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SOME FURTHER STUDIES ON IMPROVING QFD METHODOLOGY AND ANALYSIS

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NATIONAL UNIVERSITY OF SINGAPORE

2008

SOME FURTHER STUDIES ON IMPROVING QFD METHODOLOGY AND ANALYSIS

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Summary

Quality Function Deployment (QFD) starts and ends with the customer. In other words, how it ends may depend largely on how it starts. Any QFD practitioners will start with collecting the voice of the customer that reflects customer's needs as to make sure that the products will eventually sell or the service may satisfy the customer. On the basis of those needs, a product or service creation process is initiated. It always takes a certain period of time for the product or service to be ready for the customer. The question here is whether those customer-needs may remain *exactly* the same *during* the product or service creation process. The answer would be very likely to be a 'no', especially in today's rapidly changing environment due to increased competition and globalization.

The focus of this thesis is placed on dealing with the change of *relative* importance of the customer's needs during product or service creation process. In other words, the assumption is that there is no new need discovered along the time or an old one becomes outdated; only the relative importance change of the *existing* needs is dealt with. Considering the latest development of QFD research, especially the increasingly extensive use of Analytic Hierarchy Process (AHP) in QFD, this thesis aims to enhance the current QFD methodology and analysis, with respect to the change during product or service creation process, as to continually meet or exceed the needs of the customer.

The entire research works are divided into three main parts, namely, the further use of AHP in QFD, the incorporation of AHP-based priorities' dynamics in QFD, and decision making analysis with respect to the dynamics. In brief, the main contribution of this thesis is in providing some novel methods and/or approaches to enhance the QFD's use with respect to the change during product or service creation process. It is hoped that the research work may provide a first step into a better customer-driven product or service design process, and eventually increase the possibility to create more innovative and competitive products or services over time.

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CHAPTER 1
INTRODUCTION

"*The customers of tomorrow will have needs and expectations different from those of our present customers. For this reason, it is important to keep up with changing needs and expectations, and to learn how to meet these…"* (Bergman and Klefsjö, 2003: quality from customer needs to customer satisfaction)

"*Indeed a Critical-to-Quality (CTQ) valid today is not necessarily a meaningful one tomorrow; shifting social, economic and political scenes would make it imperative that except for immediate, localized projects, all CTQs should be critically examined at all times and refined as necessary*" (Goh, 2002: a strategic assessment of six sigma)

1.1 Problem Background

Quality Function Deployment (QFD) was first developed in the late 1960s by Professor Yoji Akao and Shigeru Mizuno. It was motivated by two issues (Akao and Mazur, 2003). First, it is the importance of design quality. Second, the need to deploy, prior to production startup, the important quality assurance points needed to ensure the design quality throughout the production process. According to Akao (1990), as one of the main founders, QFD can be defined as "a method for developing a design quality aimed at satisfying the customer and then translating the customer's demand into design targets and major quality assurance points to be used throughout the production phases".

QFD has become a quite popular tool in customer-focused product creation or development process. Some main benefits of using QFD may include better communication of cross-functional teamwork, lower project and product cost, better product design, and increased customer satisfaction (Hauser and Clausing, 1988; Griffin and Hauser, 1992; Hauser, 1993; Presley et al., 2000; Chan and Wu, 2002a; Xie et al., 2003). As with any other tools, QFD also has some limitations apart from its benefits. It is

limited in the sense that it is more effective for developing *incremental* products as opposed to *really* new products (Griffin, 1992). It is also found that the QFD's use might be a bit burdensome due to the incredibly big matrices (Den Ouden, 2006). Furthermore, a quite recent empirical study also found that QFD does not shorten time-to-market (Lager, 2005).

Nevertheless, taking into account its limitations, QFD does still provide a more systematic and effective approach to create higher customer satisfaction by bringing a product or service that the customer wants. In essence, QFD starts and ends with the customer. By employing QFD, everyone involved in every stage of product or service creation process may be able to see how the job one is doing can contribute to the chief end goal, namely, to meet or exceed the end customer's needs. Such mechanism is a good way to make sure that the products will eventually sell.

One important key factor for successful application of QFD is the accuracy of the main input information, namely, the Voice of Customer (VOC) (Cristiano et al., 2001). It is known that it always takes some time from the time when the customer's voice is collected until the time when the product is ready to be launched, as shown in Figure 1.1.

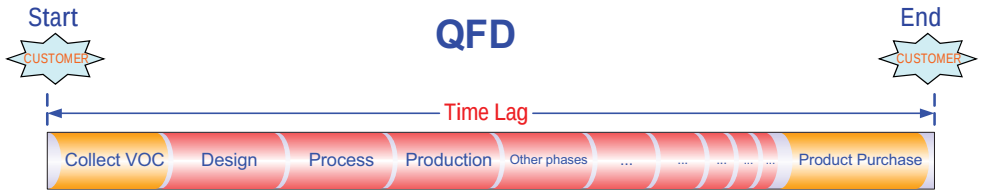


Figure 1.1 Time-lag problem when using QFD

The time-lag duration may certainly vary from one product to another. For example, if it takes one year time, then the question is whether the product which is about to be launched may still meet the customer's needs since it is created based on the customer

voice which was collected one year ago. The answer to this question is very likely to be a 'no' in the context of today's rapidly changing market. This, at the same time, assumes that the rate of change is *shorter than or the same as* the length of product or service creation time, for example, the rate of change is yearly and the product or service creation time is one year or longer.

In the existing QFD literature, there has been too little research devoted into dealing with the change of customer's needs *during* product or service creation process. What have been done in the literature to tackle such change is to use two types of approaches, namely, sensitivity analysis (Xie et al., 1998) and forecasting techniques (Shen et al., 2001; Xie et al., 2003; Wu et al., 2005; Wu and Shieh, 2006). Considering the development of QFD research in recent years, particularly the increasingly extensive research on the use of the Analytic Hierarchy Process (AHP)[1] in the QFD (Carnevalli and Miguel, 2008; Ho, 2008), those approaches might no longer be effective. Furthermore, almost all of the previous approaches, which employ forecasting techniques, only rely on a single point estimate of forecast.

This thesis is written based on a collection of the author's scientific journal publications (see Appendix E) which attempts to provide further studies on the methods or approaches in QFD with respect to the dynamics of QFD's input information during product or service creation process. Specifically, the focus is placed on the two elements in the house of quality (Figure 1.2), namely, the customer's voice (left wing) and the competitive benchmarking information (right wing). Those two parts are most likely

[1] In 2007, the inventor of AHP (Thomas L. Saaty) was awarded the *Akao Prize* for the remarkable contribution of AHP in QFD (http://www.qfdi.org/who_is_qfdi/akao_prize.html)

subject to change over time since they are obtained externally from the customer's judgment or assessment.

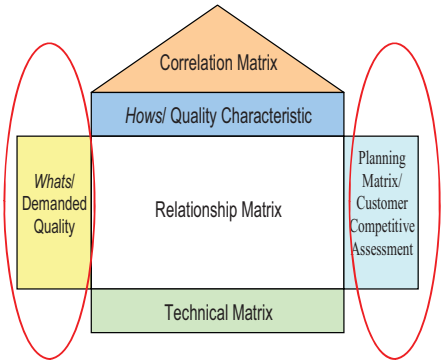


Figure 1.2 Dynamics in the House of Quality

The entire research works are divided into three focal parts, namely, the further use of AHP in QFD, the incorporation of AHP-based priorities' dynamics in QFD, and decision making analysis with respect to the dynamics. Note that the term 'dynamic' is interpreted as the change over time throughout the thesis (see Section 1.5). It is worth highlighting that the dynamics that this thesis discusses is the change of *relative* priorities, which are obtained using the AHP, over time. The word '*relative*' here implies that the priorities are dependent on a certain condition set by the people at a certain place and time. In other words, those priorities will definitely *not* remain exactly the same at all time.

An illustrative example of how the *relative* priorities of three different customer-needs or demanded qualities (DQs) change during eight periods is shown in Figure 1.3. The w_1, w_2, w_3, respectively denote the relative weights (priorities) of DQ_1, DQ_2, and DQ_3. The priorities of the needs may reflect the relative importance or customer's preference of the needs. Note that the three DQs themselves have *already existed* from the beginning of the analysis. The only change is their *relative* priorities or importance over time. In addition, the sum of the priorities of the three DQs for every period is always one (100%).

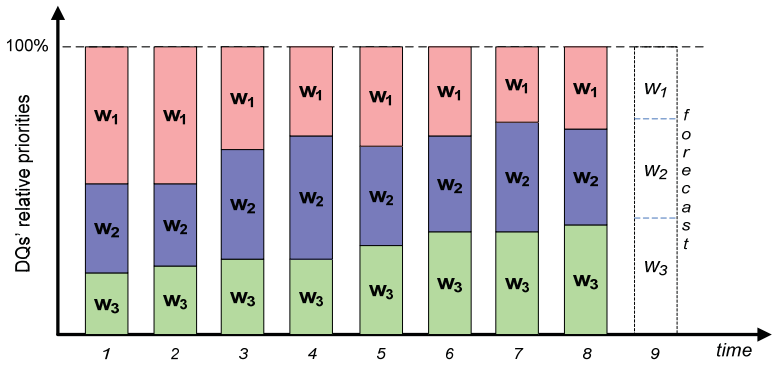


Figure 1.3 Illustration for customer's needs' relative priorities dynamics

1.2 Research Question

Reflecting upon the existing QFD literature and the problem described in Section 1.1, the following main research question is formulated:

Main research question: *How to enhance the current QFD methodology and analysis, especially when the AHP is used in QFD, with respect to the dynamics during product or service creation process as to continually meet or exceed the needs of the customer?*

To answer the above question, three more specific sub-questions are formulated with respect to the current use of AHP in QFD, the incorporation of AHP-based dynamics into the house of quality (HoQ), and how to make decision with respect to such dynamics.

Sub-question 1: *In what ways does AHP, considering its strength and weakness, contribute to an improved QFD analysis?* The AHP has been widely accepted as a realistic, flexible, simple, and yet mathematically rigorous modeling technique in multiple criteria decision making (MCDM) field. A recent survey found that the growth of AHP-related publications has been enormous during the last three decades (Wallenius et al., 2008). However, as with any other tool, the AHP is also plagued with shortcomings, such as, the rank reversal phenomenon and the exponentially growing number of pairwise comparisons as the number of alternatives being compared gets larger (Raharjo and Endah,

2006; Wang et al.,1998). Considering its strength and weakness, this thesis will attempt to answer the above question by not only explaining the ways AHP may contribute to an improved QFD analysis, but also providing a better or generalized use of AHP in QFD.

Sub-question 2: *How to use the AHP in QFD in dealing with the dynamics of priorities?* The QFD-AHP combination is found to be one of the most popular tools in the QFD and/or integrated AHP literature in recent years (Ho, 2008; Carnevalli and Miguel, 2008). The term 'integrated AHP' is used to refer to other techniques used in combination with the AHP (Ho, 2008). Most researchers use the AHP to derive the relative importance of customer's needs (Armacost et al., 1994; Lu et al., 1994; Park and Kim, 1998; Köksal and Eğitman, 1998; Zakarian and Kusiak, 1999; Kwong and Bai, 2003; Raharjo et al., 2007, 2008; Li et al., 2009). Unfortunately, there is almost no study that deals with the dynamics of AHP-based priorities.

Sub-question 3: *How to make decision in a QFD analysis with respect to the dynamics in the house of quality?* This question is a continuation of sub-question 2. The focus is on how to make decision, with respect to the change of AHP-based priorities in the HoQ during products or service creation process, as to continually meet or exceed the needs of the customer. This question may be divided into two smaller questions. One is how to use the priorities' dynamics modeling results as the input of the decision model, and the other is what kind of decision making models that can be used.

1.3 Objective and Delimitation

In general, the main objective of this thesis is to develop novel methods and/or approaches for enhancing the use of QFD, especially in combination with the AHP, in

dealing with the dynamics *during* product creation process. It is expected that those methods or approaches, in the long run, may increase the possibility to create innovative and competitive products or services. In particular, this thesis aims to achieve the following three specific objectives based on the three research sub-questions:

1. *To demonstrate the usefulness as well as to provide a better use of the AHP in QFD*.
2. *To develop a novel method to model the dynamics of AHP-based priorities in the house of quality*.
3. *To develop methods and/or approaches for decision making with respect to the modeling results as to continually meet or exceed the needs of the customer*.

Delimitation of the first objective: The usefulness and better use of the AHP in QFD is delimited to only the *first* matrix, namely, the house of quality. A real-world case study in education will be used to demonstrate the usefulness, and one empirical example based on interview and questionnaire will be used to show how to use AHP better in QFD.

Delimitation of the second objective: The novel method to model the dynamics of AHP-based priorities in the house of quality is only applied to two parts of the HoQ. One is in the customer-needs' priorities (importance rating part), and the other is in the priorities of competitive assessment of customer's needs (competitive benchmarking part). It is also delimited to the fact that it does *not* include the case of when a new customer need should be added or an old one should be removed along the time, although it may be common in practice. In other words, it only deals with the change of the *relative* priorities over time.

Delimitation of the third objective: The focus is delimited to the translation process and the decision making analysis using the modeling results. With respect to the translation process, it is *not* the objective of this thesis to elaborate how a customer need gets translated into a specific design or technical attribute, but rather how to use the relationship matrix in the HoQ to obtain the priorities of the technical attributes properly. The decision making analysis is delimited to two kinds of optimization model; one employs a utilitarian approach and the other employs a non-utilitarian approach.

1.4 Outline of the thesis

This thesis is comprised of nine chapters. Chapter 1 provides the problem background, research questions, objectives, delimitations, outline, and terminologies used in the thesis. Chapter 2 to Chapter 8 contains the main contributions of the thesis which is derived from the author's scientific publications (Appendix E). Chapter 9 concludes the thesis with the summary of main contributions and possible future research. With respect to the three sub-questions, the chapters are organized as depicted in Figure 1.4.

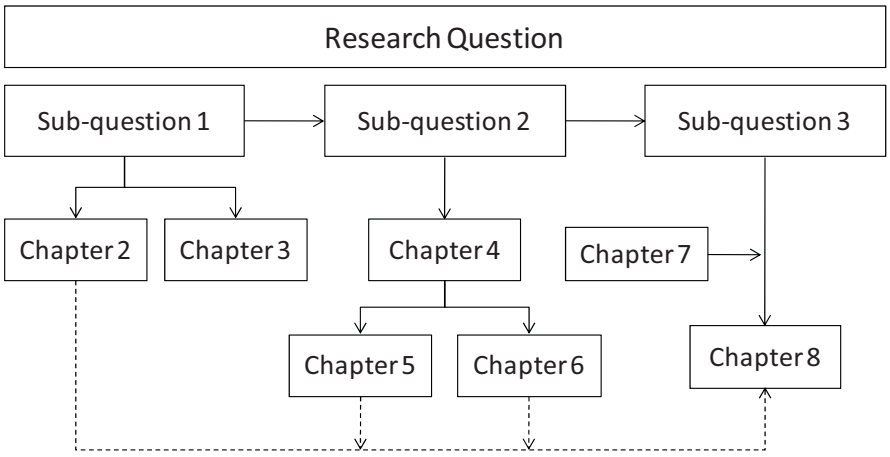


Figure 1.4 Organization of the thesis

Chapter 2 and Chapter 3 will address the first research sub-question that corresponds to the first specific objective. Chapter 2 will discuss the ways AHP may contribute to an improved QFD analysis based on the literature. Then, a real-world case study of QFD application in improving education quality is described. This is to substantiate the usefulness of AHP in QFD. The need to incorporate the dynamics of customer's needs in QFD is also indicated in Chapter 2. Chapter 3 provides a better use of the AHP in QFD via the generalized form of the AHP, namely, the Analytic Network Process (ANP). Finally, a remark on the AHP's shortcoming when the number of alternatives being compared gets larger is provided.

Chapter 4 will address the second research sub-question which corresponds to the second specific objective. A novel technique to model the dynamics of AHP-based priorities is proposed. The proposed modeling technique is applied to two areas as to advance the QFD literature. The first area (Chapter 5) is in enhancing the use of Kano's model in QFD. Based on the recent advancement, a systematic methodology to incorporate Kano's model dynamics in QFD is suggested. The second area (Chapter 6) is in enhancing the benchmarking part of QFD, that is, by including the dynamics of competitors' performance in addition to the dynamics of customer's needs.

Chapter 8 will address the third research sub-question which corresponds to the third specific objective. Before proceeding to the decision making analysis (Chapter 8), Chapter 7 will first discuss an important issue in the relationship matrix. This is owing to the fact that the relationship matrix is almost always used in deriving the technical attributes' priorities, which are the main output of the HoQ. Chapter 8 will propose a systematic methodology, using the case study in Chapter 2, to incorporate the dynamics of DQs' priorities into the decision making analysis in the QFD. Two kinds of approaches are

proposed to prioritize and/or optimize the technical attributes with respect to the future needs of the customer. The results from Chapter 5 and Chapter 6 may also be used in combination with the proposed methodology. A practical implication of the research work towards the possible use of QFD in helping a company develop more innovative products will also be discussed.

Chapter 9 concludes the thesis and provides a summary of the major contributions. Some directions for the extension of the current research are described. It is expected that the entire study in this thesis may provide a first step to better use QFD with respect to the change of customer needs' importance and their competitive assessment during product or service creation process.

1.5 Terminology

This section provides the important terminologies used in this thesis. The purpose here is to provide clearly defined terms and to avoid misinterpretation of the meaning. There are seven important terminologies used throughout this thesis.

- **demanded quality (DQ)** – this term is used to refer to customer's needs, attributes, or requirements. It is also known as the '*Whats*' in the HoQ. In this thesis, this DQ is used interchangeably with the voice of the customer (VOC). Note that the essential different between these two is in the formulation of the language, the VOC is derived from the customer's daily language, while the DQ is more formal or specific**.**
- **quality characteristic (QC)** – this term is used to refer to the design attributes or parameters, or the technical/engineering attributes. It is also known as the '*Hows*' in the HoQ.

- **priority** – this term is used to represent the weight assigned to a specific attribute, for example, the weight of a DQ or a QC. This weight or priority refers to *relative* priority that is obtained from the AHP. It is also used to represent the relative competitive assessment of a DQ.
- **DQ's priority** – In this thesis, this refers to the relative weight assigned to a DQ. It also refers to the importance rating value (IR value) of the DQ.
- **QC's priority –** This refers to the final relative weight of a QC which will usually be used in an optimization framework.
- **dynamics** – this word is used to refer to the change over time. In this thesis there are two types of dynamics. One is the dynamics in the DQs' priorities and the other is the dynamics in the DQs' competitive assessment.
- **QFD team** – This term is used to refer to a number of people from various functional groups who together use QFD. It is also used to refer to QFD users or QFD practitioners.

CHAPTER 2
A FURTHER STUDY ON THE USE OF AHP IN QFD (PART 1 OF 2) – A CASE STUDY

The purpose of this chapter is to provide the first part of a possible answer to the research question "*In what ways does AHP, considering its strength and weakness, contribute to an improved QFD analysis?*" Based on the literature, five reasons that may justify the AHP as an effective tool to derive DQs' priorities are identified (Section 2.1). To further substantiate the contribution of AHP in QFD, a real-world case study demonstrating the usefulness of AHP in QFD for improving higher education quality of an engineering department is provided (Section 2.2). A remark on AHP's shortcoming, when the number of alternatives being compared gets larger, is provided (Section 2.3). Finally, as an implication of the case study, it is concluded that there is a need to anticipate the change of customer's needs over time as to provide a better strategic planning for the education institution. A large part of this chapter is reproduced from the author's two journal papers[1].

2.1 In what ways does AHP contribute to an improved QFD analysis?

Two recent reviews (Ho, 2008; Carnevalli and Miguel, 2008) found that the QFD-AHP combination is one of the most popular tools used in the QFD and/or integrated AHP in recent years. Most of the researchers use the AHP in QFD to obtain the importance rating values of the DQs (Armacost et al., 1994; Lu et al., 1994; Park and Kim, 1998; Köksal and

[1] Raharjo, H., Xie, M., Goh, T.N., Brombacher, A.C. (2007), A Methodology to Improve Higher Education Quality using the Quality Function Deployment and Analytic Hierarchy Process, *Total Quality Management & Business Excellence*, 18(10), 1097-1115.

Raharjo, H., Endah, D. (2006), Evaluating Relationship of Consistency Ratio and Number of Alternatives on Rank Reversal in the AHP, *Quality Engineering*, 18(1), 39-46.

Eğitman, 1998; Zakarian and Kusiak, 1999; Kwong and Bai, 2003; Raharjo et al., 2007; Li et al., 2009).

Based on the literature, it can be concluded that there are at least five reasons that make the AHP an effective way to derive the DQs' priorities.

1. It provides *ratio* scale priorities (Harker and Vargas, 1987). The ratio scale priorities are of great importance to the QFD results due to the fact that only in this type of scale can the QCs' priorities be meaningful (Burke et al., 2002), especially when it is dovetailed with an optimization analysis. Another simple reason for the significance of ratio scale is the computation in the HoQ which involves multiplication operations, in which other type of scale, such as ordinal or interval scale (Stevens, 1946) is not meaningful.
2. It allows the quantified judgments to be tested on their inconsistency, which is not the case when using the traditional way, such as a rating system of 1 to 5 (Lu et al., 1994; Armacost et al., 1994).
3. It avoids 'all things are important' situation. Chuang (2001) found that the traditional way, which employs a set of absolute values, such as 1 to 5, might very likely lead to a tendency for the customers to assign values near to the highest possible scores, and thus result in somewhat arbitrary and inaccurate QCs' priorities.
4. Its internal mechanism allows the subjective knowledge or judgments of the QFD team to be systematically quantified (Raharjo et al., 2008). One example is the use of the AHP's hierarchical structure that corresponds to the use of affinity diagram or tree diagram for structuring the VOC (Raharjo et al., 2007).
5. It provides an exceptional way in effectively facilitating group decision making (Bard and Sousk, 1990; Dyer and Forman, 1992; Zakarian and Kusiak, 1999)

Hence, it is evidently clear that the AHP, according to the literature, can be considered as a beneficial tool in QFD for obtaining DQs' priorities. In the next section, the above five reasons will be empirically substantiated by a case study.

2.2 Using AHP in QFD: An education case study

The objective of this case study is to apply the QFD-AHP approach in a systematic fashion to improve higher education quality in an industrial engineering department. Most of the contents in this section are reproduced from Raharjo et al. (2007). In the following subsections, a literature review on the use of QFD in education will be provided and followed with some existing technical and practical problems which motivated the research (Section 2.2.1). Afterwards, a methodology to systematically use QFD-AHP for improving higher education quality is proposed using a step-by-step procedure and a flowchart (Section 2.2.2). A real-world case study is used to demonstrate the usefulness of the methodology (Section 2.2.3). Based on the results of the case study, a sensitivity analysis is suggested to deal with the dynamics of customer's needs (Section 2.2.4 and Section 2.2.5). Lastly, a brief conclusion and implication of the study is provided (Section 2.4).

2.2.1 QFD's use in education and some problematic areas

Since 1980s, higher education institutions have begun to adopt and apply quality management to the academic domain owing to its success in industry (Grant et al., 2002) and they have also benefited from the application of TQM (Kanji and Tambi, 1999; Owlia and Aspinwall, 1998). QFD, as one of the most useful TQM tools, has also been used

quite extensively in academia. Jaraiedi and Ritz (1994) applied QFD to analyze and improve the quality of the advising and teaching process in an engineering school. Köksal and Eğitman (1998) used QFD to improve industrial engineering education quality at the Middle East Technical University. Lam and Zhao (1998) suggested the use of the QFD and the AHP to identify appropriate teaching techniques and to evaluate their effectiveness in achieving an education objective. Bier and Cornesky (2001) critically analyzed and constructed a higher education curriculum to meet the needs of the customers and accrediting agency using QFD.

Adopting the constructivist's point of view, Chen and Chen (2001) introduced a QFD-based approach to evaluate and select the best-fit textbook based on the VOC. Kauffmann et al. (2002) also used the QFD to select courses and topics that enhance a master of engineering management program effectiveness. They further pointed out the additional benefit of QFD in the academic context, that is, to develop collegial consensus by providing an open and measurable decision process. Brackin (2002) wrote the analogy of the use of QFD in the industry with the assessment of engineering education quality by breaking down the assessment items into a set of WHATs and HOWs following the four phases of QFD. Duffuaa et al. (2003) applied the QFD for designing a basic statistics course. More recently, Sahney et al. (2004, 2006) used the QFD, in combination with SERVQUAL as well as Interpretive Structural Modeling and Path Analysis, to identify a set of minimum design characteristics to meet the needs of the student as an external customer of the educational system. Chen and Yang (2004) explored the possibility to use Internet technology by developing a Web-QFD model. They gave a real-world example of an education system in Taiwan and argued that the Web-QFD may not only provide a more efficient way of using the QFD in terms of cost, time and territory, but also may

facilitate better group decision making process. Aytaç and Deniz (2005) used the QFD to review and evaluate the curriculum of the Tyre Technology Department at the Kocaeli University Köseköy Vocational School of Higher Education.

It is clear that QFD has been extensively used in improving education quality. However, if one takes a closer look at how QFD was implemented in education, one may discover some problematic areas that need improvement. In this section, five major problems will be highlighted. They can be divided into two major categories, namely, the technical problems (the first, the second, and the third problems) and the practical ones (the fourth and the fifth problems).

The first problem is the use of absolute values for DQs' priorities. As pointed out by Chuang (2001), the customers will tend to assign a high degree of importance to most of their requirements, thus resulting in values near the highest possible score. These values will have no significant meaning (Cohen, 1995) and will later produce somewhat arbitrary and inaccurate results for prioritizing QCs. Some examples for using a set of discrete values can be found in Jaraiedi and Ritz (1994), Ermer (1995), Chen and Chen (2001), Kaminski (2004), and Chou (2004). Therefore, *relative* measurement for assessing the importance of customer requirements is suggested as a better alternative.

The second problem is the technique that is used to obtain priorities of a group's preference. Some of the studies simply proposed the use of an arithmetic mean or weighted arithmetic mean for obtaining the preference of the customer group, which seems arbitrary and not robust. This case can be found in Bier and Cornesky (2001), Hwarng and Teo (2001), Duffuaa et al. (2003), Kaminski et al. (2004), or Aytaç and Deniz (2005). A better approach would be to use a geometric mean that also formed the

foundation of a group preference method in the AHP (Ramanathan and Ganesh, 1994; Forman and Peniwati, 1998).

The third problem is the difficulty in identifying a true relationship between DQs and QCs. It seems quite unrealistic if all DQs are related to all QCs so that the QFD relationship matrix will be full blocked. It may imply that the QFD team has difficulty in assigning more discriminating relationship values between them. Examples of this case can be found in Duffuaa et al. (2003) or Lam and Zhao (1998), which used a full blocked relationship matrix.

The fourth problem is that the flexibility in using QFD in education should be enhanced, resting on the assumption that it is not just a "plug-and-play decision machine" (see Govers, 2001). There are two points to highlight. First, the number of matrices does not have to be strictly four (Hauser and Clausing, 1988). Based on the necessity of the deployment process, the QFD team may decide how many matrices or houses to use. An example given by Brackin (2002) to follow the four phases showed the inflexibility. Second, the true VOC should come from the proper and right customers. Several researchers in education do not include the students since they may have unnecessary wants and be considered too immature to judge the content of education. On the other hand, Sa and Saraiva (2001) attempted to include kindergarten children as the customers. This approach seems to be overconfident and risky.

The fifth problem lies in pooling the needs of several different customers into one group. This might possibly lead to a fallacious conclusion since one stakeholder may have a unique need which others may not consider, or even a conflicting need with respect to other customers. An example for this case can be found in Köksal and Eğitman (1998)

which combined three different stakeholders into one. If the number of DQs and QCs is not very large, each customer group may be treated separately using one HoQ.

Therefore, in view of these problems, this section attempts to fill in the gap by providing a better methodology of using AHP and QFD to improve higher education quality. It is hoped that this will help higher education institutions, in general, improve their quality in the future by providing a better education program for their nation.

2.2.2 The proposed methodology

The aim of the methodology is to use the QFD-AHP approach in a more systematic fashion in order to improve higher education quality of an industrial engineering department, taking into account the need to overcome the technical and the practical problems mentioned above. Here, the AHP will be used to obtain relative measurement, obtain group preference, and check the inconsistency of decision makers' judgments. A method proposed by Nakui (1991) was employed to ensure that no superfluous DQs or QCs are included while still maintaining the significant relationships among DQs and QCs. Each of the customers uses a separate HoQ. Note that the number of matrices or houses used can be adjusted according to the need of the deployment process. In the case study, only the first house of quality is used.

A step-by-step approach of the methodology is presented below. This procedure applies for each customer group. A flowchart of the step-by-step procedures can be seen in Figure 2.1.

Step 1. Conduct a pilot survey of customer needs. In other words, this is an in-the-field observation in order to collect the VOC from the true source of information. A variety of methods, such as contextual inquiry, direct observation, focus group,

questionnaires, and so on, can be employed. After the survey, the QFD team should sort out and organize the preliminary results. This will help the QFD team see the big picture of the customers' needs.

Step 2. Conduct one-on-one in-depth interview with the customers. In this step, adopting the Garbage-In-Garbage-Out (GIGO) philosophy, it is very crucial to select some knowledgeable decision makers which are also representative to each of the groups involved. Note that it is important to select the right students to be interviewed in order to avoid unnecessary and self-centered wants.

Step 3. Use affinity diagram to classify or sort out the DQs and construct a hierarchy based on the grouping. The higher the hierarchy, the less the effort to obtain the DQs' priorities. This hierarchy also serves as the AHP hierarchy.

Step 4. Explore each DQ hierarchically by a tree diagram and translate it into an appropriate QC. The QC is defined as the strategy or way to achieve the DQ. One DQ may be related into some QCs, and vice versa.

Step 5. Verify whether the DQs and the respective QCs are valid, otherwise, the QFD team should carry out the interview again.

Step 6. Ask the selected decision makers to make the AHP pairwise comparisons in order to derive the priorities of the DQs. The QFD team may explain to decision makers who are not familiar with the AHP mode of questioning.

Step 7. Obtain group preference using geometric mean approach (Forman and Peniwati, 1998). Then, check whether there is a need to resurvey the decision makers owing to inconsistent judgments. The *Expert Choice* software can be used to obtain the priorities of DQs as well as to do the inconsistency check.

Step 8. Construct the HoQ of each customer group. The minimum set of constructing the HoQ should exist, such as the DQs and their priorities, the QCs and their priorities. Other components (e.g. the roof, competitive assessment) might be added as necessary. The *Microsoft-Excel* software would be a good alternative to do the HoQ analysis.

Step 9. Verify the completed HoQ components. Some rules to check the relationship matrix as proposed by Nakui (1991) can be used. For example, if a DQ has no corresponding QC at all, then this DQ should be taken away.

Step 10. Compute the QCs' priorities, and obtain their rankings. The QFD team may evaluate whether there is a need to extend the deployment process by using another matrix or house. If there is a need to use another matrix, a similar process can again be conducted (Step 8).

Step 11. Conduct sensitivity analysis to provide a sense of how robust is the decision made by the QFD team if there is a change in the input data. This is also useful to anticipate future needs of customer and variability in the DQs.

Step 12. Other downstream analysis, such as gap analysis, SWOT analysis, and so forth, can be added accordingly.

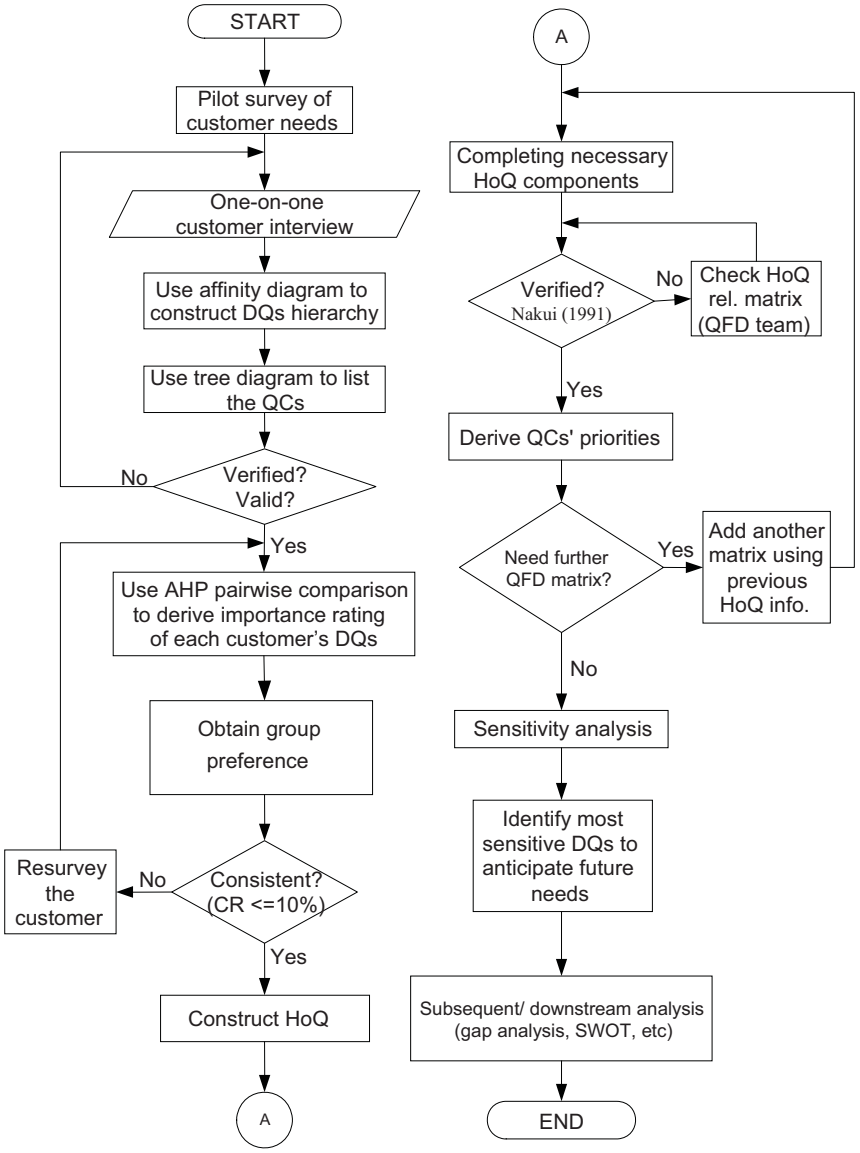


Figure 2.1 The proposed methodology of using AHP in QFD

2.2.3 The research design

The case study was carried out as a final year project at the department. The customers of the department are divided into two major groups, namely, the internal (lecturers and students) and the external customer (employers of the graduates). The data collected from the students' group comprised of several representative students from each

academic year who were still studying in the university. The students' representatives have a minimum GPA of 3.0 out of 4.0. A number of employers of the graduates were interviewed using questionnaires with the help of the graduates themselves.

Since there were relatively a small number of lecturers in the department, the interviews were carried out on a one-on-one basis in two rounds. The first round was to interview them on what they need while working at the education institution. The second round was to use the AHP's questionnaire to prioritize their needs. The translation of the DQs into possible ways to achieve them (QCs) was done by the student with the help of the department, including the author of this thesis who was working as a lecturer at that time.

The DQs' priorities are calculated through pairwise comparison questionnaires given to every decision maker. Owing to the quite large number of DQs, the comparisons will be rather tedious. Therefore, clustering is used to reduce the number of comparisons. The DQs are classified into primary DQ group and secondary DQ group using the affinity diagram approach; as an example, the complete students' group hierarchy is shown in Figure 2.2. This affinity diagram is analogous to the method of clustering and will later help reduce the number of pairwise comparisons in the AHP. In other words, increasing the level of hierarchy can minimize the workload of using the AHP (Armacost et al., 1994).

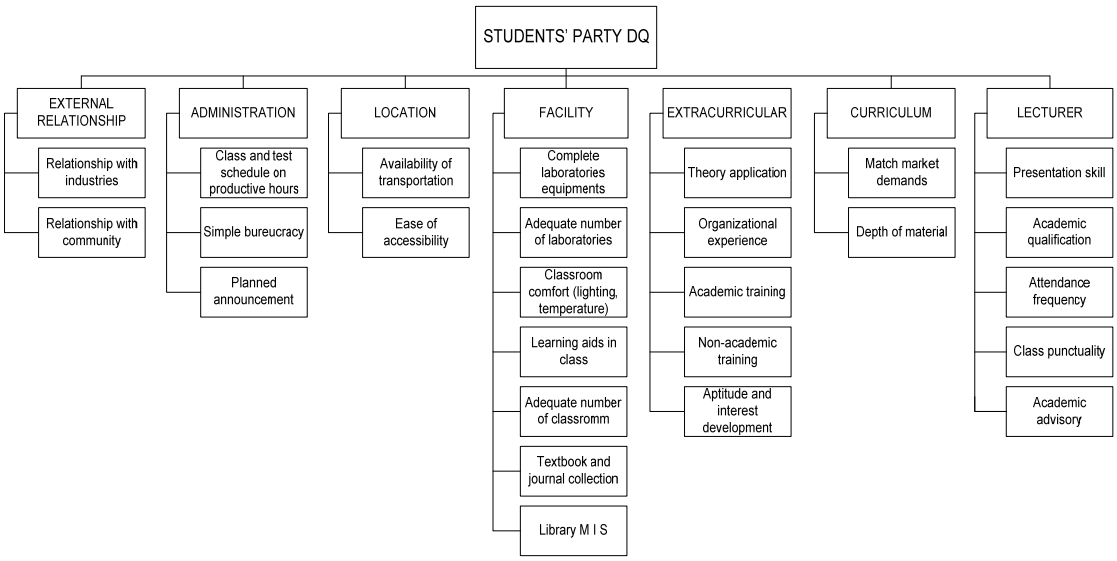


Figure 2.2 An example of students' group hierarchy

2.2.4 The results

The results are three houses of quality for each group, namely, the students' group, the lecturers' group, and the employers of graduates' group. Some samples of the HoQ charts that were produced are shown in Figure 2.3, Figure 2.4, and Figure 2.5. The alternative solutions or QCs for each customer group were derived from their respective HoQ. Note that the roof, although it might be useful, was not used in this case.

The houses of quality are of great value to the department since they now know clearly, from each group of customers, what is the most important, second most important, third, and so forth. More importantly, the HoQs also provide a set of strategies for the department to improve the education quality which is ranked by its relative priorities.

Demanded Qualities		Importance Rating	Arrange presentation skill training	Provide further education for lecturers	Provide scholarships	Develop clearer policy of working hours	Establish warning system	Provide better consultation procedure	Obtain feedback from employers	Conduct market need's survey	Obtain feedback from students	Conduct more factory visits	Seek for sponsorship	Provide development funds from university	Add new laboratories	Provide AC, lamps, and ventilation	Provide OHP, whiteboard, etc	Provide more classrooms	Buy high-quality books	Cooperate with book publishers	Improve library MIS system
Lecturer	Presentation skill	0.072	9								7										
	Academic qualification	0.015		9	9								5	7							
	Attendance frequency	0.021				9	9														
	Class punctuality	0.020				9	7														
	Academic advisory	0.024						9													
Curriculum	Match market demands	0.122							9	9		7									
	Depth of material	0.081							5	9	3	3									
Facilities	Complete laboratories equipments	0.033							5	3	5	3	9	9							
	Adequate number of laboratories	0.023											3	9	9						
	Classroom comfort (lighting, temp)	0.032											1	7		9					
	Learning aids in class	0.030											1	7	9		9				
	Adequate number of classrooms	0.020											1	9				9			
	Textbook and journal collection	0.039											1	9					9	7	
	User-friendly library information system	0.020											1	9							7

Figure 2.3 Trimmed part of HoQ for students' group

Demanded Qualities		Importance Rating	Provide research fund	Increase the number of physical facilities	Seek for sponsorship	Purchase high-quality books	Cooperate with book publishers	Improve internet lines	Add more internet lines	Provide OHP, whiteboard, transparencies, etc	Provide master / doctoral degree scholarship	Hold seminars and training for lecturers	Explain the procedure of obtaining funds	Explain the procedure of organizing academic events	Provide AC, good lighting, ventilation	Divide big classes into smaller ones	Determine the policy of max/min # of students/class	Arrange recreation semester-wise
Facilities	Research grant	0.023	9		5								7					
	Availability of physical facilities	0.019		9	3					5			7					
	Textbook and journal collection	0.110			5	9	7						7					
	Complete laboratories equipments	0.054			3					1			9					
	Fast internet connection	0.059			1			9	7				7					
	Class learning aids	0.028			1					9			3					
	Academic programme	0.056	9		1	7					9			7				
	Self-development programme	0.030			5							9		7				
Working atmosphere	Classroom comfort	0.094													9			
	Smaller number of students/class	0.211														9	9	
	Social gathering among lecturers	0.061																9

Figure 2.4 Trimmed part of HoQ for lecturers' group

DEMANDED QUALITIES / QUALITY CHARACTERISTICS		Importance Rating	Give additional courses	Teach more mostly-used comp. programs	Provide foreign language classes	Intensify discussion and presentations	Provide ethics and religion courses	Give more team assignments	Leadership training	Get involved in committee-activities	Make more reasoning problems	Give assignment with time limitation	EQ training	Invite guest lecturers from industries
Academic qualification	Above average GPA	0.025	9	7	5	9		7			9	9		
	Computer literacy	0.038		9	1									
	Foreign language skill	0.056			9									
Leadership skill	Initiative	0.072				9		7	5	7				
	Team work	0.105				5		9	7	9				
	Able to manage subordinates	0.090						9	9	7				
Interpersonal skill	Communication skill	0.070				9		7	7	7				
	Personality	0.068					9		9	7				
	Responsibility	0.149						9	9	9				
	Loyality	0.048					1	9	5					
	Honesty	0.136					9						7	
Problem solving skill	Creativity	0.031									9	7		
	Adaptability	0.058										9		9
	Critical and analytical thinking	0.054				9							1	1
QCs' absolute priorities			0.221	0.514	0.668	2.515	1.883	4.693	4.592	4.391	0.500	0.958	1.004	0.574
QCs' relative priorities			0.010	0.023	0.030	0.112	0.084	0.208	0.204	0.195	0.022	0.043	0.045	0.026
Rank			12	10	8	4	5	1	2	3	11	7	6	9

Figure 2.5 Complete HoQ for employers' group

For example, based on the level of importance, the attribute that matters most to the employers of the graduates was the 'interpersonal skill' of which the subgroups, consecutively from the highest level of importance, were 'responsibility', 'honesty', 'communication skill', 'personality', and 'loyalty'. While the primary alternative solutions for the employers' group, namely, the QCs which have high ranks were 'to give more team assignment' and 'leadership training', 'get involved in committee activities', and

'intensify discussion and presentation'. For the other groups, similar analysis was done accordingly.

2.2.5 Sensitivity analysis

The objective of the sensitivity analysis is to anticipate the change of customer's needs, in terms of their weights, over time. There are two cases to be analyzed for each customer group. The first case (Case I) is to assign equal weights to each primary DQ, which implies the situation when all attributes are equally important. The second case (Case II) is when one particular primary DQ outweighs the rest of the other requirements, which implies the situation when one specific skill is highly needed. An example for employers' group DQs' priorities change is shown in Table 2.1.

Table 2.1 DQs' priorities change for employers' group sensitivity analysis

	Academic qualification	*Leadership skill*	*Interpersonal skill*	*Prob.solving skill*
Case I	0.25	0.25	0.25	0.25
Case II	0.05	0.85	0.05	0.05

As a result of such change, the QCs' priorities, which reflect the priority order of the education institution's strategies, change as well. This can be observed by the reversal in the QCs' ranks from the HoQ. As an example, for employers' group, the initial alternative solutions, consecutively from the most important QCs, were 'to give more team assignment', 'arrange leadership training', 'get involved in committee activities', and so on. For Case I, a few of the QCs' ranks were reversed, while in Case II the priority reversal occurred more often, as shown in Table 2.2.

Table 2.2 QCs' ranks change for employer's group

Rk.	Initial	Rk.	Case I	Rk.	Case II
1	Give more team assignments	1	Give more team assignments	1	Give more team assignments
2	Leadership training	2	Leadership training	2	Get involved in committee activities
3	Get involved in committee activities	3	Get involved in committee activities	3	Leadership training
4	Intensify discussion and presentations	4	Intensify discussion and presentations	4	Intensify discussion and presentations
5	Provide ethics and religion courses	5	Give assignment with time limitation	5	Give assignment with time limitation
6	EQ training	6	Provide foreign language classes	6	Provide foreign language classes
7	Give assignment with time limitation	7	Teach more mostly-used comp.prog	7	Teach more mostly-used comp.prog
8	Provide foreign language classes	8	Invite guest lecturers from industries	8	Invite guest lecturers from industries
9	Invite guest lecturers from industries	9	Provide ethics and religion courses	9	Provide ethics and religion courses
10	Teach more mostly-used comp.prog	10	Make more reasoning problems	10	Make more reasoning problems
11	Make more reasoning problems	11	EQ training	11	EQ training
12	Give additional courses	12	Give additional courses	12	Give additional courses

The impact of changing the DQs' priorities, as to anticipate possible changes of customers' interest over time, has provided an insight into the alteration of the QCs' priorities, that is, the prioritization of the strategies. In other words, it is evident that the change of DQs' priorities may affect the final output of the QFD or the formulation of the education institution's strategic planning.

2.3 A remark on AHP's shortcoming

The previous sections have demonstrated the significance of AHP in QFD through literature review (Section 2.1) and a case study (Section 2.2). As with any other tools, the AHP, when used in QFD, is also plagued with weaknesses. There are at least two noteworthy weaknesses. First, it is the exponentially growing number of pairwise comparisons as the number of alternatives being compared gets larger (Wang et al., 1998). This weakness might be justified if a substantial amount of risk, including financial risk, is involved (Shang et al., 2004). Second, it is the possibility of rank reversal. This second weakness has received a lot of attentions from the academia (Raharjo and Endah, 2006).

