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A Methodology for Integrating Supplier Selection with Product Line Design

By

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CERTIFICATE OF ORIGINALITY

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Abstract

Product line design involves design of various product variants under a product line which aims to satisfy the needs of various market segments. In the development of product lines, it is quite common for companies to adopt sourcing strategy nowadays for reducing product cost and development time, and improving product quality. One major issue of the sourcing is supplier selection.

Previous studies have shown that companies commonly spent 60% of product cost on sourcing. Conventionally, product design and supplier selection are dealt with separately. Product design is first performed and then suppliers are selected to provide the required components or product modules. Various studies have been conducted in the areas of product line design and supply chain issues. However, only few studies found so far have investigated the optimal product line design together with supplier selection consideration. This project aims to investigate the integration of product line design with supplier selection issue.

In this research, a methodology for integrating supplier selection with product line design is proposed. The proposed methodology is able to make up the deficiencies of the previously related studies, which include (1) prices of product variants are pre-defined; (2) only single objective is considered in the integrated problem; and (3) being unable to determine market positions of product variants. The proposed methodology involves the following steps. In the methodology, the customer preferences and their perceptions of competitive products are collected first through a market survey. Then, a joint-space map is constructed, and market share models, cost models, and quality and performance models are developed. The next step is to formulate an optimization model for determining the specifications of product variants of the product line such that the profit, quality and performance of the product line can be maximized. Finally, the optimization problem is solved using a multi-objective genetic algorithm.

A case study of the product line design of portable computers was conducted to illustrate the effectiveness of the proposed methodology. The results have shown that optimal product line design with a consideration of supplier selection can be determined, and the specifications of the product variants can be generated. On the other hand, suppliers of components and modules can be selected with the considerations of minimum sourcing cost and maximum performance and quality of products. Price and position of the product variants can also be estimated. The methodology used in the study enables the effective joint decision making of product line design and supplier selection.

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List of Abbreviations

ACO	Ants Colony Optimization
AHP	Analytic Hierarchy Process
ATC	Analytical Target Cascading
CA	Coordinate Ascent
CI	Confidence Index
CPU	Central Processing Unit
DEA	Data Envelopment Analysis
EAs	Evolutionary Algorithms
ED	Euclidean Distance
ESI	Early Supplier Involvement
FI	Flexibility Index
GA	Genetic Algorithms
GH	Greedy Heuristics
GP	Goal Programming
GPU	Graphics Processing Unit
IPSO	Interactive Particle Swarm Optimization
JIT	Just-in-time
MILP	Mixed Integer Linear Programming
MOGA	Multi-Objective Genetic Algorithms
MOPSO	Multi-objective Particle Swarm Optimization
NPD	New Product Design

NPV	New Product Variant
NSGA	Non-dominated Sorted Genetic Algorithms
NSGA II	Non-dominated Sorted Genetic Algorithms II
PAES	Pareto-archived Evolution Strategy
PCs	Portable Computers
PFD	Product Family Design
PLD	Product Line Design
PSO	Particle Swarm Optimization
R&D	Research and Development
RAM	Random-Access Memory
RCS	Replaceable Component Sets
SCM	Supply Chain Management
SI	Satisfaction Index
SMART	Simple Multi-attribute Rating Technique
SPEA	Strength Pareto Evolutionary Algorithm
TCO	Total Cost of Ownership
VEGA	Vector Evaluated Genetic Algorithms

List of Notations

Notations	Meaning
I	Set of replaceable components or modules, $i \in I$
J	Set of suppliers, $j \in J$
K	Set of product variant in a product line, $k \in K$
l	Competitive product l
o	*o*th market segment in a joint space map $o \in O$
ϑ_o	Purchase probabilities of customers in the *o*th segment
ω_{ok}	Market share of the *k*th product in the *o*th segment
d_{ko}	Euclidean distance between the kth product to the ideal point of the oth segment in a joint space map
d_{lo}	Euclidean distance between the *l*th competitive product to the ideal point of the *o*th segment in a joint space map
ε_o^x	x coordinate of the center of *o*th segments in a joint space map
ε_o^y	y coordinate of the center of *o*th product in a joint space map
φ_k^x	x coordinate of the *k*th product in x axis in a joint space map.
φ_k^y	y coordinate of the *k*th product in y axis in a joint space map
ξ_l^x	x coordinate of the *l*th competitive product in a joint space map
ξ_l^y	y coordinate of the *l*th competitive product in a joint space map
f	Factor from factor analysis
S_o	Sales potential of the *o*th segments
R	Market revenue of a product line

V_k	Market demand of kth product
P_k	Retail price of the kth product
N_o	Number of customers in the oth segments.
β_f^A	Factor score of attractiveness of the fth factor.
β_f^U	Factor score of quality of the fth factor.
β_f^P	Factor score of retail price of the fth factor

Chapter 1 Introduction

1.1 Background of Study

Nowadays, companies are faced with the great challenge that larger product variety (customization) and more customized products need to be provided to satisfy diversified customer needs. It is believed that increasing product variety could help to increase sale volume and generate more profit (Tseng & Jiao, 2007). However, an increasing variety of products would raise the total product development cost (Da Silveira et al. 2001). This situation poses the dilemma for companies that they need to balance their product variety and the extent of complexity of product differentiation (Tseng & Jiao, 2007).

Product line design has been recognized widely as an effective method for targeting fragmented market niches with ideal scales of resource utilization and investment (Krishnan & Ulrich, 2001). Well-leveraged product variety and commonality in a product line can prevent a series of problems such as high inventory cost, increased development cost, resource waste and supply chain complexity but flexibility of product change and upgrade can be enhanced (Desai et al. 2001). Nowadays, companies have adopted various ways of developing product lines to satisfy customer needs for segmented markets (Marion & Simpson, 2006).

Numerous studies reviewed by Jiao et al. (2007) have contributed to the development of design approaches to product line design, product family design and platform-based product development. Generally, product positioning, product pricing, profit maximum and optimal design have been discussed often in the product line literature (Chen et al. 2009).

Product line design needs to consider customer requirements of various market segments and competitive products. Once customer requirements are defined, it is common nowadays for companies to develop their new products with the involvement of suppliers (Salvador et al. 2002). This can help them to produce their new products with lower cost, better quality and in a shorter time. Supplier selection is a critical process that affects cost, quality and performance of products. Previous studies found that sourcing cost can take up more than 50% of product cost (Love et al. 2003; Luo et al. 2011). Therefore, product cost could be reduced through the selection of the right suppliers and the customer satisfaction and competitiveness of products would be enhanced (Awasthi et al. 2009). Traditionally, supplier selection is conducted after a product design is completed. Product components of a product line are usually defined first by product development teams, and then the suppliers offering the lowest component prices are selected (Zhang et al. 2008). Nonetheless, the two separate processes can lead to suboptimal cost-saving or even poor product solutions in view of product cost, quality and performance (Gupta & Krishnan, 1999). The advantages of integrating product line design with supplier selection have been realized. However, very few studies so far have focused on developing methodologies for integrating the two issues. Component price is not only a decision-making factor for selecting suppliers. Companies should consider some other factors such as quality, reliability and performance (Shin, Benton, & Jun, 2009). A recent quality crisis in Mattel toy products alerted companies to be more aware of supplier quality (Bigelow, 2007). This indicates the importance of integrating supplier selection with product line design.

1.2 Research Scope and Objectives

The scope of the research presented here mainly involves product line design and supplier selection. The aim of the research is to investigate the integration of supplier selection with product line design. The research objectives are as follows:

a. Develop a methodology for integrating supplier selection with product line design which involves the consideration of three issues of supplier selection, namely cost, quality and performance of components.
b. Determine optimal product line designs using a multi-objective genetic algorithm.

1.3 Thesis Layout

This thesis is organized as follows: Chapter 2 presents fundamental issues relating to product line and product family design, a review of various research issues including earlier supplier involvement in new product design, integrated product line/family design and resource allocation, integrated product line/family design with postponement/decoupling, simultaneous design of product family and supply chain configuration, product line/family design with strategic sourcing decisions, integrated product line/family design with supplier selection, and mathematical modeling and algorithms in product line/family design and supply chain issues. Chapter 3 presents the proposed methodology and the formulation of an optimization model for integrating supplier selection with product line design. The use of a multi-objective genetic algorithm for solving the optimization problem is also presented. Chapter 4 presents the research implementation through a case study of a product line design for portable computers based on the proposed methodology. Chapter 5 presents the results of the implementation. Chapter 6 presents the discussion of the whole research. The last chapter presents a conclusion of this thesis and possible future work.

Chapter 2 Literature Review

2.1 Introduction

This chapter presents a review of research on product design, product line design, product family design and supply chain issues. The concepts of product line and product family design are quite similar, except that in product family design, modularity and commonality need to be studied while commonality may not be studied in product line design. Section 2.2 presents the previous research about product line design and product family design. Section 2.3 reviews new product development and supply chain issues. Section 2.4 presents a review of early supplier involvement (ESI) in product design. Section 2.5 describes previous studies that have addressed product line/family design and supply chain issues. Section 2.6 presents previous research on algorithms and mathematical modeling in product design and supply chain issues. Some discussions of the literature review are provided in the last section.

2. 2 Product Line Design and Product Family Design

2.2.1 Product line design

A product line means a series of product variants that are launched to meet the needs of various customers and achieve business goals (Kaul & Rao, 1995; Li & Azarm 2002). A product line design problem is a further extension of a single product design problem. Since it involves a study of more than one product, the modelling and solving of product line design problem are much more complicated. Most engineering literature discusses applications of optimization techniques in product line design. In the management and marketing literature, product pricing and positioning, market share, profit and product utilities have been discussed (Jiao et al.,2007; Kwong et al.,2011).

(a) Product line design with market considerations

Product line design and development requires a trade-off between the technical aspect and market aspects. Successful product line design requires close integration between the marketing and engineering issues of products (Michalek et al. 2011).

Some previous studies have investigated product line design with various marketing issues. Balakrishnan et al. (2004; 2006) proposed an artificial intelligence approach to deal with produce line design and market share. Conjoint analysis was employed for determining optimal product line design. Chen and Hausman (2000) developed a choice-based conjoint analysis to model product line selection and customer preference. Some previous studies addressed the determination of optimal product line design with pricing. Hanson and Martin (1996) presented a logit profit function to optimize product line and perform pricing. Kanan et al. (2009) examined optimal pricing policies of product lines. Some papers have described product line design with simultaneous consideration of marketing and engineering perspectives. Michalek et al. (2006) incorporated market performance and manufacturing requirements in discussing the tradeoffs between design and manufacturing cost and quantified market revenue. Later, Michalek et al. (2011) presented a comprehensive methodology which incorporated analytical target cascading (ATC) to coordinate marketing and engineering issues for product line design. Lan (2011) introduced a concurrent optimization method to determine a product line with profit maximum while engineering criteria can be satisfied. The results indicate that genetic algorithms yield effective and efficient computational results while solving large-scale product line design problems.

(b) Methods for product line design optimization

Various methods for optimizing product line design can be found in the literature. Green et al. (1989) first applied the coordinate ascent (CA) method to solve the product line design optimization problem. This method selects a product line randomly and evaluates its profitability. However, CA cannot ensure any global optimal solution. Balakrishnan and Chakravarty (2008) indicated that genetic algorithms (GA) could be better in searching for optimal solutions. A hybrid genetic algorithm with beam search was applied to the optimal product design problem by Alexouda and Paparizzos (2001). Balakrishnan and Jacob (2004) then applied the algorithm on product line design optimization. They suggested that the integrated approach is robust and can get near optimal solutions more quickly than traditional GA. Kwong et al. (2011) introduced multi-objective genetic algorithms for product line design.

Some methods were applied to entire products in a product line rather than determining attributes of products. Green and Krieger (1985) discussed optimal product line design with a greedy heuristic method. Dobson and Gregory (1993) developed a new greedy heuristic (GH) which was claimed to be better than the original GH for complex product line design problems. Steiner and Hruschka (2003) compared the GA based approach with Green and Krieger's (1985) GH approach. They reported that the GA based approach outperformed GH since GA runs generation by generation and creates higher opportunity for searching for optimal solutions. Green and Krieger (1993) suggested a divide and conquer heuristic for solving the optimal product line design problem. In their proposed method, the product line was treated as clusters of attributes. A single product was treated as a cluster. The method enables the enumeration of a product with all possible combinations of attributes while keeping the other clusters unchanged. It stops searching when no more earning could be obtained.

Some previous studies attempted to develop methods for product line design problems which involve large numbers of product variants. Belloni et al. (2008) proposed a method to evaluate the partial-formed products instead of the entire products or attributes. Kohli and Krishnamurti (1987) proposed a dynamic programming heuristic for optimal product line design. This heuristic works similar to the greedy heuristic by setting one attribute at a time. Nair et al. (1995) applied a beam search heuristic to optimal product line design. In the beam search heuristic attributes of products are combined simultaneously. The number of product variants increases one by one, instead of creating an entire product line at one time. A nested partitions heuristic was proposed by Shi et al. (2001) to solve optimal product line design problems. They considered dividing the optimal solution space into various different regions, and dividing the most promising region into smaller ones for further action.

2.2.2 Product family design

A set of products, which are developed based on a common platform and share some common components, but differentiated in some product features, can be called a product family. This is a common means of providing more product choices to customers (Meyer & Lehnerd, 1997). A product platform has been described as the set of common components, modules, or parts from which a stream of derivative products can be created and launched efficiently (Meyer & Lehnerd, 1997). Halman et al. (2006) defined that a product platform is a common base component in a product family and is not an individual. One or more modules can be replaced, added or removed from the product platform (Simpson, 2004). Robertson (1998) stated that companies can effectively develop product variants which derive from a common platform by sharing components and manufacturing process, increase market share by launching one product at a time. The challenge of product family design is to balance the commonality and variety with clear market positions for customers at different levels.

A number of research studies of product family design have been conducted (Huang et al. 2008; Jiao et al. 2007; Khajavirad et al. 2009; Kumar et al. 2009; Li and Huang 2009). In the previous research, much attention has been put on minimizing the manufacturing cost of product families while addressing the optimal commonality and modularity (Farrell & Simpson, 2003; Fellini et al. 2006; Khajavirad & Michalek 2008; Kim & Chhajed 2000; Kim & Chhajed2001). Some researchers have discussed platform-based product family design while simultaneously integrating demand models (Moore, Louviere, & Verma, 1999). The integration models can be used to estimate product costs and revenues; however, the models have some limitations in dealing with product positioning (Kumar et al., 2009). For instance, Moore et al. (1999) assumed a random number of product variants for a product family, but the considerations and discussion of commonality were ignored. Commonality and differentiation have been discussed often in the literature. However, too much commonality could lead to little differentiation of a product family, which would affect attractiveness of product variants (Robertson & Ulrich, 1998). Kumar et al. (2009) proposed a market-driven approach to product family design in which commonality, optimal configurations product variants, product line positioning and choice modeling are considered.

2.3 Supplier Selection

Supplier selection is one of the activities of supply chain management. The importance of supplier selection has been addressed in the last two decades, as this is considered as a way to increase the competitiveness of companies (Lee & Wellan 1993). The proper selection of suppliers can help to reduce product cost and increase product quality. Supplier selection can be treated as a multi-criteria decision making problem. Usually, both qualitative and quantitative factors are considered. There are two main areas of supplier selection, criteria of selection and selection methods.

In the previous studies, three common issues for supplier selection have been considered; net price, quality and delivery. A review conducted by Deshmukh and Chaudhari (2011) shows that net price, quality and delivery appear in 90%, 86% and 76% of published articles, respectively. Net price, quality and delivery were found to be the top three of all criteria for supplier selection (Weber et al., 1991). Weber et al. (1991) ranked production facilities and capacity as the fourth most popular criteria for supplier selection. A recent study conducted by Ho et al. (2010) shows that 87% of papers consider quality for supplier selection, 82% consider delivery including due date compliance, delivery efficiency, on time delivery, and delivery delays etc., and 81% consider price/cost which means component price and ordering cost. Ho et al. (2010) concluded that the most popular criteria were quality, delivery and price/cost, followed by other criteria such as manufacturing capability, and research and development.

Quite a few journal articles have described literature reviews of supplier selection methods (De Boer et al. 2001; Deshmukh & Chaudhari, 2011; Ho et al., 2010). Some papers discuss the supplier selection from management accounting or product strategy perspectives. Degraeve et al. (2000) reviewed the supplier selection criteria from the perspective of the total cost of ownership (TCO). Aksoy and Ozturk (2011) proposed a methodology for supplier selection under the Just-in-Time (JIT) production environments.

Supplier selection problem can be formulated as various mathematical programming models. Linear weighting models have been used commonly in which a weight is assigned to each criterion then a total score can be obtained for each supplier by summing up the scores and each criterion. A larger weighting is given to the criterion which is treated as more important. Talluri and Narasimhan (2003) developed linear programming models to consider the performance variability in supplier selection. Ng (2008) suggested a weighted liner programming model to maximize the supplier score. Other types of mathematical programming for supplier selection such as integer linear programming (Talluri, 2002), integer non-linear programming (Ghodsypour & O'Brien, 2001), goal programming (GP) (Karpak et al. 2001), and multi-objective programming (Narasimhan et al. 2006; Wadhwa & Ravindran, 2007) have also been found.

Data envelopment analysis (DEA) has been applied on supplier selection and evaluation (Braglia & Petroni, 2000; Garfamy, 2006; Liu, Ding, & Lall, 2000; Narasimhan et al. 2001). Weber et al. (2000) developed an integrated DEA and multi-objective programming approach to optimize order quantity. Talluri et al. (2008) also employed an integrated DEA and multi-objective programming to select potential suppliers.

Barla (2003) applied the simple multi-attribute rating technique (SMART) to solve supplier evaluation and selection problem. They discussed seven criteria for supplier selection. Seydel (2005) employed an integrated

DEA and SMART approach to evaluate suppliers. Huang and Keska (2007) summarized 101 metrics from the previous literature for supplier selection. They classified the metrics into six types; reliability, responsiveness, flexibility, cost and financial assets, and infrastructure, and safety and environment.

Chan (2003) developed a model for supplier selection based on the analytic hierarchy process (AHP). The model can be used to decide supplier selection criteria regardless of the human being's subjective decision. Chan et al. (2007) applied fuzzy extended AHP for supplier selection. Some studies integrated AHP with DEA to select suppliers (Farzipoor Saen, 2007; Sevkli et al. 2007), and mathematical modeling with AHP for supplier selection. Kull and Talluri (2008) proposed an integrated model to perform optimal supplier selection. In their model, AHP was employed to evaluate the risk scores of suppliers and a GP model was formulated based on risk target to evaluate suppliers.

Artificial intelligence has been used for supplier selection. Chen et al. (2006) proposed a fuzzy-sets based model to evaluate the suppliers. The ratings and weights are described by linguistic values. Thus, the model can be used for supplier selection based on quantitative and qualitative criteria. Chan and Kumar (2007) proposed an approach integrating AHP and fuzzy sets theory for selecting the best suppliers. Bottani and Rizzi (2008) employed AHP, fuzzy logic and cluster analysis to reduce the number of alternative suppliers and to enable the most suitable cluster of suppliers to be chosen. Ding et al. (2005) developed a GA based approach to supplier selection. In their approach, configurations of selected suppliers were provided and evaluated based on key performance indicators. Liao and Rittscher (2007) employed GA integrating with a stochastic demand model for optimal supplier selection.

From the literature, it can be seen that DEA, mathematical programming, AHP, fuzzy set theory, SMART and GA have been applied commonly on supplier selection. These approaches have been used individually or applied by integrating with other approaches for optimal supplier selection. Quantitative and qualitative data of suppliers can be handled by the approaches. On the other hand, it can be seen that quality, price and delivery are the most popular criteria for supplier selection.

2.4 New Product Development & Supply Chain Issues

A concept of "design for supply chain" has been proposed in the last decades (Lee, 1993). The term ''supply chain'' includes not only the manufacturer and suppliers, but also includes transporters, warehouses, retailers, and even customers in fulfilling customer requirements (Chopra & Meindl, 2007). Successful supply chain management relies on effective management of assets and products, information, and cash flow to maximize total profit along the supply chain (Chandra & Grabis, 2007).

Lee and Sasser (1995) first proposed and exemplified the idea of design for a supply chain management approach based on an HP case study. They discussed and compared a universal module design scheme with a regionally distributed one to meet the power supply requirements in different continents of the world. Finally, they considered trans-shipment cost, inventory cost and rework cost in the design stage. It was concluded that the cost benefit of the universal module scheme was significant due to the lower inventory investment; easier balanced stocks and more savings in re-work. Zhang et al. (1997) developed a computational model for integrating product design with supply chain issues. A more quantitative model of the integrated problem was proposed by Chu et al. (2000). Guerra and Zhang (2001) studied the issue of supplier selection and its impact on product development. A similar study was also conducted by Chu et al. (2002).

2.5 Early Supplier Involvement in Product Design

Early supplier involvement (ESI) is denoted as a form of vertical co-operation in which suppliers participate in the product concept generation, design and even development/innovation processes of manufacturers at early stage (Bidault et al. 1998). ESI adoption is divided into five levels which range from the level at which suppliers share the production information to the level where they join fully in the process from product concept generation to manufacturing. Surveys were conducted among 25 firms to investigate the ESI adoption practice (Bidault et al. 1998). Statistical analysis results show that there is no linear correlation between the parts volume ordered and the level of ESI.

Most of the empirical studies were conducted to investigate the benefits of ESI. Hartley et al. (1997) investigated 79 US small-to-medium companies and found that ESI was useful to improve product launch by reducing lead time. Ragatz et al. (1997) investigated environmental factors and management practice in integrating suppliers with new product development (NPD). Twelve management practices were found including supplier membership/participation in a purchasing company's project team, direct cross-functional intercompany communication, shared education and training, common and linked information systems (Electronic data interchange, E-mail, CAD/CAM), co-location of buyer/supplier personnel, technology sharing, formal trust development, technology information sharing, shared physical assets, formalized risk or reward sharing agreement, and joint agreement on performance measurements. Four environmental factors were found as significant differentiators. Two of the four differentiators, the strength of the supplying firm's top management commitment to their involvement and the strength of the buying firm's top management commitment to supplier integration, are the highest rated factors for successful ESI. The other two significant differentiators, familiarity with the supplier's capabilities prior to integration in the project and strength of consensus that the right supplier was selected, are the key factors that help suppliers to be involved actively in the product development process. McGinnis and Vallopra (1999) concluded that closer cooperation and coordination, new product development team roles and the technologies offered by suppliers are crucial factors for new product success with supplier involvement. McIvor and Humphreys (2004) conducted a survey on the multiple suppliers of electronic companies. They found that ESI should be addressed seriously in the product development process. Later, another investigation of 17 enterprises in the US and Japan showed that the product development process with ESI could lead to salient benefits (Pertersen et al. 2005). Parker et al. (2008) explored contingency factors to assess the levels of supplier integration. The results of their research suggested that the development of products with high degrees of newness should require earlier supplier integration.

Some conceptual models for ESI can be found in the literature. Handfield et al. (1999) stated that understanding supplier capacity and capability is not enough. Supplier assessment of the roadmap and technical expertise are also necessary. Ragatz et al. (2002) formulated a model for ESI process management and mentioned that the impact of an uncertain high technical environment can be alleviated by a closer relationship with suppliers. They claimed that cost saving, cycle time and quality improvement are salient. Petersen et al. (2005) conceptualized the “White box”, “Grey box” and “Black box” to describe the level of responsibility of supplier integration. “Black box” means that suppliers are involved in the design project mainly according to the buyer’s specification; “Gray box’ stands for design cooperation between supplier and buyer. The ‘‘Black-box’’ and ‘‘Grey-box’’ and their effects on innovation and product quality were examined by Koufteros et al. (2007).

Huang and Mak (2003) built an interface to facilitate the ESI. A customer-supplier partnership model was developed with four kinds of indices including satisfaction index (SI), flexibility index (FI), risk index and confidence index (CI). SI, FI and CI were adopted to evaluate the match or mismatch between customer requirements and supplier competency.

Jiao and Helander (2006) proposed a generic web-based product family master model to synthesize the product design, manufacturing operations and supply chain management issues. The online platform coordinates the parties of customers, research and development (R&D) teams, manufacturing units and suppliers simultaneously. Mikkola and Juliana (2006) investigated the implications of ESI in a new product development process for a hearing aid equipment manufacturer. Based on their study, they summarized that dual sourcing helped the company to reduce the sourcing risk and shorten the time-to-market of new products.

2.6 Product Line/Family Design & Supply Chain Issues

Compared with single product design with consideration of supply chain issue, the product line/family design with consideration of supply chain issues are more complicated. One of the reasons is that the number of product variants to be offered in a product line/ family is a decision variable, which largely affects the profit, market share, and development cost of the product line/family. Cannibalization of market share among product variants often happens. Any configuration change of a product variant would lead to the change of market share of the other product variants. Consequently, the total market share of the product line/family would change as well. On the other hand, parts of the design and manufacture of the product variants could be in common. Thus, the total cost of a product line/family cannot be treated as an aggregation of costs of individual product variants. Consideration of supply chain issues in product line/family design further increases the complexity of product line/family design problem. Supply chain issues of product line/families basically can be categorized into five types; sourcing/out-sourcing, decoupling/postponement, resource allocation, supply chain configuration and supplier integration/selection. A review of the research of each type is described below.

2.6.1 Product Line/Family Design and Resource Allocation

Chong et al. (1998) described that inventory cost and production volume could be high due to the complexity of product families and diversified components, and it was a difficult task to allocate appropriate resources in different manufacturing sites. Ng and Jiao (2004) developed a concept which was named the factory loading allocation problem (FLAP) to assist in optimizing loading sites. FLAP mimics the interrelationships among markets, product families, multi-tier suppliers and production volume. Jiao et al. (2009) continued to develop the concept of FLAP in which product, process and supply chain coordination were formulated as a factory loading allocation problem from a constraint satisfaction perspective. A domain based model was also proposed for the conceptualization of a multi-site manufacturing supply chain with various constraints.

Xu and Jiao (2009) applied timed colored Petri nets to model the generic product family design process. They mentioned that tasks, actors and resources could be controlled better compared to previous research which could not well represent the design process accounting for a proliferation of product variants.

2.6.2 Product Line/Family Design and Postponement

Alderson (1950) first proposed the concept of postponement and declared that the idea could be used as a cost saving application. Zinn and Bowersox (1988) defined five types of postponement: time postponement, labeling postponement, assembly postponement, packaging postponement and manufacturing postponement. Postponement can be integrated into product modularity and commonality design (van Hoek, 2001).

Garg and Tang (1997) analyzed the impact of earlier and late postponement for product families which have more than one point of differentiation under centralized inventory control and decentralized inventory policy. Based on the IBM mid-ranged computer product families, Lin et al. (2000) indicated that substantial cost savings on inventory could be achieved and computer hardware complexity could be reduced. Swaminathan and Lee (2003) revealed that the five types of postponement, which were affected by market factors, process factors and product factors, cause distinct expenses and advantages. The postponement concept was applied in product design process. Successful product postponement can gain benefits from better product architecture, product variety, commonality and components standardization. Su et al. (2005) compared time postponement with form postponement for providing diverse choices of products in cost-oriented and customer-oriented waiting time perspectives. The delaying product differentiation with a consideration of inventory systems, was analyzed from the cost and benefit perspectives (Lee & Tang, 1997).

2.6.3 Simultaneous Design of Product Line/Family and Supply Chain Configuration

Chandra and Grabis (2007) summarized supply chain configuration as a high level supply chain management (SCM) problem. Supply chain network design is a core issue of supply chain configuration problems. It is concerned with logistic design, purchasing, sales and distribution. This section reviews the research concerning product line/family design integrated with supply chain configuration.

