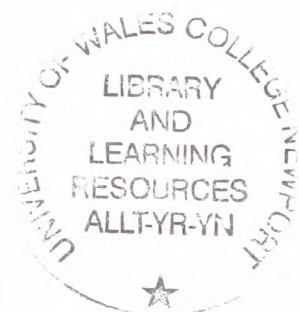


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An integrated systems approach to QFD

Thesis submitted to the University of Wales for the degree of

Doctor of Philosophy

By

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Mechatronics Research Centre
University of Wales College, Newport
October 2000

**To my mum Mary, my dad Horace,
my brothers Fredrick, Eldon, Ricky
and my sister Vicky, whose love
and support I could
not do without**

Declarations

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed V. Bouchereau (candidate)
Date 1st Dec 2000

STATEMENT 1

This thesis is a result of my own investigations, except where otherwise stated.

Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

Signed V. Bouchereau (candidate)
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STATEMENT 2

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

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Acknowledgements

I would like to express my gratitude to my supervisor, Dr. Hefin Rowlands who provided me with his supervision throughout the research. Thank you for allowing me the chance to discover the joy and heartache of "going back to the drawing board" more times than I really wanted. I am also grateful to Prof. Geoff Roberts who has helped in many ways especially insisting on developing our presentation skills both orally and in writing and of course not forgetting our bakery skills. It has all paid off.

I am also eternally indebted to Ioannis Akkizidis who encouraged me to start this PhD in the first place and for his constant help, love and support throughout this arduous, but enticing and memorable time. I could not have done it without you. "Σ' αγάπω και σ' ευχαριστώ πάρα πολύ".

I would also like to thank my colleagues in the Mechatronics Research Centre for their advice and help. Thanks are also due to University of Wales College Newport for providing me with a bursary to undertake this research.

Gratitude also goes to all my friends who kept reminding me that work without play makes me a boring girl and their constant bombardment with humorous e-mails that made me smile.

Furthermore, I would like to thank all my family members for their constant love and support during this time and throughout my life. Finally thank be to God for giving me so many opportunities and the strength to take one day at a time.

Summary

This thesis reviews Quality Function Deployment (QFD) and its relation with the Total Quality Management philosophy. In particular the thesis focuses on the inherent drawbacks of QFD and it investigates potential techniques and methods that could be integrated with QFD to overcome some of its problems. Fuzzy Logic/Fuzzy Sets and the Taguchi Method are identified as techniques and methods to be incorporated within the QFD process to provide a more consistent, quantitative and rigorous method to analyse subjective data in the QFD charts.

Two approaches are developed that integrate Fuzzy Logic and Fuzzy Set theory with QFD to identify and rectify inconsistencies in the input data in the QFD charts. Another approach that integrates the Taguchi Method and QFD is further developed to set more precise technical target values in the QFD chart. Case studies are used to illustrate the results of the developed Fuzzy-QFD and the QFD-Taguchi approaches. The synergistic approaches take into account interactions between requirements, which are not utilised in the traditional QFD charts.

In addition, it was found that the resulting data in the QFD charts are sensitive to the interaction in the correlation matrices, therefore another method is also proposed to detect inconsistencies in the correlation matrices by utilising an inference mechanism and multi-valued logic theory.

An integrated systems approach to QFD is eventually developed that forms a synergy between QFD, Fuzzy Logic/Fuzzy sets and the Taguchi Method. This results in a superior approach that combines the inherent benefits of each of the individual approaches. The integrated systems approach to QFD is a generic approach that can be used for other case studies provided that in addition to the relationship matrix and customer importance ratings, the correlation matrices and benchmarking data are readily available.

As a result of this research, the subjectivity and ill-defined data in the QFD process have been partially resolved by the application of Fuzzy Logic/Fuzzy sets. The QFD analysis has been made more rigorous by integrating it to more quantitative techniques (Fuzzy Logic/Fuzzy sets) and method (Taguchi Method). It has been identified that demands are dependent on each other in the QFD charts and how including these dependencies in the problem can change the results. This problem has been addressed by considering interactions between the demands in the Fuzzy-QFD and QFD-Taguchi approaches developed. These interactions between demands have been identified and dealt with in the developed approaches, such that they no longer provide sub-optimal solutions.

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Notations

ANOM	Analysis of Means
ANOVA	Analysis of Variance
DOF	Degrees of Freedom
DOF _I	Degrees of Freedom for interactions
DOF _O	Degrees of Freedom for an Orthogonal Array
DOF _V	Degrees of Freedom for a factor
DOM	Degrees of Membership
FMEA	Failure Mode and Effect Analysis
FPD-HOQ	Fuzzy Proportional Distribution House of Quality
FR-HOQ	Fuzzy Range House of Quality
F-Value	Fisher's Value
HOQ	House of Quality
OA	Orthogonal Array
OEC	Overall Evaluation Criteria
QFD	Quality Function Deployment
S/N	Signal to Noise ratio
SPC	Statistical Process Control
TQM	Total Quality Management
VAVE	Value Analysis Value Engineering
VOC	Voice of the Customer
VOE	Voice of the Engineers

Chapter 1.

Introduction and Outline

of Thesis

"Education is a progressive discovery of our own ignorance"
~Will Durant~

The main goals of any company are to bring their products or services to market sooner than their competitors, with lower cost and improved quality and the basic objective of making a profit. New approaches are emerging, all built around the idea of more customer focus, higher quality products and services and the bringing together of cross-functional teams. Quality Function Deployment (QFD) is one approach that helps companies translate their customer's needs into product/process design. While QFD can be significantly beneficial, it is not so simple to use. This thesis identifies some of QFD's inherent drawbacks and investigates potential tools and techniques that can help resolve some of them. In this chapter a brief review of the tools and techniques utilised during the research is presented. The aim and objectives of the research are emphasised and finally the layout of the thesis is outlined.

1.1 INTRODUCTION

Many companies depend on their warranty programs, customer complaints, and inputs from their sales staff to keep them in touch with their customers (Akao, 1990). The result is a focus on what is wrong with the existing product or service, with little or no attention on what is right or what the customer really wants. The Total Quality Management (TQM) literature has two dominant areas: continuous improvement and customer focus. The continuous improvement area has a well-established set of methods and tools such as the 7 old quality tools and the 7 new management tools (Kanji and Asher, 1996). In contrast, the customer focus area, with the exception of Quality Function Deployment (QFD) (Akao, 1983) and Concept Engineering (Burchill, 1993) is not supported by similar set of widely accepted tools and methods. The success of a product/process/service largely depends upon how they meet the customers' needs and expectations. However, studies indicate that between 35% and 44% of all products launched are considered failures in the market place (Urban, 1980) due to the fact that the development process is not planned and implemented well, there are no links between the different departments, translating the customer demands is not precise and competitive brands are not looked at. It is evident that this is a tremendous waste of money, time and resources. The way companies develop new and existing products must ultimately be changed to accommodate dynamic customer requirements, global competition and survival in the modern competitive market.

This thesis is concerned with one particular methodology, Quality Function Deployment (QFD), which addresses these issues since it is a visual connective method that helps teams focus on the needs of the customers throughout the total development cycle, from design to manufacturing to after sales services. It is well documented that the use of QFD can reduce the development time by 50%, and start-up and engineering costs by 30%

(Clausing and Pugh, 1991), (Schbert, 1989). While QFD has many benefits, some of its fundamental drawbacks have stalled its use in industry. Amongst its drawbacks (see table 2.3, chapter 2) are the complexities of its charts, the vagueness in the data collected and that the data analysis is performed on a rather subjective basis.

The main focus of this research is to address some of QFD's drawbacks, to investigate and propose tools, techniques and/or methods that could resolve some of these drawbacks and integrate them with QFD. The use of artificial intelligent techniques namely Fuzzy Logic and Fuzzy sets and management/statistical method such as the Taguchi Method are adopted in this thesis to resolve some of QFD's shortcomings.

The thesis introduces QFD and outlines its advantages and disadvantages. Fuzzy Logic/Fuzzy sets are reviewed and a way for them to be incorporated within the QFD process to define more precisely the ill-defined relationship amongst demands is developed. As a method to help set more accurate target values in QFD, the Taguchi Method is introduced. Case studies are utilised to identify the advantages and disadvantages of the proposed synergistic approaches. Finally the integration of all the techniques and methods to produce an integrated systems approach to QFD is described.

1.2 BACKGROUND TO THE PROBLEM

Much work has been published on QFD since its birth in the Kobe shipyard in Japan around 1972. Some of the most detailed work outlying the QFD methodology are documented in various literatures, in many languages (Mizuno, 1994), (Bergman, 1995), (Blumstein, 1996), (Bossert, 1991), (Cohen, 1995), (Day, 1993), (Dika, 1990), (Guinta, 1993), (King, 1989), (Mazur, 1997), (ReVelle *et al*, 1998), (Sullivan, 1986), (Terninko, 1990), (Vonderembse and Raghunathan, 1997). The first international QFD symposium was held in 1989 in Novi, Michigan, in the United States. At the time it was the only

event of its kind in the world and most applications were focused on the QFD methodology itself. Today there are regular events in over 10 countries as well as 'The Annual International Symposium' (QFD Institute, 1989-2000) that focuses on the practical issues and extensions to the QFD method.

During the practical applications of QFD, various problems have been encountered and documented (Blumstein, 1996), (Eureka and Ryan, 1994), (Zairi, 1993) (See table 2.3, chapter 2). Most research in QFD focuses on two main areas: simplification of the documentation process and computerisation of QFD. Freeze and Aaron (Freeze and Aaron, 1990) have developed a customer requirements planning (CRPII) process to simplify the process of building and renovating the House of Quality (HOQ), the first QFD phase. Knight and Kim (Knight and Kim, 1991) have attempted to automate the QFD process. In their work, a concurrent design adviser (CODA) based on QFD has been developed to provide assistance to product design. A hypertext-based group decision support system has been developed by Wolfe (Wolfe, 1994), whereby hypertext is used to extend the HOQ to an electronic collection of multiple, related Houses that span the entire system development cycle. However, effort to address the semantics in the linguistic variables has been neglected (Khoo and Ho, 1996). To fully automate the laborious manual QFD task, the interpretation of the semantics of the linguistic variables has become necessary.

1.2.1 QFD and the House of Quality

Although QFD's charts are in general comprehensive tools for showing relationship between demands in an organised way, sometimes they lack the flexibility to deal with vagueness and indecisiveness that appears in the 'Voice of the Customer' (VOC) and the 'Voice of the Engineers' (VOE). As a product or process becomes more complex, the information held in QFD's charts can become so congested to the extent that some key

issues might be overshadowed or even overlooked. To address the semantic in the VOC and the VOE, artificial intelligence techniques such as Fuzzy Logic (Fung *et al*, 1998), (Khoo and Ho, 1996), (Masud and Dean, 1993), (Liu, 1998), (Wang, 1999), Artificial Neural Networks (Zhang *et al*, 1996) and Expert systems (Crossfield and Dale, 1991), (Knight and Kim, 1991), (Kim *et al*, 1998) have been highlighted in literature for integration with QFD.

Particularly difficult tasks in QFD are the subjective decisions that have to be made when correlating the customer's demands to the engineering characteristics and setting of technical target values. Whilst analysing the traditional HOQ, it is noticeable that some of the relationships in the relationship matrix are either under or over estimated (Temponi *et al*, 1999), (Chan and Wu, 1998) and the engineering characteristic's target values are identified, independent of other engineering characteristics. There are inconsistencies in the data representing two demands that are related to each other strongly. This prompted an investigation into ways to determine these relationships and target values more precisely by utilising interactions between demands. Interactions between demands in QFD are mostly used when there is a need for trade-off analysis. During the course of this research these interactions have been identified as very useful in the QFD analysis and are thus extensively used in the developed approaches.

Fuzzy Logic/Fuzzy Set theory and the Taguchi Method for design of experiment have been identified as useful techniques/method to be integrated with QFD due to some of their intrinsic benefits. Fuzzy Logic/Fuzzy sets possess the ability to deal with qualitative, vague data and interpret them into computer languages, whereas the Taguchi Method is useful for minimising the time and effort to conduct experiments and model interactions and helps to design robust products. Two Fuzzy-QFD approaches are developed and presented in chapter 3 and applied to case studies in chapter 4. The developed Fuzzy-

QFD approaches are innovative approaches that combine and extend several ideas from other researchers (Khoo and Ho, 1996), (Liu and Jia, 1998), (Temponi *et al*, 1999). Furthermore a QFD-Taguchi approach is developed and presented in chapter 5 and applied to case studies in chapter 6 and is believed to be a unique approach to this thesis. A combined Fuzzy-QFD-Taguchi approach that forms an integrated systems approach to QFD is developed and presented in chapter 7 and is also unique to this thesis. The proceeding sub-sections overviews these techniques and their proposed integration with QFD.

1.2.2 Fuzzy Logic and Fuzzy Sets

In organisational systems composed of human beings, data is not always regular or logical. Organisations after all are biological systems, composed of and led by human beings, not numbers. Fuzzy Logic uses human linguistic (words and sentences) understanding to express the knowledge of a system (Zadeh, 1988). This knowledge consists of facts, concepts, theories, procedures and relationships. Fuzzy Logic can model vagueness in data and/or relationship in a formal way. This technique is able to manipulate fuzzy qualitative data in terms of linguistic variables. Fuzzy Logic/Fuzzy sets are proposed in this thesis as techniques to be integrated with QFD to address the ill-defined and subjective decision making process in QFD's HOQ based on interactions between demands. Fuzzy logic/Fuzzy set are selected due to their ability to deal with human linguistics that is often vague and translates these into computer languages.

The integration of Fuzzy Logic/Fuzzy sets with QFD is intended to overcome some of QFD's drawbacks and provide a more consistent, rigorous and quantitative method to analyse the customer demands and the engineering characteristics in the QFD charts. Two Fuzzy-QFD approaches are developed, the Fuzzy Range QFD and the Fuzzy Proportional Distribution QFD and case studies are used to investigate these approaches. It is believed

from the literature survey performed that the developed Fuzzy-QFD approaches are distinctive in the sense that they take both the porch and roof correlation of the HOQ into consideration for checking and updating ill-defined data both in the customer importance rating and in the relationship matrix. It is important to consider both the porch and the roof as in this way all the interdependencies can be taken into account. Other work in literature have mostly used the roof interaction (Liu, 1998), (Temponi *et al*, 1999), to update ill-defined relationship or correlation matrix data only.

1.2.3 The Taguchi Method

For a better understanding and definition of product/process design, quality related techniques and systems such as the Taguchi Method (Chu, 1996), (Fortuna, 1990), (Quinlan, 1985), (ReVelle, 1991), (Terminko, 1992), Statistical Process Control (SPC) (Huge, 1990), Failure Modes and Effects Analysis (FMEA) (Clausing, 1994) and ISO 9000 (Kymal and Hughey, 1995) have also embraced the synergy with QFD. Some of these synergistic approaches are discussed in chapter 2.

The Taguchi method, which is proposed to be integrated with QFD is a combination of an engineering approach and a statistical method to achieve improvements in product/process's cost and quality, accomplished through design optimisation (Taguchi, 1986). As part of the House of Quality (HOQ) the customers and engineers evaluate both their product/process against that of the competitors to help determine the approximate target value. Identifying these target values at the bottom of the HOQ is not an easy task. Targets are sometimes the designer's best guess (Terminko, 1995). A proposed synergistic approach that incorporates the Taguchi design of experiment method with QFD is developed and applied to set more precise technical target values in the HOQ.

The Taguchi Method is considered for its integration with QFD, as there is a need to contemplate interactions between requirements when setting target values and model the system by making use of most of the information in the HOQ. Taguchi's orthogonal arrays offer a way to reduce the number of experiments and possess specific columns to deal with interactions. It is believed from the literature survey that this QFD-Taguchi approach developed is unique to this thesis, as most of the integration of QFD and Taguchi in literature are suggested in the second QFD phase (Ross, 1988), (Ryan, 1988), (Chu, 1996) and only uses specific data from QFD such as the relationship matrix or the benchmarking data (Terninko, 1997).

1.2.4 An integrated systems approach to QFD

Finally an integrated systems approach, combining Fuzzy Logic/Fuzzy sets and the Taguchi method with QFD is developed, which aims to overcome the identified problems with the other synergistic approaches developed and presented in chapters 3 and 4 and chapters 5 and 6 respectively. This is also a distinctive approach to this thesis that combines all three methods: Fuzzy Logic/Fuzzy set theory, the Taguchi Method and QFD. From the literature survey performed, there are no known approaches that combine QFD with Fuzzy Logic/Fuzzy sets and the Taguchi Method.

1.3 AIM AND OBJECTIVES

The aim of this project is to develop an integrated systems approach to QFD to overcome some of its drawbacks (refer to Table 2.3, chapter 2) and to provide a framework for a consistent and more rigorous approach to developing the QFD charts.

The objectives of the project are to:

- Conduct a survey of case studies on QFD and identify practical implementation issues together with QFD's benefits and drawbacks,

- Analyse the QFD process, identifying any major problems,
- Perform a literature survey of the integration of other methods/tools/techniques that have been integrated with QFD,
- Identify extensions to the work done by other researchers and evaluate and combine the considered methods/tools and/or techniques with QFD or identify new ways to further assist QFD to address some of its main problems.

1.4 OUTLINE OF THESIS

- *Chapter 2* gives an overview of QFD together with how it fits in the Total Quality Management culture. It reviews QFD's relation with other quality tools and techniques, outlines its uses together with some of its benefits and drawbacks.
- *Chapter 3* gives an overview of Fuzzy Logic and Fuzzy set theory and proposes the integration of Fuzzy Logic with QFD and outlines two Fuzzy-QFD approaches developed to identify and update ill-defined data in the QFD charts.
- *Chapter 4* investigates the developed Fuzzy-QFD approaches using case studies.
- *Chapter 5* introduces the Taguchi method and develops an approach to set more precise technical target values in the QFD matrices by integrating the Taguchi method with QFD.
- *Chapter 6* investigates in particular the developed Taguchi-QFD approach by the use of case studies.
- *Chapter 7* proposes and develops an integrated systems approach to QFD by the synergistic cohesion between Fuzzy Logic/Fuzzy Set, the Taguchi Method and QFD.
- *Chapter 8* completes the thesis by identifying key contributions of the research and points out some future research directions relevant to the thesis.

Chapter 2. Quality Function Deployment (QFD)

“Quality does not happen by accident; it has to be planned”
~Joseph Juran~

Some companies seize market opportunities and grow while others fade away. Of the numerous problems that face companies in this modern world, attracting and keeping customers is one of the ultimate factors that determines whether a company survives or not. After customer needs have been identified, a way to integrate those needs into the product/process design is necessary. Quality Function Deployment (QFD) is a methodology that helps companies translate the customer demands into company objectives, from design to implementation of a product/process. QFD is overviewed in this chapter, together with its role in the Total Quality Management field. Its benefits and drawbacks are also highlighted. Some of its drawbacks necessitate alternative ways to implement the QFD process and as such other techniques and methods that could provide a helping hand to QFD are suggested.

2.1 INTRODUCTION

The world we live in today is highly customer focussed. The customers will no longer tolerate lengthy delivery times. They see new capabilities emerging that better fit their needs and they want them, not next month, nor tomorrow, but right now. Delays in bringing a product to market can result in market failures (Urban, 1980). To thrive in the worlds' business, designing products and services that excite the customer and creating new markets are critical strategies. And while growth can be achieved in many different ways, (e.g. selling through different channels, selling more to existing customers, acquisitions, geographic expansion), nothing interests a company more than creating new products or upgrading existing products to create customer delight. To succeed in developing thriving new products or improve upon existing ones is not easy (Urban, 1980). Today, with marketing techniques so much more sophisticated than ever before, companies can measure, track and compare customer's perceptions of products, therefore all companies have opportunities to compete on quality. Costs certainly justify an emphasis on quality design.

In many companies, today's typical development process involves a relatively short amount of time in the planning stage of the product development. By contrast, companies spend a great deal of time designing and redesigning the product. It is generally believed that 80% of overall costs are locked in during the design phase; the remaining 20% occur during manufacturing or implementation. It is usual to find that 70% of the cost for producing a new product is decided when only 3-4% of the effort on a project has been expended (Ouyang *et al*, 1997). Therefore companies need to spend more time in this phase. The key to shortening development time lies in a better definition of the product. By better understanding customer needs and carefully incorporating these needs into

product design, companies can reduce significantly the number of design changes in the innovation process, and reduce start-up costs and lead times for product development.

It is one thing to actually discover and measure the customer's needs and wants, but to achieve results, these findings need to be implemented, i.e. translated into company language. One process-oriented design method constructed to carry out the translation process and make sure that the findings are implemented is Quality Function Deployment (QFD). In QFD, more effort is involved in getting the information necessary for determining what the customer truly wants. This tends to increase the initial planning time in the project definition phase of the development cycle, but it reduces the overall cycle time in bringing a product to market yielding a drastic reduction in redesign. A major Japanese automotive company claimed to have reduced start-up costs by 61% between 1977 and 1984 and cut lead times for product development by one-third using QFD (Sullivan, 1986).

This chapter gives an overview of Quality Function Deployment, a brief indication of the meaning of quality especially in the QFD context. Total Quality Management (TQM) is then introduced and a brief description of QFD's relationship with TQM and other quality tools and techniques is given. The differences between QFD and the traditional quality systems are also highlighted. Additionally, the QFD process is outlined, especially the first phase, the Product Planning phase, commonly known as the 'House of Quality' or Requirements Matrix. Furthermore, the different ways to analyse the QFD charts are outlined. Finally, the benefits and problems with QFD are captured and the past and current uses of QFD in industry are also highlighted.

2.2 OVERVIEW OF QUALITY FUNCTION DEPLOYMENT (QFD)

QFD is an acronym for Quality Function Deployment. QFD originated in the late 1960s to early 1970s in Japan by Professor Yoji Akao and the late Professor Mizuno at the Kobe shipyard (Akao, 1972). In 1970, the Kobe Super-tanker Company wanted to develop the logistics for building complex cargo ships (super-tankers). Professors Akao and Mizuno were asked to create a system that would ensure that each step of the construction process would be linked to fulfilling a specific customer requirement. Thus was born QFD, which is a direct translation of the Japanese technique identifying the 'Quality Attributes' of a solution or product that are critical to a customer.

Many definitions of QFD have been proposed which reflects its many facets. Its original Japanese meaning is "Hin Shitsu" (qualities, features, attributes, characteristics) "Ki No" (function, mechanisation) "Ten Kai" (deployment, development, evolution) (Ungvari, 1991). Taken literally, the term Quality Function Deployment may seem a bit misleading. The translation is not very accurate: "Hin Shitsu" means qualities (i.e., features or attributes), not quality. QFD is not a quality tool as such, although it can certainly improve quality. Rather, it is a visually powerful planning method (Ryan, 1988). The definition of QFD most commonly used in the literature is given by:

Akao “QFD is an overall concept that provides the means of translating customer requirements into appropriate technical requirements for each stage of product or service development” (Akao, 1972).

Other definitions from quality gurus include:

Hauser and Clausing "*A set of planning and communication routines*". QFD focuses and co-ordinates skills within an organisation, first to design, then to manufacture and market goods that customers want to purchase and will continue to purchase" (Hauser and Clausing, 1988).

Bossert "*QFD is a process that provides structure to the development cycle where the primary focus is the customer requirements*" (Bossert, 1991).

Gavin "*QFD may be defined as elaborate charts to translate perceptions of quality into product characteristics and product characteristics into fabrication and assembly requirements*". In this way, the 'voice of the customer' is deployed throughout the company (Garvin, 1988).

Maddux et al. "*QFD can be defined as a system for designing a product or service based on the customer demands and involving all members of the organisation*" (Maddux et al, 1991).

Whether viewed as a concept, a set of planning and communication routines, a process, elaborate charts, a system or a method, the bottom line is that QFD focuses all the departments in a company towards the features of their product/process that are most important to their customers. It records user requirements, engineering characteristics that satisfy these user requirements and any trade-offs that might be necessary between the engineering characteristics. It involves goal setting, customer research, prioritisation, benchmarking against known standards, technical measurements, value engineering, design for assembly, classical problem solving techniques, optimisation techniques and the use of Deming's Plan-Do-Check-Act (PDCA) cycle (Dika, 1990). Steps for applying the PDCA cycle to QFD can be found in King (King, 1995).

However, QFD is primarily a people system. Nothing happens without people. As Ronald Fortuna explains in his paper (Fortuna, 1990):

'The voice of the customer is the point of departure for QFD. It drives the process. Listening to the customer, understanding the customer and interpreting and translating what the customer says forms the philosophical heart of Quality Function Deployment.'

It also brings together multifunctional teams to work together towards satisfying the customer. Companies are sometimes too internally focused, developing goods or services with a vague understanding of the customers' requirements, or they are too externally focused, trying to constantly please the customer at the expense of their own business survival (Smith and Angeli, 1995). QFD can assist companies to identify the key trade-offs between customer requirements and what is financially achievable. QFD does nothing that people did not do before, but it replaces inconsistent, intuitive decision-making processes, with a structured approach. Experienced marketers and engineers will argue that most of the information contained in the QFD matrix tells them nothing that they did not already know. It is in fact a simple concept, but it is a disciplined way to compare two sets of lists. When there are many items in the list to compare, QFD can be very helpful as the QFD matrix format allows all the information to be displayed in a consistent manner. The QFD matrices can reveal where there are commonalities, where there are clear differences and most important where there are questions (Hunter and Van Landingham, 1994).

The methodology keeps design options open longer and minimises the tendency to go to technical design too early in the project. It also provides guidance and identifies missing characteristics in a quick and visual manner. The key to QFD's potential competitive advantage is its structured application of four vital concepts:

- *Preservation of the voice of the customer*, ensuring that customer needs are not translated and distorted in the development process.
- *A cross-functional team* that provides input to product achievement from all areas of the business.
- *Concurrent engineering* allowing departments such as manufacturing who have traditionally participated later in the product life cycle, to begin planning earlier.
- *Graphical display* that shows the links from customer demands to manufacturing decisions.

2.3 WHAT IS QUALITY?

Before proceeding any further, it is important to define what quality means, especially in relation to QFD. There are various well-known definitions of quality depending on who is defining it. The International Standard for Standardisation, ISO 8402 (Quality Vocabulary, 1986), (Tuchman, 1980) defines quality as *"the totality of features and characteristics of a product or service that bears on its ability to meet a stated or implied need"*. This definition of quality is often referred to as the product-based approach (Abbott, 1955). Juran and Gryna (Juran and Gryna, 1988) define quality as "fitness for use". Crosby (Crosby, 1979) defines quality as "conformance to requirement", which is often referred to as the manufacturing-based approach. Japanese companies find that the old definition of quality, "the degree of conformance to a standard", is too narrow and consequently have started to use a new definition of quality in terms of "user satisfaction" (Wayne, 1983), (Edwards, 1968). The value-based approach defines quality in terms of cost and prices (Broh, 1982). According to this view, a quality product is one that provides performance at an acceptable price or conformance at an acceptable cost to the customer. Dr. Taguchi defines quality in a negative way as the "loss imparted to society from the time the product is shipped" (Taguchi, 1986). This loss includes the cost of customer dissatisfaction, which may lead to a loss of reputation and goodwill for the

company. Another meaning is 'fitness to latent requirements', which means meeting customer needs before customers are aware of those needs. If a company can find the latent requirement of the market, it may achieve monopoly for a while, which can be very profitable (Shiba *et al*, 1993). Shiba, Graham and Walden also points out the advantages and disadvantages of each of these quality meanings. Figure 2.1 shows different views of quality.

It is interesting to note that satisfying the customers' needs and expectations are the main factor in most of these definitions. Putting all these definitions together, quality can thus be viewed as a product/service that is adapted to customer's needs, which conforms to target specifications, is without defect, can be delivered on time, is of good value and is fit for use by the customer. Therefore it is important for a company to identify the customer's needs early in the product development cycle. The ability to define accurately these latent requirements, including design, performance, price, safety, delivery and so on, will place a company ahead of competitors in the market. QFD is geared to do just that.

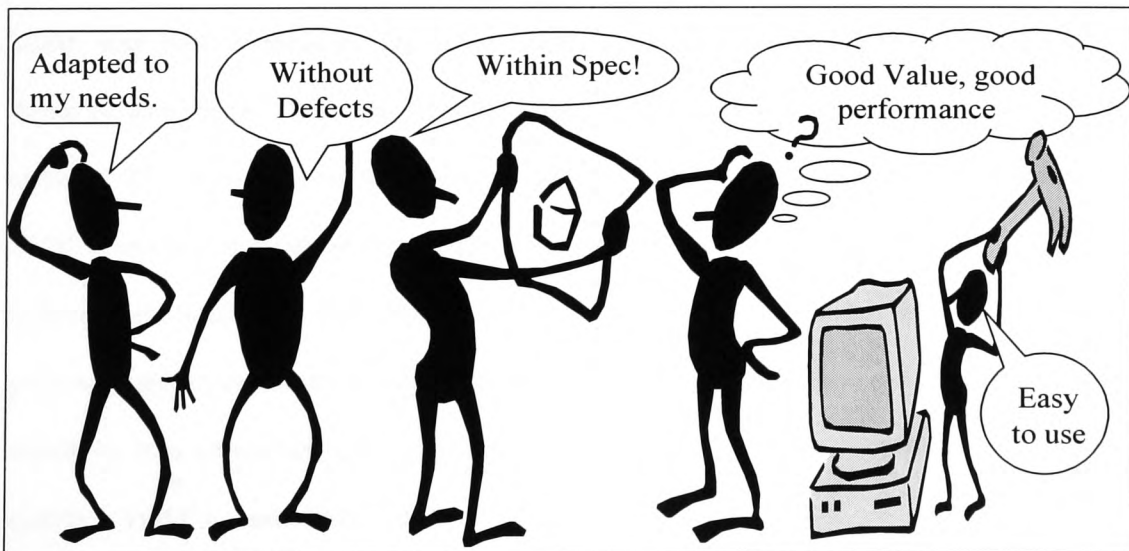


Figure 2.1 Different views of Quality

2.4 QFD IN RELATION TO TOTAL QUALITY MANAGEMENT (TQM)

The nature of the current world-wide competition generally demands from any corporation the following four abilities (Logothetis, 1992b):

1. To understand what the customer wants and to provide it, immediately on demand, at the lowest cost.
2. To provide products and services of high quality and reliability consistently.
3. To keep up with the pace of change, technological as well as political and social.
4. To be one step ahead of the customer's needs; that is, to predict what the customer will want one year or even 10 years from now.

The attainment of these abilities requires an organised approach to management - an approach of managing for total quality, of managing for effectiveness and competitiveness, involving each and every activity and person at all levels of the organisation. This is known as the Total Quality Management (TQM) approach (Feigenbaum, 1956). The Japanese call it Kaizen (Masaaki, 1986), which means, "change in small doses."

TQM was first adopted in Japan although it was developed by Walter Shewhart of America as early as 1930 (Smith and Angeli, 1995). TQM is structured so that it can be used by all employees to maintain or improve quality, cost, procedures and systems. TQM integrates fundamental management techniques, existing improvement efforts, and technical tools under a disciplined approach focused on continuous improvement. This gives customers or users a product, which is of the highest quality, within budget and on schedule. It is concerned with the quality of management rather than the management of quality. TQM's underlined aim is a focus on the customer. It achieves this by

implementing three primary factors as shown in Figure 2.2 (Smith and Angeli, 1995): people, systems and tools.

- **People:** This is the combination of company values and management style, employee's attitudes to these values.
- **Systems:** Procedures related to organisation, policy, strategy, review and improvements that document what the company does and why.
- **Tools/techniques:** All the scientific methods and tools that support the decision making through facts and data.

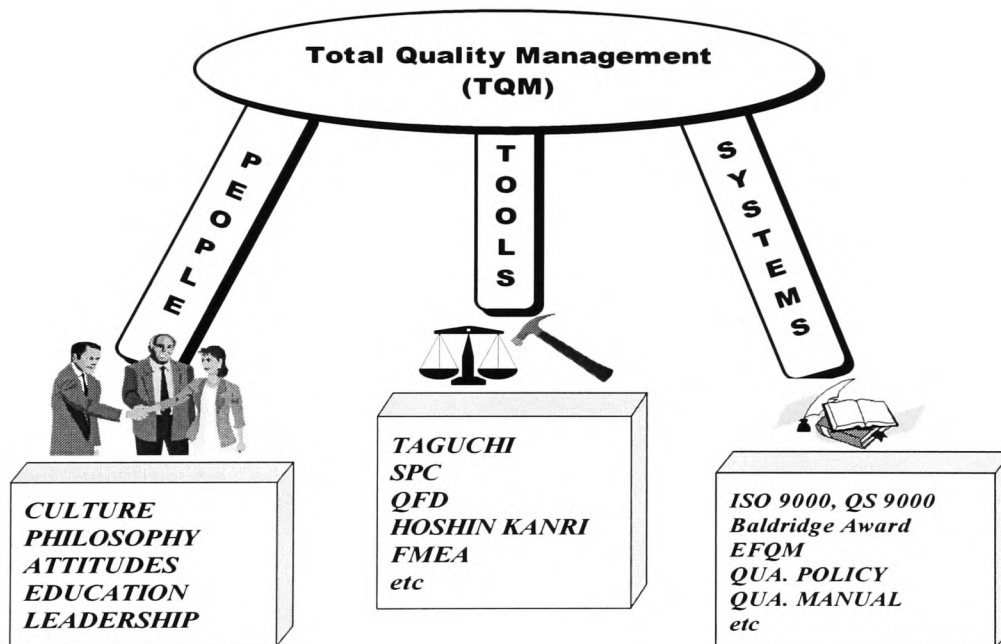


Figure 2.2 The TQM model (Smith and Angeli, 1995)

Each of the components of TQM is responsible for a particular customer feature resulting in increased market share and increased profitability. The basic principles of TQM were expressed by Feigenbaum in 1956 (Feigenbaum, 1956): “The underlying principle of this total quality view and its basic difference from all other concepts - is that, to provide a

genuine effectiveness, control must start with the design of the product and end only when the product has been placed in the hands of the customer who remains satisfied". Therefore TQM must begin at product conception and continue throughout its entire life cycle.

QFD is a useful implementation vehicle for TQM as it utilises cross-functional teams and management to integrate the organisation so that all of the department work together to achieve the common goal of satisfying customer demands. QFD helps companies to move from an inspection based approach, to designing quality into products and therefore playing a key role in any Total Quality Management (TQM) or Continuous Improvement programmes (Kanji and Asher, 1996). QFD is a combination of Total Quality Management (TQM) process elements that multifunctional teams use to act effectively in response to the voice of the customer. Guinta (Guinta, 1993) states QFD as an essential tool in implementing five of TQM's attributes:

1. Customer focus,
2. Management by facts,
3. Continuous improvement,
4. Total investments,
5. Systematic support.

King (Nakui, 1991) describes QFD as one of 14 concepts that is part of a TQM vision. Using QFD ensures that the customers needs are fulfilled.

2.4.1 QFD versus traditional quality systems

What can QFD do that is not already being done by traditional quality systems? Traditional approaches (SPC, Inspection Methods, Testing Methods) often focus on work standards, automation to eliminate human error-prone processes and quality improvement

teams to empower employees to resolve problems (Love, 1986). The inspection-based system was possibly the first scientifically designed quality control system introduced to evaluate quality. It is merely a screening process which isolates products within specifications and those out of specifications without having any direct mechanism to reduce defects (Rahman, 1995).

QFD is quite different from these traditional quality systems which aims at minimising negative quality (such as faulty products or poor service). With the traditional systems, the best you can get is 'nothing wrong'- which is no longer good enough. Apart from eliminating negative quality, positive quality must also be maximised. This creates value, leading to customer satisfaction. QFD focuses on delivering value by seeking out both spoken and unspoken needs, translating these into actions and designs, and communicating these throughout the company at the early stages of a project. Since its birth, QFD has evolved in response to some major problems in the traditional process such as; disregard for the voice of the customer, disregard of competition, concentration on each specification in isolation, little input from design and production people into product planning, different interpretations of the specifications, lack of structure, lost information and weak commitment to previous decisions.

2.4.2 A Team Approach

Unlike many other traditional tools and techniques which tend to be used on an individual basis, QFD is a powerful tool for team building and multifunctional involvement. It helps teams determine the correct methods and tools, the order of sequence of their use and enables the team to systematically reach consensus on:

- what to do,
- the best ways to do it,

- the best order in which to accomplish it,
- the staffing and resources required.

The QFD documentation process is a highly effective way for getting new members up to speed on what to do and why, allowing team members to review and recall exact details months and even years after a meeting.

2.4.3 QFD's relation to other quality tools, techniques and standards

QFD breaks new ground in managing business by bringing together various quantitative (Scoring Method, Analytical Hierarchy Process) and qualitative techniques (Affinity Diagram, Tree Diagram) to focus the business on the customer (Bossert, 1991). QFD is not a stand-alone tool. Instead it is ideally suited for integration with many other tools and techniques to either enhanced its performance or that of other tools, techniques and quality standards. When a QFD exercise is started, the QFD team has a myriad of tools available to complete the task. The most commonly used tools in QFD are known as the seven management tools, also known as the seven new planning tools of quality (Zairi, 1993). These tools (Affinity Diagram, Tree Diagram, Matrix Diagram, Interrelationship Digraph, Matrix Data Analysis, Process Decision Program Chart and Arrow Diagrams) (Bossert, 1991) are essentially management tools and are intended to promote a more creative approach to quality planning. Four of the seven management tools of TQM – affinity diagram, interrelationship digraph, tree diagram, and matrix diagram – are combined and focussed on the customer to form QFD.

- ***Affinity Diagram (KJ Diagram)***, which is normally used to organise verbal/qualitative data, can be used to understand the Voice of the Customer (WHATs) as well as organise and build up the customer demands and the engineering characteristics (HOWs).

- ***Interrelationship Digraph*** is used to show the logical progression of steps needed to complete a task, displays complex interrelationship and cause-effect relationships between existing ideas. It can be used in QFD to separate the WHATs from the HOWs and establish their sequence of use.
- ***Tree Diagram (Systems Flow)*** helps to identify tasks needed to be done and subdivide objectives into actionable elements, which can be useful in QFD to separate, identify gaps and establish the hierarchy between WHATs and HOWs.
- ***Matrix Diagram*** is the joining of two sets of tree diagrams which helps to display relationships, magnitude and polarity between lists. It forms the major part of QFD to map WHATs to HOWs and show the relationship between them.

Of the four new management tools discussed so far the Matrix Diagram has enjoyed the widest use in QFD. It is based on the principle that whenever a series of items are placed in a column (vertical) and whenever a series of items are placed in a row (horizontal), there will be intersecting points that indicate a relationship. Furthermore, the Matrix Diagram features highly visible symbols that indicate the strength of relationship between the items that intersects at that point. Thus, the Matrix Diagram is very similar to the other tools in that new cumulative patterns of relationships emerge based on the interaction between individual items.

QFD has been identified as one of the best ways to achieve "Constancy of Purpose", Point 1 of Dr. W. Edwards Deming's "Fourteen Obligations of Top Management" (Logothetis, 1992a). Simply put, "constancy of purpose" is establishing a common goal for an organisation. With a common goal, all members of the organisation have a shared understanding of what must be accomplished and can in their own way help to achieve organisational goals. QFD also abides to point 3, 'Cease dependency on inspection alone

to achieve quality' and point 9, 'Break down barriers between departments and individuals' of Deming's 14 points for management.

QFD employs a mechanism (Figure 2.3) that identifies where such tools as the Taguchi Method, Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA) and Statistical Process Control (SPC) should be used as well as documents their uses (Eureka and Ryan, 1994). It is important to find out what works best for the organisation and use whatever tools and techniques available.

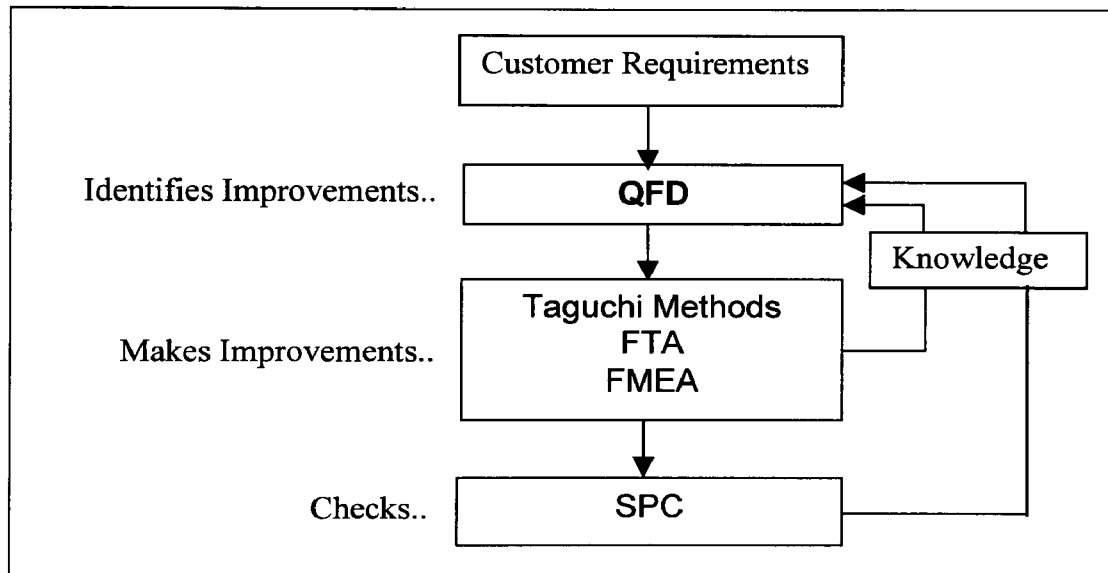


Figure 2.3 QFD helps identify where to use other tools (Eureka and Ryan, 1994)

The Taguchi Method is intended to help optimise product and process design and to help establish the critical target values. The synergy between the Taguchi Method and QFD has been proposed by various authors (Chu, 1996), (Fortuna, 1990), (Quinlan, 1985), (ReVelle, 1991), (Terninko, 1992) and is discussed more in depth in chapter 5.

QFD serves to determine the ideal product performance; causes and effects of the deviation from the ideal performance are considered by using Failure Mode and Effect Analysis (FMEA). FMEA uses the identification of different failure modes that can occur at the piece part, the subsystem and the total system level of design (Clausing, 1994).

QFD also integrates well with SPC. QFD is more concerned with design aspects and tends to work backward by starting with the end objective and then determining means by which the objective is achieved. SPC on the other hand is more “downstream” and concerned with process improvement, the prevention of defects and the reduction of variability. QFD completes the picture by joining the voice of the customer with the voice of the process, determined by SPC (Huge, 1990).

Several aspects of QFD resemble Value Analysis/Value Engineering (VAVE) (Lyman, 1992) pioneered by General Electric, USA in 1947. VAVE is concerned with the analysis of functions and their values and then identifies their components and their associated costs. It then seeks to find improvements to the components by either reducing their cost or increasing the value of their functions (Tompkins, 1989).

Don Clausing and Stuart Pugh enhanced the QFD procedure in 1991 (Clausing and Pugh, 1991) by integrating Pugh's Concept Selection Process with QFD. The Pugh Concept Selection is a way to sort out the best alternatives by benchmarking other concepts or technologies with the best-in-class product.

QFD provides a means to execute Simultaneous Engineering (SE). In the past the means for accomplishing SE was a less effective throw-it-over the wall approach. QFD can help SE or Concurrent Engineering (CE) work, as one of QFD's main benefits is to bring people together who represent different functions, which is the main goal of SE.

Simultaneous Engineering takes over from QFD to make sure that the 'voice of the customer' is used for the design of the production process (Zairi, 1993).

QFD as a benchmarking technique gives information on customers' perception of suppliers' ability to fulfil their requirements in comparison with the competition. Competitive and tactical benchmarking techniques can be included in the "House of Quality" for this purpose (Zairi, 1993).

The Quality standard ISO 9000 also lists QFD as a design activity (Kymal and Hughey, 1995). QFD has also been combined with the environmental management system ISO 14000 (Akao and Hayazaki, 1998). In the design output it is one of the tools to simplify, optimise and reduce waste. Akao (Akao and Mazur, 1998) suggests that because QFD examines both the product and the process by which the product is designed, it can be very valuable in obtaining and maintaining the automotive QS-9000 certification.

Due to QFD's ability to integrate effectively with other tools and techniques, its integration with Fuzzy Logic and Fuzzy sets and the Taguchi Method for Design of experiment are investigated to resolve some of its inherent drawbacks highlighted in Table 2.3. Their synergies are discussed in chapters 3 and 4, and chapters 5 and 6 respectively.

2.5 THE QFD PROCESS

QFD is a highly effective way of capturing information from meetings. It deals with "language of effectiveness" and uses many charts (Hauser and Clausing, 1988) to discover interrelationships between customer demands, product characteristics, and manufacturing processes. The starting point of any QFD project is the customer requirements, often referred to as the non-measurable such as "how it looks, how it feels,

durability, etc.”. These “language of effectiveness” are then converted into the “language of technology/Science” like “oven temperature, mould diameter, etc.”. This stage is referred to as the engineering characteristics or measurables. This translation is often quite complex and fuzzy and the inability to perform this translation properly can lead to customer dissatisfaction.

There are two dominant QFD models, the “Four Phase Model” (Islam and Ming, 1995), (Lecuyer, 1990) and the “Matrix of Matrices” (King, 1989), (Mizuno, 1994). The “Four Phase Model” is the most widely known and utilised. The less known and more comprehensive “Matrix of Matrices”, also known as the 30-matrix approach, provides developers with thirty matrix tools and tables, which consider development steps (cost deployment, reliability deployment) not included in the “Four-Phase” approach. This represents the full QFD approach, but QFD teams should select and adapt from this set as appropriate rather than attempt to implement it fully. The 30-matrix approach is most successful for projects that require more detailed understanding as a result of using QFD. Sometimes due to lack of time, people and money, it is not possible to implement either the “matrix of matrices” or the “four-phase” approach. For these situations, “Blitz QFD”, developed by Zultner (Zultner, 1998) can be used. Blitz QFD demonstrates how to select and deploy only the top most important ranked customer needs.

During the course of this thesis, the “four phase model” has been identified as the most widely used QFD model due to its simplicity. Owing to this fact the “four-phase model” is adopted in this thesis, as only the highest level of detail is investigated. The four-phase model of QFD (Figure 2.4) includes:

Phase 1 - Product Planning: House of Quality

Phase 2 - Product Design: Parts Deployment

Phase 3 - Process Planning

Phase 4 - Production (quality control charts).

The four phase QFD process involves the construction of the "House of Quality" (HOQ) (Hauser and Clausing, 1988) in the first phase and the completion of a further three key phases. A chart (matrix) in the form of a house represents each phase. Phase 1 gathers the voice of the customer and puts it into words accurately understood by the organisation and analyses it versus the capability and strategic plans of the organisations. This phase is known as the House of Quality (HOQ) and compares the customer's demands to engineering characteristics. The steps involved in this phase are explained in more detail in Appendix A.

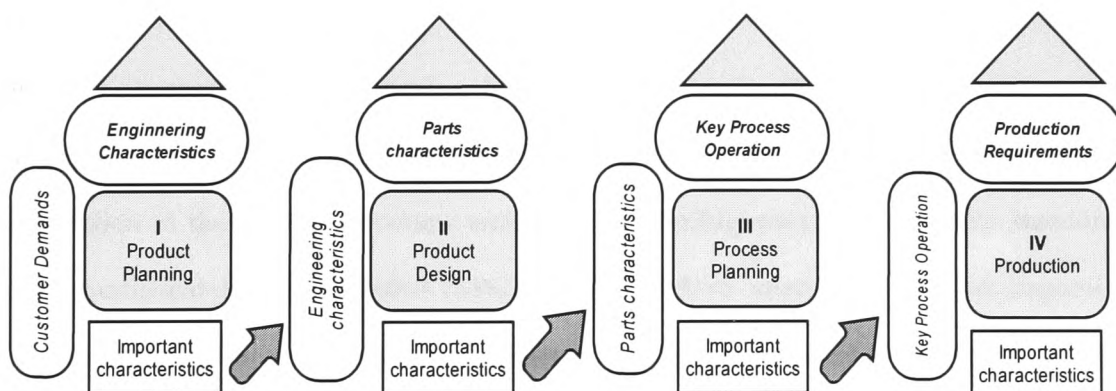


Figure 2.4 The four phases of the QFD process

The second phase, Product Design phase shows the engineering characteristics and the applied technologies or parts characteristics. This phase identifies the area of priority breakthrough that will result in dramatic growth in market share for the company. This is where new concepts are evaluated by comparing different ways/technologies to design the product. These two matrices result in a Customer Needs Document, a Concept Document, an assessment of the engineering characteristics, and the identification of

trade-offs. The Quality Tools utilised in these two matrices (and in all the matrices) are Brainstorming, Affinity Diagrams, Tree Diagrams, Matrix Diagram and Pareto Charts (Urban, 1980).

Once the concept is approved, the next phase, Process Planning phase looks at the applied technologies and the Manufacturing Steps (key process operations). Phase 3 represents the breakthrough to new technology. This is the area that has seen the largest growth in the last few years with the introduction of the Russian TRIZ (Altshuller, 1996) approach to inventive problem solving. Here is where Quality Tools like Cause and Effect Diagrams, Failure Mode Effect Analysis (FMEA), Design of Experiments and the Taguchi Methods can be utilised. The identification of key variables in the manufacturing process is the result of this phase.

The last phase, the Production phase, looks at the Manufacturing Process Steps and the Manufacturing Quality Control Steps (production requirements). It represents the production of the new product/new technology at the highest possible quality standards. Now Statistical Process Control (SPC) can be used to implement and run capability studies, as well as continue any experimentation started earlier. Estimates are obtained for process repeatability and reliability as well as to determine the testing capability. This is where process optimisation starts taking place.

Using this flow model, managers can see the potential strengths in utilising QFD. As the project progresses, other charts (matrices) may be utilised to better clarify requirements. The advantage of the model is to show how QFD flows from design concepts to a manufactured product. This process aids the difficult transition of bringing a product from development to manufacturing. It also brings all the necessary information to manufacturing so that the line operator is capable of running the process as necessary to

produce the highest quality product. The overall QFD system is based on these charts, tracing a continuous flow of information from customer requirements to plant operating instructions. The QFD charts are multifunctional tools that can be used throughout the organisation. For engineers, it is a way to summarise basic data in a usable form, for marketing it represents the customer's voice and general managers use it to discover new opportunities (Clausing and Pugh, 1991).

2.5.1 The House of Quality

The first QFD chart is normally known as the "House of Quality" (HOQ) (Hauser and Clausing, 1988) due to its shape and comprises of a number of rooms. This phase is discussed extensively in Appendix A as it is the phase that is mostly used in the QFD process and as such it is also the phase that is utilised in this research.

Seven (Franceschini and Rossetto, 1995), eight (Liu and Jia, 1998) or nine rooms (Chan and Wu, 1998) are normal in the HOQ, but it can be tailored for more or less rooms. Other names for this chart are the A1 matrix, product design matrix, What vs. How matrix, customer quality vs. supplier quality matrix, and demanded quality vs. performance measure matrix. The matrix format of the QFD phases helps the visual understanding of complex relationships. Figure A1 (Appendix A) shows a diagram of the HOQ with its many rooms and Figure A2 gives an example of the HOQ for the design of running shoes (Eccles, 1994). The different steps to build this house are explained in Appendix A.

Prior to putting the data into this matrix, intense market research needs to be carried out to determine first of all, if there is a need for the product/process, who are the potential customers, what are their needs, their problems, the importance of each of their needs and potential competitors. After the data has been gathered, the QFD team has to analyse and

check the information. A nine point check has been designed for this purpose (Nakui, 1991), (Appendix A). It is desirable to:

- Cross check the thinking of the team by looking for conflicts and contradictions in the HOQ, i.e. determine the validity of the information.
- Finalise the target value for the engineering characteristics.
- Determine the engineering characteristics upon which to perform further analysis in the subsequent QFD phases.

With the use of the HOQ, the team can set targets covering the issues that are most important to the customer and how these can be addressed technically. The QFD matrices will output valuable results depending on what kind of data was input into it.

2.5.2 Analysis of the QFD charts

The two main methods used for the analysis of the data in QFD are 'Independent Scoring' and 'Proportional Distribution' methods. Independent scoring uses individual relationships to perform the analysis. This is the method used to analyse the example of the design of running shoes (Figure A.2) and the toothpaste tube example (Figure 2.6). Traditionally this results in the standard QFD format using relationship of zero-weak-medium-strong with relative weighting of 0-1-3-9. Proportional Distribution on the other hand uses the relationship as a percentage of the overall sum, so each relationship is in proportion to the others (Saaty, 1985). This result in a non-standard format where the relationships are not the standard 0-1-3-9, but can take any value, normalised between zero and one or as a percentage. Figure 2.5 illustrates how an imaginary sample of data is transformed from the Independent Scoring to the Proportional Distribution to be entered in the HOQ.

The mathematical analysis in the Independent Scoring is quite straight forward, but it can introduce distortion in the data. In the Independent Scoring, the demanded weights, W_i

(performed row-wise) are calculated by taking the percentage customer importance rating for each customer demands, r_i and multiplying it by the row sum of the quantified relationship values, $R_{i,j}$ given in equation (2.1), where i represents the row, j the column and n , number of engineering characteristics. This demanded weight value is 688.24 in the Independent Scoring chart (Figure 2.5) for customer demand D1.

$$W_i = r_i * \sum_{j=1}^n R_{i,j} \tag{2.1}$$

The relative demanded weights are then expressed as percentages, which form the relative demanded weight column.

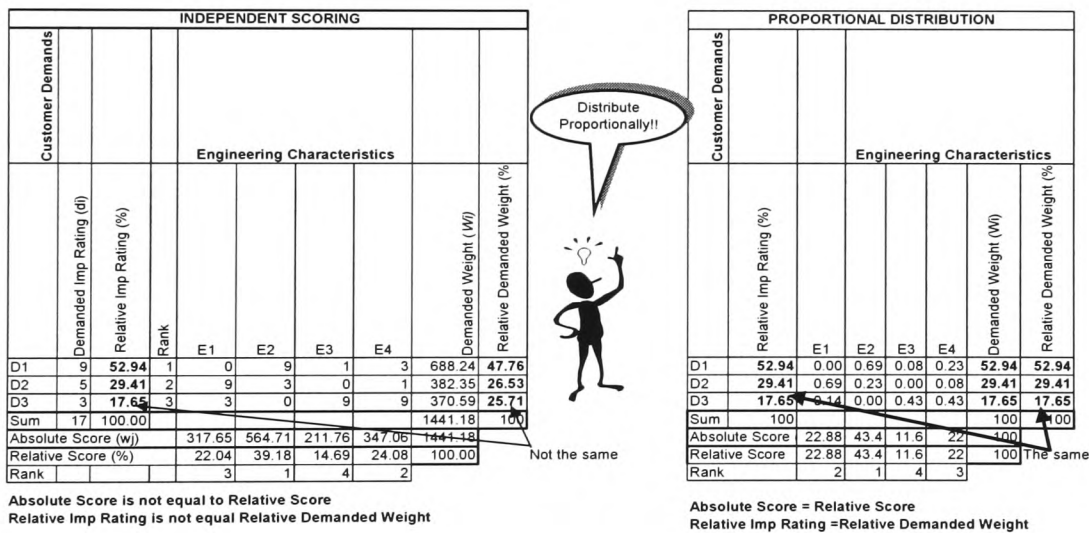


Figure 2.5 Independent Scoring HOQ transformed into Proportional Distribution HOQ

It is evident from Figure 2.5, in the Independent Scoring, the relative demanded weights (last column) for each customer demand is out of proportion with respect to the relative priorities (relative importance rating column) established for the customer requirements of 52.94%, 29.41% and 17.65% respectively. To fix this problem, Lyman (Lyman, 1990)

recommends the Proportional Distribution approach, also known as the Normalised Technical Importance Method, which normalises the relationship values contained in the relationship matrix $\underline{R} * \underline{1} = \underline{1}$. This is satisfied by dividing each of the relationship values R_{ij} in a given row by the row sum of the relationship $R_{i,j}$ values as in equation (2.2).

$$R_{i,j}^n = R_{ij} / \left\{ \sum_{j=1}^n R_{i,j} \right\} \quad (2.2)$$

This treats each relationship value as a percentage and result in an adjustment of the relative demanded weights such that they are in agreement with the degree of importance ratings. Thus the distortion is automatically compensated for. As can be seen in Figure 2.5, (Proportional Distribution) the relative importance rating equals the relative demanded weight.

Using both methods of calculations (Independent Scoring and Proportional Distribution) provides a quick indication how “balanced” the relationship matrix is (Hales *et al*, 1996). If the matrix is balanced, (most rows have approximately the same number of relationships defined) then the engineering characteristics will be ranked similarly using both calculation methods. If the matrix is unbalanced, the engineering characteristics may be ranked very differently using the Proportional Distribution method as seen in Figure 2.5. If the relationship is not balanced it should be evaluated again to verify consistency in the way relationships were defined. A set of consistency checks (Nakui, 1991) found in Appendix A can help determine common mistakes in unbalanced matrices.

The next subsection will highlight some problems with the traditional analysis of the QFD charts through the use of a case study in order to identify the necessity to integrate QFD with other techniques. Comparison is made between the two traditional approaches

(Independent Scoring and Proportional Distribution) to highlight the problematic areas, which will be exploited, in the Fuzzy-QFD approaches developed in chapters 3 and 4.

2.5.2.1 Case study 1: The design of the Toothbrite toothpaste tube

Problem definition: A major toothpaste manufacturer's (ToothBrite Inc) market share has suddenly dropped. It is suspected that this is the result of the competitor's (Crest) new Neat Squeeze dispenser and Colgate's new stand-up tube. QFD is thus used to redesign the ToothBrite Inc toothpaste tube in order to regain market share.

The HOQ for the toothpaste case study (Bahill and Chapman, 1993) is illustrated in Figure 2.6. The definitions of the demands are given in Appendix A. Figure 2.7 shows the proportionalised data of the Independent Scoring HOQ to give the Proportional Distribution HOQ. The Proportional Distribution HOQ as seen in Figure 2.7 is ranked in order of the most important characteristics, (1: most important) after the proportionalisation had been performed on the data. This was done in order to investigate whether or not the order in which the data was presented had any major impact on the results in the Fuzzy-QFD approaches introduced and developed in chapters 3 and 4.

Occasionally the QFD team spends a lot of time arguing over which relationship to place in the corresponding cell in the relationship matrix. When symbols are not appropriate, an average between the group's opinion is the only solution and numerical values are substituted into the relationship matrix. This can be observed in Figure 2.6, in the cell linking customer demand '*Tidy Tip*' and engineering characteristic '*Pleasing Appearance*' which has been given a numerical value of '5' in this example. Although linguistic terms are the basis of human communications, when developing products often people agree more readily on numbers but not always on the meaning of words (Kalargeros and Gao, 1998).

The ranking results of the Independent scoring and the Proportional Distribution for the toothpaste example are firstly compared and depicted in Figure 2.8. The ranking is arranged by the most important characteristics ("*Cost to produce*", rank 1) using the Independent Scoring results to the least important engineering characteristic ("*Amount of Effort*", rank 11). There are slight discrepancies between the ranking order of these two traditional approaches. In this comparison the importance of the engineering characteristics changes, depending on which method is used, except for one engineering characteristic "*Time to Develop*", which has the same rank order. The larger the difference in ranking between two characteristics, the greater the change in rank order between the two methods: Independent Scoring and Proportional Distribution. Engineering characteristic, "*Counter Space*" resulted in the greatest difference between the two HOQs, a rank difference of 4 units. In the Proportional Distribution approach, the engineering characteristic "*Counter Space*" has become more important.

In this example, although the two methods yield different results, the differences are not so great as those seen in Figure 2.8, and so it can be deduced that the relationship matrix is relatively balanced.

As discussed in section 2.5.2, the Proportional Distribution HOQ results in a more proportionate distribution of the data, without distorting the data. The Independent Scoring HOQ may result in high scoring for characteristics with say, only one very strong relationship, as illustrated in Figure 2.10. The Proportional Distribution is thus a more favourable method, whilst more mathematically complicated.

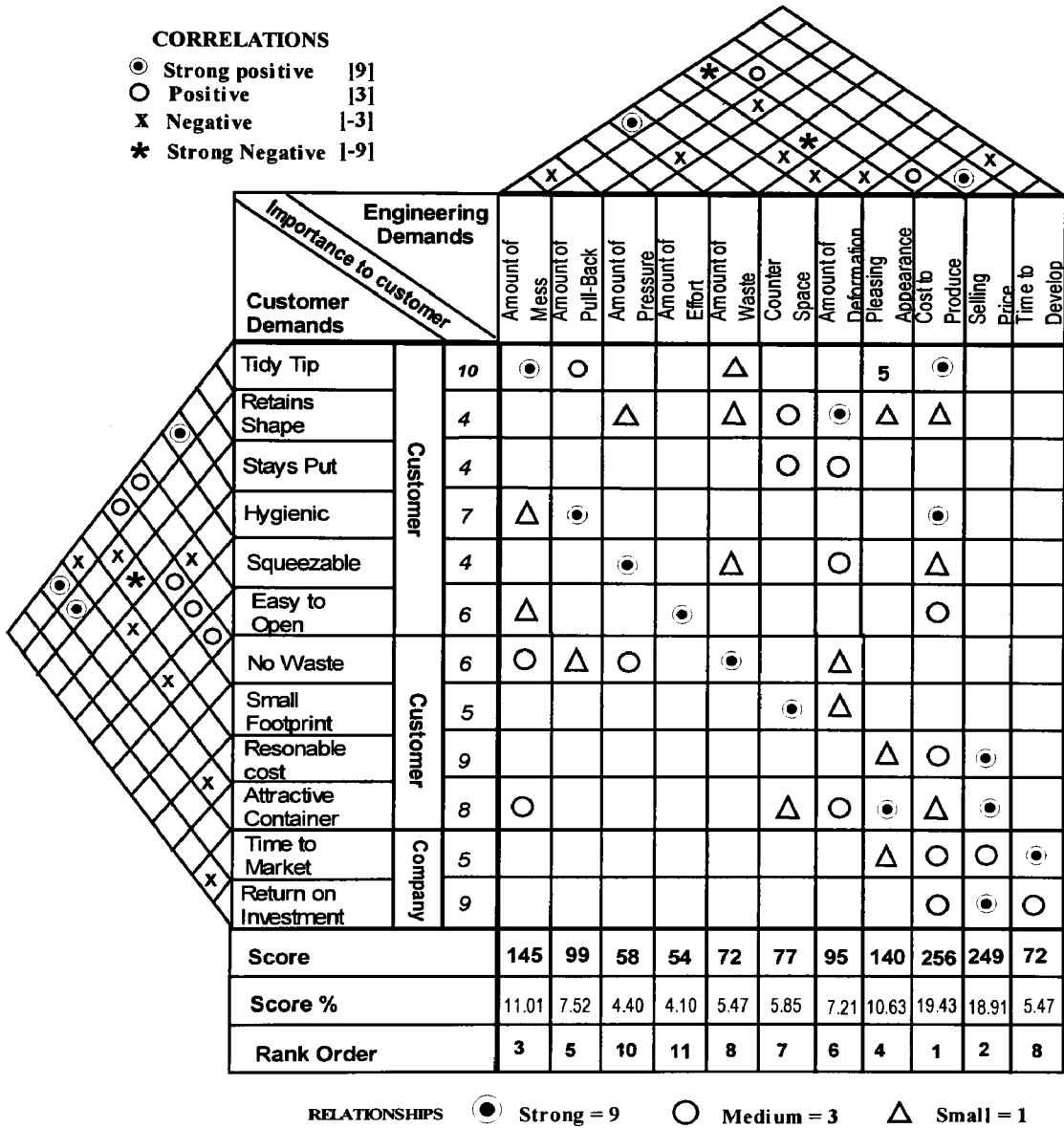


Figure 2.6 Independent Scoring HOQ (Bahill and Chapman, 1993) (Used with permission)

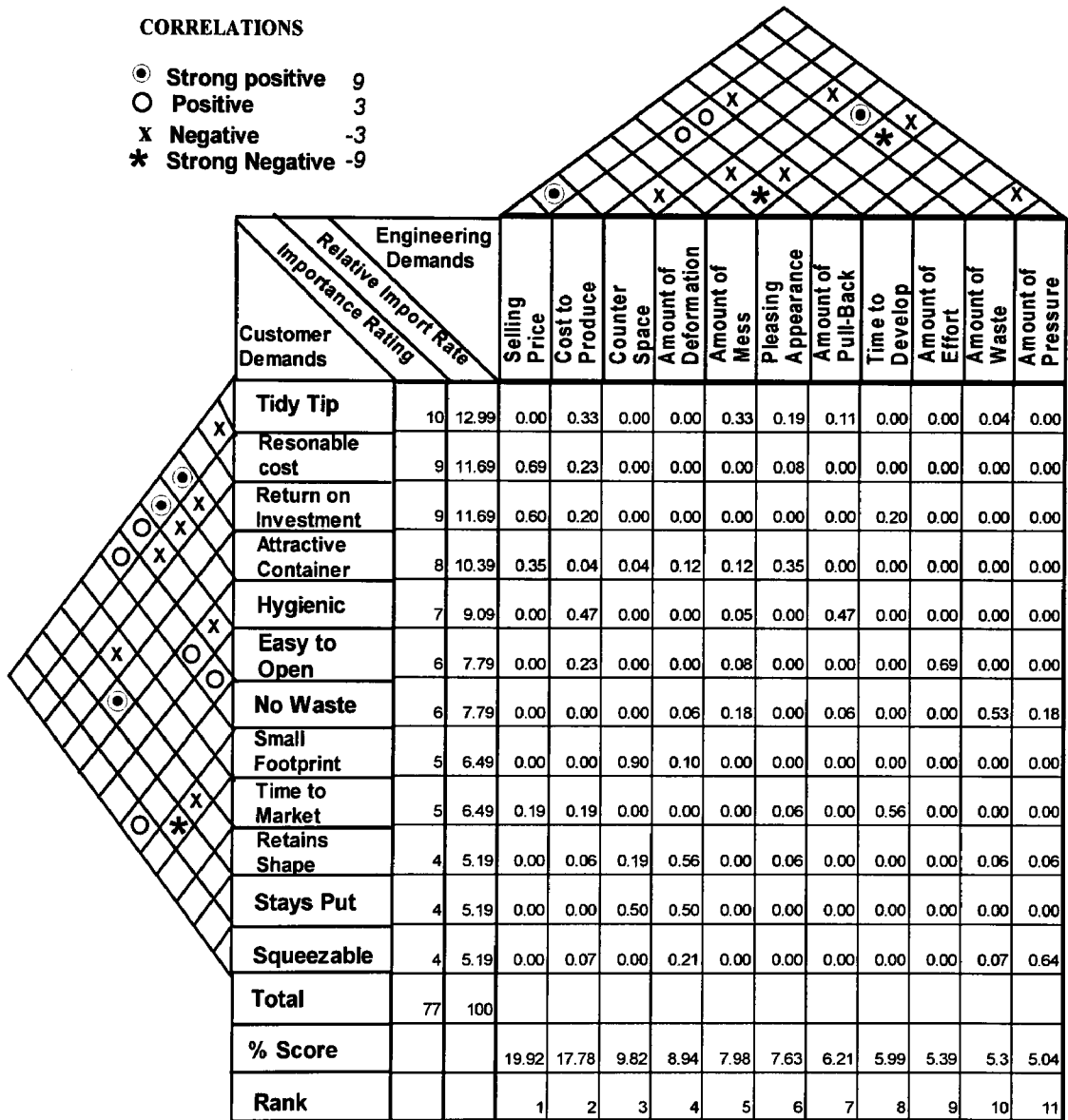


Figure 2.7 Independent Scoring results are proportionalised to give the results of the Proportional Distribution HOQ

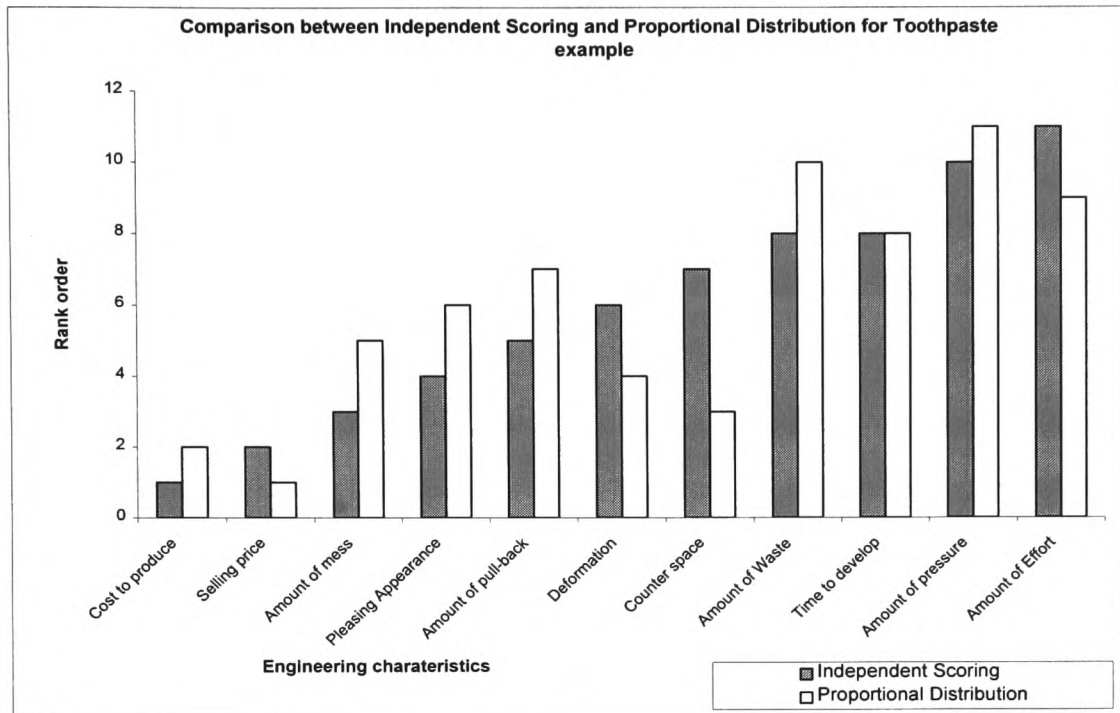


Figure 2.8 Independent Scoring versus Proportional Distribution for the design of the toothpaste tube example

If the HOQ for the toothpaste tube example in Figure 2.6 is scrutinised, the customer demand “*Retains Shape*” has no relationship with engineering characteristic “*Amount of Pull-Back*”. In actual fact the amount the tube pulls back will have an effect on whether or not the tube retains its shape, in the authors opinion. Another case is customer demand “*Squeezable*” with engineering characteristic “*Amount of effort*”, they have no relationship, but in reality in order to squeeze the tube effort will be needed. The customer demand “*Retains shape*” has a weak relationship with engineering characteristic “*Pleasing appearance*”, but in actuality, if the shape of the tube is changed, then appearance will also change and so they should be strongly related to each other. If the porch area is examined, the customer demand “*Tidy Tip*” has a strong positive correlation with say customer demand “*Attractive Container*”. If the relationship matrix is now inspected, these two customer demands have opposite relationships with say, engineering characteristic “*Selling Price*”. If these two customer demands are strongly related to each

other, it is logical to assume that they would affect the same engineering characteristic, maybe not exactly in the same way, but not so differently as in this case.

