}^{rem}= an upgrade level chosen for the l^{th} level of the k^{th} attribute of m^{th} remanufactured product

Parameters

u_{ikl} the part-worth utility of l^{th} level of the k^{th} attribute in the i^{th}market segment

γ_k^{rem} the average annual rate of change of generational difference for the k^{th} attribute

λ_{ijkmax}^{new} the maximum acceptable generational difference of the k^{th} attribute of the j^{th}new product in the i^{th} market segment

λ_{imkmax}^{rem} the maximum acceptable generational difference of the k^{th} attribute of the m^{th}remanufactured product in the i^{th} market segment

$c_{kl}^{\lambda(0)}$ the unit cost of cutting edge l^{th} level of the k^{th} attribute

τ_{kl} the annual percentage depreciation rate of the price of l^{th} level of the k^{th} attribute

5.2.1 Upper-level and Lower-level optimisations

The proposed joint optimisation of PDC involves conjoint analysis, a widely utilised technique to model customers' preferences based on part-worth utilities of attribute levels of product variants as evaluated by customers in distinct market segments (Kuzmanovic & Martic, 2012). Three types of conjoint survey techniques were reported in previous researches: rating, ranking, and choice-based types (Green et al., 2001; Baier et al., 2015; Asioli et al., 2016). The rating-based conjoint survey technique is used in this study because the results can be easily interpreted using the same units as the rating scores (Asioli et al., 2016). Conjoint survey questionnaires are designed for the new and remanufactured product profiles based on orthogonal arrays for respondents to rate. From the survey responses, part-wroth utilities of individual attribute levels are determined. Furthermore, customers can be clustered into distinct segments based on their purchase preferences using appropriate clustering techniques.

In the proposed methodology, the utility functions for the new and remanufactured product variants are determined by aggregating part-worth utilities and utilities from generational differences of individual attribute levels. The utility of the jth new and m^{th} remanufactured product variant in the i^{th} market segment denoted as $U_{ij}$and U_{ij} are modelled as a function of the weighted sum of the part-worth utilities and generational differences of individual attribute levels given in Equations (5.1) and (5.2). The part-worth utilities, u_{ikl} , represent customers perceived preferences of the l^{th} level of the k^{th} attribute in the i^{th} market segment.

$$U_{ij} = \sum_{k}^{K} \sum_{l=1}^{L_k} w_{jk} \left(u_{ikl} + \vartheta_{ijkl}{}^{new} \right) x_{jkl}^{new} + \varepsilon_{ij} \tag{5.1}$$

$$U_{im} = \sum_{k}^{K}\sum_{l=1}^{L_k} w_{jk}(\, u_{ikl} + \vartheta_{imkl}{}^{rem})\, y_{mkl}^{rem} + \varepsilon_{im} \tag{5.2}$$

The $\vartheta_{ijkl}{}^{new}$ and $\vartheta_{ijkl}{}^{rem}$ represent customers perceived utility of the generational difference of the l^{th} level of the k^{th} attribute of the new and remanufactured products, respectively in the i^{th} market segment. The perceived utilities due to the generational differences are computed as a standardised score of the attribute levels' generational differences with respect to the maximum acceptable generational differences as given in Equation (5.3) and (5.4). The w_{jk} denotes the weight given to the l^{th} level of the k^{th} attribute whereas the ε_{ij} denotes the stochastic error term of the linear regression.

$$\vartheta_{ijkl}{}^{new} = 1 - {\lambda_{ijkl}^{new}}\Big/{\lambda_{ijkmax}^{new}} \tag{5.3}$$

$$\vartheta_{imkl}{}^{rem} = 1 - {\lambda_{imkl}^{rem}}\Big/{\lambda_{imkmax}^{rem}} \tag{5.4}$$

Once the utility functions are determined, the new and remanufactured products' market shares are determined using the multinomial logit (MNL) model (Uncles et al., 1987). The MNL is a widely used technique for estimating market shares of products based on their perceived utilities. According to the MNL choice rule, the choice probabilities of the j^{th} product variant in the i^{th} market segment during the period -1 and period 2 are given by Equations (5.5) and (5.6).

$$P_{ij}^{new(1)} = \frac{\exp[\rho U_{ij}]}{\sum_{j=1}^{J}\exp[\rho U_{ij}] + \sum_{n=1}^{N}\exp[\rho U_{in}]} \tag{5.5}$$

$$P_{ij}^{new(2)} = \frac{exp[\rho U_{ij}]}{\sum_{j=1}^{J} exp[\rho U_{ij}] + \sum_{n=1}^{N} exp[\rho U_{in}] + \sum_{m=1}^{M} exp[\rho U_{im}]} \tag{5.6}$$

Where U_{in} denote the utility of n^{th} competing product in the i^{th} market. N is the total number of competing product variants. Parameter ρ denotes a positive scaling factor of the MNL model (Steiner & Hruschka, 2005). The demand functions for new product variants in period 1 and period 2 are then estimated using Equations (5.7) and (5.8) where $Q_i^{(1)}$ and $Q_i^{(2)}$ respectively denote estimated sizes of the i^{th} market segment in period 1 and period 2.

$$D_{ij}^{new(1)} = Q_i^{(1)}\left(P_{ij}^{new(1)}\right) \tag{5.7}$$

$$D_{ij}^{new(2)} = Q_i^{(2)}\left(P_{ij}^{new(2)}\right) \tag{5.8}$$

Similarly, the market share and demand function for the remanufactured product variants are in period 2 are determined using Equations (5.9) and (5.10), respectively.

$$P_{im}^{rem(2)} = \frac{\exp[\rho U_{im}]}{\sum_{j=1}^{J} \exp\left[\rho U_{ij}\right] + \sum_{n=1}^{N} \exp[\rho U_{in}] + \sum_{m=1}^{M} \exp[\rho U_{im}]} \tag{5.9}$$

$$D_{im}^{rem(2)} = Q_i^{(2)}\left(P_{im}^{rem(2)}\right) \tag{5.10}$$

Objective functions such as maximising the market share and profit; minimising the production cost and environmental impacts are often used in PDC studies. In this study, the maximisation of shared surplus introduced by (Jiao and Zhang, 2005) is adopted as an objective function for both the upper-level and lower-level optimisations. The shared surplus is computed as a ratio of the product of aggregate utilities and demands of product variants to variable costs. Hence, the shared surplus of the upper-level optimisation is given by Equation (5.11). The variables involved are decision on product variants, choice of levels, and generational differences for individual attributes. Constraints of the upper-level optimisation model are formulated in Equations (5.12) - (5.25).

$$\max F(\, x_{ij}^{new}, x_{jkl}^{new}, \lambda_{ijkl}^{new}) = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{U_{ij}}{C_{ij}} \left(D_{ij}^{new(1)} + D_{ij}^{new(2)}\right) x_{ij}^{new} \tag{5.11}$$

Subject to:

$$C_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} c_{kl}^{\lambda(0)} \exp\left(-\tau_{kl} * \lambda_{ijkl}^{new}\right) x_{ijkl}^{new} \tag{5.12}$$

$$\sum_{l=1}^{L_k} x_{jkl}^{new} = 1 \tag{5.13}$$

$$\sum_{k}^{K}\sum_{l=1}^{L_k}\left|x_{jkl}^{new} - x_{j'kl}^{new}\right| > 0, \quad \forall j \neq j' \tag{5.14}$$

$$\sum_{j}^{J} D_{ij}^{new(2)} + \sum_{j}^{J} D_{im}^{rem(2)} \leq Q_i^{(2)} \tag{5.15}$$

$$\lambda_{ijkl}^{new} <= \lambda_{ijklmax}^{new} \tag{5.16}$$

$$\left(x_{ij}^{new}, x_{jkl}^{new}\right) \epsilon \{0,1\} \tag{5.17}$$

$$\max f(y_m^{rem}, y_{mkl}^{rem}, z_{mk}^{rem}, \theta_{mk}^{rem}) = \sum_{i=1}^{I}\sum_{m=1}^{M}\frac{U_{im}}{C_{im}}\left(D_{ij}^{rem}\right)y_{im}^{rem} \tag{5.18}$$

Subject to:

$$C_{im} = \sum_{k=1}^{K}\sum_{l=1}^{L_k} c_{kl}^{\lambda(0)} \exp\left(-\tau_{kl} * \lambda_{imkl}^{rem}\right) y_{imkl}^{rem} \tag{5.19}$$

$$\sum_{l=1}^{L_k} y_{mkl}^{rem} = 1 \tag{5.20}$$

$$\sum_{k}^{K}\sum_{l=1}^{L_k}\left|y_{mkl}^{rem} - y_{m'kl}^{rem}\right| > 0, \quad \forall m \neq m' \tag{5.21}$$

$$\sum_{j}^{J} D_{ij}^{new(2)} + \sum_{j}^{J} D_{im}^{rem(2)} \leq Q_i^{(2)} \tag{5.22}$$

$$\lambda_{imkl}^{rem} <= \lambda_{imklmax}^{rem} \tag{5.23}$$

$$\lambda_{mkl}^{rem} = (\lambda_{jkl}^{new} + t * \gamma_k^{rem})(1 - z_{mkl}^{rem}) + \theta_{jkl}^{rem} \tag{5.24}$$

$$(y_{im}^{rem}, y_{mkl}^{rem}, z_{mkl}^{rem}) \epsilon \{0,1\} \quad (5.25)$$

Constraints in Equations (5.12) and (5.19) computes the variable costs of attribute levels for the new and remanufactured product variants where $c_{kl}^{\lambda(0)}$ denotes the unit cost of the cutting-edge generation of the l^{th} level of the k^{th} attribute. It is assumed that a part/module's cost with an attribute level l depreciates exponentially w.r.t its generational differences (Kwak and Kim, 2011). The parameter τ_{kl} denotes the annual cost depreciation rate of the l^{th} level of the k^{th} attribute. Constraints in Equations (5.13) and (5.20) ensure only one attribute level is selected for each of the new and remanufactured product variants, respectively. Constraints (5.14) and (5.21) respectively ensure that each of the new and remanufactured product variants offered is unique in at least one attribute level. Constraints (5.15) and (5.22) denote the capacity constraint such that the quantity of new and remanfuctured products to be offered by the company in the i^{th} market segment in period 2 is limited by the size of the market segment. Constraints (5.16) and (5.23) respectively ensure the generational differences of each of the attribute levels chosen for the new and remanufactured product variants do not exceed the maximum generational difference acceptable in each market segment. Constraints (5.17) and (5.25) restricts the decision variables to be binary. Constraint (5.24) computes generational differences for the attribute levels selected for remanufactured product variants based on upgrade decisions. The parameter γ_{k}^{rem}denote annual rate of the change in generational difference for k^{th} attribute. t represents the time in years between the sales of a new product whose generational difference was $\lambda_{jkl}^{new}$and its end-of-life when it was decided to be remanufactured.

5.3 Solving approach

5.3.1 Nested bilevel GA

The proposed bilevel optimisation model involves a 0-1 binary integer variable and a non-linear function that falls under NP-hard type problems (Sinha et al., 2018). The presence of binary decision variables in an NP-hard problem makes it difficult to solve using classical analytic approaches. Metaheuristic approaches are widely used in recent years for solving NP-hard and combinatorial optimisations (Oliveto et al., 2007). In this study, a nested bilevel GA (NBGA) outlined in Figure 5.3 is adopted to solve the bilevel optimisation problem. The NBGA involves a two-stage recursive GA approach whereby the solution of a lower-level optimisation problem serves as an input to the upper-level optimisation problem. The step-by-step procedure of the NBGA algorithm is outlined as follows:

Step 1– Initialisation: Generate a random population for the upper-level decision variables $(x_{ij}^{new}, x_{jkl}^{new}, \lambda_{ijkl}^{new})$.

Step 2– Check the population's feasibility based on upper-level constraints and pass them onto the lower-level optimisation.

Step 3 – Generate a random population for the lower-level decision variables $(y_m^{rem}, y_{mkl}^{rem}, z_{mk}^{rem}, \theta_{mk}^{rem})$. Check feasibility of the population based on lower-level constraints. Combine upper-level and lower-level decision variables and solve the lower-level optimisation.

Step 4– Check the termination condition of the lower-level optimisation. Execute multipoint crossover and uniform mutation operation if the termination check is false and repeat step 2 to update the population. If the termination check at step 2 is true, pass the lower-level decision variables as the optimum solution to the upper-level optimisation.

Step 5 -Evaluate the fitness function of the upper-level optimisation. Check termination condition of the upper-level optimisation. If false, execute multipoint crossover and uniform mutation operation to update the population of the upper-level optimisation. Repeat steps 2-4. If the termination condition is true, go to step 6.

Step 6– End the algorithm and save the upper-level and lower-level decision variables' values as the optimal solutions.

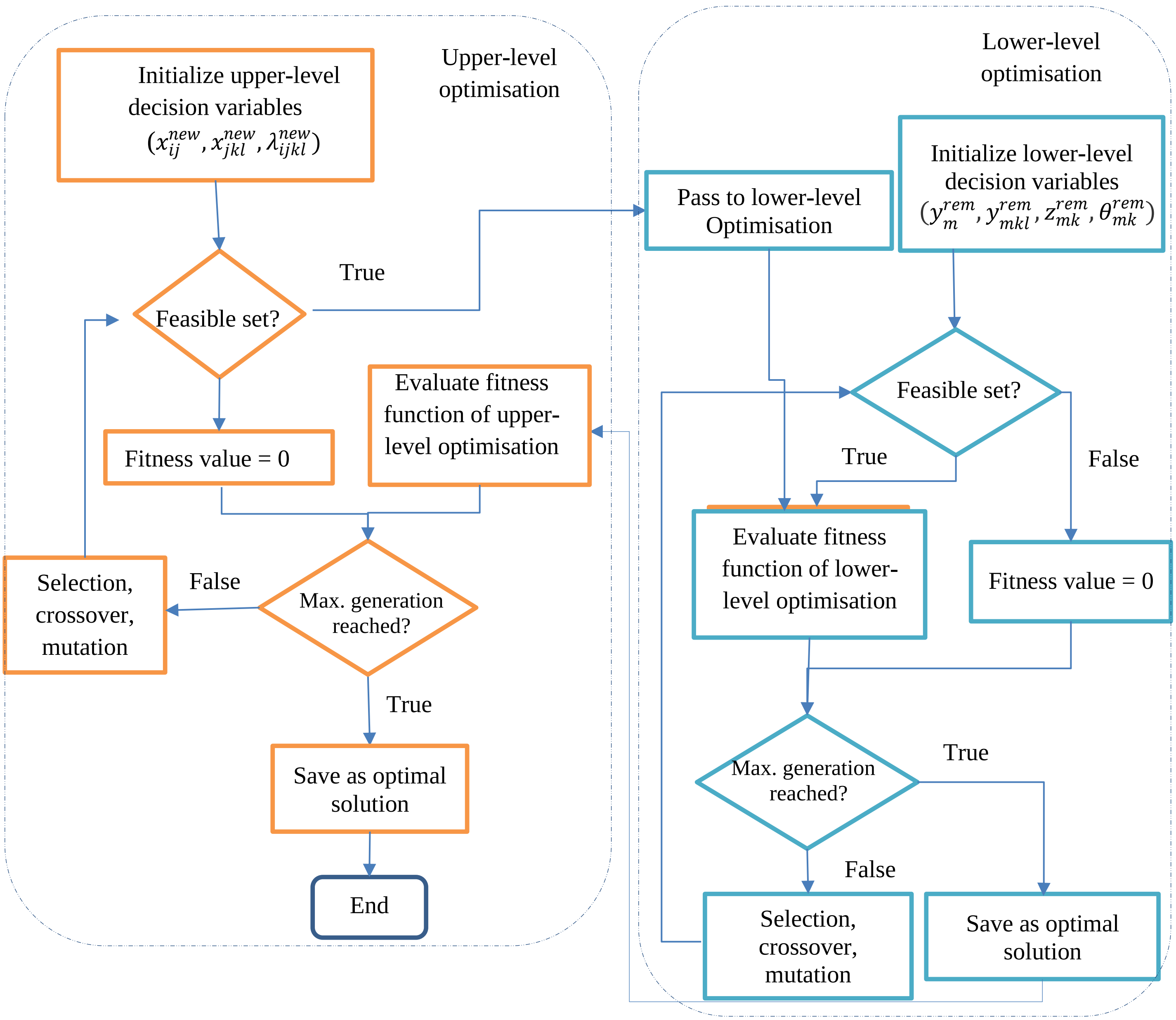


Figure 5.3 Flow chart of the NBGA solving approach

5.3.2 Chromosome encoding

The upper-level optimisation's chromosome structure consists of two segments; the first segment encodes the decision variable for selecting attribute levels. The second segment encodes the decision variable for selecting generational differences for the selected attribute levels. Hence, the upper-level optimisation has $2 \times J \times \sum_{k=1}^{K} L_k$ genes. For instance, the partial presentation of chromosome for j=1 in Figure 5.4 shows the selection of 2nd level and one generation old (generational difference=1) for the 1st attribute with; 1st level and the latest generation (generational difference=0) for the 2nd attribute; and the 1st level and two-generation old for the Kth attribute.

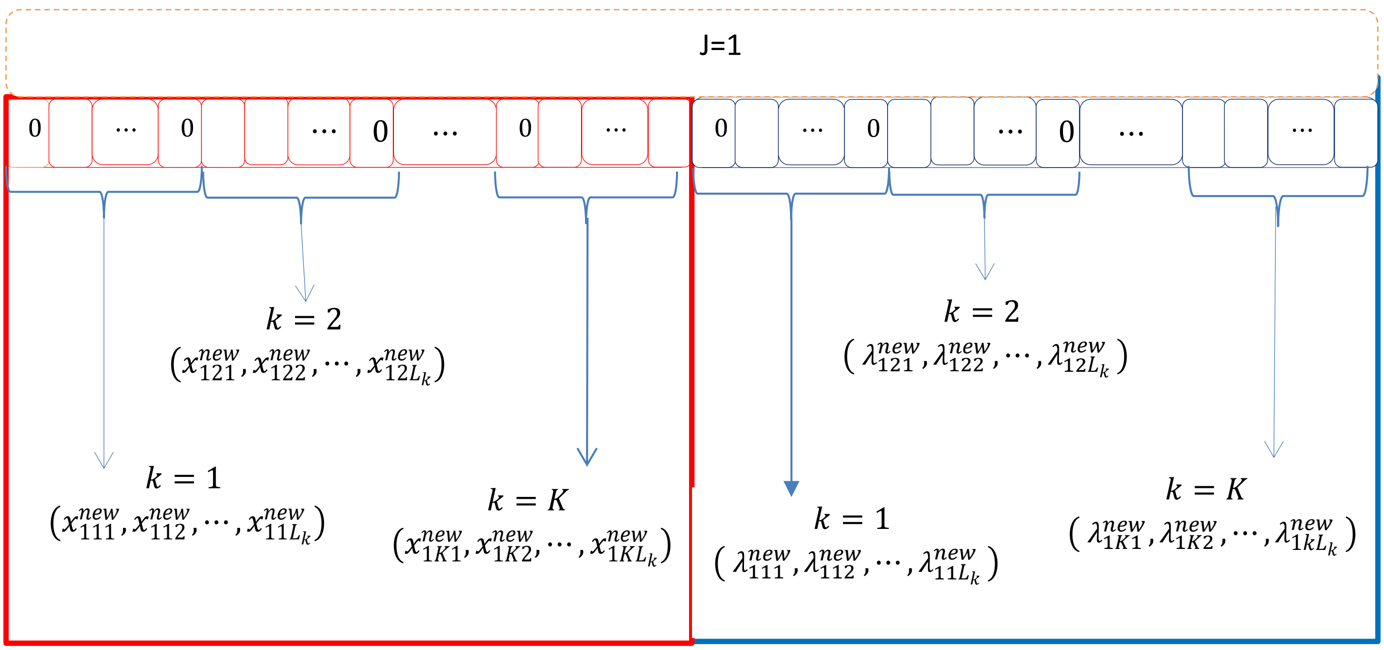


Figure 5.4 Chromosome structure of upper-level decision variables

The chromosome structure of the lower-level optimisation has three segments. The first segment encodes decision variables for the selection of attribute levels for the product configuration (i.e., y^{rem}_{mkl}). The second segment encodes decision variables for attributes upgrading (i.e., z^{rem}_{mkl}). The third segment encodes generational differences for attribute levels that require specification upgrading. Hence, the chromosome structure for the lower-level optimisation has a total of $3 \times J \times \sum_{k=1}^{K} L_k$ genes. For instance, the partial presentation of chromosome for remanufactured product variant 1(m=1) in Figure 5.5 shows the selection of 1st level for the 1st attribute, which is decided to maintain its specification (z_{111}^{rem}=0). Similarly, the chromosome structure shows the selection of 2nd level for the Kth attribute, which is decided to be upgraded to a two generations old specification (i.e., $\theta_{1K2}^{rem} = 2$).