A decision model was developed by Park (2001) to determine global product strategy and global supply chain configuration. They considered both candidate suppliers, and manufacturing sites and their capacities. The suppliers were treated as subsidiaries of an enterprise. The model integrated the variety of platforms with the consideration of supply chain configuration from the product lifecycle perspective. However, inventory cost was not considered in their model. Thonemann and Bradley (2002) studied optimal product variety with the consideration of supply chain performance. Kim et al. (2002) developed a mathematical model regarding the capacity limitation of manufacturers and component suppliers to configure a supply network of multiple products. Choi and Hong (2002) classified supply chains into three dimensions; formalization, centralization and complexity. They suggested that the three dimensions affected each other progressively. First-tier suppliers were conjectured to play an important role in product design and second-tier supplier selection. Doran (2003) investigated the impact of product variety on supply chain performance and manufacturer's lead time. Fine et al. (2005) addressed the integration issue considering product, process, and supply chain design. Supply chains, which are similar to product architecture, can be classified into two types; integral and modular. Fine et al. (2005) inferred that integral products would ideally be produced by integral supply chains, while modular products could be constituted by modular supply chains. Lamothe et al. (2006) presented a two-step approach to design a product family and supply chain. The variants of a product family and its generic bills of materials were established first. Then, supply chain and product variants were selected to reach the minimum total cost. A mixed integer linear programming (MILP) model was applied on the simultaneous product family and supply chain design. The wiring harness system of a car was used to illustrate the model. Huang et al. (2007) proposed an approach based on game theory to deal with the problem of integrating product design with supply chain configuration. Manufacturers and suppliers were both considered in the supply chain. Qian (2008) examined the impact of sale price decision of a product family in a price-dependent environment. The performance of the supply chain could be affected significantly by the sale price of product variants. Customers, retailers and manufacturers could all benefit from component commonality which leads to lower cost and quantity discount of common parts. Yadav et al. (2008) tried to optimize the profit of a product family and the cost generated from the supply chain. Market diversity, location and capacities of plants and shipping channels were considered in their research. The authors pointed out that the proposed methodology could help to reach a compromise between production cost and product variety before the final decision stage. A case study on the wiring harness supplier of an Automated Guided Vehicle was conducted to design a product family and its supply chain. Khalaf et al. (2009) presented a new model which considers product family design, process design and supply chain design simultaneously. Two approaches were compared in their study, the two-phase approach and the integrated approach. The authors pointed out that when production cost was higher than assembly costs, the integrated approach was preferred. The two-phase approach, which considers nearby facility assembly in the first phase and distant-facility production in the second phase, was found to be much better for solving complex problems. Khalaf et al. (2011) investigated module selection for a product family with minimum cost in view of manufacturing and logistics. Benefits and shortcomings of the personalization strategy versus the standardization strategy were evaluated. They reported that the benefits of standardization strategy and personalization strategy would change if the fixed cost and variable cost changed.

2.6.4 Product Line/Family Design and Strategic Sourcing Decisions

Product design and strategic sourcing decisions are treated as the most arduous and critical in multinational manufacturing companies. Novak and Eppinger (2001) investigated the relationship between product complexity and sourcing decisions in the auto industry. A simulation was employed to evaluate the performance resulting from integrating product design with sourcing decisions (Love et al. 2003). Love at al. (2003) developed a holistic approach to examine this integration which considered both manufacturing capability and capacity.

Salvador et al. (2002) analyzed six industrial product families in different industries from the operations management perspective. They indicated that the complexity of the product modularity affected the sourcing decisions. Huang et al. (2005) synthesized three aspects, platform product, manufacturing process and supply sourcing decision, to devise effective and optimal supply chain systems. A mathematical model was built to identify the impact of commonality on product families.

2.6.5 Integrated product line/family design and supplier selection

Some previous studies proposed mathematical models to integrate product line/family design with supplier selection. The models mainly aimed at minimizing the cost of product family development. Gupta & Krishnan (1999) proposed an integer-programming model and a decision support methodology to solve the problem of integrated component design and supplier selection. Their objectives were to minimize design cost and procurement cost. In their work, the cost of components includes fixed cost and variable cost. Design cost, prototyping cost and testing cost were treated as fixed cost. The variable cost was the quoted price of the components to be provided by suppliers. Before the integration, the components which are served as equivalent functions were clustered into a replaceable component set (RCS).

Balakrishnan and Chakravarty (2008) proposed a mathematical model considering product design and supplier selection for OEM companies. From the cost aspect, they considered the cost for supplier development and supplier relationship maintenance. They assumed the fixed cost was the same for each supplier and mentioned that the quantity discount provided by the supplier could probably affect the supplier selection process. In their research, the proposed model was used to trade off the focused vendors (which can provide single or several kinds of parts but possibly with lower unit price in mass production) and general vendors (which can provide variety of components) for identifying an sourcing strategy regarding discount issues of component price. Four factors related to model selection were identified; discount factor, completion ratio, number of product models and supplier fixed cost. ANOVA analysis was conducted to compare the total profit balance when the four factors fluctuated.

As customer needs for products are dynamic and uncertain, product architectures should be varied to meet the changes. Thus, the supplier selection is required to be robust. Tenneti and Allada (2008) defined the robustness of suppliers as a set of suppliers with minimum total supplier acquisition cost. Supplier acquisition cost was explained as the cost generated by acquiring and storing products from a particular supplier. This consisted of ordering cost, delivering cost, products storing fees, cost related to supplier performance check and the cost for supplier coordination and communication. In order to address this issue, the authors identified the most ideal set of suppliers that could meet the minimum requirements. They considered the solution from three aspects. First, a module was formulated according to the extent of customer satisfaction and satisfaction rating was used in the mathematical computation. Second, Taguchi's quality loss was introduced for quality loss calculation when a specification was unable to meet. Third, a cost module was developed to take into account the suppliers switch-over cost.

Luo et al. (2011) developed a model to decide a product family configuration, component supplier selection and product price for target markets. This model aims to achieve maximum profit. They also developed an optimization model for minimizing the ordering cost and procurement cost of selected suppliers. Part-worth utility from conjoint analysis was determined to evaluate the utility surplus of a product and the product with maximum utility surplus value was chosen. A genetic algorithm was applied to find the optimal solution.

2.6.6 Mathematical Modeling and Algorithms for Product Design and Supply Chain Issues

Various algorithms have been adopted to solve the optimization problems that relate to the joint decision making of product design and supplier chain issues. They mainly involve genetic algorithms and multi-objective optimization techniques.

(a) Genetic algorithms

Huang et al. (2005) applied a heuristic method, which involves genetic algorithms, to determine an integrated configuration of platform products, manufacturing processes and supply chains. Huang et al. (2007) combined genetic programming and genetic algorithms to tackle the structural and parametric optimization problems in product customization. Li et al. (2008) used tandem evolutionary algorithms (EAs) to solve a similar problem. A cooperative co-evolutionary algorithm was introduced to optimize product platform by Huang et al. (2007).

Product configuration is kept variable to meet the rapid changing market needs and improve the quality, value and service level of products. Wang and Che (2007) developed a mathematical model which aims to minimize the component cost and select suppliers based on supplier quotation and quality data. Fuzzy theory was employed to quantify the related data. The fuzzy data of the original selection criterion was transferred to single values. Genetic algorithms were adopted to search for a near-optimal solution of the problem. The integrated model can be used to solve the problem of changeable product configuration with minimum cost. Linear programming was used to verify that the optimal solution obtained from their proposed methodology was reliable.

(b) Multi-objective optimization techniques

Fonseca and Fleming (1995) defined the objectives of a multi-objective optimization problem as Pareto optimal and conflicting, and explained that the objectives cannot all be improved concurrently. Recently, Evolutionary Algorithms (EAs) have been used to solve multi-objective optimization problems relating to product line/family and supply chain. The solutions for multi-objective optimization problems can be obtained from a Pareto front based on a multi-objective genetic algorithm.

There are various types of multi-objective genetic algorithms. Schaffer (1984) proposed one that was called the Vector Evaluated Genetic Algorithm (VEGA). It treats each objective separately and realizes biased Pareto-optimal Solutions. Goldberg (1989) first introduced the notion of the non-dominated sorting, and the non-dominated sorting genetic algorithm (NSGA) was proposed by Srinivas and Deb (1994). Crossover and mutation operators of NSGA are similar to a typical genetic algorithm, but the difference lies in the work patterns of the selection operator. The authors compared the performance between NSGA and VEGA. They commented that NSGA performed better in terms of Pareto frontier findings. Later, a systematic empirical study conducted by Zitzler et al. (2000), and multi-objective evolutionary algorithms (MOEAs) were proposed. The study found that the Strength Pareto Evolutionary Algorithm (SPEA) and NSGA outperformed the other MOEAs such as VEGA, Hajela and Lin's weighted-sum based approach (HLGA), and the Niched Pareto Genetic Algotithm (NPGA) (Horn et al. 1994). NSGA-II, a new version of NSGA, was developed to overcome the NSGA shortcomings including the complex non-dominated sorting complexity, elitism missing and non-specified sharing parameter (Deb et al. 2002). The performances of elitist MOEAs such as

NSGA II, Pareto-archived evolution strategy (PAES) and SPEA were compared. The results indicated that NSGA II (Deb et al. 2002) can be closer to true front and have better diversity preserving mechanism compared with PAES and SPEA.

NSGA II has been attempted in optimizing product line/family design. D'souza and Simpson (2003) employed NSGA II to perform a trade-off between the commonality of product family and the desired performance of individual product variants. With the same optimization approach, Simpson and D'Souza (2004) introduced NSGAII to optimize product platform and products design with variable levels of platform commonality. Huang et al. (2008) studied the multi-level commonality for product family design with individual product performance. NSGA II was introduced to solve the problem. Li and Huang (2009) formulated a multi-objective model to simultaneously optimize the design of product variants and balance the commonality and differentiability in a product family. NSGA II was employed in their proposed multi-objective optimization methodology. Product family design problems in the above studies are treated as a one-stage approach. Wei et al. (2009) proposed a two-stage product platform design approach in which the product platform was identified by NSGA II in the first stage and product members on the platform were determined in the second stage. Anagnostopoulos and Mamanis (2010) formulated a tri-objective optimization problem involving the portfolio risk, expected returns and quantity of securities. The problem was solved by NSGA II.

An application of other bio-inspired heuristics for multi-objective optimization in product line/family design has been attempted. One of these is Particle Swarm Optimization (PSO). PSO has been attracting interest from many researchers for multi-objective optimization (Coello et al.2004; Coello 2006; Coello2002; Fieldsend & Singh, 2002). It imitates the concepts of birds dancing in a swarm, and makes the individual particle to store the best solutions and keeps the non-dominated solutions from the past. Interactive particle swarm optimization (IPSO) was first proposed for multi-objective particle swarm optimization (MOPSO) by Coello et al. (2004). Yadav et al (2008) formulated a multi-objective optimization model which aims to maximize profit and minimize the cost of the supply chain while keeping market diversity. Another one is Ant Clony Optimization (ACO). Tenneti and Allada (2008) applied ACO to solve a multi-objective optimization model that considers robust supplier selection and product architecture. A cell phone product family was used to evaluate the methodology. The results shows that the ACO approach to robust supplier selection can yield better results compared with the traditional supplier selection methods.

2.7 Discussion

Several studies of product design have taken supply chain design into consideration. The research works mainly integrated supply chain design with product design to minimize product costs. From the literature review, it can be noted that a number of previous studies are about product line/family design with the consideration of supply chain. However, very few previous studies can be found which are to integrate of product line design with supplier selection. In those previous studies of integrated product line design and supplier selection, some deficiencies of them can be observed. Firstly, the prices of product variants in the previous studies are commonly pre-defined. In fact, the prices need to be varied in order to determine optimal product line design solutions. Secondly, only one objective was addressed in the previous studies of the integrated problem. However, companies quite often consider several objectives in the determination of integrated supplier selection and product line design solutions. Finally, in the previous studies, although specifications of various product variants to be offered under a product line can be obtained, positions of the product variants in a competitive market are unclear.

Chapter 3 Methodology

In this chapter, a new methodology for integrating supplier selection with product line design is described which is able to make up the deficiencies of the previous works as mentioned in Section 2.7. Figure 1 shows an overview of the proposed methodology. First, a market survey is conducted to understand customers' preferences and their perceptions of competitive products. The survey results are then used to generate a joint space map. Based on this joint space map, a market share model is developed. On the other hand, it is necessary to develop a product quality model, product performance model and product cost model. The next step is to define objective functions and constraints for the integrated problem. After doing that, a multi-objective optimization model for integrating supplier selection with product line design is formulated. Once the component information including the component quality assessment score, component performance score and component cost is put, the optimization problem can be solved by NSGA II. After the solving, product line design solutions and selected suppliers for individual components are obtained. Details of the methodology are provided in Sections 3.1 to 3.3.

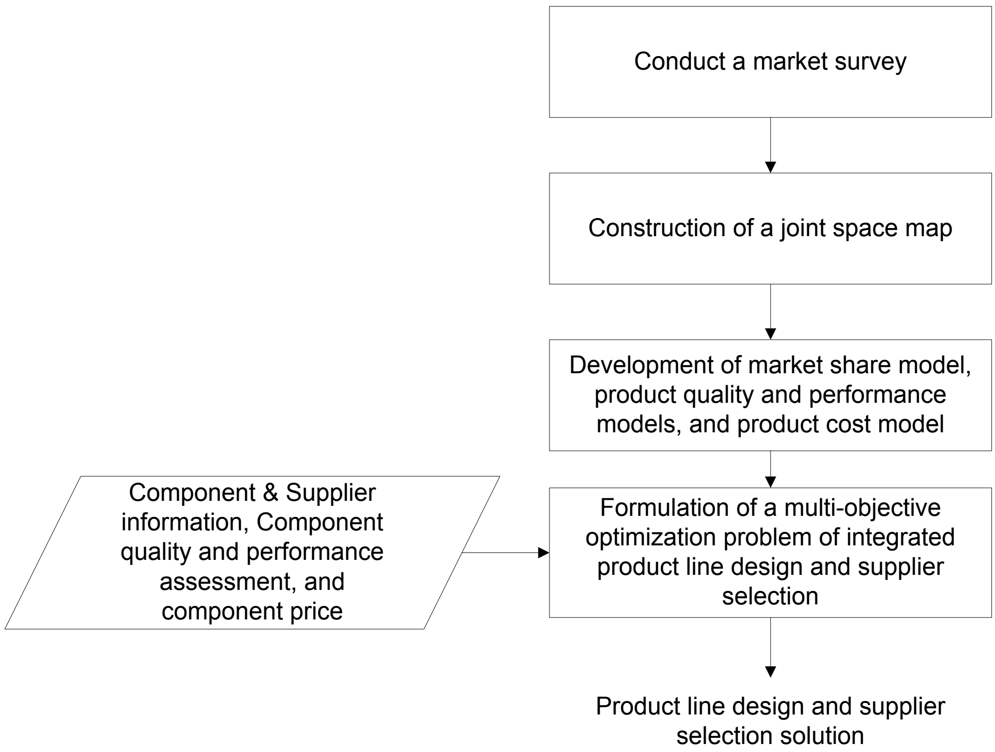

Figure 3.1 Overview of the proposed methodology

3.1 Conducting of a Market Survey

In this research, it is necessary to conduct a market survey in order to understand customer preferences and their perceptions on competitive products. A survey using questionnaires is a common tool in marketing research and was adopted in this research. The questionnaire contains a list of attributes of a particular product and customers are asked to indicate their preferences for these attributes. The customer preference information to be collected is in the form of a quantitative measure which is based on attitude scale. In addition, the questionnaire contains various types of information about competitive products including product specifications and price. Customers are asked to rate the competitive products corresponding to individual attributes.

3.2 Construction of a Joint Space Map

To build a joint space map, it is necessary to generate a perceptual map and a cluster map first. Then, the joint space map can be constructed by overlaying the perceptual map and the cluster map.

Once the survey data is obtained, factor analysis can be conducted to reduce the number of attributes to a few factors that can be adopted as the axes of perceptual maps. Usually, two primary factors are selected to generate a two dimensional perceptual map. Figure 3.2 shows an example of a perceptual map with positions of competitive products (Brand A, Brand B, Brand C and Brand D). The "Gap1" and "Gap2" shown in the perceptual map indicate that there may be possible areas for new product development.

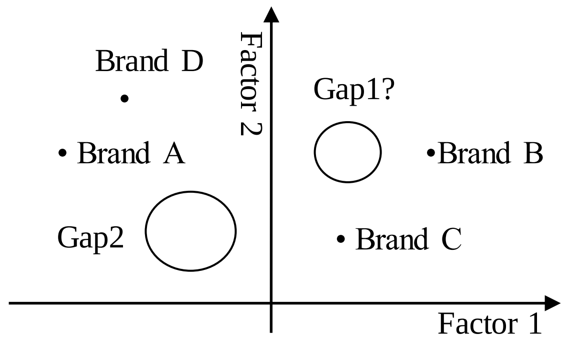

Figure 3.2 Perceptual Map

Different customers may have different preferences for product attributes. Hence, benefit segments based on survey results with regard to customer preference can be generated by cluster analysis techniques. Figure 3.3 shows an example of a cluster map where three benefit segments are formed. The "×" as shown in the figure refers to a particular customer preference for a product.

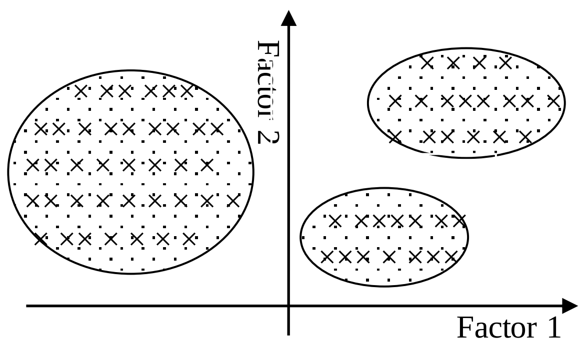

Figure 3.3 Cluster Map

A joint space map can be generated by overlaying the perceptual map onto the cluster map. Figure 3.4 shows an example of a joint space map. For each segment, an ideal point marked as '☆' in the figure can be determined which refers to an ideal brand or the most preferred brand of the corresponding segment. The market chances estimated by the various brands are proportioned inversely to the square of the distance of that brand from the ideal point.

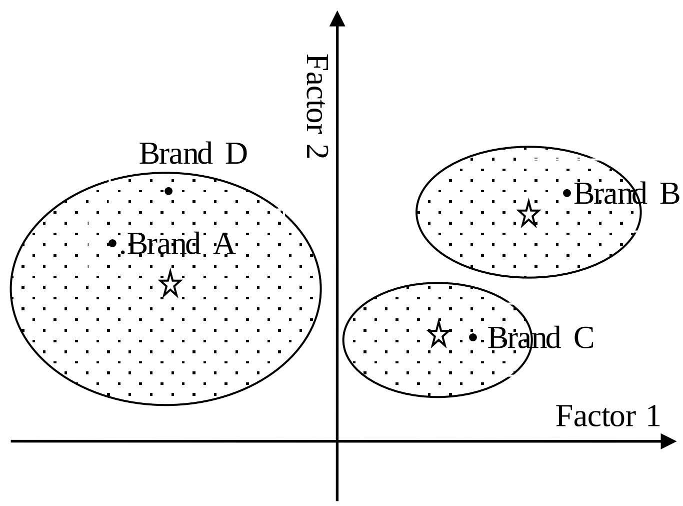

Figure 3.4 Joint space map

3.3 Mathematical Model Formulation

This section presents the development of various models such as the revenue model, market share model, product quality and performance models, and cost model for product line design. In addition, the formulation of objective functions is presented.

3.3.1 Revenue Models of Product Lines

Revenue models of product lines are used to estimate company income obtained from a product line. Joint space maps are required to develop the models. Referring to the example of a joint space map as shown in Figure 3.5, three segments can be formed. There are three competitive products denoted as A, B and C. A new product line is planned which contains three product variants denoted as x, y, z. The ideal points of each segment are denoted as ☆.

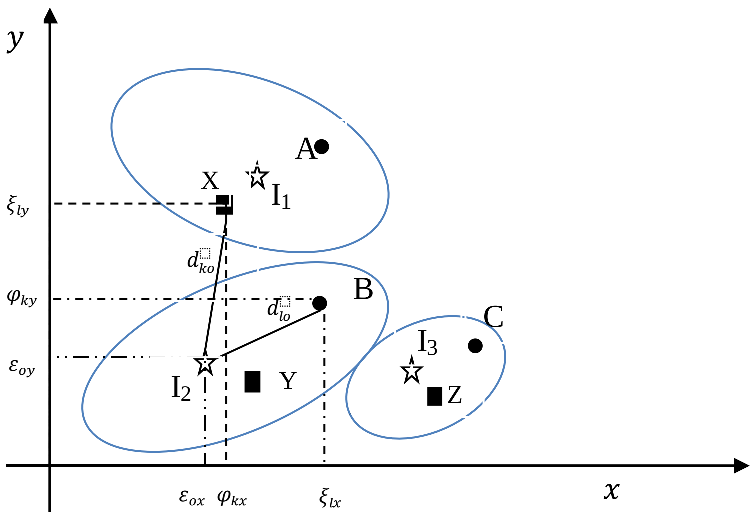

Figure 3.5 Revenue model based on a joint space map

Sales potential models are used to estimate sales volume in a particular market (Urban & Hauser, 1993). The sales potential of the *o*th market segment, S_o, is given as:

$$S_o = \vartheta_o N_o \tag{3.1}$$

where

o	oth market segments in joint space map $o \in O$
ϑ_o	Customer purchase probability in oth segment
N_o	The number of preference-homogeneous customers in the oth segments.

Market share is a measure of the preference of a customer segment for a product. After a factor analysis, factor scores can be obtained, and then the ideal product positions can be plotted on a joint space perceptual map. Each cluster stands for a segment with its own ideal product positioned in the segment in the joint space map (Crawford & Di Benedetto, 2008). According to the work of Pessemier (1982), a market share model can be formulated as the computation of the squared distance d from ideal points to each competitive or new product. Hence, the market share of kth product in the oth segment, ω_{ko}, can be described as:

$$\omega_{ko} = \frac{\frac{1}{d_{ko}^2}}{\sum_{k=1}^{K} \frac{1}{d_{ko}^2} + \sum_{l=1}^{L} \frac{1}{d_{lo}^2}} \tag{3.2}$$

where $k = 1,2,3, \dots, K;$

$o = 1,2,3, \dots, O\,;$

$l = 1,2,3, \dots, L$

I Set of replaceable components or modules, $i \in I$

K Set of the product variants in the product line, $k \in K$

l Competitive product l

o *o*th market segments in joint space map o∈O

d_{ko} Euclidean distance between the kth product to the ideal point of the *o*th segments in joint space map

d_{lo} Euclidean distance between the lth competitive product to the ideal point of the *o*th segments in joint space map

The Euclidean distance between products and ideal points can be represented as follows:

$$d_{ko} = \sqrt{(\varphi_k^x - \varepsilon_o^x)^2 + \left(\varphi_k^y - \varepsilon_o^y\right)^2}, \tag{3.3}$$

$$d_{lo} = \sqrt{(\xi_l^x - \varepsilon_o^x)^2 + \left(\xi_l^y - \varepsilon_o^y\right)^2}, \tag{3.4}$$

ε_o^x x coordinate of the ideal point of *o*th segments in a joint space map

ε_o^y y coordinate of the ideal point of *o*th product in a joint space map

φ_k^x x coordinate of the kth product in x axis of a joint space map.

φ_k^y y coordinate of the kth product in y axis of a joint space map

ξ_l^x x coordinate of the lth competitive product of a joint space map

ξ_l^y y coordinate of the lth competitive product of a joint space map

Therefore, the sales volume V of the kth product variant, V_k , can be formulated as follows:

$$V_k = \sum_{o=1}^{O} S_o \omega_{ko} \tag{3.5}$$

where

ω_{ok} Market share of the kth product in the oth segments.

S_o The sales potential of the oth segments.

V_k Sales volume of kth product

In the market survey, customer preferences for a product are collected with respect to various attributes of the product such as attractiveness, performance, and quality. After conducting factor analysis on the survey data, two factors can be obtained which will be involved to generate a joint space map. The two factors are presented in a form of the linear combination of the attributes. In this research, a pricing model was formulated with the use of the coefficient correlation matrix which was generated in factor analysis. Hence, the price P_k of kth product can be given as:

$$P_k = \frac{\varphi_k^f - \sum_{u=1}^{U} \beta_f^u A_k^u}{\beta_f^p} \tag{3.6}$$

For *f*=*x* or *y* in the 2D perceptual map

where

A_k^U Rating of the uth attribute rating of kth product

β_f^U Coefficient of *u*th attribute coefficient of *f*th factor

β_f^p Price coefficient of *f*th factor

φ_k^f Coordinates of the *k*th product in f axis in the joint space map

The coordinates of the *k*th product in f axis in the joint space map can be obtained and the P_k can be estimated using equation (3.6).

Therefore the revenue R of a product line can be formulated as

$$R = \sum_{k=1}^{K} P_k V_k \gamma_k \tag{3.7}$$

where

P_k Retail price of the *k*th product

γ_k The ratio of ex-factory price of the *k*th product and the retail price of the *k*th product

V_k Sales volume of *k*th product

From the equations (3.1) to (3.7), the following revenue model for a product line can be obtained.

$$\sum_{k=1}^{K}\left[\gamma_k\left(\frac{\varphi_k^f - \sum_{u=1}^{U}\beta_f^u A_k^u}{\beta_f^p}\right) \times \sum_{o=1}^{O}\frac{\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}}{\sum_{k=1}^{K}\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}+\sum_{l=1}^{L}\frac{1}{(\xi_l^x-\varepsilon_o^x)^2+(\xi_l^y-\varepsilon_o^y)^2}}S_o\right] \tag{3.8}$$

3.3.2 Cost models of product lines

The cost of a product line, C, can be divided into two parts, direct cost and indirect, and can be presented as follows.

$$C = C^{d} + C^{ind} \quad (3.9)$$

Where C^{d} is the direct cost of a product line and C^{ind} is the indirect cost that is difficult to connect with any one product (Magrab, 2010). Direct cost can be divided further into two parts, variable direct cost and fixed direct cost. Variable direct cost, $C^{d(var)}$, is the purchasing cost from suppliers. It changes with the ordering quantity of components. Fixed direct cost, $C^{d(fix)}$, includes the cost of product design, research & development, software development, prototypes making, licensing etc. (Magrab, 2010). It has no relationship with sourcing quantity. A model of Variable direct cost, $C^{d(var)}$, can be formulated as follows:

$$C^{d(var)} = \sum_{k=1}^{K} V_k \left[\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} E_{ijg} \alpha_{ijg} N_{igk} \right] \quad (3.10)$$

Where

k= 1,2,3, … , K;

g= 1,2,3, … , G ;

i = 1,2,3, … , I ;

j= 1,2,3, … , J

$$\alpha_{ijg} = \begin{cases} 1, \text{if ith component is selected from the jth supplier} \\ 0, \text{otherwise} \end{cases} \quad (3.11)$$

$$N_{igk} \geq 0, \text{ and integer} \quad (3.12)$$

Where

E_{ijg} the unit cost of gth component from jth supplier in ith RCS

α_{ijg} gth component is selected from jth supplier in ith RCS

N_{igk} Number of gth component to be provided by ith supplier of the kth product

V_k Sales volume of kth product

The fixed direct cost, $C^{d(fix)}$, can be described as follows:

$$C^{d(fix)} = \begin{cases} m_1 \ if \ k' = 1 \\ m_2 \ if \ k = 2, \\ \vdots \\ m_k \ if \ k = K, \end{cases} \quad (3.13)$$

Where $k= 1,2,3, \ldots , K;$

m_K Fixed cost of a product line which has k product variants

Therefore, the direct cost, C^d, can be expressed as:

$$C^{d(var)} = \sum_{k=1}^{K} V_k \left[\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} E_{ijg}\alpha_{ijg}N_{igk} \right] + m_K \quad (3.14)$$

On the other hand, the indirect cost can also be divided into two parts, variable indirect cost $C^{ind(var)}$and fixed indirect cost $C^{ind(fix)}$. The indirect variable cost, $C^{ind(var)}$, is referred to the cost associated with suppliers, such as the cost of partnership, negotiation, quality inspection and ordering. This can be described as:

$$C^{ind(var)} = \sum_{j=1}^{J} \mathrm{F_j} \vartheta_j \tag{3.15}$$

Where j= 1,2,3, … , J;

$$\vartheta_j = \begin{cases} 1, j\text{th supplier is selected} \\ 0, \text{otherwise} \end{cases} \tag{3.16}$$

Where

F_j Indirect variable cost of jth supplier

The indirect fixed cost, $C^{ind(fix)}$, refers to the cost associated with marketing and advertisement, facility maintenance and stock keeping.