The customer demands and the engineering characteristics often exhibit coupling (interaction) between them. The interactions between the customer demands in the porch area and that of the engineering characteristics in the roof area are not normally utilised to determine relationships in the HOQ matrix. During the analysis of the traditional HOQs, it is noticeable that some of the relationships in the relationship matrix are either missing, or are given a lower or higher relationship weighting than they should. As a result there is a necessity to integrate QFD with other more formal, quantitative approaches that would take into account these interactions to better define the subjective data in the HOQ. Fuzzy Logic/Fuzzy sets and the Taguchi Method are proposed to do just that and they are introduced and integrated with QFD in chapters 3 and 4 and chapters 5 and 6 respectively.

2.5.3 Variations of the QFD charts

The QFD process and the QFD charts have been found to be very flexible and can be tailored to individual companies to suit their particular application and needs. None of the standard QFD processes explained in section 2.5, are extremely rigid. Many companies have established their own QFD process that fits in with their needs (Hales *et al*, 1996). More than 80 versions of the matrices and charts have been identified in the QFD method (Wolfe, 1994). Some of the items that have been used for the customer demands (WHATs) and the engineering characteristics (HOWs) include customer demands, quality characteristics, product characteristics, manufacturing processes, quality controls, functions, alternatives, parts, components, mechanisms, product failure modes, part failure modes and new concepts. Just with these 13 items, more than 100 matrices could be formed (Bahill and Chapman, 1993). Quality technologies must often incorporate

business technologies, cost technologies, engineering technologies, human technologies, mathematical technologies, or system technologies, to be fully functional (Bicknell and Bicknell, 1995). QFD addresses all issues related to quality as defined by the customer and as a result, has many deployments (subsystems), such as Customer Deployment, Task Deployment, Schedule Deployment, Technology Deployment, Cost Deployment, Reliability Deployment, etc. Each deployment can be thought of as a tailored series of tools and techniques for dealing with one aspect of quality-as-defined-by-the-customer. Not all of these matrices are useful: King (King, 1989) explains 30 of them that are in common use. However, all the QFD methods have the "House of Quality" in common as one of their charts.

As simple as the HOQ chart appears, between seven to nine steps have been identified to complete it. It is not an easy task when done manually. A QFD exercise generates a large amount of information. As a response to the laborious and tedious efforts to implement it manually, various computer packages ranging from a simple spreadsheet, such as excel charts (Graetz, 1996), to more advanced software packages, such as QFD/CAPTURE (International Technegroup, 1990), QFDplus (Ford Motor Co., 1991) and QFD Designer (Qualisoft/Fulfillment Services, 1989), have been developed for automating the QFD process. These computer packages provide graphical interfaces and simple calculations. For more rigorous and complex calculations other computer programs needs to be developed (Wolfe, 1994), (Liu and Jia, 1998).

In the HOQ, there are a number of variations that can be used. Traditionally, the importance rating is scaled from 1 (low) to 5 (high). On some projects, the scale is changed to 1 (low) to 10 (high) when finer breakdown is needed. Other teams have even used negative scales for the customer importance rating, a -1 (negative impact) to a 5 (very high value). Some others link the numbers with words such as 1-not important, 2-

somewhat important, 3–important, 4–very important, and 5 – if not there, I will not buy the product (Bossert, 1991). In defining the relationship scales other than the logarithmic and linear scale described in Appendix A1, step 5 can be used, such as: 9-extremely strong relationship, 7-very strong, 5-strong, 3-medium, 1-weak, 0-none, blank-not evaluated yet, ?-need more data to evaluate. These intermediate values are encouraged if the person making the judgement feels they can make such fine distinctions as well as if the individual being questioned has enough expert knowledge. It is believed that in reality most people can handle 1-3 or 1-5 scales comfortably (Polinghorne, 1984). These relationship representations have fuzzy meanings in themselves. The meanings of the words ‘strong’, ‘medium’ and ‘weak’ may have different meanings to different people, therefore ambiguity and vagueness is further introduced in the QFD process.

Although symbols enhance visual comprehension, they are finally substituted by numerical values to calculate the final technical weighting. The symbols used in the HOQ often compromise accuracy which forces team members to cave in and accept one of the standard scales, therefore substituting these symbols with their numerical equivalent is not of great loss. Sensitivity analysis has been performed (Xie *et al*, 1998), (Shen *et al*, 1999) to test the robustness of the QFD model by choosing different scales for the relationship matrix and it has been found that the rank order of the technical characteristics generally does not change much. That is, the most important characteristics still remain the most important characteristics. So in fact, it does not matter which scale is used as long as it is consistent and used according to the customer’s expert knowledge of the product/process. If the customer has high domain knowledge, then a finer scale is advisable otherwise a smaller scale is more realistic.

Traditionally in defining the engineering characteristics (HOWs), measurable quantities are looked at. Other applications require different characteristics, for instance in

developing services, different services that the company provides their customers may be looked at (Bossert, 1991). These are often reflected in the various extensions to the basic QFD process. This makes it important to understand the dynamics in an organisation before implementing QFD (Nilsson *et al*, 1998) since there is not an exact format to follow when developing a QFD charts.

2.6 BENEFITS AND DRAWBACKS OF QFD

Companies who have attempted to implement QFD have reported a variety of benefits and problems with the method (Akao, 1990), (Bahill and Chapman, 1993), (Bossert, 1991), (Griffin, 1991), (King, 1987), (Nichols, 1992), (Eureka and Ryan, 1994), (Wolfe, 1994), (Zairi, 1993). Table 2.1 summarises the major tangible benefits of QFD, whereas Table 2.2 lists the intangible ones.

Despite the many reported benefits of QFD, it is not a simple technique to use. Companies who have attempted to implement it in their business operations have reported a few problems. Some are related to the level of knowledge and understanding of the technique itself. Some are related to the fact that QFD has been found to be incompatible with existing cultures, which tends to be primarily functional oriented, where activities are driven by individual contributions. Some of QFD's inherent drawbacks (Blumstein, 1996), (Eureka and Ryan, 1994), (Guinta, 1993), (Yoder and Mason, 1995), (Zairi, 1993) are listed in Table 2.3. The implementation of QFD requires significant initial investment, for example in training, time and market research. Expecting to reap the benefits after just one project may limit QFD's ability to affect future product development.

Instead of choosing not to implement QFD based on some of the drawbacks highlighted in Table 2.3, the product development team should evaluate the strengths and weaknesses of their current product development processes and decide whether QFD could be a

beneficial method for their projects. The foundation of an effective QFD project is commitment. An organisation that wants to use QFD has to believe in it. When QFD falls short of delivering expected returns, the finger is quickly pointed at the QFD method itself. If there has been a QFD failure, most often it is not one of the QFD method itself, but that of implementation (Blumstein, 1996).

Benefits of QFD - Tangible
<ul style="list-style-type: none"> • Comprehensive Documentation of the Design Process, • Shortened Time to Market, • Reduction in Design Changes, • Quantifies customer requirements, • Methodical analysis of the relationships of product characteristics and customer needs, • Encourages the experts to quantify their expertise and resolve conflicting requirements using data, • Lower production cost – problems identified early, • Shorter product development times, • Fewer problems with product on the market, • Waste elimination through minimising number of design changes, • Improved productivity through improved equipment design quality, • Prioritisation of customer requirements, • New understanding of own competitive position, • Shift of major design changes to the early stages of the development process, • More alternatives can be considered, • Increased sales, • Improved product development process resulting in better products, • Reuse of results from prior projects, • Decisions regarding product manufacture and design are made earlier in the cycle, • Reduced number of engineering bottleneck, • A practical method, • Structured and systematic product development, • Achievable business target, since they are based on excellent understanding of customer requirements and strong information system, • Focuses on target value instead of only on meeting tolerance specifications, • QFD becomes part of TQM, • Break down of broad objectives, • Reduction in customer complaints.

Table 2.1 Tangible benefits of QFD

Benefits of QFD - Intangible

- Documents true customer needs,
- Increased customer satisfaction,
- More successful product launches,
- Facilitates information processing and communication among department,
- Builds knowledge as work is documented,
- Better communication between company and customers,
- Unity in the QFD group, the team interprets the customer needs in the same way,
- Rational decisions can be made by the team,
- Improved ability to innovate, not tied to one technology,
- Identification of 'holes' in the current knowledge of the design team,
- Stop designers and business planners guessing what the product should look like,
- Constant focus on customers during product development,
- Understanding, consensus, and decision making, especially when complex relationships and trade-offs are involved,
- Increased understanding of complex relationships,
- Greater clarity of organisational and programme priorities,
- Fewer product/service changes,
- Ensures consistency between the planning and the production process.

Table 2.2 Intangible benefits of QFD

Drawbacks of QFD

- Large amount of time necessary to complete the HOQ,
- QFD charts can become large and complex and have a tendency to grow larger, (15 customer demands and 20 engineering characteristics equals 300 relationships),
- Voice of the customer, too ambiguous, too many, and have mixed demands,
- Risks of letting the method have a conserving effect on product development activities,
- Too much chart focus – the charts are simply the documentation process,
- It is necessary to spend time building the team and provide them with appropriate team skills,
- Difficult to communicate results to non-QFD users,
- Difficulties of interpreting results of the HOQ,
- Difficulties to go beyond the HOQ,
- The HOQ alone is not enough. Teams still need to carry out the work,
- Engineers think that QFD is too focused on the mechanics of scoring,
- Team members get caught up in the details of the exercise while the market window closes on them,
- Failure to integrate QFD – often QFD is seen as an "after event" documentation and not integrated properly into the project,
- Correlation between requirements and identification of target values are performed on a rather subjective basis,
- QFD is a very qualitative and subjective method,
- Need to use other tools to help QFD.

Table 2.3 Drawbacks of QFD

2.6.1 Uses of QFD

QFD is simply a method and should be applied when appropriate. QFD can prove very useful (Hutton, 1997) when:

- Customers are complaining or are not satisfied with the product, service or software.
- Market share has been consistently declining.
- Development time is extended due to excessive redesign and solving problems.
- There is a lack of true customer focus in the product development process.
- There is poor communications between departments or functions.
- There is a lack of structure to the way resources are allocated.
- There is a lack of efficient and/or effective teamwork.
- Current design methods do not facilitate predictions of performance with respect to competitive products, or prediction of customer satisfaction with the product.
- There is scope for significant improvement, in the customers' eyes, through refinement or 'fine tuning' of the current product or service.
- There are complex interrelationships, synergies and trade-offs between different design characteristics.

QFD is particularly useful for complex systems, where there are multiple customers and users, conflicting user priorities, multiple feasible solutions, conflicting potential solutions, and multiple disciplines involved. Since QFD can rank and prioritise both qualitative and quantifiable features it is an excellent method for designing new products services, or systems. QFD is even better for improving existing products or systems (Brown, 1991).

Indeed the most spectacular use of QFD in literature was in the automotive industry (Bahill and Chapman, 1993), (Dika, 1990), (Voegelé, 1993). More recent applications

have been in the service sector, such as in hospitals (Radharamanan and Godoy, 1996), customer service (Graessel and Zeidler, 1993), educational establishments' (Chen and Bullington, 1993), (Ermer, 1995), the software industry (Betts, 1990), (Eriksson, 1993), (Zultner, 1990), hardware industry (Sullivan, 1986) and the building industry (Laurikka *et al*, 1996). QFD has also been used in other applications not categorised under the other terms listed so far, such as increasing employee morale (Ekstrom, 1993). The most recent intriguing application of QFD has been the design of a Jurassic theme park in Florida (Bolt and Mazur, 1999). Green QFD (GQFD) is a new method for product development (U.S. Department of Energy, 1997) that integrates Life Cycle Costing and Life Cycle Assessment into QFD matrices and deploying environmental requirements, costing requirements and customer requirements throughout the entire product development process. Both costs and environmental impacts in every stage of the life cycle of a product or process can thus be considered.

Figure 2.9 summarises the use of QFD within different areas of industry in Sweden (Ekdahl and Gustafsson, 1997). Although Figure 2.9 represents the Swedish experience, it is likely in the authors' opinion that it is representative of the world-wide trend, especially in countries with similar economic backgrounds. The sectors with the highest penetration of QFD in Sweden are in the manufacturing industry (41%), auto (13%), whitegoods (13%), telecommunications (10%) and electronics (10%). Other sectors (13%) include building, medical equipment, service and software applications.

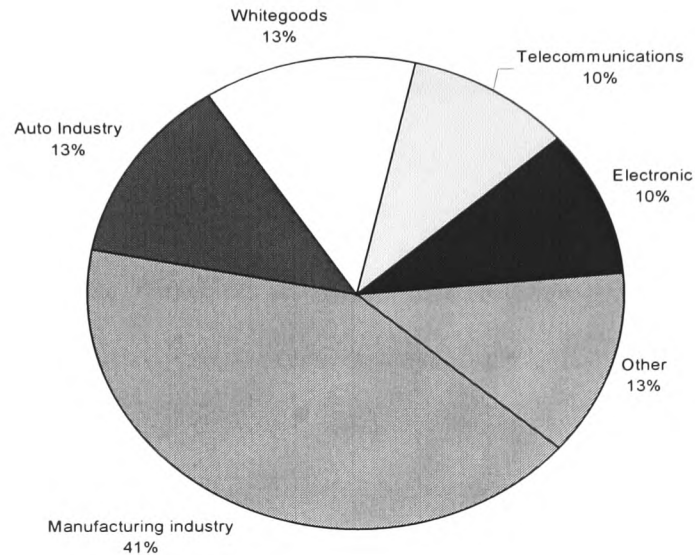
QFD in different industry sectors

Figure 2.9 QFD's application in the Swedish Industry (Ekdahl and Gustafsson, 1997)

2.7 REMARKS

The ultimate objective of QFD is to create value for the customer. QFD holds great promise for a better definition of customer demands and a systematic method to meet them. Significant educational and organisational changes are needed to fully implement its concepts in order for the benefits to be realised. This may prove difficult for companies that need quick solutions. Therefore for the full benefits of QFD to be realised, a long-term view is needed and possibly a cultural change. Part of the reason for its unpopularity may be because it is a tool that challenges working culture, which is functional in nature and puts the customer back into the production process.

Some of its inherent drawbacks (Table 2.3) have hindered its wide applications and acceptance in industry. Although many companies in different sectors have used it, QFD has not yet found popularity as a design technique. However its use is appropriate for organisations of any size. QFD is simply a method and it may fail in many situations to deliver what was promised and like other methods, it will only be as good as the people using it.

The research addresses some of its drawbacks and proposes the introduction of techniques and methods to overcome these problems.

2.8 SUMMARY

In this chapter, QFD has been introduced as a very useful method with many benefits. It has been identified to be a method that integrates well with existing quality tools and techniques and forms part of the Total Quality Management philosophy. It is very flexible and various extensions to its basic structure have been identified that can be adapted to specific projects. Its first phase, the product planning phase (HOQ), with its different steps is documented extensively in Appendix A and it is this phase that will be exploited throughout this thesis. It has been found that in the HOQ the interpretation of the ‘voice of the customer’ and the ‘voice of the engineer’ and the relationship and correlation between them is complicated due to ambiguity and vagueness. The strengths given to relationships are subjective and not well defined. Data can thus be distorted as shown by comparing the two traditional HOQs (Independent Scoring vs. Proportional Distribution) in section 2.5.2. The symbols used to define the relationships between requirements also adds an element of “fuzziness” to the QFD process as their linguistic meanings may be interpreted differently by different individuals. Demands are dependent on each other as highlighted in the porch and roof of the HOQ and there are inconsistencies in the data representing two demands that are related to each other. The QFD charts contain much

information and can be complex whereby some key issues can be overshadowed or even overlooked. Therefore the problems are:

- How can the ill-defined data in the HOQ be rectified?
- How can inconsistencies in the data representing two demands that are related to each other be detected and updated?
- How can interactions between demands help to rectify the inconsistencies and update the ill-defined relationships in the HOQ?

These are the sorts of problems that can be addressed by Fuzzy Logic/Fuzzy sets techniques, since they can deal with qualitative and vague data. Therefore, chapter 2 will investigate combining Fuzzy Logic/Fuzzy sets with QFD to identify and rectify inconsistencies in ill-defined data in the HOQ.

Chapter 3.

Fuzzy Logic/Fuzzy sets

and their integration

with QFD

“The closer one looks at the real-world problem, the fuzzier becomes its solution.”
~Lofti Zadeh~

Fuzzy Logic and Fuzzy set theory are Artificial Intelligence (AI) techniques, that enhance computer intelligence by making the computer reason more like human beings. Whereas most computers are limited to strict binary programming (0,1), fuzzy logic deals in shades of grey and partial truth. This chapter gives an overview of Fuzzy Logic and Fuzzy set theory. It then investigates the integration of these techniques with QFD and proposes two approaches that combine QFD with Fuzzy Logic/Fuzzy sets to determine the data in QFD's HOQ more precisely by considering interactions between demands.

3.1 INTRODUCTION

Various inputs, in the form of judgements and evaluations, are needed in the QFD charts as previously discussed in chapter 2. Normally the marketing department through questionnaires, interviews and focus groups collects these inputs. Often this gives rise to uncertainties when trying to quantify this information. The real world of work does not usually provide crystal clear solutions or black and white situations, so quality can be measured in some cases by hard logic data and others with qualitative or fuzzy information (Abbott, 1996). While hard logic data are important in giving feedback on the success of processes, it is the human resource in the work culture that gives meaning to the numbers. Creative, qualitative measurement is required in the varied world and culture. Fuzzy logic has great applicability to learning organisations in search of creative methods of measurement. In many circumstances, where hard logic ends is where fuzzy logic begins. At times, it is of value to integrate hard logic and fuzzy logic data, which gives a holistic view of the system.

As highlighted at the end of the preceding chapter, the interpretation of the ‘voice of the customer’ and the ‘voice of the engineer’ and the relationship between them is complicated due to ambiguity and vagueness. Furthermore the strengths that represent each relationship are subjective and as a result the analysis in the QFD process can distort the data. In addition, the symbols used to define the relationships and correlation between requirements also adds an element of “fuzziness” to the QFD process. As pointed out, in the QFD charts, interdependencies between requirements exist as identified in the porch and the roof of the HOQ. These interdependencies are useful to help detect inconsistencies between requirements that are related to each other and as a result, the ill-defined data in QFD’s charts can be rectified.

In order to reduce the uncertainty in the data collected in the QFD process, Fuzzy Logic and Fuzzy set theory are investigated as techniques to be integrated with QFD as they are useful techniques for dealing with linguistic and vague data. In this chapter, Fuzzy Logic and Fuzzy sets are firstly reviewed, then their integration with QFD, as proposed by other authors is discussed. Finally two proposed Fuzzy-QFD approaches are highlighted and the various steps to implement them are listed.

3.2 FUZZY LOGIC

Most of us have had some contact with conventional logic at some point in our lives. In conventional logic, a statement is either true or false, with nothing in between. This principle of true or false was formulated by Aristotle some 2000 years ago and has dominated Western logic ever since. Fuzziness primarily describes uncertainty or partial truth and offers a better way of representing reality. In fuzzy logic, a statement is true to various degrees, ranging from completely true through half-true to completely false (Zadeh, 1988). Notions like '*rather warm*' or '*pretty cold*' can be formulated mathematically and processed by computers. In this way an attempt is made to apply a more human-like way of thinking in the programming of computers.

Fuzzy logic uses human linguistic (words and sentences) understanding to express the knowledge of a system. This knowledge consists of facts, concepts, theories, procedures and relationships and is expressed in the form of *IF-THEN* rules. This technique is able to manipulate fuzzy qualitative data in terms of linguistic variables. Linguistic variables are characterised by ambiguity and multiplicity of meaning. Specifying good linguistic variables depend on the knowledge of the expert. For example, "Age" is a linguistic variable if its values are "*young*", "*not so young*", "*old*", and "*very old*" (Figure 3.1). In Fuzzy Logic theory, a linguistic variable can be a member of more than one group. For

instance a 30-year-old would belong to both the 'young' and 'not so young' age group to different degrees as seen in Figure 3.1.

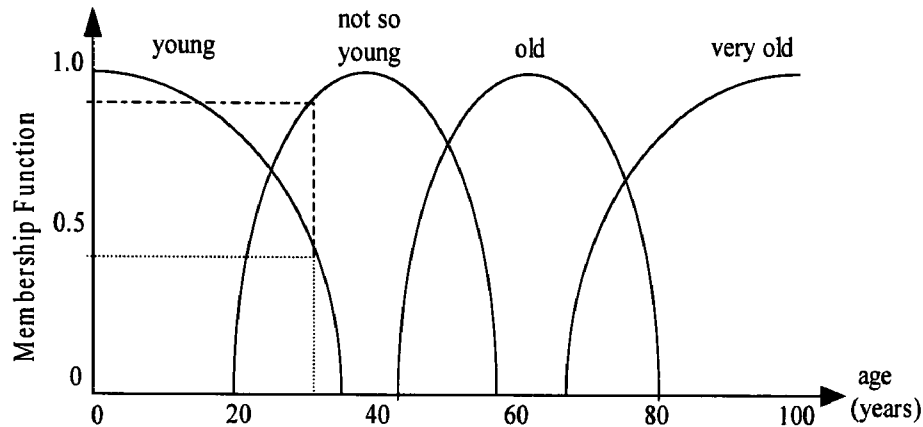


Figure 3.1 Fuzzy Logic representation of age

A collection of natural classification is used to describe the environment and occupy the human speech and thoughts. These include: [short, tall], [small, medium, large], [light, heavy], [bright, dim], [hot, cold], [frequently, seldom]. Modifiers are used to shade these classifications: [very, extremely], [rather, fairly, about, around], [moderately, close to, roughly]. Human beings possess the ability to reason with incomplete, vague, and ambiguous data to reach concrete decisions. This ability is called approximate reasoning. Fuzzy Logic allows the computer to think more like humans by giving them approximate reasoning capabilities (Heske and Heske, 1996).

Fuzzy Logic is a multi-valued logic that allows intermediate values to be defined between conventional logic like *yes/no*, *true/false*, *black/white*, etc (Yan *et al*, 1994). Similarly in QFD, the relationship 'weak, medium and strong' and the correlation 'strong or weak positive' and 'strong or weak negative' utilises multi-valued logic since the linguistic variables that represents these relationship/correlation are not crisp and can take

intermediate values. The basic idea of multi-valued logic has been explored to some extent by a number of mathematicians in this century, but the real breakthrough was made by Prof. Lotfi Zadeh of the University of California in Berkeley. In 1965 he published a paper on the theory of fuzzy sets (Zadeh, 1965). Zadeh, in his studies of complex systems, found that human interactions in organisations defy predictable behaviours and therefore, hard logic is not always an accurate way to track processes. He concluded that people reason in fuzzy terms: therefore qualitative measurement would be a more appropriate way to measure processes in the workplace. Fuzzy theory was adopted wholeheartedly by the Japanese and their advances in the field of fuzzy control have won the attention of engineers throughout the world.

3.3 FUZZY SETS

The mathematical foundations of Fuzzy Logic rest in Fuzzy set theory, which can be thought of as a generalisation of classical set theory. In mathematics, the concept of set is very simple, but very important. A set is simply a collection of objects. The objects can be almost anything - numbers, types of cars, etc. Objects either belong to the set or do not belong, similar to the idea in logic that statements are either true or false. A fuzzy set (Pedrycz and Gomide, 1998) is one to which objects can belong to a set to different degrees, called grades of membership, such that the transition from membership to non-membership is gradual rather than abrupt.

All elements in a fuzzy set contain two types of information: the degree to which the element belongs to the set and the relative standing of one element against others. In crisp sets however, the relative standing of elements does not exist since once an element belongs to the set, it does not matter where it stands in the set. A fuzzy set A can be expressed as:

$$A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n = \sum_{i=1}^n \mu_A(x_i)/x_i \quad (3.1)$$

The symbol / is called a separator. On the right of the separator an element of the set is written and on the left the membership value of the element in the set. Terms are connected by the + symbol. The function that ties a number to each element x of the universe is called the membership function $\mu(x)$. For a fuller explanation of equation (3.1), refer to Pedrycz and Gomide (Pedrycz and Gomide, 1998).

3.3.1 Membership Functions

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) and is two-dimensional. The horizontal axis contains the range of precise measurements. The vertical axis indicates the Degree of Membership (DOM) and is called the truth value axis. In practice the x-axis represents a continuous variable like temperature, pressure, humidity. However, the methods of fuzzy logic remain valid for discrete variables as well. The membership function name (short, tall) is referred to as the linguistic label. The membership function can be bell-shaped (π -curve), s-shaped (s-curve), reverse s-shaped (z-curve), triangular or trapezoidal. It should be wide enough to capture all of the meaningful range of that variable. Membership functions, (Pedrycz and Gomide, 1998) (Jantzen, 1991) can take interval values between 1 and 0 and is often shown inside straight brackets [1,0]. The higher the number, the higher the membership. The grade of membership is a subjective measure that depends on the context. A Membership Function “*Tall*” for instance should already take into account whether it refers to a 5 years old or an adult. Similarly the units are included in the curve. The input space is sometimes referred to as the universe of discourse. The universe of discourse for a fuzzy variable is defined as the range of crisp

values. The universe of discourse also depends on the context and contains all the elements of a fuzzy set.

3.3.2 Fuzzy Set Operators

When there are two or more fuzzy sets describing a problem, analytical solutions often require operations among fuzzy sets. Set operations such as 'union' (A OR B), 'intersection' (A AND B) allow constructs that are of utmost importance in any situation involving information and data processing since they help predict the outcome of long sentences. A fuller explanation of fuzzy operators can be found in (Bandemer and Gottwald, 1995), (Jantzen, 1991), (Pedrycz and Gomide, 1998), (Zadeh, 1965).

3.4 RELATIONSHIP BETWEEN FUZZY LOGIC AND FUZZY SETS

In addition to the mathematical link between Fuzzy Logic and Fuzzy sets, another way to understand the relationship between them is to examine natural language (Klir and Yuan, 1995). The use of natural language forms the backbone in the QFD process as it used to express the VOC. Expressions in natural language such as '*she looks young*' or '*she exercises a lot*' are only phrases. When they are put together in some order, a context is created that leads to reasoning. E.g. the combination of '*she looks young, she exercises a lot*' creates a context in which looking young and exercising become related. These are known as unconditional statements. Furthermore is the combination of simple expressions using linguistic connectors (operators) such as '*If she exercises a lot then she will look young*'. The *If-Then* connectors have modified the context and make it a conditional statement. In daily conversation and mathematics, sentences are connected with the words *and, or, if-then (implies), and if and only if*. These are called connectives (Jantzen, 1991).

3.4.1 Fuzzy IF-THEN Rules

A rule is normally composed of an *IF* portion and a *THEN* portion. Using the *IF-THEN* syntax of fuzzy rules eliminates the intermediate and time-consuming step of translating our knowledge into mathematical equations, Boolean decision trees, or computer software. The *IF* portion of a rule is a series of patterns which specify the facts (or data) that cause the rule to be applicable (Bandemer and Gottwald, 1995), (Zadeh, 1988). The *IF* portion of a rule can actually be thought of as the ‘whenever’ portion of a rule since pattern matching always occurs whenever changes are made to facts. The *THEN* portion of a rule is the set of actions to be executed when the rule is applicable. Fuzzy *IF-THEN* rules are often employed to capture the imprecise modes of reasoning that play an elementary role in the human ability to make decisions in an environment of uncertainty and imprecision. These rules are often provided by experts or can be extracted from numerical data. A fuzzy *IF-THEN* rule takes the form:

$$IF\ x\ is\ A\ THEN\ y\ is\ B \quad (3.2)$$

"x is A" is called the antecedent or premise whereas "y is B" is called the consequence or conclusion. Examples of *IF-THEN* rules are common in our daily linguistic expressions, such as:

- If the road is slippery then driving is dangerous.
- If acceleration is high then the car's speed will increase.
- If the tomato is red then it is ripe.

3.4.2 Fuzzy Inference

Fuzzy Inference is the process of formulating the mapping from a given input to an output using Fuzzy Logic. In order to draw conclusions from a rule base, a mechanism called the inference engine, which produces an output from the collection of *IF-THEN* rules, is

utilised. The inference engine selects a rule and then the actions of the selected rule are executed (which may affect the list of applicable rules by adding or removing facts). The inference engine then selects another rule and executes its actions. This process continues until no applicable rules remain. Figure 3.2 shows an example of a fuzzy inference system for the amount of tip to give in a restaurant depending on the quality of food and service. Information flows from left to right. The parallel nature of the rules is one of the more important aspects of fuzzy logic systems.

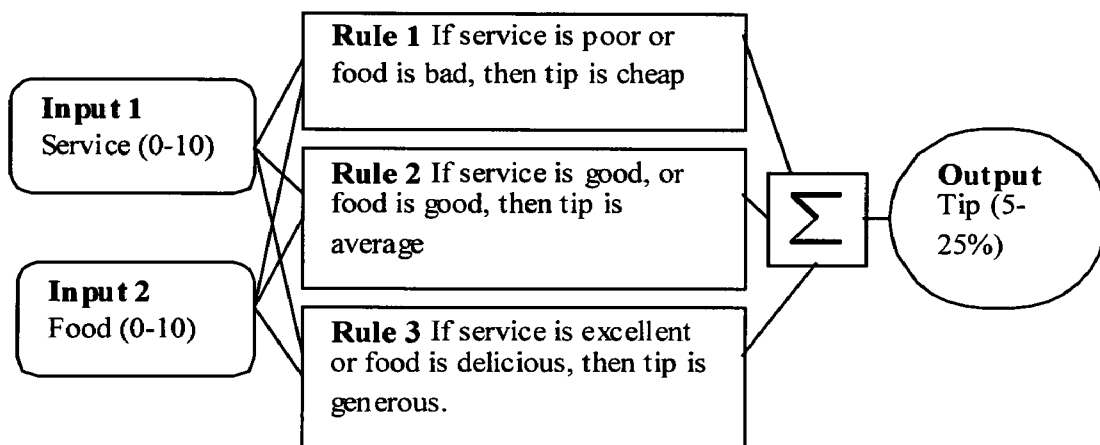


Figure 3.2 Example of a Fuzzy inference system

A fuzzy inference system employing fuzzy *IF-THEN* rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses (Klir and Yuan, 1995). The process of fuzzy inference involves membership functions, fuzzy logic operators and *IF-THEN* rules. There are two types of fuzzy inference systems: Mamdani-type and Sugeno type (The Mathworks, 1995). The Mamdani type expects the output membership functions to be fuzzy sets. Sugeno type systems can model any inference system in which the output membership functions are either linear or constant. In this case, the premise is a classical fuzzy set expression which

indicates a fuzzy subspace and the consequence is a functional relation, usually a linear function or a singleton which indicates the input-output relationship in this fuzzy subspace (Takagi and Sugeno, 1985). The latter type of inference system is employed in this thesis because in the output it does not require the use of membership functions. In the Fuzzy Proportional Distribution QFD approach developed (section 3.9), the input is a Fuzzy s-shaped membership function, but the output is the weighted average.

3.4.2.1 Steps in building a fuzzy inference system

The different steps to build a fuzzy inference system are listed below and outlined schematically in Figure 3.3.

Step 1: Knowledge acquisition

There are generally three sources of solutions;

- articulated expertise, such as explaining how to ride a bike,
- recorded performance data, such as the operation of a machine,
- mathematical formula.

These three sources indicate three domains of knowledge representation: natural language, numerical data and mathematical formula. This knowledge needs to be translated (knowledge acquisition) into the language of fuzzy inference in the form of *IF-THEN* rules.

Step 2: Fuzzify inputs

Fuzzification is the procedure by which the information provided by a crisp number or symbol is spread to its vicinity so that the close neighbourhood of the crisp number can be recognised. It enables computations in the grey areas not explicitly defined by crisp entities. For instance, the weather temperature of 30 °c can be transformed into a fuzzy set

called nice weather using a fuzzification technique so that temperatures around 30 °c would be associated to the phrase nice weather. To fuzzify the inputs is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The input is always a crisp number limited to the universe of discourse of the input variable and the output is a fuzzy degree of membership in the linguistic set (always in the interval between 0 and 1).

Step 3: Apply Fuzzy Operator

If the antecedent of a given rule has more than one part, the fuzzy operator (AND, OR, ELSE) is applied to obtain one number that represents the result of the antecedent for that rule. This number will then be applied to the output function.

Step 4: Aggregate (Combination) all outputs

Since decisions are based on the testing of all of the rules in a Fuzzy Inference System, the rules must be combined in some manner in order to make decisions. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set by means of either a union (OR) or an intersection (AND) operation.

Step 5: Defuzzify

Combining two or more fuzzy output sets (or Membership Functions) yields a new fuzzy set (or a new Membership Function) in the fuzzy inference algorithm. In most cases, the result in the form of a fuzzy set is converted into a crisp result by the defuzzification process. The most commonly used defuzzification methods are the centroid (centre of gravity, centre of weights, etc) and maxima (mean of maxima, maximum possibility, etc) (Klir and Yuan, 1995).

The following is a summary of how to develop a fuzzy model from concept to implementation:

- *System description*: Describe in words how the system should work. Identify the inputs, outputs and their relationships.
- *Specify the input and output variable ranges*: Identify extreme ranges of all inputs and outputs. Define the universe of discourse for all fuzzy variables.
- *Membership function partitioning*: partition each fuzzy variable into overlapping membership functions. Decide on number, shape, location, symmetry and overlap.
- *Rule writing*: Construct *IF-THEN* rules. Write the obvious rules first. Then write the less obvious, but intuitively correct rules. Select intersection, inference, aggregation and defuzzification methods based on the constraints of computational speed, memory use and information preservation.
- *Simulation and tuning*: Adjust Membership Functions and rules to achieve desired model performance. Computer simulation and/or testing on the target system may be necessary.

3.5 USES OF FUZZY SYSTEMS

The use of natural language in man-machine interface instead of using machine-specific language has great advantages in practice. Since computation with words is possible, computerised systems can be built by embedding human expertise expressed in daily language. The majority of fuzzy systems built to date are in process control, signal processing, image processing, operations research and in diagnostics. Some of the applications of fuzzy systems (Klir and Yuan, 1995), (Mendel, 1995), (Pham *et al*, 1992) are listed in Table 3.1 in an attempt to show the vast usage of such systems. These products/processes are examples of listening and attending to certain customers' needs. These are typical situations where QFD can be useful since the data are in linguistic, qualitative format. Fuzzy Logic can then be used to develop these products/processes.

Typically, a fuzzy system uses human friendly commands, embodies expert knowledge, yields robust performance and requires reasonable computation time and effort. Fuzzy logic is conceptually easy to understand and is flexible as it is easy to add functionality on top without starting again from scratch. It is tolerant of imprecise data since it builds this understanding into the process rather than adding it at the end. It can model non-linear functions of arbitrary complexity (Jantzen, 1991). It can be built, using experiences from the experts and is based on natural language, which is the basis for human communication.

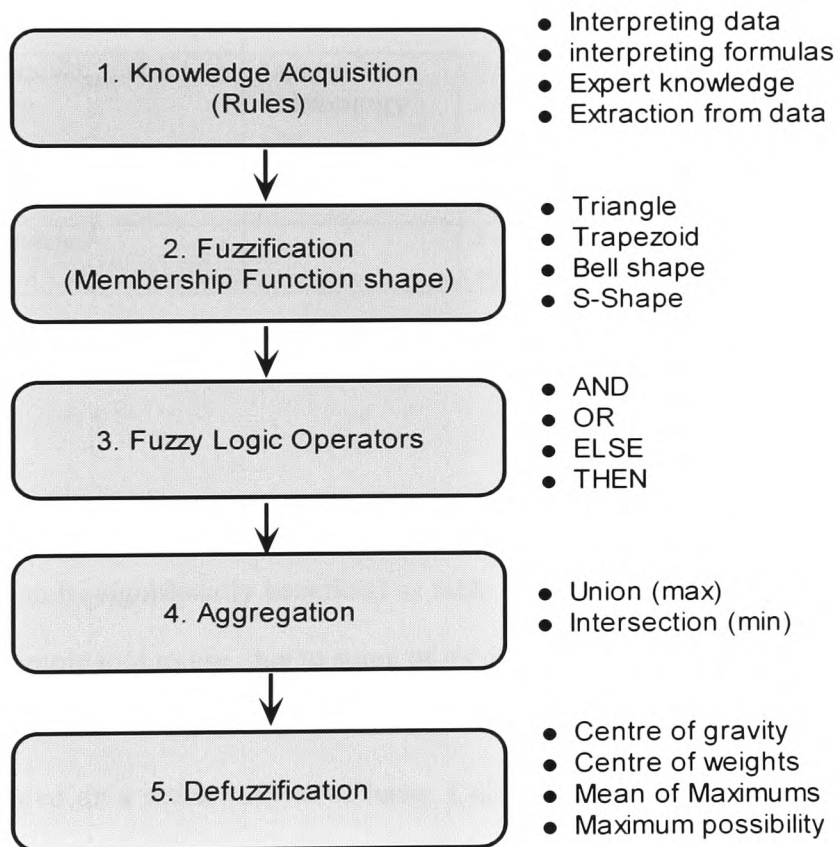


Figure 3.3 Steps in a Fuzzy Inference System

Product/Process	Company	Fuzzy Logic Role
Anti-lock brakes	Nissan	Controls brakes in hazardous cases based on car speed, wheel speed and acceleration.
Photocopy Machine	Canon	Adjusts drum voltage based on picture density, temperature and humidity.
Dishwasher	Matsushita	Adjusts cleaning cycle and rinse-and-wash strategies based on the no. of dishes, type and amount of food on the dishes.
Vacuum cleaners	Matsushita	Automatic motor-control for vacuum cleaners detecting the surface and amount of dirt.
Refrigerator/ Freezer	Sharp, Whirlpool	Sets defrosting and cooling times based on usage. A neural network learns usage habits and tunes fuzzy rules accordingly.
Palmtop computer	Sony	Recognise hand-written characters.
Golf Diagnostic System	Maruman Golf	Selects golf club based on golfer's physique and swing.
Stock trading	Yamaichi	Manages portfolio of Japanese stocks based on macroeconomic and microeconomic data.
Earthquake prediction system	Japanese Seismology Dpt.	Prediction system for early recognition of earthquakes.
Health Management	Omron	Tracks and evaluates employees' health and fitness.
Economics		Fuzzy modelling of complex marketing systems, cost-benefit analysis.

Table 3.1 Some practical application of Fuzzy systems

3.6 INTEGRATING FUZZY LOGIC AND FUZZY SETS WITH QFD

QFD can be significantly beneficial as table 2.1 and 2.2 of chapter 2 highlighted, but it is not a simple tool to use, due to some of its drawbacks, such the complexities of its charts, the vagueness in the data collected and the correlation between requirements, which is performed on a rather subjective basis. Capturing, analysing and understanding genuine customer requirements is the start of gaining satisfied customers. Customer attributes, the 'Voice Of the Customer' (VOC), tend to be linguistic and normally non-technical in nature. The adjectives in particular are not specific. *'The product must be able to last for a long time'* and *'part size must be small'* are some examples. Sometimes it is difficult for engineers to translate the VOC into specific product/process and engineering

specifications. Customer attributes might come from different customer groups in different market sectors through various means (Jantzen, 1991). A QFD team then decides on the interpretation of this VOC. The process of interpreting customer attributes is further complicated by the ambiguity, vagueness and imprecision natural in the VOC due to various reasons (Fung *et al*, 1998) such as:

- Not enough understanding or knowledge of the product, the product design or the technology used,
- Imprecision in describing the problem,
- Distortions or misinterpretation of data,

Owing to the combination of these factors, the interpretation of the linguistic VOC into some definitive engineering characteristics will involve certain transformations. The VOC usually comes in qualitative forms and is quite fuzzy with no concrete mathematical rules denoting relationship and correlation between the different demands. However their performance measures and other associated data should as far as possible be expressed quantitatively to facilitate further downstream analysis. Traditionally, the HOQ process has been seen mainly as conceptual and descriptive. Well-constructed quantitative methods have infrequently been used (Chan and Wu, 1998).

Complexities and vagueness are present in the development of the relationship and the correlation matrices in QFD (Temponi *et al*, 1999). Some of these drawbacks of QFD prompted an investigation into ways to determine the relationships in the HOQ more precisely using Fuzzy Logic and Fuzzy set theory. The next sub-section highlights some work done by other authors to integrate QFD and Fuzzy Logic/Fuzzy sets and proposes ways to further integrate QFD with Fuzzy Logic/Fuzzy sets.

3.6.1 Literature review of the use of Fuzzy Logic/Fuzzy Sets in QFD

Work has been carried out by other researchers using Fuzzy Logic and Fuzzy Sets to fuzzify the relationship (weak, medium, strong) to a fuzzy range matrix (Khoo and Ho, 1996). They have also been used to update the correlation matrix and detect inconsistencies in requirements (Liu and Jia, 1998), (Temponi *et al*, 1999). Furthermore fuzzy or crisp numbers have been utilised to compute and update the relationship matrix (Masud and Dean, 1993), or to compute and map out the desired target values in QFD (Fung *et al*, 1998). A fuzzy outranking approach to prioritise design requirements has been developed by Wang (Wang, 1999) and the use of fuzzy set theory to derive an overall customer satisfaction index has been documented by Wasserman, Mohanty, Sudjianto and Sanrow (Wasserman *et al*, 1993).

Khoo and Ho's (Khoo and Ho, 1996) approach is based on possibility theory and fuzzy arithmetic for the QFD analysis. Symbols, which represent the customer demands and engineering characteristics (weak, medium, and strong), are used to fill the relationship matrix and build the HOQ. The symbol descriptions are normally in the form of linguistic variables. These linguistic variables are first translated into fuzzy numbers as shown in Table 3.2. Instead of using exact values, ranges of values, which are more natural, are used to represent the vagueness in these three relationships, that is "weak", "medium" and "strong". The approach can handle both linguistic and crisp variables. The resultant ratings are expressed in terms of ranges of values.

Linguistic Variables	Fuzzy Number
Strong relationship	[4.0, 10.0]
Moderate relationship	[2.0, 8.0]
Weak relationship	[0.0, 6.0]

Table 3.2 Definition of linguistic variables (Khoo and Ho, 1996)

Liu and Jia (Liu and Jia, 1998) have proposed the use of Fuzzy Logic to detect inconsistency in requirements and to infer implicit relationships between requirements using Fuzzy inference rules. The approach helps to detect implicit trade-offs and impact relationships and maintain their consistency. The degree of a relationship must be a positive integer in the range 1-10. A database system was also developed to enable automatic archiving and management of the HOQs, saving the QFD team tremendous effort in handling large amount of data and knowledge. The approach only uses fuzzy inference rules to determine the output, but is not clear how the rules are developed.

Temponi, Yen and Tiao (Temponi *et al*, 1999) have developed a fuzzy logic-based extension to the HOQ for capturing imprecise requirements and have developed a heuristic inference scheme to reason about the implicit relationships between requirements. Their approach utilises the relationship in the relationship matrix of the HOQ to infer implicit correlation in the roof of the HOQ. Therefore, it is assumed that the relationship matrix data is defined correctly by the QFD team.

Masud and Dean (Masud and Dean, 1993) report the result of an enquiry on how the QFD analysis can be performed when the input variables are treated as linguistic variables with values expressed as fuzzy numbers. The reason for this consideration is that human judgement; perception and cognition are often ambiguous and are better represented by fuzzy numbers. In their paper, it is assumed that relationships are linguistic variables that have values such as weak, medium, strong. Two propositions for using fuzzy sets in QFD were developed in their study. In the first approach they developed scales, fuzzy numbers that try to mimic the numeric (1-3-9) scales of the standard QFD (Masud, 1992). The fuzzy numbers are first converted to their equivalent crisp scores and then the QFD calculations are carried out using these crisp scores. The results of this approach are crisp numbers. This approach is suggested to be used when dealing with one QFD chart that

deals with large number of rows and columns. In the second approach the QFD team would develop the measurement scales (weak, medium, strong) to fit the specific application (Masud and Dean, 1993). In this approach all the QFD calculations are performed with fuzzy numbers and the outputs are also fuzzy numbers. Triangular membership functions are used to represent the fuzzy variables (weak, medium, strong). This approach is suggested to be used when dealing with multiple QFD charts or when the charts are not large.

Fung, Popplewell and Xies (Fung *et al*, 1998) have developed a hybrid system that incorporates the principles of QFD, analytical hierarchy process (AHP) and Fuzzy set theory to tackle the complex and often imprecise problem domain encountered in customer requirement management. It offers an analytical and intelligent tool for decoding, prioritising and inferring the qualitative, vague and often imprecise VOC. As a result, the appropriate product attributes can be mapped out and their relevant design targets can be determined quantitatively and consistently.

Wang (Wang, 1999) proposed a fuzzy outranking approach to prioritise design requirements captured by QFD. A design requirement outranks other requirements only if there is sufficient evidence to support the fact that the requirement is superior or at least equal to the others. The purpose is not only to achieve customer satisfaction, but also a balanced design of a product. QFD is considered as a multi-criteria decision problem, which considers not only the technical importance related to customer needs, but also the estimated cost, technical difficulty, reliability, maintainability, etc. Most of the time a consensus between the team members or an average of their opinions is used to fill up the corresponding cell in the relationship matrix. The inputs required for QFD are presented with linguistic terms that are categorised by fuzzy sets, which are appropriate to characterise the imprecise and uncertain information.

Another area of the House of Quality, the customer evaluation of the in-house and competitors' product (room 6) has also benefited from Fuzzy Logic and Fuzzy Set Theory (Wasserman *et al*, 1993). Their work gives details on how to construct an overall customer satisfaction index to determine the best product amongst the competitors. They suggest that quantifying the customer satisfaction of the competitive product is not easily done on a linear scale, as the information contains linguistic information. To resolve this difficulty, they use the conversion scales proposed by Cheng and Hwang (Chen and Hwang, 1992) to convert linguistic terms into their fuzzy equivalents. Hence, the fuzzy set framework is adopted to transform linguistic data to a crisp score as opposed to directly using the linear scale of the customer response. Multi Attribute Decision-Making (MADM) is then used to calculate overall customer preferences.

The synergistic integration of Fuzzy logic/Fuzzy set theory with QFD described above contribute different aspects to improve data analysis and processing in the QFD process. Some of the problems with QFD highlighted in these researches are that due to imprecise and subjective design information available in the early design stage, it is more difficult to assess the relative relationship (weak, medium, strong) between customer demands and engineering characteristics with accurate quantitative values. Symbols, which represent the customer demands and engineering characteristics (weak, medium, and strong), are used to fill the relationship matrix and build the HOQ. These symbol descriptions are normally in the form of linguistic variables. Human judgement; perception and cognition are often ambiguous and are better represented by fuzzy numbers. There are inconsistencies in requirements and implicit relationships can be inferred from explicit ones. Therefore there is a need for more defining more accurately the data in the QFD charts.

The proposed Fuzzy-QFD approaches described in section 3.7, use some of the concepts of the work already described above. The first approach, Fuzzy Range QFD described in section 3.8, uses the concept of representing the original relationship values found by the Independent Scoring QFD analysis as a range of numbers (Khoo and Ho, 1996). It also employs the concept of the work by Liu and Jia (Liu and Jia, 1998) and Temponi, Yen and Tiao (Temponi *et al*, 1999) that uses the *inference mechanism* of Fuzzy Logic to infer implicit relationships (relationships that are implied though not expressed) based on explicit ones. In addition it looks at the interactions between customer demands (porch area) and engineering characteristics (roof area) to update and reprioritise the customer importance rating and the relationship matrix using ranges of numbers. So in essence the approach combines two ideas, using the range and the inference engine from the work already undertaken in this field by other authors, but it differs from previous work in the way it analyses the data. It uses both the interaction between customer demands in the porch and the interaction between engineering characteristic in the roof to detect inconsistencies in the customer importance rating and the relationship matrix and in doing so results in a more precise technical weighting calculation.

The second approach, Fuzzy Proportional Distribution QFD highlighted in section 3.9, together with its subsets uses the data from the traditional Proportional Distribution HOQ analysis, described in chapter 2. This has not been used before and so is unique to this approach. This approach also looks at interactions in the correlation matrix and uses fuzzy logic inference mechanisms (Liu and Jia, 1998), (Temponi *et al*, 1999) to infer implicit relationships based on the explicit ones. The Fuzzy Proportional Distribution QFD approach uses crisp data as its input and outputs crisp data too by the use of an S-Fuzzy membership function and the Takagi-Sugeno defuzzification algorithm, which are unique to this approach.

3.7 THE PROPOSED FUZZY QFD APPROACHES

A particularly difficult task in QFD is the subjective decisions that have to be made when correlating the customer's demands to the engineering characteristics as well as when determining the customer importance rating of each of their demands as identified in the traditional analysis of the HOQ. Development of the relationship and correlation matrices is very difficult and team members' perceptions and judgements can over or underestimate some interdependencies. In the customer importance rating for instance, the customers may know what is important to them and rank them in order of importance, but the customers may not be aware of how dependent their demands are on each other and how these demands can affect each other. For instance, the customer may tell you that they want a very hot, milky cup of tea to the same degree of importance. Assuming that cold milk is being used, if the tea is milky, then it will not be very hot. So there is a conflict between these two demands.

Two new approaches are described in this chapter that identify conflicting demands and update the corresponding data when inconsistencies are detected. They both use the traditional HOQ to begin with, but enhance its capability by making use of beneficial information hidden in the porch (Room 1A, Figure 2.5, Chapter 2) and the roof (Room 6, Figure 2.5, Chapter 2). The new approaches, bring together the traditional HOQ and Fuzzy Logic/Fuzzy set theory to offer a more dynamic, rigorous and robust algorithm for coping with statements with varying degrees of exactness and precision in the VOC and the VOE, as well as dealing with subjective and ill-defined relationships in the HOQ.

In the first approach, the Fuzzy Range QFD uses the Independent Scoring data as its input data. It then changes the data into ranges of numbers. It uses the average between the fuzzy ranges to output crisp data. In the second approach, the Fuzzy Proportional Distribution QFD uses the results of the proportional distribution HOQ as its input data.

The data is normalised between 0 and 1 in order to use the same membership function range, as the data comes from various parts of the HOQ and are scaled differently. Then the differences in the relationship data between pairs of demands are calculated and the Fuzzy S-Function (refer to section 3.9, Figure 3.7) is used to fuzzify the input and determine the degree of membership. To defuzzify the fuzzy values to their corresponding crisp values, a Takagi-Sugeno defuzzification (equation (3.12)) algorithm is used.

The two proposed approaches allow the detection of inconsistencies in the importance weighting defined by the customers and identify over or under estimated relationships in the relationship matrix defined by the QFD team by using interactions in the correlation matrices. The two approaches differ from each other in the way they analyse the data in the HOQ. The first approach is described in section 3.8 and the second approach is described in section 3.9. In the proceeding chapter (chapter 4), example case studies are used to highlight and make comparative analyses of the two approaches. Software programs have been written to automate the laborious task of identifying inconsistencies and updating the data for both approaches (See Appendix B).

3.7.1 Architecture of the Fuzzy-QFD approaches

The general architecture of the Fuzzy QFD approaches is given in Figure 3.4 and consists of:

- An interface where the QFD team can input data such as customer importance rating, correlation matrices and the relationship matrix data.
- A knowledge base containing customer and product data, fuzzy rules, and other forms of knowledge to be found in the roof and porch correlation matrix entered by the QFD team.

- A fuzzification procedure to fuzzify the input data, converting them into membership functions.
- An inference engine that uses the input data to infer new data using *IF-THEN* rules.
- A defuzzifying routine to defuzzify the data and obtain crisp data for further analysis.
- A loop that carries the output of one stage to the next QFD stage if necessary.

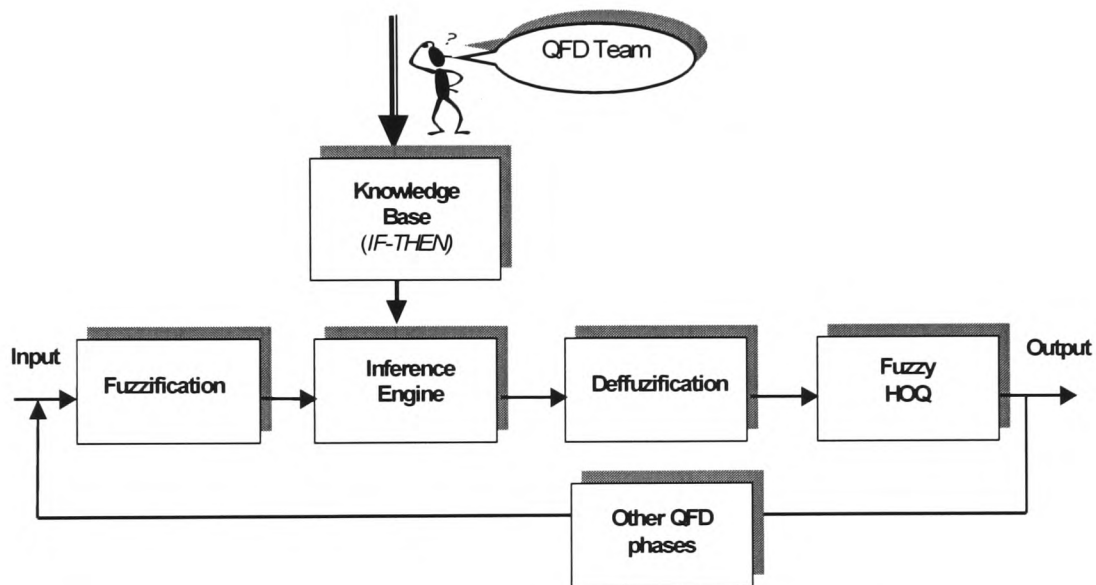


Figure 3.4 Elements of the Fuzzy-QFD approach

3.8 THE FUZZY RANGE HOUSE OF QUALITY APPROACH

The Fuzzy Range House of Quality (FR-HOQ) approach uses the Independent Scoring traditional HOQ as its input data. The Independent Scoring HOQ uses symbols. These symbols are converted to their numerical equivalent before proceeding with the analysis. The numerical equivalent of the symbols is shown as Relationship (1=weak, 3=medium, 9=strong) and as Correlation (9=strong positive, 3=weak positive, -3=weak negative, -9=strong negative). These are the standard QFD symbols and they are converted into their corresponding fuzzy range. The following steps highlight the approach:

Step 1. Fuzzy Inference rules

Fuzzy inference rules are developed to infer implicit relationships between two requirements. Three major parts in the HOQ: The porch area, the upper roof and the body of the house (relationship matrix) are used to document relationships. Intra-perspective relationships are specified in the cells of the porch and upper roof. Inter-perspective relationships are specified in the body of the house (relationship matrix). The QFD team defines relationships and these are explicit relationships. Based on these explicit relationships and interactions amongst requirements, new implicit relationships can be derived using the fuzzy inference engine. An example of a fuzzy inference rule given in the form of an *IF-THEN* rule can take the shape of:

IF "CD₁" is Very_Strongly Important to the customer AND the relationship between "CD₁" and "CD₂" is Strong_Positive (Porch Area) THEN it can be inferred that Importance rating for "CD₂" is Very_Strongly Important too.

where CD_1 represents the first customer demand and CD_2 the second customer demand. If two demands are related in a negative way, then increasing one should have the adverse effect on the other. The customer's importance ratings are re-prioritised by comparing the customer demands pairwise through intuitive reasoning against the original customer importance ratings. For example in the toothpaste case study in chapter 2, if a customer demand has a very strong positive relationship, e.g. "Tidy tip" with another "Attractive container" (Figure 2.6) then if one of them is very important to the customer, it can be deduced that the other should be as important too. Alternatively if a very strong negative relationship exists between say "Stays put" and "Small footprint" then it is reasonable to infer that if one of them is of great importance to the customer, then the other should not be.

The entire fuzzy rules are based on Table 3.3. There are sixty-four possible combinations, four possible correlation (SP, WP, WN, SN) for each pair of demands and four for the customer Importance rating/relationships: Very_Strong, Strong, Average and Weak (VS, S, A, W). The number of these rules fired depends on the number of correlation present in the porch. The correlation is always a square matrix and therefore, if for instance, twelve correlation exist between the customer demands, then the result is 12×12 , 144 *If-Then* rules. But of course it is not possible for every cell of the correlation matrix to display a correlation since only $(m/(m-1))/2$ valid cells in the correlation matrix exist. Furthermore, many rules are redundant, as they are reciprocals of each other, so less fuzzy *If-Then* rules will be fired. The software developed could deal with all 144 rules if they existed. In the toothpaste example (Figure 2.6) there are 16 correlation in the porch, so sixteen *If-Then* rules are fired, whereas the roof only has 13 correlation, so 13 rules are fired. When there is no correlation, no rule is fired. The notion is that, if a strong positive (SP) relationship exists between two customer demands, then the least important demand is increased by two ranges. If there is a weak positive (WP) relationship between two demands then the least important one is increased by one range. If the correlation is weak negative (WN), then the least important relationship is decreased by one range. And finally, if a strong negative (SN) correlation exists, then the least important demand is decreased by two ranges. Note that the increase or decrease in ranges depends on the strength of the correlation and was chosen to fit this particular set of relationship ranges. If more than four ranges existed for instance, then the increase and decrease would be by more ranges.

There exist some pre-conditions before any alterations are made and this is automatically accounted for in the computer programs developed:

- The resulting range cannot go above the maximum value of the largest range (10) in the Very Strong range, nor can it go below the minimum value of the smallest range

(0), in the weak range. This is done to keep the new values in the scope of the original values. In statistics, this is known as censored data (Montgomery and Runger, 1994).

- The parameter that is altered can only move to the same range as that of its corresponding pair, even when a strong positive or strong negative correlation exists. For example if Customer Importance 1 (CI_1) is strongly important (S) and Customer Importance 2 (CI_2) has average importance (A) and they have a Strong Positive (SP) correlation between them, the smaller range (CI_2) has to increase two ranges, but it can only increase by one range because its partner is only one range higher. This is to prevent the lower customer importance rating or relationship resulting in a higher range and thus becoming more important than its pairwise partner.
- When pairs are of the same importance, no alteration is made, as it is unknown which one should be altered, therefore a not applicable (n/a) sign is put next to it in Table 3.3.

A rule can take the form of:

- (Rule _{2,1}) *IF* CI_1 is VS *AND* CI_2 is S *AND* Corr($CI_1 \times CI_2$) is SP *THEN* CI_2 is VS
- (Rule _{2,2}) *IF* CI_1 is VS *AND* CI_2 is S *AND* Corr($CI_1 \times CI_2$) is WP *THEN* CI_2 is VS
- (Rule _{2,3}) *IF* CI_1 is VS *AND* CI_2 is S *AND* Corr($CI_1 \times CI_2$) is WN *THEN* CI_2 is A
- (Rule _{2,4}) *IF* CI_1 is VS *AND* CI_2 is S *AND* Corr($CI_1 \times CI_2$) is SN *THEN* CI_2 is W

where 'Corr' means correlation. The update for this approach is done sequentially, that is each correlation is looked at one at a time.

Cust Imp Rate		Correlation			
		Positive		Negative	
Cl_1	Cl_2	SP (increase by 2)	WP (increase by 1)	WN (decrease by 1)	SN (decrease by 2)
VS	VS	VS (n/a)	VS (n/a)	VS (n/a)	VS (n/a)
VS	S	VS (Cl_2)	VS (Cl_2)	A (Cl_2)	W (Cl_2)
VS	A	VS (Cl_2)	S (Cl_2)	W (Cl_2)	W (Cl_2)
VS	W	S (Cl_2)	A (Cl_2)	W (Cl_2)	W (Cl_2)
S	VS	VS (Cl_1)	VS (Cl_1)	A (Cl_1)	W (Cl_1)
S	S	S (n/a)	S (n/a)	S (n/a)	S (n/a)
S	A	S (Cl_2)	S (Cl_2)	W (Cl_2)	W (Cl_2)
S	W	S (Cl_2)	A (Cl_2)	W (Cl_2)	W (Cl_2)
A	VS	VS (Cl_1)	S (Cl_1)	W (Cl_1)	W (Cl_1)
A	S	S (Cl_1)	S (Cl_1)	W (Cl_1)	W (Cl_1)
A	A	A (n/a)	A (n/a)	A (n/a)	A (n/a)
A	W	A (Cl_2)	A (Cl_2)	W (Cl_2)	W (Cl_2)
W	VS	S (Cl_1)	A (Cl_1)	W (Cl_1)	W (Cl_1)
W	S	S (Cl_1)	A (Cl_1)	W (Cl_1)	W (Cl_1)
W	A	A (Cl_1)	A (Cl_1)	W (Cl_1)	W (Cl_1)
W	W	W (n/a)	W (n/a)	W (n/a)	W (n/a)

Table 3.3 Various ranges to increase or decrease the importance rating/relationships based on the correlation

Step 2. Fuzzifying the customer Importance rating

The crisp input received from the customers (importance rating) and the values in the relationship matrix are fuzzified into a range of values as in Table 3.4 instead of using crisp values. In this work the range of values for quantifying the relationship Very_Strong (VS), Strong (S), Average (A), Weak (W), were pre-determined by closely choosing values that represent the original QFD symbols (strong = 9, medium =3, weak =1, none = 0) and has a difference of about two units between the lower and upper limit of the range as seen in Table 3.4. The correlation (SP, WP, WN, SN), as seen in Table 3.5 were not altered, as they are only used to determine if an interaction exists and how strong it was. So they are used as a form of weighting factor that determines by how many ranges a customer importance rating will be increased or decreased. If for instance, there is a weak positive (WP) correlation between two demands, then the customer importance rating that is less important to the customer will be increased by 1 range, that is it will now be in the 'average' range. Table 3.3 showed the different ranges to increase or decrease the customer importance rating or relationship values based on the correlation matrix.