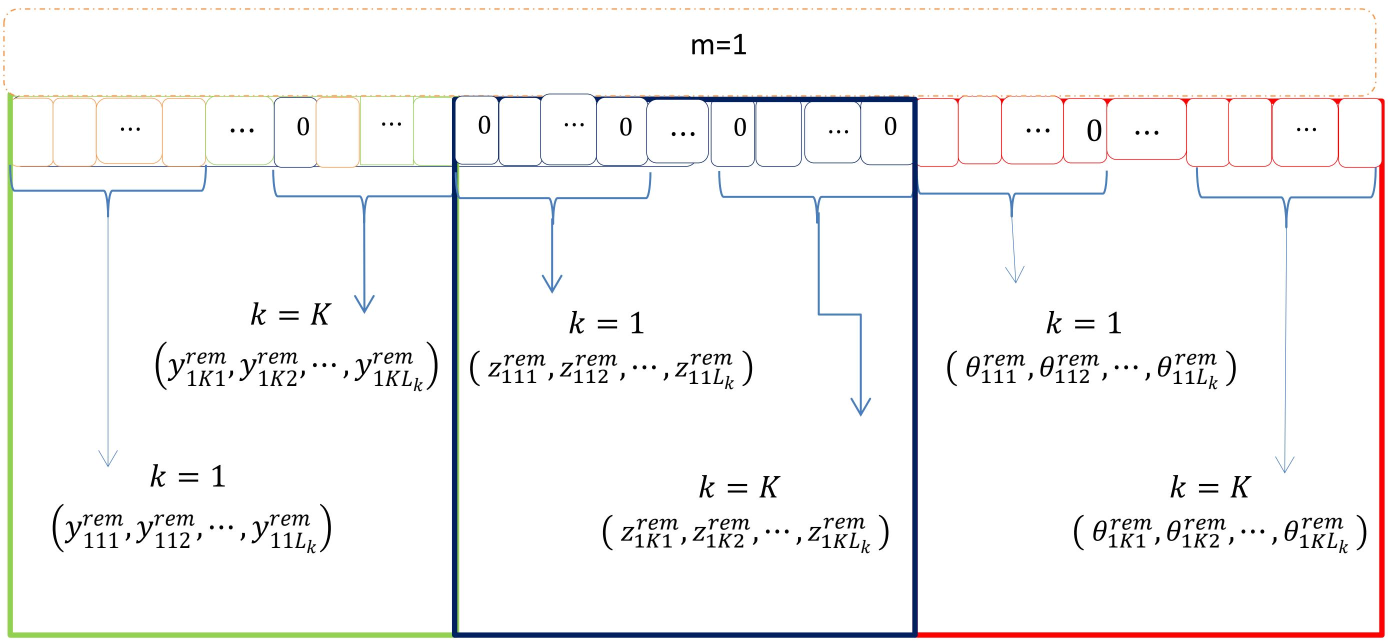


Figure 5.5 Chromosome structure of lower-level decision variables

For a crossover operation, the multipoint crossover is suited since chromosomes representing decision variables corresponding to attribute levels, and generational differences are batched together. The crossover operation creates an updated upper-level and lower-level population by randomly swapping segments of chromosomes corresponding to each decision variables. The mutation operation randomly alters genes corresponding to attribute levels' decisions, their generational differences for the upper-level optimisation. In the lower-level optimisation, the mutation operation randomly alters with small probability genes corresponding to the decisions on attribute levels, their upgrade decision, corresponding upgrade levels for attribute levels decided for an upgrade. Mutation operation helps preserve genetic diversity within a population in GA (Potts et al., 1994).

5.4 Case study

5.4.1 Description of the case study

A case study of PDC for the new and remanufactured mobile phone variants is presented to demonstrate the proposed bilevel optimisation model and the solving approach. The mobile phone design is assumed to have been designed using a modular structure. Each module representing an attribute is characterised by two or three attribute levels, representing a distinct performance level. Five functional attributes ('display size,' 'camera pixels,' 'memory,' 'security feature', and 'battery capacity') and a price are considered for the case study, which makes up a total of six attributes. The attribute levels considered are 3,3,3,2,3 and 3, respectively, for the display size', 'camera pixels,' 'memory,' 'security feature,' 'battery capacity,' and 'price'. Therefore, a full factorial design would have a total of 3×3×3× 2× 3×3 =486 possible product variants, which is significantly large for a market survey. In such a scenario, it is customary to use Taguchi's orthogonal arrays to generate a manageable number of product profiles for a market survey. In this case study, an L18 Taguchi orthogonal array is implemented to generate 18 product profiles for the conjoint analysis. The generated product profiles are divided into new and remanufactured products, as shown in Table 5.1.

For simplicity, it was assumed that a company first launches new product variants during period 1 and remanufactured product variants in period 2. Both the new and remanufactured products are assumed to be introduced to the same market (I=1) with identical purchase preferences during period 2. The sizes of the market in period 1 and period -2 are estimated as 50,000 and 80,000, respectively.

Table 5.1 L18 Orthogonal product profiles for the new and remanufactured products

Product profile	Condition	Display (inches)	Camera	Memory	Fingerprint security	Battery Capacity (mAh)	Price (hkd)
1	New	5.5	13 MP (dual) + 8 MP (selfie)	64GB + 3GB RAM,	Yes	4,000-4,500	1,400
2	New	4.7	13MP (single) + 8MP (selfie)	64GB + 3GB RAM,	Yes	2000-2500	1,400
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10	Reman.	6.8 inch	16 MP (triple) + 10MP (selfie)	256GB + 6GB RAM	Yes	4,000-4,500	2,600
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
18	Reman.	4.7	16 MP (triple) + 10MP (selfie)	128GB + 4GB RAM	No	4,000-4,500	1,400

A rating-based conjoint survey involving 35 respondents was conducted whereby each respondent was asked to rate each of the new and remanufactured product profiles on a 1-5 rating scale. A rating of 5 points indicates the most preferred profile, while a 1-point rating indicates the least preferred profile. Based on conjoint analysis, the part-worth utilities of individual attribute levels were determined, as shown in Table 5.2. Parameter settings for the estimated unit costs of the latest generation ($c_{kl}^{\lambda(0)}$); estimated annual rate of generational difference (γ_{kl}^{rem}); estimated annual cost depreciation (τ_{kl}); the maximum acceptable generational differences for new parts (λ_{ijkmax}^{new}) and remanufactured parts (λ_{imkmax}^{rem}) are also provided in Table 5.2. The figure for the rate of the generational difference indicates the frequency of the innovation cycle. For instance, a generational difference rate of $\gamma_{kl}^{rem} = 0.5$ for the 'memory' attribute indicates that a new technology (generation) emerges every two years for its attribute levels.

Table 5.2 Part-worth utilities, unit costs and parameter settings of attribute levels

Attribute	Attribute levels	Utility	Unit Cost in hkd ($c_{kl}^{\lambda(0)}$)	γ_{kl}^{rem}	τ_{kl}	λ_{ijkmax}^{new}	λ_{imkmax}^{rem}
Display (inch)	4.7inch	0.06	120	0.75	0.25	2	3
	5.5 inch	0.06	150				
	6.8 inch	-0.11	210				
Camera	13MP (single) + 8MP (selfie)	-0.61	120	1.25	0.75	3	4
	13 MP (dual) + 8 MP (selfie)	-0.11	220				
	16 MP (triple) + 10MP (selfie)	0.72	340				
Memory	64GB + 3GB RAM	-0.28	140	0.5	0.8	1	2
	128GB + 4GB RAM	0.22	220				
	256GB + 6GB RAM	0.06	320				
Fingerprint security	Yes	0.08	50	0.75	0.6	1	2
	No	-0.08	0				
Battery	2000-2500 mAh	-0.28	155	0.75	0.8	2	3
	3,000-3,500 mAh	0.06	280				
	4,000-4,500 mAh	0.22	360				
Price	1400hkd	0.22	-	-	-	-	-
	2600hkd	-0.11					
	3200hkd	-0.11					

In this case study, each attribute levels within an attribute are assumed to have an identical rate of generational differences. The cost of each attribute level is assumed to depreciate exponentially at the rate of τ_{kl} according to Equations (5.12) and (5.19) for the new and remanufactured products, respectively. Furthermore, two new product variants and two remanufactured product variants are assumed to have already been introduced by competitors in the same market. The specification and generational difference of attributes, and corresponding perceived utilities of competing products are given in Table 5.3.

Table 5.3 Attribute levels, generational differences, and utilities of competing products

Competing product	Display (inch)	Camera	Memory	Fingerprint security	Battery (mAh)	Price (hkd)	Utility
A (New)	5.5 [1]	13 MP + 8MP [1]	64GB + 3GB [0]	Yes [1]	3,000 - 3,500 [1]	1,400	2.2
B (New)	6.8 [0]	16 MP (triple) + 10MP [1]	128GB + 4GB [0]	Yes [0]	4,000 - 4,500 [0]	2,600	5.7
C (Reman)	4.7 [3]	13 MP (dual) + 8 MP [3]	128GB + 4GB [1]	Yes [1]	3,000 - 3,500 [0]	1,400	1.0
D (Reman)	6.8 [2]	16 MP (triple) + 10MP [1]	256GB + 6GB [1]	Yes [0]	4,000 - 4,500 [1]	2,600	3.0

[a] – denotes the generation difference of an attribute level relative to the cutting-edge/latest generation

5.5 Results and discussions

The hierarchical bilevel programming model is formulated for the joint optimisation of PDC for the upper level and lower-level optimisation problems. It was assumed that the company planned to launch a maximum of three new product variants in periods 1 & 2 (i.e., J=3) and three remanufactured product variants (M=3) in period 2. The NBGA discussed in section 4 was implemented to solve the bilevel optimisation model. Crossover rates of 0.8 and 0.7 are used respectively for the upper-level and lower optimisations. The mutation rate was maintained at 0.01 for both levels. Due to the large solution spaces, population sizes of 300 and 500 were used for the upper-level and lower-level optimisations, respectively. The NBGA algorithm was programmed in MATLAB R2016a and run 100 generations. The convergence of the NBGA as shown in Figure 5.6, shows that the upper-level optimisation improves after around 20 generations, whereas the lower-level starts significant improvements after 65 generations. It also reveals trade-offs between the upper and lower-level optimisations until both reach an equilibrium solution after around 80 generations.

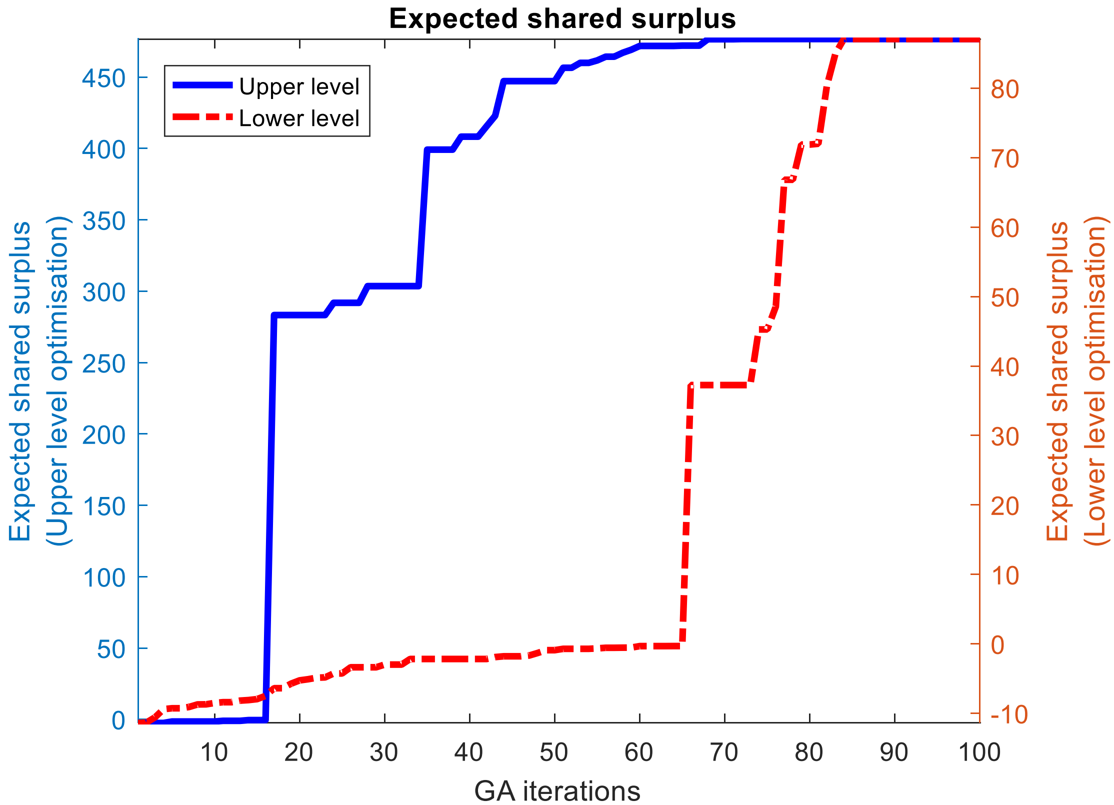


Figure 5.6 Convergence of the NBGA algorithm

The resulting PDC solutions for new product variants from the upper-level optimisation is presented in Table 5.4. The solution shows the indices of selected attribute levels and corresponding generational differences, which maximises the shared surplus of new product variants. Detailed configurations of attributes of new product profiles are presented in Table 5.5. It can be observed that a cutting-edge specification (zero generational difference) is selected for "display," "memory," and "fingerprint" attributes across new product profiles. Besides, a two-generation old technology is chosen for the "camera" attribute for product variants 1& 3. Furthermore, a one-generation technology is chosen for the "battery" attribute for new product variants 1 & 2, while a two-generation old technology is chosen for product variant 3.

Table 5.4 Optimal solutions for the upper-level optimisation

New products (J=3) Objective function= 476.7		Chromosomes (attribute levels and generational difference)																
Attribute levels	variant 1	0	1	0	0	0	1	0	1	0	1	0	0	0	1	1	0	0
	variant 2	1	0	0	1	0	0	0	0	1	0	1	0	0	1	0	1	0
	variant 3	0	1	0	0	0	1	1	0	0	1	0	0	0	1	1	0	0
Generational difference	variant 1		0			2			0		0			1				
	variant 2		0			0			0		0			1				
	variant 3		0			2			0		0			2				

Table 5.5 Optimal profiles of new product variants (upper-level optimisation)

New product	Display size (inches)	Camera	Memory	Fingerprint security	Battery (mAh)	Price (hkd)
Variant 1	5.5 [0]	16 MP (triple) + 10MP (selfie) [2]	128GB + 4GB RAM [0]	Yes [0]	4000-4500 [1]	1,400
Variant 2	4.7 [0]	13MP (single) + 8MP (selfie) [0]	256GB + 6GB RAM [0]	No	4000-4500 [1]	2,600
Variant 3	5.5 [0]	16 MP (triple) + 10MP (selfie) [2]	64GB + 3GB RAM [0]	Yes [0]	4000-4500 [2]	1,400

[a] – denotes the generation difference of an attribute level relative to the cutting-edge/latest generation

PDC solution for the lower-level optimisation is presented in Table 5.6, which shows indices of selected attribute levels and corresponding decisions for specification upgrading and generational differences chosen for attribute levels decided for upgrading. It shows attributes for each product variant that require an upgrade as follows: i) “display,” “memory,” and “fingerprint” attributes for product variant

1; ii) “camera” and “memory” attributes for product variant 2, and iii) “camera” and “fingerprint” attributes for product variant 3. Accordingly, optimal upgrade solutions for the mentioned attributes are i) an upgrade to a one-generation old technology for “display” and “memory” attributes and a cutting-edge specification for “fingerprint” attribute for product variant 1; ii) an upgrade to a one-generation old and a two-generation old technology, respectively for “camera” and “memory” attributes for product variant 2; iii) an upgrade to a three-generation old, a cutting-edge and a two-generation old technology, respectively for “camera,” “fingerprint” and “battery” attributes for product variant 3. Detail configurations for attributes of remanufactured product profiles are presented in Table 5.7.