3.3.3 Indicators of Product Configuration

In this research, product configuration is referred to a composition of pre-developed components/modules of a modular-designed product. Indicators of product configuration refer to the alternative that will be selected for the final product assembly.

$$H_k = \{G_1^k, G_2^k, G_3^k, \dots, G_i^k\} \tag{3.17}$$

Where *i=1,2,3….I; k=1,2,3,…,K;*

$G_i^k \geq 0$ and integer (3.18)

G_i^k gth alternative is selected in the ith RCS for kth product

H_k kth product configuration

3.3.4 Profit Model

Profit of a product line can be written as follows:

$$M = R - C \tag{3.19}$$

Based on (3.1) to (3.15) and (3.19), the equation (3.20) can be obtained

$$M = \sum_{k=1}^{K}\left\{\left(\gamma_k \frac{\varphi_k^f - \sum_{u=1}^{U}\beta_f^u A_k^u}{\beta_f^p} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{g=1}^{G} E_{ijg}\alpha_{ijg}N_{igk}\right)\left[\sum_{o=1}^{O}\frac{\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}}{\sum_{k=1}^{K}\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}+\sum_{l=1}^{L}\frac{1}{(\xi_l^x-\varepsilon_o^x)^2+(\xi_l^y-\varepsilon_o^y)^2}}S_o\right]\right\} - \sum_{j=1}^{J}\mathrm{F_j}\vartheta_j - m_K - C^{ind(fix)} \tag{3.20}$$

3.3.5 Product Quality and Performance Models

Supplier selection is not only based on the quoted price of the component cost but also needs to consider quality and performance of the components to be provided by the suppliers. In this research, the quality and performance of the components were considered in supplier selection. The quality volume of the kth product, U_k, can be determined using the following equation as:

$$U_k = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{g=1}^{G} u_{ik} Q_{ijg} \alpha_{ijg} \rho_{igk} \tag{3.21}$$

Where

$$\sum_{g=1}^{G} \rho_{igk} = 1 \tag{3.22}$$

$$\sum_{i=1}^{I} u_{ik} = 1 \tag{3.23}$$

$$u_{ik} \geq 0 \tag{3.24}$$

Where

u_{ik} Quality coefficient of the ith RCS of the kth product

ρ_{igk} Performance coefficient of the gth alternative in the ith RCS of the kth product

Q_{ijg} Quality value of the gth alternative of ith RCS in the kth product,

α_{ijg} gth component is selected from jth supplier in ith RCS

The quality value of a product line, U^T, can be determined using the following equation (Liao & Rittscher, 2007):

$$U^T = \sum_{k=1}^{K} U_k \tag{3.25}$$

Performance value of the product k, W_k can be calculated using the following equation:

$$W_k = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} \tau_{ik} D_{ijg} \alpha_{ijg} \rho_{igk} \tag{3.26}$$

Subject to

$$\sum_{i=1}^{I} \tau_{ik} = 1 \tag{3.27}$$

$$\tau_{ik} \geq 0 \tag{3.28}$$

Where

τ_{ik} Performance coefficient of ith RCS of the kth product

D_{ijg} Performance value of the gth alternative of ith RCS in the kth product

Performance value of a product line W^T can be calculated using the following equation.

$$W^T = \sum_{k=1}^{K} W_k \tag{3.29}$$

3.3.6 Formulation of Objective Functions

The objectives of the integrated product line design and supplier selection problem are to maximize the profit, quality and performance of a product line, and minimize its cost. Based on the equations mentioned in previous sections, three objective functions can be formulated as follows.

(a) Objective 1: Maximizing Profit

Based on (3.20), the objective function for maximizing profit of a product line, $FUNC1$, can be formulated as follows:

$$M = \sum_{k=1}^{K}\left\{\left(\gamma_k \frac{\varphi_k^f - \sum_{u=1}^{U}\beta_f^u A_k^u}{\beta_f^p} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{g=1}^{G} E_{ijg}\alpha_{ijg}N_{igk}\right)\left[\sum_{o=1}^{O}\frac{\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}}{\sum_{k=1}^{K}\frac{1}{(\varphi_k^x-\varepsilon_o^x)^2+(\varphi_k^y-\varepsilon_o^y)^2}+\sum_{l=1}^{L}\frac{1}{(\xi_l^x-\varepsilon_o^x)^2+(\xi_l^y-\varepsilon_o^y)^2}}S_o\right]\right\} - \sum_{j=1}^{J}\mathrm{F_j}\vartheta_j - m_K \tag{3.30}$$

(b) Objective 2: Maximizing Quality and Performance

The objective function for maximizing quality and performance of a product line, $FUNC2$, can be written as follows:

$$QP = \delta U^T + (1-\delta)W^T \tag{3.31}$$

Where $0 < \delta < 1$

Choice of the value of δ is dependent on whether the product line design is quality focus or performance focus. If the product line design is quality focus, the value of δ should be larger than 0.5.

Based on the equations (3.21) to (3.29) and (3.31),

FUNC2 can be rewritten as

$$QP = \delta \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} u_{ik} Q_{ijg} \alpha_{ijg} \rho_{igk} + (1-\delta) \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} \tau_{ik} D_{ijg} \alpha_{ijg} \rho_{igk} \tag{3.32}$$

(c) Objective 3: Minimizing Cost

Based on (3.10) to (3.14), the objective function for minimizing the cost of a product line, *FUNC3* can be formulated as follows:

$$C = \sum_{k=1}^{K} \left\{ \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{g=1}^{G} E_{ijg} \alpha_{ijg} N_{igk} \times \left[\sum_{o=1}^{O} \frac{\frac{1}{(\varphi_k^x - \varepsilon_o^x)^2 + (\varphi_k^y - \varepsilon_o^y)^2}}{\sum_{k=1}^{K} \frac{1}{(\varphi_k^x - \varepsilon_o^x)^2 + (\varphi_k^y - \varepsilon_o^y)^2} + \sum_{l=1}^{L} \frac{1}{(\xi_l^x - \varepsilon_o^x)^2 + (\xi_l^y - \varepsilon_o^y)^2}} S_o \right] \right\} + \sum_{j=1}^{J} \mathrm{F_j} \vartheta_j + m_K \tag{3.33}$$

3.3.7 Other Constraints

The following two constraints are necessary for the formulation of the multi-objective optimization model.

$$\vartheta_j = 1 \ \ if \sum_{i=1}^{J} \alpha_{ijg} > 0, \ \ otherwise \ \vartheta_j = 0 \tag{3.34}$$

$$When \ \alpha_{ijg} = 1, \qquad G_i = g \tag{3.35}$$

Constraint (3.34) is to ensure that the jth supplier is selected for components. Constraint (3.35) refers to the number of configuration indicators when the supplier of the *g*th alternative in the *i*th RCS is selected.

3.4 Solving the Optimization Problem Using NSGA II

After formulating an optimization model for the integrated supplier selection and product line design problem, NSGAII can be introduced to solve the optimization problem.

3.4.1 Main Procedures of NSGA II

When the NSGA II is implemented, four issues need to be considered; population size, generation, crossover probability and mutation probability. Figure 3.6 shows a flow chart of NSGA II.

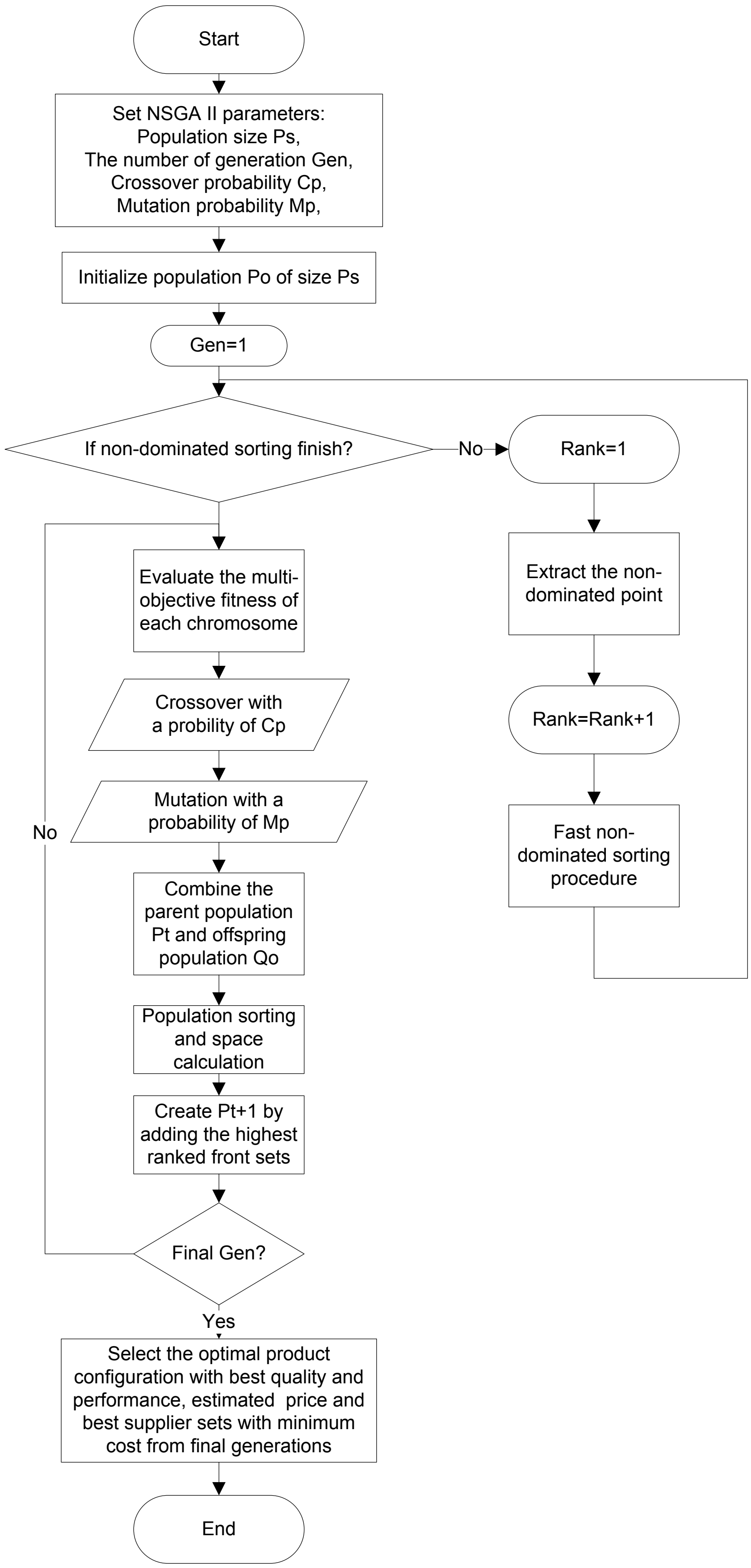

Figure 3.6 Flowchart of NSGA II

The main steps of NSGA II are described below:

S1. Generate a random parent population P_o of size P_s chromosomes. Set generation t=1.

S2. Evaluate the multi-objective fitness of each chromosome in the population which is sorted into different no-domination levels.

S3. Apply crossover probability C_p and mutation probability M_p to P_o to create offspring population Q_o of size P_s.

S4. If the stopping criterion is satisfied, stop and return to P_t.

S5. Combine parent and offspring population P_t and Q_t and set as R_t.

S6. Identify the non-dominated fronts f_1, f_2, $f_3 \ldots f_k$ in R_t based on the fast non-dominated sorting algorithm.

S7. For i=1,…k:, calculate crowding distance of the solutions in f_i , create P_{t+1} =Ø until $|P_{t+1}|+|f_i| \leq P_s$. , then set *i=i+1*

S8. Use binary tournament selection based on the crowding distance to select parents from P_{t+1}. Apply crossover and mutation to P_{t+1} to create offspring population Q_{t+1} of size P_s.

S9. Set *t =t+1*, and go to Step 4.

3.4.2 Fitness Functions

Since the three objective functions need not to be combined to become one single function, the three objective functions can be used directly as the three fitness functions respectively and no normalization process is required. Since, in this research, NSGA II is introduced to search for solutions with the minimum fitness values of the fitness functions, it is necessary to add a minus to the objective functions FUNC1 and FUNC2 for converting them into the fitness functions, FF1 and FF2, respectively. FUNC3 can be set directly as the fitness function for the objective 3, FF3.

3.4.3 Non-Dominated Sorting

The random population is ranked by non-domination sorting. For instance, if the *i*th objective functions in an individual is not worse than the other or at least in one of its objective functions, it is better than the others. This can be called non-dominated sorting (Deb et al. 2002).

3.4.4 Crowding Distance

Crowding distance is assigned to each individual after the non-dominated sorting finishes (Deb et al. 2002). Considering a series of non-dominated solutions, f_k, of the size of v, the algorithm of crowding distance is shown below:

For each t, let the crowding distance $H_t = 0$, *for t=1,2,3,...v*.

For each objective function f_k *ascending sort the set;*

Let H_t=H_v *be maximal* H_t=H_v =∞

i=2 to (v-1)

H_t=H_t+($f_{k_{i+1}} - f_{k_{i-1}}$)

3.4.5 Crowded-Comparison Operator

A crowded tournament comparison operator can be defined to compare the two individuals x and y. If the individual x has lower ranking, then the two individual $x \succ y$; Otherwise, non-dominated ranks r are equal. If the solution x has larger crowded distance compared with individual y, then $x \succ y$. The algorithm can be defined as follows.

If there two individual x, y $\ r_x < r_y$ *or* $r_x = r_y$ *and* $H_x > H_y$

then $x \succ y$

3.4.6 Chromosome Representation

Chromosome structure is set up for the variables of the objective functions, as illustrated in Figure 3.7. The structure can be divided into three parts: supplier decision variables, configuration variables, and price variables.

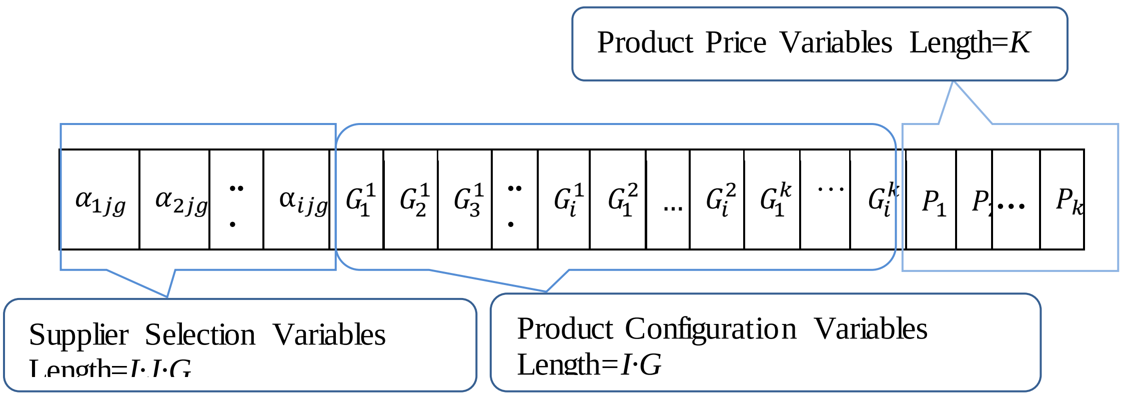

Figure 3.7 Chromosome Structure

3.4.7 Crossover and Mutation Operators

In Deb's (2002) research, real-coded NSGA-II was proved to search for better solutions compared with binary-coded NSGA II. In this research, real-coded NSGA II was adopted. Simulated Binary Crossover (SBX) (Beyer & Deb, 2001) and Polynomial mutation (Deb & Agrawal 1995) were applied to mutate the configuration of a product line.

3.4.8 Termination Condition

Deb (2002) suggested that value of generation could be the product of the number of objective functions, N_f and population size, P_s. i.e. $N_f P_s$. For some extreme cases, he recommended the number to be $N_f {P_s}^2$ or $N_f {P_s}^3$. NSGA II operations stop when the number of generations reaches a preset value.

Chapter 4 Implementation

In this chapter, the product line design of portable computers (PCs) is used to illustrate the applicability and effectiveness of the proposed methodology.

4.1 Market survey

The scenario presented in the market survey was that Company ABC would like to design a product line of PCs for a particular market. Six major competitive products of the market were identified, denoted as A, B, C, D, E and F. A market survey was conducted to understand consumer perception of the six major competitive products and their preferences regarding the purchase of a PC. In the survey, the interviewees were asked to fill out a questionnaire as shown in Appendix A. In addition, the specifications and image of the six major competitive products were provided to help the interviewees assess performance and attractiveness of the competitive products. In total, seventy valid, completed questionnaires were collected. In this research, only four attributes of PCs were studied; quality, performance, attractiveness and price.

4.2 Generation of Cluster map, Perceptual Map and Joint Space Map

In order to generate a cluster map, perceptual map and joint space map for the case, it is necessary to conduct a factor analysis first. Factor analysis is used as a statistical tool to reduce variables and generate new and non-correlated factors for understanding the structure of variables. It can keep the information in its original source as much as possible, yet make the information easy to deal with. In this research, SPSS 16 was used to carry out the factor analysis.

Table 4.1 shows the rotated factor matrix. From the matrix, it can be seen that Factor 1 is related more to quality and performance while Factor 2 is related more to attractiveness and price. The data sets obtained from the market survey were used to generate a cluster map and a perceptual map. K-means clustering method of SPSS software was used to perform the cluster analysis. Table B.4, as shown in Appendix B, shows the cluster centers. Figure 4.2 shows the cluster map generated by SPSS 16. From the Figure 4.2, it can be seen that three market segments, denoted as Seg1, Seg2, and Seg3, were generated. Segment 1 refers to the customers who expect their PCs to have medium to high quality and performance, but medium price. Segment 2 refers to the customers of the segment who do not have expectation on quality, performance, and attractiveness of their PCs, but low price. Segment 3 refers to the customers of the segment who expect their PCs to have good quality, performance and attractiveness. Table 4.2 shows the sales potential of individual market segments estimated by the marketing staff of the company.

Table 4.1 Rotated factor matrix

	Factor score	Factor 1 (*f=1*)	Factor 2 (*f*=2)
Quality	β_f^P	0.445	-0.032
Performance	β_f^u	0.577	-0.29
Attractiveness	β_f^A	-0.233	0.938
Price	β_f^P	0.3	0.237

Table 4.2 Sales potential in each segment

Segment	Segment 1	Segment 2	Segment 3	Total
Sales Potential	247759	447410	315111	1010280

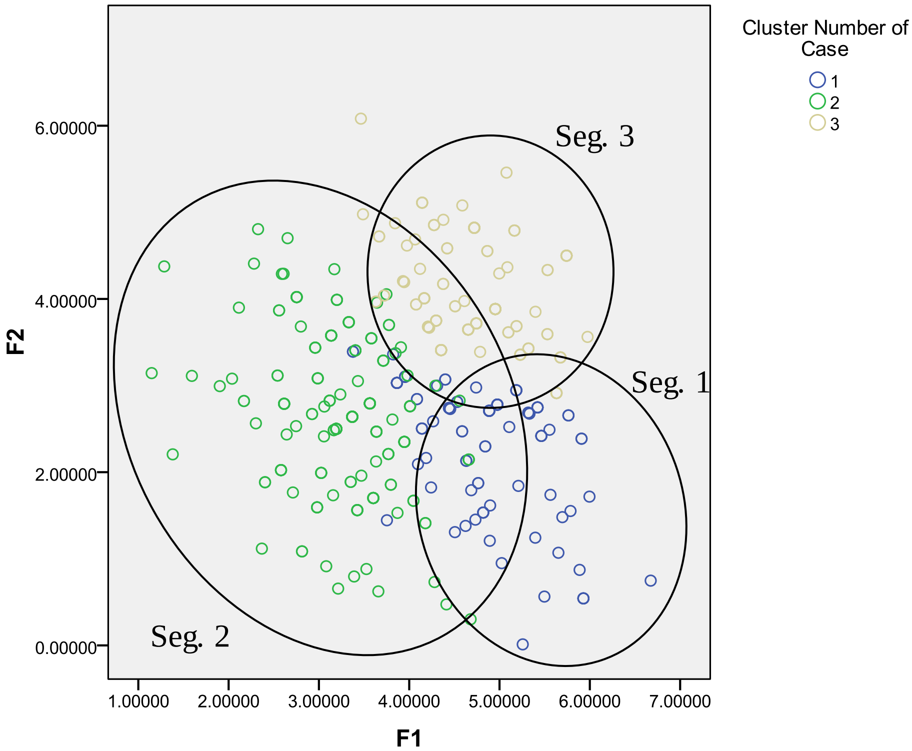

Figure 4.1 Cluster map

From the survey data, the average rating of each of the attributes of individual competitive products was calculated, as shown in Table 4.3. With the use of the factor analysis results, a perceptual map for PCs was generated as shown in Figure 4.2. The competitive structure of the PCs in the market as perceived by customers can be visualized on the perceptual map. It can be seen that the six competitive products can be cluster into four groups, in which the competitive products are quite similar in the customer perceptions. Competitive product A and C belong to the first group. Competitive product B belongs to the second group. E and D are in the third group, and F belongs to the last group. A and C are perceived by customers to be low-end products, F is perceived as a high-end products, and the others are perceived as medium-end products.

Table 4.3 Comparison of Products

Attractiveness Rating=AR Quality Rating=QR
Price Ranking=PR Performance Rating=PerR

Competitive Product	AR	QR	PR	PeR
A	2.87	3.16	2.75	2.96
B	3.22	3.36	3.99	3.06
C	2.80	2.81	3.34	3.01
D	3.45	3.9	4.99	3.97
E	3.32	3.72	5.29	3.67
F	4.03	4.13	5.99	3.94

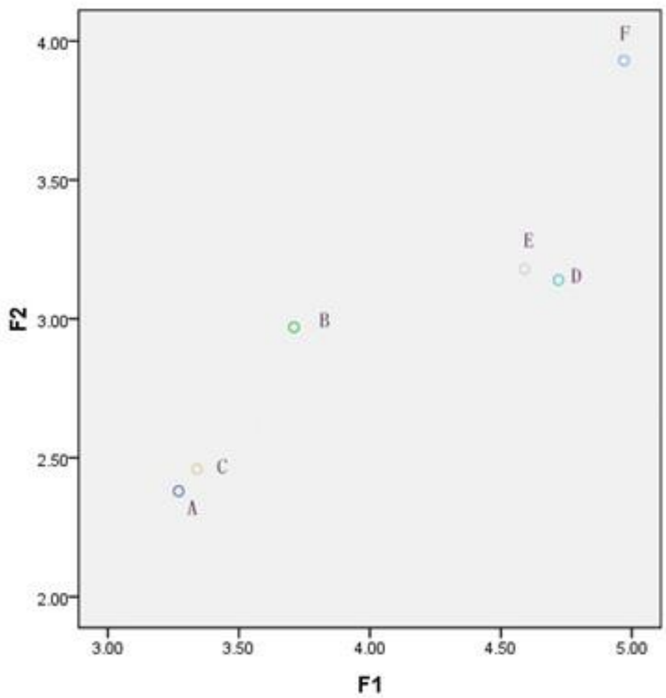

Figure 4.2 Perceptual map

A joint space map was obtained by overlaying the cluster map onto the perceptual map as shown in Figure 4.3. Competitive product A, B and C are close to the ideal point of segment 2 which contains the largest number of respondents. The competitive A, B, and C are targeted to the low-end market. E and D lie between the ideal points of segment 1 and segment 3. F is the only competitive product in the segment 3. In a given market segment, the position of a new product should be as close to the ideal point of the segment as possible in order to gain a larger market share.

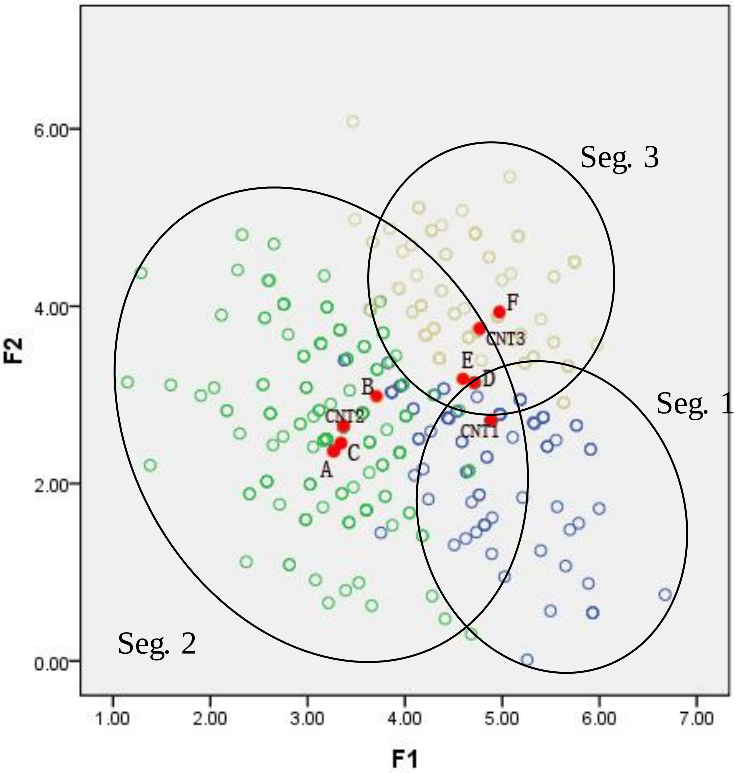

Figure 4.3 Joint space map for PCs

4.3 Product Variants

In the case study, the company needs to purchase components for the production of their new PCs. Since the components come from different suppliers with different qualitiies and performance, the components with identical functions are classified in the same replaceable component set (RCS). For example, the computing frequencies of CPU are 2.2 GHz, 2.4GHz and 2.66GHz; thus, 2.2GHz CPU, 2.4 GHz CPU, and 2.66 GHz CPU can be classified in the same RCS. In this case study, there are ten RCSs which are CPU (RCS1), RAM (RCS2), Chipset (RCS3), Hard disk (RCS4), Power supply unit (RCS5), GPU (RCS6), Mother Board (RCS7), Drive

(RCS8), Case (RCS9), Battery (RCS10). For each RCS, a set of components with the identical assembly interfaces is available from suppliers to satisfy customer needs in different market segments. The numbers of alternative components are shown in Table 4.4 in which it can be seen that the number of possible product variants is 6561. The power supply unit (RCS7), Mother Board (RCS8), Drive (RCS9) and Case (RCS10) are pre-defined so that they have no alternatives. The product variants will be chosen based on the consideration of profit, performance and cost of the product lines.

Table 4.4 Alternative components for PCs

	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
SOC	DC 2.2 GHz	200GB	4Cell	12	GPU9200	2GB (1G×2)
	DC 2.4 GHz	250GB	6cell	13	GPU9600	2GB (1G×2)
	DC 2.66 GHz	300GB	8cell	14	GPU9800	2GB (2G×1)
Alternatives	3	3	3	3	3	3
TNOPV	3×3×3×3×3×3=6561					
SOC= Specification of components DC=Dual Core TNOPV=Total number of product variants						

4.4 Performance and Quality Evaluation of Components

In the case study, the quality and performance of components to be provided by suppliers are evaluated by product development teams. The performance value of each alternative part in each RCS is shown in Table 4.5. As the of RCSs of Chipset, Power supply unit, Mother Board, Drive and Case do not have alternatives, their performance values are set as zeros, which means they are not considered in the performance comparison among product variants.

Table 4.5 Performance value of alternative component in each RCS

RCS	Alternative	Performance Value
CPU	Dual Core 2.2Ghz	3
	Dual Core 2.4Ghz	4
	Dual Core 2.66Ghz	5
RAM	2GB(1GB×2)	3
	2GB(2GB×1)	4
	4GB(2GB×2)	5
GPU	9200 with shared 794MB RAM	3
	9600 with discrete 256MB RAM	4
	9800 with discrete 512MB RAM	5
Hard Disk	200GB	3
	250GB	4
	300GB	5
Battery	4 cell	3
	6 Cell	4
	8 Cell	5
Chipset	12	3
	13	4
	14	5

Qualified suppliers were invited to submit quotations and information of components which will be provided by them. The product development team assessed the quality of the components based on the component information, track records of the components and team members' experience and knowledge. Table 4.6 shows the results of the quality assessment of the components that will be provided by suppliers. For example, supplier 1, S1, can provide a particular brand of dual core 2.2 GHz CPU. After the team assessment, the quality value of the component is 5. The quoted prices of the components can be converted into cost indexes as shown in Table 4.7.