	Relationship Matrix	Fuzzy Number
☉	Very_Strong	[>=8 -- <=10]
●	Strong	[>= 6 -- < 8]
○	Average	[>= 4 -- < 6]
△	Weak	[>= 0 -- < 4]

Table 3.4 Range of linguistic variables for relationship matrix and importance rating

Correlation	
Strong Positive (SP)	9
Weak Positive (WP)	3
Weak Negative (WN)	-3
Strong Negative (SN)	-9

Table 3.5 Numeric representation of the correlation matrices

The porch and roof data forms square matrices and their corresponding matrix formula is defined by equation (3.3) and illustrated in Figure 3.5.

$$Porch = \begin{bmatrix} A_1B_1 & A_2B_1 & A_3B_1 \\ 0 & A_2B_2 & A_3B_2 \\ 0 & 0 & A_3B_3 \end{bmatrix} \tag{3.3}$$

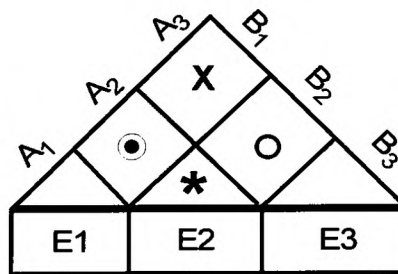


Figure 3.5 Representation of the correlation matrix

The representation of these particular correlation in the correlation matrix (Figure 3.5) will therefore take the form of:

$$Porch = \begin{bmatrix} 0 & SP & WN \\ 0 & SN & WP \\ 0 & 0 & 0 \end{bmatrix} \quad (3.4)$$

where SP represents Strong Positive correlation, WN represents Weak Negative correlation, SN represents Strong Negative correlation and WP represents Weak Positive correlation. It is essential to combine the result of all the interacting pairs to determine which final range the altered customer importance rating will be in. These updated fuzzy ranges C_{ij} , where i represents the row and j the column (equation (3.5)), are placed in the Importance Rating Room of the Fuzzy Range HOQ and are used for multiplication later on.

$$C_{ij} = [a_i, b_j] \quad (3.5)$$

Step 3. Using the Porch correlation matrix (Room 1A) to update the relationship matrix

Using the same logic as described in step 2, if there exists relationship in the porch area between customer demands, then it is reasonable to believe that the very strongly related demands should affect the engineering characteristics to a certain degree in the same way as its pairwise partner. Negative correlation should affect the relationship matrix the opposite way; i.e. increasing one will decrease the other. So the relationships in the relationship matrix are updated according to their correlation in the porch. This new matrix is stored for later use.

Step 4. Using the Roof correlation Matrix (Room 6) to update the relationship matrix

Again using the same logic as in steps 2 and 3, the roof interrelationships between engineering characteristics are used to infer non-explicit relationships in the relationship

matrix. Once more the relationships in the relationship matrix are updated according to their correlation with their pairwise engineering characteristic partner in the roof. The new matrix is again stored for later retrieval.

Step 5. The resultant relationship matrix

Combining the result of step 3 and step 4 together using fuzzy addition (equation (3.6)) and fuzzy averaging (equation (3.7)) (Kaufmann and Gupta, 1985), gives the final relationship matrix \overline{R}_{ij} .

$$R_{ij} = [a_i, a_j] + [b_i, b_j] = [a_i + b_i, a_j + b_j] \quad \text{Fuzzy addition (3.6)}$$

$$\overline{R}_{ij} = \left[\frac{a_i + b_i}{2}, \frac{a_j + b_j}{2} \right] \quad \text{Fuzzy averaging (3.7)}$$

Step 6. The Scoring Range

The resultant relationship matrix \overline{R}_{ij} found in step 5 is multiplied with the updated Customer Importance rating range C_{ij} arrived at in step 2, using Fuzzy Multiplication (Kaufmann and Gupta, 1985) as shown in equation (3.8).

$$\overline{R}_{ij} \cdot C_{ij} = [a_i, a_j] \cdot [b_i, b_j] = [a_i \cdot b_i, a_j \cdot b_j] \quad \text{Fuzzy Multiplication (3.8)}$$

The output of the Fuzzy Range HOQ approach is the range of numbers labelled 'Score Range'. Interpreting the fuzzy ranges may be somewhat difficult, as the ranges sometimes overlap and others have large differences between the lower and upper limit. For this work, these fuzzy ranges have been transformed into their equivalent percentage crisp score by averaging them as discussed in step 7, to make comparison possible and to output meaningful data. However if the subsequent QFD phases were employed in the

study, it would be desirable for the fuzzy ranges to be utilised as the inputs to next QFD phase. This enables the full cycle of the QFD process to be automated.

Step 7. Defuzzification

In order to practically visualise the result, the fuzzified range now has to be defuzzified. Defuzzification is the conversion of a fuzzy quantity to a precise quantity. The simplest defuzzification procedure used in this case was to compute the average between the upper and lower limits of the range. The defuzzified data is presented as the percentage crisp scoring at the bottom of the Fuzzy HOQ (See Figure 4.2 in chapter 4). The percentage crisp score, $S_{\%}$ is computed by equation (3.9), where E_{Upper} and E_{Lower} denotes the upper and lower limit of the n^{th} engineering characteristic's weighting consecutively. This result is then ranked, with 1 being of the most important engineering characteristic.

$$S_{\%} = \left(\frac{(E_{Upper} + E_{Lower})/2}{\sum_{i=1}^n E} \right) * 100\% \quad (3.9)$$

3.8.1 Software

Programs in MATLAB (Matrix Lab) version 5.3 were written to automate steps 1-7. Since the data from the HOQ is in matrix format, MATLAB was the most appropriate programming language to use because it is a high-level matrix/array language. Listings of the programs are given in Appendix B. A flow chart (Figure 3.6) illustrates the steps of the developed Matlab programs. To clarify these steps further, examples are employed in the next chapter.

3.8.2 Remarks on the Fuzzy Range QFD Approach

With the relationship matrix, the customer importance rating and scoring, all expressed in terms of ranges of values, the approach provides an overall picture about the design requirements that can help to ensure that the decisions made in the selection procedure are not biased to any specific value. This means that the values given by the customer and the QFD team do not have to conform to the exact numeric values that represent the relationship. A strong relationship for instance can be described in the range 8-10, not an exact 9. A relationship could be 9 ± 1 , including the mean and the variance, instead of just the mean. Many psychologists (Sherif and Sherif, 1970), (Polinghorne, 1984) have proved that people mentally perceive preferences as ranges, not as a number on a scale and thus it is unfair to pinpoint an opinion down to a single numerical value. They suggest that an individual's opinion could be characterised in terms of three different measures: the range of opinions the individual is willing to support, their mean position on the scale and the one opinion selected that best represent an attitude.

The Fuzzy Range approach is limited in some sense that the ranges have a definite upper and lower limit defined by the QFD team. The updates are also done sequentially, that is looking at every single correlation one at a time and updating the customer importance rating or the relationship matrix accordingly. The approach is also biased towards more important demands as only the less important demands are altered, that is the more important demands dictate the outcome of the less important ones. Although the weaker customer importance rating/relationship helps in contributing to the technical importance weighting (Scoring), the stronger customer importance rating/relationship has more impact on the technical importance weighting. This was done to reciprocate the idea of the original Independent Scoring HOQ method, where strong relationship/demands have stronger influences on the outcome.

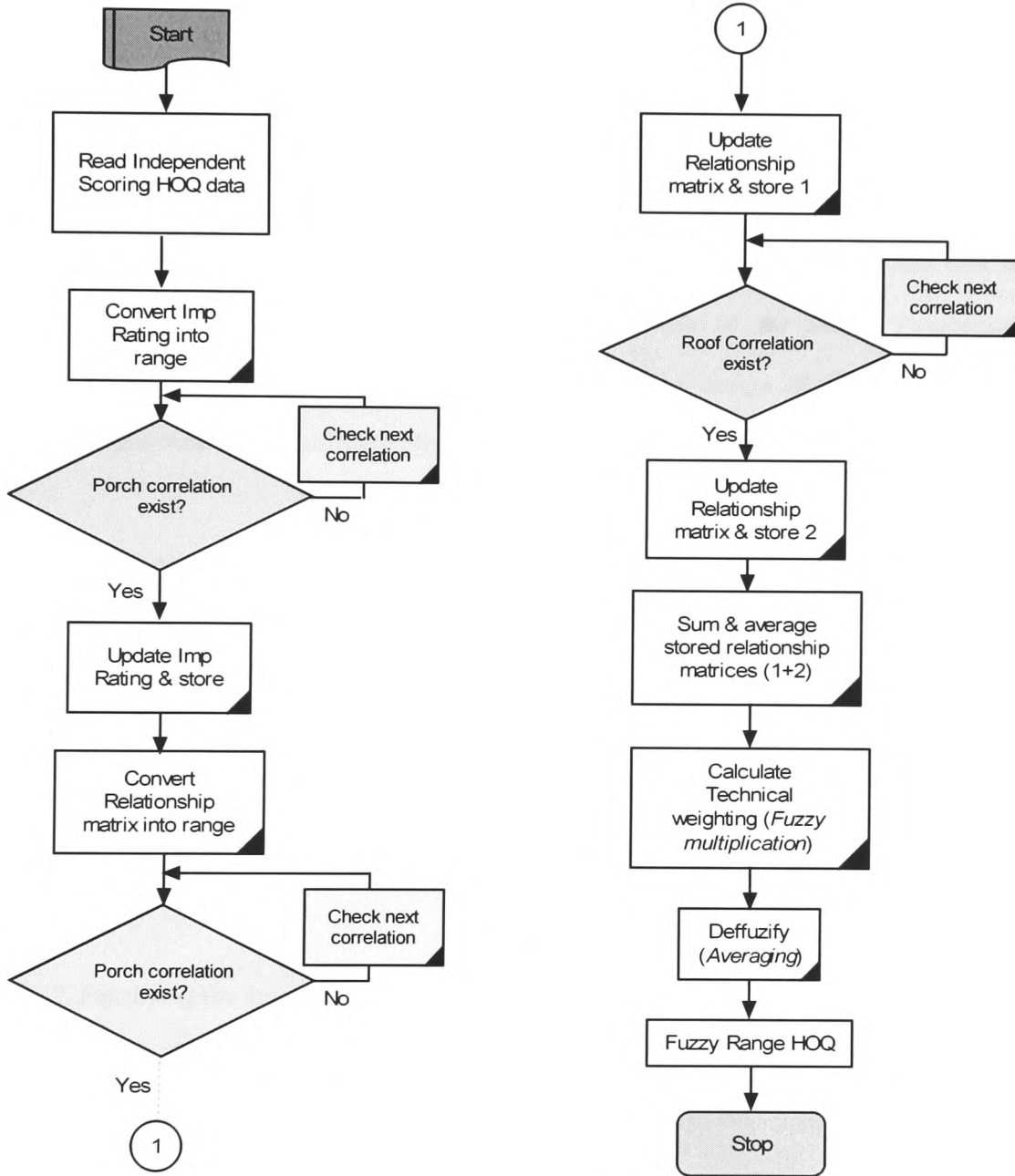


Figure 3.6 Flow chart for Fuzzy-Range HOQ approach

3.9 THE FUZZY PROPORTIONAL DISTRIBUTION HOUSE OF QUALITY APPROACH

The Fuzzy Proportional Distribution House of Quality (FPD-HOQ) approach uses the traditional Proportional Distribution HOQ results as its input data. In order to obtain this data, the Original Independent Scoring data had to be proportionalised resulting in the Proportional Distribution Method. The idea of the Fuzzy Proportional Distribution approach stems from the Fuzzy Range approach. The limitations of the Fuzzy Range approach, namely the results are biased towards more important demands and that the data is limited to a predefined range initiated the idea of the Fuzzy Proportional Distribution approach. The required steps involved in the design of the FPD-HOQ are now outlined with the intention to clearly clarify the approach.

Step 1. Fuzzy Inference rules

Fuzzy inference rules are developed to infer implicit relationship between two requirements. This step is similar to step 1, section 3.8 of the Fuzzy Range approach. The customer's importance ratings are re-prioritised by comparing the customer demands pairwise through intuitive reasoning against the original customer importance ratings and rules are thus formed in a similar manner to step 1 in the Fuzzy Range QFD approach.

Step 2. Fuzzifying the inputs

The crisp data from the proportional distribution method are fuzzified in the range 0 to 1. Each crisp value u resulting from the traditional Proportional Distribution HOQ is normalised to its normalised value \bar{u} (Jantzen, 1991) on a standard universe, [0 1] according to:

$$\bar{u} = \frac{u - u_{\min}}{u_{\max} - u_{\min}} \quad (3.10)$$

Here u_{\min} is the smallest value in the series of data and u_{\max} is the largest. As the data comes from various parts of the HOQ and are scaled differently, the data is normalised in order to use the same membership function range. These normalised data then need to be de-normalised to revert to their original state again using equation (3.10), in this case to find u .

Based on the correlation (9=strong positive, 3=weak positive, -3=weak negative, -9=strong negative) the Fuzzy S-function (Cox, 1994) was chosen to represent the correlation. This function is highly appropriate for representing concepts such as "very large" or "very negative" (The Mathworks, 1995). As the QFD analysis relies heavily on strong relationships, the S-Function gives a good interpretation of this phenomenon resulting in high degree of correlation when the relationships are strong, and low correlation when relationships are weak in a non linear fashion.

Figure 3.7a represents positive correlation, whereas Figure 3.7b represents negative correlation. The axis labelled "Difference" is a representative of negative correlation, not negative difference. At the extreme ends of the curve, a change in the input causes a very small change in the output. For instance when the difference is small (refer to Figure 3.7a), the Degree of Membership (DOM) is also small, and so the effect will be small too. Not much difference is seen in the output if the input difference is say, 0.1 or 0.2, as they are both small.

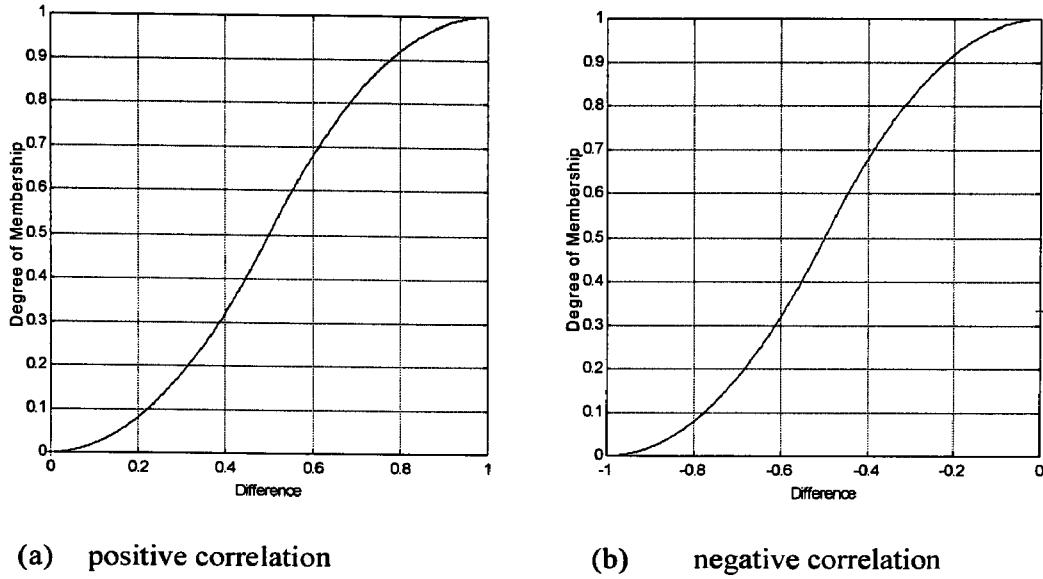


Figure 3.7 S-Function Curves

The S-Function curve is represented mathematically (Jantzen, 1991) by equation (3.11):

$$s(x_l, x_r, x) = \left. \begin{cases} 0 & , x < x_l \\ \frac{1}{2} + \frac{1}{2} \cos \left(\frac{x - x_l}{x_r - x_l} \pi \right) & , x_l \leq x \leq x_r \\ 1 & , x > x_r \end{cases} \right\} \quad (3.11)$$

where x_l is the left breakpoint and x_r is the right break point.

Step 3. Using the Porch correlation matrix to update the importance rating

The customer demands are compared, and where there is a relationship between two demands, the difference between their demanded weights (Importance rating) is calculated. Each difference forms the input data, and using the fuzzy S-function, the degree of membership is calculated. If the numeric difference between two customer importance ratings is large and they have a strong positive correlation between them, then their degree of membership will be large and positive. This is depicted in Figure 3.7a. If

the first customer importance rating has a positive correlation with another customer demand, then this is shown in Figure 3.7a. If now the first customer importance rating has a negative correlation with yet another customer demand, this is outlined in Figure 3.7b.

The S-function graphs in Figure 3.7a and Figure 3.7b represents situations when strong correlation exists. If a weak correlation exists, then the degree of membership found is divided by 3, since the strong correlation is three times the weak correlation (i.e. $3 \times 3 = 9$). Table 3.6 summarises the rules, where a small difference can be anything between 0 to say 0.3, medium difference between 0.3 to 0.65 and a large difference can be between say 0.65 to 1.

Cust Imp Rate	Correlation			
	Positive		Negative	
	SP (increase)	WP (increase)	WN (decrease)	SN (decrease)
Large	Large	Large/3	Small/3	Small
Medium	Medium	Medium/3	Medium/3	Medium
Small	Small	Small/3	Large/3	Large

Table 3.6 Fuzzy PD HOQ rule table

A rule can take the form of:

- IF Correlation (CI_1 & CI_2) is SP AND Difference (CI_1 & CI_2) is Large THEN DOM is large, therefore update CI_1 or CI_2 positively large.
- IF Correlation (CI_1 & CI_2) is WP AND Difference (CI_1 & CI_2) is Large THEN DOM is large/3, therefore update CI_1 or CI_2 positively large/3.
- IF Correlation (CI_1 & CI_2) is WN AND Difference (CI_1 & CI_2) is Large THEN DOM is small/3, therefore update CI_1 or CI_2 negatively small/3.
- IF Correlation (CI_1 & CI_2) is SN AND Difference (CI_1 & CI_2) is Large THEN DOM is small, therefore update CI_1 or CI_2 negatively small.

Again the number of rules depends on how many correlation exist in the porch, so the consequent part (*THEN*) of the rule is the summation of the Degree of Membership (DOM) of each of the antecedent part.

When logical connectives are used, in this case *AND*, the degree of fulfilment of the antecedent is computed as a combination of the membership degrees of the individual propositions using Fuzzy Logic operators. To defuzzify these fuzzy inputs, the Takagi-Sugeno defuzzification technique was used (Takagi and Sugeno, 1985). In the Takagi-Sugeno model, the inference is reduced to a simple algebraic expression as given in equation (3.12)

$$y = \frac{\sum_{i=1}^k \beta_i(x) y_i}{\sum_{i=1}^k \beta_i(x)} \quad (3.12)$$

where β_i is the degree of membership of the i^{th} antecedent rule and y_i is the i^{th} input antecedent and k is the number of antecedent rules. Each customer demand is checked against all the other demands and for each difference the corresponding Degree of Membership (DOM) is displayed on the appropriate S-Function Curve, depending on whether the correlation is positive or negative. All these data then go to compute the Takagi-Sugeno defuzzified output. The defuzzified Takagi-Sugeno results are then de-normalised and added to the original customer importance rating. In this way, the original customer importance rating can either be increased depending on how many positive interrelationships it had with other customer demands, or decreased depending on the negative correlation.

Two different methods were used to obtain the final Takagi-Sugeno output in this study. Firstly the analysis was ran once, in only one loop and the results of the Takagi-Sugeno

were used to update the importance rating. That means that when a new result is obtained it is not used as input to the next loop. In the second method, a looping system was adopted whereby the updated results then go to form the input to a second loop and based on the previous derived data, new data is obtained (See Figure 3.8). In this looping method, the first loop changes the results of the first importance rating only. The newly updated results are recorded in a temporary buffer, called 'input to the next loop' in Figure 3.8 and they are then re-called and are used to update the second importance rating and so on. This iterative process is carried out in order to use the latest data from previous loops and does not rely solely on the initial data. The process continues until no more correlation is detected.

Step 4. Using the Porch correlation matrix to update the relationship matrix

Using the same logic as in step 2, if there exists relationship in the porch area between customer demands, then it is reasonable to assume that the very strongly related demands should affect the engineering characteristics to certain degree in the same way as their pairwise partner. Again their differences are calculated and charted and their defuzzified Takagi-Sugeno results are stored for later analysis. Both ideas from step 3, the non-looping and the looping method were also used here.

Step 5. Using the Roof correlation Matrix to update the relationship matrix

Again using the same logic as in step 4, the roof interrelationships between engineering characteristics are used to infer non-explicit relationships in the relationship matrix. The data, which is still normalised, is stored for later retrieval.

Step 6. The resultant relationship matrix

The result from steps 4 and 5, are now combined together and then averaged to calculate the new resultant relationship matrix. These results then need to be de-normalised using equation (3.10).

Step 7. The resultant Technical weighting (Score)

The de-normalised importance rating, d_i is now multiplied with each individual de-normalised relationship, R_{ij} in each column, and the importance weighting for the engineering characteristic, w_j , for each column is computed by equation 2.1, chapter 2. Note that only the magnitude of the engineering characteristic weighting for the ranking (Baxter, 1995) is considered. This is because it is important to capture the negative relationships and thus realise which engineering characteristics affect the customer demands in a negative way. Therefore their rank order is not diminished by their negativity.

3.9.1 Software

Programs in MATLAB 5.3 were developed to automate steps 1-7. A flow diagram representing these programs is depicted in Figure 3.8. The listing of some of the programs can be found in Appendix B.

3.9.2 Remarks on the Fuzzy Proportional Distribution QFD Approach

In the Fuzzy Proportional Distribution approach, both the customer demands with low and high importance increased or decreased, unlike in the Fuzzy Range approach. There are no restrictions to how much a customer importance rating is altered. There are no definite boundaries in calculating differences or DOM and this makes this approach more mathematically involved, thus more quantitative than the Fuzzy Range approach.

3.10 SUMMARY

This chapter has introduced the concept of Fuzzy Logic and Fuzzy set theory together with their practical applications. Due to some of their capabilities such as their ability to deal with linguistic terms, their model-free implementation capabilities and their speed, they form highly adequate techniques to be integrated with QFD to resolve some of QFD's drawbacks such as ill-defined relationships. Research performed by other authors to integrate Fuzzy Logic and Fuzzy sets with QFD has also been highlighted. New general Fuzzy-QFD approaches are proposed, the Fuzzy Range QFD approach and the Fuzzy Proportional Distribution QFD approach. The main challenges faced during the development of these two Fuzzy-QFD approaches were:

- How to create the rules?
- How to identify a way to check for inconsistencies based on correlation between demands?
- What data to update and how to update this data?
- How to select the fuzzification and defuzzification methods?

The proceeding chapter utilises case studies to investigate the applicability of the developed Fuzzy-QFD approaches from this chapter, where comparative studies between the two approaches and the original HOQ data will be performed to identify their main advantages and disadvantages.

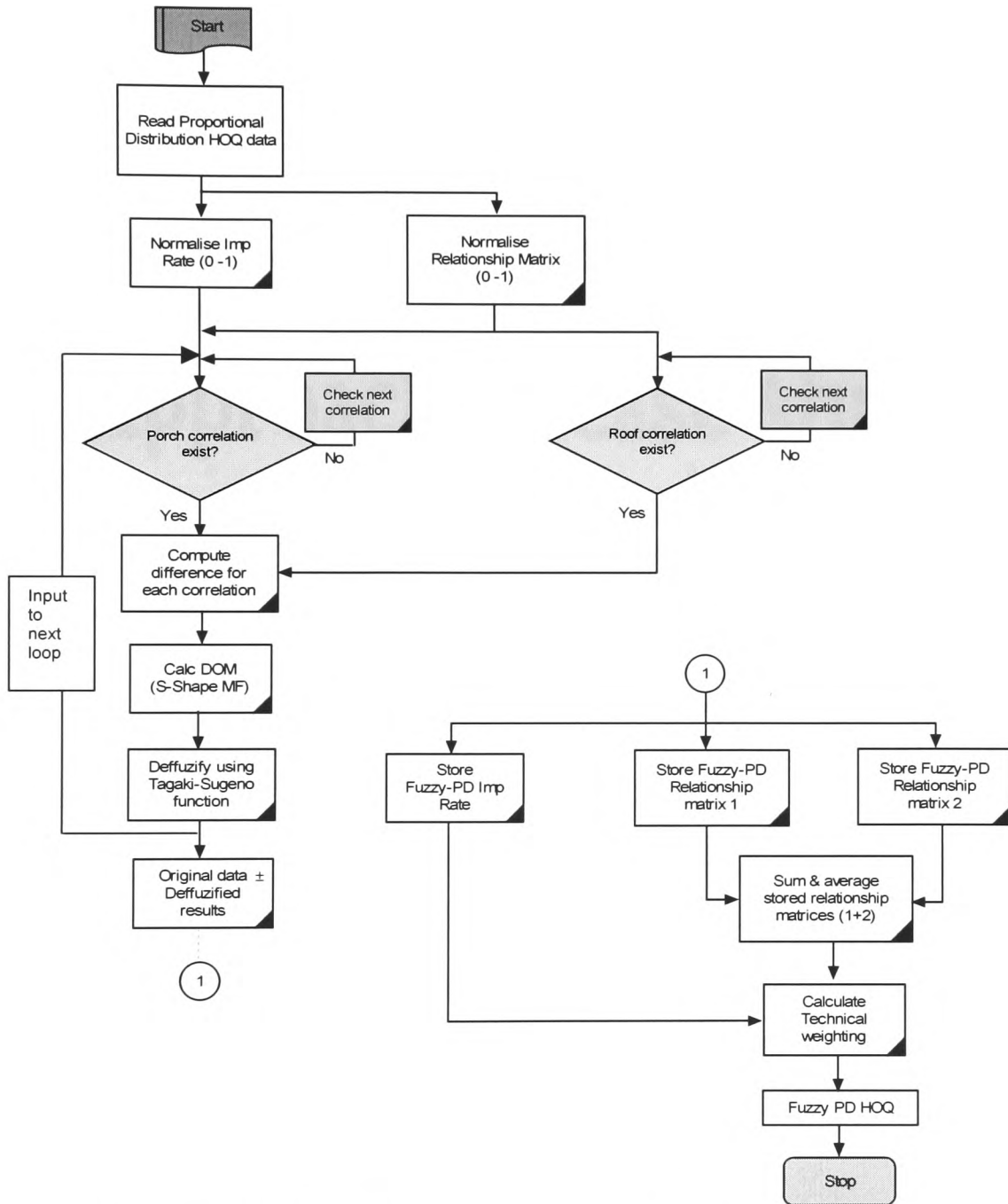


Figure 3.8 Flow chart for the Fuzzy Proportional Distribution QFD approach

Chapter 4.

The Fuzzy–QFD

Approaches: case studies

"Valid learning does not occur unless you continuously go back to reality..."
~ Ray Stata ~

In this chapter, the proposed Fuzzy-QFD approaches developed in chapter 3, are investigated through the use of case studies. The result of the two Fuzzy-QFD approaches, the Fuzzy Range and Fuzzy Proportional Distribution, are compared to the traditional QFD results. The two approaches are then compared to each other and finally sensitivity analyses are performed to test the robustness of the developed approaches.

4.1 INTRODUCTION

Two Fuzzy-QFD approaches have been developed and highlighted in chapter 3: the Fuzzy Range HOQ (the integration of Fuzzy Logic and the traditional Independent Scoring HOQ) and the Fuzzy Proportional Distribution HOQ (the integration of Fuzzy Logic with the traditional Proportional Distribution HOQ). The Independent Scoring HOQ and the Proportional Distribution HOQ were extensively discussed in chapter 2.

The two Fuzzy QFD approaches outlined in chapter 3, can be applied to any case study provided the correlations in the porch and the roof are identified. The Fuzzy Range QFD approach is firstly presented and applied to three case studies in order to form a general conclusion about the approach. The Fuzzy Proportional Distribution QFD approach is applied to the same case studies to enable variations on the Fuzzy Proportional Distribution HOQ to be developed and compared. The two Fuzzy-QFD approaches are then compared with each other. The similarities and differences between the results of the traditional approaches and the fuzzy approaches are also highlighted. Sensitivity analyses are finally performed using a systematic proposed method, which checks and updates the correlation matrix data (porch and roof) to test the robustness of the new approaches.

4.2 HEURISTIC CASE STUDIES USING FUZZY RANGE HOQ APPROACH (FR-HOQ)

To highlight the Fuzzy Range QFD (FR-HOQ) approach, three heuristic case studies are utilised and outlined below. The first case study was introduced in the previous chapter. The steps required to analyse any example are the same as those given in section 3.8 of chapter 3. Hence for any other examples analysed thereof, only the results and a discussion of the results will be given.

4.2.1 Case study 1: The design of a toothpaste tube using the FR-HOQ

The original HOQ for this example is given in Figure 4.1, (Bahill and Chapman, 1993). Steps 1-7 were executed using the programs developed for the Fuzzy Range HOQ (FR-HOQ) approach (Appendix B) and the final results for the FR-HOQ for this example are shown in Figure 4.2. The results are laid out differently to the original Independent Scoring HOQ, found in Figure 4.1, where ranges of values are used instead of symbols and the engineering characteristic's weightings are given as ranges and as a percentage crisp score.

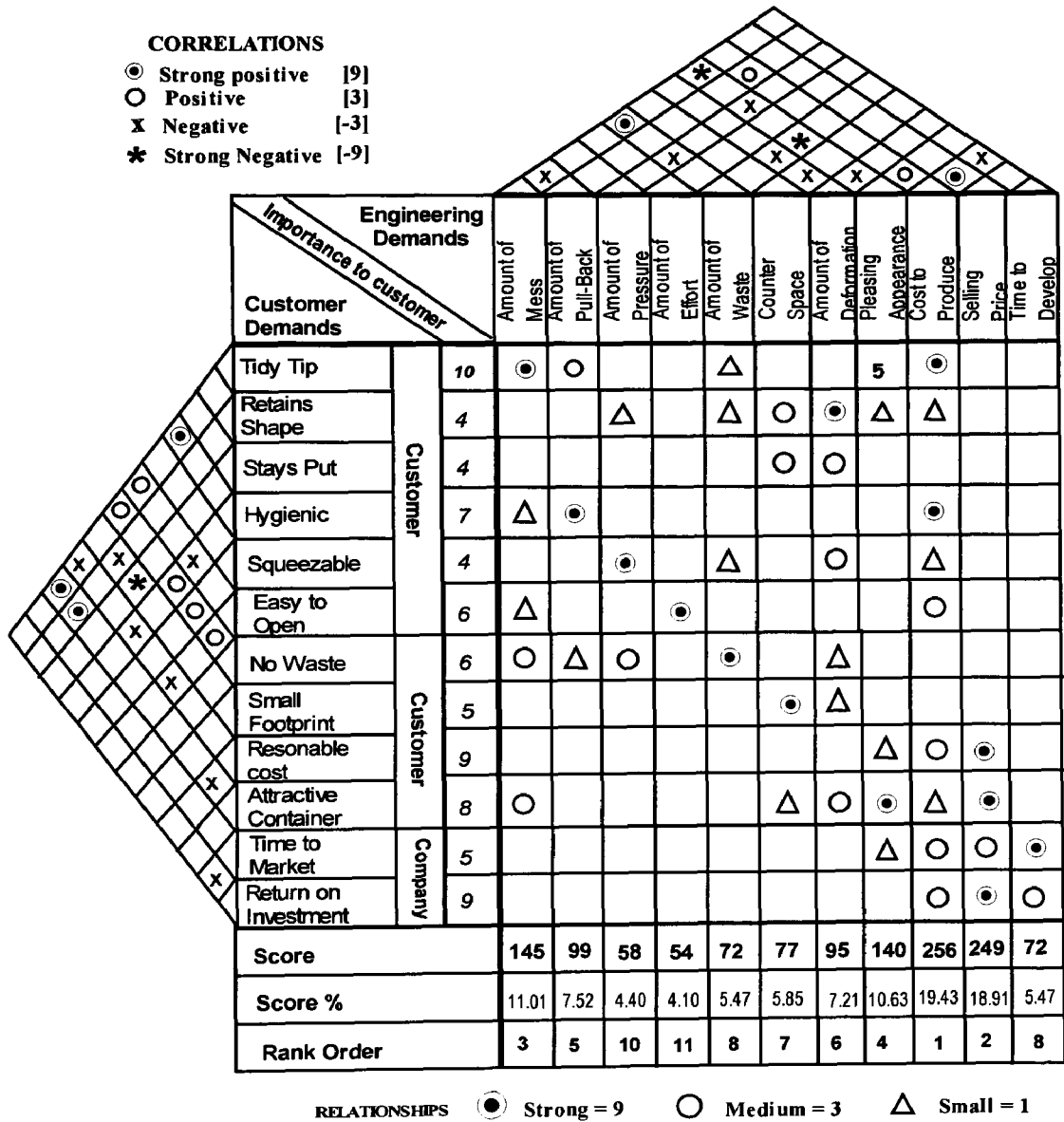


Figure 4.1 Independent Scoring HOQ (Bahill and Chapman, 1993) (Used with permission)

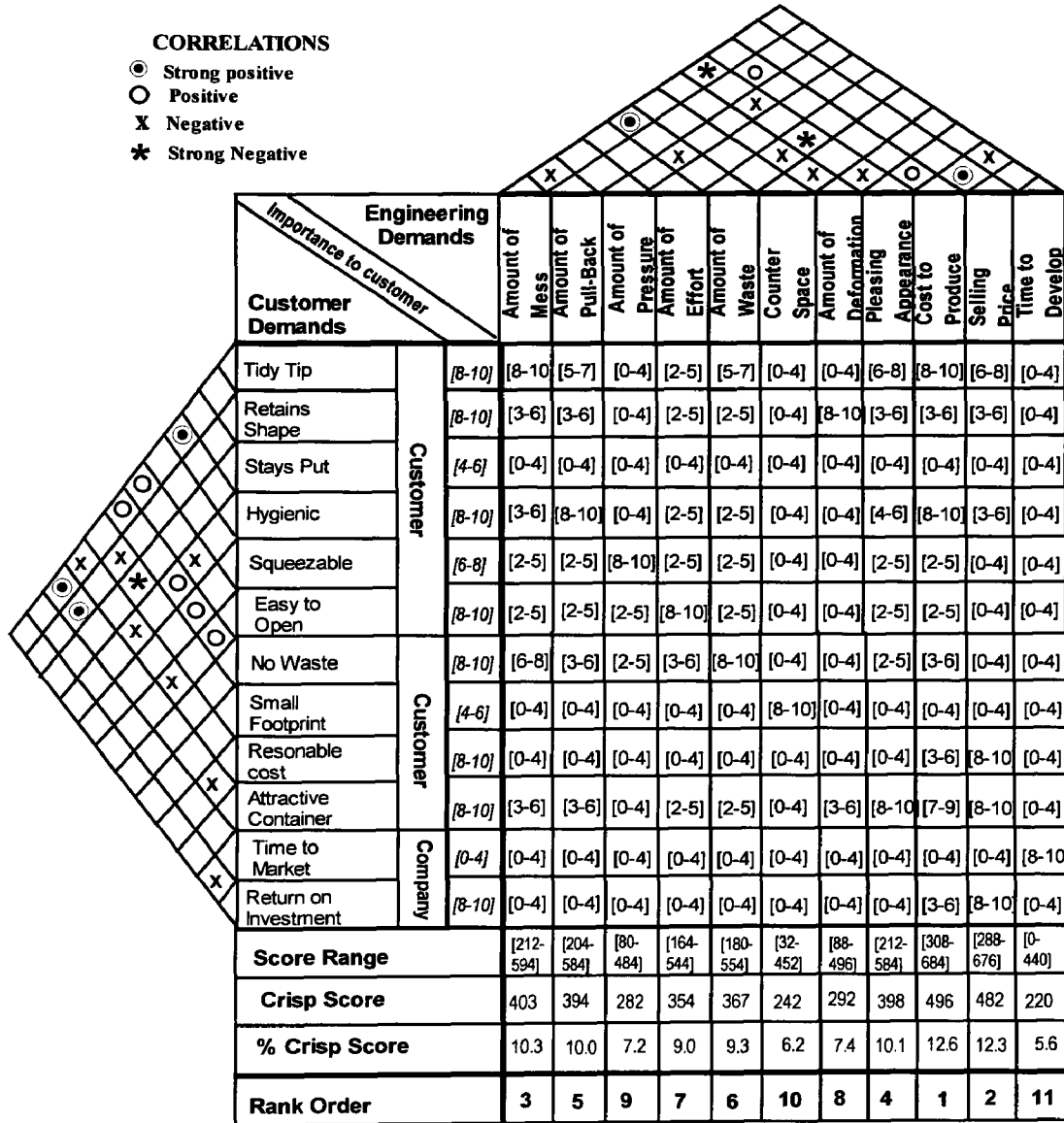


Figure 4.2 The Fuzzy Range HOQ for the toothpaste tube example

4.2.1.1 Remarks

The top five ranking of the engineering characteristics in the original HOQ, that is the “*Cost to Produce*”, “*Selling Price*”, “*Amount of Mess*”, “*Pleasing Appearance*” and “*Amount of Pull-Back*” were still the top five in the same ranking order in the Fuzzy Range HOQ. The change in ranking order of the engineering characteristics can be seen more clearly from the graphical interpretation of the results depicted in Figure 4.3, which compares the ranking order of the new Fuzzy Range HOQ approach to the traditional Independent Scoring HOQ approach. Overall eight out of the eleven (73%) engineering characteristics gave similar ranking order, within one or two ranking differences to the original Independent Scoring HOQ. The engineering characteristics that have considerably changed are “*Amount of Effort*” by four rank order, “*Counter Space*” and “*Time to develop*” both by three rank order.

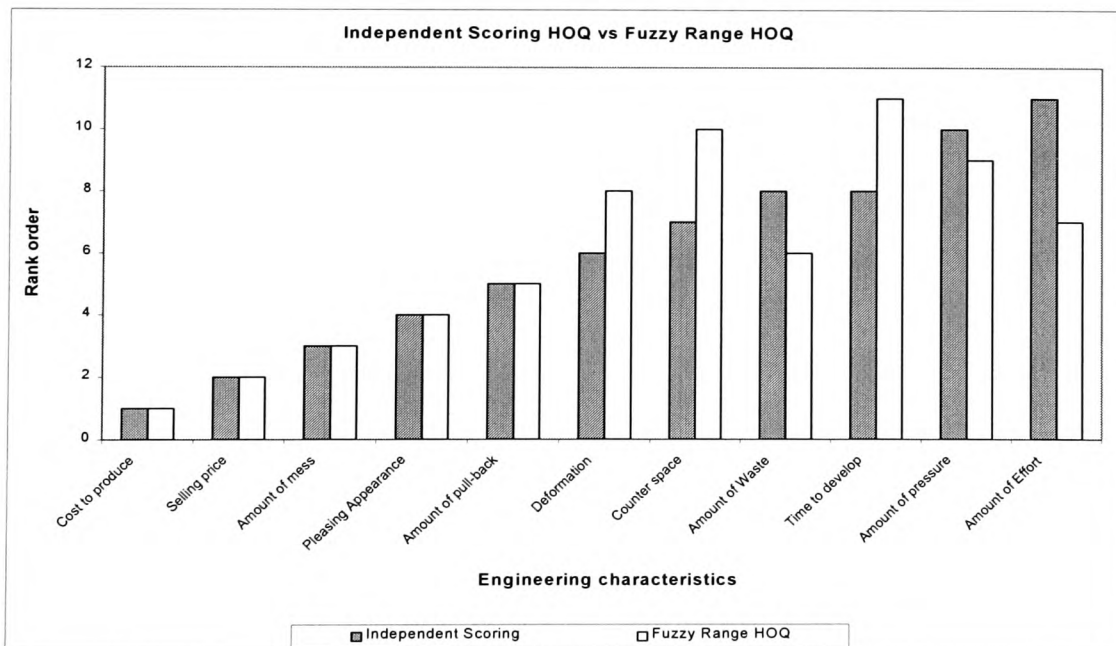


Figure 4.3 Independent Scoring HOQ vs. the Fuzzy Range HOQ for toothpaste example

4.2.2 Case study 2: Room layout design of a research Centre using FR-HOQ

Problem statement: The students of the Mechatronics Research Centre at University of Wales College Newport, UK required a new design for the room layout of their research Centre to accommodate the ever increasing number of new students. A QFD study was performed, primarily to find out what the students (the main customer) desired in their new room layout. The results are presented in the Independent Scoring HOQ displayed in Figure 4.4.

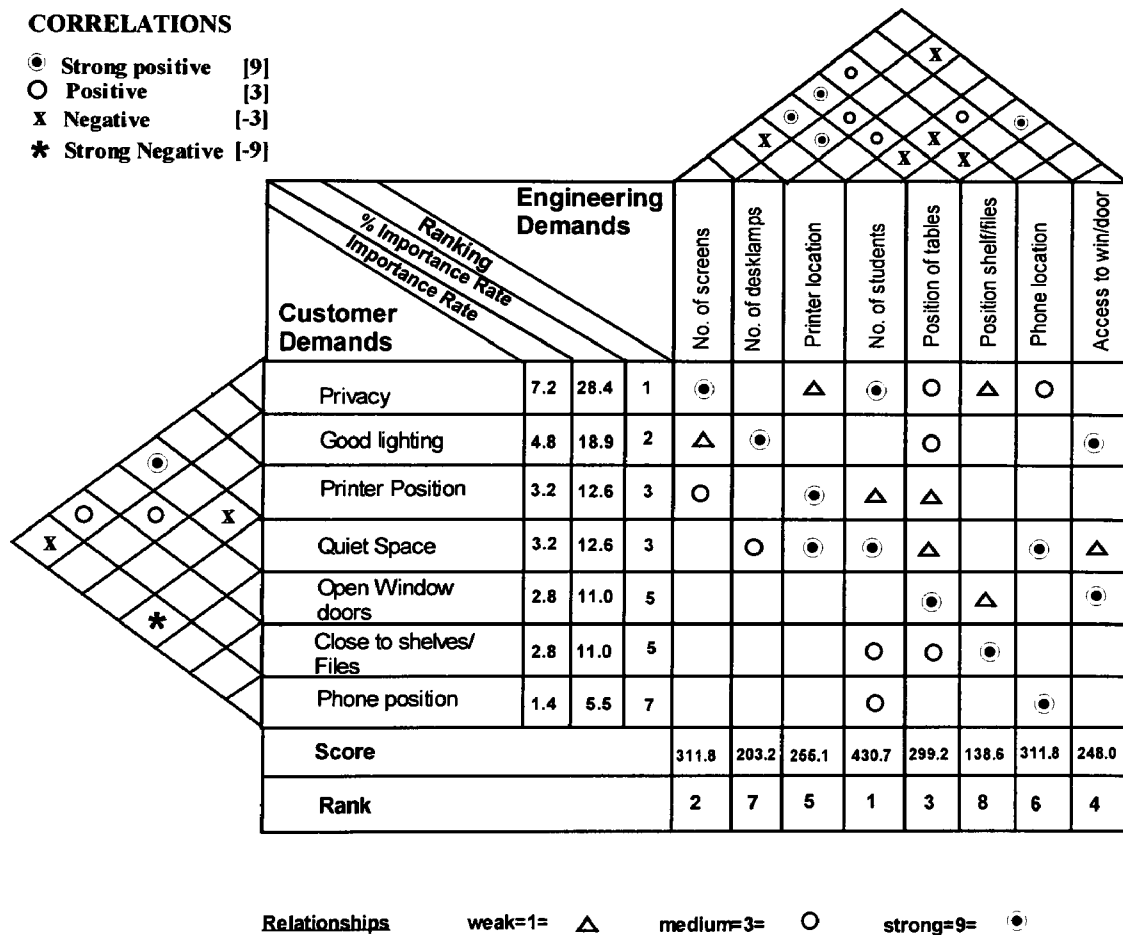


Figure 4.4 HOQ for the design of a research Centre room layout

In Figure 4.4, for instance, the customer demands, “Privacy” and “Quiet Space” are strongly related to each other in the porch and they are not related to say the engineering characteristic “No. of screen” in the same way. In fact they are related in totally opposite ways. Therefore one of the relationships in the relationship matrix has been over or under emphasised.

The software programs (Appendix B) are executed and the results of the Fuzzy Range HOQ for the design of the research Centre room layout are shown in Figure 4.5. Six out of the eight (75%) engineering characteristics are within two rank differences of the original Independent Scoring HOQ. The results are graphically displayed in Figure 4.6.

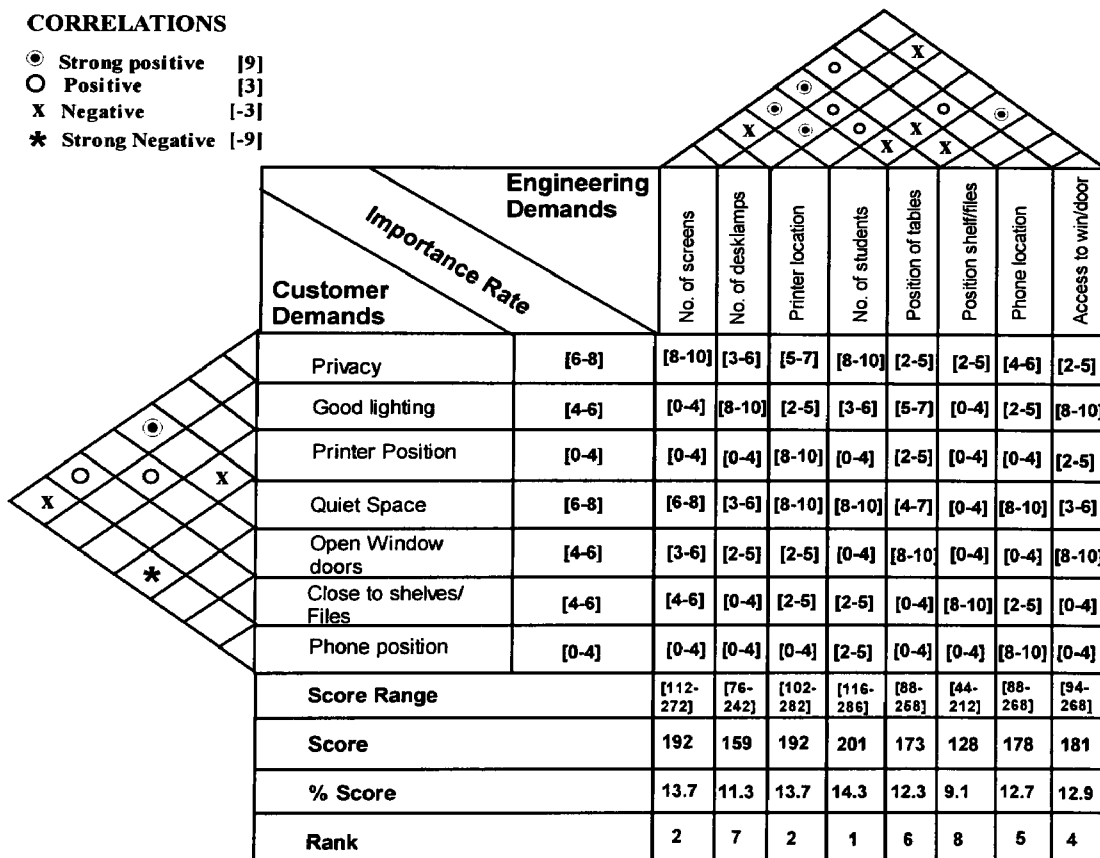


Figure 4.5 The Fuzzy Range HOQ for the design of a research Centre room layout

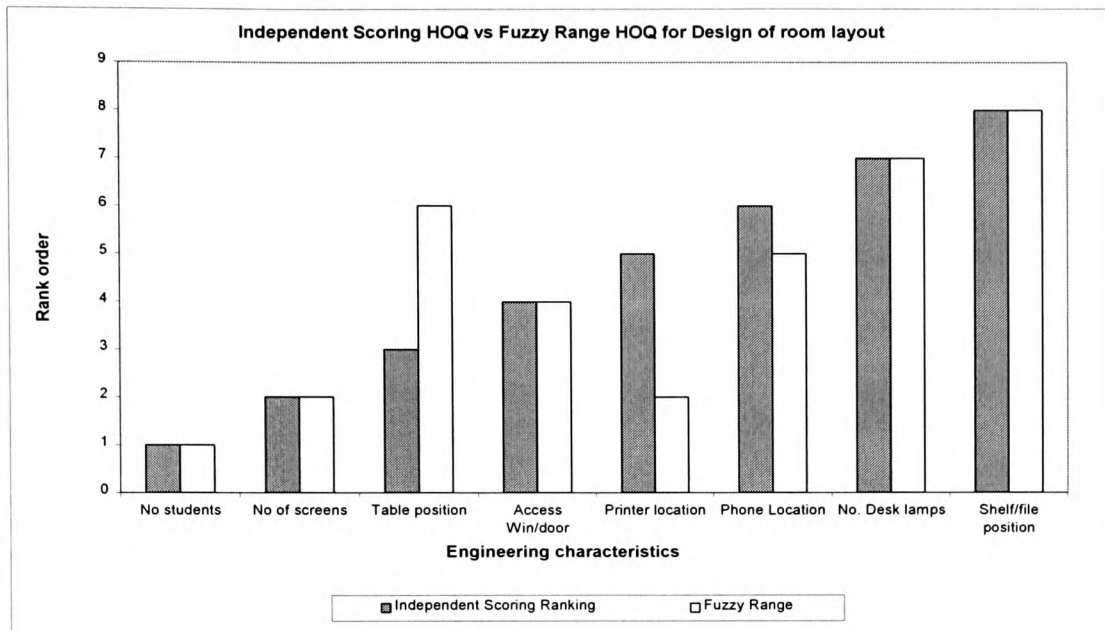


Figure 4.6 Independent Scoring HOQ vs. the FR-HOQ for the design of a room layout

4.2.2.1 Remarks

As can be observed from Figure 4.6, there are little discrepancies between the original Independent Scoring HOQ results compared to the FR-HOQ results. The main differences occur for engineering characteristic “*Table Position*”, which has decreased in rank from 3 to 6 and “*Printer location*”, which has increased from rank 5 to rank 2.

4.2.3 Case study 3: The design of running shoes using the FR-HOQ

A manufacturing company wanted to determine what are its customer needs for the new design of running shoes. The original HOQ for the design of running shoes (Eccles, 1994) is illustrated in Figure 4.7 and the result of the Fuzzy Range HOQ approach is depicted in Figure 4.8. The comparison between the Original Independent Scoring HOQ and the Fuzzy Range HOQ can be seen in Figure 4.9.

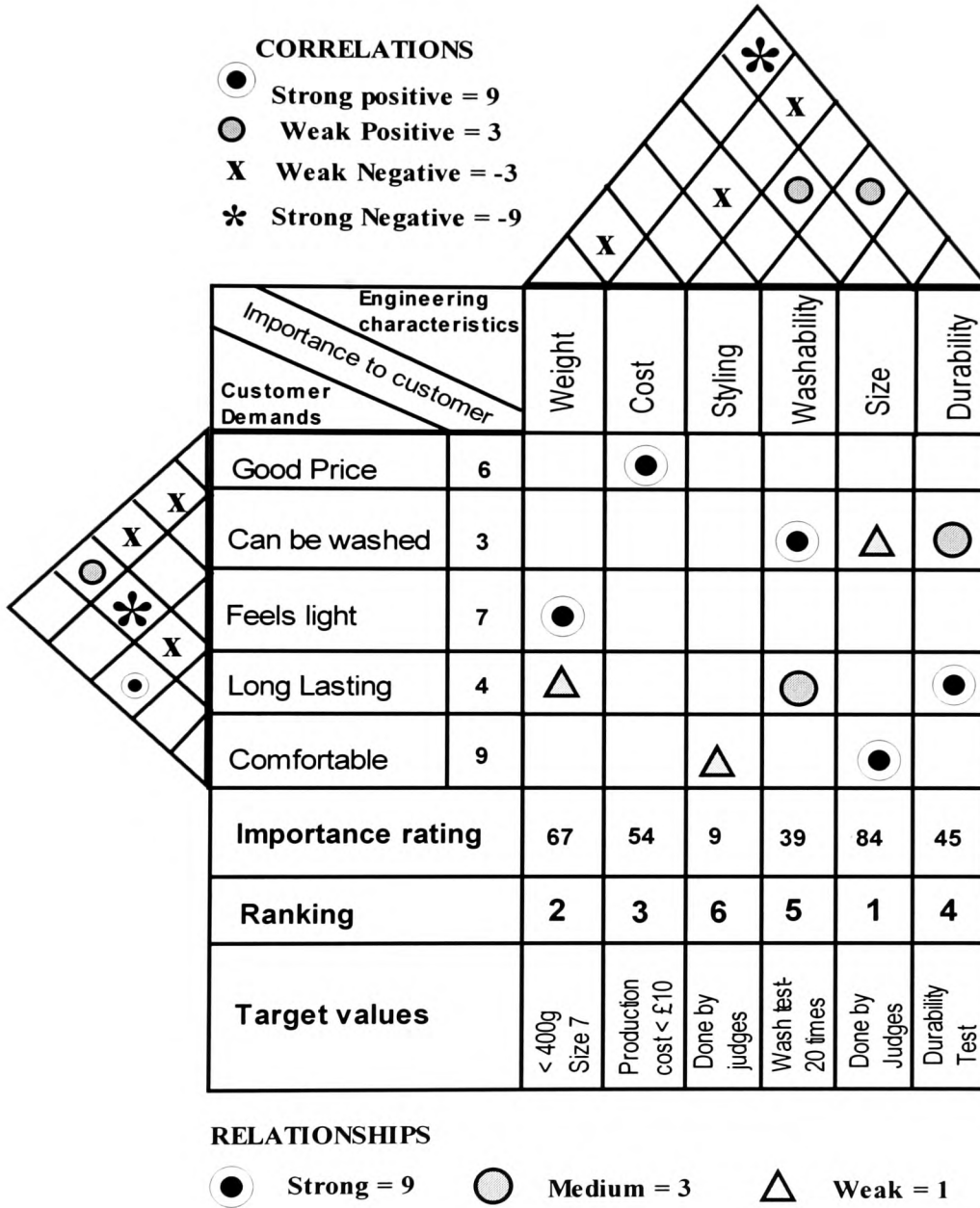


Figure 4.7 The HOQ for the design of running shoes (Eccles, 1994)

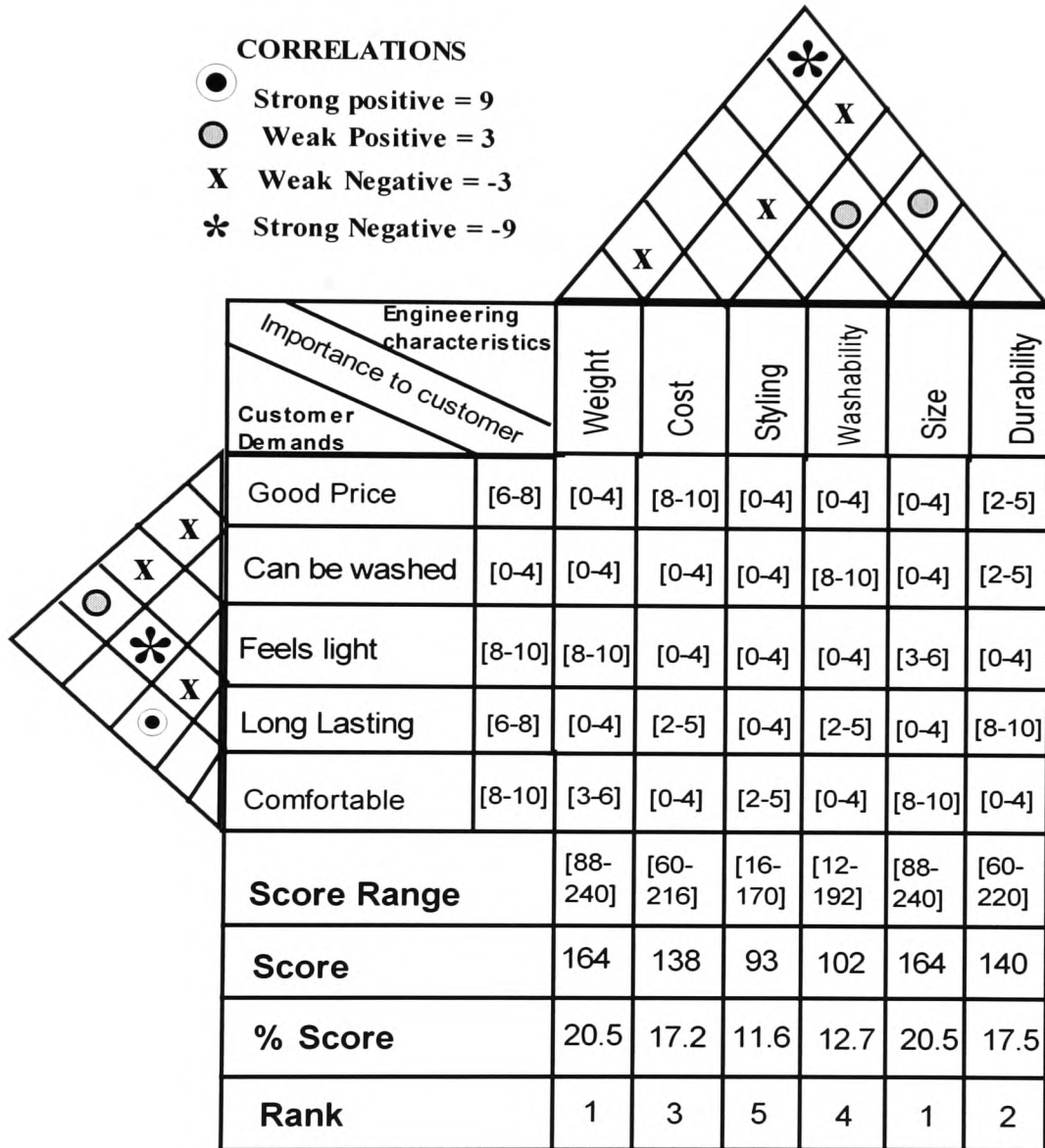


Figure 4.8 The Fuzzy Range HOQ for running shoes example

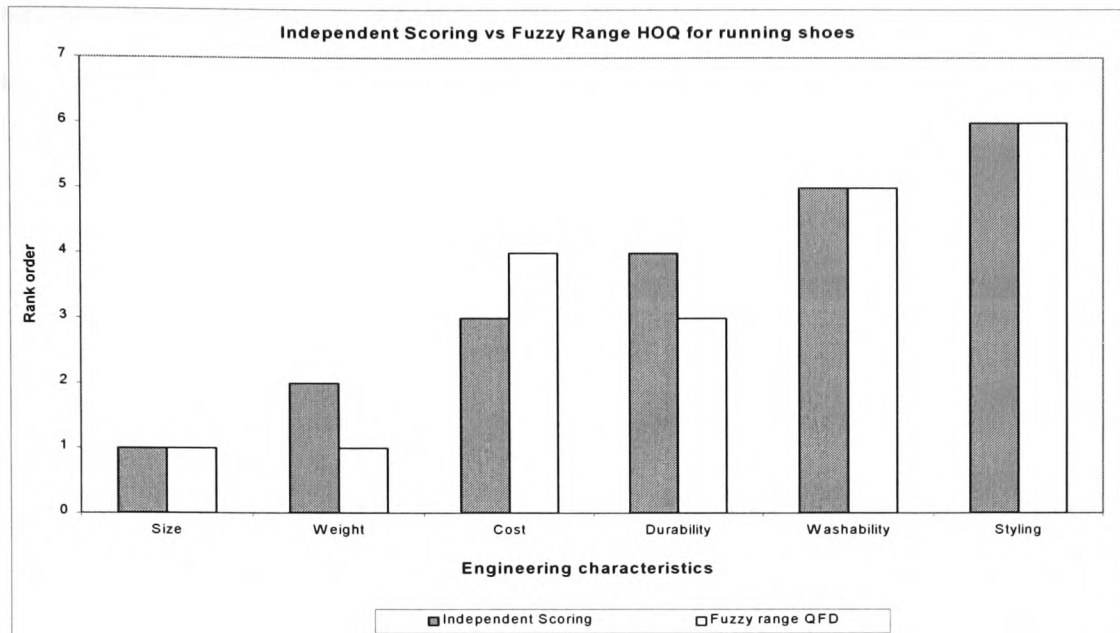


Figure 4.9 Independent Scoring vs. the Fuzzy Range HOQ for running shoes example

4.2.3.1 Remarks

From Figure 4.9, it can be observed that little discrepancies exist between the two HOQs. Three out of six (50%) engineering characteristics have the exact rank order and the other three are within one rank difference, totalling to 100% of the engineering characteristics within one rank difference.

4.3 DISCUSSION

Table 4.1 shows the result of the similarities and dissimilarities between the results of the Fuzzy Range HOQ approach compared to the Independent Scoring approach for the three case studies. Furthermore it shows the statistical significance of the results, performed by Spearman's rank correlation method described in details in Appendix B. Appendix B also shows an example of how to calculate the Spearman's rank correlation test (Clarke and Cooke, 1992), by comparing the engineering characteristic's rank order for the Independent Scoring HOQ to the Fuzzy Range HOQ for the toothpaste case study. The

null hypothesis $H_0 = r_s = 0$, means that there is no relation (no similarities) between the two variables, whereas the alternative hypothesis, $H_1 = r_s \neq 0$, means that there is some relation (similarities), positive or negative between the rankings. As can be observed from Table 4.1, there were many similarities between the rankings of the traditional HOQ and the Fuzzy Range HOQ for all the three case studies. If the results of the Fuzzy Range HOQ approach is investigated, it can be found that for the case of the 'design of running shoes' more similar rankings were observed (100%) compared to the other two case studies. This may be because there were much less correlations in the roof and porch compared to the other two case studies as well as less requirements (Figure 4.7). That means that there were fewer interactions and as such less influence of each demand on other demands, therefore quite similar to the Independent Scoring results. The toothpaste case study resulted in even less similar ranking than the other two cases. This may be due to the fact that there were many requirements and many interactions between demands in this case study (Figure 4.1). The second case study, although it did not have a large number of requirements, had a lot of interactions (Figure 4.4). As a result, it can be said that the Fuzzy Range HOQ approach would be more beneficial and suitable for analysing more complex problems where there are many interactions between demands.

Fuzzy Range HOQ vs. Independent Scoring HOQ							
Case study	Exact rank order	No. of dissimilar rank		No. of similar rank		Spearman correlation	Significance
		Within 2 rank order		Total	% similar rank		
Toothpaste tube	5	3	3	11	73	0.80	99%
Mechatronics room	5	1	2	8	75	0.77	95%
Running shoes	3	3	0	6	100	0.80	99%

Table 4.1 Fuzzy Range HOQ approach vs. the Independent Scoring results for the case studies

Since there is no known 'correct' rank order, the observations arrived at for the three examples do not render themselves to a logical interpretation of the result. The ranking of the engineering characteristics were not expected to be exactly the same between the two HOQs, but they were not expected to be too different either as this would suggest that the

original results or the new results are not compatible. Indeed the similarities between the two sets of results (Independent Scoring HOQ vs Fuzzy Range HOQ) for each of the three examples (see Table 4.I), identified by the percentage of similar ranks, but more importantly by the significance of the statistical testing (Spearman's rank correlation), goes to confirm that there were no major inconsistencies in the various judgements and evaluations provided by the new Fuzzy Range HOQ approach. The Fuzzy Range HOQ approach needs to output results that are consistent with the QFD team's judgement, expertise and opinions, but by taking into account interactions between characteristics and tune the original data after finding inconsistencies or even missed relationships. The concepts of the Fuzzy Range HOQ approach implies that the results are more robust than the traditional HOQ results since vital correlation information is not used in the traditional HOQ approach. This can serve as an aid for the QFD team.

4.4 HEURISTIC CASE STUDIES USING THE FUZZY PROPORTIONAL DISTRIBUTION HOQ APPROACH (FPD-HOQ)

In order to make comparison between the newly developed Fuzzy Range HOQ approach and the proposed Fuzzy Proportional Distribution HOQ approach discussed in chapter 3, it is necessary to use the same data for the analysis of the FPD-HOQ approach, therefore the same heuristic case studies will again be used. Only the first two examples will be used as many different methods are tested and compared (see Figure 4.10). The following sub-sections explain each method and show their graphical results.

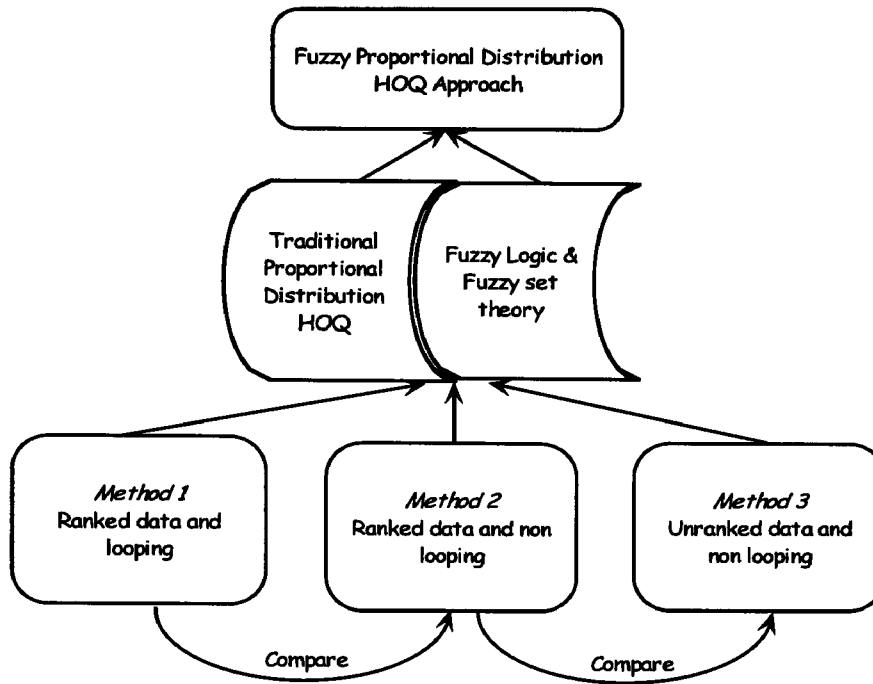


Figure 4.10 Fuzzy-PD HOQ methods tested

4.4.1 Fuzzy Proportional Distribution HOQ (FPD-HOQ Ranked-loop)

The aim of this section is to verify whether the ranking and looping method described in chapter 3, (section 3.9, step 3), had any effect on the end results. The idea of ranking the data was to investigate whether the order in which the data was put into the program had any effect on the end results. It was assumed that if the most important demands were placed first, they would have a greater influence on the demands that followed them than if they were placed last in the iteration. Then a looping method was performed whereby the consecutive loops use the results of the preceding loop as explained in step 3, section 3.9. So say in the first loop, there were 3 correlations, that means three pairs of data were affected and so their new results will be used in the next loop to update other demands that have some correlations with the customer demands in the first loop. This was done in order not to rely solely on the original data, but to use the newest updated data. The results were then compared to the unranked, non-looping method.