Table 5.6 Optimal solutions for the lower-level optimisation

<table>
<tr><th colspan="2">Remanufactured products (M=3)
Objective function=87.1</th><th colspan="17">Chromosomes (attribute levels and generational difference)</th></tr>
<tr><td rowspan="3">Attribute Levels</td><td>variant 1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td></tr>
<tr><td>variant 2</td><td>0</td><td>1</td><td>0</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td></tr>
<tr><td>variant 3</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td rowspan="3">Upgrade decision</td><td>variant 1</td><td colspan="3">1</td><td colspan="3">0</td><td colspan="3">1</td><td colspan="2">1</td><td colspan="3">0</td><td colspan="3"></td></tr>
<tr><td>variant 2</td><td colspan="3">0</td><td colspan="3">1</td><td colspan="3">1</td><td colspan="2">0</td><td colspan="3">0</td><td colspan="3"></td></tr>
<tr><td>variant 3</td><td colspan="3">0</td><td colspan="3">1</td><td colspan="3">0</td><td colspan="2">1</td><td colspan="3">0</td><td colspan="3"></td></tr>
<tr><td rowspan="3">Generational difference</td><td>variant 1</td><td colspan="3">1*</td><td colspan="3">4</td><td colspan="3">1*</td><td colspan="2">0*</td><td colspan="3">3</td><td colspan="3"></td></tr>
<tr><td>variant 2</td><td colspan="3">3</td><td colspan="3">1*</td><td colspan="3">2*</td><td colspan="2">2</td><td colspan="3">3</td><td colspan="3"></td></tr>
<tr><td>variant 3</td><td colspan="3">3</td><td colspan="3">3*</td><td colspan="3">2</td><td colspan="2">0*</td><td colspan="3">2*</td><td colspan="3"></td></tr>
</table>

[*] – an attribute is decided to be upgraded to the designated generational difference

Table 5.7 Optimal profiles of remanufactured product profiles (lower-level optimisation)

Product attribute/ Levels		Display size (inches)	Camera	Memory	Fingerprint security	Battery (mAh)
New product variant (J=3)	Variant 1	5.5 [0]	16 MP (triple) + 10MP (selfie) [2]	128GB + 4GB RAM [0]	Yes [0]	4000-4500 [1]
	Variant 2	4.7 [0]	13MP (single) + 8MP (selfie) [0]	256GB + 6GB RAM [0]	No	4000-4500 [1]
	Variant 3	5.5 [0]	16 MP (triple) + 10MP (selfie) [2]	64GB + 3GB RAM [0]	Yes [0]	4000-4500 [2]
Remanufactured product variant (M=3)	Variant 1	6.8 1*	13 MP (dual) + 8 MP (selfie) [4]	128GB + 4GB RAM 1*	No	4000-4500 [3]
	Variant 2	5.5 [3]	16 MP (triple) + 10MP (selfie) 1*	256GB + 6GB RAM 2*	Yes [2]	2000-2500 [3]
	Variant 3	6.8[3]	13MP (single) + 8MP (selfie) 3*	256GB + 6GB RAM [2]	No	2000-2500 2*

[*] – an attribute is decided to be upgraded to the designated generational difference

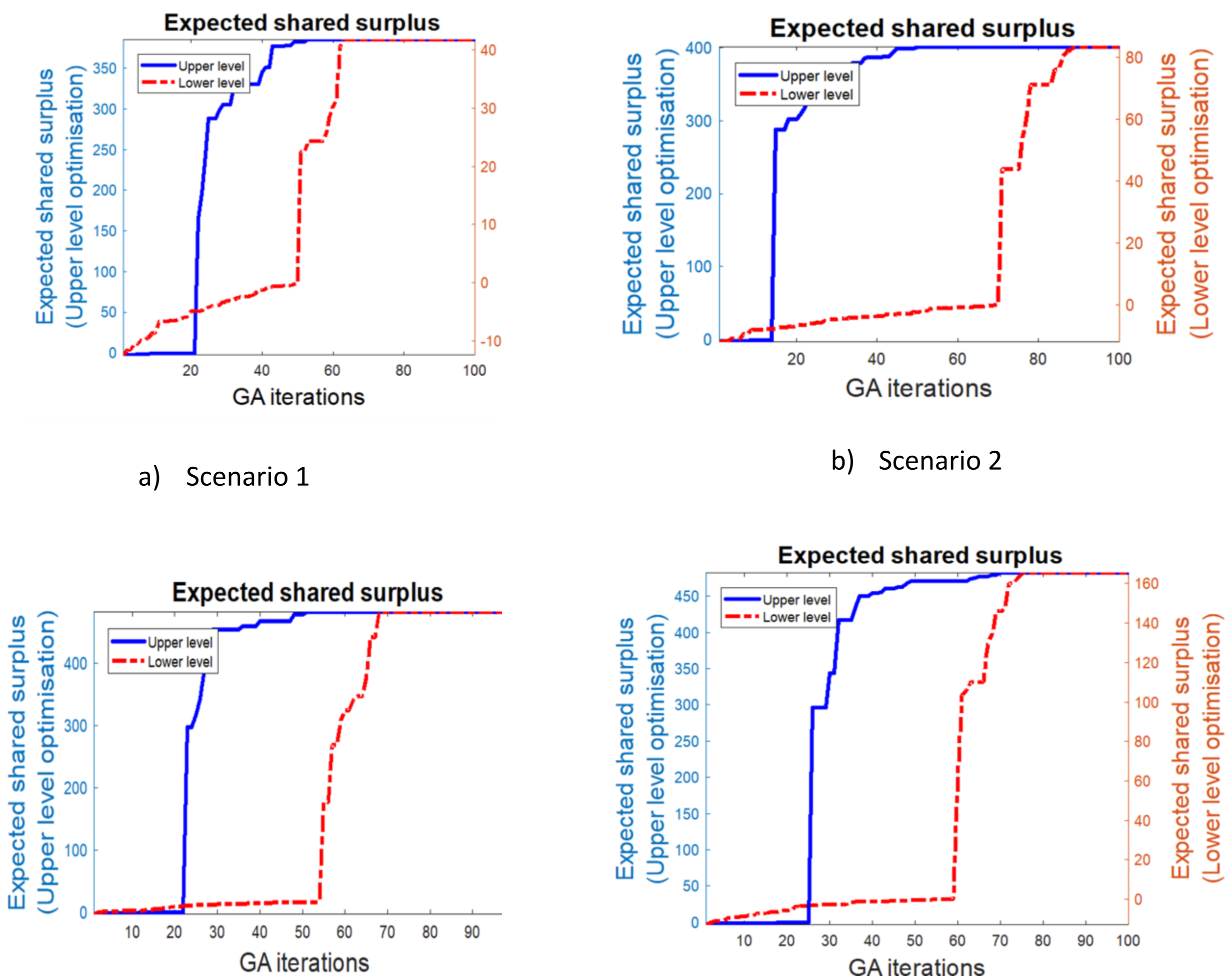
5.6 Sensitivity Analysis

The effects of changes in estimated parameters on the expected shared surpluses of the upper and lower-level optimisations are analysed and discussed in this section. Four scenarios presented in Table 5.8 have been investigated, each representing an increase/decrease of two parameters: i) price depreciation rate (τ_{kl}) and ii) generational difference rate (γ_k^{rem}) of attributes.

Table 5.8 Parameter settings for each of the scenarios

Scenario	1	2	3	4
Parameter settings (τ_{kl}, γ_k^{rem})	($0.5\tau_{kl}$,$0.5\ \gamma_k^{rem}$)	($0.5\ \tau_{kl}$,$1.5\ \gamma_k^{rem}$)	($1.5\ \tau_{kl}$,$0.5\gamma_k^{rem}$	($1.5\ \tau_{kl}$,$1.5\gamma_k^{rem}$)

The corresponding NBGA convergence is shown in Figure 5.7. The summary of comparisons among the scenarios is depicted in Figure 5.8. The result shows that scenario 1 leads to 52% and 19% decreases in shared surpluses for the lower-level and upper-level optimisations, respectively.



a) Scenario 1

b) Scenario 2

c) Scenario 3

d) Scenario 4

Figure 5.7 Convergence of the NBGA algorithm for each of the scenarios

The result reveals that improvements in customers' perceived utilities for remanufactured products due to a reduced rate of generational differences are less significant than an increase in remanufacturing cost due to a reduced cost depreciation rate. Scenario 2 reveals the loss of customers' perceived utility for remanufactured products due to the increase in the rate of generational differences. Besides, it shows an increase in remanufacturing cost due to a reduction in cost depreciation rates. The cumulative effect is insignificant on a shared surplus (ratio of utility to cost) for the lower-level optimisation. However, the impact has been significant for upper-level optimisation with 16% reductions of shared surplus for new product variants, which can be due to an increase in the cost of new product manufacturing. Similar insights can be obtained from results of scenarios 3 & 4, which show increments in the shared surpluses for lower-level optimisations (remanufactured product variants) due to an increase in the rates of generational differences and cost depreciation.

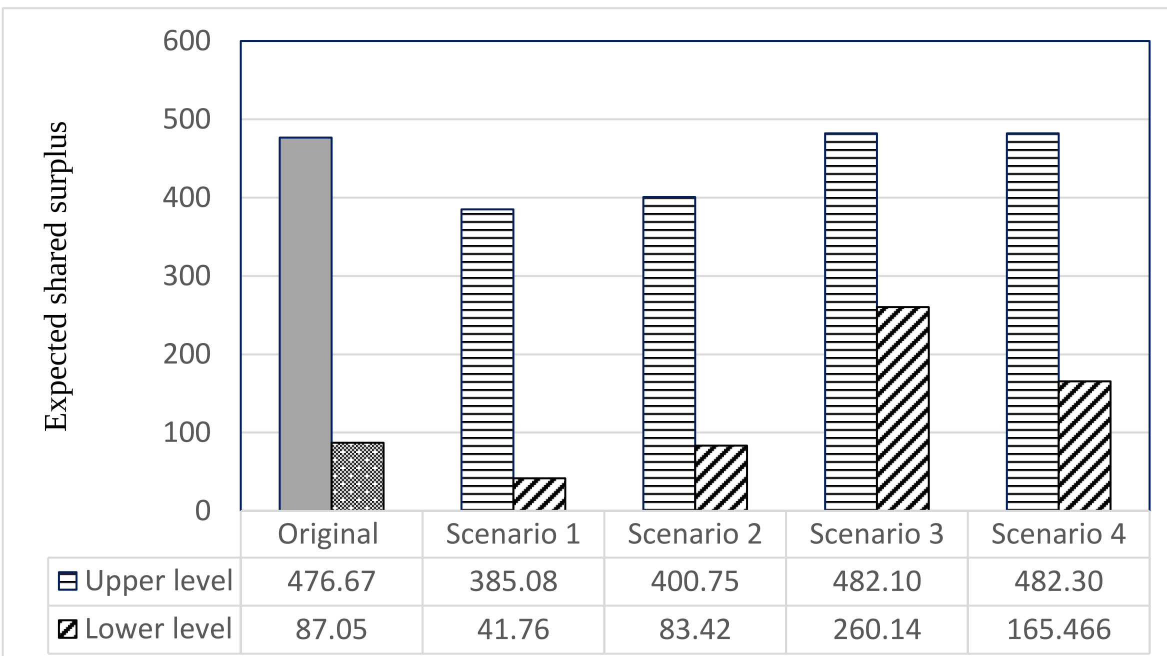


Figure 5.8 Comparison of shared surpluses of each of the scenarios

5.7 Chapter Summary

The joint optimisation of PDC for the new and remanufactured product variants involves upgrading specifications for remanufactured products due to technological obsolescence of parts/modules. The upgrading decision is affected by the original specification of new products sold in the previous periods and the timing of used product returns. Hence, the upgrading of used parts should be considered during the early-stage of product development when configurations for the new and remanufactured products are determined. The decisions entail a hierarchical two-stage framework whereby specification configuration decisions for the new products (first stage) serve as an input for the specification and upgrading decisions for the remanufactured products (second stage). In this study, a non-linear integer bilevel programming (NLIBP) is formulated to model the hierarchical PDC optimisation problem. Maximisation of shared surplus, which emphasises a trade-off between customer preferences, market share, and product costs, is considered an objective function for both the upper-level and lower-level optimisations. Nested bilevel GA (NBGA) is presented for solving the bilevel optimisation model.

To demonstrate the proposed bilevel optimisation model and the NBGA solving approach, a case study of PDC for the new and remanufactured mobile phones is conducted. The results reveal that the proposed approach can leverage the conflicting trade-offs between PDC decisions for the new and remanufactured products to generate equilibrium solutions. The sensitivity analysis results show an overestimation or underestimation of parameters significantly impacts the lower-level optimisation. The proposed methodology for the joint PDC can serve as a useful decision-making tool for design teams during the early design stage.

In this research, crisp estimates were used to calculate the part-worth utilities of individual attribute levels, which are used to compute the market shares of new and remanufactured product variants. Future work can consider the part-worth utilities' fuzziness that emanate from respondents' subjective judgments during the conjoin analysis. Furthermore, customers’ preferences were assumed to be static in this research, and hence future studies can consider the dynamic nature of customers' preferences/market demands for the PDC.

Chapter 6 Methodology for Forecasting Used Product Returns for Remanufacturing

This chapter presents a methodology for forecasting used product returns based on new product sales from a remanufacturing perspective. Section 6.1 describes the proposed DLM based forecasting model. A methodology for estimating the parameters of the DLM is discussed in section 6.2. A case study is presented in section 6.3 to demonstrate the proposed forecasting model's applicability and the parameter estimation methodology. Section 6.4 presents the validation of the proposed methodology and parameter estimation approach. Section 6.5 summarises the findings and outlines the future research direction.

6.1 The proposed DLM based forecasting model

This section discussed the proposed methodology for forecasting used product returns. The proposed DLM for the forecasting of used products based on new product sales data is presented in Equation (6.1).

$$m_t^{ret} = \sum_{k=1}^{t-1} \beta_k n_{t-k} + \varepsilon_{t\,;} \quad \forall t = 2,3,..T \tag{6.1}$$

Where m_t^{ret} is the forecasted quantity of used product returns in period t; β_k known as the delay function, which denotes the proportion of new products sold during $(t - k)^{th}$ period (i.e., n_{t-k}) that is available for return in period t (m_t^{ret}). The term ε_t denotes a normally distributed random error, i.e., $\varepsilon_t \sim N(0, \sigma^2)$.

The choice of the lag function of the DLM, β_k , and its parameters' estimates influence the forecasting accuracy. Traditionally, Bayesian inference was widely employed for estimating of the parameters of β_k (Clottey et al., 2012; Clottey & Benton, 2014; Toktay et al., 2003), which involves solving the posterior distribution given in Equation (6.2).

$$p\left(\theta/_{data}\right) = \frac{p\left(data/_{\theta}\right)p(\theta)}{\int p\left(data/_{\theta}\right)p(\theta)d\theta}, \quad \theta = (\theta_1, \theta_2, \cdots, \theta_D)^T \tag{6.2}$$

Where p (θ) denotes the prior probability of the parameter θ; and p (data/ θ) denotes the likelihood of the data (i.e., the return data) given the estimate of parameter θ. The expression in the denominator, i.e., the product of the likelihood and the prior function, is known as the marginal likelihood function. The minimum of the mean-squared error (MSE) of a parameter estimate, given as $\hat{\theta}_{i_{MMSE}} = \int \theta_i$ p$(\theta_i/data)$dθ_i requires solving the integral $\int$ p$(\theta/data)$dθ_i d$\theta_{i+1} \cdots$ dθ_D. However, solving the integral for a non-trivial marginal likelihood function using conventional analytical approach is difficult.

In this research, the Markov Chain Monte Carlo (MCMC) simulation and Bayesian inference are proposed for the estimation of the parameters of a DLM. The proposed approach can efficiently sample values for parameters regardless of the type and complexity of posterior distributions. The MCMC sampling procedure works in such a way that each drawn sample depends only on a previously sampled value (Jiang et al., 2008). The sampling procedure and parameter estimation approach are discussed in detail in section 6.2.

6.2 Estimation of parameters of a DLM forecasting model

Traditionally, the least-squares regression and the MLE approach are widely used for parameter estimations. However, the least-squares method's multicollinearity issue and the difficulty associated with the MLE method for a slightly complex function make both candidates unsuitable for estimating parameters of DLM’s lag function (Beerli, 2006; Choi et al., 2011). Thus, in this research, the MCMC and Bayesian inference approach is proposed for the parameter estimation. The proposed approach enables efficient sampling of distributions irrespective of the type and complexity of the underlying lag function. According to the MCM procedure, each new sample drawn depends on the previously drawn sample state (Jiang et al., 2008), which makes it easier to apply. The framework of the proposed forecasting model is depicted in Figure 6.1.

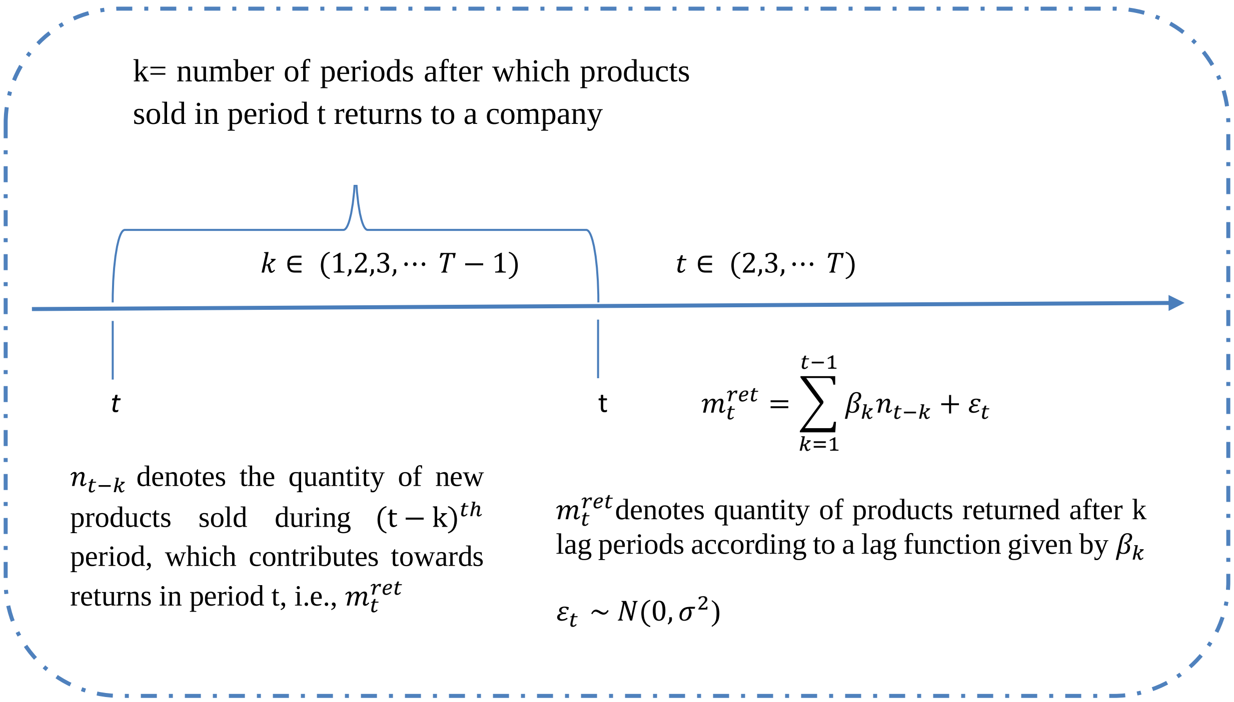


Figure 6.1 Framework of proposed forecasting model

The lag function is expressed in terms of a probability distribution function which can take various forms depending on the return pattern. For example, a high initial return rate that diminishes over subsequent periods such as the returns of defective products can be modelled using a geometric distribution. In remanufacturing, however, used product returns have characteristics of a lower initial rate of returns from previously sold products. Nevertheless, customers often do not have extra incentives to keep their used products for a longer period, which entails a subsequent higher initial return rate followed by a diminishing rate. Such a return pattern can be modelled using a negative binomial distribution. Thus, a negative binomial function given in Equation (6.3) is chosen for the lag function of the proposed DLM based forecasting methodology.

$$\beta_k = \mathrm{p}\binom{k+r-1}{r} q^r (1-q)^k \text{, where p} \in [0,1], \forall k = 1,2,3, \text{and } r > 0 \qquad (6.3)$$

Where p denotes the return probability of a new product sold in the previous period; q is the conditional probability of the return of a new product in the next period given p; parameter r denotes the lag corresponding to the largest β_k coefficient. For instance, r takes a value of 2 for a return pattern in which most of the product returns come from new products sold before two months (for a monthly return period).

