Decision support system for front-end product development

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2010

Zhai, L. Y. (2010). Decision support system for front-end product development. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/38583>

<https://doi.org/10.32657/10356/38583>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**A DECISION SUPPORT SYSTEM FOR FRONT-END
PRODUCT DEVELOPMENT**

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**SCHOOL OF MECHANICAL AND AEROSPACE
ENGINEERING**

2010

A DECISION SUPPORT SYSTEM FOR FRONT-END PRODUCT DEVELOPMENT

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A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2010

ACKNOWLEDGEMENT

I am very grateful to my supervisors, Professor Khoo Li Pheng and Associate Professor Zhong Zhaowei, for their kind assistance, encouragement and supervision since the beginning of this project. I am deeply impressed by their positive and serious attitude towards research. Special thanks are due to Professor Khoo Li Pheng, who was also my M.Eng supervisor several years ago. Thanks for his care, encouragement, and guidance as a mentor in both my career and life throughout the years.

Deep gratitude is also due to the Department of Mechatronics and Design, School of MAE, NTU, for providing the Teaching Assistantship for me to undertake this research.

I would also like to express my gratitude to my best friends who have lent me various support emotionally or technically, in particular Mr Chia Yak Khoong, Mr Soh Beng Choon, Mr Koh Wee Hock, and Mr San Linn.

Special thanks are due to my wife, Jane and my son, Zihan for their understanding, patience and support. I love you.

Finally but most importantly, I wish to take this opportunity to thank my parents, who love me, encourage me and support me all the time, all the way.

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SUMMARY

In the highly competitive global market, manufacturers are facing ever increasing challenges in improving customer satisfaction and perceptions of their products while reducing product development time and cost. In such a context, efficient analysis of various design information and effective decision-making play a critical role in tackling such challenges and determining the success of a product development process. However, decision-making in product development is never an easy task due to the complexity of design problems, ambiguity of design information, subjectivity in judgments and contradiction of objectives. In order to address the above mentioned issues in a product design decision-making process, during the front-end product development process in particular, this work establishes a prototype decision support system composed of a potpourri of decision support tools for product planning and design concept evaluation. A design knowledge representation platform to handle various uncertainties inherent in the design information is first proposed. Two novel concepts known as rough number and rough boundary interval which form the backbone of this work are then derived based on the basic notions of rough set theory and interval mathematics. Subsequently, the proposed new concepts are embedded into Quality Function Deployment (QFD) analysis and a rough number enabled QFD decision support tool is realized to translate customer needs into product design requirements. To further improve customer satisfaction, the affective satisfaction aspect in particular, a dominance-based rough set approach to affective design decision support tool has been developed to uncover latent affective design rules from uncertain and nonlinear design information. On the other hand, in order to facilitate decision-making in the design concept selection process, a rough number enabled grey relation analysis decision support tool has been proposed and realized to deal with multi-objective design concept evaluation. Finally, an integrated prototype decision support system composed of the aforementioned three decision support tools has been implemented and demonstrated using a case study. The results of the case study have shown that the decision support system developed is able to facilitate decision-making activities in the front-end product development process by handling the uncertainty, nonlinearity, subjectivity and contradictory objectives in a systematic and effective way, and provide more insights into the analyzed results, which will benefit a product development process in many aspects including improved product quality, more satisfied customers, and reduced product development cost and time.

LIST OF PUBLICATIONS

The following publications have been generated from this research work:

Refereed International Journal Papers:

1. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2007a), Integrating rough numbers with interval arithmetic: a novel approach to QFD analysis, *HKIE Transactions*, 14(4), 2007, pp.74-81 (shortlisted for the *HKIE Outstanding Paper Award for Young Engineers/Researchers 2007*).
2. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2008), A rough set enhanced fuzzy approach to quality function deployment, *International Journal of Advanced Manufacturing Technology*, 37(5-6), 2008, pp.613-624.
3. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2009a), A dominance-based rough set approach to Kansei Engineering in product development. *Expert Systems with Applications*, 36(1), 2009, pp.393-402.
4. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2009b), Design concept evaluation in product development using rough sets and grey relation analysis, *Expert Systems with Applications*, 36(3), 2009, pp.7072-7079.
5. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2009c), A rough set based decision support approach to improving consumer affective satisfaction in product design, *International Journal of Industrial Ergonomics*, 39(2), 2009, pp.295-302.
6. Zhai L.Y., Khoo L.P. and Zhong Z.W. (2009d), A rough set based QFD approach to the management of imprecise design information in product development, *Advanced Engineering Informatics*, 23(2), 2009, pp.222-228.

International Conference Paper:

Zhai L.Y., Khoo L.P. and Zhong Z.W. (2007b), Rough number assisted decision-making under uncertainty in quality function deployment, in *Proceedings of the 8th International Conference on Intelligent Technologies (InTech07)*, 12-14 Dec 2007, Sydney, Australia. pp.219-227.

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CHAPTER 1 INTRODUCTION

1.1 Background of the Research

1.1.1 Customer-Oriented Product Development

Product development is a sophisticated process involving many complex activities, usually starting from the perception of a market opportunity and ending with the production, delivery and sale of a product. In the new global market, which is full of competitions, the economic success of a manufacturing company depends largely on its ability to gauge the real needs of customers and respond promptly to meet these needs by developing innovative products at low cost. Achieving such a goal is not solely a marketing, design or manufacturing problem, but is a customer-oriented product development problem (Ulrich and Eppinger, 2004).

The philosophy of customer-oriented product development is to elicit the right requirements from customers early in a product development process and make the right product the first time. First and foremost, by understanding customer needs and desires, the product development team can focus their development efforts on product features that will deliver the most value to their customers. Without this crucial information, all the efforts and resources of the team are predicated on what often proves to be an educated guess. Frequently, in product development practice, a poor understanding of the customer requirements for a product in the early development stages is the reason for costly mistakes and

rework in the later stages of the development process. Essentially, an effective and efficient analysis of customers' requirements in the early stages of a product development process not only enables a company to create better products and secure more satisfied customers, but also provides a framework for organizing a more efficient development process by reducing the development cost and time.

Customer-oriented product development has become the contemporary trend of product development practice in the new global market flooded with many competitive products. In the new environment, a manufacturing company's bottom line of success is measured not by the sophistication of its technology, but by how well its product can meet customers' various needs. In such a context, customer-oriented product development provides a powerful tool that enables a company to grow towards a long term value-driving strategy in the new global environment. Frequently, many manufacturing companies fail to maintain continuous growth in the intense competition largely because they are unable to keep developing new products that can delight their customers. In fact, if a company does not develop new products that possess strong value in customers' eyes, it will indeed lose in the competition (Antis, *et al.*, 2002).

As an example, Motorola, the pioneer and market leader in wireless communication technology and once the first and largest mobile phone manufacturer in the world, lost its leadership position to other competitors during the late 1990s and early 2000s, largely due to its failure in anticipating and responding to the changing customer needs (Crockett *et al.*, 2005; Lashinsky, 2005). For instance, the company failed to gauge and respond to customers' growing demand for digital phones in the years 1995 to 1996, as well as the

demand for color phones and camera phones in the years 2002 to 2003. The once mobile phone giant was unable to regain part of its lost glory until it started to give prime importance to customer needs in 2005 (Lashinsky, 2005). As such, to survive and succeed in the intense competition, a company's products developed must be able to focus on the real needs of customers and deliver enough value that customers would pay for. In order to achieve this, the product development process must take into account the input from customers and bridge the communication between customers and the product development team, especially during the early stages of a product development process.

As such, the critical issue for a customer-oriented product development is to get the product development process started right, which is the key element that helps drive values out to customers and return the required profits to the company. In such a context, the early phases of a product development process become very important as they have a remarkable impact on the success of the product to be developed. The key elements in the early phases of a product development process usually include market analysis, benchmarking, gathering and processing the voice of customers, product design concept generation and selection, and so on (Ulrich and Eppinger, 2004). In the early phases of a product development process, special attention should be paid to the analysis of customer requirements because it is crucial for the success of the product development. However, in the new global environment, customer needs can be in various types and always change with the advent of new technologies. For example, customers might not only expect the basic performance, i.e. functional needs, of a product, but also want the design of the product to meet their emotional preferences, i.e. affective needs. It should be

noted that in the new global environment where technological monopoly is almost impossible, when technology is unable to differentiate a product from its competitors, affections associated with the product usually will determine its success.

As a result, in the new global competitive market, a successful product development process must be able to gauge true customer needs and efficiently transform various customer needs into innovative products. Towards this end, Quality Function Deployment (QFD) (Akao, 1990; Cohen, 1995) and affective design (Nagamachi, 1991) also known as Kansei Engineering are two useful approaches to translate the respective functional and affective needs of customers into product characteristics and elements. QFD is a structured approach to analyzing customer needs and translating them into specific product development plans in order to meet these needs. The voice of customers (VOCs) is the term to describe the customer needs in QFD. In developing QFD, customer needs are analyzed using a product planning matrix called the house of quality (HOQ), where they are systematically translated into product design requirements. On the other hand, affective design is a method for translating the feelings and impressions of customers, namely affective needs into product features. Affective design focuses on understanding and gauging the emotional aspect of customer needs, discovering the relationships between these needs and product design features, and finally translating them into unique product design elements that can affectively delight customers. Compared with QFD, affective design addresses the emotional side of customer needs while QFD focuses more on the functional side. In fact, QFD and affective design complement each other. When used together, QFD can provide the

focus on functional superiority and affective design can make the product inspirational and appealing.

1.1.2 Decision Support Systems for Front-End Product Development

Product development is essentially a complex process involving many decision-making activities, from start to end, determining what product to develop and how development resources are to be allocated. A successful product development process is usually achieved through appropriate management of the product development information and using effective decision support tools to make prudent decisions so as to reduce unfounded suppositions and guessing. With the increasing complexity of product development activities and involvement of multidisciplinary information in the development process, decision-making processes play an even more crucial role in determining the success of a product development. Effective and efficient decision-making in product development processes will remarkably reduce product development cost and time, and therefore consequently enhance the competitive edge and improve the profitability of the manufacturing company. In this respect, decision-making in the early stages of a product development process has an especially significant impact on the success of the product, as up to 70% or more of the final product cost is determined in the early design phases (Ullman, 1997; Ben-Arieh and Li, 2003). Thus, the introduction and integration of effective decision support systems into the front-end product development process is of utmost importance.

However, decision-making in product development processes is never an easy task due to the complexity of problems, uncertainties in the data, subjectivity

in judgments and contradiction of objectives (Clemen and Reilly, 2001), especially in the early stages of a product development process. For example, as mentioned earlier, customers' input is an important source of information to support decision-making activities in the front-end product development process. However, such input from customers is usually captured through a variety of channels such as interviews, surveys and observations, and various uncertainties might be inherent in the data obtained, which will impact the decision-making process. In addition, decision-making activities in the front-end product development process such as the evaluation and selection of design concepts often involve a variety of constraints and multiple competing or even conflicting objectives. As a result, techniques and methods must be developed to help decision-makers quantify and model these constraints and objectives, and make tradeoffs among competing targets (Hazelrigg, 1998; Li and Azarm, 2001; Herrmann and Schmidt, 2002).

In order to tackle various issues in product development decision-making, systematic decision support methods or tools must be developed to facilitate product development processes in a timely and cost-effective manner (Simon, 1997). The decision support systems developed should be able to analyze various quantitative and qualitative data and perform corresponding calculations in order to assess the impact of every factor involved in the product development decision. In this regard, fuzzy set based approach has received extensive attention in product design practice due to its capability of handling uncertainties in product design data. However, fuzzy set theory has its limitations in analyzing product design data and making design decisions, among which the determination of fuzzy membership functions is one of the challenging issues (Zhai *et al.*, 2008). Besides

fuzzy set theory, rough set theory (Pawlak, 1982) and grey relation analysis (Deng, 1989) are the other two promising decision support methodologies that suit the context of decision-making in product development processes (Zhai *et al.*, 2007a; 2009b). Rough set theory, which was introduced by Pawlak (1982) in the early 1980's, provides a novel mathematical tool for dealing with imprecision, vagueness and uncertainty. It focuses on the discovery of hidden patterns in imprecise data and can be used as a basis to perform formal reasoning, knowledge representation and discovery (Pawlak, 1991). On the other hand, grey relational analysis as a part of the grey system theory developed by Deng (1982) in the 1980's, provides a simple but powerful systematic approach to solving decision-making problems with complicated interrelationships between multiple factors and variables. Detailed advantages of using rough set theory and grey relational analysis in product development decision-making will be elaborated in Section 2.7.2 and Section 2.7.3. It is postulated that the fusion of the two decision support methods into the front-end product development process will significantly improve the product development productivity.

1.2 Objectives of the Research

This research aims to address the critical issues concerning the realization of a decision support system for the front-end product development process. The overall objectives of the research are:

1. To establish an effective design information and knowledge representation platform that is able to accommodate and analyze

imprecise, uncertain and subjective design information in the front-end product development process;

2. To develop an effective decision support tool that is able to facilitate decision-making processes by incorporating customers' functional needs into product design features, so as to improve customer satisfaction and product development productivity;
3. To develop a decision support tool that is able to gauge and translate customers' affective needs into product design elements systematically so as to further improve customer satisfaction;
4. To develop an effective and efficient decision support tool that is able to facilitate the evaluation and selection of design concepts in a multi-objective decision-making environment under uncertainty.

Based on the above, it is envisaged that a potpourri of decision support tools can be realized to assist product designers in improving product development productivity and customer satisfaction so as to enhance the competitive edge of a manufacturing company in the new global market.

1.3 Scope of the Research

The scope of this research is limited to addressing the decision-making issues in front-end product development, namely the product planning and concept development processes. More specifically, it focuses on establishing the theoretical bases for the various approaches proposed in this research. Firstly, it will concentrate on the transformation of various customer needs into product design features or characteristics. The customer needs considered in this research include

both functional needs and affective needs. Improving the effectiveness and efficiency of the decision-making activities involved in the transformation process under uncertainty are the focus of this part of the research. Secondly, this research will concentrate on the design concept selection aspect, with the focus on improving the effectiveness and efficiency of the multi-objective design concept evaluation process under uncertainty. The other aspect of the concept development process, i.e. design concept generation, which constitutes another big research area, is not included in the scope of this research. Finally, a prototype integrated decision support system for the front-end product development process composed of a potpourri of decision support tools will be implemented. To demonstrate the capability of the developed system, a case study in which a simple market survey on mobile phone designs perceived by a group of college students will be conducted.

1.4 Organization of the Thesis

This thesis is organized into 8 chapters. Chapter 2 presents a broad and thorough literature review on the key issues and related investigations in the front-end product development process. These include the critical challenges for product development processes in the new global environment, typical methodologies and tools for product design and development, and decision support systems for product development with related issues. Chapter 3 outlines the framework and methodology of the research work based on the major findings and gaps identified from the literature review in Chapter 2. Chapter 4 describes a novel design information representation scheme based on the proposed novel concepts of rough number and rough boundary interval, which are derived from the basic concepts of

rough set theory. The novel design information representation scheme is then incorporated into the QFD analysis to realize a Rough_QFD decision support tool. Chapter 5 presents a dominance-based rough set approach to affective design and a Rough_Kansei decision support tool is developed to discover Kansei knowledge in the environment under uncertainties. Chapter 6 proposes a multi-objective design concept evaluation approach based on rough numbers and grey relational analysis. A rough grey decision support tool is developed to facilitate design concept evaluation processes under various constraints and uncertainties. Chapter 7 describes the implementation of the potpourri of decision support tools and a case study concerning a mobile phone design is presented to illustrate and validate the proposed approaches. The last chapter, Chapter 8 summarizes the main conclusions reached in this work and highlights the overall direction of the future work of this research.

CHAPTER 2 LITERATURE REVIEW

2.1 Product Development and Its Front-End Process – An Overview

Product development is a process through which a manufacturing company transforms data on market opportunities and technical possibilities into information assets for commercial production (Clark and Fujimoto, 1991). It includes a sequence of steps or activities, which a company employs to conceive, design, and commercialize a product. In general, product development is an interdisciplinary activity requiring contributions from nearly all the functions of a company, with major focus on the followings:

- Marketing function: mediates the interaction between the company and its customers through understanding product opportunities, definition of market segments and customer needs as well as sales and related services.
- Design function: plays the leading role in defining the physical form of a product to best meet customer needs through engineering design (mechanical, electrical, software, etc.) and industrial design (aesthetics, ergonomics, user interfaces, etc.).
- Manufacturing function: is primarily responsible for designing and operating the production system in order to produce the product.

In general, a well-defined product development process not only can assure product quality, but also make it easier for the management and improvement of the process. Figure 2.1 presents a generic product development process composed of six phases (Ulrich and Eppinger, 2004). The first two phases, product planning and concept development, are usually referred to as the front-end product development process, which requires extensive integration across different functions of the development team. The front-end product development process usually includes the following activities: identifying customer needs, analyzing competitive products, establishing target design requirements, generating product concepts, evaluating and selecting design concepts, and so on.

Figure 2. 1 A generic product development process (Ulrich and Eppinger, 2004)

More specifically, the product planning phase identifies the portfolio of products to be developed by a company and the timing of their introduction to the market. Product planning decisions are usually made based on the considerations of the competitive environment including customer needs, changes in technology, and information on the success of existing products. Poor product planning often causes a plague of inefficiencies such as inadequate coverage of target markets, poor timing of market entry, poor allocation of development resources, frequent error-correction during the development process, and so on.

Concept development phase focuses on establishing the link between customer needs and product specifications. It creates an information channel between customers in the target market and the designers of the product. Without this channel, technical tradeoffs are not likely to be made correctly, innovative solutions to customer needs may never be discovered, and the designers may never be able to develop a product that satisfies customer needs. Obviously, in the front-end product development process, identification and analysis of customer needs are of great importance as they are closely related to concept generation, concept evaluation and selection, competitive benchmarking, and the establishment of product specifications. An effective analysis of customer needs can ensure that the product to be developed is focused on customer requirements and provides a fact base for justifying the product specifications (Ulrich and Eppinger, 2004).

2.2 Challenges for Product Development Process

The characteristics of product development process evolve over time. In an increasingly competitive global environment, manufacturing companies strive to improve product quality while reducing product development time and cost. On the one hand, intensive competitions reduce the windows of opportunity, and manufacturing companies have fewer chances to win back business once they lose. On the other hand, well-informed customers have various fast-changing needs and expect rapid responses from manufacturers. In such a situation, effective analysis of design information and efficient decision-making of product development process have a significant impact on the success of the product to be developed. It is well known that a product of modest complexity may need many decisions in order to maximize the success of the product (Ulrich and Eppinger, 2004). In fact,

decision-making is one of the most important yet difficult issues in product development. It is important because small variations in a design decision can have significant economic implications. It is difficult because product development decisions usually must be made quickly based on incomplete or imprecise design information.

While many companies earnestly want to develop more successful products with limited resources, the improvement of product development productivity becomes more crucial in the global competition, which refers to higher responsiveness to market opportunities and less expenses spent on product development. With the product development process shifting from time-based competition to productivity-based competition, manufacturing companies must find ways to streamline and rationalize their product development processes through effective and efficient decision support systems (McGrath, 2004). Such decision support systems are expected to be able to facilitate product development activities by addressing the product development challenges including reduction of product development cost and time, and improvement of customer satisfaction.

2.2.1 Reduction of Product Development Cost and Time

Product development is a costly activity and many companies may spend millions of dollars to develop a new product. While maintaining or improving product quality, companies are forced to reduce product development cost and time in order to improve profitability (McGrath and Romeri, 1994). The ever-increasing competitions in the global market have made the product development cost rapidly emerging as one of the most crucial factors determining the success of a product.

The pressure of cost reduction constitutes the main reason for manufacturing companies to carry out extensive research into optimization and decision-making strategies in product development processes, besides the efforts in the domain of business operation strategy such as outsourcing product development tasks to low labor-cost countries and deploying collaborative product development systems (McGrath, 2004). On the other hand, the intense global competition and shorter product life cycles have compelled the need to launch new products to market faster than ever (Smith and Reinertsen, 1998). It has been reported that over the last two decades, many companies have reduced their time-to-market by 40-60 percent across all new products on average, where efficient decision support systems have played a big part (McGrath, 2004).

As known, product development is a very complex process that has to meet and satisfy various design requirements and constraints simultaneously. Reduction of product development time depends on and affects concurrent execution of other development activities and requirements. For example, shortening the time-to-market may help in reducing the product development cost because, frequently, a shorter development time means a shorter staffing and resource occupation. However, speedy product development may require more research expenses which indirectly inflate product development cost. It may also degrade the product performance or quality. Typically, contemporary product development requires designers to make multiple tradeoffs and decisions during the process. As a result, the cost and speed of product development depend very much on the effectiveness and efficiency of communication, management of design knowledge, and decision support throughout the process (McGrath, 2004).

2.2.2 Improvement of Customer Satisfaction

Today's manufacturing companies compete on price, adaptability and the variety of products, which are all driven by customer satisfaction (Agard and Kusiak, 2004). Customers are usually aware of their basic needs and purchase a product according to their preferences without knowing much of the product technical details offered by the manufacturer. This is especially true for contemporary high-tech products in which the influx of new technologies allows users to appreciate the functionality of the product without the necessity to understand its technological details. In such a context, the parameters or variables that customers use to express their requirements and appreciations are usually ambiguous, uncertain and imprecise. As a result, such input information from customers is often poorly understood by product designers, resulting in tedious or even invalid product configuration tasks that are based on vague suppositions and implicit inferences. This has created an increasing gap between customers' mental models of a product and the product's technical architecture proposed by designers, which is deemed as one of the biggest obstacles to achieving customer satisfaction.

In order to develop a product that satisfies customers' requirements, it is necessary to identify what customers exactly need by capturing the voice of customers (VOCs). However, it should be noted that VOCs are usually diverse and there is no monolithic voice of customers. In the market, there are a variety of different customer needs and even within one buying unit, there are multiple customer voices such as women versus men and young versus old. These diverse customer voices must be considered, reconciled, prioritized and balanced in order

to make sensible product development decisions and develop successful products that maximize customer satisfaction.

2.3 Product Development Methodologies

2.3.1 Concurrent Product Development Process

As mentioned earlier, intense competitions in the highly dynamic global market have compelled manufacturing companies to reduce product development cost and time and respond as quickly as possible to customer requirements (Blackburn, 1991). However, product development activities often face a dilemma, namely the conflict between the requirement to reduce the time-to-market and development cost, and the requirement to improve product quality and customer satisfaction. As a result, many tradeoffs have to be made simultaneously during the process of product development. In this regard, concurrent engineering (CE) provides a revolutionary approach to product development using parallel processing techniques to process complex evaluation and decision-making tasks (Hoque *et al.*, 2005; Xu *et al.*, 2007).

In a concurrent product development process, multi-functional teams are formed involving specialists from every aspect of the product life cycle so that design goals and constraints from all subsystems can be considered and appropriate tradeoffs can be made during the initial stages of the design process (Hartley, 1998). Concurrent product development is able to achieve both improvement in product quality and reduction in cost and time, through the multi-fold implementation strategy (Swink, 1998). Many well-known companies including General Motors, Chrysler, Ford, Motorola, Hewlett Packard and Intel have adopted

concurrent product development process to develop their new products (Swamidass, 2002). Although the application of concurrent product development process is able to significantly improve the productivity of product development, its implementation is not always an easy job. On the one hand, the existing hierarchical organizational structures of a manufacturing company can hamper the multidisciplinary interactions required in concurrent product development. On the other hand, in some cases, a concurrent product development process still has to involve some sequential iterations due to communication or geographical barriers among design teams that are not collocated or even not part of the same company (Swink, 1998). Moreover, in a concurrent product development process, the simultaneous evaluation of multiple aspects such as cost, quality and time will further increase the complexity of the product development task, which requires sufficient accurate information and effective decision support systems to facilitate decision-making activities. However, in the earlier stages of a product development process, it is often very difficult to obtain sufficient accurate information to support decision-making. Instead, product designers can only rely on low quality, incomplete or even inconsistent information to make decisions (Belecheanu *et al.*, 1999).

2.3.2 Design for Six Sigma (DFSS)

Closely related to concurrent product development, Design for Six Sigma (DFSS) provides a structured concurrent (or parallel) approach to product design. Contrasted with the traditional Six Sigma process which focuses on the evolutionary and continuous improvement of manufacturing or service process, DFSS has a different objective of determining the needs of customers and the

business, and driving those needs into the product design solutions. To be more specific, DFSS is relevant to complex product development processes, especially in the context of unprecedented product development, whereas traditional Six Sigma usually occurs after initial product design and development has largely completed. Essentially, Six Sigma practice is usually considered as a method to solve existing process problems such as fire-fighting, whereas DFSS is considered as a proactive product development approach that seeks to avoid process problems by using systems engineering techniques at the outset for fire prevention, for example.

DFSS is a powerful tool to tackle the challenges of product development, namely reducing product development cost and time, and improving customer satisfaction. The techniques used in DFSS include tools and systems to model the product development process and facilitate the decision analysis in order to assure customer satisfaction with the product designed (Wang, 2005). DFSS tools and systems can help to minimize the effect of uncertainty or variations of the design information in the product development process in a systematic and scientific way (Phadke, 1989). It utilizes specialized tools such as Quality Function Deployment (QFD), Axiomatic Design, TRIZ and Design of Experiments (DOE) to provide an efficient and cost-effective way to improve product development processes. In the next section, one of the typical tools used in DFSS, namely QFD will be thoroughly reviewed.

2.4 Quality Function Deployment (QFD)

2.4.1 The Four Phases of QFD

Quality Function Deployment (QFD) is an important and widely used product development methodology which is related to concurrent engineering in essence but different in practice. As a revolutionary methodology for product development, QFD originated in Japan in the 1970s and became increasingly popular in the western world in the 1980s. Since its inception, it has been successfully employed in many organizations to improve product development processes and to achieve competitive advantages (Guinta and Praizler 1993; Shillito 1994). A successful application of QFD can produce better products or services that are highly focused on and responsive to customer needs, with a reduced design cost, fewer resources and shorter time (ReVelle *et al.* 1998).

The fundamental philosophy of QFD is the belief that products should be designed to reflect customers' desires. In general, QFD provides a comprehensive methodology that enables manufacturing companies to realize customer oriented products in a systematic manner by using transparent analytic and prioritization methods. QFD employs elaborate charts that are used to translate customer needs into product characteristics, and subsequently, into manufacturing and assembly requirements, through which the voice of customers can be communicated throughout the product development process. QFD provides a useful tool to assist the planning and realization of high quality products or services that is able to meet or even exceed customer expectations by bridging the communication gap between customers and designers.

Typically, QFD uses four basic inter-linked phases that cover the entire course of the product development process (Figure 2.2). In each phase, a structured matrix is used to help plan and communicate critical product or process information. Generally, the functions of the four QFD phases are as follows:

Phase 1: Product Planning – To translate customer needs (CNs) into product design attributes which are usually called design requirements (DRs) in QFD;

Phase 2: Part Deployment – To translate design requirements into product or part characteristics;

Phase 3: Process Planning – To translate product or part characteristics into manufacturing operations; and

Phase 4: Production/Operation Planning – To translate manufacturing operations into day to day production operations and controls.

Figure 2. 2 The four phases of QFD (adapted from Karsak, 2004)

It should be noted that the four phases of QFD are successively connected, where the output of the precedent phase is used as the input to the successive phase. Using such a structured approach, QFD communicates and deploys the voice of customers throughout the entire product development process to achieve customer satisfaction.

Among the four phases of QFD, the first phase is of fundamental and strategic importance to product development because an effective analysis of customer needs in Phase 1 is critical to the success of the entire QFD process. Essentially, the first phase of QFD provides a bridge that links the voice of customers with the voice of designers, along with competitive benchmarking information. More specifically, the first phase of QFD contains the following information: customer needs and their importance ratings; relationships between customer needs and design requirements; degree of customer satisfaction with the company's and the competitors' products; and measures of design objective levels for both the company's and the competitors' products (Moskowitz and Kim, 1997).

2.4.2 The House of Quality (HOQ)

As mentioned in Section 2.4.1, in the implementation of QFD, each phase uses a structured matrix chart to translate its inputs into outputs, and such a structured matrix chart is called the House of Quality (HOQ) in QFD methodology. HOQ is the most important concept in QFD as it provides a useful communication and decision-making tool in each phase of QFD, and drives the entire product development process as a unified conceptual engine (Hauser and Clausing, 1988; Shillito, 1994). Because HOQ and the first phase of QFD are so important for a

product development process, most research works concerning QFD like to put the focus on the first phase of QFD and develop the HOQ for the first phase only (Chan and Wu, 2005). As a result, HOQ has turned itself to be a representative model of the QFD methodology, and many researchers even refer HOQ as the first phase of QFD (Akao, 1990; Griffin and Hauser, 1993; ReVelle *et al.*, 1998; Xie *et al.*, 2003). In order to make the illustration easier and more understandable, this thesis will follow the convention of the majority of research works in this domain and refer to HOQ as the first phase of QFD.

The basic concept of HOQ is to manage the early stage product design information by systematically registering the voice of customers and the voice of designers, translating customer needs into technical requirements, and then ranking these technical requirements in order to facilitate the decision-making activities in product design. To be more specific, developing a HOQ starts from the process of customer requirements about a product solicited through market research, from which a set of customer needs (CNs, usually called “WHATs” in a HOQ) are extracted and their importance are evaluated by customers. Accordingly, a set of technical design requirements (DRs, also known as “HOWs” in a HOQ) that can fulfill these CNs are identified and evaluated by the design team (Chan and Wu, 1998). At this stage, the design team needs to evaluate the relationships between the CNs and DRs as well as the interactions among the DRs, and determine the improvement levels of the DRs by taking into account the technical, cost and other organizational constraints. The final output of a HOQ is a set of prioritized technical design requirements, which will be transferred into the next phase of QFD analysis. In other words, HOQ focuses on the prioritized CNs and translates

these needs into prioritized DRs, and then communicates them throughout the product development process in a systematic manner to ensure that product design details can be quantified and controlled.

The above procedure of developing a HOQ can be illustrated using Figure 2.3. It begins with the identification of CNs, followed by priority analysis of these needs based on customer perceptions. After the identification and evaluation of DRs, the priorities of DRs are analyzed using the relationship matrix between CNs and DRs. Finally, the prioritized DRs are used to assist product planning, which is the next phase of deployment.

Figure 2. 3 Procedures of developing a HOQ

Obviously, HOQ provides a useful framework to assist decision-making in product development. However, there are still some specific issues that need to be addressed when developing a HOQ. As mentioned earlier, HOQ manages the initial design information in the front-end product development process, where customers and designers express their needs and conceptions using linguistic

qualifiers. As a result, the importance of CNs, the relationship between CNs and DRs and the interaction among DRs are often expressed informally in subjective and vague terms and linguistic variables. Such design information usually cannot be effectively processed mathematically. Traditionally, subjective and ad hoc techniques are employed to address this issue (Khoo and Ho, 1996). These techniques rely much on subjective assumptions and personal knowledge and thus lack objectivity and generality (Zhai *et al.*, 2007a; 2007b). Due to the uncertainty and vagueness of the initial design information in HOQ, it is often difficult to effectively translate the real needs of customers into technical requirements. This, as a result, may affect the priority analysis in the HOQ and subsequently lead to inappropriate decision-making in product development. Therefore, how to effectively represent and analyze the initial design information in HOQ still remains a challenge.