Through a series of computer experiments and simulations, the author found that the probability of rank reversal may get higher as the number of alternative and/or the inconsistency of the decision gets larger. The detailed research methodology used in the experiments can be found in Raharjo and Endah (2006). This finding is relevant to this thesis since the use of AHP in QFD often involves a lot of alternatives, which is usually reflected by the relatively large house of quality. This means that the chance of a rank reversal to occur is indeed very high, especially when there is an alternative added or deleted. Such case has, unfortunately, not been fully explored in this thesis and might be an interesting study in the future.

2.4 Conclusion and implication

The aim of this chapter was to answer the question "*In what ways does AHP, considering its strength and weakness, contribute to an improved QFD analysis?*" Based on the literature, five reasons on the AHP's contribution towards an improved QFD analysis are identified. To further substantiate the contribution of AHP in QFD, a real-world case study demonstrating the usefulness of AHP in QFD for improving higher education quality of an engineering department has been provided. The case study also empirically supports the five reasons since all of them were experienced while conducting the study. Additionally, a remark on AHP's shortcoming, when the number of alternatives being compared gets larger, is also provided.

Some points to highlight in improving the use of the QFD in higher education, which have been discussed in this study, are:

- It is important to use a *relative* measurement rather than a set of absolute values for representing the importance rating values of DQs in QFD, and the AHP can be considered as a beneficial tool to serve this purpose.
- A considerable attention should be paid to obtain a group preference. Using a geometric mean would generally be better compared to using arithmetic mean in the case where the group acts synergistically towards a common goal. A further treatment on this issue can be found in Chapter 3 (Section 3.4.5).
- A careful check should be conducted to identify the true relationship between the DQs and QCs in order to give a useful result. The QFD can be tailored to suit the particular need of the users, for example, in determining how many house of quality to use. In addition, for each customer, this study suggests that there should be one corresponding QFD analysis.

For the case study, it can be concluded that endeavors that the higher education institution should take as a main priority were to develop overall facility, reevaluate existing curriculum, reduce unnecessary bureaucracy, improve lecturers' qualification, and provide more leadership/team training. Furthermore, in order to design effective and efficient strategies, other subsequent/downstream analysis can be added, such as the gap analysis, Strengths-Weaknesses-Opportunity-Threat (SWOT) analysis, optimization, and so forth. An example of a downstream analysis, that is, to further use the relative QCs' priorities which are in ratio scale as a basis for decision making, will be explained in Chapter 8.

Alternative solutions (QCs) that are generated from the HoQ depend fully on level of importance of the customer requirements (DQs). As shown in the sensitivity analysis, changes in the DQs' priorities may alter the priority order of the QCs; it may therefore affect the education institution's strategic planning. Such analysis is useful in the sense that it may enable the education institution to be alert, proactive, and forward thinking towards the dynamics of customer's needs.

Referring back to the research problem (Section 1.1), it may now be rather clear that unless the change of DQs' priorities over time, that is, during product or service creation process, is systematically anticipated, it is quite likely that the QFD team may end up with misleading strategies if they rely on the past voice of the customer, that is, the priorities collected at the start of the QFD's use. In other words, it may be concluded that there is a need to anticipate the change of customer's needs, in terms of their weights, over time as to provide a better strategic planning for the institution. In the next section, a further use of AHP in QFD will be proposed via a generalized model.

CHAPTER 3
A FURTHER STUDY ON THE USE OF AHP IN QFD (PART 2 OF 2) – A GENERALIZED MODEL

The purpose of this chapter is to provide the second part of a possible answer to the research question "*In what ways does AHP, considering its strength and weakness, contribute to an improved QFD analysis?*" Chapter 2 has described the first part of the answer. To further show the AHP's contribution in QFD, a generalized model is proposed. The objective is to provide a more generic framework for QFD users to systematically analyze and accurately quantify the subjective judgment, experience, and knowledge of the design team. The advantage of the model is two-fold. First, it provides an alternative way to construct the HoQ since all the elements are represented in the model. Second, it provides more flexibility to take other relevant factors, such as the new product development risk, into account when deriving the QCs' priorities. This chapter is reproduced from "Dealing with Subjectivity in Early Product Design Phase: A Systematic Approach to Exploit QFD Potentials", by Raharjo H, Brombacher AC, Xie M. 2008. Published in *Computers and Industrial Engineering*.

3.1 Introduction

Since the focus of the QFD is on the early phase of products or services design process, most of the input parameters are therefore highly subjective in nature (Xie et al., 2003; Kim et al., 2007). Based on the survey results over 400 companies in the U.S. and Japan, Cristiano et al. (2000) showed that the QFD analysis may only require a simple and practical decision aid based upon the experience and judgment of the team. This is mainly

attributed to the fact that the QFD was born out of an industry need for ensuring design quality. Hence, the accuracy level of these subjective experience and judgment will significantly determine the quality of the QFD results.

In view of this, a method or approach that is capable to systematically analyze and accurately quantify those subjective experience and judgments of the QFD team is highly required. In the literature, the Analytic Hierarchy Process (Saaty, 1983, 1994), of which generalized form is called the Analytic Network Process (Saaty, 1996), is known as one of the most powerful management science tools to serve this purpose. The AHP/ANP has been widely accepted as a realistic, flexible, simple, and yet mathematically rigorous modeling technique in multiple criteria decision making field (Saaty, 1986; Liberatore, 1987; Sarkis and Sundarraj, 2006; Vaidya and Kumar, 2006). The AHP/ANP framework can be considered as a powerful and necessary tool for making any strategic decision since it is capable of taking into consideration multiple dimensions of information from multi-party, either qualitative or quantitative, into the analysis (Dyer and Forman, 1992; Meade and Sarkis, 1998; Meade and Presley, 2002).

In using the AHP in new product development field, Calantone et al. (1999) wrote that "*the AHP helps managers make more rational decisions by structuring the decision as they see it and then fully considering all of the information*". In other words, the AHP/ANP effectively facilitates managers in quantifying their subjective judgments, experience, and knowledge of the complex system in an intuitive and natural way (Mustafa and Al-Bahar, 1991; Dey, 2004) by systematically taking into account all the relevant factors and their relative effects as well as interactions simultaneously.

As discussed in Chapter 2, the AHP has been used to derive DQs' priorities in QFD (Armacost et al., 1994; Lu et al., 1994; Park and Kim, 1998; Köksal and Eğitman, 1998;

Zakarian and Kusiak, 1999; Kwong and Bai, 2003; Raharjo et al., 2007; Li et al., 2009). More recently, the use of the generalized form of AHP, namely, the ANP has been growing considerably due to its very exceptional strength in addressing the inner-relationship and interrelationship among the HoQ's components (see Karsak et al., 2002; Büyüközkan et al., 2004; Ertay et al., 2005; Kahraman et al., 2006; Partovi, 2006, 2007; Pal et al., 2007).

The use of ANP in QFD, in general, can be categorized into two types. The first type, of which model has been used by quite many researchers (Karsak et al., 2002; Büyüközkan et al., 2004; Ertay et al., 2005; Kahraman et al., 2006; Pal et al., 2007), is mainly based on the network model described in Saaty and Takizawa (1986). Compared to the recent development of the ANP method, it might be considered as rather preliminary (see Section 3.2.2). While the second type, which can be considered as a better advancement of the use of ANP in QFD, employs the network model proposed recently by Partovi (Partovi, 2006, 2007). However, the model is still rather restricted in the sense that it uses ANP in addressing only two elements of HoQ, namely, the relationship matrix and the correlation matrix (the roof of HoQ).

To fill in the niche of using ANP in QFD more effectively, a generic network model, which serves as a generalized model from the previous research work, is proposed in this chapter. Specifically, it takes into account the product design risk, competitors' benchmarking information, and feedback information among the factors involved. It is hoped that by using the proposed network model, the accuracy of the QFD results can be further enhanced. In other words, by providing an effective way of quantifying and analyzing QFD team's subjective experience, knowledge, and judgments systematically,

the proposed model enables QFD practitioners to exploit more potentials of QFD as a useful early product or service design tool.

In the next section (Section 3.2), a brief review of the AHP/ANP and its use in QFD will first be provided. Section 3.3 describes the significance of some factors that are selected to be included in the proposed network model. Then, the proposed network model, which is the key contribution, is elaborated in Section 3.4. To give some practical insights when using the proposed network model, an illustrative example was developed (Section 3.5). The illustrative example is provided to show how the proposed ANP model works in practice. It is important to note that this is *neither* a full case study of ANP-QFD application that results in a real product *nor* a part of a company's work. The main purpose here is rather to show how the model may work within *realistic* setting. Finally, a discussion of the proposed method as well as possible future work will be described in Section 3.6.

3.2 The ANP and its use in QFD

3.2.1 The ANP and the AHP

In dealing with large-scale strategic decisions with a high level of complexity, the AHP has been accepted as one of the most important tools to systematically quantify the subjective judgment of the decision makers (Zahedi, 1986; Bard and Sousk, 1990; Rajasekera, 1990; Melachrinoudis and Rice, 1991; Mustafa and Al-Bahar, 1991; Suh et al., 1994; Goh et al., 1998; Greiner et al., 2003; Dey, 2004; Wang et al., 2005; Vaidya and Kumar, 2006). The generalization of the AHP, which is the ANP (Saaty, 1996), has received an increasingly high attention recently (Meade and Sarkis, 1998; Meade and

Presley, 2002; Karsak et al., 2002; Shang et al., 2004; Kahraman et al., 2006; Sarkis and Sundarraj, 2006).

The difference between AHP and ANP, in general, can be summarized in Table 3.1. According to Shang et al. (2004), the ANP model, from a practical point of view, provides practitioners with a generic model capable of being modified or enhanced, and yet accountable, while from a research point of view, it gives researchers a novel methodology for tackling strategic, tactical or operational decisions.

Table 3.1 Difference between AHP and ANP

Aspect	AHP	ANP
Structure	Unidirectional	Multidirectional
Type of relation	Hierarchical	Network
Nature of relationship	Linear	Non-linear
Nature of problem	Simple	Complex
Environment	Static	Dynamic
Feedback	No	Yes

3.2.2 Existing ANP's use in QFD and its limitations

Recently, the trend of ANP increased use in QFD, as to overcome the limitation in the use of AHP, has been remarkable. Some examples of the ANP's use in QFD can be found in Karsak et al. (2002), Büyüközkan et al. (2004), Ertay et al. (2005), Kahraman et al., (2006), Partovi (2006, 2007), and Pal et al. (2007). As mentioned previously, throughout all the use of ANP in QFD, they can be categorized into two types.

The first type, of which examples can be found in Karsak et al. (2002), Büyüközkan et al. (2004), Ertay et al. (2005), Kahraman et al. (2006), and Pal et al. (2007), basically employs the network model described in Saaty and Takizawa (1986). However, compared

to the recent development of the ANP method, it is rather preliminary. There are two limitations worth highlighting for this network model. First, it is the fact that it only considers two clusters, which implies that the QFD team may only study the interrelationship or inner-relationship among DQs and QCs irrespective of other relevant important factors in the QFD itself, such as the competitive benchmarking information. Moreover, there is no consideration of feedback information, which is one important characteristic that clearly distinguishes ANP from AHP. In other words, the model proposed is rather of restrictive form. Second, it is the computation which uses simple matrix multiplications rather than the limit supermatrix approach (Saaty, 1996; Saaty and Vargas, 1998). This implies that the approach may not be generalized easily.

The second type rests on the analytical model that was developed by Partovi (2006, 2007). It is argued that this framework adds quantitative precision to an otherwise *ad hoc* decision making process. However, the use of the ANP in Partovi (2006, 2007) is still rather limited, in the sense that it only addresses the relationship matrix and the correlation matrix (the roof of HoQ). Furthermore, the use of the market segments as the first input in the network model might make this approach rather difficult to be generalized since not all QFD study may have such input. On the other hand, a fuller use of the ANP to deal with the subjectivity inherent in the other elements of HoQ, such as the DQs or the competitive benchmarking information, might further enhance the accuracy of the QFD results.

In view of these facts, this chapter proposes a more effective use of ANP in QFD using a generic framework that is versatile enough to be customized for a particular firm. Apart from taking into account the feedback information, it also considers the competitors' benchmarking information for the DQs and QCs as well as the new product development risk. The proposed network model may also be regarded as a generalized

network model for the existing ANP model in QFD. It is hoped that the proposed network model, by employing a systematic and effective approach for eliciting the team's judgments, may give more accurate information of the inner-relationship or interrelationship among the factors that may be crucial to the QFD team's success.

3.3 Some important factors in product design using QFD

This section provides some background of the three important factors that are suggested to be used in the proposed network model in Section 3.4, those are, the new product development risk, the benchmarking information, and the feedback information consideration.

3.3.1 New product development (NPD) risk

The success of product innovation or new product development is necessarily related to the ability of a firm to identify and manage the prevalent risks at the early stage of product development (Keizer et al., 2002, 2005). Generally, risks are by nature subjective and usually managed through a team effort, therefore the AHP/ANP can be regarded as one of the most appropriate approaches to quantify, predict, analyze, and develop strategies to better manage them (Dey, 2004). With regard to a risk management problem, Mustafa and Al-Bahar (1991) wrote that the AHP is useful in documenting, communicating an explicit, common, and shared understanding of risk, and thus become a living picture of the management's understanding of the risk involved.

Based on the work of Keizer et al. (2005) in providing an integral perspective on NPD risk for supporting the success of breakthrough innovation projects, three risk categories,

within the ten most frequently perceived risk issues in the study, are suggested for inclusion in the proposed network model. The three risk categories are 'the consumer acceptance and marketing risk', 'the supply chain risk', and 'the technology risk'. Each of these risk categories comprises of many other types of risk, which will be described in the next subsections. Note that these suggested risks are neither complete nor exhaustive. Other relevant risk suitable to a particular firm or design process can be added accordingly using the risk reference framework (RRF) proposed in Keizer et al. (2005).

A. *Consumer Acceptance and Marketing Risk*

This category may include the risk of consumers' conviction that they get value for money, product's appeal to generally accepted values, product easy-in-use advantages, fit of new product with consumer habits and/or user conditions, product offering additional enjoyment, and so forth. For the sake of simplicity in using the generic network model, this consumer acceptance and marketing risk may be associated with one or more detailed risk elements mentioned above. Note that, in the study reported by Keizer et al. (2005), this type of risk ranked in the first place as the most frequently perceived risk issue.

More importantly, it is worth highlighting that most of the elements in this category are closely related with users' or consumers' expectation problem. In fact, this type of problem has increasingly become a major source of customer complaints in the recent decades, especially in the consumer electronics industry. Brombacher et al. (2005) showed that the percentage of 'No Fault Found' has been significantly rising over the last two decades. Such complaint (No Fault Found) refers to the situation where the product still meets the technical specification, but is rejected because it does not satisfy the customer's expectation (see Den Ouden et al., 2006; Lu et al., 2007). This situation gives rise to a

newly developed class of product's quality and reliability problem, namely, the 'soft reliability problem' (Den Ouden, 2006; Brombacher et al., 2005)

B. *Supply Chain Risk*

Nowadays, it is virtually impossible for a company to work independently without relying on other companies. In other words, a company has to be able to work interdependently with a network of companies. Minderhoud and Fraser (2005) wrote that it is increasingly common for products to be created by a globally distributed chain involving multiple locations and companies. In other words, the product development processes are getting more globally dispersed. This situation gives rise to more exposure to risk, particularly in the supply chain. Therefore, there is an evident need to proactively manage supply chain risk (Chopra and Sodhi, 2004; Finch, 2004; Tang, 2006). This category may include the risk of constant and predictable product quality, capacity to meet peak demands, reliability of each supplier in delivering according to requirements, long term supply performance, suppliers' readiness to accept modifications, and so forth. With regard to using the proposed network model, this supply chain risk can be associated with a more specific element that is relevant, as explained previously.

C. *Technology Risk*

This risk category may include the product and manufacturing technology risk, for example, the fulfillment of the new products' intended function, the interaction of product in-use with sustaining materials, the components' properties and functions, production's equipment and tools, the production system requirement, and so forth. Including the technology risk in the proposed network model may help QFD team translate

technological advancements into products/services that meet customer needs, which is one of the three levels of uncertainty that characterizes companies operating in rapidly changing markets (Mullins and Sutherland, 1998). Furthermore, in dealing with the complex task of prioritizing technology which involves many subjective criteria and uncertainty, the AHP/ANP has been proven to be effective and practical (Melachrinoudis and Rice, 1991; Suh et al., 1994). In using the proposed network model, this technology risk may likewise be associated to one or more detailed elements described in the risk reference framework (Keizer et al., 2005).

3.3.2 Benchmarking information

A benchmarking process provides insights necessary to effectively pinpoint the critical success factors that set the most successful firms apart from their competitors, or to a greater extent, that separates the winners from the losers (Cooper and Kleinschmidt, 1987, 1995). Korpela and Tuominen (1996) developed an AHP-based decision support system for a continuous logistics benchmarking process to support logistics strategic management. In view of the fact that a benchmarking process is a team effort, they further concluded that the AHP is an effective tool for conducting group sessions in an analytical and systematic manner.

In general, the QFD utilizes benchmarking information in two parts, namely, the customer satisfaction benchmarking and the technical performance benchmarking. According to the benchmarking types classification point of view (Zairi, 1992; Madu and Kuei, 1993; or Camp, 1995), this chapter will only deal with the competitive or external benchmarking, that is to deal with the ‘best-in-class’ competitors in the industry.

3.3.3 Feedback information

A feedback arc in the network model uniquely supplies useful information of the cluster interrelationship, which is not possible in the case of a hierarchy. For example, in the case of the proposed network model, the feedback arc from the QCs to the DQs provides essential information to evaluate the DQs with respect to the QCs, as to complement the counterpart relationship, that is, the relative importance of the QCs with respect to the DQs.

A very simple example to signify the necessity of a feedback arc can be found in Saaty (1996), which is known as the two-bridge problem, "Two bridges, both strong, but the stronger is also uglier, would lead one to choose the strong but ugly one unless the criteria themselves are evaluated in terms of the bridges, and strength receives a smaller value and appearance a larger value because both bridges are strong". In brief, without considering the feedback arc, one may not be able to capture a complete interrelationship of the clusters. In other words, the results' accuracy of the analysis may be doubtful.

3.4 The proposed generalized model

The proposed model, which is based on the ANP, gives a more generic framework for QFD users to systematically analyze and accurately quantify the subjective judgment, experience, and knowledge of the design team. The network model, while taking into account several important factors in new product design phase, such as new product development risk, benchmarking information, and feedback information simultaneously, enables a fuller use of QFD as a customer-driven tool.

In the next subsections, the proposed network model will first be described, and followed with the elaboration of its correspondence to the elements in the HoQ. Then, a step-by-step procedure to use the proposed network model, which is based on the HOQ's elements, is suggested. The types of questions that are used to elicit the QFD team's judgments will be explained subsequently. Finally, some considerations of the group decision making process and the use of fuzzy theory along with the proposed model are discussed.

3.4.1 The model

The proposed network model is shown in Figure 3.1. It consists of five clusters, that is, the Goal, which is to achieve best product design, the demanded quality (DQ), the quality characteristic (QC), the new product development risk (NPD Risk), and the competitors' benchmarking information. Each cluster comprises of several nodes, for example, the DQ cluster has *m* nodes. The arcs used in the network model can be categorized into three main types, namely, the outer dependence arc, the inner-dependence arc, and the feedback arcs.

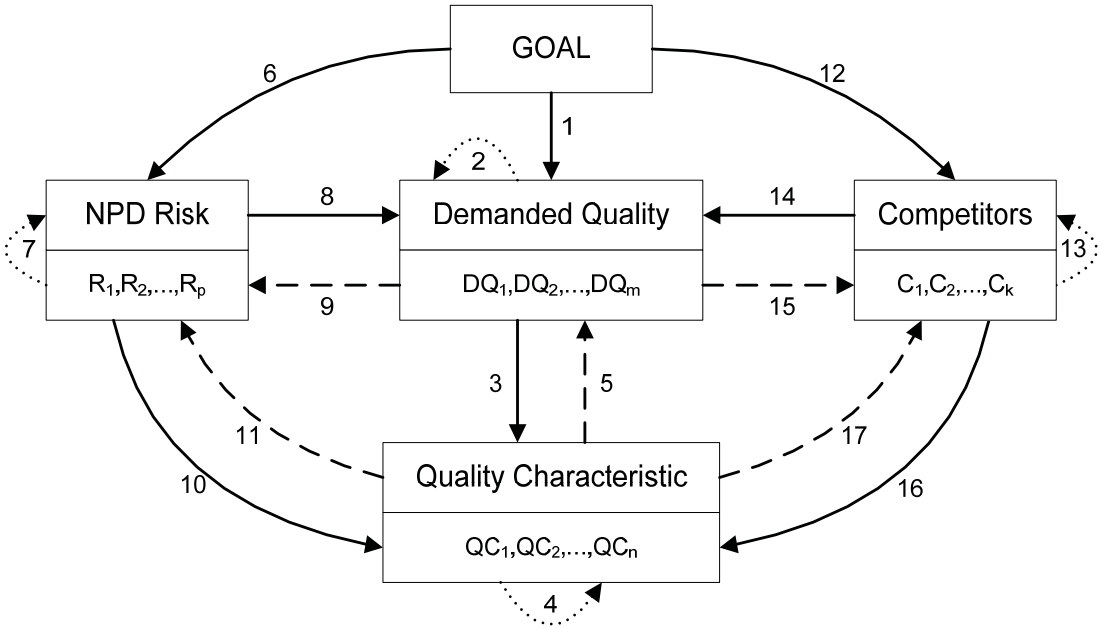


Figure 3.1 The proposed ANP framework for QFD

The outer dependence arcs, which are denoted in arcs number 1, 3, 6, 8, 10, 12, 14, 16 (solid lines) of Figure 3.1, show a dependence condition between the controlling and controlled cluster. A controlling cluster (source) is the cluster from which the arc emanates, while a controlled cluster (sink) is the cluster which the arc points to. The inner-dependence arcs (a loop), which are denoted in arcs number 2, 4, 7, 13 (dotted lines), show a dependence condition among the elements within a cluster. The feedback arc looks similar to the outer dependence arc, but with a reverse direction. In the network model above, it is shown in arc number 5, 9, 11, 15, 17 (dashed lines).

3.4.2 The model and the HoQ's components

It is interesting to see that all of the components in the HoQ, which is the main part of the QFD methodology, can be represented by the most of the arcs described in Figure 3.1. Specifically, the demanded quality (DQ) part or voice of the customer (VOC), which is the most critical determinant of the QFD success (Cristiano et al., 2001), is represented in

arcs 1, 2, 5, 8, and 14. The quality characteristics (QC) part corresponds to arcs 3, 4, 10, and 16. The relationship matrix, which is in the center part of the HoQ, is represented in arcs 3 and arc 5. The DQ's competitive benchmarking information is represented in arc 15, while the QC's competitive benchmarking information is represented in arc 17. Note that arc 14 and arc 16, respectively, corresponds to the competitive target setting stage for the DQ and the QC. Finally, the correlation matrix or the roof of the HoQ, which represents the interrelationship among the QCs, is represented in arc 4.

In dealing with the roof of the HoQ, which is a vital and yet often ignored or oversimplified part in the QFD (Kwong et al., 2007), the proposed network model provides a more effective way in handling the roof matrix correlation values. Unlike the traditional QFD, it offers a more flexible approach in accounting for the inner-relationship among the QCs. More specifically, it eliminates the need to carry out a post-analysis evaluation of the roof matrix correlations values for adjusting the QCs priorities, and at the same time, relaxes the symmetrical assumption of the relationship between the QCs (Partovi, 2006, 2007).

To sum up, it can be said that the proposed network model has addressed all of the most important components in the HoQ. Thus, it provides a better way to exploit the QFD potentials. In other words, by using the proposed network model, QFD users are able to accurately fill in the values of all elements in the HOQ in a more systematic manner. Hence, the accuracy of the result may be significantly improved, particularly with the incorporation of some other important information which is beyond the basic QFD framework, such as the interrelationship among the DQs and the consideration of the NPD risk with respect to a constantly changing environment.

3.4.3 A suggested step-by-step procedure for using the model

After constructing the network model of the design problem, the next step is to elicit the QFD team's judgments. The judgment elicitation process is carried out using the ANP/AHP's pairwise comparison question (Saaty, 1983, 1986). The detailed question for each arc will be explained in the next subsection (Section 3.4.4). It is worth highlighting that in each pairwise comparison matrix, the aggregated preference of the QFD team can be obtained either using a consensus vote or geometric mean (see Section 3.4.5). After taking the aggregated preference, the relative importance weight of the pairwise comparison matrices can be computed using the eigenvector method (Saaty, 1994). The *Super Decision* software may be used for this purpose. It can also be used to do an inconsistency check of the judgments. If the inconsistency level goes beyond a threshold value, for example, 10%, then a resurvey or another round of judgment elicitation process can be conducted (Saaty, 1994, 1996).

To make the judgment elicitation process more efficient, a step-by-step procedure of using the proposed network model, which is based on the sequence that is used in the QFD method, is suggested as follows. Note that, for all the arcs, in the case of no relationship, a blank can be added accordingly (Partovi, 2006, 2007).

A. General network framework

Step 1. Adopt the generic (proposed) model, modify if necessary.

B. Listening to the customer

Step 2. Add necessary nodes within each cluster. For the DQ cluster, the nodes are obtained based on customer's survey data. Note that the guidance of the QFD team in helping the customers express their 'voices' or judgments is essential in this VOC collection phase. For the QC cluster, the NPD risk cluster, and the

Competitors cluster, the nodes can be obtained based on the judgment, experience, and knowledge of the team.

Step 3. Elicit the QFD team's judgment using the pairwise comparison for arc 1 and arc 2. Arc 1 is used to obtain the priorities of the DQs, while arc 2 is used to obtain the inner relationship among the DQs.

C. The relationship matrix

Step 4. Elicit the QFD team's judgment using the pairwise comparison for arc 3 and arc 5. These two arcs show the bidirectional relationship between the DQs and the QCs.

D. The HOQ roof

Step 5. Elicit the QFD team's judgment using the pairwise comparison for arc 4. As mentioned previously, this eliminates the need to carry out a post-analysis evaluation of the roof matrix correlations values (Partovi, 2006, 2007).

E. The competitors' general information

Step 6. Elicit the QFD team's judgment using the pairwise comparison for arc 12 and arc 13. Arc 12 is used to obtain general information on how strong one competitor is compared to the others, while arc 13 is used to obtain information on the inner relationship among the competitors themselves.

F. The competitor performance evaluation

Step 7. Elicit the QFD team's judgment using the pairwise comparison for arc 15 and arc 17. Arc 15 is used to evaluate the competitors' performance with respect to the DQs, while arc 17 is used to evaluate their performance with respect to the QCs.

G. The NPD risk information

Step 8. Elicit the QFD team's judgment using the pairwise comparison for arc 6 to arc 11. Note that this additional information is beyond the basic HOQ, it is included here for improving the QFD results' accuracy, considering the market dynamics.

H. The competitive target setting for DQs

Step 9. Elicit the QFD team's judgment using the pairwise comparison for arc 14. When eliciting the judgments for arc 14, the design team might consider three previous factors, those are, the priorities of the DQs (arc 1), the general information of the competitors (arc 12), and the competitors performance with respect to the DQs (arc 15).

I. Obtaining QCs' priorities for technical target setting

Step 10. Elicit the QFD team's judgment for the clusters to obtain a cluster matrix using the pairwise comparison.

Step 11. Construct the unweighted supermatrix using the derived priorities. Afterwards, construct the weighted supermatrix by multiplying the unweighted supermatrix by the cluster matrix.

Step 12. Compute the limit supermatrix by raising the weighted supermatrix to the power of $2k+1$, where k is an arbitrarily large number to allow convergence. The supermatrix concept is parallel to the Markov chain process (Saaty, 1983).

Step 13. Normalize the converged or stable priorities.

J. The competitive target setting for QCs

Step 14. Elicit the QFD team's judgment using the pairwise comparison for arc 16. It is suggested that when eliciting the judgment for this arc, the QFD team may consider the QCs priorities obtained from Step 13, the general information of the

competitors (arc 12), and the competitors' performance with respect to the QCs (arc 17). Note that this is in line with the standard QFD methodology, where the competitive target setting or the competitive technical assessment (Chan and Wu, 2002b) for the QCs is done after knowing the priorities of the QCs.

K. The final priorities

Step 15. After filling the information for arc 16, repeat Step 11 to Step 13, and obtain the final priorities for all clusters. Other further analysis can be employed subsequently, such as optimization.

3.4.4 Types of questions to elicit decision makers' judgments

Based on the relationships that are established in the network model, this subsection describes the type of pairwise comparison questions that are used to elicit the relative importance between and within the five corresponding clusters. According to the arc's number in Figure 3.1, Table 2.2 shows the questions that can be used to elicit the QFD team's judgments. Note that the questions may be phrased differently, but with the same meaning, to suit a particular condition.

Table 3.2 Questions for eliciting QFD team's judgments

Arc	Question
1	With respect to achieving best design, how important is DQ_1 compared to DQ_2?
2	With respect to controlling DQ_1, how important is DQ_2 compared to DQ_3?
3	With respect to satisfying DQ_1, how important is QC_1 compared to QC_2?
4	With respect to controlling QC_1, how important is QC_2 compared to QC_3?
5	With respect to QC_1, how important is DQ_1 compared to DQ_2?
6	With respect to achieve best design, how sensitive is $Risk_1$ compared to $Risk_2$?
7	With respect to controlling $Risk_1$, how important is $Risk_2$ compared to $Risk_3$?

8	With respect to $Risk_1$, how sensitive is DQ_1 compared to DQ_2?
9	With respect to DQ_1, how is the occurrence likelihood of $Risk_1$ compared to $Risk_2$?
10	With respect to $Risk_1$, how sensitive is QC_1 compared to QC_2?
11	With respect to QC_1, how is the occurrence likelihood of $Risk_1$ compared to $Risk_2$?
12	With respect to achieving the best design, how strong is $Competitor_1$ compared to $Competitor_2$?
13	With respect to $Competitor_1$, how important is $Competitor_2$ compared to $Competitor_3$?
14	With respect to $Competitor_1$, how important is DQ_1 compared to DQ_2?
15	With respect to DQ_1, how strong is $Competitor_1$ compared to $Competitor_2$?
16	With respect to $Competitor_1$, how important is QC_1 compared to QC_2?
17	With respect to QC_1, how strong is $Competitor_1$ compared to $Competitor_2$?

3.4.5 Group decision making using the AHP/ANP

Since QFD is a team tool (Huang and Mak, 2002; Büyüközkan and Feyzioğlu, 2005), it is therefore necessary to have an effective group decision making process. With respect to this need, the AHP/ANP's internal mechanism provides a suitable answer (Dyer and Forman, 1992). When using the proposed network model, the QFD team is required to aggregate preference of individuals into a consensus rating. There are two major ways of deriving the group preference, one is to use a consensus vote and the other is to use a geometric mean (Aczel and Saaty, 1983; Shang et al., 2004).

With respect to consensus building, Bard and Sousk (1990) wrote "*from the standpoint of consensus building, the AHP methodology provides an accessible data format and a logical means of synthesizing judgment. The consequences of individual responses are easily traced though the computations and can be quickly revised when situation*

warrants". However, the consensus vote approach might not be easy to use since it requires an agreement of all the team's members for each entry in the pairwise comparison matrices.

Nevertheless, if it is assumed that the team is a collection of synergistic individuals who act together towards a common goal, as in the case of the QFD team, rather than separate individuals, then the geometric mean approach is the most suitable method (Forman and Peniwati, 1998). Moreover, the geometric mean of the set of individual judgments preserves the ratio scale and satisfies the reciprocal property to guarantee that the eigenvector method still holds (Aczel and Saaty, 1983). The geometric mean approach, which is suggested in using the proposed framework, can be expressed as follows:

$$a_{ij}^{G} = \left[\prod_{k=1}^{n} a_{ij}^{k} \right]^{1/n} \tag{3.1}$$

where:

n = the number of decision makers

a_{ij}^{G} = the group judgment of the (i,j) element in the reciprocal matrix

Note that the formula above assumes that the individuals are of equal importance; otherwise, one may use the weighted geometric mean.

3.4.6 Fuzziness in the AHP/ANP

Another important thing to highlight is the incorporation of fuzziness in the judgment of the QFD team when using the AHP/ANP model. The fuzzy theory is expected to help the QFD team better quantify the subjectivity, particularly in terms of representing linguistic expression (see Kwong and Bai, 2003; Kahraman et al., 2006). Nevertheless, by

its very nature, the internal mechanism of the AHP/ANP in eliciting judgment has taken into account the fuzziness in decision maker's judgment (Saaty, 2006; Saaty and Tran, 2007). Therefore, the applying fuzzy theory into the AHP context will be of little value and further complicate the process. As noted by Saaty (2006), "*Enforce judgments by an outsider who likes fuzzy number crunching needs proof of the validity of its outcome, and we have shown by examples the outcome is not only close to what the AHP obtains without fuzziness but can also be worse, so it is unjustified to use fuzzy in the AHP*."

In sum, to deal with the subjectivity of judgments inherent in the QFD process, it is suggested to use either the AHP/ANP approach or the fuzzy theory approach separately since combining both approaches will further complicate the process and be of little additional value. Some examples for using fuzzy theory separately from the AHP/ANP in the QFD can be found in Khoo and Ho (1996), Kim et al. (2000), Karsak (2004), Chen et al. (2004, 2006), or Fung et al. (2006). The issue of "which approach performs better in dealing with the subjectivity of judgments in the QFD process" is beyond the scope of this thesis and might be an interesting topic to be addressed in the future.

3.5 An illustrative example

This section provides an illustrative example that was developed by the author after having intensive discussions with people who are knowledgeable in dealing with the increasingly important soft reliability problem (see Section 3.3.1.A), especially for consumer electronic products in European countries. Due to the soft reliability problem, there are more and more products being returned to the company although they are not defective (Brombacher et al., 2005; Den Ouden, 2006). One of the effective ways to tackle

this problem is to improve product's "ease of use" (Sciarrotta, 2003), for example, by designing a satisfactory out-of-box experience for the consumer.

It is quite natural that users, after purchasing a consumer electronic product, want to get start to work productively as soon as possible (Fouts, 2000; Marcus, 2005). The first impression the users may have on the products as well as the company may depend largely on the out-of-box experience, which includes the experience in taking the product out of the box (unpacking), setting up its hardware and software, and putting it into use (Ketola, 2005; IBM, 2007).

For the sake of simplicity and to give readers some insights on how the proposed network model may work in practice, this illustrative example will focus on one element of the entire out-of-box experience of a PC media center, that is, the software setup and configuration phase. The objective of this example is to design a software setup experience that may satisfy users' needs. The users' needs or demanded qualities become the first ingredient of the QFD process. Afterwards, the QFD team translates those DQs into QCs. Lastly, considering the NPD risk, the benchmarking information, and the feedback information, the QFD team systematically decide the importance of the quality characteristics. The importance of the QCs, which is the final result, is reflected quantitatively in terms of relative priorities. Those priorities can be dovetailed with the other subsequent analysis, such as optimization with regard to the limited resources (see Chapter 8).

Following closely the step-by-step procedure described in Section 3.4.3, the implementation of the proposed network model for achieving a best software setup experience may proceed as follows:

Step 1: Adopt the generic (proposed) network model, modify if necessary. The generic ANP model (Figure 3.1) was applied to a software setup design, and the resulting network model is shown in Figure 3.2. The objective was to best design a software setup experience using QFD, while considering the design risk and the competitors.

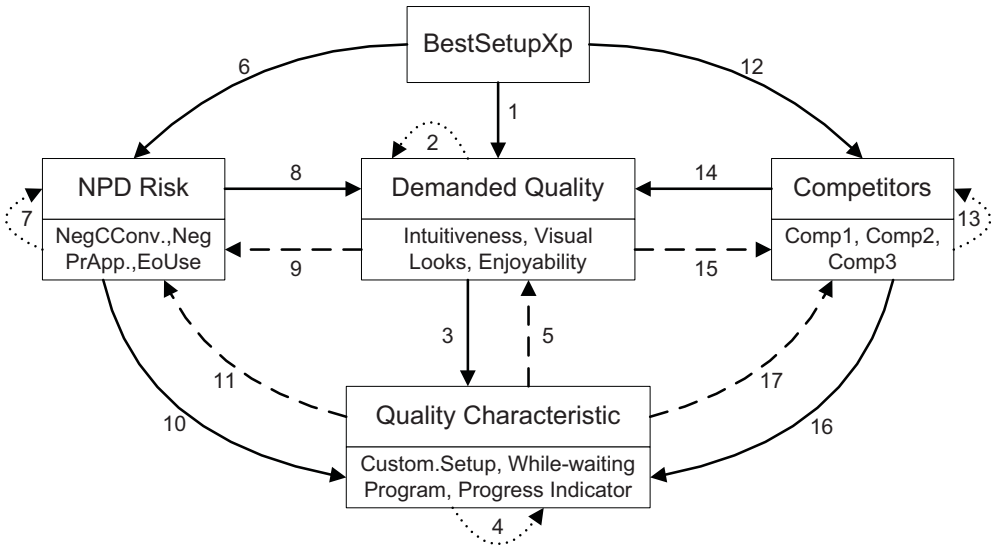


Figure 3.2 Network model for the example

Step 2: Add necessary nodes within each cluster. For the sake of simplicity, it is assumed that there are three elements in each of the main clusters. The DQ cluster comprises of three elements, namely, *Intuitiveness*, *Visual Looks*, and *Enjoyability*. The QC cluster has three elements, namely, *Customized Setup*, *While-waiting Program*, and *Progress Indicator*. Note that, apart from interviewing the design experts, users' complaints reported in the study of Wijtvliet (2005) were also considered in obtaining the elements of the DQ and QC.

Since this particular example deals with out-of-box experience in software setup design, then the most relevant risks are those within the category of *Consumer Acceptance*

and Marketing risk (see Section 3.3.1). Hence, for the NPD Risk cluster, the three elements, using the risk reference framework (Keizer et al., 2005), are *Negative Consumers' Conviction*, *Negative Product's Appeal*, and *Ease of Use Risk*. Lastly, there are three fictitious 'best-in-class' competitors that were selected for this study, those are, the first competitor (*Comp1*), the second competitor (*Comp2*), and the third competitor (*Comp3*).

In terms of the DQ, the focus area of *Comp1*, *Comp2*, and *Comp3* are the *Intuitiveness*, the *Enjoyability*, and the *Visual Looks* of the software setup process, respectively. In terms of the QC, *Comp1* focuses more on designing user-friendly *Customized Setup*, *Comp2* focuses more on developing enjoyable *While-waiting Program*, while *Comp3* has a typically elegant *Progress Indicator*. Additionally, *Comp1* and *Comp2* have been competing for each other, while *Comp3* is a new player for producing the PC Media Center. *Super Decision* software was used to construct the network model and obtain the final priorities.

After constructing the network model of the PC design problem, the next step is to elicit the QFD team's judgments for each of the arcs accordingly. A sample of a pairwise comparison questionnaire, along with some information for guiding the users and designer to express their judgments and experience, can be found in Appendix A. The typical pairwise comparison question for each arc (listed in Table 3.2) was used to elicit the QFD team's judgments.

With regard to the aggregated group preference, it is assumed that a consensus vote was achieved. Otherwise, the geometric mean can be used (see Section 3.4.5). For each of the pairwise comparison matrix, a maximum inconsistency value of 0.1 (Saaty, 1994) was

used to decide whether there is a need to do a resurvey. The priorities of each pairwise comparison matrix were computed using the *Super Decision* software.

To make the judgment elicitation process more efficient, it was carried out according to the HoQ's elements, as described in Section 3.4.3. The judgments results, which are grouped by the arc' category, can be found in Appendix B.

Step 3: Elicit the QFD team's judgment using the pairwise comparison for arc 1 and arc 2. The result for arc 1 (Table B1), of which data were obtained from the customer, shows that the customer regards the *Intuitiveness* of a software setup as the most important thing (0.714). The question used for arc 2 might be like: "With respect to controlling *Visual Looks*, how important is *Intuitiveness* compared to *Enjoyability*?". Table B2 shows that, with respect to controlling *Visual Looks*, the *Intuitiveness* has more influence than the *Enjoyability* (by three times), which is intuitively justifiable.

Step 4: Elicit the QFD team's judgment using the pairwise comparison for arc 3 and arc 5. Arc 3 represents the QFD team's judgment on how important the QCs are with respect to satisfying the DQs, while arc 5 represents the feedback information to evaluate the DQs with respect to the QCs. The question used for arc 3 can be like: "With respect to satisfying *Intuitiveness*, how important is *Customized Setup* compared to *While-waiting Program*?", and as shown in Table B1, the *Customized Setup* is five times more important than the *While-waiting Program*. The results for all pairwise comparisons done for arc 3 can be summarized as follows. The *Customized Setup* plays the most important role on *Intuitiveness* (0.637), while the *While-waiting Program* on the *Visual Looks* (0.714) and the *Enjoyability* (0.709).

The pairwise comparison question used for arc 5 can be like: "With respect to *Progress Indicator*, how important is *Enjoyability* compared to *Visual Looks*?". It is easy

to see that the *Visual Looks* of a progress indicator can be much more important than its *Enjoyability*. On the other hand, for the *Customized Setup*, its *Enjoyability* appeared to be the most important thing to be improved upon. This is reasonable because a *Customized Setup* should basically be intuitive. For the *While-waiting Program*, its *Intuitiveness* appeared to the most important attribute (see Table B3). Again, this is because it is assumed that the basic function of a *While-waiting Program* is to make the waiting process enjoyable. Note that this type of information has enabled the QFD team to take into account the important feedback, which is not possible when using the AHP. Unfortunately, it has been largely overlooked in the existing literature.

Step 5: Elicit the QFD team's judgment using the pairwise comparison for arc 4. The question posed can be like: "With respect to controlling *While-waiting Program*, how important is *Customized Setup* compared to *Progress Indicator*?". It is shown that all the controlled QCs have the same importance level. After further investigation with the design experts, such condition took place because the level of this information (granularity) is very specific. Therefore, this information may only be reserved to the programmer of the software. As for this example, they are assumed to be equally important.

Step 6: Elicit the QFD team's judgment using the pairwise comparison for arc 12 and arc 13. Arc 12 (Table B1) gives the priorities of the best-in-class competitors towards achieving the best design of a software setup experience. The questions posed for this arc can be like: "With respect to achieving best software setup experience, how strong is *Comp1* compared to *Comp2*?". The result shows that *Comp1* (0.500) appeared to be the strongest competitor. Arc 13 shows the relationship among the competitors themselves. As shown in Table B2, *Comp1* and *Comp2* are competing with each other. While *Comp3*, as a new player, regards the two other competitors as equally important.

Step 7: Elicit the QFD team's judgment using the pairwise comparison for arc 15 and arc 17. These two arcs evaluate the strength of the competitors with respect to the DQs and QCs. Readers may check that the results shown in Table B3 agree with the competitors' profile described previously. The question posed can be like: "With respect to *Intuitiveness*, how strong is *Comp1* compared to *Comp2*?".

Step 8: Elicit the QFD team's judgment using the pairwise comparison for arc 6 to arc 11. With respect to the risks involved, the question posed for arc 6 can be like "With respect to the risk of software setup experience, how sensitive is *Negative Consumer's Conviction* compared to *Ease of Use Risk*?". Note that, for all priorities in this study, it is assumed that the higher the values, the more important they become. Thus, in the case of the risk involved, the emphasis is placed on those relatively riskier elements since they are very critical in creating customers satisfaction/dissatisfaction. It can be seen from Table B1 that the *Ease of Use Risk* is the most sensitive one, and thus it receives the highest priority.

Arc 7 represents the inner relationship among the risks themselves. It is worth noting that there are two 'NA' (Not Applicable) judgments in this cluster (Table B2). This is due to the fact that the entities being compared lack a contextual meaning. For example, a question like "With respect to controlling *Negative Product's Appeal*, how important is *Negative Consumer's Conviction* compared to *Ease of Use Risk*?" is virtually impossible to answer since there is no relationship among the entities.

For arc 8, the question posed can be like: "With respect to giving rise to *Negative Consumers' Conviction*, how sensitive is the *Intuitiveness* compared to the *Visual Looks*?". As shown in Table B1, the *Intuitiveness* is five times riskier or more sensitive than the *Visual Looks*. From the results in arc 8, it can be said that the intuitiveness of software

setup process is the most sensitive item that will cause negative consumer's conviction and ease of use risk, while the visual looks appears to be the most sensitive in giving rise to negative product's appeal. With respect to all the risks (Arc 10 in Table B1), the *Customized Setup* appeared to be the most sensitive QC. This is quite reasonable since the customized setup is the first thing that the users encounter. Furthermore, the two other QCs may, in general, also be controlled by the customized setup. A similar question as in arc 8 can be used accordingly.

Arc 9 and arc 11 evaluate the occurrence likelihood of the risks with respect to the DQs and QCs. The question posed can be like: "With respect to *While-waiting Program*, how is the occurrence likelihood of *Negative Consumers' Conviction* compared to *Ease of Use Risk*?". As shown in Table B3, the *Ease of Use* is the least important risk with respect to the *While-waiting Program*. This is quite intuitive since a while-waiting program has no explicit relationship with the ease of use part of a software setup. Other results can be interpreted accordingly.

Step 9: Elicit the QFD team's judgment using the pairwise comparison for arc 14. The question posed can be like: "With respect to *Comp1*, how important is *Intuitiveness* compared to *Visual Looks*?". The result for this question (Table B1) shows that the *Intuitiveness* is seven times more important (very strong) than the *Visual Looks*. It is easy to see that such a high value was assigned due to the fact that the *Intuitiveness* is the most important attribute from the customer's perspective (see arc 1) and *Comp1* performs very well with respect to this attribute (see arc 15). Moreover, *Comp1* is also the strongest competitor (arc 12).