The quality coefficient u_{ik} and performance coefficient τ_{ik} are set as shown in Table 4.8. Quality value and performance value of a product variant can be obtained based on the equations (3.21) and (3.26).

Table 4.6 Quality assessment of components

RCS	Q_{ijg}	Component	Quality assessment
C1	Q_{1j1}	Dual Core 2.2 GHz	S1=5 S2=3 S3=4
	Q_{1j2}	Dual Core 2.4 GHz	S1=5 S2=3 S3=4
	Q_{1j3}	Dual Core 2.66 GHz	S1=2 S2=3 S3=4
C2	Q_{2j1}	Hard Disk 200	S5=2 S6=3 S7=4 S8=5
	Q_{2j2}	Hard Disk 250	S5=3 S6=4 S7=4 S8=5
	Q_{2j3}	Hard Disk 320	S5=4 S6=4 S7=5 S8=6
C3	Q_{3jg}	Battery 4 cells	S7=5 S11=4 S12=3
		Battery 6 cells	S7=3 S11=4 S12=5
		Battery 8 cells	S7=5 S11=3 S12=4
C4	Q_{4jg}	Chipset 12	S5=3 S6=4 S7=5 S9=2
		Chipset 13	S5=3 S6=4 S7=5 S9=2
		Chipset 14	S5=3 S6=4 S7=5 S9=4
C5	Q_{5j1}	GPU 9200	S1=4 S2=3 S3=5 S4=2
	Q_{5j2}	GPU 9800	S1=5 S2=2 S3=4 S4=3
	Q_{5j3}	GPU 9800	S1=5 S2=2 S3=4 S4=3
C6	Q_{6j1}	RAM 2GB(1G×2)	S5=2 S6=5 S7=3 S8=4
	Q_{6j2}	RAM 2GB(2G×1)	S5=2 S6=5 S7=4 S8=3
	Q_{6j3}	RAM 4GB(2G×2)	S5=3 S6= S6=5 S7=4 S8=2
C7	Q_{7jg}	Power Supply Unit	S1=4 S2=2 S3=5 S4=3
C8	Q_{8jg}	Mother Board	S4=2 S5=3 S7=6 S9=5 S10=4
C9	Q_{9jg}	Drive	S4=5 S6=6 S7=3 S10=4
C10	Q_{10jg}	Case	S4=4 S6=2 S7=6 S9=5 S10=3

Si means the *i*th supplier.

Table 4.7 Unit cost of components provided by suppliers

Name	E_{ijg}		Cost indexes
C1	E_{1j1}	Dual Core 2.2 GHz	S1=0.58 S2=0.33 S3=0.35
	E_{1j2}	Dual Core 2.4 GHz	S1=0.5 S2=0.2 S3=0.33
	E_{1j3}	Dual Core 2.66 GHz	S1=0.48 S2=0.45 S3=0.7
C2	E_{2j1}	Hard Disk 200	S5=0.13 S6=0.26 S7=0.36 S8=0.5
	E_{2j2}	Hard Disk 250	S5=0.33 S6=0.46 S7=0.47 S8=0.68
	E_{2j3}	Hard Disk 320	S5=0.35 S6=0.36 S7=0.67 S8=0.88
C3	E_{3jg}	Battery 4 cells	S7=0.39 S11=0.32 S12=0.25
		Battery 6 cells	S7=0.32 S11=0.45 S12=0.65
		Battery 8 cells	S7=0.78 S11=0.36 S12=0.45
C4	E_{4jg}	Chipset 12	S5=0.32 S6=0.41 S7=0.53 S9=0.24
		Chipset 13	S5=0.36 S6=0.48 S7=0.58 S9=0.32
		Chipset 14	S5=0.65 S6=0.76 S7=0.98 S9=0.77
C5	E_{5j1}	GPU 9200	S1=0.12 S2=0.16 S3=0.28 S4=0.18
	E_{5j2}	GPU 9800	S1=0.39 S2=0.29 S3=0.48 S4=0.34
	E_{5j3}	GPU 9800	S1=0.45 S2=0.31 S3=0.59 S4=0.62
C6	E_{6j1}	RAM 2GB(1G×2)	S5=0.11 S6=0.18 S7=0.14 S8=0.16
	E_{6j2}	RAM 2GB(2G×1)	S5=0.21 S6=0.33 S7=0.32 S8=0.27
	E_{6j3}	RAM 4GB(2G×2)	S5=0.29 S6=0.38 S7=0.33 S8=0.22
C7	E_{7jg}	Power Supply Unit	S1=0.35 S2=0.4 S3=0.48 S4=0.41
C8	E_{8jg}	Mother Board	S4=0.04 S5=0.05 S7=0.08 S9=0.075 S10=0.053
C9	E_{9jg}	Drive	S4=0.088 S6=0.09 S7=0.045 S10=0.078
C10	E_{10jg}	Case	S4=0.06 S6=0.03 S7=0.15 S9=0.12 S10=0.048

Since RCSs of mother board, drive and case, power supply unit have no alternatives and they are treated as common modules for the product line, performance of them is not considered

Table 4.8 Quality coefficient $u_{ik}$and performance coefficient τ_{ik} setting

Part	Name	u_{ik}	τ_{ik}
C1	Dual Core 2	0.18	0.3
C2	Hard Disk	0.13	0.15
C3	Battery	0.09	0.12
C4	Chipset	0.15	0.2
C5	GPU	0.09	0.08
C6	RAM	0.07	0.15
C7	Power Supply	0.05	N/A
C8	Mother Board	0.13	N/A
C9	Case	0.08	N/A
C10	Drive	0.03	N/A

4.5 Data Structure and NSGA II

In this research, NSGA II was implemented using MATLAB programming language for solving the multi-objective optimization problem. In the following, data structure and NSGA II implementation are described.

4.5.1 Data Structure

There are two types of data structure, which are two dimensional (2D) data matrix and three dimensional (3D) data matrix. For example, the performance assessment of alternative in RCS 1 is formulated as a matrix as a 2D matrix below:

		Alternative 1	Alternative 2	Alternative 3	
Performance Value	[	3	4	5	]

The data, E_{ijg}, as shown in Table 4.5 are presented as a 3D matrix , shown in Figure 4.4. The cube has three dimensions, alternative dimension (G), component dimension (I) and supplier dimension (J). For example, the number, 0.35, circled in the Figure 4.5, refers to the cost of alternative 2 in the RCS 1 which is provided by supplier 3. The data, Q_{ijg}, are also presented in a similar structure.

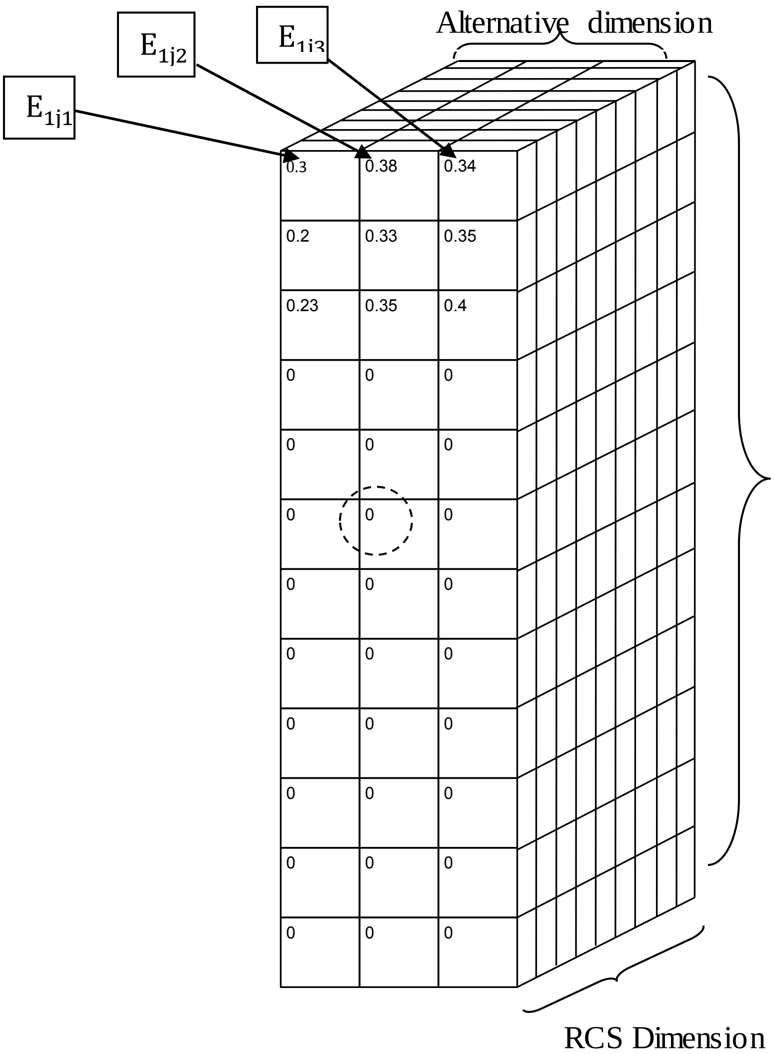

Figure 4.4 3D data matrix in MATLAB

4.5.2 Initial Parameters Setting

The population size of the NSGAII was set as 50, and the crossover probability and mutation probability were set as 0.8 and 0.2, respectively. The maximum number of generation performed in NSGAII was set as 500.

4.5.3 Chromosome Design

The structure of the chromosome is a string which consists of three sections. The variables of supplier selection are the first section in the chromosome. The second section is the decision variables of product variants (configuration). The third section is the product price. In the case study, there are three cases of chromosome design as describe below.

a) In the first case, there are 10 components/modules (i.e I=10), twelve suppliers (i.e. J=12), and one product variant (K=1). Each gene in the supplier section of the chromosome contains alternative suppliers. An example of the first case is shown in Figure 4.5;

b) In the second case, there are ten components/modules (i.e I=10), twelve suppliers (i.e. J=12), and two product variants (K=2). As the number of suppliers does not change, the length of the supplier decision section is twice in comparison with that of the first case. The extension is made for each section. Figure 4.6 shows the chromosome design for the second case.

c) In the third case, there are ten components/modules (i.e I=10), twelve suppliers (i.e. J=12) and three product variants (K=3). The chromosome design for the third case is shown in Figure 4.7.

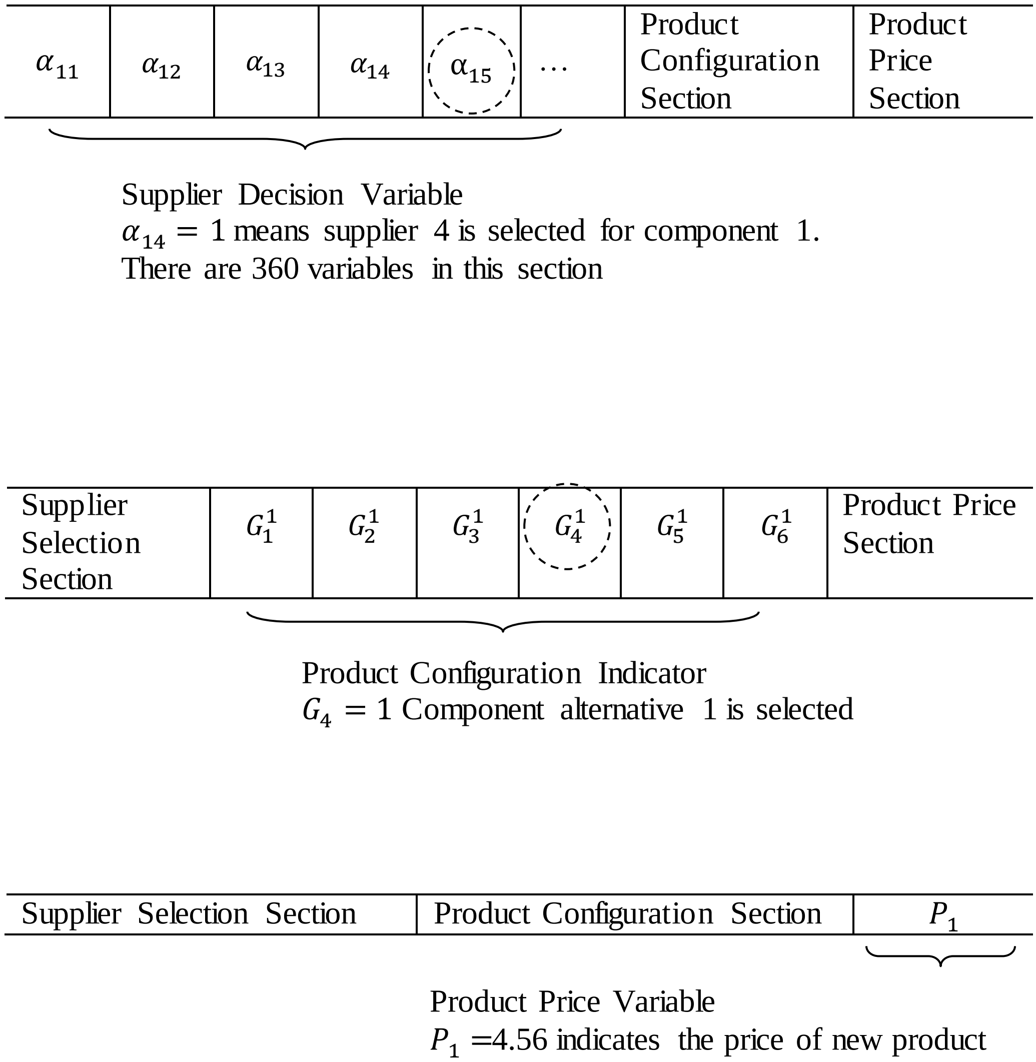

Figure 4.5 Chromosome design (one product variant)

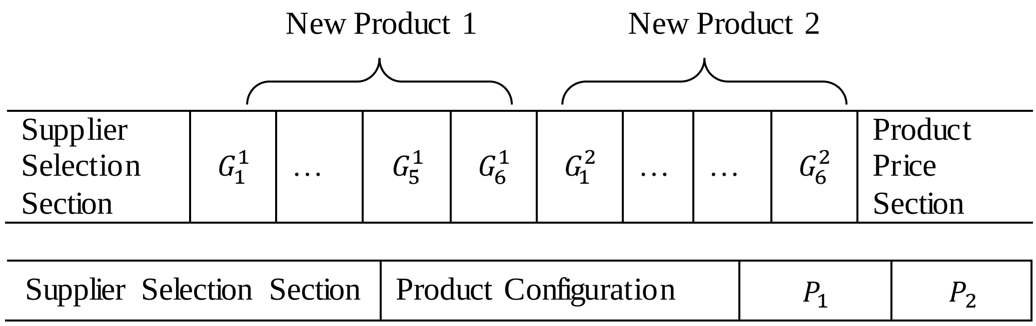

Figure 4.6 Chromosome design (two product variants)

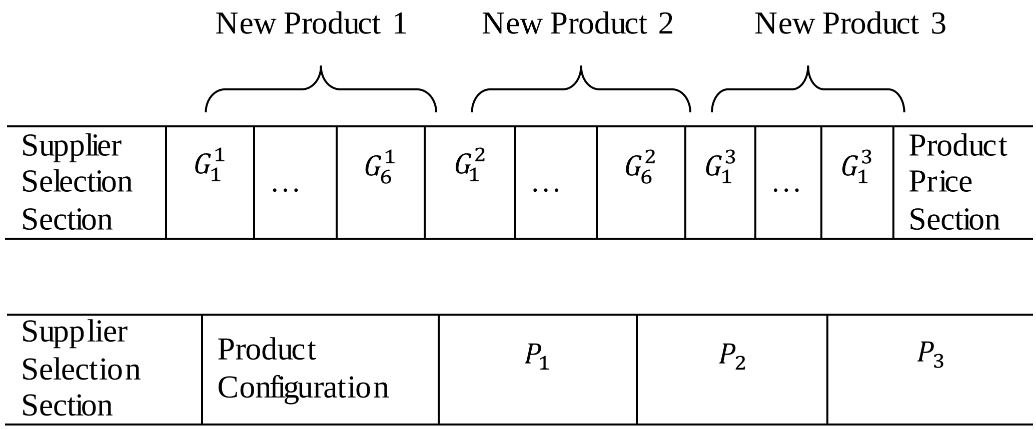

Figure 4.7 Chromosome designs (three product variants)

4.5.4 Parameters in NSGA II Program

Binary tournament selection is used in the NSGA II based on the crowded-comparison operator. The arguments are pool size of the mating pool. It is common to set it to be a half of the population size. Therefore, in this study, the pool size was set as 25, as the half of the population size, 50. NSGA-II uses a binary tournament selection. Thus, the tournament size is set as 2 for this research. Crossover probability, pc, was set as 0.9 and mutation probability, pm, was set as 1/n, where n is the number of decision variables. For instance, there are three product variants in a product line. The decision variables are 381 so the mutation probability is pm=1/381. Since real-coded NSGA II has been proved to outperform binary-coded one in optimal solutions searching (Deb et al. 2002) and real-coded GA can be directly used on real variables (Deb & Agrawal 1995), in this research, real-coded NSGAII was adopted. Distribution indices, for both crossover and mutation operators, were set as 20.

4.5.5 Filtering Mechanism

In this research, NSGA II is used to find the solution with minimum fitness value. Therefore components or modules with the minimum unit cost are chosen, i.e. the supplier decision variables α_{ijg} indicate one. In the data matrix of E_{ijg} and Q_{ijg}, the elements are set as zeros when suppliers will not provide the components or modules. The "zero" elements are chosen by the algorithms if there is not a filter, because the algorithms will treat the "zero" elements as minimum unit costs or quality values. In this study, the filters were designed to make the decision variables always equal to zero when the suppliers could not provide the components or modules. Figure 4.8 illustrates the mechanism.

E_{ijg}

0.53	0.45	0.32	0.34	0	0	0	0	0	0

α_{ij} , real-coded

Parent1

0.11	0.45	0.64	0.52	0.01	0.31	0.42	0.55	0.68	0.52

Parent2

0.23	0.65	0.45	0.78	0.45	0.66	0.36	0.52	0.68	0.74

Crossover

Offspring1

0.11	0.45	0.45	0.52	0.01	0.31	0.42	0.55	0.68	0.52

Offspring2

0.23	0.65	0.64	0.78	0.78	0.45	0.66	0.36	0.52	0.68

....

Filter

1	1	1	1	0	0	0	0	0	0

Decoding process:

α_{ij}=1, when the gene ≥0.5; α_{ij}=0, when the gene <0.5

Finally, the output of α_{ij} is

α_{ij}

0	0	1	0	0	0	0	0	0	0

Supplier 3 is selected due to minimum cost

Figure 4.8 The filtering mechanism

Chapter 5 Results

In the case study, the MATLAB program was run dozens of times in order to obtain the average numerical results due to the heuristic nature of NSGA II.

5.1 Searching Results Analysis of NSGA II

Initially, the population was set as 50. The pool size was one half of the population size. The tournament size was set as 2 and the distribution indices in crossover and mutation were both set as 20.

5.1.1 Fitness Value of Each Objective Function

a) Three product variants in a product line

The results of NSGA II searching with respect to the FF1 are shown in Figure 5.1. The fitness value fluctuated, generation after generation, via the reproduction process. The smallest fitness value was found at about the 440th generation.

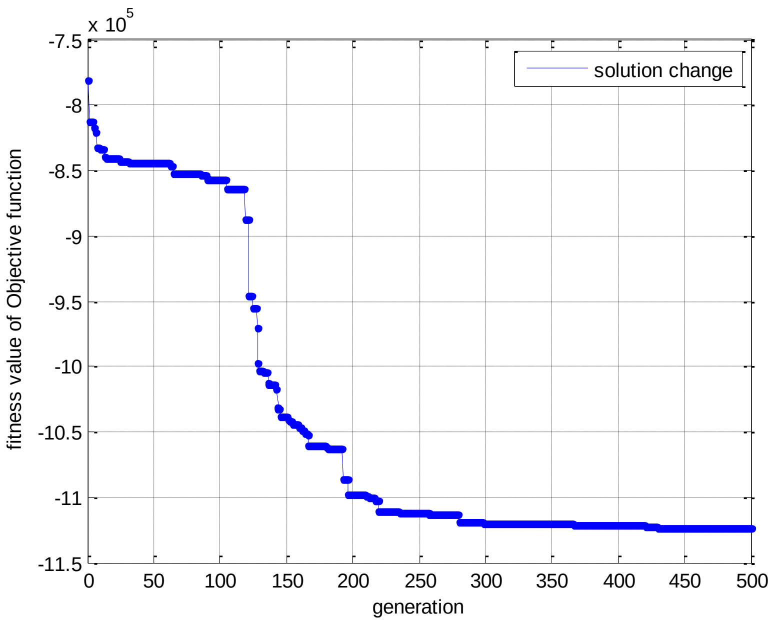

Figure 5.1 Fitness value of FF1 (three product variants)

The results of the NSGA II searching, with respect to the FF2 are shown in Figure 5.2. The fitness value fluctuated, generation after generation, via the reproduction process. It can be noted that the smallest fitness value can be found at about the 340th generation.

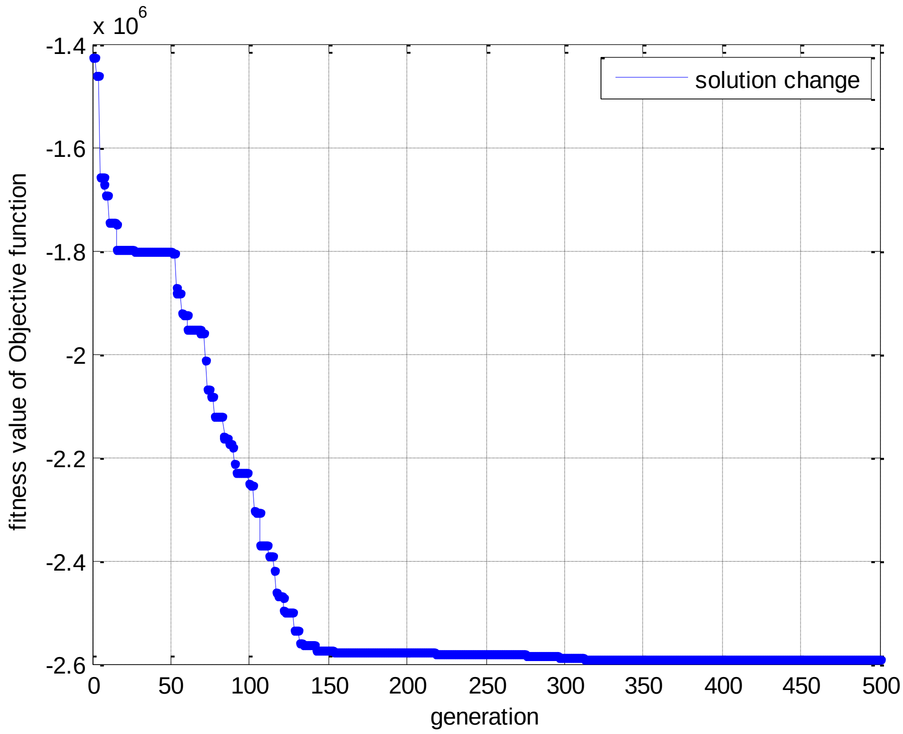

Figure 5.2 Fitness value of FF2 (three product variants)

The results of the NSGA II searching with respect to the FUNC3 under the 500 generations are shown in Figure 5.3. The fitness values become smaller throughout generations via the reproduction process. The smallest fitness value can be found at nearly the 500th generations.

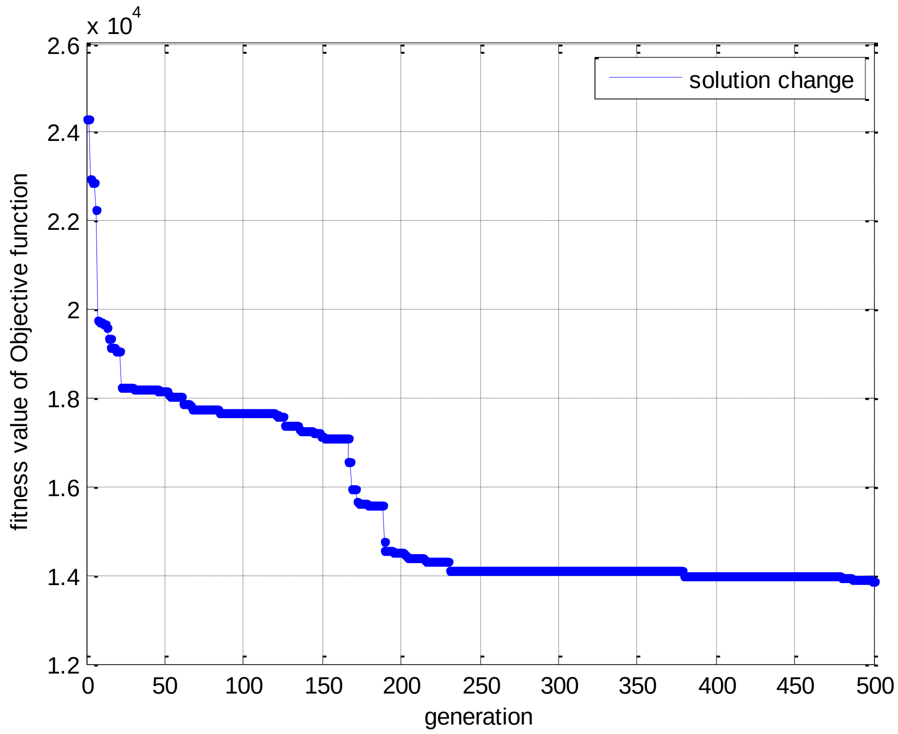

Figure 5.3 Fitness value of FF3 (three product variants)

b) Two product variants in a product line

The results of the NSGA II searching with respect to the FF1 are shown in Figure 5.4. The best fitness value can be found at about the 160th generations. After the 200th generation, the minimum fitness value nearly remains the same.

Figure 5.5 shows the result of the NSGA II searching with respect to FF2 under the same conditions. The lowest point was recorded at around the 350th generations. After about the 240th generation, the fitness value remains unchanged.

Figure 5.6 shows the NSGA II searching results with respect to FF3, From the figure, it can be seen that the fitness value drops to the smallest value at about the 430th generation..