2.5 Affective Design in Product Development

As discussed in Section 2.2.2, the incorporation of customer needs into product design has become a necessity for the success of a product development. However, customer needs may evolve over time and can be very personal, especially in today's fast-changing and highly competitive global market. Keen competitions have resulted in profuse product alternatives on the market and an increasing number of customers like to express their individual expectations and personal tastes about a product. As a result, even mass-produced products have to be adaptable to meet individual customer demands in terms of product functionality, product form, design style and many other aspects (Shimizu *et al.*, 2004). In order to maintain a competitive edge in a market filled with products of

equally satisfying quality and functionality, a well-designed product should be able to not only meet the basic functionality requirements, but also satisfy consumers' affective needs or feelings and connect emotionally with the highly informed, multi-cultural, and globally minded customers. For example, in some product segments, customers make their purchase decisions more and more on feelings and emotional appeal. In this regard, affective design methodology, also known as Kansei Engineering, which was originated from Japan in the 1980s, provides a novel approach to design customer affections into a product (Nagamachi, 1991). Kansei is a Japanese word which refers to customers' affections (i.e. emotional impressions) or feelings about a product. It may be evoked by the product form, style, color, function, price, etc. and affected by customers' emotions and personal sense of values (Lee *et al.*, 2002). Since its inception, affective design has been widely recognized as an effective tool for customer-oriented product development, which is able to translate customer affections into the product design elements (Nagamachi, 2002).

Affective design focuses on understanding customers' emotional and sensory needs about a product and identifies unique attributes of the product design that can delight customers and improve customer satisfaction, through a collection of techniques such as statistical analysis, artificial intelligence, graphics, and so on (Nagamachi, 1991). In other words, affective design is a product design methodology that addresses the emotional quality characteristics that customers seek in a product by linking the unconscious wants and needs of customers with technical responses of the product design. Compared with QFD, affective design addresses the emotional side of a product development while

QFD focuses more on the functional side. In fact, QFD and affective design complement each other. When used together, QFD can provide focus on functional superiority and affective design can make the product inspirational and appealing.

In affective design, the most important issue is to formalize the knowledge that relates customer affections, i.e. Kansei, with the product design elements (Nagamachi, 1995). Figure 2.4 shows a generalized affective design system. In the system, customers' perceptions about a number of design alternatives of a product are represented in the form of Kansei words such as "compact", "deluxe" and 'sporty', and quantified by the degree of appreciation such as semantic scale ratings. On the other hand, each design alternative of the product can be decomposed into a set of design elements. With the assistance of appropriate mathematical tools, the relations between the quantified Kansei words and design elements, i.e. Kansei knowledge, can possibly be established.

Figure 2. 4 Generalized affective design in product development

Toward this end, many research works have used various techniques such as regression analysis, quantification theory, neural networks, genetic algorithms, fuzzy logic, and rough sets to extract Kansei knowledge for affective design (Schütte, 2005). For example, Jindo and Hirasago (1997) reported the application of affective design in the interior design of passenger cars using semantic differential methods and multivariate analysis to gather the relationships between various interior design solutions and the desirable impressions. Ishihara *et al.* (1995; 1997) presented an automatic semantic structure analyzer and a Kansei expert system builder using self-organizing neural networks for automated Kansei rule building. More recently, Chen *et al.* (2006) proposed a prototype system using self-organizing map neural networks to consolidate the relationships between affective requirements and formal elements. More sophisticated methods such as genetic algorithms and fuzzy logic have also been used by some researchers to capture the mappings between Kansei words and product design elements (Tsuchiya *et al.*, 1996, 1999; Yanagisawa and Fukuda, 2003). Recently, rough set theory has also been applied to affective design due to its ability to handle vague information and uncertainty (Nishino *et al.*, 2001; Okuhara *et al.*, 2005; Nagamachi *et al.*, 2006).

Among the various tools and techniques developed for affective design, statistical analysis plays an important role and is widely accepted as the most systematic tool for affective design. For example, the linear regression model of type I quantification theory is one of the most popular tools to derive the relationships between customer affections and product design elements (Schütte *et al.*, 2004). However, such statistical tools assume linear relations among the

variables used in the analysis, which may not be true in real cases. In fact, customer affections are frequently vague in nature and the behavior of affective response of customers is usually nonlinear (Ishihara *et al.*, 1995; Tsuchiya *et al.*, 1996; Arakawa *et al.*, 1999; Kinoshita *et al.*, 2006). When there are non-linear characteristics in the system, statistical analysis will become inappropriate because it is based on the hypothesis of normal distribution (Nagamachi *et al.*, 2006). On the other hand, similar to the voice of customers in QFD, customer affections are usually expressed using descriptive terms and contain vagueness and uncertainty due to diverse opinions of customers. Such kind of semantic uncertainty, in contrast to stochastic uncertainty, is in fact not suitable to be analyzed using probability and statistics (Wu and Chen, 2008). While fuzzy analysis seems to excel in dealing with such semantic uncertainties in affective design (Nagasawa, 1999; Fukuda *et al.* 2000; Yan *et al.*, 2008), it requires discreet deliberation in handling crisp information. That is, a domain-meaningful method, i.e. membership function, is needed to fuzzify each variable whose value is naturally estimated as an ordinal real value (Carnahan *et al.*, 1994). Although some other sophisticated methods such as neural networks have been used in affective design to address the above issues, such methods are often transparent to the users and most importantly, they require large amount of training data which are usually not available in product development practices (Petiot and Yannoub, 2004; Zhai *et al.*, 2009a; 2009c). As a result, effective extraction of Kansei knowledge from the nonlinear and uncertain Kansei data still remains a challenge for affective design.

2.6 Design Concept Evaluation

As discussed in Section 2.1, in front-end product development, design concept development (including design concept generation and design concept evaluation) will take place once customer needs and design requirements have been identified (see Figure 2.1). Design concept development is an iterative process in which the design concept generation and design concept evaluation activities supplement each other (Ulrich and Eppinger, 2007). Design concept generation is essentially a process of creation and innovation, in which a design team constructs a clear product prototype based on a prioritized list of design requirements. Design requirements specifically describe what a product must do first and foremost and what additional features and attributes will further enhance the product's competitive advantages in the market. There are many methods and techniques that can assist the generation of design concepts. These include general methodologies such as product benchmarking, systematic exploration, design by analog, brainstorming and so on, as well as specific techniques such as TRIZ, axiomatic design, to name a few (Liu *et al.* 2003; Yan *et al.*, 2006; Ulrich and Eppinger, 2007). Although various design concept generation techniques may play an important role in product concept development, they are never more important than controlling the evaluation of the generated design concepts, because innovative and high quality product design solutions are usually inspired by and further improved upon the feedbacks from an effective and objective evaluation of various design alternatives (Ulrich and Eppinger, 2007).

On the other hand, the importance of design concept evaluation is apparent because a poor selection of design concept in the earlier stage of product

development can rarely be compensated at later design stages and can give rise to a great expense of re-design costs and delay in product development process (Nevins and Whitney, 1989). Hence, the pressure of “doing it right at the first time” due to demanding customer expectations and stringent technical, cost and time constraints has led designers to adopt various techniques to evaluate design concepts effectively and objectively in order to determine the design concept(s) that will result in the best possible product at the early stage of a product development process.

Design concept evaluation is essentially a complex multi-criteria decision-making process which involves various information and data ranging from initial customer needs to resources and constraints of the manufacturing company. It is a difficult task because the knowledge available to support decision-making is very limited at the front-end stage of a product development process. More importantly, such knowledge and data usually contain uncertainties. Design concept evaluation process, as a result, need to assess the imprecise and vague information as well as the heterogeneous data, and incorporate preferences of customers that are highly subjective. Traditionally, these uncertainties are handled by domain experts based on their heuristic “rules of thumb”, which has been historically done on an *ad hoc* basis (Rosenman, 1993; Thurston and Crawford, 1994). This may impair the solution credibility and the rigor of the evaluation process. Objective decisions can hardly be made. As a result, the quest for more effective and objective methodologies to systematically evaluate design concepts in the early stage of a product design process has attracted much research interests.

Generally, the methods developed to assist design concept evaluation can

be classified into two categories, namely the non-numerical methods and the numerical methods. The former includes typical methods such as concept screening (Ulrich and Eppinger, 2004) and concept selection (Pugh, 1996) whereas the latter encompasses decision matrices (King and Sivaloganathan, 1999), utility function analysis (Thurston, 1991; Thurston and Carnahan, 1992), fuzzy sets (Otto and Antonsson, 1991; Wang, 2001), and analytic hierarchy process (AHP) (Marsh *et al.*, 1991; Ayag, 2005), to name a few. Generally, non-numerical methods are relatively simple and fast, and are more suitable for quick screening of design concepts in simple applications (Pugh, 1991; Ayag and Ozdemir, 2007). On the contrary, numerical methods are more systematic and can assist designers to achieve more accurate evaluations, especially for complex design concepts.

Amongst the various numerical tools developed for design concept evaluation, fuzzy set theory and AHP method have received the most attention due to their ability in handling uncertainty in multi-criteria decision-making (Scott, 2002). As mentioned earlier, evaluators' judgment and assessment of various attributes and criteria in design concept evaluation may contain ambiguity and multiplicity of meaning. The nature of vagueness and uncertainty of design concept evaluation process has made fuzzy set theory a topic of considerable interest to many researchers. For example, Thurston and Carnahan (1992) stated that fuzzy set theory could be applied to the early stage of preliminary design evaluation under multiple attributes or in situations based on semantic assessment of relative performance levels. Many researchers (Carnahan *et al.*, 1994; Khoo and Ho, 1996; Sun *et al.*, 2000; Wang, 2001; Tsai and Hsiao, 2004) have successfully used fuzzy set theory in engineering design evaluation. More recently, Huang *et al.*

(2006) had integrated fuzzy set theory with genetic algorithms and neural networks to formulate an integrated approach for design concept generation and evaluation. However, as mentioned by the authors, the proposed approach has complex algorithm structures and requires a lengthy training process.

On the other hand, AHP as one of the most widely used multi-criteria decision-making techniques, has been adapted to evaluate product design concepts through its score-ranking mechanism. In order to deal with the vagueness and uncertainty involved, AHP is usually integrated with fuzzy set theory to realize a fuzzy AHP approach to design concept evaluation (Ayag, 2005). Although the fuzzy AHP method offers many advantages for design concept evaluation, it can be a time-consuming process with the increase in the number of design criteria and design concept alternatives. This may result in a huge evaluation matrix, and the needs to conduct a large number of pair-wise comparisons (Carmone *et al.*, 1997; Ayag and Ozdemir, 2007). In addition, as suggested by Saaty (1980), the consistency in the pair-wise comparisons must be controlled at a high level because a low consistency may lead AHP analysis to meaningless results. This critical requirement may force evaluators to iteratively adjust their judgments and thus the objectivity of assessments may be distorted (Brunelli¹ and Fedrizzi¹, 2007). Furthermore, it is important to note that due to the possible interactions and dependencies between higher-level and lower-level elements, not all design concept evaluation problems can be hierarchically structured (Ayag and Ozdemir, 2007), which may limit the application of AHP in design concept evaluation.

In summary, product design concept evaluation is an important yet difficult task at the early stage of a product development process. How to effectively and

objectively evaluate design concepts under uncertainty remains a challenge.

2.7 Decision Support Systems for Product Development

2.7.1 Challenges for Decision-Making in Product Development

Decision support systems were originated by information system researchers and technologists in the late 1960's. A decision support system is an interactive computer-based system to help decision makers complete decision process tasks and make sensible decisions. Decision support systems have found themselves many applications in various industry sections. More specifically, in the domain of product development, decision support systems play a significant role and have received much attention from both academia and industries. Essentially, product development is driven by a decision-making process which determines what products to develop and how development resources are to be allocated. However, product development is characterized by high degree of complexity and uncertainty (Chen *et al.*, 2006). As a result, product development decisions are hard to make and require special decision-making support systems and tools. As summarized by Clemen and Reilly (2001), decisions in product development are difficult mainly due to the following four reasons:

- 1) Complexity of the problem;
- 2) Inherent uncertainty in the situation;
- 3) Bias of subjective perspectives;
- 4) Conflicting objectives.

Firstly, product development is a complex problem involving multidisciplinary information flow and cross-functional team cooperation. A product development process can be viewed as an information flow governed by decision-makers who make design decisions under time and budget constraints (Herrmann and Schmidt, 2002). Hence, it is particularly challenged by the need to incorporate information inputs from many multidisciplinary aspects into the decision-making process. The presence of cross-functional teams has made product development much more complex, since information flow and decision-making do not follow the hierarchical lines of authority.

Secondly, product development process has to deal with uncertain information and imprecise data, especially during the front-end stage of a product development process. A significant characteristic of early-stage product design is the existence of imperfect knowledge such as subjective opinions and imprecise data. Conventional engineering models and tools used for product design usually cannot handle such uncertainties properly (Pons and Raine, 2004). In order to facilitate decision-making in early stages of product design, it is necessary to develop effective methodologies to process various forms of uncertainties. For example, considering the uncertainties involved in product design tasks, Khoo *et al.* (2003) proposed a dynamic fuzzy decision support scheme that is able to provide a reasonable plan for an inherent iterative, complex product design. The plan generated could guide design tasks scheduling and could be adjusted dynamically according to the occurrence of some unexpected events.

Thirdly, in the early phase of a product development process, most of the input parameters are highly subjective in nature. Therefore any decision support

systems for product development must allow for subjective inputs (Clemen and Reilly, 2001). In fact, subjective judgments or personal opinions are always important ingredients of initial design information and they have remarkable impact on early design decisions in a product development process. As a result, reasonable quantitative judgment and appropriate numerical representation of these subjective parameters are of high importance for effective decision-making in product development. An effective quantitative decision analysis can provide the structure and guidance for systematic thinking in the early stages of a product development process.

Lastly, decision-making in product development often involves multiple objectives, therefore techniques and methods must be developed to help decision-makers quantify and model these objectives and make tradeoffs among competing ones (Hazelrigg, 1998; Li and Azarm, 2001; Herrmann and Schmidt, 2002). In practice, product development teams must decompose the design problem, try to satisfy a variety of constraints and make tradeoffs between multiple competing or even conflicting objectives. Similar to other decision support tools, a product development decision support system needs to analyze various quantitative and qualitative data and perform corresponding calculations in order to assess the impact of every factor involved so as to improve the product design.

In order to tackle the above challenges for decision-making in product development, systematic decision support methods or tools must be developed to assist product development processes in a timely and cost-effective manner (1997). The decision support systems developed for product development processes can act as a consultant for decision-makers to overcome their lack of expertise and

enhance the product development productivity (Liberatore and Stylianou, 1995a, 1995b; Matsatsinis and Siskos, 1999; Petrus and Cristo, 2007). Basically, a successful decision support method or tool should be able to tackle the above critical challenges for decision-making in product development processes (Hoque *et al.*, 2005; Xu *et al.*, 2007). In this regard, rough set theory (Pawlak, 1982) and grey relation analysis (Deng, 1989) are two promising decision support methodologies that suit the context of decision-making in product development processes (Zhai *et al.*, 2008; 2009b). In the next two sub-sections, a brief review of rough set theory and grey relation analysis as well as their applications in decision support systems are presented.

2.7.2 Rough Set Based Decision Support Systems

Rough set theory, which was introduced by Pawlak (1982) in the early 1980's, provides a novel mathematical tool of dealing with imprecision, vagueness and uncertainty. It focuses on the discovery of hidden patterns in imprecise data and can be used as a basis to perform formal reasoning, knowledge representation and discovery (Pawlak, 1991). Since its inception, rough set theory has rapidly established itself in many real-life applications such as decision-making, knowledge acquisition, and information retrieval, to name a few (Pawlak, 2002; Khoo and Zhai, 2001b, 2001c; Zhai *et al.*, 2001). Compared with other techniques dealing with uncertainty and vagueness, rough set theory has shown unique advantages and robustness in solving such problems (Pawlak, 1997; Zhai *et al.* 2002; Zhai *et al.*, 2006). The most salient advantage of rough set theory in dealing with uncertainty is that it does not require any preliminary or additional judgment about the data such as probability distributions and probability assignment in

statistics and the Dempster-Shafer theory of evidence, or grades of membership in fuzzy set theory (Pawlak, 1991; Pawlak *et al.*, 1994). In addition, rough set theory excels in situations where the data size is too small to employ standard statistical methods (Pawlak, 1991).

Mathematically, rough set theory provides a collection of tools with full mathematical rigor to deal with data analysis under uncertainty. It has a formal model of knowledge defined as a family of indiscernibility relations so that the knowledge has a clearly defined mathematical sense, and can be analyzed and manipulated using mathematical techniques provided by rough set theory (Pawlak, 1991). Rough set theory overlaps, to some extent, with some other theories dealing with uncertainty and vagueness, especially with the Dempster-Shafer theory of belief functions (Slowinski, 1992) and the fuzzy set theory (Wygralak, 1989; Dubois and Prade, 1987; 1990). Nevertheless, rough set theory can be viewed as an entity of its own rights as an independent, complementary, and not competing discipline (Pawlak, 1991). For example, the main difference between rough set theory and the Dempster-Shafer theory is that the latter uses belief functions as the main tool to deal with uncertainty, while rough set theory makes use of lower and upper approximations to handle vagueness and uncertainty (Khoo and Zhai, 2001c, 2001d; Zhai *et al.* 2008). The relationship between rough set theory and fuzzy set theory is rather complicated and there are many research works devoted to investigate their differences and commonalities as well as the possibilities of their integration (Dubois and Prade, 1990; Chanas and Dorota, 1992; Liu *et al.*, 2006; Sun *et al.*, 2008). In brief, both fuzzy set theory and rough set theory provide useful tools to handle semantic uncertainties (in contrast to stochastic

in data analysis (Wu and Chen, 2008). However, fuzzy set theory uses deliberated domain-meaningful membership functions to characterize the fuzziness in data (Carnahan *et al.*, 1994) whereas rough set theory uses the concept of approximations to discover the hidden uncertainties inherent in data (Pawlak, Sikder and Gangopadhyay, 2007; Zhai *et al.*, 2008).

The basic philosophy of rough set theory for decision support is based on the idea of classification. The capability of classifying objects or observations based on a set of attributes is a fundamental feature of any decision-making processes to behave rationally in the given environment (Pawlak, 1994). In decision analysis, rough set theory is able to deal with both quantitative and qualitative input data and no prior judgment is needed. As the output of the analysis, it is able to acquire posterior knowledge regarding the relevance of the attributes to the quality of approximations, where the approximations established lay the foundation for deriving decision rules (Pawlak, 1991). The unique characteristics of rough set theory make it a particularly useful tool in many decision support applications covering a broad range of industry domains (Slowinski 1993; Pawlak *et al.*, 1994; Sankar and Andrzej, 1999). For example, Podraza *et al.* (2003) presented a decision support system for medical staff based on complex data analysis using rough set theory. Shen and Loh (2004) developed a rough set based decision support system to guide investors in market timing decisions. And more recently, Aviso *et al.* (2008) applied rough sets in an environmental decision support system.

In the specific domain of product development, rough set theory has also established many successful applications. For example, Shi *et al.* (2007) used

rough set for association rule mining of Kansei knowledge to assist a cell phone design. Tseng and Huang (2008) proposed an approach to model modular products and formulate design knowledge into design rules based on rough set theory. Alisantoso and Khoo (2009) proposed a rough set based approach to early analysis of design concepts. Barnes and Lillford (2009) presented a decision support framework to assist the development of emotionally appealing products by eliciting user needs early in the development process. In summary, it is envisaged that rough set theory suits very well the uncertain environment of product development processes, where the design information is highly imprecise but the size of data is not sufficient to employ other sophisticated methods such as statistics, genetic algorithms or neural networks (Zhai *et al.*, 2009b). However, it should be noted that although rough set theory excels in many aspects for dealing with various uncertainties, it must be integrated with other product development methods in order to fully tackle the challenges for product development processes.

2.7.3 Grey Relational Analysis and Multi-Objective Decision-Making

Grey relational analysis is a part of the grey system theory developed by Deng (1982) in the 1980s. The concept of grey relational analysis is based on the combined concepts of system theory, space theory and control theory (Deng, Grey relational analysis is suitable for solving decision problems with complicated interrelationships between multiple factors and variables. One of the salient advantages of grey relational analysis is that it only relies on the original data and does not need additional judgments or assumptions (Wu, 2003). In addition, compared with other multi-objective decision-making tools, grey relational analysis is relatively simple and straightforward (Kuo *et al.*, 2008).

The basic idea of grey relational analysis is to analyze and quantify the correlations between the reference factors and other compared factors of a decision system through a mathematical model (Deng, 1989). Different from statistical methods which compare the relations between individual variables, grey relational analysis analyzes the relational grade for discrete data sequences (Tsai *et al.*, 2003). In simple words, grey relational analysis compares the distance or difference between each discrete data sequence and the reference sequence. Grey relational analysis usually does not have the stringent requirements for the sample size and the data distribution function as needed in the statistic analysis (Li *et al.*, 2008). Therefore it excels in solving multi-objective evaluation problems where the data distribution function may not be known and the amount of data may not be sufficient for statistical analysis.

Since its inception, grey relational analysis has rapidly developed into a widely used method for solving multi-objective decision-making problems (Wu, 2003). Multi-objective decision-making is a discipline that supports decision makers who are facing numerous and conflicting objectives in the process of evaluation. Usually, such decision-making processes inherently involve uncertainties with respect to parameter inputs, especially when multiple decision makers are involved (Zhang *et al.*, 2005). In such a context, it is very common that tradeoffs must be made in a transparent process. In this respect, grey relational analysis is a powerful tool to assist decision-making processes by analyzing multiple performance characteristics for evaluation. For example, Lin and Lin (2002) combined orthogonal array and grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics.

Kao and Hocheng (2003) used grey relational analysis to optimize the process parameters on electrochemical polishing of stainless steel. Chiang and Hsieh combined Taguchi method with grey relational analysis to investigate the optimal design of the process parameters with multiple quality characteristics in machining processes. Li *et al.* (2008) developed a grey-based rough decision-making approach to assist supplier evaluation and selection. More recently, Lu *et al.* (2009) employed grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling.

In product development processes, making decisions with insufficient data and contradictive objectives is usually a norm for decision makers. Grey relational analysis is one of the most promising methods that suit the context or environment of such decision-making activities. As a result, in the domain of product design and development, grey relational analysis has established many successful applications. For example, Hsu and Wen (2000) applied grey relational analysis to assist the design of airline networks. Lai *et al.* (2005) presented a new approach to determine the best design combination of product form elements for matching a given product image. In their work, a grey relational analysis model was used to examine the relationships between product form elements and product image, through which to identify the most influential elements of product form for a given product image. Lin and Lin (2006) applied grey relational analysis to evaluate the performance of a tribological system design. More recently, Akay and Kulak combined grey theory, fuzzy sets and information axiom to form a grey-fuzzy information axiom for solving product concept evaluation problems. However, it should be noted that grey relational analysis must be integrated with appropriate

tools dealing with uncertainties in order to address the complicated decision-making issues in product development processes.

2.8 Summary

New era of product development is facing ever increasing challenges due to more demanding and fast-changing customer needs, lower development cost and shorter development time. Thus, in order to ensure a continual success in the market place, manufacturing companies are required to respond swiftly to market and technology changes. Many product development methodologies such as concurrent product development and DFSS have been developed and specialized tools such as QFD have been employed to address the above challenges. However, existing methodologies and tools usually lack the capability of dealing with the highly complex, uncertain, subjective and multi-objective decision-making activities involved in product development processes. Therefore it is highly desirable to develop and incorporate an effective and efficient decision support system to assist decision-making activities under various uncertainties in a product development process. It is envisaged that such a decision support system will play an important role in improving both customer satisfaction and the productivity of a product development process, by addressing the following issues:

1. Effective representation of design information/knowledge

As discussed in Section 2.7.1, at early stages of a product development process, the initial design information and knowledge about a product is usually uncertain, subjective and imprecise. Conventional methods for the process of such design information and knowledge rely much on experts' domain knowledge and

personal experience, which is unreliable and inefficient. As such, new methods that can represent and analyze such design information and knowledge in a more reliable and effective way are highly desirable.

2. Design the right product to meet customer needs

In the new global market, many competitions in product development are driven by customer needs and satisfaction to these needs. Recognition and incorporation of customer needs in the early stages of a product development process is critically important for the success of a product. Towards this end, effective means to systematically and efficiently understand and translate customer needs into product design requirements are desired.

3. Present the product in the right manner to delight customers

Fast-changing and diverse customer tastes and affective needs have subverted the traditional way of product development which focuses simply on customers' satisfaction with basic functional requirements of a product. A successful product development must be able to discover latent affective needs of customers and meet these needs with more innovative design by presenting the product in the right manner, so as to delight customers and further improve customer satisfaction.

4. Effective evaluation of product design concepts

A successful product development relies much on the right design decisions made at the early stage of a development process. This requires an effective evaluation of various design concepts. Evaluation of product design concepts is an

important yet difficult task due to the uncertain, subjective and imprecise information, as well as the conflicting objectives involved. As such, it is desirable to develop an effective system to assist decision-making in the front-end product development process.

In summary, major findings from the literature review have identified the necessity of developing effective and efficient decision support systems to facilitate decision-making activities in the front-end product development process, with special focus on product planning and design concept evaluation phases. It is postulated that the realization of a potpourri of decision support tools focusing on the four requirements listed above could help improve product development productivity significantly and enhance the competitive advantages of a manufacturing company.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Kano's Model for Customer-Oriented Product Development

The literature review presented in Chapter 2 has singled out the gaps of the research on the front-end issues in product development. These gaps, which concern product development challenges in the global market, outline the needs to develop effective and efficient decision support systems to facilitate reasoning of imperfect information extracted from the front-end product development process, so as to improve customer satisfaction and productivity. Indeed, product development involves intensive decision-making activities, especially in the early phases of a product development process. Basically, decision-making in early product development phases is characterized by the needs to handle various vague, uncertain, incomplete and subjective design information, most of which is sourced from customer-oriented market and technology analysis. As a result, the decision support systems developed for front-end product development should be equipped with the ability to deal with the above-mentioned characteristics of design information.

As mentioned in Chapter 2, customer-oriented product development has become a necessity in the intense competitive global market. Although customers hardly spark any true innovations for product development and they are usually unaware of any state-of-the-art development activities, their inputs to product development are extremely valuable. Obtaining valid customer inputs is a science itself. Market research companies use scientific methods such as critical incident

analysis, focus groups, content analysis and surveys to identify the voice of customers (VOCs). Systematic analysis of these VOCs will discover the true needs of customers based on which a product can be developed. In fact, satisfaction of customer needs (CNs) has become the most important issue that determines the success of a product development. In this regard, Kano's model can be used to describe the relationship between customer satisfaction and product quality (Figure 3.1). The model can be represented using an (x, y) graph, with the x-axis denoting the degree that a product fulfills customers' requirements, and the y-axis recording customers' satisfaction levels. The key contribution of Kano's model is that it goes beyond the simple question of CNs and probes more deeply into product features that will generate additional advantages in competition. It is an important model to address the prioritization of CNs in a logical fashion, which can assist product designers to manage the product development process at the six-sigma level (Pyzdek, 2003).

Figure 3. 1 Kano's model for customer satisfaction

More specifically, the Kano's model separates product features into three broad categories.

(1) Basic Features

These are the mandatory and must-have features, which are necessary to enter the market (i.e. threshold requirements). Failing which, customers will not be satisfied with the product. In other words, these features must be present in the product and must be functionally doing what they are designed to do.

(2) Performance Features

These are the product features that the better (or more) they are fulfilled, the more customers are satisfied. In the Kano's model they are usually represented as a linear performance, which are also the focus of most market research concerning the spoken VOCs.

(3) Exciting Features/Delighters

These are the product features that customer will not be disappointed with too much even if they are absent, but a couple of such features can provide greater customer satisfaction and often add an extra premium to a product. In other words, delighters are those features that customers may not have expected, but receive as a bonus.

However, it should be noted that the above classification of product features is not invariable. For example, delighters often vary with customers, and they usually move over time to the performance or basic requirements and finally

become a part of customers' expectations. With the advance in technologies, very often what was once exciting enough to delight customers (e.g. remote control for a TV) may become an expected feature later and will not generate any excitement. Once a product feature becomes expected, the manufacturing company will not get any credit for providing it, instead, the manufacturer will risk a negative reaction if failing to provide it. Using the mobile phone design as an example, the Kano's model can be explained as follows:

(1) Making and receiving calls is the basic requirement for a mobile phone.

Customers will expect this feature/function but it will not be spoken by customers as such a function is taken for granted (i.e. basic or mandatory) for a phone. A mobile phone manufacturer will not get any credit for providing such a feature. However, it will definitely fail to satisfy customers if this basic feature is not provided.

(2) Battery life is a performance feature. Customers may expect it to last at least 24 hours after it is fully recharged. If the battery can last for 36 hours or even longer, customers will be very happy; however, if the battery can only last for 12 hours or even less, customers will be very unhappy. The longer the battery life is, the better is customers' satisfaction.

(3) Dual-SIM function could be an exciting feature of a mobile phone. Some customers may be delighted if the phone has a dual-SIM function, especially for those business personnel who want to separate their business life from their privacy.

Generally, a successful product must have an appropriate combination of basic, performance and excitement features. Kano's model forms the backbone for

the analysis on how a product is to be perceived by the market and often leads to a better understanding of CNs in various degrees of depth, which can facilitate the product development process towards more successful products. However, excitement features are often missing in many product development processes because the analysis about the latent CNs, the affective needs of customers for example, is usually not easy. Inspired by the Kano's model and the requirement of DFSS mentioned in Chapter 2, this research focuses on the analysis of various customer needs during the front-end product development process and propose a systematic methodology to handle uncertain design information in order to facilitate decision-making processes in product development. The framework of the research will be elaborated in the next section.

3.2 Framework of the Research

This research aims to address the four critical issues identified in Chapter 2 (Section 2.8) in order to develop an effective decision support system for the front-end product development process, namely

- 1) Techniques to represent and process uncertain product design information and knowledge;
- 2) Tools to analyze and incorporate customers' functional needs into product design;
- 3) Tools to analyze and translate customers' affective needs into product design; and
- 4) Methods to improve the effectiveness and efficiency of design concept evaluation process.

After addressing the above four issues, a prototype integrated decision support system for front-end product development process will be developed based on a potpourri of methodologies including rough set theory and grey analysis, and incorporated with QFD, affective design and DFSS concept. Figure 3.2 presents a rocket-shape model that outlines the framework of the research, in which the HOQ and DFSS concepts constitute the main body structure and lay the foundation for customer-oriented product development, the VOC analysis and affective design modules function as the two boosters that bring customer satisfaction to a greater height, and the design concept evaluation module plays the role of the control centre which controls the overall product development quality. The techniques developed to represent and process uncertain design information will form the common platform to address various uncertainties involved in the above three modules. More details of the framework are elaborated below.

The motivation of this research comes from the new challenges for product development in the global competitive market. As mentioned in Chapter 2, the new challenges for product development due to both customer expectations and market competitions have driven the product development process into the era of DFSS standard. As a proactive and systematic customer-oriented product development approach, DFSS requires a comprehensive understanding of various CNs as well as the critical quality that a successful product should achieve. In this regard, as a systematic method for analyzing CNs, the VOC analysis in QFD can be used to identify and prioritize the critical functional requirements of a product in order to satisfy CNs at the basic and performance level in Kano's model. This is to ensure that the product developed can "do the right thing" that customers really need.