Once the distribution of a lag function is determined, the DLM forecasting model is formulated by substituting Equation (6.3) into Equation (6.1) which gives Equation (6.4).

$$m_t^{ret} = \mathrm{p}q^r \sum_{k=1}^{t-1} \binom{k+r-1}{r} (1-q)^k n_{t-k} + \varepsilon_t \tag{6.4}$$

The DLM given by Equation (6.3) can also be written as m_t^{ret}= $\mathrm{p}q^r N\gamma$ +ε_t . The expressions for γ and N are given below. The γ is a column vector of $\binom{k+r-1}{r}(1-q)^k$ terms for each value of k, whereas N is a $(T-1)\times(T-1)$ matrix of independent variables, i.e n_{t-k}.

$$\gamma=\begin{bmatrix} (1-q) \\ \binom{r+1}{r}(1-q)^2 \\ \binom{r+2}{r}(1-q)^3 \\ \vdots \\ \binom{t+r-2}{r}(1-q)^{\mathrm{t}-1} \end{bmatrix} \quad \mathrm{N}=\begin{bmatrix} n_1 & 0 & 0 & 0 & \cdots \\ n_2 & n_1 & 0 & 0 & \cdots \\ n_3 & n_2 & n_1 & 0 & \cdots \\ \vdots & & \cdots & & \\ n_{T-1} & n_{T-2} & \cdots n_2 & n_1 & \end{bmatrix}$$

The negative binomial distribution takes different forms based on the estimate of parameter r. Hence, Equation (6.4) can take a different form depending on the value of parameter r. For example, if r=2, the DLM forecasting model takes a form given in Equation (6.5).

$$m_t^{ret} = pq^2\binom{2}{2}(1-q)n_{t-1} + pq^2\binom{3}{2}(1-q)^2 n_{t-2} + \cdots + \varepsilon_t \tag{6.5}$$

Koyck transformation (Franses & Oest, 2004) is applied, which involves subtracting $(1-\mathrm{q})$ m_{t-1}^{ret} from m_t^{ret} to update the expression for m_t^{ret} as illustrated in Equations (6.6) and (6.7).

$$(1-q)\ m_{t-1}^{ret} = pq^2(1-q)^2 n_{t-2} + 2pq^2(1-q)^3 n_{t-3} + \cdots + \varepsilon_{t-1} \tag{6.6}$$

$$m_t^{ret} = (1-q)m_{t-1}^{ret} + pq^2(1-q)n_{t-1} + 2pq^2(1-q)^2n_{t-2} + \cdots + \varepsilon_t - (1-q)\varepsilon_{t-1} \quad (6.7)$$

Rearranging the terms and subtracting Equation (6.9) from Equation (6.7), m_t^{ret} can be expressed as given in Equation (6.10).

$$m_{t-1}^{ret} = (1-q)m_{t-2}^{ret} + pq^2(1-q)n_{t-2} + 2pq^2(1-q)^2n_{t-3} + \cdots + \varepsilon_{t-1} - (1-q)\varepsilon_{t-2} \quad (6.8)$$

$$(1-q)\ m_{t-1}^{ret} = (1-q)^2m_{t-2}^{ret} + pq^2(1-q)^2n_{t-2} + 2pq^2(1-q)^3n_{t-3} + \cdots + \varepsilon_{t-1} - (1-q)\varepsilon_{t-2} \quad (6.9)$$

$$m_t^{ret} = 2(1-q)m_{t-1}^{ret} - (1-q)^2m_{t-2}^{ret} + pq^2n_{t-2} + u_t \quad (6.10)$$

Where the error term, u_t, is given as $u_t = \varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\varepsilon_{t-2}$. Unlike linear regression, which assumes independence and Gaussian distribution for the errors (white noises), the error terms in Equation (6.10) are correlated. This is due to the interdependence between the return data (dependent variables), i.e., $m_1^{ret}, m_2^{ret}, m_3^{ret} \ldots m_T^{ret}$, and the time-lagged sales data (independent variables), i.e., n_{t-k}. Thus, a covariance matrix of the error vector $(u_3, u_4, u_5, \ldots u_T)'$ with a variance of σ^2 is expressed as $\sum_u = \sigma^2 V$, where V is a $(T-2) \times (T-2)$ matrix whose elements are the coefficients of the error vector, as given below. The detailed derivation is presented in appendix A.

$$V = \begin{bmatrix} 1+4(1-q)^2+(1-q)^4 & -2(1-q)(1+(1-q)^2) & (1-q)^2 & 0 & \cdots & 0 \\ -2(1-q)(1+(1-q)^2) & 1+4(1-q)^2+(1-q)^4 & -2(1-q)(1+(1-q)^2) & (1-q)^2 & \cdots & 0 \\ (1-q)^2 & -2(1-q)(1+(1-q)^2) & 1+4(1-q)^2+(1-q)^4 & -2(1-q)(1+(1-q)^2) & \cdots & 0 \\ 0 & (1-q)^2 & -2(1-q)(1+(1-q)^2) & 1+4(1-q)^2+(1-q)^4 & \cdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1+4(1-q)^2+(1-q)^4 \end{bmatrix}$$

Once the covariance matrix is determined, the estimates for the DLM parameters are obtained by solving the joint likelihood function given in Equation (6.11).

$$L(p, q, r, \sigma^2/m_t^{ret}) \propto \frac{|V|^{\frac{-(T-1)}{2}}}{\sigma^{(T-1)}} \exp\left\{-\frac{1}{2\sigma^2}(m_t^{ret} - pq^rN\gamma)' \text{ x } V^{-1}(m_t^{ret} - pq^rN\gamma)\right\} \quad (6.11)$$

An MCMC method is proposed to solve the joint likelihood function and an MCMC based Bayesian inference approach to determine the parameters' estimates. The procedure is outlined in Figure 6.2, which involves four steps: (1) running a Monte-Carlo simulation to generate estimates for each parameter (i.e., initialization) ; (2) implementing the Markov chain approach to sample new values for each parameter based on previously generated initial estimates; (3) implement component-wise Metropolis Hasting's (MH) algorithm to sample from the posterior distribution (Carlo, 2004) and calculate the related posterior probabilities and (4) accept or reject the newly generated sample parameters from the posterior distribution to determine parameter estimates.

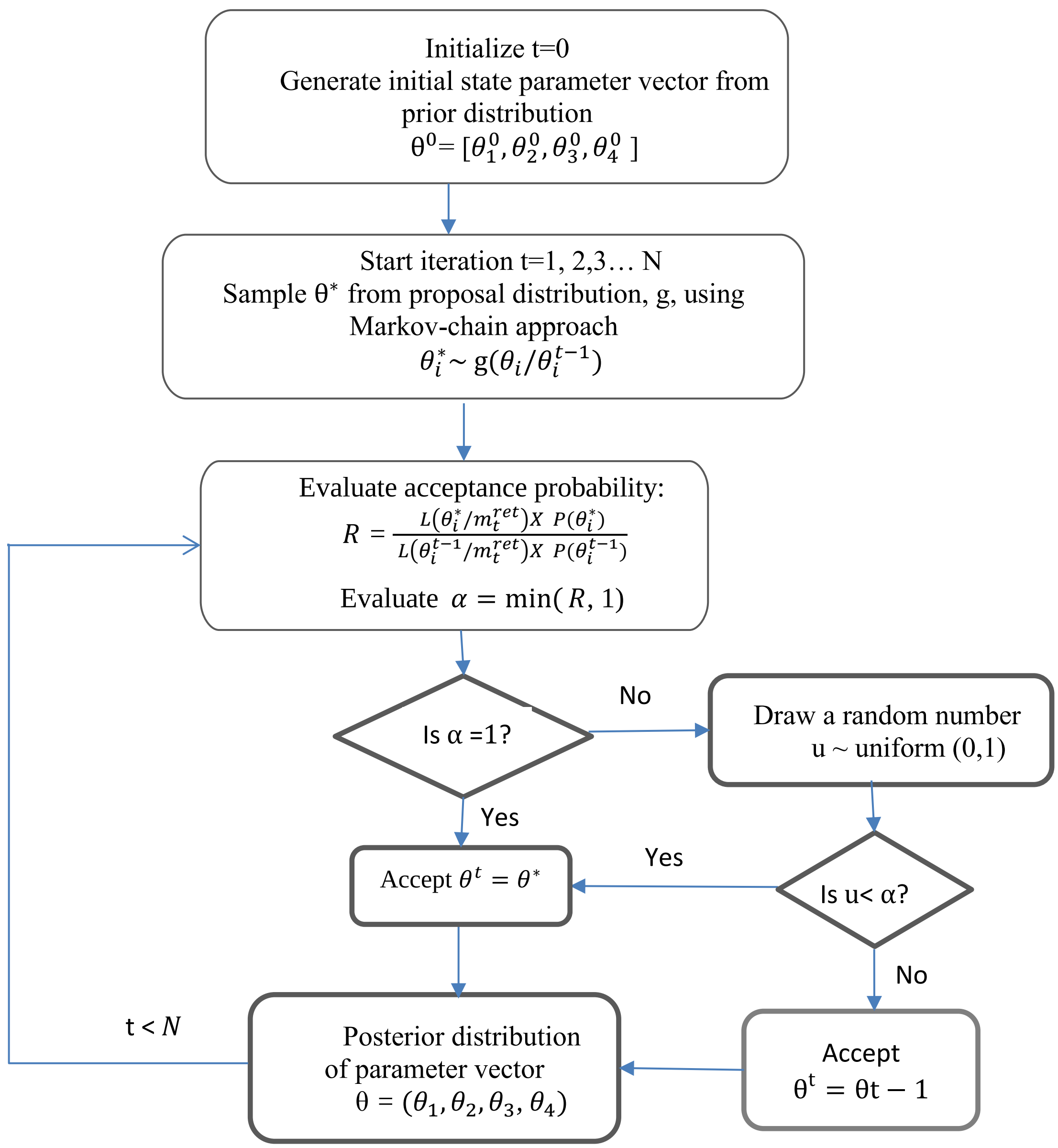


Figure 6.2 Component-wise MH algorithm for parameter estimation

The parameter estimation algorithm requires the joint distribution of the prior, p(θ), of a parameter vector $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)'$. In this study, uniform distribution with zero mean and a unit standard deviation, i.e., N (0, 1), is used for the joint prior distribution for p and q. An inverse-gamma prior, i.e., inverse-gamma(a, b), is used for σ^2 where a>0 & b>0 respectively are the shape and scale parameters of the distribution (Gelman, 2006). On the other hand, an integer value between one and six is assumed for the parameter r of the lag function. Thus, once the joint prior distributions of the parameters are specified, the posterior probability distribution is computed as the product of the joint prior distribution and the likelihood function, i.e., p(θ$/m_t^{ret}$) ∝ $L(\theta/m_t^{ret})$X p(θ). The component-wise MH algorithm shown in Figure 6.2 is then implemented to draw samples from the joint posterior distribution of the parameter vector. Finally, estimates of the parameters are determined and substituted in the DLM given in Equation (6.4).

6.3 Implementation

A case study is presented in this section to demonstrate the proposed DLM for forecasting used product returns based on new products sold during previous periods. The proposed MCMC and Bayesian inference approach are implemented for the estimation of parameters of the DLM. The sales data for a period of 24 months is simulated using the Bass diffusion model (Bass, 1969) given in Equation (6.12).

$$n_t = \tau_1 \bar{N} + (\tau_2 - \tau_1) N(t) - \frac{\tau_2}{N} [N(t)]^2 \tag{6.12}$$

Where n_t denotes the sales of new products in period t; $\bar{N}$ denotes the market potential; N(t) is the aggregate sales of new products until period t; τ_1 denotes the coefficients of innovation and τ_2 denotes the coefficient of imitation. For the case study, $\bar{N}$ =50,000 units are assumed. Besides, $\tau_1 = 0.03$ and $\tau_2 = 0.38$ are assumed for coefficients of innovation and imitation (Chandrasekaran & Tellis, 2007). The negative binomial distribution was assumed to model the lag function. Based on the study conducted by Toktay et al. (2003), the lag function parameters were initially set as p= 0.5, q=0.58, and r=2. The sales data was generated using Equation (6.12) and the corresponding returns of used products computed using a DLM are shown in Figure 6.3. The simulated data are assumed to represent the actual sales patterns, whereas the computed return units are assumed to represent the actual returns pattern, which are known apriori.

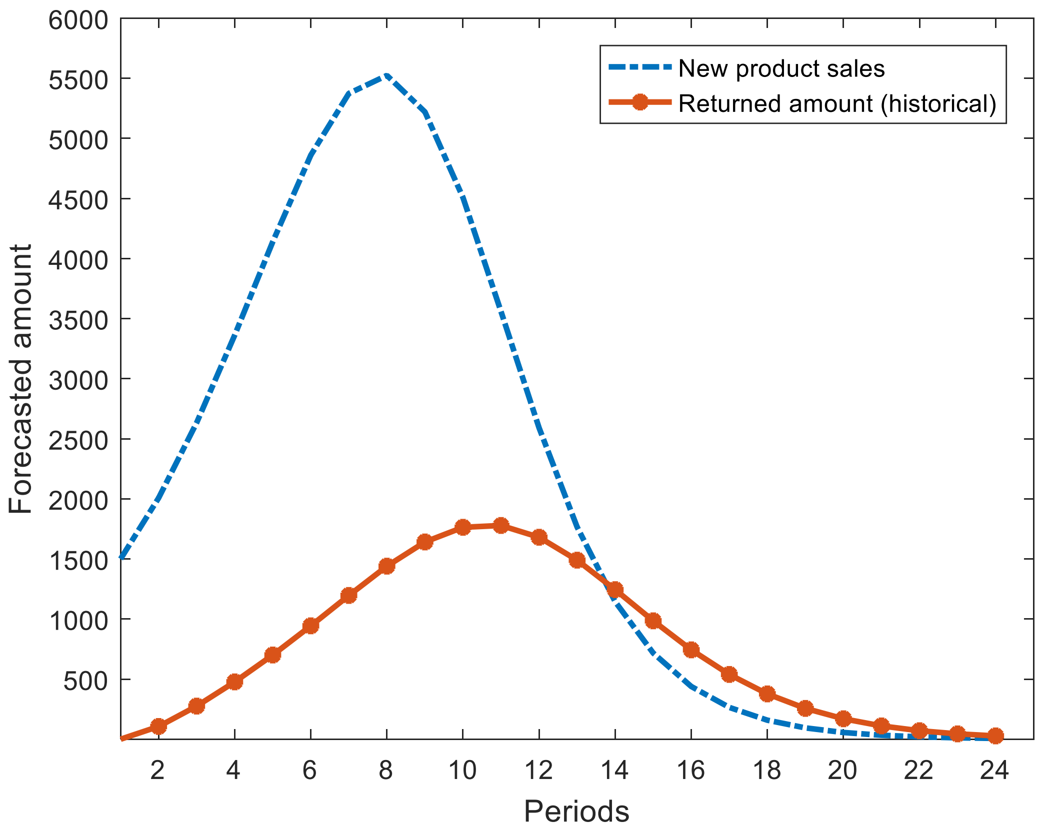


Figure 6.3 Simulated pattern of new product sales and quantity of used product returns

The proposed MCMC method and Bayesian inference approach were implemented in MATLAB to estimate the lag function parameters (i.e., parameters of the negative binomial distribution). For a parameter vector θ= (p, q, r), the component-wise MH algorithm illustrated in Figure 6.2 was run for

1000 iterations to draw samples from posterior distributions. The subsequent Markov Chain sampling is affected by the first few initial samples, also known as 'bun-in' or 'warm-up' samples, which are usually removed to reduce the effect. In this case study, the first 200 iterations were removed as 'burn-in' samples, as shown in Figure 6.4 and Figure 6.5.

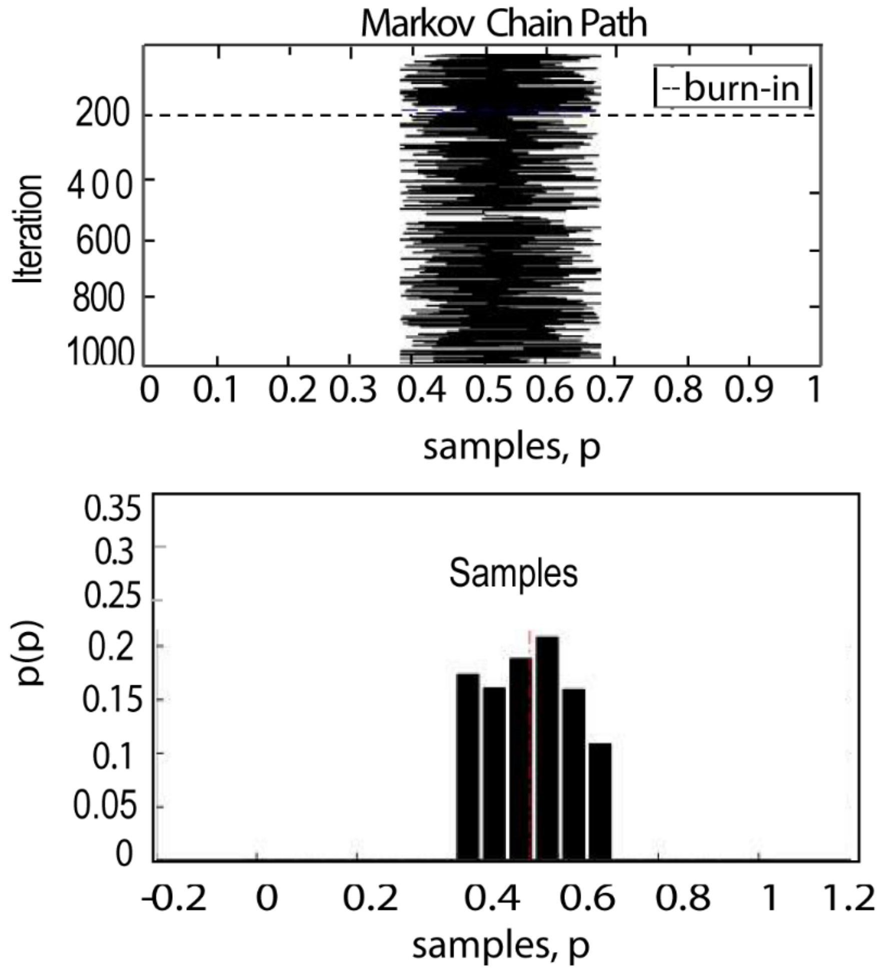


Figure 6.4 Markov Chain path and posterior distribution of p

Furthermore, the speed and efficiency of the MH algorithm are affected by the sample size, the joint prior distribution, the software, and the speed of the computer used. In this case study, the component-wise MH algorithm was written in MATLAB and implemented using a core-i5 computer to generate 1000 samples for the joint posterior distributions in about 35 seconds.