Step 10: Elicit the QFD team's judgment for the clusters to obtain a Cluster Matrix using the pairwise comparison. For the sake of simplicity, it is assumed that all the

clusters in the network model carry equal weight. The resulting cluster matrix is shown in Table 3.3.

Table 3.3 Cluster matrix

Cluster	1.GOAL	2.DQ	3.Risk	4.Competitors	5.QC
1.GOAL	0.000	0.000	0.000	0.000	0.000
2.DQ	0.333	0.500	0.333	0.333	0.500
3.Risk	0.333	0.000	0.333	0.000	0.000
4.Competitors	0.333	0.000	0.000	0.333	0.000
5.QC	0.000	0.500	0.333	0.333	0.500

Step 11: Construct the unweighted supermatrix using the derived priorities. The unweighted supermatrix is shown in Table 3.4. Note that this matrix constitutes all the previously derived priorities. For example, with respect to the goal (objective), the priority of each DQ element (see the third column of Table 3.4 under "Goal"), namely, the *Intuitiveness* (0.714), the *Visual Looks* (0.143), and the *Enjoyability* (0.143), is exactly the same as obtained in Table B1 (arc 1). Likewise, the remaining parts in Table 3.4 can be interpreted accordingly.

Table 3.4 Unweighted supermatrix without arc 16

		1.GOAL	2.DQ			3.Risk			4.Competitors			5.QC		
		B.SetupXp	Intuitive	Vlooks	Enjoy.	NegCCon	NegPrAp	EoURisk	Comp1	Comp2	Comp3	CustSet	Wh-wait	ProInd
1.GOAL	B.SetupXp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2.DQ	Intuitive	0.714	0.000	0.750	0.500	0.714	0.125	0.750	0.778	0.683	0.637	0.260	0.600	0.286
	Vlooks	0.143	0.750	0.000	0.500	0.143	0.750	0.125	0.111	0.117	0.258	0.327	0.200	0.571
	Enjoy.	0.143	0.250	0.250	0.000	0.143	0.125	0.125	0.111	0.200	0.105	0.413	0.200	0.143
3.Risk	NegCCon	0.143	0.208	0.238	0.550	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.595	0.300
	NegPrAp	0.143	0.131	0.625	0.240	0.250	0.000	0.000	0.000	0.000	0.000	0.167	0.276	0.600
	EoURisk	0.714	0.661	0.137	0.210	0.750	0.000	0.000	0.000	0.000	0.000	0.667	0.128	0.100
4.Competitors	Comp1	0.500	0.750	0.113	0.167	0.000	0.000	0.000	0.000	0.750	0.500	0.750	0.200	0.106
	Comp2	0.250	0.125	0.179	0.667	0.000	0.000	0.000	0.750	0.000	0.500	0.125	0.683	0.193
	Comp3	0.250	0.125	0.709	0.167	0.000	0.000	0.000	0.250	0.250	0.000	0.125	0.117	0.701
5.QC	CustSet	0.000	0.637	0.143	0.179	0.659	0.600	0.732	0.000	0.000	0.000	0.000	0.500	0.500
	Wh-wait	0.000	0.105	0.714	0.709	0.156	0.200	0.130	0.000	0.000	0.000	0.500	0.000	0.500
	ProInd	0.000	0.258	0.143	0.113	0.185	0.200	0.138	0.000	0.000	0.000	0.500	0.500	0.000

To derive the final weights of the proposed network model, a column stochastic supermatrix is needed (Saaty, 1996). Therefore, the unweighted supermatrix is multiplied by the cluster matrix to obtain the weighted supermatrix. The resulting weighted supermatrix, which is column stochastic, is shown in Table 3.5.

Table 3.5 Weighted supermatrix without arc 16

		1.GOAL	2.DQ			3.Risk			4.Competitors			5.QC		
		B.SetupXp	Intuitive	Vlooks	Enjoy.	NegCCon	NegPrAp	EoURisk	Comp1	Comp2	Comp3	CustSet	Wh-wait	ProInd
1.GOAL	B.SetupXp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2.DQ	Intuitive	0.238	0.000	0.188	0.125	0.238	0.063	0.375	0.389	0.342	0.318	0.065	0.150	0.071
	Vlooks	0.048	0.188	0.000	0.125	0.048	0.375	0.063	0.056	0.058	0.129	0.082	0.050	0.143
	Enjoy.	0.048	0.063	0.063	0.000	0.048	0.063	0.063	0.056	0.100	0.052	0.103	0.050	0.036
3.Risk	NegCCon	0.048	0.052	0.060	0.137	0.000	0.000	0.000	0.000	0.000	0.000	0.042	0.149	0.075
	NegPrAp	0.048	0.033	0.156	0.060	0.083	0.000	0.000	0.000	0.000	0.000	0.042	0.069	0.150
	EoURisk	0.238	0.165	0.034	0.052	0.250	0.000	0.000	0.000	0.000	0.000	0.167	0.032	0.025
4.Competitors	Comp1	0.167	0.188	0.028	0.042	0.000	0.000	0.000	0.000	0.375	0.250	0.188	0.050	0.027
	Comp2	0.083	0.031	0.045	0.167	0.000	0.000	0.000	0.375	0.000	0.250	0.031	0.171	0.048
	Comp3	0.083	0.031	0.177	0.042	0.000	0.000	0.000	0.125	0.125	0.000	0.031	0.029	0.175
5.QC	CustSet	0.000	0.159	0.036	0.045	0.220	0.300	0.366	0.000	0.000	0.000	0.000	0.125	0.125
	Wh-wait	0.000	0.026	0.179	0.177	0.052	0.100	0.065	0.000	0.000	0.000	0.125	0.000	0.125
	ProInd	0.000	0.065	0.036	0.028	0.062	0.100	0.069	0.000	0.000	0.000	0.125	0.125	0.000

Step 12: Compute the limit supermatrix by raising the weighted supermatrix to the power of $2k+1$, where k is an arbitrarily large number to allow convergence. The long term priorities or stable weighted values of the weighted supermatrix, which are reflected in the limit supermatrix, are shown in Table 3.6. All the clusters appeared to converge.

Table 3.6 Limit supermatrix without arc 16

		1.GOAL	2.DQ			3.Risk			4.Competitors			5.QC		
		B.SetupXp	Intuitive	Vlooks	Enjoy.	NegCCon	NegPrAp	EoURisk	Comp1	Comp2	Comp3	CustSet	Wh-wait	ProInd
1.GOAL	B.SetupXp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2.DQ	Intuitive	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185	0.185
	Vlooks	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105
	Enjoy.	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062
3.Risk	NegCCon	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
	NegPrAp	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
	EoURisk	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
4.Competitors	Comp1	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117
	Comp2	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
	Comp3	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
5.QC	CustSet	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
	Wh-wait	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064
	ProInd	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049

Step 13: Normalize the converged or stable priorities. Since the next step is to obtain the judgment of the design team for QC competitive target setting, then it is easier to first normalize the stable QCs priorities. After normalization, the priorities for the *Customized Setup*, the *While-waiting Program*, and the *Progress Indicator*, respectively, are 46.3%, 30.3%, and 23.4%. This information reflects the impact level of each QC on the customer needs considering all factors in the proposed model.

Step 14: Elicit the QFD team's judgment using the pairwise comparison for arc 16. Using the information obtained in Step 13 along with the information on the strength and

performance of each competitor with respect to the QCs (see arc 12 and arc 17), the QFD team may set a competitive target value for the QCs. The question posed can be like: "With respect to *Comp2*, how important is *Customized Setup* compared to *While-waiting Program*?". As shown in Table B1, the *Customized Setup* is only two times more important than the *While-waiting Program*. One the one hand, this is due to the fact that the *Customized Setup* has the largest impact on customer needs (Step 13) and *Comp2* is not the strongest competitor (arc 12). On the other hand, one may not set a too low value for the *While-waiting Program* since *Comp2* performs very well in making a good *While-waiting Program* (arc 17).

Step 15: After filling the information for arc 16, repeat Step 11 to Step 13, and obtain the final priorities for all clusters. The resulting limit matrix considering all the arcs (arc 1 to arc 17) is shown in Table 3.7. The normalized final priorities, which are obtained after the QC competitive target setting stage, are shown in Table 3.8.

Table 3.7 Limit supermatrix after QC's target setting (with arc 16)

		1.GOAL	2.DQ			3.Risk			4.Competitors			5.QC		
		B.SetupXp	Intuitive	Vlooks	Enjoy.	NegCCon	NegPrAp	EoURisk	Comp1	Comp2	Comp3	CustSet	Wh-wait	ProInd
1.GOAL	B.SetupXp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2.DQ	Intuitive	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148
	Vlooks	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
	Enjoy.	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057
3.Risk	NegCCon	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
	NegPrAp	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
	EoURisk	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071
4.Competitors	Comp1	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095	0.095
	Comp2	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075
	Comp3	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
5.QC	CustSet	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146
	Wh-wait	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088
	ProInd	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070

Table 3.8 QC priorities before and after target setting phase

QC priorities without arc 16			Final QC priorities		
CustSet	Wh-wait	ProInd	CustSet	Wh-wait	ProInd
0.463	0.303	0.234	0.481	0.289	0.230

As can be observed in Table 3.8, taking into account all the relevant factors in the network model, the *Customized Setup* received the highest score of importance (48.1%), then followed by the *While-waiting Program* (28.9%) and the *Progress Indicator* (23.0%). It is also interesting to see that after the QC competitive target setting stage, the value of the *Customized Setup* increased and the *While-waiting Program* decreased a little, while the *Progress Indicator* remained relatively the same.

These final priorities (Table 3.8) are of great importance to the QFD team either for prioritization or optimization purpose. Finally, subsequent QFD phases and further analysis, such as optimization techniques (Karsak et al., 2002; Kahraman et al., 2006; Demirtas and Ustun, 2007), can be carried out based on these accurately obtained relative priorities.

3.6 Discussion

The aim of this chapter was to answer the question "*In what ways does AHP, considering its strength and weakness, contribute to an improved QFD analysis?*" As to provide a better use of AHP in QFD, a generalized model, which is based on the ANP framework, is proposed. The main contribution lies in the proposed generic model which can be used to assist QFD users to better quantify their subjective judgments and experience in a more systematic fashion. Interestingly, not only can the network model address all elements in the HoQ, which may therefore serve as a substitutive procedure to the traditional QFD method, but it also takes into account other important factors in the product design context, such as the new product development risk.

Furthermore, it also serves as a generalized model of the use of ANP in QFD from the previous research (Karsak et al., 2002; Büyüközkan et al., 2004; Ertay et al., 2005; Kahraman et al., 2006; Partovi, 2006, 2007; Pal et al., 2007). In other words, the proposed model may function as "double" generalized model in the sense that it generalizes the use of the ANP in QFD, while the ANP itself is a generalized form of the AHP.

Some advantages of using the proposed network model may include the reduction of human judgment error, transparent evaluation, and improved efficiency. More importantly, the flexibility of the QFD in adapting to the constantly changing environment can be significantly improved as a sensitivity analysis to dynamically evaluate the network model can be carried out at any time. As with other ANP applications, a major possible drawback is the trade-off between the model complexity and the required time to complete the pairwise comparisons (Meade and Presley, 2002; Shang et al., 2004; Ravi et al., 2005; Sarkis and Sundarraj, 2006). Nevertheless, when a substantial amount of risk, including financial risk, is involved, then a systematic and structured analysis of dealing with the problem can be fully justified. Note that the numerical outcomes of the method are less important than the systematic thinking environment it offers.

With regard to the implementation and to avoid a too mechanistic application of the proposed network model, there are some points worth noting, as the author learnt from the interview process with the design experts. First, the terms used in the questionnaire for each cluster in the model should be clearly explained, for example, what it means by 'intuitiveness' should be clearly defined beforehand (see Appendix A). Second, the meaning of Saaty's fundamental scale used in the pairwise comparison for eliciting decision maker's judgments should also be explained clearly (Appendix A). These two points are the most relevant operational difficulty that QFD team might encounter when

using the model. In addition, the proposed model, to a certain extent, is limited since it has not taken into account all possible factors. However, this also, at the same time, shows the versatility of the model, which allows further expansion to suit the condition of a particular company.

Now, it may become more evident that the AHP has been beneficial in improving a QFD analysis. As indicated in this chapter and also Chapter 2, the AHP's priorities obtained at one point in time may not remain exactly the same at another point in time. To deal with this change, a sensitivity analysis has been suggested. However, a better way would be to systematically follow the change, and predict the future condition based on the past pattern. This issue will be dealt in the next chapter (Chapter 4).

CHAPTER 4
DEALING WITH THE DYNAMICS OF RELATIVE PRIORITIES: PROPOSING A NEW MODELING TECHNIQUE

In the previous chapters, the usefulness of AHP in QFD has been demonstrated through a case study and a generalized model. However, how the QFD-AHP approach can be used to deal with the change during product or service creation process has not yet been discussed. The purpose of this chapter is to provide a possible answer to the research question "*How to use the AHP in QFD in dealing with the dynamics of priorities?*" To the extent of what is described in the delimitation section, a new modeling technique called compositional double exponential smoothing (CDES), which is simple and time-efficient, is proposed to model the dynamics of AHP's relative priorities. This chapter is reproduced from "On Modeling Dynamic Priorities in the Analytic Hierarchy Process using Compositional Data Analysis", by Raharjo H, Xie M, Brombacher AC. 2009. Published in *European Journal of Operational Research*.

4.1 Introduction

As mentioned in Section 3.6, when using the AHP in QFD, it is very likely that the AHP priorities derived at one point in time might change in the near future, especially in the context of a rapidly changing environment. Thus, a timely update has to be carried out in order not to make a fallacious decision thereafter. In other words, to enable the system to respond differently and continuously over time of its operation, there is a significant need to follow the changes over time as to better anticipate the future. In the AHP literature, such problem might be tackled using the dynamic judgment method as

described in Saaty (1988, 1994, 2007) or Fiala (2006). This approach basically employs a time dependent function to model the change of the pairwise comparison matrix elements' value over time.

However, this approach has overlooked another important premise in the AHP itself, and is therefore self-contradictory. The shortcomings of this approach, namely, the failure to preserve consistency over time and the inflexibility issue will be discussed in detail in Section 4.2. In order to model the dynamic judgments, it is suggested that one should focus on the final priorities and observe the changes thereafter. In other words, the emphasis is placed on the dynamic priorities which result from dynamic judgments. In modeling the dynamic priorities, it is important to highlight that the time dependent model should take into account the unity constraint due to the AHP's normalization procedure.

With respect to such priorities modeling, some forecasting methods that have been developed in the study of compositional data will be of useful alternatives. There are two recent studies addressing this compositional data change over time problem. First, it is the study given in von Eynatten et al. (2003), which proposed the use of non-centered principal component analysis (PCA) to investigate the trend in compositional data evolution. Second, it is the study described in Wang et al. (2007), which proposed the use of the dimension-reduction approach through a hyperspherical transformation (DRHT) for forecasting compositional data. However, with respect to a rapidly changing environment, especially when there is a limited number of historical data, these two studies still have not adequately addressed the need to provide a more flexible approach to model the change of the compositional data over time. Therefore, to fill in this niche and to better deal with the AHP priorities change over time in today's rapidly changing environment, this chapter proposes the use of compositional exponential smoothing, namely,

Compositional Single Exponential Smoothing (CSES) and Compositional Double Exponential Smoothing (CDES), which are relatively simple and time-efficient.

In the next section (Section 4.2), some limitations of the existing methods will be discussed, particularly the shortcoming of Saaty's dynamic judgment approach. The weakness of compositional linear trend modeling and the DRHT approach will also be discussed subsequently. Section 4.3 provides a brief description of the fundamentals in the compositional data analysis which is used in this chapter/thesis. The main contribution of this chapter, which is the use of compositional exponential smoothing method, will be elaborated in Section 4.4. Afterwards, an illustrative example will be provided to substantiate the validity of the proposed method and to give some practical insights (Section 4.5).

In general, this work has contributed primarily to the extension of the AHP's use in dealing with a constantly changing environment as well as to the advancement of the compositional data literature. In particular, the proposed mathematical model in this chapter provides a useful way to model the dynamics of the AHP-based priorities in QFD, such as the DQs' priorities and the competitive assessment of DQs (see Section 1.1).

4.2 Existing approaches and research motivation

4.2.1 Shortcoming of Saaty's time dependent approach

In his book (Saaty, 1988, 1994), Professor Saaty proposed the method to model dynamic judgment in the AHP, that is, by expressing the elements of the pairwise comparison matrix as a function of time. The typical form of a judgment matrix in dynamic form is as follows:

$$A(t) = \begin{bmatrix} a_{11}(t) & a_{12}(t) & \cdots & a_{1n}(t) \\ a_{21}(t) & a_{22}(t) & \cdots & a_{2n}(t) \\ \vdots & \vdots & \vdots\vdots & \vdots \\ a_{n1}(t) & a_{n2}(t) & \cdots & a_{nn}(t) \end{bmatrix}$$

Owing to the time dependence of the coefficients of the matrix, the main difficulty with this approach lies in deriving the eigenvectors of priorities when dealing with higher order matrix, for example, a matrix with order more than 4.

Nevertheless, this approach has seriously overlooked two important facts which render it rather difficult in dealing with the AHP priorities change over time. First, it is the consistency ratio that is not preserved as the passage of time. This phenomenon will lead to a self-contradictory result simply because AHP's own premise does not allow a consistency ratio (CR) value to be more than a certain threshold value, that is, 0.1. Second, it is the rigidity of this approach in adapting to possible change pattern in the AHP matrix priorities. The next two subsections will demonstrate these two shortcomings in detail using an example adopted from Saaty (2007).

4.2.1.1 The failure to preserve consistency over time

Let suppose there is a 3-by-3 pairwise comparison matrix with each element is a function of time as follows:

$$A(t) = \begin{bmatrix} 1 & a(t) & b(t) \\ 1/a(t) & 1 & c(t) \\ 1/b(t) & 1/c(t) & 1 \end{bmatrix}$$

It is assumed that after the curve fitting phase, the function of each matrix element can be expressed as $a(t) = 0.1 + t^3$, $b(t) = 1 + 2t^2$, and $c(t) = 1 + \frac{1}{2}e^t$ (see Saaty, 2007). Afterwards, the priorities as well as the Consistency Ratio (CR) values can easily be tabulated by

inputting the time variable (t) realization values into the above equations. Table 4.1 shows the priorities and the CR values of the matrix starting from t=0 until t=2.1. As can be seen in Table 4.1, most of the CR values range beyond the threshold value, that is, 0.1, and they can be graphically observed in Figure 4.1. Thus, it violates the AHP's own premise. Moreover, a closer examination of the condition from t=2.1 onwards would show not only the CR value will still continue to increase, but also the values of the pairwise comparison matrix elements will fall outside the range of the AHP fundamental scale of 1 to 9.

Table 4.1 The priorities change over time using Saaty's method

t	*a(t)*	*b(t)*	*c(t)*	w_1	w_2	w_3	*CR*
0	0.10	1.00	1.50	0.122	0.648	0.230	35.6%
0.1	0.10	1.02	1.55	0.123	0.652	0.225	34.7%
0.2	0.11	1.08	1.61	0.129	0.651	0.220	32.9%
0.3	0.13	1.18	1.67	0.144	0.640	0.216	28.9%
0.4	0.16	1.32	1.75	0.169	0.618	0.213	22.9%
0.5	0.23	1.50	1.82	0.204	0.587	0.209	16.3%
0.6	0.32	1.72	1.91	0.247	0.550	0.203	10.6%
0.7	0.44	1.98	2.01	0.295	0.510	0.195	6.2%
0.8	0.61	2.28	2.11	0.347	0.469	0.184	3.1%
0.9	0.83	2.62	2.23	0.400	0.429	0.171	1.2%
1	1.10	3.00	2.36	0.451	0.391	0.158	0.2%
1.1	1.43	3.42	2.50	0.501	0.355	0.144	0.0%
1.2	1.83	3.88	2.66	0.547	0.322	0.131	0.5%
1.3	2.30	4.38	2.83	0.589	0.293	0.118	1.5%
1.4	2.84	4.92	3.03	0.628	0.266	0.106	3.0%
1.5	3.48	5.50	3.24	0.663	0.242	0.095	4.9%
1.6	4.20	6.12	3.48	0.694	0.221	0.085	7.3%
1.7	5.01	6.78	3.74	0.722	0.202	0.076	10.0%
1.8	5.93	7.48	4.02	0.747	0.185	0.068	13.1%
1.9	6.96	8.22	4.34	0.769	0.171	0.061	16.5%
2	8.10	9.00	4.69	0.788	0.157	0.054	20.3%
2.1	9.36	9.82	5.08	0.806	0.146	0.048	24.4%

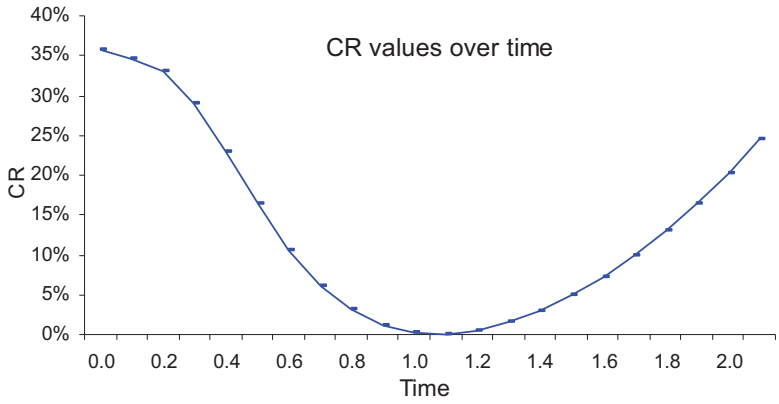


Figure 4.1 Consistency Ratio (CR) values over time using Saaty's method

Although this example is rather empirical, it has shed some light to the typical problem that one might encounter when trying to model the dynamic judgments using Saaty's method. In other words, it can be said that this time dependent method does not give any guarantee that the resulting consistency ratio value will fall within the tolerable limit as prescribed by the AHP itself. In short, this approach is potentially self-contradictory.

4.2.1.2 The rigidity of dynamic judgment approach

The rigidity of Saaty's time dependent approach may easily be proven graphically through a ternary diagram of the final priorities resulting from the dynamic judgments. Figure 4.2 shows the ternary diagram for the final priorities of the above example (Saaty, 2007). It can be seen that the priorities can only take one single side of the ternary diagram. In particular, the priority values assigned to alternative 1 (w_1) will become larger and larger as the passage of time. This is also indicated by the trend which monotonically goes upward to reach the peak of the triangle.

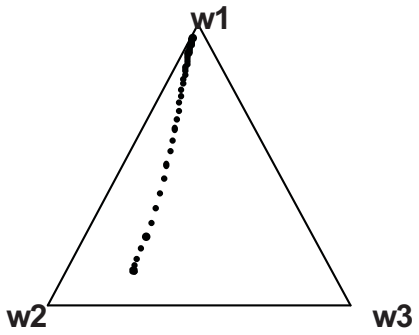


Figure 4.2 Ternary diagram of Saaty's method (Saaty, 2007)

Then, one may naturally ask why this trend is considered as another shortcoming of the approach. There are two answers for this question. First, practically speaking, it is virtually inconceivable that the importance of an entity or alternative may continuously get higher or lower throughout the time, particularly in the context of today's rapidly changing environment. Second, technically speaking, this approach shows a considerably high degree of rigidity in comparison with the possible change patterns of the AHP's priorities resulting from a randomly generated 3-by-3 pairwise comparison matrix, as can be seen in Figure 4.3.

Figure 4.3 was obtained using a set of values resulting from a randomly generated third-order AHP reciprocal matrix with one thousand replications. The CR values that were used in producing the values range from 0 to 0.1. They are grouped based on five equally divided intervals, namely, 0-0.02, 0.02-0.04,…,0.08-0.1. For each CR group, the procedure to generate the random matrix is as follows.

1. For each element in the 3-by-3 pairwise comparison matrix, for example, a_{12}, randomly choose one value of AHP ratio-scale weights {1/9, 1/8,...,9}. Note that each ratio-scale weight has an equally likely probability to be selected.

2. Compute CR value for the generated reciprocal matrix. If it falls within the pre-specified group, for example, 0-0.02, then, the final priorities of the reciprocal matrix are recorded. Otherwise, generate another random reciprocal matrix again (back to the step 1). The iteration stops when the number of recorded matrix equals to the required number of replications. Finally, all the priorities of the recorded reciprocal matrices are plotted according to the CR group in a ternary diagram.

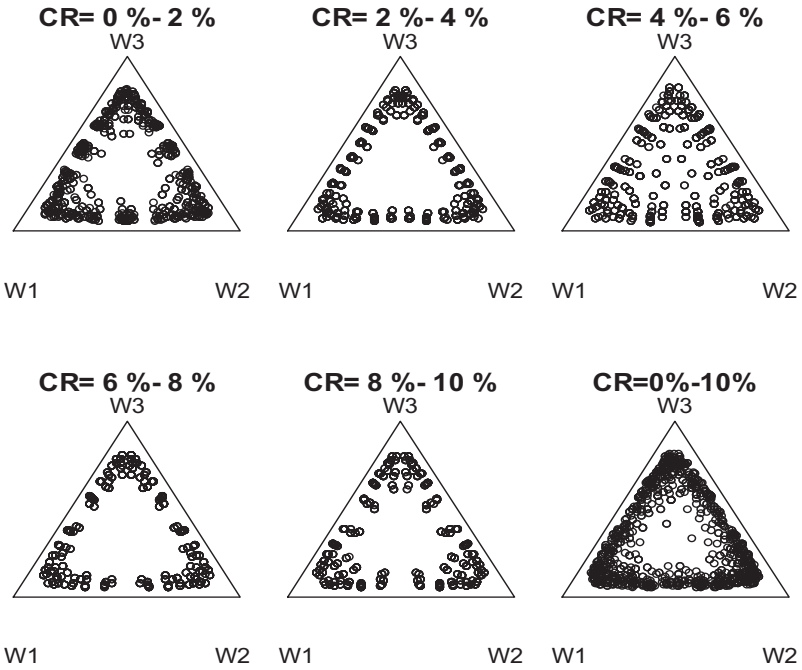


Figure 4.3 Ternary diagrams of a random AHP matrix with 1000 replications using pre-specified CR range

It can be seen that the final priorities of the randomly generated AHP matrices, which have CR values less than or equal to 0.1, are mostly distributed near the perimeter of the ternary diagram on all sides of the triangle. Therefore, it is clear that the dynamic judgment approach appears to be highly rigid in this sense. In other words, another better

approach to capture the AHP priorities change behavior over time, which may possibly scatter near all sides of the perimeter of the ternary diagram, is evidently required.

4.2.2 Limitation of compositional linear trend

In attempt to model the compositional change in chemical major element data from a weathering profile developed on granitoid rocks, von Eynatten et al. (2003) proposed the use of non-centered principal component analysis (PCA) to estimate the leading perturbation vector of the process (**p**). Basically, their compositional linear trend model can be written as $\mathbf{y} = \mathbf{a} \oplus (k \otimes \mathbf{p})$, where **a** is the initial composition and **p** is the direction of the trend. The initial composition (**a**) can be estimated by considering the condition of the process, for example, by taking the geometric mean of the first two observations, which can be mathematically expressed as $0.5 \otimes (\mathbf{x}_1 \oplus \mathbf{x}_2)$. The non-centered PCA method also gives the proportion of the total variability explained by the linear trend. For more technical details, interested readers may refer to von Eynatten et al. (2003). A more recent study on the application of this approach can be found in von Eynatten (2004).

Since it is a linear approximation, it will not, by its nature, have an adequate adaptability when it is used to fit the AHP priorities change over time. As shown in Figure 4.3, most of the data points are scattered along the perimeter of the ternary diagram. Intuitively, the compositional linear trend may only fit the data for one side of the triangle. Therefore, the linear trend approximation is very likely to fail in capturing the behavior of the AHP matrix priorities change. The illustrative example in Section 4.5 will clearly show such limitation.

4.2.3 Limitation of the DRHT approach

To resolve the difficulty in maintaining non-negativity and unit-sum in forecasting compositional data over time, Wang et al. (2007) proposed a dimension-reduction approach through a hyperspherical transformation ("DRHT" hereafter). Basically, the procedure is to map the compositional data vector onto a hypersphere, and use some mathematical models, such as regression technique, to fit the change of the angle data series and finally transform them back into the compositional form. This DRHT approach might be considered as a significant contribution to the advancement of the compositional data literature, particularly when dealing with forecasting issue.

Nevertheless, the DRHT approach seems to rely rather heavily on the selection of the mathematical model when fitting the angle data series. This might pose a difficulty for the users in selecting an appropriate model, some trade-offs between the goodness of fit and the parsimony principle, which is bought at the expense of model complexity, has to be done. This condition, to some extent, shows the weakness of the approach, particularly when dealing with more volatile change in the data, such as the AHP priorities change that will be demonstrated in the example (Section 4.5). In addition, the ability to deal with zero values in the compositional data is also argued to be another advantage of the DRHT approach. However, this situation could hardly occur in the AHP context, or if it does, then there will be no need to do the pairwise comparison because the dominance condition is clear.

4.3 Compositional data fundamentals

4.3.1 Simplex sample space

The sample space of the compositional data is called the Simplex space (Aitchison, 1982; 2003). Specifically, the *D*-part simplex space can be expressed as follows:

$$S^D = \left\{ X = [x_1, x_2, ..., x_D]; x_i > 0; \sum_{i=1}^{D} x_i = k \right\}, \text{ where } k \text{ is a constant.} \quad (4.1)$$

In the context of the AHP priorities, the value of *k* is equal to 1 since the priority of each entity or alternative is a normalized score resulting from the AHP internal procedure.

4.3.2 Operations in the simplex

There are four important terminologies in terms of the operations in the simplex space, namely, the closure operator, the perturbation operation, the power transformation, and the inner product. For any vector $Z = [z_1, ..., z_d] \in \Re_+^d$, the closure operator $C[\cdot]$ is obtained by dividing each component by the sum of all the components and multiplying the result by the constant *k*, which is described in the definition of the simplex space (4.1):

$$C[Z] = \left(\frac{kz_1}{\sum_{i=1}^{d} z_i}, \frac{kz_2}{\sum_{i=1}^{d} z_i}, ..., \frac{kz_d}{\sum_{i=1}^{d} z_i} \right) \quad (4.2)$$

Let $X = [x_1, ..., x_D]$ and $Y = [y_1, ..., y_D]$, where $X, Y \in S^D$, then the main two operations in the simplex, namely, the perturbation and the power transformation, can be written as in (4.3) and (4.4), respectively:

$$X \oplus Y = C[x_1 y_1, x_2 y_2, ..., x_D y_D] \quad (4.3)$$

$$k \otimes X = C[x_1^k, x_2^k, ..., x_D^k], \text{ where } k \in \Re_+ \quad (4.4)$$

whereas the other operation such as difference (Θ) may simply derived from the above equations, for example:

$$X\Theta Y = X \oplus (-1 \otimes Y) \tag{4.5}$$

The inner product of two vectors composition (X,Y) can be written as follows:

$$\langle X, Y \rangle_a = \sum_{i=1}^{D} \ln \frac{x_i}{g(X)} \ln \frac{y_i}{g(Y)} \tag{4.6}$$

where $g(X) = \sqrt[D]{\prod_{i=1}^{D} x_i}$, $g(Y) = \sqrt[D]{\prod_{i=1}^{D} y_i}$

For a brief mathematical review of the compositional data basics with simple examples, interested readers may refer to Tolosana-Delgado et al. (2005).

4.4 The proposed method: compositional exponential smoothing

The objective of the proposed method is to model the trend of importance over time of the entities or alternatives being compared and to provide forecast in the near future. Specifically, it is to model the change of the AHP final priorities over time or simply the dynamic priorities, which are assumed to come from AHP reciprocal matrices that do not have consistency problem, namely, having CR no more than 0.1. In other words, those dynamic priorities are assumed to result from consistent judgments over time or simply consistent dynamic judgments. Note that unlike Saaty's approach, this proposed method does not suffer from the problems mentioned in Section 4.2.

Since the final priorities are in normalized (summed to unity) form, they can be cast as a compositional data problem. The proper sample space of the compositional data, as elaborated in Aitchison (1982), is the simplex space (S^D), rather than the real sample

space ($\Re$). Therefore, a novel approach, by staying in the simplex space, is proposed to deal with the AHP priorities dynamics using the idea of exponential smoothing approach. Because the exponential smoothing approach is applied in the simplex space, it is worth highlighting that the resulting forecast values can always satisfy the unity constraint.

4.4.1 General procedure

The proposed method, which will be described in the next subsections, can be applied using a simple forecasting procedure (see Hanke and Wichern, 2005). Generally, the procedure to use the proposed method can be described as follows:

1. Collect the necessary historical data, that is, the AHP final priorities of the entities or alternatives over time. This step assumes that the company/user has been using the AHP for a certain period of time, and the AHP was used to derive the importance of entities or alternatives with respect to the existing condition during that period. In addition, these priorities over time should come from consistent judgments, as prescribed by the AHP internal mechanism.
2. Obtain a visual view of the change of the historical AHP priorities data over time. A time series plot can be drawn using Cartesian coordinate system or a ternary diagram.
3. Use the proposed method, namely, the compositional single or double exponential smoothing method, which is described in the next subsections, to fit the historical priorities data.
4. Select the best coefficient of the model based on which that gives the lowest value of fitting error (see Section 4.4.5).

5. Fit the historical priorities data using the optimal model parameter, and obtain the next period forecast. Note that the difference between the actual observation and the fitted data serves as a measure of forecast error (see Section 4.4.4).

4.4.2 Compositional single exponential smoothing (CSES)

Let $Y_t = [y_{t1}, y_{t2}, ..., y_{tD}]$, where $y_{ti} \in \Re_+$, denote a vector of an observation of *D*-part compositional data at time point *t* which is also subject to the sum constraint $\sum_{i=1}^{D} y_{ti} = 1$, then Y_t can be regarded as a vector in the simplex sample space S^D at time point *t*. Following the widely known single exponential smoothing formula (Hanke and Wichern, 2005), the compositional single exponential smoothing (CSES) formula can be analogously expressed as in (4.7).

$$\hat{Y}_t = \alpha \otimes Y_{t-1} \oplus (1-\alpha) \otimes \hat{Y}_{t-1}, \text{ where } 0 \le \alpha \le 1 \tag{4.7}$$

Interestingly, the real space single exponential smoothing shares some similarities with the CSES. When α=0, then $\hat{Y}_t$ would be equal to $\hat{Y}_{t-1}$, which can be easily shown as follows:

$$\hat{Y}_t = 0 \otimes Y_{t-1} \oplus 1 \otimes \hat{Y}_{t-1}$$

$$\hat{Y}_t = C\left[y^0_{1(t\text{-}1)}, y^0_{2(t\text{-}1)}, ..., y^0_{D(t-1)}\right] \oplus C\left[\hat{y}^1_{1(t\text{-}1)}, \hat{y}^1_{2(t\text{-}1)}, ..., \hat{y}^1_{D(t-1)}\right]$$

$$= C[1, 1, ..., 1] \oplus \hat{Y}_{t-1} = \hat{Y}_{t-1} \tag{4.8}$$

Note that $C[1, 1, ..., 1]$ is the identity vector in the simplex space. By the same token, when α=1, then $\hat{Y}_t$ would be reduced to Y_{t-1}. This fact is exactly the same as that of in the real space ($\Re$). Therefore, when α ranges between 0 and 1, it is hoped that it can perform

equally well and give time-efficient forecasts as in the real space. In the example section below, this assertion will be shown to be valid.

4.4.3 Compositional double exponential smoothing (CDES)

Brown's double exponential smoothing (Brown and Meyer, 1961) technique is generally useful for modeling trend in the data. The model may analogously be adopted into the simplex space as in the CSES case. Thus, the compositional double exponential smoothing (CDES) formula, where $0 \le \alpha \le 1$ and $p \in \Re_+$, is given as follows:

$$S_t = \alpha \otimes Y_t \oplus (1-\alpha) \otimes S_{t-1} \tag{4.9}$$

$$S_t^{'} = \alpha \otimes S_t \oplus (1-\alpha) \otimes S_{t-1}^{'} \tag{4.10}$$

$$A_t = 2 \otimes S_t \Theta S_t^{'} \tag{4.11}$$

$$B_t = \frac{\alpha}{1-\alpha} \otimes (S_t \Theta S_t^{'}) \tag{4.12}$$

$$\hat{Y}_t = A_t \oplus B_t \otimes p \tag{4.13}$$

In Section 4.5, the CDES method performance will be shown to be more superior to that of the CSES, especially in modeling the AHP priorities change when there is a data trend along the sides of the ternary diagram.

4.4.4 Fitting Error Measurement

According to the sample space, two measures of goodness of fit, which basically reflect the distance between compositional vector *X* and vector *Y*, will be used in this chapter. First, the distance in the real space, that is, the Euclidean distance which is

expressed as in (4.14). Second, the distance in the simplex space, that is, the Aitchison distance which is expressed as in (4.15).

$$d_E(X,Y) = \sqrt{\sum_{i=1}^{D}(x_i - y_i)^2} \tag{4.14}$$

$$d_a(X,Y) = \sqrt{\sum_{i=1}^{D}\left(\ln\frac{x_i}{g(X)} - \ln\frac{y_i}{g(Y)}\right)^2}\text{, where } g(X) = \sqrt[D]{\prod_{i=1}^{D} x_i}\text{, } g(Y) = \sqrt[D]{\prod_{i=1}^{D} y_i} \tag{4.15}$$

These two distances, which are a scalar quantity, are used as the primary yardstick to judge the goodness of fit of the model used. In general, the smaller the value of the distance, the better the model is. The Aitchison distance can be considered as a more superior distance measure than the Euclidean distance since it has all the necessary properties of scale invariance, permutation invariance, perturbation invariance and subcompositional dominance (Aitchison et al., 2000). Thus, the Aitchison distance will later be emphasized more when comparing the existing methods and the proposed methods. However, the Euclidean distance will still be displayed as a complement.

4.4.5 Smoothing constant and initialization

The selection of alpha (α) parameter, which is the smoothing constant, can be carried out by choosing a grid of values between 0 and 1 that yields the best goodness of fit or the lowest forecast residual. There are some ways to select the optimal alpha (see Makridakis et al., 1998). In this thesis, a simple iterative procedure based on trial-error approach is suggested. In other words, the optimal alpha is derived iteratively by selecting a value between 0 and 1 that yields the minimum Aitchison or Euclidean distance using a constant increment.

Since exponential smoothing method is intrinsically recursive, it starts with some or predefined initial values. A good discussion on initial values selection can be found in Gardner (1985) or Makridakis et al. (1998). For simplicity, it is suggested to use the average of the first *m* observations (Hanke and Wichern, 2005). Specifically, the average of the first three to five observation data is recommended to be used. Note that the average is obtained using the operation in the simplex.

4.4.6 Ternary diagram

Ternary diagram can be regarded as a standard tool in analyzing compositional data, particularly for visualizing three-part compositions, which is also the highest dimension degree which human being can deal with. It is also called a reference triangle, or barycentric coordinate space (see Aitchison, 1986), and is mainly used in geological sciences or political sciences (for example, Katz and King, 1999). Basically, it is another look at the $\{ x + y + z = 1 \}$ plane in the $\Re^3$ Cartesian coordinate system space, which consists of *x*-axis, *y*-axis, and *z*-axis.

4.5 An illustrative example

The example data were generated from a *simulation* result of random AHP pairwise comparison matrices which have CR values ranging from 0 to 0.1. The procedure that was used for generating these data is similar to that of in Section 4.2.1.2 (Figure 4.3). The data are basically a set of simulated third-order AHP matrix priorities for twelve periods. In other words, there are twelve sets of simulated three customer attributes' (DQs) priorities.

Those priorities are tabulated in Table 4.2 ("*Data*" column). Graphically, the three entities' priorities change over time pattern is shown in the ternary diagram in Figure 4.4.

Table 4.2 The actual, fitted, and forecast data of the example

	Data			*CSES (α*=0.9)*			*CDES (α*=0.5)*			*PCA (V.E=88.5%)*			*DRHT*		
t	w_1	w_2	w_3	w'_1	w'_2	w'_3	w'_1	w'_2	w'_3	w'_1	w'_2	w'_3	w'_1	w'_2	w'_3
1	0.7959	0.0830	0.1211	0.9963	0.2081	0.1242	0.7499	0.1566	0.0935	0.8279	0.0968	0.0754	0.7855	0.0978	0.1167
2	0.7429	0.1939	0.0633	0.7931	0.0887	0.1183	0.7499	0.1566	0.0935	0.7271	0.1693	0.1036	0.7430	0.1613	0.0957
3	0.6738	0.2255	0.1007	0.7519	0.1803	0.0678	0.7428	0.1939	0.0633	0.6672	0.2153	0.1175	0.6797	0.2382	0.0821
4	0.5969	0.3458	0.0572	0.6822	0.2208	0.0969	0.6713	0.2375	0.0912	0.5863	0.2803	0.1333	0.5999	0.3254	0.0747
5	0.4434	0.3874	0.1692	0.6074	0.3320	0.0605	0.5708	0.3720	0.0572	0.4470	0.4002	0.1528	0.5084	0.4187	0.0729
6	0.4272	0.4997	0.0731	0.4614	0.3847	0.1540	0.4036	0.4488	0.1477	0.4249	0.4201	0.1549	0.4107	0.5128	0.0764
7	0.3643	0.5783	0.0574	0.4322	0.4887	0.0791	0.3532	0.5658	0.0810	0.3704	0.4706	0.1590	0.3124	0.6019	0.0856
8	0.2290	0.6955	0.0754	0.3711	0.5695	0.0594	0.2962	0.6521	0.0517	0.2345	0.6059	0.1596	0.2194	0.6792	0.1014
9	0.1140	0.8142	0.0718	0.2414	0.6847	0.0739	0.1807	0.7593	0.0600	0.1192	0.7376	0.1432	0.1374	0.7376	0.1250
10	0.0754	0.6955	0.2290	0.1235	0.8042	0.0724	0.0803	0.8599	0.0598	0.0758	0.7958	0.1284	0.0718	0.7701	0.1581
11	0.1283	0.5954	0.2764	0.0801	0.7135	0.2064	0.0476	0.7519	0.2005	0.1335	0.7198	0.1466	0.0266	0.7711	0.2024
12	0.1048	0.4991	0.3961	0.1227	0.6081	0.2692	0.0775	0.5933	0.3292	0.1198	0.7368	0.1433	0.0035	0.7370	0.2595
Forecast (t=13)				**0.1068**	**0.5108**	**0.3824**	**0.0811**	**0.3906**	**0.5283**	**0.1073**	**0.7528**	**0.1399**	**0.0015**	**0.6679**	**0.3306**

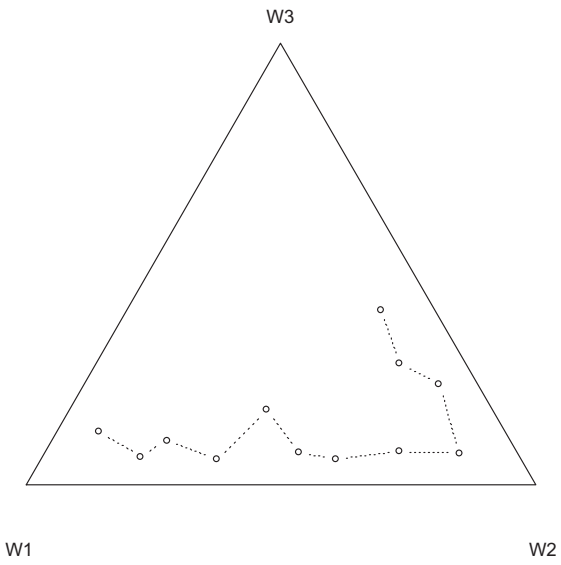


Figure 4.4 Ternary diagram of the relative priorities change over 12 periods

To provide a more realistic description of the simulated data, it is assumed that this AHP priorities change takes place in a *fictitious* education institution. The aim is to provide a contextual setting of how those data may be obtained and interpreted practically.

Recently, due to the rapid educational technologies change, the teaching learning environment paradigm has evolved drastically into computer-supported education system (Pahl, 2003). In view of this, a regular online survey was conducted each month to observe the preference of the students so that a better design of education system can be provided. For simplicity, let suppose that there are three kind of facilities being considered, those are, the "textbooks availability", "lecture web-casting", and "adaptive/personalized learning". Using the AHP pairwise comparison questionnaires, some representative students were selected and asked to quantify their judgment or preference on the importance of these three entities. It is assumed that a consensus was reached among the respondents. In the case when there was an inconsistency in their judgments, a resurvey was conducted (Saaty, 1994).

As depicted in Figure 4.4, the importance value of "textbooks availability" (w_1) appears to decrease as the passage of time, and this trend is compensated with the increase in the importance value of "lecture web-casting" (w_2). This happened because the internet bandwidth has been increasing significantly since last year, which results in higher and higher feasibility for audio/video streaming. Moreover, as the personal computers or internet connection become more affordable as the passage of time, the students' interest for "lecture web-casting" has substantially increased over time.

However, in the last two months, there has been another 'trend' in the importance of "adaptive/personalized learning" (w_3) system, which was not realized previously. This changing need of the students can be explained by the reason that they have already had satisfactory computer or internet facility. As a result, having a personalized/adaptive learning system based on each student ability and convenience generates more and more interests among the students. This phenomenon has to be properly anticipated and

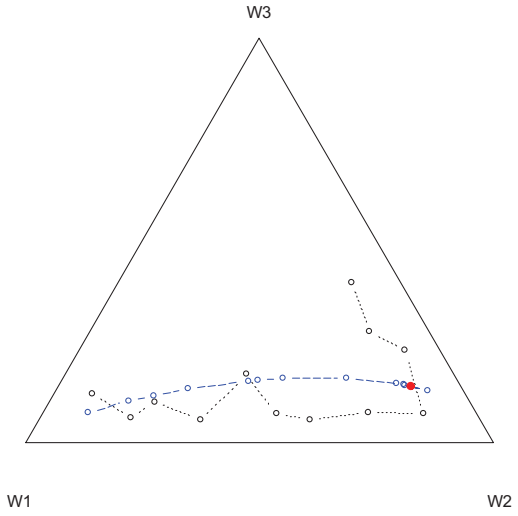
reflected when designing a flexible education system which is expected to be able to cope with the evolution/change cost-effectively and, at the same time, increase the chance of including innovative developments.