4.4.1.1 Case study 1: The design of a fuzzy toothpaste tube using FPD-HOQ

First the data was ranked according to the most important characteristics as shown in the Proportional Distribution HOQ in Figure 4.11. The results obtained from the FPD-HOQ approach using the looping method, together with the ranked data is depicted in Figure 4.12.

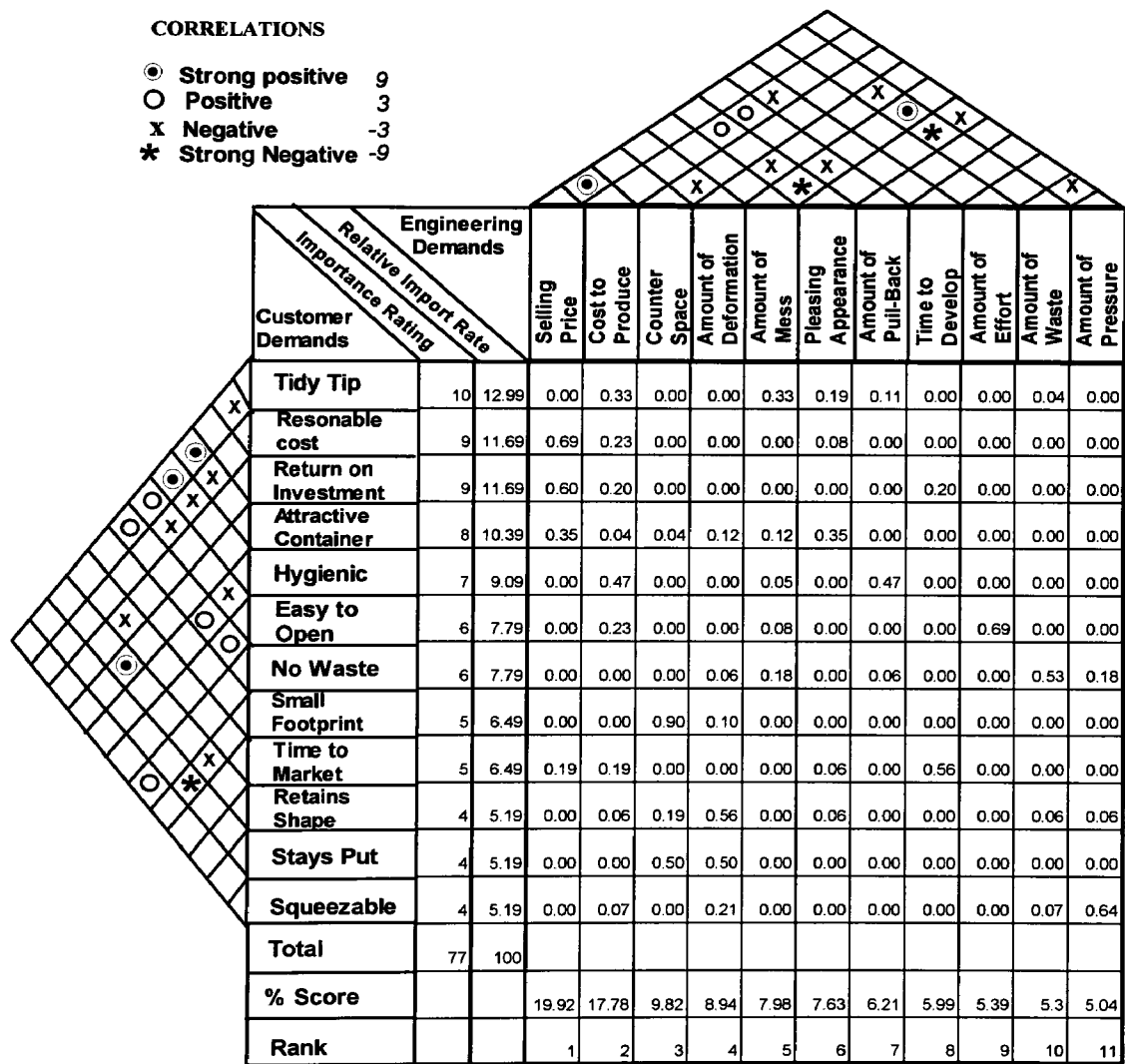


Figure 4.11 Independent Scoring results are proportionalised to give the results of the Proportional Distribution HOQ

It is noticeable from both Figure 4.1 (Independent Scoring HOQ) and Figure 4.11 (Proportional Distribution HOQ) that the ranking order of the engineering characteristics resulting from the FPD-HOQ, Figure 4.12, has been altered. This is shown graphically in Figure 4.13, which compares the traditional Proportional Distribution results from Figure 4.11 to the FPD-HOQ ranked looping results of Figure 4.12.

From Figure 4.13, it can be seen that the top two ranking "*Selling price*" and "*Cost to produce*" in both HOQs are still the top two ranking. Generally the two sets of results have similar rank order, but a big difference in the ranking order for "*Amount of Mess*", "*Amount of Effort*" and "*Pleasing Appearance*" between the two houses in Figure 4.13 can be observed. If the engineering characteristic "*Amount of Mess*" is investigated further, it can be seen that it depicts many negative interactions with other engineering characteristics, which affects the ranking in the FPD-HOQ, but not in the original HOQ. This is why the ranking of this particular engineering characteristic has decreased. "*Pleasing Appearance*" has decreased in its rank order probably due to the many negative correlations it possesses with other engineering characteristics too.

The comparison between the FPD-HOQ (ranked-loop) and the original Proportional Distribution HOQ shows eight out of eleven, 73% with similar rankings (within 2 rank differences), with four out of this eight having exactly the same rank order. The comparison between the FPD-HOQ and the Independent Scoring HOQ (Figure 4.14), also shows eight similar rankings (within 2 rank differences), but only two out of this eight depicts exactly the same rank order. So the results of the FPD-HOQ resembles much more the original Proportional Distribution HOQ. This is expected, since the data used in this approach stems from the original Proportional Distribution HOQ.

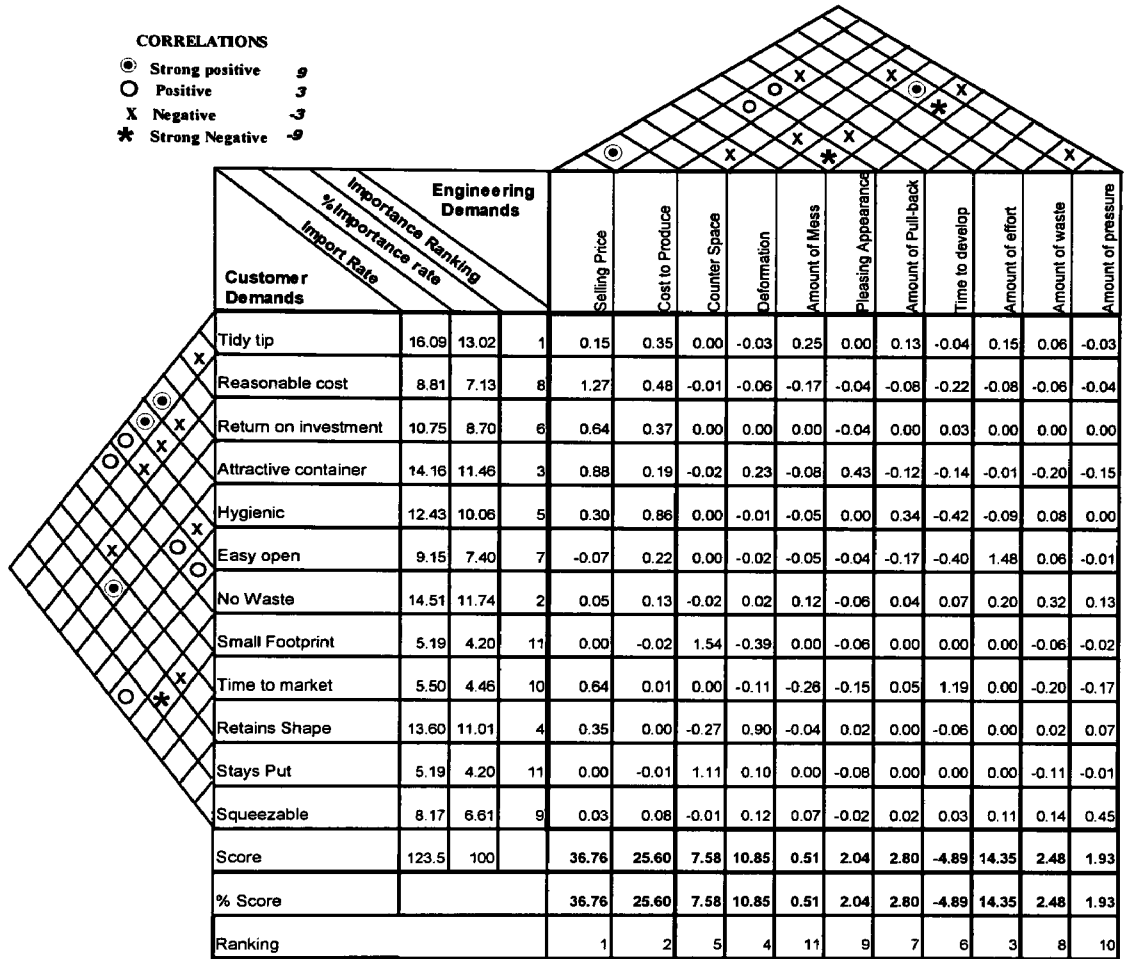


Figure 4.12 Results of FPD-HOQ (ranked-loop) for toothpaste case study

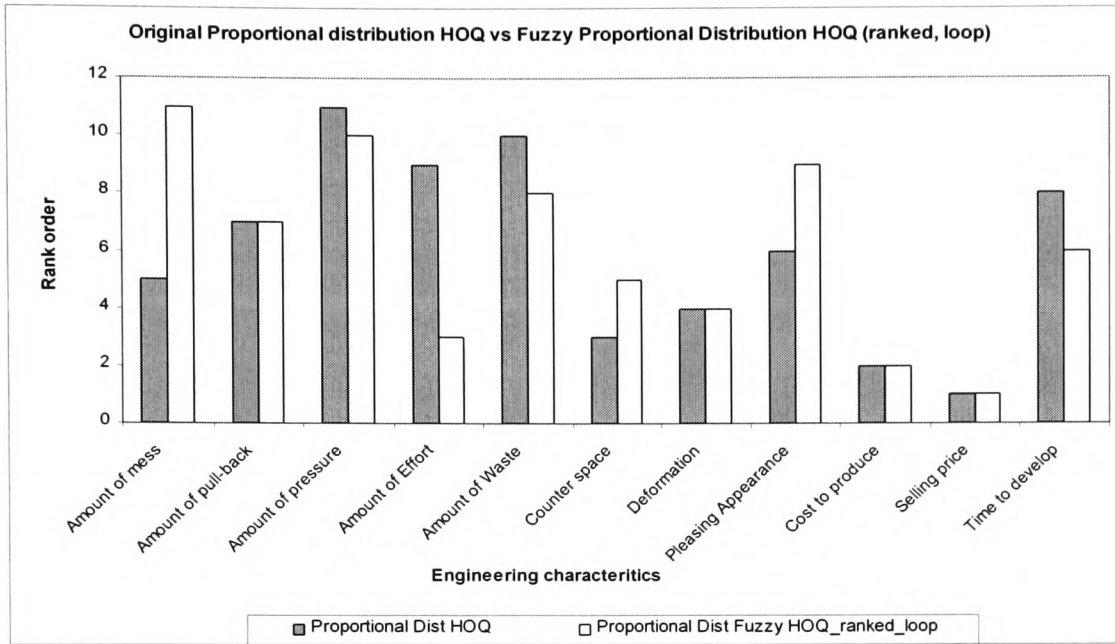


Figure 4.13 Original Proportional Distribution HOQ vs. FPD-HOQ (ranked, loop) for toothpaste example

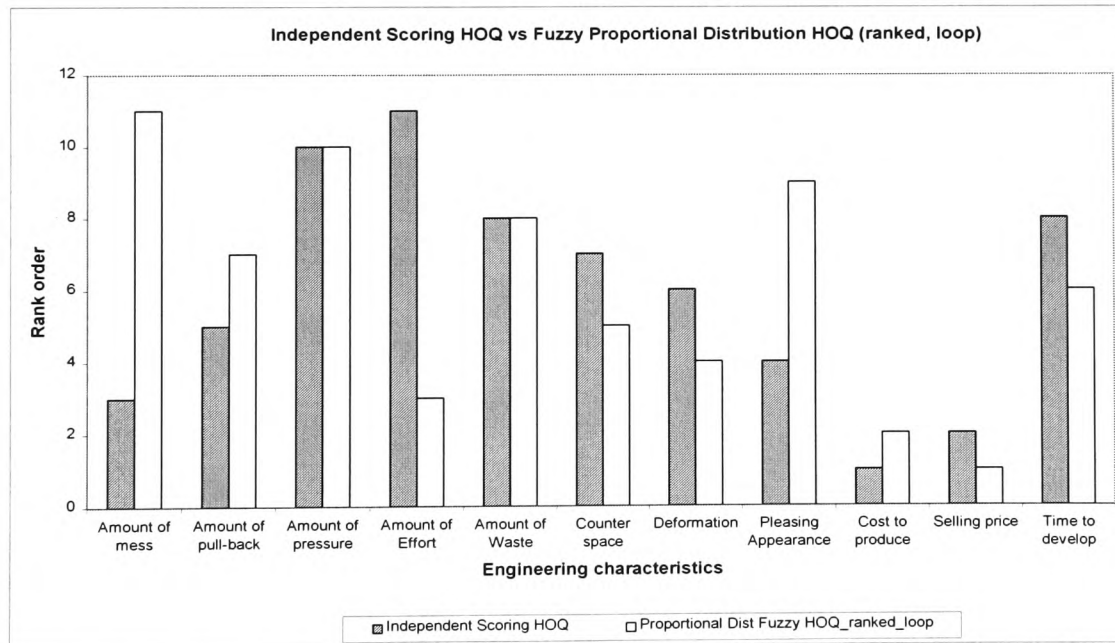


Figure 4.14 Original Independent Scoring HOQ vs. FPD-HOQ (ranked, loop) for toothpaste example

4.4.1.2 Case study 2: The design of a Research Centre room layout

The Independent Scoring results are firstly transformed to the Proportional Distribution as previously explained (chapter 2) and the Proportional Distribution HOQ is shown in Figure 4.15. These two traditional HOQ are then compared with each other and the similarities and differences can be seen in Figure 4.16. It can be observed that the ranking between the two traditional methods follow exact trends except for engineering characteristics “No. of screens” and “Printer location” that have the reverse ranking order. It can thus be said that this matrix is also balanced.

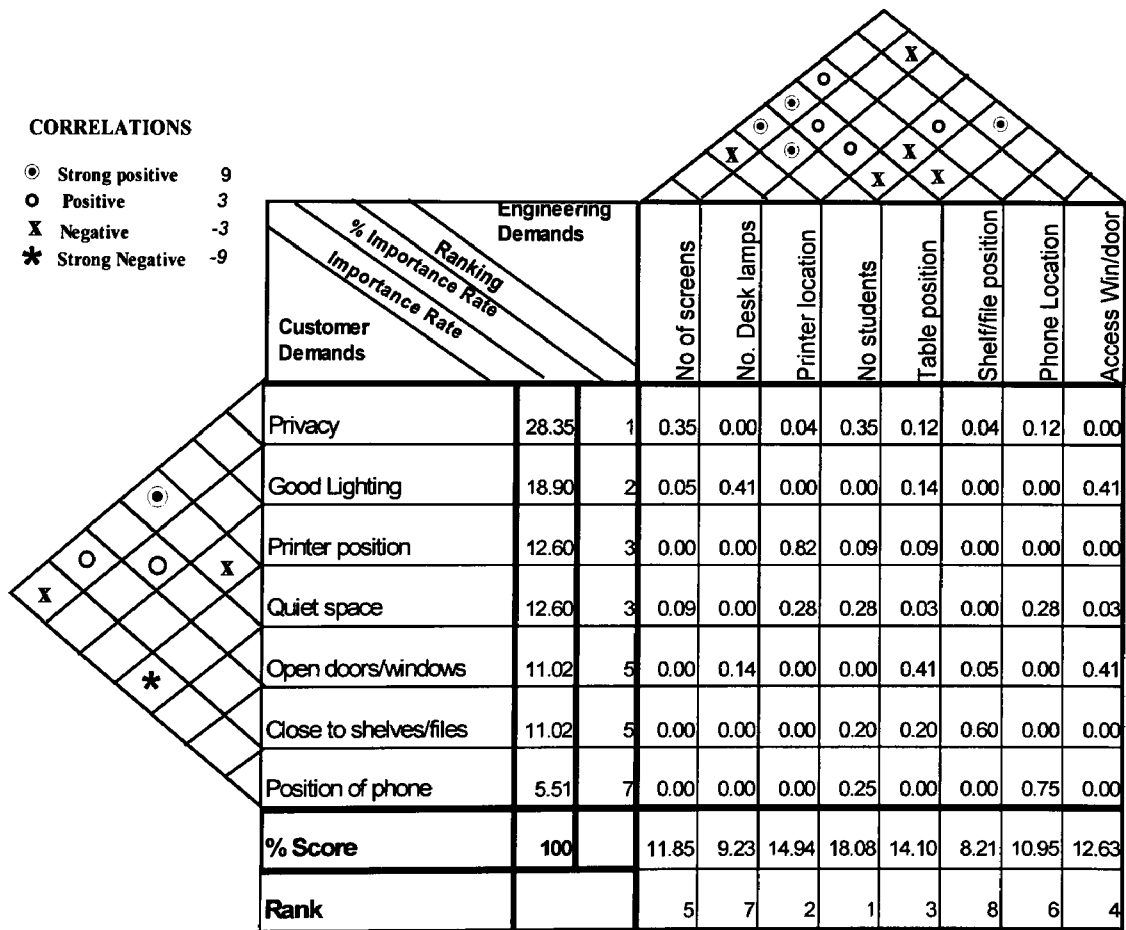


Figure 4.15 Proportional Distribution HOQ for the research Centre room layout

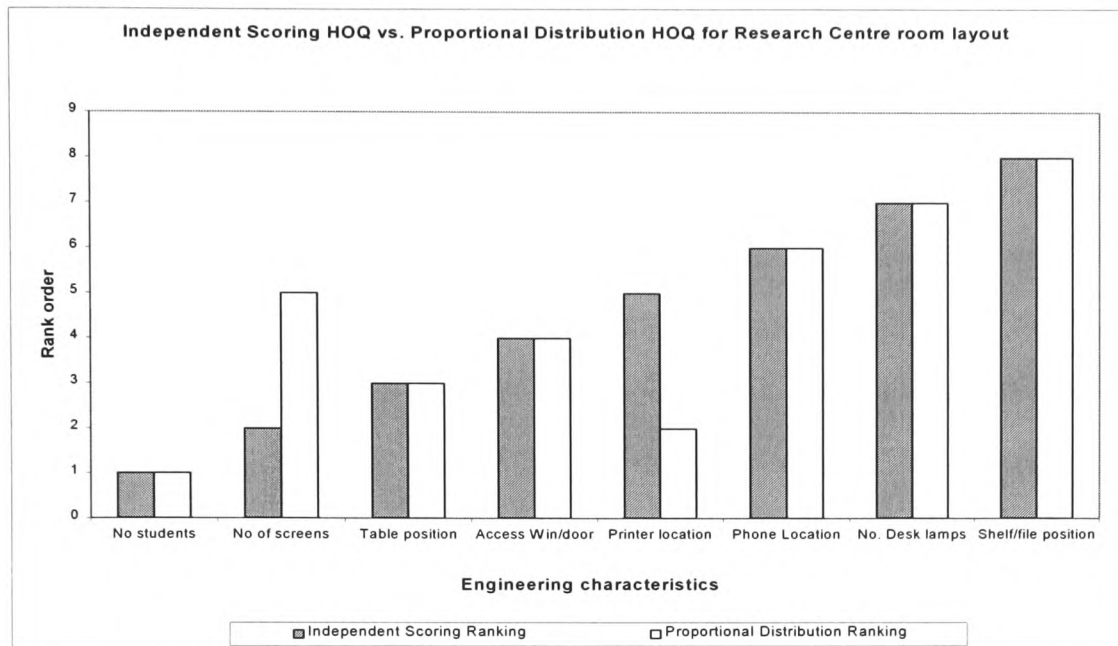


Figure 4.16 Independent Scoring HOQ vs. the Proportional Distribution HOQ for the design of a research Centre room layout.

The results of the FPD-HOQ ranked, looped data for this example is given in Figure 4.17. The results are then compared to the original proportional distribution HOQ and depicted in Figure 4.18. It can be observed that the FPD-HOQ approach has yielded somewhat different rank order, with only five engineering characteristics out of the eight, 63% giving similar rank order (within two ranks). The engineering characteristics that have changed its rank order drastically are “No. of desk lamps”, “Position of shelf/files” and “Access to Windows/doors”. “Access to Windows/doors” has decreased in its importance after the FPD-QFD approach, whereas “No. of desk lamps” and “Position of shelf/files” have increased in their importance. If engineering characteristic “No. of desk lamps” is looked at further, it can be seen to be related to customer demand “Good lighting”, which was a very important demand in the original independent scoring HOQ (Figure 4.4) and is still an important demand in the FPD-HOQ approach (Figure 4.17). “No. of desk lamps” also has more positive correlations in the roof and porch than negative ones. So its increased in importance is justified.

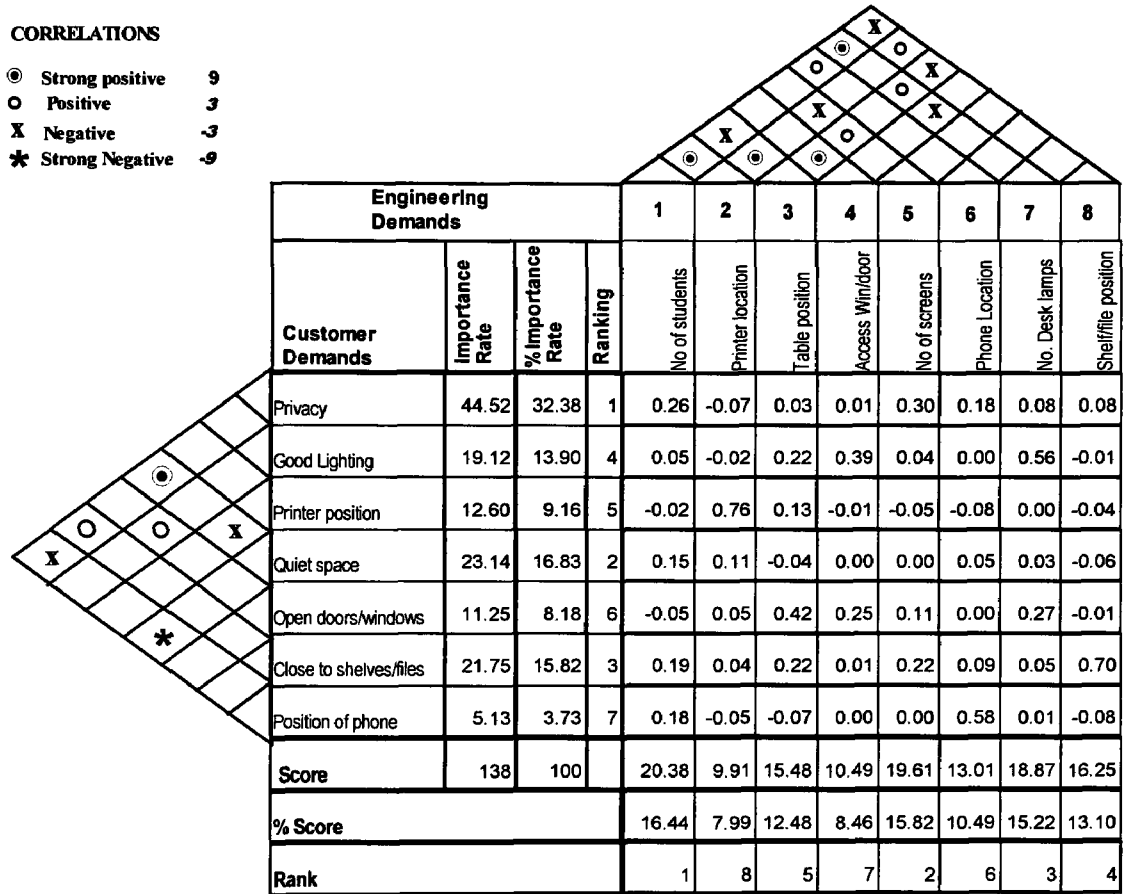


Figure 4.17 FPD-HOQ for research Centre room layout (ranked, loop)

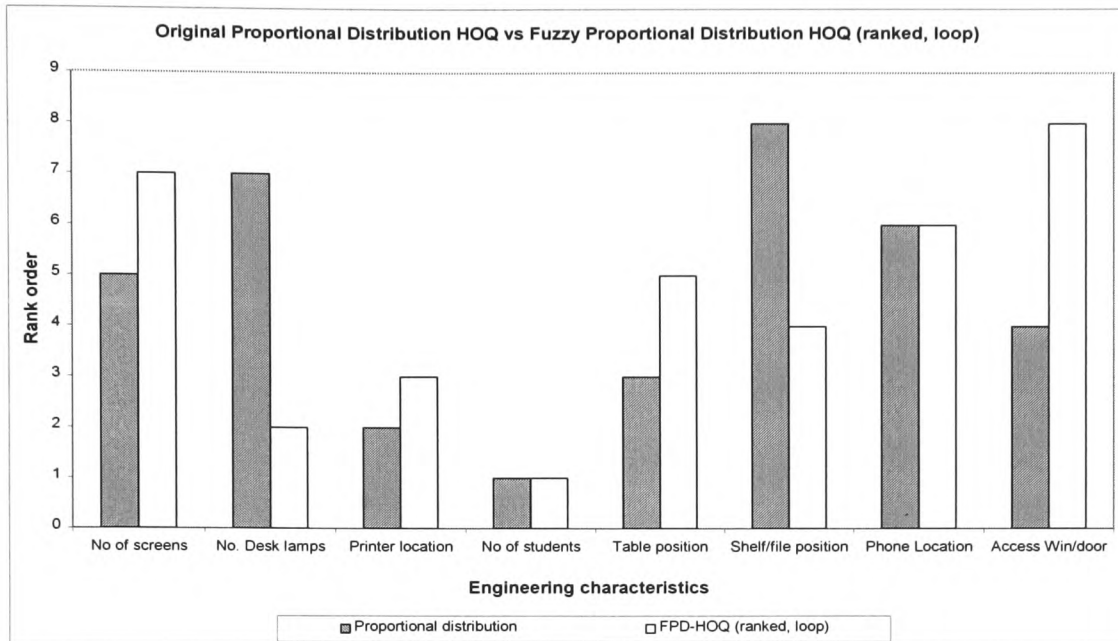


Figure 4.18 Original Proportional Distribution HOQ vs. the FPD-HOQ (ranked, loop) for the design of Research Centre room layout

The new FPD-HOQ engineering characteristic rank order is also compared to the original Independent scoring HOQ and the result is depicted in Figure 4.19. In this Figure, it can be observed that four out of the eight, 50% of the engineering characteristics gave similar rank order (in the order of two rank differences). Two out of these four had exactly the same rank order, that is engineering characteristics "No. of students" and "Phone location". For this example, the resulting data from the FPD-HOQ approach also resembles much more the original proportional Distribution HOQ than the original Independent Scoring HOQ. Again this is expected, since the data used in this approach stems from the original Proportional Distribution HOQ.

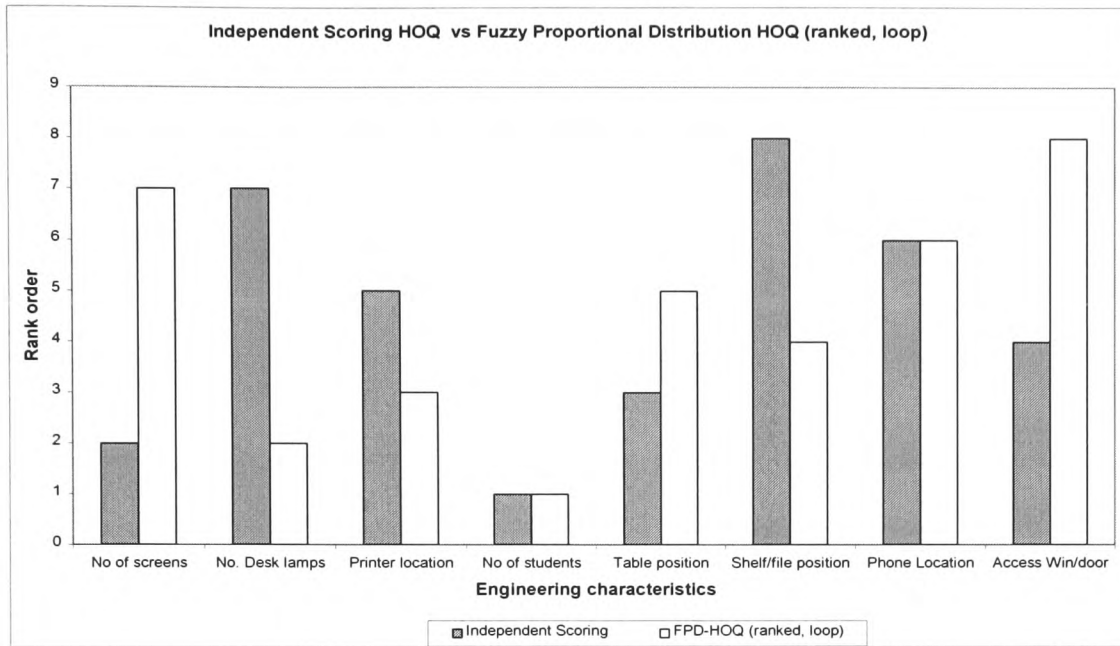


Figure 4.19 Original Independent Scoring HOQ vs. the FPD-HOQ approach (ranked, loop) for the design of a Research Centre room layout

Table 4.2 displays the results of the two case studies for the FPD-HOQ (ranked, loop), comparing the results of the Independent Scoring HOQ, the original Proportional Distribution HOQ with the FPD-HOQ. It can be observed from this table that the toothpaste case study resulted in more similar rank order than the research Centre room layout example, as well as being more statistically significant, especially when compared to the original Proportional Distribution HOQ. The N/S means that the result is not statistically significant, i.e. there are fewer similarities between the results.

Case study	Exact rank order	No. of dissimilar rank		Total	% similar rank	Spearman correlation	Significance
		Within 2 rank order					
Toothpaste (PD)	1	7	3	11	73	0.57	95%
Toothpaste (IS)	4	4	3	11	73	0.21	N/S
Research Centre (IS)	2	2	4	8	50	-0.07	N/S
Research Centre (PD)	2	3	3	8	63	0.21	N/S

Table 4.2 Results of the two case studies for FPD-HOQ (ranked, loop)

4.4.2 FPD-HOQ ranked-loop versus FPD-HOQ ranked non-loop

The aim of this section is to verify whether using the looping method had any effect on the end results. The FPD-HOQ that was ranked, again using the looping method was compared with the ranked but non-looped results.

4.4.2.1 Case study 1: The design of a toothpaste tube

The results for this case study are shown in Figure 4.20. The comparison between the two sets of results (FPD-HOQ ranked, loop vs. FPD-HOQ ranked, non-loop) shows that there were no major differences in the ranking of the engineering characteristics. Nine out of eleven, 82% gave similar rank results (within two ranks). The only main difference is for engineering characteristic “*Time to develop*”.

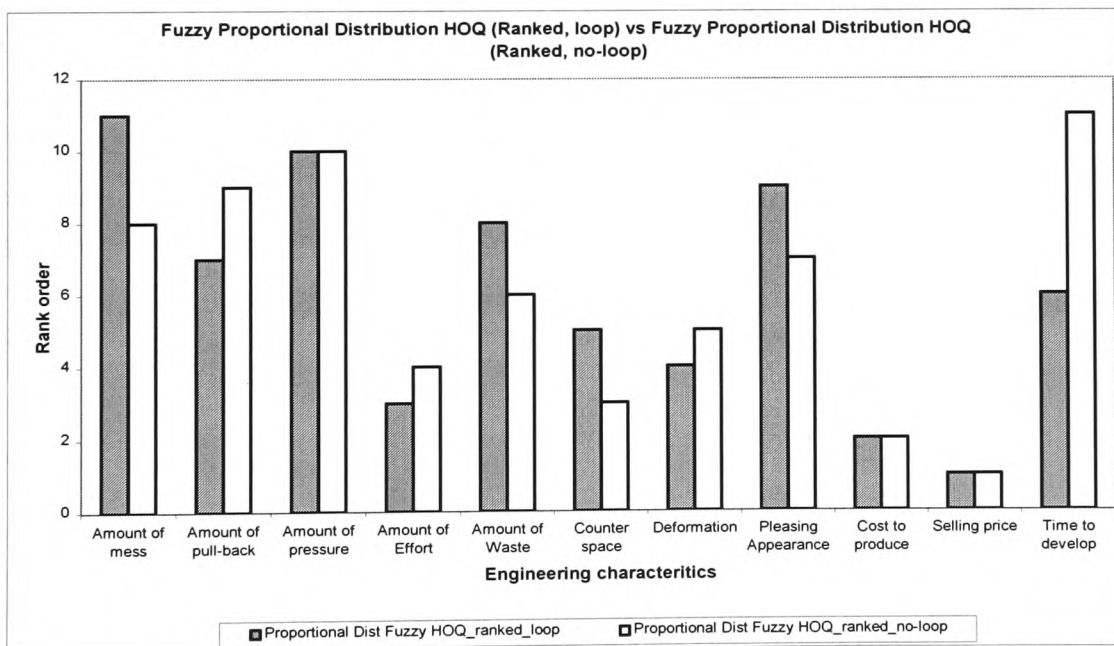


Figure 4.20 FPD-HOQ (ranked, loop) vs. FPD-HOQ (ranked, non-loop) for toothpaste example

4.4.2.2 Case study 2: The design of a Research Centre room layout

The comparison between the ranked-loop data and the ranked, non-loop data for this example is illustrated in Figure 4.21. The two graphs show similar pattern, with all of the results, 100% within two rank differences, except for a few minor discrepancies especially for "Phone location".

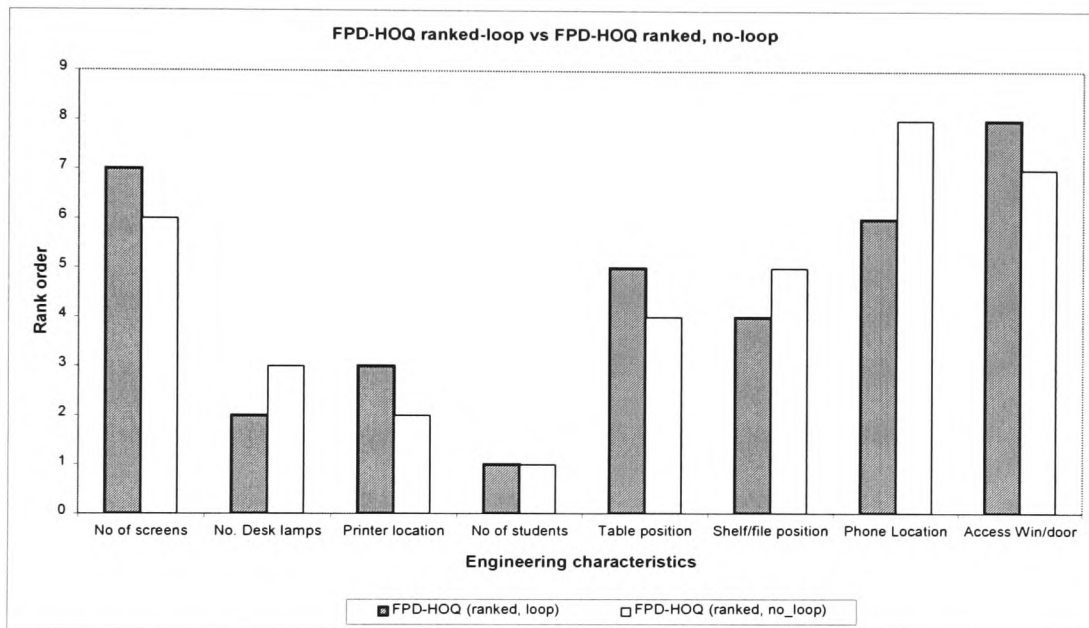


Figure 4.21 FPD-HOQ ranked-loop vs. the FPD-HOQ ranked, non-loop for research Centre room layout example

Table 4.3 shows the result of the similarities and dissimilarities between the two case studies for the FPD-HOQ (ranked, loop) compared to the FPD-HOQ (ranked, non-loop) data. It can be seen that the results are statistically significant. Therefore, it can be deduced that whilst using the ranking of the demands method, it did not matter whether the looping approach or the non-looping approach was used. Clearly the non-looping method uses less complex algorithms, requires less programming effort and thus less computational time. Although this may be the case, the looping method because of its

iterative action, utilising the most updated data is more sensitive and conceptually more correct, as the attainment of new results depends on the result of the previous loop.

Fuzzy Proportional Distribution HOQ (ranked, loop) vs. ranked, non-loop							
Case study	Exact rank order	No. of dissimilar rank	No. of similar rank	Total	% similar rank	Spearman correlation	Significance
Toothpaste	3	6	2	11	82	0.76	99%
Research Centre (IS)	1	7	0	8	100	0.88	99%

Table 4.3 FPD-HOQ (ranked, loop) vs. FPD-HOQ (ranked, non-loop) for the case studies

4.4.3 FPD-HOQ (Ranked, non-loop) versus FPD-HOQ (unranked, non-loop)

The aim of this section is to identify whether ranking both the customer and engineering characteristics prior to the analysis had any major impact on the results. Using the non-looping method, (since it was decided from the previous section that the non-looping method uses less computational time and its result was not significantly different from the looping one), the ranked results were compared to the unranked results.

4.4.3.1 Case study 1: The design of a toothpaste tube

The result for the unranked, non-looping method is depicted in Figure 4.22. Similar trends were being followed between the two sets of results, as can be seen in Figure 4.22. In fact there are eight engineering characteristics with similar (within two ranks) ranks, (73%) and out of this eight, five have exactly the same rank order. This Figure depicts more engineering characteristics having exactly the same rank order so far. Only three engineering characteristics "Amount of pull-back", "Deformation" and "Time to develop" portrayed slight discrepancies between the two methods.

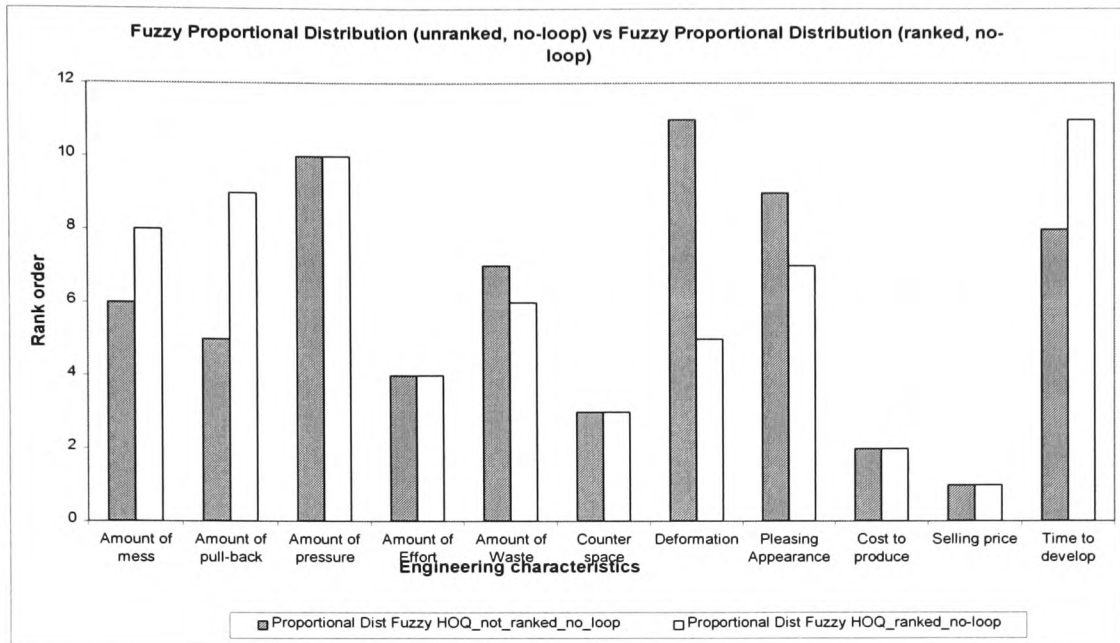


Figure 4.22 FPD-HOQ (unranked, non-loop) vs. FPD-HOQ (ranked, non-loop) for toothpaste example

4.4.3.2 Case study 2: The design of a Research Centre room layout

The comparison between the ranked-loop data and the ranked, non-loop data for this example is illustrated in Figure 4.23. It can also be seen in this Figure that there are more discrepancies between the two sets of data compared to the toothpaste tube case study, with five out of eight (63%) engineering characteristics within two rank differences. The results are not statistically significant. The dissimilarities occur for engineering characteristics "No. of screens", "Printer location" and "Phone location".

Table 4.4 shows the result of the similarities and dissimilarities between the two case studies for the FPD-HOQ (ranked, non-loop) data compared to the FPD-HOQ (unranked, non-loop) data.

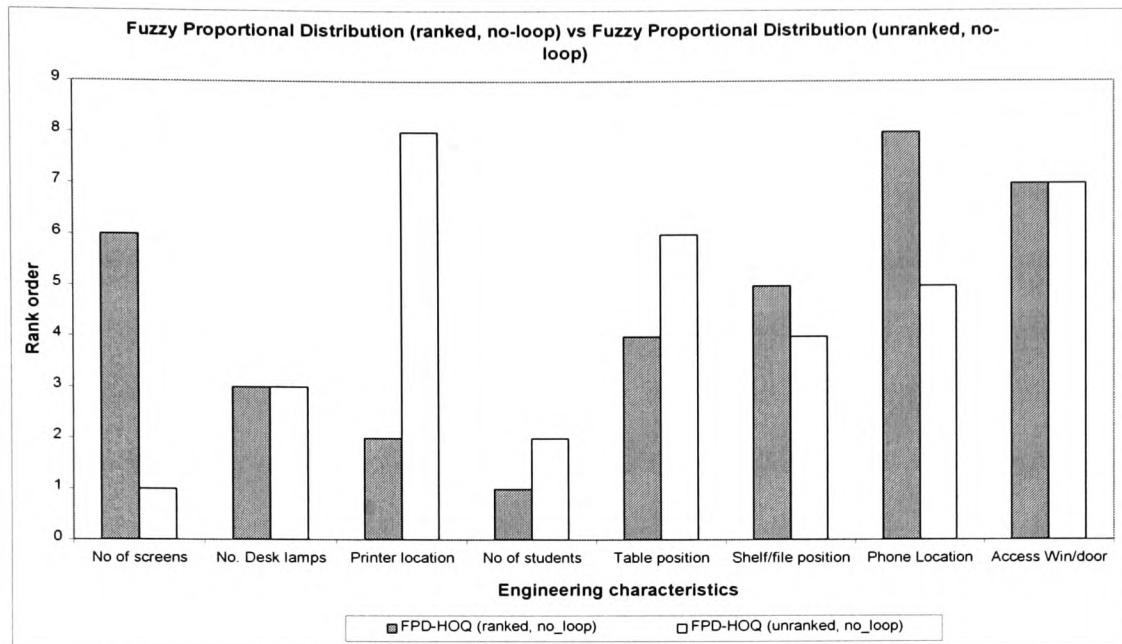


Figure 4.23 Comparison between FPD ranked, non-loop and FPD unranked, non-loop

Case study	No. of dissimilar rank		No. of similar rank	Total	% similar rank	Spearman correlation	Significance
	Exact rank order	Within 2 rank order					
Toothpaste	5	3	3	11	73	0.70	95%
Research Centre (IS)	2	3	3	8	63	0.10	N/S

Table 4.4 FPD-HOQ (ranked, non-loop) vs. FPD-HOQ (unranked, non-loop) for the case studies

From the results of these two case studies, ranking the data with the most important characteristics first before the analysis could have an impact on the results, depending on the complexity of the case study. Ranking the data requires more complex programming and more computational time, although the concept may be conceptually more logical, as the more important ones will dictate the outcome of the less important ones. The non-ranking of the data requires less complex programming and less time as the data is in a similar format to the original raw data.

4.4.4 Remarks

It can be observed from the different methods discussed so far that the ranked, looping method possibly gives more accurate results as it places more emphasis on more important demands by placing them first in the iteration as well as uses the results of the preceding loop to compute results of the new loop. This can definitely be observed for the toothpaste case study, which was more complex. Its comparison with the unranked, non-looping result shows very little discrepancies, so the unranked with non-looping method provides a good combination where computational time and programming complexities are kept to a minimum. Therefore the hypothesis that the order in which the demands are placed may have an effect on the results does not entirely hold, so the data can be used in its original format especially if the problem at hand is complex, with many requirements and interactions.

4.5 FPD-HOQ (UNRANKED, NON-LOOP) VERSUS FUZZY RANGE HOQ

This section compares the result of the Fuzzy Proportional Distribution with the Fuzzy Range approach. Since the Fuzzy Range HOQ uses the unranked data for its analysis, it is necessary to compare it with the unranked results of the Fuzzy Proportional Distribution HOQ. The non-looping idea will also be used, as suggested in the previous section, it uses less computational time and requires less complex programming. Again the two case studies, i.e. 'the Design of a toothpaste tube' and 'the Design of a research Centre room layout' will be used for comparative purposes.

4.5.1 Case Study 1: Design of a toothpaste tube

The comparative results between these two approaches (FR-HOQ vs. FPD-HOQ) are depicted in Figure 4.24. As can be seen from Figure 4.24, there are a few discrepancies between the ranking order of these two houses. Five out of the eleven, (45%) engineering

characteristics have similar ranking (i.e. within two rank differences), with the rest having quite different rankings, especially for engineering characteristics “*Counter Space*” and “*Pleasing appearance*”. Although it may appear that there is a relation between these two methods, the Spearman’s ranking correlation r_s was calculated to be 0.5, which is not statistically significant.

The FPD-HOQ approach has increased the ranking order of “*Amount of Effort*”, “*Counter Space*” and “*Time to develop*”, i.e. made these characteristics more important and decreased the order of “*Amount of Mess*”, “*Amount of Deformation*” and “*Pleasing Appearance*”, i.e. they are now less important.

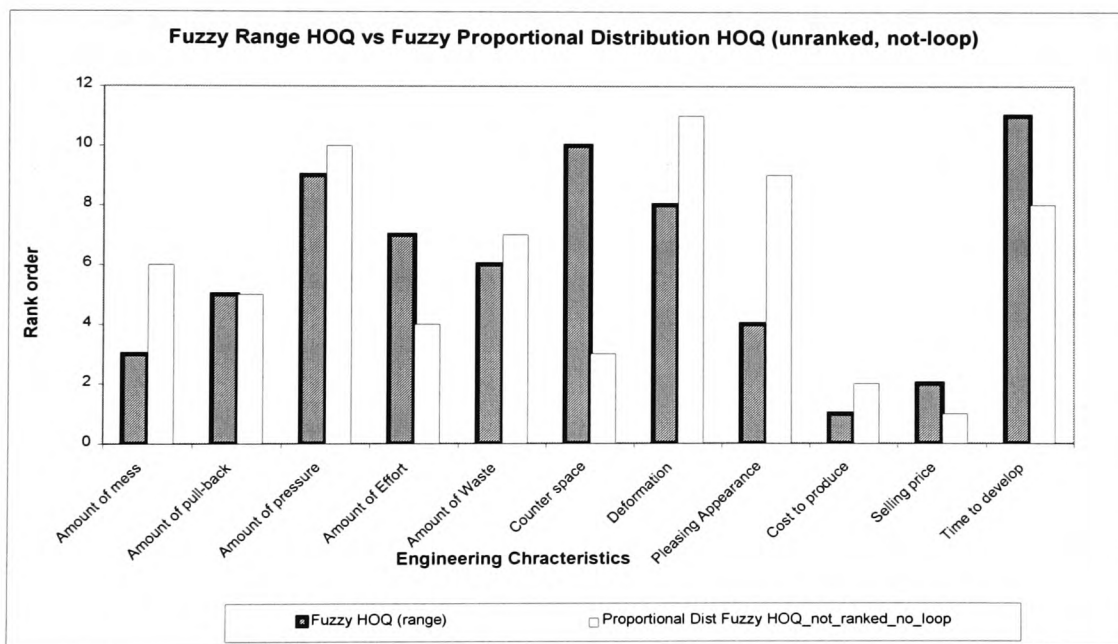


Figure 4.24 Fuzzy Range HOQ vs. FPD-HOQ (unranked, non-loop)

All the different methods were compared with the intention of showing the similarities and differences in the engineering characteristic's rank order. It can be observed from Figure 4.25 that about seven of the eleven (64%) engineering characteristics gave similar

rank order (within two rank differences). The engineering characteristics that gave very different rank order between the different HOQs were “*Amount of Effort*” and “*Amount of Deformation*”.

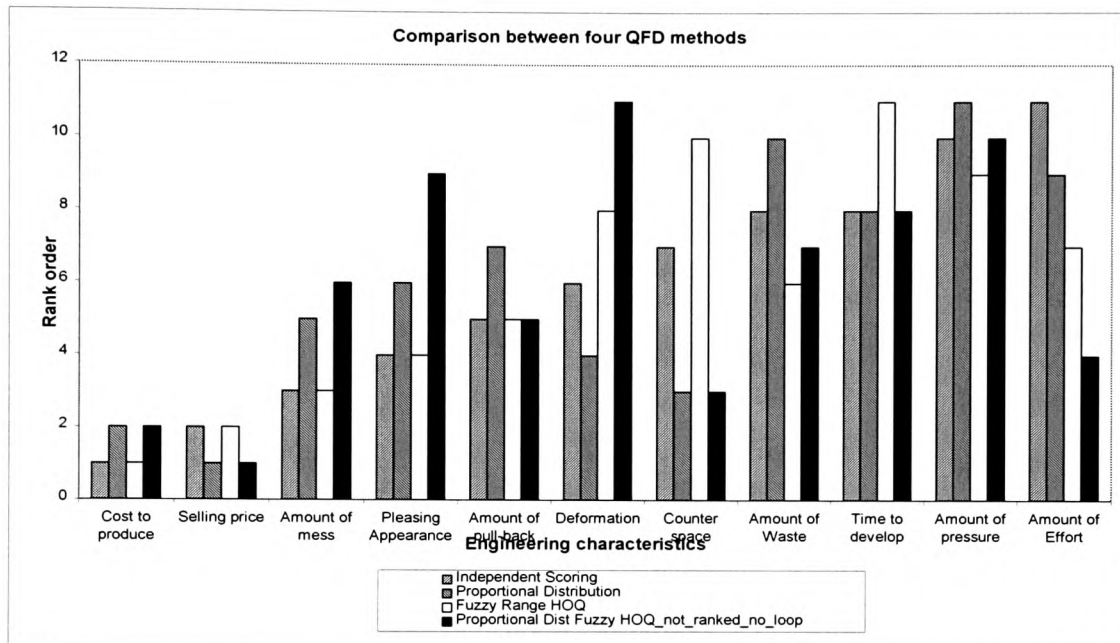


Figure 4.25 Independent Scoring HOQ vs. Proportional Distribution HOQ vs. Fuzzy Range HOQ vs. Fuzzy Proportional Distribution HOQ (unranked, non-loop)

4.5.2 Case study 2: The design of a research Centre room layout

The comparison between the Fuzzy Range HOQ and the Fuzzy Proportional Distribution HOQ for the unranked, non-loop data is illustrated in Figure 4.26. Four out of the eight (50%) engineering characteristics show similar ranking order (within two rank differences). This is not statistically significant as the Spearman’s calculated rank correlation r_s was 0.058, meaning that there is very little relation between these two approaches. The engineering characteristics with the most differences are “*No. of desk lamps*”, “*Printer Location*”, “*Shelf/ file position*” and “*Access to windows/doors*”. All the different QFD HOQs are compared and their results are depicted in Figure 4.27.

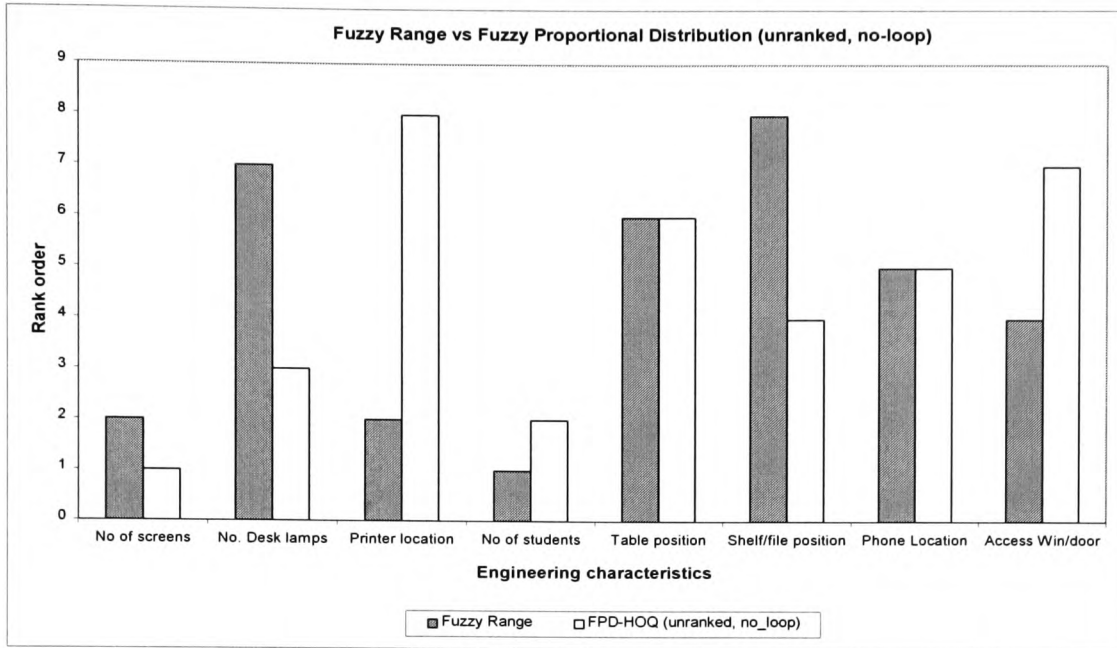


Figure 4.26 Fuzzy Range HOQ vs. Fuzzy Proportional Distribution HOQ (unranked, non-loop) for research Centre room layout

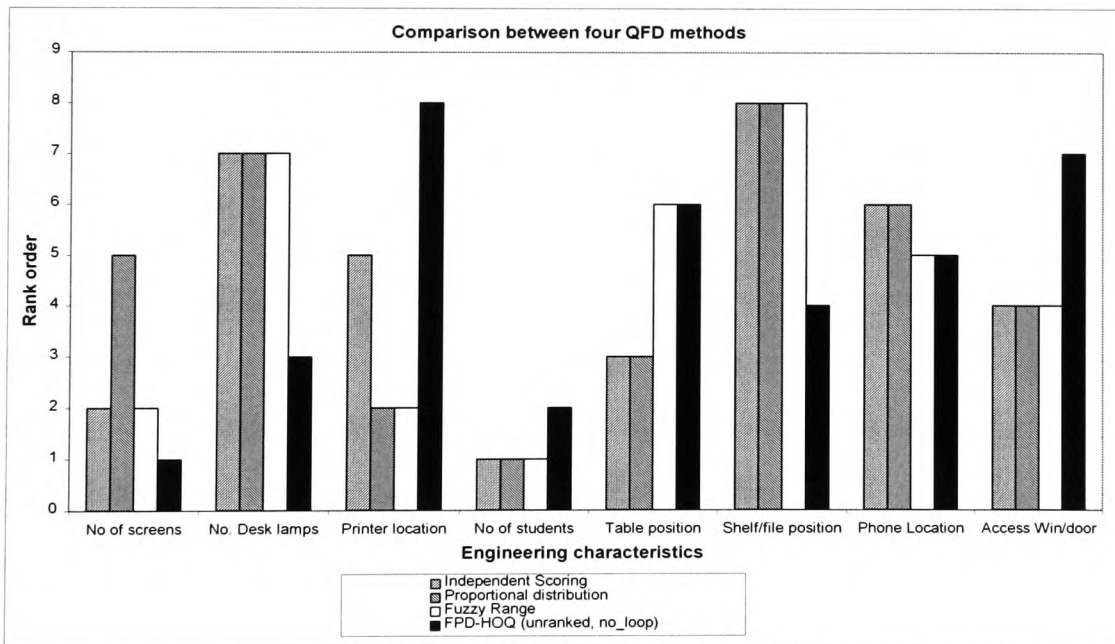


Figure 4.27 Independent Scoring HOQ vs. Proportional Distribution HOQ vs. Fuzzy Range HOQ vs. Fuzzy Proportional Distribution HOQ (unranked, non-loop)

It can be observed from Figure 4.27 that about six of the eight (75%) engineering characteristics gave similar rank order (within two rank differences). The engineering characteristics that gave very different rank order between the different HOQs are “*Printer location*” and “*Table position*”.

4.5.3 Remarks

For both case studies, comparing the Fuzzy Range HOQ approach to the Fuzzy Proportional Distribution HOQ approach showed that there are more dissimilarities than similarities in the engineering characteristic’s rank order. This means that they have yielded different results and are thus not related to each other. Table 4.5 compares the different aspects of the Fuzzy Range HOQ to the Fuzzy Proportional Distribution HOQ. The two developed approaches analyse the data in the HOQ in different ways as shown in the first half of the table. The second half of the table shows their differences in terms of complexity, robustness, accuracy etc. Which approach should be adopted depends on what the QFD team would like to do with the result. For instance, the Fuzzy Range HOQ approach uses less computational time and the programming required is less complex (See Table 4.5). It is a better approach if the results were to be brought to the next QFD phase, since it uses ranges of numbers, where the elements of error (mean and variance) are encapsulated within the ranges. It is a more robust approach as indicated by the sensitivity analysis in section 4.6. The use of range is known to be a ‘robust statistic’ (Chatfield, 1983), (Montgomery and Runger, 1994). This approach is more biased towards the more important demands, as it alters weaker demands, whether in a positive or negative direction, but not the strong demands. It is also bounded by the limit of the ranges defined by the QFD team.

In the Fuzzy Proportional Distribution approach, both the most important demands and the least important demands can either be increased or decreased, instead of logically

increasing or decreasing the ranges according to the correlation between demands. So there are no lower or upper limit in which to increase or decrease the demands. This approach is mathematically more rigorous and yields more precise results at the expense of more computational time and more complex programming. The approach is also more sensitive to the input data as demonstrated by the sensitivity analysis in section 4.6.

Comparison between Fuzzy-QFD approaches		
	Fuzzy Range HOQ	Fuzzy Proportional Distribution HOQ
<i>Initial data</i>	Uses Independent Scoring HOQ	Uses Proportional Distribution HOQ
<i>Inference rules</i>	IF-THEN	IF-THEN
<i>Fuzzification</i>	Range	Crisp
<i>Computation</i>	Difference in range	Difference in crisp values
<i>MF</i>	Range	S-Function (loop, rank, no-loop, unranked)
<i>Defuzzification</i>	Average	Takagi-Sugeno
<i>Output</i>	Range & crisp	Crisp
<i>Programming effort</i>	Less	More
<i>Complexity</i>	Less	More
<i>Robustness</i>	More	Less
<i>Sensitive</i>	Less	More
<i>Limits</i>	Range	No limit
<i>Accuracy</i>	Less, more intuitive	More, more mathematical
<i>Usefulness</i>	Results brought to next QFD phase	Only considering HOQ

Table 4.5 Comparison between the Fuzzy Range HOQ approach and the Fuzzy Proportional Distribution HOQ approach

Even when comparing all the methods (Independent Scoring, Proportional Distribution, Fuzzy Range QFD, Fuzzy Proportional Distribution QFD), there were more similarities between the different methods than differences, especially for the more complex case studies. This suggests that the proposed Fuzzy-QFD approaches output results that are consistent with the original QFD results, but has somewhat fine-tuned the result as was shown by the amount of similar rank order of the engineering characteristics.

4.6 SENSITIVITY ANALYSIS

When a method based on multiple criteria such as QFD is being used, the results of each criterion need to be weighted in order to arrive at the final score. The results are then placed in a rank order, from highest to lowest priority, on the basis of their final scores.

This initial rank order is often submitted to sensitivity analysis, which aims to find out which factors have important effects and which do not. Sensitivity analysis involves changing or shifting weights or parameters in order to gain information on the so-called 'robustness' of the results (Collion and Kissi, 1994). This analysis can be conducted in various ways, such as through group analysis and discussion, or by means of mathematical procedures in which either the measurement methods or the criteria weights are modified.

Since the correlation matrices in the porch or roof are used as weighting factors and are not altered in the proposed Fuzzy QFD approaches, sensitivity analyses were performed which involved changing, adding or taking away a few correlations either in the porch or roof or both. The correlation matrices defined by the QFD team can also be subjective, similar to the relationship matrix and the customer importance rating as highlighted in the Fuzzy-QFD approaches developed. The QFD team can sometimes over or underestimate interdependencies in the correlation matrices as suggested by Temponi, Yen and Tiao (Temponi *et al*, 1999) and Liu and Jia (Liu and Jia, 1998). This is yet another problem with the QFD process. The approach that integrates the Taguchi Method and QFD (QFD-Taguchi approach) in the proceeding chapter makes extensive use of these interactions in the correlation matrix to define the technical target values more precisely. Therefore a way to analyse and rectify over or under emphasised correlations would be helpful, both to the developed Fuzzy-QFD approaches and to the QFD-Taguchi approach.

The sensitivity analysis is performed after the result of yet another proposed method, which aims to identify missing or conflicting correlations in the correlation matrices. The proposed method suggest that if a customer demand is related to another customer demand, which in turn is related to a third customer demand, then it can be inferred that

the third customer demand will be correlated with the first customer demand. So implicit correlations can be inferred from explicit ones. A rule can take the form of:

IF C1 and C2 are correlated *AND* C2 and C3 are correlated, *THEN* C1 and C3 should be correlated (assuming C1 and C3 were not correlated).

In this way missing or contradicting correlations in the correlation matrix can be rectified. This work has been carried out by Liu and Jia (Liu and Jia, 1998) except in their paper it is not clear how the consequent part of the rules are developed. In the work of Temponi, Yen and Tiao (Temponi *et al*, 1999), rules identified from rule tables are utilised to represent the relationship 'strong', 'medium' and 'weak' found in the relationship matrix to infer correlations in the roof. Their work assumes that the relationship matrix in the HOQ has been identified correctly by the QFD team as the determination of the roof correlation matrix depends on the relationship matrix.

A structured approach using multi-valued logic (Klir and Yuan, 1995) to determine the consequent part of the rule to infer implicit correlations based on explicit correlations in both the porch and the roof is proposed and developed here. Four valued logic is used in this case because four correlations (SP, WP, WN, SN) exist in the correlation matrices. The logical truth table for four valued logic is illustrated in Table 4.6, which uses the AND logic operator (\wedge), since the antecedent part of the rules are connected by the AND operator.

\wedge	0	1	2	3
0	0	0	0	0
1	0	1	1	1
2	0	1	2	2
3	0	1	2	3

Table 4.6 Truth table for 4-valued logic

The correlation is represented by SN = 0, WN = 1, WP = 2 and SP = 3. The vertical axis of the table represents the first antecedent part of the rule and the horizontal axis represents the second antecedent part of the rule. In total there are sixteen, (4 x 4) rules. Along the diagonal for instance the rules can be:

- (Rule _{1,1}) *IF* C1 is related to C2 by SN (0) *AND* C2 is related to C3 by SN (0), *THEN* C1 and C3 are related by SN (0).
- (Rule _{2,2}) *IF* C1 is related to C2 by WN (1) *AND* C2 is related to C3 by WN (1), *THEN* C1 and C3 are related by WN (1).
- (Rule _{3,3}) *IF* C1 is related to C2 by WP (2) *AND* C2 is related to C3 by WP (2), *THEN* C1 and C3 are related by WP (2).
- (Rule _{4,4}) *IF* C1 is related to C2 by SP (3) *AND* C2 is related to C3 by SP (3), *THEN* C1 and C3 are related by SP (3).

The updated correlations are placed in the correlation matrix. Only the first level is performed as other correlations could be inferred based on the newly defined correlations in the second or third level. These correlations are considered insignificant and thus negligible. If a conflict occurs, say two or three rules give different outputs, or a correlation already exist in the corresponding cell, the QFD experts are alerted and they decide on the most suitable correlation based on their expertise.

Therefore the sensitivity analysis is performed after one loop has been calculated and the results after the alterations are compared to the results of the Fuzzy-QFD approaches. Only the toothpaste case study will be used in the sensitivity analysis. First the Fuzzy Range HOQ will be analysed. Note that the alteration in the correlation matrix is the same irrespective of which method is being used. It is also applicable for the original HOQs. Equation (4.1) shows the porch correlation in its original format.

$$RS_Porch = \begin{bmatrix} 0 & 0 & 0 & SP & 0 & WP & WP & 0 & WN & SP & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN & 0 & SP & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & SN & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & WN & WP & 0 & WN & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & WP & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & WP & 0 & WN & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (4.1)$$

After using the proposed method, only two new correlations were identified in the porch, i.e. correlation between C4 & C10 (WN) and C6 & C10 (WN), thus further implying that C4 & C6 are correlated (WN), which confirms the original correlation in that cell. Three original correlations were confirmed as the new correlations derived were exactly the same as the original, whereas a few others were discarded in favour of the original ones. The new porch correlation after the alterations is depicted in equation (4.2).

$$RS_Porch = \begin{bmatrix} 0 & 0 & 0 & SP & 0 & WP & WP & 0 & WN & SP & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN & 0 & SP & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & SN & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & WN & WP & 0 & WN & WN & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & WP & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & WP & 0 & WN & WN & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & WN \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (4.2)$$

The results of the engineering characteristic's weighting and rank order after the porch correlation is altered are compared to the results of the Fuzzy-Range HOQ. Figure 4.28 shows the result of the sensitivity analysis for the Fuzzy Range approach for the toothpaste example when alterations were made to the porch correlation matrix only.

The same method was then used to identify missing and contradicting correlations in the roof. Figure 4.29 presents the results of the sensitivity analysis of the Fuzzy Range HOQ with alterations only in the roof using the proposed method. In total 11 new correlations were identified in the roof, with others confirming or contradicting the original correlations. The new correlations were placed in a matrix similar to equation(4.2), but this time the matrix was 11 by 11. (This correlation matrix is shown in Appendix B). Finally, both the changes found for the porch and roof correlation were then used simultaneously to calculate the overall sensitivity of the Fuzzy Range QFD approach. The results are displayed in Figure 4.30. The Spearman's rank correlation was calculated for the case when alterations were made both to the roof and the porch correlation matrices and it was calculated to be 0.95, which is 99% statistically significant. This means that the two sets of results are dependent on each other. Therefore changes in both correlation matrices affect the engineering characteristic's ranking order.