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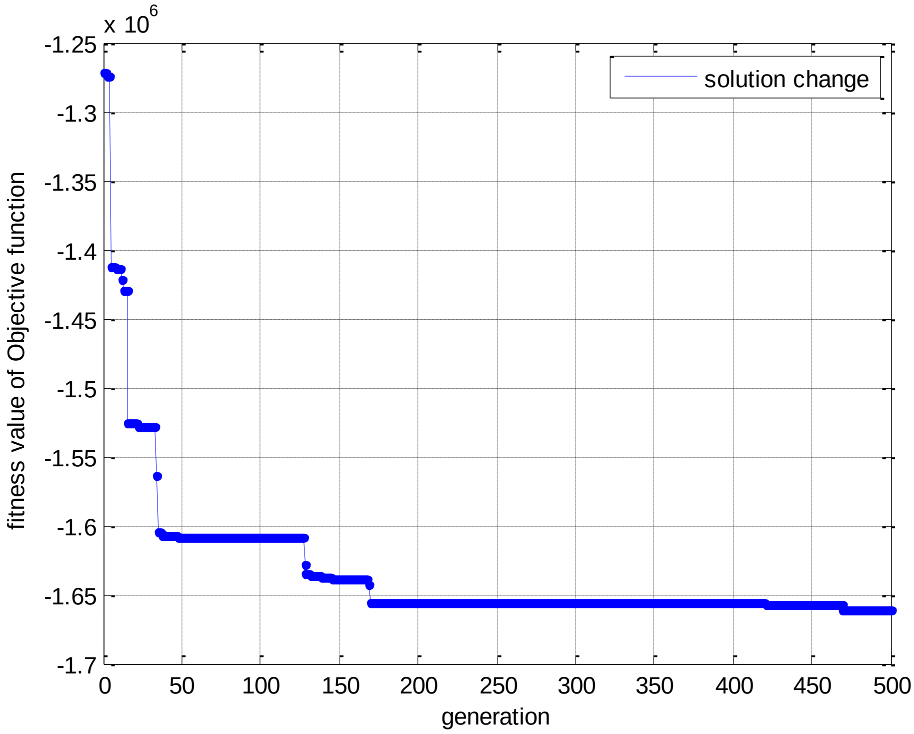

Figure 5.4 Fitness value of FF1 (two product variants)

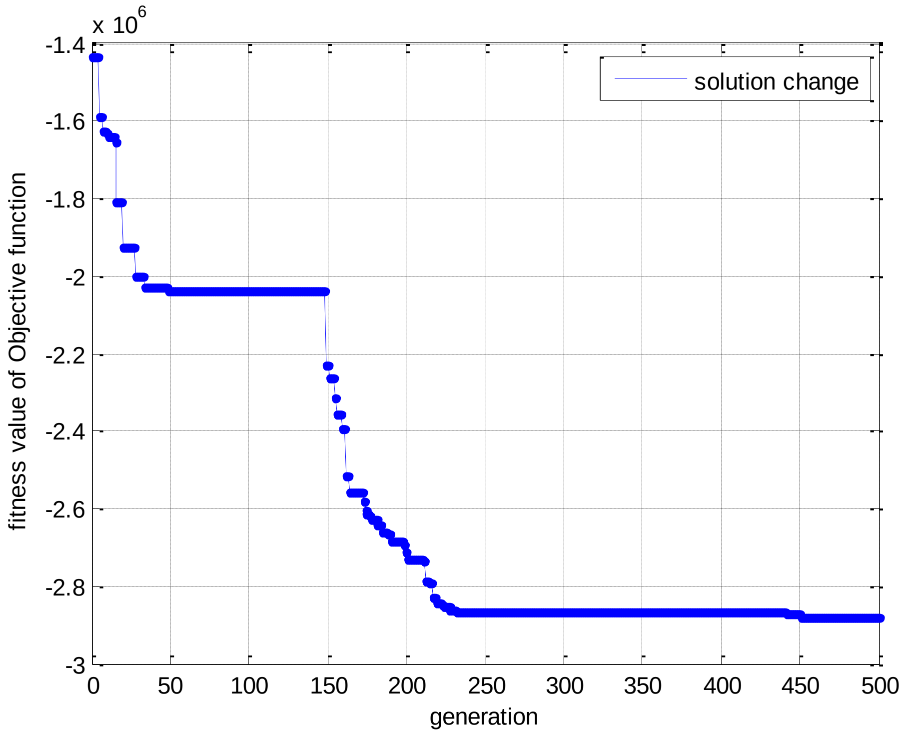

Figure 5.5 Fitness value of FF2 (two product variants)

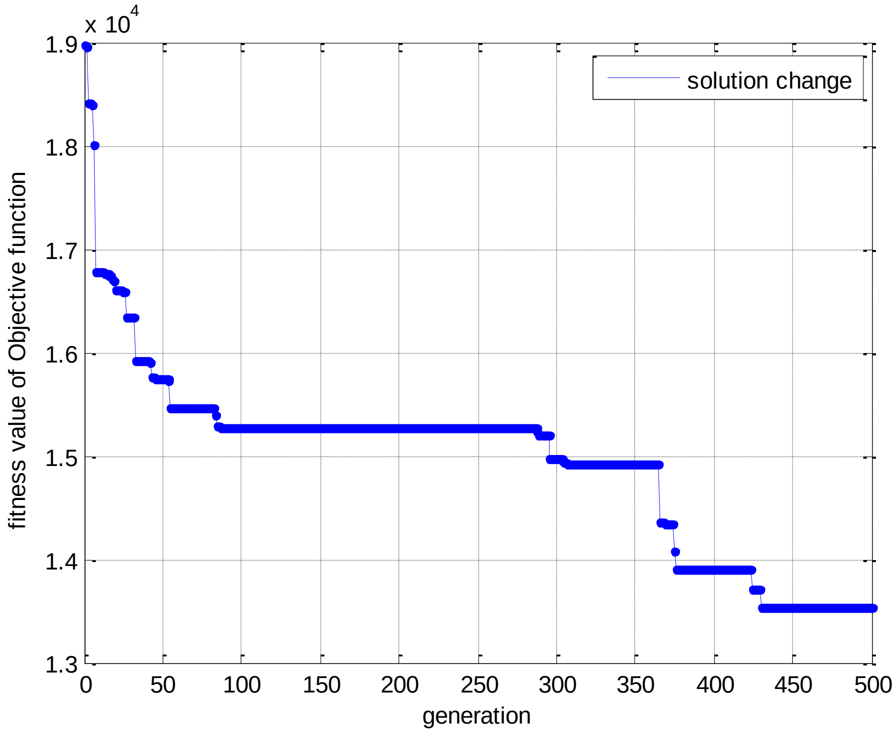

Figure 5.6 Fitness value of FF3 (two product variants)

c) One product variant in a product line

Figure 5.7 shows the NSGA II searching results of FF1 for the case of one product variant. It can be seen that the smallest fitness value can be obtained at about the 270th generations. Figure 5.8 and Figure 5.9 show the NSGAII searching results of FF2 and FF3 respectively.

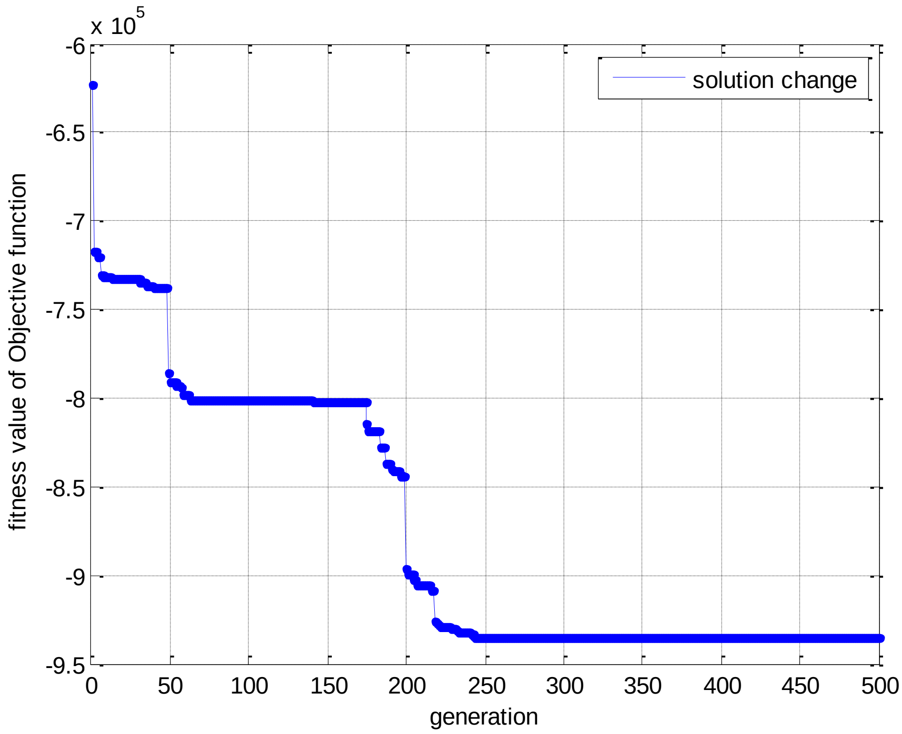

Figure 5.7 Fitness value of FF1 (one product variant)

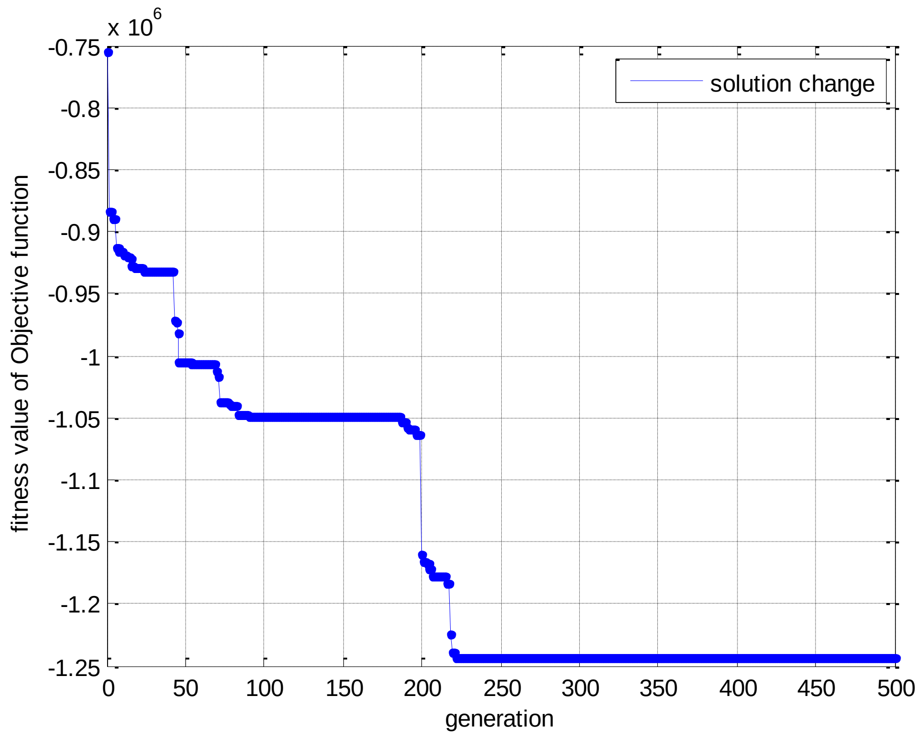

Figure 5.8 Fitness value of FF2 (one product variant)

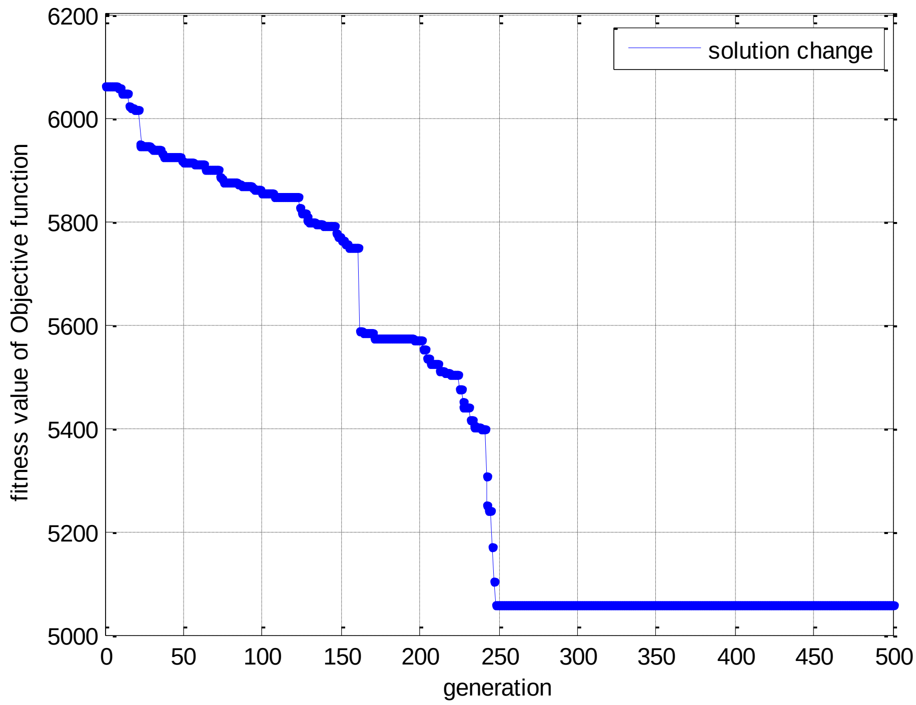

Figure 5.9 Fitness value of FF3 (one product variant)

5.1.2 Pareto Optimal Solutions

After executing the MATLAB program of NSGAII, the Pareto optimal solutions can be generated. Figure 5.10 shows the Pareto solutions of the product line which contains three product variants. When the total quality and performance of product variants increase to a certain value, it can be noted that the total costs of the product variants increase dramatically.

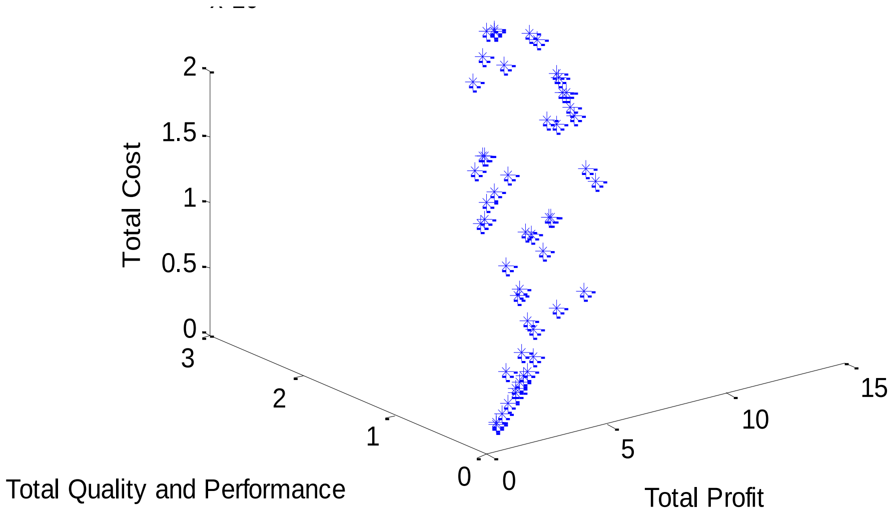

Figure 5.10 Pareto solutions (three product variants)

Figure 5.11 shows the Pareto solutions of the product line, which contain two product variants. The total profit does not increase sharply when the total quality and performance of product variants reach to a certain value.

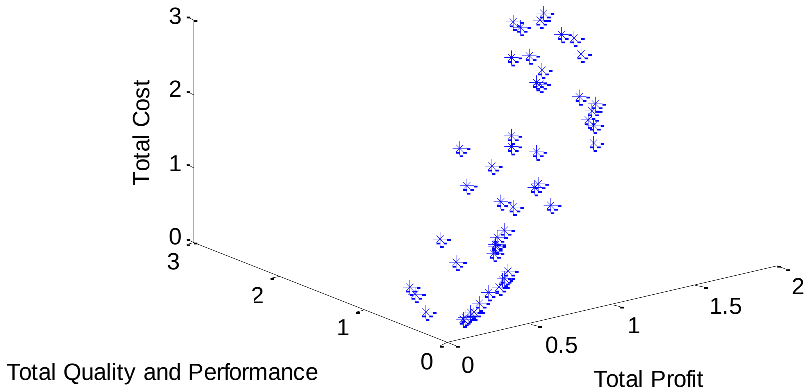

Figure 5.11 Pareto solutions (two product variants)

Figure 5.12 shows Pareto solutions of the product line which only contains one product variant. The surface is narrow and slightly concave. It can be noted that the total profit is smaller than that of the previous two cases. The total cost increases higher when the total quality and performance value increase.

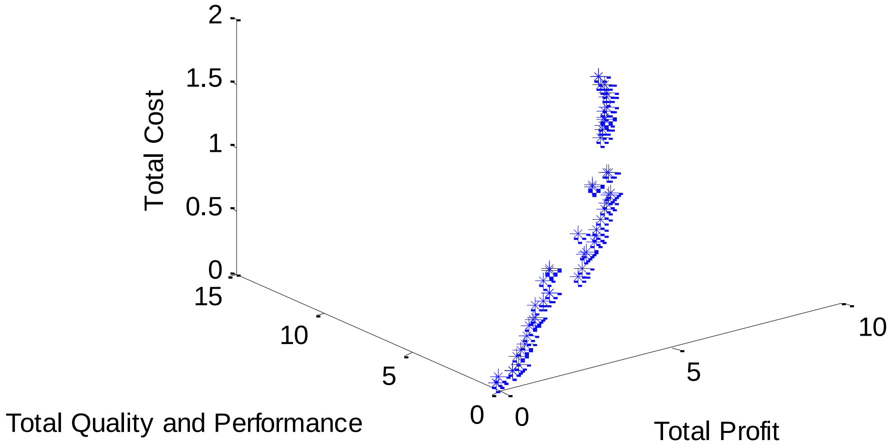

Figure 5.12 Pareto solutions (one product variant)

5.2 Positions of New Products

It has been mentioned in Chapter 3 that the positions of new products in a joint space map can be determined. Since there is a number of Pareto optimal solutions generated by NSGA II, the positions of product variants of a PC product line can be numerous. Figure 5.13, Figure 5.14 and Figure 5.15 show the respective product positions of the three alternative product lines.

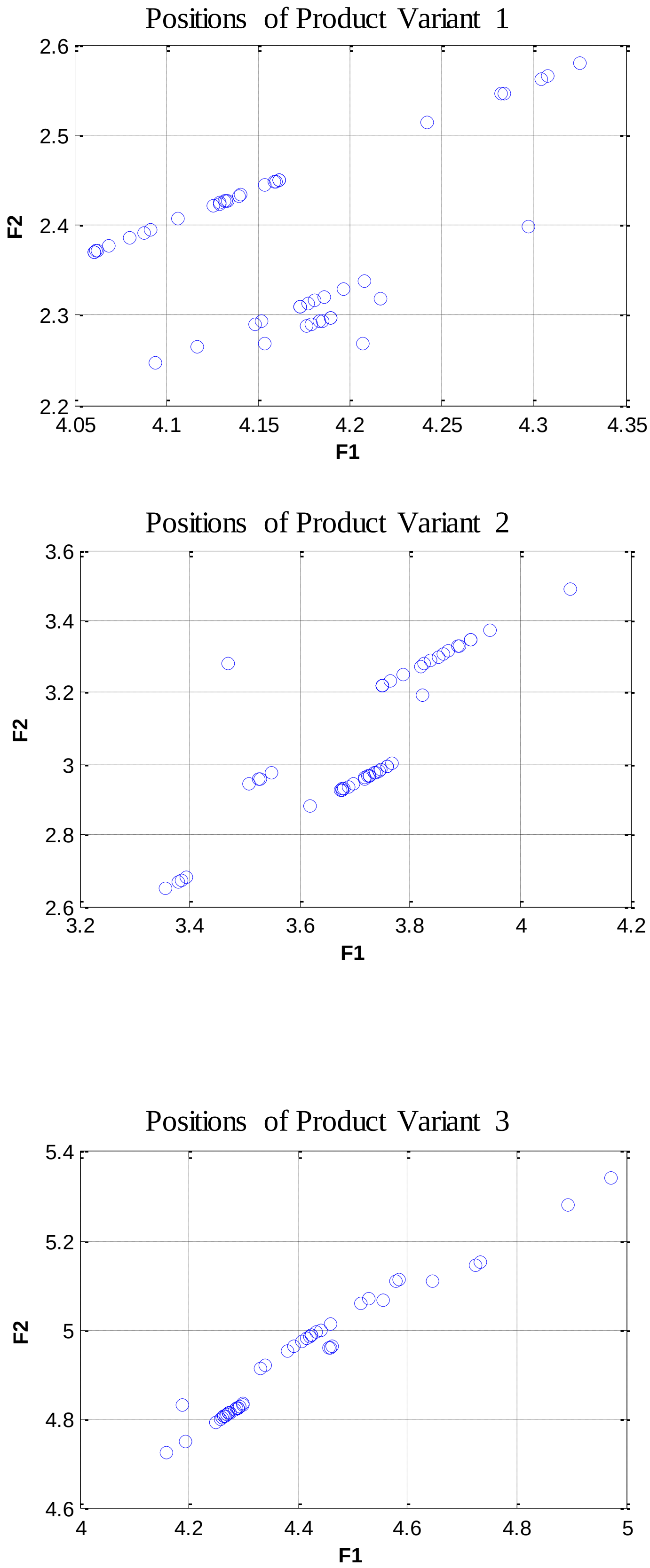

Figure 5.13 Product positions for a product line (3 product variants)

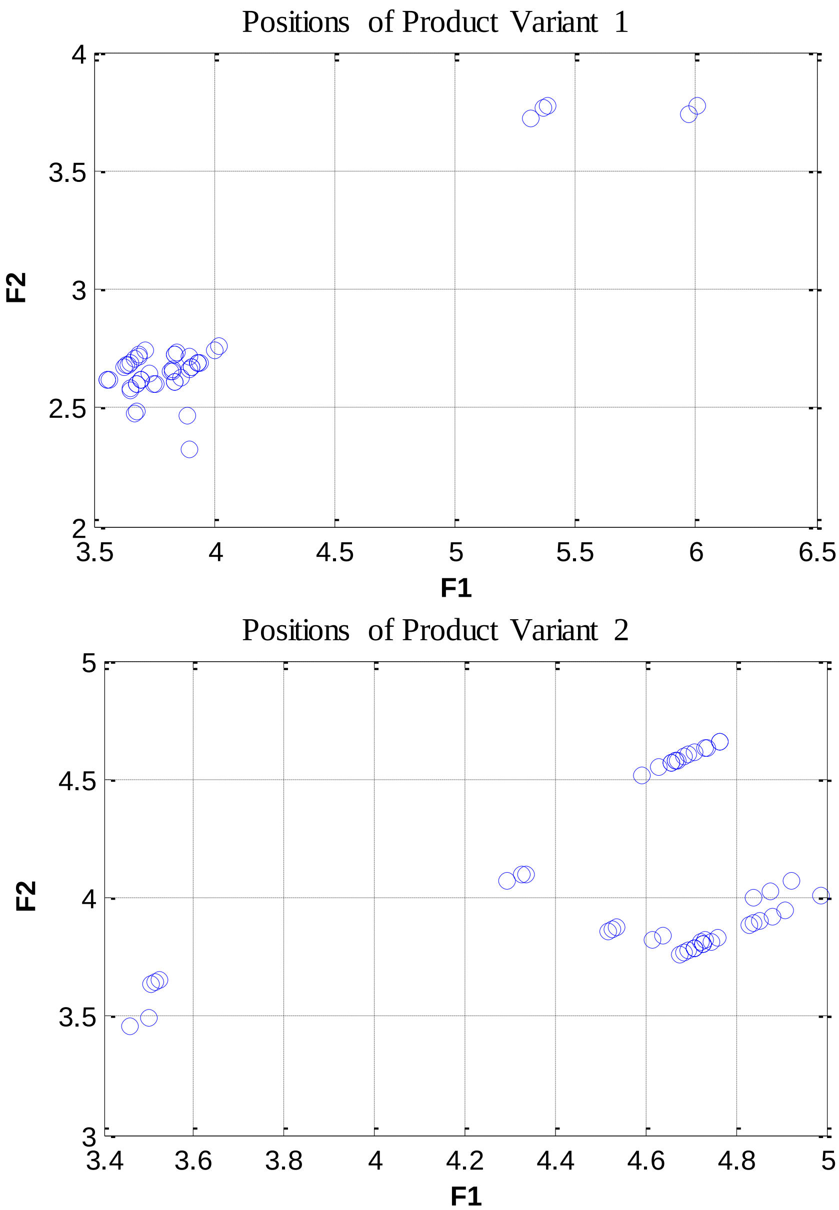

Figure 5.14 Product positions for a product line (2 product variants)

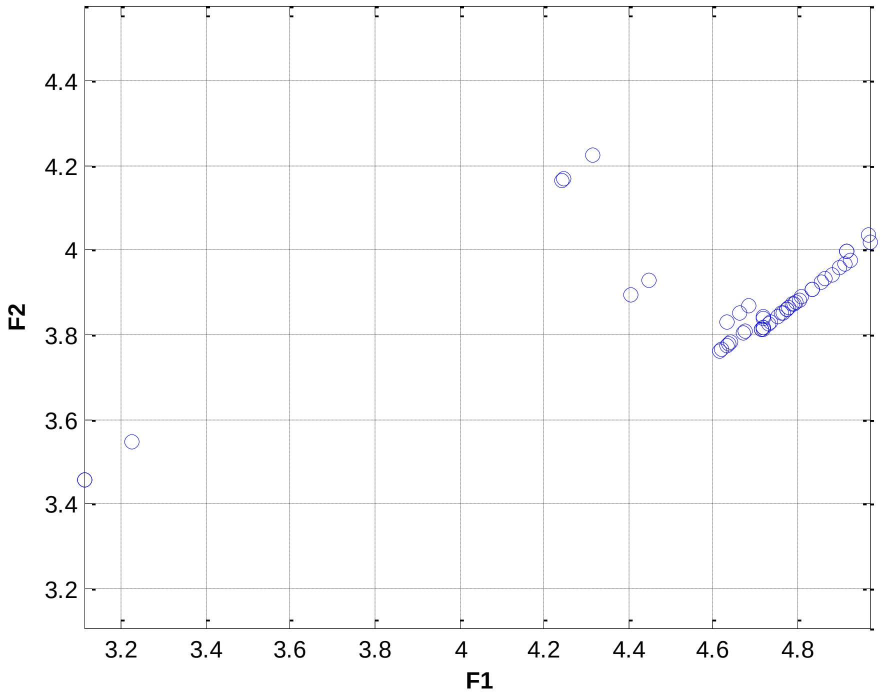

Figure 5.15 Product positions for a product line (one product variant)

5.3 Solutions of Product Line Design and Supplier Selection

NPD teams of companies commonly consider various objectives simultaneously for a product line design. The objectives may have intrinsic conflicts with each other. Therefore, an NPD team needs to carry out a trade-off among the objectives while considering a product line design. In the case study, a number of Pareto optimal solutions for the PC product line design were generated as shown in Appendix C. NPD teams commonly need to consider various factors such as trade-off among objectives, a company's business strategy and competitive strategy and a company's cash flow when selecting a Pareto optimal solution as the product line design solution. Suppose the product development team of Company ABC selected three alternative solutions for product line design; the 15th solution (three product variants in a product line) of Table C.1, C.2, C.3, C.4, the 33rd solution (two product variants in a product line) of Table C.6, C.7, and the 23st solution (one product variant in a product line) of Table C.10 (Tables C.1 to C.4, C.6, C.7 and C.10 can be found in Appendix C). The three alternative solutions of the product line design and the corresponding selected suppliers of components for PCs are shown in Tables 5.1, 5.2 and 5.3 respectively. The perceptual maps for the three cases are shown in Figures 5.16, 5.17, 5.18 respectively.