In the next section, the twelve-month importance data or the dynamic priorities will be modeled using four methods, namely, the principal component analysis (PCA) method, the dimension-reduction through a hyperspherical transformation (DRHT) method, the compositional single exponential smoothing (CSES) method, and the compositional double exponential smoothing (CDES) method. The procedure of modeling the dynamic priorities using the four methods follows what was described in Section 4.4.1. It will be demonstrated that the CDES method graphically and analytically performs better than the PCA method and the DRHT method. Specifically, the CDES method will have a lower fitting error mean value and a much lower fitting error variability value, by more than a half, compared to that of the DRHT method. Afterwards, the residuals of all the models will be statistically analyzed in the following subsection.

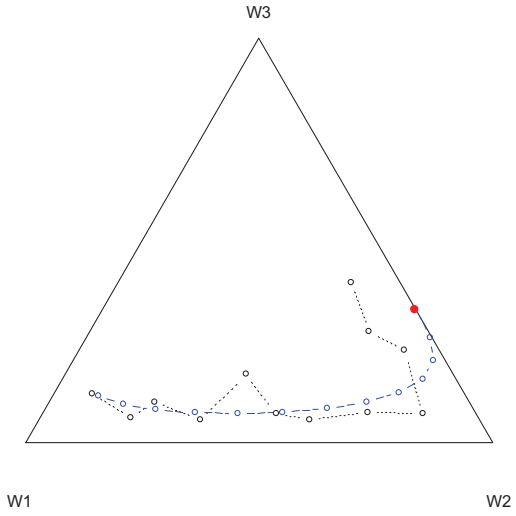
4.5.1 Model building and forecasting process using four methods

First, the historical data in the form of compositional data was fitted using the non-centered PCA as described in von Eynatten et al. (2003) or von Eynatten (2004). The initial value was obtained from the geometric mean of the first two observations. The historical actual data as well as the fitted plot, while staying in the simplex space, can be seen in Figure 4.5a. In the ternary diagram, an empty-dot is used to denote the actual and the fitted data point, while a full dot is used to indicate the forecasted point. A ‘dotted’ line and a ‘long-dash’ line are used to link the historical actual observations and the fitted data, respectively. By visual inspection, the non-centered PCA method appears to have

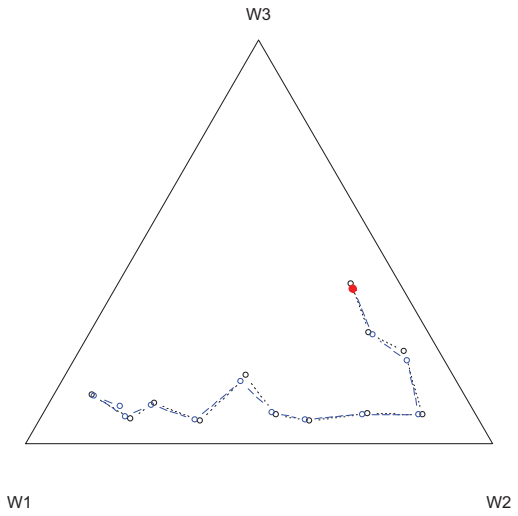
difficulty to adapt to the change of the priorities over time even though the value of the variation explained by this method is relatively high (88.5%). The fitted data as well as the forecasted composition is shown in Table 4.2 ("*PCA*" column). As a result of the inflexibility, this method produced a forecasted point which is not in the same direction as the data 'trend'. Note that the k value of the forecasted point was obtained from $k_{12+1} = k_{12} + |k_{12} - k_{11}|$.



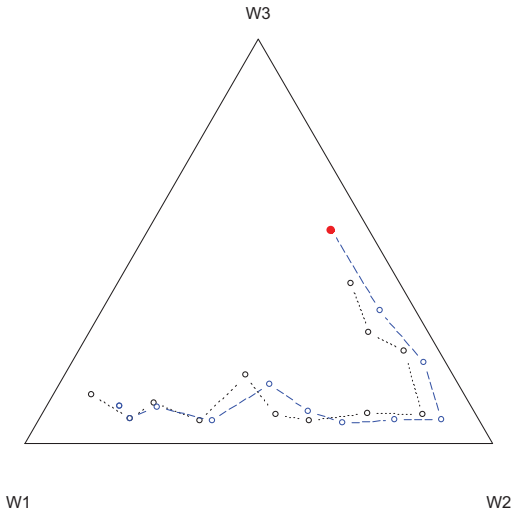
(a) The PCA Method



(b) The DRHT Method



(c) The CSES Method



(d) The CDES Method

Figure 4.5 Ternary diagram of fitting historical data using four methods (a-d)

Second, the DRHT method using second-order polynomial was used to fit the compositional data. After the mapping process onto the hypersphere, the second-order polynomial was employed, and the best-fit equations for the second and the third angle data series are expressed in (4.16) and (4.17). After fitting the angle data series, a forecasted point was obtained. Lastly, the angle data series were transformed back into the compositional data. The fitted and the forecasted values can be found in Table 4.2 ("*DRHT*" column).

$$\theta_2^t = -0.0009t^2 - 0.094t + 1.3264 \tag{4.16}$$

$$\theta_3^t = -0.0051t^2 + 0.0494t + 1.1779 \tag{4.17}$$

Graphically, the plot is shown in the ternary diagram (Figure 4.5b). Again, the fitted data appear to lag behind the trend. This further substantiates the fact that the DRHT method does not show the required capability to adapt to this rather volatile change.

Third, the Compositional Single Exponential Smoothing (CSES) method, of which initial value was chosen to be the average of the first three observations, was used to fit the data as shown in Figure 4.5c. This method turns out to be better, in terms of the ability to follow the data trend, than that of the previous two methods as can be inspected visually. However, the fitted data using CSES method still appear to lag behind the actual data. As a result, it may have a larger fitting mean error and might still be considered deficient. The complete numerical results for each observation point are provided in Table 4.2 (see "*CSES*" column). Note that the value of α^*=0.9 was chosen to give the minimum mean value of the Aitchison distance (d_a) between the actual and the fitted data. It is easy to see that this relatively high value of alpha is due to the rather volatile change in the actual data.

Fourth, the Compositional Double Exponential Smoothing (CDES) method, which is particularly more powerful in handling data trend, was used to fit the data as shown in Figure 4.5d. Graphically, the CDES method appears to be the best among the others, particularly in following the trend of the data. It provides much greater adaptability to the priorities change over time and, as a result, a better forecasted point. Table 4.2 ("*CDES*" column) shows the numerical fitted and forecasted data. The value of α^{*}=0.5 was chosen using the same way as in the CSES case. In particular, the CDES method can be said to perform better than the DRHT method in terms of both the fitting and forecasting process. This is again depicted clearly in the Cartesian coordinate system plot (Figure 4.6). It appears that the DRHT method fails to follow the trend after time point 9.

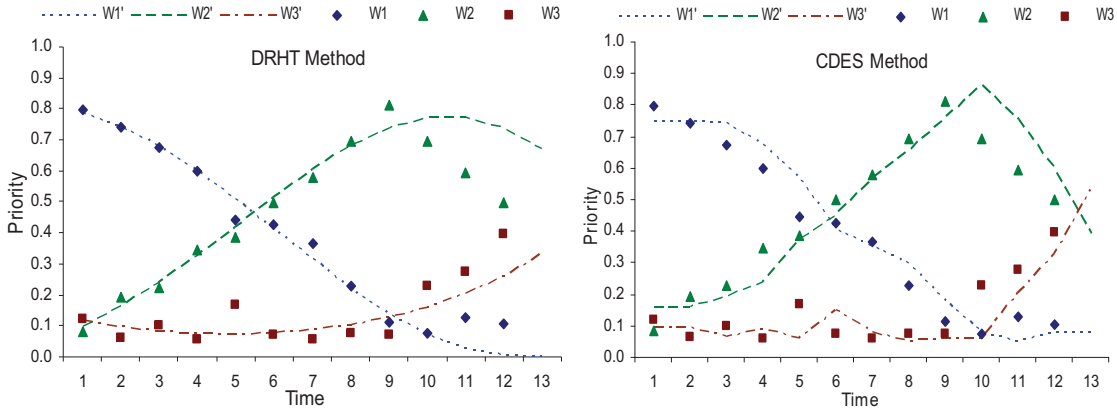


Figure 4.6 Plot of actual, fitted and forecasted priorities using the DRHT and the CDES method

4.5.2 Residual analysis of the four models

The residual analysis was carried out based on the two distance measures, as previously mentioned. Table 4.3 shows the residual values of the four methods. In terms of Euclidean distance, the DRHT approach gives the lowest mean value with a relatively high variability compared to the other methods. However, in terms of Aitchison distance,

which is a better measure of distance in the compositional sense, the DRHT method gives slightly higher mean value yet with much higher variability than that of the CDES approach. More precisely, the fitting error variability of the DRHT method (=0.7702) is relatively larger compared to that of the CDES method (=0.2932) by more than two times (0.7702/0.2932=2.63). Therefore, it can be concluded that the CDES approach performs much better in this respect. Although the PCA method gives slightly lower mean and variability value than that of the CDES, this method can be regarded as less favorable due to its linear nature, which makes it difficult to produce a good forecast, as shown graphically in Figure 4.5a. The CSES method performs no better than the CDES approach as also shown graphically in Figure 4.5c. Thus, the main focus is now given to the CDES and the DRHT method.

Table 4.3 Residual of the four methods using Euclidean and Aitchison distance

	Euclidean Distance				*Aitchison Distance*			
t	CSES (α*=0.9)	CDES (α*=0.5)	PCA (V.E=88.5%)	DRHT	CSES (α*=0.9)	CDES (α*=0.5)	PCA (V.E=88.5%)	DRHT
1	0.2363	-	0.0575	0.0187	0.6635	-	0.4731	0.1559
2	0.1289	0.0485	0.0498	0.0460	1.0024	0.4316	0.4731	0.4326
3	0.0961	0.0846	0.0207	0.0233	0.3637	0.3982	0.1511	0.1954
4	0.1564	0.1357	0.1010	0.0271	0.6943	0.5985	0.7956	0.2456
5	0.2044	0.1703	0.0211	0.1203	0.9635	0.9935	0.1012	0.7762
6	0.1447	0.0933	0.1142	0.0213	0.7243	0.6422	0.6966	0.0622
7	0.1145	0.0289	0.1482	0.0636	0.3540	0.3023	0.9227	0.3974
8	0.1906	0.0834	0.1231	0.0322	0.5742	0.4490	0.6690	0.2695
9	0.1817	0.0872	0.1048	0.0962	0.6863	0.4841	0.5944	0.4633
10	0.1966	0.2360	0.1421	0.1030	1.2262	1.2136	0.5375	0.3414
11	0.1455	0.1917	0.1799	0.2161	0.4764	0.8672	0.6204	1.3269
12	0.1683	0.1188	0.3474	0.2925	0.4614	0.3499	1.0592	2.8212
Mean	0.1637	0.1162	0.1175	0.0884	0.6825	0.6118	0.5912	0.6240
StDev	0.0405	0.0625	0.0882	0.0864	0.2683	0.2932	0.2785	0.7702

Using the Aitchison distance obtained for the CDES and the DRHT method, a basic statistical analysis of the residual can be carried out as shown in Table 4.4. Using the Anderson-Darling normality test, it is interesting to highlight that the CDES approach

gives approximately normal residuals, while the DRHT method does not. This again gives support to the fact that the CDES method performs better than the DRHT method. Furthermore, the large standard deviation value of the residual of the DRHT method also implies that the accuracy of the prediction will not be high. In other words, the future uncertainty obtained by using this method will be relatively high.

Table 4.4 Residual statistic and normality test based on Aitchison distance

	Mean	*StDev*	*Min*	*Q1*	*Median*	*Q3*	*Max*	*Skewness*	*Kurtosis*	*P-value (A-D Test)*
CDES	0.612	0.293	0.302	0.398	0.484	0.867	1.214	1.07	0.17	0.107
DRHT	0.624	0.770	0.062	0.208	0.369	0.698	2.821	2.50	6.61	<0.005

4.5.3 Solving the example data using Saaty's approach

Saaty's dynamic judgment approach has, in general, a different starting point as compared to the dynamic priority approach, which is proposed in this chapter. Specifically, the difference lies in the fact that they employ different input data. The input of Saaty's approach is the dynamic judgments which are expressed in terms of functions in the literal sense (Saaty, 2007). To select these functions, one need not have explicit historical data. It is this approach that may very likely cause the self-contradictory problem, as highlighted in Section 4.2.1. As opposed to Saaty's approach, the dynamic priority approach does not use some standard or predefined functions as the input. Instead, it relies heavily on the historical data, that is, the change of priorities over time, in order to forecast the future priorities.

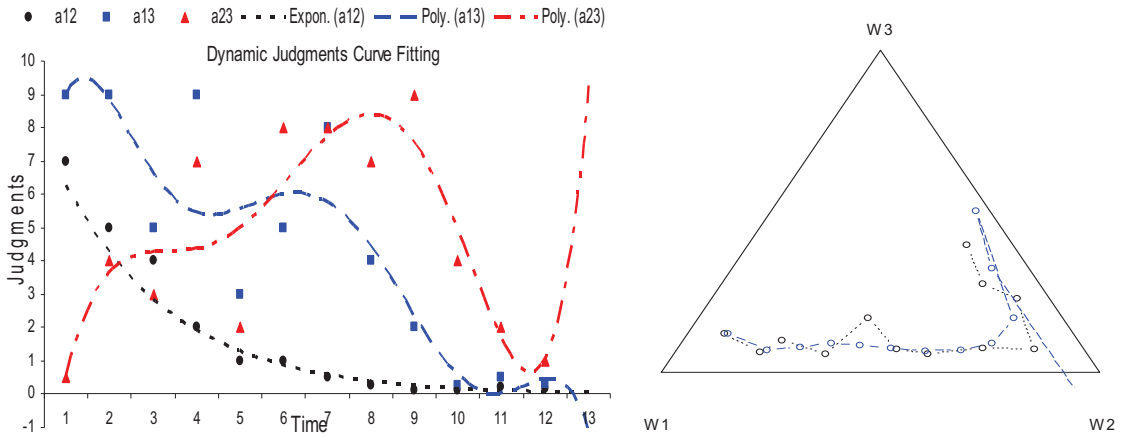
Now, suppose that Saaty's dynamic judgment approach is applied to the example data. Here, the aim is to see whether the dynamic judgment approach might work well in the case when historical judgments are available. The twelve-month judgments data for the example, which have consistency ratio no more than 0.1, are shown in Table 4.5. The 3-

by-3 reciprocal matrix elements' values are represented in the 'a_{12}', 'a_{13}', and 'a_{23}' columns of Table 4.5. The 'w_1', 'w_2', and 'w_3' columns show the final priorities of the judgments, as used in the previous analysis. The 'CR' column shows the consistency ratio of judgment for the corresponding month.

Table 4.5 Judgment data and fitting results using the dynamic judgment approach

t	a_{12}	a_{13}	a_{23}	w_1	w_2	w_3	CR	a_{12}'	a_{13}'	a_{23}'	w_1'	w_2'	w_3'	CR'
1	7.00	9.00	0.50	0.7959	0.0830	0.1211	8.61%	6.27	8.97	0.53	0.7875	0.0905	0.1219	9.38%
2	5.00	9.00	4.00	0.7429	0.1939	0.0633	6.14%	4.23	8.80	3.67	0.7247	0.2071	0.0682	3.08%
3	4.00	5.00	3.00	0.6738	0.2255	0.1007	7.39%	2.85	6.63	4.28	0.6438	0.2769	0.0793	3.57%
4	2.00	9.00	7.00	0.5969	0.3458	0.0572	1.87%	1.92	5.47	4.38	0.5684	0.3416	0.0900	1.79%
5	1.00	3.00	2.00	0.4434	0.3874	0.1692	1.58%	1.30	5.58	5.01	0.5045	0.4096	0.0860	0.22%
6	1.00	5.00	8.00	0.4272	0.4997	0.0731	2.12%	0.87	6.02	6.31	0.4381	0.4870	0.0750	0.08%
7	0.50	8.00	8.00	0.3643	0.5783	0.0574	4.62%	0.59	5.77	7.74	0.3627	0.5693	0.0680	0.53%
8	0.25	4.00	7.00	0.2290	0.6955	0.0754	6.59%	0.40	4.42	8.42	0.2822	0.6477	0.0701	0.74%
9	0.11	2.00	9.00	0.1140	0.8142	0.0718	4.62%	0.27	2.35	7.53	0.2002	0.7102	0.0896	0.23%
10	0.14	0.25	4.00	0.0754	0.6955	0.2290	6.59%	0.18	0.58	4.91	0.1128	0.7187	0.1685	1.69%
11	0.20	0.50	2.00	0.1283	0.5954	0.2764	0.48%	0.12	0.03	1.67	0.0314	0.4660	0.5026	30.96%
12	0.17	0.33	1.00	0.1048	0.4991	0.3961	4.62%	0.08	0.46	1.05	0.0851	0.5927	0.3222	27.62%

To do a curve fitting for each of the pairwise comparison elements, one may need to first observe the graphical plot of the judgments change over time, as depicted in Figure 4.7a. A full dot, square, and triangle are used to denote the actual change of element 'a_{12}', 'a_{13}', and 'a_{23}' over time, respectively. For element 'a_{12}', it is easy to see that an exponential function may fit the data well. However, for element 'a_{13}' and 'a_{23}', the change appears to be rather volatile, thus, a polynomial function might be a good alternative. Using curve fitting software, the best-fit exponential function of element 'a_{12}' has an R-square of 91.51%, while the best-fit six-order polynomial functions of element 'a_{13}' and 'a_{23}' have R-squares of 78.7% and 74.45%, respectively. Since those best-fit functions are reasonably good, they are used for the dynamic judgments analysis.



(a) **(b)**

Figure 4.7 (a) Plot of actual, fitted and forecasted judgments values using Saaty's approach, (b) Ternary diagram of actual, fitted, and forecasted priorities using Saaty's approach

The resulting fitted data are shown in Table 4.5, under the column 'a_{12}'', 'a_{13}'', and 'a_{23}''. The corresponding final priorities of the fitted data are also given next to them. A closer look at the consistency ratio (CR) values of the fitted data reveals that from the eleventh month onwards, the CR values range beyond 0.1. Graphically, the fitted and forecasted judgment data can be seen in Figure 4.7a. A 'dash', 'long-dash', and 'dash and long-dash' line are used to indicate the fitted and forecasted values of 'a_{12}', 'a_{13}', and 'a_{23}', respectively.

In sum, there are two important points that can be empirically observed here. First, although a set of consistent judgments data were used, namely, having CR values no more than 0.1, the dynamic judgment approach still has a problem in preserving the consistency value when fitting the historical data. In other words, representing judgments change using functions in literal sense, as suggested by Professor Saaty (Saaty, 1988, 1994, 2007), is very likely subject to a self-contradictory problem, that is, failure in preserving consistency ratio over time, regardless of the availability of historical data.

Second, the dynamic judgment approach also has a serious weakness when it comes to forecasting stage. As shown in Figure 4.7a, the forecasted judgments values fall outside the AHP fundamental scale range of 1 to 9. Furthermore, as a result of this condition, the forecasted priorities can no longer preserve the unity constraint, as shown in the ternary diagram (Figure 4.7b). This is simply due to the fact that one of the forecasted judgment values is negative. These two points again confirm what was previously mentioned as the shortcoming of Saaty's method (see Section 4.2.1). Hence, considering these limitations, this approach can be said to be intrinsically inadequate to be used for forecasting purpose as to compare with the four methods in the previous analysis.

4.6 Discussion and limitations

4.6.1 Dynamic judgments and dynamic priorities

The basic relationship between dynamic judgments and dynamic priorities is that the dynamic priorities result from dynamic judgments. A further question would be which one is easier to deal with both practically and theoretically. What has been proposed in the literature is to model dynamic judgments using mathematical models, such as curve fitting method (Saaty, 1988, 1994, 2007). However, apart from its limitation in dealing with higher order matrices, this approach also suffers from the potentially self-contradictory problem and the rigidity issue, as has been demonstrated in Section 4.2.1. Therefore, theoretically speaking, an extra caution is required to use this approach, although it might be practically easier to deal with.

In view of this, it is suggested that one may directly model the final priorities of the judgments that change over time, or simply the dynamic priorities. By so doing, the

problems encountered using the dynamic judgment approach might be avoided. However, a necessary condition that has to be satisfied when using the dynamic priority approach is the availability of some historical judgment data. Furthermore, these historical judgment data are assumed to come from consistent AHP reciprocal matrices, namely, having CR values no more than 0.1. In other words, the dynamic priority approach employs a set of consistent judgments over time.

A major advantage of using the dynamic priority approach, as was shown in this chapter, is to have a greater flexibility in dealing with the change of priorities over time. This is particularly useful in dealing with today's rapidly changing environment. On the other hand, a possible limitation of the dynamic priority approach is the less emphasis on the change of the pairwise comparison matrix elements over time.

4.6.2 Short-term and long-term forecast

The compositional exponential smoothing method, as with general exponential smoothing methods, is most suitable for short-term forecasting. However, when the historical data get larger, the CSES or CDES method might not be the best method due to the possibility of excessive fitting. For long-term forecasting, where the number of data is relatively large, there may be two alternatives to handle such situation. First, it is to use other more suitable or advanced forecasting methods, for example, the multivariate time series analysis for compositional data (Quintana and West, 1988; Grunwald et al., 1993; Brunsdon and Smith, 1998). Note that the DRHT method might also be suitable for this purpose. Second, it is to truncate some of the historical data considering its recentness and relevance, and use the exponential smoothing approach. This approach is appropriate especially when dealing with a highly dynamic environment, in which earlier data might

quickly become outdated and irrelevant. Thus, it is of little use to include them in the analysis.

4.6.3 Computation efficiency

To improve the computation efficiency of the proposed compositional exponential smoothing method (see equation 4.7 to 4.13), it is possible to simplify the traditional power transformation operation (see equation (4.4)) into the following equation:

$$k \otimes X = \left[x_1^k, x_2^k, ..., x_D^k\right] \tag{4.18}$$

By omitting the closure operator, it may not only save several steps in the computation process, but it may also avoid possible computational errors which are due to excessive division in the compositional data, especially when the amount of data gets larger. Note that using equation (4.18) will not change the final results of the proposed approach.

4.7 Conclusion

The purpose of this chapter was to provide a possible answer to the research question "*How to use the AHP in QFD in dealing with the dynamics of priorities?*" A new modeling technique called compositional exponential smoothing is proposed to model the dynamics of AHP's relative priorities. Both kinds of the proposed compositional exponential smoothing technique, namely, the CSES and the CDES, have been demonstrated to be useful in modeling the AHP priorities change over time. Essentially, both of them share a similar mechanism as the standard exponential smoothing technique (Hanke and Wichern, 2005). The main difference is that all the mathematical operations

are done within the context of compositional data, which is precisely the form of AHP-based priorities.

In terms of identifying and forecasting short-term trend, the proposed method, especially the CDES technique, has been shown to be more superior than other methods, such as the DRHT method or the PCA method, in providing much greater adaptability in modeling the AHP priorities change over time.

A major benefit of the proposed technique is that the fact that it is relatively simple and time-efficient compared to that of other more advanced techniques, such as multivariate time series techniques. At the expense of model complexity, using multivariate time series or other approaches will possibly give lower values of fitting error. Nevertheless, to deal with limited number of data within the context of a highly dynamic environment, the proposed approach can be considered adequate to serve the purpose of modeling the dynamic priorities. The fact that it does not require an extensive set of historical data precisely meets the need of modeling the AHP-based priorities in QFD since there will only be a limited number of historical data.

For future extension of the proposed technique, a further investigation on the accuracy of the proposed approach as the component of the composition, namely, the number of alternatives or entities being compared, gets larger might be an interesting issue. A study of the impact of multi-level hierarchy in the AHP on the dynamic priorities might also be considerable for future research.

In the next two chapters, the applications of the proposed CDES technique in improving QFD analysis with respect to the change during product or service creation process are provided. The first application is to apply the CDES technique in modeling Kano's model dynamics (Chapter 5), and the second one is to apply the CDES technique

in modeling the change of DQs' competitive assessment over time (Chapter 6). Both applications will show how the new modeling technique proposed in this chapter may contribute to an improved QFD analysis. Another example of possible application of the proposed technique, although beyond the scope of this thesis, would be in business forecasting field, such as aggregate production planning.

CHAPTER 5
APPLICATION OF THE MODELING TECHNIQUE (PART 1 OF 2) – INTEGRATING KANO'S MODEL DYNAMICS INTO QFD

The purpose of this chapter is to demonstrate one application of the new modeling technique (Chapter 4) as to improve QFD analysis. The modeling technique will be applied to model the dynamics of Kano's model, that is, the fact that what delighted the customer yesterday is asked today and will be expected tomorrow. Such dynamics can be regarded as one example of change during product or service creation process (Section 1.1). In the literature, Kano's model has been incorporated into QFD analysis to better identify and obtain more accurate DQs. However, almost none of the existing QFD research has considered the dynamics of Kano's model. It will be shown that the application of the CDES technique may not only extend the use of Kano's model in QFD, but also advance the academic literature on modeling the life cycle of quality attributes quantitatively. This chapter is reproduced from "Integrating Kano's Model and Its Dynamics into QFD for Multiple Product Design", by Raharjo H, Brombacher AC, Goh TN, Bergman B. Published in *Quality and Reliability Engineering International*.

5.1 Introduction

QFD's application success is largely determined by the accuracy of the main input information, that is, the voice of the customer or the DQs (Cristiano et al., 2001). To better identify and obtain more accurate DQs, the use of Kano's model (Kano et al. 1984) has been incorporated into QFD analysis by several researchers (Matzler and Hinterhuber, 1998; Shen et al., 2000; Tan and Shen, 2000; Tan and Pawitra, 2001; Xie et al., 2003;

Sireli et al., 2007; Lai et al., 2007; Tontini, 2007). It provides a unique way of classifying the DQs based on their different impact on total customer satisfaction in early stage of products or services development.

Nevertheless, the existing QFD literature has paid too little attention to the fact that what now delights the customer will become an expected need in the near future (Kano, 2001). When using Kano's model for identifying and obtaining more accurate DQs, it is proposed that QFD users may, in line with previous research, monitor the change and follow its pattern over time so that a forecast can be obtained (Xie et al., 2003; Wu et al., 2005; Wu and Shieh, 2006; Raharjo et al., 2006). The forecast, which serves as a reflection of future needs, may be used to better deal with the change during product or service creation process (Section 1.1). In addition, there is also a lack of uniform quantitative methodology in integrating Kano's model into QFD (Matzler and Hinterhuber, 1998; Shen et al., 2000; Tan and Shen, 2000; Xie et al., 2003; Sireli et al., 2007; Van de Poel, 2007).

To fill in the niche, this chapter proposes a methodology to quantitatively model Kano's model dynamics, and integrate the results into QFD analysis for multiple product design. In the following sections, the research gap that motivated this work will first be described (Section 5.2). Afterwards, the forecasting method to model Kano's model dynamics is briefly explained in Section 5.3. Using the forecasting results as the input, the optimization framework for multiple product design is elaborated in Section 5.4. To give some practical insights, an illustrative example is also provided (Section 5.5). Finally, Section 5.6 provides a summary of the novel contributions and some discussions on the potential extension of this work.

5.2 Kano's model in QFD: existing approaches and research gap

5.2.1 Kano's model and its dynamics

Essentially, Kano's model categorizes customer needs into three major attributes, namely, must-be (M), one-dimensional (O), and attractive (A). A must-be (M) attribute is associated with those needs that are not mentioned explicitly or taken for granted by the customer, the non-existence will cause a great deal of dissatisfaction while the existence does not bring a significant satisfaction. A one-dimensional (O) attribute reflects the spoken needs of the customer, the more it is fulfilled, the more the customer becomes satisfied in proportional way to the degree of fulfillment. While an attractive attribute (A) is known as delighters, which means a little improvement on the product/service performance will make a significant increase in the level of customer satisfaction. This attribute serves as the largest determinant of the customer satisfaction degree, and is particularly useful for providing innovative products/services. Some other attributes are indifferent (I), reverse (R), and questionable (Q) (see CQM, 1993). Kano believes that the VOC, either it is spoken or unspoken, can be exploited through a questionnaire (Kano et al. 1984; CQM, 1993; Matzler and Hinterhuber, 1998).

In this chapter, the focus will be placed on four attributes, namely, attractive (A), one-dimensional (O), must-be (M), and indifferent (I). It is worth noting that as the passage of time, what now excites the customer (A) will become an expected requirement (O/M) in the near future because it will have become a common thing (A → O or A→ M). Based on an empirical evidence of using remote-control device for a television set, Kano (2001) provided an interesting theory of quality attribute dynamics which follows a life-cycle such as the following: indifferent → attractive → one-dimensional → must-be.

In line with this stream of research, Witell and Fundin (2005) provided an empirical study to show the dynamics of customer attributes in e-service. They found that when the e-service was introduced, it was perceived as indifferent (I). After a relatively short time, it was then seen as an attractive (A) attribute since the customer started to realize the importance of that particular attribute. Unfortunately, they did not provide a formal methodology to account for Kano attributes' change over time. In fact, the notion of life cycle of quality attributes can be regarded as one of the most interesting and fruitful developments of the theory of attractive quality during the last two decades (Löfgren and Witell, 2008).

Therefore, this chapter attempts to fill in this gap by providing a quantitative model to monitor the change of Kano's attribute or category over time. There are two reasons of using this approach. First, it enables the firm to monitor the progress of how well a company satisfies its customer, and to observe how fast the rate of obsolescence of their product/service's over time. Thus, the firm may better anticipate the change cost-effectively and further react differently and continuously over time. Second, it is to provide predicted values that reflect the future needs of the customer. Such information is very useful in formulating the firm's next strategy, especially for anticipating the time lag problem from the VOC collection point to the point where the product is ready to market (Section 1.1).

5.2.2 Kano's model for multiple product design in QFD

Some previous studies have shown that there is a lack of uniform quantitative methodology to integrate Kano's model into QFD (Matzler and Hinterhuber, 1998; Shen et al., 2000; Tan and Shen, 2000; Tan and Pawitra, 2001; Xie et al., 2003; Van de Poel,

2007, Tontini, 2007). In response to this lack, Sireli et al. (2007) presented a simple yet effective technique to make use of 'one-time' information obtained from Kano questionnaire for simultaneously designing multiple products with features improving over time. Using a case study of a relatively new and complex graphical weather product for pilots in NASA, they wrote that the proposed integration methodology is especially useful and time-saving for introducing innovative products into the market.

Nevertheless, their approach, as some were already mentioned in the paper's future work, has oversimplified some important issues that might likely cause the QFD fail to serve its main function. There are two major shortcomings, namely, the technical side and the practical side which are worth highlighting for the improvement of the existing approach described in Sireli et al. (2007):

1. The exclusion of customer requirement which has an 'inconclusive' category. Let suppose that the inconclusive condition occurs between an attractive (A) category and a one-dimensional (O) category, then the exclusion of this customer requirement will certainly induce a failure in the attempt of capturing the VOC. As a result, the QFD team might end up producing unwanted product/service. This problem is, in fact, introduced by the use of the statistical analysis described in Fong (1996).
2. Too high reliance on the role of decision maker. Although decision maker's role in selecting which entities to include in a particular product design is inevitably important, too high reliance on this, however, will not only give rise to higher chance of human error, but also take much more time than it should. For example, consider a situation where there are 50 features to be mapped to 5 product classes. When the selection process is done manually, it is very likely that one may end up with a non-optimal solution with respect to the cost involved. It can even be worse if so much

time has been spent on it. Another possible problem may be that one might forget that one or more features, due to design constraints, should not be put together in a product class or mapped into several product classes. Such problems happen because of the difficulty of human beings to deal with many items and constraints at the same time. Therefore, a more formal and systematic procedure of doing the selection, for example, by employing an optimization model, might be a good alternative.

To overcome the first deficiency, it is suggested that the QFD practitioners may instead use the 'traditional' technique, which has been applied in many Kano's model application, that is to use the most frequent observation (mode) approach (see CQM, 1995; or Matzler and Hinterhuber, 1998). As to account for the robustness of the results, two sources of variability will be taken into account (see Section 5.4.2). To resolve the second weakness, a quantitative model is proposed for optimizing the multiple product design. The model is particularly useful when the QFD size is prohibitively large, which is generally an inherent problem in QFD. After constructing the necessary quantitative model, the optimization can be carried out using software instead of relying on manual approach.

5.3 Modeling Kano's model dynamics

5.3.1 The Input

The main input of the proposed mathematical model is the Kano questionnaire results, which are in *percentage* data form (see CQM, 1993 or Matzler and Hinterhuber, 1998). Generally, it describes the percentage of the attractive, one-dimensional, must-be, and

other categories for each of the customer attributes. Since Kano questionnaire results are in percentage data form (summed to unity), then they can be regarded as a compositional data problem. The focus here is to model the change pattern of the percentage data over time for each category. The proposed compositional data modeling method (Chapter 4), namely, the CDES technique will be adopted to model the Kano category change over time.

5.3.2 The CDES method

The CDES approach proposed in Chapter 4 can be simply applied using a simple forecasting framework (Hanke and Wichern, 2005). Basically, one needs to collect the necessary historical data, that is, the Kano questionnaire results over a certain period of time. Afterwards, to obtain a visual view of the historical data change behavior, a time series plot can be drawn using the Cartesian coordinate system. When using the proposed approach, one may select the best coefficient of the model based on which that gives the lowest value of fitting error (see Section 4.4). Finally, using the optimal smoothing constant (α^*), the fitting and the forecasting process can be carried out accordingly.

Let $Y_t = [y_{t1}, y_{t2}, ..., y_{tD}]$, where $y_{te} \in \Re_+$, denote a vector of an observation of D-part compositional data at time point t which is also subject to the sum constraint $\sum_{e=1}^{D} y_{te} = 1$, then Y_t can be regarded as a vector in the simplex sample space S^D at time point t. This Y_t represents the percentage of the Kano model category resulting from the Kano questionnaire, for example, if the percentage distribution at time point t for the attractive,

one-dimensional, must-be, and indifferent attribute is, respectively, 30%, 40%, 20%, and 10%, then it can be represented as $Y_t = [y_{t1} = 0.3, y_{t2} = 0.4, y_{t3} = 0.2, y_{t4} = 0.1]$.

The CDES formula for modeling Kano's model dynamics, where $0 \le \alpha \le 1$ and $q \in \Re_+$, is given as follows:

$$S_t = \alpha \otimes Y_t \oplus (1-\alpha) \otimes S_{t-1} \tag{5.1}$$

$$S_t^{'} = \alpha \otimes S_t \oplus (1-\alpha) \otimes S_{t-1}^{'} \tag{5.2}$$

$$A_t = 2 \otimes S_t \Theta S_t^{'} \tag{5.3}$$

$$B_t = \frac{\alpha}{1-\alpha} \otimes (S_t \Theta S_t^{'}) \tag{5.4}$$

$$\hat{Y}_t = A_t \oplus B_t \otimes q \tag{5.5}$$

5.3.3 Selection of model parameter

As also described in Chapter 4, the selection of alpha (α) parameter, which is the smoothing constant, can be carried out by choosing a grid of values between 0 and 1 that yields the best goodness of fit or the lowest forecasting residual. A simple iterative procedure based on trial-error approach is suggested, that is, by selecting a value between 0 and 1 that yields the smallest Aitchison distance using a constant increment. Since exponential smoothing method is intrinsically recursive, it starts with some predefined initial values. For simplicity, the average of the first three observations data is recommended to be used in this chapter.

5.3.4 Fitting error measurement

The distance between compositional vector X and vector Y in the simplex space is called the Aitchison distance (Ad), of which expression is shown in (5.6). This distance, which is a scalar quantity, is used as the primary yardstick to judge the goodness of fit of the model proposed. In general, the smaller the value of the distance, it implies that the better the model is.

$$Ad(X,Y) = \sqrt{\sum_{e=1}^{D}\left(\ln\frac{x_e}{g(X)} - \ln\frac{y_e}{g(Y)}\right)^2}\ , \text{where } g(X) = \sqrt[D]{\prod_{e=1}^{D} x_e}\ ,\ g(Y) = \sqrt[D]{\prod_{e=1}^{D} y_e} \qquad (5.6)$$

5.4 Kano Optimization for Multiple Product Design

The main input of the optimization method is the forecasted values from previous section (Section 5.3), that is, the forecasted *percentage* data of each Kano's model category. In the context of a rapidly changing environment, this forecasted data should become the main input for QFD analysis because the past voice of customer might be no longer relevant as the customer preference may have changed during the product creation process (see Chapter 1). A deeper treatment of this issue will be provided in Chapter 8. In line with the work done in Sireli et al. (2007), this optimization stage is designed for optimizing multiple product design with feature improving over time.

Let m and n denote, respectively, the number of basic DQ that each product variant must have, and the number of subcomponent of each DQ. Take a simple example, a product, such as a laptop, has to have 'weight' and 'keyboard' as the basic DQ. While the types of weight (e.g: 'ultra-light' or 'light') or the types of the keyboard (e.g: 'glowing' or 'spill-resistant') are considered as the subcomponents. In the next subsections, how the

forecasted Kano percentage data can be effectively used for deriving the final weights of each DQ, while considering the variability involved, will be described. Afterwards, the proposed optimization model along with the three main constraints will be discussed in detail.

5.4.1 Deriving weights from forecasted Kano percentage data

To incorporate the results of forecasted Kano percentage data into QFD, one needs to first determine the category of each DQ according to the Kano's model. In this chapter, only four categories, namely, attractive (A), one-dimensional (O), must-be (M), and indifferent (I), are considered. The decision into which category each DQ falls is made based on the most frequent observation results (CQM, 1995; Matzler and Hinterhuber, 1998).

A ratio-scale weight (Harker and Vargas, 1987), which is similar to the Analytic Hierachy Process (AHP) fundamental scale, is proposed to be assigned to each Kano category for the corresponding DQ_{ij}. For the four main categories (A, O, M, I), the weight assignment is expressed in (5.7).

$$W_{ij}^{KN} \in \left\{ w_{ij}^{A} = 9, w_{ij}^{O} = 5, w_{ij}^{M} = 3, w_{ij}^{I} = 1 \right\}, \qquad \forall i = 1,..., m, \quad \forall j = 1,..., n \tag{5.7}$$

where W_{ij}^{KN} denotes the unadjusted weight of Kano category.

For the case when there is more than one mode value in the results, a compromise value can be obtained by selecting the mid-point between the corresponding categories. For example, if the percentage amount of 'A' and 'O' of a particular attribute is the same, then a value of 7 [=(9+5)/2], that is, the mid-point between the weight of 'A' and 'O', is

assigned to W_{ij}^{KN}. The W_{ij}^{KN} will later be adjusted by its variability (Section 5.4.2) and importance level (Section 5.4.3) to obtain the final weights to be used in the optimization model.

It is worth highlighting that the W_{ij}^{KN} represents the weight of the attributes or features to be selected in the design process. For example, an attractive (A) attribute or feature will have a much higher priority to be included in a product rather than a must-be (M) one. The reason is because such attribute (A) may generate greater customer satisfaction and eventually create a competitive advantage to the company. Note that these weights do *not* imply the existence of the basic attributes that a product must have, for example, a keyboard is a basic must-have attribute or feature for a laptop. The optimization model will be used to determine such existence (see Section 5.4.4).

5.4.2 Deriving adjusted weights

To account for the robustness of the results, the weight resulting from the previous section is adjusted by two factors. First, it is the forecast-based variability, which is reflected in the standard deviation of forecast error (s_{ij}^{KN}). Second, it is the variability within the forecasted percentage data, which is reflected by the standard deviation of the transformed percentage data. The second variability is also referred as the degree of discrimination (δ_{ij}^{R}). The adjusted weight (W_{ij}^{adj}) can then be expressed as follows:

$$W_{ij}^{adj} = W_{ij}^{KN} - \lambda_{ij}^{s} s_{ij}^{KN} + \lambda_{ij}^{d} \delta_{ij}^{R}, \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.8}$$

where:

δ_{ij}^{R} = degree of discrimination of DQ_{ij}

λ_{ij}^{d} = trade-off value between Kano unadjusted weight and within category variability

$(0 \le \lambda_{ij}^{d} \le 1)$

λ_{ij}^{s} = trade-off value between forecasted values and its variability $(0 \le \lambda_{ij}^{s} \le 1)$

s_{ij}^{KN} = standard deviation of forecasting residual

The weight is adjusted by a minus quantity of the forecast-based variability, which is reflected in the standard deviation of the forecasting error. The lower the value of s_{ij}^{KN}, the better it becomes, since it implies that the model can adequately fit the historical data. In other words, the future uncertainty or the variability in the forecasted values is relatively low (see Chapter 8). On the other hand, a plus quantity of the variability within the forecasted percentage data is also used to adjust the weight. This is because the higher the value of δ_{ij}^{R}, the better the result becomes, since it implies that the particular DQ's category is clearly distinguished from the others.

To validly compute the standard deviation of the forecasted category (δ_{ij}^{R}), the forecasted data has to be first transformed since they are expressed in the form of compositional data (Aitchison, 2003). The purpose of the transformation is to map the compositional data into the real space ($\Re$), then the standard statistical analysis can be applied accordingly. There are several transformation techniques available (Aitchison, 2003). In this thesis, it is proposed to use the centered log-ratio transformation, which is expressed as in (5.9). After the transformation, the standard deviation of the forecasted percentage data can be obtained accordingly using the sample standard deviation formula.

$$clr(X) = \left(\ln \frac{x_1}{g(X)}, \ln \frac{x_2}{g(X)}, ..., \ln \frac{x_D}{g(X)} \right), \text{ where } g(X) = \sqrt[D]{\prod_{e=1}^{D} x_e} \tag{5.9}$$

5.4.3 Deriving DQ importance rating[1] using Kano results

After obtaining the adjusted Kano weight, the final weights of the DQ, which is commonly referred to as the Strategic Importance Rating (SIR) (see Chan and Wu, 2002b), can be computed using formula (5.10) below, where *IR* is the importance rating for each of the DQs. Note that the *IR* of the DQ can also be obtained using the AHP method (see Chapter 2).

$$SIR_{ij} = W_{ij}^{adj} * IR_{ij} \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.10}$$

Fortunately, the *IR* weight can be alternatively obtained by making use of the impact value of customer satisfaction (*S*) or dissatisfaction (*DS*) of the Kano results, as was also done in Sireli et al. (2007). Generally, the *S* and the *DS* value are obtained using the formula expressed in (5.11) and (5.12), respectively. The (*A*, *O*, *M*, *I*) here refers to the forecasted percentage data for the corresponding category. A superscript '*S*' is added to indicate that the corresponding category is in the simplex space (S^D).

$$S_{ij} = \frac{A_{ij}^S + O_{ij}^S}{A_{ij}^S + O_{ij}^S + M_{ij}^S + I_{ij}^S}, \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.11}$$

$$DS_{ij} = \frac{M_{ij}^S + O_{ij}^S}{A_{ij}^S + O_{ij}^S + M_{ij}^S + I_{ij}^S}, \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.12}$$

In this thesis, instead of taking the maximum of the *S* and *DS* (Sireli et al., 2007), a compromise value (β) between both factors is used to provide more flexibility for the

[1] The term 'importance rating', instead of 'priority', is used in this chapter because the IR values are not derived using the AHP approach.

decision makers. The value of β, which ranges from 0 to 1, represents how much the importance of achieving customer satisfaction as compared to avoiding customer dissatisfaction. It may simply be obtained by asking the decision makers on the importance of both factors. For example, if achieving customer satisfaction is three times more important than avoiding customer dissatisfaction, then the value of β equals to 0.75. Afterwards, the *IR* values for corresponding DQs can be obtained using expression (5.13).

$$IR_{ij} = \beta * S_{ij} + (1-\beta) * DS_{ij}, \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.13}$$

5.4.4 The Optimization Model

The purpose of the optimization model is to provide a more formal and systematic process in designing multiple product using forecasted Kano data. As stated previously, the model is very useful when the size of the QFD is relatively large, and reliance on human efforts to do the selection process is virtually impossible. The objective of the model is to allocate each DQ to the relevant product class as to maximize the strategic importance rating (SIR) of each product in the corresponding class. The four generic product classifications, namely, the basic product, the entry-level product, the advanced product, and the high-end product, as proposed in Sireli et al. (2007), can be used as a starting point for the example of product classes or variants.

Let p denote the number of product classes available $\{k=1,2,\ldots, p\}$, then the customer requirement for the i-th basic (must-have) feature with the j-th subcomponent can be expressed as DQ_{ijk} , which takes on binary value {0,1}, with '1' indicating that the corresponding DQ belongs to the k class and '0' otherwise. The 'quality' of a particular product class (Q_k) will be used to represent the contribution margin or the absolute profit

per unit of each product class (Malik and Sullivan, 1995). Some criteria can be used to determine the value or priority of each particular class' 'quality' (Pollack-Johnson and Liberatore, 2006), and the AHP (Saaty, 1980) is a useful tool in this respect. Finally, the objective function of the model can be formulated as in (5.14).

$$Max\ \ Z = \sum_{k=1}^{p}\sum_{j=1}^{n}\sum_{i=1}^{m} SIR_{ij} * Q_k * DQ_{ijk} \text{ , where } DQ_{ijk} \in \{0,1\} \tag{5.14}$$

The above objective function may subject to several constraints. The main three constraints will be described as follows:

a. *Cost Limitation*

With respect to budget allocation for each product class (B_k), this cost limitation constraint should be imposed in the model. For the corresponding DQ, a unit cost of C_{ij} can be estimated and included in the constraint.

$$\sum_{j=1}^{n}\sum_{i=1}^{m} C_{ij} * DQ_{ijk} \le B_k, \qquad \forall k = 1,...,p \tag{5.15}$$

b. *Product Features Constraint*

There are two types of features for this multiple product design problem as also described previously, the first type is the basic or must-have feature, and the second type is the subcomponent of the product features. However, for a chosen particular product feature, one may not choose more than 1 subcomponent. For example, it does not make sense to have two types of weight at the same time ('ultra-light' and 'light') for a laptop. On the other hand, one may choose more than one kind of keyboard feature for a laptop, for example, to have both 'glowing' and 'spill-resistant' features in a keyboard is perfectly fine.