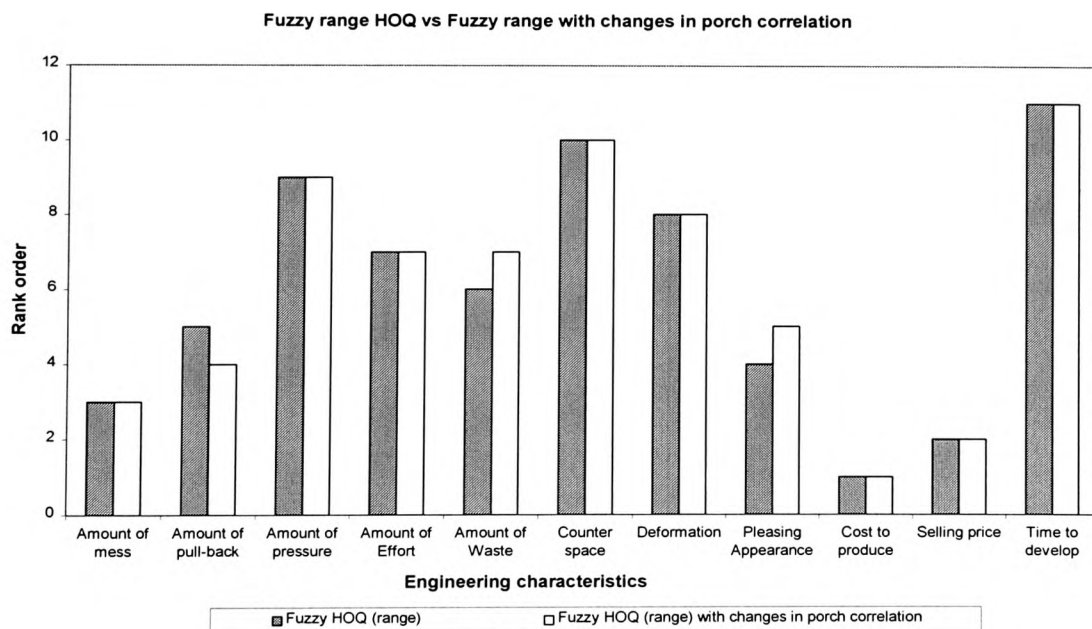


Figure 4.28 Fuzzy Range HOQ vs. Fuzzy-Range HOQ when a few alterations are made in the porch correlation

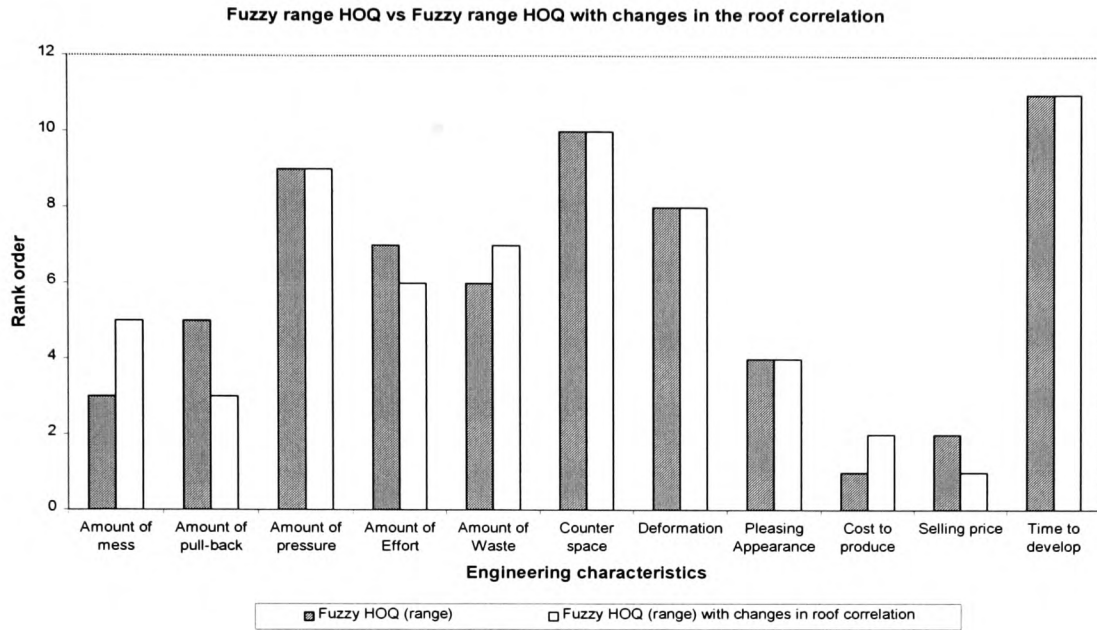


Figure 4.29 Fuzzy Range HOQ vs. Fuzzy-Range HOQ when a few alterations are made in the roof correlation

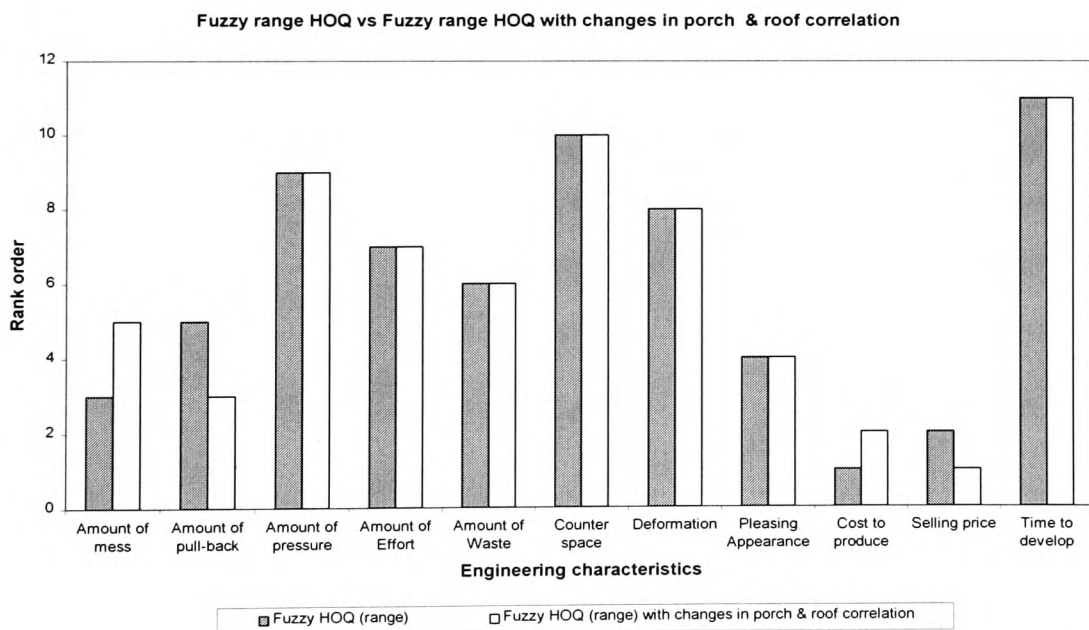


Figure 4.30 Fuzzy Range HOQ vs. Fuzzy Range HOQ when a few alterations are made in the porch and roof correlation

The changes in the porch were applied to the Fuzzy Proportional Distribution HOQ approach and the results are compared to the FPD-HOQ (unranked, non-loop) and depicted in Figure 4.31. Then the changes to the roof only were applied and the results are displayed in Figure 4.32. Finally both changes in the porch and roof correlation were combined and the results are shown in Figure 4.33. The computed Spearman's rank correlation, r_s , for the case when alterations were made both in the roof and in the porch was 0.75, which is 99% statistically significant.

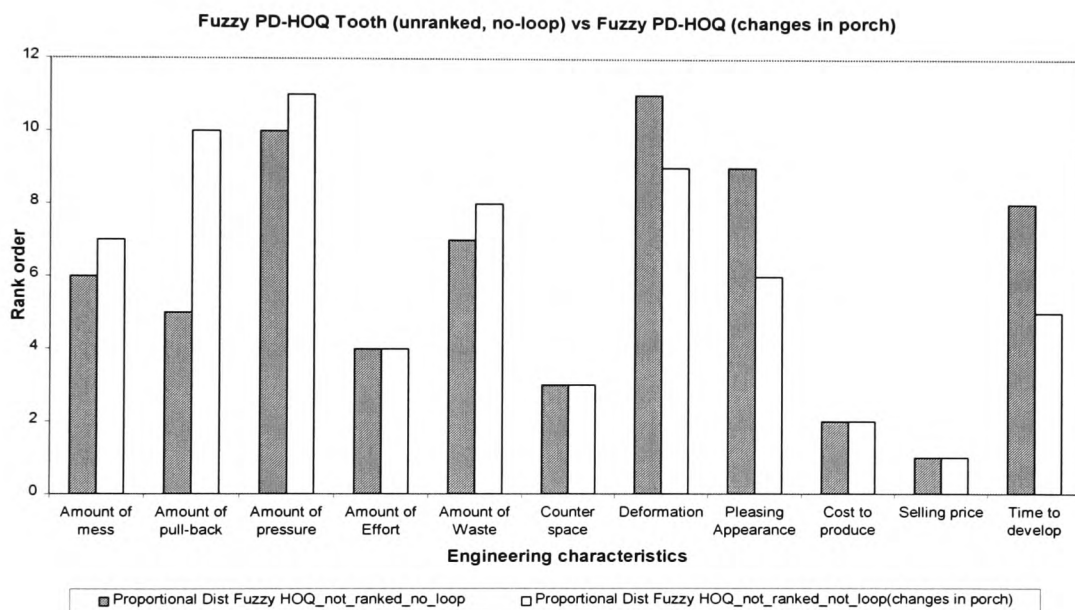


Figure 4.31 Fuzzy PD-HOQ (unranked, non-loop) vs. Fuzzy PD-HOQ (unranked, non-loop) when a few correlation are altered in the porch

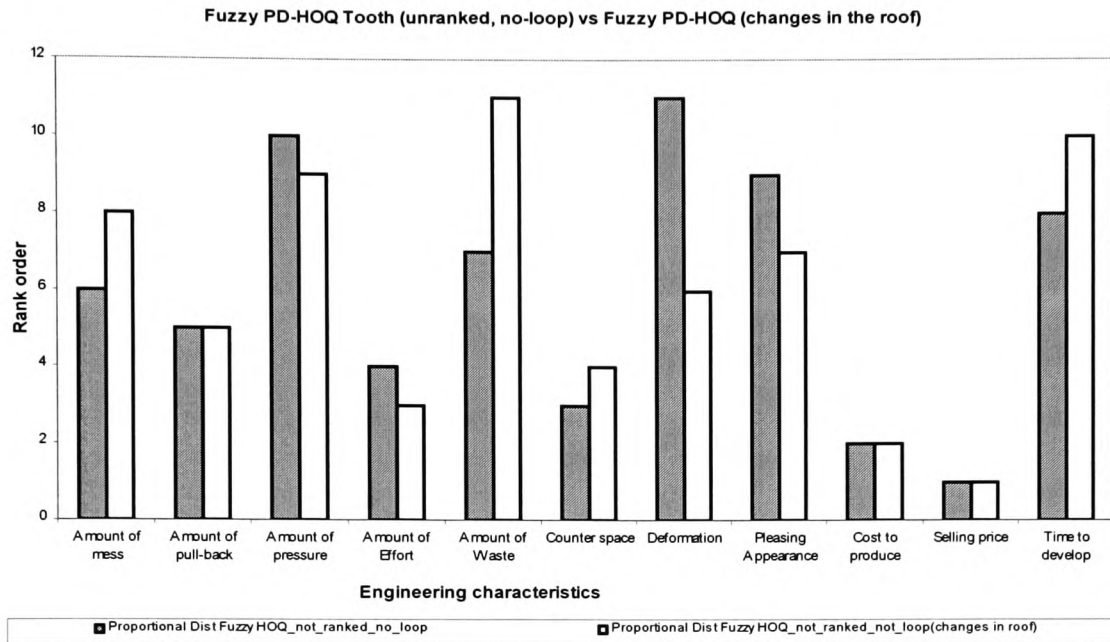


Figure 4.32 Fuzzy PD-HOQ (unranked, non-loop) vs. Fuzzy PD-HOQ (unranked, non-loop) when a few correlation are altered in the roof

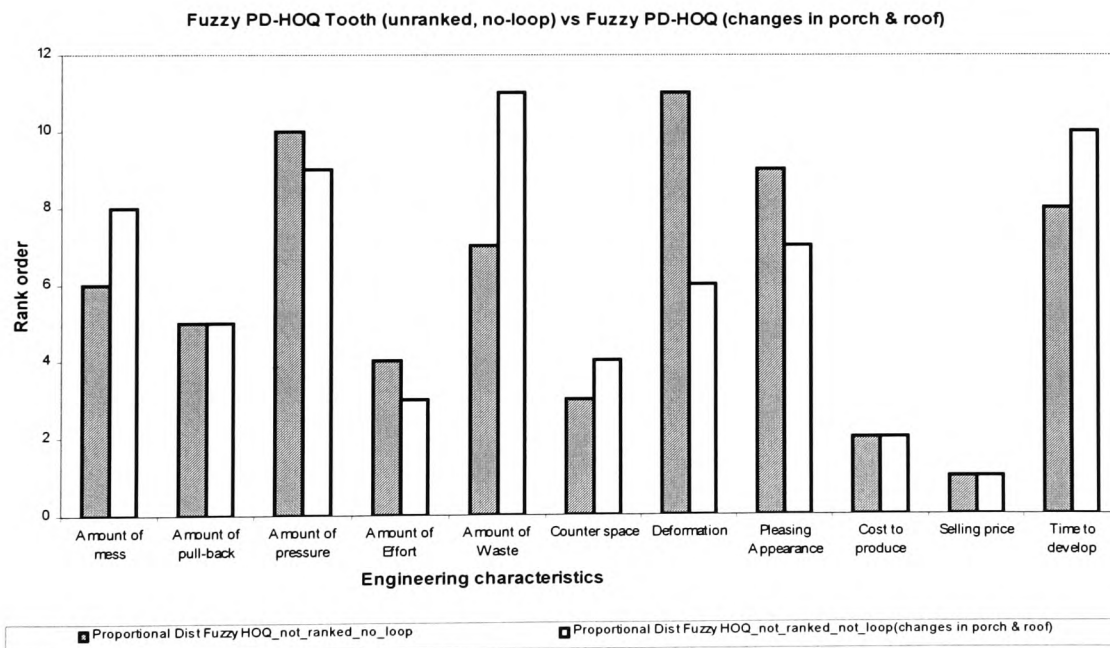


Figure 4.33 Fuzzy PD-HOQ (unranked, non-loop) vs. Fuzzy PD-HOQ (unranked, non-loop) when a few correlation are altered in the porch and roof

4.6.1 Remarks

For the Fuzzy Range HOQ, Figure 4.28 to Figure 4.30, it can be observed that even when changes are made to the correlation matrices, insignificant changes occur in the engineering characteristic's rank order (see Table 4.7). This is because the range as was pointed out earlier is a 'robust statistic' and so is insensitive to minor changes in the input data. Consequently, it can be concluded that the Fuzzy-Range QFD approach is a robust approach. On the other hand, differences between the two sets of data for the Fuzzy Proportional Distribution HOQ can be observed in Figure 4.31 to Figure 4.33. A large change in rank order occurred for about three engineering characteristics (see Table 4.7). Therefore, the FPD-HOQ approach is more sensitive to changes in the correlation input data. Although, the Spearman's rank correlation figure and the % of similar ranks are lower for the FPD-HOQ compared to the FR-HOQ, in this case we are more interested about the amount of differences between the results rather than similarities. Differences between the results suggest that the engineering characteristic's rank order have been affected by the changes in the correlation matrices.

Sensitivity Analysis					
Alterations	No. of similar rank		No. of dissimilar rank	Total	% similar rank
	Exact rank order	Within 2 rank order			
Porch (Fuzzy-Range)	9	2	0	11	100%
Roof (Fuzzy-Range)	5	6	0	11	100%
Porch & Roof (Fuzzy-Range)	7	4	0	11	100%
Porch (Fuzzy-PD)	4	4	3	11	73%
Roof (Fuzzy-PD)	3	6	2	11	82%
Porch & Roof (Fuzzy-PD)	3	6	2	11	82%

Table 4.7 Results of sensitivity analysis when data in the porch, roof and the combination of porch and roof were altered for the Fuzzy-Range and the FPD-HOQ approaches

Thus it can be concluded that having the correct input data, especially the correlation matrix data, is very important in the Fuzzy Proportional Distribution QFD approach. A

way to find inconsistencies and missed correlation data has been introduced in this section by using the inference engine and the four-valued logic truth table.

4.7 SUMMARY

In this chapter Fuzzy Logic and Fuzzy set theory, which were introduced in chapter 3 as techniques to quantitatively analyse the data in the QFD process have been applied to case studies. The main problems identified at the end of chapter 2 were concerned with:

- How can the ill-defined data in the HOQ be rectified?
- How can inconsistencies in the data representing two demands that are related to each other be detected and updated?
- How can interactions between demands help to rectify the inconsistencies and update the ill-defined relationships in the HOQ?

These problems have been partially addressed by the developed Fuzzy-QFD approaches. The two Fuzzy-QFD approaches developed, (Fuzzy Range HOQ and Fuzzy Proportional Distribution HOQ), provide a framework to detect inconsistencies in the data due to ambiguity and vagueness in the VOC and the VOE. Furthermore they facilitate trade-offs between conflicting requirements as well as identify under or over estimated relationships in the relationship matrix and the customer importance rating based, on the interactions between demands in the correlation matrices.

The similarities between the results of the Fuzzy-QFD approaches with the original HOQ's results indicate that there were no significant inconsistencies in the various judgements and evaluations provided by the Fuzzy-QFD approaches. It has also been identified that the more complex case study (design of the toothpaste tube) has been influenced more, (i.e more sensitive), by the developed approaches than the less complex cases. This may be due to the fact that first of all in these cases, there are more requirements and secondly, there are more interactions between requirements. Since the

developed approaches is reliant on these interactions and if there are more requirements, it is likely that there would be more interactions between the requirements, the developed approaches are more geared towards such systems.

The sensitivity analysis performed suggested that the data in the correlation matrices have a significant impact on the results, more so for the Fuzzy Proportional Distribution HOQ than for the Fuzzy Range HOQ. A way to determine these correlations more precisely by using an inference mechanism together with multi-valued logic has been outlined.

Although the Fuzzy-QFD approaches have addressed some aspects of the subjectivity in QFD's HOQ, interactions between requirements are seldom used in QFD to help determine the target value for each engineering characteristic. However, this interaction information is available in the roof of QFD's HOQ. Therefore yet another problem exists, that is, how to set the technical target values in the HOQ, considering interactions between demands, whilst using the minimum effort and time. The Taguchi Method is useful for modelling interactions and minimising the amount of effort and time needed to reach a decision. Because of the Taguchi Method's ability to model interactions, whilst minimising the amount of effort and time for the modelling, the next chapter investigates its integration with QFD. In particular the Taguchi Method is used to model the correlation data in the roof of the HOQ and to define more precisely the choice of technical target values.

Chapter 5.

The Taguchi Method and its integration with QFD

"If one assumes a linear model (i.e. no interactions), thinking it correct, then one is a man removed from natural Science or reality..."
~Genichi Taguchi~

The Taguchi method is a quality and engineering approach that uses experimental design methods for efficient characterisation of a product/process, combined with a statistical analysis of its variability. In this chapter the Taguchi Method of design of experiments is outlined specifically its parameter design phase. How the Taguchi Method can be incorporated within the QFD process is also discussed in relation to current research to combine these two methods. A QFD-Taguchi approach that can help to set more precise engineering target values in the HOQ is also proposed.

5.1 INTRODUCTION

The House of Quality (HOQ) exhibits much useful information that is often used in isolation. As part of the HOQ, the customers and engineers benchmark both their

product/process against that of the competitors to help determine the approximate technical target values. Targets are usually decided upon according to the experience and judgement of the product designers or imposed by some external body such as safety or environmental standards. Accurate target values are essential for supporting subsequent process planning and production activities.

The greater the degree of complexity of the system, the greater the chance of difficulties in the assembly process and as a result the final system may fail to meet specification even if each individual part is within their tolerance limits. Subsystems often exhibit coupling (interaction) between them. Interactions between requirements are seldom used in QFD to help determine the target value for each engineering characteristic. However, this interaction information is available in the roof of QFD's HOQ. Most of this information can be used by the Taguchi Method to design a system that performs near optimum performance when interactions are considered. As a result, more precise technical target values can be obtained, to be used in the HOQ. In addition, the QFD process helps the project team select the factors that need further investigation. This is a requirement for the Taguchi Method.

The chapter will introduce concepts such as the quality characteristics, quality loss function, orthogonal arrays and robustness of the Taguchi Method. The mathematical model of a process response is demonstrated by the means of regression analysis. Furthermore the analysis of results are demonstrated by the analysis of means and analysis of variance techniques. An approach is proposed, which combines QFD and the Taguchi Method to help determine more precise technical target values in the HOQ. The approach is named QFD-Taguchi.

5.2 THE TAGUCHI METHOD

The objective of the Taguchi Method is to improve product/process design through the identification of easily controllable factors and their levels (Taguchi, 1986). This minimises the variation in product response while keeping the mean response on target (Logothetis, 1992). The Taguchi method mainly deals with off-line quality control. The off-line quality control involves a four step approach (Lochner and Matar, 1990):

1. correctly identifying customers needs and expectations,
2. designing a product that will meet customer's expectations,
3. designing a product which can be consistently and economically manufactured,
4. developing clear specifications, standards, procedures and equipment for manufacturing.

The goal of off-line quality control is to identify factors (parameters) that can be controlled (control factors) and to reduce the sensitivity of engineering designs to uncontrollable factors (noise). A noise factor is an uncontrollable source of variation in the functional characteristics of a product. Variability comes from many sources: independent or dependent variables or interactions among variables such as humidity, material ageing, inconsistency in the materials used etc. The way to reduce these uncontrollable factors (noise) in off-line quality control is through a three-step design process (Taguchi, 1986), (Belavendram, 1995) which is concerned with:

- system design: determine the material, technology,
- parameter design: determine the factors, levels, interactions,
- tolerance design: for tightening the specifications limits.

5.3 PARAMETER DESIGN OF THE TAGUCHI METHOD

The Taguchi Method is mainly concerned with the parameter design process. Parameter design provides a means of both reducing cost and improving quality by making effective use of experimental design methods. This involves the determination of factor (parameter) values and the combination of factor levels that reduces the effect of noise through experimentation, resulting in a robust design. The Taguchi method is most effective when applied to experiments with multiple factors. There are certain steps in the parameter design stage, which Dr. Taguchi suggests to be taken in carrying out experimental studies (Logothetis, 1992):

1. Planning

- a. *Define the problem*: Provide a clear statement of the problem to be solved.
- b. *Determine the objective*: Identify the output quality characteristic(s) (criteria) to be studied and determine the method of measurement.
- c. *Conduct a brainstorming session*: Managers and operators closely related to the product/process should identify the controllable and uncontrollable factors and the appropriate factor levels (quantitative or qualitative).

2. Design

- a. *Design the experiment*: Calculate the number of observations to be taken and select the appropriate orthogonal array.
- b. *Conduct the experiment*: Perform the experiment as dictated by the rows of the chosen orthogonal array and collect the responses.
- c. *Derive the Mathematical model* that describes the experiment.

3. Analysis

- a. *Analyse the data*: Evaluate the response for each trial run and analyse them using the appropriate statistical analysis techniques.

- b. Interpret the results:** Select the optimum factor levels that result in the appropriate output quality characteristic chosen. Predict the product/process performance under optimal conditions.
- c. Run a confirmatory experiment:** Run a confirmatory experiment at the optimum level chosen to verify the predicted results.

5.4 PLANNING PHASE

The purpose of product/process development is to improve the performance characteristics of a product/process relative to the customer's needs. The aim of experimentation should be to better understand how to reduce and control variation and so decisions have to be made concerning which factors affect the performance of a product/process. A designed experiment is the simultaneous evaluation of two or more factors for their ability to affect the resultant average or variability of a product/process quality characteristic. The planning phase is by far the most important and most difficult phase during an experiment (Ross, 1996).

5.4.1 The quality characteristic (criterion)

Every product is designed to perform some intended function. Measurable characteristics, generally known as the quality characteristic are used to express how well the product performs this function. A quality characteristic (response) in the context of an industrial experiment is the performance characteristic of a product which is most critical to customers and often reflects the product quality (Antony, 1997). It is important to choose and measure an appropriate response for the experiment. Generally, any quality characteristic will have a target. Whether the quality characteristic is measured by a single criterion, or a combination of multiple criteria, the measure will possess one of the following target characteristics (Belavendram, 1995), (Phadke, 1989):

- ***the bigger the better***, a non-negative measurable characteristic that has an ideal state or target of infinity (∞). An example is fuel efficiency.
- ***the smaller the better***, a non-negative measurable characteristic that has an ideal state or target of zero (0). An example is tyre wear on a car.
- ***the nominal the best***, a measurable characteristic with a specific user-defined positive or negative target. An example is a battery of 9 volts.
- ***continuous –continuous***, a measurable characteristic where both the signal factor and quality characteristic take positive or negative continuous values. An example is a voltmeter readings.
- ***digital –digital***, here both the signal factor and the quality characteristic are digital, i.e. whenever 0 or 1 is transmitted, it should be received as 0 or 1 respectively. An example is digital communication systems.

The aim of experimentation in engineering is to find ways to minimise the deviation of a quality characteristic from its target. This can be achieved only by identifying the factors that affect the quality characteristic in question and by changing the appropriate factor levels so that the deviations are minimised and the quality characteristic is on target. These quality characteristics may be quantitative, such as temperature in a room, by considering factors such as heat and/or humidity level. It may also be qualitative, such as how tasty a cup of coffee is by measuring aroma, flavour, etc. Obviously the taste of the cup of coffee will be a vital criterion, but how can the taste be measured? Qualitative evaluations are often decided upon by panel judges on a predefined scale. If more than one person is on the judging panel, which is desirable, how can the result be brought together? An average of the group's decision is often taken. The coffee can be rated on a predefined scale, e.g. 1 to 5, 5 being very tasty. This rule will influence the quality characteristic. For instance here the larger the number, the tastier the coffee and so it is

preferred. Thus, a quality characteristic of "bigger the better" can be used as a measure for the quality characteristic of taste.

Other criteria may be used to describe the cup of coffee, such as temperature, amount of caffeine etc. It is often the case that several criteria are used to judge a product. These criteria are not always of equal importance and this needs to be reflected in the decision making process.

5.4.1.1 Overall Evaluation Criteria (OEC)

Multiple objectives (criteria) are quite frequent in engineering projects. No matter what the applications, it can be product optimisation, process studies, or problem solving, the need to satisfy more than just one criterion is very frequent. Since the criteria are different, experimental results are generally analysed one criteria at a time. The 'one criteria at a time' approach does not guarantee that the best design obtained for one criterion will also be desirable for the other criteria (Roy, 1990). Different criteria, each having different importance can be combined together to output one response by using the Overall Evaluation Criterion (OEC) (Roy, 1990). The OEC can be defined as:

$$OEC = (y_1 / y_{1max}) * w_1 + (y_2 / y_{2max}) * w_2 + \dots \quad (5.1)$$

where y_1 is the measured value of the first criterion, y_{1max} is the maximum value that can be given to that particular criterion and w_1 is the importance weighting of the first criterion. Each criterion may have different units of measurements, quality characteristic (smaller-the-better, nominal-the-best, larger-the-better) and relative weight. For example, in a game of golf a smaller score is better, whereas in basketball, a larger score is better. In order for the results to be meaningful, one of the quality characteristic's result (golf score) needs to be changed by subtracting it from a fixed number and then add it to the

other quality characteristic's result (basketball score). See Roy (Roy, 1990) for an example case study involving multiple criteria. In order to combine these different criteria, they must first be normalised and weighted accordingly. The measured value is divided by the maximum value to normalise it and get rid of the measurement units. The result is then multiplied by the importance weighting, a dimensionless number and all the results are added up in dimensionless terms. The OEC will then form the result of each experimental run defined in the orthogonal array, which will be discussed in section 5.5.2.

5.4.2 Target values

The 'ideal' quality a customer can receive is that every product delivers the target performance each time the product is used, under all intended-operating conditions, and throughout the product's intended life (Taguchi and Wu, 1989). Target values provide specific, measurable objectives, which guide product design and allow designs to be evaluated objectively.

According to Dr. Taguchi, quality is best when product characteristics are on target, as illustrated in Figure 5.1. As the product characteristics deviate from the target values, quality decreases and customer dissatisfaction and loss increases. Quality, according to Dr. Taguchi, relates to cost and loss in monetary terms, not only to the manufacturer at the time of production, but also to the consumer and society as a whole. He describes quality as *"The quality of a product is the (minimum) loss imparted by the product to the society from the time the product is shipped"* (Taguchi, 1985). Some losses relate to harmful effects to society (e.g. pollution), while others relate to variation in the functional performance of the product. Quality as defined by Taguchi is thus related to monetary loss.

5.5 DESIGN PHASE

The design phase in the Taguchi Method is concerned with the actual experiment. Dr. Taguchi has been particularly recognised for three major contributions to the design phase of a product/process:

1. The Quality Loss Function.
2. Orthogonal arrays.
3. Robustness.

5.5.1 Quality Loss Function (QLF)

Quality costs are usually measured in terms of scrap, rework, and warranty. These are factors that indirectly affect market share. Dr. Taguchi calls these costs, loss. Dr. Taguchi uses a simple quadratic function called Quality Loss Function (QLF) to evaluate quantitatively the hidden costs or long-term losses related to engineering/management time, inventory, and customer dissatisfaction (Clausing, 1988). Minimisation of the Loss Function minimises economic loss due to running at non-optimum conditions. According to Dr. Taguchi, loss continually increases not only when it is outside specification, but also whenever the product deviates from the target value. Mathematically the Loss Function is represented by an equation that includes a cost constant, k (based on costs and specification limits), variance, S^2 (a measure of the variability of the spread of a distribution), the average, \bar{y} (a measure of the location of the distribution) and the desired target, T (Ross, 1988). The Quality Loss Function is given as:

$$L(x) = k(S^2 + (\bar{y} - T)^2) \quad (5.2)$$

The QLF curve (Figure 5.1) is centred on the target value, which provides the best performance in the eyes of the customer (Clausing, 1988). Any deviation from this target causes the cost to increase. Since the QLF evaluates quality in financial terms, it is a tool

for engineering management planning, i.e., for finding the balance between cost and quality that can increase profit.

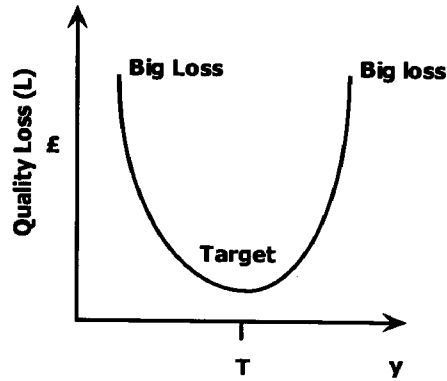


Figure 5.1 Quality Loss Function Curve

5.5.2 Orthogonal Arrays (OAs)

Experimentation tries to determine the best material, the best temperature, etc., which will operate together within a system to produce a desired quality characteristic such as durability, yield, reliability, etc., taking cost into account. Dr. Taguchi has developed a system of tabulated designs (arrays) that allow for the maximum number of main effects to be estimated in an unbiased (orthogonal) manner, with a minimum number of runs in the experiment. The basis for designing an experiment using the Taguchi method is usually performed by fractional factorial orthogonal arrays. A factorial design is used to evaluate two or more factors simultaneously. The advantages of fractional factorial designs over one-factor-at-a-time experiments are that they are more efficient, less costly and they allow interactions to be detected and studied in the appropriate column of the orthogonal array (Logothetis, 1992). Appropriate columns of the orthogonal array need to be allocated to the main factors and to the interactions to avoid confounding, which is the inability to distinguish main effects from interactions (Phadke, 1989).

An orthogonal array (OA) is a fractional factorial matrix of numbers arranged in rows and columns to assure a balanced, not mixed and statistically independent study of the levels of factors and/or interaction of factors (Barker, 1990). OAs can define a balanced study of different environmental conditions where every level of a factor occurs with every level of all other factors the same number of times and all the columns can be evaluated independently of one another (Peace, 1993). Each column represents a specific factor or interaction and each row represents the state of the factors in a given experiment.

OAs are used for designing efficient experiments and analysing experimental data and are very effective in translating very small amounts of data into meaningful results. They are cost efficient, since the design of an OA does not require that all combinations of all factors be tested. So, the experimental matrix can be smaller without losing any vital information. For example, an L4 orthogonal array, (Table 5.1) can incorporate three different factors (A, B, C) at two levels or two factors and their interaction (A, B, AxB) while requiring only four experimental runs (Roy, 1990). A full factorial would require 8 experiments (2^3).

Experiment	Factor A	Factor B	AxB Interaction
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

Table 5.1 An L4 (2^3) orthogonal array

Taguchi's standard orthogonal array can be found in most design of experiment textbooks (Taguchi, 1986), (Taguchi *et al*, 1989), (Logothetis, 1992), (Roy, 1990). Choosing an orthogonal array can be done by matching the degrees of freedom (number of independent measurements available to estimate sources of information) for the

experiment with that of an appropriate orthogonal array. In general, the number of degrees of freedom associated with a factor (DOF_v) is equal to one (one is due to the overall mean) less than the number of levels for that factor (Belavendram, 1995). Refer to equation (5.3).

$$DOF_v = \text{number of levels} - 1 \quad (5.3)$$

The degree of freedom for orthogonal arrays, (DOF_o), is one less than the number of experiments (see equation (5.4)).

$$DOF_o = \text{number of experiments} - 1 \quad (5.4)$$

5.5.2.1 Interactions

Often prediction of process behaviour is not intuitively obvious, due to the presence of interactions. Interactions between control factors exist when the effect of one control factor is dependent on the level of another control factor. There are two approaches to dealing with interactions:

1. Study control factor interactions to quantify their effects.
2. Engineer the design to minimise the likelihood of significant interactions and thus avoid having to estimate them.

Interactions quite often influence the compromises in target values set after technical benchmarking. A method to resolve conflicts amongst factors is to utilise the Theory of Inventive Problem Solving (TIPS), known as TRIZ in Russia where it was invented (Altshuller *et al*, 1997). Using the TRIZ methodology, it is possible to generate concepts for reducing negative effects and improving the performance of the design. TRIZ uses a patent (official document detailing great inventions) to cultivate a thorough understanding

of the constraints, resources, historical solutions and harmful and useful functions of a system. The QFD, TRIZ and Taguchi methods have been integrated by Terninko (Terninko, 1997) and the Taguchi-TRIZ synergy by Jugulum (Jugulum and Sefik, 1998).

Interactions can be estimated using certain types of orthogonal arrays. These arrays have the properties to assign the interactions to certain columns that represent interactions between two factors. The columns for the factors are chosen according to the interactions that the investigator assumes may or may not be present in the process.

The degree of freedom for interactions, (DOF_I), is the product of the degrees of freedom of each factor (DOF_f) multiplied by the number of factors, (see equation (5.5)).

$$DOF_I = \text{number of factors} * \prod_1^n (\text{number of levels} - 1) \quad (5.5)$$

Dr. Taguchi incorporated the interaction tables and linear graphs, where interactions between factors can be studied (Barker, 1990). Linear graphs represent the interaction information graphically and make it easier to assign factors and interactions to the various columns of an orthogonal array. The investigator consults linear graphs corresponding to the chosen orthogonal array, to determine which columns to choose for factors and which ones for interactions. The dots in the linear graph represent the main factors and the lines represent the interacting column between two factors (Phadke, 1989). In general, an orthogonal array can have many linear graphs. The different linear graphs are useful for planning case studies having different requirements. Examples of linear graphs for an L27 orthogonal array are shown in Figure 6.3, page 6-5 and Figure 6.10, page 6-24 of chapter 6.

The interaction effect between two factors, say factor A and B (AxB) can be measured by finding the effect of factor (A) at high level of B (B2) and the effect of A at low level of B (B1). The interacting effect between factor A and factor B (Lochner and Matar, 1990) is:

$$AxB = \frac{(B2_{A2} - B2_{A1}) - (B1_{A2} - B1_{A1})}{2} \quad (5.6)$$

The analysis of the means (ANOM) quantify whether interactions exist or not (Fowlkes and Creveling, 1995). The result of factor interactions can be shown by plotting the average values of the response at the different levels of the interacting factors. The amount of interaction is indicated by the parallelism of the graphs. Figure 5.2 shows interaction graphs with (a) no interaction (the lines are parallel), (b) little positive interaction and (c) large negative interactions (the lines are going in opposite directions and crossing).

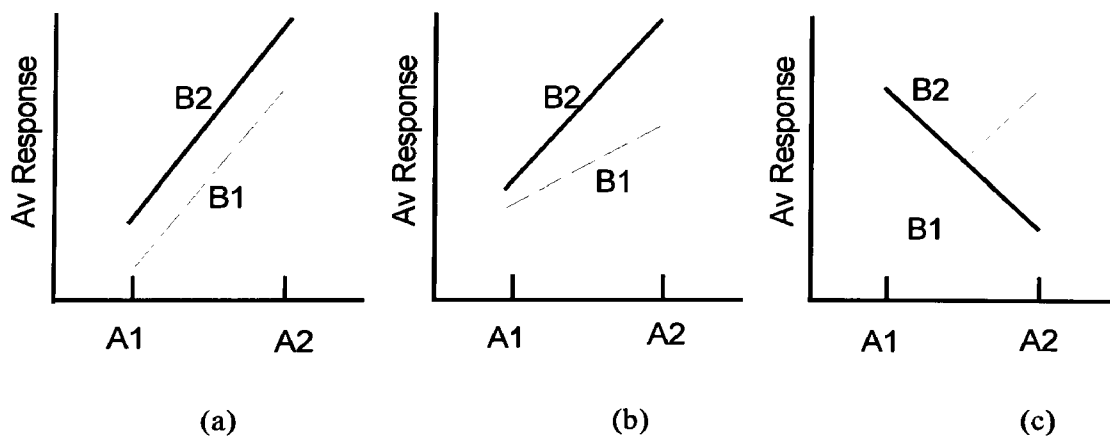


Figure 5.2 Interaction plots (a) No interaction, (b) little positive interaction, (c) large negative interaction

5.5.3 Robustness

Dr. Taguchi's approach allows experiments to be performed and prototypes to be tested on multiple factors at the same time, so that the product/process becomes insensitive to uncontrollable factors. The stability of a product/process's performance in the face of noise factors is called *Robustness*. It produces consistent, high-level performance despite being subjected to a wide range of changing customer and manufacturing conditions and provides a more efficient, cost-effective way to improve products and processes. Improving robustness allows the engineer to improve quality without increasing costs. Dr. Taguchi uses a measurement called the Signal to Noise (S/N) ratio as an indicator of the robustness.

5.5.3.1 Signal to Noise (S/N) ratio

S/N ratio measures variability around the target performance and thus is a measure of how robust a system is. It measures how well variability has been minimised and gives a sense of how close the design is to the optimum performance of the product/process (Roy, 1990). In order to calculate the S/N ratio, it is necessary to repeat each experiment. The larger the S/N ratio, the more robust the product will be against noise (Taguchi, 1993). Different S/N ratios are used depending on whether the quality characteristic described in section 5.4.1, has a "bigger the better", "smaller the better", or "nominal the best" response (Peace, 1993). For a "bigger the better" quality characteristic, the S/N ratio is computed as:

$$S / N = -10 \log_{10} \left\{ \frac{1}{n} \sum \frac{1}{y^2} \right\} \quad (5.7)$$

For a "smaller the better" quality characteristic the S/N ratio is computed as:

$$S/N = -10 \log_{10} \left\{ \frac{1}{n} \sum y^2 \right\} \quad (5.8)$$

For the “nominal is best” quality characteristic, the S/N ratio can be computed as:

$$S/N = 10 \log_{10} (\bar{y}^2 / s^2) \quad (5.9)$$

where \bar{y} is the sample mean and s is the sample standard deviation of the n experiments.

For the other types of S/N ratio refer to (Belavendram, 1995), (Phadke, 1989), (Fowlkes and Creveling, 1995).

5.5.4 Conducting the experiment

After deciding on which quality characteristic to use, which factors and their levels as well as which interactions to study, the experiment is conducted as dictated by the chosen orthogonal array and the results for all the trials are collected. The average factor effect as well as interaction can then be computed. If the trials were repeated, S/N ratios can also be calculated.

5.5.5 Mathematical Model

In many experiments it is often desirable not only to identify the important factors, but also to make a reliable estimate of the response variable using these factors. In numerous problems there are two or more variables that are related and it is of interest to model and explore them. The relationship between these variables is characterised by a mathematical model called a *regression model*. The term regression means average relationship (Bartee, 1968). The use of such a model serves to express the results of an experiment quantitatively, to facilitate understanding, interpretation and implementation. Furthermore, a mathematical model based on the collected data enables the extrapolation

of the data to estimate other levels of the factors that may be more appropriate. The mathematical relationship between a dependent variable (response) Y and an independent variable (regressor) X , can be calculated by a linear regression model (Logothetis and Wynn, 1989). The equation of a straight line can be used to theoretically model the linear regression, and takes the form:

$$Y = \alpha + \beta X + \varepsilon \quad (5.10)$$

where α is the intercept, β is the gradient (regression coefficient) and ε is a residual term or the effect of unmeasured parameters in the experiment (Bartee, 1968). Therefore α and β needs to be calculated so that the line has the best possible fit, such that the residual term ε is minimised. The principle of least square can be adopted to fit a straight line as briefly reviewed in Appendix C. The method can be generalised to situations involving more than one independent variable (multiple linear regression). When more than one independent variable X exist, a multiple linear regression model can be fitted, which takes the form of:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon \quad (5.11)$$

where X_1, \dots, X_k are k independent variables of interest, α is the regression constant and β_1, \dots, β_k are the regression coefficients which can be estimated once more using the least square principle. Models that are more complex in appearance than equation (5.11) can often still be analysed by the multiple linear regression techniques (Montgomery, 1997). Interaction terms such as $\beta_{12} X_1 X_2$ in equation (5.12) can also be modelled if the interaction term is equivalent to another factor, say $\beta_3 X_3$.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \varepsilon \quad (5.12)$$

When qualitative factor levels are considered, the variables X_1, X_2 , etc are defined on a coded scale from -1 to 1 (Montgomery, 1997). For 2 levels a scale of -1 representing the low level and 1 representing the high can be chosen. For three levels, -1 can represent the low-level, 0 the intermediate-level and 1 the high-level.

5.6 ANALYSIS PHASE

Having appropriately designed the experiment and obtained the results, formal methods for statistically analysing them is necessary. These methods help to determine the effect of each factor and/or interactions and can determine which factor levels should be chosen as optimum to give a robust product/process.

5.6.1 Analysis of Means (ANOM)

Dr. Taguchi uses the orthogonal array to measure the effect of a factor on the average result, as well as to determine the variation from the mean. This method is known as the analysis of means. The analysis of means is also known as “average effect”, “factorial effect” or “main effect” (Roy, 1990). By using orthogonal arrays the data analysis is simplified. The effects of the various factors can be determined by computing simple averages as in equation (5.13).

$$\bar{F}_l = \frac{\sum_{i=1}^q R_i}{q_l} \quad (5.13)$$

where \bar{F}_l is the average effect of factor F at level l , R is the result of each experimental trial i , q is the number of experimental trials containing the desired level l . For instance, to compute the average performance of factor A at level 1 (A1), add all the response results (R) for all experiments that includes A1 and then divide by the number of experimental trials. The average effects can then be plotted for a visual inspection as

depicted in Figure 6.4, chapter 6. The estimates of the factor effects are then used to determine the optimum factor settings (Fowlkes and Creveling, 1995).

5.6.2 Analysis of Variance (ANOVA)

The relative contributions of factors are determined by comparing their variances. The statistical technique of Analysis of Variance (ANOVA) is used for this purpose (Logothetis, 1992), (Phadke, 1989). The aim of analysis of variance is to test differences in means (for groups or variables) for statistical significance. This is accomplished by analysing the variance, which is done by partitioning the total variance into the component that is due to true random error and the components that are due to differences between means.

A study of the ANOVA helps to determine which factors need to be controlled and which do not, by computing their significance using Fisher's test (F-Test) (Chatfield, 1983). The F-test is designed to test if two population variances are equal. It does this by comparing the ratio of two variances. So, if the variances are equal, the ratio of the variances will be 1. The ANOVA results are normally presented in a table format as in Table 5.2 (Roy, 1990), where a large F-value (Fisher's value) means that the factor or interaction is significant. The significance is computed by comparing the F-Ratios with the critical value from Fisher's tables (Roy, 1990), (Logothetis, 1992).

Factor	Sum of Squares (SS)	DOF (f)	Variance Mean Squares (V)	Variance-Ratio (F)	Pure Sum of Squares (S')	% Contribution (P%)
A	S_A	f_A	$V_A = S_A / f_A$	V_A / V_e	$S_A - (V_e * f_A)$	$(S'_A / S_T) * 100$
B	S_B	f_B	$V_B = S_B / f_B$	V_B / V_e	$S_B - (V_e * f_B)$	$(S'_B / S_T) * 100$
A x B	S_{AxB}	f_{AxB}	$V_{AxB} = S_{AxB} / f_{AxB}$	V_{AxB} / V_e	$S_{AxB} - (V_e * f_{AxB})$	$(S'_{AxB} / S_T) * 100$
Error (e)	S_e	f_e	$V_e = S_e / f_e$		$(S_A + S_B + S_{AxB}) + V_e$	$(S'_e / S_T) * 100$
Total	S_T	f_T				

Table 5.2 ANOVA table

SS is a measure of the deviation of the experimental data from the mean value of the data.

V is the variance that measures the distribution of the data about the mean of the data.

The error e , is due to experiments.

5.6.3 Selecting optimum levels

By considering the ANOVA, the ANOM and the interaction plot in respect to the chosen quality characteristic (bigger-the-better, nominal-the-best, smaller-the-better), the optimum factor levels can be chosen. The interaction graph also shows the amount of interaction present together with its polarity by considering the slope of the lines. A final experiment should then be run at the selected optimal factor levels to verify the predicted results.

5.7 SYNERGY BETWEEN THE TAGUCHI METHOD AND QFD

The power of the Taguchi Method lies in its ability to arrive at a greatly improved design or process in a short time, using a relatively small amount of experiments. Some of the benefits of the Taguchi Method can prove useful for exploitation in QFD to resolve some of its problems. These include:

- interactions between characteristics in the roof area of the HOQ are not modelled .
The Taguchi Method can take into account these interactions using its orthogonal array,
- customer and technical benchmarking are useful for setting target values in QFD, but only the mean responses (customer & technical) are utilised. The Taguchi method can optimise target values using the Loss Function by also utilising the variance of the responses,
- determining the nature of relationships between demands and optimising the conflicts in QFD is subjective. The Taguchi Method, can thus be useful to show the strength of

the relationship by considering the magnitude of the interactions from the interaction graph,

- customer satisfaction in QFD can be improved by designing robust products that are insensitive to variations in environmental conditions, by using the Taguchi Method.

One of the reasons why QFD is so powerful is that it helps determine and rank critical items to which quality technology and engineering effort should be applied. In addition QFD will also identify conflicting engineering characteristics. In these instances, the use of experimental design methods, including the Taguchi Method, can provide some remarkable results. Some Japanese companies assign most of their quality improvements in the last 10 years to the use of design of experiments (Fortuna, 1990). However they also give credit to QFD as a planning technique that provides most of the vital information for a good design of experiment. In fact, Fortuna (Fortuna, 1990) suggests that those serious about QFD should learn more about experimental design and other tools commonly used with QFD, such as Fault Tree Analysis (FTA) and Failure Mode and Effect Analysis (FMEA).

There are various literatures (Terninko, 1992), (Terninko, 1995), (ReVelle, 1991), (Ross, 1988) that have stated the benefits of combining QFD and the Taguchi Design of experiments. Although there are various citations of the synergy between these two methods, most of them are theoretical in nature and little actual practical work has been highlighted. This may be due the fact that the benefits of the synergy between these two methods are so great that it is seen as proprietary and confidential to those that have used it. A few citations of work undertaken to bring these two methods together are outlined below.

Terninko (Terninko, 1992), (Terninko, 1995) suggests that most QFD applications stop after the HOQ matrix. Of the few applications that reach deployment into manufacturing, determination of the best manufacturing conditions is not a precise process. He suggests that Taguchi's philosophy of robust design is particularly useful for establishing the best operating conditions for manufacturing. Terninko (Terninko, 1992) has proposed that the concept of Taguchi's Quality Loss Function, offers an improved way to accomplish technical benchmarking at the bottom of the House of Quality. Technical benchmarking is necessary to rationally select target values for performance measures where identifying the target value is not an easy task. Targets are sometimes the designer's best guess. Data collected for technical benchmarking should be gathered in a real environment. QFD attempts to do just that by going to the gemba, that is the total environment where the customer lives and work. Different customer environments can be used to find the average performance and the variation of a product/process.

ReVelle (ReVelle, 1991) in his paper explains that QFD assumes that the customer requirements (the WHATs) are constant, i.e., either as unchanging over time or as the same for all customers at a given point. It does not address those situations where they are dynamic. He suggests that customer requirements are dynamic and cannot be controlled by a supplier. Using the Taguchi inner-outer array table, a method to identify the most robust engineering characteristics (the HOWs) to satisfy the range of customer importance rating is presented. The Outer Array is used to represent the Customer Demands (WHATs) with the corresponding orthogonal array. In this way the customer demands are treated as noise. The engineering characteristics (HOWs) are represented as an Inner Array. The customer then tests all the different combinations of the product and a customer agreement index is placed in the resultant matrix. The Signal-to-Noise (S/N) ratio (Bigger-is-better, Nominal-is-best, or Smaller-is-better) is then calculated. The predicted value of the S/N ratio is then used to identify the most robust parameters at optimal factor

level. As a result, a robust requirement matrix is created, which is insensitive to changes in the needs of the customer. His methodology requires extreme contact with the customers, who need to rate their satisfaction level regarding the chosen quality characteristic for every experiment performed. This requires a lot of time and effort on behalf of the customers.

Ross (Ross, 1988) proposes that the Taguchi Methods, design of experiments and QFD are complementary tools that should be used during the off-line phase of a product/process life cycle.

5.8 THE QFD-TAGUCHI APPROACH

Determining the relationships between the customer demands and the engineering characteristic is extremely important. Since each engineering characteristic can affect more than one customer demand and since the engineering characteristic for one customer demand may have an adverse impact on another customer demand, these relationships are complex. Since these relationships are complex, failure to identify and understand the interaction between customer demands and engineering characteristics can lead to product failure. A preliminary target value must be set for each engineering characteristic. To set technical target values in QFD, the results of competitive benchmarking are very helpful. Engineering assessments of competing products and the firm's own products allow the organisation to compare its performance with that of its competitors and set target values. This information is readily available in QFD 's HOQ (room 7, Figure 2.5, chapter 2).

Normally, target values for the engineering characteristics in QFD are set on an individual basis (Fung *et al*, 1998). Consequently many or all subsystems may be functioning to target values within a system, but when these subsystems are put together

to form the whole system, often the system fails to perform to target. If there is a negative impact (interaction) between two engineering characteristics, identified in the roof of the HOQ, the design must be compromised unless the negative impact is resolved. For example, the design requirements for a diesel engine may include targets for acceleration and emissions. These two requirements might have strong negative correlation in the sense that as emissions improve, the acceleration gets worse. These conflicts influence the compromises in target values set after performing technical benchmarking.

The HOQ in QFD, outputs a chart in the form of a matrix that possess useful information for designing experiments with multiple evaluation criteria. An approach named QFD-Taguchi, that outputs the response based on the standard Taguchi orthogonal array is proposed by solely using the information found in the HOQ to objectively determine target values for engineering characteristics based on interactions between them. The approach numerically calculates the results using the OEC defined in equation (5.1), based on the information found in the QFD's HOQ matrix.

5.8.1 Steps in the QFD-Taguchi approach

The proposed QFD-Taguchi approach is a general approach that can be implemented by the steps outlined below to define new target values based on the interaction in the roof of the HOQ. The steps are as follows:

1. Determine the important control factors (engineering characteristics) to include in the study and identify the desired quality characteristic. The most important factors to be included in the experiment can be identified by the engineering characteristic's scoring and ranking at the bottom of the HOQ. Therefore QFD can help in this decision. The customer demands form the desired quality criteria, each with different importance as defined in the customer importance-rating column of the HOQ. Moreover, the

customer benchmarking provides the evaluation of the company's own product/process and that of the competitors. The response is the measure of the level of satisfaction the customer has with each competitive product. This is measured on a scale of 1 to 5 in QFD's HOQ, where 1 represent little satisfaction and 5 represents a lot of satisfaction. Therefore a “larger the better” quality characteristic is desirable to measure the level of customer satisfaction.

2. Define the factor levels, in this case these are the different competitors found in the customer and technical evaluation part of the HOQ.
3. Choose an appropriate orthogonal array.
4. Calculate the response, the Overall Evaluation Criteria (OEC), based on the rows of the chosen orthogonal array. The engineering characteristics (factors) are linked to the customer evaluation through the relationship matrix and so the relationship matrix can be used to relate the customer evaluation to the technical evaluation.

The combination of all this information in the QFD matrix can thus be integrated with Taguchi's Design of Experiments to calculate the OEC (the response) based on the different experimental runs defined by the chosen orthogonal array. The customer demands (criteria), and their corresponding customer evaluation (satisfaction level), together with the strength of corresponding relationship in the relationship matrix are used to determine the OEC. The individual OEC response Y for each criterion c with k number of satisfaction value can be expressed as in equation (5.14).

$$Y_c = \sum_{n=1}^k \left[CS_n * \left| R_{n_j} \right| \right] \quad (5.14)$$

where CS_n is the satisfaction value for each customer demand, R_{nj} is the value of each individual relationship in the corresponding row i , column j , of the relationship matrix resulting from the Proportional Distribution HOQ. This calculated OEC does not yet include the interaction terms.

5. Model the system by using the OEC response to calculate the regression coefficients of the linear regression model. Since the interaction terms have not yet been included in the OEC calculation, first the regression model of the main factors needs to be determined. Using the least square program developed in Matlab, (Appendix C) the regression coefficients ($\beta_0, \beta_1, \beta_2, etc$) can be calculated by using:

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (5.15)$$

6. By including the interaction terms in the regression model, new OEC responses can be calculated which will represent both main effect and interactions. When the interaction terms found in the roof of the HOQ are included to the regression model, the two sets of data have different ranges, (regression coefficient $\hat{\beta}_m$ is in the range $[\beta_{\min}, \beta_{\max}]$ and the interaction coefficients I is in the range $[I_{\min}, I_{\max}]$. For the data to be in the same range for further analysis, the ranges needs to be mapped into each other. It is assumed for this part that the interactions are as important as the main factors. Therefore a linear mapping as in equation (5.16) is used. Only the magnitude of the interaction terms will be used, where n is the intercept of the line and m the gradient.

$$p = n + mq \quad (5.16)$$

where

$$n = \beta_{\min} - (I_{\min} * m) \quad (5.17)$$

$$m = \frac{\beta_{\max} - \beta_{\min}}{I_{\max} - I_{\min}} \quad (5.18)$$

The OEC responses are re-calculated based on the regression model including interaction. The new OEC responses are determined using the least square method, but this time \hat{Y} is the unknown. On this occasion equation (5.19) has to be solved to find \hat{Y} (Bartee, 1968):

$$\hat{Y} = \hat{\beta} * X \quad (5.19)$$

7. Analyse the new responses by Analysis of Means and Analysis of Variance and plot interaction graphs to determine which level (competitor) gives the optimum output (i.e. optimum target values).

Figure 5.3 shows all the steps of the QFD-Taguchi approach in a flow chart manner, where the shaded area show the different methods used together with its tools.

5.9 SUMMARY

This chapter has given an overview of the Taguchi Method for design of experiment. It has also reviewed work undertaken by other researchers to incorporate the Taguchi Method with QFD. An approach named the QFD-Taguchi method has been proposed to set more precise engineering characteristic target values in QFD's HOQ, taking into account interactions between the engineering characteristics. The approach maps the QFD data into a mathematical model by utilising the least square method and enables the study of interactions amongst the engineering characteristics and the setting of factor levels based on these interactions. It combines all the data in QFD's HOQ together to calculate the Overall Evaluation Criterion (OEC) response. It requires the customer importance rating data, the relationship matrix data, the customer and technical evaluation data, the

engineering characteristic weighting and the interactions in the roof of the HOQ. The main challenges faced in developing this approach were to:

- decide on the factors, levels, orthogonal array, quality criterion,
- decide how to combine all these data and model the system,
- decide how to include interactions.

The approach is a general one that can be applied to various case studies as documented in the next chapter, chapter 6, which aims to show the feasibility of the developed QFD-Taguchi approach.

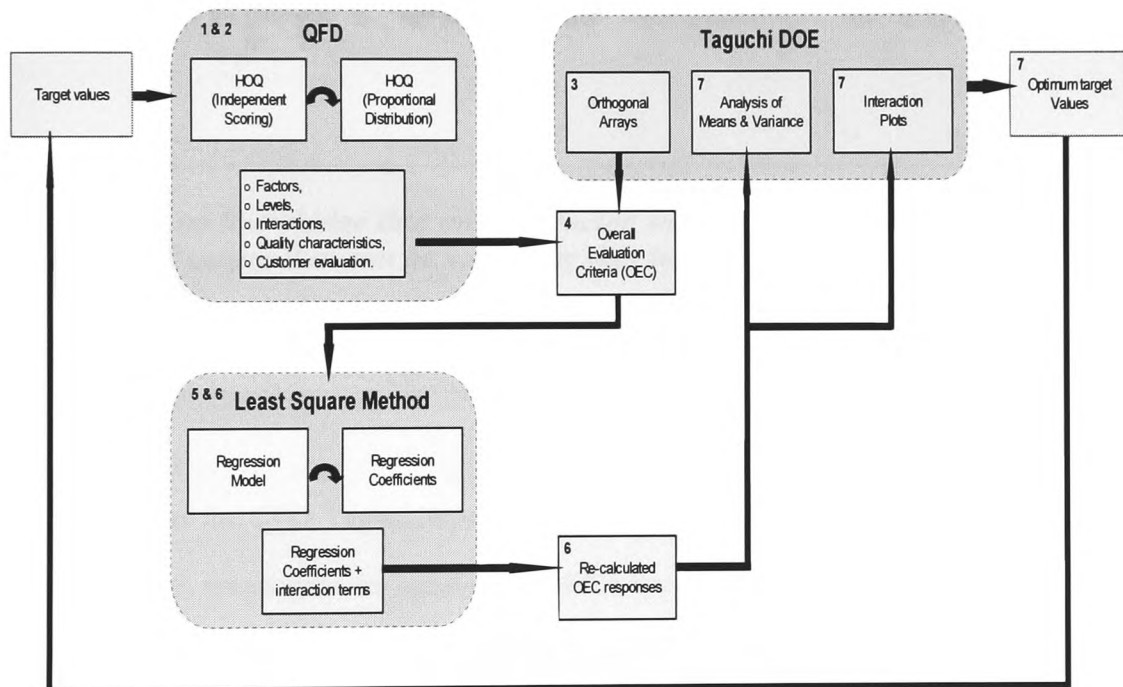


Figure 5.3 Flow chart showing the steps needed in the QFD-Taguchi approach

Chapter 6.

The QFD-Taguchi

Approach: case studies

"We have no knowledge that any one factor will exert its effects independently of all others that can be varied, or that its effects are particularly related to variations in these other factors..."
~Ronald Fisher~

In this chapter the QFD-Taguchi approach developed in the previous chapter is applied to case studies to investigate the capabilities of the approach.

6.1 INTRODUCTION

Two worked examples are utilised to delineate the result of the synergistic integration of the Taguchi Method and QFD by following the seven steps listed in chapter 5. A comparative study between the developed QFD-Taguchi method is undertaken with the original Proportional Distribution HOQ results. Since the QFD-Taguchi approach uses the Overall Evaluation Criteria (OEC) technique of calculation described in chapter 5, section 5.4.1.1, a study is performed which considers each quality criterion separately and

the results are compared. This aims to test the viability of the use of the OEC technique in the QFD-Taguchi approach. The comparisons are documented and discussed.

6.2 CASE STUDIES APPLIED TO THE QFD-TAGUCHI APPROACH

6.2.1 Case study 1: Design of a paper roll used for printing

A company decides to make a paper roll for printers (Fortuna, 1990). The customer demands are acquired by market research, and the engineering characteristics defined. The HOQ is illustrated in Figure 6.1. In order to make the relationship more proportional, the Independent scoring HOQ (Figure 6.1) is converted to the Proportional Distribution HOQ as discussed in chapter 2. Part of the Proportional Distribution HOQ is depicted in Figure 6.2. These data form the input to the QFD-Taguchi approach.

Note that the first engineering characteristic "*Paper width*" and the last engineering characteristic "*Paper colour*" have not been included in the Proportional Distribution HOQ, as they had low importance rating and possess no interactions with other engineering characteristics. Although, including these two engineering characteristics in an orthogonal array such as an L27 poses no problems, as there exist columns to study them, the calculation of the OEC is greatly increased. So it was decided not to include them at all.

In this manner, QFD serves as a screening process for the Taguchi Method, allowing the identification of important factors that need to be studied further. The customer evaluation is linked to the technical evaluation through the relationship matrix. Therefore each customer satisfaction is related to the engineering characteristics through the relationship matrix. Utilising the relationship matrix, the correlation matrix (roof), the customer evaluation and the customer importance rating, the best factor levels may be defined to help determine the technical target values in the HOQ. The customer and technical satisfaction are measured from a scale of 1 to 5, where 5 is the maximum satisfaction. Since it is of interest to satisfy both the customers and the engineer, then a “larger the better” quality characteristic is used.

In this example, for the different companies (Com), *Us* will be used instead of *X*, *Com 1* instead of *Com A* and *Com 2* instead of *Com B*. Therefore looking at the technical evaluation in Figure 6.1 a combination of *Com 1* for “*Paper Thickness*”, *Com 2* for “*Roll Roundness*”, *Com 1* for “*Coating Thickness*” and *Com 1* for *Tensile Strength* would give a good set for the optimum target values. The example will thus determine which company, i.e. which level should be chosen.

6.2.2 Steps in the QFD-Taguchi approach

The 7 steps, outlined in chapter 5, section 5.8.1 of the proposed QFD-Taguchi approach are now followed for this example.

6.2.2.1 Defining the factors and levels

Four factors need to be studied: *Paper Thickness (PT)*, *Roll Roundness (RR)*, *Coating Thickness (CT)* and *Tensile Strength (TS)*. Three interactions have been identified in the roof of the HOQ in Figure 6.1:

- *Paper Thickness* and *Roll Roundness (PTxRR)* having a strong negative correlation,

- *Paper Thickness* and *Coating Thickness (PTxCT)* having a weak positive correlation,
- *Paper Thickness* and *Tensile Strength (PTxTS)* having a strong positive correlation.

6.2.2.2 Choosing the appropriate orthogonal array

Consequently four factors and three interactions all at three levels (*Us*, *Com 1*, *Com 2*) will be studied, resulting in 20 degrees of freedom as seen in Table 6.1.

	Degree of freedom	Total
Factors	$4 \times (3-1)$	8
Interactions	$2 \times (3-1) + 2 \times (3-1) + 2 \times (3-1)$	12
Total Degree of Freedom		20

Table 6.1 Calculation of Degrees of freedom for paper roll example

An L27 orthogonal array with 26 degrees of freedom is thus sufficient to perform the experiment. The allocation of interaction columns can be determined by using Taguchi's linear graphs or interaction table for an L27 (Phadke, 1989b). There are many linear graphs for the L27 (Barker, 1990), however, the linear graph shown in Figure 6.3 allows the desired factors and/or interactions to be studied with minimal effect of confounding for this example.

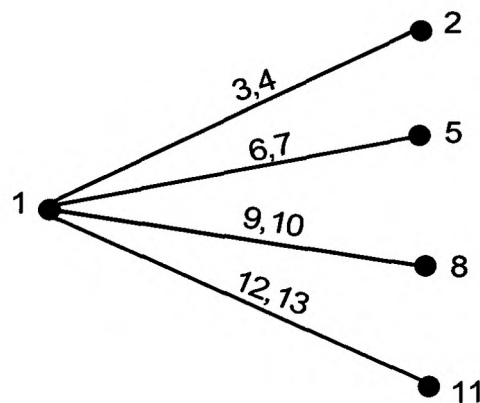


Figure 6.3 Linear graph for an L27 orthogonal array

the relationship matrix are used to determine the OEC responses. The OEC responses are calculated using the Proportional Distribution HOQ data in Figure 6.2. Table 6.3 shows the result of the OEC calculation based on the experiment set out by the L27 orthogonal array. For the first experiment when all the levels are at level 1 (Us):

$$\text{Response for Paper will not tear (Y1)} = CS(Us)*R_{PT} + CS(Us)*R_{RR} + CS(Us)*R_{CT} + CS(Us)*R_{TS}$$

Mathematically:

$$\text{Response for Paper will not tear (Y1)} = 1*0.14 + 1*0.43 + 0*0.0 + 1*0.43 = 1.0$$

$$\text{Response for Consistent Finish (Y2)} = 0*0.0 + 0*0.0 + 2.8*1.0 + 0*0.0 = 2.8$$

$$\text{Response for No Ink Bleed (Y3)} = 5*0.75 + 0*0.0 + 5*0.25 + 0*0.0 = 5.0$$

$$\text{Response for Prints Clearly (Y4)} = 0*0.0 + 3.5*0.25 + 3.5*0.75 + 0*0.0 = 3.5$$

The OEC for experiment 1 (PT , RR , CT , TS) all at level 1 (Us) (See Table 6.3) is:

$$\text{OEC (Exp 1)} = (Y1/Y1_{max}) * w1 + (Y2/Y2_{max}) * w2 + (Y3/Y3_{max}) * w3 + (Y4/Y4_{max}) * w4$$

$$\text{OEC (Exp 1)} = (1.0/5)*33\% + (2.8/5)*11\% + (5.0/5)*22\% + (3.5/5)*33\% = 57.87 \text{ (2dp).}$$

The weights $w1$, $w2$, $w3$ & $w4$ represent the customer importance rating from Figure 6.2.