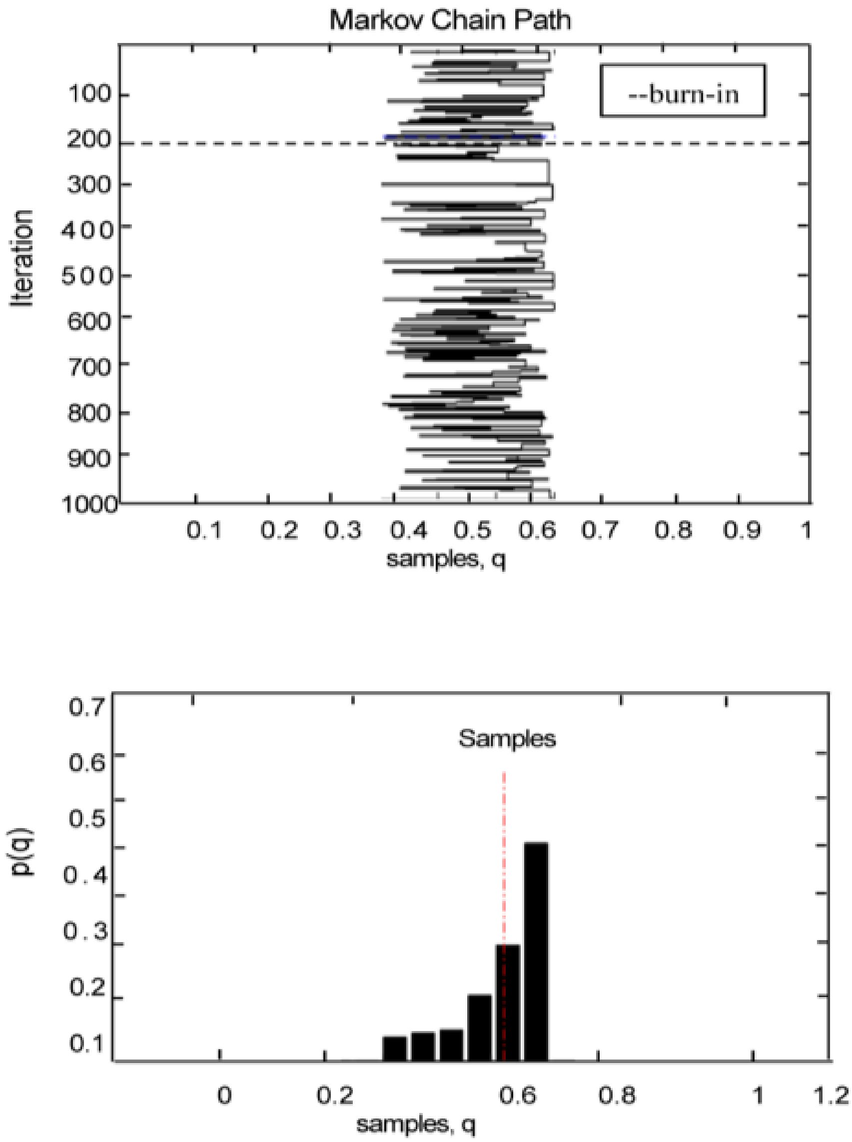


Figure 6.5 Markov Chain path and posterior distribution of q

The vector of the posterior means, $\hat{\theta}_i = E(\theta_i|\theta_i^1, \theta_i^1, \theta_i^1, \ldots\ldots \theta_i^N)$, was computed as $\bar{\theta}_i = \frac{\sum_{i=1}^{N} \theta_i}{N}$ to determine estimates of each parameter θ_i. N denotes the size of the sample. In the experiment, a posterior mean equivalent to 0.55 and 0.62, respectively, were obtained for parameters p and q. The determined posterior means were then employed in the lag function of the DLM to forecast used product returns, presented in Table 6.1.

Table 6.1 Forecasting errors when parameters are estimated using the proposed approach

Period	m_t^{ret} (actual returns)	m_t^{ret} (forecasted)	Relative Forecasting error (%)
2	106	115	8.5
3	275	293	6.2
4	477	500	4.7
5	701	727	3.7
6	943	971	3.0
7	1196	1225	2.4
8	1440	1467	1.9
9	1641	1662	1.3
10	1763	1775	0.7
11	1778	1777	0.1
12	1681	1664	1.0
13	1490	1460	2.0
14	1245	1206	3.1
15	985	942	4.3
16	743	703	5.5
17	539	502	6.8
18	377	347	7.9
19	256	232	9.3
20	170	153	10.3
21	110	98	11.6
22	70	62	12.2
23	44	38	13.5
24	28	23	15.2
			MAPE = 5.9 % VoE = 0.002

The “actual returns” column refers to the forecasts obtained using the initial parameters’ settings, whereas the ‘forecasted’ column indicates the forecasted quantity obtained based on the estimated parameters.

6.4 Validation of the forecasting methodology

The deviations between actual and forecasted returns were computed using the mean absolute percent error (MAPE) and the variance of errors (VoE) to validate the proposed forecasting methodology. The MAPE and VoE measures are given in Equation (6.13) and Equation (6.14).

$$\mathrm{MAPE} = \frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \frac{\left|m_t^{ret}(\theta) - m_t^{ret}(\bar{\theta})\right|}{m_t^{ret}(\theta)} \cdot 100 \quad (6.13)$$

$$\mathrm{VoE} = \frac{1}{\mathrm{T}-1}\sum_{t=1}^{\mathrm{T}} \left(\frac{\left|m_t^{ret}(\theta) - m_t^{ret}(\bar{\theta})\right|}{m_t^{ret}(\theta)} - \mathrm{MAPE}/100\right)^2 \quad (6.14)$$

Where $m_t^{ret}(\theta)$ and $m_t^{ret}(\bar{\theta})$ denote the actual and the forecasted quantity of used product returns during the period t and $\bar{\theta} \in (\bar{\theta}_1, \bar{\theta}_2, \bar{\theta}_3, \bar{\theta}_4)'$ denotes the vector the parameter means. The parameter estimation approach is compared with the maximum likelihood estimate (MLE) approach. The MLE approach involves the maximisation of the log-likelihood function shown in Equation (6.15), which requires partially differentiating the function as illustrated in Equations (6.16-6.18).

$$\begin{aligned} &\ln L(p, q, r, \sigma^2/m_t^{ret}) \\ &= \frac{-(T-1)}{2}\ln(|V|) - (T-1)\ln(\sigma) - \frac{1}{2\sigma^2}(m_t^{ret} - pq^r N\gamma)'\, V^{-1}(m_t^{ret} - pq^r N\gamma\ ) \end{aligned} \quad (6.15)$$

$$\frac{\partial}{\partial p}\ln L(p, q, r, \sigma^2/m_t^{ret}) = \frac{V^{-1}}{2\sigma^2}(2q^2 m_t^{ret} N\gamma - 2pq^2 N\gamma) = 0 \quad (6.16)$$

$$\frac{\partial}{\partial q}\ln L(p, q, r, \sigma^2/m_t^{ret}) = \frac{V^{-1}}{2\sigma^2}(2p^2 m_t^{ret} N\gamma - 2p^2 q N\gamma) = 0 \quad (6.17)$$

$$\frac{\partial}{\partial \sigma}\ln L(p, q, r, \sigma^2/m_t^{ret}) = \frac{-(T-1)}{\sigma} - \frac{1}{\sigma^3}((m_t^{ret} - pq^r N\gamma)' V^{-1}(m_t^{ret} - pq^r N\gamma\ ) = 0 \quad (6.18)$$

The algorithm was written in MATLAB to obtain estimates for the parameters p and q, respectively as 0.45 and 0.53. The results were then substituted in the lag function of the DLM forecasting model given in Equation (6.4) for forecasting the timing and quantity of used product returns. The values of MAPE and VoE forecasting error measures obtained using the proposed parameter estimation approach are shown in Table 6.1 and the MLE approach in Table 6.2. The MAPE and VoE results show that the proposed parameter estimation approach gives better forecasting accuracy than the MLE approach. The patterns of used product returns when parameters are estimated using the proposed parameter estimation approach and MLE approach are shown in Figure 6.6.

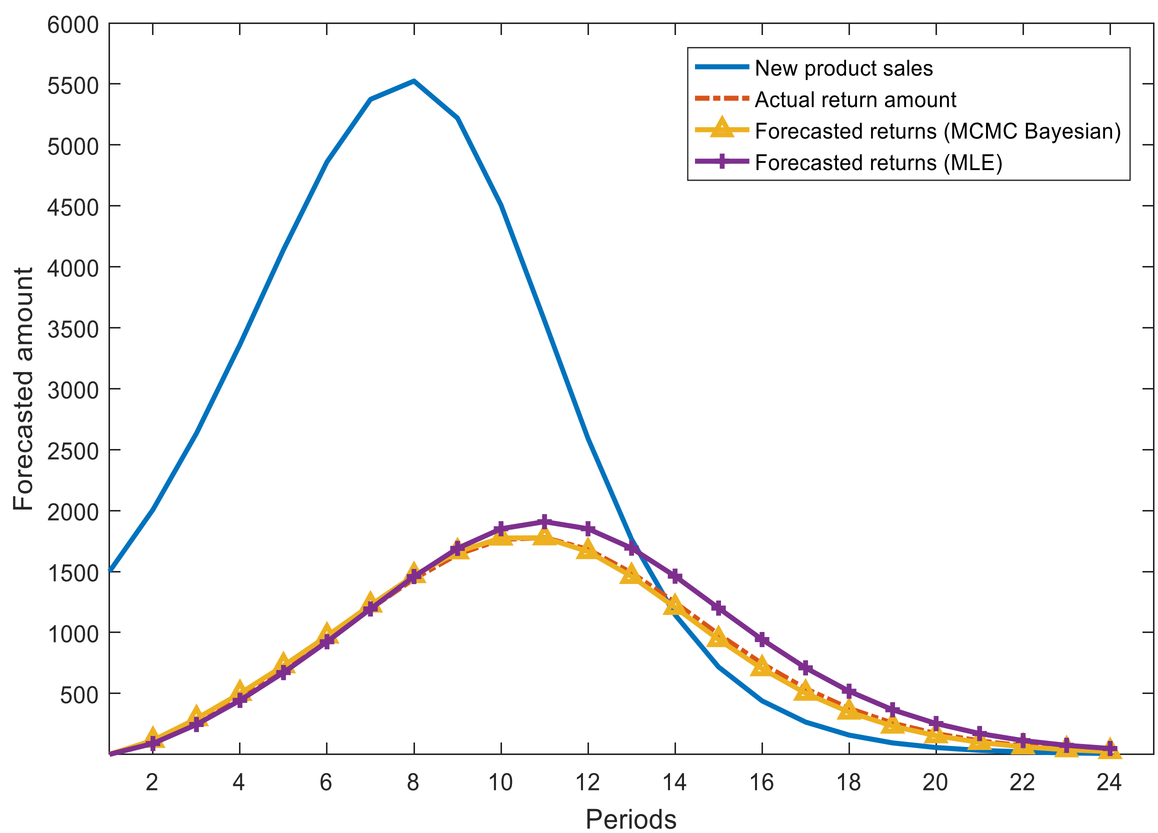


Figure 6.6 Forecast patterns vis-à-vis parameter estimation approaches

Table 6.2 Forecasting errors when parameters are estimated using the MLE approach

Period	m_t^{ret}(actual)	m_t^{ret} (MLE Approach)	Relative Forecasting error (%)
2	106	89	16.0
3	275	245	11.0
4	477	443	7.2
5	701	671	4.2
6	943	924	2.0
7	1196	1193	0.3
8	1440	1459	1.3
9	1641	1690	3.0
10	1763	1851	5.0
11	1778	1909	7.3
12	1681	1851	10.2
13	1490	1692	13.5
14	1245	1462	17.4
15	985	1200	21.8
16	743	942	26.6
17	539	710	31.8
18	377	518	37.3
19	256	366	43.0
20	170	253	48.9
21	110	171	54.9
22	70	113	60.9
23	44	74	67.2
24	28	48	72.6
			MAPE = 24.5 %
			VoE = 0.051

The periodic relative forecasting errors corresponding to the proposed parameter estimation approach and the MLE approach are shown in Figure 6.7. The graph shows that the MLE parameter estimation approach resulted in a bad forecast compared with forecasts based on parameters estimated using the proposed approach. This is evident, particularly for returns with longer lags (i.e., past the 12th period), where the MLE approach resulted in an error of >20%. On the contrary, the proposed parameter estimation method has led to a good forecasting accuracy on all the forecasts until the 20th period with forecasting errors of <10%.

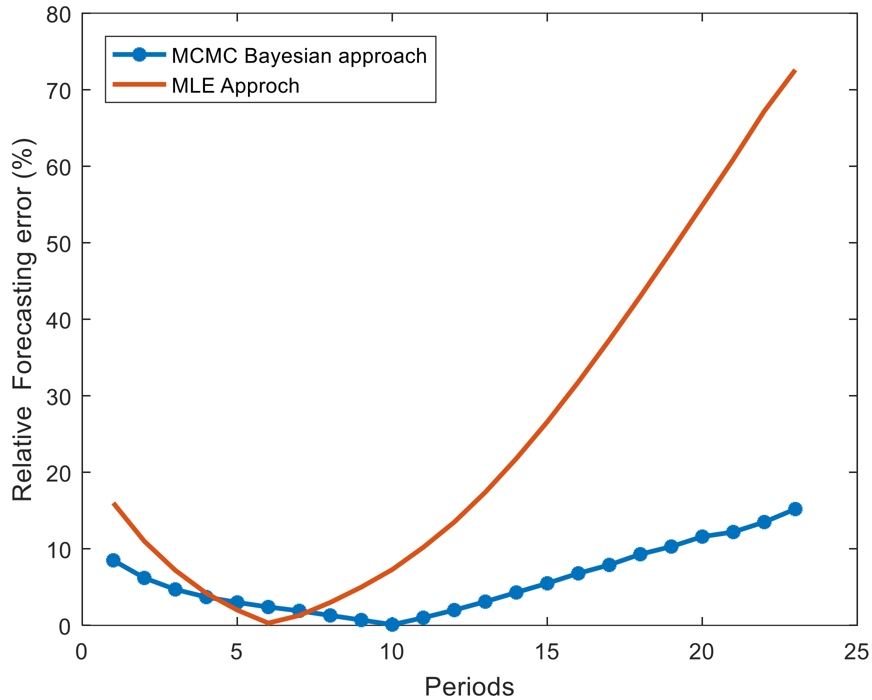


Figure 6.7 Relative forecasting errors (MCMC Bayesian vs. the MLE approach)

6.4.1 The cost saved by the proposed forecasting methodology

The cost saved by the proposed forecasting methodology was also investigated using a hypothetical case study involving a company that offers both the new and remanufactured products to the market. Bass diffusion model with parameter settings of $\tau_1 = 0.03$ and τ_2=0.38 for the innovation and imitation coefficients respectively was used to generate the demand for a market size of Q_t= 20,000 units. The simulated demand data for the remanufactured products and the pattern of used returns based on new product sales are shown in Figure 6.8.

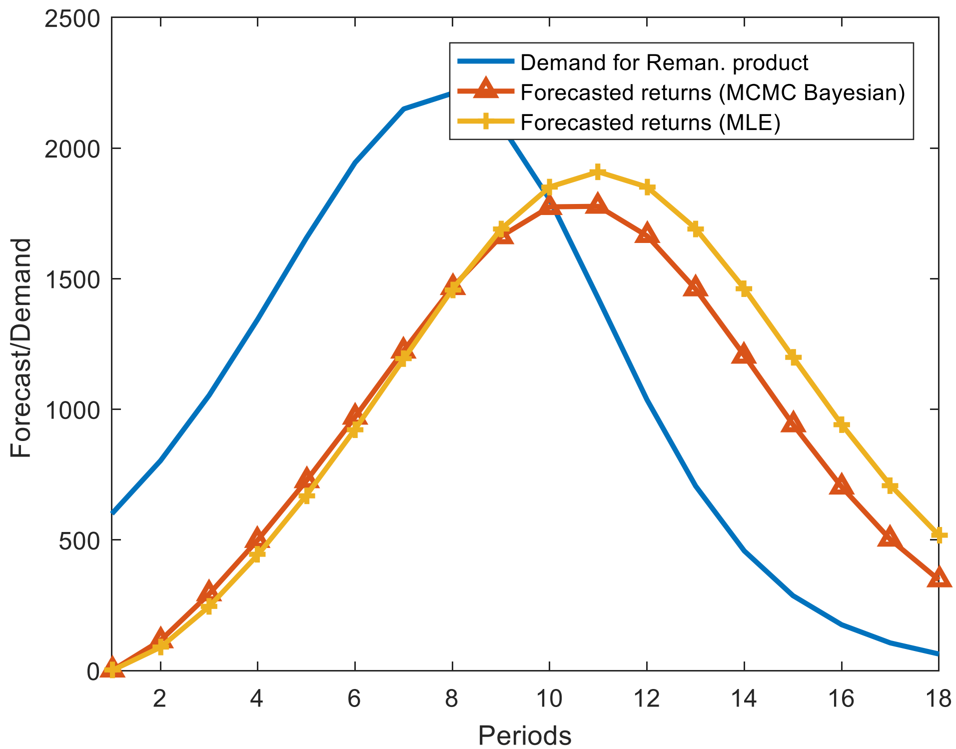


Figure 6.8 Demand for remanufactured products Vs. the pattern of used product returns

The graph shows that the supply of used parts is less than the demand for remanufactured products for the first 11 planning periods and subsequently becomes excess.

An experiment was conducted to investigate the impact of forecast overestimation and underestimation on the cost of remanufacturing. It was assumed that parts are purchased in a bundle from a third party at the cost of 30$/bundle. When the quantity of used products (i.e., used parts) is inadequate to satisfy the demand for remanufactured products, new parts are purchased as a substitute at a higher price of 45$ per bundle. Due to the forecast overestimation during the first 11 periods, as discussed earlier, the company incurs an extra 15$ /bundle/period to purchase new parts to substitute the deficit of used products. On the contrary, because of the forecast underestimation (i.e., more used parts available that exceed the demand for remanufactured products), it was assumed that the company incurs an inventory cost of 0.5$/bundle/period.

This study introduces the penalty cost of forecasting accuracy. The penalty function is computed aggregating the discounted penalty cost of forecast overestimation (DPFO) and the discounted penalty cost of forecast underestimation (DPFU), as given in Equations (19) - (20).

$$\text{DPFO}= \sum_{t=2}^{T}[(D_t - m_t^{ret}(\text{proposed})) * 15\$ * (1+\delta)^{-t}] \tag{6.19}$$

$$\text{DPFU} = \sum_{t=2}^{T}[\,(m_t^{ret}(\text{proposed}) - D_t) * 0.5\$(1+\delta)^{-t}] \tag{6.20}$$

$$\text{Aggregated penalty cost of forecasting accuracy} = \text{DPFO} + \text{DPFU} \tag{6.21}$$

Where δ denotes the discount rate, assumed to be 3% per a given period for this experiment. The penalty costs of forecast overestimation (DPFO) and underestimation (DPFU) for the forecasts obtained using the proposed methodology and the MLE approach are presented in Table 6.3.