Figure 3. 2 Framework of the research

However, as mentioned before, the basic analysis of VOCs alone can hardly contribute any innovations to a product design as the exciting features/delighters of a product are usually not the ones that customers expect or are aware of. As a result, the analysis of the latent or unspoken CNs, for example, the affective needs of customers, will significantly improve the level of customer satisfaction by delighting them through the way of appreciation, if the additional affective features are incorporated in the product designed. In this respect, affective design (i.e. Kansei engineering) as a powerful means to translate customer affective needs into product features can work together with QFD to formulate a comprehensive QFD (CQFD) analysis, and ensure that the product is presented “in the right manner”. Through a comprehensive analysis using the house of quality (HOQ), a more complete collection of critical-to-quality (CTQ) characteristics including both performance features and delighters can be obtained to ensure a higher level of customer satisfaction in Kano’s model.

After the CTQ characteristics of a product have been identified, initial product design concepts or design alternatives are generated and evaluated by the design team before detailed design is carried out. Design concept generation is a separate big research domain and numerous research works have been conducted to investigate this issue (e.g. Khoo *et al.*, 2002; Jin and Li, 2007). Considering the objective of this research, this thesis will not cover the process of design concept generation and instead, it will focus on the process of design concept evaluation. In the front-end product development process, design concept evaluation is a very important issue as a right decision based on an effective design concept evaluation determines the success of a product. Essentially, design concept evaluation should

be conducted with a holistic view considering both internal constraints and external requirements, and should be evaluated with the objective to achieve the six sigma level of quality as early as the design concepts are generated. In this regard, grey analysis as an efficient multi-objective decision-making method, can be integrated with rough set theory and formulate a rough-grey evaluation of product design concepts. This is to ensure that uncertain design information can be analyzed and, as a result, the product development process can be carried on “with the right decision” that leads to success.

The above framework of the research can be fulfilled by the flow chart shown in Figure 3.3, with three major modules sharing a common rough set based design information representation platform. The three modules are:

- 1) Rough set enhanced QFD analysis (Rough_QFD) module;
- 2) Dominance-based rough set enabled Kansei analysis (Rough_Kansei) module; and
- 3) Rough set based grey analysis for design evaluation (Rough_Grey) module.

Figure 3.3 Flow chart of a decision support system for front-end product development

As shown in Figure 3.3, conventional customer needs, i.e. functional needs, and Kansei needs, i.e. non-functional needs such as latent emotional needs, are collected through customer surveys. As mentioned before, various CNs collected from surveys are usually characterized by uncertain, vague and nebulous descriptions. In this research, a rough set based design information representation platform is proposed to translate the initial design inputs into quantitative CNs that are workable in numerical analysis. These quantitative CNs will then be sent to the module called rough set enhanced QFD analysis (Rough_QFD), through which the CNs and corresponding design requirements (DRs) will be prioritized. Similarly, a survey focusing on customers' affective needs is conducted and customers'

responses will be quantified by the rough set based design information representation platform before they are sent to the dominance-based rough Kansei analysis module (Rough_Kansei). The results of Rough_QFD analysis and Rough_Kansei analysis will then be incorporated and translated into quantitative terms known as critical-to-quality (CTQ) characteristics (i.e. important product features to customers in workable terms). With the guidance of DFSS principles, the CTQ characteristics can be used to generate design concepts by the product development team. Subsequently, each of these design concepts is assessed by a group of product design specialists based on a collection of evaluation criteria as well as the external and internal constraints. The scorecard ratings of design concepts, after being processed by the rough set based design information representation platform, will be sent to the Rough_Grey evaluation module to identify the best design solution according to the objectives specified.

Based on the aforementioned framework outlined for the research, the following five major tasks have been implemented in this work:

1. A novel product design information representation platform is proposed based on the basic concepts of rough set theory, with the ability of accommodating and analyzing the various imprecise, uncertain and subjective design information in the front-end product development process.
2. An enhanced QFD methodology is developed with corresponding algorithms to manipulate the product design data derived from the rough set based design information representation platform.

3. A systematic affective design analysis is proposed using the concept of dominance-based rough set theory, with the ability of discovering the hidden Kansei knowledge between product features and customer affections.
4. A multi-objective evaluation system is established by integrating grey analysis and rough set theory, with the ability of evaluating design concepts and identifying the best design solution.
5. An integrated decision support system for the front-end product development process composed of three decision support tools is implemented. A case study concerning the front-end decision-making processes in a mobile phone design is presented to demonstrate the capability of the developed system.

Obviously, rough set theory is the foremost methodology that penetrates each of the first four tasks of this research. Indeed, rough set theory has turned out to be of substantial importance to artificial intelligence (AI) and cognitive sciences over the last two decades since its inception in the early 80's, especially in applications such as decision support systems and human knowledge representations which have to deal with large amount of imprecise and uncertain data. In order to better understand the methodology used in this research, the basic notions of rough set theory will be introduced in the next section.

3.3 Rough Set Theory and Product Design Information

Rough set theory was proposed by Pawlak (1982) as a novel mathematical tool to handle imprecise, vague and uncertain data. It overlaps, to some extent,

with many other theories dealing with uncertainty and vagueness, especially with fuzzy set theory. Nevertheless, rough set theory can be viewed in its own right, as an independent and complementary discipline to fuzzy sets (Pawlak, 1991).

Approximations are the basic and most important tools (operators) in rough set philosophy to deal with uncertainty and vagueness. Essentially, the approximation space and the lower and upper approximations of a set form two important notions of rough set theory (Khoo *et al.*, 1999). In general, the data to be analyzed by rough set theory comprise a set of objects described by multi-valued attributes, which can be represented by a structure called information table. Mathematically, an information table can be represented by the 4-tuple $S = \langle U, Q, V, f \rangle$, where U is the universe composed of a finite set of objects, $Q = \{q_1, q_2, \dots, q_m\}$ is a finite set of attributes describing objects in the universe, $V = \bigcup_{q \in Q} V_q$ in which V_q is the domain of the attribute q , and $f: U \times Q \rightarrow V$ is the information function such that $f(x, q) \in V_q$ for every $q \in Q$ and $x \in U$. Table 3.1 is a typical information table with its rows and columns corresponding to objects and attributes respectively. All the objects in the table can be classified into two classes based on their decision attribute values, namely class ‘0’ and class ‘1’ as follows

$$C_0 = \{x_1, x_4, x_5, x_8, x_9, x_{10}\} \quad \text{Class} = 0 \quad (d = 0)$$

$$C_1 = \{x_2, x_3, x_6, x_7\} \quad \text{Class} = 1 \quad (d = 1)$$

However, objects x_5 and x_7 are indiscernible in view of descriptions q_1 and q_2 , although the two objects belong to different classes. Indiscernibility

relation, also known as equivalence relation, is one of the most important concepts in rough set theory. It is caused by imprecise information about the objects in the universe U under observation. Mathematically, if $x, y \in U$, $P \in Q$, then x and y are indiscernible by the set of attributes P , denoted as $x \hat{P} y$, iff $f(x, q) = f(y, q)$ for every $q \in P$.

Table 3.1 Vague classes with indiscernible descriptions

Objects (U)	Attributes		Class (d)
	q_1	q_2	
x_1	1	0	0
x_2	1	1	1
x_3	1	2	1
x_4	0	0	0
x_5	0	1	0
x_6	0	2	1
x_7	0	1	1
x_8	0	2	0
x_9	1	0	0
x_{10}	0	0	0

Similarly, objects x_6 and x_8 are also indiscernible based on the two attributes q_1 and q_2 . The indiscernibility between the objects in Table 3.1 causes vagueness of the two classes, and thus each class will have a non-empty boundary region. Rough set theory offers a means to describe these vague classes through the lower and upper approximations. For any class, called C , its lower approximation ($\underline{R}(C)$) contains all the objects in the universe U that can be certainly classified as belonging to class C by the set of attributes, R , such that

$$\underline{R}(C) = \bigcup \{Y \in U / R: Y \subseteq C\}$$

The upper approximation of C ($\bar{R}(C)$) contains all the objects in U that can be possibly classified as belonging to class C by the set of attributes, R , such that

$$\bar{R}(C) = \bigcup \{Y \in U / R: Y \cap C \neq \emptyset\}$$

Objects belonging only to the upper approximation but not the lower approximation compose the boundary region (BN_R) or the doubtful area, which represents the set of objects that cannot be certainly classified as belonging to class C or its complement by the set of attributes R . Mathematically, a boundary region can be expressed as

$$BN_R(C) = \bar{R}(C) - \underline{R}(C)$$

The boundary region of a class is caused by vague descriptions to it and the degree of vagueness is represented by the range of the boundary region. Such a class with a non-empty boundary region is called a rough set. As a special case, if the boundary region of a class is empty, the class is precise.

Based on the basic notions discussed above, the approximations of classes C_0 and C_1 in Table 3.1 can be easily obtained (Figure 3.4). More specifically, the lower approximation of class C_0 is given by

$$\underline{R}(C_0) = \{x_1, x_4, x_9, x_{10}\};$$

and its upper approximation is

$$\overline{R}(C_0) = \{x_1, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}\}.$$

Thus, the boundary region of Class C_0 is given by

$$BN_R(C_0) = \overline{R}(C_0) - \underline{R}(C_0) = \{x_5, x_6, x_7, x_8\}.$$

For Class C_1 , the approximations can be similarly obtained as follows.

$$\underline{R}(C_1) = \{x_2, x_3\};$$

$$\overline{R}(C_1) = \{x_2, x_3, x_5, x_6, x_7, x_8\}; \text{ and}$$

$$BN_R(C_1) = \overline{R}(C_1) - \underline{R}(C_1) = \{x_5, x_6, x_7, x_8\} = BN_R(C_0).$$

Figure 3. 4 Basic notions of rough set theory

The above analysis of rough set theory has unique advantages in handling uncertainty and vagueness compared with other techniques. Generally, the most

outstanding advantage of rough set theory is that it does not require any preliminary or additional information about the data to be handled such as the prior and posterior probabilities in Bayesian reasoning or the grade of membership in fuzzy set theory (Pawlak *et al.*, 1995). Furthermore, it is able to deal with situations where the data set is too small for statistical analysis, like the information table shown. Rough set theory is a simple but powerful tool which provides a collection of mathematical techniques to handle vague data with full mathematical rigor. It includes a formal model of knowledge representation which can be defined by a family of indiscernibility relations and accordingly, knowledge can be clearly defined by a mathematical model and manipulated using mathematical techniques (Pawlak, 1991).

As mentioned before, initial product design information is usually collected from surveys and such information often suffers from incompleteness, inconsistency, vagueness and uncertainty. As a result, such design information must be processed by appropriate methods so that the subsequent decision-making process is able to produce justified and rational design decisions. In this regard, rough set theory suits the characteristics of the product design information very well and can be employed to process the data. Essentially, the initial design information elicited from surveys or interviews is a collection of diverse responses. Such information can be easily transformed into an information table based on which rough set analysis can be carried out. A detailed process of transforming survey data into an information table for rough set analysis will be elaborated in Chapter 4 of this thesis.

3.4 Summary

Product development is a complex process involving intensive decision-making activities, and very often, design decisions are made without having complete and precise information. This is especially true in the early stages of a product development process, where plenty of uncertainty and vagueness exist. To ensure the success of a product development, what is most important is to “design the right thing, in the right manner” and use an effective method to evaluate the design concepts generated so as to carry on the development process “with the right decision”. Based on the principles of DFSS and the Kano’s model for customer satisfaction, this chapter outlines the framework of the research which includes four major tasks. The first task is to develop an effective design information representation platform, in which an unified design information representation scheme is proposed based on rough sets in order to facilitate the subsequent data manipulations in product development process. The second task is to develop an enhanced QFD methodology which ensures that the product developed can functionally do the right things that customers really need. These two tasks will be included in Chapter 4 of this thesis. The third task is to propose a rough set enabled affective design which ensures that additional product features are presented in the right manner to order to delight customers and improve customer satisfaction (Chapter 5). The fourth task is to establish an effective design concept evaluation system based on the integration of grey analysis and rough set theory, in order to assist designers to evaluate various design concepts generated according to multiple criteria and constraints (Chapter 6). Through the accomplishments of the above mentioned four tasks, this research is expected to

provide a comprehensive and well-defined framework to deal with front-end issues in product development, with special emphasis to assist decision-making in the process.

CHAPTER 4 A ROUGH SET ENHANCED

QUALITY FUNCTION

DEPLOYMENT

4.1 Introduction

As discussed in Chapter 3 (please refer to Figure 3.3), a decision support system for front-end product development starts from the understanding of the initial design information about customer needs (CNs), which is usually elicited from customer surveys. CNs are linguistic descriptions of customers' expectation about a product, and very often such descriptions are imprecise, uncertain, or incomplete. As a consequence, an appropriate process of CNs is of great importance as it has a direct impact on the subsequent analysis and decision-making in a product development process. Traditionally, the process of CNs is based on the domain knowledge and personal experience of product designers, which is usually subjective and arbitrary.

As mentioned in Chapter 2, quality function deployment (QFD) is a useful tool for translating CNs into product design requirements (DRs). In the process of QFD analysis, customers' perceptions on CNs are usually solicited from survey studies and a set of DRs that can fulfill these CNs are identified and evaluated by the product design team. Customers' perceptions and designers' evaluations often contain subjective and vague statements which can be expressed by linguistic terms such as 'low importance', 'high importance', 'strong relationship', 'weak

relationship', and so on. Such linguistic terms usually cannot be effectively represented by crisp numbers due to the ambiguities inherent in the descriptions. Since its inception, QFD has inspired many researchers to develop various techniques to process imprecise CNs and DRs in order to accommodate ambiguities and quantify linguistic terms, and eventually facilitate the decision-making process in product development. Among these techniques, the fuzzy number based method has received the most attention due to its ability in handling vagueness and uncertainty (Khoo and Ho, 1996; Temponi *et al.*, 1999; Chen and Weng, 2003). Essentially, fuzzy numbers use fuzzy intervals to describe vagueness and uncertainty, and such intervals can be manipulated using the arithmetic operations provided by the fuzzy set theory. As typical examples, Khoo and Ho (1996) used symmetrical triangular fuzzy numbers (STFNs) to perform QFD analysis. Chan *et al.* (1999) used STFNs to analyze the voice of customers. Some researchers also employed techniques of fuzzy arithmetic and fuzzy defuzzification to handle CNs (Wang, 1999; Shen *et al.*, 2001). More recently, Roder and Tibken (2006) proposed an integrated framework to determine DRs in product development based on fuzzy-QFD and a fuzzy optimization model. Many other fuzzy approaches based on fuzzy arithmetic, and/or fuzzy defuzzification (Zhou, 1998; Wang, 1999; Shen *et al.*, 2001; Vanegas and Labib, 2001) had also been developed to deal with imprecise and vague descriptions of CNs. As known, fuzzy numbers handle vagueness by quantifying the vagueness levels using a domain-meaningful method (i.e. membership function) to fuzzify each variable (Carnahan *et al.*, 1994). In order to present a clear image about the concept of fuzzy number based techniques in QFD analysis, a brief introduction to the basic

notions of fuzzy numbers and fuzzy membership functions is presented in the next section.

4.2 Fuzzy Number and Fuzzy Membership Function

Fuzzy set theory has been widely used to deal with uncertainty and vagueness since its inception. In fuzzy set theory, a set without a clear boundary can be defined by a partial membership instead of a crisp membership as that in the classical set theory. More specifically, in fuzzy set theory, an element can belong to a set to a certain degree k ($0 < k < 1$), in contrast to the classical set theory where an element must definitely belong or not belong to a set. However, the issue pertaining to how to define the value of k has invited much discussion, and frequently, a so-called membership function is used to produce the value. In this respect, because the linear form is the simplest and the most practical way to construct a membership function, a triangular form membership function has found many applications in both academia and industry (Selim and Mehmet, 2001). Accordingly, the fuzzy description of a set can be represented by a triangular fuzzy number (TFN) denoted as (L, C, U) , where L and U are the lower and upper limits of the fuzzy number, and C is the value with the maximum grade of membership (Figure 4.1).

Figure 4. 1 Triangular fuzzy membership function

In QFD analysis, the ambiguous design information can be quantified by fuzzy numbers, provided that its membership function can be identified. The selection of an appropriate membership function directly affects the quality and reliability of the quantification as well as the subsequent QFD analysis. Usually a membership function is predetermined by domain experts based on their domain knowledge and personal experience, and in most cases, a triangular membership function is the selection due to its simplicity. However, this arbitrary selection of membership functions may result in poor agreements with actual facts as reported in literature (Selim and Mehmet, 2001).

Different from crisp numbers, fuzzy numbers are represented in the form of intervals and therefore their arithmetic operations are much more complicated (Alefeld and Herzberger, 1983). The arithmetic operations of fuzzy numbers are adopted from interval mathematics (Kearfott and Kreinovich, 1996). For example, the addition or subtraction operation between two TFNs would yield a TFN, but the multiplication or division operation will not produce a TFN in the strict sense of mathematics. However, in order to simplify the calculation, the result of multiplication or division operation between two TFNs is usually treated as a TFN as an approximation in real practice (Bector, 2005). For instance, if $TFN_1 = [L_1, U_1]$ and $TFN_2 = [L_2, U_2]$ are two TFNs, where L_1 and L_2 are their lower limits, and U_1 and U_2 are their upper limits respectively, then

$$TFN_1 + TFN_2 = [L_1, U_1] + [L_2, U_2] = [L_1 + L_2, U_1 + U_2] \quad (4.1)$$

$$TFN_1 \times k = [L_1, U_1] \times k = [kL_1, kU_1], \quad TFN_2 \times k = [L_2, U_2] \times k = [kL_2, kU_2]; \quad (4.2)$$

where k is a constant, and

$$\begin{aligned}
 TFN_1 \times TFN_2 &= [L_1, U_1] \times [L_2, U_2] \\
 &= [\min(L_1 \times L_2, L_1 \times U_2, U_1 \times L_2, U_1 \times U_2), \max(L_1 \times L_2, L_1 \times U_2, U_1 \times L_2, U_1 \times U_2)] \\
 &\cong [L_1 \times L_2, U_1 \times U_2]
 \end{aligned} \tag{4.3}$$

because $L_1 \leq U_1$ and $L_2 \leq U_2$.

Obviously, the above arithmetic operations between two fuzzy numbers may cause rapid enlargement of the resultant fuzzy boundary interval, especially for the multiplication operation (Yu *et al.*, 2002). This can be observed from the following example:

If $TFN_1 = [2, 4]$ and $TFN_2 = [6, 8]$, based on the arithmetic operations depicted in Equations (4.1) and (4.3), the addition and multiplication of the two fuzzy numbers are as follows:

$$TFN_A = TFN_1 + TFN_2 = [2, 4] + [6, 8]$$

$$= [2 + 6, 4 + 8]$$

$$= [8, 12]; \text{ and}$$

$$TFN_M = TFN_1 \times TFN_2 = [2, 4] \times [6, 8]$$

$$\cong [2 \times 6, 4 \times 8]$$

$$= [12, 32].$$

where TFN_A and TFN_M are the resultant sum and product of TFN_1 and TFN_2 .

The enlargement of resultant fuzzy boundary intervals increases the fuzziness of the resultant fuzzy numbers, which is not desirable in many applications. For example, in QFD analysis, the increase of fuzziness will lower the confidence level of the data and eventually affect the decision-making process in product development (Zhai *et al.*, 2007a; 2007b).

Another important issue in fuzzy number application is the selection of membership function(s). Usually, fuzzy membership functions are either predetermined by users based on their domain knowledge and personal experience, or simply adopted from prevailing research results without any justifications. For example, as reported in the recent work by Kim *et al.* (2007), the modeling of fuzziness of the product design data requires the designers to assign the degree of uncertainty and the distribution function for the input data based on the users' domain knowledge and personal judgments. As a consequence, the fuzzy boundary intervals determined based on such subjective judgments may not be in good agreement with actual facts and subsequently lead to inappropriate decision making in a product development process. In order to address the above issues in the analysis of vague design information in developing a QFD, this chapter proposes two concepts termed rough number and rough boundary interval based on the basic principles of rough set theory. It is postulated that rough number and rough boundary interval are able to effectively characterize the vagueness of product design information and thus facilitate the analysis in developing a QFD.

4.3 Rough Number and Rough Boundary Interval

As discussed in Chapter 3, rough set theory as a promising and unique mathematical tool dealing with vagueness and uncertainty, has received much attention since its inception in the 1980s (Pawlak, 1982; Zhai *et al.*, 2006). In rough set theory, the measure of vagueness is neither assumed by users nor determined by membership functions. Instead, it is computed based on the vagueness inherent in the data by means of approximations – one of the most important concepts of rough set theory (Khoo and Zhai, 2001b). Although sometimes treated as a complement of fuzzy set theory, rough set theory has its unique advantages in dealing with vagueness and uncertainty. Unlike such methods as fuzzy set theory, Dempster–Shafer theory and statistical methods, rough set theory does not require any auxiliary information or subjective judgment in data analysis.

The concepts of rough number and rough boundary interval are inspired by the study on the basic characteristics of the data involved in QFD analysis. As mentioned in Section 2.4, the initial input data for QFD analysis are customer ratings on the importance of each customer need. The diversity of customer opinions in such ratings results in the uncertainty and vagueness of the input data. Table 4.1 is a typical example of an information table that registers customers' ratings on the importance of a set of customer needs for a bicycle design. In the table, seven representative customers (Ct_1 to Ct_7) identified eleven key customer needs (W_1 to W_{11}) and assigned importance ratings to each of them respectively. The integer values in the table are the customer ratings based on the 9-point scale

system, where “1” means “very low importance” and “9” means “very high importance”.

Table 4. 1 Customer perceptions on the importance of WHATs for a bicycle design

WHATs	Customers						
	Ct_1	Ct_2	Ct_3	Ct_4	Ct_5	Ct_6	Ct_7
W_1 (Easy to use)	7 [6,8]	5 [4,6]	7 [6,8]	3 [2,4]	5 [4,6]	7 [6,8]	5 [4,6]
W_2 (Safe)	9 [8,10]	9 [8,10]	9 [8,10]	7 [6,8]	9 [8,10]	9 [8,10]	7 [6,8]
W_3 (Comfortable)	7 [6,8]	5 [4,6]	7 [6,8]	9 [8,10]	7 [6,8]	9 [8,10]	7 [6,8]
W_4 (Light weight)	7 [6,8]	7 [6,8]	5 [4,6]	5 [4,6]	9 [8,10]	7 [6,8]	7 [6,8]
W_5 (Durable)	7 [6,8]	9 [8,10]	5 [4,6]	7 [6,8]	9 [8,10]	9 [8,10]	7 [6,8]
W_6 (Expansion space)	3 [2,4]	5 [4,6]	5 [4,6]	1 [0,2]	7 [6,8]	5 [4,6]	3 [2,4]
W_7 (Trendy looking)	7 [6,8]	7 [6,8]	9 [8,10]	5 [4,6]	9 [8,10]	7 [6,8]	7 [6,8]
W_8 (Rust resistance)	5 [4,6]	7 [6,8]	9 [8,10]	7 [6,8]	7 [6,8]	9 [8,10]	9 [8,10]
W_9 (Easy to maintain)	5 [4,6]	7 [6,8]	7 [6,8]	9 [8,10]	7 [6,8]	5 [4,6]	7 [6,8]
W_{10} (Easy to store)	3 [2,4]	3 [2,4]	1 [0,2]	5 [4,6]	3 [2,4]	5 [4,6]	3 [2,4]
W_{11} (Cheap)	9 [8,10]	7 [6,8]	9 [8,10]	5 [4,6]	7 [6,8]	9 [8,10]	9 [8,10]

Notes: 1) $W_1 - W_{11}$: customer needs; $Ct_1 - Ct_7$: customers.

2) 9-point scale system: 1 = very low; 3 = low; 5 = moderate; 7 = high; 9 = very high.

3) [] represents symmetric triangular fuzzy number (STFN).

4) See Section 4 for detailed descriptions of $W_1 - W_{11}$.

Apparently, due to the diversity of customer opinions, the same customer need may receive different importance ratings from different customers, which causes inconsistencies as shown in the table. Taking the first customer need (W_1) in Table 4.1 as an example, its importance ratings collected from seven customers are listed in Table 4.2 in accordance to the format of an information table. In rough set

theory, an information table can be used to identify and analyze the inconsistencies in the classification of observations (Zhai *et al.*, 2001). In fact, the difference in the rating values received from different customers can also be viewed as a classification of customers' opinions based on a set of attributes or criteria which are transparent to customers (see the condition attributes in Table 4.2). In Table each customer represents an observation and the customer's rating is treated as the decision attribute in the information table. Similarly, the customer importance ratings for each customer need in Table 4.1 can be converted into an information table (Table 4.2), which can be processed by rough set theory.

Table 4. 2 Transformed information table for importance ratings of W_1

Customers	Condition attributes of W_1				Decision (C)
	Attribute 1	Attribute 2	...	Attribute n	
Ct_1					7
Ct_2					5
Ct_3					7
Ct_4					3
Ct_5					5
Ct_6					7
Ct_7					5

Note: Shaded blocks represent attribute values that are transparent to customers.

Further investigations into Table 4.2 find a significant difference from the information table used in the classical rough set theory (see Table 3.1). The classes (or decisions) in classical rough set theory do not have any order, and the numbers used to represent the classes do not have any physical meanings. For example, "0" and "1" used to represent the two classes in Table 3.1 can be replaced by other symbols such as " a " and " b " and they will not affect the subsequent analysis. However, in Table 4.2, the values attained by the classes are ordered integers which have physical meanings. The absolute values of the ratings represent the

levels of customers' preferences, namely the bigger the value is, the more important is the customer need. In order to use rough set theory to analyze the design information discussed above, this work attempts to extend the basic notions of classical rough set theory and propose two novel concepts termed rough number and rough boundary interval, which are elaborated as follows.

Definition 1

Assume that U is the universe containing all the objects registered in an information table, and these objects belong to n classes, i.e. $R = \{C_1, C_2, \dots, C_n\}$. If the classes are ordered in the manner of $C_1 < C_2 < \dots < C_n$, then for any class $C_i \in R$, $1 \leq i \leq n$, the lower approximation of C_i can be defined as

$$\underline{Apr}(C_i) = \bigcup \{Y \in U / R(Y) \leq C_i\}; \quad (4.4)$$

the upper approximation of C_i can be expressed as

$$\overline{Apr}(C_i) = \bigcup \{Y \in U / R(Y) \geq C_i\}. \quad (4.5)$$

where Y is an arbitrary object in U .

Accordingly, the boundary region of C_i is given by

$$\begin{aligned} Bnd(C_i) &= \bigcup \{Y \in U / R(Y) \neq C_i\} \\ &= \{Y \in U / R(Y) > C_i\} \bigcup \{Y \in U / R(Y) < C_i\} \end{aligned} \quad (4.6)$$

Definition 1 makes use of the upper and lower approximations to describe the ordered classes. It is extended from the basic rough set theory described in Chapter 3. In simple words, for a class, C , in a set of ordered classes, the lower approximation of C contains all the objects in the information table that have class values equal to or less than C ; the upper approximation of C contains all the objects in the same information table that have class values equal to or greater than C ; and the boundary region of C contains all the objects in the information table that have different class values other than C . Based on the approximations of a class defined above, the so-called rough number and its lower and upper limits, as well as its rough boundary interval can be defined as follows.

Definition 2

If the lower approximation of C_i is defined as

$$\underline{Apr}(C_i) = \bigcup \{Y \in U / R(Y) \leq C_i\}; \text{ and}$$

the upper approximation of C_i is defined as

$$\overline{Apr}(C_i) = \bigcup \{Y \in U / R(Y) \geq C_i\},$$

then the class, C_i , can be represented by its rough number (RN) composed of the lower limit ($\underline{Lim}(C_i)$) and the upper limit ($\overline{Lim}(C_i)$).

Mathematically,

$$\underline{Lim}(C_i) = \frac{1}{M_L} \sum R(Y) | Y \in \underline{Apr}(C_i); \quad (4.7)$$

where M_L is the number of objects contained in the lower approximation of C_i , and

$$\overline{Lim}(C_i) = \frac{1}{M_U} \sum R(Y) | Y \in \overline{Apr}(C_i); \quad (4.8)$$

where M_U is the number of objects contained in the upper approximation of C_i .

The interval between the lower limit ($\underline{Lim}(C_i)$) and the upper limit ($\overline{Lim}(C_i)$) is known as the rough boundary interval, which is denoted as $RBnd(C_i)$ as follows:

$$RBnd(C_i) = \overline{Lim}(C_i) - \underline{Lim}(C_i). \quad (4.9)$$

Definition 2 enables a vague class (e.g. C_i) to be expressed by a so-called rough number (denoted as $RN(C_i)$) consisting of the lower limit (i.e. $\underline{Lim}(C_i)$) and the upper limit (i.e. $\overline{Lim}(C_i)$) of the said class as follows.

$$RN(C_i) = [\underline{Lim}(C_i), \overline{Lim}(C_i)] \quad (4.10)$$

where “ $[$ ” and “ $]$ ” denote the lower and upper boundaries of the rough number.

Briefly, the lower limit of a class is the mean value of the classes contained in its lower approximation whereas the upper limit of a class is the mean value of the classes contained in its upper approximation. The rough boundary interval of a class is the difference between its upper and lower limits, which describes the

vagueness of the said class. A class with a larger rough boundary interval is said to be vaguer, or less precise.

4.4 Representation of Importance Ratings Using Rough Numbers

Based on the two definitions discussed in Section 4.3, the rough approximations and rough number for the classes concerning the importance ratings in Table 4.1 can be easily derived. Taking W_1 in Table 4.1 as an example, there are three classes involved in the evaluation of the importance of W_1 , namely classes ‘3’ (rated by Customer 4), ‘5’ (rated by Customers 2, 5 and 7), and ‘7’ (rated by Customers 1, 3 and 6). Based on Equations (4.4), (4.5) and (4.6) of Definition 1, the lower and upper approximations and the boundary region of each class can be calculated and depicted in Table 4.3.