Table 5.1 Product line design (three product variants)

	Product variant 1 (NPV1)	Product variant 2 (NPV2)	Product variant 1 (NPV3)
Product position	x=4.26 y=2.69	x=3.17 y=2.92	x=5.01 y=4.91
Configuration	RCS1=3, RCS2=1, RCS3=1, RCS4=1, RCS5=3, RCS6=1,	RCS1=3, RCS2=2, RCS3=2, RCS4=2, RCS5=1, RCS6=1,	RCS1=3, RCS2=2, RCS3=3, RCS4=2, RCS5=1, RCS6=2,
Supplier Selection (Supplier =S)	S1 (RCS7) S2 (RCS1, RCS5) S6 (RCS6) S7 (RCS2, RCS9) S9 (RCS4,RCS8, RCS10) S12 (RCS3)	S1(RCS5, RCS7) S2 (RCS1) S6 (RCS6) S7 (RCS2) S9 (RCS4,RCS8, RCS10) S12 (RCS3)	S1 (RCS7) S2 (RCS1,RCS5) S6 (RCS2) S7 (RCS6,RCS9) S9 (RCS4,RCS8, RCS10) S11 (RCS3)

Table 5.2 Product line design (two product variants)

	NPV1	NPV2
Coordinates	*x*=3.63 *y*=2.65	*x*=4.30 *y*=3..94
Alternatives Configuration	RCS1=2, RCS2=2, RCS3=2, RCS4=2, RCS5=2, RCS6=1	RCS1=3, RCS2=3, RCS3=3, RCS4=1, RCS5=1, RCS6=2
Supplier Selection (Supplier=S)	S1 (RCS5, RCS7) S2 (RCS1), S4 (RCS8) S5 (RCS2, RCS6), S7 (RCS10), S9 (RCS4), S10 (RCS9) S11 (RCS3)	S1 (RCS1, RCS7) S3 (RCS5) S4 (RCS8) S6 (RCS6) S7 (RCS2, RCS3, RCS4, RCS10) S10 (RCS9)

Table 5.3 Product line design (one product variant)

	NPV1
Coordinates	*x*=4.84 *y*=3.96
Alternatives Configuration	RCS1=3, RCS2=3, RCS3=2, RCS4=2, RCS5=3, RCS6=3
Supplier selection (Supplier=S)	S1 (RCS1), S3 (RCS7), S4 (RCS5, RCS9), S5 (RCS6), S6 (RCS10) , S7 (RCS2, RCS3, RCS4), S10 (RCS8),

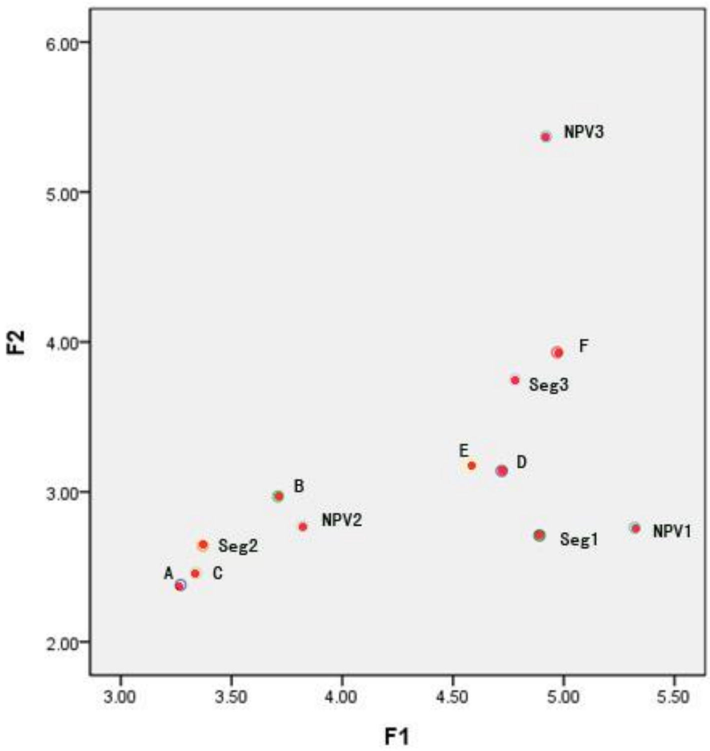

Figure 5.16 Perceptual map (three product variants)

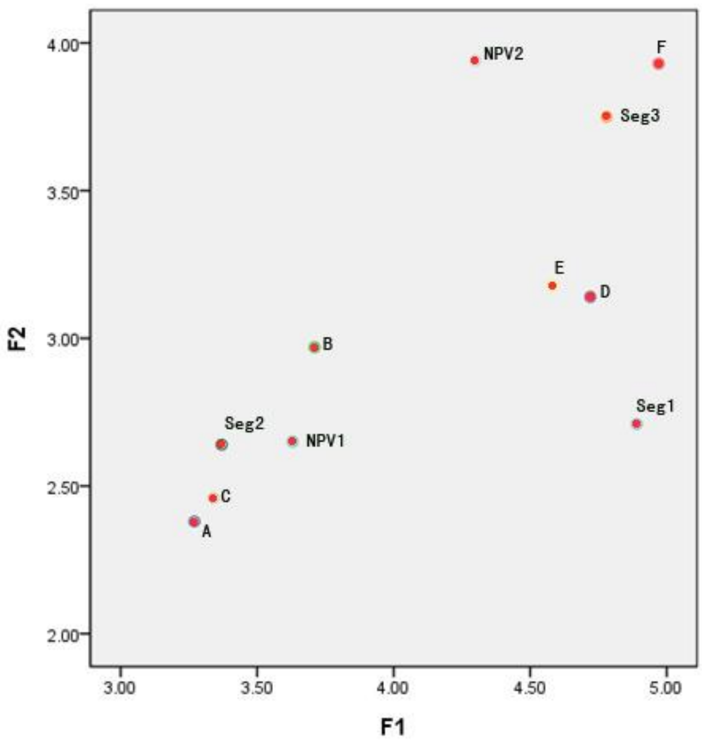

Figure 5.17 Perceptual map (two product variants)

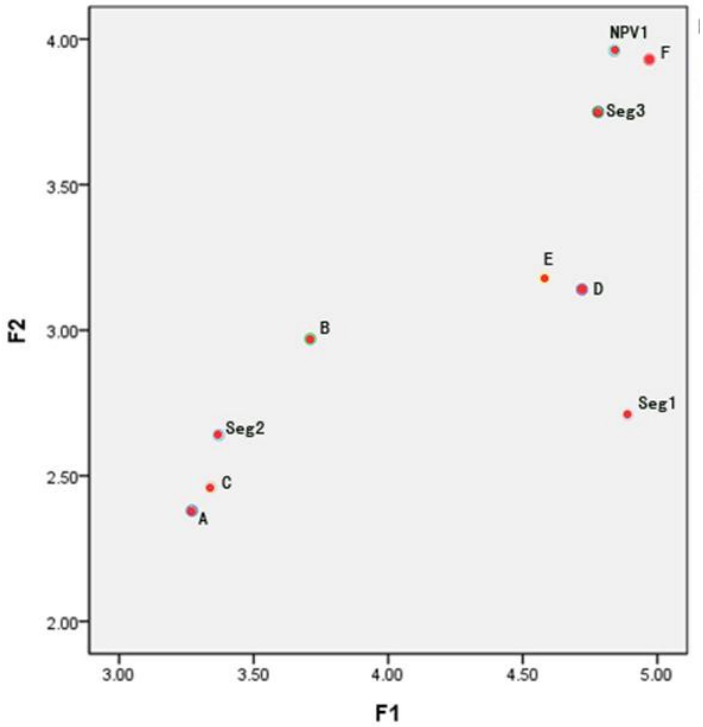

Figure 5.18 Perceptual map (one product variant)

Table 5.4 summarizes the three alternative product line designs for PCs. From the table, it can be seen that the estimated profit of the first alternative solution is the highest while the 2nd alternative solution leads to the best quality and performance of the product line. The development cost of the 3rd alternative solution is the least. Thus, the product development team can select one of the three alternatives in consideration of various factors as mentioned before. For example, if the team aims at obtaining the maximum profit from the product line and feels comfortable about the development cost, and product quality and performance, the 1st alternative solution can be considered. If the team aims at obtaining a solution with maximum product quality and performance, but they are satisfied with the profit and market share, the 2nd alternative solution can be considered.

Table 5.4 Product line design and comparison

Product Line Design		1st alternative (3 NPV)			2nd alternative (2 NPV)		3rd alternative (1 NPV)
		NPV1	NPV2	NPV3	NPV1	NPV2	NPV1
Total Profit		9.33			9.20		5.57
Total Cost		1.26			1.09		0.58
Total P & Q		12.5			15.9		7.2
Est.Price ($HKD)		9,280	2,560	11,780	5,000	10,573	9,800
Ms	SG1	19.3%	2.6%	1.7%	5.7%	4.3%	6.0%
	SG2	1.6%	37%	0.2%	22.7%	0.4%	0.52%
	SG3	3.1%	1.2%	3.9%	1.5%	20.5%	49.5%
Total Ms		26.1%			19.5%		17.1%

NPV= New Product Variant Market Share = Ms P&Q= Performance and Quality Est.= Estimated SG=Segment

Chapter 6 Discussion

In this study, a methodology was developed for integrating supplier selection with product line design. However, there are two pre-requisites regarding the application of the methodology. First, in this research, evaluation of performance and quality of the components to be provided by suppliers has to be done first. For each component to be provided by suppliers, the product development teams need to rate its performance and quality based on their experience and judgment and the component specifications. Secondly, Information and track records of suppliers, and the quoted prices, performance ratings and quality ratings of components to be provided by suppliers should be organized in a proper electronic way such that these information and data can be accessed for solving the integrated problem.

A mathematical decision model was formulated for maximizing the profit of a product line, maximizing quality and performance of product variants, and minimizing the cost of the product line. In the decision model, the quality and performance of product variants were quantified and summed up using a weighed-sum method. NSGA-II was applied to solve the optimization problem. As real-coded NSGA II was adopted in this study, the parameters of the integrated model were set as their original recommended values for generating Pareto optimal solutions. For example, distribution indices for both crossover and mutation operators were set as 20 and the pool size was set as a half of the population size. Some trials were performed to investigate the effect of the change of the parameter settings on the obtained

Pareto optimal solutions. After the trial, no apparent change of generated. Pareto optimal solutions could be observed. For the execution of NSGA II, several generation values such as $N_f P_s$, $N_f P_s{}^2$, and $N_f P_s{}^3$ (Refer to Section 3.38)were tried for searching for optimal results. It was found that there were no very obvious differences between the NSGA optimal results respectively based on the generation value $N_f P_s$ and the generation value, $N_f P_s{}^2$. The fitness values became stable after a certain number of generations. Hence, the generation value was set as 500 in this research, which is much larger than $N_f P_s$, but much less than $N_f P_s{}^2$. The integrated model was implemented by the MATLAB software programming language. The performance data of the components were organized in a 2D matrix, and the quoted prices and quality of the components were organized in 3D matrix cubes. The data structure presented in the matrices can help reduce the complexity of the data process, especially when the number of suppliers and components increases. The supplier selection problem and product variant configurations in this study were treated as assignment problems and the matrix data structures can help to simplify the solving processes.

In this thesis, a methodology for integrating product line design with supplier selection is described. Based on the proposed methodology, a number of Pareto optimal solutions of product line design and supplier selection can be generated. The solutions include the prices of product variants and their estimated market shares, selected suppliers positions of the product variants, and their configurations. Companies can consider various factors such as a trade-off among profit, product line development cost and product quality, company's competitive strategy and company's cash flow when selecting a Pareto optimal solution as the product line design and supplier selection solutions. The information can help product development teams to identify major competitive products of individual product variants and have better understanding of the competition environment. The information can also be useful for companies to formulate proper competitive and marketing strategies for their new products. The proposed methodology enables product development teams to perform the integrated supplier selection and product line design systematically and human subjective judgment on product line design and supplier selection to be reduced. From Table 5.14, three alternative solutions were generated. It can be observed that the market share of a particular market segment of the 2^{nd} and the 3^{rd} alternative solutions is quite large because the positions of product variants of the two solutions are quite close to their individual idea points. However the actual market share could be less than the estimated values because not all the competitive products were included in the case study. Therefore, the market share values obtained, as shown in the table, are better to be used for comparison purpose.

Although the effectiveness of the proposed methodology was demonstrated in the Chapter 5, some limitations of it have been observed.

- In this research, the methodology was developed to solve the integrated problem where a number of components of product variants are outsourced. Therefore, if a new product involves very few outsourced components, the proposed methodology may not be found applicable.

- The cost model used in this research is in a linear form and the unit costs related to attributes are assumed to be independent to each other. However, this may not be true in a real-world environment. The development of non-leaner cost models is necessary to improve the accuracy of the cost estimation.
- For the NSGA II, the chromosome was set as randomly initialized. Therefore, the optimal solutions obtained are different for different generations. It is necessary to run the MATLAB program of NSGA II many times in order to average the searching results. This will lead to a long computational time.
- If the integrated problem involves quite a number of product variants, components and suppliers, a long chromosome of NSGA II is required. The length of chromosomes and the population size can have a large effect on the efficiency of the solving. Normally, longer chromosomes and larger size of population of NSGA II require more computer memory size and longer computational time.
- There are various criteria for supplier selection such as delivery, R&D capability, price, quality and production capability. In this research, only the criteria of supplier selection, component quality and component price, were considered, in order to reduce the complexity of the problem and the implementation effort.

- For some cases, where two components have the same specifications, same price, same performance and same quality, but are provided from different suppliers, a supplier is selected randomly among those suppliers as a solution.
- If the selected supplier cannot provide the component(s) due to various reasons, a substitute supplier cannot be suggested by the integrated model.

Chapter 7 Conclusion and Future Work

7.1 Conclusion

In this research, a new methodology for integrating supplier selection with product line design has been described and implemented using a case study. The developed methodology is able to make up the deficiencies of the previous methodologies for the similar integrated problem which include (1) prices of product variants are pre-defined; (2) only single objective is considered in the integrated problem; and (3) market positions of product variants are unknown. The integrated supplier selection and product line design is formulated as a multi-objective optimization problem and it is solved by using NSGA II. Pareto optimal solutions of product line design and corresponding supplier selection can be generated, from which product development teams can select one as their solution for the product line design and supplier selection with the consideration of various factors. A case study of product line design for portable computers was implemented using the MATLAB programming language to demonstrate the effectiveness of the proposed methodology. The major contributions of this study are summarized as follows.

- A new methodology for integrating supplier selection with product line design was developed to make up the deficiencies of the previous studies as mentioned in Section 2.7. Based on the methodology, optimal configurations of individual product variants to be offered in a product line and their component suppliers can be determined.

- In this research, the integrated problem was formulated as a multi-objective optimization problem. By solving the problem, the tradeoff of the several objectives of the problem for determining product line design solutions and suppliers under different scenarios can be realized.
- In this research, positions of product variants of a product line can be determined and shown in a joint space map. This can help product development team/marketing team personnel to have better understanding about the market positions of the product variants and the competitive environment, and formulate proper competitive strategies and marketing strategies.

7.2 Future work

This study on integrating supplier selection with product line design has raised several future research issues.

- In the development of the proposed methodology, it is assumed that the market demand is static. In reality, market demand can be quite dynamic. Future work could consider the dynamic effect in the integrated supplier selection and product line design problem
- In the Chapter 5, it was noted that the chromosome is quite lengthy although the integrated problem of the case study is not very complex. Therefore, new structures of chromosome should be studied to improve the effectiveness of the proposed methodology.

- Suppliers may provide price discounts to buyers who place orders for large quantities of components. The price discount can be introduced in the methodology in order to generate more accurate results.
- Since delivery performance is one of the key criteria for supplier selection, further study could include it in the integrated problem for supplier selection.
- The methodology was implemented using the MATLAB programming language. The supplier data are input to the MATLAB program in the form of a data matrix. This process is quite tedious, especially when a large number of suppliers are involved. A program can be considered to develop which can directly import and transfer the data from a supplier database of a company to the MATLAB program.
- Some latest solving techniques for multi-objective optimization problems have been proposed in recent literature such as multi-objective particle swarm optimization. Those new techniques could be explored to solve the integrated problem in future work.
- Another extension of this study could consider the integrated issue of product family design and supply chains. The design and cost of supply chain, modularity and commonality of product family and problem formulation could be examined.

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Appendix A

Questionnaire Sample

1. Gender

☐ Male ☐ Female

2. How much would you pay if you intend to purchase a portable computer at this moment?

☐Below $ 6000 ☐ $6001-$9999 ☐ $10000-$14999 ☐ Above $15000

3. How would you rate the importance of each following attribute while purchasing a portable computer for yourself? Use the scale 1 to 5 with their meaning s as show below.

5- Very important 4-Important 3-Moderate important 2-Not important

1- Not very important

Quality______ Performance_______ User friendliness_______

Comfort to carry_______ Attractiveness______ Price_______ Brand_____

4. How would you rate the following 6 portable computers corresponding to each attribute? Use the scale 1 to 5 with their meaning as shown below:

5- very good 4-good 3-Moderate 2-Bad 1-Very bad

You can refer to the attached specifications and images of the computers for assessing the six computers.

Table A.1

Product	A	B	C	D	E	F
Quality						
Performance						
Comfort to carry (Size, weight)						
Attractiveness (color, design)						
	Please rank the six computers with 1 to 6. '1' is the least preferable and '6' is the most preferable					
Rank						
Price	$5498	$6688	$7980	$9980	$10580	$11980

Appendix B

1. Factor analysis

KMO and Barlett's test of Sphericity and Varimax rotation were selected in factor analysis. The rotated factor matrix was generated by SPSS.

Table B.1 Component score coefficient matrix

Attributes	F1	F2
Quality	0.445	-0.032
Performance	0.577	-0.29
Attractiveness	-0.233	0.938
Price	0.3	0.237

2. Cluster analysis and perceptual map data

K-means cluster analysis of SPSS was used in the SPSS. The number of cases in each cluster is shown in Table B.2 Final cluster centers are shown Table B.3.

Table B.2 Number of cases in each cluster

Cluster	1	103.000
	2	186.000
	3	131.000
	Valid	420.000
	Missing	0.000

Table B.3 Final cluster centers

	Cluster 1	Cluster 2	Cluster 3
Quality	4	3	4
Performance	4	3	4
Attractiveness	3	3	4
Price	5	3.33	5.42

From Table B.1 and Table B.3, the coordinates of cluster centers can be obtained as shown in Table B.4.

Table B.4 Cluster centers (Ideal points)

	X(factor 1)	Y(factor2)
Cluster 1	4.89	2.71
Cluster 2	3.37	2.64
Cluster 3	4.78	3.75

The averages of attributes are shown in Table B.5

Table B.5 Average attributes of each competitive product

	Quality	Perf.	Attr.	Price
Competitive product A	3.16	2.96	2.87	2.75
Competitive product B	3.36	3.06	3.22	3.99
Competitive product C	2.81	3.01	2.80	3.34
Competitive product D	3.90	3.97	3.45	4.99
Competitive product E	3.72	3.67	3.32	5.29
Competitive product F	4.13	3.94	4.03	5.99

Perf=Performance Attr=Attractiveness

Positions of the six competitive products in the perceptual map can be obtained based on the coefficient matrix in Table B.1 so shown in Table B.6

Table B.6 Positions of competitive products

	X(factor 1)	Y(factor2)
Competitive product A	3.27	2.38
Competitive product B	3.71	2.97
Competitive product C	3.34	2.46
Competitive product D	4.72	3.14
Competitive product E	4.58	3.18
Competitive product F	4.97	3.93

Appendix C

1. Three products in a product line

Table C.1 Product variant 1 (Case 1)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a new product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	5.30	3.65	4.35	0.830	0.006	0.037	5.03	2.69
2	5.79	3.78	4.50	0.330	0.005	0.035	5.32	2.76
3	5.46	3.65	4.35	0.731	0.006	0.039	5.07	2.73
4	1.00	3.65	4.12	0.035	0.023	0.008	3.60	1.74
5	2.22	3.39	3.92	0.050	0.044	0.012	3.74	2.10
6	1.12	3.65	4.12	0.036	0.024	0.009	3.64	1.77
7	5.76	3.78	4.50	0.337	0.005	0.034	5.31	2.75
8	5.67	3.22	4.10	0.747	0.008	0.054	4.80	2.86
9	5.76	3.65	4.30	0.565	0.006	0.043	5.13	2.81
10	4.38	2.96	3.90	0.157	0.023	0.027	4.18	2.63
11	5.28	2.96	3.90	0.310	0.012	0.045	4.45	2.84
12	5.65	3.78	4.50	0.377	0.005	0.034	5.28	2.73
13	5.14	2.96	3.90	0.283	0.015	0.041	4.41	2.81
14	4.95	2.96	3.90	0.246	0.017	0.037	4.35	2.76
15	5.79	3.78	4.50	0.328	0.005	0.035	5.32	2.76
16	4.64	2.96	3.90	0.193	0.016	0.031	4.26	2.69
17	5.18	2.96	3.90	0.291	0.012	0.042	4.42	2.82
18	5.71	3.78	4.50	0.358	0.005	0.034	5.29	2.74
19	5.18	2.96	3.90	0.289	0.012	0.042	4.42	2.81
20	4.59	2.96	4.02	0.219	0.010	0.030	4.31	2.64
21	5.04	2.96	3.90	0.263	0.012	0.039	4.38	2.78
22	5.29	2.96	3.90	0.313	0.014	0.045	4.45	2.84
23	5.21	2.96	3.90	0.296	0.012	0.043	4.43	2.82
24	5.39	3.65	4.35	0.777	0.006	0.038	5.05	2.71
25	5.19	2.96	3.90	0.292	0.011	0.043	4.43	2.82
26	5.00	2.96	4.02	0.315	0.014	0.038	4.44	2.74

27	4.99	2.96	3.90	0.254	0.016	0.038	4.37	2.77
28	5.69	3.78	4.50	0.364	0.005	0.034	5.29	2.74
29	5.18	2.96	3.90	0.290	0.012	0.042	4.42	2.82
30	4.81	2.96	3.90	0.219	0.011	0.034	4.31	2.73
31	5.71	3.78	4.50	0.355	0.005	0.034	5.29	2.74
32	5.18	2.96	3.90	0.291	0.012	0.042	4.42	2.82
33	1.07	3.65	4.12	0.036	0.023	0.009	3.62	1.75
34	5.70	3.78	4.50	0.360	0.005	0.034	5.29	2.74
35	5.65	3.65	4.35	0.597	0.005	0.041	5.13	2.78
36	5.72	3.78	4.50	0.356	0.005	0.034	5.29	2.74
37	5.42	3.52	4.15	0.948	0.008	0.046	4.89	2.78
38	4.49	2.96	3.90	0.170	0.010	0.029	4.21	2.65
39	5.09	2.96	3.90	0.273	0.015	0.040	4.40	2.79
40	5.00	2.96	3.90	0.255	0.017	0.038	4.37	2.77
41	4.68	2.96	3.90	0.198	0.017	0.032	4.27	2.70
42	5.70	3.78	4.50	0.361	0.005	0.034	5.29	2.74
43	5.29	2.96	3.90	0.313	0.014	0.045	4.45	2.84
44	4.48	2.96	3.90	0.170	0.021	0.028	4.21	2.65
45	5.05	2.96	3.90	0.263	0.011	0.039	4.38	2.78
46	5.10	2.96	3.90	0.275	0.015	0.041	4.40	2.80
47	5.17	2.96	3.90	0.288	0.011	0.042	4.42	2.81
48	5.46	3.52	4.15	0.931	0.007	0.047	4.90	2.79
49	4.58	2.96	3.90	0.183	0.018	0.030	4.24	2.67
50	5.71	3.78	4.50	0.359	0.005	0.034	5.29	2.74

Table C.2 Alternatives configuration of RCS of product variant 1 (Case 1)

No.	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
1	3	3	2	2	2	1
2	3	3	2	2	2	2
3	3	3	2	2	2	1
4	2	2	2	3	2	2
5	2	1	2	3	2	2
6	2	2	2	3	2	2
7	3	3	2	2	2	2
8	3	2	1	1	3	1

9	3	2	2	2	2	2
10	3	1	1	1	3	1
11	3	1	1	1	3	1
12	3	3	2	2	2	2
13	3	1	1	1	3	1
14	3	1	1	1	3	1
15	3	3	2	2	2	2
16	3	1	1	1	3	1
17	3	1	1	1	3	1
18	3	3	2	2	2	2
19	3	1	1	1	3	1
20	3	1	1	2	3	1
21	3	1	1	1	3	1
22	3	1	1	1	3	1
23	3	1	1	1	3	1
24	3	3	2	2	2	1
25	3	1	1	1	3	1
26	3	1	1	2	3	1
27	3	1	1	1	3	1
28	3	3	2	2	2	2
29	3	1	1	1	3	1
30	3	1	1	1	3	1
31	3	3	2	2	2	2
32	3	1	1	1	3	1
33	2	2	2	3	2	2
34	3	3	2	2	2	2
35	3	3	2	2	2	1
36	3	3	2	2	2	2
37	3	2	2	2	2	1
38	3	1	1	1	3	1
39	3	1	1	1	3	1
40	3	1	1	1	3	1
41	3	1	1	1	3	1
42	3	3	2	2	2	2
43	3	1	1	1	3	1
44	3	1	1	1	3	1
45	3	1	1	1	3	1
46	3	1	1	1	3	1
47	3	1	1	1	3	1
48	3	2	2	2	2	1
49	3	1	1	1	3	1
50	3	3	2	2	2	2

Table C.3 Product variant 2 (Case 1)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	1.15	3.91	4.39	0.011	0.165	0.019	3.69	2.63
2	1.47	3.61	4.62	0.050	0.100	0.022	3.78	2.65
3	1.15	3.91	4.39	0.017	0.158	0.020	3.69	2.63
4	2.22	3.52	3.73	0.031	0.024	0.008	3.45	3.08
5	4.00	3.34	3.93	0.076	0.026	0.014	4.02	3.45
6	3.98	3.52	3.85	0.056	0.016	0.010	4.05	3.47
7	1.96	3.61	4.50	0.056	0.075	0.024	3.86	2.80
8	1.08	3.22	3.88	0.007	0.123	0.011	3.06	2.78
9	1.56	3.61	4.62	0.033	0.084	0.024	3.81	2.67
10	1.05	3.22	4.00	0.026	0.249	0.011	3.13	2.74
11	1.20	3.17	4.23	0.025	0.298	0.014	3.28	2.71
12	1.72	3.61	4.62	0.052	0.077	0.023	3.86	2.70
13	1.14	3.04	4.08	0.021	0.180	0.012	3.12	2.74
14	1.00	3.04	4.08	0.022	0.165	0.011	3.07	2.71
15	1.83	3.61	4.50	0.053	0.086	0.023	3.82	2.77
16	1.28	3.22	4.00	0.026	0.370	0.012	3.19	2.79
17	1.13	3.17	4.23	0.025	0.315	0.013	3.26	2.69
18	1.66	3.61	4.62	0.052	0.082	0.023	3.84	2.69
19	1.13	3.17	4.23	0.025	0.319	0.013	3.26	2.69
20	1.07	3.17	4.23	0.027	0.545	0.012	3.24	2.68
21	1.07	3.17	4.23	0.025	0.351	0.013	3.24	2.68
22	1.14	3.04	4.08	0.021	0.162	0.012	3.12	2.74
23	1.21	3.17	4.23	0.025	0.330	0.014	3.28	2.71
24	1.19	3.91	4.39	0.014	0.154	0.020	3.70	2.63
25	1.26	3.17	4.23	0.026	0.352	0.014	3.30	2.72
26	1.02	3.04	4.08	0.020	0.177	0.011	3.08	2.71
27	1.05	3.04	4.08	0.022	0.173	0.011	3.09	2.72
28	1.65	3.61	4.62	0.052	0.083	0.023	3.83	2.69
29	1.22	3.17	4.23	0.026	0.345	0.014	3.29	2.71
30	1.14	3.17	4.23	0.028	0.504	0.013	3.26	2.69
31	1.72	3.61	4.62	0.054	0.076	0.023	3.86	2.70
32	1.13	3.17	4.23	0.025	0.315	0.013	3.26	2.69
33	2.24	3.52	3.73	0.031	0.025	0.008	3.46	3.09
34	1.74	3.61	4.62	0.054	0.075	0.023	3.86	2.71
35	1.00	3.91	4.39	0.024	0.182	0.019	3.64	2.59
36	1.43	3.61	4.62	0.047	0.108	0.022	3.77	2.63
37	1.16	3.91	4.39	0.003	0.144	0.020	3.69	2.63
38	1.04	3.35	4.15	0.030	0.648	0.012	3.27	2.69
39	1.18	3.04	4.08	0.022	0.196	0.012	3.13	2.75
40	1.02	3.04	4.08	0.022	0.166	0.011	3.08	2.71
41	1.20	3.22	4.00	0.026	0.314	0.012	3.17	2.77
42	1.61	3.61	4.62	0.051	0.087	0.023	3.82	2.68

43	1.14	3.04	4.08	0.021	0.162	0.012	3.12	2.74
44	1.04	3.22	4.00	0.025	0.244	0.011	3.12	2.74
45	1.24	3.17	4.23	0.027	0.426	0.014	3.29	2.72
46	1.10	3.04	4.08	0.021	0.174	0.012	3.10	2.73
47	1.26	3.17	4.23	0.026	0.363	0.014	3.30	2.72
48	1.15	3.91	4.39	0.004	0.141	0.021	3.69	2.63
49	1.21	3.22	4.00	0.026	0.331	0.012	3.17	2.78
50	1.53	3.61	4.62	0.049	0.094	0.022	3.80	2.66