Table 6.3 Penalty costs (DPFO and DPFU) of forecasts

	DPFO	DPFU	Aggregated penalty cost of forecasting accuracy
Proposed forecasting methodology	\$25,430.4	\$2,047.5	\$27,477.9
Forecasting based on MLE approach	\$94,363.6	\$3,328.3	\$97,691.92
The cost saved by the proposed forecasting method			\$70,214

The result has shown that the proposed forecasting methodology offers better cost savings than forecasts obtained using the MLE approach.

6.5 Chapter summary

Product take-back legislation is increasingly being adopted by governments worldwide, which mandate manufacturers to track and collect used products that consumers no longer wish to keep. Companies engaged in remanufacturing depend on a streamlined supply of used product returns. The accurate forecasting of used product returns in remanufacturing requires knowledge of the quantity and timing of new products sold in previous periods. Besides, the quantity and timing uncertainty of used product returns makes forecasting in remanufacturing a complex task. This is because traditional forecasting techniques such as time-series forecasting methods cannot capture the relationship between new products' sales in previous periods and the available quantity and timing of used product returns.

In this research, a forecasting methodology based on a DLM is proposed for forecasting the available quantity and timing of used product returns. The forecasting accuracy of a DLM is affected by the lag function type and its parameters. Bayesian inference, which previous studies have used for parameter estimation, involves solving the marginal likelihood function, which is often difficult to compute analytically. To overcome the difficulty, this study proposes an MCMC and Bayesian inference approach for faster parameter estimation. The proposed MCMC method involves sampling from the joint posterior distribution of the parameters irrespective of the distribution's complexity. A simulation experiment was conducted to demonstrate the proposed forecasting model and the parameter estimation approach. The MAPE and VoE forecasting error measures were computed to validate the proposed forecasting methodology. The results showed smaller MAPE and VoE values for forecasts obtained based on the proposed parameter estimation approach. Two scenarios for forecast overestimation and forecast underestimation were considered to investigate the cost savings resulting from the forecasting accuracy. The result showed significant cost savings for the proposed parameter estimation approach compared with the MLE approach.

Chapter 7 Estimation of Market Share for New and Remanufactured Product

In chapter 6, a forecasting methodology was presented, which addresses the quantity and timing uncertainty of used product returns. Another set of uncertainty in remanufacturing industry concerns the estimation of market share for remanufactured products under uncertainty. To this end, this chapter presents a methodology for modelling customers' preferences and for estimating the market share of new and remanufactured products under uncertainty. Figure 7.1 shows the methodology framework.

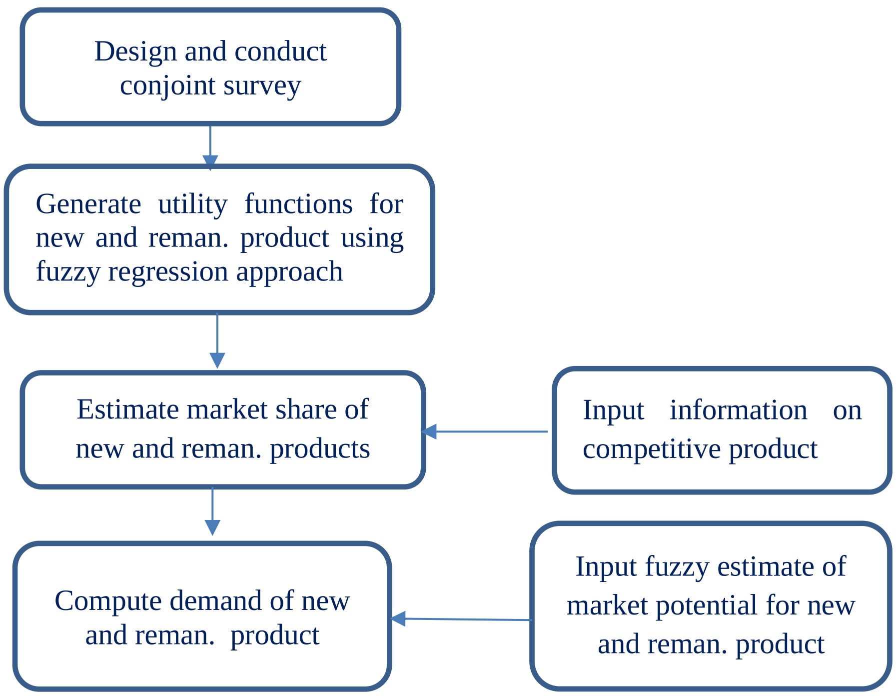


Figure 7.1 Framework of the methodology for estimating market share and demand

The methodology involves conjoint analysis to determine utility functions of the new and remanufactured product profiles. A rating-based conjoint method is employed in this study in which respondents are asked to rate product profiles using a pre-defined rating scale. Based on the survey responses, the utility function for new and remanufactured products are then determined. One of the uncertainties that arise when using conjoint analysis to model customers' preferences emanates from survey data's imprecision due to respondents' subjective ratings. The fuzzy regression approach proposed by Aydin et al. (2014) and

Kwong et al. (2016) is employed in this study to address the fuzziness of customers' ratings which arise from their subjective judgments. Besides, the technique also addresses the fuzziness of market potential estimates provided by marketing executives.

7.1 Determining fuzzy utility function

In this study, product profiles' utility functions are determined using the fuzzy utility function given in Equation (7.1).

$$\tilde{U}_j = (\alpha_0, c_0) + \sum_{k=1}^{M} \sum_{l=1}^{N_k} ((\alpha_{jkl}, c_{jkl}) x_{jkl}) \tag{7.1}$$

Where $\tilde{U}_j$ denotes the independent variable, which represents respondents' rating of the jth product profile; (α_{kl}, c_{kl}) are fuzzy coefficients which represent the central and spreads, respectively; x_{kl} denotes the dummy variable, which takes a value of 1 or 0 depending on whether the lth level of the kth attribute is selected for a product profile; and M represents the available number of attributes, and N_k represents the number of levels of the kth attribute. The membership function of the fuzzy coefficient, $\tilde{A}_j = (\alpha_j, c_j)$, is defined as shown in Equation (7.2).

$$\mu_{\tilde{A}}(a_j) = \begin{cases} 1 - \dfrac{|a_j - \alpha_j|}{c_j}, & \alpha_j - c_j \leq a_j \leq \alpha_j + c_j \\ 0, & \text{otherwise} \end{cases} \tag{7.2}$$

Using extension principle (Zimmermann, 2010), the membership function for the fuzzy number, $\tilde{U}_j$, can be obtained using Equation (7.3).

$$\mu_{\tilde{U}_j}(u_j) \begin{cases} 1 - \dfrac{|u_j - \alpha^T x_j|}{c^T x_j}, & x_j \neq 0 \\ 1, & x_j = 0, u_j = 0 \\ 0, & Otherwise \end{cases} \tag{7.3}$$

where, $c^T x_j$=$(c_0, c_{1,} c_{1,} \dots c_k)$ and $\alpha^T x_j$=$(\alpha_0, \alpha_{1,} \alpha_{1,} \dots \alpha_k)$ represent a set of k+1 central and spread values, respectively. Hence, the lower bound, the central value, and the upper bound values of the dependent variable, $\widetilde{U}_j$=($\widetilde{U}_j{}^L, \widetilde{U}_j{}^{h=1}, \widetilde{U}_j{}^u$) can be estimated as $\widetilde{U}_j{}^L = (\alpha - c)^T x_j$; $\widetilde{U}_j{}^{h=1} = \alpha^T x_j$; and $\widetilde{U}_j{}^u = (\alpha + c)^T x_j$, respectively (F. Liu, 2008). The h-factor measures the degree of fitness of the fuzzy linear model and takes a value between 0 and 1. The h-factor is used to support the membership function. An increase in the h-factor (see the non-symmetric triangular fuzzy number in Figure 7.2 can increase the spreads' magnitude.

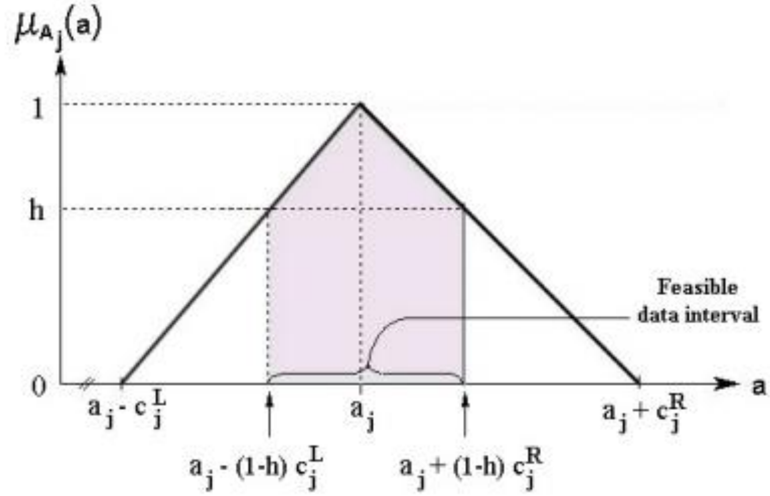


Figure 7.2 Effect of different h-factor values on the spreads

The method proposed by Tanaka et al. (1989) is adopted to determine the coefficients corresponding to the centre and spreads. The method involves solving the linear programming (LP) model presented in Equations (7.4) - (7.8). The LP model's objective given in Equation (7.4) minimises the fuzzy outputs' total spread.

$$\text{Min} \sum_{j=0}^{n} (c_j \sum_{j}^{M} |x_{ij}|) \tag{7.4}$$

Subject to the following constraints:

$$\sum_{j=1}^{n} \alpha_j\, x_{ij} + (1-h)\sum_{j=0}^{n} c_j |x_{ij}| \geq \bar{u}_i + (1-h)e_i \tag{7.5}$$

$$\sum_{j=1}^{n} \alpha_j\, x_{ij} - (1-h)\sum_{j=0}^{n} c_j |x_{ij}| \leq \bar{u}_i - (1-h)e_i, \tag{7.6}$$

$$x_{i0} = 1, \forall i = 1,2,3 \ldots M, j = 0,1,2, \ldots n \tag{7.7}$$

$$c_j \geq 0, \alpha_j \in \mathbb{R},\ 0 \leq h \leq 1, \tag{7.8}$$

The constraint in Equation (7.5) defines the upper bound of the estimated data, while Equation (7.6) defines the lower bound of the estimated data. The $\bar{u}_i$ and e_i represent the centre and spreads of the ith dependent fuzzy variable, respectively, whereas M and n respectively denote the number of product profiles and independent variables. The dependent variable's initial condition is defined by Equation (7.7). Equation (7.8) ensures the non-negativity and the limit for the value of h-factor.

7.2 Estimation of market share and market demand

After products' utility functions are determined, the market share and demand values can be computed using the multinomial logit (MNL) model given in Equations (7.9) - (7.12) (Aydin et al., 2014; Kwong et al., 2016). The computational procedure requires as input estimates of utilities of competitive products and the company's own products.

$$\widetilde{\mathrm{MS}}_{\mathrm{n}} = \frac{e^{\tilde{U}_n}}{\sum_{c=1}^{C} e^{\tilde{U}_c} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_n} + e^{\tilde{U}_r}} \tag{7.9}$$

$$\widetilde{MS}_r = \frac{e^{\tilde{U}_r}}{\sum_{c=1}^{C} e^{\tilde{U}_c} + \sum_{k=1}^{K} e^{\tilde{U}_k} + e^{\tilde{U}_n} + e^{\tilde{U}_r}} \tag{7.10}$$

$$\widetilde{D}_r = \widetilde{MP}_r * \widetilde{MS}_r = \widetilde{MP}_r * \frac{e^{\widetilde{U}_r}}{\sum_{t=1}^{T} e^{\widetilde{U}_t} + \sum_{k=1}^{K} e^{\widetilde{U}_k} + e^{\widetilde{U}_n} + e^{\widetilde{U}_r}} \quad (7.11)$$

$$\widetilde{D}_n = \widetilde{MP}_n * \widetilde{MS}_n = \widetilde{MP}_n * \frac{e^{\widetilde{U}_n}}{\sum_{t=1}^{T} e^{\widetilde{U}_t} + \sum_{k=1}^{K} e^{\widetilde{U}_k} + e^{\widetilde{U}_r} + e^{\widetilde{U}_n}} \quad (7.12)$$

Where, $\widetilde{MS}_n$ and $\widetilde{MS}_r$ represent the market shares of new and remanufactured products, respectively. $\widetilde{U}_n$, $\widetilde{U}_r$, $\widetilde{U}_c$ and $\widetilde{U}_k$ indicate the utility values of the new, remanufactured, competitive, and company's existing products, respectively. $\widetilde{MP}_n$ and $\widetilde{MP}_r$ denote fuzzy estimates of the new and remanufactured products' market potentials expressed using triangular fuzzy numbers (TFNs) as (l_n, a_n, r_n) and (l_r, a_r, r_r), respectively. The first, second, and third values in the set represent the left, the centre, and the right spreads of the market potentials, respectively. The central values are determined by computing the arithmetic mean of the fuzzy estimates of market potentials. The spreads are obtained using Equations (7.13) - (7.16).

$$\mathrm{l_n} = \mathrm{a_n} - \min_{\mathrm{k}=1,2,3\ldots\mathrm{K}} \mathrm{a_{nk}} \quad (7.13)$$

$$\mathrm{l_r} = \mathrm{a_r} - \min_{\mathrm{k}=1,2,3\ldots\mathrm{K}} \mathrm{a_{rk}} \quad (7.14)$$

$$\mathrm{r_n} = \max_{\mathrm{k}=1,2,3\ldots\mathrm{K}} \mathrm{a_{nk}} - \mathrm{a_n} \quad (7.15)$$

$$\mathrm{r_r} = \max_{\mathrm{k}=1,2,3\ldots\mathrm{K}} \mathrm{a_{rk}} - \mathrm{a_r} \quad (7.16)$$

where, a_{nk} and a_{rk} denote the market potentials as estimated by k^{th} marketing personnel for the new and remanufactured products, respectively.

7.3 Defuzzification of TFNs

For a given TFN (shown in Figure 7.3), the corresponding crisp values can be determined using the centroid defuzzification formula given in Equation (7.17) (Ross,2010).

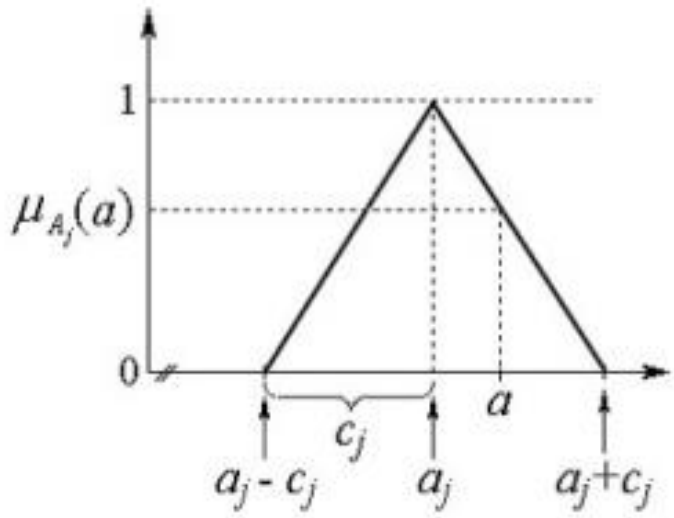


Figure 7.3 Symmetric triangular fuzzy numbers (Shapiro, 2005)

$$x^* = \frac{\int x\mu_{\tilde{A}}(x)dx}{\int \mu_{\tilde{A}}(x)dx} \tag{7.17}$$

Where, x^* and $\mu_{\tilde{A}}$ denote the crisp value and the fuzzy membership function, respectively for the fuzzy coefficient $\tilde{A}$.

7.4 Implementation

This section presents a case study to demonstrate the applicability of the methodology for modelling customer satisfaction and estimating the market demand for both the new and remanufactured products. The case study concerns a company that offers both new and remanufactured laptops (referred to as ‘refurbished’ in this section) to the market. The attributes and corresponding levels shown in Table 7.1, are defined for the new and refurbished laptops based on preliminary survey of specifications of laptop brands in the market.

Table 7.1 Attributes and levels used in conjoint analysis

index (k)	Attribute	Level
1	Screen size	13.3 /14.1/15.6 inch
2	RAM capacity	4/6/8GB
3	Processor speed	Core i3/ i5 / i7
4	Storage capacity (SSD+HDD)	(32GB + 1TB)/ (128GB + 500GB)/ 256GB
5	Battery Life	4-6/ 7-9/10-11 hrs
6	Degree of upgrading and replacement by a customer	Low Medium High
7	Price	5,500/8,000/10,500 HKD

An L18 orthogonal array was designed to generate 18 new and refurbished laptop profiles which are used in the conjoint survey questionnaire. Table 7.2 shows the conjoint survey questionnaire, which was distributed among 60 undergraduate students at The Hong Kong Polytechnic University, to rate them using linguistic scales (1= “very bad,” & 5= “very good”).

Table 7.2 Survey questionnaire for conjoint analysis

Product Profile	Product Condition	Screen Size (inch)	RAM	Processor (Intel)	Storage capacity		Battery Life	Degree of upgrading and replacement	Price (HKD)	Rating (1-5)
					SSD	HDD				
1	New	13.3	4 GB	Core i3	32	1	4-6	Low	5,500	
2	New	13.3	6 GB	Core i5	12	5	7-9	Medium	8,000	
3	New	13.3	8 GB	Core i7	25	N	9-	High	10,500	
4	New	14.1	4 GB	Core i3	12	5	7-9	High	10,500	
5	New	14.1	6 GB	Core i5	25	N	9-	Low	5,500	
6	New	14.1	8 GB	Core i7	32	1	4-6	Medium	8,000	
7	New	15.6	4 GB	Core i5	32	5	9-	Medium	10,500	
8	New	15.6	6 GB	Core i7	12	5	4-6	High	5,500	
9	New	15.6	8 GB	Core i3	25	N	7-9	Low	8,000	
10	Refurbished	13.3	4 GB	Core i7	25	N	7-9	Medium	5,500	
11	Refurbished	13.3	6 GB	Core i3	32	1	9-	High	8,000	
12	Refurbished	13.3	8 GB	Core i5	12	5	4-6	Low	10,500	
13	Refurbished	14.1	4 GB	Core i5	25	N	4-6	High	8,000	
14	Refurbished	14.1	6 GB	Core i7	32	1	7-9	Low	10,500	
15	Refurbished	14.1	8 GB	Core i3	12	5	9-	Medium	5,500	
16	Refurbished	15.6	4 GB	Core i7	12	5	9-	Low	8,000	
17	Refurbished	15.6	6 GB	Core i3	25	N	4-6	Medium	10,500	
18	Refurbished	15.6	8 GB	Core i5	32	1	7-9	High	5,500	

In the questionnaire, ‘refurbished’ refers to the laptops composed of higher proportion of remanufactured components; however, they have the same warranty services as the brand-new laptops. The “degree of upgrading and replacement” attribute has the following levels: i) “low degree” implies only the RAM and SSD can be added and/or replaced by the user; ii) ‘medium degree’ implies only the RAM, SSD, HDD, and power supply can be added and/or replaced by the user; and iii) ‘high degree’ implies the RAM, SSD, HDD, power supply, keyboard and display panel can be added and/or replaced by the user.