These conditions can be mathematically represented by the following two constraints:

$$\sum_{j=1}^{n} DQ_{ijk} = 1 \quad \forall i = 1,...,m, \quad \forall k = 1,...,p \tag{5.16a}$$

$$\sum_{j=1}^{n} DQ_{ijk} \geq 1, \qquad \forall i = 1,...,m, \quad \forall k = 1,...,p \tag{5.16b}$$

The mutually exclusive and collectively exhaustive condition are represented in (5.16a), while the condition where there can be more than 1 subcomponent to be included is expressed in (5.16b). In view of this, the QFD users may first decide which product feature has the required property accordingly.

c. *Product Class Constraint*

In some cases, it is intuitively justifiable that one particular product feature can only mapped into one particular product class, especially for the mutually exclusive product feature. Constraint (5.17) imposes a limitation that a specific product feature is, at maximum, allowed to be mapped into one product class.

$$\sum_{k=1}^{p} DQ_{ijk} \leq 1, \qquad \forall i = 1,...,m, \quad \forall j = 1,...,n \tag{5.17}$$

5.5 An illustrative example

To show the applicability of the proposed methodology, an example of a hypothetical laptop design is used. Let suppose that a *fictitious* laptop company wants to design two classes (p=2) of innovative feature-enhancing products for mobile computing, namely, laptop 'AA' (high-end product) and laptop 'AB' (advanced product), simultaneously. For the sake of simplicity, it is assumed that there are three main components or features, those are, 'weight', 'thickness', and 'keyboard'. Each of the main components is assumed

to have two subcomponents. The 'weight' component consists of two subcomponents, namely, 'ultra-light (±1 pound)' (DQ_{11}) and 'light (±3 pounds)' (DQ_{12}). The 'thickness' component consists of 'ultra-thin (±0.3 inches)' (DQ_{21}) and 'thin (±0.6 inches)' (DQ_{22}), and the 'keyboard' component consists of 'glowing' (DQ_{31}) and 'spill-resistant' (DQ_{32}).

It is clear that the subcomponents of the first two main components are mutually exclusive and collectively exhaustive. For example, a laptop must have one type of weight, and it is also impossible to have two types of thickness for one laptop. On the other hand, a laptop may have more than one feature for its 'keyboard', which is the third main component. In addition, for product differentiation purpose, it is decided that each of the 'weight' subcomponent can maximum be mapped into one particular class of product. In other words, the two classes of laptop will not have the same weight.

5.5.1 Modeling Kano's model dynamics

5.5.1.1 The input

It is assumed that a set of Kano questionnaire results, which was based on an online survey conducted every two months for a certain group of customer, is already available. The results from the last nine observations for each DQ_{ij} are shown in the first left block of Table 5.1-Table 5.3. It is worth noting that the typical Kano questionnaire results are in *percentage* data form (see CQM, 1993 or Matzler and Hinterhuber, 1998). It describes the percentage of the Kano categories for each customer attribute. For example, as shown in Table 5.1, in the last period (t=9), there are 53% (A=0.53) of the customer surveyed regarded DQ_{11} (ultra-light weight) as an attractive attribute.

Table 5.1 Actual, fitted, forecasted, and fitting error values for DQ_{11} and DQ_{12}

	DQ_{11}				DQ'_{11}						DQ_{12}				DQ'_{12}				
t	A	O	M	I	A'	O'	M'	I'	Ad	t	A	O	M	I	A'	O'	M'	I'	Ad
1	0.18	0.07	0.05	0.70	0.203	0.067	0.046	0.684	-	1	0.35	0.08	0.05	0.52	0.379	0.114	0.039	0.468	-
2	0.22	0.06	0.04	0.68	0.203	0.067	0.046	0.684	0.179	2	0.38	0.12	0.04	0.46	0.379	0.114	0.039	0.468	0.052
3	0.21	0.07	0.05	0.67	0.225	0.058	0.038	0.678	0.276	3	0.40	0.15	0.03	0.42	0.381	0.123	0.040	0.456	0.362
4	0.37	0.09	0.06	0.48	0.213	0.071	0.051	0.666	0.631	4	0.46	0.18	0.04	0.32	0.408	0.169	0.026	0.397	0.458
5	0.44	0.13	0.11	0.32	0.421	0.096	0.064	0.419	0.604	5	0.50	0.23	0.08	0.19	0.487	0.207	0.041	0.265	0.718
6	0.46	0.16	0.14	0.24	0.500	0.144	0.128	0.228	0.148	6	0.44	0.30	0.12	0.14	0.506	0.262	0.109	0.123	0.226
7	0.49	0.19	0.15	0.17	0.489	0.181	0.171	0.160	0.154	7	0.36	0.36	0.16	0.12	0.394	0.347	0.169	0.089	0.301
8	0.52	0.22	0.17	0.09	0.500	0.214	0.173	0.112	0.211	8	0.30	0.40	0.22	0.08	0.293	0.410	0.212	0.085	0.082
9	0.53	0.23	0.18	0.06	0.518	0.242	0.185	0.054	0.117	9	0.22	0.46	0.28	0.04	0.234	0.430	0.282	0.054	0.270
10	**?**	**?**	**?**	**?**	**0.534**	**0.238**	**0.189**	**0.039**	*0.290**	**10**	**?**	**?**	**?**	**?**	**0.152**	**0.495**	**0.334**	**0.019**	*0.309**

) Mean of Ad using α = 0.644

) Mean of Ad using α = 0.742

Table 5.2 Actual, fitted, forecasted, and fitting error values for DQ_{21} and DQ_{22}

	DQ_{21}				DQ'_{21}						DQ_{22}				DQ'_{22}				
t	A	O	M	I	A'	O'	M'	I'	Ad	t	A	O	M	I	A'	O'	M'	I'	Ad
1	0.08	0.06	0.04	0.82	0.113	0.070	0.050	0.767	-	1	0.62	0.10	0.06	0.22	0.572	0.141	0.093	0.194	-
2	0.11	0.07	0.05	0.77	0.113	0.070	0.050	0.767	0.026	2	0.56	0.15	0.10	0.19	0.572	0.141	0.093	0.194	0.089
3	0.16	0.08	0.06	0.70	0.109	0.070	0.050	0.770	0.338	3	0.52	0.18	0.13	0.17	0.555	0.154	0.103	0.188	0.283
4	0.19	0.09	0.05	0.67	0.170	0.082	0.062	0.686	0.262	4	0.48	0.26	0.16	0.10	0.496	0.197	0.148	0.160	0.546
5	0.22	0.10	0.06	0.62	0.217	0.095	0.051	0.637	0.147	5	0.40	0.33	0.19	0.08	0.431	0.311	0.184	0.073	0.123
6	0.27	0.11	0.08	0.54	0.254	0.107	0.060	0.579	0.262	6	0.34	0.38	0.23	0.05	0.333	0.397	0.214	0.056	0.142
7	0.33	0.11	0.09	0.47	0.311	0.117	0.085	0.487	0.109	7	0.22	0.42	0.28	0.08	0.274	0.435	0.258	0.032	0.858
8	0.35	0.12	0.09	0.44	0.380	0.114	0.099	0.407	0.157	8	0.18	0.41	0.34	0.07	0.156	0.455	0.316	0.073	0.193
9	0.38	0.13	0.11	0.38	0.397	0.123	0.098	0.382	0.123	9	0.12	0.38	0.40	0.10	0.130	0.414	0.389	0.066	0.411
10	**?**	**?**	**?**	**?**	**0.406**	**0.139**	**0.132**	**0.324**	*0.178**	**10**	**?**	**?**	**?**	**?**	**0.077**	**0.337**	**0.450**	**0.135**	*0.331**

) Mean of Ad using α = 0.594

) Mean of Ad using α = 0.713

Table 5.3 Actual, fitted, forecasted, and fitting error values for DQ_{31} and DQ_{32}

	DQ_{31}				DQ'_{31}						DQ_{32}				DQ'_{32}				
t	A	O	M	I	A'	O'	M'	I'	Ad	t	A	O	M	I	A'	O'	M'	I'	Ad
1	0.42	0.28	0.16	0.14	0.383	0.304	0.183	0.130	-	1	0.58	0.16	0.09	0.17	0.495	0.203	0.125	0.178	-
2	0.38	0.31	0.18	0.13	0.383	0.304	0.183	0.130	0.027	2	0.46	0.21	0.13	0.20	0.495	0.203	0.125	0.178	0.136
3	0.35	0.32	0.21	0.12	0.378	0.314	0.178	0.130	0.198	3	0.44	0.24	0.16	0.16	0.446	0.213	0.132	0.209	0.351
4	0.29	0.36	0.28	0.07	0.330	0.327	0.230	0.113	0.522	4	0.38	0.29	0.18	0.15	0.420	0.254	0.175	0.152	0.166
5	0.24	0.41	0.32	0.03	0.241	0.376	0.336	0.046	0.401	5	0.34	0.33	0.22	0.11	0.343	0.322	0.199	0.136	0.230
6	0.18	0.37	0.38	0.07	0.190	0.436	0.360	0.014	1.437	6	0.28	0.38	0.24	0.10	0.296	0.366	0.248	0.090	0.129
7	0.15	0.34	0.42	0.09	0.134	0.346	0.431	0.089	0.109	7	0.22	0.43	0.28	0.07	0.234	0.420	0.264	0.082	0.164
8	0.12	0.31	0.41	0.16	0.117	0.306	0.459	0.118	0.301	8	0.15	0.49	0.34	0.02	0.173	0.468	0.306	0.053	0.865
9	0.09	0.27	0.40	0.24	0.091	0.268	0.397	0.244	0.022	9	0.10	0.51	0.38	0.01	0.105	0.516	0.369	0.010	0.069
10	**?**	**?**	**?**	**?**	**0.064**	**0.223**	**0.370**	**0.343**	*0.377**	**10**	**?**	**?**	**?**	**?**	**0.065**	**0.517**	**0.413**	**0.005**	*0.264**

) Mean of Ad using α = 0.822

) Mean of Ad using α = 0.693

Based on the historical data trend, the two main questions now are what this attribute will become in the next two months, and how high the future uncertainty is. With respect to the time lag problem mentioned earlier, such information is very useful for the QFD team in order not to produce an unwanted product or service. To answer the questions, it is

necessary to first model the historical data of each DQ using the proposed compositional double exponential smoothing (CDES) technique (see equation (5.1)-(5.5)).

5.5.1.2 Selection of model parameter

The average of the first three observations was used as the initial value. The optimal value of the parameter, that is, the optimal smoothing constant (α^*), was derived iteratively by selecting a value between 0 and 1 that yields the smallest Aitchison distance using a constant increment (see Section 5.3.3). The optimal alpha (α^*) for each DQ, which is used for fitting and forecasting, is shown below the actual data block column in Table 5.1-Table 5.3. For example, as shown in Table 5.1, the optimal alpha for DQ_{11} is 0.644 (α^*=0.644).

The fitted, forecasted, and fitting error values are also shown in Table 5.1-Table 5.3, next to the actual data block column for each corresponding DQ. The fitted values using the CDES method are those values from t=1 until t=9 under the heading 'DQ'_{11}' (with prime), while the forecasted values are shown in the bolded values. For example, for DQ_{11} (Table 5.1), when t=9, the fitted value for the attractive attribute is 51.8% (A'=0.518), as compared to the actual value which is 53% (A=0.53). The forecasted value is equal to 53.4% (A'=0.534, bolded), that is, the value when t=10.

5.5.1.3 Fitting error measurement

For each corresponding DQ, the last column of Table 5.1-Table 5.3, under the heading 'Ad', shows the fitting error values which are obtained using Aitchison distance (see equation (5.6)). For example, when t=9, the distance between the actual compositional

data and the fitted one is equal to 0.117 (Ad=0.117). It is also worth noting that the values shown in the last row (t=10) under the heading 'Ad' is the average of the fitting error values for the corresponding DQ, for example, the average fitting error values for DQ_{11} is 0.290.

5.5.1.4 Results' interpretation

The graphical representation of the fitting and forecasting results is shown in Figure 5.1-Figure 5.3. A full triangle, diamond, square, and dot are used to denote the actual historical data point for the attractive (A), one-dimensional (O), must-be (M), indifferent (I) category, respectively. Dash and dotted lines are used to show the fitted and forecasted data point for each DQ. Some realistic descriptions of the DQs change over time are given as follows.

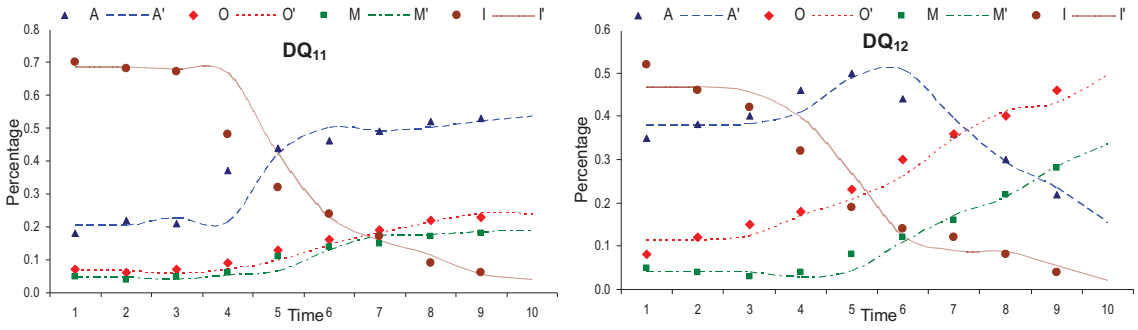


Figure 5.1 Graph of actual, fitted, and forecasted values for DQ_{11} and DQ_{12}

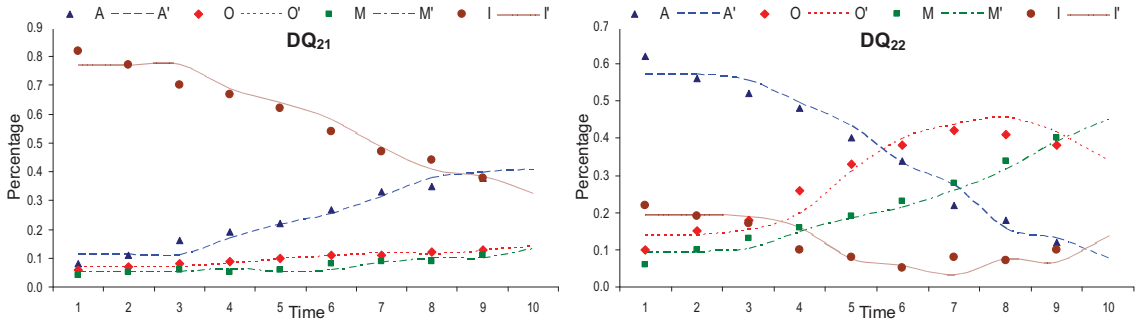


Figure 5.2 Graph of actual, fitted, and forecasted values for DQ_{21} and DQ_{22}

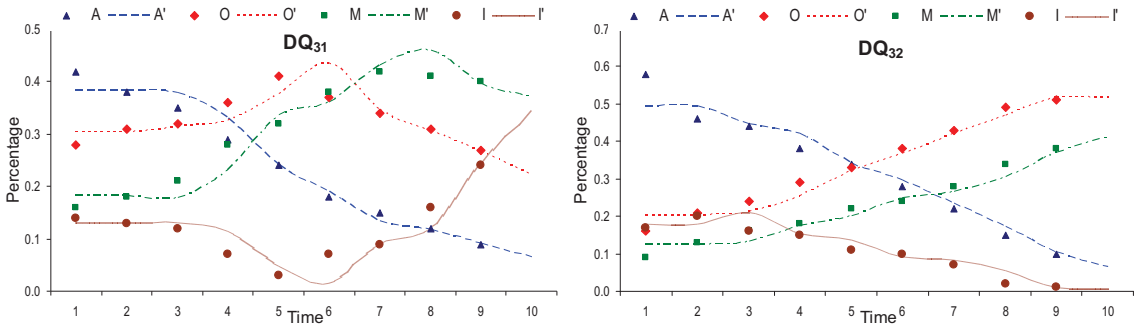


Figure 5.3 Graph of actual, fitted, and forecasted values for DQ_{31} and DQ_{32}

Initially, an ultra-light laptop (DQ_{11}), was not attractive to the customers. The customers are indifferent of this attribute for quite some time. This might be a common phenomenon for some customers who receive new features of product, which is also supported in the empirical study by Witell and Fundin (2005). However, starting from the fourth period, it gradually becomes an attractive attribute since the customers started to realize the significance of an ultra-light laptop (Figure 5.1). This change might be subject to a number of factors, which is beyond the scope of this thesis, such as competitors' products. Such situation also applies to DQ_{12} (light), but with a faster change. After the fifth period, the DQ_{12} started to become obsolete. Then, beginning from the seventh period, as can be observed in Figure 5.1, it becomes one-dimensional attribute. There is also an inclination to become a must-be attribute in the end of the observation.

For 'thickness' component, initially, an ultra-thin size (DQ_{21}), appears to be neutral for the customers. In other words, most of the customers are indifferent with this attribute as they might not be able to appreciate this (see Figure 5.2). This is not the case for the 'thin' size (DQ_{22}), which was initially attractive, it quickly becomes one-dimensional. As the passage of time, more and more customers begin to realize the importance of a thinner laptop for mobile computing. Based on the trend in the change pattern, the forecasted

values for period ten (t=10) show that the 'ultra-thin' size will become an attractive attribute, and the 'thin' size will become a must-be attribute.

As for the 'keyboard', the 'glowing' feature (DQ_{31}) appears to have an exceptionally fast rate of obsolescence. It was initially an attractive attribute, but it has become a must-be attribute within a few periods (see Figure 5.3). Moreover, as shown in the forecasted values (Table 5.3), this attribute might become an indifferent attribute in the future. In contrast to DQ_{31}, the 'spill-resistant' (DQ_{32}) seems to have a relatively slow rate of change (Figure 5.3). In the first four periods, it was an attractive attribute. However, it slowly becomes one-dimensional attribute. Subsequently, it shows an inclination to become a must-be attribute in the future.

5.5.2 Kano optimization for multiple product design

The main input for the optimization stage is the results from the forecasting stage (Section 5.5.1). The objective of this optimization stage is to allocate each DQ to the relevant product class as to maximize the strategic importance rating (SIR) of each product in the corresponding class (see equation (5.14)). To obtain the SIR value for each DQ, there are several steps to be taken as expressed in equation (5.7)-(5.13). The necessary information for deriving the SIR value is shown in Table 5.4. Superscripts '*S*' and '*R*' are used to indicate, respectively, the forecasted Kano percentage data and the transformed forecasted Kano percentage data. In other words, the results from the previous section are those values under the heading 'A^S', 'O^S', 'M^S', 'I^S', for the corresponding DQ.

Table 5.4 Input data for optimization model

			A^S	O^S	M^S	I^S	G_x	A^R	O^R	M^R	I^R	δ^R
Weight	ultra-light	DQ_{11}	0.534	0.238	0.189	0.039	0.18	1.11	0.31	0.07	-1.49	1.09
	light	DQ_{12}	0.152	0.495	0.334	0.019	0.15	0.03	1.21	0.82	-2.06	1.46
Thickness	ultra-thin	DQ_{21}	0.406	0.139	0.132	0.324	0.22	0.61	-0.47	-0.52	0.38	0.58
	thin	DQ_{22}	0.077	0.337	0.450	0.135	0.20	-0.95	0.53	0.82	-0.39	0.82
Keyboard	glowing	DQ_{31}	0.064	0.223	0.370	0.343	0.21	-1.17	0.08	0.58	0.51	0.81
	spill-resistant	DQ_{32}	0.065	0.517	0.413	0.005	0.09	-0.33	1.74	1.52	-2.93	2.17

			Cat	W^{KN}	s^{KN}	W^{adj}	S_{ij}	DS_{ij}	$IR_{\beta=.7}$	SIR_{ij}	C_{ij}
Weight	ultra-light	DQ_{11}	A	9	0.21	9.88	0.77	0.43	0.67	6.61	12
	light	DQ_{12}	O	5	0.21	6.24	0.65	0.83	0.70	4.38	8
Thickness	ultra-thin	DQ_{21}	A	9	0.10	9.48	0.54	0.27	0.46	4.38	5
	thin	DQ_{22}	M	3	0.26	3.55	0.41	0.79	0.53	1.87	3
Keyboard	glowing	DQ_{31}	M	3	0.46	3.35	0.29	0.59	0.38	1.27	7
	spill-resistant	DQ_{32}	O	5	0.26	6.91	0.58	0.93	0.69	4.74	4

5.5.2.1 Deriving weights from the forecasted Kano percentage data

Based on the forecasted Kano percentage data, one needs to first determine to which category a DQ belongs. For example, for the case of DQ_{11}, since its attractive category has the largest value (A^S=0.534), then it belongs to attractive attribute. Thus, a ratio scale weight of '9' is assigned to this DQ ($W_{11}^{KN} = 9$, see equation (5.7)). Afterwards, this weight is adjusted by two factors to improve its robustness.

5.5.2.2 Deriving adjusted weights

The first factor, namely, the forecast-based variability (s_{ij}^{KN}), can be obtained by computing the standard deviation of the fitting values error for the corresponding DQ. The resulting values of this factor for the laptop design example is shown in Table 5.4 under the heading 'S^{KN}'. Note that the data used to derive the s_{ij}^{KN} are the same as those that are used to compute the mean of the Aitchison distance ('Ad') in Table 5.1-Table 5.3.

To compute the second factor, which is the degree of discrimination (δ_{ij}^{R}), a transformation of the forecasted percentage Kano data is needed. Using formula (5.9), the transformed percentage data are shown in Table 5.4 under the heading 'A^R', 'O^R', 'M^R', 'I^R'. The superscript 'R' is used to indicate that the values are in the real space ($\Re$). The 'G_x' column (Table 5.4) denotes the geometric mean of the forecasted Kano percentage data. The degree of discrimination values for this example data are shown in Table 5.4 under the heading 'δ^R'.

The adjusted Kano weight (W_{ij}^{adj}) is obtained using formula (5.8). For the sake of simplicity, the trade-off values of the adjusting factors are assumed to be the same ($\lambda_{ij}^{d} = \lambda_{ij}^{s} = 1$). The resulting values of the adjusted weight are shown in Table 5.4 under the heading 'W^{adj}'.

5.5.2.3 Deriving DQ importance rating using Kano results

Since the SIR value is the product of the adjusted weight (W_{ij}^{adj}) and the importance rating (*IR*) (see formula (5.10)), then the *IR* values need to be computed. For simplicity, it is again assumed that a compromise value of 0.7 (β=0.7) is used for the importance of customer satisfaction (*S*) as compared to customer dissatisfaction (*DS*). Using equation (5.11)-(5.13), the S_{ij}, DS_{ij}, and the *IR* values can be derived. The resulting values are shown in Table 5.4, respectively, under the heading 'S_{ij}', 'DS_{ij}', and '$IR_{\beta=.7}$'. The final SIR values are also shown in Table 5.4, under the heading 'SIR_{ij}'.

5.5.2.4 The optimization model

Let assume that the 'quality' values (Q_k) of the high-end and advanced product, which can be obtained from the AHP technique, are Q_1 =0.6 and Q_2 =0.4, respectively. The objective function, as expressed in formula (5.14), can now be applied using the resulting SIR and 'quality' values. Using the general optimization model proposed in Section 5.4 and taking into account the available constraints, namely, the budget, product features, and product class constraint, the optimization model for the illustrative example can be formulated as follows:

$$Max\ \ Z = \sum_{k=1}^{2}\sum_{j=1}^{2}\sum_{i=1}^{3} SIR_{ij} * Q_k * DQ_{ijk} \text{ , where } DQ_{ijk} \in \{0,1\} \tag{5.18}$$

$$\sum_{j=1}^{2}\sum_{i=1}^{3} C_{ij} * DQ_{ijk} \le B_k, \qquad \forall k = 1,2 \tag{5.19}$$

$$\sum_{j=1}^{2} DQ_{ijk} = 1, \quad \forall i = 1,2 \quad \forall k = 1,2 \tag{5.20}$$

$$\sum_{j=1}^{2} DQ_{3jk} \ge 1, \quad \forall k = 1,2 \tag{5.21}$$

$$\sum_{k=1}^{2} DQ_{1jk} \le 1, \quad \forall j = 1,2 \tag{5.22}$$

It is also assumed that the given budget for the high-end product and the advanced product for this example are B_1 =\$30, B_2 =\$22, respectively. The unit cost (C_{ij}) for each DQ is given in the last column of Table 5.4.

The optimal solution for the above model is shown in Table 5.5. To sum up, laptop 'AA', which is a high-end class, will have 'ultra-light (±1 pound)' weight, 'ultra-thin

(±0.3 inches)' thickness, and both of the keyboard features, while laptop 'AB', which is an advanced class, will have 'light (±3 pounds)' weight, 'ultra-thin (±0.3 inches)' thickness, and only 'spill-resistant' feature for the keyboard.

Table 5.5 Multiple product design optimization results

DQ_{ijk}	(i=1, j=1)	(i=1, j=2)	(i=2, j=1)	(i=2, j=2)	(i=3, j=1)	(i=3, j=2)
k=1	1	0	1	0	1	1
k=2	0	1	1	0	0	1

5.6 Conclusion

The purpose of this chapter was to demonstrate one application of the new modeling technique (Chapter 4) as to improve QFD analysis. The modeling technique has been shown to be effective in formally modeling the dynamics of Kano's model so that one may know how fast the change over time is. Monitoring the change of quality attributes (Kano's model attributes) over time may not only help strengthen the QFD input by providing a timely update of customer's needs information, but may also be useful for tackling the problem described in Chapter 1.

Furthermore, based on the results of the Kano's model dynamics modeling phase, a further QFD analysis that extends the research on using Kano's model in QFD for multiple product design (Sireli et al., 2007) has also been suggested. Specifically, the extension is two-fold. One is to suggest the use of the optimization model, which is particularly useful when the number of DQs is relatively large. The other is to improve the robustness of the results by incorporating two sources of variability, namely, forecast-based variability and within category variability of the forecasted data.

For future works, there are two interesting issues that may be worth investigating. First, it is the incorporation of modular product design concept into the multiple product design process in QFD. The use of modular design concept in QFD, although it is quite limited, can be found in Kreng and Lee (2004) or Takai, (2006). Second, it is a further investigation on the relationship between Kano's model dynamics and the innovation adoption framework or life cycle (Rogers, 2003). For example, a certain high-tech product feature may already be regarded as a must-be attribute by the early market innovators, while it may still be perceived as an attractive one by the late majority market. Thus, further research on how this issue be taken into account in the design process might be worth pursuing.

In sum, this chapter has not only extended the use of Kano's model in QFD analysis, but it has also advanced the academic literature on modeling the life cycle of quality attributes quantitatively. To further demonstrate the usefulness of the new modeling technique (Chapter 4), the next chapter (Chapter 6) will describe another application of the technique in improving QFD analysis, that is, in enhancing the benchmarking analysis of QFD with respect to the problem described in Chapter 1.

CHAPTER 6
APPLICATION OF THE MODELING TECHNIQUE (PART 2 OF 2) – DYNAMIC BENCHMARKING IN QFD

The purpose of this chapter is to demonstrate another application of the new modeling technique (Chapter 4) as to improve QFD analysis. The modeling technique will be applied to model the change of DQs' competitive assessment over time, apart from the DQs' priorities. As mentioned previously (Section 1.1), another important change during product or service creation process is the change of competitive assessment of the DQs. This is due to fact that the competitors' performance naturally changes over time. Therefore, to improve the likelihood of success of a QFD application, such factor may not be overlooked. In other words, it is important to keep pace with the change when formulating competitive strategies. This chapter provides the way to integrate both the dynamics of DQs' priorities and DQs' competitive assessment, along with their interaction, in a QFD analysis. This chapter is reproduced from "Dynamic Benchmarking Methodology for QFD", by Raharjo H, Chai KH, Xie M, Brombacher AC. To appear in *Benchmarking: An International Journal*.

6.1 Introduction

A competitive advantage, generally, can be gained if a company produces a product that not only addresses what the customer values most, but also performs better than its competitors in terms of quality, cost, and timeliness. However, these two factors, namely, the customer needs and competitors' performance, change over time, and yet there are still a number of product design processes that seem to have oversimplified this fact. In the

QFD literature, the former factor has been quite well addressed, for example, see Shen et al. (2001), Xie et al. (2003), Wu et al. (2005), Wu and Shieh (2006), Raharjo et al. (2006). Unfortunately, there is too little attention paid to the latter, which is equally critical. To design or upgrade a product successfully using QFD, it may not be sufficient to only observe the change of DQs' priorities over time because during the product creation process, competitive condition, especially, competitors' performance changes as well. Therefore, to improve the likelihood of success of a product design or upgrade process, both of these factors and their dynamics should be taken into account.

This chapter aims to address this issue, that is, how the dynamics of these two factors along with their interaction can be integrated into a QFD analysis. For simplicity, the suggested approach is referred to as dynamic benchmarking methodology. The methodology essentially comprises of two novel approaches. First, it is the use of the new modeling technique, as described in Chapter 4, to model the trend of DQs' priorities and their competitive assessment. Note that, in contrast to the traditional practice which mostly uses a direct rating scale of, for example, 1-to-5 or 1-to-9 (Hauser and Clausing, 1988; Cohen, 1995), the importance rating values and the competitors' benchmarking information are obtained using the AHP's *relative* measurement. Second, it is the approach, which is called the strength-weakness-opportunity-threat (SWOT)-based competitive weighting scheme, to derive weights by analyzing the interaction between the two factors. In addition, this proposed weighting scheme also serves as a more systematic way to substitute the traditional QFD customer competitive target setting and sales point value determination.

The following sections are organized as follows. Section 6.2 will describe the need of dynamic benchmarking in QFD based on what have been done in the literature. Then, the

proposed benchmarking methodology is elaborated in Section 6.3. To illustrate how the proposed methodology works practically, an illustrative example is provided (Section 6.4). Section 6.5 will elaborate how the competitive weighting scheme is used to derive the final DQ's weight, namely, the strategic importance rating (Chan and Wu, 2002b), by considering the two factors' interaction. Finally, the novel contribution and possible extensions are discussed (Section 6.6).

6.2 The need of dynamic benchmarking: literature review and research gap

A benchmarking process can be regarded as a continuous and proactive search for the best practices leading to a superior performance of a company (Camp, 1995). Successful benchmarking may lead to an improved return on investment ratio, increased market competitiveness, cost reductions, higher chance of identifying new business opportunities, and enhanced transparency and performance (Ramabadran et al., 2004; Braadbaart, 2007). It provides insights necessary to effectively pinpoint the critical success factors that set the most successful firms apart from their competitors, or to a greater extent, that separates the winners from the losers (Cooper and Kleinschmidt, 1987, 1995). Specifically, the benchmarking information can serve as a foundation for a company to formulate strategic decisions effectively (Spendolini, 1992).

An important fact worth highlighting is that, as the passage of time, the company as well as the competitors' condition will certainly change. Therefore, benchmarking process should not remain static. The importance of dynamic benchmarking has been realized by several researchers. Min et al. (1997) used the AHP for competitive benchmarking and

substantiated the need of dynamic benchmarking that is capable of evaluating the changing degree of clinic's patient satisfaction over time. In attempt to identify tools, methodologies, and metrics that can serve as enablers for making benchmarking in agile environments effective and efficient, Sarkis (2001) highlighted the importance of forward thinking (proactive) approach in benchmarking, such as by using forecasting techniques, on the basis of historical data, to obtain future benchmarks.

Min et al. (2002) analyzed the changing hotel's customer needs over time and demonstrated the importance of dynamic benchmarking to strive for continuous service quality improvement. Unfortunately, they only focused on two data points in time, namely, year 1995 and year 2000, which is very likely inadequate for observing the change over time. Salhieh and Singh (2003) proposed a dynamic framework using principles of systems dynamics to incorporate benchmarking for university effective policy design. However, their approach can be considered 'reactive' since they relied on a feedback mechanism. Tavana (2004) proposed a dynamic benchmarking framework, which uses the AHP and additive Multiple Criteria Decision Making (MCDM) model, for technology assessment at NASA.

In the existing QFD literature, the issue of benchmarking has been, to some extent, oversimplified. Some previous attempts can be found in Lu et al. (1994), Ghahramani and Houshyar (1996), Gonzáles et al. (2005), Iranmanesh et al. (2005), or Ginn and Zairi, (2005). Using a real world case study, Kumar et al. (2006) demonstrated that there is a synergistic effect in integrating benchmarking with QFD methodologies for companies that seek higher levels of financial and strategic performance through product improvement. Gonzáles et al. (2008) demonstrated the effective application of QFD and benchmarking to enhance academic programmes. More recently, Lai et al. (2008) showed

the importance of competitor information for deriving QFD's customer requirements ranking. With respect to this, they developed a new ranking method that is based on fuzzy mathematics.

Nevertheless, almost none of the existing studies have adequately addressed the need to provide a more formal and systematic approach to use dynamic benchmarking in QFD. As mentioned previously, the competitive condition may change during product creation process, therefore how to appropriately deal with such change is of great necessity. Pursuing the 'proactive' stream of research in dealing with the market dynamics, as first initiated by Shen et al. (2001) or Xie et al. (2003), this chapter attempts to fill in this gap by proposing the use of a forecasting technique for monitoring, apart from the change of customer preferences (DQs' priorities), the change of the benchmarking information (DQs' competitive assessment) in the QFD.

It is worth noting that the AHP's *relative* measurement is suggested for deriving both DQs' priorities and their competitive assessment. Examples of the use of the AHP-based approach for benchmarking can be found in Korpela and Tuominen (1996), Min et al. (1997), Chan et al. (2006), Chen and Huang (2007), Dey et al. (2008), Tavana (2008) or Raharjo et al. (2008). In the end, it is expected that having known the timely update of information on the change of competitors' performance and the change of customer preference over time, along with their interaction, the QFD decision making process may be improved.

6.3 The proposed dynamic benchmarking methodology

This section describes the proposed dynamic benchmarking methodology for QFD. Section 6.3.1 provides necessary information on how one may obtain the input data from the customer through the use of the AHP. Then, the step-by-step procedure to use the proposed methodology is elaborated in Section 6.3.2.

6.3.1 The input

Similar to most methodologies in benchmarking, the input of the proposed dynamic benchmarking methodology mainly relies on the customer data of a specific market segment. The customer's opinion or judgment is required to assess the importance of a DQ and how well the company and the competitors satisfy it. Traditionally, those data, namely, the importance rating and the customer competitive assessment are obtained based on a direct rating of 1 to 5. Such approach might very likely lead to a tendency for the customers to assign values near to the highest possible scores, and eventually result in somewhat arbitrary and inaccurate results (Cohen, 1995; Chuang, 2001).

To remedy this problem, some researchers proposed the use of the AHP for eliciting the importance rating (see Chapter 2). However, there appears to have been almost no study to improve the judgment elicitation process for the benchmarking part or the DQs' competitive assessment. A better and more rigorous approach is needed to avoid the weakness of the traditional approach. Therefore, the AHP approach is proposed to be used as a tool to elicit customer's judgments not only for the importance rating part (DQs' priorities), but also for the benchmarking part (DQs' competitive assessment).

As prescribed in the AHP procedure, the judgments are elicited using the pairwise comparison question (Saaty, 1994). For the DQ's priority part, the following question can be used:

- "With respect to the design of the (new) product, how important is the first DQ (DQ_1) compared to the second DQ (DQ_2)?"

While for the benchmarking part, the following question can be used:

- "With respect to DQ_1, how good is the performance of $Competitor_1$ compared to $Competitor_2$?"

Note that these questions can be tailored to suit a particular condition of the problem at hand.

The key point here is that, in assessing the competitors' performance in the HoQ, this AHP approach is much more relevant compared to the standard rating approach, such as using a scale of 1 to 5 (Cohen, 1995). This is because the AHP uses a *relative* measurement while the rating approach uses an absolute measurement. In the context of DQs' competitive assessment, a 'good' performance, to some extent, is determined *relatively* by the performance of 'best-in-class' competitors. As pointed out by Lai et al. (2008), a company may perform poorly in meeting a particular DQ, however, if its competitors are not as good, it might stand out in the market although the customer satisfaction level is relatively low. In other words, how good the performance of a company on a certain DQ is depends *relatively* on other companies' performance on the same DQ. Thus, this clearly shows the relevance of the AHP's relative measurement.

The results of the pairwise comparisons are the priorities of the entities being compared in ratio-scale (Harker and Vargas, 1987). As has been mentioned previously, if

the judgment elicitation is carried out every month, it is most likely that the priorities will change over time. Now, how to make use of this information for improving QFD analysis is the question that this chapter attempts to answer. The forecasting method described in Chapter 4, namely, the compositional double exponential smoothing (CDES) technique, will be used to model the priorities' change over time.

6.3.2 The step-by-step procedure

The following step-by-step procedure is suggested to be used for the proposed dynamic benchmarking methodology.

Step 1: Obtain the DQs' priorities from the customer using the AHP procedure.

Step 2: Obtain the customer competitive assessment on our product compared to the 'best-in-class' competitors in the industry using the AHP procedure. This type of benchmarking can be considered as the competitive or external benchmarking (Zairi, 1992; Madu and Kuei, 1993; Camp, 1995).

Step 3: Record the priorities and collect data periodically for a certain length of time, for example, every month until nine months.

Step 4: Model the priorities change over time, and obtain a forecast.

Step 5: Obtain forecasted values of both the DQs' priorities and DQs' competitive assessment. These forecasted values basically reflect the future voice of the customer. They should be used for the QFD input at least because of two reasons. One is to avoid the time-lag problem (see Chapter 1). The other is to design a new or to upgrade an existing product to meet the future needs of the customer while considering the future competitors' performance.

Step 6: Conduct competitive analysis using the proposed competitive weighting scheme (see Section 6.5)

Step 7: Obtain the final priorities of the DQs, namely, the strategic importance rating (SIR).

It is worth noting that, for Step 2, it is of critical importance to correctly select the ’best-in-class’ competitors since failing to do so may lead to an inferior outcome of the benchmarking endeavor. If the competitor’ class is too high, the company will never achieve the unrealistically high target, and will likely end up in frustration. On the other hand, if the company compares itself to a competitor of much lower tier, then the company will never improve, but remain in a state of complacency.

The ’best-in-class’ may imply that they share at least similar price classification and market segment. Shen et al. (2000) proposed an intuitively interesting way to develop this idea, that is, to use hierarchical benchmarks for strategic competitor selection. For example, after being able to reach local-class standard, the company should strive for higher class (regional-class) and gradually moving towards world-class performance. In the case when a company is already perceived as a world-class company, it does not then mean that the company cannot improve themselves since there is always a better way to do things.

6.4 An illustrative example

To illustrate the proposed approach, consider the following example. Suppose that there are three DQs being monitored. It is assumed that the historical data for a period of

nine months for the DQs' priorities and the competitive assessment priorities are already available. These data are generated from a simulation of AHP reciprocal matrices using the fundamental scale of 1-to-9 (see Section 4.2.1.2). All the generated matrices have consistency ratio value of less than 0.1. For the sake of simplicity, it is assumed that there is no problem in *Step 1* and *Step 2*.

6.4.1 The input

Step 3: The DQs' priorities (IR values) for the last nine periods are shown in Table 6.1. For example, in the first period (t=1), DQ_1 is regarded by the customer as the most important attribute (0.667), while the other DQs are not that important. On the other hand, in the last period (t=9), DQ_3 becomes the most important attribute (0.413). Note that the DQs' priorities in a certain period always sum up to unity because of the AHP procedure which uses normalization.

Table 6.1 DQs' priorities (IR values) over time

	IR			IR			
t	DQ_1	DQ_2	DQ_3	DQ'_1	DQ'_2	DQ'_3	Err (Ad)
1	0.667	0.222	0.111	0.647	0.230	0.123	-
2	0.648	0.230	0.122	0.647	0.230	0.123	0.0052
3	0.625	0.238	0.136	0.648	0.230	0.122	0.1031
4	0.540	0.297	0.163	0.623	0.239	0.138	0.2748
5	0.493	0.311	0.196	0.521	0.308	0.172	0.1344
6	0.550	0.240	0.210	0.454	0.332	0.214	0.3670
7	0.413	0.327	0.260	0.518	0.247	0.236	0.3639
8	0.333	0.333	0.333	0.385	0.324	0.291	0.1996
9	0.327	0.260	0.413	0.284	0.340	0.376	0.3171
10		*forecast*		0.309	0.197	0.495	
					a*=0.57, Err StDev=		0.1322

The data which are shown next to the original data block column are the fitted data and the forecast result using the CDES technique (Chapter 4). For example, the forecasted

priorities for DQ_1, DQ_2, and DQ_3, respectively, in the coming period (t=10), are 0.309, 0.197, and 0.495. A more detailed explanation of the figures in Table 6.1 will be provided in the next subsection.

The DQs' competitive assessment priorities, which are also obtained using the AHP, of the company (Z) and the two best-in-class competitors, namely, competitor A and competitor B, for each DQ are shown in Table 6.2 to Table 6.4. For example, in Table 6.2, the customer of the specific segment in the first period (t=1) perceived that company B performs the best (0.413) as relatively compared to the other companies. However, in the last period (t=9), company A was perceived as the best one (0.558). The fitted and forecasted data in Table 6.2 to Table 6.4 will be explained in the next subsection.

Table 6.2 Customer competitive assessment over time for DQ_1

	DQ_1			DQ_1			
t	Z	A	B	Z'	A'	B'	Err(Ad)
1	0.260	0.327	0.413	0.284	0.358	0.358	-
2	0.333	0.333	0.333	0.284	0.358	0.358	0.1884
3	0.260	0.413	0.327	0.341	0.330	0.330	0.3502
4	0.500	0.250	0.250	0.264	0.417	0.319	0.8516
5	0.413	0.260	0.327	0.524	0.243	0.234	0.4057
6	0.260	0.327	0.413	0.467	0.230	0.303	0.7479
7	0.200	0.400	0.400	0.261	0.310	0.429	0.3723
8	0.169	0.443	0.387	0.169	0.408	0.423	0.1224
9	0.122	0.558	0.320	0.134	0.472	0.394	0.2714
10		*forecast*		0.084	0.665	0.252	
						α*=0.57, Err StDev=	0.2578

Table 6.3 Customer competitive assessment over time for DQ_2

	DQ_2			DQ_2			
t	Z	A	B	Z'	A'	B'	Err(Ad)
1	0.500	0.250	0.250	0.414	0.304	0.282	-
2	0.413	0.327	0.260	0.414	0.304	0.282	0.1081
3	0.333	0.333	0.333	0.413	0.326	0.261	0.3251
4	0.327	0.260	0.413	0.336	0.339	0.324	0.3587
5	0.250	0.250	0.500	0.310	0.267	0.423	0.2727
6	0.140	0.333	0.528	0.233	0.235	0.532	0.6076
7	0.163	0.297	0.540	0.123	0.298	0.578	0.2618
8	0.109	0.309	0.582	0.123	0.290	0.587	0.1298
9	0.097	0.333	0.570	0.088	0.297	0.615	0.1481
10		*forecast*		0.086	0.357	0.557	
						α*=0.48, Err StDev=	0.1627

Table 6.4 Customer competitive assessment over time for DQ_3

	DQ_3			DQ_3			
t	Z	A	B	Z'	A'	B'	Err(Ad)
1	0.260	0.413	0.327	0.240	0.380	0.380	-
2	0.260	0.327	0.413	0.240	0.380	0.380	0.1902
3	0.200	0.400	0.400	0.258	0.332	0.410	0.3117
4	0.250	0.500	0.250	0.209	0.382	0.409	0.5881
5	0.260	0.413	0.327	0.239	0.494	0.268	0.2746
6	0.210	0.550	0.240	0.258	0.448	0.294	0.3354
7	0.333	0.333	0.333	0.217	0.550	0.233	0.7323
8	0.413	0.260	0.327	0.318	0.382	0.300	0.4728
9	0.400	0.200	0.400	0.425	0.259	0.316	0.3501
10		*forecast*		0.378	0.149	0.473	
					α*=0.45, Err StDev=		0.1792

6.4.2 The process

Step 4: The CDES method (Chapter 4) is adopted to model the change of the AHP priorities over time and to obtain a forecast. The results of the fitting process and the forecasted priorities for the DQs and their customer competitive assessment are shown in Table 6.1-Table 6.4 (next to the original data block column).

All of the tables above (Table 6.1-Table 6.4) have two block-columns next to the original data block-column. The first block-column, next to the original data, shows the results of the fitting and forecasting process, while the second one shows the deviation (error) between the original data and the fitted value. Note that the interpretation for these two block-columns is the same for all the tables.

Take an example, in Table 6.4, the fitted values at t=9 for the company (Z), competitor A, and competitor B, respectively, are Z'=0.425, A'=0.259, B'=0.316. These values are obtained using the CDES technique described in Chapter 4. The initial values for the CDES technique are obtained from the first three observations shown in Table 6.1 to Table 6.4. The Aitchison distance is used as the measure of the difference between the original data and the fitted data, that is, the forecasting error or residual. The forecasting

residual are those values in the 'Err(Ad)' column. The 'Ad' here stands for Aitchison distance. The optimal parameter (α^*) for the CDES is derived iteratively by selecting a value between 0 and 1 that gives the minimum average Aitchison distance. More detailed information of the technique can be found in Chapter 4. The term 'Err StDev', which is shown in Table 6.1 to Table 6.4, is used to denote the standard deviation of the forecasting residual.