Table C.4 Alternatives configuration of RCS product variant 2

No.	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
1	2	3	1	3	2	3
2	2	3	2	3	3	3
3	2	3	1	3	2	3
4	2	2	2	1	2	1
5	2	2	3	2	2	1
6	2	2	2	2	2	1
7	2	3	2	2	3	3
8	3	2	2	1	1	1
9	2	3	2	3	3	3
10	3	2	2	2	1	1
11	3	2	3	2	1	2
12	2	3	2	3	3	3
13	3	2	3	2	1	1
14	3	2	3	2	1	1
15	2	3	2	2	3	3
16	3	2	2	2	1	1
17	3	2	3	2	1	2
18	2	3	2	3	3	3
19	3	2	3	2	1	2
20	3	2	3	2	1	2
21	3	2	3	2	1	2
22	3	2	3	2	1	1
23	3	2	3	2	1	2
24	2	3	1	3	2	3
25	3	2	3	2	1	2
26	3	2	3	2	1	1
27	3	2	3	2	1	1
28	2	3	2	3	3	3
29	3	2	3	2	1	2
30	3	2	3	2	1	2

31	2	3	2	3	3	3
32	3	2	3	2	1	2
33	2	2	2	1	2	1
34	2	3	2	3	3	3
35	2	3	1	3	2	3
36	2	3	2	3	3	3
37	2	3	1	3	2	3
38	3	2	2	2	1	2
39	3	2	3	2	1	1
40	3	2	3	2	1	1
41	3	2	2	2	1	1
42	2	3	2	3	3	3
43	3	2	3	2	1	1
44	3	2	2	2	1	1
45	3	2	3	2	1	2
46	3	2	3	2	1	1
47	3	2	3	2	1	2
48	2	3	1	3	2	3
49	3	2	2	2	1	1
50	2	3	2	3	3	3

Table C.5 Product variant 3 (Case 1)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	8.00	3.04	3.66	0.002	0.002	0.016	4.70	5.43
2	8.00	3.34	3.81	0.009	0.002	0.017	4.92	5.37
3	8.00	3.04	3.66	0.003	0.002	0.016	4.70	5.43
4	8.00	3.52	3.85	0.013	0.002	0.017	5.02	5.36
5	7.85	3.65	4.12	0.013	0.002	0.019	5.19	5.24
6	7.99	3.52	3.85	0.013	0.002	0.017	5.02	5.35
7	7.90	3.34	3.81	0.009	0.002	0.017	4.89	5.35
8	6.22	3.3	4.38	0.006	0.003	0.039	4.70	4.79
9	7.83	3.34	3.81	0.006	0.002	0.017	4.87	5.33
10	5.81	3.17	4.23	0.018	0.003	0.040	4.43	4.74
11	5.92	3.3	4.38	0.016	0.002	0.044	4.61	4.72
12	7.59	3.34	3.81	0.009	0.002	0.019	4.80	5.28
13	5.55	3.3	4.38	0.018	0.003	0.050	4.50	4.63
14	6.06	3.3	4.38	0.017	0.003	0.042	4.65	4.75
15	8.00	3.34	3.81	0.009	0.002	0.017	4.92	5.37

16	5.89	3.17	4.23	0.017	0.002	0.039	4.45	4.76
17	5.28	3.3	4.38	0.018	0.003	0.053	4.42	4.57
18	7.57	3.34	3.81	0.009	0.002	0.019	4.79	5.27
19	5.30	3.3	4.38	0.018	0.003	0.053	4.42	4.57
20	5.96	3.3	4.38	0.018	0.002	0.044	4.62	4.73
21	5.97	3.3	4.38	0.017	0.002	0.044	4.62	4.73
22	5.66	3.3	4.38	0.017	0.003	0.048	4.53	4.65
23	5.81	3.3	4.38	0.016	0.002	0.046	4.57	4.69
24	8.00	3.04	3.78	0.003	0.002	0.016	4.77	5.39
25	5.87	3.3	4.38	0.016	0.002	0.045	4.59	4.71
26	6.10	3.3	4.38	0.015	0.003	0.042	4.66	4.76
27	5.97	3.3	4.38	0.017	0.003	0.044	4.62	4.73
28	7.52	3.34	3.81	0.009	0.002	0.019	4.77	5.26
29	5.43	3.3	4.38	0.018	0.003	0.051	4.46	4.60
30	5.99	3.3	4.38	0.018	0.002	0.043	4.63	4.74
31	7.47	3.34	3.81	0.009	0.002	0.019	4.76	5.25
32	5.30	3.3	4.38	0.018	0.003	0.053	4.42	4.57
33	8.00	3.52	3.85	0.013	0.002	0.017	5.02	5.36
34	7.55	3.34	3.81	0.009	0.002	0.019	4.79	5.27
35	8.00	3.04	3.66	0.005	0.002	0.016	4.70	5.43
36	8.00	3.34	3.81	0.008	0.002	0.017	4.92	5.37
37	8.00	3.04	3.78	0.001	0.002	0.016	4.77	5.39
38	5.71	3.17	4.23	0.018	0.001	0.040	4.40	4.72
39	5.83	3.3	4.38	0.017	0.003	0.046	4.58	4.70
40	6.08	3.3	4.38	0.017	0.003	0.042	4.65	4.75
41	5.97	3.17	4.23	0.017	0.002	0.038	4.48	4.78
42	7.45	3.34	3.81	0.009	0.002	0.020	4.76	5.24
43	5.64	3.3	4.38	0.017	0.003	0.048	4.52	4.65
44	5.71	3.17	4.23	0.018	0.003	0.040	4.40	4.72
45	5.89	3.3	4.38	0.017	0.002	0.045	4.60	4.71
46	5.93	3.3	4.38	0.017	0.003	0.044	4.61	4.72
47	5.87	3.3	4.38	0.016	0.002	0.045	4.59	4.71
48	8.00	3.04	3.66	0.001	0.002	0.015	4.70	5.43
49	5.98	3.17	4.23	0.017	0.002	0.038	4.48	4.78
50	7.87	3.34	3.81	0.008	0.002	0.017	4.88	5.34

Table C.6 Alternatives configuration of RCS of product variant 3

No.	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
1	2	2	3	1	1	1
2	2	2	3	1	2	1
3	2	2	3	1	1	1

4	2	2	2	2	2	1
5	2	2	2	3	2	2
6	2	2	2	2	2	1
7	2	2	3	1	2	1
8	3	2	3	2	1	3
9	2	2	3	1	2	1
10	3	2	3	2	1	2
11	3	2	3	2	1	3
12	2	2	3	1	2	1
13	3	2	3	2	1	3
14	3	2	3	2	1	3
15	2	2	3	1	2	1
16	3	2	3	2	1	2
17	3	2	3	2	1	3
18	2	2	3	1	2	1
19	3	2	3	2	1	3
20	3	2	3	2	1	3
21	3	2	3	2	1	3
22	3	2	3	2	1	3
23	3	2	3	2	1	3
24	2	2	3	2	1	1
25	3	2	3	2	1	3
26	3	2	3	2	1	3
27	3	2	3	2	1	3
28	2	2	3	1	2	1
29	3	2	3	2	1	3
30	3	2	3	2	1	3
31	2	2	3	1	2	1
32	3	2	3	2	1	3
33	2	2	2	2	2	1
34	2	2	3	1	2	1
35	2	2	3	1	1	1
36	2	2	3	1	2	1
37	2	2	3	2	1	1
38	3	2	3	2	1	2
39	3	2	3	2	1	3
40	3	2	3	2	1	3
41	3	2	3	2	1	2
42	2	2	3	1	2	1
43	3	2	3	2	1	3
44	3	2	3	2	1	2
45	3	2	3	2	1	3
46	3	2	3	2	1	3

47	3	2	3	2	1	3
48	2	2	3	1	1	1
49	3	2	3	2	1	2
50	2	2	3	1	2	1

Table C.7 Supplier Selection for a product line (three product variants) (C=Component/Module)

NPV1

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	2	7	12	9	1	7	1	9	7	9
2	2	7	12	9	2	6	1	9	7	9
3	2	7	12	9	1	7	1	9	7	9
4	2	6	7	5	2	8	2	9	7	9
5	2	6	7	5	3	8	1	9	7	9
6	2	8	7	5	2	8	1	4	7	9
7	2	7	12	9	2	5	1	9	7	9
8	1	8	12	7	3	6	1	4	7	10
9	2	6	12	9	2	6	1	9	7	9
10	1	5	12	7	3	6	4	4	7	4
11	1	8	7	6	4	6	1	4	10	4
12	2	7	12	9	2	6	1	9	7	9
13	1	8	7	6	3	6	1	4	10	4
14	1	8	7	6	3	6	1	4	10	4
15	2	7	12	9	2	6	1	9	7	9
16	1	5	12	7	4	6	4	10	7	4
17	1	8	7	6	3	6	1	4	10	4
18	2	7	12	9	2	6	1	9	7	9
19	1	8	7	6	4	6	1	4	10	4
20	1	8	7	7	3	6	1	4	10	4
21	1	8	7	6	3	6	1	4	10	4
22	1	5	12	6	3	6	2	4	10	4
23	1	8	7	6	3	6	1	4	10	4
24	2	7	12	9	1	7	1	9	7	9
25	1	8	7	6	4	6	1	4	10	4
26	1	8	7	7	3	6	1	4	10	4
27	1	8	7	6	3	6	1	4	10	4
28	2	7	12	9	2	5	1	9	7	9
29	1	8	7	6	3	6	1	4	10	4
30	1	8	7	6	3	6	1	4	10	4

31	2	7	12	9	2	5	1	9	7	9
32	1	8	7	6	4	6	1	4	10	4
33	2	6	7	5	2	8	2	9	7	9
34	2	7	12	9	2	6	1	9	7	9
35	2	7	12	9	1	7	1	9	7	9
36	2	7	12	9	2	6	1	9	7	9
37	2	6	12	9	1	7	1	9	7	9
38	1	5	12	7	4	6	4	4	7	4
39	1	5	7	6	3	6	2	4	10	4
40	1	8	7	6	3	6	1	4	10	4
41	1	8	12	7	4	6	3	10	7	4
42	2	7	12	9	2	5	1	9	7	9
43	1	8	12	6	4	6	2	4	10	4
44	1	5	12	7	4	6	4	4	7	4
45	1	8	7	6	3	6	3	4	10	4
46	1	8	7	6	3	6	1	4	10	4
47	1	8	7	6	4	6	1	4	10	4
48	2	6	12	9	2	7	1	9	7	9
49	1	8	12	7	4	6	3	10	7	4
50	2	7	12	9	2	6	1	9	7	9

NPV2

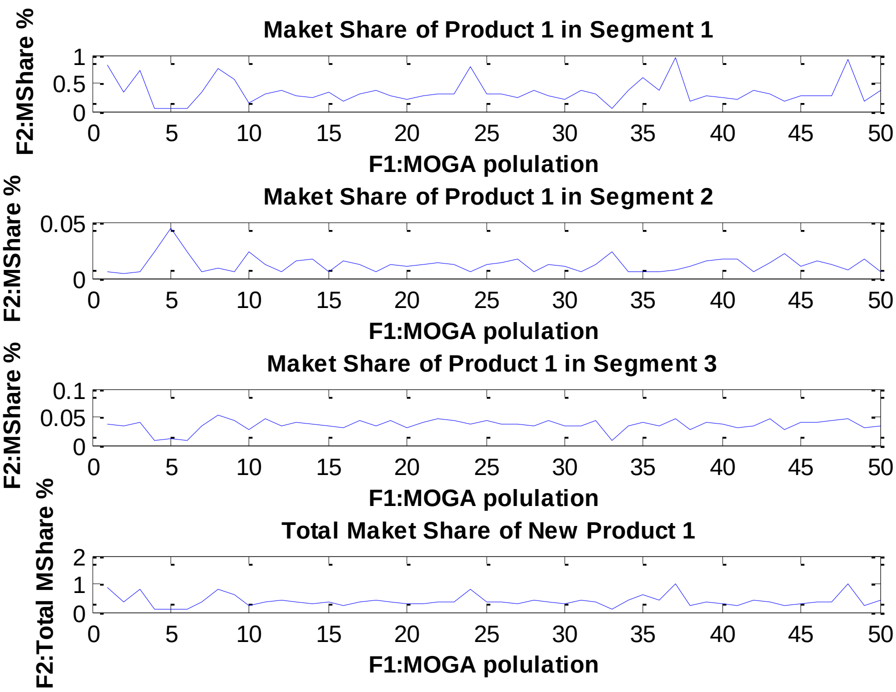
No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	2	7	7	9	1	8	1	9	7	9
2	2	7	12	9	1	8	1	9	7	9
3	2	7	7	9	1	8	1	9	7	9
4	2	6	7	5	2	5	2	9	7	9
5	2	6	11	5	3	8	1	9	7	9
6	2	8	7	5	2	5	1	4	7	9
7	2	7	12	9	1	6	1	9	7	9
8	1	8	12	7	4	6	1	4	7	10
9	2	7	12	9	1	8	1	9	7	9
10	1	8	12	7	4	6	4	4	7	4
11	1	8	7	7	4	8	1	4	10	4
12	2	7	12	9	1	8	1	9	7	9
13	1	8	7	7	4	6	1	4	10	4
14	1	8	7	7	4	6	1	4	10	4
15	2	7	12	9	1	6	1	9	7	9
16	1	8	12	7	4	6	4	10	7	4

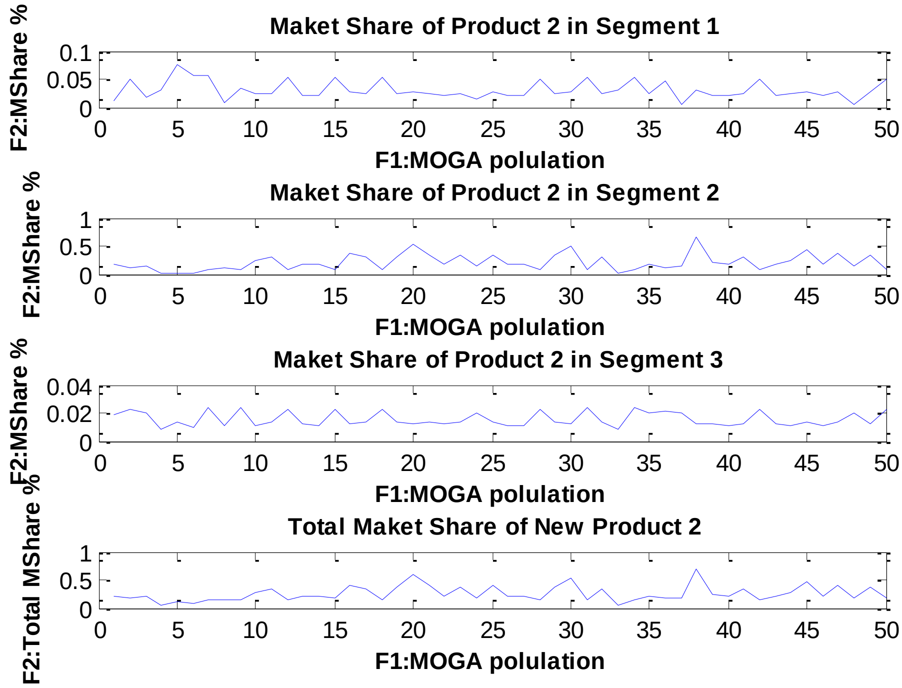
17	1	8	7	7	1	8	1	4	10	4
18	2	7	12	9	1	8	1	9	7	9
19	1	8	7	7	1	8	1	4	10	4
20	1	8	7	7	1	8	1	4	10	4
21	1	8	7	7	1	8	1	4	10	4
22	1	8	7	7	4	6	2	4	10	4
23	1	8	12	7	1	8	1	4	10	4
24	2	7	7	9	1	8	1	9	7	9
25	1	8	12	7	1	8	1	4	10	4
26	1	8	7	7	1	6	1	4	10	4
27	1	8	7	7	4	6	1	4	10	4
28	2	7	12	5	1	8	1	9	7	9
29	1	8	7	7	1	8	1	4	10	4
30	1	8	7	7	4	8	1	4	10	4
31	2	7	12	5	1	8	1	9	7	9
32	1	8	7	7	1	8	1	4	10	4
33	2	6	7	5	2	5	2	9	7	9
34	2	7	12	9	1	8	1	9	7	9
35	2	7	7	9	1	8	1	9	7	9
36	2	7	12	9	1	8	1	9	7	9
37	2	7	7	9	1	8	1	9	7	9
38	1	8	12	7	4	8	4	4	7	4
39	1	8	7	7	4	6	2	4	10	4
40	1	8	7	7	4	6	1	4	10	4
41	1	8	12	7	4	6	3	10	7	4
42	2	7	12	5	1	8	1	9	7	9
43	1	8	7	7	4	6	2	4	10	4
44	1	8	12	7	4	6	4	4	7	4
45	1	8	7	7	4	8	3	4	10	4
46	1	8	7	7	1	6	1	4	10	4
47	1	8	12	7	1	8	1	4	10	4
48	2	7	7	9	2	8	1	9	7	9
49	1	8	12	7	4	6	3	10	7	4
50	2	7	12	9	1	8	1	9	7	9

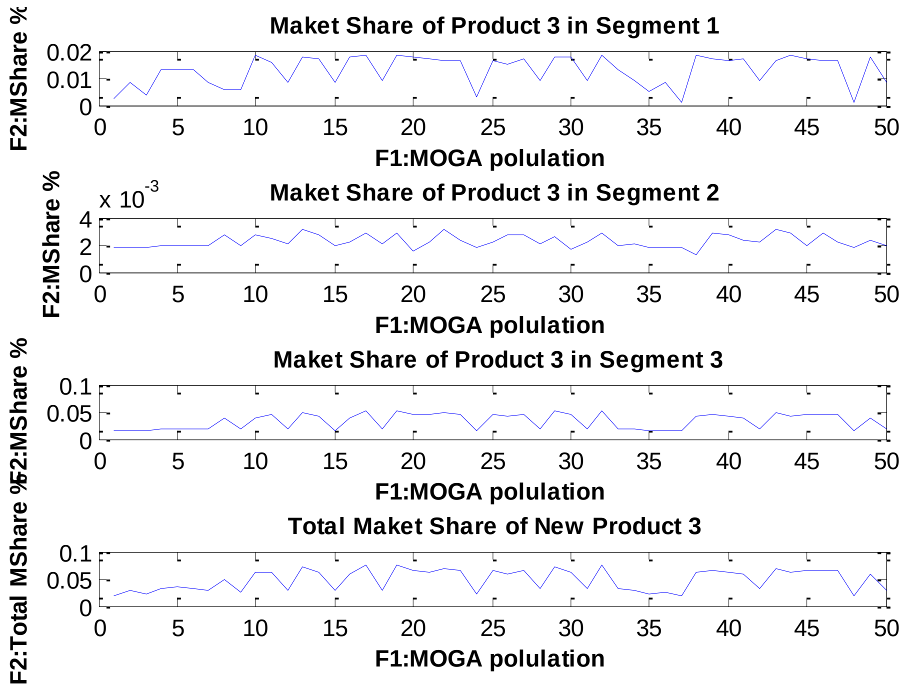
NPV3

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	2	6	12	9	1	7	1	9	7	9
2	2	6	11	9	2	7	1	9	7	9
3	2	6	11	9	1	7	1	9	7	9
4	2	6	7	5	2	5	2	9	7	9
5	2	6	7	5	3	8	1	9	7	9
6	2	8	7	5	2	5	1	4	7	9
7	2	6	11	9	2	7	1	9	7	9
8	1	8	7	7	4	7	1	4	7	10
9	2	6	7	9	2	7	1	9	7	9
10	1	8	7	7	4	8	4	4	7	4
11	1	8	7	7	4	5	1	4	10	4
12	2	6	11	9	2	7	1	9	7	9
13	1	8	7	7	4	5	1	4	10	4
14	1	8	7	7	4	7	1	4	10	4
15	2	6	11	9	2	7	1	9	7	9
16	1	8	7	7	4	8	4	10	7	4
17	1	8	7	7	1	5	1	4	10	4
18	2	6	11	9	2	7	1	9	7	9
19	1	8	7	7	1	5	1	4	10	4
20	1	8	7	7	1	7	1	4	10	4
21	1	8	7	7	1	7	1	4	10	4
22	1	8	7	7	4	7	2	4	10	4
23	1	8	12	7	1	5	1	4	10	4
24	2	6	11	9	1	7	1	9	7	9
25	1	8	12	7	1	7	1	4	10	4
26	1	8	7	7	1	7	1	4	10	4
27	1	8	7	7	4	7	1	4	10	4
28	2	6	11	9	2	7	1	9	7	9
29	1	8	7	7	1	5	1	4	10	4
30	1	8	7	7	4	7	1	4	10	4
31	2	6	11	9	2	7	1	9	7	9
32	1	8	7	7	1	5	1	4	10	4
33	2	6	7	5	2	5	2	9	7	9
34	2	6	11	9	2	7	1	9	7	9
35	2	6	11	9	1	7	1	9	7	9
36	2	6	11	9	2	7	1	9	7	9
37	2	6	12	9	1	7	1	9	7	9
38	1	8	7	7	4	8	4	4	7	4
39	1	8	7	7	4	7	2	4	10	4

40	1	8	7	7	4	7	1	4	10	4
41	1	8	7	7	4	8	3	10	7	4
42	2	6	11	9	2	7	1	9	7	9
43	1	8	7	7	4	7	2	4	10	4
44	1	8	7	7	4	8	4	4	7	4
45	1	8	7	7	4	7	3	4	10	4
46	1	8	7	7	1	7	1	4	10	4
47	1	8	12	7	1	7	1	4	10	4
48	2	6	11	9	1	7	1	9	7	9
49	1	8	7	7	4	8	3	10	7	4
50	2	6	7	9	2	7	1	9	7	9




Maket Share of Product 2 in Segment 1
F2:MShare %
F1:MOGA polulation
Maket Share of Product 2 in Segment 2
F2:MShare %
F1:MOGA polulation
Maket Share of Product 2 in Segment 3
F2:MShare %
F1:MOGA polulation
Total Maket Share of New Product 2
F2:Total MShare %
F1:MOGA polulation


Maket Share of Product 3 in Segment 1
F2:MShare %
F1:MOGA polulation
Maket Share of Product 3 in Segment 2
x 10-3
F2:MShare %
F1:MOGA polulation
Maket Share of Product 3 in Segment 3
F2:MShare %
F1:MOGA polulation
Total Maket Share of New Product 3
F2:Total MShare %
F1:MOGA polulation

2. Two product variants in a product line

Table C.8 Product variant 1 (Case 2)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	7.03	3.19	3.77	0.081	0.006	0.773	4.89	3.75
2	2.31	3.32	3.85	0.052	0.318	0.014	3.58	2.61
3	6.94	3.19	3.77	0.084	0.006	0.857	4.86	3.73
4	1.00	3.19	3.65	0.026	0.087	0.009	3.01	2.36
5	1.72	3.19	3.65	0.033	0.382	0.011	3.23	2.53
6	7.00	3.19	3.77	0.082	0.006	0.804	4.88	3.75
7	1.24	3.19	3.65	0.028	0.134	0.009	3.08	2.42
8	2.16	3.32	3.85	0.049	0.403	0.014	3.53	2.57
9	3.15	3.32	3.85	0.078	0.079	0.023	3.83	2.81
10	2.47	3.32	3.85	0.056	0.242	0.014	3.62	2.65
11	2.44	3.32	3.85	0.055	0.254	0.014	3.62	2.64
12	2.55	3.32	3.85	0.058	0.208	0.015	3.65	2.66
13	2.94	3.32	3.85	0.071	0.108	0.021	3.77	2.76
14	3.13	3.32	3.85	0.077	0.081	0.023	3.82	2.80
15	2.52	3.32	3.85	0.057	0.217	0.015	3.64	2.66
16	3.04	3.32	3.85	0.074	0.093	0.022	3.80	2.78
17	2.97	3.32	3.85	0.072	0.103	0.021	3.77	2.76
18	2.45	3.32	3.85	0.056	0.251	0.016	3.62	2.64
19	6.36	3.19	3.77	0.104	0.008	0.553	4.69	3.60
20	2.50	3.32	3.85	0.057	0.229	0.015	3.63	2.65
21	6.95	3.19	3.77	0.083	0.006	0.843	4.87	3.74
22	2.22	3.32	3.85	0.050	0.369	0.013	3.55	2.59
23	2.34	3.32	3.85	0.053	0.303	0.014	3.59	2.62
24	2.21	3.32	3.85	0.050	0.371	0.014	3.55	2.59
25	2.20	3.32	3.85	0.050	0.380	0.014	3.54	2.58
26	7.24	3.19	3.77	0.074	0.005	0.556	4.95	3.80
27	2.23	3.32	3.85	0.050	0.363	0.014	3.55	2.59
28	2.60	3.32	3.85	0.060	0.189	0.017	3.66	2.68
29	1.35	3.19	3.65	0.029	0.158	0.010	3.11	2.44
30	7.19	3.19	3.77	0.076	0.005	0.624	4.94	3.79
31	2.12	3.32	3.85	0.048	0.418	0.015	3.52	2.56
32	2.55	3.32	3.85	0.058	0.207	0.016	3.65	2.67
33	2.50	3.32	3.85	0.057	0.227	0.015	3.63	2.65
34	1.00	3.19	3.65	0.026	0.089	0.009	3.01	2.36
35	2.12	3.32	3.85	0.048	0.422	0.013	3.52	2.56
36	1.43	3.19	3.65	0.030	0.194	0.009	3.14	2.46
37	2.52	3.32	3.85	0.057	0.220	0.016	3.64	2.66
38	2.69	3.32	3.85	0.062	0.162	0.017	3.69	2.70

39	2.92	3.32	3.85	0.070	0.111	0.020	3.76	2.75
40	7.16	3.19	3.77	0.077	0.005	0.654	4.93	3.78
41	7.12	3.19	3.77	0.078	0.006	0.691	4.92	3.78
42	2.43	3.32	3.85	0.055	0.258	0.015	3.61	2.64
43	2.61	3.32	3.85	0.060	0.188	0.017	3.67	2.68
44	1.14	3.19	3.65	0.027	0.112	0.009	3.05	2.39
45	1.04	3.19	3.65	0.026	0.093	0.009	3.02	2.37
46	7.02	3.19	3.77	0.081	0.006	0.783	4.89	3.75
47	7.35	3.19	3.77	0.071	0.005	0.472	4.98	3.83
48	6.93	3.19	3.77	0.084	0.006	0.861	4.86	3.73
49	7.30	3.19	3.77	0.072	0.005	0.512	4.97	3.82
50	2.54	3.32	3.85	0.058	0.212	0.016	3.65	2.66

Table C.9 Alternatives configuration of RCS of product variant 1

No.	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
1	2	2	1	2	1	2
2	2	2	2	2	2	1
3	2	2	1	2	1	2
4	2	1	2	2	2	1
5	2	1	2	2	2	1
6	2	2	1	2	1	2
7	2	1	2	2	2	1
8	2	2	2	2	2	1
9	2	2	2	2	2	1
10	2	2	2	2	2	1
11	2	2	2	2	2	1
12	2	2	2	2	2	1
13	2	2	2	2	2	1
14	2	2	2	2	2	1
15	2	2	2	2	2	1
16	2	2	2	2	2	1
17	2	2	2	2	2	1
18	2	2	2	2	2	1
19	2	2	1	2	1	2
20	2	2	2	2	2	1
21	2	2	1	2	1	2
22	2	2	2	2	2	1
23	2	2	2	2	2	1
24	2	2	2	2	2	1
25	2	2	2	2	2	1
26	2	2	1	2	1	2

27	2	2	2	2	2	1
28	2	2	2	2	2	1
29	2	1	2	2	2	1
30	2	2	1	2	1	2
31	2	2	2	2	2	1
32	2	2	2	2	2	1
33	2	2	2	2	2	1
34	2	1	2	2	2	1
35	2	2	2	2	2	1
36	2	1	2	2	2	1
37	2	2	2	2	2	1
38	2	2	2	2	2	1
39	2	2	2	2	2	1
40	2	2	1	2	1	2
41	2	2	1	2	1	2
42	2	2	2	2	2	1
43	2	2	2	2	2	1
44	2	1	2	2	2	1
45	2	1	2	2	2	1
46	2	2	1	2	1	2
47	2	2	1	2	1	2
48	2	2	1	2	1	2
49	2	2	1	2	1	2
50	2	2	2	2	2	1