For the conjoint analysis, all attributes are coded using dummy variables such that an attribute with k levels will have $k-1$ dummy variables. A dummy variable takes either a one or zero value depending on the presence of an attribute. An example of dummy variable definition for attribute “screen size” is illustrated in Table 7.3. Table 7.4 shows product profiles with coded dummy variable sets. Dummy variable sets, (X_1), (X_{21}, X_{22}), (X_{31}, X_{32}), (X_{41}, X_{42}), (X_{51}, X_{52}), (X_{61}, X_{62}), (X_{71}, X_{72}), and (X_{81}, X_{82}) represent attributes for “product condition,” “screen size,” “RAM,” “processor,” “storage device,” “battery life,” “degree of upgrading and replacement,” and “price”, respectively.

Table 7.3 Example of dummy variable coded for “screen size” attribute

	X21	X22
13.3 inch	1	0
14.1 inch	0	1
15.6 inch	0	0

Table 7.4 Coded product profiles with dummy variables

Product Profile	Product Condition	Screen Size (inch)		RAM capacity		Processor (Intel)		Storage (SSD +HDD)		Battery Life		Upgrade + Replacement		Price (HKD)	
	X_1	X_{21}	X_{22}	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	1	0	1	0	1	0	1	0	1	0	1	0	1	0
2	1	1	0	0	1	0	1	0	1	0	1	0	1	0	1
3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	0	1	1	0	1	0	0	1	0	1	0	0	0	0
5	1	0	1	0	1	0	1	0	0	0	0	1	0	1	0
6	1	0	1	0	0	0	0	1	0	1	0	0	1	0	1
7	1	0	0	1	0	0	1	1	0	0	0	0	1	0	0
8	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0
9	1	0	0	0	0	1	0	0	0	0	1	1	0	0	1
10	0	1	0	1	0	0	0	0	0	0	1	0	1	1	0
11	0	1	0	0	1	1	0	1	0	0	0	0	0	0	1
12	0	1	0	0	0	0	1	0	1	1	0	1	0	0	0
13	0	0	1	1	0	0	1	0	0	1	0	0	0	0	1
14	0	0	1	0	1	0	0	1	0	0	1	1	0	0	0
15	0	0	1	0	0	1	0	0	1	0	0	0	1	1	0
16	0	0	0	1	0	0	0	0	1	0	0	1	0	0	1
17	0	0	0	0	1	1	0	0	0	1	0	0	1	0	0
18	0	0	0	0	0	0	1	1	0	0	1	0	0	1	0

7.4.1 Determining fuzzy utilities for the new and refurbished laptops

Based on respondents' rating for each product profile, FR model was used to determine the new and refurbished laptops' fuzzy utility function. The FR algorithm was implemented in MATLAB and the results are presented in Table 7.5, which shows coefficients of the fuzzy utility function.

Table 7.5 Results of fuzzy coefficients

	Const.	X1	X21	X22	X31	X32	X41	X42	X51	X52	X61	X62	X71	X72	X81	X82
Centre	3.41	0.30	-0.05	0.10	-0.17	-0.03	-1.19	-0.49	0.00	0.01	-0.05	-0.19	-0.23	-0.08	0.43	0.14
Spread	0.67	0.00	0.14	0.06	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

The corresponding fuzzy utility function for the new and refurbished laptops can be determined using centre estimates only, as follows:

$$\mathrm{U(new)} = 3.41 + 0.3X_1 - 0.05X_{21} + 0.10X_{22} - 0.17X_{31} - 0.03X_{32} - 1.19X_{41} - 0.49X_{42} + 0.01X_{52} - 0.05X_{61} - 0.19X_{62} - 0.23X_{71} - 0.08X_{72} + 0.43X_{81} + 0.14X_{82}$$

$$\mathrm{U(refurb.)} = 3.41 - 0.05X_{21} + 0.10X_{22} - 0.17X_{31} - 0.03X_{32} - 1.19X_{41} - 0.49X_{42} + 0.01X_{52} - 0.05X_{61} - 0.19X_{62} - 0.23X_{71} - 0.08X_{72} + 0.43X_{81} + 0.14X_{82}$$

For the case study, it is assumed that the company plans to offer the following new and refurbished laptops, whose specifications are shown in Table 7.6.

Table 7.6 Specifications of new and reman. laptops planned to be offered

Attributes	New	Reman
Screen size	15.6 inch	15.6 inch
RAM capacity	8 GB	8 GB
Processor type	Core i5	Core i5
Storage capacity	128 GB (SSD) + 500 GB (HDD)	128 GB (SSD) + 500 GB (HDD)
Battery hours	7-9 hrs	7-9 hrs
Degree of upgrade and replacement	Medium	Low
Price	8,000 HKD	5,500

It is assumed that new products that are launched to the primary market are targeted at quality-conscious customers, and the refurbished laptops are targeted at price-sensitive customers in the secondary market. It is further assumed that customers in the primary market often substitute brand new laptops with refurbished ones while customers in the secondary market buy refurbished laptops only. Six competitive products, three new and three refurbished laptops, are considered substitutes for the new laptops offered in the primary market. Similarly, four competitive refurbished laptop brands are considered as direct competitors for the refurbished laptops. Table 7.7 shows details of the specifications of competitive products.

Table 7.7 Specification of competitive products

	Competitive Product	Screen size	Ram capacity	Processor type	Storage capacity	Battery life	Degree of upgrade	Price (HKD)
NEW	A	14.1	6 GB	Core i3	32GB + 1 TB	4-6 hrs	Low	5,500
	B	14.1	6GB	Core i5	128 GB+ 500GB	7-9 hrs	Medium	8,000
	C	15.6	8GB	Core i7	256 GB	10-11 hrs	High	10,500
Refurb.	D	14.1	8 GB	Core i5	128 GB+ 500GB	4-6 hrs	Low	5,500
	E	14.1	8GB	Core i7	128 GB+ 500GB	7-9 hrs	Medium	8,000
	F	15.6	8GB	Core i7	256 GB	10-11 hrs	High	10,500

Fuzzy utilities for the new and refurbished laptops and the competitive products were computed using the fuzzy utility function obtained earlier. Table 7.8 shows the computed fuzzy utilities for the new and refurbished laptops and laptop brands offered by competitors for the primary and secondary markets.

Table 7.8 The centre, left, and right spreads of utility values for products

New laptop		A		B		C	
Centre	Spread	Centre	Spread	Centre	Spread	Centre	Spread
3.1	0.82	2.74	0.91	3.17	0.91	3.71	0.67
Refurb. laptop		**D**		**E**		**F**	
Centre	Spread	Centre	Spread	Centre	Spread	Centre	Spread
2.94	0.82	3.18	0.88	3.39	0.85	3.41	0.9

7.4.2 Estimation of market potentials and market shares

Estimated market potentials for the primary and secondary markets were provided by five marketing executives, as shown in Table 7.9 below.

Table 7.9 Estimated market potentials for the primary and secondary market

Marketing executive	Estimation of market potential for primary market	Estimation of market potential for secondary market
1	40,000	8,000
2	45,000	12,000
3	50,000	10,000
4	48,000	14,000
5	46,000	9,000
Average	$a_n = 45{,}800$	$a_r = 10{,}600$

The centre and spread magnitudes were then computed using Equations (7.13) – (7.16) as follows:

$$\widetilde{MP}_n=(l_n, a_n, r_n) = (5.8, 45.8, 4.2) *1000$$

$$\widetilde{MP}_r=(l_n, a_n, r_n) = (2.6, 10.6, 3.4) *1000$$

Next, based on the estimates of fuzzy utilities (Table 7.8) and using the MNL model given in Equations (7.9) and (7.10), the estimates of market shares of were computed. Besides, using the upper bound, centre, and lower bound estimates of the product utilities, market shares of products in the primary and secondary markets for: i) the worst, ii) the normal, and iii) the best case scenarios were computed. The results are shown in Table 7.10 and Table 7.11.

Table 7.10 Estimated market shares in the primary market

	New	Refurb.	A	B	C	D	E	F
Worst scenario	0.023	0.019	0.014	0.023	0.051	0.023	0.030	0.030
Normal scenario	0.11	0.09	0.08	0.12	0.20	0.12	0.14	0.15
Best scenario	0.11	0.09	0.08	0.12	0.20	0.12	0.14	0.15

Table 7.11 Estimated market shares in the secondary market

	Refurb.	D	E	F
Worst scenario	0.04	0.05	0.07	0.07
Normal scenario	0.18	0.23	0.29	0.29
Best scenario	0.55	0.64	0.69	0.71

7.4.3 Estimation of market demands

Based on the estimated market shares and fuzzy market potentials, the market demands for the new and refurbished laptops are computed using Equations (7.11) and (7.12) as shown in Table 7.12 and Table 7.13.

Table 7.12 Estimated fuzzy market demands in the primary market (in 1000s)

	Worst scenario	Normal scenario	Best scenario
New	(0.13, 1.04, 0.1)	(0.63, 4.95, 0.45)	(2.24, 17.70, 1.62)
Refurb.	(0.11, 0.87, 0.08)	(0.53, 4.22, 0.39)	(1.51, 11.92, 1.09)
A	(0.08, 0.65, 0.06)	(0.44, 3.46, 0.32)	(1.83, 14.44, 1.32)
B	(0.13, 1.04, 0.10)	(0.67, 5.31, 0.49)	(2.46, 19.44, 1.78)
C	(0.29, 2.31, 0.21)	(1.15, 9.12, 0.84)	(3.11, 24.59, 2.25)
D	(0.14, 1.08, 0.10)	(0.68, 5.37, 0.49)	(2.44, 19.27, 1.77)
E	(0.18, 1.40, 0.13)	(0.84, 6.62, 0.61)	(2.75, 21.70, 1.99)
F	(0.17, 1.37, 0.13)	(0.86, 6.75, 0.62)	(2.84, 22.44, 2.06)

Table 7.13 Estimated fuzzy market demands in the secondary market (in 1000s)

	Worst scenario	Normal scenario	Best scenario
Refurb.	(0.10, 0.42, 0.13)	(0.48, 1.95, 0.63)	(1.43, 5.84, 1.87)
D	(0.13, 0.54, 0.17)	(0.61 2.48 0.79)	(1.65, 6.73, 2.16)
E	(0.18, 0.71, 0.23)	(0.75, 3.06, 0.98)	(1.80, 7.36, 2.36)
F	(0.18, 0.71, 0.23)	(0.76, 3.12, 1.00)	(1.84, 7.48, 2.40)

The fuzzy market demand estimates for the primary and secondary markets are aggregated to determine the total fuzzy market demand for the new and refurbished laptops, as shown in Table 7.14.

Table 7.14 Total fuzzy market demand for the new and refurbished laptops

	Worst scenario	Normal scenario	Best scenario
New	(0.13, 1.04, 0.1)	(0.63, 4.95, 0.45)	(2.24, 17.70, 1.62)
Refurb.	(0.21, 1.29, 0.21)	(1.01, 6.17, 1.01)	(2.94, 17.76, 2.97)

The crisp values for the market demand for the new and refurbished laptops under the three scenarios are estimated using the centroid defuzzification method given in Equation (7.17) as follows.

$$MD_n^{W*} = \frac{(\int_{0.91}^{1.04}(x-0.91)x\,dx) + (\int_{1.04}^{1.14}(1.14-x)x\,dx)}{(\int_{0.91}^{1.04}(x-0.91)\,dx) + (\int_{1.04}^{1.14}(1.14-x)\,dx)} = 1{,}025$$

$$MD_n^{N*} = \frac{(\int_{4.32}^{4.95}(x-4.32)x\,dx) + (\int_{4.95}^{5.4}(5.4-x)x\,dx)}{(\int_{4.32}^{4.95}(x-4.32)\,dx) + (\int_{4.95}^{5.4}(5.4-x)\,dx)} = 4{,}862$$

$$MD_n^{B*} = \frac{(\int_{15.46}^{17.70}(x-15.46)x\,dx) + (\int_{17.70}^{19.32}(19.32-x)x\,dx)}{(\int_{15.46}^{17.7}(x-15.46)\,dx) + (\int_{17.70}^{19.32}(19.32-x)\,dx)} = 17{,}395$$

$$MD_r^{W*} = \frac{(\int_{1.08}^{1.29}(x-1.08)x\,dx) + (\int_{1.29}^{1.5}(1.5-x)x\,dx)}{(\int_{1.08}^{1.29}(x-1.08)\,dx) + (\int_{1.29}^{1.5}(1.5-x)\,dx)} = 1{,}290$$

$$MD_r^{N*} = \frac{(\int_{5.16}^{6.17}(x-5.16)x\,dx) + (\int_{6.17}^{7.18}(7.18-x)x\,dx)}{(\int_{5.16}^{6.17}(x-5.16)\,dx) + (\int_{6.17}^{7.18}(7.18-x)\,dx)} = 6{,}170$$

$$MD_r^{B*} = \frac{(\int_{14.82}^{17.76}(x-14.82)x\,dx) + (\int_{17.76}^{20.73}(20.73-x)x\,dx)}{(\int_{14.82}^{17.76}(x-14.82)\,dx) + (\int_{17.76}^{20.73}(20.73-x)\,dx)} = 17{,}775$$

Where MD_n^{W*}, MD_n^{N*}, $MD_n^{B*}$are crisp values of market demands for the new laptops under the 'worst,' 'normal,' and 'best' case scenarios, respectively. Whereas MD_r^{W*}, MD_r^{N*} MD_r^{B*} denote estimated market demands for the refurbished laptops under the 'worst,' 'normal' and 'best' case scenarios, respectively.

7.5 Validation of fuzzy regression model

The mean absolute percentage error (MAPE), the variance of error (VoE), and the index of confidence (IC) were computed using Equations (7.18) – (7.22) to validate the fuzzy regression model. The IC measures the degree of variation of individual utility values (U_j) corresponding to the upper bound (U_U) and lower bound (U_L) values (H. F. Wang and Tsaur, 2000).

$$MAPE = \frac{1}{J}\sum_{j=1}^{J}\frac{\left|\widetilde{U}_j - U_{j|}\right|}{U_j} \tag{7.18}$$

$$VoE = \frac{1}{J-1}\sum_{j=1}^{J}\left(\frac{\left|\widetilde{U}_j - U_{j|}\right|}{U_j} - MAPE\right)^2 \tag{7.19}$$

$$IC = 1 - \frac{SSE}{SST} \tag{7.20}$$

$$SSE = 2 * \sum_{j=1}^{N}\left(U_j - \sum_{j=1}^{J}\left(c_{jkl}x_{jkl}\right)\right)^2 \tag{7.21}$$

$$SST = \sum_{j=1}^{N}\left(U_j - \sum_{j=1}^{J}\left(c_{jkl} - (1-h)a_{jkl}\right)x_{jkl}\right)^2 + \sum_{j=1}^{N}\left(\sum_{j=1}^{J}\left(c_{jkl} + (1-h)a_{jkl}\right)x_{jkl} - U_j\right)^2 \tag{7.22}$$

Where J denotes the total number of product profiles, U_j and $\widetilde{U}_j$ respectively denote estimated values of observed and fuzzy utility for the jth product profile. SSE and SST are the sum of square error and the sum of the squared total, respectively. The error estimates were computed in MATLAB as 1.45%, 0.98, and

0.00024 for MAPE, IC, and VoE, respectively. According to Kwong et al. (2016), a model whose MAPE value is less than 10% is considered a good model. The model also exhibited a higher IC value and close to zero VoE, which indicates that the model has good fitness. Therefore, the obtained fuzzy regression model can predict the utility of product profiles with good accuracy and thus can be used to compute fuzzy demand estimates for the new and refurbished product profiles.

7.6 Chapter Summary

This chapter presented a fuzzy regression methodology for modelling customer satisfaction and estimating market demands for new and remanufactured products. A rating-based conjoint analysis and fuzzy regression were employed to determine the new and remanufactured products' fuzzy utility functions. The resulting fuzzy utility values were integrated into the multinomial logit (MNL) model to determine the market shares' estimates for the new and remanufactured products. Using the left, centre, and right spreads of the utilities, the market share estimates under three scenarios: 'worst,' 'normal' and 'best' cases were determined.

The estimated fuzzy market shares and fuzzy market potentials are then combined to determine the market demand for the new and remanufactured products under the 'worst,' 'normal' and 'best' case scenarios. A case study on a company that offers both new and refurbished laptops was conducted to determine market share estimates. The fuzzy regression approach was applied to generate fuzzy utility functions for the new and refurbished laptop brands. The MAPE, VoE, and IC error measures were computed to validate the fuzzy regression models. The results showed that generated models predict the utilities of both new and refurbished brands with good accuracy.

Chapter 8 Conclusions, Limitations and Future Research Directions

This chapter summarizes the findings and significant contributions of the research. Finally, the limitations of the research and future research directions are outlined.

8.1 Conclusions

Nowadays, companies worldwide are subjected to more stringent extended producer responsibility (EPR) legislation which mandates them for the take-back and recovery of EoL and EoU products. Remanufacturing has received increasing attention from academia and industry as a sustainable product recovery due to environmental, social, and economic performances. Literature review of previous research on remanufacturing shows the design of a product and the uncertainty regarding used product returns are the major issues that affect the successful remanufacturing of used products. To address the research gap, a framework for integrated product design considering used product returns uncertainty is proposed. Four methodologies are proposed, which form the key objectives of this research, as mentioned in chapter 1. These are: i) a methodology for fastening methods selection which considers product assembly and disassembly concerns simultaneously during early-stage product design; ii) a hierarchical optimisation model to determine optimal configurations for new and remanufactured products considering specification upgrading for used products; iii) a methodology for forecasting EoL product returns based on a distributed lag model (DLM) and; iv) a methodology for estimating market demand and customer satisfaction for new and remanufactured products.

Companies that offer the new and remanufactured products to the market need to consider design concerns that affect the manufacturability of new products and the remanufacturability of used products. Product design factors that facilitate the assembly process during the manufacturing of new products can become challenging to dismantle during the disassembly of used products for remanufacturing and vice-versa. Hence, early-stage design decisions such as fastening methods selection should consider product assembly and disassembly concerns simultaneously. In this research, a novel methodology for fastening methods selection called FMSRem is proposed. The FMSRem helps designers determine optimal fastening methods during the early design stage to facilitate product assembly and disassembly processes while minimising the overall assembly and disassembly costs. A case study is implemented to demonstrate the applicability of the proposed methodology. The results indicate that the fastening methods selected based on the proposed methodology provide a significant saving in the overall cost of product assembly and disassembly. Different rates of used product returns and the required degree of product disassembly were investigated to compare the proposed methodology with a traditional DFA approach. The results have also shown that the proposed methodology outperforms the DFA approach in overall cost savings.