The OEC calculation for experiment 2 to 27 follows the same pattern. Note that the interaction effect has yet to be included in calculating the responses.

Exp No.	Column 1 Paper Thickness	Column 2 Roll Roundness	Column 5 Coating Thickness	Column 8 Tensile strength	OEC
1	Us	Us	Us	Us	57.867
2	Us	Us	Com 1	Com1	64.943
3	Us	Us	Com 2	Com2	71.961
4	Us	Com 1	Us	Com1	69.710
5	Us	Com 1	Com 1	Com2	72.822
6	Us	Com 1	Com 2	Us	72.478
7	Us	Com 2	Us	Com2	72.800
8	Us	Com 2	Com 1	Us	68.551
9	Us	Com 2	Com 2	Com1	79.532
10	Com 1	Us	Us	Us	61.032
11	Com 1	Us	Com 1	Com1	64.145
12	Com 1	Us	Com 2	Com2	63.800
13	Com 1	Com 1	Us	Com1	68.911
14	Com 1	Com 1	Com 1	Com2	64.662
15	Com 1	Com 1	Com 2	Us	75.643
16	Com 1	Com 2	Us	Com2	64.640
17	Com 1	Com 2	Com 1	Us	71.716
18	Com 1	Com 2	Com 2	Com1	78.734
19	Com 2	Us	Us	Us	59.572
20	Com 2	Us	Com 1	Com1	55.323
21	Com 2	Us	Com 2	Com2	66.304
22	Com 2	Com 1	Us	Com1	60.089
23	Com 2	Com 1	Com 1	Com2	67.166
24	Com 2	Com 1	Com 2	Us	74.184
25	Com 2	Com 2	Us	Com2	67.144
26	Com 2	Com 2	Com 1	Us	70.256
27	Com 2	Com 2	Com 2	Com1	69.912

Table 6.3 Factors & levels with OEC results for paper roll example

6.2.2.4 Modelling the system

Using the least square program developed in Matlab (Appendix C), the regression coefficients ($\beta_0, \beta_1, \beta_2, etc$) can be calculated for the main factors $\hat{\beta}_m$. The regression model will serve as the new model by which interaction coefficients will be included and the responses recalculated based on this model. The calculation of the regression model requires the response matrix Y_m (equation (6.1)) and the coded factor level matrix X_m (equation (6.2)). The factor levels were coded as follows: -1 for low level, 0 for intermediate level and 1 for high level as seen in equation (6.2). The calculated regression coefficients are given in equation (6.3).

	OEC
$Y_m =$	57.867
	64.943
	71.961
	69.710
	72.822
	72.478
	72.800
	68.551
	79.532
	61.032
	64.145
	63.800
	68.911
	64.662
	75.643
	64.640
	71.716
	78.734
	59.572
	55.323
	66.304
	60.089
	67.166
	74.184
	67.144
	70.256
	69.912

(6.1)

	Bo	PT	RR	CT	TS
$X_m =$	1	-1	-1	-1	-1
	1	-1	-1	0	0
	1	-1	-1	1	1
	1	-1	0	-1	0
	1	-1	0	0	1
	1	-1	0	1	-1
	1	-1	1	-1	1
	1	-1	1	0	-1
	1	-1	1	1	0
	1	0	-1	-1	-1
	1	0	-1	0	0
	1	0	-1	1	1
	1	0	0	-1	0
	1	0	0	0	1
	1	0	0	1	-1
	1	0	1	-1	1
	1	0	1	0	-1
	1	0	1	1	0
	1	1	-1	-1	-1
	1	1	-1	0	0
	1	1	-1	1	1
	1	1	0	-1	0
	1	1	0	0	1
	1	1	0	1	-1
	1	1	1	-1	1
	1	1	1	0	-1
	1	1	1	1	0

(6.2)

$$\hat{\beta}_m = \begin{bmatrix} 67.92 \\ -2.26 \\ 4.35 \\ 3.93 \\ 3.11 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{matrix} \quad (6.3)$$

Therefore the fitted regression model for only the main factors, Y_m , for this example is:

$$Y_m = 67.92 - 2.26 PT + 4.35 RR + 3.93 CT + 3.11 TS \quad (6.4)$$

6.2.2.5 Adding the interaction coefficients

The interaction terms are now added, where:

$PTxRR = -9/9 = -1$, $PTxCT = 3/9 = 0.33$ and $PTxTS = 9/9 = 1$. The interaction coefficients are therefore:

$$I = \begin{bmatrix} -1.0 \\ 0.33 \\ 1.0 \end{bmatrix} \quad (6.5)$$

The interaction terms are taken from the roof of the HOQ. Since the two sets of data, (equation (6.3)) and (equation (6.5)) have different ranges, where the regression coefficient $\hat{\beta}_m$ is in the range $[\beta_{\min}, \beta_{\max}]$ and the interaction coefficients, I , is in the range $[I_{\min}, I_{\max}]$, the mapping of the interaction matrix, I range onto the $\hat{\beta}_m$ range is performed. Here $\beta_{\max} = 4.35$, $\beta_{\min} = -2.26$, $I_{\max} = 1$ and $I_{\min} = 0.33$. Note that only the magnitude of the interaction is considered, since a negative interaction could be interpreted as smaller compared to a positive one, because of its sign. Here negative interactions are considered as important as positive ones. The first regressor β_0 is not included in the mapping as it is a constant. The mapping equation becomes $p = -5.516 + 9.866q$. Therefore the regression coefficient vector $\hat{\beta}_I$ including interaction takes the form:

$$\hat{\beta}_I = \begin{bmatrix} 67.92 \\ -2.26 \\ 4.35 \\ 3.93 \\ 3.11 \\ 4.35 \\ -2.26 \\ 4.35 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{13} \\ \beta_{14} \end{matrix} \quad (6.6)$$

The new regression equation results in:

$$Y_I = 67.92 - 2.26 \beta_1 + 4.35 \beta_2 + 3.93 \beta_3 + 3.11 \beta_4 + 4.35 \beta_{12} - 2.26 \beta_{13} + 4.35 \beta_{14} \quad (6.7)$$

where β_{12} is the interaction between *Paper Thickness* (PT) β_1 and *Roll Roundness* (RR) β_2 , whereas β_{13} is the interaction between *Paper Thickness* (PT) β_1 and *Coating Thickness* (CT) β_3 . β_{14} is the interaction between *Paper Thickness* (PT) β_1 and *Tensile Strength* (TS) β_4 . Using the regression equation in equation (6.7), new OEC responses are determined using the least square method, but this time Y is the unknown. The values of the response Y_I can be calculated based on the regression model in equation (6.7) by multiplying the regression coefficient vector $\hat{\beta}_I$ in equation (6.6) with X_I in equation (6.8).

	Bo	PT	RR	CT	TS	PTxRR	PTxCT	CTxTS
$X_1 =$	1	-1	-1	-1	-1	-1	-1	-1
	1	-1	-1	0	0	-1	0	0
	1	-1	-1	1	1	-1	1	1
	1	-1	0	-1	0	0	-1	1
	1	-1	0	0	1	0	0	-1
	1	-1	0	1	-1	0	1	0
	1	-1	1	-1	1	1	-1	0
	1	-1	1	0	-1	1	0	1
	1	-1	1	1	0	1	1	-1
	1	0	-1	-1	-1	1	1	-1
	1	0	-1	0	0	1	-1	0
	1	0	-1	1	1	1	0	1
	1	0	0	-1	0	-1	1	1
	1	0	0	0	1	-1	-1	-1
	1	0	0	1	-1	-1	0	0
	1	0	1	-1	1	0	1	0
	1	0	1	0	-1	0	-1	1
	1	0	1	1	0	0	0	-1
	1	1	-1	-1	-1	0	0	-1
	1	1	-1	0	0	0	1	0
	1	1	-1	1	1	0	-1	1
	1	1	0	-1	0	1	0	1
	1	1	0	0	1	1	1	-1
	1	1	0	1	-1	1	-1	0
	1	1	1	-1	1	-1	0	0
	1	1	1	0	-1	-1	1	1
	1	1	1	1	0	-1	-1	-1

(6.8)

The new OEC values from the Regression Analysis (OEC Int RA) are thus calculated and displayed in Table 6.4.

Exp	PT (1)	RR (2)	CT (5)	TS (8)	OEC (Int_RA)
1	Us	Us	Us	Us	52.3500
2	Us	Us	Com1	Com1	61.4800
3	Us	Us	Com2	Com2	70.6100
4	Us	Com1	Us	Com1	68.5100
5	Us	Com1	Com1	Com2	77.6400
6	Us	Com1	Com2	Us	64.3900
7	Us	Com2	Us	Com2	84.6700
8	Us	Com2	Com1	Us	71.4200
9	Us	Com2	Com2	Com1	80.5500
10	Com1	Us	Us	Us	66.0800
11	Com1	Us	Com1	Com1	68.9400
12	Com1	Us	Com2	Com2	68.7400
13	Com1	Com1	Us	Com1	56.1400
14	Com1	Com1	Com1	Com2	62.7200
15	Com1	Com1	Com2	Us	71.8500
16	Com1	Com2	Us	Com2	62.9700
17	Com1	Com2	Com1	Us	78.8800
18	Com1	Com2	Com2	Com1	74.9600
19	Com2	Us	Us	Us	60.4900
20	Com2	Us	Com1	Com1	60.2900
21	Com2	Us	Com2	Com2	63.1500
22	Com2	Com1	Us	Com1	67.3200
23	Com2	Com1	Com1	Com2	63.4000
24	Com2	Com1	Com2	Us	79.3100
25	Com2	Com2	Us	Com2	57.3800
26	Com2	Com2	Com1	Us	66.5100
27	Com2	Com2	Com2	Com1	73.0900

Table 6.4 OEC responses after interactions are included in the regression model

6.2.2.6 Analysing the responses

Analysis of Means:

Since the criteria is for "larger the better" characteristic, then a larger OEC response average is desirable. The average effect response table in Table 6.5 identifies *RR*, *PTxRR* and *PTxTS* as the most important factor (larger difference between factor level), *CT* as the second, *TS* as the third and finally *PT* and *PTxCT*.

Figure 6.4 shows the optimum results for the average factorial response, which are circled. This is only for the main factors. It can thus be observed that *PT*: *US* (Level -1),

RR: Com2 (Level 1), CT: Com2 (Level 1) and TS: Com2 (Level 1), can be chosen for the optimum output for the main factors only. The interactions are drawn in order to calculate the optimum combination of the levels for the whole system. The interaction plots are depicted in Figure 6.5, Figure 6.6 and Figure 6.7.

	PT	RR	PTxRR	CT	PTxCT	TS	PTxTS
Us	70.180	63.570	63.570	63.990	70.180	64.810	63.570
Com 1	67.920	67.920	67.920	67.920	67.920	67.920	67.920
Com 2	65.660	72.270	72.270	71.850	65.660	71.030	72.270
Difference	4.520	8.700	8.700	7.860	4.520	6.220	8.700
Rank	6	1	1	4	6	5	1

Table 6.5 Average Response table of factor effects for paper roll example

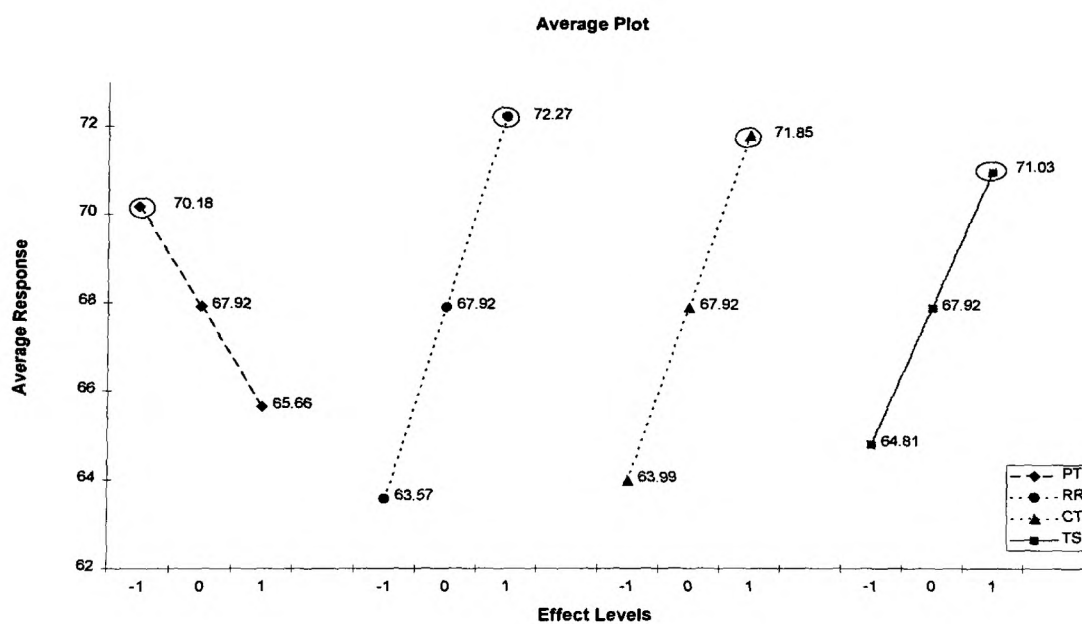


Figure 6.4 Means effect response plot for paper roll example

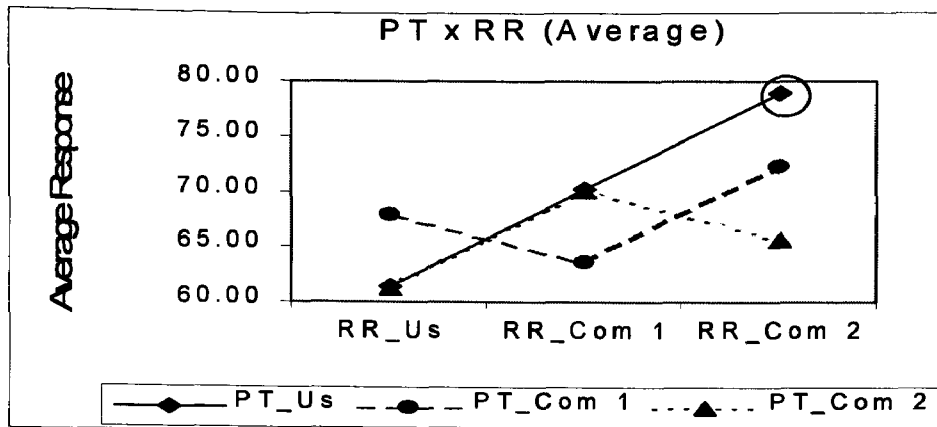


Figure 6.5 Interaction between Paper thickness (PT) and Roll roundness (RR)

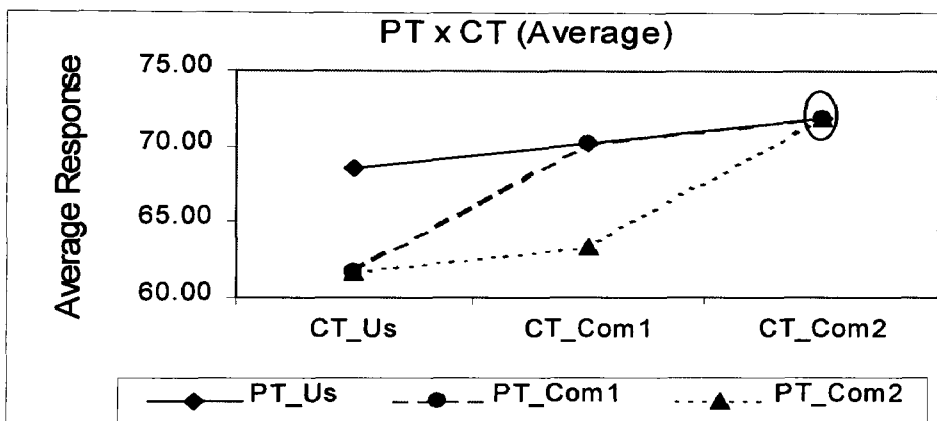


Figure 6.6 Interaction between Paper thickness (PT) and Coating thickness (CT)

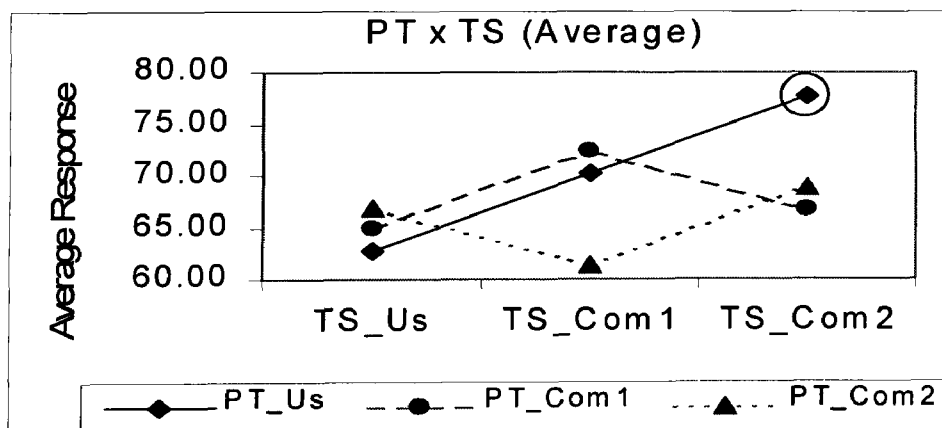


Figure 6.7 Interaction between Paper thickness (PT) and Tensile strength (TS)

Analysis of Variance:

The AVOVA is performed to identify how statistically significant the results are and the percentage contribution of each factor and/or interactions and its table is depicted in Table 6.6. The result of the ANOVA table agrees with the Average response table in Table 6.5, with *RR* contributing to 18.7% and *PTxT* and *PTxRR* contributing to about 16.9% each. In this case most of the main factors and the investigated interactions are statistically significant (99%), with high F-ratios except *PT* which was pooled as an error term due to its small Sum of Squares value (Fowlkes and Creveling, 1995). Two of the three interactions are significant as can be seen in both Table 6.6 and Table 6.5.

Factor	Sum Square (SS)	dof	mean sq (MSS)	F-Ratio	S'	% Contribution	Rank
PT x TS	340.66	4	85.17	5.57	279.45	16.86	3
PT x RR	340.65	4	85.16	5.57	279.44	16.86	3
RR	340.64	2	170.32	11.13	310.035	18.70	2
CT	278.06	2	139.03	9.09	247.455	14.93	5
TS	174.15	2	87.08	5.69	143.545	8.66	6
Error	183.63	12.00	15.30	1.00	367.26	22.15	1
ST	1657.79	26.00				100.00	

Table 6.6 ANOVA table for Paper roll example

The percentage contribution of the error is approximately 22%, which shows that the process is showing sufficient variability, but is stable and in control. An error between 15% and 30% shows that the system is showing enough variability (Lapin, 1997), (Montgomery and Runger, 1994). From Figure 6.5, it can be observed that interaction exists between *Paper thickness* and *Roll Roundness* since the lines are not parallel. In fact antisynergistic interactions exist. That means that the factor levels that maximise the response are not consistent: they depend in a critical way on the other factor levels. Whenever interaction plots cross antisynergistic interactions are present (Fowlkes & Creveling, 1995). *PT* level: *Us* and *RR* level *Com2* can be chosen as the optimum level in

this interaction plot as they have the highest responses. Figure 6.6 also shows interactions between $PT \times CT$. In this plot any level of PT can be chosen as the responses for each of the three levels are similar, but CT level $Com2$ is the optimum factor level. Figure 6.7 also shows interaction between $PT \times TS$ and the optimum factor level in this plot is again PT level Us and TS level $Com2$. The first and the last figures indicate that PT should be set at level Us . The final optimum target levels found by the main factor effect from using the software WinRobust v1.02 together with the interaction plots in Figure 6.5 through to Figure 6.7 is given in Table 6.7 and compared with the original target values set in QFD's HOQ.

Factors	QFD-Taguchi Approach	Original Target values from QFD
Paper Thickness	Us	Company 1
Roll Roundness	Company 2	Company 2
Coating Thickness	Company 2	Company 1
Tensile Strength	Company 2	Company 1

Table 6.7 New target values for paper roll example

6.2.3 Discussion

Table 6.7 shows that the QFD-Taguchi approach results in a different set of target values to the ones arrived at in the original HOQ in Figure 6.1. In fact three of the target values have changed, those for *Paper Thickness*, *Coating Thickness* and *Tensile Strength*. Notice that this combination ($PT: Us$, $RR: Com2$, $CT: Com2$, $TS: Com2$) was not one of the trials ran in Table 6.2. The combinations of factor levels that were not included in the experiment can still be predicted by fractional factorial methods such as the Taguchi Method.

Roll Roundness (RR) was given the top ranking in the analysis of means table (Table 6.5) and the result for its technical evaluation is the best (4/5). Since RR has a strong negative

interaction with *PT*, *PT* has moved down to the second best level, (from level *Com 1* to level *Us*) a compromise in the design. This is in line with the importance rating of these two characteristics where *RR* was ranked first in the analysis of means table, as well as in the original HOQ. Refer to Figure 6.1 for a visual inspection. *PT* is related strongly to customer demand “*No ink bleed*”. If the customer evaluation is further investigated, level: *Us* was ranked the highest (5/5) for this customer demand. Basically, the customers are very satisfied with Company *Us* for customer demand “*No ink bleed*”, yet the technical evaluation is saying that company *A* is best. So these two evaluations are not compatible in the original HOQ.

It can be observed that the QFD-Taguchi approach did not only choose the optimum levels whilst considering interactions amongst the engineering characteristic, but the two competitive evaluations have been brought in agreement as seen in Table 6.8. The customer demands in the last column are strongly related to the engineering characteristics in the first column. The original QFD technical target values (column 2) are compared to the original customer satisfaction (target values) for each customer demands and they are not similar. After the QFD-Taguchi analysis, the technical target values (column 3) is similar to the original customer satisfaction (target values) for each customer demands (column 5).

Case 1: paper Roll				
	Technical target values		Customer target values	
Eng characteristics	Original QFD HOQ	QFD-Taguchi approach	Original QFD HOQ	Customer demands
Paper thickness	Company 1	Us	Us	No ink bleed
Roll Roundness	Company 2	Company 2	Company 2	Paper will not tear
Coating thickness	Company 1	Company 2	Company 2	Prints clearly
Tensile strength	Company 1	Company 2	Company 2	Paper will not tear

Table 6.8 The two competitive evaluations in agreement

6.2.4 Case study 2: Design of a thumbtack

A Company wants to develop a new thumbtack (Baxter, 1995) to determine which engineering characteristics are the most important to satisfy their customer demands. Extensive market research was performed and the final HOQ is depicted in Figure 6.8. For this example, negative relationships are defined in the relationship matrix, but note that in calculating the absolute technical weighting for each engineering characteristic, the absolute relationship value is used. This shows that even if customer demands relate to engineering characteristics in a negative way, they are very important (in a negative way) in deciding which engineering characteristics are most important and will be carried to the next QFD phase. Other ways to deal with these negative relationships have been proposed (Green *et al*, 1995), (Temponi *et al*, 1999). Since this example uses the absolute relationship values for multiplication with the customer importance rating, then the rest of this section will be based on this idea.

Target values have been defined independently by the designers after reviewing how the competing products compare both technically and in the eyes of the customers. Table 6.9 highlights the conclusion reached by the designers for setting each target value based on the technical evaluation.

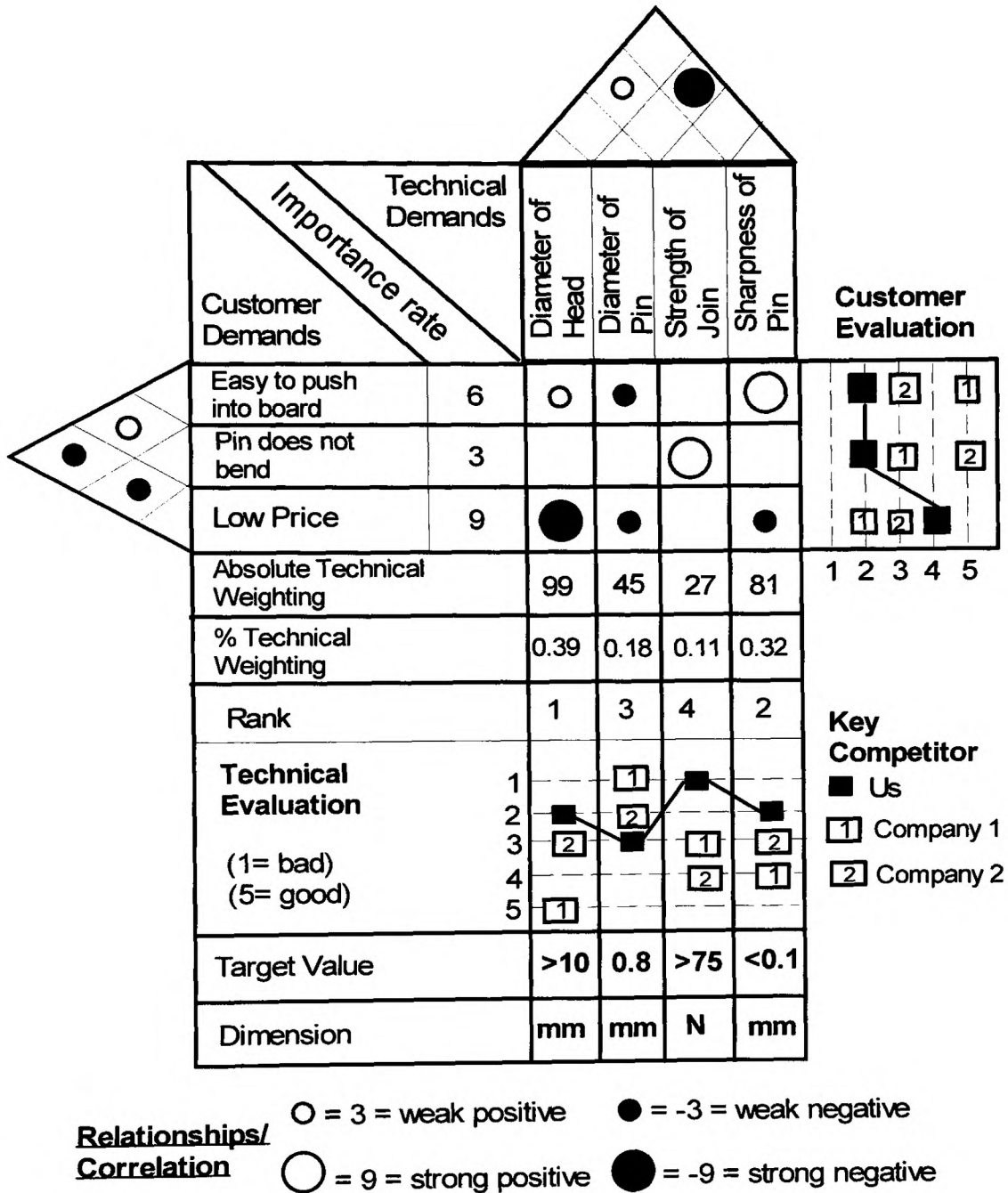


Figure 6.8 HOQ for the design of a thumbtack (Baxter, 1995)

Factors	Our Company	Company 1	Company 2	Target Value
Tack Head Diameter	7 mm	10.5 mm	8.5 mm	>10mm (Com 1)
Pin head Diameter	1.1 mm	0.8 mm	0.9 mm	0.8mm (Com 1)
Strength of Join	55 N	70 N	75 N	> 75 N (Com 2)
Sharpness of Pin Head	0.2 mm	0.1 mm	0.15 mm	<0.1mm (Com 1)

Table 6.9 Target values determined from competing product for thumbtack example

The conclusions for achieving the target values were based on:

- The larger the *Diameter of the Tack Head*, the easier the customers find it to push into the board. A tack head greater than 10mm is therefore chosen,
- Having a large *Pin Head Diameter* is concluded to have little benefit although it adds to cost and makes the tack slightly more difficult to push into the board. It is decided to reduce the pin diameter from the existing product's 1.1mm to 0.8mm,
- The *Strength of the Join* between the pin and the tack head is tested using a purpose built test rig. A target value of more than 75N is selected to exceed the best of the two competing products,
- The *Sharpness of the Pin Head* is given a target of less than 0.1mm radius of curvature to exceed the best competitor.

Note that these target values are set independently of each other. Referring to the technical evaluation in Figure 6.8, a quick observation would suggest that the combination of *company 1* for the “*Diameter of Tack Head*”, *Us* for the “*Diameter of Pin Head*”, *company 2* for the “*Strength of Join*” and *company 1* for the “*Sharpness of Pin*” would result in the optimised target values, as these are the levels ranked the highest technically. This combination is similar to the justification given in Table 6.9, but not quite the same. Again this combination does not take interaction into consideration. The *Strength of the Join* is “weak positively” correlated to the *Diameter of the Tack Head*, as can be seen in the roof of the HOQ in Figure 6.8. That means that the bigger the *Diameter of the Tack Head* the stronger the *Join*. This suggests that when one characteristic is made bigger, then the other should also be increased. On the other hand, the *Diameter of the Pin Head* is “strong negatively” correlated to the *Sharpness of the Pin Head*. That is, when the *Diameter of the Pin Head* is increased, the *Sharpness of the Pin* decreases. So they have an adverse effect on each other.

From the customer's evaluation in Figure 6.8, a combination of the three different companies, *company 1* for “*Easy to push into board*”, *company 2* for “*Pin does not bend*” and *Us* for “*Low price*”, would be the ideal combination as they are ranked highly by the customers.

A portion of the Proportional Distribution HOQ is shown in Figure 6.9. This data forms the input to the QFD-Taguchi approach.

	Imp Rate	% Imp Rate	Head Diameter	Pin diameter	Strength of join	Sharpness of pin
Easy to push into board	6	33.33	0.200	-0.200	0.000	0.600
Pin does not bend	3	16.67	0.000	0.000	1.000	0.000
Low Price	9	50.00	-0.600	-0.200	0.000	-0.200
Sum of Imp Rating	18	100.00				
% Score			36.67	16.67	16.67	30.00
Rank			1	3	3	2

Figure 6.9 Proportional Distribution HOQ for thumbtack example

6.2.5 Steps in the QFD-Taguchi approach

The seven steps outlined in the QFD-Taguchi approach in chapter 5, section 5.8.1 will now be followed for the thumbtack example.

6.2.5.1 Defining the factors and levels

For this example, four factors need to be studied: *Diameter of the Tack Head (HD)*, *Pin Head Diameter (PD)*, *Strength of Join (SJ)* and *Sharpness of the Pin Head (PS)*. Each factor will be studied at 3 levels, our company (*Us*), company 1 (*Com 1*) and company 2

(Com 2). Two sets of interactions will also be studied, *Diameter of the Tack Head x Strength of the Join (HD x SJ)* and *Sharpness of the Pin Head x Pin Head Diameter (PS x PD)* as indicated in the roof of the HOQ, in Figure 6.8.

6.2.5.2 Choosing an appropriate orthogonal array

For these four factors and two sets of interactions at two levels, the calculation for the degree of freedom is as shown in Table 6.10.

	Degree of freedom	Total
Factors	$4 \times (3-1)$	8
Interactions	$2 \times (3-1) + 2 \times (3-1)$	8
Total Degree of Freedom		16

Table 6.10 Calculation of Degrees of freedom for thumbtack example

Therefore, 16 degrees of freedom in total is required. As four factors at three levels are needed, the smallest orthogonal array from Taguchi's standard orthogonal array is an L18. Since for an L18, interactions between three levels are not possible due to confounding effect (Taguchi, 1986), the next orthogonal array is an L27 with 26 degrees of freedom and requiring only 27 experiments as opposed to 81 (3^4) for the full factorial. Since in this case study, the requirements for the interactions are different, the triangular linear graph (Figure 6.10) for an L27 is used to identify the placement of main factors and interactions. The factor *Tack Head Diameter (HD)* can be placed in column 1 of the orthogonal array, its interacting partner, *Strength of Join (SJ)* can be placed in column 2, leaving columns 3 and 4 for studying their interaction (*HDxSJ*) (See Table 6.11 and Figure 6.10). *Pin Head sharpness (PS)* can be placed in column 5, and its interacting partner *Pinhead Diameter (PD)* in column 9, where columns 3 & 13 are used to study their interactions. Note that column 3 is used twice as interacting columns here, therefore confounding may occur. Confounding is the inability to distinguish the effects of main

factors and interactions (Phadke, 1989). No matter where the main factors and interactions are placed in the L27, confounding occurs for this example. For this example it was found that column 3 had no effect in the average response table (Appendix C), and so the confounding effect is zero. This may not always be the case and in other situations where confounding is present, a larger orthogonal array or the use of a full factorial array, may be necessary.

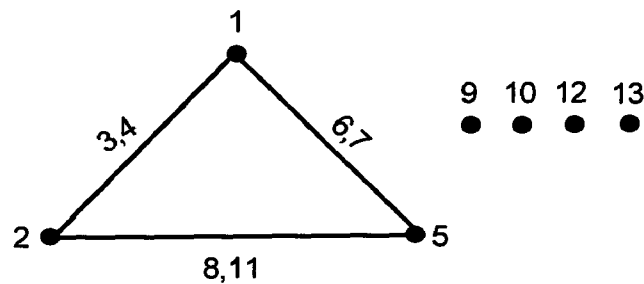


Figure 6.10 Triangular linear graph for an L27

Other interactions can also be studied if they were of interest. For instance, the interactions between $HD \times PS$ can be studied in columns 6 & 7, in columns 8 & 10 the interaction between $HD \times PD$ can be studied, column 8 & 11, interaction between $SJ \times PS$ and column 6 & 12, interaction between $SJ \times PD$, providing that confounding does not occur. Table 6.11 illustrates the placement of main factors in the L27 orthogonal array as well as possible factor interactions.

Run	1 HD	2 SJ	3	4	5 PS	6	7	8	9 PD	10	11	12	13
1	Us	Us	1	1	Us	1	1	1	Us	1	1	1	1
2	Us	Us	1	1	Com1	2	2	2	Com1	2	2	2	2
3	Us	Us	1	1	Com2	3	3	3	Com2	3	3	3	3
4	Us	Com1	2	2	Us	1	1	2	Com1	2	3	3	3
5	Us	Com1	2	2	Com1	2	2	3	Com2	3	1	1	1
6	Us	Com1	2	2	Com2	3	3	1	Us	1	2	2	2
7	Us	Com2	3	3	Us	1	1	3	Com2	3	2	2	2
8	Us	Com2	3	3	Com1	2	2	1	Us	1	3	3	3
9	Us	Com2	3	3	Com2	3	3	2	Com1	2	1	1	1
10	Com1	Us	2	3	Us	2	3	1	Com1	3	1	2	3
11	Com1	Us	2	3	Com1	3	1	2	Com2	1	2	3	1
12	Com1	Us	2	3	Com2	1	2	3	Us	2	3	1	2
13	Com1	Com1	3	1	Us	2	3	2	Com2	1	3	1	2
14	Com1	Com1	3	1	Com1	3	1	3	Us	2	1	2	3
15	Com1	Com1	3	1	Com2	1	2	1	Com1	3	2	3	1
16	Com1	Com2	1	2	Us	2	3	3	Us	2	2	3	1
17	Com1	Com2	1	2	Com1	3	1	1	Com1	3	3	1	2
18	Com1	Com2	1	2	Com2	1	2	2	Com2	1	1	2	3
19	Com2	Us	3	2	Us	3	2	1	Com2	2	1	3	2
20	Com2	Us	3	2	Com1	1	3	2	Us	3	2	1	3
21	Com2	Us	3	2	Com2	2	1	3	Com1	1	3	2	1
22	Com2	Com1	1	3	Us	3	2	2	Us	3	3	2	1
23	Com2	Com1	1	3	Com1	1	3	3	Com1	1	1	3	2
24	Com2	Com1	1	3	Com2	2	1	1	Com2	2	2	1	3
25	Com2	Com2	2	1	Us	3	2	3	Com1	1	2	1	3
26	Com2	Com2	2	1	Com1	1	3	1	Com2	2	3	2	1
27	Com2	Com2	2	1	Com2	2	1	2	Us	3	1	3	2

1x2 1x2 1x5 1x5 1x9 1x9 2x5 2x9 5x9
 5x9 2x9 2x5

Table 6.11 L27 orthogonal array for thumb tack example

6.2.5.3 Calculating the OEC responses

The OEC responses are calculated using the Proportional Distribution HOQ in Figure 6.9. For the first experiment when all the levels are at level 1 (*Us*):

$$\text{Response for Easy to push into board (Y1)} = CS(Us) * R_{HD} + CS(Us) * R_{SJ} + CS(Us) * R_{PS} + CS(Us) * R_{PD}$$

In mathematical terms:

$$\text{Response for Easy to push into board (Y1)} = 2 * 0.2 + 0 * 0.0 + 2 * 0.6 + 2 * 0.2 = 2.0$$

$$\text{Response for Pin does not bend (Y2)} = 0 * 0.0 + 2 * 1.0 + 0 * 0.0 + 0 * 0.0 = 2.0$$

$$\text{Response for Low Price (Y3)} = 4 * 0.60 + 0 * 0.0 + 4 * 0.20 + 4 * 0.20 = 4.0$$

The OEC for experiment 1, where all factors (*HD*, *SJ*, *PS*, *PD*) are at level 1 (*Us*) (See Table 6.12) is:

$$\text{OEC (Exp 1)} = (Y1/Y1max) * w1 + (Y2/Y2max) * w2 + (Y3/Y3max) * w3$$

$$\text{OEC (Exp 1)} = (2.0/5)*33\% + (2.0/5)*17\% + (4.0/5)*50\% = 60.00 \text{ (2dp).}$$

The OEC calculation for experiment 2 to 27 follows the same pattern.

Table 6.12 shows the results for the 27 experiments calculated based on the combination laid out by the L27 orthogonal array.

Exp	Column 1 Head Diameter	Column 2 Strength of Join	Column 5 Pin Sharpness	Column 9 Pin Diameter	OEC
1	Us	Us	Us	Us	60.000
2	Us	Us	Com1	Com1	67.840
3	Us	Us	Com2	Com2	61.280
4	Us	Com1	Us	Com1	63.360
5	Us	Com1	Com1	Com2	70.600
6	Us	Com1	Com2	Us	65.360
7	Us	Com2	Us	Com2	69.520
8	Us	Com2	Com1	Us	78.080
9	Us	Com2	Com2	Com1	72.120
10	Com1	Us	Us	Com1	51.920
11	Com1	Us	Com1	Com2	59.160
12	Com1	Us	Com2	Us	53.920
13	Com1	Com1	Us	Com2	54.680
14	Com1	Com1	Com1	Us	63.240
15	Com1	Com1	Com2	Com1	57.280
16	Com1	Com2	Us	Us	62.160
17	Com1	Com2	Com1	Com1	70.000
18	Com1	Com2	Com2	Com2	63.440
19	Com2	Us	Us	Com2	54.640
20	Com2	Us	Com1	Us	63.200
21	Com2	Us	Com2	Com1	57.240
22	Com2	Com1	Us	Us	58.720
23	Com2	Com1	Com1	Com1	66.560
24	Com2	Com1	Com2	Com2	60.000
25	Com2	Com2	Us	Com1	65.480
26	Com2	Com2	Com1	Com2	72.720
27	Com2	Com2	Com2	Us	67.480

Table 6.12 Factors and levels with OEC results for thumbtack example

6.2.5.4 Modelling the system

The OEC results Y_m are transformed into a matrix format as in equation C.5 (Appendix C). The coding matrix is displayed as in equation C.6. The regression coefficient matrix, $\hat{\beta}_m$ for this example is found in equation C.7. The new OEC values including interactions from the Regression Analysis (OEC Int RA) are displayed in Table 6.13.

Exp	HD (1)	SJ (2)	PS (5)	PD (9)	OEC (Int_RA)
1	Us	Us	Us	Us	57.1700
2	Us	Us	Com1	Com1	62.9100
3	Us	Us	Com2	Com2	68.6500
4	Us	Com1	Us	Com1	69.7900
5	Us	Com1	Com1	Com2	60.2300
6	Us	Com1	Com2	Us	66.9900
7	Us	Com2	Us	Com2	67.1100
8	Us	Com2	Com1	Us	73.8700
9	Us	Com2	Com2	Com1	64.3100
10	Com1	Us	Us	Com1	60.0100
11	Com1	Us	Com1	Com2	50.4500
12	Com1	Us	Com2	Us	57.2100
13	Com1	Com1	Us	Com2	64.3500
14	Com1	Com1	Com1	Us	71.1100
15	Com1	Com1	Com2	Com1	61.5500
16	Com1	Com2	Us	Us	62.6900
17	Com1	Com2	Com1	Com1	68.4300
18	Com1	Com2	Com2	Com2	74.1700
19	Com2	Us	Us	Com2	54.5700
20	Com2	Us	Com1	Us	61.3300
21	Com2	Us	Com2	Com1	51.7700
22	Com2	Com1	Us	Us	52.9100
23	Com2	Com1	Com1	Com1	58.6500
24	Com2	Com1	Com2	Com2	64.3900
25	Com2	Com2	Us	Com1	72.5500
26	Com2	Com2	Com1	Com2	62.9900
27	Com2	Com2	Com2	Us	69.7500

Table 6.13 OEC responses after interaction is included in the regression model for thumb tack example

6.2.5.5 Analysing the responses

Analysis of Means:

Since the criteria is for "larger the better" characteristic, then a larger OEC response average is desirable. The response table (Table 6.14) identifies *SJ* and *PSxPD* as the most important (larger difference between factor levels), *HD* and *HDxSJ* as second, then *PS* and finally *PD*. *HDxPS* and *SJxPS* do not really have a ranking as their average factor effect is zero.

	HD (1)	SJ (2)	HDxSJ	PS	HDxPS	PD	SJxPS	PSxPD
Us	65.670	58.230	65.670	62.350	63.330	63.670	63.330	58.230
Com 1	63.330	63.330	63.330	63.330	63.330	63.330	63.330	63.330
Com 2	60.990	68.430	60.990	64.310	63.330	62.990	63.330	68.430
Difference	4.680	10.200	4.680	1.960	0.000	0.680	0.000	10.200
Rank	3	1	3	5	7	6	7	1

Table 6.14 Average response table of main factor effects for thumbtack example

Figure 6.11 shows the optimum results for the average factorial response, which are circled. This is only for the main factors. As a result, it can be observed that *HD*: *Us* (Level -1), *SJ*: *Com2* (Level 1), *PS*: *Com2* (Level 1) and *PD*: *Us* (Level -1), but still this is not showing interactions. In order to calculate the overall optimum combination of the levels, it is desirable to study the factor interactions. The interaction plots are depicted in Figure 6.12 and Figure 6.13.

Analysis of Variance:

The ANOVA (Table 6.15) was performed to identify how statistically significant the results are and the percentage contribution of each factor and/or interactions. The ANOVA table gives similar results to the average response table (Table 6.14). The rank order is exactly the same, identifying *SJ* and *PSxPD* as the most important contributors, then *HDxSJ* and *HD*. It is also to be noted that the main factors *SJ*, *HD* and the interaction *PSxPD* and *HDxSJ* are all 99% statistically significant as their F-ratios are high. It also

identifies that the $PS \times PD$ interaction has a larger contribution of 40.61% compared to only 8.55% for $HD \times SJ$.

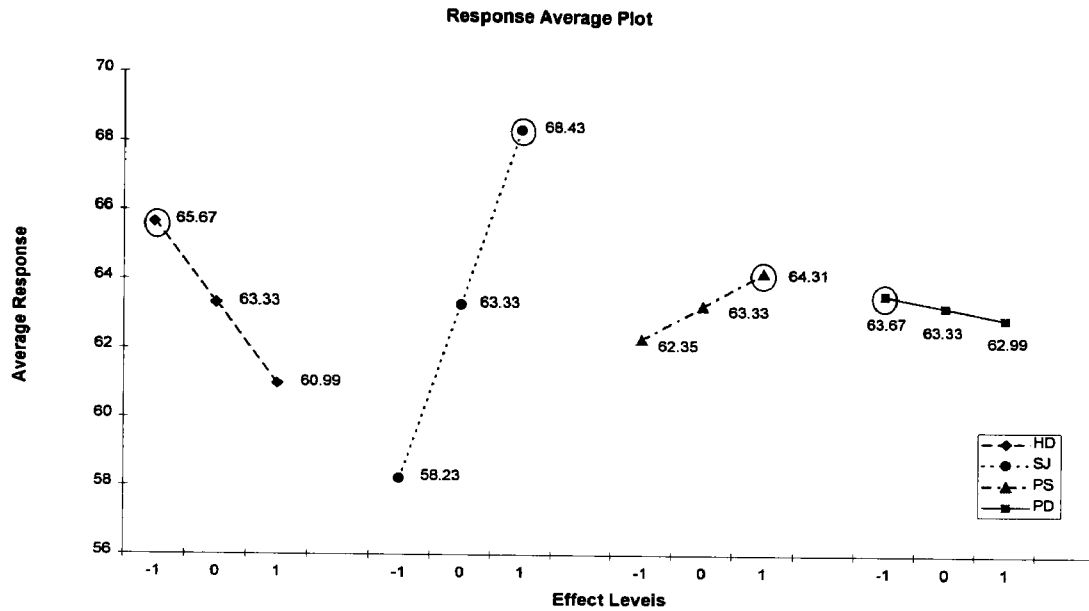


Figure 6.11 Main factor effects response plot for thumbtack example

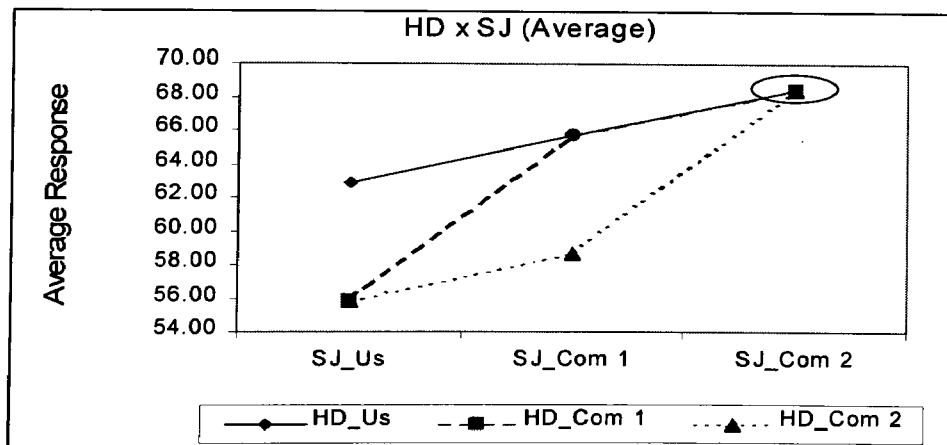


Figure 6.12 Interaction between Head Diameter (HD) and Strength of Join (SJ)

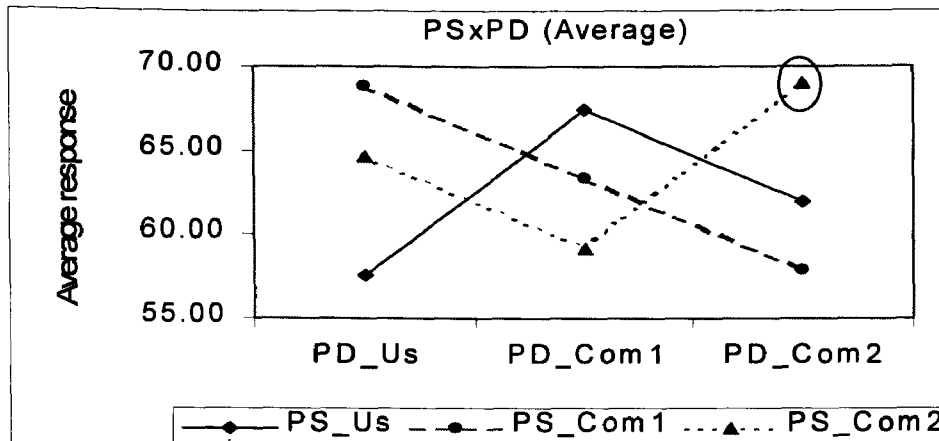


Figure 6.13 Interaction between Pin Sharpness (PS) and Pin Diameter (PD)

Factor	Sum Square (SS)	dof	mean sq (MSS)	F-Ratio	S'	% Contribution	Rank
SJ	468.16	2	234.08	168.58	465.38	40.37	2
PSxPD	468.16	4	117.04	84.29	468.16	40.61	1
HDxSJ	98.55	4	24.64	17.74	98.55	8.55	3
HD	98.54	2	49.27	35.48	98.54	8.55	3
Error	19.44	14.00	1.39	1.00	38.88	3.37	5
ST	1152.85	26.00				100.00	

Table 6.15 ANOVA table for Thumb Tack example

The percentage contribution of the error is approximately 3%, which shows that the process is showing very little variability. This would suggest that the variability is too small, i.e. the test data are too similar in this case study and as such may not be an appropriate example to test the QFD-Taguchi approach. This may be because this case study is less complex, displaying fewer interactions than the previous case study.

From Figure 6.12, it can be observed that interaction exist between *HD* and *SJ* since the lines are not parallel. From this figure, any level of *HD* can be chosen as all the levels have similar responses, but *SJ* should be chosen at level *Com2*. The optimum levels are circled. Since any level of *HD* can be chosen, other factors such as cost should be taken into account to make a decision. Since no other influencing factors are known, for this

work the main factor response table (Table 6.14) and plot (Figure 6.11) are thus looked at to reach a decision. The response table and plot indicates that *HD* should be chosen at level: *Us* as this level has the largest average response of 65.67. This level is circled in Figure 6.11.

Figure 6.13 also shows interactions between *PDxPS*. By visually inspecting this figure the levels of the factors could be set at *PD: Com 2, PS: Com2* or *PD:Us* and *PS: Com1* as their responses are very similar. The largest average response (69.07) is at *PS: Com2* and *PD: Com2*. If there were any conflicts between the choice of level of a factor between these two plots, the interaction *PSxPD* would be given priority as it is statistically more significant. The final optimum target levels found are given in Table 6.16 and compared with the original target values from QFD.

Factors	QFD-Taguchi Approach	Original Target values from QFD
Tackhead Diameter (HD)	Us	> Company 1
Pin head diameter (PD)	Company 2	Company 1
Strength of Join (SJ)	Company 2	> Company 2
Sharpness of pin (PS)	Company 2	< Company 1

Table 6.16 New target values for the thumbtack example using the QFD-Taguchi approach

6.2.6 Discussion

Table 6.16 shows that the QFD-Taguchi approach results in a different set of target values compared to the ones arrived at in the HOQ. In fact three of the target values have changed, those for *Tack Head Diameter*, *Pin Head Diameter* and *Sharpness of Pin Head*. Notice that this combination was not a trial ran (*Us, Com2, Com2, Com2*) in Table 6.12. The rank order of importance of the main factors have also changed with *Strength of Join (SJ)* having rank 1 and *Head Diameter (HD)* rank 2 as opposed to the Proportional Distribution HOQ (Figure 6.9) where *SJ* was ranked third and *HD* was ranked first. The

change in rank is maybe due to the fact that these two factors are related to each other positively, so their rank order should nearly be the same.

If the customer's competitive evaluation is looked at further, it can be seen to relate to the chosen optimum levels by the QFD-Taguchi approach. For example, for *Tack Head Diameter* Company *Us* was chosen. At first glance this may seem inappropriate since a larger *HD* is preferable as suggested in Table 6.9 and was decided upon by the QFD team. *HD* has a strong relationship with "*Low price*", which the customer evaluation has identified Company *Us* as being the best (4 out of 5) on "low price". Therefore the customers were very satisfied with the prices for Company *Us*, and in order to keep the price low and hence the customer satisfaction high, which is strongly related to and thus affected by *HD*, then a smaller *HD* is selected resulting in low price and satisfying the customers. For *PD*, Company 2 was identified by the QFD-Taguchi approach as the optimum target level. In the relationship matrix, *PD* is related weakly to two customer demands "*Easy to push into Board*" and "*Low Price*" and for "*Easy to push into Board*" the customers were very satisfied with Company 1, whereas for "*Low Price*", the customer gave Company *Us* the highest satisfaction. Therefore since this factor (*PD*) possess no strong relationships with any of the customer demands, a compromise between them is made and level: Company 2 is chosen instead. The other two factors give similar results. Consequently not only have interactions been considered in the approach but also the two competitive evaluations are in agreement as seen in Table 6.17.

Case 2: Thumbtack				
	Technical target values	Technical target values	Customer target values	
Eng characteristics	Original QFD HOQ	QFD-Taguchi approach	Original QFD HOQ	Customer demands
Head Diameter	Company 1	Us	Us	Low Price
Pin Diameter	Company 1	Company 2	Us, Company 1	Easy to push into board, Low Price
Strength of Join	Company 2	Company 2	Company 2	Pin does not bend
Pin Sharpness	Company 1	Company 2	Company 1	Easy to push into board

Table 6.17 The two competitive evaluation in agreement

6.3 REMARKS

A different combination of factor levels were obtained using the combined QFD-Taguchi approach using the OEC calculation compared to the target values set in the original HOQ (Independent Scoring). In the QFD's HOQ, each engineering characteristic (factor) is considered independently and their target value (optimum level) is determined by trying to surpass the target value set by competitive companies. In the QFD-Taguchi approach, the target values are set in relation to other engineering characteristics, considering interactions between the characteristics. This new approach provides a more reasonable way to set target values, when interactions between requirements exist. When interactions do not exist, then the approach gives the same combination as that given in QFD's original HOQ. Other factors such as cost and time will also have an effect on the chosen target values, but at least interactions between engineering characteristics have been taken into account and not been ignored altogether.

When comparing the two case studies, it was observed that the first case study, which possess more interactions and is therefore more complex as opposed to the second case study, showed more variability between the factors and the error term. It may be the case that the QFD-Taguchi approach is more suitable for complex situations, where variability between factors and error can be detected easier.

As well as considering interactions between engineering characteristics, the approach has tried to interpret the customer demands as a function of the engineering characteristics and factor levels (companies) have been chosen that have rendered the two competitive evaluations in agreement. One of the incompatibilities in the QFD HOQ lies in the relationship between customer's competitive evaluation and the technical competitive evaluation (Santos, 1993). Customer demands and engineering characteristics that have

strong relationship are expected to have equally high or low quality rating in both the customer's competitive evaluation and the technical competitive evaluation. If they are not, there may be incompatibilities either in the customer demands, in the evaluation of the customer's satisfaction, in the measurement of the engineering characteristics or in the relationship matrix. In one direction, customer satisfaction is used to incorporate quality into engineering characteristics: in the other direction, customer satisfaction is evaluated by means of engineering characteristics. Where strong relationship exist in the relationship matrix, the customer and technical evaluation should be in agreement as the same language is being used in both directions (Santos, 1993). Improvements in these measurable, engineering characteristics contribute to product design and to customer satisfaction. The goal of product design is to maximise customer satisfaction at minimum cost, this is the same as maximising the target levels of the engineering characteristics. According to this approach, the correct setting of factor levels will achieve customer satisfaction, here seen as a measurable characteristic.

The OEC calculation described in section 5.4.1.1 of chapter 5, depends very much on the weighting (w_1 , w_2 , w_3 , etc) defined by the customer importance weighting in QFD. The customers normally provide this weighting. This importance weighting is also subjective in the QFD analysis, as in addition, interactions between the customer demands also exist in the porch of the HOQ, but are often ignored when prioritising the customer importance weighting of each customer demand. Since these weightings can bring an element of error in the OEC calculation, a way to determine them more precisely is needed.

An approach that integrates QFD and Fuzzy Logic (Fuzzy-QFD) to determine more precise customer rating and the relationship weights, taking into account interactions between requirements has been developed and extensively described in chapters 3 and 4. The Fuzzy-QFD approach can be used to determine more precise customer importance

weightings before calculating the OEC responses in the QFD-Taguchi approach described in this chapter. One shortcoming of this approach is that it only maps interactions that are given to it by the QFD team. The QFD team can also sometimes be subjective in the correlation matrices, therefore placing the inappropriate magnitude of interactions in a cell, or even missing certain interactions altogether. The lack of improper interacting effect cannot be rectified by the QFD-Taguchi approach as it only maps the given interaction. A way to define the correlation matrices more appropriately will definitely help this approach. A way to accomplish this was proposed in chapter 4 by utilising an inference mechanism and four-valued logic. Furthermore, good benchmarking data, customer and technical competitive evaluations are a prerequisite to obtaining good valid results in the QFD-Taguchi approach developed.

6.4 THE OEC APPROACH VERSUS A NON-OEC APPROACH

It is essential to investigate whether one quality characteristic at a time approach (non-OEC) would result in the same conclusion as the OEC approach. Therefore the thumbtack example will be repeated in exactly the same way as in the OEC approach except instead of having a combined result, three sets of results corresponding to the three quality characteristics, "*Easy to Push into board*", "*Pin does not bend*" and "*Low price*" will be calculated. The results are determined in exactly the same way as before except now there are three different sets of results and performing 27 experiments for each criterion. Four factors at three levels, and two sets of interaction will still be investigated, therefore 27 experiments are performed as before. For each quality characteristic:

Easy to Push into board

Response for *Easy to push into board* (Y1) = $2*0.2 + 0*0.0 + 2*0.6 + 2*0.2 = 2.0$

The responses before interactions are added and after interactions are added (Int_RA) for experiment 2 to 27 are given in Table 6.18.

Exp	HD (1)	SJ (2)	PS (5)	PD (9)	Response	Response (Int_RA)
1	Us	Us	Us	Us	2.0000	2.5333
2	Us	Us	Com1	Com1	4.4000	2.9333
3	Us	Us	Com2	Com2	2.8000	3.3333
4	Us	Com1	Us	Com1	2.6000	2.9333
5	Us	Com1	Com1	Com2	4.0000	3.3333
6	Us	Com1	Com2	Us	2.6000	3.4333
7	Us	Com2	Us	Com2	2.2000	3.3333
8	Us	Com2	Com1	Us	3.8000	3.4333
9	Us	Com2	Com2	Com1	3.2000	3.8333
10	Com1	Us	Us	Com1	3.2000	3.3333
11	Com1	Us	Com1	Com2	4.6000	3.7333
12	Com1	Us	Com2	Us	3.2000	3.8333
13	Com1	Com1	Us	Com2	2.8000	2.8333
14	Com1	Com1	Com1	Us	4.4000	2.9333
15	Com1	Com1	Com2	Com1	3.8000	3.3333
16	Com1	Com2	Us	Us	2.6000	2.9333
17	Com1	Com2	Com1	Com1	5.0000	3.3333
18	Com1	Com2	Com2	Com2	3.4000	3.7333
19	Com2	Us	Us	Com2	2.4000	3.2333
20	Com2	Us	Com1	Us	4.0000	3.3333
21	Com2	Us	Com2	Com1	3.4000	3.7333
22	Com2	Com1	Us	Us	2.2000	3.3333
23	Com2	Com1	Com1	Com1	4.6000	3.7333
24	Com2	Com1	Com2	Com2	3.0000	4.1333
25	Com2	Com2	Us	Com1	2.8000	2.8333
26	Com2	Com2	Com1	Com2	4.2000	3.2333
27	Com2	Com2	Com2	Us	2.8000	3.3333

Table 6.18 Responses for quality characteristic "Easy to push into board" before and after interactions are added

The average response table for quality characteristic "Easy to push into board" (EPB) is given in Table 6.19. It can be seen from this table that *PS* and *HD x SJ* have the highest differences and so are the most important factors for the quality characteristic "Easy to push into board", *HD* and *PD* come second and the rest are insignificant.

EPB	HD	SJ	HDxSJ	PS	HDxPS	PD	SJxPS	PSxPD
Us	3.233	3.333	3.033	3.033	3.333	3.233	3.333	3.333
Com 1	3.333	3.333	3.333	3.333	3.333	3.333	3.333	3.333
Com 2	3.433	3.333	3.633	3.633	3.333	3.433	3.333	3.333
Difference	0.200	0.000	0.600	0.600	0.000	0.200	0.000	0.000
Rank	3	5	1	1	5	3	5	5

Table 6.19 Average response table for "Easy to push into board" (EPB)

The interaction plots are depicted in Figure 6.14 and Figure 6.15.

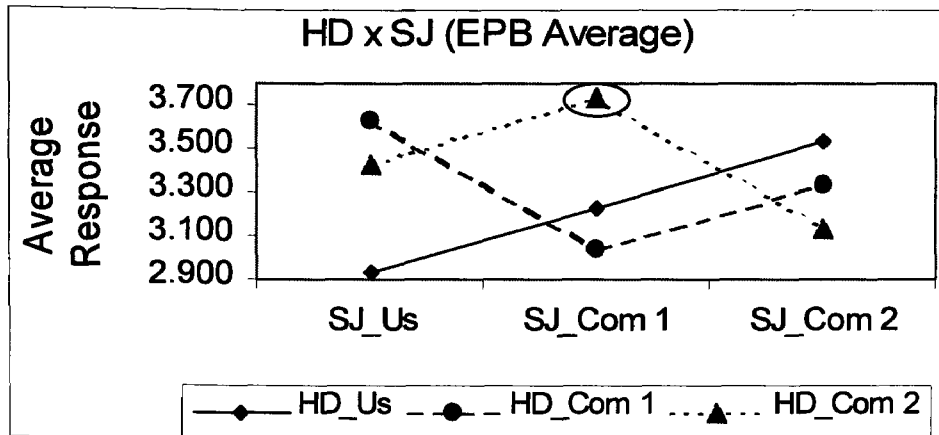


Figure 6.14 HDxSJ interaction for "Easy to push into board"

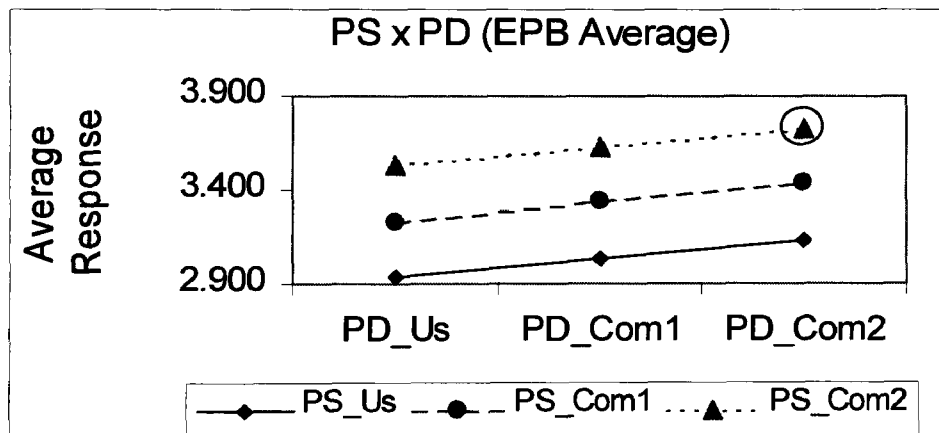


Figure 6.15 PSxPD interaction for "Easy to push into board"

From Figure 6.14, HD should be set at level; Com2, while SJ at level: Com1. In Figure 6.15, PS should be set at level: Com2 and PD also at level: Com2.

Pin does not Bend

Response for *Pin does not bend* (Y_2) = $0 \cdot 0.0 + 2 \cdot 1.0 + 0 \cdot 0.0 + 0 \cdot 0.0 = 2.0$

The responses for experiment 2 to 27 are given in Table 6.20 for before and after interactions.

Exp	HD (1)	SJ (2)	PS (5)	PD (9)	Response	Response (Int_RA)
1	Us	Us	Us	Us	2.0000	0.3333
2	Us	Us	Com1	Com1	2.0000	0.3333
3	Us	Us	Com2	Com2	2.0000	0.3333
4	Us	Com1	Us	Com1	3.0000	3.3333
5	Us	Com1	Com1	Com2	3.0000	3.3333
6	Us	Com1	Com2	Us	3.0000	3.3333
7	Us	Com2	Us	Com2	5.0000	6.3333
8	Us	Com2	Com1	Us	5.0000	6.3333
9	Us	Com2	Com2	Com1	5.0000	6.3333
10	Com1	Us	Us	Com1	2.0000	3.3333
11	Com1	Us	Com1	Com2	2.0000	3.3333
12	Com1	Us	Com2	Us	2.0000	3.3333
13	Com1	Com1	Us	Com2	3.0000	1.8333
14	Com1	Com1	Com1	Us	3.0000	1.8333
15	Com1	Com1	Com2	Com1	3.0000	1.8333
16	Com1	Com2	Us	Us	5.0000	4.8333
17	Com1	Com2	Com1	Com1	5.0000	4.8333
18	Com1	Com2	Com2	Com2	5.0000	4.8333
19	Com2	Us	Us	Com2	2.0000	1.8333
20	Com2	Us	Com1	Us	2.0000	1.8333
21	Com2	Us	Com2	Com1	2.0000	1.8333
22	Com2	Com1	Us	Us	3.0000	4.8333
23	Com2	Com1	Com1	Com1	3.0000	4.8333
24	Com2	Com1	Com2	Com2	3.0000	4.8333
25	Com2	Com2	Us	Com1	5.0000	3.3333
26	Com2	Com2	Com1	Com2	5.0000	3.3333
27	Com2	Com2	Com2	Us	5.0000	3.3333

Table 6.20 Responses for quality characteristic "Pin does not bend"

The average response table is given in Table 6.21. It can be seen from this table that *SJ* and *HD x SJ* have the highest score and so are the most important factors for the quality characteristic "Easy to push into board", and the rest are insignificant as they have differences of zero. This is obvious from the HOQ, as the only factor that affects the quality characteristic "Pin does not Bend" (PNB) is *SJ*, and through its interaction with *HD*, *HDxSJ* is important too. The interaction plots are depicted in Figure 6.16 and Figure 6.17.