The graphical plot of the actual, fitted, and forecasted values of the DQs' priorities is shown in Figure 6.1, while the customer competitive assessment's priorities for DQ_1, DQ_2, and DQ_3 are shown in Figure 6.2, 6.3, and 6.4, respectively. The full triangle, diamond, and square are used to plot the actual data, while the dash, dotted, and dash-and-dotted lines are used to show the fitted and forecasted values.

6.4.3 The output and analysis

Step 5: The forecasted priorities of the DQs and their customer competitive assessment are given in the last row of Table 6.1-Table 6.4 (t=10).

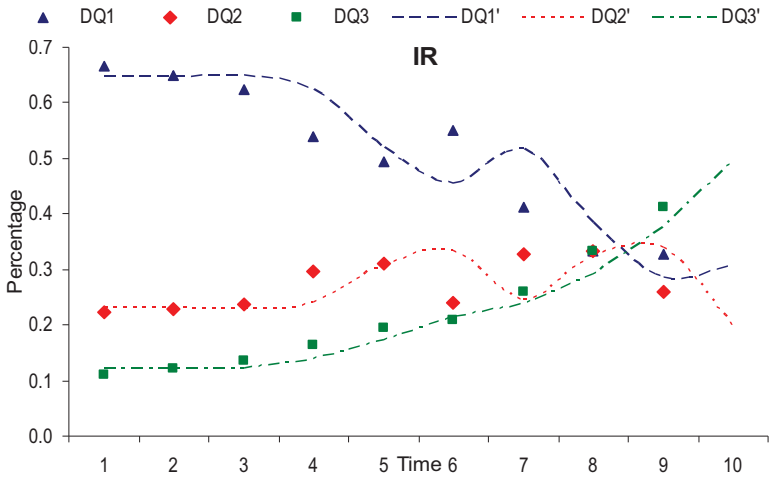


Figure 6.1 Graphical plot of the actual, fitted, and forecasted values of the DQs' priorities

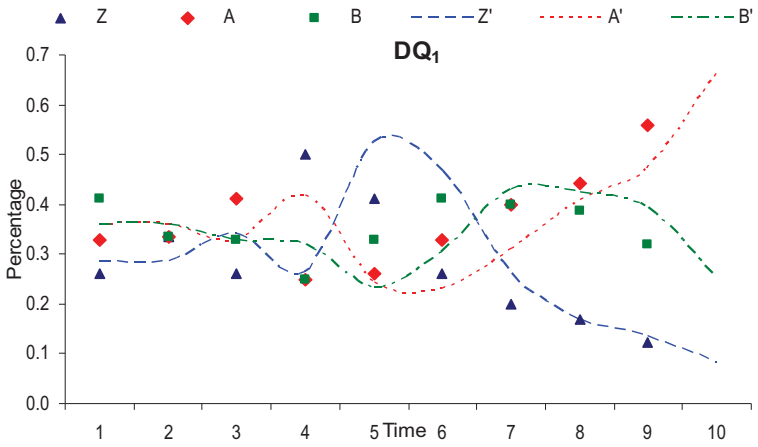


Figure 6.2 Graphical plot of the actual, fitted, and forecasted values of the customer competitive assessment priorities for DQ_1

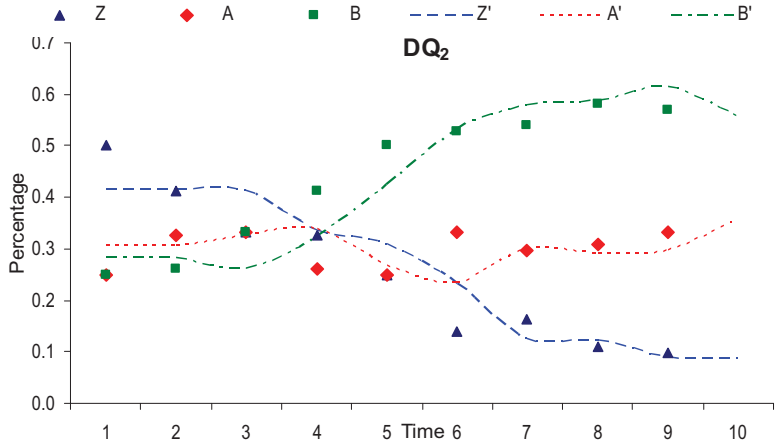


Figure 6.3 Graphical plot of the actual, fitted, and forecasted values of the customer competitive assessment priorities for DQ_2

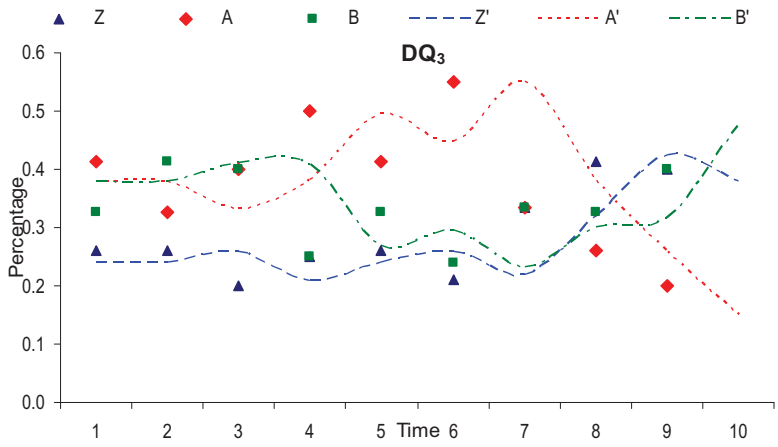


Figure 6.4 Graphical plot of the actual, fitted, and forecasted values of the customer competitive assessment priorities for DQ_3

The graphical plot of the forecasting results for the customer competitive assessment for each DQ is shown in Figure 6.5. The forecasted relative performance values for company Z, competitor A, competitor B are denoted by the solid line, long-dash line, and dash line, respectively. The forecasted priority for each DQ (forecasted IR value or 'F.IR') is denoted by a full dot.

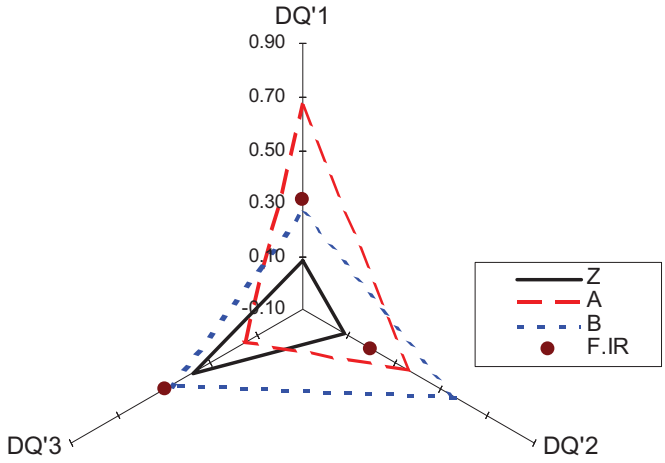


Figure 6.5 The radar diagram portraying the future competitive assessment

It can be seen that with respect to DQ_1 and DQ_2, which will not become very important attributes, the predicted performance of company Z is the lowest compared to the others. While with respect to DQ_3, which will become a very important attribute, the predicted performance of company Z is between competitor A and competitor B. The following section will show how the interaction of the two projected future conditions may enhance the decision making process in the QFD analysis, particularly in determining the strategic importance rating (SIR) of the customer needs (DQs).

6.5 The competitive weighting scheme: A SWOT-based approach

Taking into account the interaction between the forecasted DQs' priorities, which may reflect the future needs of the customer, and the forecasted priorities of the DQs' competitive assessment, which may reflect the future performance of the competitors, a competitive weighting scheme is proposed. The basic idea is to assign a multiplier to the DQ based on the forecasting results obtained from previous section. As compared to the traditional QFD, this approach may provide a more formal and systematic way for QFD practitioners in carrying out the customer target setting and sales point determination in the house of quality.

The proposed competitive weighting scheme is based on the idea of strength-weakness-opportunity-threat (SWOT) analysis. The framework is shown graphically in Figure 6.6. The *x*-axis denotes the forecasted competitors' *relative* performance, while the *y*-axis denotes the forecasted *relative* priority of a customer need (DQ). The weighting scheme can basically be divided into four groups as follows:

1. *Strength* (I)

   This case is for the situation when both the future competitors' relative performance and the future relative importance are rather low. In other words, the competitors' performance will be relatively lower than that of the company on a less important attribute. Thus, a multiplier value of 1 is assigned to this type of attribute. Note that the term 'less important' here does *not* mean 'unimportant' since an unimportant attribute will not be included in the DQ's list.

2. *Weakness* (II)

   This is for the situation when the competitors will relatively perform better than the company on a relatively less important attribute. Thus, a multiplier value of 3 is assigned. In the case when the competitors' relative performance will be equally good compared to the company, a multiplier value of 2 is assigned.

3. *Opportunity* (III)

   This is for the situation when the future competitors' relative performance will be relatively lower than that of the company on a relatively more important attribute. Thus, this case may be regarded as an opportunity for the company to differentiate itself from the competitors. A multiplier value of 7 is assigned.

4. *Threat* (IV)

   If the future competitors' relative performance will be relatively better than the company on a relatively more important attribute, then this signals a threat. The QFD team should place a special attention to such case. Thus, a multiplier value of 9 is assigned. A multiplier value of 8 can be assigned for the case when the future competitors' relative performance will be equally good compared to the company's.

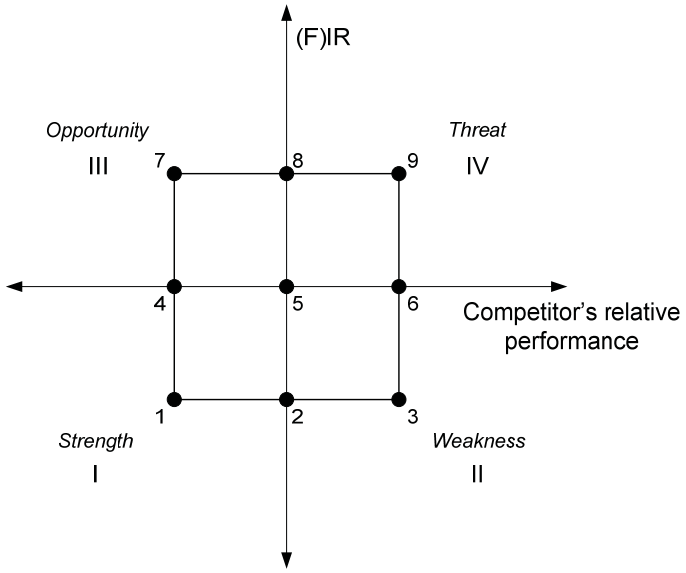


Figure 6.6 The proposed weighting scheme

For the in-between multiplier values other than described in the paragraph above, such as, 4, 5, 6, a similar interpretation can be used accordingly. Take for an example, a multiplier of 6 is assigned when the future competitors' relative performance will be relatively better than that of the company on a moderately important attribute. Table 6.5 shows the complete information on the proposed weighting scheme based on the *x*-axis and the *y*-axis.

Table 6.5 The proposed competitive weighting scheme

IR	CRP	weight	Note
Low	Low	1	Strength
Low	Medium	2	S-W
Low	High	3	Weakness
Medium	Low	4	S-O
Medium	Medium	5	S-W-O-T
Medium	High	6	W-T
High	Low	7	Opportunity
High	Medium	8	O-T
High	High	9	Threat

The 'IR' here refers to the forecasted IR values of the customer attributes (DQs' priorities), while the 'CRP' stands for the forecasted competitors' relative performance. A

multiplier value (weight) is assigned according the IR and CRP level, for example, a weight of 2 is assigned when the IR level is low and the CRP level is medium. The 'Note' column indicates the position of the weight in Figure 6.6, for example, 'S-W' indicates that its position lies between strength (S) and weakness (W). It is worth noting that the weight used in Table 6.5 may be regarded as a ratio-scale weight, which is similar to the scale used in the AHP (Harker and Vargas, 1987; see also Section 5.4.1). For example, a DQ which has a weight of '6' is three-time more important than a DQ which has a weight of '2', and so on.

Step 6: With respect to the example data, the weight or the competitive multiplier for the i-th DQ (CM_i) is shown in Table 6.6. For example, DQ_3 will become a very important attribute in the next period, and the performance of the company's product (Z) is between competitor A and B, therefore, a multiplier value of 8 is assigned to DQ_3. Another example, DQ_2 will not become a very important item in the future, however, the competitors' performance will be better compared to our company (Z), a multiplier value of 3 is therefore assigned to represent the company's weakness (see Table 6.5).

Table 6.6 The determination of final DQs' priority

	IR	*Z*	*A*	*B*	$ErrStDev^{norm}$	*CM*	CM^{norm}	*SIR*
DQ'_1	0.309	0.084	0.665	0.252	0.430	6	0.353	0.218
DQ'_2	0.197	0.086	0.357	0.557	0.271	3	0.176	0.110
DQ'_3	0.495	0.378	0.149	0.473	0.299	8	0.471	0.671

Step 7: The strategic importance rating (SIR) values of the i-th DQ, where i=1, 2,…, m, are obtained by adjusting the IR values with the competitive multiplier and its future uncertainty's measure (forecasting residual's standard deviation). The idea of estimating future uncertainty from the forecasting residual information will be further elaborated in

Section 8.2. It basically says that the precision level of the fitting process of the historical data reflects the precision level of the forecast results. In other words, with respect to Table 6.6, the higher the value of the standard deviation which implies a lower precision level of the fitting process, the lower the value of the SIR may become. The following compositional operation is suggested to obtained the SIR values, that is, $SIR = IR \oplus CM^{norm} \Theta ErrStDev^{norm}$.

Here, it is important to first normalize the CM_i and the forecasting residual's standard deviation (Err StDev) so that the compositional operation (Section 4.3.2) can be carried out. The value of 'Err StDev' for each DQ is shown in Table 6.2 to Table 6.4. According to the SIR values, as shown in Table 6.6, DQ_3 should receive the highest attention (SIR of DQ_3=67%), followed by DQ_1, and DQ_2. After obtaining the SIR values, subsequent analysis may be carried out, that is how to translate or relate the DQs with the QCs, and finally derive the QCs' priorities for decision making purpose. Such analysis will be dealt further in Chapter 8.

6.6 Conclusion

The purpose of this chapter was to demonstrate another application of the new modeling technique (Chapter 4) as to improve QFD analysis. The modeling technique (CDES) has been applied to model the change of both the DQs' priorities and DQs' competitive assessment over time. Specifically, this chapter has provided a more systematic way to integrate both the dynamics of DQs' priorities, which may reflect customer preference, and the dynamics of DQs' competitive assessment, which may reflect competitors' performance, along with their interaction, into a QFD analysis.

The ultimate goal of analyzing the dynamics of these two factors as well as their interaction is to come out with a better strategy when using QFD for dealing with a rapidly changing environment. One example of such environment is the consumer electronics market. Stalk and Webber (1993) wrote that "*Managers, to be both effective in their work and, ultimately, successful in sustained competition, must continue to push their strategic thinking to keep pace…Strategy is and always has been a moving target*". The importance of keeping pace with the change when formulating competitive strategies is precisely the main message of this chapter.

Compared to the previous research, this chapter has extended the traditional QFD in three ways. First, it is the use of the AHP *relative* measurement in eliciting the judgments of the customer not only for the importance rating, but also for the customer competitive assessment. As explained in Section 6.3, a *relative* measurement may be regarded as a better approach to assess the competitive condition compared to an absolute measurement. This is because a 'good' performance is, to some extent, determined relatively by the best-in-class competitors.

Second, it is the incorporation of the competitors' dynamics in terms of the change of customer competitive assessment over time. A timely update of customer competitive assessment information can be very useful to continually evaluate the current performance, identify areas for improvement, and eventually set goals for the future. Another advantage of considering the dynamics of competitors is to tackle the change of competitors' performance during product creation process as to avoid producing unwanted products or products that are more inferior than the competitors'. Third, it is the use of the SWOT-based competitive weighting scheme to analyze the interaction of both factors taking into account their dynamics. It is expected that using the weighting scheme may improve the

accuracy of the final DQ's priority, which in the end may hopefully increase the likelihood of success of a product design or upgrade process.

The limitation of the proposed methodology is that it might take a certain amount of time and efforts to collect the necessary data over time. However, it might be justified considering the improved accuracy of the QFD's results. It is worth noting that the data collection should be carried out in a specific customer segment. For future research, a case study to showcase the effectiveness of the proposed methodology is certainly of great value. One potential extension is to apply the approach in developing innovative products using QFD (Miguel, 2007).

In the next chapter (Chapter 7), a closer look at how the final DQs' priorities, either those obtained in this chapter or in Chapter 5, be translated into QCs' priorities through the QFD's relationship matrix is provided. Specifically, the need to use normalization in the relationship matrix will be thoroughly investigated. Afterwards, the decision making issues based on the QCs' priorities will be discussed in Chapter 8.

CHAPTER 7
A FURTHER STUDY ON QFD'S RELATIONSHIP MATRIX: INVESTIGATING THE NEED OF NORMALIZATION

The last two chapters (Chapter 5 and 6) have shown the applications of the proposed new modeling technique (Chapter 4). Both of the applications end with enhanced analysis of the DQs via improving their priorities' accuracy. After obtaining better DQs' priorities, the next step is to translate those DQs into QCs and finally obtain QCs' priorities. Almost all translations employ the so-called relationship matrix, which shows the strength of relationship between the DQs and the QCs. The purpose of this chapter is to provide a further study on the relationship matrix by investigating the need of normalizing it. It will be shown that that either using or ignoring normalization, any QFD practitioner may still be subject to misleading results. This therefore implies that normalization is *not* a trivial issue. Through empirical examples, this chapter provides some guidelines for QFD practitioners to decide when normalization is (not) necessary, especially when it causes rank reversal. This chapter is reproduced from "On Normalizing the Relationship Matrix in Quality Function Deployment", by Raharjo H, Xie M, Brombacher AC. To be submitted to an international journal.

7.1 Introduction

The most important function of QFD is to translate DQs into QCs (Chan and Wu, 2002a; Xie et al., 2003). How one DQ gets translated into one or more QCs may vary from one case to another, and this is beyond the scope of this thesis. Nevertheless, almost all translations do employ the so-called relationship matrix, which shows the strength of

relationship between the DQs and the QCs. It is this relationship matrix that becomes the focal point of this chapter. It is of critical importance because it determines, together with the DQs' priorities, the final output of the house of quality, that is, the QCs' priorities.

To obtain a more meaningful interpretation, some researchers suggest the use of normalization in the relationship matrix. The most popular normalization technique in the literature is the one proposed by Wasserman (Wasserman, 1993)[1]. Unfortunately, such normalization also comes with some serious shortcomings (see Section 7.2). On the other hand, there are also many other QFD researchers that do not use normalization or simply ignore it. It is probably because most of them are not aware of the potential risk of having misleading results. In other words, either using or ignoring normalization, any QFD practitioner may still be subject to misleading results. This therefore implies that normalization is *not* a trivial issue.

Unfortunately, there appears to have been almost no study that adequately addresses this relationship matrix normalization issue in QFD at the moment. Therefore, this chapter attempts to fill in this niche by providing a more detailed and fair explanation on the relationship matrix normalization issue in QFD, particularly when it causes rank reversal. In Section 7.3.1, it will be shown that the rank reversal, as a result of normalization, is desirable. However, in Section 7.3.2, it will be shown otherwise. An empirical rule of thumb for QFD practitioners to know whether normalization may lead to desirable results is proposed in Section 7.4. It is especially useful when the size of the house of quality gets larger. Finally, Section 7.5 concludes and provides possible extensions for future research.

[1] According to Science Citation Index database, it has received 99 times citations as per May, 2009

It is expected that this work will eventually provide important information for any QFD practitioner when dealing with the relationship matrix.

7.2. The QFD relationship matrix: some problems and research gap

7.2.1 Some problems in QFD relationship matrix

The relationship matrix is basically used for showing the relationship between the DQs and the QCs. Traditionally, the relationship matrix employs a scale of '1-3-9' to represent the strength of association or relation between a certain DQ and a QC (Akao, 1990; Xie et al., 2003). There have been some debates on the use of this scale. Two worth noting problems that arise are whether this scale is mathematically sound and why not choosing other scales, such as, '1-3-5' or else.

The latter problem (scales selection) seems to be not really critical. A QFD practitioner may basically select a scale that best represents their judgments. With respect to this, Ghiya et al. (1999) carried out some experiments to test the robustness of the QFD results when the traditional scale ('1-3-9') is replaced by others. Following the most common practice, a scale of '1-3-9' is used in this chapter.

On the other hand, the former problem (mathematical soundness), is of critical importance. The underlying question is whether the scale, for example, '1-3-9' belongs to ordinal, interval, or ratio scale (Stevens, 1946). Otto of Massachusetts Institute of Technology (Otto, 1995) showed that the QFD relationship matrix operates with *ratio* scales. The reason is because it uses a zero value to anchor the scale. The *zero* value, which is shown by a blank relationship, simply says that the technical attribute (QC) does *nothing* to the customer need (DQ).

In this chapter, the above mathematical soundness problem is useful to preempt the possibility to surmise that the normalization problem is caused by the types of scale, that is, ordinal, interval, or ratio. In other words, the problem with normalization still exists even though a ratio scale, which is the highest type of scale (Stevens, 1946), is assumed or used.

It is worth highlighting that a ratio scale will be assumed throughout this thesis since it is the only scale that may make the analysis meaningful. Some basic consequences when using ratio scale for the scoring system of the relationship matrix, such as, the score can be any real number from '0' to '9', '9' is three times more correlated than '3', '3' is three times more correlated than '1', and so on (Burke et al., 2002) are also assumed.

7.2.2 The research gap

As mentioned previously, the most popular normalization method for the QFD relationship matrix is the one proposed by Wasserman (Wasserman, 1993). Assuming that there are *m* DQs and *n* QCs, the mathematical expression to normalize the relationship values between the i-th DQ and the j-th QC (R_{ij}) according to Wasserman is as follows:

$$R_{ij}^{norm} = \frac{\sum_{k=1}^{n} R_{ik} \cdot \gamma_{kj}}{\sum_{j=1}^{n}\sum_{k=1}^{n} R_{ij} \cdot \gamma_{jk}}, \; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \qquad (7.1)$$

where:

R_{ij}^{norm} : the normalized relationship values between the i-th DQ and the j-th QC.

γ_{jk} : the value to denote the degree of correlation between the j-th QC and the k-th QC and vice versa (symmetrical). This value is shown in the roof of the HoQ.

Note that the value of γ_{jk} is not normalized so that the highest value of the correlation is 9. The value of the R_{ij}^{norm} can be interpreted as the incremental change in the level of fulfillment of the i-th DQ when the j-th QC is fulfilled to a certain level.

When the correlation between the QCs (γ_{jk}) is assumed to be non-existent, then the above formula can be reduced to a simple row normalization procedure as follows:

$$R_{ij}^{norm} = R_{ij} / \sum_{j=1}^{n} R_{ij} \tag{7.2}$$

The final priorities of the QCs can be computed by taking the product of R_{ij}^{norm} and IR_i , as expressed in formula (7.3).

$$AS_j = \sum_{i=1}^{m} R_{ij}^{norm} . IR_i \,, \;\; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{7.3}$$

where:

AS_j = Absolute Score of QC_j

IR_i = Importance Rating of DQ_i or DQ_i's priority

Those final priorities, either in terms of absolute or relative scores, are of critical importance to the QFD practitioners because they determine all subsequent decisions and processes. For example, suppose there are four houses of quality used. Then, if there is inaccuracy in the first house, then the error would certainly be propagated into the second, third, and fourth houses. In other words, the entire product creation process will go wrong. As a result, not only will it incur unnecessarily huge cost, but it will also result in producing unwanted products.

The accuracy of the priorities, as can be observed from the formula, depends on the accuracy of the importance rating (IR_i) values and the normalized relationship values (R_{ij}^{norm}). In this chapter, it is assumed that the importance rating values have no problem, that is, they are properly obtained and in ratio scale (see also Chapter 2). The emphasis is placed on the relationship matrix values.

The result of the normalization (R_{ij}^{norm}), either considering the roof of the HoQ (see formula 7.1) or ignoring it (see formula 7.2), is uniform relationship values across the technical attributes. Recently, Van de Poel (2007) shows that normalization procedure in the house of quality is methodologically problematic in the sense that it does not satisfy the 'independence of irrelevant alternatives' condition. In other words, the final priorities, as well as the ranking, may change when a new alternative is added or an old one is deleted. He also argues that further sophistication of the existing QFD approaches would be of little value if this core problem is not adequately addressed. In fact, such problem is not new. A similar problem, which is known as rank reversal phenomenon, can also be found in the AHP, see Belton and Gear (1983) or Raharjo and Endah (2006).

Another shortcoming of normalization in the QFD relationship matrix was also pointed out by Shin and Kim (2000). They showed that under some certain conditions, the normalization may induce undesirable rank reversal in the technical characteristics. It is worth noting that this rank reversal is *not* due to the addition of a new alternative or deletion of an old one. Nevertheless, those studies are incomplete since they only tell half of the story. Furthermore, they seem to overlook the importance of normalization in the HoQ. Hence, this chapter attempts to fill in this gap by providing a fairer or better explanation on the need of normalization in the relationship matrix.

7.3. The pros and cons of normalization in QFD

7.3.1 The pros

There are at least two reasons why normalization is desirable to be carried out in a QFD analysis. First, it is to have a proportional demanded weight of the customer needs (DQs), see Wasserman (1993) for details. In this chapter, it is represented by 'RW' (row weight), and its relative value is represented by 'RRW' (relative row weight). Note that the 'RW' is obtained from multiplying the importance rating (IR) by the sum of relationship values in one row. Second, it is to avoid a misleading prioritization result. This second point may be a novel case which has not been exposed in the existing literature.

Below is an example of such case. Before normalization, the HoQ example in Table 7.1 gives counter intuitive results as follows. Note that 'RS' is used to denote the relative score of the absolute score of QC_j (AS_j, see formula 7.3).

Table 7.1 HoQ example when normalization is desirable: before normalization

	IR	QC_1	QC_2	QC_3	QC_4	RW	RRW
DQ_1	0.1	9	1	3	9	2.2	0.42
DQ_2	0.8	0	1	1	0	1.6	0.30
DQ_3	0.1	3	3	0	9	1.5	0.28
AS		1.2	1.2	1.1	1.8		
RS		0.23	0.23	0.21	0.34		
Rank		*2*	*2*	*4*	*1*		

1. QC_4 has the highest priority. This is clearly misleading because it has no relationship with the most important customer need (DQ_2), which has importance rating (*IR*) value of 0.8.

2. QC_1 and QC_2 have the same priorities (0.23). This should not be the case, because QC_2 is clearly much more important than QC_1 since it has a relationship with all the DQs, especially the most important one.
3. QC_3 has the lowest priority, although it has relationship with two DQs, of which one of them is the most important customer need (DQ_2).

However, once normalization is carried out, in this case using (7.2), it turns out that the results become much more reasonable and in line with common sense (see Table 7.2). The above three problems have all disappeared. This example signifies the importance of normalization in the QFD without which one would end up with misleading results. It is worth noting that normalization causes *desirable* rank reversal here.

Table 7.2 HoQ example when normalization is desirable: after normalization

	IR	QC_1	QC_2	QC_3	QC_4	RRW
DQ_1	0.1	0.41	0.05	0.14	0.41	0.1
DQ_2	0.8	0	0.5	0.5	0	0.8
DQ_3	0.1	0.2	0.2	0	0.6	0.1
RS		0.06	0.42	0.41	0.10	
Rank		*4*	*1*	*2*	*3*	

7.3.2 The cons

This subsection, in contrast to the preceding one, shows that normalization is sometimes undesirable since it causes a serious problem in the QFD results. According to previous research, there are at least two significant problems which may occur as a result of normalization. First, it is the possibility of producing fallacious prioritization results, especially when a new QC is added or an old one is deleted. For a complete example of this case, interested readers may refer to Van de Poel (2007).

Second, it is the possibility of *undesirable* rank reversal due to normalization (Shin and Kim, 2000). However, the reason of why it occurs was not adequately explained. The following example demonstrates such situation, in which normalization does lead to misleading results. In Table 7.3, it is clear that QC_2 is the most important one since it has a strong relationship with DQ_1 (IR_1=0.3) and a moderate relationship with DQ_4 (IR_4=0.2). Furthermore, it is also obviously much more important than QC_3.

Table 7.3 HoQ example when normalization is undesirable: before normalization

	IR	QC_1	QC_2	QC_3	RW	RRW
DQ_1	0.3	3	9	0	3.6	0.49
DQ_2	0.3	0	0	3	0.9	0.12
DQ_3	0.2	1	0	1	0.4	0.05
DQ_4	0.2	9	3	0	2.4	0.33
AS		2.9	3.3	1.1		
RS		0.40	0.45	0.15		
Rank		*2*	*1*	*3*		

However, once normalization is carried out using formula (7.2), the outcome (Table 7.4) shows an undesirable result. QC_3, which was the least important, becomes the most important one, while QC_2, which was the most important, becomes the least important one. It turns everything upside down. It is easy to see that QC_2 is much more important than QC_3 because, with respect to the DQs which have importance rating value of 0.3 and 0.2, QC_2 has three-time stronger relationships than QC_3 does (see Table 7.3). For example, with respect to the DQ which has an importance rating value of 0.3, QC_3 has a '3' (R_{23}), while QC_2 has a '9' (R_{12}) which is three-time of '3' ($R_{12}=3R_{23}$).

Table 7.4 HoQ example when normalization is undesirable: after normalization

	IR	QC_1	QC_2	QC_3	RRW
DQ_1	0.3	0.25	0.75	0	0.3
DQ_2	0.3	0	0	1	0.3
DQ_3	0.2	0.5	0	0.5	0.2
DQ_4	0.2	0.75	0.25	0	0.2
RS		0.33	0.28	0.40	
Rank		*2*	*3*	*1*	

7.4 Some observations and a proposed rule of thumb

Having observed the two cases above, one might naturally ask whether normalization in the relationship matrix is really necessary in QFD. In Section 7.3.1, it is shown that normalization should be done to obtain reliable results, while in Section 7.3.2, it is shown otherwise. There appears to be a possible confusion here, but ignorance is definitely not bliss in this respect.

7.4.1 Some observations

If one takes a closer look at the two examples above, one might find at least two general facts. First, normalization may change the final relative scores of the QCs. Second, normalization may induce rank reversal when the magnitude of change is relatively high. As shown in the two illustrative examples, the change may be (un)desirable.

Before going further to discuss how one can know whether a change is desirable or not, it is useful to first know why the change, which may cause rank reversal, happens. The main reason *why* it happens is that normalization converts the *absolute* values of the number into *relative* values. Such conversion can possibly make some numbers, which are low in terms of their absolute values, have much higher magnitude in terms of their relative values. It is precisely this condition that causes rank reversal in the two illustrative

examples in Section 7.3. In other words, rank reversal may happen *when* there are relatively few *and* weak relationships between DQs and QCs in a row. For example, if there are only two '1's ('1'=weak relationship) in a row, then they will be changed into two '0.5's after normalization.

Now, the next issue is how one can know that rank reversal, as a result of normalization, is desirable or not. By observing the two illustrative examples, the following empirical analysis can be made:

1. It may be desirable when a very important customer need is weakly related to a few technical attributes.
2. It may be undesirable when some relatively not very important customer needs are weakly related to a few technical attributes.

For the first situation, which is exemplified in Section 7.3.1, the rank reversal is desirable because it helps avoid the problem of 'under' translating the very important customer need, see the row of DQ_2 (Table 7.1 and Table 7.2). While for the second situation, which is exemplified in Section 7.3.2, the rank reversal is undesirable because it causes 'over' translation of the relatively not very important needs, see the row of DQ_2 and DQ_3 (Table 7.3 and Table 7.4).

The above observations can be easily made since the size of the matrix is relatively small. However, in most of the cases, the size of a QFD relationship matrix is relatively large. This means that reliance on manual observation is at stake. Therefore, a kind of guideline or rule of thumb would be very useful for QFD practitioners to decide whether they need normalization or not. In the next subsection (Section 7.4.2), a guideline, which may serve as the rule of thumb, will be proposed. Afterwards, a real-world QFD example will be used to validate the proposed guideline (Section 7.4.3).

7.4.2 A proposed rule of thumb

The following guideline is proposed as a rule of thumb for QFD practitioners to decide whether they need normalization in the relationship matrix.

Step 1. Normalize the relationship matrix using formula (7.1).

Step 2. Check if there is a significant[2] change in the final relative scores of the QCs after normalization. If there is, then proceed to the next step, otherwise, go to Step 4. Note that rank reversal may occur when there are *one or more* big[3] differences between the RRW_i and the IR_i. The larger the matrix size, the more number of big differences is required for a rank reversal to occur.

Step 3. Check if the change is desirable or not by comparing the relative row weight (RRW_i) and importance rating value (IR_i) of each DQ. The change may be desirable when those DQs which have low[4] RRW values have *one or more* relatively *high* IR values. Otherwise, it may be undesirable, that is, when those DQs which have low RRW values have *one or more* relatively *low* IR values. In the case when it is undesirable, the normalized matrix should not be used.

Step 4. Sanity check.

The rationale behind the proposed rule of thumb is described as follows. To judge whether normalization may lead to desirable results, it is first necessary to compare the results before and after normalization (Step 1). There are two possible outcomes, namely, they are significantly different or not. If the results before and after normalization are not

[2] A 'significant' change may be interpreted as a change that causes rank reversal.
[3] A 'big' difference is defined as a difference of more than two-time higher or less than half-time lower than the value.
[4] Pareto diagram can be used to classify those RRW which have 'low' values, for example, using the reciprocal value of RRW.

significantly different, then the use of normalization is optional. For the sake of simplicity, a 'significant' change can be interpreted as a change that causes rank reversal (Step 2). It is possible that there might be a significant change that does not necessarily cause rank reversal. However, the investigation of such condition is beyond the scope of this thesis.

As the rule of thumb, it may be said that rank reversal may occur when there are one or more big differences between the RRW_i and the IR_i. The reason why it suggests for more than one big difference is because the RRW is a *relative* value. In other words, when one RRW value becomes very small (less than half lower) in comparison with the IR value, then this will most likely cause at least one other RRW value to become relatively higher in comparison with the corresponding IR value.

If there is a rank reversal, then the next step is to indicate whether it is desirable or not (Step 3). A more objective way to do this is by comparing the relative row weight (RRW_i) and importance rating value (IR_i) of each DQ using the following rule of thumb:

1. It may be desirable when those DQs which have low RRW values have *one or more* relatively *high* IR values. This is because normalization helps avoid the problem of under-translating very important DQs, namely, those DQs which have high IR values. If the relationship matrix is not normalized, then the values of those very important DQs will tend to diminish when multiplied by the low relationship value.
2. It may be undesirable when those DQs which have low RRW values have *one or more* relatively *low* IR values. This is because normalization causes the problem of over-translating the relatively not very important DQs, namely, those DQs which have low IR values. If the relationship matrix is normalized, then the values of those relatively not important DQs will tend to inflate when multiplied by the

normalized relationship value.

This guideline can be regarded as a way to verify the proposed rule of thumb and to decide whether normalization is really needed in the QFD relationship matrix. It is worth highlighting that the above proposed rule of thumb can also be applied to verify the two illustrative examples in Section 7.3. Finally, a sanity check can be carried out before subsequent downstream analysis.

7.4.3 A validation example

A recent real-world QFD application, which is published in a reputable journal (Sireli et al., 2007), was taken as a case study to validate how the proposed rule of thumb may work in practice. Two houses of quality of quite large size were adopted for the purpose of illustrating how QFD practitioners may decide whether normalization is necessary or not.

For the first HoQ example, it was taken from page 388 of the paper (Sireli et al., 2007), under the heading 'Combined Model for the Basic Product'. For the sake of simplicity, the DQs' and QCs' detailed names are not included.

Step 1: Normalize the relationship matrix using formula (7.1). Since the correlation matrix is non-existent, formula (7.2) can be used to normalize the relationship matrix. The original and the normalized HoQ can be seen in Table 7.5 and Table 7.6, respectively.

Step 2: Check if there is a significant change in the final relative scores of the QCs after normalization. It is easy to see that there is a rank reversal after normalization. The fourth and the fifth ranks are reversed. It is also interesting to see that the rank reversal happens because there are more than one big difference between the RRW_i and the IR_i, as precisely prescribed in the rule of thumb.

Table 7.5 HoQ of combined model for the basic product before normalization

	IR	QC_1	QC_2	QC_3	QC_4	QC_5	QC_6	QC_7	QC_8	RW	RRW	1/RRW
DQ_1	0.149	1	1	0	1	1	1	1	1	1.043	0.070	14.3
DQ_2	0.152	1	1	0	1	1	1	1	1	1.064	0.072	14.0
DQ_3	0.153	1	1	0	1	1	1	1	1	1.071	0.072	13.9
DQ_4	0.136	9	9	0	1	1	9	3	9	5.576	0.375	2.7
DQ_5	0.142	1	9	0	1	1	0	0	0	1.704	0.115	8.7
DQ_6	0.146	1	0	0	0	0	1	1	0	0.438	0.029	33.9
DQ_7	0.124	9	9	0	1	1	9	3	0	3.968	0.267	3.7
AS		3.08	4.07	0	0.86	0.86	2.94	1.38	1.68			
RS		0.21	0.27	0	0.06	0.06	0.2	**0.09**	**0.11**			
Rank		*2*	*1*	*8*	*6*	*6*	*3*	***5***	***4***			

Table 7.6 HoQ of combined model for the basic product after normalization

	IR	QC_1	QC_2	QC_3	QC_4	QC_5	QC_6	QC_7	QC_8	RRW
DQ_1	0.149	0.14	0.14	0	0.14	0.14	0.14	0.14	0.14	0.149
DQ_2	0.152	0.14	0.14	0	0.14	0.14	0.14	0.14	0.14	0.152
DQ_3	0.153	0.14	0.14	0	0.14	0.14	0.14	0.14	0.14	0.153
DQ_4	0.136	0.22	0.22	0	0.02	0.02	0.22	0.07	0.22	0.136
DQ_5	0.142	0.08	0.75	0	0.08	0.08	0	0	0	0.142
DQ_6	0.146	0.33	0	0	0	0	0.33	0.33	0	0.146
DQ_7	0.124	0.28	0.28	0	0.03	0.03	0.28	0.09	0	0.124
RS		0.19	0.24	0	0.08	0.08	0.18	**0.14**	**0.09**	
Rank		*2*	*1*	*8*	*6*	*6*	*3*	***4***	***5***	

Step 3. Check if the change is desirable or not by comparing the relative row weight (RRW_i) and importance rating value (IR_i) of each DQ. First, one needs to decide which DQs that have 'low' RRW values. For this purpose, a pareto diagram can be employed for the reciprocal RRW values (1/RRW) as shown in Figure 7.1.

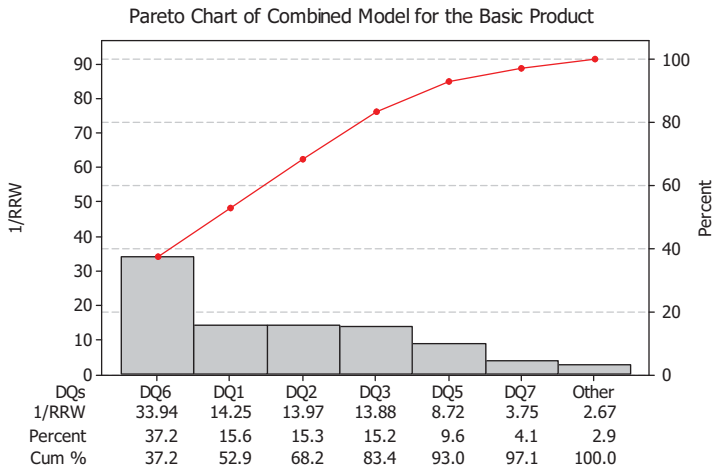


Figure 7.1 Pareto chart of combined model for the basic product

It can be seen that DQ_1, DQ_2, DQ_3, and DQ_6 may belong to the DQ group which have low RRW values. Since DQ_6 corresponds to a quite high IR value (IR_6= 14.6%) and DQ_3 corresponds to the highest IR value (IR_3=15.3%), then it is clear that the rank reversal is desirable. In other words, the normalization is necessary to be carried out. Finally, a sanity check (Step 4) can be done for subsequent analysis.

For the second HoQ example, it was also taken from page 388 of the paper (Sireli et al., 2007), under the heading 'Combined Model for the High-End Product'. For the sake of simplicity, the DQs' and QCs' detailed names are again not included.

Step 1: Normalize the relationship matrix using formula (1). Since the correlation matrix is non-existent, formula (2) can again be used to normalize the relationship matrix. The original and the normalized HoQ can be seen in Table 7.7 and Table 7.8, respectively.

Step 2: Check if there is a significant change in the final relative scores of the QCs after normalization. It is easy to see that there is a rank reversal after normalization. The rank of QC_2 and QC_3 are reversed. Initially, QC_3 has a higher rank than QC_2, but it is the other way around after normalization. It is again confirmed that what is prescribed in the

rule of thumb is correct, that is, the rank reversal happens because there are more than one big difference between the RRW_i and the IR_i.

Table 7.7 HoQ of combined model for the high-end product before normalization

	IR	QC_1	QC_2	QC_3	QC_4	QC_5	QC_6	QC_7	QC_8	RRW
DQ_1	0.073	0.19	0.02	0.00	0.19	0.02	0.19	0.19	0.19	0.073
DQ_2	0.066	0.19	0.02	0.00	0.19	0.02	0.19	0.19	0.19	0.066
DQ_3	0.070	0.19	0.02	0.00	0.19	0.02	0.19	0.19	0.19	0.070
DQ_4	0.077	0.19	0.02	0.00	0.19	0.02	0.19	0.19	0.19	0.077
DQ_5	0.081	0.19	0.02	0.00	0.19	0.02	0.19	0.19	0.19	0.081
DQ_6	0.049	0.20	0.00	0.00	0.20	0.20	0.20	0.20	0.00	0.049
DQ_7	0.067	0.24	0.03	0.00	0.08	0.08	0.24	0.24	0.08	0.067
DQ_8	0.080	0.19	0.19	0.00	0.02	0.02	0.19	0.19	0.19	0.080
DQ_9	0.098	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.098
DQ_{10}	0.075	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.075
DQ_{11}	0.065	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.065
DQ_{12}	0.068	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.068
DQ_{13}	0.061	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.061
DQ_{14}	0.071	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.071
RS		0.295	**0.025**	**0.071**	0.087	0.025	0.295	0.112	0.091	
Rank		*1*	***7***	***6***	*5*	*7*	*1*	*3*	*4*	

Table 7.8 HoQ of combined model for the high-end product after normalization

	IR	QC_1	QC_2	QC_3	QC_4	QC_5	QC_6	QC_7	QC_8	RW	RRW	1/RRW
DQ_1	0.073	9	1	0	9	1	9	9	9	3.431	0.111	9.03
DQ_2	0.066	9	1	0	9	1	9	9	9	3.102	0.100	9.99
DQ_3	0.070	9	1	0	9	1	9	9	9	3.29	0.106	9.42
DQ_4	0.077	9	1	0	9	1	9	9	9	3.619	0.117	8.56
DQ_5	0.081	9	1	0	9	1	9	9	9	3.807	0.123	8.14
DQ_6	0.049	1	0	0	1	1	1	1	0	0.245	0.008	126.44
DQ_7	0.067	9	1	0	3	3	9	9	3	2.479	0.080	12.50
DQ_8	0.080	9	9	0	1	1	9	9	9	3.76	0.121	8.24
DQ_9	0.098	9	0	0	0	0	9	0	0	1.764	0.057	17.56
DQ_{10}	0.075	9	0	0	0	0	9	0	0	1.35	0.044	22.95
DQ_{11}	0.065	9	0	0	0	0	9	0	0	1.17	0.038	26.48
DQ_{12}	0.068	9	0	0	0	0	9	0	0	1.224	0.040	25.31
DQ_{13}	0.061	9	0	0	0	0	9	0	0	1.098	0.035	28.21
DQ_{14}	0.071	0	0	9	0	0	0	0	0	0.639	0.021	48.48
AS		7.978	1.154	0.639	3.633	0.697	7.978	4.675	4.224			
RS		0.258	**0.037**	**0.021**	0.117	0.022	0.258	0.151	0.136			
Rank		*1*	***6***	***8***	*5*	*7*	*1*	*3*	*4*			

Step 3. Check if the change is desirable or not by comparing the relative row weight (RRW_i) and importance rating value (IR_i) of each DQ. To decide which DQs that have low RRW values, a pareto diagram can be employed for the reciprocal RRW values (1/RRW) as shown in Figure 7.2.

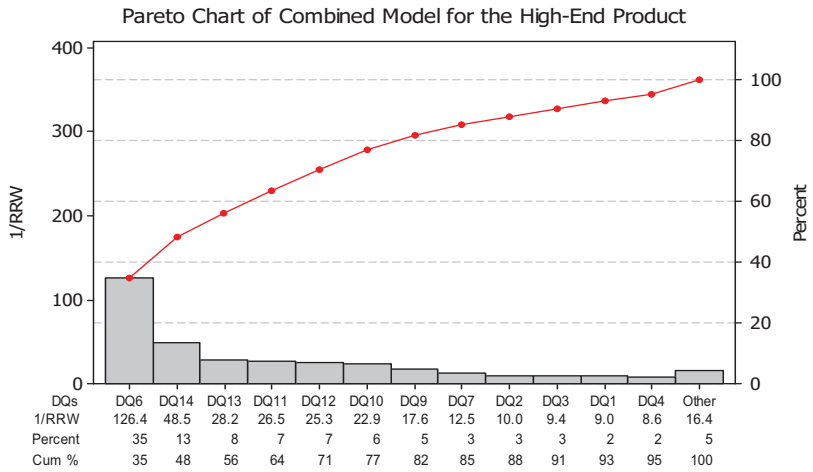


Figure 7.2 Pareto chart of combined model for the high-end product

It can be seen that DQ_6 has the lowest RRW value compared to the others. The next one is DQ_{14}, although it is not that low relatively compared to DQ_6. The fact that DQ_6 corresponds to the *lowest* IR value (IR_6=4.9%) and DQ_{14} does not correspond to a very high IR value (IR_{14}= 7.1%) provides a strong evidence that the rank reversal is undesirable. In other words, normalization is not needed here. Finally, a sanity check can be done for subsequent QFD analysis (Step 4).