Table 4.3 Approximations of classes (W_1)

Class (C)	3	5	7
$\underline{Apr}$ (Lower approximation)	$\{Ct_4\}$	$\{Ct_4, Ct_2, Ct_5, Ct_7\}$	$\{Ct_1, Ct_2, Ct_3, Ct_4, Ct_5, Ct_6, Ct_7\}$
$\overline{Apr}$ (Upper approximation)	$\{Ct_1, Ct_2, Ct_3, Ct_4, Ct_5, Ct_6, Ct_7\}$	$\{Ct_1, Ct_2, Ct_3, Ct_5, Ct_6, Ct_7\}$	$\{Ct_1, Ct_3, Ct_6\}$
Bnd (Boundary region)	$\{Ct_1, Ct_2, Ct_3, Ct_5, Ct_6, Ct_7\}$	$\{Ct_1, Ct_3, Ct_4, Ct_6\}$	$\{Ct_2, Ct_4, Ct_5, Ct_7\}$

Using Equations (4.7) – (4.10), the lower and upper limits, the rough boundary interval and the rough number of class ‘3’ can be calculated as follows:

$$\text{Lower limit: } \underline{Lim}(3) = R(Ct_4) = 3;$$

$$\text{Upper limit: } \overline{Lim}(3) =$$

$$(R(Ct_1)+R(Ct_2)+R(Ct_3)+R(Ct_4)+R(Ct_5)+R(Ct_6))+R(Ct_7))/7$$

$$= (7+5+7+3+5+7+5)/7$$

$$= 5.57;$$

$$\text{Rough boundary interval: } RBnd(3) = \overline{Lim}(3) - \underline{Lim}(3)$$

$$= 5.57 - 3$$

$$= 2.57$$

$$\text{Rough number: } RN(3) = [\underline{Lim}(3), \overline{Lim}(3)]$$

$$= [3, 5.57]$$

Similar calculations can be carried out for the other two classes used in the evaluation of W_1 , i.e. classes ‘5’ and ‘7’. The rough numbers and rough boundary intervals calculated for the three classes are presented in Table 4.4. It is interesting to note that using rough numbers, each class of importance ratings can be denoted by a unique rough number, whose lower and upper limits are computed based on the whole collection of customers’ importance ratings for a particular WHAT. Thus, a rough number contains the information indicating not only the preference of an individual customer but also the diversity of all other customers’ opinions. In other words, the boundaries of rough numbers and the sizes of rough boundary intervals are associated with the distribution and diversity of customer perceptions.

Another salient feature of rough numbers is that the definition of lower and upper limits of a rough number rewards a class that is more “popular” (i.e. with more occurrences in the list of classes) by giving a smaller rough boundary

This feature of rough numbers complies with the fact that a class receiving more votes is more certain compared to those classes receiving fewer votes. For in Table 4.1, three out of seven customers rated the importance of W_1 with a value of '5' and a value of '7' respectively, but only one out of seven customers rated the importance of W_1 with a value of '3'. As a result, class '5' and class '7' have smaller rough boundary intervals compared to class '3' (Table 4.4). According to the mathematical implication of rough boundary interval, a class with a smaller rough boundary interval is less vague or in other words, more precise. However, it should be noted that this feature of rough numbers will not show the above advantage when the classes involved are randomly distributed (i.e. the classes evenly spread over the available options). For evenly or randomly distributed classes, a relatively larger rough boundary interval will be obtained for each class and all the intervals will be of similar size. This can be demonstrated by the following example:

If seven customers' response to the importance rating of W_1 in Table 4.1 is in even or random distribution as shown below:

1, 3, 5, 7, 9, 3, 7

Then the rough number and rough boundary interval for each class is calculated as follows:

$$RN(1)=\lceil 1, 5 \rceil; \quad RBnd(1)=4$$

$$RN(3)=\lceil 2.33, 5.67 \rceil; \quad RBnd(3)=3.34$$

$$RN(5)=\lceil 3, 7 \rceil; \quad RBnd(1)=4$$

$$RN(7)=\lceil 4.33, 7.67 \rceil; \quad RBnd(1)=3.34$$

$$RN(9)=[5, 9]; \quad RBnd(1)=4$$

Obviously, the rough boundary interval obtained for each class is relatively larger. For example, the rough boundary intervals obtained for classes “3”, “5”, and “7” above are all larger than those obtained in Table 4.4, which are 2.57, 1.5, and 1.43 respectively. They are also larger than the fuzzy intervals determined by STFNs, which are fixed at 2 as shown in Table 4.5. The above artificial example shows that the proposed methods will not be able to show advantages over existing methods such as STFNs when dealing with randomly distributed input data in which there are not any common perceptions. In other words, using rough numbers in QFD analysis assumes that there are some tendencies in the perceptions (i.e. importance ratings) recognised by the majority of customers. In the worst case, if customer ratings are indeed in random distribution like the example shown above, it means that customers’ preferences are very diverse and the rating values (i.e. classes) voted by customers are very uncertain (nearly random values). In such a case, one has to accept the fact that no methods are able to effectively gauge the severe uncertainty inherent in such data, and neither can they effectively determine the proper importance level of the customer need involved.

Table 4. 4 Comparison of rough boundary intervals (for W_1)

Class	Rough number	Rough boundary interval	Percentage of responses
3	[3, 5.57]	2.57	14.3% (1/7)
5	[4.5, 6]	1.5	42.9% (3/7)
7	[5.57, 7]	1.43	42.9% (3/7)

Notes: [] represents rough numbers

The unique characteristic endues rough numbers with great potential to suppress the enlargement of rough boundary intervals in developing QFD. As known, QFD is a team process involving a number of evaluators. When a good agreement among the evaluators' perceptions is achieved, the resultant rough boundary intervals will become smaller. This advantage of rough numbers is especially significant when they are used to analyze the relationships between WHATs and HOWs, where the diversity in experts' perceptions is expected to be low because of the similar professional knowledge possessed by these domain experts. This would indeed help in suppressing the enlargement of the resultant rough boundary intervals in developing a QFD.

It should be noted that the notions of rough number shares some commonalities with those of fuzzy number which has inarguably pioneered the interval-based fuzzy-QFD analysis. Rough numbers employ similar concept of intervals but differentiate itself from fuzzy numbers in the determination of interval boundaries. As discussed in Section 4.2, fuzzy boundary intervals are usually determined by the predefined uniform membership functions and thus do not possess the capabilities of adjusting or reducing their interval sizes, even when the consensus of evaluators' perceptions has been achieved. For example, Table 4.5 shows a comparison of importance ratings for the first customer need (W_1) represented by symmetric triangular fuzzy numbers (STFNs) and rough numbers. Using STFNs, the importance ratings are represented by fuzzy numbers whose lower and upper limits are simply defined as "rating value $- p$ " and "rating value $+ p$ " respectively, where p is a value determined by domain experts, for example, $p = 1$ in Table 4.5. All the fuzzy numbers in Table 4.5 have identical fuzzy boundary

intervals, which are fixed at 2. Obviously, this is unlikely in reality. Although some research work (e.g. Kim *et al.*, 2007) claimed that people can assign different fuzzy boundary intervals to different linguistic terms, such assignments are still determined based on users' knowledge or by subjective judgments. As a result, the notion of rough number is able to effectively describe customers' true perceptions on the importance ratings in QFD analysis.

Table 4. 5 Representation of importance ratings using STFNs and rough numbers (for W_1)

	Crisp Rating Values		
	3	5	7
Customers	Ct_4	Ct_2, Ct_5, Ct_7	Ct_1, Ct_3, Ct_6
STFN	[2, 4]	[4, 6]	[6, 8]
Rough number (RN)	$\lceil 3, 5.57 \rceil$	$\lceil 4.5, 6 \rceil$	$\lceil 5.57, 7 \rceil$

Notes: $\lceil \]$ and $\lceil \]$ represent STFNs and rough numbers respectively

Further investigations reveal that the rough numbers obtained for the ratings of a WHAT tends to be closer to the “true value” of the importance rating of the said WHAT, compared with the corresponding STFNs used (Figure 4.2). For example, consider the importance ratings of W_1 in Table 4.5 again. Intuitively, or from a statistical point of view, the “true value” of the importance rating (crisp value) for W_1 should be some value between “5” and “7”, since out of the seven customers three vote “5”, another three vote “7”, and only one votes “3” for its importance level. Therefore, as shown in Figure 4.2, the three rough numbers obtained for the three rating classes are all closer to the perceived “true value” of the importance rating for W_1 , compared to the corresponding STFNs.

Figure 4. 2 A comparison between STFNs and rough numbers in representing importance ratings.

Although possessing different characteristics, rough numbers and fuzzy numbers share similar mathematical implications. Both of them can be used to describe vague information, and the degree of vagueness is measured by the range of the boundary intervals. This is consistent with the interval analysis in interval mathematics, where the concept of ‘intervals’ (also known as ‘bounds’) consisting of lower and upper limits is used to describe vague data (Alefeld and Herzberger, 1983). Interval mathematics also provides a set of arithmetic operations for interval computation, including the interval arithmetic introduced in Equations (4.1) – (4.3) (Moore, 1979; Kearfott and Kreinovich, 1996). In this work, the addition and multiplication operations of interval mathematics are extended for the computation of rough numbers. For example, if $RN_1 = [L_1, U_1]$ and $RN_2 = [L_2, U_2]$ are two rough numbers, the interval arithmetic operations shown in Equations (4.1) – (4.3) can be adopted to compute the rough numbers when developing the QFD.

4.5 A Rough Number Enabled QFD Analysis

This section presents a rough number enabled novel approach to QFD analysis based on the notions of rough number and rough boundary interval, with the assistance of interval arithmetic operations (Figure 4.3). It starts with the identification of the WHATs (CNs) and customer perceptions on the importance of these WHATs are established through survey. Subsequently, the aforementioned concepts of rough number and rough boundary interval are used to quantify the customer perceptions in the form of rough importance ratings. The final importance ratings of the WHATs are then calculated through interval arithmetic operations of the rough numbers. Upon completion, the HOWs (TRs) that can fulfill the WHATs are identified and their importance associated with each of the WHATs are evaluated by a team of design experts. The relationship between each pair of the WHAT-HOW can be similarly quantified by rough numbers and subsequently a correlation matrix can be established. Using the correlation matrix, together with the final importance ratings of the WHATs computed previously, the importance ratings of the HOWs will be determined. Finally, the prioritization of the HOWs is carried out based on their final importance ratings, which is critical to facilitate decision-making in product development.

Figure 4. 3 Procedures of QFD analysis using rough numbers

The data used in the following case study are extracted from an in-house project conducted by final year students in a product design course. The details of the project are outside the scope of this thesis, and thus, are not elaborated here. A brief description of the project is presented as follows. A local bicycle manufacturer was planning to improve one of its bicycle designs for youngsters through a QFD analysis. A customer survey targeting subjects between 20 and 25 years of age was conducted. There were eleven key customer needs (i.e. $W_1 - W_{11}$ in Table 4.1) identified for the improved design. These customer needs are:

W_1 : Easy to use; W_2 : Safe; W_3 : Comfortable; W_4 : Light weight; W_5 : Durable; W_6 : Expansion space; W_7 : Trendy looking; W_8 : Rust resistance; W_9 : Easy to maintain; W_{10} : Easy to store; and W_{11} : Cheap.

For the simplicity of illustration, the responses of seven representative subjects were extracted from the survey data and their perceptions on the importance of each customer need are tabulated in Table 4.1 as shown in Section 4.3.

4.5.1 Prioritization of CNs

As discussed in Section 4.4, the customer perceptions on the importance of the WHATs shown in Table 4.1 can be easily quantified by rough numbers using Equations (4.4) – (4.10) and the results are presented in Table 4.6. It is interesting to note that in Table 4.6, for different WHATs, i.e. W_i in the table, the same level of importance ratings are denoted by identical crisp values and identical STFNs, but by different rough numbers. For example, in Table 4.1, Customer 1 rates both W_1 and W_3 as “highly important”, which are expressed as crisp value “7” and STFN “[6, 8]” respectively in Table 4.1. However, as shown in Table 4.6, the rough numbers calculated for “highly important” are different for W_1 and W_3 . More specifically, for W_1 , “highly important” = $\lceil 5.57, 7 \rceil$, and for W_3 , “highly important” = $\lceil 6.6, 7.67 \rceil$ (see Table 4.6). This is because, for a particular WHAT, a rough number considers not only individual customer’s perception but also the opinions of other customers. As the diversity of customers’ opinions varies for different WHATs, it will result in different rough numbers even for the same linguistic terms associated with different WHATs. On the other hand, a STFN only considers the linguistic term used to describe the perception of a single customer and relies

on the pre-determined fuzzy membership function to assign the fuzzy number. Thus, compared to STFNs, rough numbers are able to provide a more comprehensive and overall view about the importance ratings of the WHATs in QFD.

Table 4. 6 Quantification of customer survey data using rough numbers

WHATs	Customers							Relative Importance Ratings (RIR)
	Ct_1	Ct_2	Ct_3	Ct_4	Ct_5	Ct_6	Ct_7	
W_1	[5.57,7]	[4.5,6]	[5.57,7]	[3.5,5.7]	[4.5,6]	[5.57,7]	[4.5,6]	[4.74,6.37]
W_2	[8.43,9]	[8.43,9]	[8.43,9]	[7.8,4.3]	[8.43,9]	[8.43,9]	[7.8,4.3]	[8.02,8.84]
W_3	[6.6,7.67]	[5.7,2.9]	[6.6,7.67]	[7.29,9]	[6.6,7.67]	[7.29,9]	[6.6,7.67]	[6.57,8.00]
W_4	[6.33,7.4]	[6.33,7.4]	[5.6,7.1]	[5.6,7.1]	[6.71,9]	[6.33,7.4]	[6.33,7.4]	[6.00,7.43]
W_5	[6.5,8]	[7.57,9]	[5.7,5.7]	[6.5,8]	[7.57,9]	[7.57,9]	[6.5,8]	[6.74,8.37]
W_6	[2.33,4.67]	[3.67,5.5]	[3.67,5.5]	[1.4,1.4]	[4.14,7]	[3.67,5.5]	[2.33,4.67]	[2.97,5.28]
W_7	[6.6,7.67]	[6.6,7.67]	[7.29,9]	[5.7,2.9]	[7.29,9]	[6.6,7.67]	[6.6,7.67]	[6.57,8.00]
W_8	[5.7,5.7]	[6.5,8]	[7.57,9]	[6.5,8]	[6.5,8]	[7.57,9]	[7.57,9]	[6.74,8.37]
W_9	[5.6,7.1]	[6.33,7.4]	[6.33,7.4]	[6.71,9]	[6.33,7.4]	[5.6,7.1]	[6.33,7.4]	[6.00,7.43]
W_{10}	[2.6,3.67]	[2.6,3.67]	[1.3,2.9]	[3.29,5]	[2.6,3.67]	[3.29,5]	[2.6,3.67]	[2.57,4.00]
W_{11}	[7.86,9]	[6.33,8.33]	[7.86,9]	[5.7,8.6]	[6.33,8.33]	[7.86,9]	[7.86,9]	[7.01,8.65]

Notes: [] represents rough number.

Based on the flowchart of developing a HOQ as depicted in Figure 4.3, the relative importance rating of a WHAT is calculated by averaging all the customer ratings for that WHAT, using the interval arithmetic operations listed in Equations (4.1) to (4.3). The relative importance ratings indicate the overall importance levels (perceived by customers) for the WHATs relative to each other. Taking W_1 as an example, its relative importance rating, denoted as $RIR(W_1)$, is calculated as follows:

$$RIR(W_1) = ([5.57,7] + [4.5,6] + [5.57,7] + [3.5,5.7] + [4.5,6] + [5.57,7] + [4.5,6]) / 7$$

$$= \lceil (5.57+4.5+5.57+3+4.5+5.57+4.5)/7, (7+6+7+5.57+6+7+6)/7 \rceil$$

$$= \lceil 4.74, 6.37 \rceil$$

The relative importance ratings of other WHATs can be similarly calculated and they are listed in the last column of Table 4.6. The relative importance ratings, together with the competitive priority ratings and improvement ratios, are then used to calculate the final importance ratings of the WHATs using the following equation (Chan and Wu, 2005):

$$FIR(W_i) = RIR_i \times CPR_i \times IR_i \quad (4.11)$$

where W_i refers to the i th WHAT; $FIR(W_i)$ refers to the Final Importance Rating of W_i ; RIR_i refers to the Relative Importance Rating of W_i ; CPR_i refers to the Competitive Priority Rating of W_i ; and IR_i refers to the Improvement Ratio of W_i , respectively.

Here, it should be noted that the interval arithmetic operations (see Equations (4.1) to (4.3)) were extended to manipulate rough numbers, as discussed earlier in Section 4.4.

In developing the HOQ, the determination of competitive priority ratings and improvement ratios is a complex process. Usually it is carried out through a series of customer competitive analysis. Firstly, the manufacturer will identify its major competitors that produce similar products in the market. Secondly, a number of representative customers will be invited to rate the relative performance of the manufacturer's as well as the competitors' products with regard to each WHAT, using the semantic rating scales. These customers' ratings will identify the

business position of the manufacturer in the form of a customer comparison matrix, from which the customer competitive priority rating of each WHAT can be calculated (Chan and Wu, 2005). Thirdly, based on its own resources available and the relative performance of the competitors, the manufacturer will set the goal of improvement for each WHAT, so as to better satisfy the CNs and thus enhance its competitive position in the market. Finally, by examining the gap between the target performance level and the current performance level, the improvement ratio for each WHAT can be determined. This is a complex market research process which is beyond the scope of this work, and thus, is not elaborated here. However, for the completeness and clarity of illustration, this study assumes that the competitive priority ratings and improvement ratios of WHATs are already available as shown in Table 4.7.

Table 4. 7 Competitive priority ratings and improvement ratios of WHATs

WHATs	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}	W_{11}
Competitive Priority Ratings (CPR)	1.20	1.50	1.50	1.00	1.00	1.00	1.20	1.00	1.00	1.00	1.00
Improvement Ratios (IR)	1.33	1.65	1.50	1.10	1.00	1.00	1.35	1.35	1.00	1.05	0.75

Using W_1 as an example again, its final importance rating can be calculated based on Equation (4.11) as shown below.

$$\begin{aligned}
 FIR(W_1) &= RIR_1 \times CPR_1 \times IR_1 \\
 &= [4.74, 6.37] \times 1.20 \times 1.33 \\
 &= [4.74 \times 1.20 \times 1.33, 6.37 \times 1.20 \times 1.33]
 \end{aligned}$$

$$= [7.57, 10.17]$$

Similar calculations can be carried out for the remaining WHATs.

For the purpose of comparison, it is necessary to normalize the final importance ratings so that they have maximum ratings of unity. For crisp numbers, normalization is realized by dividing each crisp value by the maximum value attained. For STFNs and rough numbers, this is achieved by dividing the lower and upper limits of each fuzzy number or rough number by their largest upper limits respectively. The normalized rough numbers and STFNs for the final importance ratings of W_1 to W_{11} are represented using bar charts as shown in Figure 4.4(a) and Figure 4.4(b) respectively. These bar charts can be used to rank the importance levels of the WHATs, which will be elaborated below.

Figure 4. 4 Ranking of the final importance ratings of WHATs

As mentioned before, one of the primary objectives of QFD analysis is to understand and prioritize customer needs. This is facilitated by ranking the

WHATs according to their final importance ratings. However, when the importance ratings are represented by fuzzy numbers or rough numbers in the form of intervals instead of crisp values, some rules must be established to guide the ranking process. Based on the principles of interval comparison (Bortolan and Degani, 1985; Grzegorzewski, 1998), this work proposes the following rules for rough number ranking process:

For any two rough numbers, $RN_1 = [L_1, U_1]$ and $RN_2 = [L_2, U_2]$, where L_1 and L_2 , U_1 and U_2 represent their lower and upper limits respectively:

- (i) If one rough boundary interval is not strictly bound by another, then the order of ranking can be easily determined. That is:

If $U_1 > U_2$ and $L_1 \geq L_2$, or $U_1 \geq U_2$ and $L_1 > L_2$, then $RN_1 > RN_2$ (Figure 4.5(a)), where “>” means “is more important or superior than”;

- (ii) If $U_1 = U_2$ and $L_1 = L_2$, then $RN_1 = RN_2$ (Figure 4.5 (b));

However, if $U_1 > U_2$ and $L_1 < L_2$, or $U_2 > U_1$ and $L_2 < L_1$, then ranking becomes more cumbersome and several possibilities are available. Here, it should be noted that there have been many research works devoted to compare fuzzy numbers by looking at the mean value or the expected value of fuzzy numbers (Dubois and Prade, 1987; Jimenez, 1996). However, the methods reported in these research works assumed that the fuzzy membership functions or the uncertainty distribution functions are known, which is not even possible in rough numbers. Moreover, the

concepts of mean values and expected values involve very complex computations which are not likely to be applicable in the product design practice. For simplicity and without loss of generality, in this work, median, which is defined as the mean of the lower and upper limits of a rough number, is used for ranking rough numbers. Suppose M_1 is the median of RN_1 and M_2 is the median of RN_2 :

(iii) If $U_2 < U_1$ and $L_2 > L_1$:

If $M_1 \leq M_2$, then $RN_1 < RN_2$ (Figure 4.5(c) and Figure

4.5(d));

If $M_1 > M_2$, then $RN_1 > RN_2$ (Figure 4.5(e));

(iv) Similar rules can be applied if $U_1 < U_2$ and $L_1 > L_2$.

Note: Vertical axis indicates the level of importance.

Figure 4. 5 Ranking rules for rough numbers

The ranking rules proposed above can be applied to both rough numbers and fuzzy numbers, or other types of numbers that are represented in the form of intervals. Using these ranking rules, one can easily find that Figures 4.4(a) and

4.4(b) produce identical ranking orders of the WHATs, with the most important WHAT identified as W_2 . Accordingly, the ranking order of the eleven WHATs is as follows.

$$W_2 > W_3 > W_7 > W_8 > W_1 > W_5 > W_4 > W_9 > W_{11} > W_6 > W_{10}$$

4.5.2 Prioritization of TRs

As known, another major objective of QFD analysis is to identify and prioritize the technical requirements that fulfill the customer needs so as to facilitate the decision-making in product development. In this case study of the bicycle design, six design experts formed a team to evaluate the key customer needs identified and consequently proposed twelve technical requirements (HOWs) in order to fulfill these needs. The HOWs identified include: H_1 (Seat height), H_2 (Loading capacity), H_3 (Minimum turning radius), H_4 (Seat contact area), H_5 (Illumination distance), H_6 (Body frame dimension), H_7 (Gear speed), H_8 (Colour choices), H_9 (Density-strength ratio), H_{10} (Tyre pressure), H_{11} (Brake force), and H_{12} (Suspension stiffness). The importance rating of each HOW in terms of fulfilling each WHAT was assessed by every team member. Table 4.8 summarizes the evaluations of the six domain experts. For the purpose of illustration, only the first and last two rows are shown in the table.

Table 4. 8 Expert perceptions on the relationships between HOWs and WHATs

WHATs	HOWs											
	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8	H_9	H_{10}	H_{11}	H_{12}
W_1	9,7,9 ,9,9, 7		9,9,7 ,7,9, 7		3,1,3 ,3,3, 3	3,3,3 ,5,3, 5	3,5,5 ,3,5, 3				3,5,3 ,5,5, 3	3,5,3 ,3,3, 3
W_2	3,1,3 ,3,3, 3	1,3,1 ,1,3, 1	9,7,9 ,9,9, 9		9,7,9 ,9,9, 7	7,9,7 ,7,9, 9	3,5,5 ,3,5, 3		5,7,3 ,5,5, 5	9,7,9 ,9,9, 7	9,9,9 ,9,9, 7	5,5,3 ,5,5, 3
...		...		...								
W_{10}		3,3,3 ,3,3, 1				9,7,9 ,7,9, 9						
W_{11}		3,3,5 ,3,3, 5			3,3,5 ,5,3, 3	5,3,3 ,3,5, 3	3,5,3 ,5,3, 3		9,9,7 ,9,7, 9		3,3,3 ,3,3, 1	3,5,3 ,3,3, 3

Notes: 1) 9-point scale system: 1 = very low; 3 = low; 5 = moderate; 7 = high; 9 = very high;
 2) Each entry contains six importance ratings. A blank entry refers to 'no direct relation' between the corresponding WHAT–HOW pair.

Similarly to the computation of the relative importance ratings of the WHATs, the correlations between WHATs and HOWs can be quantified using rough numbers. Table 4.9 shows a part of the correlation matrix represented by rough numbers. Apparently, lower diversity in experts' opinions brings about smaller rough boundary intervals, which agrees favorably with the actual facts and logic.

Table 4. 9 Correlation matrix using rough numbers

WHATs	HOWs											
	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8	H_9	H_{10}	H_{11}	H_{12}
W_1	[7.89, 8.78]		[7.5, 8.5]		[2.39, 2.95]	[3.22, 4.11]	[3.5, 4.5]				[3.5, 4.5]	[3.06, 3.61]
W_2	[2.39, 2.95]						...					[3.89, 4.78]
...				...								
W_{11}		[3.22, 4.11]			[3.11, 3.89]	[3.22, 4.11]	[3.22, 4.11]		[7.89, 8.78]		[2.39, 2.95]	[3.06, 3.61]

The correlation matrix, together with the final importance ratings of the WHATs computed earlier, is carried forward to calculate the HOWs' initial importance ratings based on the simple additive weighting (SAW) method (Cohen, 1995):

$$IIR(H_i) = \sum_{j=1}^N (FIR(W_j) \times C(W_j H_i)) \quad (4.12)$$

where H_i refers to the i th HOW; $IIR(H_i)$ refers to the Initial Importance Rating of H_i ; $FIR(W_j)$ refers to the Final Importance Rating of W_j ; $C(W_j H_i)$ refers to the Correlation between W_j and H_i ; and N is the total number of WHATs.

Taking H_1 as an example, its initial importance rating $IIR(H_1)$ is:

$$\begin{aligned} IIR(H_1) &= FIR(W_1) \times C(W_1 H_1) + FIR(W_2) \times C(W_2 H_1) + \dots + FIR(W_{11}) \times C(W_{11} H_1) \\ &= \lceil 7.57, 10.17 \rceil \times \lceil 7.89, 8.78 \rceil + \lceil 19.85, 21.88 \rceil \times \lceil 2.39, 2.95 \rceil + \dots \\ &\quad + \lceil 5.26, 6.49 \rceil \times 0 \\ &= \lceil 207.38, 307.00 \rceil \end{aligned}$$

Similar to the assessment of WHATs, the evaluation on the final importance of HOWs also requires the competitive priority rating and improvement ratio for each HOW. In practice, these values are usually obtained through a technical competitive analysis. Such an analysis is to establish or enhance the competitive advantages of the manufacturer over its competitors through a series of comparisons of the technical performance of the HOWs. The

technical parameters of the product are then used to form a technical comparison matrix, from which the technical competitive priority ratings can be calculated. Subsequently, based on the technical performance of its own and its competitors' products, the manufacturer can subsequently set a technical performance goal for each HOW in order to better fulfill the WHATs identified. By examining the gaps between these goals and the current technical performance levels, the manufacturer are able to identify the improvement ratios for the HOWs. The above-mentioned technical competitive analysis is usually a very tedious process involving much confidential information and is outside the scope of the proposed research. Thus, it is not included in this thesis. Instead, it would assume that the technical competitive priority ratings and technical improvement ratios are already available as shown in Table 4.10.

Table 4. 10 Improvement ratios and technical competitive priority ratings of HOWs

HOWs	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8	H_9	H_{10}	H_{11}	H_{12}
Technical Competitive Priority Ratings (TCPR)	0.117	0.102	0.112	0.126	0.117	0.104	0.123	0.118	0.101	0.110	0.104	0.118
Technical Improvement Ratios (TIR)	1.212	1.313	1.204	1.218	1.222	1.313	1.227	1.128	1.326	1.123	1.204	1.313

According to the procedure for the development of the HOQ, the final technical rating of each HOW can be determined as follows:

$$FTR(H_i) = IIR_i \times TCPR_i \times TIR_i \quad (4.13)$$

where H_i refers to the i th HOW; $FTR(H_i)$ is the Final Technical Rating of H_i ; IIR_i refers to the Initial Importance Rating of H_i ; $TCPR_i$ and TIR_i are the Technical Competitive Priority Rating of H_i and the Technical Improvement Ratio of H_i , respectively.

Upon completion of the computation, the normalized rough numbers for the twelve HOWs' final technical ratings are represented using a bar chart as shown in Figure 4.6(a). For the purpose of comparison, the corresponding bar chart of the normalized STFNs is depicted in Figure 4.6(b). Obviously both methods produce identical ranking orders of the HOWs, in which H_6 is identified as the most important HOW and the overall priorities of HOWs are as follows.

$$H_6 > H_9 > H_3 > H_7 > H_5 > H_{12} > H_{10} > H_1 > H_{11} > H_4 > H_2 > H_8$$

Figure 4. 6 Prioritization of technical requirements

Further studies using other case studies (Zhai *et al.*, 2008, 2009d) have also confirmed that the two methods usually produce identical or very similar ranking orders in most cases. However, it should be noted that the rough number based method has shown its advantages as it is able to provide more insights into the

rankings. A comparison between Figures 4.6(a) and 4.6(b) shows that the rough boundary interval of each final technical rating in Figure 4.6(a) is much smaller than the corresponding fuzzy boundary interval in Figure 4.6(b). Moreover, less overlapping is observed for the rough boundary intervals shown in Figure 4.6(a) compared to that in Figure 4.6(b). Such characteristics also apply to the comparison between Figure 4.4(a) and 4.4(b). As known, the size of a boundary interval represents the measure of vagueness (Ozkan and Turksen, 2007). Thus, a smaller rough boundary interval implies that the corresponding final technical rating obtained using rough numbers contains less uncertainty compared to that obtained using STFNs. The result of the comparative study has successfully shown that the rough number enabled QFD analysis can suppress the expansion rate of rough boundary intervals, which would significantly improve the discernibility of the final technical ratings and thus facilitate the decision making in product development.

4.6 Summary

This chapter proposes a new method for QFD analysis using two novel concepts, namely rough number and rough boundary interval, which are extended from the basic principles of rough set theory. A rough number enabled novel approach to QFD analysis is implemented by integrating the two novel concepts with interval arithmetic operations. The novel approach presented in this work provides another promising alternative to address one of the critical issues in QFD analysis, namely the quantification and analysis of uncertain design information in developing a HOQ. Using rough numbers in QFD analysis, the initial lower/upper limits of rough numbers will be automatically determined by the inherent

uncertainty of the data, without any needs for subjective justifications. The result of a comparative study has shown that the proposed rough number based approach can provide more insights into the vague design information and can effectively suppress the enlargement of rough boundary intervals in developing QFD. As a result, the rough number enabled QFD analysis is able to produce more discernible rankings of the design requirements, which can facilitate the decision-making and better fulfill customer requirements in product development.

CHAPTER 5 A DOMINANCE-BASED ROUGH SET APPROACH TO IMPROVE CUSTOMER AFFECTIVE SATISFACTION

5.1 Introduction

As highlighted in Chapter 3, contemporary product design concerns more and more about customers' tastes and preferences from the perspective of affection. A good product design should meet both the functional (i.e. physical) requirements of the product and the affective (i.e. emotional) needs of customers. In a diverse and highly competitive market, successful products must be not only embedded with cutting edge technologies but also presented in a desirable manner. In other words, customers' affective satisfaction with a product design have become increasingly important in determining the success of the product. In such a context, affective design (also known as Kansei engineering) as an effective methodology to translate customer affections into product design requirements, should be incorporated with the QFD analysis discussed in Chapter 4, in order to formulate a more comprehensive product design framework to improve customer satisfaction (see Figure 3.2 in Chapter 3).