PNB	HD	SJ	HDxSJ	PS	HDxPS	PD	SJxPS	PSxPD
Us	3.333	1.833	1.833	3.333	3.333	3.333	3.333	3.333
Com 1	3.333	3.333	3.333	3.333	3.333	3.333	3.333	3.333
Com 2	3.333	4.833	4.833	3.333	3.333	3.333	3.333	3.333
Difference	0.000	3.000	3.000	0.000	0.000	0.000	0.000	0.000
Rank	3	1	1	3	3	3	3	3

Table 6.21 Average response table for "Pin does not bend" (PNB)

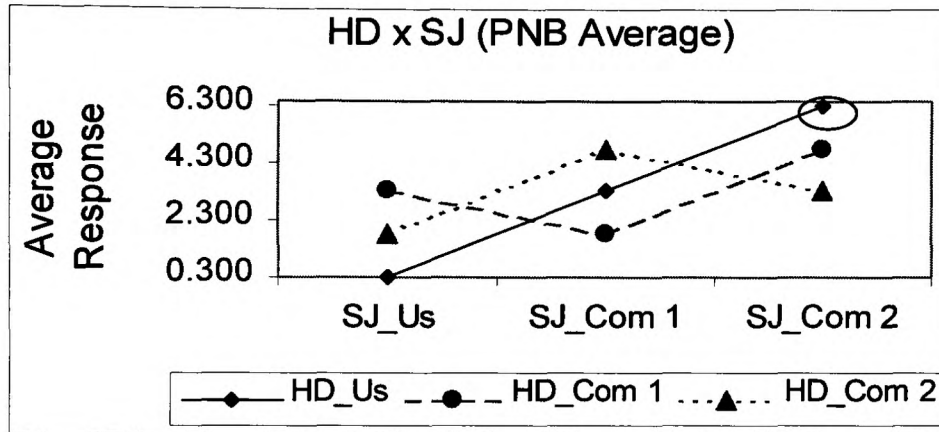


Figure 6.16 HDxSJ interaction for "Pin does not bend"

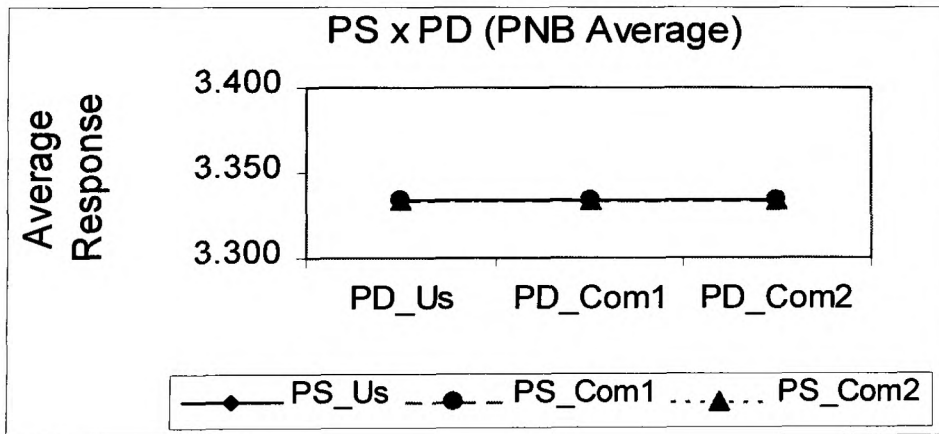


Figure 6.17 PSxPD interaction for "Pin does not bend"

From Figure 6.16, HD should be set at level; Us, while SJ at level: Com2. In Figure 6.17, all the plots are overlaid on top of each other, so any level can be chosen for PS and PD.

Low Price

Response for *Low Price* (Y_3) = $4 \times 0.60 + 0 \times 0.0 + 4 \times 0.20 + 4 \times 0.20 = 4.0$

The responses for experiment 2 to 27, before and after interactions are given in Table 6.22.

The average response table is given in Table 6.23. It can be seen from this table that *HD* and *PSxPD* have the highest differences and so are the most important factors for the quality characteristic "*Low Price*", *PS* and *PD* come second and the rest are insignificant as they have differences of zero. The interaction plots are displayed in Figure 6.18 and Figure 6.19.

Exp	HD (1)	SJ (2)	PS (5)	PD (9)	Response	Response (Int_RA)
1	Us	Us	Us	Us	4.0000	3.8000
2	Us	Us	Com1	Com1	3.2000	3.3000
3	Us	Us	Com2	Com2	3.6000	2.8000
4	Us	Com1	Us	Com1	3.6000	3.1000
5	Us	Com1	Com1	Com2	3.4000	3.5000
6	Us	Com1	Com2	Us	3.8000	3.3000
7	Us	Com2	Us	Com2	3.8000	3.3000
8	Us	Com2	Com1	Us	3.6000	3.1000
9	Us	Com2	Com2	Com1	3.4000	3.5000
10	Com1	Us	Us	Com1	2.4000	2.8000
11	Com1	Us	Com1	Com2	2.2000	3.2000
12	Com1	Us	Com2	Us	2.6000	3.0000
13	Com1	Com1	Us	Com2	2.6000	3.0000
14	Com1	Com1	Com1	Us	2.4000	2.8000
15	Com1	Com1	Com2	Com1	2.2000	3.2000
16	Com1	Com2	Us	Us	2.8000	3.5000
17	Com1	Com2	Com1	Com1	2.0000	3.0000
18	Com1	Com2	Com2	Com2	2.4000	2.5000
19	Com2	Us	Us	Com2	3.2000	2.7000
20	Com2	Us	Com1	Us	3.0000	2.5000
21	Com2	Us	Com2	Com1	2.8000	2.9000
22	Com2	Com1	Us	Us	3.4000	3.2000
23	Com2	Com1	Com1	Com1	2.6000	2.7000
24	Com2	Com1	Com2	Com2	3.0000	2.2000
25	Com2	Com2	Us	Com1	3.0000	2.5000
26	Com2	Com2	Com1	Com2	2.8000	2.9000
27	Com2	Com2	Com2	Us	3.2000	2.7000

Table 6.22 Responses for quality characteristic "*Low Price*"

LP	HD	SJ	HDxSJ	PS	HDxPS	PD	SJxPS	PSxPD
Us	3.300	3.000	3.000	3.100	3.000	3.100	3.000	3.300
Com 1	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000
Com 2	2.700	3.000	3.000	2.900	3.000	2.900	3.000	2.700
Difference	0.600	0.000	0.000	0.200	0.000	0.200	0.000	0.600
Rank	1	5	5	3	5	3	5	1

Table 6.23 Average response table for "Low Price" (LP)

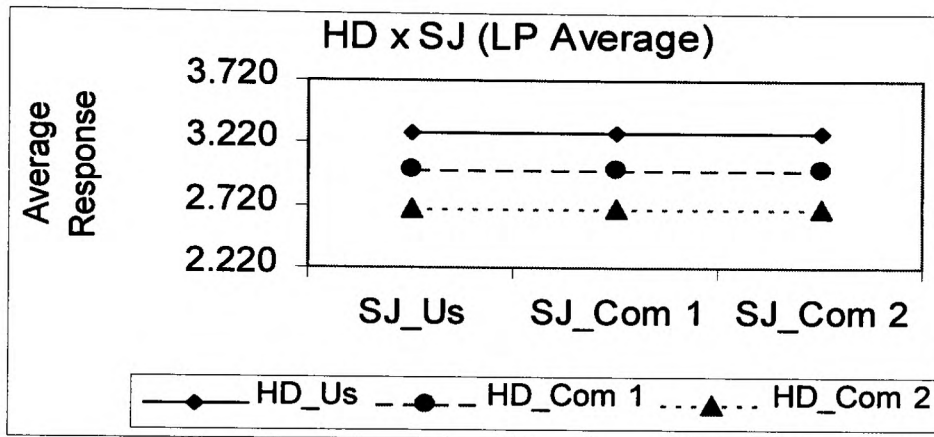


Figure 6.18 HDxSJ interaction for "Low Price"

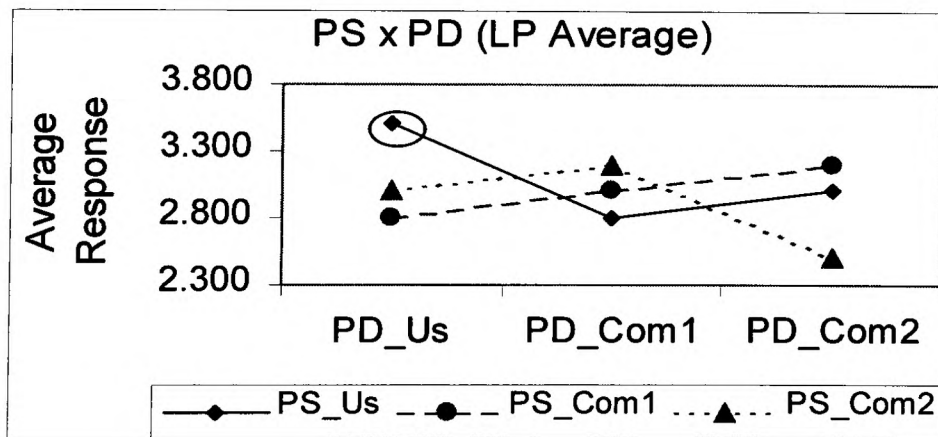


Figure 6.19 PSxPD interaction for "Low Price"

From Figure 6.18, the optimum level for *HD* is level: *Us*, whereas any level can be chosen for *SJ*. In Figure 6.19, *PS* can be chosen at level: *Us* and *PD* at level: *Us* too. Table 6.24 tabulates the optimum factor levels found by the interaction plots and eventually tries to combine all the results to output only one level for each factor. Some of the chosen levels contradict each other, therefore other sources of information to determine which level to choose are sought. The first thing to look at is how many interactions exist between factors. If high interactions (lines cross, in opposite direction), detected by the interaction graphs are present, then the optimum levels from the interaction plot are chosen. If the interaction plot portray few interactions, then the factor level with the highest average response is chosen.

For *HD*, level: *Us* was chosen as the optimum since it is the common level for two quality criteria and it ranked the highest for the quality characteristic "*Low Price*" with average response of 3.3 (Table 6.23). For *SJ*, *Com2* was chosen since it had the highest response of 3.43 (Table 6.19) for quality criterion "*Easy to push into board*", which also shows antisnergistic interaction between *HD*×*SJ* (Figure 6.14). *Com2* was chosen for *PS* since it had the highest response of 3.63 (Table 6.19) for quality criterion "*Easy to push into board*". For *PD* the ultimate choice was *Com2* as it had the highest response for quality characteristic "*Easy to push into board*" in Table 6.19.

Quality characteristic	Factors			
	HD	SJ	PS	PD
Easy to Push into board	Com2	Com1	Com2	Com2
Pin does not bend	Us	Com2	Any	Any
Low Price	Us	Any	Us	Us
Decision	Us	Com2	Com2	Com2

Table 6.24 Summary of chosen factor levels

6.4.1 Remarks

Section 6.4 investigated whether using the Overall Evaluation Criteria (OEC), which combines many variables together to calculate the response, gave significantly different results to the 'one criteria' at a time approach. The final choice of optimum level using the non-OEC technique was the same as the choice arrived at using the OEC response for the thumbtack example (Table 6.16). This confirms that the OEC calculations give a good approximation of the results whilst combining all the data together and saving time and continuous repeats of the same experiments for each individual quality characteristic. This has also been found by Roy (Roy, 1990) in his practical applications of the OEC technique. The one criterion at a time (non-OEC) often gives contradicting results and a compromise has to be made as to which level to choose. This problem is compensated for when using the OEC calculation. Therefore, when multiple objectives (different units of measurements, different importance weighting, different quality characteristics) exist, a multiple criteria technique such as the OEC technique is more suitable.

6.5 SUMMARY

In this chapter, the integration of the Taguchi Design of Experiment method with the QFD process discussed in chapter 5 was investigated further by using case studies. Another problem identified at the end of chapter 4, was how to set the technical target values in the HOQ, considering interactions between demands, whilst using the minimum effort and time. The developed QFD-Taguchi approach has partially addressed this problem. The two worked examples have shown that the QFD-Taguchi approach identifies different sets of target values as optimal that renders the two competitive evaluations (customer & technical) in agreement. In comparing the ANOVA results for the two case studies considered, it was found that the more complex case study showed more variability, which means the results are more significant. So, it can be said that the

developed QFD-Taguchi approach is more suited to complex problems, but further analysis on complex case studies needs to be done to confirm this.

The approach combines all the data in QFD's HOQ together into an Overall Evaluation Criteria (OEC), which gives similar output results to the non-OEC approach. The non-OEC approach was performed to test the viability of the OEC technique and it was found that the OEC technique is a good way to combine all the data into one response. This saves time and reduces the amount of experiments needed, since only one set of experiment is needed, resulting in significant time reduction to perform the experiments. This has been shown in section 6.4.

The QFD-Taguchi approach is dependent upon identifying the correct weightings defined by the customer importance rating, the relationships in the relationship matrix, good correlation matrix data and good benchmarking data in QFD's HOQ. Fuzzy Logic/Fuzzy sets have been proved as useful techniques for identifying and rectifying conflicting data in the HOQ. Their integration with QFD was the subject of chapters 3 and 4. Since the Fuzzy-QFD approaches help to fine-tune the relationship matrix data and the customer importance rating data, they can help the QFD-Taguchi approach.

Thus the proceeding chapter is concerned with integrating the Fuzzy-QFD approaches with the QFD-Taguchi approach to form an integrated systems approach to QFD, mainly to overcome the main drawback of the QFD-Taguchi approach, which is the need to have for good initial data (relationship matrix, customer importance rating). The integrated approach will also investigate the robustness of the QFD-Taguchi approach described in this chapter, as the initial data will have been altered following the use of the Fuzzy-QFD approaches.

Chapter 7.

An integrated systems approach to QFD

"It is good to keep it simple, but not simpler"
~ Albert Einstein ~

An integrated systems approach to QFD is developed in this chapter that combines QFD, Fuzzy Logic/Fuzzy set theory and the Taguchi method. This approach integrates the Fuzzy Proportional Distribution QFD approach together with the QFD-Taguchi approach. It is developed to bring the intrinsic benefits of all the methods together to form a quantitative, robust approach that can deal with imprecise data in QFD's HOQ by utilising interaction between requirements found in the correlation matrices. Furthermore it is used to test how robust the QFD-Taguchi approach developed in the preceding chapter is to input data since the Fuzzy-QFD approach that is applied at the beginning alters the data in the HOQ.

7.1 INTRODUCTION

In the previous chapter (chapter 6), a new approach to determine more precise engineering characteristic target values in the HOQ, named QFD-Taguchi was introduced. The Overall Evaluation Criterion (OEC) was used to calculate the overall response. This OEC calculation depends very much on the customer importance rating and this rating can sometimes be subjective and can lead to over prioritised or under prioritised importance ratings. In chapters 3 and 4, Fuzzy Logic and Fuzzy sets were introduced as techniques that could help determine these importance ratings more accurately by utilising the correlation matrices (porch and roof). In this chapter, the Fuzzy Proportional Distribution QFD approach is adopted to update and re-prioritise the customer importance ratings and the relationship matrix in the HOQ in order to reduce the subjectivity in the customer and QFDs' team subjective input. Instead the ratings are developed from the correlation between demands, making the ratings more robust. These updated customer importance ratings and the relationship matrix data are then used for the OEC calculation in the QFD-Taguchi approach.

The synergy between these three methods is named the Fuzzy-QFD-Taguchi approach and forms an integrated systems approach to QFD, which is the subject of this chapter. The same examples will be used as in the preceding chapter so that comparative studies can be performed. The Fuzzy-QFD approach, which will fine-tune and alter the data in the HOQ, will also be used to test the robustness of the QFD-Taguchi approach developed in the preceding chapter.

7.2 AN INTEGRATED SYSTEMS APPROACH

A system is a set of inter-related components or ideas, theories and procedures working together towards a common objective, whereas an integrated systems approach means having various parts or aspects linked closely to enable the realisation of successful

systems. It focuses on defining customer needs and required functionality early in the development cycle, documenting requirements, then proceeding with the design. It integrates all the disciplines and speciality groups into a team effort forming a structured development process that proceeds from concept to production to operation, which considers both the business and the technical needs of all customers with the goal of providing a quality product that meets the user's needs. The advantages of an integrated systems approach are that it brings together the benefits of each individual method while suppressing the disadvantages (Middendorf and Engelmann, 1997). Generally, integration results in a more superior design, whereby if one technique fails the others take over, so it can tolerate faults.

7.3 AN INTEGRATED SYSTEMS APPROACH TO QFD

The integrated systems approach to QFD developed in this chapter is named Fuzzy-QFD-Taguchi, which brings together Fuzzy Logic/Fuzzy sets theory, the Taguchi Method and QFD. The approach firstly utilises the Fuzzy Proportional Distribution QFD approach described in chapter 3, section 3.9. This Fuzzy-QFD approach is chosen over the Fuzzy Range QFD approach as the input data is crisp, which is desirable for the QFD-Taguchi approach. The steps of the Fuzzy-QFD-Taguchi approach are illustrated in Figure 7.1 and include:

1. The QFD Independent Scoring HOQ is normalised into the Proportional Distribution HOQ as explained in chapter 2.
2. The Proportional Distribution HOQ is in turn transformed into the Fuzzy Proportional Distribution HOQ as demonstrated in chapter 3.
3. An Orthogonal array is chosen depending on the number of factors, levels and interactions to be studied.

4. The quality criteria (customer demands), number of factors, their levels, interactions, customer importance rating, relationship matrix and customer evaluation from the Fuzzy Proportional Distribution HOQ are all used to calculate the OEC responses.
5. The least squares method is utilised to obtain a regression model and thus the regression coefficients.
6. The interaction coefficients are included in the regression equation and the OEC responses are recalculated.
7. The data is analysed using the Analysis of Means and ANOVA techniques.
8. The interaction plots are drawn to choose the optimum factor level.
9. New target values are derived and compared to the original ones and these are then fed back in the Fuzzy-QFD HOQ, ready for the next QFD phase.

This integrated systems approach to QFD is being developed to overcome the main disadvantages of the QFD-Taguchi approach. The main concerns are that the QFD-Taguchi approach depends not only on the correct interaction terms in the correlation matrices, but also the correct relationship matrix as well as customer importance rating data. Since the Fuzzy-QFD approaches developed in chapters 3 and 4 is concerned with identifying and fine tuning ill-defined data in both the relationship matrix and the customer importance rating, it can usefully be adopted prior to the QFD-Taguchi approach. Furthermore, the Fuzzy-QFD approaches developed require that the interaction terms be properly identified for the approaches to yield good results. The method that stems from the sensitivity analysis of chapter 4, which combines an inference mechanism with four-valued logic to determine missed interactions in the correlation matrices is suggested to be used for identifying more precise interaction terms. This can prove useful for both the Fuzzy-QFD approaches and the QFD-Taguchi approach, which are sensitive to these interactions.

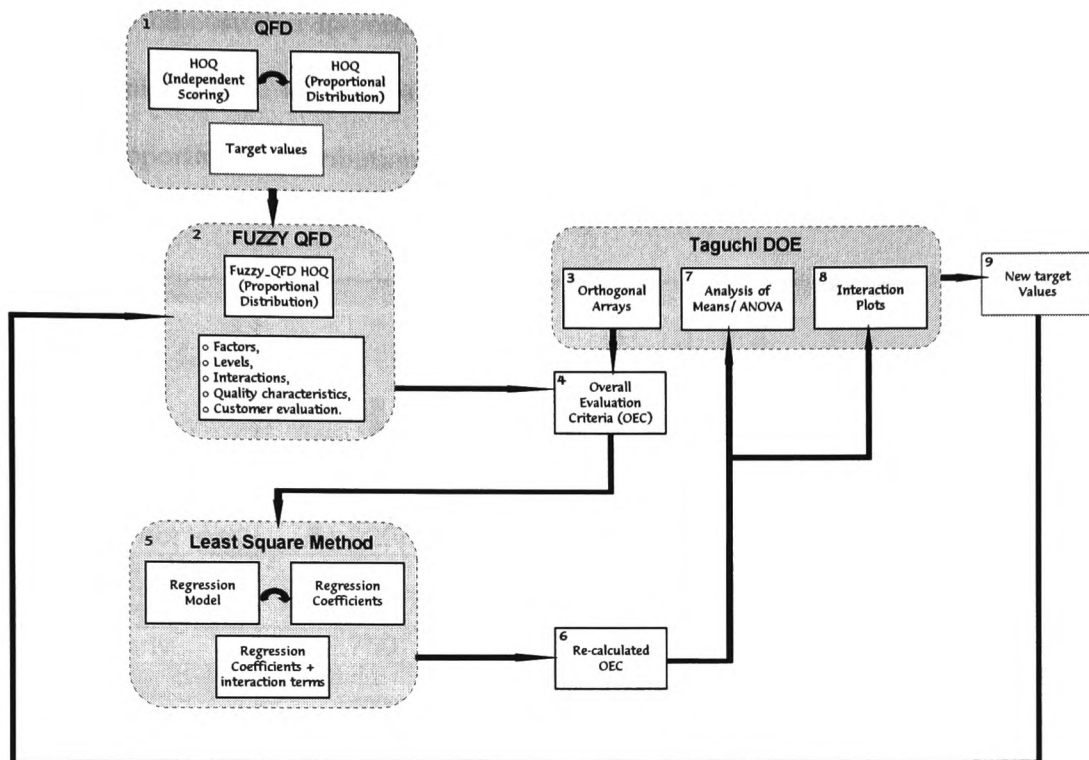


Figure 7.1 Flow chart showing the steps required in the Fuzzy-QFD-Taguchi approach

7.4 CASE STUDIES

In this section, the same two case studies employed in chapter 6 are utilised to verify the integrated system's approach to QFD in order to necessitate comparison between the two chapters. Using the Fuzzy Proportional Distribution QFD approach is not only intended to update ill-defined data in the HOQ, but also to test the sensitivity of the QFD-Taguchi approach to changes in the input data in the HOQ. Therefore 27 experiments will again be utilised, as the same number of factors, levels and interactions will be investigated.

7.4.1 Case study 1: Paper Roll example

As in the previous section, the original HOQ (Figure 6.1) is first converted to the Proportional HOQ (Figure 6.2). Then the fuzzification procedure as described in chapter 3, section 3.9, step 1, is applied and new data is obtained and displayed in Figure 7.2.

Notice that the customer importance rating, the relationship matrix, the technical scoring and the ranking have all been altered after the Fuzzy-QFD approach compared to the original Proportional Distribution results found in Figure 6.2.

	Imp_Rate	% Imp_Rate	Paper thickness	Roll Roundness	Coating thickness	Tensile strength
Paper will not tear	51.320	28.594	0.158	0.232	0.246	0.365
Consistent finish	42.590	23.730	0.192	0.087	0.569	0.152
No ink bleed	42.810	23.852	0.472	0.002	0.298	0.228
Prints clearly	42.760	23.824	0.224	0.116	0.539	0.120
Sum of Imp_Rate	179.480	100.000				
% Score			25.657	11.530	40.480	22.333
Rank			2	4	1	3

Figure 7.2 Fuzzy Proportional Distribution HOQ for Paper Roll example

7.4.2 Fuzzy OEC Results

The combination of the customer demands (quality criteria), and their corresponding customer evaluation (satisfaction level), together with the strength of corresponding relationship in the relationship matrix are used to determine the Fuzzy OEC results. Table 7.1 shows the result of the Fuzzy OEC calculations based on the experiment set out by the L27 orthogonal array.

The Fuzzy OEC for experiment 1 (*PT*, *RR*, *CT*, *TS*) all at level 1 (*Us*) is:

Response for *Paper will not tear* (*Y1*) = $1*0.158+1*0.232+1*0.246+1*0.365 = 1.00$

Response for *Consistent Finish* (*Y2*) = $2.8*0.192+2.8*0.087+2.8*0.569+2.8*0.152 = 2.8$

Response for *No Ink Bleed* (*Y3*) = $5*0.472 + 5*0.002 + 5*0.298 + 5*0.228 = 5.0$

Response for *Prints Clearly* (*Y4*) = $3.5*0.224+3.5*0.116+3.5*0.539+3.5*0.120 = 0.49$

Fuzzy OEC(Exp1)=(Y1/Y1max)*w1+(Y2/Y2max)*w2+(Y3/Y3max)*w3+(Y4/Y4max)* w4

Fuzzy OEC(Exp 1)=(1.0/5)*28.6+(2.8/5)*23.7+(5.0/5)*23.9+(3.5/5)*23.8=59.530 (3dp).

The Fuzzy OEC calculation for experiment 2 to 27 follows the same pattern.

Exp	PT	RR	CT	TS	Fuzzy OEC
1	Us	Us	Us	Us	59.5300
2	Us	Us	Com1	Com1	63.4600
3	Us	Us	Com2	Com2	71.0200
4	Us	Com1	Us	Com1	64.6900
5	Us	Com1	Com1	Com2	67.6500
6	Us	Com1	Com2	Us	69.4800
7	Us	Com2	Us	Com2	67.9000
8	Us	Com2	Com1	Us	65.1300
9	Us	Com2	Com2	Com1	73.6600
10	Com1	Us	Us	Us	61.5700
11	Com1	Us	Com1	Com1	64.5300
12	Com1	Us	Com2	Com2	66.3600
13	Com1	Com1	Us	Com1	65.7600
14	Com1	Com1	Com1	Com2	62.9900
15	Com1	Com1	Com2	Us	71.5200
16	Com1	Com2	Us	Com2	61.5900
17	Com1	Com2	Com1	Us	67.1700
18	Com1	Com2	Com2	Com1	74.7200
19	Com2	Us	Us	Us	65.5000
20	Com2	Us	Com1	Com1	61.0800
21	Com2	Us	Com2	Com2	69.6100
22	Com2	Com1	Us	Com1	66.2500
23	Com2	Com1	Com1	Com2	62.3100
24	Com2	Com1	Com2	Us	73.8000
25	Com2	Com2	Us	Com2	66.4900
26	Com2	Com2	Com1	Us	65.5100
27	Com2	Com2	Com2	Com1	75.2100

Table 7.1 Fuzzy_PD OEC results for paper roll example

7.4.3 The Regression Model

Using the same least square program developed in the previous chapter, the regression coefficients ($\beta_0, \beta_1, \beta_2, etc$) can be calculated for the main factors $\hat{\beta}_m$. The regression model will serve as the new model by which interaction coefficients will be included and the response recalculated based on this model. The calculation of the regression model

requires the response matrix Y_m , (equation (C.14)) and the coded factor level matrix X_m (equation (C.15)). The calculated regression coefficients are given in equation (C.16). The fitted regression for the main factors only, Y_m is given in equation (C.17) and the regression coefficient vector $\hat{\beta}_l$ is given in equation (C.19). The new Fuzzy OEC values (YI) from the Regression Analysis (Fuzzy_OEC Int RA) after the Fuzzy-QFD-Taguchi approach are thus calculated and displayed in Table 7.2.

Exp	PT	RR	CT	TS	Fuzzy OEC (Int_RA)
1	Us	Us	Us	Us	52.9300
2	Us	Us	Com1	Com1	62.0500
3	Us	Us	Com2	Com2	71.1700
4	Us	Com1	Us	Com1	62.8000
5	Us	Com1	Com1	Com2	71.9200
6	Us	Com1	Com2	Us	65.2300
7	Us	Com2	Us	Com2	72.6700
8	Us	Com2	Com1	Us	65.9800
9	Us	Com2	Com2	Com1	75.1000
10	Com1	Us	Us	Us	69.7500
11	Com1	Us	Com1	Com1	67.3200
12	Com1	Us	Com2	Com2	71.6400
13	Com1	Com1	Us	Com1	57.6000
14	Com1	Com1	Com1	Com2	61.3800
15	Com1	Com1	Com2	Us	70.5000
16	Com1	Com2	Us	Com2	62.6700
17	Com1	Com2	Com1	Us	71.2500
18	Com1	Com2	Com2	Com1	69.3600
19	Com2	Us	Us	Us	64.0100
20	Com2	Us	Com1	Com1	68.3300
21	Com2	Us	Com2	Com2	65.9000
22	Com2	Com1	Us	Com1	69.0800
23	Com2	Com1	Com1	Com2	67.1900
24	Com2	Com1	Com2	Us	75.7700
25	Com2	Com2	Us	Com2	56.9300
26	Com2	Com2	Com1	Us	66.0500
27	Com2	Com2	Com2	Com1	69.8300

Table 7.2 OEC response after Fuzzy-QFD-Taguchi approach for paper roll example

7.4.4 Analysis of Means

A criteria is for "larger the better" characteristic is chosen since both the customer and technical evaluation uses the satisfaction level as measurement, then a larger Fuzzy OEC response average is desirable. The average effect response table in Table 7.3 identifies *PTxRR*, *CT* and *PTxTS* as the most important factor, *TS* as the second, *RR* as the third, *PT* and *PTxCT* as the fourth and finally *RRxCT*, *RRxTS* and *CTxTS*. The QFD team did not in fact identify the last three interactions and they have no effect anyway. The corresponding average response plot of main factor effect is depicted in Figure 7.3.

	PT	RR	PTxRR	CT	PTxCT	TS	PTxTS
Us	66.650	65.900	63.160	63.160	66.650	65.230	63.160
Com 1	66.830	66.830	66.830	66.830	66.830	66.830	66.830
Com 2	67.010	67.760	70.500	70.500	67.010	68.430	70.500
Difference	0.360	1.860	7.340	7.340	0.360	3.200	7.340
Rank	6	5	1	1	6	4	1

Table 7.3 Average response table for Paper roll example after Fuzzy-QFD-Taguchi approach

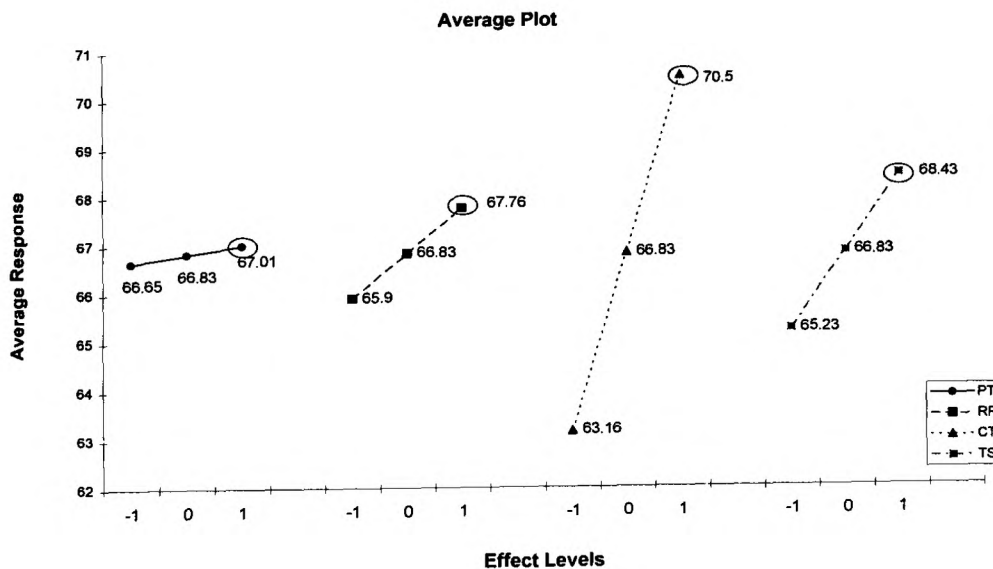


Figure 7.3 Average response plot for paper roll example

The interactions are depicted in Figure 7.4 and Figure 7.5. Figure 7.6 shows the interaction between $PT \times CT$, which was not significant in the ANOVA table (Table 7.4), but is used to identify the level of CT , which cannot be identified by the other figures. The Sum of Squares for the main factors, HD and RR were pooled into the error term as they were small compared to the other factors and interactions.

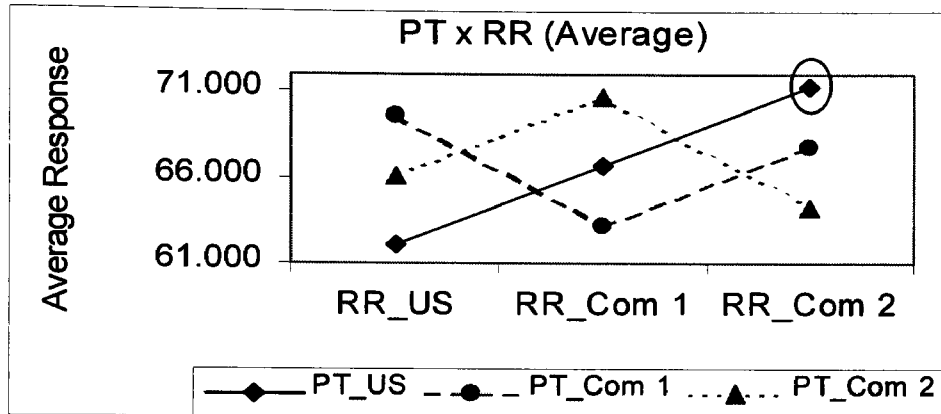


Figure 7.4 Interaction between $PT \times CT$ for paper roll example

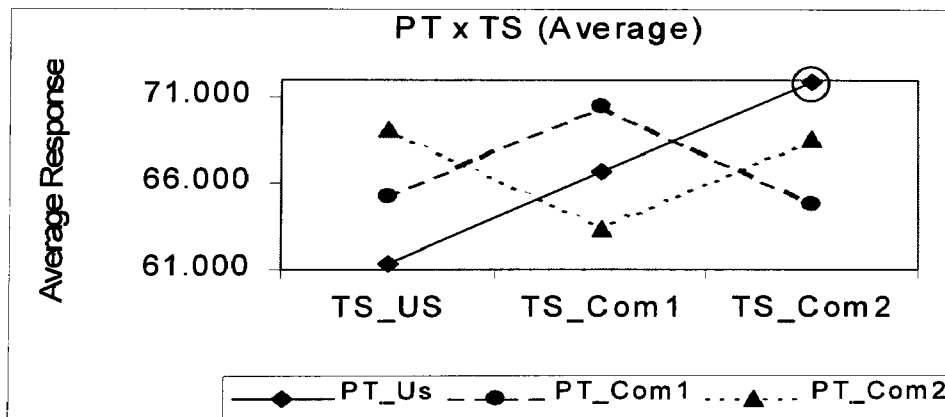


Figure 7.5 Interaction between $PT \times TS$ for paper roll example

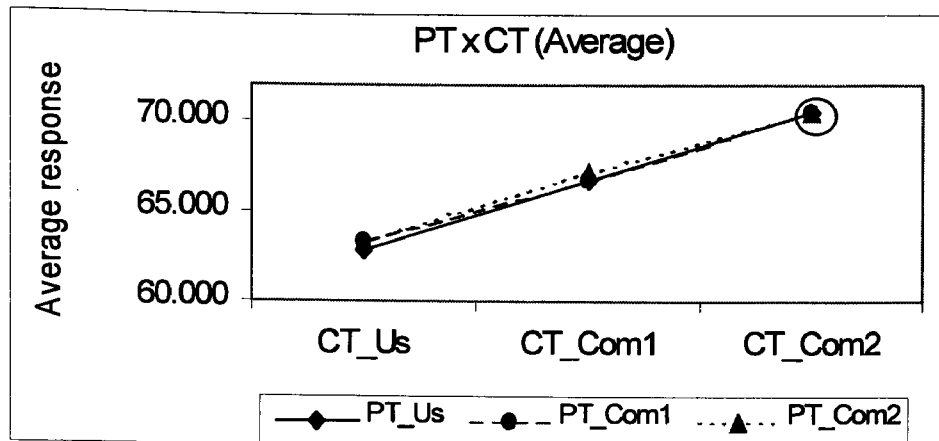


Figure 7.6 Interaction between $PT \times CT$ for paper roll example

7.4.5 Analysis of Variance (ANOVA)

The ANOVA table (Table 7.4) identifies the main factors CT , TS and the interactions $PT \times TS$ and $PT \times RR$ as the most significant having high F-ratios since the error is very small. These results agree with the Average response table (Table 7.3).

Factor	Sum Square (SS)	dof	mean sq (MSS)	F-Ratio	S'	% Contribution	Rank
CT	242.48	2	121.24	102.37	240.11	30.39	1
$PT \times TS$	242.48	4	60.62	51.19	237.74	30.09	2
$PT \times RR$	242.48	4	60.62	51.19	237.74	30.09	2
TS	46.12	2	23.06	19.47	43.75	5.54	4
Error	16.58	14.00	1.18	1.00	33.16	4.20	5
ST	790.14	26.00				100.00	

Table 7.4 ANOVA table after Fuzzy-QFD-Taguchi approach for paper roll example

From Figure 7.4, it can be observed that interaction exist between $PT \times RR$ and in this plot PT level: Us and RR level: $Com2$ are the optimum factor levels as this combination of levels have the largest response. Figure 7.5 shows the interaction between $PT \times TS$. In this figure PT can be chosen at level: Us and TS at level: $Com2$. Furthermore Figure 7.5

shows very slight interaction between $PT \times CT$ and the optimum factor level in this plot is CT level: $Com2$ and any level for PT can be chosen as all the levels have similar responses. The final optimum target levels resulting from the Fuzzy-QFD-Taguchi approach are given in Table 7.5 and compared with the original target values set in QFD.

Factors	Fuzzy-QFD-Taguchi Approach	Original Target values from QFD
Paper Thickness	Us	Company 1
Roll Roundness	Company 2	Company 2
Coating Thickness	Company 2	Company 1
Tensile Strength	Company 2	Company 1

Table 7.5 New target values for paper roll example after the Fuzzy-QFD-Taguchi approach

The Fuzzy-QFD-Taguchi approach results in a different set of target values compared to the ones arrived at in the original HOQ. In fact three of the target values have changed, those for *Paper Thickness*, *Coating Thickness* and *Tensile Strength*.

7.5 FUZZY-QFD-TAGUCHI APPROACH VERSUS QFD-TAGUCHI APPROACH FOR PAPER ROLL EXAMPLE

Since the Fuzzy-QFD approach altered the data in the HOQ, the Fuzzy_OEC results in Table 7.1, are different from the OEC results in Table 6.3 of chapter 6. The differences can be observed in Figure 7.7. Note that the figures are for illustrative purposes only and do not represent a continuous response.

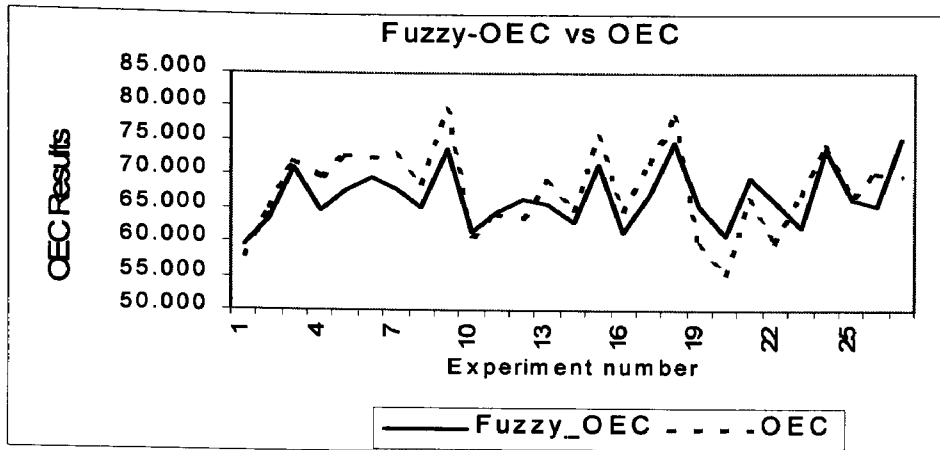


Figure 7.7 Fuzzy-OEC vs. the original OEC results

The differences between the two sets of results can be found in experiment 4, 5, 9, 19, 20, 22 and 27. After including the interaction terms in the regression equation, new OEC values are calculated. These are also graphically compared with and without the Fuzzy OEC approach. The comparative results are depicted in Figure 7.8. The minor differences between the two sets of results can be found in experiment 4, 5, 7, 8, 9, 17, 18 and 20.

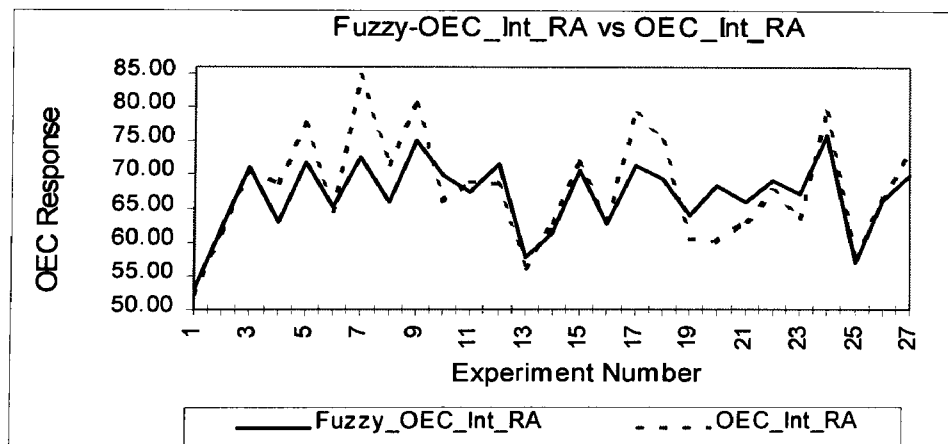


Figure 7.8 Fuzzy_OEC_Integration_Regression Analysis vs OEC_Integration_Regression Analysis

If the Average response tables are compared, it can be observed that the importance of factors and/or interactions has changed as shown in Table 7.6. The main changes can be found in the ranking of *RR*, *PTxRR* and *CT*. The rank of the main factor *RR*, has decreased in the Fuzzy-QFD-Taguchi approach most probably due to its negative interaction with *PT*. *PTxRR* has also decreased in its rank order in the Fuzzy-QFD-Taguchi approach, probably due to *RR*'s decrease in rank order. On the other hand, *CT* has increased in its order of importance.

Factors	Fuzzy_OEC_Int_RA	OEC_Int_RA
	Rank	Rank
PT (1)	6	6
RR (2)	5	1
PTxRR (4)	3	1
CT (5)	1	4
PTxCT (7)	6	6
CTxTS (9)	4	5
TS (10)	1	1
PTxTS (11)	8	8
RRxTS(12)	8	8
CTxTS (13)	8	8

Table 7.6 Fuzzy_OEC responses vs. OEC responses after interaction are added

The interaction graphs have also changed their orientations slightly, but the overall results are exactly the same, giving the same choice of optimum factor levels.

A comparison of the engineering characteristics ranking order for only the main factors from all the different methods/approaches used so far that combines to form the integrated systems approach to QFD is listed in Table 7.7. Note that they are listed in the order of use. It can be seen that the third engineering characteristic's (*CT*), rank order have not altered much, but the other three factor's rank order seem to have changed more drastically. It is not so easy to comment on the changes in rank order of the different

methods as only four factors were being considered. A difference between a rank 2 and a rank 4 may seem trivial here, but if more factors were under consideration, the difference between a rank 2 and 4 may not appear so important.

Method	Rank Order			
	PT	RR	CT	TS
1. Independent Scoring HOQ	2	1	1	2
2. Proportional Dist HOQ	3	2	1	4
3. Fuzzy-QFD HOQ	2	4	1	3
4. QFD-Taguchi HOQ	4	1	2	3
5. Fuzzy-QFD-Taguchi HOQ	4	3	1	2

Table 7.7 Comparison in the engineering characteristic's rank order for all the methods used for the systems approach to QFD

7.5.1 Case study 2: Thumbtack example

As in the previous chapter (Chapter 6), the original HOQ (Figure 6.8) for the “Thumbtack” example is first converted to the Proportional HOQ (Figure 6.9). Then the fuzzification procedure in the Fuzzy-QFD approach as described in chapter 3, section 3.9, step 1, is applied and new data is obtained and displayed as in Figure 7.9. Remember that the % Scoring is obtained by taking the absolute value of each relationship and multiplying it to the % Customer Importance rating (% Imp_Rate) and then summing up each column. In this way, negative relationships are given the same importance, just in a negative sense (Baxter, 1995), (Hauser and Clausing, 1988), (Temponi *et al*, 1999).

Notice that the customer importance rating, the relationship matrix, the technical scoring and the ranking have all been altered after the Fuzzy-QFD approach in Figure 7.9 compared to Proportional Distribution HOQ Figure 6.9.

	Imp Rate	%Imp Rate	Head Diameter	Pin diameter	Strength of join	Sharpness of pin
Easy to push into board	0.325	28.27	-0.164	-0.386	0.204	0.246
Pin does not bend	0.325	28.27	-0.111	-0.044	0.786	-0.059
Low Price	0.500	43.45	-0.500	-0.178	-0.110	-0.212
Sum of Imp Rating	1.151	100.00				
% Score			29.521	19.882	32.786	17.801
Rank			2	3	1	4

Figure 7.9 Fuzzy-QFD Proportional Distribution HOQ for Thumb Tack example

Head Diameter (HD) and *Pin Diameter (PD)* have changed their rank position very little. *Strength of Join (SJ)* and *Pin Sharpness (PS)* on the other hand have had their rank order changed more dramatically. *SJ*, a less important engineering characteristic has increased in importance considerably after considering the porch and roof correlation. The reason why *SJ* may have increased in rank order is because of the many positive interactions *SJ* has with other demands such as *HD* in the roof and indirectly with customer demand "Easy to push into board" via the porch correlation. Table 7.8 shows the engineering characteristics (factors) rank order for the Proportional Distribution method compared to the Fuzzy-QFD proportional distribution approach.

PS, which possessed a higher rank order has now decreased its ranking position. *PS* has a negative correlation with *PD* in the roof of the HOQ, as well as a negative relationship with customer demand "Low Price" in the relationship matrix, which in turn has a negative correlation with customer demand "Easy to push into Board" in the porch.

Method	Factor Rank Order			
	Head Diameter (HD)	Pin Diameter (PD)	Strength of Join (SJ)	Pin Sharpness (PS)
Fuzzy-QFD (PD)	2	3	1	4
Proportional Distribution (PD)	1	3	3	2

Table 7.8 Rank order of the engineering characteristics for the Fuzzy-QFD HOQ compared to the Proportional Distribution HOQ for thumbtack example

7.5.2 Fuzzy OEC Results

In this section, the Fuzzy-QFD Proportional Distribution results from Figure 7.9, are used to calculate the Fuzzy OEC responses. The combination of the customer demands (quality criteria) and their corresponding customer evaluation (satisfaction level), together with the strength of corresponding relationships in the relationship matrix are utilised to determine the Fuzzy_OEC results. The customer importance rating and the relationships in the relationship matrix are obtained from Figure 7.9. The Fuzzy_OEC responses are calculated as follows:

$$\text{Response for Easy to push into board (Y1)} = 2 \times 0.164 + 2 \times 0.204 + 2 \times 0.246 + 2 \times 0.386 = 2.00$$

$$\text{Response for Pin does not bend (Y2)} = 2 \times 0.111 + 2 \times 0.786 + 2 \times 0.059 + 2 \times 0.044 = 2.00$$

$$\text{Response for Low Price (Y3)} = 4 \times 0.500 + 4 \times 0.110 + 4 \times 0.212 + 4 \times 0.178 = 4.00$$

The Fuzzy_OEC for experiment 1 (HD, SJ, PS, PD) all at level 1 (Us) is:

$$\text{Fuzzy_OEC (Exp 1)} = (Y1/Y1max) * w1 + (Y2/Y2max) * w2 + (Y3/Y3max) * w3$$

$$\text{Fuzzy_OEC (Exp 1)} = (2.0/5) \times 28.27\% + (2.0/5) \times 28.27\% + (4.0/5) \times 43.45\% = 57.38$$

The Fuzzy OEC calculations for experiment 2 to 27 follow the same pattern. The results are displayed in Table 7.9.

Exp No.	HD (1)	SJ (2)	PS (5)	PD (9)	Fuzzy_OEC
1	Us	Us	Us	Us	57.376
2	Us	Us	Com 1	Com 1	61.900
3	Us	Us	Com 2	Com 2	59.307
4	Us	Com 1	Us	Com 1	67.071
5	Us	Com 1	Com 1	Com 2	65.572
6	Us	Com 1	Com 2	Us	63.918
7	Us	Com 2	Us	Com 2	72.288
8	Us	Com 2	Com 1	Us	71.727
9	Us	Com 2	Com 2	Com 1	75.157
10	Com 1	Us	Us	Com 1	55.798
11	Com 1	Us	Com 1	Com 2	54.299
12	Com 1	Us	Com 2	Us	52.645
13	Com 1	Com 1	Us	Com 2	59.470
14	Com 1	Com 1	Com 1	Us	58.910
15	Com 1	Com 1	Com 2	Com 1	62.340
16	Com 1	Com 2	Us	Us	65.625
17	Com 1	Com 2	Com 1	Com 1	70.149
18	Com 1	Com 2	Com 2	Com 2	67.556
19	Com 2	Us	Us	Com 2	57.223
20	Com 2	Us	Com 1	Us	56.663
21	Com 2	Us	Com 2	Com 1	60.093
22	Com 2	Com 1	Us	Us	61.834
23	Com 2	Com 1	Com 1	Com 1	66.358
24	Com 2	Com 1	Com 2	Com 2	63.765
25	Com 2	Com 2	Us	Com 1	73.073
26	Com 2	Com 2	Com 1	Com 2	71.574
27	Com 2	Com 2	Com 2	Us	69.920

Table 7.9 Factors and levels with their corresponding Fuzzy_OEC results for Thumbtack example

7.5.3 The Regression Model

Using the same least square program developed in the chapters 5 and 6, the regression coefficients ($\beta_0, \beta_1, \beta_2, etc$) can be calculated for the main factors $\hat{\beta}_m$. The regression model will serve as the new model by which interaction coefficients will be included and the response recalculated based on this model. The results of the software can be found in Appendix C, section C.4.2. The final Fuzzy OEC responses after using the Fuzzy-QFD-Taguchi approach are listed in Table 7.10.

Exp	HD	SJ	PS	PD	Fuzzy_OEC (Int_RA)
1	Us	Us	Us	Us	50.8000
2	Us	Us	Com1	Com1	58.5300
3	Us	Us	Com2	Com2	66.2600
4	Us	Com1	Us	Com1	71.7200
5	Us	Com1	Com1	Com2	57.0700
6	Us	Com1	Com2	Us	64.8000
7	Us	Com2	Us	Com2	70.2600
8	Us	Com2	Com1	Us	77.9900
9	Us	Com2	Com2	Com1	63.3400
10	Com1	Us	Us	Com1	62.0300
11	Com1	Us	Com1	Com2	49.4500
12	Com1	Us	Com2	Us	57.1800
13	Com1	Com1	Us	Com2	64.9500
14	Com1	Com1	Com1	Us	70.6100
15	Com1	Com1	Com2	Com1	58.0300
16	Com1	Com2	Us	Us	63.4900
17	Com1	Com2	Com1	Com1	71.2200
18	Com1	Com2	Com2	Com2	76.8800
19	Com2	Us	Us	Com2	55.2600
20	Com2	Us	Com1	Us	62.9900
21	Com2	Us	Com2	Com1	50.4100
22	Com2	Com1	Us	Us	55.8700
23	Com2	Com1	Com1	Com1	61.5300
24	Com2	Com1	Com2	Com2	69.2600
25	Com2	Com2	Us	Com1	77.0300
26	Com2	Com2	Com1	Com2	64.4500
27	Com2	Com2	Com2	Us	70.1100

Table 7.10 Fuzzy_OEC results after interaction is included in the regression model for thumbtack example

7.5.4 Analysis of Means

Since the criteria is for "larger the better" characteristic, (larger customer and engineering satisfaction level in the customer and competitive evaluation) then a larger Fuzzy OEC response average is desirable. The response table (Table 7.11) identifies *SJ* and *PSxPD* as the most important, *HD* and *HDxSJ* as second, *SJxPS* as third, then *PS* and finally *PD* and *HDxPS*. The last two, *HDxPS* and *PD* do not really have a ranking as their average factor effect is zero. The response table shows some effect coming from the interaction *SJxPS*,

which was not identified in the QFD analysis. This may be due to noise or an actual interaction since its value is not so small compared to the second main effect.

	HD (1)	SJ (2)	HDxSJ (4)	PS (5)	HDxPS (7)	PD (9)	SJxPS (11)	PSxPD (13)
Us	64.53	56.99	64.53	63.49	63.76	63.76	63.07	56.99
Com 1	63.76	63.76	63.76	63.76	63.76	63.76	63.76	63.76
Com 2	62.99	70.53	62.99	64.03	63.76	63.76	64.45	70.53
Difference	1.54	13.54	1.54	0.54	0.00	0.00	1.38	13.54
Rank	3	1	3	6	7	7	5	1

Table 7.11 Average response table for Fuzzy-QFD-Taguchi for Thumbtack example

Figure 7.10 shows the optimum results for the average factorial response, which are circled. This is only for the main factors. As a result, it can be observed that HD: Us (Level -1), SJ: Com2 (Level 1), PS: Com2 (Level 1) and for PD any level can be chosen for the optimum output, but still this is not considering interactions. In order to calculate the optimum output, but still this is not considering interactions. In order to calculate the optimum combination of the levels, it is desirable to study factor interactions. The interaction plots are depicted in Figure 7.11 through to Figure 7.13.

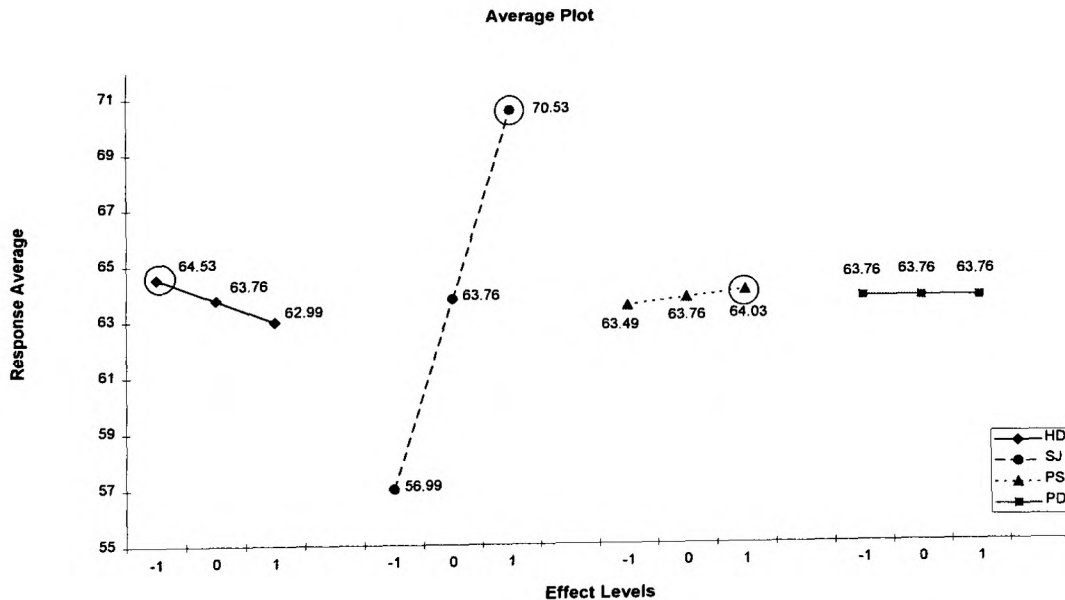


Figure 7.10 Main factor average response plot for Thumbtack example after Fuzzy-QFD-Taguchi approach

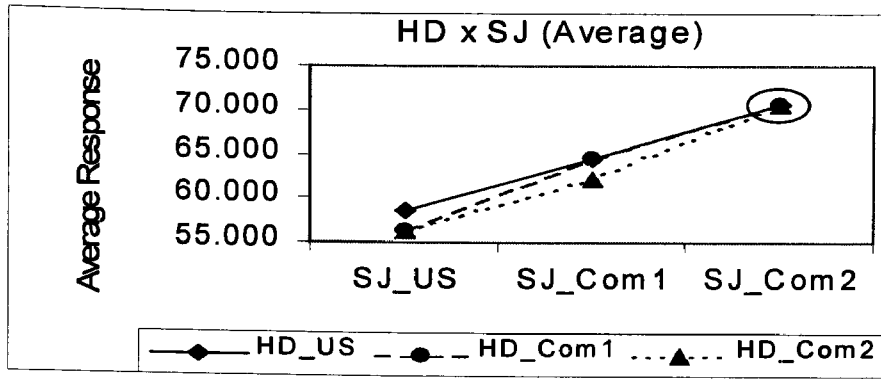


Figure 7.11 Interaction between HDxSJ after Fuzzy-QFD-Taguchi approach

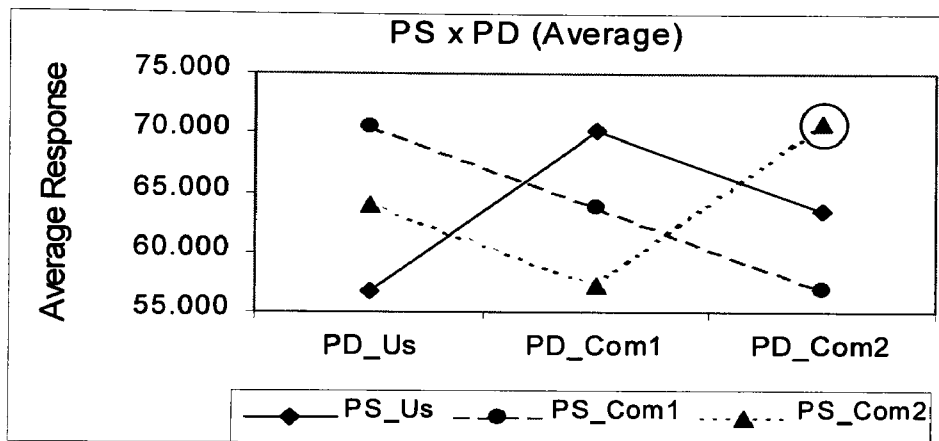


Figure 7.12 Interaction between PSxPD after Fuzzy-QFD-Taguchi approach

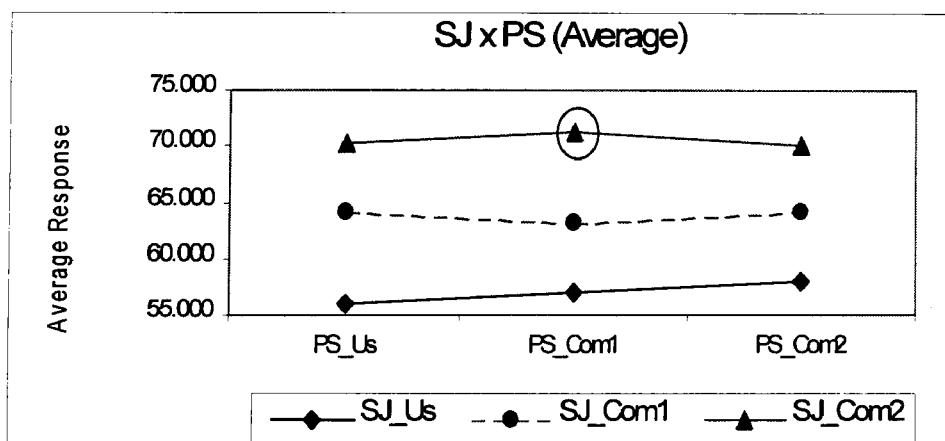


Figure 7.13 Interaction between SJxPS after Fuzzy-QFD-Taguchi approach

7.5.5 Analysis of Variance (ANOVA)

The ANOVA was performed to test the significance and percentage contributions of the factors and the interactions. The results are depicted in Table 7.12. Only two main factors are seen to be of significance, *SJ* and *HD*. This was also observed in the Average Response table Table 7.11. The investigated interactions were both significant (99%), with high F-ratios although *PSxPD* has the highest contribution of 49%. The Sum of Squares for the main factor *PD* was much smaller than the others, therefore it was pooled and included in the error terms.

Factor	Sum Square (SS)	dof	mean sq (MSS)	F-Ratio	S'	% Contribution	Rank
SJ	825.06	2	412.53	599.73	823.68	48.99	1
PSxPD	825.06	4	206.27	299.87	822.31	48.91	2
HDxSJ	10.73	4	2.68	3.90	7.98	0.47	5
HD	10.73	2	5.37	7.80	9.35	0.56	4
Error	9.63	14.00	0.69	1.00	19.26	1.15	3
ST	1681.21	26.00				100.00	

Table 7.12 ANOVA table for Thumb Tack after Fuzzy-QFD-Taguchi approach

From Figure 7.11, it can be observed that interactions exist between *HD* and *SJ* since the lines are not parallel. From this figure, any level of *HD* can be chosen since they all have the same response, but *SJ* should be chosen at level: *Com2*. Figure 7.12 also shows interactions and here also, any factor level can be chosen although *PD: Com2* and *PS: Com2* displays a slightly larger average response. This can also be seen on the average response table (Table 7.11) and Figure 7.10. Figure 7.13 was drawn to investigate the interaction between *SJxPS*, which showed up as having an effect in the average response table, Table 7.11. There are some interactions in this figure as the lines are not parallel, but the interaction is minimal compared to the other two interaction plots in Figure 7.11 and Figure 7.12. This effect may be due to noise or in fact a slight interaction. In reality there may be a small interaction between these two factors, as it is believed that if the pin

is very sharp, then the join does not have to be so strong as it is easier to push the pin into the board and thus requires less force. Consequently if the pin is not very sharp the join has to be stronger as more force is required to push the pin into the board. In this interaction plot, *SJ* is again suggested to be set at level: *Com 2*, whereas the level of *PS* is suggested to be set at *Com 1*, which contradicts the previous figure (Figure 7.12). Because the response for *PS: Com2* in Figure 7.12, is taken from an interaction plot that was statistically more significant, it will be chosen. Since *HD* could take any level in the interaction plots, by observing the average response plot (Figure 7.10), *HD* can be set at level: *Us*, as this level had the biggest response. In this example a compromise had to be made to obtain the optimum levels since there is not much difference in the resulting responses. The final optimum target levels derived by the Fuzzy-QFD-Taguchi approach are given in Table 7.13 and compared to the original target values set by the QFD team.

Factors	Fuzzy-QFD-Taguchi Approach	Original Target values from QFD
Head Diameter (HD)	Us	> Company 1
Pin head Diameter (PD)	Company 2	Company 1
Strength of Join (SJ)	Company 2	> Company 2
Sharpness of Pin (PS)	Company 2	< Company 1

Table 7.13 New target values for thumb tack example after Fuzzy-QFD-Taguchi approach

Table 7.13 shows that the Fuzzy-QFD-Taguchi approach results in a different set of target values compared to the ones arrived at in the original HOQ. In fact three of the target values have changed, those for *Tack Head Diameter*, *Pin Head Diameter* and *Sharpness of Pin Head*. Notice that this combination was not one of the trials ran (*Us*, *Com2*, *Com2*, *Com2*) in Table 7.9.

7.6 FUZZY-QFD-TAGUCHI VERSUS QFD-TAGUCHI APPROACH FOR THUMB TACK EXAMPLE

Since the Fuzzy-QFD approach altered the data in the HOQ, the Fuzzy_OEC results in Table 7.9, are different from the OEC results in Table 6.11 of chapter 6. The differences can be seen in Figure 7.14. Note that these graphs are not representative of continuous data, but discrete data points. They are for illustrative purposes only.

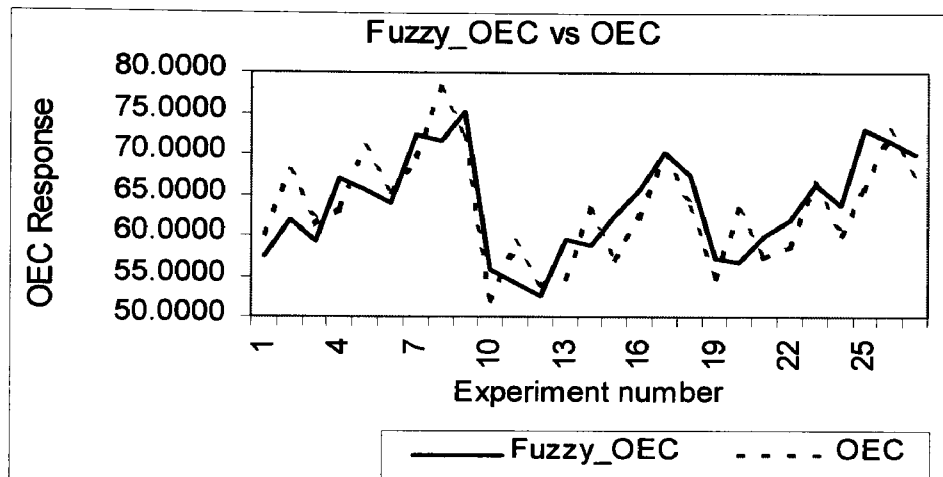


Figure 7.14 Fuzzy_OEC results vs. the original OEC results for thumbtack example

After the interactions were included, comparison between the Fuzzy_OEC (Int_RA) and the OEC (Int_RA) was also performed and shown in Figure 7.15.

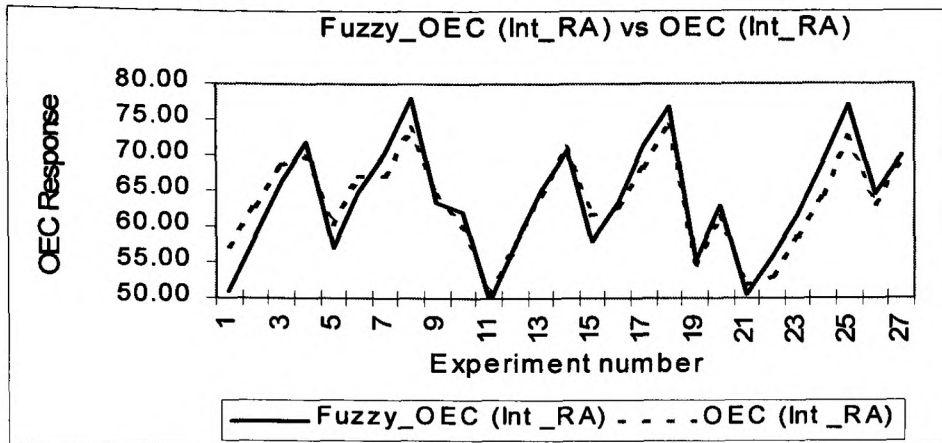


Figure 7.15 Fuzzy_OEC(Int_RA) results vs. the original OEC(Int_RA) results for thumbtack example

In Figure 7.15, the major differences can be found in experiments 1, 2, 8, 24 and 25, whereas all the other results are very similar. Alternatively in Figure 7.14, the two plots display more variances between the two sets of data. The major differences between the two sets of results can be found in experiments 2, 5, 8, 15, 20 and 25. If the average response tables are compared, it can be observed that the importance of factors and/or interactions has not changed although their magnitude has. The interaction *SJxPS* has become more important than the main factor *PS* in the Fuzzy-QFD-Taguchi approach as shown in Table 7.14. As explained before the *SJxPS* interaction may be due to a real effect or may be due to noise.

Factors	Fuzzy_OEC (Int_RA)	OEC (Int_RA)
	Rank	Rank
HD (1)	3	3
SJ (2)	1	1
HDxSJ (4)	3	3
PS (5)	6	5
HDxPS (7)	7	7
PD (9)	7	6
SJxPS (11)	5	7
PSxPD (13)	1	1

Table 7.14 Fuzzy-QFD-Taguchi approach vs. QFD-Taguchi approach for thumbtack example

Therefore, it has been observed that even if the Fuzzy_QFD approach altered the results in the proportional distribution HOQ, it was not significant enough to make a major change either in the average response rank order or in the interaction plots. The final optimum level has thus not been altered.