7.5 Conclusion

The aim of this chapter was to further investigate the relationship matrix that is almost always used in translating the DQs into the QCs and finally obtain QCs' priorities. Specifically, the focus is placed on the need of normalization in the relationship matrix. It

is hoped that the work in this chapter will provide a better or fairer explanation on the need of normalization in the QFD relationship matrix, especially when it causes rank reversal. The existing literature, as has been described, does not provide adequate information on this issue. Some researchers might say that it is necessary to carry out normalization to have more meaningful results, while some others might say normalization make things worse by opening up the possibility of rank reversal when one technical attribute is added or deleted. Still, some others might not bother about this. Probably, it is regarded as a non-added value step in the HoQ.

This chapter has shown that, in all cases, any QFD practitioner should be aware that normalization, in general, is *not* a trivial issue when dealing with the relationship matrix. In particular, if the RRW value of the relationship matrix exhibits a special pattern as described in this chapter, then it indicates that rank reversal may happen when normalization is done. The question is whether such reversal is desirable or not. Based on some empirical observations, a rule of thumb is proposed for any QFD practitioner to know when such reversal may be desirable, that is, when normalization may lead to better results.

Since the rule of thumb is based on an empirical basis, it might not work perfectly for every single case, especially for large-sized HoQ. Hence, this opens up a new challenge for future research to complement the current findings. Some approaches, such as, computer simulations or validation by more real-world case studies might be considered. For other possible future works, there are at least two clear directions to pursue. First, it might be interesting to investigate how one can know, in the case of *no* rank reversal, that the change due to normalization is (un)desirable. Second, the incorporation of fuzzy theory to facilitate a more precise quantification of the words, such as 'weak', 'few',

'high', and so on might be a considerable option. In sum, it is expected that this work, as a first step, will provide an important guideline or useful insights for QFD practitioners in general when dealing with the relationship matrix.

In the next chapter (Chapter 8), taking into account the need of normalization discussed thoroughly in this chapter, how the DQs' priorities will be used to obtain QCs' priorities and finally be used as the main input for decision making will be described. For the decision making purpose, two kinds of approaches are suggested for prioritizing and/or optimizing the QCs. The objective is to better meet the changing needs of the customer considering the research problem discussed in Chapter 1.

CHAPTER 8
A FURTHER STUDY ON PRIORITIZING QUALITY CHARACTERISTICS IN QFD

The purpose of this chapter is to provide a possible answer to the research question "*How to make decision in a QFD analysis with respect to the dynamics in the house of quality?*" To the extent of what is described in the delimitation section, this chapter will answer the question by proposing a methodology, which may use two kinds of decision making approaches, to prioritize or optimize the QCs with respect to the dynamics in the HoQ. The methodology employs the modeling technique proposed in Chapter 4 as the tool to forecast the dynamics. To show how the methodology works in practice, the case study described in Chapter 2 is used to provide the contextual setting. The notion of *future uncertainty* to improve forecast' precision will also be introduced. It is hoped that the proposed methodology might help QFD-users better deal with the future needs of the customer. A large part of this chapter is reproduced from the author's two papers[1].

8.1 Introduction

In the context of a customer-driven product or service design process, a timely update of customer needs information may not only serve as a useful indicator to observe how things change over time, but it also provides the company a better ground to formulate strategies to meet the future needs of its customer. This chapter proposes a systematic

[1] Raharjo, H., Xie, M., Brombacher, A.C. (2006), Prioritizing Quality Characteristics in Dynamic Quality Function Deployment, *International Journal of Production Research*, 44(23), 5005-5018. (received *IJPR highly-commended PhD prize* 2007)

Raharjo, H., Xie, M., Brombacher, A.C., A systematic methodology to deal with the dynamics of customer needs in Quality Function Deployment, *Submitted to an international journal*.

methodology to better deal with customer needs' dynamics, in terms of their relative weights (priorities), in the QFD.

The work in this chapter will extend the existing QFD research in three directions. First, it provides the way to model the change of *relative* priorities of the DQs over time. This is owing to the fact that the AHP has been applied quite extensively in QFD (see Chapter 1 and Chapter 2), and yet there has been almost no tool to model the dynamics. Second, it proposes the notion of future uncertainty, which is an interval estimate of the future needs, as a way to improve the forecast precision. This is to complement the previous research which use only a point estimate of the future needs (Min and Kim, 2008; Raharjo et al., 2006; Wu and Shieh, 2006; Wu et al., 2005). Third, it proposes the use two quantitative decision making approaches that take into account the decision maker's attitude towards risk in optimizing or prioritizing the QCs with respect to the future needs of the customer.

This chapter is organized as follows. In the next section (Section 8.2), the notion of dynamic QFD (DQFD) will be described in terms of its significance, model, and tools used. Section 8.3 will elaborate the proposed systematic methodology to deal with the customer needs' dynamics along with their future uncertainty using two decision making approaches. An example based on a real world application of QFD (Raharjo et al., 2007; see Chapter 2) will be provided to illustrate how the proposed methodology works in practice (Section 8.4). Section 8.5 will discuss the issue of forecasting technique's selection and a possible implication of the methodology to development of innovative products. Finally, a summary of the main contributions and possible future works are provided in Section 8.6.

8.2 The dynamic QFD (DQFD)

This section describes the notion of dynamic QFD (DQFD) that can be considered as an extension of the standard QFD (Cohen, 1995) since it takes into account the change over time. The emphasis here is placed on the need to deal with the dynamics in the relative weights of customer needs (DQs' priorities)[2]. Those weights are commonly referred to as 'importance rating' in the house of quality (HoQ). The following subsections will first explain why it is important to consider such change. Afterwards, how to quantitatively incorporate it in the HoQ along with its future uncertainty will be elaborated.

8.2.1 Why is it important to incorporate customer needs' dynamics?

QFD starts and ends with the customer. As explained in the research problem (Section 1.1), it is known that it always takes some time from the time when the customer voice is collected until the time when the product is ready to be launched (see also Figure 1.1). The time-lag duration may certainly vary from one product to another. For example, if it takes one year time, then the question is whether the product which is about to be launched may still meet the customer needs since it is created based on the customer voice which was collected one year ago. The answer to this question is very likely to be a 'no' in the context of today's rapidly changing market.

Since the accuracy of information in the DQs critically determines the success of a QFD application (Cristiano et al., 2001), it is of considerable importance to take into account the change during product or service creation process. In Chapter 2 and Chapter 3,

[2] The dynamics of DQs' competitive assessment, as described in Chapter 6, may also be included in a similar way. For simplicity, only the dynamics in DQs' priorities is included in the DQFD in this chapter

a sensitivity analysis has been suggested as a way to investigate the impact of DQs' priorities change on the QCs' priorities. It has been shown in Chapter 2 that a change in the DQs' priorities does *alter* the QCs' ranks and priorities. This implies that the change results in different policy of the QFD user (see Chapter 2.2.5).

One weakness of a sensitivity analysis is that one may not see the change pattern over time. With respect to this, some researchers proposed a better approach to deal with the change in DQs' importance, that is, by formally incorporating time dimension in the HoQ using forecasting techniques, such as double exponential smoothing (Xie et al., 2003), fuzzy trend analysis (Shen et al., 2001), grey theory (Wu et al., 2005), and Markov chain analysis (Wu and Shieh, 2006). Along the same line, Min and Kim (2008) studied the cumulative effect of DQs over time on one target customer value (CV) at a final point of time. Nevertheless, all of the above mentioned studies rely only on a point estimate of the forecast. It might be better to not only use a point estimate, but also an interval estimate as as a complement which at the same time may serve as the measure of future uncertainty.

In the next subsection, how the forecasting results of the VOC, both in terms of point estimate and interval estimate, are incorporated in the HoQ will be described. For ease of reference, the enhanced QFD will be referred to as Dynamic QFD (DQFD).

8.2.2 The DQFD model

The dynamic QFD (DQFD) model extends the input data of the traditional QFD model (Cohen, 1995) by employing a set of VOC data, in terms of importance rating values, which are obtained in a certain period of time. Thus, it may serve as a more generalized model of the traditional QFD. The basic dynamic QFD model for m DQs and n QCs is shown in Figure 8.1.

QC_1	γ_{11}	…	…	γ_{1n}							
QC_2	γ_{21}	…	…	γ_{2n}							
…	…	…	…	…	VOC dynamics						
QC_n	γ_{n1}	…	…	γ_{nn}							
DQ \ QC	QC_1	QC_2	⋮	QC_n	Importance rating (t=1)	Importance rating (t=2)	⋮	Importance Rating (t=k)	Forecasted IR (t=k+1)	Forecasting Residual StdDev (t=k+1)	
DQ_1	R_{11}	R_{12}	…	R_{1n}	$IR_{1,1}$	$IR_{1,2}$	…	$IR_{1,k}$	$IR_{1,k+1}$	Sd_1	
DQ_2	R_{21}	…	…	R_{2n}	$IR_{2,1}$	…	…	$IR_{2,k}$	$IR_{2,k+1}$	Sd_2	
…	…	…	…	…	…	…	…	…	…	…	
DQ_m	R_{m1}	…	…	R_{mn}	$IR_{m,1}$	…	…	$IR_{m,k}$	$IR_{m,k+1}$	Sd_m	
Mean of forecasted QC_j priority	$\hat{\mu}_1$	$\hat{\mu}_2$	…	$\hat{\mu}_n$							
StDev of forecasted QC_j priority	$\hat{\sigma}_1$	$\hat{\sigma}_2$	…	$\hat{\sigma}_n$							

Figure 8.1 The DQFD model

It is quite common to first normalize the relationship matrix (R_{ij}), while considering the correlation among the QCs, using the method proposed by Wasserman (1993). A detailed discussion on the need of normalization in the relationship matrix is provided in Chapter 7. The priorities of the QCs in the DQFD model can be computed by taking the product of R_{ij}^{norm} and the forecasted importance rating ($IR_{i,k+1}$), as expressed in formula (8.1) below.

$$\hat{\mu}_j = \sum_{i=1}^{m} R_{ij}^{norm} . IR_{i,k+1} \ , \ \ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{8.1}$$

where

$\hat{\mu}_j$ = mean of forecasted priority of QC_j

$IR_{i,k+1}$ = forecasted importance rating of DQ_i or DQ_i's priority.

k = last period of observation or number of observations

Those QCs' priorities are of critical importance to the QFD practitioners because they determine all subsequent decisions and processes. One important idea in the DQFD is to not only incorporate the forecasted point, but also the uncertainty measure (interval estimate) of the forecast (see subsection 8.2.4 for more detailed explanation). In Figure 8.1, the future uncertainty of the forecasted importance rating is represented by the standard deviation of the forecasting residual (Sd_i). These Sd_i values can be transmitted into the standard deviation of QC_j's forecasted priority using the principle of variance addition below:

$$\hat{\sigma}_j = \sqrt{\sum_{i=1}^{m} R_{ij}^{norm} * \hat{\sigma}_i^2}, \quad \forall\ j = 1, 2, ..., n \tag{8.2}$$

where $\hat{\sigma}_j$ is the standard deviation of QC_j's forecasted priority and $\hat{\sigma}_i^2$ is the variance of the forecasting residual of IR_i or the squared value of Sd_i . Note that such computation may slightly reduce the value of the transmitted variance due to the multiplication of normalized scores (R_{ij}^{norm}).

8.2.3 The forecasting technique

The purpose of using a forecasting technique in the DQFD is to model the change of the importance rating values (DQs' priorities) over time. The newly developed short-term forecasting technique, namely, the CDES technique will be used to model the change of DQs' priorities over time. The details of the technique can be found in Chapter 4. An important fact that should be noted with respect to the use of forecasting technique is that a good forecasting method will ideally result in errors which follow a 'Gaussian white noise' process, namely, a process which is normally, independently, identically distributed

(NIID) with a zero mean value and a constant variance. In the next subsection, how the information from the Gaussian white noise error may be used as an estimate of future uncertainty of the forecasted importance rating will be elaborated.

8.2.4 Estimation of future uncertainty

The rationale of future uncertainty's estimation is built upon the idea of how well one may learn from the past experience, that is, how precisely one can model or learn from the past data may critically determine how precisely one may estimate or understand the future. On the ground of this reason, it is suggested that the future uncertainty be estimated from the fitting imprecision of the forecasting model, which is represented by the *variance* of the Gaussian white noise error.

For the proposed forecasting technique (Raharjo et al., 2009), the Aitchison distance (Aitchison, 2003), which is a scalar quantity, is used as the primary yardstick to judge the goodness of fit of the model. For a given time *t*, the measure of discrepancy between the actual importance rating values (IR) and the fitted ones (IR') for DQ_i (i=1,…, m) is as follows:

$$Ad_i(IR, IR') = \left(\ln \frac{IR_i}{g(IR)} - \ln \frac{IR'_i}{g(IR')} \right), \text{ where } g(IR) = \sqrt[m]{\prod_{i=1}^{m} IR_i}\ ,\ g(IR') = \sqrt[m]{\prod_{i=1}^{m} IR'_i} \quad (8.3)$$

Note that the sum of all the m IR values, for a given time t, is equal to 1 since they are normalized, as a result of using the AHP. In the example section (Section 8.4), a full residual analysis based on the properties of Gaussian white noise will be demonstrated.

After computing the forecasting residual, the forecasted points along with their variances will be transmitted to the QCs' priorities using formula (8.1) and (8.2). Since a linear combination of several normal random variables is also normal, the forecasted QCs'

priorities, which are shown in the last two rows of Figure 8.1, can be regarded as several normally distributed processes with a mean value of $\hat{\mu}_j$ and a standard deviation value of $\hat{\sigma}_j$. Thus, the problem is now how one may prioritize or optimize those QCs with respect to their mean and standard deviation values. This problem will be discussed in the next subsection.

8.2.5 Decision making

The general objective the decision making process is to meet the future needs of the customer with greater confidence while considering the time lag problem (Section 1.1). Two kinds of decision making models are suggested as the tools for prioritizing and/or optimizing the QCs. One is based on a utilitarian approach, that is, using stochastic dominance approach, and the other is based on a non-utilitarian approach, that is, using Taguchi's Quality Loss Function (QLF) approach and Zero One Goal Programming (ZOGP).

In the *utilitarian* approach, the stochastic dominance (SD) approach (Hadar and Russel, 1974; Levy, 1998) is proposed to stochastically order the QCs. The stochastic ordering results will become the basis to construct an SD constraint to be used in the optimization model. The reason of choosing SD approach is two-fold. One is due to its simplicity and theoretical rigor, and the other is its ability to consider the QFD team's attitude towards risk in making the decision. The SD approach does not require specific information of decision maker's utility function, but the result can still be consistent with the preference of most decision makers (Hadar and Russel, 1974). In the QFD literature, the SD technique has been suggested by Kim et al. (2007) to deal with the uncertainty which

comes from 'heterogeneity' in customer's perception. This chapter will provide a more extensive application of the SD technique in QFD, especially in combination with the optimization model.

With respect to the same problem, that is, to prioritize and/or optimize the QCs based on their forecasted mean and standard deviation values, another equally plausible approach, without considering decision maker's attitude towards risk (*non-utilitarian*), can be employed. The idea is to use the combination of Taguchi's loss function approach and the goal programming (Raharjo et al., 2006). The loss function approach is used to minimize the deviation from the target mean and target variability. In other words, the more it deviates away from the target value, the larger the loss will incur. The goal programming is used to select only the 'important' QCs which have larger priorities and lower variability while considering the decision maker's preference.

It is worth noting that these two models can also be applied to the case when Kano's model is used to obtain the forecasted DQs' priorities (Chapter 5) or when using the competitive assessment of the DQs (Chapter 6). What is basically needed, as the main input in the optimization models, is the forecasted DQs' priorities and their future uncertainty which is estimated from the variance of forecast residual. The next section (Section 8.3) will describe how these two models can be used systematically within the proposed methodology.

8.3 The proposed methodology

This section consists of three subsections. The first subsection (Section 8.3.1) describes the proposed methodology. The methodology consists of 10 systematic steps

which may employ two kinds of decision making approaches. The first six steps (Step 1 to Step 6) are the common steps for using both approaches. They employ the same forecasting technique (Raharjo et al., 2009; Chapter 4), the same way of estimating future uncertainty, and the same way of obtaining the forecasted mean and standard deviation of QCs' priorities.

The next four steps are different; one may choose which decision making approach to use. If the utilitarian approach is chosen, then follow the next four step indicated by 'a' (Step 7a to Step 10a). Otherwise, if the non-utilitarian approach is chosen, then follow the next four step indicated by 'b' (Step 7b to Step 10b). Section 8.3.2 describes the utilitarian approach, while Section 8.3.3 describes the non-utilitarian approach. Both decision making approaches will be tested in the example section using the case study described in Chapter 2 (Raharjo et al., 2007).

8.3.1 A step-by-step procedure

The objective of the proposed methodology is to provide a systematic approach to deal with the dynamics of customer needs. A step-by-step procedure, starting from the construction of the DQFD until the prioritization stage, is provided as follows. Note that, as mentioned previously, the 10-step methodology comprised of six common steps and four specific steps depending on which approach to use.

Step 1: Construct the HoQ using basic QFD steps, such as collecting customer needs using in-depth interview or direct observation, structuring the needs using affinity diagram, and finally prioritizing them using the AHP (Griffin and Hauser, 1993; Cohen 1995: Raharjo et al., 2007).

Step 2: Translate the DQs into appropriate QCs and fill up the elements in the house of quality.

Step 3: Record the AHP-based importance rating values (DQs' priorities) for k periods, that is, $IR_{i,t}$, $IR_{i,t+1}$, $IR_{i,t+2}$,…, $IR_{i,k}$ (see Figure 8.1, indicated as 'VOC dynamics'). Note that these IR values over time should be obtained from a specific segment of customer.

Step 4: Fit the DQs' priorities data change over time using the proposed forecasting technique (Raharjo et al., 2009; Chapter 4), and obtain the future uncertainty's estimate, that is, the standard deviation of forecasting residual. If the forecasting residual, which is obtained from equation (8.3), follows Gaussian white noise process, then proceed to the next step. Otherwise, another forecasting technique is called for (see Section 8.5.1).

Step 5: Obtain the forecasted IR ($IR_{i,k+1}$) for each DQ using the forecasting method.

Step 6: Compute the mean and standard deviation of forecasted QCs' priorities using formula (8.1) and (8.2), respectively.

8.3.2 Optimization model 1: Utilitarian approach

Basically, the SD approach is comprised of some rules which are used to decide the stochastic ordering of the alternatives being compared. The way to use those rules is to start from the lowest order to a higher order. In the case when the lower order rule does not give a conclusive solution, then a higher order rule is used. Having known those rules, one can use them for ranking the QCs with respect to their mean and standard deviation values.

Step 7a: Plot the cumulative density function (CDF) of all QCs according their mean and standard deviation values together in one graph. This step is very useful for screening purpose because some QCs that obviously dominate the others can be easily detected by visual inspection.

Step 8a: Check for first-order dominance using the CDF curves. The CDF curve will reveal those QCs that first-order stochastically dominate the others. Specifically, if QC_a first-order dominates QC_b, then the CDF of QC_a is always to the right of that of QC_b. The assumption here is the larger the value of the QC, the more important it becomes. In addition, if QC_a first-order stochastically dominates QC_b ($QC_a \succ_{(1)} QC_b$), then QC_a also stochastically dominates QC_b by second-degree, third-degree, and so forth. However, the reverse is not true.

Step 9a: Check if there is a crossing among the CDF curves. If so, then check for higher order dominance, otherwise, proceed to the next step. In most cases, no more than third-order dominance needs to be checked.

Step 10a: Stochastically order the QCs according to the dominance relationship result, and construct a resource allocation constraint based on the stochastic ordering.

The stochastic ordering reflects the preference of the decision maker on the QCs. In other words, a bigger portion of available resources should be allocated to those QCs that dominate the others. Unfortunately, unlike the mean-variance method, the SD approach, which considers the entire return distribution rather than selected moments, does not provide a straightforward way for diversification purpose (Levy, 1998). Thus, it is not

easy to decide precisely what percentage of the resources that should be allocated in the stochastically ordered alternatives.

The stochastic ordering result is used as the basis for resource allocation in the sense that it restricts the amount of resources which are allocated among the QCs. For example, if there exists QC_a *o*-order stochastically dominates QC_b or $QC_a \succ_{(o)} QC_b$, then the amount of resource allocated to QC_a should be higher than that of QC_b. It can be quantitatively expressed as $X_a - X_b \geq \delta$, where δ is the minimum amount of acceptable difference between the allocated resource in QC_a and QC_b.

To show how the SD results can be applied in an optimization framework, a simple customer satisfaction optimization model based on Xie et al (2003) is adopted. The objective is to maximize the total customer satisfaction (*Z*) by optimizing the available resources, for example, the allocated cost for each QC with respect to its target value. The complete optimization model is given in (8.4)-(8.8). The SD result, namely, the stochastic ordering of the QCs, is translated into equation (8.7). It is worth noting that the value of *Z* will only range from zero to one, with '0' indicates total dissatisfaction and '1' maximum total customer satisfaction.

$$Maximize\ Z = \sum_{j=1}^{n}\sum_{i=1}^{m} IR_{i,k+1}.R_{ij}^{norm}.X_j/C_j \tag{8.4}$$

Subject to:

$$\sum_{j=1}^{n} X_j \leq B \tag{8.5}$$

$$\sum_{j=1}^{n} R_{ij}^{norm} X_j/C_j \geq SL_i \qquad \forall i = 1,2,...,m \tag{8.6}$$

$$X_a/C_a - X_b/C_b \geq \delta_r, \quad if\ \exists QC_a \succ_{(o)} QC_b, \quad \forall a,b = 1,2,...,n \tag{8.7}$$

$$0 \le X_j / C_j \le 1 \tag{8.8}$$

where:

X_j = the amount of resource/budget allocated to QC_j

C_j = the cost required to increase QC_j to its target value

B = the amount of budget available for quality improvement

$IR_{i,k+1}$ = forecasted importance rating value of DQ_i

SL_i = minimum satisfaction level of DQ_i

o = order of dominance

δ_r = the minimal difference of fulfillment between two corresponding QCs. The subscript r is used to allow various values for the difference between the two QCs.

8.3.3 Optimization model 2: Non-utilitarian approach

For the non-utilitarian approach, an intuitively simple objective function based on the idea of ZOGP combined with the Quality Loss Function (QLF) approach (Ames et al., 1997) is proposed. The loss function approach is adopted to penalize the deviation from the target mean and target variability, while the goal programming is adopted to select only the 'important' QCs based on the decision maker's preference.

Step 7b: Apply the mathematical model below (Raharjo et al., 2006) to prioritize and/or optimize the QCs. The main difference of this model from the one used in the utilitarian approach is the definition of the decision variable (X_j). The decision variable here is a binary set or $X_j \in \{0,1\}$, with '1' indicates that the QC is selected, while '0' indicates otherwise. The constraints are the minimum customer satisfaction level and the limitation on budget, which are the same as

the utilitarian case. Some other constraints can directly be added as deemed necessary, such as time, manpower, and others.

$$Min\ Z = \sum_{j=1}^{n} \left[\left(\frac{\bar{y}_j^{norm} - Y_j^*}{\alpha_j} \right)^2 + \left(\frac{s_j^{norm} - S_j^*}{\beta_j} \right)^2 \right] X_j \tag{8.9}$$

Subject to:

$$\sum_{j=1}^{n} R_{ij}^{norm} * X_j \geq SL_i \qquad \forall i = 1, 2, 3, ..., m \tag{8.10}$$

$$\sum_{j=1}^{n} C_j X_j \leq B \tag{8.11}$$

where:

$$X_j = \begin{cases} 1, \text{if } QC_j \text{ is selected} \\ 0, \text{if } QC_j \text{ is not selected} \end{cases}$$

$\bar{y}_j^{norm}$ = the normalized forecasted mean of QC_j.

s_j^{norm} = the normalized forecasted standard error of QC_j.

Y_j^* = A target value for the mean value of QC_j.

S_j^* = A target value of the standard deviation of QC_j.

α_j = weight assigned to deviation of mean value from the target $(0 < \alpha_j \leq 1)$

β_j = weight assigned to deviation of the variability from the target $(0 < \beta_j \leq 1)$

The proposed model uses the concept of QLF to select the QC based on the limitation in the resources while achieving minimum customer satisfaction level of DQ_i (SL_i). It uses the normalized mean value ($\bar{y}_j^{norm}$) and normalized standard deviation value (s_j^{norm}) to

provide a common ground for the objective function. For each QC, the model will impose a quadratic weighted penalty on the deviation from the target values set for the mean (Y_j^*) and the standard deviation (S_j^*).

Step 8b: Define the model parameters based on decision maker's preference. For simplicity, it may be assumed that the target value for each QC is the same for the mean value $Y_1^* = Y_2^* = ... = Y_n^* = Y^*$ and also the same for the standard deviation $S_1^* = S_2^* = ... = S_n^* = S^*$. Since the mean value has the Larger-The-Better (LTB) characteristic, then the target mean may be set to Y^* = 100%. While the standard deviation has the Smaller-The-Better (STB) characteristic, the target value for the standard deviation may be set to a given value or if it is not given, then S^* = 0% can be used. It is easy to see that the weights assigned to the deviation from the target mean and the target variance, which are α_j and β_j, reflect the preference of the decision maker towards QC_j in terms of its mean value and its standard deviation, respectively. Because of the inverse relation, the lower the value of these parameters, the more sensitive they become, and vice versa. It is possible that each QC has different weights on the importance of its mean and standard deviation. However, for simplicity, it may again be assumed that $\alpha_1 = \alpha_2 = ... = \alpha_n = \alpha$ and $\beta_1 = \beta_2 = ... = \beta_n = \beta$.

Step 9b: Solve the model and conduct sensitivity analysis of the parameters' change.

Step 10b: Proceed with downstream QFD analysis using the selected QCs.

8.4 An example

This section provides an example of how one may apply the proposed methodology by following the step-by-step procedure described in Section 8.3. The education case study described in Chapter 2 (Raharjo et al., 2007) will be used as the basis for providing the contextual setting. For simplicity, only the HoQ, which was built for the employers of graduates (Figure 2.5 in Chapter 2), is used for illustrating how the proposed methodology works in practice.

The proposed methodology is applied in the education case study in order to provide a more forward-thinking strategy for the education institution. The objective of modeling the dynamics of DQs' priorities of the employers of graduates is two-fold. One is to get better informed of the dynamics in the needs of the external customer (the employers of graduates), and the other is to proactively enhance the design of the education system to meet the future needs of the customer.

The input of the methodology is the DQs' priorities data over time and the HoQ of the employers of graduates, and the output is the prioritized QCs. If the utilitarian approach is used, then the final output is the amount of resources or budget allocated to QC_j. If the non-utilitarian approach is used, then the final output is the selected QCs. The first six common steps are as follows.

Step 1 and Step 2: These two steps to obtain the HoQ of the external customer for the case study have been described in Chapter 2. The completed HoQ is shown in Figure 2.5 (Chapter 2).

Step 3: Record the DQs' priorities values for k periods. For the sake of illustrating how the methodology works practically, a few simplifications to the HoQ in Figure 2.5 are

done. First, the DQs are condensed into the four primary DQs. Second, only five QCs, which have the highest ranks, are selected for the analysis. The simplified HoQ is shown in Figure 8.2.

QUALITY CHARACTERISTICS / DEMANDED QUALITIES	Importance Rating	QC_1 (Intensify discussion and presentations)	QC_2 (Provide ethics and religion courses)	QC_3 (Give more team assignments)	QC_4 (Leadership training)	QC_5 (Get involved in committee-activities)
DQ_1 (Academic Qualification)	0.119	7		7		
DQ_2 (Leadership Skill)	0.267	5		9	7	9
DQ_3 (Interpersonal Skill)	0.471	3	7	7	9	7
DQ_4 (Problem solving Skill)	0.143	5		5	3	3
QC_j priority		4.296	3.297	7.248	6.537	6.129
Rank		**4**	**5**	**1**	**2**	**3**

Figure 8.2 Simplified HoQ for employers of graduates

The initial importance rating values for the four main DQs, namely, 'academic qualification' (IR_1=0.119), 'leadership skill' (IR_2=0.267), 'interpersonal skill' (IR_3=0.471), 'problem solving skill' (IR_4=0.143), are obtained by summing up all the corresponding secondary DQs in Figure 2.5. Note that all those AHP-based priorities are relative, that is, they depend on the condition of the employers at a particular time. For example, for the case study data, it appears that the interpersonal skill (IR_3=0.471) is the most important one, but it will not be so all the time. When the employers have a lot of graduates who are well-trained in interpersonal skill, it is very likely that its relative importance will decrease. On the other hand, other skill might become relatively more important. In fact, such

change in relative importance will always occur. What is important here is to be able to observe and model the change over time, and make a better decision based upon it.

The department usually carries out a yearly survey to the employers of the graduates. Due to some reasons, the author has not been able to get all the yearly data. Therefore, an alternative solution using simulation is suggested to illustrate how the proposed methodology works in practice. The data from the second period until the ninth period were simulated from a set of selected randomly generated four-order AHP matrices with consistency ratio values less than or equal to 10% (see Section 4.2.1.2 for the simulation method).

Step 4: Fit the DQs' priorities data change over time using the proposed forecasting technique. The actual DQs' priorities data (IR values) for each DQ for nine years are shown in the first block-column of Table 8.1. For example, the IR values from the simplified HoQ (Figure 8.2) can be found in the first row (t=1). The data which are shown next to the first block-column (Table 8.1) are the fitted data using the compositional double exponential smoothing method (Raharjo et al., 2009). For example, for year 9 (t=9), the fitted priorities for DQ_1, DQ_2, DQ_3, DQ_4 are 0.113, 0.338, 0.403, and 0.146, respectively.

Table 8.1 Actual, fitted, forecasted, and fitting error values of all IR

t	IR_1	IR_2	IR_3	IR_4	IR'_1	IR'_2	IR'_3	IR'_4	Ad_1	Ad_2	Ad_3	Ad_4
1	0.119	0.267	0.471	0.143	0.120	0.262	0.468	0.150	-	-	-	-
2	0.110	0.252	0.488	0.150	0.120	0.262	0.468	0.150	-0.069	-0.014	0.063	0.021
3	0.132	0.265	0.445	0.157	0.114	0.256	0.480	0.150	0.113	-0.005	-0.116	0.008
4	0.109	0.283	0.455	0.152	0.124	0.261	0.461	0.155	-0.107	0.101	0.005	0.001
5	0.113	0.297	0.465	0.125	0.115	0.275	0.456	0.154	0.011	0.112	0.053	-0.176
6	0.129	0.307	0.434	0.129	0.113	0.291	0.460	0.136	0.111	0.035	-0.077	-0.070
7	0.119	0.313	0.412	0.156	0.122	0.306	0.443	0.130	-0.054	-0.005	-0.102	0.160
8	0.108	0.339	0.403	0.149	0.121	0.317	0.420	0.142	-0.098	0.078	-0.032	0.053
9	0.113	0.333	0.385	0.169	0.113	0.338	0.403	0.146	-0.022	-0.037	-0.068	0.127
10		*forecast*			*0.117*	*0.326*	*0.367*	*0.191*				
					α^*=0.308, StDev of Ad_i =				0.087	0.057	0.068	0.106

The third block-column shows the fitting error values which are expressed in terms of Aitchison distance, see formula (8.3). The optimal parameter (α^*=0.308) for the CDES is derived iteratively by selecting a value between 0 and 1 that gives the minimum average Aitchison distance. In the last row of Table 8.1, the standard deviation of the forecasting residual ('StDev of Ad_i'), which serves as the measure of future uncertainty, is provided for each IR.

Before proceeding to the next step, it is interesting to see the validity of the future uncertainty's estimate. As explained, the future uncertainty is estimated from the variance of the forecasting residual which follows Gaussian white noise process with a zero mean and a constant variance. Table 8.2 shows that the descriptive statistics and the normality (Anderson-Darling) test of the forecasting residual for each DQ. Table 8.3 further shows the hypothesis testing of the mean value of the error against zero using *Minitab* software.

Table 8.2 Descriptive statistics and normality test of forecasting residual

	Mean	*StDev*	*Min*	*Q1*	*Median*	*Q3*	*Max*	*Skewness*	*Kurtosis*	*P-value (A-D Test)*
Ad_1	-0.014	0.087	-0.107	-0.091	-0.038	0.086	0.113	0.720	-1.000	*0.235*
Ad_2	0.033	0.057	-0.037	-0.012	0.015	0.095	0.112	0.340	-1.780	0.274
Ad_3	-0.034	0.068	-0.116	-0.096	-0.050	0.041	0.063	0.400	-1.480	0.511
Ad_4	0.015	0.106	-0.176	-0.052	0.014	0.108	0.160	-0.500	0.450	0.715

Table 8.3 Mean value test of forecasting residual

One-Sample T: Ad_1; Ad_2; Ad_3; Ad_4

Test of mu = 0 vs not = 0

Variable	N	Mean	StDev	SE Mean	95% CI	T	P
Ad1	8	-0.0144	0.0870	0.0308	(-0.0871; 0.0584)	-0.47	0.655
Ad2	8	0.0331	0.0572	0.0202	(-0.0148; 0.0809)	1.63	0.146
Ad3	8	-0.0342	0.0684	0.0242	(-0.0913; 0.0230)	-1.41	0.201
Ad4	8	0.0154	0.1061	0.0375	(-0.0733; 0.1042)	0.41	0.693

It can be concluded through the *p-values* that there is *not* enough evidence to say that the forecasting error does not follow normal distribution with a zero mean value. Finally,

Table 8.4 shows the independence test using *t-test* and Ljung-Box test. Both tests confirm that the Ad_i are all independently distributed, that is, no autocorrelation exists.

Table 8.4 Independence test of forecasting residual

		ACF	t-test (2-sided)		Ljung-Box test	
			t-statistic	*p-value*	*LBQ*	*p-value*
Ad_1	Lag 1	-0.360	-1.017	0.343	1.478	0.224
	Lag 2	-0.276	-0.695	0.509	2.491	0.288
Ad_2	Lag 1	-0.007	-0.019	0.986	0.000	0.982
	Lag 2	-0.277	-0.783	0.460	1.021	0.600
Ad_3	Lag 1	-0.267	-0.754	0.476	0.812	0.368
	Lag 2	-0.263	-0.695	0.510	1.731	0.421
Ad_4	Lag 1	0.206	0.584	0.578	0.487	0.485
	Lag 2	-0.154	-0.417	0.689	0.801	0.670

Step 5: Obtain the forecasted IR ($IR_{i,k+1}$) for each DQ using the forecasting method. The forecasted priorities using the CDES method are shown in the last row (t=10) of Table 8.1, right below the fitted data. For example, the forecasted priorities for IR_1, IR_2, IR_3, and IR_4, respectively, for the coming period (t=10), are 0.117, 0.326, 0.367, and 0.191.

The graphical plot of the actual, fitted, and forecasted importance rating values (DQs' priorities) over time is shown in Figure 8.3. The full triangle, diamond, square, and dot are used to plot the actual data, while the long-dashed, dashed, dash-and-dotted, and dotted lines are used to show the fitted and forecasted values of IR_1, IR_2, IR_3, and IR_4, respectively.

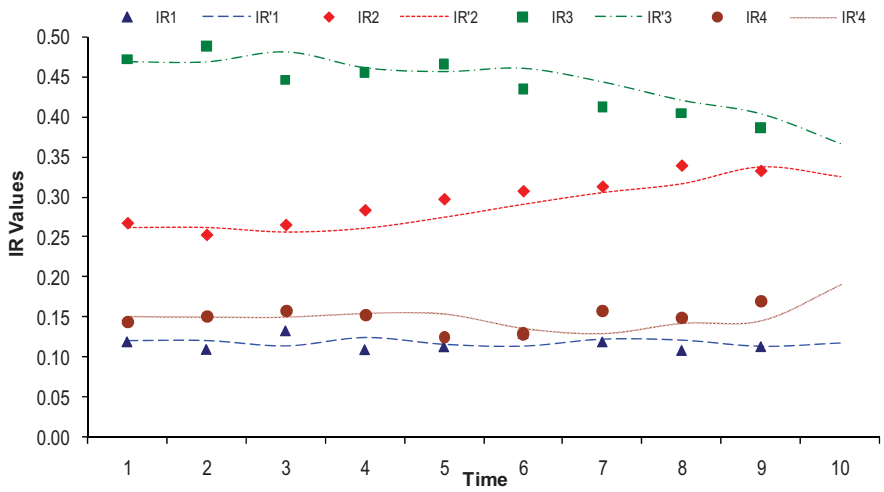


Figure 8.3. Graphical plot of the actual, fitted, and forecasted importance rating values

It can be seen from Figure 8.3 that the relative importance of DQ_2 ('leadership skill') becomes higher over time, while the relative importance of DQ_3 ('interpersonal skill') becomes less and less important over time. The relative importance of DQ_1 ('academic qualification') appears to remain constant over time, while the relative importance DQ_4 ('problem solving skill') has a slight tendency to be higher in the last periods.

Step 6: Compute the mean and standard deviation of forecasted QCs' priorities using formula (8.1) and (8.2), respectively. The resulting values, namely, the mean and the standard deviation of the forecasted QCs' priorities are shown in the DQFD (Figure 8.4). Based on the proposed rule of thumb described in Chapter 7, the relationship matrix is normalized using formula (7.2). Note that the ranks of the QCs do not change after normalization is done.

DQ \ QC	QC_1 (Intensify discussion and presentations)	QC_2 (Provide ethics and religion courses)	QC_3 (Give more team assignments)	QC_4 (Leadership training)	QC_5 (Get involved in committee-activities)	Importance Rating (t=1)	Importance Rating (t=2)	…	Importance Rating (t=8)	Importance Rating (t=9)	**Forecasted IR (t=10)**	**Forecasting Residual StDev (t=10)**	**Forecasting Residual Variance (t=10)**
DQ_1 (Academic qualification)	0.50	0	0.50	0	0	0.119	0.110	…	0.108	0.113	**0.117**	0.087	**0.0076**
DQ_2 (Leadership skill)	0.17	0	0.30	0.23	0.30	0.267	0.252	…	0.339	0.333	**0.326**	0.057	**0.0033**
DQ_3 (Interpersonal skill)	0.09	0.21	0.21	0.27	0.21	0.471	0.488	…	0.403	0.385	**0.367**	0.068	**0.0047**
DQ_4 (Problem solving skill)	0.31	0	0.31	0.19	0.19	0.143	0.150	…	0.149	0.169	**0.191**	0.106	**0.0113**
Mean of forecasted QC_j priority	*0.206*	*0.078*	*0.294*	*0.212*	*0.211*								
StDev of forecasted QC_j priority	*0.091*	*0.031*	*0.096*	*0.064*	*0.064*								

Figure 8.4 The DQFD for the employers of graduates

What is worth highlighting here is the use of the forecasted QCs' priorities, which are derived from the future needs of the customer, as a basis for optimizing the QCs. By doing so, the department may better tackle the time-lag problem discussed in Section 1.1 in the sense that it may better anticipate the future needs of the employer early in the education process. Suppose that we are now at the ninth period (t=9), that is, year nine. It is known that the department produces most of the graduates every year (in the annual commencement ceremony). Therefore, for this year planning (year nine), the basis of the decision, for example, budget allocation, should be on the next year's needs, namely, the forecasted priorities at year ten. Such action will help the department make a better decision in the sense that it will train at least the last year students the required skills so that when those students graduate next year (year ten), they will hopefully meet the skills required in the job place better.

In short, the above example shows the importance of taking into account the change of customer-needs' priorities *during* service creation time, that is, during one year education

period before the students graduate. Note that the example assumes that the real rate of change is yearly. The next two subsections will provide a further analysis on the results obtained from the first six steps for decision making purpose, that is, for optimizing and prioritizing the QCs using the two proposed approaches.

8.4.1 Using optimization model 1: Utilitarian approach

Step 7a: Plot the cumulative density function (CDF) of all QCs according their mean and standard deviation values together in one graph. The CDF of all QCs are shown in Figure 8.5.

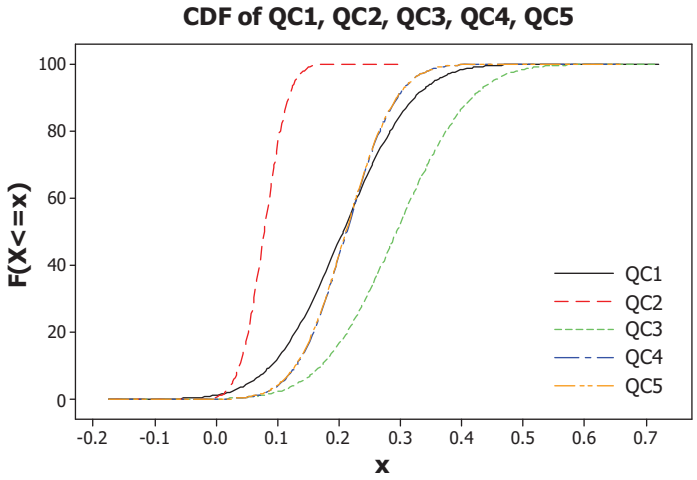


Figure 8.5 Plot of CDF of all QCs

Step 8a: Check for first-order dominance using the CDF curves. For normal distribution, it is well-known that if $A \sim N(\mu_A, \sigma_A)$ and $B \sim N(\mu_B, \sigma_B)$, then A will first order stochastically dominates B, or $A \succ_{(1)} B$, if and only if $\mu_A > \mu_B$ and $\sigma_A = \sigma_B$. Furthermore, A will second order stochastically dominate B, or $A \succ_{(2)} B$, if and only if $\mu_A \geq \mu_B$ and $\sigma_A \leq \sigma_B$ with at least one strong inequality holds (see Levy, 1998). By

inspection, one may check whether there exist such conditions in the QCs shown in Figure 8.4. It appears that there is a first order dominance relation between QC_4 and QC_5 ($QC_4 \succ_{(1)} QC_5$) since $\hat{\mu}_4 > \hat{\mu}_5$ and $\hat{\sigma}_4 \approx \hat{\sigma}_5$. QC_5 also clearly second order stochastically dominates QC_1 ($QC_5 \succ_{(2)} QC_1$) since $\hat{\mu}_5 > \hat{\mu}_1, \hat{\sigma}_5 < \hat{\sigma}_1$. Hence, based on the above rule of thumb, the following relationship can be derived $QC_4 \succ_{(1)} QC_5 \succ_{(2)} QC_1$.

The relationship between QC_3 and QC_4 cannot be directly concluded; neither can the relationship between QC_1 and QC_2. However, by looking at the CDF curves of all QCs in Figure 8.5, everything turns out to be very clear, the overall dominance relationship is $QC_3 \succ_{(1)} QC_4 \succ_{(1)} QC_5 \succ_{(2)} QC_1 \succ_{(1)} QC_2$. Here, it can be concluded that the CDF curves plot does significantly help the QFD team know the dominance relationship quickly.

Step 9a: Check if there is a crossing among the CDF curves. There is a crossing in the CDF plot, but the relationship has been concluded using the rule of thumb in Step 8a, namely, $QC_5 \succ_{(2)} QC_1$.

Step 10a: Stochastically order the QCs according to the dominance relationship result, and construct a resource allocation constraint based on the stochastic ordering. The stochastic ordering result is $QC_3 \succ_{(1)} QC_4 \succ_{(1)} QC_5 \succ_{(2)} QC_1 \succ_{(1)} QC_2$. This simply says that all decision makers, who prefer more to less and are risk-averse, will agree with the stochastic ordering. Consequently, more resources and efforts should be allocated to those QCs that are more preferred.

The optimization model described in formula (8.4) to (8.8) is used for illustrating the proposed methodology. Suppose that there is an amount of $18K reserved for this year's quality improvement efforts in the department. This available budget should be properly

allocated for the fulfillment of the QCs so that the future total customer satisfaction level will be maximized. According to the department's decision, the cost of improvement of each QC to achieve its maximum possible target value (best possible state), namely, the fulfillment cost (C_j) is \$7K, \$6K, \$6K, \$11K, \$9K, for QC_1, QC_2, QC_3, QC_4, QC_5, respectively. For example, if an amount of \$11K is allocated to QC_4, in this case for developing 'leadership training', then this QC may be improved to its best possible state. One example of ways for developing 'leadership training' might be asking reputable leaders to train the students or to provide some workshops.

Then, for the sake of simplicity, the minimum satisfaction level for each DQ (Xie et al., 2003) is assumed to be the same, that is, 50%, or $SL_i = 0.5,\ \forall i = 1,...,4$. It is again assumed that there is no difference in the amount of QC fulfillment, thus $\delta_r = 0, \forall r = 1,...,4$. Note that the last value of the subscript *r*, that is, four (*r*=4), denotes the number of the stochastic dominance constraints used to represent the stochastic ordering result (see formula (8.7) and (8.15)). The complete formulation according to the total customer satisfaction optimization model in (8.4)-(8.8) is as follows.

$$Maximize\ Z = 0.029X_1 + 0.013X_2 + 0.049X_3 + 0.019X_4 + 0.024X_5 \tag{8.12}$$

Subject to:

$$X_1 + X_2 + X_3 + X_4 + X_5 \le 18 \tag{8.13}$$

$$0.071X_1 + 0.083X_3 \ge 50\%;\ 0.024X_1 + 0.05X_3 + 0.021X_4 + 0.033X_5 \ge 50\%;$$

$$0.013X_1 + 0.035X_2 + 0.035X_3 + 0.025X_4 + 0.024X_5 \ge 50\%;$$

$$0.045X_1 + 0.052X_3 + 0.017X_4 + 0.021X_5 \ge 50\% \tag{8.14}$$

$$X_3/6 - X_4/11 \ge 0;\ X_4/11 - X_5/9 \ge 0;$$

$$X_5/9 - X_1/7 \geq 0\,;\, X_1/7 - X_2/6 \geq 0 \tag{8.15}$$

$$0 \leq X_1/7 \leq 1\,;\; 0 \leq X_2/6 \leq 1\,;\; 0 \leq X_3/6 \leq 1\,;$$

$$0 \leq X_4/11 \leq 1\,;\; 0 \leq X_5/9 \leq 1 \tag{8.16}$$

The solution for the above optimization model is shown in Table 8.5. An example of interpreting the result is as follows. An amount of \$6K should be allocated to QC_3, which results in 100% fulfillment of its target value, while none of the budget should be allocated to QC_2. This solution is fully consistent with the stochastic ($QC_3 \succ_{(1)} QC_4 \succ_{(1)} QC_5 \succ_{(2)} QC_1 \succ_{(1)} QC_2$) since QC_3 is the most preferred one, while QC_2 is the least preferred. The total customer satisfaction that can be obtained from this solution is 55% (Z=55%).