As suggested by Nagamachi (1999), there are four major issues that need to be considered in affective design: (1) extraction of customer affections about the product in terms of ergonomic and affective evaluations; (2) identification of

design elements of the product; (3) acquisition of Kansei knowledge; and (4) establishment of a Kansei Engineering System (KES) to assist the product development process. Among the four, acquisition of Kansei knowledge, which concerns the discovery of relationships between customer affections and design elements, is a core issue and plays a crucial role in affective design (Nagamachi, 1995). Kansei knowledge can be extracted from the design information describing customer affections about a product, which is usually solicited through customer surveys using a semantic differential (SD) scale technique (Okuhara *et al.*, 2005; Chang *et al.*, 2006). However, it should be noted that in many situations human Kansei has nonlinear characteristics and therefore cannot be directly analyzed by using statistical techniques which are based on the hypothesis of normal distributions (Nagamachi, 2006). For instance, the size or dimensions of a mobile phone may increase linearly from “small” to “big” but customers’ Kansei for “portable – not portable” changes in a non-linear manner. On the other hand, similar to the customer needs discussed in QFD analysis in Chapter 4, affective design information collected from customer surveys is usually inherent with imprecision, uncertainty and fuzziness, which brings another challenge to Kansei knowledge acquisition.

Rough set theory as an effective knowledge acquisition tool equipped with systematic analytical power in dealing with imprecision, uncertainty and nonlinearity, has lent affective design a promising alternative for Kansei knowledge acquisition. For example, Nishino *et al.* (2005) developed a variable precision Bayesian rough set model to seek the lower and upper approximations of the decision rules derived from affective design data, where the lower

approximation provides a crisp solution about the affective design while the upper approximation produces a more ambiguous and uncertain solution leading to more inventive design ideas (Nagamachi *et al.*, 2006). However, as discussed in the work by Nishino *et al.* (2005), their rough set model required users to define tolerance relations between products, which was a major hurdle for the application of the rough set model to Kansei knowledge acquisition.

This chapter describes a systematic analytical approach to Kansei knowledge acquisition based on rough set theory, which is able to extract affective design rules from imprecise and nonlinear design information. The remaining of the chapter is organized as follows. Section 2 investigates the characteristics of affective design problems and discusses the feasibility of applying rough set theory to affective design. Section 3 presents a brief review on the dominance-based rough set theory, which is an extension of classical rough sets. A dominance-based rough set approach to extract Kansei knowledge is proposed and demonstrated using an illustrative example in Section 4. Major conclusions reached in this work are summarized in Section 5.

5.2 Affective Design and Rough Set Theory

5.2.1 Modeling of Affective Design Problems

Affective design usually utilizes certain stimuli (e.g. product samples) or questionnaires to collect consumers' appreciations, in the form of ratings associated with each Kansei word, to various design concepts (Nagamachi, 1995). Figure 5.1 presents a schematic model of affective design problems. In the model, customers' ratings for a Kansei word constitute the quantified affection or feeling

of customers evoked by a product design concept. On the other hand, each design concept is formed by a collection of design elements such as material, shape, dimension, color, and so on. Each design element has its own domain of categories or range of values. For example, a color element may have a domain of categories such as “red”, “white”, “yellow” and so on. Apparently, Kansei knowledge acquisition is essentially a process to discover the relationships between the design elements and various affections of customers. In a more systematic manner, affective design data can be represented in the form of an information table, as shown in Table 5.1.

Figure 5.1 Modelling of affective design problems

In Table 5.1, a product design is decomposed into N design elements, and there are M different design concepts developed for Kansei evaluation. Each

design element can take different values from its category domain or value range as described in Fig. 5.1. Every design concept is evaluated by a group of k customers and each customer assigns a rating score to each one of the collection of L Kansei words. In fact, Table 5.1 can be viewed as a decision table in which the design elements are the condition attributes and the rating scores attained by Kansei words are the decision attributes. Thus, the affective design problem can be transformed into a multi-criteria decision-making issue, which can be addressed using advanced knowledge discovery tools such as rough set theory.

Table 5.1 Affective design information table

Design No.	Design Elements (Condition Attributes)				Ratings for Kansei Words (Decision Attributes)												
	DE_1	DE_2	...	DE_N	KW_1				KW_2				...	KW_L			
					Ct_1	Ct_2	...	Ct_k	Ct_1	Ct_2	...	Ct_k		Ct_1	Ct_2	...	Ct_k
1	c_{11}	c_{12}	...	c_{1N}	$d(1)_{11}$	$d(1)_{12}$	...	$d(1)_{1k}$	$d(2)_{11}$	$d(2)_{12}$	...	$d(2)_{1k}$	...	$d(L)_{11}$	$d(L)_{12}$	...	$d(L)_{1k}$
2	c_{21}	c_{22}	...	c_{2N}	$d(1)_{21}$	$d(1)_{22}$	...	$d(1)_{2k}$	$d(2)_{21}$	$d(2)_{22}$	...	$d(2)_{2k}$	...	$d(L)_{21}$	$d(L)_{22}$	...	$d(L)_{2k}$
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
M	c_{M1}	c_{M2}	...	c_{MN}	$d(1)_{M1}$	$d(1)_{M2}$	...	$d(1)_{Mk}$	$d(2)_{M1}$	$d(2)_{M2}$	...	$d(2)_{Mk}$	...	$d(L)_{M1}$	$d(L)_{M2}$	...	$d(L)_{Mk}$

Note: 1) DE stands for Design Element; KW stands for Kansei Word; Ct stands for Customer;

2) c_{ij} ($i=1, 2, \dots, M; j=1, 2, \dots, N$) and $d(x)_{iy}$ ($x=1, 2, \dots, L; y=1, 2, \dots, k$) symbolize the values of condition attributes and decision attributes, respectively.

5.2.2 Rough Sets and Kansei Knowledge Acquisition

As known, the classical rough set theory was originally proposed for the purpose of addressing inconsistencies in the classification of non-ordinal classes whose values do not have any preference order (Pawlak, 1991). In addition, the condition attributes considered in an information table in the classical rough set theory must have a finite number of discrete non-ordinal values, and continuous-valued condition attributes must be discretized before being processed by rough sets (Khoo and Zhai, 2001a). This is because, as mentioned in Section 3.3,

classification using the classical rough set theory is based on the equivalence relations also known as indiscernibility relations (Pawlak, 1982). As a result, the classical rough set theory is not able to handle uncertainties associated with attributes that have ordinal values or scales such as product quality, size, and so on (Greco *et al.*, 2001). However, in affective design problems, the decision classes, i.e. the Kansei ratings, are in the form of ordinal values – the larger the more preferred. In addition, it is very often that some condition attribute values such as the dimensions of a product are given on preference-ordered scales (Zhai *et al.*, 2009a; 2009c). Such attributes with preference-ordered value domains are usually called criteria in decision theory so as to differentiate them from the regular attributes with cardinal values without any preference orders (Greco *et al.*, 2002). Essentially, in a decision table with preference-ordered attributes and decision classes, positive semantic correlations between the criteria and the decision classes are usually expected. That is, an improvement of one criterion at least should not downgrade the corresponding decision class when other criteria are kept unchanged. Such semantic correlations spanned over the condition attributes and decision classes are called the dominance principles, also known as the Pareto principles in decision theory. In affective design, the violation of dominance principles is quite common due to the diversity of customers' opinions. For example, suppose there are two design concepts and the condition attribute values of the first design are all superior to those of the second design. However, due to the diversity of customers' preference, the second design may receive higher rating scores than the first one, which, as a consequence, causes the violation of dominance principles.

From rough set point of view, the violation of dominance principles can also be treated as a type of inconsistency. However, such inconsistency cannot be handled by the equivalence relations of classical rough sets and must be processed by new methods (Greco *et al.*, 2001). In fact, classical rough set theory even cannot identify such inconsistencies, because the classification in classical rough sets is based on the equivalence (or indiscernibility) relations instead of the dominance relations. In classical rough sets, the two design concepts in the above example are discernible because they have different condition attribute values. Thus, there is nothing wrong if they receive different ratings from different customers. This example shows that classical rough sets have the risk of drawing wrong knowledge when dealing with affective design data with preference orders.

Therefore, in order to use rough set theory to analyze affective design data, the classical rough set theory must be extended to handle ordinal data. In this regard, the dominance-based rough sets proposed by Greco *et al.* (1999; 2002) provide a possible approach to process affective design information. Dominance-based rough sets are extended from classical rough sets by substituting the equivalence relations by the dominance relations in the approximations of decision classes. In the next section, basic notions of the dominance-based rough sets are introduced.

5.3 Basic Notions of Dominance-Based Rough Sets

Similarly, as in the classical rough set theory, dominance-based rough sets also use information tables to analyze data (Greco *et al.*, 1999; 2002). Formally, an information table is a four-tuple:

$$S = \langle U, Q, V, f \rangle$$

where

U is a finite set of objects (universe);

$Q = C \cup D = \{q_1, q_2, \dots, q_m\}$ is a finite set of attributes (including a condition attribute set C and a decision attribute set D);

V_q is the domain of the attribute q ;

$$V = \bigcup_{q \in Q} V_q; \text{ and}$$

$f: U \times Q \rightarrow V$ is the information function such that $f(x, q) \in V_q$ for each $q \in Q, x \in U$.

For simplicity, let $D = \{d\}$, which classifies U into a finite number of classes $Cl = \{Cl_t, t \in T\}$ and $T = \{1, \dots, n\}$. Each $x \in U$ belongs to one and only one class, $Cl_t \in Cl$. The classes from Cl are preference-ordered according to increasing order of class indices, that is, for all $r, s \in T$ such that $r > s$, the objects from Cl_r are preferred to the objects from Cl_s . In other words, the classes Cl represent a comprehensive evaluation of the objects in U : the worst objects are in Cl_1 , the best objects are in Cl_n , and the other objects belong to the remaining classes Cl_r , according to an evaluation improving with the index $r \in T$.

Due to the preference order in the set of classes Cl , the sets to be approximated are not the single classes but the ‘upward union’ and ‘downward union’ of classes respectively. The upward union of classes is defined as:

$$Cl_t^{\geq} = \bigcup_{s \geq t} Cl_s; \text{ and}$$

the downward union of classes is defined as:

$$Cl_t^{\leq} = \bigcup_{s \leq t} Cl_s$$

where $t = 1, 2, \dots, n$.

The statement $x \in Cl_t^{\geq}$ means “ x belongs to at least class Cl_t ”, whereas $x \in Cl_t^{\leq}$ means “ x belongs to at most class Cl_t ”. In other words, the union, $Cl_t^{\geq}$, is a set of objects belonging to class Cl_t or a more preferred class, while $Cl_t^{\leq}$ is a set of objects belonging to class Cl_t or a less preferred class. It should be noted that for $t = 2, \dots, n$, there is $Cl_t^{\geq} = U - Cl_{t-1}^{\leq}$.

The bipartition in the dominance-based rough sets divides the universe into the upward and downward unions of classes, $Cl_t^{\geq}$ and $Cl_{t-1}^{\leq}$, for $t = 2, \dots, n$. As a result of this division, the objects from the upward union, $Cl_t^{\geq}$, is preferred over those from the downward union, $Cl_{t-1}^{\leq}$. When extracting knowledge with respect to an upward union, $Cl_t^{\geq}$, all the objects belonging to $Cl_t^{\geq}$ are considered positive and all the objects belonging to $Cl_{t-1}^{\leq}$ negative. Analogically, when extracting knowledge with respect to a downward union, $Cl_{t-1}^{\leq}$, all the objects belonging to $Cl_{t-1}^{\leq}$ are considered positive and those belonging to $Cl_t^{\geq}$ negative.

Let $\succeq_q$ be a *weak preference relation* on U (also known as outranking relation) representing a preference on the set of objects with respect to criterion q , and $x \succeq_q y$ means “ x is at least as good as y with respect to criterion q ”. It is said that x *dominates* y with respect to $P \subseteq C$ (or, x *P-dominates* y), can be denoted by $x D_P y$, if $x \succeq_q y$ for all $q \in P$.

Without loss of generality, assuming that the domains of all criteria are ordered such that the preference increases with the value, $x D_P y$ is equivalent to: $f(x, q) \geq f(y, q)$ for all $q \in P$. Observe that for each $x \in U$, $x D_P x$, that is, P -dominance is reflexive. Analogically, $x D_R y$ in decision criteria space X_R , $R \subseteq D$.

Given $P \subseteq C$ and $x \in U$, the granules of knowledge used in the dominance-based rough sets for the approximation of the unions $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are open sets defined by dominance cones with respect to x , namely

- 1) A set of objects dominating x , called *P-dominating set*, $D_P^+(x) = \{y \in U: y D_P x\}$; and
- 2) A set of objects dominated by x , called *P-dominated set*, $D_P^-(x) = \{y \in U: x D_P y\}$.

Given a set of criteria $P \subseteq C$, the inclusion of an object $x \in U$ to the upward union of classes $Cl_t^{\geq}$, for $t = 2, \dots, n$, creates an inconsistency due to the violation of the dominance principles if one of the following conditions holds:

- 1) x belongs to class Cl_t or higher classes but is P -dominated by an object y belonging to a class lower than Cl_t , that is, $x \in Cl_t^{\geq}$ but $D_p^+(x) \cap Cl_{t-1}^{\leq} \neq \emptyset$; or
- 2) x belongs to a lower class than Cl_t but P -dominates an object y belonging to class Cl_t or higher classes, that is, $x \notin Cl_t^{\geq}$ but $D_p^-(x) \cap Cl_t^{\geq} \neq \emptyset$.

In such a case, it is said that x belongs to $Cl_t^{\geq}$ with some ambiguity. On the contrary, if $x \in Cl_t^{\geq}$ and there is no inconsistency in accordance to the dominance principle, it is said that x belongs to $Cl_t^{\geq}$ without any ambiguity with respect to $P \subseteq C$. This means that all objects that P -dominate x belong to $Cl_t^{\geq}$, namely, $D_p^+(x) \subseteq Cl_t^{\geq}$.

For $P \subseteq C$, the set of all objects belonging to $Cl_t^{\geq}$ without any ambiguity constitutes the P -lower approximation of $Cl_t^{\geq}$, and is denoted by $\underline{P}(Cl_t^{\geq})$, and the set of all objects that have the possibility of belonging to $Cl_t^{\geq}$ forms the P -upper approximation of $Cl_t^{\geq}$, and is denoted by $\overline{P}(Cl_t^{\geq})$:

$$\underline{P}(Cl_t^{\geq}) = \{x \in U: D_p^+(x) \subseteq Cl_t^{\geq}\},$$

$$\overline{P}(Cl_t^{\geq}) = \{x \in U: D_p^-(x) \cap Cl_t^{\geq} \neq \emptyset\} = \bigcup_{x \in Cl_t^{\geq}} D_p^+(x), \text{ for } t = 1, \dots, n.$$

Analogously, one can define the P -lower approximation and P -upper approximation of $Cl_t^{\leq}$ as follows:

$$\underline{P}(Cl_t^{\leq}) = \{x \in U: D_p^-(x) \subseteq Cl_t^{\leq}\},$$

$$\overline{P}(Cl_t^{\leq}) = \{x \in U: D_p^+(x) \cap Cl_t^{\leq} \neq \emptyset\} = \bigcup_{x \in Cl_t^{\leq}} D_p^-(x), \text{ for } t = 1, \dots, n.$$

Therefore, the classification patterns to be discovered in the dominance-based rough sets are functions representing $Cl_t^{\geq}$ and $Cl_t^{\leq}$ by granules $D_p^+(x)$ and $D_p^-(x)$.

All the objects belonging to both $Cl_t^{\geq}$ and $Cl_t^{\leq}$ with some ambiguities constitute the *P-boundary* of $Cl_t^{\geq}$ and $Cl_t^{\leq}$, which are denoted by $Bn_p(Cl_t^{\geq})$ and $Bn_p(Cl_t^{\leq})$, respectively. They can be represented in terms of upper and lower approximations as follows:

$$Bn_p(Cl_t^{\geq}) = \overline{P}(Cl_t^{\geq}) - \underline{P}(Cl_t^{\geq}), \text{ and}$$

$$Bn_p(Cl_t^{\leq}) = \overline{P}(Cl_t^{\leq}) - \underline{P}(Cl_t^{\leq}), \text{ for } t = 1, \dots, n.$$

As such, the inconsistencies in the information table (in the sense of the dominance principles) can be addressed by the dominance-based rough sets through the concepts of approximations discussed above.

5.4 A Dominance-Based Rough Set Approach to Affective Design

In this section, a dominance-based rough set approach to extracting Kansei knowledge will be proposed for affective design. The new approach is based on the affective design modeling framework depicted in Figure 5.1 and the basic notions of the dominance-based rough sets introduced in Section 5.3. Figure 5.2 is a

schematic flowchart of the proposed approach. Briefly, the proposed approach starts with an information table gleaned from Kansei survey data. As discussed in Section 5.2.2, dominance principles must be established for each condition attribute in the information table, so that inconsistencies can be identified and handled by the dominance-based rough set notions introduced in Section 5.3. After the dominance-based rough set approximations have been established for each Kansei class union, Kansei rules can be extracted and evaluated based on the approximation quality of each class union. The Kansei rules extracted can be used to guide the product design improvement so as to enhance customer affective satisfaction.

Figure 5. 2 Dominance-based rough set approach to Kansei knowledge extraction

As an example, Table 5.2 presents a typical affective design information table obtained from a Kansei survey, which concerns customer evaluations on a set of alternatives of a sports car design. In the table, the collection of design elements is treated as the condition attribute set, C , and the Kansei to be evaluated is treated as the decision attribute set, D . For simplicity of illustration, each design alternative is represented by 3 design elements (i.e. $C=\{q_1, q_2, q_3\}$) and each design element has 2 categories, namely $q_1=Body-shape$ (Streamline or Square), $q_2=Headlight-shape$ (Circle or Oval), and $q_3=Wheel-rim$ (11-spoke or 5-spoke). To keep the size of the information table manageable for illustration purpose and without loss of generality, this example assumes that two customers from the focus group (Marshall and Rossman, 1999) of the survey are invited to give their ratings for each of the design alternatives pertaining to the Kansei $d=Sporty$ (i.e. $D=\{d\}$). Apparently, the maximum number of design alternatives is 8 and the corresponding total number of entries in the information table should be 16, as shown in Table 5.2. Customers' ratings on the Kansei of 'sporty' for each design alternative are recorded by a 5-point scale system where '1' represents the "least sporty" and '5' represents the "most-sporty". The 16 objects are arranged in ascending order of the ratings attained as shown in Table 5.2.

Table 5. 2 A Kansei information table in ascending order of Kansei ratings

Object No	Design Elements (Condition Attribute Set C)			Kansei Word Rating (Decision Attribute Set D)
	Body-shape (q_1)	Headlight-shape (q_2)	Wheel-rim (q_3)	Sporty (d)
1 ♥ ×	Square	Circle	5-spoke	1
2 ×	Square	Circle	11-spoke	2
3	Square	Circle	11-spoke	2
4	Streamline	Circle	11-spoke	3
5	Streamline	Circle	11-spoke	3
6	Square	Oval	11-spoke	3
7	Square	Oval	11-spoke	3
8 ♥	Square	Circle	5-spoke	3
9	Square	Oval	5-spoke	4
10	Square	Oval	5-spoke	4
11 +	Streamline	Oval	11-spoke	4
12 ♣ * ♦	Streamline	Oval	5-spoke	4
13 + ♣	Streamline	Oval	11-spoke	5
14 *	Streamline	Circle	5-spoke	5
15	Streamline	Circle	5-spoke	5
16 ♦	Streamline	Oval	5-spoke	5

Note: ×, +, *, ♣, ♥, and ♦ indicate inconsistent object pairs. For example, object 1 and object 2 (both are marked by “×” in the table) are a pair of inconsistent objects.

In dominance-based rough sets analysis, the domain values of a condition attribute are preference-ordered and semantically correlated with the decision class of the object, namely an increase (or a decrease) in the attribute value will cause upgrading (or downgrading) of the class that the corresponding object belongs to. However, in affective design data, some condition attributes only have categorized values which do not have visible preference orders. For example, all the condition attributes (i.e. design elements) in Table 5.2 take categorized values such as “square”, “streamline”, “circle”, “oval” and so on, whose preference orders are invisible. In fact, this is a common phenomenon in affective design data. It could be either because the nature of the design element does not permit ordinal numerical data such as the colors of a design, or due to budget and design

constraints, the manufacturer may only be able to prepare a limited number of choices for the design elements even though it can take ordinal numerical values such as the maximum speed of a car. Moreover, in some instances, the ordinal numerical values of a design element may not be in concordance with the preference order of the decision classes. For example, an increase in the value of a design element may not necessarily result in an upgrade in the corresponding decision class, but rather lead to a downgrade of the associated decision class, the number of spokes of the wheel in Table 5.2, for example. Thus, in order to use the dominance-based rough sets to analyze the affective design data, it is necessary to find out the semantic correlations spanned over the condition and decision parts, namely the dominance principle. In the following sub-section, the concept of category score is introduced to identify the hidden preference order among the categories of a design element based on the data in the information table.

5.4.1 Category Score and Preference Order

It is noted that different categories of a condition attribute correspond to different customer ratings, i.e. decision classes, in the information table. Thus, by comparing the total score attained by each category will indicate the preference order of the categories. In this regard, a concept termed *Category Score* is proposed to discern the preference order of categories associated with a design element. Here, a category score refers to the average value of ratings attained by the said attribute category as follows.

$$Score(Att.Cat) = \frac{1}{N} \sum D(Att.Cat)$$

where

$D(Att.Cat)$ is the decision class value of the object in which the condition attribute “ Att ” takes the category value “ Cat ”, and N is the total number of such objects in the information table.

Apparently, the score attained by a category indicates the category’s importance with reference to the decision classes. For example, a category with a higher score is more associated with the upper-bound of the decision classes while one with a lower score is more associated with the lower-bound of the decision classes. Thus, by comparing the category scores attained can reveal the semantic correlations over the condition and decision parts of the information table.

For example, each category score of the design element *Body-shape* based on the data depicted in Table 5.2 can be calculated as follows:

$$Score(Body-shape.Streamline) = (3+3+4+4+5+5+5+5)/8 = 4.25$$

$$Score(Body-shape.Square) = (1+2+2+3+3+3+4+4)/8 = 2.75$$

Therefore,

$$Score(Body-shape.Streamline) > Score(Body-shape.Square)$$

Obviously, the category ‘*Streamline*’ of the design element ‘*Body-shape*’ is more associated with the upper-bound of the decision classes, i.e. more sporty, as shown in the information table, while the category ‘*Square*’ is more related to the lower-bound of the decision classes, i.e. less sporty. In the sense of preference

order or outranking concept in the dominance-based rough sets as explained in Section 5.3, it is said that ‘*Streamline*’ dominates ‘*Square*’, and is denoted as:

$$\text{Body-shape.Streamline} \succ \text{Body-shape.Square}$$

where ‘ $\succ$ ’ means outranking or dominating (see Section 5.3).

Similarly, the category scores of other categories in Table 5.2 can be easily calculated and listed as follows:

$$\text{Score(Headlight-shape.Circle)} = (1+2+2+3+3+3+5+5)/8 = 3$$

$$\text{Score(Headlight-shape.Oval)} = (3+3+4+4+4+4+5+5)/8 = 4$$

Hence,

$$\text{Headlight-shape.Oval} \succ \text{Headlight-shape.Circle}; \text{ and}$$

$$\text{Score(Wheel-rim.11-spoke)} = (2+2+3+3+3+3+4+5)/8 = 3.125$$

$$\text{Score(Wheel-rim.5-spoke)} = (1+3+4+4+4+5+5+5)/8 = 3.875$$

Thus,

$$\text{Wheel-rim.5-spoke} \succ \text{Wheel-rim.11-spoke}$$

As a result, the preference orders (outranking relations) of the categories associated with each of the design elements can be established and used for dominance-based rough set analysis.

5.4.2 Two Types of Inconsistencies and Rough Set Analysis

Essentially, there are two types of inconsistencies in the information table for affective design, namely Type I inconsistency caused by indiscernibility relations and Type II inconsistency due to the violation of dominance principles. The proposed concept of category score can be used to establish the dominance principles for the detection of Type II inconsistencies in the information table. For example, the outranking relations derived from Table 5.2 as described in Section 5.4.1 can be used to establish the dominance principles and detect the Type II inconsistencies in the Table. More specifically, Table 5.3 is a simplified information table that is obtained by removing duplicate objects from Table 5.2. In Table 5.3, two types of inconsistencies can be identified. There exists inconsistency in each of the object pairs (x_1, x_5) , (x_7, x_9) , and (x_8, x_{11}) in Table 5.3 because each pair of objects are indiscernible in terms of condition attributes but are classified into different decision classes. Such inconsistencies are caused by the diverse opinions of customers when they evaluate the same design alternative. These inconsistencies belong to “Type I inconsistency” and can be easily detected by intuition or by the indiscernibility relations of classical rough sets. However, there is another type of inconsistencies in Table 5.3, which are caused by violating the dominance principles established. For example, objects x_1 and x_2 are discernible by the set of condition attributes and they belong to different classes. Thus, there is nothing wrong if they are analyzed using classical rough sets. However, considering the preference orders of the categories identified, one can find that $x_1 \succeq_{q_i} x_2$ for every $q_i \in C$ ($i=1, 2, 3$), but $x_2 \succeq_d x_1$, namely, x_1 dominates x_2 in every condition attribute value but the decision class of x_1 is dominated by the

decision class of x_2 , which violates the dominance principles established. This is the inconsistency that can only be identified by the dominance-based rough sets and it is termed “Type II inconsistency” in this work. Similar inconsistencies can be found in the object pairs of (x_8, x_9) and (x_8, x_{10}) . As highlighted by Greco *et al.* (2001), identification of inconsistencies caused by the violation of dominance principles is very important for an information table that contains ordinal attribute values, without which wrong or misleading knowledge could be drawn from the information table.

Table 5.3 The simplified information table

No	Design Elements (Condition Attribute Set C)			Kansei Word Rating (Decision Attribute Set D)
	Body-shape (q_1)	Headlight- shape (q_2)	Wheel-rim (q_3)	Sporty (d)
x_1 ♥ ×	Square	Circle	5-spoke	1
x_2 ×	Square	Circle	11-spoke	2
x_3	Streamline	Circle	11-spoke	3
x_4	Square	Oval	11-spoke	3
x_5 ♥	Square	Circle	5-spoke	3
x_6	Square	Oval	5-spoke	4
x_7 +	Streamline	Oval	11-spoke	4
x_8	Streamline	Oval	5-spoke	4
♣ * ♦				
x_9 + ♣	Streamline	Oval	11-spoke	5
x_{10} *	Streamline	Circle	5-spoke	5
x_{11} ♦	Streamline	Oval	5-spoke	5

Note: ×, +, *, ♣, ♥, and ♦ indicate inconsistent object pairs.

5.4.3 Analysis of Affective Design Data Using Dominance-Based Rough Sets

Using the basic notions of the dominance-based rough sets introduced in Section 3, both Type I and Type II inconsistencies can be addressed and the

approximations of the upward unions of classes in Table 5.3 are obtained as follows:

$$\underline{P}(Cl_5^{\geq}) = \emptyset;$$

$$\overline{P}(Cl_5^{\geq}) = \{x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$Bn_P(Cl_5^{\geq}) = \{x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$\underline{P}(Cl_4^{\geq}) = \{x_6, x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$\overline{P}(Cl_4^{\geq}) = \{x_6, x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$Bn_P(Cl_4^{\geq}) = \emptyset;$$

$$\underline{P}(Cl_3^{\geq}) = \{x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$\overline{P}(Cl_3^{\geq}) = \{x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$Bn_P(Cl_3^{\geq}) = \{x_1, x_5\};$$

$$\underline{P}(Cl_2^{\geq}) = \{x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}\};$$

$$\overline{P}(Cl_2^{\geq}) = U;$$

$$Bn_P(Cl_2^{\geq}) = \{x_1, x_2, x_5\};$$

Analogically, the approximations of downward unions of the classes depicted in Table 5.3 can be obtained but are not repeated here. It is important to

note that the objective of analyzing affective design data is to discover the relationships between the product design elements and the human Kansei of the product. Thus, the knowledge extracted from the upward unions of the upper bound of the decision classes is more important for affective design analysis. In this example, the approximations of $Cl_5^{\geq}$ and $Cl_4^{\geq}$ are further analyzed to identify the best compositions of design element attributes that can maximize the Kansei of ‘sporty’.

As shown above, the lower approximation of the upward union of class ‘5’ is empty, i.e., $\underline{P}(Cl_5^{\geq}) = \emptyset$, which means that there is not any composition of the design element categories that can assure the highest rating (class 5) for the Kansei of ‘sporty’. The next non-empty lower approximation of upward union is $\underline{P}(Cl_4^{\geq})$, from which the designers can derive the Kansei knowledge that ensures the Kansei of ‘sporty’ to be rated at least class ‘4’. Moreover, because $\overline{P}(Cl_4^{\geq}) = \underline{P}(Cl_4^{\geq})$, the knowledge extracted from either the lower approximation or the upper approximation is certain and can properly represent the relationship between the design elements and the Kansei of ‘sporty’. More specifically, the Kansei knowledge extracted from the approximation can be represented as follows:

$$(Headlight-shape \geq Oval) + (Wheel-rim \geq 5-spoke) \leftrightarrow Sporty \geq 4$$

$$(Body-shape \geq Streamline) + (Headlight-shape \geq Oval) \leftrightarrow Sporty \geq 4$$

$$(Body-shape \geq Streamline) + (Wheel-rim \geq 5-spoke) \leftrightarrow Sporty \geq 4$$

5.4.4 Quality of Partition

In order to describe the quality of the partition which separates the objects in the universe into the upward union and downward union of a class, Cl_t , a concept known as *partition quality* is proposed. It describes the confidence level of the classification. Mathematically, a partition quality is defined as follows:

$$\gamma(Cl_t^{\geq}) = \frac{|P(Cl_t^{\geq})| + |P(Cl_{t-1}^{\leq})|}{|U|} \quad (2 \leq t \leq n); \text{ and}$$

$$\gamma(Cl_t^{\leq}) = \frac{|P(Cl_t^{\leq})| + |P(Cl_{t+1}^{\geq})|}{|U|} \quad (1 \leq t \leq n-1).$$

where $||$ denotes the cardinality of a set (i.e. the total number of objects included in a set).

The partition quality can be expressed based on either the upward union of Cl_t in the form of $\gamma(Cl_t^{\geq})$ or the downward union of Cl_t in the form of $\gamma(Cl_t^{\leq})$, depending on the concern of interest. For example, the partition quality expressed based on the upward union of Cl_t is defined as $\gamma(Cl_t^{\geq})$, which is the ratio of the total number of objects that can be certainly classified into $Cl_t^{\geq}$ and $Cl_{t-1}^{\leq}$ to the total number of objects in the universe U . The definition of $\gamma(Cl_t^{\leq})$ can be interpreted in the similar manner. It can be easily proved that $\gamma(Cl_t^{\geq}) = \gamma(Cl_{t-1}^{\leq})$, for $2 \leq t \leq n$.

Essentially, the partition quality of a class, Cl_t , indicates the granularity roughness of the knowledge that differentiates the objects into either $Cl_t^{\geq}$ and $Cl_{t-1}^{\leq}$ (if the partition quality is expressed by $\gamma(Cl_t^{\geq})$) or $Cl_t^{\leq}$ and $Cl_{t+1}^{\geq}$ (if the partition quality is expressed by $\gamma(Cl_t^{\leq})$). Fig. 5.2 presents a schematic graph of the partition quality expressed by $\gamma(Cl_t^{\geq})$. When the knowledge granularity is fine enough to completely separate $Cl_t^{\geq}$ and $Cl_{t-1}^{\leq}$ ($2 \leq t \leq n$) without any ambiguity, $\gamma(Cl_t^{\geq})$ will take the maximum value of '1' (Fig. 5.2(a)). Otherwise there is no clear boundary between $Cl_t^{\geq}$ and $Cl_{t-1}^{\leq}$, and the two sets will overlap with each other. In such a situation, $\gamma(Cl_t^{\geq})$ can only take a value between '0' and '1' (same for the rest), depending on the degree of ambiguity between the two sets (Fig. 5.2(b)).