Table C.10 Product variant 2 (Case 2)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	5.65	3.84	4.08	0.036	0.005	0.035	4.708	4.253
2	3.75	3.95	4.08	0.873	0.020	0.060	4.19	3.80
3	1.74	3.95	4	0.125	0.101	0.028	3.54	3.35
4	1.00	4.12	4.4	0.100	0.060	0.021	3.62	3.05
5	1.74	3.95	4	0.126	0.101	0.028	3.54	3.35
6	1.23	3.99	4.17	0.095	0.098	0.023	3.50	3.17
7	1.36	3.99	4.17	0.104	0.090	0.024	3.54	3.21
8	4.77	3.95	4.23	0.495	0.011	0.063	4.58	4.00
9	1.78	3.99	4.02	0.128	0.088	0.029	3.58	3.35
10	1.16	4.12	4.32	0.108	0.064	0.022	3.63	3.11
11	1.52	3.99	4.17	0.117	0.081	0.025	3.59	3.24
12	2.05	3.95	4	0.160	0.076	0.032	3.63	3.42

13	1.84	3.95	4	0.134	0.092	0.029	3.57	3.37
14	2.03	3.95	4	0.157	0.077	0.031	3.63	3.42
15	3.40	3.95	4.08	0.657	0.025	0.053	4.08	3.72
16	1.96	3.95	4	0.150	0.083	0.030	3.60	3.40
17	2.06	3.95	4	0.162	0.075	0.032	3.64	3.42
18	1.86	3.95	4	0.138	0.090	0.029	3.58	3.38
19	1.91	3.95	4	0.144	0.087	0.030	3.59	3.39
20	1.90	3.95	4	0.144	0.087	0.030	3.59	3.39
21	2.05	3.95	4	0.156	0.076	0.032	3.63	3.42
22	4.52	3.86	4.35	0.569	0.012	0.057	4.53	3.91
23	1.73	3.95	4	0.124	0.102	0.028	3.54	3.34
24	1.99	3.95	4	0.152	0.080	0.031	3.61	3.41
25	4.64	3.86	4.35	0.514	0.011	0.058	4.57	3.94
26	1.74	3.95	4	0.127	0.101	0.028	3.54	3.35
27	1.95	3.95	4	0.148	0.083	0.030	3.60	3.40
28	1.87	3.95	4	0.140	0.090	0.029	3.58	3.38
29	2.10	3.95	4	0.169	0.073	0.032	3.65	3.43
30	1.73	3.95	4	0.125	0.102	0.028	3.54	3.34
31	4.66	3.86	4.05	0.762	0.013	0.079	4.40	4.03
32	1.64	3.95	4	0.117	0.110	0.027	3.51	3.32
33	4.31	3.86	4.05	0.962	0.016	0.073	4.30	3.94
34	2.20	3.95	4	0.184	0.067	0.034	3.68	3.46
35	1.07	4.12	4.4	0.104	0.058	0.021	3.64	3.07
36	2.05	3.95	4	0.158	0.076	0.032	3.63	3.42
37	4.66	3.86	4.05	0.763	0.013	0.079	4.40	4.03
38	1.62	3.95	4	0.117	0.113	0.027	3.50	3.32
39	4.54	3.86	4.05	0.842	0.014	0.077	4.37	4.00
40	4.90	3.86	4.05	0.600	0.012	0.081	4.48	4.08
41	1.60	3.95	4	0.114	0.114	0.027	3.50	3.31
42	2.29	3.95	4	0.200	0.062	0.035	3.70	3.48
43	4.07	3.86	4.05	0.986	0.018	0.069	4.23	3.89
44	2.00	3.95	4	0.156	0.079	0.031	3.62	3.41
45	2.15	3.95	4	0.172	0.070	0.033	3.66	3.44
46	2.09	3.95	4	0.165	0.073	0.032	3.64	3.43
47	4.55	3.86	4.05	0.834	0.014	0.077	4.37	4.00
48	4.58	3.86	4.05	0.813	0.014	0.078	4.38	4.01
49	1.67	3.95	4	0.121	0.108	0.027	3.52	3.33
50	2.13	3.95	4	0.174	0.071	0.033	3.66	3.44

Table C.11 Alternatives configuration of RCS of product variant 2

No.	RCS1	RCS2	RCS3	RCS4	RCS5	RCS6
1	2	3	2	1	2	2
2	3	3	3	1	1	2
3	2	3	1	1	2	2
4	2	2	2	2	1	2
5	2	3	3	1	1	2
6	2	3	1	1	2	2
7	2	3	3	1	1	2
8	2	3	3	1	1	2
9	2	3	3	1	1	2
10	3	3	3	1	1	2
11	3	3	3	1	1	2
12	3	3	3	1	1	2
13	2	3	3	1	1	2
14	2	3	3	1	1	2
15	3	3	3	1	1	2
16	2	3	3	1	1	2
17	2	3	3	1	1	2
18	2	3	3	1	1	2
19	2	3	2	1	2	2
20	3	3	3	1	1	2
21	2	3	2	1	2	2
22	3	3	3	1	1	2
23	3	3	3	1	1	2
24	2	3	3	1	1	2
25	2	3	3	1	1	2
26	2	3	2	1	2	2
27	2	3	3	1	1	2
28	2	3	3	1	1	2
29	2	2	3	2	1	2
30	2	2	2	1	2	2
31	2	2	2	1	1	2
32	2	3	3	1	1	2
33	3	3	3	1	1	2
34	2	2	3	1	1	2
35	2	3	3	1	1	2
36	2	3	3	2	1	2
37	2	3	3	1	1	2
38	2	3	3	1	1	2
39	2	3	3	1	1	2
40	2	2	2	1	2	2

41	2	2	2	1	2	2
42	2	3	3	1	1	2
43	2	3	3	1	1	2
44	2	3	3	1	1	2
45	2	2	2	2	1	2
46	2	3	2	1	2	2
47	2	2	2	1	2	2
48	2	3	1	1	2	2
49	2	2	2	1	2	2
50	2	3	3	1	1	2

Table C.12 Supplier Selection for a product line (two product variants)

NPV1 (C=Component/Module)

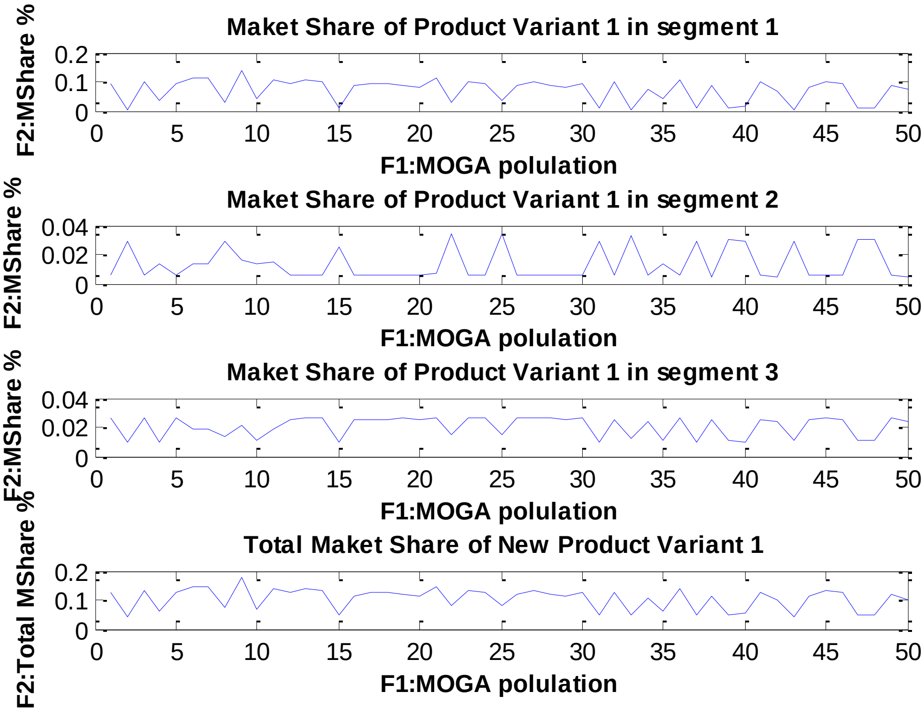
No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	2	6	7	7	2	7	2	5	6	6
2	2	5	12	9	3	5	1	4	10	7
3	1	6	12	7	2	7	2	5	6	6
4	2	5	12	9	4	5	1	4	4	7
5	2	5	7	6	3	5	1	4	10	6
6	1	6	12	7	2	7	2	5	6	6
7	2	5	7	6	3	5	1	4	10	6
8	2	5	11	9	1	5	1	4	10	7
9	2	5	11	6	3	5	1	4	10	7
10	2	5	11	9	1	5	1	4	10	7
11	2	5	11	9	3	5	1	4	10	7
12	2	5	11	9	1	5	1	4	10	7
13	2	5	11	6	1	5	1	4	10	7
14	2	5	11	6	3	5	3	4	10	7
15	2	5	11	9	1	5	1	4	10	7
16	2	5	11	9	3	5	1	4	10	7
17	2	5	11	9	1	5	1	4	10	7
18	2	5	11	9	1	5	1	4	10	7
19	2	6	7	7	2	7	2	5	6	6
20	2	5	11	9	1	5	1	4	10	7
21	2	6	7	7	2	7	2	5	6	6
22	2	5	12	9	3	5	1	4	10	7
23	2	5	11	9	1	5	1	4	7	7

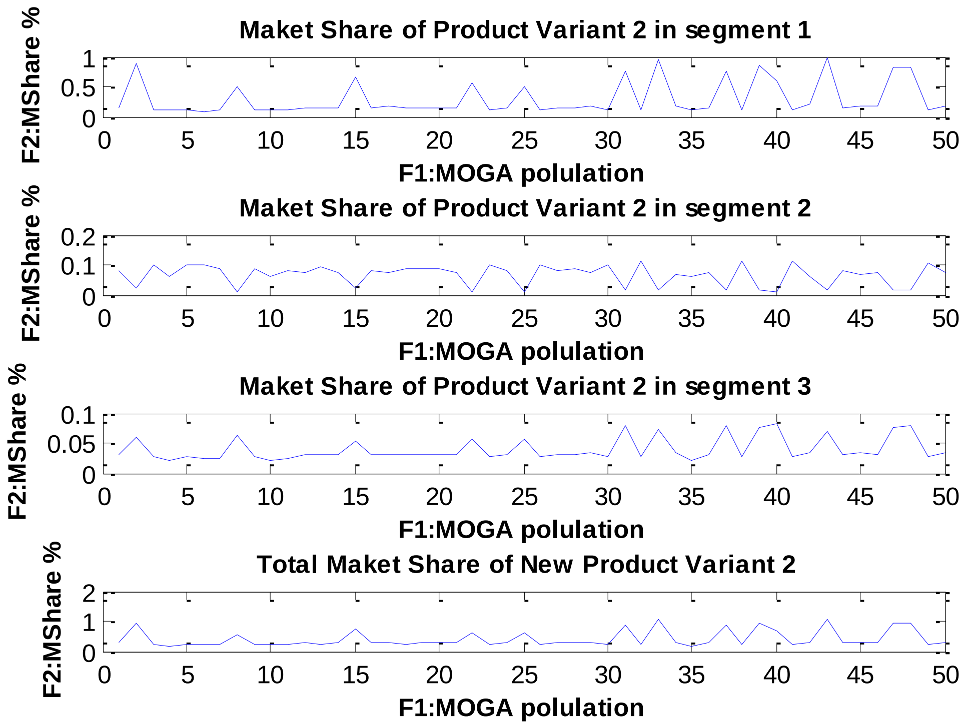
24	2	5	11	9	1	5	1	4	10	7
25	2	5	11	9	1	5	1	4	10	7
26	2	7	7	7	2	5	3	5	6	7
27	2	5	11	9	1	5	1	4	10	7
28	2	5	11	9	1	5	1	4	10	7
29	2	8	12	9	4	5	1	4	7	7
30	2	7	12	7	2	5	3	5	6	6
31	2	8	12	6	4	5	1	4	4	7
32	2	5	12	9	1	5	1	4	7	7
33	2	5	11	9	1	5	1	4	10	7
34	2	5	11	9	3	7	1	4	10	6
35	2	5	11	9	1	5	1	4	10	7
36	2	8	12	6	3	7	1	4	4	6
37	2	5	11	9	1	5	1	4	10	7
38	2	5	11	9	1	5	1	4	10	7
39	2	5	11	9	1	5	1	4	10	7
40	2	7	12	7	2	5	3	5	6	6
41	2	7	12	7	2	5	3	5	6	6
42	2	5	12	9	1	5	1	4	10	7
43	2	5	11	9	1	5	1	4	10	7
44	2	5	7	9	3	5	1	4	10	6
45	2	5	12	9	4	5	1	4	4	7
46	2	6	7	7	2	7	2	5	6	6
47	2	7	12	7	2	5	3	5	6	10
48	2	6	12	7	2	7	2	5	6	6
49	2	7	12	7	2	5	3	5	6	10
50	2	5	11	9	1	5	1	4	10	7

NPV2 (C=Component/Module)

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	2	5	11	7	1	7	2	5	6	6
2	1	7	7	7	3	6	1	4	10	7
3	1	5	12	7	1	7	2	5	6	6
4	2	8	12	9	2	5	1	4	4	7
5	2	5	7	6	2	7	1	4	10	6
6	1	5	12	7	1	7	2	5	6	6
7	2	5	7	6	2	7	1	4	10	6
8	2	7	7	7	3	6	1	4	10	7
9	2	7	7	7	3	6	1	4	10	7
10	1	7	7	7	3	6	1	4	10	7
11	1	7	7	7	3	6	1	4	10	7

12	1	7	7	7	3	6	1	4	10	7
13	2	7	7	7	3	6	1	4	10	7
14	2	7	7	7	3	6	3	4	10	7
15	1	7	7	7	3	6	1	4	10	7
16	2	7	7	7	3	6	1	4	10	7
17	2	7	7	7	3	6	1	4	10	7
18	2	7	7	7	3	6	1	4	10	7
19	2	5	11	7	2	7	2	5	6	6
20	1	7	7	7	3	6	1	4	10	7
21	2	5	11	7	1	7	2	5	6	6
22	1	7	7	7	3	6	1	4	10	7
23	1	7	7	7	3	6	1	4	7	7
24	2	7	7	7	3	6	1	4	10	7
25	2	7	7	7	3	6	1	4	10	7
26	2	5	11	5	1	5	3	5	6	7
27	2	7	7	7	3	6	1	4	10	7
28	2	7	7	7	3	6	1	4	10	7
29	2	8	7	9	3	5	1	4	7	7
30	2	7	11	5	1	5	3	5	6	6
31	2	8	12	7	3	6	1	4	4	7
32	2	7	7	7	3	6	1	4	7	7
33	1	7	7	7	3	6	1	4	10	7
34	2	5	7	6	1	5	1	4	10	6
35	2	7	7	7	3	6	1	4	10	7
36	2	8	7	6	2	7	1	4	4	6
37	2	7	7	7	3	6	1	4	10	7
38	2	7	7	7	3	6	1	4	10	7
39	2	7	7	7	3	6	1	4	10	7
40	2	7	11	5	1	5	3	5	6	6
41	2	7	11	5	1	5	3	5	6	6
42	2	7	7	7	3	6	1	4	10	7
43	2	7	7	7	3	6	1	4	10	7
44	2	5	7	6	2	7	1	4	10	6
45	2	8	12	9	2	5	1	4	4	7
46	2	5	11	7	1	7	2	5	6	6
47	2	7	11	5	1	5	3	5	6	10
48	2	5	12	7	1	7	2	5	6	6
49	2	7	11	5	1	5	3	5	6	10
50	2	7	7	7	3	6	1	4	10	7


Maket Share of Product Variant 1 in segment 1
F2:MShare %
F1:MOGA polulation
Maket Share of Product Variant 1 in segment 2
F2:MShare %
F1:MOGA polulation
Maket Share of Product Variant 1 in segment 3
F2:MShare %
F1:MOGA polulation
Total Maket Share of New Product Variant 1
F2:Total MShare %
F1:MOGA polulation


Maket Share of Product Variant 2 in segment 1
F2:MShare %
F1:MOGA polulation
Maket Share of Product Variant 2 in segment 2
F2:MShare %
F1:MOGA polulation
Maket Share of Product Variant 2 in segment 3
F2:MShare %
F1:MOGA polulation
Total Maket Share of New Product Variant 2
F2:MShare %
F1:MOGA polulation

3. One product in a product line

Table C.13 Product variant 1 (Case 3)

Qty=Quality Per=Performance Ms=Market Share
F=Coordinates of a product variant

No.	Price	Qty	Per	Ms1	Ms2	Ms3	F1	F2
1	4.37	3.75	4.80	0.070	0.006	0.721	4.68	3.84
2	4.43	3.75	4.80	0.069	0.006	0.728	4.69	3.85
3	1.50	4.09	3.85	0.036	0.032	0.024	3.42	3.42
4	1.50	4.09	3.85	0.036	0.032	0.024	3.42	3.42
5	1.78	4.09	3.85	0.038	0.027	0.027	3.50	3.49
6	5.50	3.75	4.80	0.048	0.004	0.206	5.02	4.11
7	5.12	3.75	4.80	0.055	0.005	0.356	4.90	4.02
8	5.18	3.66	4.68	0.051	0.005	0.318	4.81	4.07
9	4.97	3.96	4.15	0.043	0.005	0.183	4.57	4.16
10	4.73	3.75	4.80	0.063	0.006	0.613	4.78	3.92
11	5.43	3.75	4.80	0.050	0.004	0.226	5.00	4.09
12	4.76	3.75	4.80	0.062	0.006	0.591	4.79	3.93
13	4.97	3.96	4.15	0.043	0.005	0.183	4.57	4.16
14	4.69	3.75	4.80	0.064	0.006	0.634	4.77	3.92
15	4.94	3.75	4.80	0.059	0.005	0.467	4.85	3.97
16	4.99	3.96	4.15	0.043	0.005	0.182	4.58	4.17
17	4.73	3.83	3.95	0.039	0.006	0.112	4.33	4.17
18	4.63	3.84	4.88	0.068	0.006	0.711	4.84	3.87
19	5.05	3.96	4.15	0.042	0.005	0.178	4.60	4.18
20	3.84	4.09	3.85	0.043	0.009	0.089	4.12	3.98
21	4.47	3.75	4.80	0.068	0.006	0.727	4.71	3.86
22	4.94	3.6	4.65	0.054	0.006	0.368	4.70	4.02
23	4.90	3.75	4.80	0.060	0.005	0.495	4.84	3.96
24	4.86	3.96	4.15	0.044	0.006	0.187	4.54	4.14
25	4.66	3.75	4.80	0.064	0.006	0.655	4.76	3.91
26	4.61	3.75	4.80	0.065	0.006	0.682	4.75	3.90
27	5.27	3.75	4.80	0.053	0.005	0.286	4.95	4.05
28	4.71	3.75	4.80	0.063	0.006	0.626	4.78	3.92
29	4.78	3.75	4.80	0.062	0.005	0.572	4.80	3.94
30	4.57	3.75	4.80	0.066	0.006	0.702	4.74	3.88
31	4.89	3.6	4.65	0.054	0.006	0.380	4.68	4.01
32	4.44	3.66	4.68	0.063	0.007	0.455	4.59	3.89
33	4.58	3.75	4.80	0.066	0.006	0.698	4.74	3.89
34	4.85	3.6	4.65	0.055	0.006	0.386	4.67	4.00
35	4.81	3.75	4.80	0.061	0.005	0.558	4.81	3.94
36	5.21	3.66	4.68	0.051	0.005	0.308	4.82	4.07
37	4.99	3.96	4.15	0.043	0.005	0.181	4.58	4.17
38	3.62	4.09	3.85	0.044	0.010	0.079	4.06	3.93

39	4.88	3.96	4.15	0.044	0.006	0.187	4.55	4.14
40	4.77	3.75	4.80	0.062	0.006	0.580	4.80	3.93
41	4.63	3.75	4.80	0.065	0.006	0.669	4.76	3.90
42	4.83	3.75	4.80	0.061	0.005	0.538	4.82	3.95
43	5.09	3.96	4.15	0.042	0.005	0.176	4.61	4.19
44	4.74	3.83	3.95	0.039	0.006	0.112	4.34	4.17
45	4.73	3.83	3.95	0.039	0.006	0.112	4.33	4.17
46	4.81	3.75	4.80	0.061	0.005	0.552	4.81	3.94
47	5.34	3.75	4.80	0.051	0.004	0.258	4.97	4.07
48	4.76	3.83	3.95	0.039	0.006	0.112	4.34	4.17
49	4.39	3.75	4.80	0.070	0.006	0.725	4.69	3.84
50	4.89	3.75	4.80	0.060	0.005	0.497	4.83	3.96

Table C.14 RCS Alternative Selection of product variant 1

No.	C1	C2	C3	C4	C5	C6
1	3	3	2	2	3	3
2	3	3	2	2	3	3
3	2	2	2	2	2	1
4	2	2	2	2	2	1
5	2	2	2	2	2	1
6	3	3	2	2	3	3
7	3	3	2	2	3	3
8	3	3	2	1	3	3
9	2	3	1	1	2	3
10	3	3	2	2	3	3
11	3	3	2	2	3	3
12	3	3	2	2	3	3
13	2	3	1	1	2	3
14	3	3	2	2	3	3
15	3	3	2	2	3	3
16	2	3	1	1	2	3
17	2	2	1	1	2	3
18	3	3	3	2	3	3
19	2	3	1	1	2	3
20	2	2	2	2	2	1
21	3	3	2	2	3	3
22	3	3	2	2	2	3
23	3	3	2	2	3	3
24	2	3	1	1	2	3
25	3	3	2	2	3	3
26	3	3	2	2	3	3

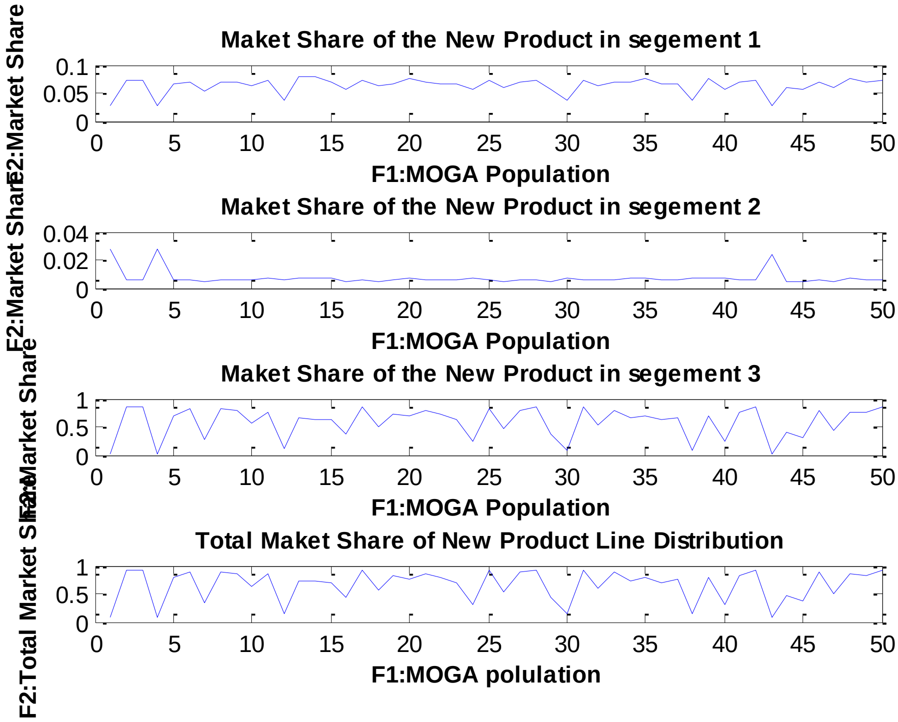
27	3	3	2	2	3	3
28	3	3	2	2	3	3
29	3	3	2	2	3	3
30	3	3	2	2	3	3
31	3	3	2	2	2	3
32	3	3	2	1	3	3
33	3	3	2	2	3	3
34	3	3	2	2	2	3
35	3	3	2	2	3	3
36	3	3	2	1	3	3
37	2	3	1	1	2	3
38	2	2	2	2	2	1
39	2	3	1	1	2	3
40	3	3	2	2	3	3
41	3	3	2	2	3	3
42	3	3	2	2	3	3
43	2	3	1	1	2	3
44	2	2	1	1	2	3
45	2	2	1	1	2	3
46	3	3	2	2	3	3
47	3	3	2	2	3	3
48	2	2	1	1	2	3
49	3	3	2	2	3	3
50	3	3	2	2	3	3

Table C.15 Supplier Selection for a product line (one product variant)

(C=Component/Module)

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	1	5	7	7	4	5	4	5	10	7
2	1	7	7	7	4	5	3	7	4	6
3	2	5	11	6	2	5	3	7	6	6
4	2	5	11	6	2	5	3	7	6	6
5	2	5	11	6	2	5	3	4	9	6
6	1	7	7	7	4	5	3	7	4	6
7	2	7	7	5	4	5	3	7	4	6
8	2	7	7	9	4	5	3	7	4	6
9	3	8	12	6	1	6	1	9	6	7
10	1	7	7	7	4	5	3	7	4	6
11	1	7	7	7	4	5	3	7	4	7
12	2	7	7	7	4	5	3	7	4	6

13	3	8	12	6	3	6	1	9	6	7
14	2	7	7	7	4	5	3	7	4	6
15	2	7	7	7	4	5	3	7	4	6
16	3	6	12	6	1	6	4	9	6	7
17	3	6	12	7	3	6	4	9	6	7
18	1	7	7	7	4	5	3	7	4	7
19	3	6	12	6	1	6	1	9	6	7
20	2	5	11	6	2	6	3	4	6	6
21	1	7	7	7	4	5	3	7	4	6
22	2	7	7	7	3	5	3	4	4	6
23	1	7	7	7	4	5	3	10	4	6
24	3	8	12	6	3	6	1	9	6	7
25	2	7	7	7	4	5	3	7	4	6
26	1	7	7	7	4	5	3	7	4	7
27	1	5	7	7	4	5	4	7	4	4
28	1	7	7	7	4	5	3	4	4	6
29	2	7	7	7	4	5	3	7	4	6
30	1	7	7	7	4	5	3	7	4	6
31	2	7	7	7	3	5	3	10	4	6
32	1	7	7	9	4	5	3	7	4	7
33	1	7	7	7	4	5	3	7	4	6
34	2	7	7	7	3	5	3	4	4	6
35	2	7	7	7	4	5	3	7	4	6
36	2	7	7	9	4	5	3	7	4	6
37	3	8	12	6	1	6	4	9	6	7
38	2	5	11	6	2	5	3	7	6	6
39	3	8	12	6	3	6	4	9	6	7
40	2	7	7	7	4	5	3	7	4	6
41	1	7	7	7	4	5	3	7	4	7
42	2	7	7	7	4	5	3	7	4	6
43	3	8	12	6	1	6	1	9	6	7
44	3	6	12	7	3	6	4	9	6	7
45	3	6	12	7	3	6	4	9	6	4
46	1	7	7	7	4	5	3	7	4	6
47	2	7	7	5	4	5	3	7	4	6
48	3	6	12	6	3	6	4	9	6	7
49	1	7	7	5	4	5	3	4	4	6
50	1	7	7	7	4	5	3	10	4	6


Maket Share of the New Product in segement 1
F2:Market Share
0.1
0.05
0
0 5 10 15 20 25 30 35 40 45 50
F1:MOGA Population
Maket Share of the New Product in segement 2
F2:Market Share
0.04
0.02
0
0 5 10 15 20 25 30 35 40 45 50
F1:MOGA Population
Maket Share of the New Product in segement 3
F2:Market Share
1
0.5
0
0 5 10 15 20 25 30 35 40 45 50
F1:MOGA Population
Total Maket Share of New Product Line Distribution
F2:Total Market Share
1
0.5
0
0 5 10 15 20 25 30 35 40 45 50
F1:MOGA polulation