Table 8.5 Optimization results with SD constraint

With SD Constraint (Z=55%)					
Variable	X_1	X_2	X_3	X_4	X_5
Allocation	0.27	0.00	6.00	6.45	5.28
Fulfillment	3.8%	0%	100%	58.7%	58.7%

Now, suppose if the stochastic dominance constraints, those expressions in (8.15), are relaxed and the model is solved once again using the software. The purpose here is to illustrate what would happen if one ignored the future uncertainty factor in the customer needs. The result is shown in Table 8.6. In contrast to the previous result, the result, although having a slightly higher customer satisfaction value (Z=57%), is totally *not* in agreement with the stochastic ordering. For example, QC_2, which is the least preferred

one, has 27% level of fulfillment while none of the resource is allocated to QC_4, which is much more preferred than QC_2.

Table 8.6 Optimization results without SD constraint

Without SD Constraint (Z=57%)					
Variable	X_1	X_2	X_3	X_4	X_5
Allocation	1.35	1.65	6.00	0.00	9.00
Fulfillment	19.4%	27.4%	100%	0%	100%

In sum, the optimization model results in an optimal policy to allocate the department yearly budget. The policy may be considered as 'optimal' not only because it has taken into account the resources limitation, but it has also considered the future needs of the customer along with their uncertainty. Furthermore, the budget allocation policy has also taken into account the change of the external customer's needs during the service creation process, that is, during the one year education time before the students graduate.

Another finding is that unless the future uncertainty factor, which is represented by the variance of the forecasting residual, in the DQs is taken into account, it is very likely that one might end up with a fallacious allocation policy with respect to the decision maker's attitude towards risk in the future needs. This is also to say that considering the point estimate alone is not sufficient and might lead to misleading optimization results. After optimizing the fulfillment of each QC, the QFD team may use the result for other subsequent downstream analysis.

8.4.2 Using optimization model 2: Non-utilitarian approach

Step 7b: Apply the mathematical model below (Raharjo et al., 2006) to prioritize and/or optimize the QCs. Using all the information provided in Section 8.4.1, another

approach can be used. The only difference here is the definition of the decision variable (X_j). The decision variable indicates the inclusion or exclusion of a QC rather than its fulfillment, thus, once it is included it implies that it is fully fulfilled since an amount of C_j is allocated.

Step 8b: Define the model parameters based on decision maker's preference. Assume that the target values for the mean and the standard deviation are, respectively, 100% (and 0% ($Y^* = 100\%$; $S^* = 0\%$). It is also known that the education institution places a higher emphasis on the mean value rather than variability value. Thus, the value of α is assigned to be 0.1, while the value of β=0.6. The *normalized* mean and standard deviation values for the forecasted QCs' priorities in Figure 8.4 are $\bar{y}_j^{norm} \in \{20.6, 7.8, 29.4, 21.2, 21.2\}$ and $s_j^{norm} \in \{26.2, 9.1, 27.7, 18.6, 18.4\}$. Then, the mathematical model can be written as follows:

$$Min\ Z = \left[\left(\frac{20.6-100}{0.1}\right)^2 + \left(\frac{26.2}{0.6}\right)^2\right]X_1 + \left[\left(\frac{7.8-100}{0.1}\right)^2 + \left(\frac{9.1}{0.6}\right)^2\right]X_2 + \ldots + \left[\left(\frac{21.2-100}{0.1}\right)^2 + \left(\frac{18.4}{0.6}\right)^2\right]X_5 \tag{8.20}$$

Subject to:

$$0.5X_1 + 0.5X_3 \geq 50\%;\ 0.17X_1 + 0.3X_3 + 0.23X_4 + 0.3X_5 \geq 50\%;$$

$$0.09X_1 + 0.21X_2 + 0.21X_3 + 0.27X_4 + 0.21X_5 \geq 50\%;$$

$$0.31X_1 + 0.31X_3 + 0.19X_4 + 0.19X_5 \geq 50\% \tag{8.21}$$

$$7X_1 + 6X_2 + 6X_3 + 11X_4 + 9X_5 \leq 18 \tag{8.22}$$

$$X_j \in \{0,1\}\ \forall\ j = 1, 2, ..., 5 \tag{8.23}$$

Step 9b: Solve the model and conduct sensitivity analysis of the parameters' change. The above model can be solved easily using *Excel-solver* or other software. Considering the current constraints, namely, the maximum budget is \$18K and the minimum satisfaction level for each DQ is 50%, *no* solution can be obtained. In other words, it is impossible to achieve 50% satisfaction level for each customer need if there is only \$18K available. If the minimum satisfaction level is slightly lowered to 48%, then the optimal solution is to select QC_3 and QC_4. This solution is in line with the result from the other approach (subsection 8.4.1).

Among the selected QCs, further prioritization can still be done based on the value of the quality loss incurred for the corresponding QC. Thus, in this case, the further prioritization, in the order of the lowest quality loss, is QC_3 and then QC_4. This is again consistent with the SD results in previous subsection. A sensitivity analysis can further be carried out for the effect of changing the parameters, see Raharjo et al. (2006) for an example.

Step 10b: Proceed with downstream QFD analysis using the selected QCs. The focus of the next downstream QFD process should be on the QC_3 first, and followed by QC_4.

There are at least two main advantages of using this non-utilitarian approach. First, it may not only efficiently prioritize the QCs, but also can effectively reduce the size of the HoQ. This is a worth noting advantage since most of the QFD applications are inherently plagued with the problem of a prohibitively large-sized HoQ which makes the QFD process very tedious and time consuming. Second, as has been shown, a further prioritization process in the optimal solution, that is, among the selected QCs, can still be carried out based on the quality loss value incurred.

8.5 Discussions

8.5.1 Selection of forecasting technique

There are at least two reasons why the CDES method (Raharjo, et al., 2009) is selected. First, it is suitable for the situation when there is only a minimal number of historical data. Second, it is relatively simple and time-efficient compared to other time series methods, especially for modeling the dynamics of AHP-based priorities. It is possible that the CDES method may end up with errors which do not follow Gaussian white noise process. In such case, other forecasting techniques, such as multivariate time series technique, is called for. What is more important here is the fact that a proper and adequate forecasting technique will result in Gaussian white noise error, of which variance is proposed as the measure of future uncertainty of the forecasted points.

8.5.2 A possible implication to development of innovative products

The proposed methodology might be potentially useful for the possible application of QFD in developing innovative products, such as consumer electronics products which are launched in a highly dynamic market (Minderhoud and Fraser, 2005). In a highly dynamic market, the change of customer preference may have a great impact on the company (Bhattacharya, 1998). The cost of not producing a product that the customer wants might be tremendously large, it is therefore very reasonable to make extra efforts to monitor and follow the customer preference change over time.

Consider the cellular phone, in the past, the importance of ‘user-interaction’ (tactual quality) might be relatively lower than the importance of ‘good audio function’ (audio quality), but nowadays, the importance of ‘user-interaction’, such as the touch-screen

command, may be relatively higher than the importance of 'good audio function', such as FM Radio. So the *relative* change over time of one attribute over the other attributes is precisely the situation where the DQFD explained in this thesis might have a possible contribution towards the development of innovative products.

Prescriptively speaking, to accurately assess the importance of those DQs over time, a series of well-controlled customer surveys to a *specific* market segment should be done. However, this will not only involve a huge cost, but also a considerable amount of time. Another alternative way, which is more descriptive, is to infer the priorities by observing the change of commercial specification of a product over time. The reason is because the firm will not put anything unimportant in their top advertisement list. Interestingly, a recent study by Hsee et al. (2009) found that the product specification also influences customer preference. There appears to be a reciprocal effect between customer preference and commercial specification. However, this issue is beyond the scope of this thesis.

The example of the change of commercial specification of a cellular phone for a specific segment over time is shown in Table 8.7. The data were taken from Nokia official website[3]. It is the published commercial specification for Nokia 6000s series phones, which are specifically targeted for *mainstream* market, from 2007 to 2008. All the 6000s series phones' commercial specifications during the last two years were first observed (see Appendix C and D). Then, for each quarter which is intended for the 'planned market introduction' (P.M.I, in Table 8.7) of the specific series, one representative series is selected. Note that the 6000s series are not always launched every quarter.

[3] Source: http://www.nokia.com/press/media_resources/documents/

Table 8.7 Example of customer preference dynamics from commercial specification

P.M.I	Q1, 2007	Q2, 2007	Q3, 2007	Q4, 2007	Q2, 2008	Q3, 2008
Model	Nokia 6086	Nokia 6110	Nokia 6267	Nokia 6301	Nokia 6300i	Nokia 6600f
Key Feature	•Stylish fold design with intuitive keypad and large colordisplay •*Music player (MP3, MP4, AAC, AAC+, eAAC+, WMA)* •*Enhanced audio quality* •…	•Navigator key for fast and easy access •3G multimedia: video call, fast download of games, *music, video and ringing tones*. •…	•Sleek and compact fold design with large keypad and clear high-resolution color display •Dedicated keys for easy access to music •High quality video recording up to DVD resolution and playback in full VCR quality •…	•Clear and easy to read display with 16.7 million colors •…	•Nokia Maps to help navigate and find the way •…	•240x320 OLED 16 million color main display •Hidden outer display •Tap commands: double tap to turn on hidden outer display / snooze alarm / first silence, then reject call •…
Additional Features	•*Stereo FM Radio with Visual Radio* •…	•*Music player supporting MP3, MP4, M4A, AAC, eAAC+, WMA* •*Stereo FM radio and support for Visual Radio* •…	•*Music player supporting MP3, MP4, AAC, eAAC+ and Windows Media Audio* •*FM stereo radio supporting Visual Radio* •…	•*Music player supporting MP3, AAC, eAAC+* •*FM stereo radio supporting Visual Radio* •*Nokia Audio Messaging* •…	•2.0" TFT QVGA color display •*Music player (MP3, AAC, AAC+, eAAC+, WMA) and FM stereo radio with RDS* •…	•*Stereo music player supporting MP3, AAC, AAC+, eAAC+ and WMA, and stereo FM Radio* •…

For the sake of simplicity, only three DQs, which represent customer's needs, are observed, namely, 'Good audio quality (A)', 'Good display (D)', and 'Good interaction or tactual quality (T)'. It can be seen from Table 8.7, that 'A' is very much important in first quarter of 2007. The '*music player*' (italicized) is considered as the key feature. After a while, it becomes an additional feature. For 'Good display (D)' (underlined), it is quite relative, in some quarters, this feature is very important, while not in some other quarters. Finally, the tactual feature 'T' (highlighted) seems to become increasingly important. Initially, there is 'intuitive key pad', then 'dedicated keys', and 'tap commands' in the end. In other words, this feature has become more and more important relatively compared to the others.

In brief, the above example has shown that the importance of customer's needs change over time. The main reason is that it is *relative* and may depend on a number of factors at a certain point of time. The worth noting point here is that this observation might shed some light to the possibility of applying the method and/or approaches proposed in this

thesis in developing more innovative products. A further discussion is provided in Section 9.3 (Chapter 9).

8.6 Conclusions

The purpose of this chapter was to provide a possible answer to the research question "*How to make decision in a QFD analysis with respect to the dynamics in the house of quality?*" This chapter has answered the question by proposing a systematic methodology, which may use two kinds of decision making approaches, to prioritize or optimize the QCs with respect to the future needs of the customer. The methodology employs the modeling technique proposed in Chapter 4 as the tool to forecast the dynamics of DQs' priorities.

To show how the methodology works in practice, the case study described in Chapter 2 is used to provide the contextual setting. The notion of *future uncertainty* to improve forecast precision has also been introduced. It is hoped that the proposed methodology might help QFD-users better deal with the future needs of the customer, especially in tackling the problem described in Section 1.1.

The proposed methodology places a heavy emphasis on the need to monitor and follow the change of customer's preference over time. It is because a timely update of customer needs information may provide useful feedback for the company to react differently and continuously over time as to formulate strategies or to upgrade its products or services to meet the changing needs of its customer.

From a methodological standpoint, there are three areas that might be worth investigating for future work. First, it might be interesting to investigate how one may deal

with the condition when there will be inclusion of a new customer need (DQ) or exclusion of an old one as the passage of time. Second, in the use of stochastic dominance approach in QFD, how one may know precisely the percentage of the resources to be allocated in the stochastically-ordered QCs remains a challenging issue to be addressed. Furthermore, if the QFD team has a risk seeking attitude, the proposed stochastic dominance approach may no longer apply. Third, the incorporation of fuzzy logic theory in the optimization models may also be considered.

From a practical standpoint, a worth noting aspect is the difference between the real rate of change of customer preference and the observation period, that is, how often the data should be collected. For example, it would be of little value if the customer needs' information is collected monthly, while the real change rate is yearly. Finally, more real-world applications of the proposed methodology would certainly be of great value to showcase the usefulness of the dynamic QFD in practice.

CHAPTER 9

CONCLUSION AND FUTURE RESEARCH

"*To keep an important thing important is an important thing*" (Raharjo, 2009: reflection on thesis)

9.1 Conclusion

The main objective of this thesis was to develop novel methods and/or approaches for enhancing the use of QFD, especially in combination with the AHP, in dealing with the dynamics during product or service creation process. With respect to the three specific objectives set in Chapter 1, the conclusion can be stated as follows.

1. The thesis has demonstrated the usefulness of the AHP in QFD and has provided a better use of it by proposing a generalized use of the AHP in QFD.
2. The thesis has developed a new method to model the dynamic of AHP-based priorities in the house of quality.
3. The thesis has developed two methods and/or approaches for decision making with respect to the modeling results as to continually meet or exceed the needs of the customer.

The key message in this thesis is that QFD practitioners, to be able to better deal with the change *during* product or service creation process (Section 1.1), need to continually monitor and follow the change of over time. By doing so, not only a timely update of customer's needs information may be obtained, but also the future needs may be projected based on the pattern of past data. As shown in the education case study example, the future needs should become the basis of the decision making so that the "product", taking into account its creation time, may eventually meet the changing needs of the customer. In

addition, for the subsequent periods, it is also important to keep updating the customer's needs data so that the QFD practitioners may react differently and continuously over time with better strategies as to upgrade its products or services.

To briefly conclude the thesis, an illustration using the concept of "*doing the right things right the first time continuously*" is employed. Almost all previous QFD research focuses on "*doing the right things the first time*", that is, to begin with the needs of the customer in early stage of product or service development process. What makes the thesis different is that it attempts to complement the existing QFD research by not only doing the right things the first time, but also *doing it right continuously*. Hence, it is hoped that this may eventually increase the possibility of a successful QFD application.

9.2 Major contributions

All the research efforts in order to achieve the objective are reflected in the nine papers in Appendix E; almost all of them have been published in internationally reputable journals[1]. The major contributions towards the advancement of QFD methodology and analysis can be summarized into three points, which correspond to Chapter 2 to Chapter 8, as follows. Note that these contributions are mainly on the *theoretical* development of QFD considering that the methods and/or approaches have not yet been proven to have a demonstrated value in tackling the change during product creation process in industries.

1. The use of the AHP in QFD has been thoroughly studied. From a practical standpoint, the QFD-AHP method has been successfully applied in improving higher education quality of an industrial engineering department (Chapter 2). From a theoretical point

[1] Science Citation Index journals

of view, the use of the AHP in QFD has been significantly enhanced using the generalized model (Chapter 3). The generalized model has been tested on a realistic example based on interview and questionnaire data. Additionally, a new finding on the weakness of AHP when the number of alternatives gets larger is also provided (Chapter 2). Such finding might serve as useful information when dealing with a large-sized house of quality.

2. It has been shown that the AHP may be considered as a beneficial tool for deriving DQs' priorities in QFD. Besides, it can also be applied to obtain the DQs' competitive assessment due to its *relative* measurement approach (Chapter 6). In response to the increasingly extensive research on AHP's use in QFD (Carnevalli and Miguel, 2008; Ho, 2008) in recent years, a new method to model the priorities' dynamics is proposed (Chapter 4). The method is very useful in modeling the AHP-based priorities' dynamics, especially for better tackling the change of customer's needs and competitors' performance during product or service creation process. Furthermore, the method has also been applied to model Kano's model dynamics (Chapter 5). It is the first time that the life cycle of quality attributes is analyzed quantitatively via mathematical modeling.
3. To improve the forecast precision, an interval estimate, in addition to the point estimate of future needs, is suggested (Chapter 8). The interval estimate, which at the same time serves as the estimate of future uncertainty, is derived from the variance of forecasting residual. A closer look at the relationship matrix with respect to the need of normalization is also carried out (Chapter 7). This issue is of great importance since the relationship matrix values, together with the DQs' priorities, determine the final output of the HoQ, namely, the QCs' priorities. Finally, two kind of optimization

models are proposed to facilitate the decision making process with respect to the future needs (Chapter 8).

9.3 A note on the practical implication of DQFD for innovative products

A study by Griffin (1992) on evaluating QFD's use in US firms has identified three factors that increase the success of a QFD application, namely, service projects, less complex projects, and incremental change. In line with her finding, this thesis has attempted to apply the dynamic QFD (DQFD) to a relatively small service project, namely, the education case study (Chapter 2). As has been partly addressed in Section 8.5.2, this section further discusses the potential of the proposed methods and/or approaches in this thesis in developing innovative products in a broader perspective. Some important questions to address may include what kind of innovative product that can be developed using DQFD, what type of innovation is most suitable, which market segment, and so forth.

A recent study by Miguel (2007) found that QFD may help develop innovative products, but it is limited to additions to existing lines, product repositioning, and product improvement. In line with his finding, the extent to which the methods and/or approaches proposed in this thesis might be useful is limited to *incremental* products, as opposed to breakthrough or radical product. The term 'incremental products' here is used to refer to a set of products which are continuation of the existing ones, for example, by improving or adding existing *features*. One example of the products may be the consumer electronics products of which features are enhanced over time, such as televisions or cellular phones.

Furthermore, the uncertainty that is dealt with in this thesis is *parametric* uncertainty, as opposed to structural uncertainty, in the sense that the structure of the problem is already known and only the parameters are uncertain. For example, the customer's needs are already known, but the parameter (importance rating value) is uncertain. Finally, to such kind of products, the most appropriate target market might be the *early* and/or *late majority* market (Rogers, 2003).

Consider again the cellular phone example described in Section 8.5.2, by observing the change of the *features* in the commercial specification, one may infer that the *relative* importance of the existing customer's needs (DQs) changes over time. Suppose the product creation time of the cellular phone is one quarter, and so is the real rate of DQs' importance change. A quarterly observation is therefore carried out to monitor and follow the change of customer's needs over time. Then, for the purpose of developing the 6000s series cellular phones which will be launched next quarter, there is no reason to not consider the forecasted importance or priorities for next quarter as the main basis of customer's needs information. This is where the proposed methods and/or approaches in this thesis might be useful. Certainly, this case is simplified for the sake of illustration purpose.

In short, it can be said that the proposed methods and/or approaches should *neither* be intended for developing really new products (clean sheet designs) *nor* more complex projects (Griffin, 1992). Such information may help set the boundary of what to expect from the proposed methods and/or approaches in this thesis, especially when using QFD in developing more innovative products.

9.4 Future research

There are two quite important assumptions in this thesis, of which relaxation may open up several interesting issues for future research. First, it is assumed that the real rate of change is known and the same as the length of product or service creation time (see Chapter 8). Second, it is assumed that the customer's needs (DQs) have already existed from the beginning of the analysis and the only change is in their relative importance or priorities (see Chapter 1).

With respect to the first assumption, this thesis has not delved into the case when there is a difference between the rate of change and the length of product or service creation time. For example, if the length of product creation time is one year and the rate of change is monthly, then it would be interesting to study when the product concept may still be kept open to change. This is also related to the use of further matrices in the QFD, apart from the house of quality. In addition, the rate of change and the length of product or service creation time might be uncertain. How to take into account such issue in DQFD analysis may deserve an attention for future work.

With respect to the second assumption, a study on how QFD practitioners may deal with the situation when there will be inclusion of a new customer need or exclusion of an old one along the time might be worth pursuing. Other more specific future research directions can be found in the final section of Chapter 2 to Chapter 8.

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Appendix A. Sample of questionnaire to elicit QFD team's judgments

Detailed Information of "Software Setup Experience" for a PC Media Center

Users profile: Novice/ Occasional/ Expert (select one)

Goal: Obtaining the priorities of the QCs by quantifying subjectivity involved.

Demanded Qualities/ Customer Wants:

1. **Intuitiveness:**
   - how intuitive the software setup phase is (for first-use) so it may effectively help users easily understand what to do.
2. **Visual Looks:**
   - how elegant, beautiful, eye-catching the impression it brings to the users.
3. **Enjoyability:**
   - how enjoyable the process of installation is.

Quality Characteristics/ Design Attributes:

1. **Customized Setup:**
   - This refers to a kind of "recommended" or guided settings based on the user's expertise in installing the software. Most of default-values are provided beforehand for non-expert users.
2. **While-waiting Program:**
   - This refers to the program executed during the installation process, can be in the form of (classical) music, display for advertisement, or showcase of the products' potentials. The users may choose to enjoy the program or just leave during the waiting period.
3. **Progress Indicator:**
   - This refers to positive feedback that user may see while the installation is running so he/she may know what is going on or where he/she is before the setup ends.

Consumer Acceptance Risk

1. **Negative Consumer's Conviction**
   - Do the consumers *get value for money* when they first time install the software of the product, compared with competitive products?
   - Bad first impression will seriously affect the consumers' perception on the product/brand.
2. **Negative Product's Appeal**
   - Does the product have appeal to generally accepted values (e.g. health, safety, nature, environment)? Does it negatively affect human's senses? In the case of software setup, it might be associated with how negative the visual looks or sound is.
3. **Ease-of-use Risk**
   - Product's easy-in-use advantages, compared with competitive products. This risk might be associated with the difficulty level that users may encounter in doing the software setup. It is possible that the users cannot use it at all.

Benchmarking Product:

"Best-in-class" Competitors:

1. Competitor 1= Comp1
2. Competitor 2= Comp2
3. Competitor 3= Comp3

Note:

- Circle "NA", if entities are not comparable or has no meaning.
- Information on the scale used in the questionnaire:

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Strong importance	Experience and judgment strongly favor one activity over another
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate/grey values	

Sample of Questionnaire:

1. How important are the customer wants? (this should be based on customer's survey/data)

Arc 1: *Wrt.achieving best SoftSetup.xp, how important is...compared to...?* **Circle if "Y"**

Intuitiveness 9 8 7 6 (5) 4 3 2 1 2 3 4 5 6 7 8 9 **Vis.Looks** NA

Intuitiveness 9 8 7 6 (5) 4 3 2 1 2 3 4 5 6 7 8 9 **Enjoyability** NA

Vis.Looks 9 8 7 6 5 4 3 2 (1) 2 3 4 5 6 7 8 9 **Enjoyability** NA

2. How important are the design attributes wrt. customer wants?

Arc 3: *Wrt.satisfying "Intuitiveness", how important is ..... compared to .....?*

Custom.Setup 9 8 7 6 (5) 4 3 2 1 2 3 4 5 6 7 8 9 **While-wait.Prog** NA

Custom.Setup 9 8 7 6 5 4 (3) 2 1 2 3 4 5 6 7 8 9 **ProgIndicator** NA

While-wait.Prog 9 8 7 6 5 4 3 2 1 2 (3) 4 5 6 7 8 9 **ProgIndicator** NA

. . .

11. Inner relation of risks

Arc 7: *Wrt.controlling "Consumer's Conviction", how important is...compared to...?*

ProdAppeal 9 8 7 6 5 4 3 2 1 2 (3) 4 5 6 7 8 9 **Ease of Use** NA

Wrt.controlling "Product's Appeal", how important is ..... compared to .....?

ConsConvict 9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9 **Ease of Use** (NA)

Wrt.controlling "Ease-of-use",how important is ..... compared to .....?

ConsConvict 9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9 **ProdAppeal** (NA)

13. How important is the customer wants wrt. design attributes (feedback)?

Arc 5: *Wrt."Customized Setup", how important is ..... compared to .....?*

Intuitiveness 9 8 7 6 5 4 3 2 (1) 2 3 4 5 6 7 8 9 **Vis.Looks** NA

Intuitiveness 9 8 7 6 5 4 3 2 1 (2) 3 4 5 6 7 8 9 **Enjoyability** NA

Vis.Looks 9 8 7 6 5 4 3 2 (1) 2 3 4 5 6 7 8 9 **Enjoyability** NA

Appendix B. Judgments results based on arc's category

Table B1. Outer-dependence arcs

Arc					Wi	CR
1	*Wrt.Best Setup.Xp*	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	5.00	5.00	0.714	
	Vis.Looks	0.20	1.00	1.00	0.143	
	Enjoyability	0.20	1.00	1.00	0.143	0.000
3	*Wrt.Intuitiveness*	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	5.00	3.00	0.637	
	While-wait.Prog	0.20	1.00	0.33	0.105	
	ProgIndicator	0.33	3.00	1.00	0.258	0.033
	Wrt.Vis.Looks	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	0.20	1.00	0.143	
	While-wait.Prog	5.00	1.00	5.00	0.714	
	ProgIndicator	1.00	0.20	1.00	0.143	0.000
	Wrt.Enjoyability	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	0.20	2.00	0.179	
	While-wait.Prog	5.00	1.00	5.00	0.709	
	ProgIndicator	0.50	0.20	1.00	0.113	0.046
6	*Wrt.Best Setup.Xp*	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	1.00	0.20	0.143	
	(-)ProdAppeal	1.00	1.00	0.20	0.143	
	EoUseRisk	5.00	5.00	1.00	0.714	0.000
8	*Wrt.(-)ConsConvict.*	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	5.00	5.00	0.714	
	Vis.Looks	0.20	1.00	1.00	0.143	
	Enjoyability	0.20	1.00	1.00	0.143	0.000
	Wrt.(-)ProdAppeal	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	0.17	1.00	0.125	
	Vis.Looks	6.00	1.00	6.00	0.750	
	Enjoyability	1.00	0.17	1.00	0.125	0.000
	Wrt.EoUseRisk	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	6.00	6.00	0.750	
	Vis.Looks	0.17	1.00	1.00	0.125	
	Enjoyability	0.17	1.00	1.00	0.125	0.000
10	*Wrt.(-)ConsConvict.*	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	5.00	3.00	0.659	
	While-wait.Prog	0.20	1.00	1.00	0.156	
	ProgIndicator	0.33	1.00	1.00	0.185	0.025

Arc					Wi	CR
	Wrt.(-)ProdAppeal	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	3.00	3.00	0.600	
	While-wait.Prog	0.33	1.00	1.00	0.200	
	ProgIndicator	0.33	1.00	1.00	0.200	0.000
	Wrt.EoUseRisk	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	6.00	5.00	0.732	
	While-wait.Prog	0.17	1.00	1.00	0.130	
	ProgIndicator	0.20	1.00	1.00	0.138	0.003
12	*Wrt.Best Setup.Xp*	Comp1	Comp2	Comp3		
	Comp1	1.00	2.00	2.00	0.500	
	Comp2	0.50	1.00	1.00	0.250	
	Comp3	0.50	1.00	1.00	0.250	0.000
14	*Wrt.Comp1*	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	7.00	7.00	0.778	
	Vis.Looks	0.14	1.00	1.00	0.111	
	Enjoyability	0.14	1.00	1.00	0.111	0.000
	Wrt.Comp2	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	5.00	4.00	0.683	
	Vis.Looks	0.20	1.00	0.50	0.117	
	Enjoyability	0.25	2.00	1.00	0.200	0.021
	Wrt.Comp3	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	3.00	5.00	0.637	
	Vis.Looks	0.33	1.00	3.00	0.258	
	Enjoyability	0.20	0.33	1.00	0.105	0.033
16	*Wrt.Comp1*	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	4.00	6.00	0.701	
	While-wait.Prog	0.25	1.00	2.00	0.193	
	ProgIndicator	0.17	0.50	1.00	0.106	0.008
	Wrt.Comp2	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	2.00	3.00	0.528	
	While-wait.Prog	0.50	1.00	3.00	0.333	
	ProgIndicator	0.33	0.33	1.00	0.140	0.046
	Wrt.Comp3	Custom.Setup	While-wait.Prog	ProgIndicator		
	Custom.Setup	1.00	3.00	2.00	0.528	
	While-wait.Prog	0.33	1.00	0.33	0.14	
	ProgIndicator	0.50	3.00	1.00	0.333	0.046

Table B2. Inner-dependence arcs

Arc				W_i	CR
2	*Wrt.Intuitiveness*	Vis.Looks	Enjoyability		
	Vis.Looks	1.00	3.00	0.750	
	Enjoyability	0.33	1.00	0.250	0.000
	Wrt.Vis.Looks	Intuitiveness	Enjoyability		
	Intuitiveness	1.00	3.00	0.750	
	Enjoyability	0.33	1.00	0.250	0.000
	Wrt.Enjoyability	Intuitiveness	Vis.Looks		
	Intuitiveness	1.00	1.00	0.500	
	Vis.Looks	1.00	1.00	0.500	0.000
4	*Wrt.Custom.Setup*	While-wait.Prog	ProgIndicator		
	While-wait.Prog	1.00	1.00	0.500	
	ProgIndicator	1.00	1.00	0.500	0.000
	Wrt.While-wait.Prog	Custom.Setup	ProgIndicator		
	Custom.Setup	1.00	1.00	0.500	
	ProgIndicator	1.00	1.00	0.500	0.000
	Wrt.ProgIndicator	Custom.Setup	While-wait.Prog		
	Custom.Setup	1.00	1.00	0.500	
	While-wait.Prog	1.00	1.00	0.500	0.000

Arc				W_i	CR
7	*Wrt.(-)ConsConvict.*	(-)ProdAppeal	EoUseRisk		
	(-)ProdAppeal	1.00	0.33	0.250	
	EoUseRisk	3.00	1.00	0.750	0.000
	Wrt.(-)ProdAppeal	(-)ConsConvict.	EoUseRisk		
	(-)ConsConvict.	1.00	NA	-	
	EoUseRisk	NA	1.00	-	-
	Wrt.EoUseRisk	(-)ConsConvict.	(-)ProdAppeal		
	(-)ConsConvict.	1.00	NA	-	
	(-)ProdAppeal	NA	1.00	-	-
13	*Wrt.Comp1*	Comp2	Comp3		
	Comp2	1.00	3.00	0.750	
	Comp3	0.33	1.00	0.250	0.000
	Wrt.Comp2	Comp1	Comp3		
	Comp1	1.00	3.00	0.750	
	Comp3	0.33	1.00	0.250	0.000
	Wrt.Comp3	Comp1	Comp2		
	Comp1	1.00	1.00	0.500	
	Comp2	1.00	1.00	0.500	0.000

Table B3. Feedback arcs

Arc					Wi	CR
5	*Wrt.Custom.Setup*	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	1.00	0.50	0.260	
	Vis.Looks	1.00	1.00	1.00	0.327	
	Enjoyability	2.00	1.00	1.00	0.413	0.046
	Wrt.While-wait.Prog	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	3.00	3.00	0.600	
	Vis.Looks	0.33	1.00	1.00	0.200	
	Enjoyability	0.33	1.00	1.00	0.200	0.000
	Wrt.ProgIndicator	Intuitiveness	Vis.Looks	Enjoyability		
	Intuitiveness	1.00	0.50	2.00	0.286	
	Vis.Looks	2.00	1.00	4.00	0.571	
	Enjoyability	0.50	0.25	1.00	0.143	0.000
9	*Wrt.Intuitiveness*	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	2.00	0.25	0.208	
	(-)ProdAppeal	0.50	1.00	0.25	0.131	
	EoUseRisk	4.00	4.00	1.00	0.661	0.046
	Wrt.Vis.Looks	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	0.33	2.00	0.238	
	(-)ProdAppeal	3.00	1.00	4.00	0.625	
	EoUseRisk	0.50	0.25	1.00	0.136	0.016
	Wrt.Enjoyability	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	2.00	3.00	0.550	
	(-)ProdAppeal	0.50	1.00	1.00	0.240	
	EoUseRisk	0.33	1.00	1.00	0.210	0.016
11	*Wrt.Custom.Setup*	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	1.00	0.25	0.167	
	(-)ProdAppeal	1.00	1.00	0.25	0.167	
	EoUseRisk	4.00	4.00	1.00	0.667	0.000
	Wrt.While-wait.Prog	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	2.00	5.00	0.595	
	(-)ProdAppeal	0.50	1.00	2.00	0.276	
	EoUseRisk	0.20	0.50	1.00	0.128	0.005

Arc					Wi	CR
11	*Wrt.ProgIndicator*	(-)ConsConvict.	(-)ProdAppeal	EoUseRisk		
	(-)ConsConvict.	1.00	0.50	3.00	0.300	
	(-)ProdAppeal	2.00	1.00	6.00	0.600	
	EoUseRisk	0.33	0.17	1.00	0.100	0.000
15	*Wrt.Intuitiveness*	Comp1	Comp2	Comp3		
	Comp1	1.00	6.00	6.00	0.750	
	Comp2	0.17	1.00	1.00	0.125	
	Comp3	0.17	1.00	1.00	0.125	0.000
	Wrt.Vis.Looks	Comp1	Comp2	Comp3		
	Comp1	1.00	0.50	0.20	0.113	
	Comp2	2.00	1.00	0.20	0.179	
	Comp3	5.00	5.00	1.00	0.709	0.046
	Wrt.Enjoyability	Comp1	Comp2	Comp3		
	Comp1	1.00	0.25	1.00	0.167	
	Comp2	4.00	1.00	4.00	0.667	
	Comp3	1.00	0.25	1.00	0.167	0.000
17	*Wrt.Custom.Setup*	Comp1	Comp2	Comp3		
	Comp1	1.00	6.00	6.00	0.750	
	Comp2	0.17	1.00	1.00	0.125	
	Comp3	0.17	1.00	1.00	0.125	0.000
	Wrt.While-wait.Prog	Comp1	Comp2	Comp3		
	Comp1	1.00	0.25	2.00	0.200	
	Comp2	4.00	1.00	5.00	0.683	
	Comp3	0.50	0.20	1.00	0.117	0.021
	Wrt.ProgIndicator	Comp1	Comp2	Comp3		
	Comp1	1.00	0.50	0.17	0.106	
	Comp2	2.00	1.00	0.25	0.193	
	Comp3	6.00	4.00	1.00	0.701	0.008

Appendix C. Published commercial specification of Nokia's 6000s series planned to be introduced in 2007

P.M.I	Q1, 2007		Q2, 2007	Q3, 2007				Q4, 2007
Model	Nokia 6086	Nokia 6300	Nokia 6110	Nokia 6500c	Nokia 6500s	Nokia 6121c	Nokia 6267	Nokia 6301
Key Feature	• Stylish fold design with intuitive keypad and large colordisplay • Quad-band+UMAover WLAN world phone • WLAN 802.11b/g 2.4 Ghz • VGA camera with 4x digital zoom, video recorder • Music player (MP3, MP4, AAC, AAC+, eAAC+, WMA) • MicroSD card reader for expandable memory of up to 2GB • Wireless connectivity via Bluetooth • Enhanced audio quality	• Elegant slim stainless steel design • Clear and easy to read display • 2 Megapixelcamera with 8x digital zoom and full screen viewfinder • HotswapMicroSDcard reader for storing pictures and music (up to 2 GB) • Voice dialing, voice commands and voice recording	• Fully integrated GPS Navigation solution: Nokia Navigator application & navigable map for turn-by-turn voice-guided navigation • Navigator key for fast and easy access • HSDPA up to 3.6 Mbps for fast web browsing and downloading • 3G multimedia: video call, fast download of games, music, video and ringing tones. • Support for 2 GB memory card	• Sleek, seamless case crafted from 360 degrees of anodized aluminum • 2 Megapixel camera with 8x digital zoom and dual LED flash • Extra-large 1 GB internal memory for music, images and more • Unified MicroUSB port for charging, data and audio	• 3.2 megapixel camera with Carl Zeiss optics, auto focus, dual LED flash and 8x digital zoom • 3G multimedia: video calls, fast downloading, easy web browsing and videoconferencing • TV Out function for sharing images and videos • Built-in applications including Flickr, Adobe Photoshop and PictBridge • Smooth slide design with elegant stainless steel case, protected against scratches and fingerprints	• Compact 3G/HSDPA smartphone • Fast web browsing and downloading • Email with attachment viewer • 2 megapixel camera with flash, 4x digital zoom and panorama mode • Video calls with 2nd camera • Calendar with easy PC synchronizing	• Sleek and compact fold design with large keypad and clear high-resolution color display • Dedicated keys for easy access to music • 2 megapixel camera with flash and 8x digital zoom, secondary camera for video calls • High quality video recording up to DVD resolution and playback in full VCR quality • Video calls and video sharing • WCDMA and quadband GSM functionality for world wide usage	• Seamless coverage and handover between WLAN and GSM network through UMA • Elegant slim stainless steel design • Clear and easy to read display with 16.7 million colors • 2 Megapixel camera with 8x digital zoom and full screen viewfinder • Hotswap MicroSD card reader for storing pictures and music (up to 4 GB)
Additional Features	• Stereo FM Radio with Visual Radio • Nokia Xpress audio messaging, Push to talk • Integrated Handsfree Speaker • Flight and demo mode • XHTML browser • Voice recording, voice commands • Macromedia Flash Player 2.0 • Streaming (3GPP)	• FM stereo radio and music player supporting MP3, AAC, eAAC+ • MMS for sharing pictures • Video player • Push to talk • Integrated hands-free speaker	• Two integrated cameras with a dedicated capture key (2 megapixel/CIF+), panorama mode & lens protection slide • Music player supporting MP3, MP4, M4A, AAC, eAAC+, WMA • Stereo FM radio and support for Visual Radio • External microSDmemory card • E-mail with attachment support (jpeg, 3gpp, MP3, ppt, doc, xls, pdf)	• Music player supporting MP3, AAC, eAAC+ • Video player • Integrated hands-free speaker • Bluetooth • Dual-band 3G technology	• 2.2" 16 million color screen • Front camera for video calls integrated into the earpiece • Push e-mail with attachments • Stereo FM radio with RDS • Music player supporting MP3, MP4, AAC, eAAC+ and WMA • Support for microSD memory card up to 4GB	• Stereo FM Radio with Visual Radio support • Music player (MP3, M4A, eAAC+, WMA) • Video recording • Video streaming • Text-to-speech functionality • MicroSD slot support up to 2GB	• Music player supporting MP3, MP4, AAC, eAAC+ and Windows Media Audio • FM stereo radio supporting Visual Radio • Push e-mail with attachment support • Support for microSD memory card up to 4GB • XHTML browser • Bluetooth with stereo support	• Music player supporting MP3, AAC, eAAC+ • FM stereo radio supporting Visual Radio • Music and video streaming • Bluetooth technology • Push to talk • Nokia Audio Messaging • Games including Snake in 3D

Appendix D. Published commercial specification of Nokia's 6000s series planned to be introduced in 2008

P.M.I	Q2, 2008		Q3, 2008					
Model	Nokia 6124	Nokia 6300i	Nokia 6210	Nokia 6220	Nokia 6650	Nokia 6212	Nokia 6600f	Nokia 6600s
Key Feature	• Vodafone exclusive product • Compact 3G/HSDPA converged device • Fast web browsing and downloading • 2 megapixel camera with flash, 4x digital zoom and panorama mode	• WLAN for connecting to home wireless networks and accessing fast broadband connections • Seamless VoIP integration enabling easy and affordable VoIP calls • Nokia Maps to help navigate and find the way	• Intuitive pedestrian and car navigation • High-speed HSDPA data connection for fast web browsing and downloading • 'Accelerometer' rotates the screen between portrait and landscape mode • Full multimedia computer capabilities	• Advanced imaging features with 5 megapixel camera • Easy sharing of photos and videos, attached with location information–online sharing to web, phone to phone, or on TV screen • Built-in GPS: Nokia Maps 2.0 with integrated GPS, Assisted GPS (A-GPS) support, pre-installed maps in microSD • HSDPA data connection for fast web browsing and downloading • WidSets service preloaded • Adaptive Multi Rate–Wideband(AMR-WB) speech coding technology	• Exclusive to T-Mobile International • T-Mobile service My Faves keeps you in touch with the people that matter to you the most • Stylish fold design with 2.2"TFT QVGA color display • Easy sharing of photos and videos – online sharing to web or phone to phone • Built-in GPS: Nokia Maps 1.2 with integrated GPS, Assisted GPS (A-GPS) support, pre-installed maps in microSD • HSDPA data connection for fast web browsing and downloading	• Enhanced Near Field Communication (NFC) user experience • Slimline design • 3G connectivity for fast and easy download, web browsing and video streaming	• Smooth-back fold design with electromagnetic opening mechanism and dampened hinge for smooth motion • 240x320 OLED 16 million color main display • Hidden outer display • Tap commands: double tap to turn on hidden outer display / snooze alarm / first silence, then reject call • 2 megapixel camera with 8x digital zoom • VGA video recording at 15fps	• Compact and sophisticated shape, metal and glossy surfaces, accent colors • 2.2 inches 240x320 16 million color display • 3.2 megapixel camera with AF and double flash • VGA video recording at 15fps • Accelerometer for tap commands • Nokia Maps for localization experience
Additional Features	• Stereo FM radio • Stereo music player (MP3, M4A, eAAC+ and WMA music formats), MTP support • Video recording • Video streaming • Text-to-speech functionality • MicroSD slot support up to 8Gb • Email attachment viewer	• 2.0" TFT QVGA color display • 2 megapixel camera with 8x digital zoom • Music player (MP3, AAC, AAC+, eAAC+, WMA) and FM stereo radio with RDS • Support for 4GB microSD memory card	• 2.4"inch TFT QVGA color display • Web browser • Instant messaging • Push Email • Music player, Visual Radio and stereo FM radio • ~120 MB for user memory & 1GB microSD card, support for up to 8GB memory	• 2.2"TFT QVGA color display • Web browser • Instant messaging • Email with attachments • Music player(MP3, AAC, AAC+, eAAC+, WMA) and FM stereo radio with RDS • Support for 8GB microSD memorycard	• Web browser • Email with attachments • Music player (MP3, AAC, AAC+, eAAC+, WMA) and FM stereo radio • Support for 8GG microSD memory card • 2 Megapixel camera with LED flash	• 2.0" TFT QVGA color display • 2 megapixel camera with 8x digital zoom, flash • Media player supporting MP3, MP4, AAC, AAC+, eAAC+, H.263, H.264 • Support for up to 4GB microSD memory card	• Video call • Stereo music player supporting MP3, AAC, AAC+, eAAC+ and WMA, and stereo FM Radio • 18MB free user memory plus support for microSD • memory card up to 4 GB • HTML browser, Java MIDP2.0, OMA DRM 1.0 and 2.0 • Bluetooth	• Stereo music player supporting MP3, AAC, AAC+, eAAC+ and WMA, and FM Radio • 18MB free user memory plus support for microSD memory card up to 4GB • XHTML browser, Java MIDP2.0, OMA DRM 1.0 and 2.0 • Bluetooth

Appendix E. Author's list of publications

1. Raharjo, H., Xie, M., Brombacher, A.C. (2006), Prioritizing Quality Characteristics in Dynamic Quality Function Deployment, *International Journal of Production Research*, 44(23), 5005-5018. (IJPR Highly Commended PhD Prize Award 2007, 2nd place out of 18 candidate papers)

2. Raharjo, H., Endah, D. (2006), Evaluating Relationship of Consistency Ratio and Number of Alternatives on Rank Reversal in the AHP, *Quality Engineering*, 18(1), 39-46.

3. Raharjo, H., Xie, M., Goh, T.N., Brombacher, A.C. (2007), A Methodology to Improve Higher Education Quality using the Quality Function Deployment and Analytic Hierarchy Process, *Total Quality Management & Business Excellence*, 18(10), 1097-1115.

4. Raharjo, H., Brombacher, A.C., Xie, M. (2008), Dealing with Subjectivity in Early Product Design Phase: A Systematic Approach to Exploit QFD Potentials, *Computers and Industrial Engineering*, 55(1), 253-278.

5. Raharjo, H., Xie, M., Brombacher, A.C. (2009), On Modeling Dynamic Priorities in the Analytic Hierarchy Process using Compositional Data Analysis, *European Journal of Operational Research*, 194 (3), 834-846.

6. Raharjo, H., Brombacher, A.C., Goh, T.N., Bergman, B., Integrating Kano's Model and Its Dynamics into QFD for Multiple Product Design, *Quality and Reliability Engineering International*, DOI: 10.1002/qre.1065. (in-press)

7. Raharjo, H., Chai, K.H., Xie, M., Brombacher, A.C., Dynamic Benchmarking Methodology for QFD, to appear in *Benchmarking: An International Journal*.

8. Raharjo, H., Xie, M., Brombacher, A.C., On Normalizing the Relationship Matrix in Quality Function Deployment, *to be submitted to an international journal*.

9. Raharjo, H., Xie, M., Brombacher, A.C., A systematic methodology to deal with the dynamics of customer needs in Quality Function Deployment, *submitted to an international journal*.