Fig. 5.2 Schematic graph of partition quality

As mentioned earlier, knowledge acquisition in affective design concerns more about the relationships between the design elements and the upper bound of Kansei ratings, as designers are keen to identify the best compositions of design elements that can maximize the satisfaction to the customer Kansei of interest. The

partition quality of the upper bound Kansei ratings can help to describe the reliability of the knowledge discovered. For example, in the example discussed above, the partition quality of each Kansei rating can be calculated as follows (based on the upward union of Cl_i in the form of $\gamma(Cl_i^{\geq})$):

$$\gamma(Cl_5^{\geq}) = \frac{|\underline{P}(Cl_5^{\geq})| + |\underline{P}(Cl_4^{\leq})|}{|U|} = \frac{0+6}{11} = 0.55;$$

$$\gamma(Cl_4^{\geq}) = \frac{|\underline{P}(Cl_4^{\geq})| + |\underline{P}(Cl_3^{\leq})|}{|U|} = \frac{6+5}{11} = 1;$$

$$\gamma(Cl_3^{\geq}) = \frac{|\underline{P}(Cl_3^{\geq})| + |\underline{P}(Cl_2^{\leq})|}{|U|} = \frac{8+1}{11} = 0.82;$$

$$\gamma(Cl_2^{\geq}) = \frac{|\underline{P}(Cl_2^{\geq})| + |\underline{P}(Cl_1^{\leq})|}{|U|} = \frac{8+0}{11} = 0.73;$$

Obviously, only the partition qualities of the upper bound Kansei ratings (i.e. $\gamma(Cl_5^{\geq})$ and $\gamma(Cl_4^{\geq})$ in this case) make sense in the evaluation of the knowledge extracted. However, the partition quality of the highest Kansei rating (i.e. class 5) score is very low with $\gamma(Cl_5^{\geq}) = 0.55$, which is the lowest among all. This serves as an indication to the designer that the existing design alternatives composed of the three design elements have difficulties in achieving the maximum Kansei of ‘sporty’ among customers. In other words, the compositions of the three design elements cannot deliver a clear image of the highest Kansei of ‘sporty’. This is also in concordance with the fact that $\underline{P}(Cl_5^{\geq}) = \emptyset$, which means that there is no consensus among customers concerning the highest Kansei of ‘sporty’ based on

the existing designs. Thus, the designer will have to change or involve more design elements if the maximum satisfaction to the customer's Kansei of 'sporty' is expected. On the other hand, the upward union $Cl_4^{\geq}$ has the highest partition quality with $\gamma(Cl_4^{\geq}) = 1$. This simply indicates that there exist design element compositions which can assure "class 4" Kansei of 'sporty' and consensus concerning the knowledge of such designs is achieved among customers.

In summary, based on the relationships identified between the design elements and the customer Kansei, the designer can establish the Kansei knowledge of interest. Together with the partition qualities attained by respective Kansei class unions, the affective design knowledge can be further evaluated and then used to recommend modifications and improvements to the product design, so as to discover the best compositions of design elements that maximize customer satisfaction to the target Kansei requirements. As such, the proposed approach provides an effective means for design knowledge acquisition in affective design, which can facilitate the establishment of a decision support system for affective design.

5.5 Summary

Affective design data analysis conventionally relies on statistical tools which assume that affective design data possess linear characteristics. The nonlinearity and uncertainty inherent in the affective design data have encouraged much research efforts to focus on the development of new tools for affective design analysis. This chapter proposed a dominance-based rough set approach to analyze affective design data in product development. Two novel concepts, namely

category score and partition quality, are proposed and incorporated into the dominance-based rough sets for affective design analysis. The proposed approach is able to detect and handle two types of inconsistencies inherent in the affective design data, which are caused by indiscernibility relations (known as Type I inconsistency) and dominance relations (known as Type II inconsistency), respectively. An illustrative example is used to demonstrate the capability of the proposed approach. The result shows that the best compositions and respective category values of design elements that maximize customer affective satisfaction to specific Kansei requirements can be easily identified. Furthermore, the granularity roughness of the knowledge extracted from the imprecise affective design data is evaluated by the quality of partitions associated with respective class unions. The Kansei knowledge established can be used to advise designers on the modification and improvement of the product design in order to achieve the target Kansei requirements and improve customers' affective satisfaction. It should be noted that although the example used in this chapter is simple for the purpose of clarity in illustration, the novel approach proposed can be easily generalized to handle more complex context which involves multi-category design elements and more customer evaluations.

CHAPTER 6 PRODUCT DESIGN CONCEPT EVALUATION USING ROUGH GREY ANALYSIS

6.1 Introduction

As mentioned in Chapter 3 (see Figure 3.2), in the front-end product development process, initial product design concepts or design alternatives are to be generated by the design team after the critical-to-quality (CTQ) characteristics have been identified (Tennant, 2002). These CTQ characteristics include both the design requirements to fulfill stated customer needs (i.e. the functional needs discussed in Chapter 4) and the product presentation manner to satisfy latent customer needs (i.e. the affective needs discussed in Chapter 5). A product design concept is an approximate description of the technology, working principles, and form of the product. It is a concise description of how the product will satisfy various customer needs (Ulrich and Eppinger, 2004). As discussed in Chapter 3, product design concept generation is a separate big research domain and numerous research works have been conducted to investigate this issue (e.g. Khoo *et al.*, 2002; Jin and Li, 2007). Considering the objective of this research, this chapter will not cover the design concept generation process. Instead, it will focus on the evaluation process of design concepts.

Product design concept evaluation is the process of evaluating various design concepts or alternatives with respect to critical customer needs and other criteria, comparing the relative strengths and weaknesses of the concepts, and

selecting one or more design concepts for further investigation or development. Product design concept evaluation is often considered one of the vital activities in the product development process. It is widely accepted in the literature that more than 70% of the product development cost is committed at this stage, after which the product development will converge towards a detailed design process (Ullman, 1997; Ben-Arieh and Li, 2003). Essentially, design concept evaluation should be conducted with a holistic view considering both internal constraints and external requirements, and should be evaluated with the objective to achieve the six sigma level of quality as early as the design concept is launched. As a result, the ability to effectively evaluate design ideas is an essential element in achieving a successful product development. However, given the need for companies to produce more innovative products in an increasingly competitive market and environment full of uncertainty, the activity of judging among a range of competing design options requires additional assistance in maintaining objective evaluation throughout the development process (Scott, 2002). For example, during design concept evaluation, a decision-maker's (i.e., product designer's) judgments on design alternatives may always contain ambiguity and multiplicity of meaning. Furthermore, human assessment on qualitative attributes is always subjective and thus imprecise. As reviewed in Chapter 2, due to such vagueness and uncertainties, most existing methods for product design concept evaluation cannot effectively handle the uncertainties associated with the evaluation process. As a result, some new methods must be developed to handle the imprecise, incomplete, uncertain and qualitative design knowledge acquired from multidisciplinary knowledge carriers, such as designers and consumers.

In this chapter, a novel method based on grey relation analysis and rough

set theory, i.e. rough-grey analysis, is proposed to facilitate the product design concept evaluation process. The method proposed fuses the strength of rough sets in handling vagueness with the merit of grey relation analysis in modeling multi-criteria evaluation. The rest of the chapter is organized as follows. Section 6.2 presents a brief review of the basic notions of grey relation analysis. Section 6.3 proposes a rough number enabled design concept evaluation method also known as rough-grey analysis. Section 6.4 outlines the implementation of the proposed system using an illustrative example. The results obtained show that the proposed rough-grey analysis has provided a novel alternative to perform design concept evaluation, in which the vague design information and subjective judgments can be modeled and analyzed more effectively and objectively. Finally, the major conclusions of the chapter are summarized in Section 6.5.

6.2 Grey Relation Analysis and Product Design Evaluation

6.2.1 Basic Principles of Grey Relation Analysis

Grey relation analysis was proposed by Deng (1982) in early 1980s as a robust but simple and straightforward multi-criteria decision-making technique. It is able to handle both incomplete and imprecise information, especially in situations where there is not enough data and the sample distribution pattern is unknown (Zhang *et al.*, 2005). Grey relation analysis can be used to evaluate the original data directly and does not need additional interactions during the process. Since its inception, grey relation analysis has received much attention and has been widely used in many applications such as performance evaluations and multi-criteria decision-making (Chang *et al.*, 1999; Tsai *et al.*, 2003; Chan, 2006).

The basic characteristics of grey relation analysis are very similar to those of the rough set theory, which is a mathematical tool, as mentioned previously, widely used to handle vagueness and uncertainty. Briefly, rough set theory can handle vagueness and uncertainty even though the data set is small in size and its distribution is unknown (Pawlak, 1991). Rough set analysis merely relies on the original data without the need for auxiliary information (Khoo *et al.*, 1999; Zhai *et al.*, 2009b). Although grey relation analysis and rough set theory share some common advantages in dealing with uncertainty and vagueness, each of them has its own strength. Basically, grey relation analysis provides a well-structured analytical framework for multi-criteria decision-making processes but it lacks the ability in characterizing the subjective perceptions of designers in the evaluation process, where rough set theory may help because rough sets can facilitate effective representation of vague information or imprecise data. As such, this work explores the possibility of realizing a novel approach to address design concept evaluation problems through the integration of grey relation analysis and rough set theory.

In general, grey relation analysis is an effective technique that can be used to assist decision-making in an environment of uncertainty and in situations with multiple attributes, by examining the similarity of each alternative to an ideal solution. Figure 6.1 presents a schematic diagram to show the mechanism of grey relation analysis. The reference data sequence (denoted as “o” in Figure 6.1) indicates an ideal solution to a problem with the best performance for each of the criteria considered. All the candidate solutions to be evaluated (i.e. the data sequences denoted by “□” and “Δ” in Figure 6.1) are compared with the reference

data sequence based on each criterion. Grey relation analysis provides an impact evaluation model that measures the degree of similarity of each candidate solution to the reference based on the grade of relation (Deng, 1989). A candidate solution with a higher grade of relation is more similar to the ideal solution and thus should be retained. In other words, grey relation analysis is a method to analyze the relational grade of discrete data sequences.

Figure 6. 1 Comparison of data sequences in grey relation analysis

More specifically, traditional grey relation analysis includes the following six steps (Wu, 2003).

Step 1 Construct an initial decision matrix (X). Assuming that there are n data sequences characterized by m criteria,

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(m) \\ x_2(1) & x_2(2) & \dots & x_2(m) \\ \dots & \dots & \dots & \dots \\ x_n(1) & x_n(2) & \dots & x_n(m) \end{bmatrix} \quad (6.1)$$

where $x_i(j)$ is the entity in the i th data sequence corresponding to the j th criterion.

Step 2 Normalize based on the characteristics of three types of criteria, namely larger-the-better, smaller-the-better, or nominal-the-best:

$$\text{larger-the-better} \quad x'_i(j) = \frac{\frac{x_i(j) - \min_{i=1}^n [x_i(j)]}{\max_{i=1}^n [x_i(j)] - \min_{i=1}^n [x_i(j)]}}{\frac{n}{n}} \quad (6.2)$$

$$\text{smaller-the-better} \quad x'_i(j) = \frac{\frac{\max_{i=1}^n [x_i(j)] - x_i(j)}{\max_{i=1}^n [x_i(j)] - \min_{i=1}^n [x_i(j)]}}{\frac{n}{n}} \quad (6.3)$$

nominal-the-best

$$x'_i(j) = 1 - \frac{|x_i(j) - x_{obj}(j)|}{\max \left\{ \max_{i=1}^n [x_i(j)] - x_{obj}(j), x_{obj}(j) - \min_{i=1}^n [x_i(j)] \right\}} \quad (6.4)$$

where $x_{obj}(j)$ is the target value for the j th criterion, and

$$\min_{i=1}^n [x_i(j)] \leq x_{obj}(j) \leq \max_{i=1}^n [x_i(j)].$$

Obviously, after the above mentioned normalization process, all the three types of criteria have been transformed into the “larger-the-better” type, with the maximum value at “1” when $x_i(j) = \max_{i=1}^n [x_i(j)]$ (for the “larger-the-better” type), $x_i(j) = \min_{i=1}^n [x_i(j)]$ (for the “smaller-the-better” type), or $x_i(j) = x_{obj}(j)$ (for the “nominal-the-best” type), respectively.

Step 3 Construct the normalized matrix and generate the reference sequence based on Equations (6.2)-(6.4):

$$\text{normalized matrix } X' = \begin{bmatrix} x'_1(1) & x'_1(2) & \dots & x'_1(m) \\ x'_2(1) & x'_2(2) & \dots & x'_2(m) \\ \dots & \dots & \dots & \dots \\ x'_n(1) & x'_n(2) & \dots & x'_n(m) \end{bmatrix} \quad (6.5)$$

$$\text{reference sequence } x'_0 = x'_0(1), x'_0(2), \dots, x'_0(m) \quad (6.6)$$

where $x'_0(j)$ is the reference value in relation to the j th criterion and is determined by the largest normalized value of each criterion, i.e.

$$x'_0(j) = \max_{i=1}^n \{x'_i(j)\}.$$

Step 4 Calculate the difference between a normalized entity and its reference value, and construct the difference matrix as follows:

$$\Delta_{0i}(j) = |x'_0(j) - x'_i(j)| \quad (6.7)$$

$$\Delta = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \dots & \Delta_{01}(m) \\ \Delta_{02}(1) & \Delta_{02}(2) & \dots & \Delta_{02}(m) \\ \dots & \dots & \dots & \dots \\ \Delta_{0n}(1) & \Delta_{0n}(2) & \dots & \Delta_{0n}(m) \end{bmatrix} \quad (6.8)$$

Step 5 Calculate the grey relational coefficient for each entity:

$$\gamma_{0i}(j) = \frac{\min_{i=1}^n \min_{j=1}^m \Delta_{0i}(j) + \zeta \times \max_{i=1}^n \max_{j=1}^m \Delta_{0i}(j)}{\Delta_{0i}(j) + \zeta \times \max_{i=1}^n \max_{j=1}^m \Delta_{0i}(j)} \quad (6.9)$$

where ζ ($0 \leq \zeta \leq 1$) is known as the distinguishing coefficient or the index for distinguishability. The smaller ζ is, the higher its distinguishability is. In most situations, ζ takes the value of 0.5 because this value usually offers moderate distinguishing effects and good stability (Chang and Lin, 1999).

Step 6 Calculate the grey relational degree. A grey relational degree is a weighted sum of the grey relational coefficients given by the following equation:

$$\Gamma_{0i} = \sum_{j=1}^m [w(j) \times \gamma_{0i}(j)], \quad \sum_{j=1}^m w(j) = 1 \quad (6.10)$$

where $w(j)$ is the weight of the j th criterion, which is usually assigned by users according to the context of applications.

Γ_{0i} is the grey relational degree that indicates the magnitude of correlation (i.e. similarity) measured between the compared sequence (i.e. the i th data sequence) and the reference sequence. Therefore, using the grey relational degrees calculated, the candidate sequences in the initial decision matrix (X) shown in Equation (6.1) can be prioritized and the one with the highest degree of relation will be identified as the data sequence that represents the best solution (i.e. closest to the ideal data sequence).

6.2.2 Formulation of Design Concept Evaluation Problems

As mentioned in Section 6.1, design concept evaluation is a complex decision-making process involving many criteria which include design requirements and constraints such as customer needs, product cost, and development time. The design concepts generated during the conceptual design phase are compared based on these criteria so that the best can be identified. For example, Table 6.1 shows a typical design concept evaluation problem. The objective of the evaluation is to identify the best design concept that can maximize the satisfaction of customers based on the criteria used. In Table 6.1, a collection of criteria $C_1, C_2, \dots$, and C_m specified by the design team may be classified into three types: namely “larger-the-better”, “nominal-the-best”, and “smaller-the-better” based on their characteristics. For every design concept proposed by the design team, A_i , its performance against each criterion is evaluated by the design team and registered in the table.

Table 6.1 An example of information table for design concept evaluation

Design Concepts	Evaluation Criteria	C_1	C_2	...	C_m
	Type	Larger-the-better	Smaller-the-better		Nominal-the-best
A_1		A_1C_1	A_1C_2		A_1C_m
A_2		A_2C_1	A_2C_2		A_2C_m
...					
A_n		A_nC_1	A_nC_2		A_nC_m

Apparently, such an information table suits the data processing using the grey relation analysis introduced earlier, with the rows and columns of the table representing the discrete data sequences and the criteria respectively. In a more general form, suppose $X = \{x_1, x_2, \dots, x_n\}$ is a finite set of n design concepts

generated during the conceptual design phase, and each design concept is evaluated according to m criteria, denoted as $C = \{c_1, c_2, \dots, c_m\}$. The performance of any design concept x_i ($\forall i \in \{1, 2, \dots, n\}$) with respect to each criterion c_j ($j = 1, 2, \dots, m$) will compose a discrete data sequence $x_i = \{x_i(1), x_i(2), \dots, x_i(m)\}$. Thus, the evaluation of design concepts will be transformed into a problem, which compares discrete data sequences using grey relation analysis.

However, it is important to note that the subjective judgments solicited from the design team members are usually vague, uncertain or even inconsistent. As a result, crisp descriptions and precise analytical processes are not suitable to deal with such information. In order to address this issue, this work proposes to use rough set theory to quantify the vague design information and suggests a novel rough-grey analysis for design concept evaluation. In the next section, rough sets and rough numbers are introduced, and are used to integrate with the modified grey relation analysis.

6.3 Rough-Grey Analysis for Design Concept Evaluation

6.3.1 Rough Numbers and Design Concept Evaluation

Traditionally, fuzzy set theory has been widely used to model and analyze the design evaluation problems. However, as suggested by Jin (2003), selection of membership functions is critical for the performance of a fuzzy system. This has been one of the challenging research topics in the field of fuzzy set applications. More specifically, in the applications of subjective evaluations and heuristics, where fuzzy sets are used to model the cognitive process of human beings, the determination of membership functions is usually based on intuition, personal

judgment and experience (Jain, 1999; Jin, 2003). For the sake of simplicity in practice, some simple functions such as triangular, trapezoid, or bell-shaped memberships have been selected by many researchers without much justification for the appropriateness of the selections (Li and Azarm, 2002). Although some more sophisticated and objective methods such as neural networks can be employed to tune the membership functions through learning/training processes (Wang, 1994; Sanchez *et al.*, 2006), in the early stages of product development, such learning/training processes may not be realistic or even feasible because the data available is very limited (Seo *et al.*, 2002).

Inspired by the advantages of rough numbers in dealing with vague and uncertain design information, this chapter proposes a new approach to design concept evaluation through the fusion of grey relation analysis with rough numbers. The salient feature of the new method proposed is that it only uses the information inherent in the given data and retains the objectivity of the original design information. The vagueness and uncertainty of the original data are represented by means of the boundary region of rough numbers instead of membership functions (Zhai *et al.*, 2008).

As discussed in Chapter 4, the basic concept of rough numbers proposed by the author (Zhai *et al.*, 2007a; 2008) provides a novel tool to quantify people's vague perceptions involved in the product development process. To emphasize again here, although a rough number has a similar form as a fuzzy number with its lower and upper limits indicating the two boundaries of an interval, the lower and upper limits of a rough number are automatically calculated through a collective analysis of the given data instead of assigned by the predetermined membership

functions. As a result, a rough number enabled design concept evaluation is expected to be able to better reflect the true perceptions of evaluators and thus provides a more objective evaluation of the product design concepts (Zhai *et al.*, 2009b). A brief outline for the definition of rough numbers is given in Section 4.3.2 in Chapter 4. In the following section, designers' evaluations are processed using the concept of rough numbers and subsequently the design concepts (in the form of data sequences of rough numbers) are analyzed using the rough-grey relation analysis proposed.

6.3.2 Rough Number Enabled Grey Relation Analysis

Traditional grey relation analysis introduced in Section 6.2.1 was designed for the analysis of discrete data sequences characterized by crisp values. Different from the crisp data used in the aforementioned grey relation analysis, rough numbers are presented in the form of intervals and thus the difference of rough numbers from the reference values needs to be re-defined. For example, the difference (also known as distance in some cases) between two crisp values a and b can be easily calculated as $|a-b|$. However, for two rough numbers in the form of intervals, their difference (or distance) cannot be similarly determined (Gonzalez and Vila, 1991; Chakraborty and Chakraborty, 2006). Inspired by the concept of fuzzy distance (Bouchon-Meunier *et al.*, 1986; Lowen and Peeters, 1998), this work proposes a so-called Difference Coefficient (DC) to depict the distance between two rough numbers. To be more specific, the procedures of rough-grey analysis are presented below.

Procedure of rough-grey analysis

- 1) Suppose that there are n data sequences represented in the form of rough numbers (intervals) and each data sequence is evaluated by m criteria. The data sequences would compose the following matrix:

$$X = \begin{bmatrix} [x_{11}^-, x_{11}^+] & [x_{12}^-, x_{12}^+] & \dots & [x_{1m}^-, x_{1m}^+] \\ [x_{21}^-, x_{21}^+] & [x_{22}^-, x_{22}^+] & \dots & [x_{2m}^-, x_{2m}^+] \\ \dots & \dots & \dots & \dots \\ [x_{n1}^-, x_{n1}^+] & [x_{n2}^-, x_{n2}^+] & \dots & [x_{nm}^-, x_{nm}^+] \end{bmatrix} \quad (6.11)$$

where $[x_{ij}^-, x_{ij}^+]$ represents a rough number, x_{ij}^- and x_{ij}^+ are the lower and upper limits respectively.

- 2) Generate the reference sequence based on the characteristic of each criterion. Obviously, for the criterion that belongs to the “larger-the-better” category, its ideal value is the largest value that it may take. Thus, in this work, the largest upper limit of all the rough numbers that this criterion takes is selected as its reference value. Similar analysis can be done for the criterion for the category of “smaller-the-better”. As for the category of “nominal-the-best”, the objective value of the criterion is naturally selected as its reference value. Mathematically,

$$\text{Larger-the-better: } x_0(j) = \max_{i=0}^n (x_{ij}^+)$$

$$\text{Smaller-the-better: } x_0(j) = \min_{i=0}^n (x_{ij}^-)$$

$$\text{Nominal-the-best: } x_0(j) = x_j^{obj}$$

where x_j^{obj} is the objective value for the j th criterion.

Hence, the reference sequence is:

$$x_0 = x_0(1), x_0(2), \dots, x_0(m) \quad (6.12)$$

- 3) Calculate the Difference Coefficient (DC) based on the characteristic of each criterion: “larger-the-better”, “smaller-the-better”, or “nominal-the-best”. The Difference Coefficient is essentially a measure to depict the “distance” between a rough number and its reference value. It is also a rough number in the form of an interval bound by its lower and upper limits.
- i) For the category of “larger-the-better”, the Difference Coefficient of its value (in terms of rough number) is calculated using the distance between the rough number and the reference value as follows.

$$\begin{aligned} \Delta_{ij}^{-} &= x_0(j) - x_{ij}^{+} = \max_{i=1}^n \left[x_{ij}^{+} \right] - x_{ij}^{+} \text{ and} \\ \Delta_{ij}^{+} &= x_{ij}^{-} - x_0(j) = \max_{i=1}^n \left[x_{ij}^{+} \right] - x_{ij}^{-} \end{aligned} \quad (6.13)$$

- ii) Similarly, for the category of “smaller-the-better”,

$$\Delta_{ij}^{-} = x_{ij}^{-} - x_0(j) = x_{ij}^{-} - \min_{i=1}^n \left[x_{ij}^{-} \right] \text{ and}$$

$$\Delta_{ij}^{+} = x_{ij}^{+} - x_0(j) = x_{ij}^{+} - \min_{i=1}^n [x_{ij}^{-}] \quad (6.14)$$

iii) As for the category, “nominal-the-best”, there are two possibilities:

- (a) If the value (rough number) of the criterion does not contain the objective value, namely $x_{ij}^{obj} \notin [x_{ij}^{-}, x_{ij}^{+}]$, the lower and upper limits of the Difference Coefficient are given by the minimum and maximum distances between the objective value and the two limits of the rough number, which are defined as follows:

$$\begin{aligned} \Delta_{ij}^{-} &= \min \{ |x_{ij}^{-} - x_j^{obj}|, |x_{ij}^{+} - x_j^{obj}| \} \\ \Delta_{ij}^{+} &= \max \{ |x_{ij}^{-} - x_j^{obj}|, |x_{ij}^{+} - x_j^{obj}| \} \end{aligned} \quad (6.15)$$

- (b) If the value (rough number) of the criterion contains the objective value, namely $x_{ij}^{obj} \in [x_{ij}^{-}, x_{ij}^{+}]$, the upper limit of the Difference Coefficient is still defined as the maximum distance between the objective value and the two limits of the rough number, whereas its lower limit is defined as the negative magnitude of the minimum distance between the objective value and the two limits of the rough number as follows.

$$\begin{aligned} \Delta_{ij}^{-} &= -\min \{ |x_{ij}^{-} - x_j^{obj}|, |x_{ij}^{+} - x_j^{obj}| \} \\ \Delta_{ij}^{+} &= \max \{ |x_{ij}^{-} - x_j^{obj}|, |x_{ij}^{+} - x_j^{obj}| \} \end{aligned} \quad (6.16)$$

The above definitions are able to indicate the location of the objective value between the lower and upper limits of the rough number, by comparing the magnitudes of the lower and upper limits of the Difference Coefficient. For example, if the objective value falls onto the midpoint between the lower and upper limits of the rough number, the lower and upper limits of the corresponding Difference Coefficient will have equal magnitudes but with opposite signs. This unique characteristic of the Difference Coefficient can “reward” those entities whose lower and upper limits are symmetrically located with respect to the objective value, by “raising” the priority of the corresponding data sequence in the subsequent manipulations. This advantage of the Difference Coefficient will be further elaborated later in this section.

- 4) Establish the Difference Coefficient matrix as follows.

$$\Delta = \begin{bmatrix} [\Delta_{11}^-, \Delta_{11}^+] & [\Delta_{12}^-, \Delta_{12}^+] & \dots & [\Delta_{1m}^-, \Delta_{1m}^+] \\ [\Delta_{21}^-, \Delta_{21}^+] & [\Delta_{22}^-, \Delta_{22}^+] & \dots & [\Delta_{2m}^-, \Delta_{2m}^+] \\ \dots & \dots & \dots & \dots \\ [\Delta_{n1}^-, \Delta_{n1}^+] & [\Delta_{n2}^-, \Delta_{n2}^+] & \dots & [\Delta_{nm}^-, \Delta_{nm}^+] \end{bmatrix} \quad (6.17)$$

- 5) Normalize the Difference Coefficient matrix as follows

$$\Delta'_{ij}{}^- = \frac{\Delta_{ij}^-}{\max_{i=1}^n \{ \max [|\Delta_{ij}^-|, |\Delta_{ij}^+|] \}} \quad (6.18)$$

$$\Delta'_{ij}{}^+ = \frac{\Delta_{ij}^+}{\max_{i=1}^n \{ \max [|\Delta_{ij}^-|, |\Delta_{ij}^+|] \}}$$

and so as to obtain the normalized Difference Coefficient matrix:

$$\Delta' = \begin{bmatrix} [\Delta'_{11}^-, \Delta'_{11}^+] & [\Delta'_{12}^-, \Delta'_{12}^+] & \dots & [\Delta'_{1m}^-, \Delta'_{1m}^+] \\ [\Delta'_{21}^-, \Delta'_{21}^+] & [\Delta'_{22}^-, \Delta'_{22}^+] & \dots & [\Delta'_{2m}^-, \Delta'_{2m}^+] \\ \dots & \dots & \dots & \dots \\ [\Delta'_{n1}^-, \Delta'_{n1}^+] & [\Delta'_{n2}^-, \Delta'_{n2}^+] & \dots & [\Delta'_{nm}^-, \Delta'_{nm}^+] \end{bmatrix} \quad (6.19)$$

- 6) Calculate the normalized Difference Index (DI) of each data sequence. Basically, the Difference Index is a measure proposed in this work to indicate the dissimilarity of a data sequence from its reference data sequence, represented in the form of rough numbers (i.e. an interval), mathematically

$$DI_i = \sum_{j=1}^m \left[w_j \times \Delta'_{ij} \right] \quad (6.20)$$

where w_j is the weight of the j th criterion.

- 7) Prioritize the data sequences based on the Difference Index (DI). A data sequence with a smaller DI is probably closer to the ideal solution.

Apparently, the major difference between the rough-grey analysis proposed above and the original grey relation analysis rests with the facts that:

- (1) The proposed rough-grey analysis uses rough numbers to represent the performance of each of the data sequences, instead of crisp values as in traditional grey relation analysis. As mentioned in Section 6.3.1, rough number representations can better capture and handle uncertainties in the design concept evaluation.

- (2) The proposed rough-grey analysis suggests two new measures to describe the deviation of a data sequence from its reference sequence, one of which is coined Difference Coefficients (DC) as shown in Equations (6.13)-(6.16), and the other is known as Difference Index (DI) as depicted in Equation (6.20). The former is an indicator focusing on the “micro-level” or “local” deviation of each individual entity in the decision matrix from the corresponding value in the reference sequence, whereas the latter is a “macro-level” or “global” indicator showing the holistic dissimilarity of a data sequence from the reference data sequence. Working together, the two indicators are capable of describing the “difference” between two data sequences more clearly – with the information concerning the difference between both “individuals” (i.e. entities or data points) and “groups” (i.e. data sequences).
- (3) As mentioned before, the definition of DC shown in Equation (6.16) allows negative values for the lower limits of the resultant rough numbers when the objective value of the criterion falls in the range of the rough number to be examined. This unique characteristic of the DC helps in rewarding the rough numbers that are “closer” to the objective value. Figure 6.2 provides an example to illustrate this.

Figure 6. 2 Comparison of Difference Coefficients for various rough numbers

It is assumed that the objective value of the criterion (nominal-the-best) is 0.5, and A , B , C , and D are four rough numbers whose ranges all cover the objective value (Figure 6.2(a)). More specifically, $A = [0.3, 0.6]$, $B = [0.5, 0.8]$, $C = [0.4, 0.6]$, and $D = [0.5, 0.7]$, where “[]” represents a rough number as introduced in Chapter 4 of this thesis. Apparently, C is the best candidate as the objective value coincides with the mid-point of its interval, namely it can well satisfy the target value, whereas B is the worst because it has the largest distance from the objective value, i.e. it can hardly satisfy the target value. Figure 6.2(b) shows the Difference Coefficients (DCs) calculated using Equation (6.16). Taking A as an example, $DC(A) = [-|0.6-0.5|, |0.3-0.5|] = [-0.1, 0.2]$. The Difference Coefficients calculated are depicted in Figure 6.2(b) and it produces the order of $DC(C) < DC(A) < DC(D) < DC(B)$, based on the ranking rules of rough numbers (Zhai *et al.*, 2007a; 2008). This shows that the definition given in Equation (6.16) can properly characterize the deviation of a rough number from the corresponding objective value and provides good candidates with smaller Difference Coefficients.