Furthermore, early-stage product design decisions regarding configurations of new and remanufactured products should consider specification upgrading due to technological obsolescence of used parts/modules. However, specification upgrading decisions for used product returns are affected by the original specification of new products sold in the previous periods and the timing of used product returns. A non-linear integer bilevel programming (NLIBP) is proposed in this research to model the hierarchical PDC decision-making and to address the conflicting trade-offs involved. The bilevel optimisation is formulated as a Stackelberg leader-follower model whereby the new product design team acts as a leader and the remanufactured design team acts as a follower. Maximisation of shared surplus, which emphasises a trade-off between customer preferences, market share, and product costs, is considered an objective function for both the upper-level and lower-level optimisations. The bilevel optimisation model is solved using Nested bilevel GA (NBGA).

The accurate forecasting of EoL product returns is a critical factor for the successful implementation of remanufacturing. However, unlike conventional time-series forecasting techniques, the uncertainty regarding the quantity and timing of EoL product returns makes forecasting in remanufacturing a complex task. A DLM based forecasting methodology is proposed to address the uncertainty of used product returns in remanufacturing. The proposed forecasting methodology considers new product sales in previous periods to forecast the quantity and timing of EoL product returns in future periods. An MCMC based Bayesian inference approach is proposed to estimate the parameters of a DLM. A case study is also conducted to demonstrate the applicability of the proposed forecasting methodology. The forecasts' MAPE and VoE were computed to validate the proposed forecasting methodology and the parameter estimation approach. The results were compared with forecasting errors when estimates of DML are obtained using the MLE approach. The results show that the proposed parameter estimation approach provides better forecasting accuracy than the MLE approach in terms of MAPE and VoE. Besides, the cost savings under the overestimation and underestimation cases were also investigated. The result has shown that the proposed approach provides significant cost savings and better forecasting accuracy than the MLE approach.

A combination of rating-based conjoint analysis and fuzzy regression is utilized to model customer preferences and estimate market demands for the design attributes of new and remanufactured products. The resulting fuzzy regression model was then integrated into MNL to estimate fuzzy market demands for the new and remanufactured products. The centroid defuzzification method is employed to obtain the crisp estimates of market demands for new and remanufactured products under the three scenarios: ‘worst,’ ‘normal,’ and ‘best’ cases. A case study is conducted on a company that offers new and refurbished laptop brands to illustrate the methodology. An L18 based orthogonal array was used for the conjoint survey, and the fuzzy regression model was then solved in MATLAB to obtain fuzzy coefficients of the utility function. The MAPE and IC of the utility values were computed to validate the model’s fitness. The fuzzy and crisp estimates of market demand for the new and remanufactured products under three scenarios: ‘the worst,’ ‘the normal,’ and ‘the best’ cases were also investigated.

The major contributions of the research are summarized as follows:

- A novel methodology is proposed to determine appropriate fastening methods during the early design stage, simultaneously considering assembly and disassembly concerns. The proposed methodology can serve as a decision support tool during the early-stage design to determine optimal fastening methods that minimise the overall assembly and disassembly costs. The effects of the demand for new and remanufactured products and the quality uncertainty of used product returns were also investigated.
- Accurate forecasting of EoL product returns is required for successful remanufacturing. However, unlike the traditional time-series forecasting techniques, forecasting in remanufacturing is a complex task due to the quantity and timing uncertainty of used product returns. The forecasting of used product returns from a remanufacturing perspective has not been sufficiently addressed in previous studies. A DLM based forecasting method is proposed in this research to address the quantity and timing uncertainty of used product returns. Furthermore, the estimation of DLM parameters is a challenging task that has not been sufficiently addressed in previous research. An MCMC based Bayesian approach is proposed in this research to estimate parameters of the lag function of a DLM.
- Product design configuration considering specification upgrading of used products for remanufacturing has not been addressed in previous studies. A hierarchical optimisation model based on bilevel programming is proposed to determine optimal design configurations for new and remanufactured products considering specification upgrading for used parts/modules.

8.2 Research limitations

This research has five major limitations which are outlined as follows. These limitations provide avenues for future research which is discussed in the next section.

- The first limitation is related to the factors considered in the proposed fastening methods selection methodology. Even though several factors could affect fastening methods selection during early-stage design, this research mainly considered the assembly and disassembly factors.
- The second limitation of this research is that it assumes complete disassembly of used products during remanufacturing. However, in certain instances, partial disassembly can be sufficient to recover vital components from used product returns. A sensitivity analysis was conducted to determine the effects of partial disassembly requirements on the choices of fastening methods.
- The third limitation of this research is that customers' preferences for new and remanufactured products were assumed to be static across all planning periods.
- The fourth limitation is related to the assumption taken regarding the quantity and timing uncertainty of used product returns. The return pattern for used products was assumed to follow a known distribution function during the entire return period. However, used product returns often exhibit different patterns across different return periods depending on the type of product/industry.
- The fifth limitation is related to the uniform quality assumption considered for used product returns. However, used product returns often have varying quality levels which result in an uncertain quality distribution.

8.3 Future research directions

In order to bridge the limitation in this research, the following topics were identified as avenues for future studies.

- The proposed fastening methods selection can be extended in future studies to consider comprehensive factors that affect the remanufacturability of a product design. More specifically, in future studies, fastening methods selection should integrate design for cleaning, design for inspection and design for testing concerns during the early design stage. The cases of partial disassembly requirement for used products can also be investigated.
- To determine the market demand for new and remanufactured products, use of sentiment analysis techniques and the dynamic nature of customers' preferences can be investigated in future studies.
- Furthermore, the use of a non-homogeneous Markov chain can be investigated for the forecasting of non-homogenous used product return patterns more accurately. Future studies should also consider integrating the quality distribution of used product returns in the forecasting model.

APPENDIX A: Survey Questionnaire Used for Conjoint Analysis

The purpose of this survey is to investigate customers' preferences of product attributes to develop a design methodology for both new and refurbished products. To this end, the following short questionnaire is prepared to collect consumer preferences of various profiles of new and refurbished notebook computers. You are kindly requested to contribute few minutes from your valuable time to fill out this questionnaire. Rest assured that all the information collected will be used solely for the research project and kept confidential. Thank you very much for your kind assistance in advance.

1. Gender: ☐ Male ☐ Female

2. Status: ☐ Full-time study ☐ Full-time employed

   ☐ Others (please specify) ________________

3. How would you rate the importance of each following attribute while purchasing a notebook computer for yourself? Use the scale 1 to 5 with their meanings as shown below:

   5– Very important 4– Important 3 – Moderate important 2 – Slightly important 1 – Not important

   Brand _______
   Performance ________
   Weight and size (Slim design) _______
   Battery Life _______
   Easy to upgrade and replace components by customers ______
   Environmental friendliness _______________
   (e.g., consumes less energy; parts can be recycled)
   Quality ______
   Price ______

4. Please rate the following notebook computer profiles using the scales 1 to 5 with their meanings given below.

5 – Very good   4 - Good   3 - Moderate   2 - Bad   1 – Very bad

Specs / Product	Product Condition (See Note 1)	Screen Size (inch)	RAM	Processor (Intel)	SSD	HDD	Battery Life	Degree of upgrading and replacement by customer (See Note 2)	Price (HKD)	Rating
1	New	13.3	4 GB	Core i3	32GB	1TB	4-6 hrs	Low	5,500	
2	New	13.3	6 GB	Core i5	128GB	500GB	7-9 hrs	Medium	8,000	
3	New	13.3	8 GB	Core i7	256GB	Nil	9-11 hrs	High	10,500	
4	New	14.1	4 GB	Core i3	128GB	500GB	7-9 hrs	High	10,500	
5	New	14.1	6 GB	Core i5	256GB	Nil	9-11 hrs	Low	5,500	
6	New	14.1	8 GB	Core i7	32GB	1TB	4-6 hrs	Medium	8,000	
7	New	15.6	4 GB	Core i5	32GB	500GB	9-11 hrs	Medium	10,500	
8	New	15.6	6 GB	Core i7	128GB	500GB	4-6 hrs	High	5,500	
9	New	15.6	8 GB	Core i3	256GB	Nil	7-9 hrs	Low	8,000	
10	Refurbished	13.3	4 GB	Core i7	256GB	Nil	7-9 hrs	Medium	5,500	
11	Refurbished	13.3	6 GB	Core i3	32GB	1TB	9-11 hrs	High	8,000	
12	Refurbished	13.3	8 GB	Core i5	128GB	500GB	4-6 hrs	Low	10,500	
13	Refurbished	14.1	4 GB	Core i5	256GB	Nil	4-6 hrs	High	8,000	
14	Refurbished	14.1	6 GB	Core i7	32GB	1TB	7-9 hrs	Low	10,500	
15	Refurbished	14.1	8 GB	Core i3	128GB	500GB	9-11 hrs	Medium	5,500	
16	Refurbished	15.6	4 GB	Core i7	128GB	500GB	9-11 hrs	Low	8,000	
17	Refurbished	15.6	6 GB	Core i3	256GB	Nil	4-6 hrs	Medium	10,500	
18	Refurbished	15.6	8 GB	Core i5	32GB	1TB	7-9 hrs	High	5,500	

Notes

1. Refurbished products have a high percentage of reused components; however, they have the same warranty of product service as new ones.
2. **'Low,'** '**Medium'** and '**High'** degrees are defined as follows:
   - Low degree: Only RAM and SSD can be added and/or replaced by a customer.
   - Medium degree: Only RAM, SSD, HDD, and power supply can be added and/or replaced by a customer.
   - High degree: RAM, SSD, HDD, power supply, keyboard, and display panel can be added and/or replaced by a customer.

APPENDIX B: Computation of the Covariance Matrix for the Error Vector of a DLM

The detailed derivation for the covariance matrix of the error vector of a DLM is presented as follows. For the error vector u $\in$ $(u_3, u_4, u_5, \ldots u_T)'$ in a DLM where $u_t = \varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\varepsilon_{t-2}$ for t=3,4,5 … T, the error terms $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-1}$ are assumed to be normally distributed according to ~N(0, σ^2). The corresponding covariance matrix denoted as Σ_u is represented by a $(T-2) \times (T-2)$ matrix as presented below.

$$\sum\nolimits_u = \begin{bmatrix} \mathrm{Cov}(u_t, u_t) & \mathrm{Cov}(u_t, u_{t+1}) & \mathrm{Cov}(u_t, u_{t+2}) & \cdots & \cdots & \mathrm{Cov}(u_t, u_T) \\ \mathrm{Cov}(u_{t+1}, u_t) & \mathrm{Cov}(u_{t+1}, u_{t+1}) & \mathrm{Cov}(u_{t+2}, u_{t+3}) & \cdots & \cdots & \mathrm{Cov}(u_{t+1}, u_T) \\ \mathrm{Cov}(u_{t+2}, u_t) & \mathrm{Cov}(u_{t+3}, u_{t+2}) & \mathrm{Cov}(u_{t+2}, u_{t+2}) & \cdots & \cdots & \mathrm{Cov}(u_{t+2}, u_T) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathrm{Cov}(u_T, u_t) & \mathrm{Cov}(u_T, u_{t+1}) & \mathrm{Cov}(u_T, u_{t+2}) & \cdots & \cdots & \mathrm{Cov}(u_T, u_T) \end{bmatrix}$$

The detailed derivation for the elements of the covariance matrix is illustrated as follows:

Cov (u_t, u_t)= E $[(u_t - \mathrm{E}\,(u_t))(u_t - \mathrm{E}\,(u_t))]$ = E $[{u_t}^2]$

= E $((\varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\ \varepsilon_{t-2})^{\ 2})$; for t=3,4,5 … T

= E $(\varepsilon_t^2 - 4(1-q)\varepsilon_t\varepsilon_{t-1} + 2(1-q)^2\varepsilon_t\varepsilon_{t-2} + 4(1-q)^2(\varepsilon_{t-1})^2\ - 4(1-q)^3\varepsilon_{t-1}\varepsilon_{t-2} +$

$(1-q)^4\varepsilon_{t-2}^2)$

= E $(\varepsilon_t^2) - 4(1-q)E(\varepsilon_t\varepsilon_{t-1}) + 2(1-q)^2E(\varepsilon_t\varepsilon_{t-2}) + 4(1-q)^2E((\varepsilon_{t-1})^2) -$

$4(1-q)^3\mathrm{E}(\varepsilon_{t-1}\varepsilon_{t-2}) +\ (1-q)^4\mathrm{E}(\varepsilon_{t-2}^2)$

= σ^2+ $4(1-q)^2\sigma^2$ +$(1-q)^4\ \sigma^2$ = $\sigma^2\ (1 + 4(1-q)^2 + (1-q)^4\ )$

Cov (u_t, u_{t+1})= E $[(u_t - \mathrm{E}\,(u_t))(u_{t+1} - \mathrm{E}\,(u_{t+1}))]$ = E $[u_t u_{t+1}]$

= E $[\varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\ \varepsilon_{t-2}\ )(\varepsilon_{t+1} - 2(1-q)\varepsilon_t + (1-q)^2\ \varepsilon_{t-1}]$

= E $[\varepsilon_t\varepsilon_{t+1} - 2(1-q)\varepsilon_t^2 + (1-q)^2\varepsilon_t\varepsilon_{t-1} - 2(1-q)(\varepsilon_{t-1}\varepsilon_{t+1}) + 4(1-q)^2\varepsilon_t\varepsilon_{t-1} -$

$2(1-q)^3\varepsilon_{t-1}^2 + (1-q)^2\varepsilon_{t+1}\varepsilon_{t-2} -\ 2(1-q)^3(\ \varepsilon_t\varepsilon_{t-2}) + (1-q)^4\varepsilon_{t-1}\varepsilon_{t-2}]$

= E $(\varepsilon_t\varepsilon_{t+1}) - 2(1-q)E(\varepsilon_t^2) + (1-q)^2E(\varepsilon_t\varepsilon_{t-1}) - 2(1-q)E(\varepsilon_{t-1}\varepsilon_{t+1}) +$

$4(1-q)^2E(\varepsilon_t\varepsilon_{t-1}) - 2(1-q)^3E(\varepsilon_{t-1}^2) + (1-q)^2E(\varepsilon_{t+1}\varepsilon_{t-2}) - \ 2(1-$

$q)^3E(\ \varepsilon_t\varepsilon_{t-2}) + (1-q)^4E(\varepsilon_{t-1}\varepsilon_{t-2})$

= $-2(1-q)\sigma^2$ $-2(1-q)^3\sigma^2$ = $-2\sigma^2((1-q)$+ $(1-q)^3)$ = $-2\sigma^2(1-q)$(1+$(1-q)^2)$

Cov (u_t, u_{t+2}) = E$(\varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\ \varepsilon_{t-2}\ )(\varepsilon_{t+2} - 2(1-q)\varepsilon_{t+1} +$

$(1-q)^2\ \varepsilon_t\ )$

= E $(\varepsilon_t\varepsilon_{t+2} - 2(1-q)\ \varepsilon_t\varepsilon_{t+1}$+$(1-q)^2\varepsilon_t^2 - 2(1-q)\varepsilon_{t-1}\varepsilon_{t+2} + 4(1-q)^2\varepsilon_{t-1}\varepsilon_{t+1}$+

$2(1-q)^3\ \varepsilon_t\varepsilon_{t-1} + (1-q)^2\ \varepsilon_{t-2}\varepsilon_{t+2}$ $-2(1-q)^3\varepsilon_{t-2}\varepsilon_{t+1} + \ (1-q)^4\varepsilon_t\varepsilon_{t-2}\ )$

= E $(\varepsilon_t\varepsilon_{t+2}) - 2(1-q)E(\varepsilon_t\varepsilon_{t+1})$+$(1-q)^2E(\varepsilon_t^2) - 2(1-q)E(\varepsilon_{t-1}\varepsilon_{t+2}) +$

$4(1-q)^2E(\varepsilon_{t-1}\varepsilon_{t+1})$ +$2(1-q)^3$E$(\varepsilon_t\varepsilon_{t-1}) + (1-q)^2E(\varepsilon_{t-2}\varepsilon_{t+2})$ $-2(1-$

$q)^3E\ (\varepsilon_{t-2}\varepsilon_{t+1}) + \ (1-q)^4E(\varepsilon_t\varepsilon_{t-2})$

= $(1-q)^2\sigma^2$

Cov (u_t, u_{t+3}) = E$(\varepsilon_t - 2(1-q)\varepsilon_{t-1} + (1-q)^2\ \varepsilon_{t-2}\ )(\varepsilon_{t+3} - 2(1-q)\varepsilon_{t+2} +$

$(1-q)^2\ \varepsilon_{t+1}\ )$

= E$(\varepsilon_t\varepsilon_{t+3} - 2(1-q)\ \varepsilon_t\varepsilon_{t+2}$+$(1-q)^2\varepsilon_t\varepsilon_{t+1} - 2(1-q)\varepsilon_{t-1}\varepsilon_{t+3} + 4(1-$

$q)^2\ \varepsilon_{t-1}\varepsilon_{t+2} - 2(1-q)^3\varepsilon_{t-1}\varepsilon_{t+1}$+$(1-q)^2\ \varepsilon_{t-2}\varepsilon_{t+3} - 2(1-q)^3\varepsilon_{t-2}\varepsilon_{t+2}$ +

$(1-q)^4\ \varepsilon_{t-2}\varepsilon_{t+1})$

= E $(\varepsilon_t\varepsilon_{t+3}) - 2(1-q)E(\varepsilon_t\varepsilon_{t+2})$+$(1-q)^2E(\varepsilon_t\varepsilon_{t+1}) - 2(1-q)E(\varepsilon_{t-1}\varepsilon_{t+3}) +$

$4(1-q)^2$E$(\varepsilon_{t-1}\varepsilon_{t+2}) - 2(1-q)^3E(\varepsilon_{t-1}\varepsilon_{t+1})$+$(1-q)^2E(\varepsilon_{t-2}\varepsilon_{t+3}) - 2(1-$

$q)^3E(\varepsilon_{t-2}\varepsilon_{t+2})$ + $(1-q)^4$ E$(\varepsilon_{t-2}\varepsilon_{t+1})$

= 0

It follows that the non-diagonal terms, i.e., Cov (u_t, u_{t+3}), for t=3,4,5, …, T will be all zeros.

Compiling all the terms, the covariance matrix, i.e., Σ_u can be presented as follows.

$$\sum_u = \begin{bmatrix} 1+4(1\text{-}q)^2+(1\text{-}q)^4 & -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & (1\text{-}q)^2 & 0 & \cdots & 0 \\ -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & 1+4(1\text{-}q)^2+(1\text{-}q)^4 & -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & (1\text{-}q)^2 & \cdots & 0 \\ (1\text{-}q)^2 & -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & 1+4(1\text{-}q)^2+(1\text{-}q)^4 & -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & \cdots & 0 \\ 0 & (1\text{-}q)^2 & -2(1\text{-}q)\left(1+(1\text{-}q)^2\right) & 1+4(1\text{-}q)^2+(1\text{-}q)^4 & \cdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1+4(1\text{-}q)^2+(1\text{-}q)^4 \end{bmatrix}$$

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