6.4 An Example

6.4.1 Evaluation of An Iron Design Using Rough-Grey Relation Analysis

This section presents an illustrative example to demonstrate the design concept evaluation using the proposed rough-grey relation analysis. Table 6.2 shows a simple example concerning the evaluation of design concepts of an electric iron. The objective of the evaluation is to identify the best design concept that can maximize the satisfaction to both customer requirements and business constraints (e.g. product cost). In this example, a collection of five evaluation criteria (i.e. C_1 : Heat-up rate; C_2 : Contact area; C_3 : Working temperature; C_4 : Energy loss; and C_5 : Material cost) solicited through a QFD analysis are used for the assessment, among which C_1 and C_2 are the type of “larger-the-better”, C_3 is the type of “nominal-the-best”, whereas C_4 and C_5 are the type of “smaller-the-better” (Table 6.2). Suppose there are four design concepts, namely A_1 , A_2 , A_3 and A_4 , which are generated during the conceptual design phase. For every design concept proposed, its performance in relation to each criterion is evaluated by the design team comprising several design specialists. More specifically, for every design concept evaluated under a certain criterion, each team member suggests a value based on his own perception, and therefore the performance of the said design concept in relation to the said criterion can be described by a collection of such values. According to the basic notions of rough numbers introduced in Section 4.3.2, such values can be synthesized into rough numbers as shown in Table 6.2.

Table 6. 2 Decision matrix of an iron design evaluation

Design Concepts	Evaluation Criteria	C_1 : Heat-up rate	C_2 : Contact area	C_3 : Working temperature	C_4 : Energy loss	C_5 : Material cost
	Type	Larger-the-better	Larger-the-better	Nominal-the-better (Target =6.8)	Smaller-the-better	Smaller-the-better
A_1		[1.5,2.5]	[106.5,117.5]	[5.0,7.0]	[18.5,19.5]	[7.0,8.5]
A_2		[2.0,3.5]	[114.5,125.5]	[6.0,8.6]	[26.5,27.5]	[6.5,8.5]
A_3		[5.5,7.8]	[100.5,115.5]	[4.5,5.5]	[17.5,18.5]	[3.0,5.0]
A_4		[7.0,8.5]	[88.5,97.5]	[9.5,10.5]	[10.5,16.5]	[4.5,6.5]
Reference value		8.5	125.5	6.8	10.5	3.0
Weight		[0.0,0.10]	[0.30,0.35]	[0.10,0.15]	[0.25,0.30]	[0.20,0.25]

Based on the types of the evaluation criteria, the reference sequence can be easily identified using Equation (6.12), and is shown in the second-last row of Table 6.2. More specifically, for the “larger-the-better” type of criterion, its reference value is the maximum upper limit associated with the said criterion, for example, “8.5” for criterion C_1 in Table 6.2. Similarly, for the “smaller-the-better” type of criterion, its reference value is the minimum lower limit associated with the said criterion, 3.0 for criterion C_5 in Table 6.2. Using Equations (6.13)–(6.16), the Difference Coefficient matrix can be established as shown in Table 6.3. As mentioned in Section 6.3.2, the Difference Coefficient matrix provides useful information about each design concept’s ability in fulfilling each evaluation criterion.

Table 6. 3 Difference Coefficient matrix

Design Concepts	Evaluation Criteria	C_1 : Heat-up rate	C_2 : Material Cost	C_3 : Working temperature	C_4 : Energy loss	C_5 : Contact area
A_1		[6,7]	[4,5.5]	[-0.7,1.3]	[8,9]	[8,19]
A_2		[5,6.5]	[3.5,5.5]	[-0.8,1.8]	[16,17]	[0,11]
A_3		[0.7,3]	[0,2]	[1.3,2.3]	[7,8]	[10,25]
A_4		[0,1.5]	[1.5,3.5]	[2.7,3.7]	[0,6]	[28,37]

After the Difference Coefficient matrix is normalized using Equation (6.18), the Difference Index of each design concept can be calculated using Equation (6.20), taking into account the weight of each criterion given in Table 6.2. Figure 6.3 displays the Difference Index of each design concept in the form of a bar chart. Apparently, a design concept with smaller Difference Index is “closer” to the ideal design solution and should be selected. Based on the ranking rules of rough numbers proposed in Section 4.4.1 (Zhai *et al.*, 2007a; 2008), Figure 6.3 depicts the ranking order for the four design concepts examined and identifies that design concept A_3 has the smallest Difference Index compared with the ideal design solution, followed by A_1 , A_4 and A_2 .

Figure 6. 3 Priority ranking of design concepts based on Difference Index

6.4.2 Discussion

The rough-grey analysis proposed in this chapter provides a novel alternative of the traditional methods to perform design concept evaluation in the early stages of product development. Compared with other existing methods, the new method proposed has the advantage of accommodating uncertainties of the design information, which is a critical issue in the early phases of product development. Using the concept of rough numbers, the uncertainty and vagueness in the subjective perceptions of evaluators can be easily captured and objectively characterized in the form of rough intervals.

In addition, the new concepts of Difference Coefficient (DC) and Difference Index (DI) proposed in this work have successfully extended the traditional grey relation analysis to entertain rough numbers in the form of intervals and formulated a rough-grey analysis for design concept evaluation. The result of the example used in this work shows that rough-grey relation analysis not only can identify the best solution by prioritizing the design concepts, but also provides measures of confidence for the evaluation (i.e. Difference Index) in the form of the rough intervals. For example, the difference indices shown in Figure 6.3 have different sizes of rough interval, which indicate different confidence levels for the evaluation. Such information can be used as auxiliary references for decision-making in product development, which is not available in other approaches using crisp values.

6.5 Summary

Design concept evaluation is a critical task in the early phases of product development as it has significant impact on both the quality and the cost of a product to be developed. However, design concept evaluation is usually hindered by the vagueness and uncertainty of the design information involved. This chapter proposes a rough number enabled grey relation analysis with the aim to develop a systematic method to model and analyze the design concept evaluation under uncertainty. In the proposed rough-grey analysis for design concept evaluation, the raw design information in the early phases of product development is characterized by rough numbers in the form of intervals, which can be solicited through a collective analysis about the perceptions of designers. Two new measures known as Difference Coefficients and Difference Index have been proposed to differentiate and prioritize the design concepts. The result of the example presented in this work shows that the proposed rough-grey analysis has provided a novel alternative of existing methods to perform design concept evaluations in the early stages of product development, with the capability in accommodating uncertainties and vagueness.

CHAPTER 7 SYSTEM IMPLEMENTATION

AND A CASE STUDY

7.1 System Implementation

7.1.1 System Integration

As discussed in Chapter 3 (see Figure 3.3), this research aims to develop a prototype decision support system composed of a potpourri of decision support tools to facilitate decision-making activities in the front-end product development process. The prototype system consists of three main decision support tools, namely the rough set enhanced QFD (i.e. Rough_QFD) decision support tool, the dominance-based rough set enabled affective design (i.e. Rough_Kansei) decision support tool, and the rough set based grey analysis (i.e. Rough_Grey) decision support tool for design concept evaluation. Details of the three decision support tools have been elaborated in Chapters 4, 5 and 6 respectively. As discussed in Chapter 3, the three decision support tools share a common design information representation platform proposed based on rough sets, which is capable of dealing with vague and uncertain design information in the product development process. The prototype system can be illustrated as a 3-D model describing the relationships among the three decision support tools and the common design information representation platform (Figure 7.1). As shown in the figure, the rough set based design information representation platform lays the foundation for developing the three decision support tools. On the one hand, the Rough_QFD decision support tool (i.e. X axis) will facilitate the decision analysis of functional design requirements and ensure to “design the right thing” that customers really need. On

the other hand, the Rough_Kansei decision support tool (Y axis) will facilitate the acquisition of affective design knowledge and ensure the product to be designed “in the right manner” that can delight customers affectively. Finally, the Rough_Grey decision support tool for design concept evaluation (Z axis) will be used to assist decision-making in the evaluation of design concepts and ensure that unnecessary mistakes or rework in the downstream product design activities can be reduced “with the right selection” of the optimal design concept. It is postulated that the above-mentioned integrated decision support model is able to improve product quality, enhance customer satisfaction, and reduce product design cost and time. In this research, the prototype decision support system was implemented using MATLAB software on a personal computer. MATLAB was chosen as the system development platform because it has excellent matrix manipulation functions and provides a user friendly GUI. In the following sub-sections, implementation of each decision support tool is elaborated in detail.

Figure 7. 1 Integration of the decision support system

7.1.2 Rough_QFD Decision Support Tool

The implementation of the Rough_QFD decision support tool follows the flowchart of QFD analysis described in Chapter 4 of this thesis. The inputs to the Rough_QFD decision support tool include four data files prepared in the format of Microsoft Excel spreadsheets. They are:

- 1) Data file registering customers' ratings for customer needs (CNs), with rows corresponding to different CNs and columns corresponding to different customers;
- 2) Data file recording competitive priority ratings (in the first row) and improvement ratios (in the second row) for different CNs (in columns);
- 3) Data file recording designers' perceptions on the relationships between technical design requirements (DRs) and CNs, with rows corresponding to different DR-CN pairs and columns corresponding to different designers; and
- 4) Data file recording competitive priority ratings (in the first row) and improvement ratios (in the second row) for different DRs (in columns).

The GUI of Rough_QFD decision support tool is shown in Figure 7.2. It is divided into two sections with a similar layout. The first section is for the prioritization of CNs (i.e. the "Customer Need Analysis" section in Figure 7.2) and the second section is for the prioritization of DRs (i.e. the "Technical Requirement Analysis" section in Figure 7.2). In each section, there are three function buttons on the left, among which the first two buttons are to load data files and the third button is to display the results graphically on the right hand side of the window.

The outputs of the Rough_QFD decision support tool include an interim result, i.e. the ranking of the importance ratings of CNs (also known as WHATs in QFD), and the final result, i.e. the ranking of the importance ratings of DRs (also known as HOWs in QFD). Both the interim and final results are presented in the form of bar charts as shown in Figure 7.2.

Figure 7. 2 GUI of the Rough_QFD decision support tool

7.1.3 Rough_Kansei Decision Support Tool

The implementation of the Rough_Kansei decision support tool is based on the dominance-based rough set approach to affective design proposed in Chapter 5 of this thesis. The input of the Rough_Kansei decision support tool is a Kansei information table (in the Microsoft Excel spreadsheet format) registering

customers' Kansei ratings evoked by different combinations of design elements, while the output of the decision support tool is the Kansei knowledge (i.e. the affective design rules) extracted from the Kansei information table.

Figure 7.3 shows the GUI of the Rough_Kansei decision support tool. As shown in the figure, after the Kansei rating data (i.e. the Kansei information table) is uploaded, the dominance principles for each design element (i.e. the condition attribute in the information table) will be established using the concept of Category Score proposed in Chapter 5, and the results are displayed on the left hand side of the window provided. The dominance principles established will then be used to identify and analyze the inconsistencies in the Kansei information table. To make the system easy to use for the users who are not familiar with rough set notions, the sophisticated dominance-based rough set manipulations such as the partition of class unions and the calculation of Partition Quality are encapsulated in the process of extracting Kansei knowledge (affective design rules). For simplicity of demonstration, the GUI shown in Figure 7.3 chooses the class union with the highest Partition Quality and extracts the corresponding affective design rules. The results of the analysis, including the Partition Quality for each class union and the affective design rules extracted, are displayed on the right hand side of the window provided. As discussed in Chapter 5, the rules extracted will be able to guide the designers to improve or adjust the design elements so as to enhance the affective satisfaction of customers in a product design.

Figure 7.3 GUI of the Rough_Kansei decision support tool

7.1.4 Rough_Grey Decision Support Tool

The implementation of the Rough_Grey decision support tool is based on the procedure of the rough number enabled grey analysis for design concept evaluation proposed in Chapter 6 of this thesis. The input of the Rough_Grey decision support tool is the design concept evaluation data (in the Microsoft Excel spreadsheet format) which registers the "scores" that every design concept has obtained with regard to each individual evaluation criterion. The output of the system is the ranking order of the design concepts based on their final scores

obtained. From the ranking order, the best design concept can be identified and selected for the next phase of detailed design process.

Figure 7.4 is the GUI of the Rough_Grey decision support tool. After the design concept evaluation data is uploaded, the Difference Coefficient matrix will be established, in which each entry describes the difference (or distance) between the score attained by a criterion and the criterion's reference value. This is accomplished by comparing each design concept's score sequence with the reference sequence that represents the ideal or best design solution. Upon normalization and taking into account the weight vector of the criteria, the so-called Difference Index for each design concept will be calculated. The ranking of the Difference Indices of the design concepts is presented in the form of a bar chart as shown in Figure 7.4. Based on the bar chart, the design concept with the smallest Difference Index will be the best design concept because it has the smallest distance (or difference) from the ideal design solution. To make the user interface simple and easy to use, the tedious matrix manipulations discussed in Chapter 6 are capsulated in the two function buttons (i.e. "Calculate Difference Coefficient Matrix" and "Prioritization of Design Concepts") shown in Figure 7.4. Some critical instructions will be displayed in the "Note" window next to the two buttons during the evaluation process. The final output of the Rough_Grey decision support tool (i.e. the bar chart) is displayed in the window provided upon the completion of evaluation.

Figure 7.4 GUI of the Rough_Grey decision support tool

7.2 A Case Study

7.2.1 Descriptions

This case study concerns a decision support analysis in the front-end stages of a mobile phone product development process. It is well known that a mobile phone is a kind of product with a very short product cycle in a highly competitive global market. Therefore, an efficient and effective gauge and response to various customer needs, including both functional and affective needs, and a right selection of design concept, will be of crucial importance for the development of a

successful mobile phone. Based on the framework outlined in Chapter 3 of this thesis, this case study will focus on the front-end issues in the development of a mobile phone product, using the potpourri of decision support tools described in Chapters 4, 5, and 6 to facilitate the decision-making activities in the process. However, it should be noted that the primary objective of this case study is to demonstrate the concepts and algorithms developed for the decision support tools proposed in this work. Therefore, the details of the market research process concerned in this case study will not be fully presented here and the verification of the survey data is not included in this work due to the limited knowledge and resources available.

This case study involves two customer surveys, namely a QFD survey and a Kansei survey. The QFD survey is used to gauge customers' functional needs about a mobile phone design and the Kansei survey is to discover customers' latent affective needs about the design. For convenience of conducting the surveys and for the purpose of illustration, the customer segment of this case study is selected as college students, i.e. youngsters between 19 – 25 years of age. The QFD survey questionnaire (see Appendix 1) is prepared based on a preliminary investigation of the most popular mobile phones for youngsters in Singapore in the year 2008. Details of analysis of the case study include three parts, namely the Rough_QFD analysis, the Rough_Kansei analysis and the Rough_Grey analysis, which will be elaborated in the next section.

7.2.2 Analysis and Discussion

7.2.2.1 Rough_QFD Analysis

As discussed in Chapter 4, QFD analysis involves complex market research that concerns both customers and product designers, especially in the product benchmarking process through which the product competitive priority ratings and improvement ratios are identified. In real industry practice, the product benchmarking process involves confidential business information which is not allowed to be disclosed. In order to simplify this complex market research process, a focus group based approach (Goodman *et al.*, 2004; Lee *et al.*, 2006) was adopted for this case study. Figure 7.5 shows a schematic flowchart of the simplified focus group based process to acquire the necessary data needed for a QFD analysis.

Figure 7. 5 A simplified market research process for QFD analysis

First of all, a set of key customer needs, i.e. the basic and performance functions of a mobile phone are gleaned from a few channels including interviews and group discussions with 50 college students, mobile phone review reports in magazines, and so on. In this case study, 20 key customer needs (i.e. WHATs), denoted by $W_1 - W_{20}$, are identified through the above process and they are listed in Table 7.1.

Table 7. 1 Key customer needs (WHATs)

No.	Descriptions
W_1	MP3
W_2	Battery standby/talking time
W_3	Data transfer
W_4	Phone book capacity
W_5	Handwriting input
W_6	Voice command
W_7	Camera
W_8	Radio
W_9	GPS
W_{10}	Dual SIM
W_{11}	Voice recorder
W_{12}	Web access
W_{13}	Voice quality/stability time
W_{14}	Touch screen
W_{15}	Game
W_{16}	MMS
W_{17}	Hands free
W_{18}	SMS capacity
W_{19}	Dictionary
W_{20}	Multi-band

Subsequently, two focus groups, i.e. one customer focus group consisting of 10 customers (represented by college students from different engineering

schools and majors, 5 males and 5 females) and one designer focus group composed of 10 design engineers (represented by final year students specialized in product design, 5 males and 5 females), are formed. The number of participants in each focus group is determined based on a thorough literature review concerning focus group related market analysis, in which some researchers prefer a group size ranging from 8-12 (Kitzinger and Barbour, 1999), 6-12 (Lindlof, 1995), 6-8 (Krueger, 1998), or 5-6 (Green and Hart, 1999). Brown (1999) suggests that the group should consist of 4-12 if the group is homogeneous and 6-12 if heterogeneous. Therefore, without loss of generality, the group size of the focus group is fixed as 10 in this case study. On the one hand, the customer focus group is responsible for evaluating the importance of the CNs. In addition, the customer focus group is also responsible for determining the competitive priority ratings and improvement ratios for the CNs, through group discussion on benchmarking and competitive products. On the other hand, the designer focus group is responsible for identifying the technical design requirements (DRs, i.e. the HOWs) that can meet the key CNs (i.e. the WHATs), and subsequently assigning the correlations between each pair of CN and DR. Similarly as in the customer focus group, the designer focus group is also responsible for determining the competitive priority ratings and improvement ratios for the DRs, through group discussion on benchmarking and competitive products.

In this case study, the importance ratings of the CNs are collected using a 9-point scale system, where “1” means “very low importance” and “9” means “very high importance”. Based on the CNs identified, 15 critical technical design requirements (DRs, i.e. the HOWs), denoted by $H_1 - H_{15}$, are identified by the

designer focus group through group discussion and their capabilities of fulfilling the CNs (i.e. the correlations between the WHATs and the HOWs) are evaluated using the 9-point scale system. The details of the technical design requirements identified are listed in Table 7.2. The raw data collated for this case study is attached in Appendix 1.

Table 7. 2 Critical technical design requirements (HOWs)

No.	Descriptions
H_1	Software synthesis
H_2	Battery material
H_3	Sound module
H_4	CPU module
H_5	Power saver module
H_6	Hardware interface module
H_7	Transmitter module
H_8	Operating system module
H_9	Battery capacity
H_{10}	Casing material
H_{11}	User interface module
H_{12}	LCD module
H_{13}	Heat transfer module
H_{14}	Memory module
H_{15}	Camera module

Using the Rough_QFD decision support tool developed in this work, the results of the QFD analysis of this case study are shown in Figure 7.6. The bar chart of the final importance ratings of the CNs (WHATs) in Figure 7.6 produces the following ranking order:

$$W_2 > W_{13} > W_{18} > W_3 > W_{12} > W_7 > W_8 > W_{15} > W_1 > W_{19} > W_{14} > W_5 > W_4$$

$$W_{16} > W_{20} > W_9 > W_{11} > W_6 > W_{17} > W_{10}$$

Analogically, the bar chart of the final importance ratings of the DRs (HOWs) in the figure produces the following ranking order:

$$H_9 > H_7 > H_4 > H_5 > H_{11} > H_{15} > H_{14} > H_2 > H_8 > H_3 > H_6 > H_1 > H_{12} > H_{13} > H_{10}$$

Figure 7. 6 Results of QFD analysis of the case study

The ranking order of the CNs obtained in this case study agrees favorably with the result received from the preliminary market investigation carried out by the author prior to this case study. The preliminary investigation through interviews and group discussions with 50 college students has shown that the top five functions/features that young college students care the most are the battery performance, voice quality, SMS capacity, data transfer, and web access. The

ranking order of the customer needs obtained in this case study has uncovered some unique characteristics of the customer segment of young college students. For example, besides the common concerns of most customers about the battery performance and voice quality, some important mobile phone functions/features for businessmen or professionals such as dual SIM card, multi-band, and hands free, may not be considered with high priority by college students. Instead, they care more about the data transfer, SMS capability, web access and entertainment functions (such as games and music). This could be due to the unique lifestyle and environment that college students live in. College students like to share information with peers very frequently through SMS and web access, and the entertainment provided by mobile phones could be the major channel for them to relax between tight lecture schedules.

As discussed in Chapter 4, the information about the ranking orders of the CNs and DRs obtained is very important for product designers to plan the next phase of product development, namely to determine what to design and how to allocate the resources. It should be noted that the Rough_QFD decision support tool developed in this work is able to provide more information than just a ranking order for product designers. For example, in this case study, the initial rating data collected from customers and product designers is inherent with uncertainties due to the diversity of opinions and subjective judgments. Conventional approaches to QFD analysis usually either ignore such uncertainties or describe them using a fixed measure. However, Rough_QFD can successfully accommodate such uncertainties in the initial data by introducing a new concept of rough numbers with adaptive interval sizes (in contrast to fixed interval sizes) and eventually

reflect them in the final importance ratings of the WHATs and HOWs. In Rough_QFD results, uncertainties in the final importance ratings are indicated by the length of the bars, where the smaller a bar length is, the less uncertain (i.e. more reliable) is the rating value. Therefore, Rough_QFD is not only able to identify the ranking orders of the WHATs and HOWs, but also able to provide the reliability information of each final importance rating obtained, which can possibly be used as an additional piece of useful information for product designers to make the right decisions.

7.2.2.2 Rough_Kansei Analysis

As mentioned in Section 7.1, the Rough_Kansei decision support tool is to discover the latent affective needs of customers in order to design a product that can affectively delight customers. This case study is used to examine the affective preferences of young college students about the mobile phone handset casing design. Based on a thorough review of reports in the online mobile phone magazines together with the result of a preliminary investigation to young college students through interviews, it is found that the most preferable affection concerning a mobile phone outlook is 'stylish design'. As a result, a Kansei survey is conducted in this case study in order to find out the most important design elements that can evoke their Kansei of stylish. In the survey, a collection of product samples are presented to a focus group composed of 10 customers (students from different engineering schools and majors, 5 males and 5 females) for their evaluation on the Kansei of stylish using a 5-point scale system.

The mobile phone handset design concepts used in the survey basically include three major design elements, namely the material, color and body type. Each design element takes two or three category values for ease of illustration. More specifically, the design element of material may take either “more plastic” or “more metal”, the design element of color may take either “black”, “red” or “silver”, and the design element of body type may take either “monoblock” or “fold”. It is important to note that the product samples presented for Kansei evaluation should include all possible combinations of the three design elements. In this case study, there are 12 (i.e. $2 \times 2 \times 3 = 12$) possible design element combinations in total. The focus group is invited to rate the Kansei of stylish for each product sample using the 5-point scale system where ‘1’ represents ‘the least stylish’ and ‘5’ represents ‘the most stylish’. The original data from the survey is attached in Appendix 2.

It should be noted that in this case study, product designers are more interested in the design element combinations which can evoke customers’ strong Kansei of stylish. Therefore, the Kansei knowledge (i.e. affective design rules) should be acquired from the upper bound of the Kansei rating classes namely 3, 4, and 5 in the 5-point scale system. Using the Rough_Kansei decision support tool developed, the following dominance principles are identified for the three design element based on the original Kansei data obtained:

For the design element of material:

More metal > More plastic

For the design element of color:

Silver > Black > Red

For the design element of body type:

Fold > Monoblock

Subsequently, based on the dominance principles identified, Kansei knowledge (i.e. affective design rules) can be extracted as follows:

IF {(Material $\geq$ More metal) and (Colour $\geq$ Red) and (Type $\geq$ Fold)}
THEN {Stylish $\geq$ 5};

IF {(Material $\geq$ More metal)}
THEN {Stylish $\geq$ 4};

IF {(Material $\geq$ More metal) or (Colour $\geq$ Silver) or (Type $\geq$ Fold)}
THEN {Stylish $\geq$ 3}

The above results with Rough_Kansei GUI are presented in Figure 7.7.

Figure 7.7 Results of the Rough_Kansei analysis

The above affective design rules acquired can be used to guide the mobile phone handset design by translating customers' Kansei of stylish into the design elements of the handset. At the same time, the Partition Qualities attained by respective Kansei class unions can serve as indicators of the quality of the affective design rules acquired. For instance, in this case study, the Partition Quality for the Kansei rating class '5' has a very low value (i.e. 0.529) (see Figure 7.7), which simply implies that among the observations belonging to the upward union of the class '5', only 52.9% of them certainly have a strong Kansei of stylish. The low Partition Quality in fact carries an important information to the designers that the existing design samples of the handset design are not able to evoke customers'

strong Kansei of stylish. In other words, none of the combinations of the three design elements can deliver a clear image of stylish to customers. As a result, the designers will have to modify or involve more design elements if they want to obtain a stronger Kansei of stylish. On the other hand, the upward union of the rating class '4' has a higher Partition Quality (i.e. 0.765) and the upward union of the rating class '3' has the highest Partition Quality (i.e. 1.0). This implies that the combinations of the existing three design elements with current category values can only assure a moderate (at most class '3') Kansei of stylish. As a result, customers seeking stronger (higher than '4') Kansei of stylish may not be satisfied with any samples of the handset design. Therefore, the designer may have to modify the design by either providing more category values for the existing design elements or involving more design elements, or both, if a very high Kansei of stylish is concerned in the handset design.

7.2.2.3 Rough_Grey Analysis

This part of the case study will use the proposed Rough_Grey decision support tool to evaluate the mobile phone design concepts generated. In this case study, five prototype mobile phone design concepts (denoted by D_1 , D_2 ..., and D_5) are proposed by a group of five design engineers (represented by five final year students specialized in product design based on the previous analysis of the customer needs (including both functional and affective needs). The objective of the evaluation is to identify the best design concept that can maximize the satisfaction to the evaluation criteria and business constraints such as development time, cost, technical difficulties, and so on. In this case study, a collection of six

evaluation criteria have been identified to evaluate the design concepts. The descriptions of these evaluation criteria are listed in Table 7.3.

Table 7. 3 Descriptions of the evaluation criteria

No.	Criteria	Type
1	Number of modular parts	Larger-the-better
2	Available space for LCD (cm ²)	Larger-the-better
3	Number of new functions or features	Larger-the-better
4	Prototype development time (week)	Smaller-the-better
5	Overall weight (g)	Smaller-the-better
6	Overall cost (\$)	Smaller- the-better

For every design concept proposed, its performance with regard to each criterion is evaluated by the design team (see Appendix 3). As discussed in Chapter 6, the diversity of evaluators' opinions and subjective judgments can be accommodated by the concept of rough numbers in the proposed Rough_Grey analysis. Using the Rough_Grey decision support tool developed, the ranking order of the five design concepts proposed are shown in Figure 7.8. Obviously, the design concept D_2 is the best design concept based on the six evaluation criteria as it has the smallest difference (distance) with the ideal design solution (represented by the reference sequence in Rough_Grey analysis).

Figure 7. 8 Results of Rough_Grey analysis

7.3 Summary

Based on the methods and approaches described in Chapters 4, 5, and 6, a prototype integrated decision support system composed of a potpourri of decision support tools has been implemented to assist product designers in decision-making during the front-end product development process. The implementation of the integrated decision support system is founded on the base of a rough set based design information representation platform which addresses the uncertainty issue in design information representation, and realized by incorporating QFD, affective design and grey relational analysis to address the other three critical issues in the front-end product development process, namely the analysis of customers' functional needs, the discovery of affective design rules, and the evaluation of

design concepts. Three decision support tools, i.e. the Rough_QFD decision support tool, the Rough_Kansei decision support tool, and the Rough_Grey decision support tool are implemented using the MATLAB software.

The capability of the proposed decision support tools is demonstrated using a mobile phone development case study. In the case study, it has been shown that the uncertain design information is well handled by the proposed rough set based design information representation platform. The decision support tools developed are able to effectively gauge the functional needs of customers, uncover the latent affective needs and Kansei knowledge, and evaluate the design concepts generated in a meaningful and objective manner. The result of the case study has shown that the proposed decision support tools are able to facilitate the decision-making activities in the front-end product development process and provide more insights into the analyzed results.

CHAPTER 8 CONCLUSION AND FUTURE WORK

8.1 Conclusion

In the new global economic environment, manufacturing companies are facing ever increasing intense competitions and product development processes are confronted with critical challenges, namely improving customer satisfaction while reducing product development time and cost. On the other hand, product development is essentially a complex process involving many decision-making activities such as determining what product to develop and how development resources are to be allocated. In practice, a successful product development process is usually achieved through appropriate management of product development information and using effective decision support tools to make prudent decisions so as to eliminate costly mistakes and rework in the later stages of the process. Therefore, effective and efficient decision-making in a product development process plays a very crucial role for the success of a product as it could drastically reduce product development cost and time, improve product quality, and consequently enhance the competitive edge and improve the profitability of the manufacturing company.

From the literature review, it has been established that customer oriented product development provides an effective approach to improving customer satisfaction. However, there is still much to be desired in order to achieve a

system-wide solution, especially in the front-end product development process including product planning and product design concept evaluation, where decision support systems could play an important role. However, decision-making in product development processes is never an easy task due to the complexity of problems, uncertainties in the design information, subjectivity in judgments and contradiction of objectives. Frequently, design decisions have to be made based on vague and incomplete information. In such a context, this research attempts to investigate the management of different types of uncertainties in design information and knowledge in product development processes, based on which a decision support system composed of a potpourri of decision support tools is developed to facilitate decision-making activities in a product development with a special emphasis on the front-end stages of the process.

In the global market flooded with many competitive products, the success of a product depends largely on its ability to gauge the real needs of customers early in the product development process and respond promptly to meet these needs by developing innovative products at the lowest cost. Frequently, in product development, a poor understanding of the customer requirements for a product in the early development stages can be the main cause of failure of the development process. As such, an effective and efficient analysis of customers' requirements in the early stages of a product development process is needed to facilitate the understanding of customer needs and bridge the communication between customers and the product development team. It has been established that although existing tools such as QFD have provided systematic approaches to analyze customer needs, they are not able to adequately deal with various uncertainties

inherent in the design data. To address this issue, a product design information representation platform is proposed in this work based on the novel concepts of rough number and rough boundary interval, which are derived by the author from the basic principles of rough set theory. Integrated with the arithmetic operations of interval mathematics, the proposed rough number based design information representation has been incorporated into QFD analysis to formulate a rough number enabled QFD (Rough_QFD) decision support tool. The proposed Rough_QFD decision support tool successfully integrates the advantages of QFD and the novel concept of rough numbers, where the former provides a systematic structure to translate customer needs into technical design requirements and the latter provides a meaningful way of dealing with uncertainties inherent in the design information. Related investigations concerning the comparison between rough numbers also have been examined for the realization of the Rough_QFD analysis.

It has been established that many competitions in product development are driven by customer needs and satisfaction to these needs. In a competitive global market, a manufacturing company's bottom line of success is measured not by the sophistication of its technology, but by how well its product can meet various customer needs. Essentially, besides the basic performance, i.e. functional needs, of a product, well-informed customers may have latent higher level needs such as emotional satisfaction, i.e. affective needs. Recognition and incorporation of affective needs in a product development process is very important for the development of an innovative product that can delight customers affectively, especially when technology is unable to differentiate a product from its

competitors, where affections associated with the product usually determine its success. As such, a comprehensive understanding of both functional and affective needs of customers is needed to develop a successful and competitive product. Although some existing methods such as affective design, i.e. Kansei Engineering, have been established to address the issue of affective needs in product development, such methods are not adequate to deal with the nonlinearity and uncertainties inherent in the problem. To address this issue, this research work proposed a dominance-based rough set approach to affective design. A Rough_Kansei decision support tool has been developed to gauge the customers' affective needs and discover the relationships between these needs and the product design elements. The Kansei knowledge in the form of design rules extracted by the Rough_Kansei decision support tool can be used to support decision-making activities in the product development process. It has been shown that the proposed Rough_Kansei decision support tool successfully transforms the affective design problem into a dominance-based rough set model and uses rough set principles to handle nonlinearity and uncertainty. Related investigations including the management of inconsistencies in affective design data and assessment of the extracted Kansei knowledge have also been carried out for the realization of the Rough_Kansei analysis.

Design concept selection is another crucial decision-making activity in the front-end product development process after various types of customer needs have been translated into critical-to-quality characteristics and product design alternatives have been generated. Making the right decision in design concept selection is very important for a product development process as it has a profound

impact on the success of successive product development activities. In fact, it has been established that up to 70% or more of the final product cost is determined when the design concept is selected (Ullman, 1997; Ben-Arieh and Li, 2003). Although many numerical and non-numerical methods have been developed to assess design concepts in product development processes, most existing design concept evaluation methods are found to be relatively unreliable and ineffective either because they rely too much on the subjective judgments of designers, or due to their inability in handling uncertainty effectively. To address this issue, a rough number enabled grey relational analysis has been proposed and developed to facilitate the decision-making in product design concept selection. The proposed Rough_Grey decision support tool successfully integrates the strengths of grey relational analysis and the concept of rough number developed in this work, where the former provides a simple but robust means for multi-objective design concept evaluation while the latter provides a meaningful way of handling various uncertainties during evaluation. The Rough_Grey decision support tool developed has been shown to be able to provide more insights into the evaluation results and reduce unfounded suppositions and guessing during design evaluation. Further investigations into the management of various types of criteria and measurement of rough distances (differences) have also been performed for the realization of the Rough_Grey analysis.

The above-mentioned work has established the basic framework and essential components for the establishment of an integrated decision support system for front-end product development process. An integrated decision support system that guides the front-end product development process with 3 “R”s, namely

designing the “right” thing i.e. functional needs, presenting in the “right” manner, i.e. affective needs, and making the “right” selection, i.e. design concept, is implemented in this work. The capability of the decision support system is illustrated using a case study concerning the design of a mobile phone. The results of the case study have shown that the prototype decision support system developed is able to facilitate the decision-making activities in the front-end product development process by effectively and systematically treating uncertainty, nonlinearity, subjectivity and contradictive objectives in decision analysis. The proposed concepts of rough numbers and rough boundary intervals coupled with the rough set based design information and knowledge representation platform developed in this work are able to provide more insights into the decision analysis results. It has been shown that the decision support system developed is able to analyze both quantitative and qualitative design data, and carry out numerical computations and analysis in order to assess the impact of every factor involved in the decision-making process. It is envisaged that the decision support system developed in this work will enable a company to create better products and have more satisfied customers, and provide a framework for organizing a more efficient development process by reducing the development cost and time.

This research has successfully completed the five tasks defined in Chapter 3 (see Section 3.2), through which the four objectives set in Chapter 1 have been achieved by addressing the critical issues in the development of an effective decision support system for the front-end product development process. The contribution of the work undertaken by the author can be summarized as follows:

- A novel design information and knowledge representation platform based on the two novel concepts of rough number and rough boundary interval, which are derived from the basic concepts of rough set theory. (Zhai *et al.*, 2007a; 2007b)
- A rough number enabled hybrid Rough_QFD decision support tool to incorporate customer needs into product design under uncertainties. (Zhai *et al.*, 2008; 2009d)
- A dominance-based rough set approach to affective design (Rough_Kansei decision support tool) to discover Kansei knowledge under uncertainties. (Zhai *et al.*, 2009a; 2009c)
- A multi-objective design concept evaluation approach based on rough numbers and grey relational analysis (Rough_Grey decision support tool) to facilitate design concept evaluation processes under various constraints and uncertainties. (Zhai *et al.*, 2009b)
- A framework and an integrated decision support system for the front-end product development process composed of the aforementioned decision support tools (Chapter 7).

8.2 Future Work

The work presented in this thesis has demonstrated the profound potential of improving the effectiveness and efficiency of decision-making activities through integrating decision support tools in a product development process. To further extend this research, the following future work is recommended:

- 1) Further enhance the rough set based design information representation platform, and extend the platform to manage different types of design information and product design knowledge in product development, such as past design rules and past design capabilities, etc;
- 2) On the basis of 1), integrate the developed decision support system with the conceptual design process so as to realize a more comprehensive decision support cum conceptual design support system for the front-end product development process.

It is anticipated that the establishment of the above-mentioned future work could stretch the capability of the decision support system developed in this work and further improve the productivity of the front-end product development process. Manufacturing companies equipped with such a decision support cum conceptual design support system for product development could possibly gain a competitive edge in the new global competitive environment.

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APPENDIX 1 QFD SURVEY QUESTIONNAIRE AND DATA

1. QFD Survey Questionnaire

Dear Sir/Madam

The following survey is to study the importance of mobile phone features/functions perceived by customers. Your responses and personal particulars will be treated strictly confidential and reserved for academic research only. It may take you about 5-10 minutes to complete the survey. Thank you.

If “9” represent “very high” importance and “1” represents “very low” importance, please rate the following features/functions of a mobile phone.

Customer Needs	Importance Ratings				
	Very low				Very high
Voice quality/stability	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Phone book capacity	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Battery standby/talking time	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
MMS	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Camera	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
MP3	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Hands free	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Web access	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Dictionary	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Voice recorder	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Handwriting input	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Radio	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Game	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Voice command	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Data transfer	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐

Appendix 1 QFD Survey Questionnaire and Data

GPS	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Dual SIM	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Multi-band	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Touch screen	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
SMS capacity	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
Other functions that you think important for a mobile phone:					
1. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
2. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
3. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
4. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
5. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
6. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
7. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
8. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
9. _____	1 ☐	3 ☐	6 ☐	8 ☐	9 ☐
10. _____	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐
	1 ☐	3 ☐	5 ☐	7 ☐	9 ☐

2. QFD Survey Data

Importance ratings of CNs

CNs	Customer Ratings									
W_1	7	5	7	3	5	7	5	5	7	5
W_2	9	9	9	7	9	9	7	9	9	7
W_3	7	7	7	7	7	9	7	7	9	7
W_4	7	7	5	5	9	7	7	9	7	7
W_5	7	9	5	7	9	9	7	9	9	7
W_6	3	5	5	3	7	5	3	7	5	3
W_7	7	7	9	5	9	7	7	9	7	7
W_8	5	7	9	7	7	9	9	7	9	9
W_9	5	7	7	9	7	5	7	7	5	7
W_{10}	3	3	1	5	3	5	3	3	5	3
W_{11}	9	7	9	5	7	9	9	7	9	9
W_{12}	7	5	7	3	5	7	5	5	5	5
W_{13}	9	9	9	7	9	9	7	9	9	7
W_{14}	7	5	7	9	7	9	7	7	9	7
W_{15}	7	7	5	5	9	7	7	9	7	7
W_{16}	7	9	5	7	9	5	7	9	9	7
W_{17}	3	5	5	1	7	5	3	7	5	3
W_{18}	7	7	9	9	9	7	7	9	7	7
W_{19}	5	7	9	7	7	9	9	7	9	9
W_{20}	5	7	7	9	7	9	7	7	5	7

3. Correlations between CNs and DRs

CN-DR Pairs	Correlation Ratings									
H_1W_1	9	7	9	9	9	7	7	9	7	9
H_1W_2	3	1	3	3	3	3	1	3	3	3
H_1W_3	7	9	7	9	7	9	9	9	9	7
H_1W_4	0	0	0	0	0	0	0	0	0	0
H_1W_5	0	0	0	0	0	0	0	0	0	0
H_1W_6	0	0	0	0	0	0	0	0	0	0
H_1W_7	0	0	0	0	0	0	0	0	0	0
H_1W_8	0	0	0	0	0	0	0	0	0	0
H_1W_9	0	0	0	0	0	0	0	0	0	0
H_1W_{10}	0	0	0	0	0	0	0	0	0	0
H_1W_{11}	0	0	0	0	0	0	0	0	0	0
H_1W_{12}	0	0	0	0	0	0	0	0	0	0
H_1W_{13}	1	3	1	1	3	1	3	1	1	1
H_1W_{14}	0	0	0	0	0	0	0	0	0	0
H_1W_{15}	1	3	1	1	1	1	3	1	1	1
H_1W_{16}	0	0	0	0	0	0	0	0	0	0
H_1W_{17}	9	7	9	5	9	9	7	5	9	9
H_1W_{18}	3	3	3	3	5	3	3	3	3	1
H_1W_{19}	0	0	0	0	0	0	0	0	0	0
H_1W_{20}	0	0	0	0	0	0	0	0	0	0
H_2W_1	3	3	3	3	3	1	3	3	1	3
H_2W_2	3	3	5	3	3	5	3	3	5	3
H_2W_3	9	9	7	7	9	7	9	7	7	9
H_2W_4	9	7	9	9	9	9	7	9	9	9
H_2W_5	9	9	7	7	9	7	9	7	7	9
H_2W_6	0	0	0	0	0	0	0	0	0	0
H_2W_7	0	0	0	0	0	0	0	0	0	0
H_2W_8	0	0	0	0	0	0	0	0	0	0
H_2W_9	0	0	0	0	0	0	0	0	0	0
H_2W_{10}	0	0	0	0	0	0	0	0	0	0
H_2W_{11}	0	0	0	0	0	0	0	0	0	0
H_2W_{12}	0	0	0	0	0	0	0	0	0	0
H_2W_{13}	0	0	0	0	0	0	0	0	0	0
H_2W_{14}	0	0	0	0	0	0	0	0	0	0
H_2W_{15}	0	0	0	0	0	0	0	0	0	0
H_2W_{16}	9	9	7	7	7	9	9	7	9	9
H_2W_{17}	0	0	0	0	0	0	0	0	0	0
H_2W_{18}	1	1	3	1	3	1	1	1	1	1
H_2W_{19}	0	0	0	0	0	0	0	0	0	0
H_2W_{20}	5	3	5	5	3	5	3	5	5	5
H_3W_1	0	0	0	0	0	0	0	0	0	0
H_3W_2	0	0	0	0	0	0	0	0	0	0
H_3W_3	0	0	0	0	0	0	0	0	0	0
H_3W_4	0	0	0	0	0	0	0	0	0	0
H_3W_5	3	1	3	3	3	3	1	3	3	3
H_3W_6	9	7	9	9	9	7	7	9	7	9
H_3W_7	0	0	0	0	0	0	0	0	0	0
H_3W_8	1	3	1	1	1	1	3	1	1	1
H_3W_9	1	3	1	1	3	1	3	1	1	1
H_3W_{10}	0	0	0	0	0	0	0	0	0	0
H_3W_{11}	5	5	5	5	5	5	5	3	5	5
H_3W_{12}	0	0	0	0	0	0	0	0	0	0
H_3W_{13}	3	3	5	3	3	3	3	3	3	3
H_3W_{14}	0	0	0	0	0	0	0	0	0	0
H_3W_{15}	3	3	5	5	3	3	3	5	3	3
H_3W_{16}	3	3	3	5	3	5	3	5	5	3
H_3W_{17}	7	9	7	7	9	9	9	7	9	7
H_3W_{18}	3	5	3	5	5	3	5	5	3	3
H_3W_{19}	7	9	7	9	7	7	9	9	7	7
H_3W_{20}	9	7	9	7	9	9	7	7	9	9
H_4W_1	1	3	3	3	5	3	3	3	3	1
H_4W_2	7	9	7	7	9	9	9	7	9	7
H_4W_3	1	3	1	1	3	1	3	1	1	1

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H_4W_4	0	0	0	0	0	0	0	0	0	0
H_4W_5	9	7	9	7	9	9	7	7	9	9
H_4W_6	5	3	3	3	5	3	3	3	3	5
H_4W_7	3	5	5	3	5	3	5	3	3	3
H_4W_8	3	5	5	3	5	3	5	3	3	3
H_4W_9	3	3	1	3	3	3	3	3	3	3
H_4W_{10}	0	0	0	0	0	0	0	0	0	0
H_4W_{11}	5	5	3	5	5	5	5	5	5	5
H_4W_{12}	0	0	0	0	0	0	0	0	0	0
H_4W_{13}	0	0	0	0	0	0	0	0	0	0
H_4W_{14}	7	7	7	9	9	7	7	9	7	7
H_4W_{15}	3	5	3	5	3	3	5	5	3	3
H_4W_{16}	0	0	0	0	0	0	0	0	0	0
H_4W_{17}	3	5	3	5	3	3	5	5	3	3
H_4W_{18}	0	0	0	0	0	0	0	0	0	0
H_4W_{19}	0	0	0	0	0	0	0	0	0	0
H_4W_{20}	1	3	1	1	1	1	3	1	1	1
H_5W_1	0	0	0	0	0	0	0	0	0	0
H_5W_2	0	0	0	0	0	0	0	0	0	0
H_5W_3	0	0	0	0	0	0	0	0	0	0
H_5W_4	9	5	7	9	7	9	5	9	9	9
H_5W_5	0	0	0	0	0	0	0	0	0	0
H_5W_6	0	0	0	0	0	0	0	0	0	0
H_5W_7	0	0	0	0	0	0	0	0	0	0
H_5W_8	0	0	0	0	0	0	0	0	0	0
H_5W_9	0	0	0	0	0	0	0	0	0	0
H_5W_{10}	5	7	5	5	5	5	7	5	5	5
H_5W_{11}	0	0	0	0	0	0	0	0	0	0
H_5W_{12}	9	9	9	9	7	9	9	9	9	9
H_5W_{13}	7	9	7	9	9	9	9	9	9	7
H_5W_{14}	0	0	0	0	0	0	0	0	0	0
H_5W_{15}	0	0	0	0	0	0	0	0	0	0
H_5W_{16}	9	9	7	9	7	9	9	9	9	9
H_5W_{17}	5	7	7	7	7	5	7	7	5	5
H_5W_{18}	0	0	0	0	0	0	0	0	0	0
H_5W_{19}	9	9	7	9	7	9	9	9	9	9
H_5W_{20}	0	0	0	0	0	0	0	0	0	0
H_6W_1	9	7	9	9	9	7	7	9	7	9
H_6W_2	3	5	3	5	5	3	5	5	3	3
H_6W_3	0	0	0	0	0	0	0	0	0	0
H_6W_4	5	5	3	5	5	3	5	5	3	5
H_6W_5	0	0	0	0	0	0	0	0	0	0
H_6W_6	0	0	0	0	0	0	0	0	0	0
H_6W_7	0	0	0	0	0	0	0	0	0	0
H_6W_8	3	5	3	5	5	3	5	5	3	3
H_6W_9	0	0	0	0	0	0	0	0	0	0
H_6W_{10}	0	0	0	0	0	0	0	0	0	0
H_6W_{11}	3	5	3	5	5	3	5	5	3	3
H_6W_{12}	9	9	9	9	9	7	9	9	7	9
H_6W_{13}	0	0	0	0	0	0	0	0	0	0
H_6W_{14}	0	0	0	0	0	0	0	0	0	0
H_6W_{15}	3	5	3	5	5	3	5	5	3	3
H_6W_{16}	0	0	0	0	0	0	0	0	0	0
H_6W_{17}	0	0	0	0	0	0	0	0	0	0
H_6W_{18}	0	0	0	0	0	0	0	0	0	0
H_6W_{19}	1	3	3	3	5	3	3	3	3	1
H_6W_{20}	0	0	0	0	0	0	0	0	0	0
H_7W_1	3	3	3	3	3	1	3	3	1	3
H_7W_2	3	5	3	3	3	3	5	3	3	3
H_7W_3	5	5	3	5	5	3	5	5	3	5
H_7W_4	5	5	3	5	5	5	5	5	5	5
H_7W_5	0	0	0	0	0	0	0	0	0	0
H_7W_6	3	5	3	3	3	3	5	3	3	3
H_7W_7	0	0	0	0	0	0	0	0	0	0
H_7W_8	3	5	3	3	3	3	5	3	3	3
H_7W_9	0	0	0	0	0	0	0	0	0	0
H_7W_{10}	0	0	0	0	0	0	0	0	0	0
H_7W_{11}	0	0	0	0	0	0	0	0	0	0
H_7W_{12}	3	5	3	3	3	3	5	3	3	3
H_7W_{13}	0	0	0	0	0	0	0	0	0	0

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H_7W_{14}	0	0	0	0	0	0	0	0	0	0
H_7W_{15}	9	9	7	9	7	9	9	9	9	9
H_7W_{16}	5	7	7	5	7	5	7	5	5	5
H_7W_{17}	0	0	0	0	0	0	0	0	0	0
H_7W_{18}	9	9	7	9	7	9	9	9	9	9
H_7W_{19}	0	0	0	0	0	0	0	0	0	0
H_7W_{20}	9	7	9	9	9	7	7	9	7	9
H_8W_1	3	5	3	5	5	3	5	5	3	3
H_8W_2	0	0	0	0	0	0	0	0	0	0
H_8W_3	5	5	3	5	5	3	5	5	3	5
H_8W_4	0	0	0	0	0	0	0	0	0	0
H_8W_5	0	0	0	0	0	0	0	0	0	0
H_8W_6	0	0	0	0	0	0	0	0	0	0
H_8W_7	3	5	3	5	5	3	5	5	3	3
H_8W_8	0	0	0	0	0	0	0	0	0	0
H_8W_9	0	0	0	0	0	0	0	0	0	0
H_8W_{10}	1	3	1	1	1	1	3	1	1	1
H_8W_{11}	1	3	1	1	3	1	3	1	1	1
H_8W_{12}	0	0	0	0	0	0	0	0	0	0
H_8W_{13}	5	5	7	5	5	5	5	5	5	5
H_8W_{14}	0	0	0	0	0	0	0	0	0	0
H_8W_{15}	3	3	5	3	3	3	3	3	3	3
H_8W_{16}	0	0	0	0	0	0	0	0	0	0
H_8W_{17}	3	3	5	5	3	3	3	5	3	3
H_8W_{18}	3	3	3	5	3	5	3	5	5	3
H_8W_{19}	7	9	7	7	9	9	9	7	9	7
H_8W_{20}	3	5	3	5	5	3	5	5	3	3
H_9W_1	7	9	7	9	7	7	9	9	7	7
H_9W_2	9	7	9	7	5	9	7	7	9	9
H_9W_3	1	3	3	3	3	3	3	3	3	1
H_9W_4	7	9	7	7	9	9	9	7	9	7
H_9W_5	1	3	1	1	3	1	3	1	1	1
H_9W_6	0	0	0	0	0	0	0	0	0	0
H_9W_7	9	7	9	7	9	9	7	7	9	9
H_9W_8	5	3	3	3	5	3	3	3	3	5
H_9W_9	3	5	5	3	5	3	5	3	3	3
H_9W_{10}	3	5	5	3	5	3	5	3	3	3
H_9W_{11}	3	3	1	3	3	3	3	3	3	3
H_9W_{12}	0	0	0	0	0	0	0	0	0	0
H_9W_{13}	5	5	5	5	5	7	5	5	7	5
H_9W_{14}	3	1	3	3	3	3	1	3	3	3
H_9W_{15}	7	9	7	9	7	9	9	9	9	7
H_9W_{16}	0	0	0	0	0	0	0	0	0	0
H_9W_{17}	0	0	0	0	0	0	0	0	0	0
H_9W_{18}	0	0	0	0	0	0	0	0	0	0
H_9W_{19}	0	0	0	0	0	0	0	0	0	0
H_9W_{20}	0	0	0	0	0	0	0	0	0	0
$H_{10}W_1$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_2$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_3$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_4$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_5$	1	3	1	1	3	1	3	1	1	1
$H_{10}W_6$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_7$	1	3	1	1	1	1	3	1	1	1
$H_{10}W_8$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_9$	9	7	9	9	9	9	7	5	9	9
$H_{10}W_{10}$	1	3	3	3	5	3	3	3	3	1
$H_{10}W_{11}$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_{12}$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_{13}$	3	3	3	3	3	1	3	3	1	3
$H_{10}W_{14}$	3	3	5	3	3	5	3	3	5	3
$H_{10}W_{15}$	9	9	7	7	9	7	9	7	7	9
$H_{10}W_{16}$	9	7	9	9	9	9	7	9	9	9
$H_{10}W_{17}$	9	9	7	7	9	7	9	7	7	9
$H_{10}W_{18}$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_{19}$	0	0	0	0	0	0	0	0	0	0
$H_{10}W_{20}$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_1$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_2$	9	7	7	9	7	9	7	9	9	9
$H_{11}W_3$	0	0	0	0	0	0	0	0	0	0

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$H_{11}W_4$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_5$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_6$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_7$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_8$	5	7	5	5	5	5	7	5	5	5
$H_{11}W_9$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_{10}$	9	9	9	9	7	9	9	9	9	9
$H_{11}W_{11}$	7	9	7	9	9	9	9	9	9	7
$H_{11}W_{12}$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_{13}$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_{14}$	9	9	7	9	7	9	9	9	9	9
$H_{11}W_{15}$	5	7	7	5	7	5	7	5	5	5
$H_{11}W_{16}$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_{17}$	9	9	7	9	7	9	9	9	9	9
$H_{11}W_{18}$	0	0	0	0	0	0	0	0	0	0
$H_{11}W_{19}$	9	7	9	9	9	7	7	9	7	9
$H_{11}W_{20}$	3	5	3	5	5	3	5	5	3	3
$H_{12}W_1$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_2$	5	5	3	5	5	3	5	5	3	5
$H_{12}W_3$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_4$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_5$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_6$	3	5	3	5	5	3	5	5	3	3
$H_{12}W_7$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_8$	5	5	3	5	5	7	5	5	7	5
$H_{12}W_9$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{10}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{11}$	7	7	7	9	9	7	7	9	7	7
$H_{12}W_{12}$	3	5	3	5	3	3	5	5	3	3
$H_{12}W_{13}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{14}$	3	5	3	5	3	3	5	5	3	3
$H_{12}W_{15}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{16}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{17}$	1	3	1	1	1	1	3	1	1	1
$H_{12}W_{18}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{19}$	0	0	0	0	0	0	0	0	0	0
$H_{12}W_{20}$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_1$	9	7	7	9	7	9	7	9	9	9
$H_{13}W_2$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_3$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_4$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_5$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_6$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_7$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_8$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_9$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_{10}$	1	3	1	1	3	1	3	1	1	1
$H_{13}W_{11}$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_{12}$	1	3	1	1	1	1	3	1	1	1
$H_{13}W_{13}$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_{14}$	9	7	9	7	9	9	7	7	9	9
$H_{13}W_{15}$	1	3	3	3	5	3	3	3	3	1
$H_{13}W_{16}$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_{17}$	0	0	0	0	0	0	0	0	0	0
$H_{13}W_{18}$	3	3	3	3	3	1	3	3	1	3
$H_{13}W_{19}$	3	3	5	5	3	5	3	3	5	3
$H_{13}W_{20}$	9	9	7	7	9	7	9	7	7	9
$H_{14}W_1$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_2$	3	5	3	3	3	3	5	3	3	3
$H_{14}W_3$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_4$	3	5	3	3	3	3	5	3	3	3
$H_{14}W_5$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_6$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_7$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_8$	3	5	3	3	3	3	5	3	3	3
$H_{14}W_9$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_{10}$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_{11}$	9	9	7	9	7	9	9	9	9	9
$H_{14}W_{12}$	5	7	7	3	7	5	7	3	5	5
$H_{14}W_{13}$	0	0	0	0	0	0	0	0	0	0

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$H_{14}W_{14}$	9	9	7	9	7	9	9	9	9	9
$H_{14}W_{15}$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_{16}$	9	7	9	9	9	7	7	9	7	9
$H_{14}W_{17}$	3	5	3	5	5	3	5	5	3	3
$H_{14}W_{18}$	0	0	0	0	0	0	0	0	0	0
$H_{14}W_{19}$	5	5	3	5	5	3	5	5	3	5
$H_{14}W_{20}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_1$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_2$	5	7	5	5	5	5	7	5	5	5
$H_{15}W_3$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_4$	9	9	9	9	7	9	9	9	9	9
$H_{15}W_5$	7	9	7	9	9	9	9	9	9	7
$H_{15}W_6$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_7$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_8$	9	9	7	9	7	9	9	9	9	9
$H_{15}W_9$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{10}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{11}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{12}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{13}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{14}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{15}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{16}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{17}$	1	3	1	1	3	1	3	1	1	1
$H_{15}W_{18}$	5	7	7	5	7	5	7	5	5	5
$H_{15}W_{19}$	0	0	0	0	0	0	0	0	0	0
$H_{15}W_{20}$	9	9	7	9	7	9	9	9	9	9

Appendix 2 Kansei Rating Data

Material	Color	Bodu type	Kansei Ratings
More plastic	Black	Monoblock	2
More metal	Red	Fold	5
More metal	Black	Fold	5
More plastic	Red	Monoblock	1
More plastic	Red	Fold	4
More plastic	Black	Fold	3
More metal	Red	Fold	5
More plastic	Red	Fold	4
More metal	Silver	Fold	5
More plastic	Black	Fold	3
More plastic	Red	Fold	4
More plastic	Red	Monoblock	2
More metal	Red	Fold	5
More plastic	Red	Monoblock	2
More metal	Black	Fold	5
More plastic	Silver	Monoblock	3
More metal	Red	Fold	5
More plastic	Black	Fold	3
More plastic	Red	Fold	4
More plastic	Black	Monoblock	2
More plastic	Silver	Monoblock	3
More metal	Silver	Fold	5
More metal	Silver	Monoblock	4
More metal	Black	Fold	5
More plastic	Red	Fold	3
More plastic	Silver	Monoblock	3
More plastic	Silver	Fold	5
More plastic	Silver	Fold	5
More plastic	Black	Monoblock	1
More metal	Red	Monoblock	4
More plastic	Red	Fold	3
More metal	Black	Monoblock	4
More plastic	Silver	Monoblock	3
More plastic	Silver	Fold	3
More metal	Silver	Monoblock	4
More plastic	Black	Fold	3

Appendix 2 Kansei Rating Data

More metal	Silver	Fold	5
More metal	Red	Monoblock	4
More plastic	Silver	Monoblock	3
More plastic	Silver	Fold	3
More metal	Black	Fold	4
More plastic	Silver	Fold	5
More plastic	Red	Fold	3
More metal	Silver	Monoblock	4
More metal	Black	Monoblock	5
More plastic	Silver	Fold	3
More metal	Black	Fold	5
More plastic	Red	Monoblock	2
More plastic	Black	Fold	3
More metal	Red	Fold	5
More metal	Silver	Monoblock	4
More metal	Black	Monoblock	5
More metal	Red	Monoblock	4
More metal	Red	Monoblock	4
More plastic	Red	Monoblock	2
More plastic	Black	Monoblock	2
More metal	Red	Monoblock	4
More plastic	Black	Monoblock	1
More metal	Black	Monoblock	5
More metal	Red	Monoblock	4
More metal	Silver	Monoblock	4
More plastic	Red	Monoblock	2
More metal	Red	Fold	5
More metal	Black	Fold	4
More plastic	Red	Fold	4
More metal	Silver	Fold	5
More plastic	Black	Fold	3
More metal	Silver	Fold	5
More metal	Silver	Fold	5
More plastic	Red	Fold	3
More metal	Silver	Fold	5
More metal	Silver	Fold	5
More metal	Red	Monoblock	4
More plastic	Black	Monoblock	2
More metal	Silver	Monoblock	4
More metal	Red	Fold	5
More metal	Silver	Monoblock	4
More metal	Red	Fold	5
More plastic	Silver	Monoblock	3

Appendix 2 Kansei Rating Data

More metal	Black	Fold	4
More plastic	Black	Fold	3
More metal	Black	Monoblock	4
More plastic	Silver	Fold	5
More metal	Black	Fold	4
More plastic	Black	Monoblock	1
More metal	Black	Monoblock	5
More metal	Black	Fold	5
More metal	Black	Monoblock	4
More plastic	Red	Monoblock	1
More plastic	Red	Monoblock	1
More plastic	Black	Fold	3
More metal	Silver	Fold	5
More metal	Black	Monoblock	4
More plastic	Silver	Monoblock	3
More metal	Silver	Fold	5
More plastic	Red	Fold	3
More metal	Black	Monoblock	5
More metal	Silver	Monoblock	4
More plastic	Black	Fold	3
More metal	Red	Monoblock	4
More metal	Red	Monoblock	4
More plastic	Red	Monoblock	2
More plastic	Silver	Monoblock	3
More plastic	Black	Monoblock	2
More plastic	Silver	Fold	3
More metal	Black	Fold	4
More metal	Silver	Monoblock	4
More metal	Black	Monoblock	4
More plastic	Red	Monoblock	1
More plastic	Black	Monoblock	2
More plastic	Silver	Monoblock	3
More plastic	Silver	Fold	3
More metal	Red	Fold	5
More plastic	Black	Fold	3
More plastic	Silver	Fold	5
More plastic	Black	Monoblock	1
More plastic	Silver	Monoblock	3
More metal	Silver	Monoblock	4
More metal	Red	Fold	5
More metal	Red	Monoblock	4

Appendix 3 Design Concept Evaluation Data

Design Concepts	Evaluators	Criteria					
		Number of modular parts	Available space for LCD (cm ²)	Number of new functions or features	Prototype development time (week)	Overall weight (g)	Overall cost (\$)
Design Concept 1 (D ₁)	Evaluator 1	9	15	3	4	100	170
	Evaluator 2	12	13	5	3	95	150
	Evaluator 3	11	16	5	3	100	140
	Evaluator 4	9	15	5	4	95	160
	Evaluator 5	10	14	6	3	100	150
Design Concept 2 (D ₂)	Evaluator 1	14	15	7	3	90	120
	Evaluator 2	13	14	8	3	105	130
	Evaluator 3	12	12	5	3	100	140
	Evaluator 4	12	17	6	3	95	150
	Evaluator 5	16	15	6	2	100	110
Design Concept 3 (D ₃)	Evaluator 1	10	16	5	3	95	150
	Evaluator 2	11	14	7	2	100	140
	Evaluator 3	12	15	6	2	90	130
	Evaluator 4	10	16	5	4	85	150
	Evaluator 5	14	12	5	2	110	100
Design Concept 4 (D ₄)	Evaluator 1	12	14	5	3	105	140
	Evaluator 2	8	14	6	4	110	170
	Evaluator 3	10	12	6	3	105	150
	Evaluator 4	9	15	7	4	110	160
	Evaluator 5	11	12	5	3	130	150
Design Concept 5 (D ₅)	Evaluator 1	11	10	3	2	135	130
	Evaluator 2	9	14	2	4	140	160
	Evaluator 3	10	18	3	3	110	160
	Evaluator 4	12	16	3	3	100	150
	Evaluator 5	8	14	2	4	120	200