A comparison of the engineering characteristics ranking order for only the main factors from all the different methods/approaches developed in this thesis that combines to form the integrated systems approach to QFD is listed in Table 7.15. Note that they are listed in the order of use. It can be seen that the first two engineering characteristic's (HD and PD) rank order have not altered much (i.e. HD from 1 to 2; PD from 3 to 4), but for SJ and PS there is a more drastic change. It is not so easy to comment on the changes in rank order of the different methods as only four factors were being considered.

Method	Rank Order			
	HD	PD	SJ	PS
1. Independent Scoring HOQ	1	3	4	2
2. Proportional Dist HOQ	1	3	3	2
3. Fuzzy-QFD HOQ	2	3	1	4
4. QFD-Taguchi HOQ	2	4	1	3
5. Fuzzy-QFD-Taguchi HOQ	2	4	1	3

Table 7.15 Rank order of factors for methods used for the systems approach to QFD

7.7 DISCUSSION AND REMARKS

In both examples used, although the Fuzzy-QFD approach changed the data in the HOQ, the end results, i.e. the choice of factor levels remained unchanged. This is not surprising, as the Taguchi design of experiment method results in robust choices of factor levels in the face of noise (i.e. changes in the environmental conditions). In this case the noise can be considered as the changes and updates that the Fuzzy-QFD method made. It has thus

been shown in this chapter that the QFD-Taguchi approach developed is insensitive to small changes in the HOQ data and thus is a robust approach. The Fuzzy-QFD-Taguchi approach gives a more robust/reliable solution compared to the pure QFD-Taguchi approach, since both the correlation matrices have been taken into account.

Although the Fuzzy-QFD-Taguchi approach brings together all the advantages of the developed approaches, it suffers from one main disadvantage of all the other methods/approaches put together, that is it relies heavily on correct identification of interactions both in the porch and the roof of the HOQ. The method identified during the sensitivity analysis in chapter 4, which uses an inference mechanism together with the four-valued logic to help detect missing interactions in the correlation matrices can be most helpful to overcome the main drawback of the developed integrated systems approach to QFD. This method can be used prior to the Fuzzy-QFD-Taguchi approach described in this chapter to define more precise correlation.

7.8 SUMMARY

In this chapter an integrated systems approach to QFD was developed. The main challenges faced in developing this approach were:

- How to combine the Fuzzy-QFD approaches to the QFD-Taguchi approach?
- How can the correlation matrix data be updated

To overcome the first challenge, the Fuzzy-QFD (Fuzzy Proportional Distribution HOQ) approach developed in chapters 3 and 4, was applied prior to the QFD-Taguchi approach for the purpose of fine-tuning the data to help determine more precisely the technical target values in the HOQ. To resolve the second challenge, the approach that was developed for performing the sensitivity analysis, which combines an inference mechanism with four-valued logic, is proposed to be adopted prior to any of the other developed approaches to identify and rectify the correlation matrix data.

Although the Fuzzy-QFD approach identified and altered conflicting and missing data in the HOQ, the alteration of the data did not cause the optimum choice of factor levels arrived at in the QFD-Taguchi approach described in chapter 5, to be transformed. These changes in the data can be considered as noise and it has thus been shown that the QFD-Taguchi method is a robust method, insensitive to small amount of noise in the data.

The synergy between Fuzzy Logic, QFD and the Taguchi Method, forming the Fuzzy-QFD-Taguchi approach described in this chapter is a superior, although longer approach to any of the individual approach since it corrects and improves the subjective data in the HOQ. As such the customer importance rating data and the relationship matrix data are defined more precisely resulting in the importance weighting of the engineering characteristics to be identified more accurately. In addition, by using the interactions in the roof of the HOQ, more precise target factor levels can be obtained, which also helps to bring the technical and the customer competitive evaluation in accord.

The next chapter is the concluding chapter, where the whole thesis will be reviewed and the main contribution of the work in this thesis will be highlighted. Concluding remarks and further work will also be presented.

Chapter 8. Conclusion and further work

"The important thing is not to stop questioning"
~ Albert Einstein ~

8.1 INTRODUCTION

After a period of increasing professionalism in almost all areas of research and technology, the new era is to embrace the interaction of different approaches, to form multi-functional disciplines. It is time to take advantage of other methods and to incorporate them within the QFD process, to realise its full potential. QFD is a method that plans and organises data in a logical and systematic way, but it is rather a qualitative method. The union of QFD with quantitative methods will yield even greater benefits from its application. QFD certainly does not represent a totally new or radical idea, but what it does provide is a disciplined, structured way to achieve specific product

objectives and translate customer demands into requirements that people in an organisation can understand and act on.

The ultimate objective of QFD is to create value for the customer. QFD holds great promise for a better definition of customer demands and a systematic method to meet them. Significant educational and organisational changes will be needed to fully implement its concepts in order for the benefits to be realised. This may prove difficult for companies that need quick solutions. Therefore for the full benefits of QFD to be realised, a long-term view is needed and possibly a cultural change.

While QFD can be significantly beneficial, it is not a simple tool to use (Freeze and Aaron, 1990). Amongst its drawbacks highlighted in Table 2.3 of chapter 2 are that it is a complex and very time-consuming process, the data collected can be vague and ambiguous, the correlation between requirements and the setting of target values is rather ambiguous and subjective. Therefore, there is a need to remove this ambiguity.

This thesis has given an overview of QFD with its links with TQM and other quality tools and standards together with its advantages and limitations. Due to some of QFD's limitations, the main aims and objectives of the research were to investigate tools and techniques that could be incorporated with the QFD process that might help to improve the QFD process. Two approaches have been developed that combine QFD with Fuzzy logic/Fuzzy sets. The application of the theory of Fuzzy Logic and Fuzzy Sets to QFD provides a more quantitative method for detecting inconsistencies and determining the data in the relationship matrix in QFD by making use of the correlation between requirements. The engineering characteristic's target values in QFD can also be subjective and the Taguchi Method for design of experiment has been integrated with QFD to set these target values more precisely by utilising interactions in the correlation matrix.

8.2 RESULTS OF RESEARCH

As a result of this research:

- the subjectivity and ill-defined data in the QFD process, have been partially resolved by the application of Fuzzy Logic/Fuzzy sets,
- the QFD analysis has been made more rigorous by integrating it to more quantitative techniques (Fuzzy Logic/Fuzzy sets) and method (the Taguchi Method),
- it has been identified that demands are dependent on each other and how including them in the problem can change the results. This problem has been addressed by considering interactions between the demands in the Fuzzy-QFD and QFD-Taguchi approaches developed,
- interactions has been identified and dealt with in the developed approaches, such that they no longer provide sub-optimal solutions .

These problems have been identified and dealt with through the various approaches proposed and developed, which are summarised in the following sections.

8.3 FUZZY-QFD APPROACHES

The Fuzzy-QFD approaches developed in this work brings together the traditional HOQ and the artificial intelligent Fuzzy Logic/Fuzzy set theory to offer more dynamic and tolerant algorithms for coping with statements with varying degrees of exactness and precision in the VOC and the VOE, utilising interactions between demands. The QFD team opinions are used to initialise the calculations in the first instance and the inference mechanism of Fuzzy Logic is used to infer implicit relationships based on the explicit ones obtained in the QFD analysis. In this manner inconsistencies in requirements can be detected, recorded and a trade-off can be performed.

Two Fuzzy-QFD approaches, the Fuzzy Range HOQ AND THE Fuzzy Proportional Distribution HOQ. The Fuzzy Range HOQ (FR-HOQ) approach makes use of the original Independent Scoring HOQ results as its input data. This approach uses ranges of values to represent the relationship matrix in the HOQ. It makes use of the interactions in the correlation matrices (porch, roof), fuzzy IF-THEN rules and the fuzzy inference engine to identify over or underestimated relationship and customer importance ratings. The Fuzzy Proportional Distribution (FPD-HOQ) QFD approach, which again combines Fuzzy Logic/Fuzzy set theory with QFD, makes use of the traditional Proportional Distribution data as its input and the fuzzy S-Function to determine the degree of membership. Again this approach utilises the interactions in the correlation matrices (porch, roof), fuzzy IF-THEN rules and the fuzzy inference engine to identify over or underestimated relationship and customer importance ratings.

The two Fuzzy-QFD approaches developed do not restrain the traditional analysis of the HOQ in any way, but it uses the data from its analysis, to enhance and fine-tune the results by making use of conflicting and complementary correlation in the porch and the roof of the HOQ. Case studies were applied in chapter 4 to document and test the proposed approaches. The two Fuzzy-QFD approaches assert slightly different concepts as well as different results. There were more similarities between the final rank order of the engineering characteristics between the four approaches, (Traditional Independent Scoring, Proportional Distribution, Fuzzy Range HOQ and Fuzzy Proportional Distribution HOQ) than differences as illustrated in Figure 4.25 and Figure 4.27 of chapter 4. The similarities between the results of the Fuzzy-QFD approaches to the original QFD results indicate that there were no significant inconsistencies in the various judgements and evaluations provided by the Fuzzy-QFD approaches.

While the case studies in chapter 4, confirm that the new Fuzzy-QFD approaches are feasible, an analysis on a real ongoing industrial project would be advantageous. This would enable the QFD team to make a judgement on whether the Fuzzy-QFD approaches indeed improved the results to form a more general opinion about the plausibility of the developed approaches. Which of the two Fuzzy-QFD approaches is the best is not easy to say. A table was drawn, table 4.5 in chapter 4 to compare the two approaches. It is believed that the second approach, the Fuzzy Proportional Distribution, although being more computationally demanding and more complex as was shown in table 4.5 of chapter 4, is a more accurate and fairer approach as it produces higher resolution and more sensitive and accurate results. The only condition is that the correlation matrix data (porch and roof) should be accurately determined. The Fuzzy Range HOQ approach is less mathematical and is mostly based on intuition. Since most of the QFD projects stop after the first phase (HOQ) anyway, it is often not necessary to bring the most important characteristics to the second phase, so the Fuzzy Range HOQ approach will not be used to its full potential, whereas the Fuzzy Proportional Distribution HOQ approach will.

In order to identify which is the best approach, two QFD studies need to be undertaken in parallel on the same product. The end result would determine which product best satisfies the customers. In saying that, it is not very easy to conduct such a comparative study, since the success of the approaches or indeed QFD depends on many factors, such as the expertise of the team members, as the teams will not be the same. If the same team is used, the knowledge gained from undertaking one QFD exercise will influence greatly decisions made on the other QFD exercise.

Even in the correlation matrices (porch and roof) discrepancies can occur, as they too are based on subjective opinions of the QFD team although to a lesser extent compared to the relationship matrix. The sensitivity analysis performed in chapter 4, confirmed that

altering the correlation matrix has an effect on the result, although not so significant in the Fuzzy Range approach, compared to the Fuzzy Proportional Distribution approach. The customer importance ratings and the relationship matrix data need not be so precisely analysed in the first instance, as the new Fuzzy-QFD approaches will update the original results based on the interactions between demands. The two approaches can also be used in the subsequent QFD phases provided the correlation matrices are determined. Both approaches seem to be more suited to more complex problems, (seen by the statistical testing performed on the results), where there are many requirements and interactions. This is not surprising, as the approaches depend very much on the interactions in the correlation matrices. Utilising the approaches on more complex case studies in the future should confirm this finding. In the Fuzzy Range HOQ approach, only one set of range mimicking the original HOQ was used. Future work can look at other ranges and overlapping of the ranges.

Since the approaches rely greatly on having the right correlation in the roof and porch to start with, a way to determine these correlations more precisely before analysing the whole HOQ using an inference mechanism and multi-valued logic was also presented. The multi-valued logic truth table, because it uses the AND (minimum) operator gives more emphasis on the truth value zero (Strong Negative correlation) as indicated in Table 4.6 in chapter 4. If the truth-value zero corresponded to the 'Strong Positive' correlation instead of "Strong Negative" correlation, then different rules would be obtained.

The purpose of using the multi-valued logic truth table in this work was to determine a systematic way to perform the sensitivity analysis. It was also used to highlight that the correlation matrix data plays a major role in determining the end results in the proposed Fuzzy-QFD approaches and thus the QFD team needs to be conscious of that. The proposed method is feasible, although more work has to be done to identify what is the

best way to tackle the problem concerning which logic operator to use or how to define which correlation should be given what truth value. Maybe two truth tables are required, one representing the positive correlation and the other negative correlation. This work can be considered in the future.

The computer programs developed, although very flexible require the input data (correlation matrices, relationship matrix, customer importance rating) to be entered in a particular format. A user friendly interface is required which would guide the users to the appropriate way in which to input the data. A user friendly interface design can be explored in the future.

8.4 THE QFD-TAGUCHI APPROACH

The Taguchi Method requires the formulation of the problem statement, the identification of the quality characteristic to be investigated, the identification of the various factors and their levels and any interactions between factors through brainstorming session as discussed in the planning phase of the parameter design stage, Section 5.3 of chapter 5. This is one of the most time consuming stages of the Taguchi process. The HOQ and other QFD charts provide all this information in some form or other, therefore QFD in this sense can help the Taguchi Method by providing a starting point for designing the experiments. QFD does not only identify these factors, but it also identifies which of the factors are the most important and needs to be studied further. QFD lacks the ability to quantify many relationships in its HOQ, where relationship and correlation are based on opinions rather than quantitative data. As intuitive as it may be, using various symbols to represent relationship and correlation, the lack of quantitative data is one of its drawbacks.

Setting target values for each engineering characteristic in QFD's HOQ is done independently of other engineering characteristics. This is not ideal, since in real life, factors exhibit coupling and this should be taken into account when setting their target values. This interaction information is readily available in the roof of the HOQ in QFD.

A new approach has been described in chapters 5 and 6, which combines QFD and the Taguchi Method to help determine more precise technical target values, while considering each requirement as part of a whole system. Thus interdependencies are taken into account, rather than viewing each requirement as a secluded entity. The HOQ contains much useful information that is often used in isolation. Most of this information can be combined and used by the QFD-Taguchi approach developed in chapters 5 and 6, to design a system that performs near optimum performance when interactions are considered. As a result, more precise technical target values can be achieved, to be used in the QFD process.

The approach maps the QFD data into a mathematical model that enables the study of interactions amongst the engineering characteristics and the setting of factor levels based on these interactions. The interaction terms may have been over emphasised, as they were considered as equally important as the main factors. During the mapping of the interaction terms onto the main factors terms, the maximum interaction coefficient was equal to the maximum factor coefficient term and the minimum interaction coefficient was equal to the minimum factor coefficient as can be observed in the regression equations in chapter 6. This may have caused some of the interaction effects to have high percentage contributions as seen in the ANOVA tables (Table 6.6 and 6.15). In a real application, it is doubtful that interactions will be as important as the main factors and this should be taken into account. It is thus advisable to consider the interactions as contributing to only a percentage of the main factors, say 10% or 20%. How much the

interactions should contribute can be further investigated. Expert knowledge of the system's dynamic behaviour would identify these interaction contributions.

The QFD-Taguchi approach also makes use of the Overall Evaluation Criteria (OEC), which brings together the different quality criteria of the product/process into one response instead of analysing one criterion at a time. In this way, the optimum factor level obtained for one quality criterion is also desirable for the other quality criteria. The OEC calculation very much depends on the weights of each criterion, which are dependent on the customer importance ratings in QFD. These weights are subjective and may not be very accurate at times. The Fuzzy-QFD approaches described in chapters 3 and 4 can determine more precise customer importance rating and the relationship data, taking into account interactions between requirements and can be used to determine more precise data before calculating the OEC response in the Taguchi-QFD approach. It was found that the OEC analysis was a very robust way to calculate the responses, since when compared with the 'one quality criterion at a time' method, it yielded similar results as highlighted in section 6.4 of chapter 6. Thus using the OEC can save time and money as there is no need to repeat each experiment for each individual quality criteria and then try to investigate which factor levels are optimum.

The two worked examples have shown that the QFD-Taguchi approach identifies different sets of target values as optimal compared to the original target values in the HOQ. Furthermore the QFD-Taguchi approach renders the two competitive evaluations (customer & technical) in the HOQ in agreement. For this research, the Taguchi method was combined with QFD to identify more precise technical target values in QFD's first chart, the HOQ. As suggested in some literature (Quinlan, 1985), (Chu, 1996), (Ross, 1988), (Ryan, 1988), the Taguchi Method is more appropriate to be combined with QFD in the second QFD phase, the product design phase. The QFD-Taguchi approach

developed in chapters 5 and 6, would in fact be more suitable for the second phase since more quantitative data is available in this phase. The quality criterion would then be the engineering characteristics and the factors would be the parts characteristics (Refer to Figure 2.4 of chapter 2). The first QFD phase, the HOQ was utilised for this research, since there is little work in literature that extends to the second QFD phase and so data for this phase was not readily available for case studies. Investigating the applicability of this approach to subsequent QFD phases is an avenue for future research.

8.5 THE INTEGRATED SYSTEMS APPROACH TO QFD

The synergy between Fuzzy Logic, QFD and the Taguchi Method, forming the integrated systems approach to QFD described in chapter 7 is a superior, although longer approach to any of the individual approaches. Firstly it corrects and improves the subjective data in the HOQ and as such the customer importance ratings and the relationship matrix data are defined more precisely resulting in the importance weightings of the engineering characteristics to be identified more accurately. In addition, by using the interactions in the roof of the HOQ, more precise technical target factor levels can be obtained, which also helps to bring the technical and the customer competitive evaluation in accord. It was also used to test the robustness of the QFD-Taguchi approach as the Fuzzy-QFD approach that precedes the QFD-Taguchi approach helps to fine-tune the data in the HOQ. These alterations in the data can represent noise in the QFD-Taguchi approach. It was found that the QFD-Taguchi approach was in fact a robust approach as the results (choice of factor levels) were the same as the original QFD-Taguchi approach. The integrated systems approach suffers from one main disadvantage of all the other methods/approaches put together, that is it relies heavily on the correct identification of interactions both in the porch and the roof of the HOQ.

The method developed during the sensitivity analysis in chapter 4, using the inference mechanism and the four-valued logic, can help to determine missed interaction in the correlation matrix. It can thus be incorporated with the integrated systems approach to QFD to give an even better analysis of the subjective data in the QFD process. This incorporation can be done in the future after identifying which logical operator or which truth-value should be assigned to which correlation label. This proposed method that identifies correlation in the correlation matrices can first be used to identify the missing correlation data. Then the Fuzzy-QFD approaches, which rely heavily on these correlation data, can be applied to identify and update ill-defined customer importance rating and relationship matrix data. Finally the QFD-Taguchi approach, which relies on having firstly, correct correlation data and secondly, correct customer importance ratings and relationship matrix data, can be employed to determine more precise technical target values in the QFD charts.

Since the case studies used to demonstrate the developed approaches were not similar in terms of their complexity, i.e. amount of requirements, amount of interactions between requirements, this may have affected the main conclusions about each approach. It is likely that the developed approaches are more suited to complex problems. More variability could be found in the examples with more requirements and more interactions (the toothpaste example as opposed to the design of the running shoes for the Fuzzy-QFD approaches and the design of the paper roll as opposed to the thumbtack example for the QFD-Taguchi approach). Therefore it would be a good idea to investigate case studies where the level of complexity is similar. This would give an overall idea of the applicability of the developed approaches. Another future work could look at the results of the original Independent Scoring HOQ, the original Proportional Distribution HOQ, the Fuzzy Range HOQ and the Fuzzy Proportional Distribution HOQ approaches to calculate different OEC responses. These could then form different y responses to input

in the QFD-Taguchi approach. In this way variations in each approach can be studied and comparisons between the various approaches can be made.

8.6 SUMMARY

In this chapter the whole thesis has been overviewed outlining the main results and contributions of the research. The developed approaches have been summarised and conclusions and further work has also been highlighted. The aims and objectives of the research was to develop an integrated systems approach to QFD to overcome some of its drawbacks and to provide a framework for a consistent and more rigorous approach to developing the QFD charts. These have been mostly achieved through the various approaches developed, with some new areas identified that can be investigated in the future as well as further improvements to the work already undertaken.

The research has highlighted that some of QFD's drawbacks can be partially overcome by the methods and techniques investigated, but there are other problems that need to be addressed. The QFD process alone is not enough, whereas its integration with other methods/tools/techniques can enhance its applicability. Integrating various methods/techniques and tools together to form an integrated approach is even better, as demonstrated in this thesis since it brings the advantages of each individual approach together while suppressing the disadvantages.

The research outlined in this thesis has been thoroughly enjoyed where various journal and conference papers listed in Appendix D have been published together with attendance and participation at national and international gatherings.

Appendix A.

The House of Quality

This Appendix documents the necessary steps to complete the House of Quality (HOQ) in QFD and highlights the nine checks that should be performed to identify if the HOQ has been completed correctly. Furthermore it gives more explanations on the demands found in the HOQ for the design of the toothpaste tube example in section Figure 2.6.

A.1 STEPS IN BUILDING THE HOUSE OF QUALITY

As can be seen from Figure A.1, there are approximately nine steps involved in building the House of Quality, each relating to the different rooms.

Step 1: Customer Requirements 'Whats' (Room 1): 'Voice of the Customer'. The critical first step for any quality initiative is understanding the 'Voice of the Customer' (VOC). The VOC is increasingly recognised as the key to success in capturing and retaining customers. Businesses succeed by offering products and services that meet customer requirements profitably. Businesses retain their customers by continuing to please them. Understanding the true needs of the customers requires work on the part of designers and planners. To be useful in planning and design, the VOC must be pro-active, enabling a company to predict the results of its actions. Many companies begin projects

by generating "voices" internally - using existing market research data, brainstorming with engineers, etc.

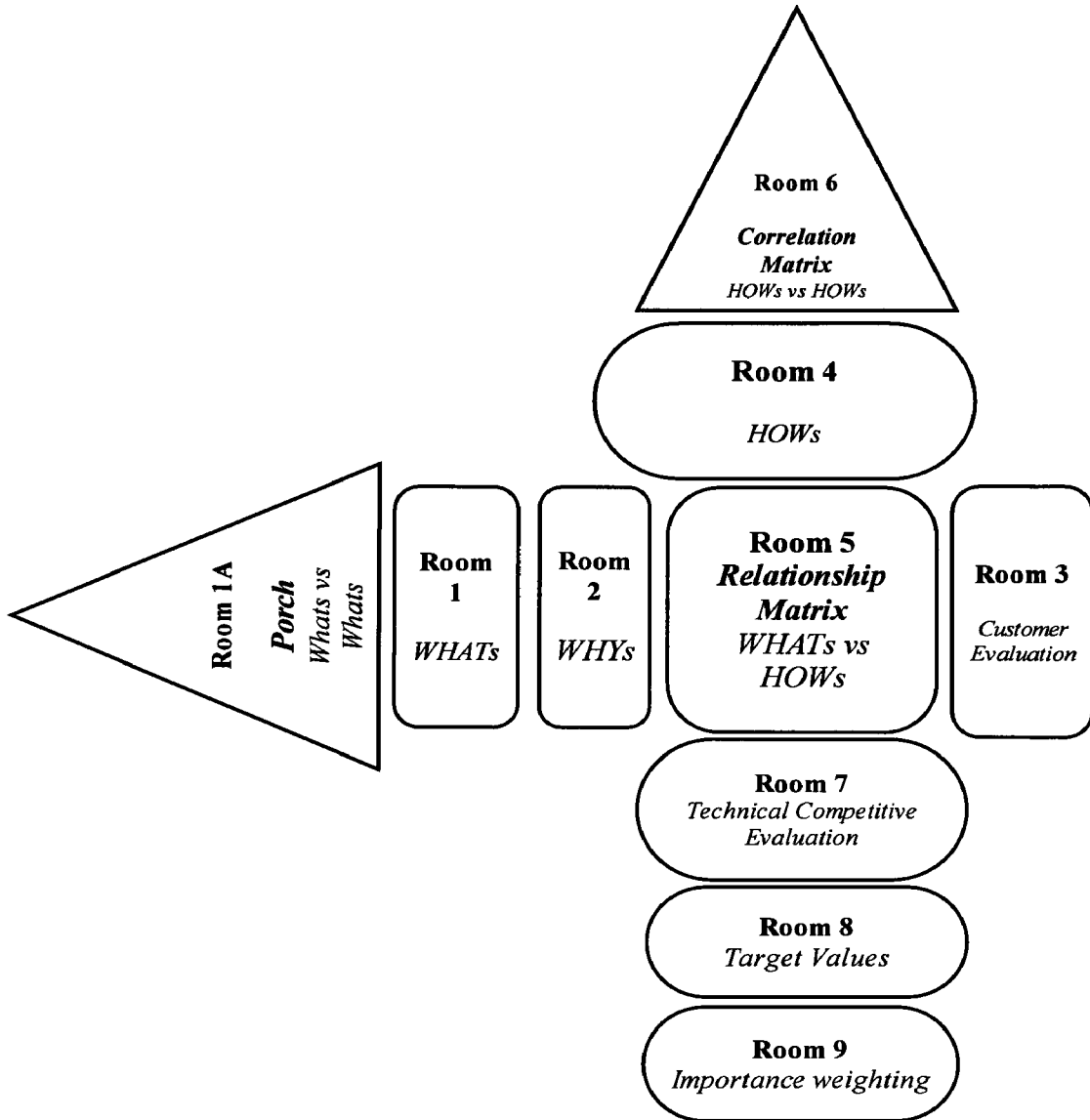


Figure A.1 The House of Quality with its many rooms

sight of other potential solutions. Figure A.3 illustrates the complexity involved in capturing the customer demands through the use of a cause and effect diagram (King and Moran, 1990).

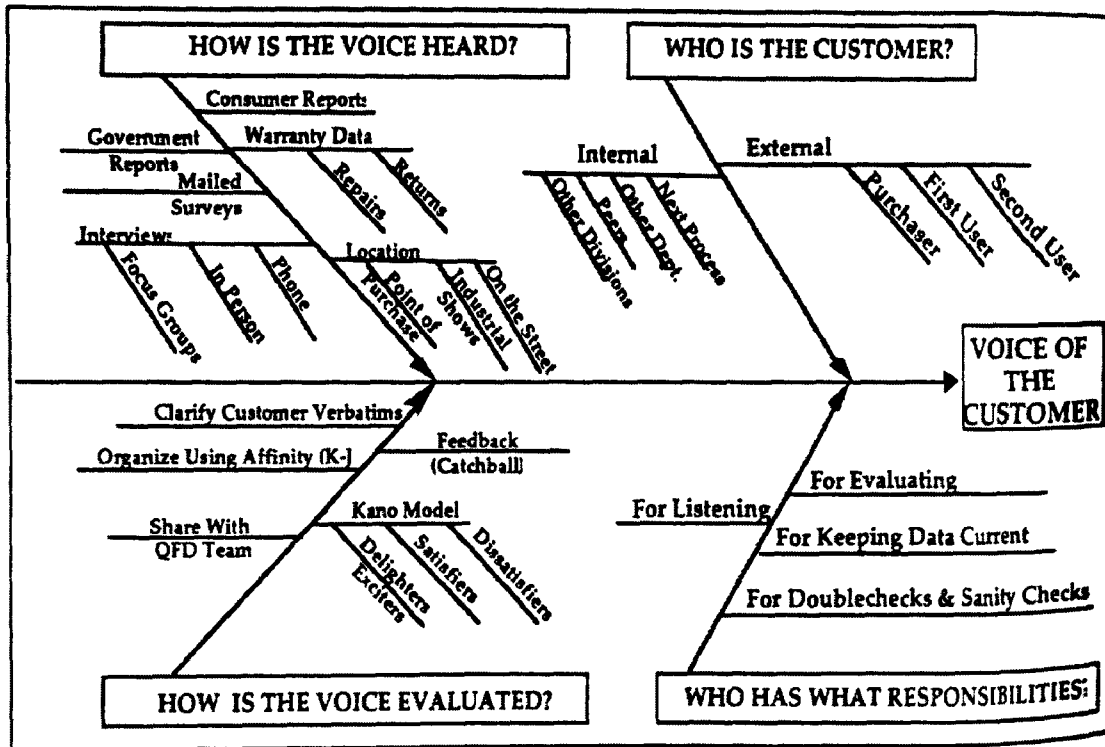


Figure A.3 Different ways in which the voice of the customer is gathered (King and Moran, 1990).

Sources of the customer input are market survey, focus groups, warranty claims and interviews, and a method known as going to the gemba, a Japanese word to describe the true source of information. The gemba is where the customer is studied while using the product/process under natural conditions, the customers' home or work place. Going to the gemba and analysing the voice of the customer is a better way to obtain a complete and accurate set of both spoken and unspoken requirements. When going to the gemba use of video taping, audio-taping, direct conversations, direct interviewing are some useful techniques to capture the VOC. The voice of the customer table is a direct tool to

record all the relevant information when going to the gemba (Mazur, 1997). The voice of the customer table has three components: customer verbatim, context of use and integration of verbatim and context. This expanded list of customer information is divided into demanded qualities, functions, reliability issues, safety, failure modes, solutions etc. Some of the information that is gathered from the customers will fall under:

- Needs: *"I know I will get my delivery when I need it"*.
- Target values: *"Delivered the same day I call"*.
- Solutions: *"I want to talk to the same representative every time I call"*.

Swanson (Swanson, 1995) outlined a set of techniques developed to gather, structure and prioritise the VOC. Furthermore a formal software method VOCALYST[®] (Klein, 1999) for gathering the VOC has been developed that can provide input to the QFD matrices.

It is unlikely that customers will define all their preferences even with a very efficient method of gathering customer data. The design team may also need to supplement the customers' list to satisfy the requirements of internal or external customers, such as the health and safety board. Through a graphical model Dr. Noriaki Kano, (Kano and Seraku, 1984), a Japanese professor clarified why customer input can be insufficient. This model, (Figure A.4) known as the Kano map shows relationships between product and service attributes and customer satisfaction. There are three main types of customer requirements to consider: expected quality, one-dimensional quality and exciting quality. The arrow on the bottom right hand side of Figure A.4, ① "*expected quality*" (unspoken) represents details that customers expect, and are dissatisfied if they do not receive them. They are basic requirements such as safety. These requirements must be fulfilled before the company is said to be a performer. The "*demand quality*" (one-dimensional quality) ② arrow illustrates instances where customers express what they want and where their satisfaction depends on product/service conformance to the expressed requirement. Both

the basic expectations ① and the demanded quality ② must be met before the company can be seen as proactive and excellent by providing “*exciting characteristics*” ③ that the customers are not expecting. Their absence does not dissatisfy, but their presence excites. Products and services must meet all three types of requirements. However, as time elapses the exciting and demanded quality will become the expected characteristics. What delights the customer today will become expected tomorrow.

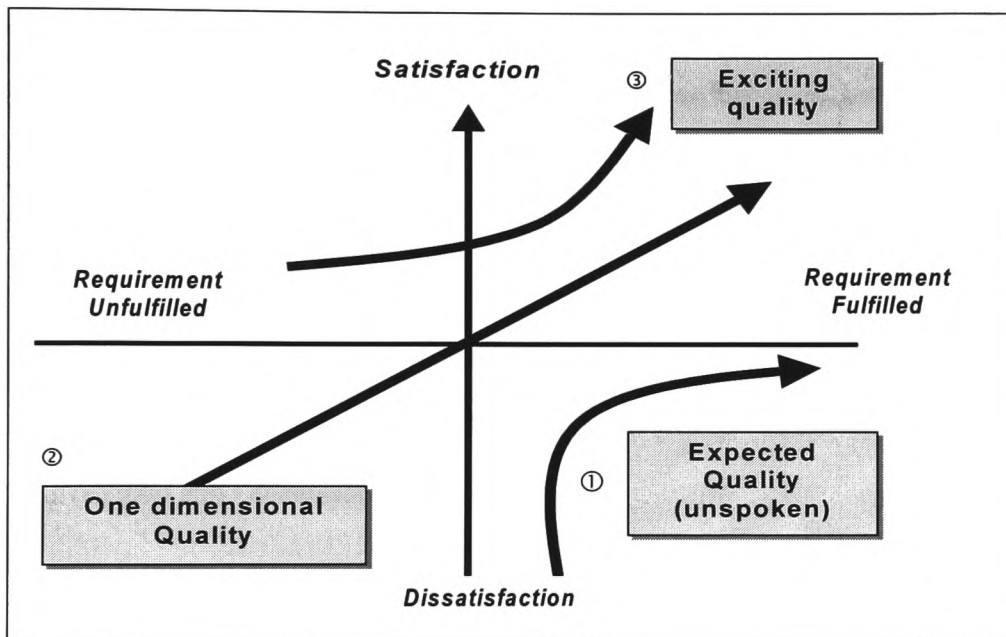


Figure A.4 The Kano Map (Kano and Seraku, 1984)

The Kano Model has been included in the QFD process to recognise basic features from performance features and excitement features in the VOC (Freeze and Aaron, 1990). If no previous customer, markets, or survey data is available, then using the Kano model (Figure A.4) has proven quite accurate (Plowman, 1999). Set ‘expected quality’ ① as high priority, ‘one dimensional quality’ ② as medium, and ‘exciting quality’ ③ as low in QFD to tie in the “language of affection” to the “language of science”.

Regardless of the method chosen, it is important to obtain the VOC. What the customer wants will determine whether new technologies are needed, whether simple improvements are possible, or whether a revolutionary concept is required.

Step 2: Customer Importance Ratings (Room 2): Owing to their diverse and linguistic nature, customer demands usually need to be categorised prior to further analysis. Before undertaking a QFD or similar exercise, there is a need to know how important each need is relative to the others. Which are critical, which less so? Customers rate the importance of each of their demands. The importance rating, d_i , can use any scale, but is generally a 1 (low) to 5 (high) scale or 1 (low) to 10 (high). Some customers would state that "everything is important." In the purest sense, that may be true, but there is also a hierarchy of importance. The importance of each customer demand can be obtained through market research, the use of Affinity Diagrams (Bossert, 1991), or through other techniques such as the Analytical Hierarchy Process (AHP) (Saaty, 1985) or Conjoint Analysis (Ekdahl and Gustafsson, 1997).

These importance ratings play a significant role in determining the importance of the engineering characteristics as their weights are multiplied with each relationship in the relationship matrix (Step 5). When trade-offs have to be made, importance rating can become very valuable too.

Step 2A: Porch Correlation (Room 1A): Interrelationships often exist between customer demands. Positive (strong = 9, weak = 3), no correlation and negative (strong = -9, weak = -3) correlation are used here to show the dependencies of customer demands upon other customer demands. The terms "positive" and "negative" should not be associated with "goodness" or "badness". They are simply words describing the effect that the achievement of one demand has on another. A positive correlation indicates that two

customer demands may complement each other and a negative correlation indicates that two customer demands affect each other. The discovery of negative correlation and the trade-off activity they transmit should be viewed as extremely beneficial. Negative correlation in the porch is important, because they point out conflicting customer demands that will make optimisation difficult or perhaps make model validation impossible. Therefore trade-offs between these conflicting demands, especially when they are strong negative is necessary (Bahill and Chapman, 1993).

Symbols, as shown in Figure A.2 and Figure A.5 are used for ease of visibility to represent each correlation. There are $(m(m-1))/2$, valid cells in the side roof (porch), where m is the number of customer demands. Its purpose is to alert the designers to interactions, needs that are dependent on each other. Sometimes a creative solution can be found that satisfies all needs, but usually designers have to trade off one customer demand against another (Hauser and Clausing, 1988). This matrix is an extension of the basic HOQ (Freeze and Aaron, 1990), (Bahill and Chapman, 1993) and it is not often mentioned in the QFD literature. Identifying correlation amongst demands has vital consequences to the end result and this room is one area where this research will exploit.

Step 3: Customer Rating of the Competition (Room 3): Companies that want to match or exceed their competition must first know where they stand relative to others. Comparison with the competition can identify opportunities for improvements. The customers are asked how the product or service rates in relation to the competition if a similar product already exists. The current product standing also tends to be rated on a scale of 1 (low) to 5 (high), although other scales can be used. This rating is what the customer thinks of your product or of the new product. Focus groups, warranty claims and customer complaints are the most common sources for this information (Freeze and Aaron, 1990), (Bossert, 1991). At the same time, the competitors' products are evaluated. It is

imperative that the same scale be used here as was used for the company's own product. This is where some insight can be gained on how the customer sees weaknesses in your product and that of your competitors. Marketing will recognise this room as a perceptual map (Hauser and Clausing, 1988). The resulting symbol graph (Figure A.2) forms a clear picture of how well or how poorly your company's product compares with the competition for each of the customer demands identified. This area can also be used to compare different concepts or technologies (Clausing and Pugh, 1991).

Step 4: Engineering Characteristics, 'Hows' (Room 4): 'Voice of the Engineer'. Now the product needs to be described in the language of the engineer, and these are placed in the columns along the top of the HOQ. This translation process, moving from the raw qualitative customer demands to quantitative engineering characteristics is probably the most critical step in QFD (Freeze and Aaron, 1990). This is a list of what your company can measure and control in order to ensure that you are going to satisfy the customer's requirements. The engineering characteristics (functions, quality characteristics or design requirements) are attributes concerning the product or service that can be measured. Typically, the entries on this list are parameters for which a means of measurement and a measurable target value can be established. It is desirable to keep these characteristics as concept-independent as possible. The question to ask here is, these are what the customer wants, how can our company measure them? The most common error at this point is to jump to design solutions. The tendency to derive solutions at this stage conceals creativity and reduces potential competing solutions prematurely.

Step 5: Relationship Matrix (Room 5): The relationship matrix is the core element of the QFD process and the most tedious to prepare. This is where the team determines the relationship between customer needs and the company's ability to meet those needs. The team seeks consensus on these relationships, basing them on expert engineering

experience, customer response, and tabulated data from statistical studies or controlled experiments (Hauser and Clausing, 1988). The relationship analysis must be done in a column-based manner. To accomplish this, the question “if this engineering characteristic is provided, modified or deleted, how does this affect each customer demand?” If done by row, which seems more intuitive, then the analysis yields answers to question “how well does each engineering characteristic meet the customer demands?” Answering this, forces the team into thinking about design far too early in the process. QFD should not be used in this way, as the results are less advantageous (Plowman, 1999).

The relationships are represented by symbols as shown in Figure A.2 and Figure A.5 for ease of visibility, but this often brings even more vagueness and ambiguity in determining these relationships. Normally only positive relationships are used. The use of negative relationships has also been suggested by Fung Popplewell and Xie (Fung *et al*, 1998), Green, Cooke and Wild (Green *et al*, 1995), Baxter (Baxter, 1995) and Hauser and Clausing (Hauser and Clausing, 1988). When negative relationships are identified, these indicate the compromises needed in the company's engineering characteristics in order to meet the customer requirements.

RELATIONSHIPS	CORRELATIONS
● Strong = 9	● Strong positive = 9
○ Medium = 3	○ Weak Positive = 3
△ Weak = 1	X Weak Negative = -3
	* Strong Negative = -9

Figure A.5 Symbols representing relationships and correlation

The most common weighting methods (Shin and Kim, 2000), (Franceschini and Rupil, 1999) are; equal weight (all priorities = 1), linear weighting (no relationship = 0, weak = 1, medium = 3, strong = 5), and exponential weighting (no relationship = 0, weak = 1, medium = 3, strong = 9). The exponential scheme is most often used since the high priority items are given a weight of 9 and cannot be diluted or contradicted by the medium priority items (Plowman, 1999). A symbol representing each relationship is placed in its corresponding cell in the relationship matrix. The result should be a sparsely populated matrix that clearly links the most important engineering characteristics to meet the customer demands. There should be at least one "strong relationship" engineering characteristic for each customer demand (Freeze and Aaron, 1990). There are $m \cdot n$ valid cells in the relationship matrix, where m is the number of customer demands and n the number of engineering characteristics. Each relationship R_{ij} is entered in their corresponding cell.

Determining the relationships between customer demands and engineering characteristics is extremely important and care should be taken. Since the engineering characteristics can affect more than one customer demand and since the engineering characteristic for one customer demand may have an adverse impact on another customer demand, or engineering characteristics, these relationships are quite complex. Because these relationships are so complex, failure to identify and understand the interaction between the customer demands in the porch (Room 1A) and the engineering characteristics in the roof (Step 6) can easily lead to market failure (Noori and Radford, 1995). This aspect is exploited in the research and discussed in the Fuzzy-QFD approaches developed in chapters 3 and 4 as well as in the QFD-Taguchi approach developed in chapters 5 and 6 respectively.

Step 6: Correlation Matrix (Room 6): Team members must examine how each of the engineering characteristics impact upon each other. Its purpose is to alert the systems designers to interactions, to inform the engineers on who else to notify if a design change is made. A positive correlation indicates that two engineering characteristics may complement each other and a negative correlation indicates that two engineering characteristics may have an adverse effect on each other. A strong negative correlation for instance indicates that two engineering characteristics are not compatible. Research and Development (R&D) or innovation efforts designed to resolve these incompatibilities are therefore needed and often lead to significant breakthroughs and new competitive advantage. If incompatibilities cannot be solved, then trade-offs may be necessary. There are $(n(n-1))/2$ valid cells in the roof, where n is the number of engineering characteristics. Again symbols (Figure A.5) to represent these correlation are used for ease of visibility and the results are placed in the roof of the HOQ. In many ways, the roof contains the most critical information for engineers because they use it to balance the trade-offs when addressing the customer benefits (Hauser and Clausing, 1988). This is also an area that will be exploited throughout the research.

Step 7: Technical Analysis of Competitive Products (Room 7): To better understand the competition, the engineering department conducts a comparison of competitor's engineering characteristics. Engineering assessments of competing products and the company's own products allow the company to compare its performance with that of its competitors and set target values that reflect world-class performance. This information can lead companies to establish realistic and measurable target values. At least two competitors should be chosen, the competitor known for the least cost and the competitor known for the highest quality (Freeze and Aaron, 1990). In the competitive analysis study, such things as service calls or warranty data will serve as sources of information to compare the engineering characteristics with that of the competitors'.

Step 8: Target Values for Engineering Characteristics (Room 8): The team evaluates what the customer wants and what the competition offers to establish a realistic target value. The target column is on the same scale (1-5), as those for the technical characteristics of the company's own product and that of the competitors. The decision here is to improve, remain equal to the competition, or remain behind the competition. Improvement is desired in most companies, but may not be attainable if the competition is considered better. In these cases, parity may be the only option, unless due to some constraints a lesser position may be taken. Reality sometimes forces this decision, so the team must be made aware of constraints to the design if there are any. The team establishes the target values for those HOWs, which are considered to be most important. On small matrices this may include all of the HOWs. However, on large matrices it is usually a good idea to focus only on those HOWs which are "important enough", defined by their importance weighting.

Step 9: Importance Weighting (Room 9): This numerical calculation is the product of the cell value (Room 5) and the customer importance rating (Room 2). Numbers are added up in their respective columns to determine the importance of each engineering characteristic. The importance rating, d_i given by the customer in Step 2 is now multiplied with each individual relationship, $R_{i,j}$ in a column, derived by the QFD team in step 5, and the engineering importance weighting, w_j for each column is computed by:

$$w_j = \sum_{i=1}^m d_i * R_{i,j} \quad (A.1)$$

where i represents the rows, j the columns and m the number of customer demands. The engineering characteristic with the highest weight is considered as the most important characteristic to meet most of the customer demands. The most important engineering characteristic importance weighting is usually ranked as 1. The most important

engineering characteristics will then be brought to the next QFD phase together with its weighting to form the rows (WHATs) of the next matrix. On small matrices, all of these engineering characteristics will be brought forward, but on large matrices only the most important characteristics will be brought to the next phase.

A.2 EXPLANATION OF DEMANDS IN QFD HOQ:

Customer demands (explanations)

1. **Tidy Tip:** The tip stays clean & neat.
2. **Retains Shape:** The container retains its original shape.
3. **Stays Put:** The container does not roll off the counter.
4. **Hygienic:** Toothpaste that touched the brush cannot be drawn back into container.
5. **Squeezable:** People want to squeeze the container, they do not want a pump.
6. **Easy open:** The cap opens and closes easily.
7. **No waste:** Almost all the toothpaste comes out, but not all over the bath.
8. **Small footprint:** Container takes up little counter space.
9. **Reasonable cost:** It should cost about the same as present container.
10. **Attractive container:** The sales department says it must look good.
11. **Time to market:** The amount of time needed before the product can be sold.
12. **Return on Investment:** Profit divided by money and value of facilities provided.

Engineering characteristic (explanations)

1. **Mess:** amount of toothpaste on tip
2. **Pull-Back:** amount of toothpaste pulled back after dispensing.
3. **Pressure:** pressure needed to get the toothpaste out.
4. **Effort:** no. of turns/time/effort to remove cap.
5. **Waste:** amount of toothpaste left in container when its finished.
6. **Counter Space:** amount of space needed by container
7. **Deformation:** amount of change in shape of container when half empty.
8. **Pleasing Appearance:** based on cust survey results.
9. **Cost to produce:** cost to manufacture the product.
10. **Selling price:** Sales price for 1 item.
11. **Time to develop:** Time needed to develop the product

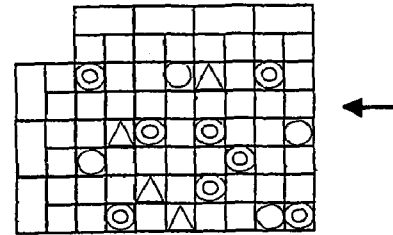
A.3 THE NINE HOUSE OF QUALITY CHECKS

The nine checks (Nakui, 1991) that should be performed on QFD's HOQ to check if it has been completed properly are highlighted below.

9 House Of Quality Checks⁶

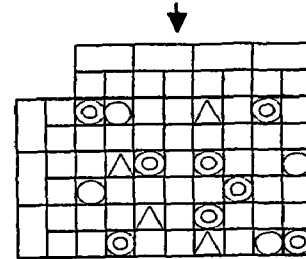
1. Empty rows.

Demanded Quality items with no relating Quality Characteristics means there is no way to assure DQ will be achieved. Go back to DQ and define new QC.



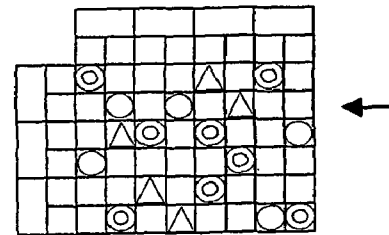
2. Empty columns.

Quality Characteristics that do not relate to Demanded Quality. Unnecessary QC make the matrix cumbersome. Check to be sure these are QC, they relate to the product or service and not the usage environment or the user.



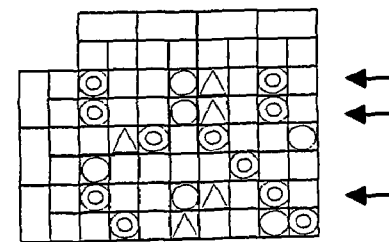
3. Rows with no strong relationships.

Demanded Quality is difficult to achieve without at least one strongly related Quality Characteristic. Use expert help to extract strongly related QC.



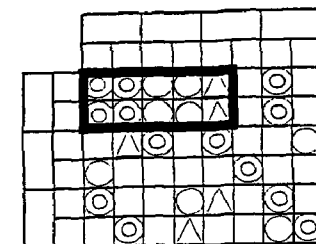
4. Rows that repeat identical relationships.

Demanded Quality relationships are repeating, indicating a problem with the DQ hierarchy. Examine DQ Classification Hierarchy (Tree) to assure that levels of detail are arranged properly. A common problem is 4th level details being mixed in with 3rd level. This can cause serious problems later on if this repetition causes some QC to be weighted too heavily.



5. Clusters of relationships

Possible hierarchy problems in either Demanded Quality Classification Hierarchy (Tree), Quality



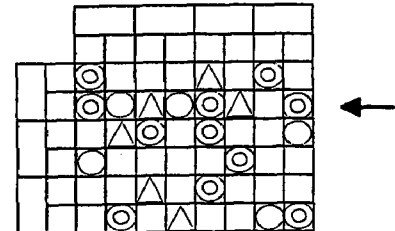
⁶ Adapted from "Comprehensive QFD" by Satoshi Nakui of GOAL/QPC in *The Transactions of the Third Symposium on QFD*, June 1991.

Characteristic Classification Hierarchy (Tree) or both. Review and correct. Possible that quality characteristics are inappropriate.

6. Row with too many relationships

Demanded Quality item may actually be a cost, reliability or safety item. Remove from House Of Quality for deployment in Reliability Deployment, Cost Deployment or Safety Deployment.

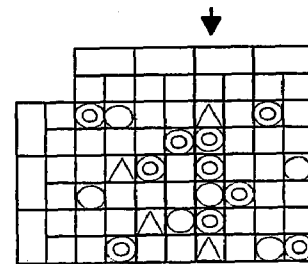
Demanded Quality item may be 1st or 2nd level mixed in with lower levels. Review hierarchy in DQ Classification Hierarchy (Tree).



7. Column with too many relationships

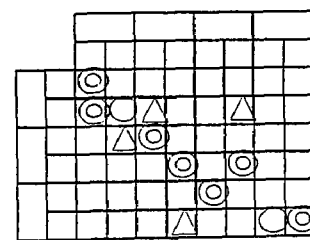
Quality Characteristic may actually be a cost, reliability or safety item. Remove from House Of Quality for deployment in Reliability Deployment, Cost Deployment or Safety Deployment.

Quality Characteristic may be 1st or 2nd level mixed in with lower levels. Review hierarchy in QC Classification Hierarchy (Tree).



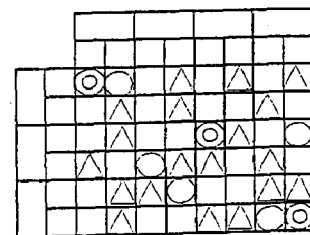
8. Diagonal line across matrix with few other relationships

Demanded Quality items may in fact be Quality Characteristics worded differently or implementation methods. DQ should represent voice of the customer *not* engineer.



9. Too many weak relationships

Clearer Quality Characteristics need to be developed. Quality Characteristics should relate strongly to at least one Demanded Quality item.



Appendix B.

Fuzzy QFD: Software

This appendix lists some of the programs developed for the Fuzzy-QFD approaches. It also introduces the Spearman's rank correlation statistical test. In addition it shows the alterations made to the roof correlation matrix used in the sensitivity analysis in chapter 4.

B.1 LISTING OF COMPUTER PROGRAMS

B.1.1 Programs for Fuzzy Range QFD Approach (Mechatronics room layout example)

%CustWeightUpdate allows the customer importance rating to be updated depending on the porch relationship.

%Uses a range instead of a pure number

%File to find range of cust_imp rating using the porch relationship

%Importance Rating

```
CD=0;
Cust_Dem=[];
Cust_Weight_sub=0;
Cust_Weight1=[];
Cust_Weight=[];
Cust_Weighting=[];
```

%Customers Input; importance rating

```
Cust_Imp=[7.2; 4.8; 3.2; 3.2; 2.8; 2.8; 1.4]; %original data
```

```
%Limits of VS S A W to be used to transform the Cust_Imp into range and output the result as ranges
```

```
%VS=[8 10];
```

```
%S=[6 8]
```

```
%A=[4 6]
```

```
%W=[0 4]
```

```
vs_min =8; % lower limit of very_strong
vs_max =10; % upper limit of very_strong
s_min =6; % lower limit of strong
s_max =8; % upper limit of strong
a_min =4; % lower limit of average
a_max =6; % upper limit of average
w_min =0; % lower limit of weak
w_max =4; % upper limit of weak
```

```
VS=[vs_min vs_max];
```

```
S=[s_min s_max];
```

```
A=[a_min a_max];
```

```
W=[w_min w_max];
```

```
LimMat=[VS; S; A; W]; %Matrix for resulting cust_imp range
```

```
%Definition within which range are the inputs
```

```
for l=1:size(Cust_Imp)
    if Cust_Imp(l)>=vs_min
        if Cust_Imp(l)<=vs_max
            Cust_Weight_sub=VS;
        end
    end
    if Cust_Imp(l)>=s_min
        if Cust_Imp(l)<s_max
            Cust_Weight_sub=S;
        end
    end
    if Cust_Imp(l)>=a_min
        if Cust_Imp(l)<a_max
            Cust_Weight_sub=A;
        end
    end
    if Cust_Imp(l)>=w_min
        if Cust_Imp(l)<w_max
            Cust_Weight_sub=W;
        end
    end
    Cust_Weight=[Cust_Weight; Cust_Weight_sub];
end
```



```

        Cust_Dem_i_ =Cust_Dem(i,:);
        Cust_Dem_j_ =Cust_Dem(j,:);

%checks for inequality of different Customer Demands

for r=1:size(LimMat)
    if Cust_Dem(i,:)==LimMat(r,:)
        Chek_CD1=r;
    end
        if Cust_Dem(j,:)==LimMat(r,:)
            Chek_CD2=r;
        end
    end
    if Chek_CD1<Chek_CD2
        A=[LimMat(Chek_CD1,:); LimMat(Chek_CD2,:)];
        winner=max(A); %the max number is the winner
        loser=min(A); %the min number is the loser
        difference=abs(Chek_CD1-Chek_CD2);
        for d=1:N_relation_no %check the parameter number
            if Chek_CD2<=4-win_par(d)
looser_final=LimMat(Chek_CD2+win_par(d),:);
                k=j;
            end
        end
    elseif Chek_CD1>Chek_CD2
        for d=1:N_relation_no%check the parameter number
            if Chek_CD1<=4-win_par(d)
looser_final=LimMat(Chek_CD1+win_par(d),:);
                k=i;
            end
        end
    end
    if k>0
        Cust_Dem(k,:)=looser_final;
        Cust_Dem_ =Cust_Dem;
    end
end
end

%*****
%                               POSITIVE LOOP
%*****

for P_relation_no=1:size(P_Relation_Matrix)
    if RS_Porch(i,j)==P_Relation_Matrix(P_relation_no)
        k=0;
        Cust_Dem_ =Cust_Dem;
        P_relation_no_ =P_relation_no;
        row=i;
        colum=j;
        Cust_Dem_i_ =Cust_Dem(i,:);
        Cust_Dem_j_ =Cust_Dem(j,:);
        %check for inequality of different Customer Demands

```

```

for r=1:size(LimMat)
    if Cust_Dem(i,:)==LimMat(r,:)
        Chek_CD1=r;
    end
        if Cust_Dem(j,:)==LimMat(r,:)
            Chek_CD2=r;
        end
    end
    if Chek_CD1<Chek_CD2
        A=[LimMat(Chek_CD1,:); LimMat(Chek_CD2,:)];
        winner=max(A);
        looser=min(A);
        difference=abs(Chek_CD1-Chek_CD2);
        for d=1:P_relation_no %check the parameter number
            if looser_final~=Cust_Dem(i,:)
                if Chek_CD2>win_par(d)
                    looser_final=LimMat(Chek_CD2-win_par(d,:));
                    k=j;
                end
            end
        end
    elseif Chek_CD1>Chek_CD2
        for d=1:P_relation_no %check the parameter number
            if looser_final~=Cust_Dem(j,:)
                if Chek_CD1>win_par(d)
                    looser_final=LimMat(Chek_CD1-win_par(d,:));
                    k=i;
                end
            end
        end
    end
    if k>0
        Cust_Dem(k,:)=looser_final;
        Cust_Dem_=Cust_Dem;
    end
end
end
end
end

Cust_W=Cust_Dem; %prints the updated customer importance rating

for n=1:size(Cust_W,1)
    for m=1:size(Cust_W,2)
        IR=Cust_W(n,m);
        Cust_Weighting=[Cust_Weighting; IR];
    end
end

Cust_Weighting_view=Cust_Weighting; %prints the updated customer %importance
rating

```



```

vs_min =8;
vs_max =10;
s_min   =6;
s_max   =8;
a_min   =4;
a_max   =6;
w_min   =0;
w_max   =4;

VS=[vs_min vs_max];
S=[s_min s_max];
A=[a_min a_max];
W=[w_min w_max];

LimMat=[VS; S; A; W];
% Definition within which range the inputs are

for l=1:size(Cust_Imp)
    if Cust_Imp(l)>=vs_min
        if Cust_Imp(l)<=vs_max
            Imp_Rate_Side_sub=VS;
        end
    end
    if Cust_Imp(l)>=s_min
        if Cust_Imp(l)<s_max
            Imp_Rate_Side_sub=S;
        end
    end
    if Cust_Imp(l)>=a_min
        if Cust_Imp(l)<a_max
            Imp_Rate_Side_sub=A;
        end
    end
    if Cust_Imp(l)>=w_min
        if Cust_Imp(l)<w_max
            Imp_Rate_Side_sub=W;
        end
    end
    Imp_Rate_Side=[Imp_Rate_Side; Imp_Rate_Side_sub];
end
Imp_Rate_Side_view=[Imp_Rate_Side_view Imp_Rate_Side]; %Changes the
relationship matrix into their relevant ranges

% Matrix with number of correction -distance-

win_par=[1; 2; 3];

% RelationShips
VSP=3;
SP=2;
WP=1;
WN=-1;
SN=-2;

```

```
VSN=-3;
```

```
P_Relation_Matrix=[WP; SP; VSP];
N_Relation_Matrix=[WN; SN; VSN];
```

```
% Map of the Porch Relations
```

```
RS_Porch=[ 0 0 0 SP 0 WP WN; %1st customer demand
           0 0 0 0 WP 0 0; %2nd customer demand
           0 0 0 WN 0 0 0;
           0 0 0 0 0 0 SN;
           0 0 0 0 0 0 0;
           0 0 0 0 0 0 0;
           0 0 0 0 0 0 0];
```

```
Cust_Dem=Imp_Rate_Side;
```

```
%Correction to Customer's importance rating
```

```
for i=1:size(RS_Porch,1)
    for j=1:size(RS_Porch,2)
        loser_final=[0 0];
```

```
%*****
% NEGATIVE LOOP
%*****
```

```
    for N_relation_no=1:size(N_Relation_Matrix)
        if RS_Porch(i,j)==N_Relation_Matrix(N_relation_no)
            k=0;
            Cust_Dem_=Cust_Dem;
            N_relation_no_=N_relation_no;
            row=i;
            column=j;
            Cust_Dem_i_=Cust_Dem(i,:);
            Cust_Dem_j_=Cust_Dem(j,:);
            % check for inequalities in different Customer Demands
            for r=1:size(LimMat)
                if Cust_Dem(i,:)==LimMat(r,:)
                    Chek_CD1=r;
                end
                if Cust_Dem(j,:)==LimMat(r,:)
                    Chek_CD2=r;
                end
            end
            if Chek_CD1<Chek_CD2
                A=[LimMat(Chek_CD1,:); LimMat(Chek_CD2,:)];
                winner=max(A);
                loser=min(A);
                difference=abs(Chek_CD1-Chek_CD2);
                for d=1:N_relation_no %check the parameter number
                    if Chek_CD2<=4-win_par(d)
                        loser_final=LimMat(Chek_CD2+win_par(d),:);
```

```

        k=j;
    end
    end
elseif Chek_CD1>Chek_CD2
    for d=1:N_relation_no%check the parameter number
        if Chek_CD1<=4-win_par(d)
            looser_final=LimMat(Chek_CD1+win_par(d),:);
            k=i;
        end
    end
    end
    if k>0
        Cust_Dem(k,:)=looser_final;
        Cust_Dem_=Cust_Dem;
    end
end
end
end
%*****
%POSITIVE LOOP
%*****

for P_relation_no=1:size(P_Relation_Matrix)
    if RS_Porch(i,j)==P_Relation_Matrix(P_relation_no)
        k=0;
        Cust_Dem_=Cust_Dem;
        P_relation_no_=P_relation_no;
        row=i;
        colum=j;
        Cust_Dem_i_=Cust_Dem(i,:);
        Cust_Dem_j_=Cust_Dem(j,:);

        % check for inequality of different Customer Demands

        for r=1:size(LimMat)
            if Cust_Dem(i,:)==LimMat(r,:)
                Chek_CD1=r;
            end
            if Cust_Dem(j,:)==LimMat(r,:)
                Chek_CD2=r;
            end
        end
        if Chek_CD1<Chek_CD2
            A=[LimMat(Chek_CD1,:); LimMat(Chek_CD2,:)];
            winner=max(A);
            looser=min(A);
            difference=abs(Chek_CD1-Chek_CD2);
            for d=1:P_relation_no
                if looser_final~=Cust_Dem(i,:)
                    if Chek_CD2>win_par(d)
                        looser_final=LimMat(Chek_CD2-win_par(d),:);
                        k=j;
                    end
                end
            end
        end
    end
end

```

```

    end
elseif Chek_CD1>Chek_CD2
    for d=1:P_relation_no
        if looser_final~=Cust_Dem(j,:)
            if Chek_CD1>win_par(d)
                looser_final=LimMat(Chek_CD1-win_par(d),:);
                k=i;
            end
        end
    end
end

end
if k>0
    Cust_Dem(k,:)=looser_final;
    Cust_Dem_=Cust_Dem;
end

end

end
end

Cust_Dem_view=Cust_Dem';          %Interchanges the rows and columns
RShipMat_Porch_view=[RShipMat_Porch_view; Cust_Dem_view]; %Shows the result
of the relationship matrix using the porch relationship
Cust_Dem=Cust_Dem;
RShipMat_Porch=[RShipMat_Porch Cust_Dem];
end %Loop No 1
RShipMat_Porch_=RShipMat_Porch; %Shows the result of the relationship matrix
using the porch relationship in the required format

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

%CombRelate combines the result obtained from the file: SidePorchCust and the file:
TopRoofEng together with the original relationship matrix if required to give a new
relationship matrix

clear all
MatRoofPorchDev2=[]; %uses only the porch and roof
%combinational relationship matrix to work out the new resultant matrix

MatRoofPorchDev3=[]; %uses the porch, roof and original given relationship matrix to
work out the new resultant matrix

MatRoofPorch_sub=[];

SidePorchCust;          % Calls this file; Porch relationship
TopRoofEng;            % Calls this file; Roof relationship

Imp_Rate_Top_=Imp_Rate_Top;
Imp_Rate_Side_view_=Imp_Rate_Side_view;

RShipMat_Roof_=RShipMat_Roof;

```



```

Mul_02c=[];
Mul_02d=[];
for x3=1:2:size(Mul_02,2)
    Mul_02c=[Mul_02c Mul_02(1,x3)];
end
for x4=2:2:size(Mul_02,2)
    Mul_02d=[Mul_02d Mul_02(1,x4)];
end
Mul_02c;
Mul_02d;
Mul_03=[Mul_02c+Mul_02d]/2

```

XX

B.2 PROGRAMS FOR FUZZY PROPORTIONAL DISTRIBUTION QFD APPROACH

% METHOD 1: RANKED, LOOP DATA

%This file loads inputs from the QFD team (Mechatronics room layout ranked loop)

```
function [RelShipMat,RelShipMat_orig,Imp_Rating,Imp_Rating_orig]=Input_data
```

```
%
```

```
%
```

LOAD FILES

```
%
```

```
load loop
```

```
load RelShipMat_update_denorm
```

```
load Imp_Rating_update_denorm
```

```
%
```

```
%
```

NORMALISATION (0-1) OF Relationship Matrix

```
%
```

```
if loop==1
```

%Ranked relationship matrix

```
RelShipMat=[    0.346  0.038  0.115  0.000  0.346  0.115  0.000  0.038;%C1
               0.000  0.000  0.136  0.409  0.045  0.000  0.409  0.000;%C2
               0.091  0.818  0.091  0.000  0.000  0.000  0.000  0.000;
               0.281  0.281  0.031  0.031  0.094  0.281  0.000  0.000;
               0.000  0.000  0.409  0.409  0.000  0.000  0.136  0.045;
               0.200  0.000  0.200  0.000  0.000  0.000  0.000  0.600;
               0.250  0.000  0.000  0.000  0.000  0.750  0.000  0.000;];
```

%Unranked relationship matrix

```
%RelShipMat=[ 0.346  0.000  0.038  0.346  0.115  0.038  0.115  0.000;
%              0.045  0.409  0.000  0.000  0.136  0.000  0.000  0.409;
%              0.000  0.000  0.818  0.091  0.091  0.000  0.000  0.000;
%              0.094  0.000  0.281  0.281  0.031  0.000  0.281  0.031;
%              0.000  0.136  0.000  0.000  0.409  0.045  0.000  0.409;
%              0.000  0.000  0.000  0.200  0.200  0.600  0.000  0.000;
%              0.000  0.000  0.000  0.250  0.000  0.000  0.750  0.000;];
```

```

RelShipMat_orig=RelShipMat;
RelShipMat_min=min(min(RelShipMat));
RelShipMat_max=max(max(RelShipMat));
for i=1:size(RelShipMat,1)
    for j=1:size(RelShipMat,2)
        RelShipMat_norm(i,j)=(RelShipMat(i,j)-RelShipMat_min)/(RelShipMat_max-
RelShipMat_min);
    end
end
RelShipMat=RelShipMat_norm;
else
RelShipMat=RelShipMat_update_denorm;
RelShipMat_orig=RelShipMat;
RelShipMat_min=min(min(RelShipMat));
RelShipMat_max=max(max(RelShipMat));
for i=1:size(RelShipMat,1)
    for j=1:size(RelShipMat,2)
        RelShipMat_norm(i,j)=(RelShipMat(i,j)-RelShipMat_min)/(RelShipMat_max-
RelShipMat_min);
    end
end
RelShipMat=RelShipMat_norm;
End

```

```

%
% _____
%                               NORMALISATION OF Imp_Rating
% _____

```

```

if loop==1
    Imp_Rating =[28.35; 18.90; 12.60; 12.60; 11.02; 11.02;
    5.51];
    Imp_Rating_orig=Imp_Rating;
    Imp_Rating_min=min(Imp_Rating);
    Imp_Rating_max=max(Imp_Rating);
    for i=1:size(Imp_Rating,1)
        Imp_Rating_norm(i,1)=(Imp_Rating(i,1)-Imp_Rating_min)/(Imp_Rating_max-
Imp_Rating_min);
    end
    Imp_Rating=Imp_Rating_norm;
else
    Imp_Rating =Imp_Rating_update_denorm;
    Imp_Rating_orig=Imp_Rating;
    Imp_Rating_min=min(Imp_Rating);
    Imp_Rating_max=max(Imp_Rating);
    for i=1:size(Imp_Rating,1)
        Imp_Rating_norm(i,1)=(Imp_Rating(i,1)-          Imp_Rating_min)/(Imp_Rating_max-
Imp_Rating_min);
    end
    Imp_Rating=Imp_Rating_norm;
end
end

```

```

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

```



```

        Cor_in, DOF_Cor(r,q), 'r+');
        title(['Correlation:      ',num2str(Cor_in),      '      with      Degree:
',num2str(DOF_Cor(r,q))]);
        grid;
        DOF_TS_Cust_Imp_Rate(l,q)=DOF_Cor(r,q); %Outputs DOF related to
each difference.
        elseif RS_Porch(g,k)==2; %Loop when correlation is Strong positive, i.e., =2
        Cor_in = Imp_Rating_update1(l+add,q); %Inputs the difference of
relationships
        DOF_Cor(r,q) = interp1(S_correlation',S_antecedent_correlation',Cor_in');
        plot(S_correlation,S_antecedent_correlation,...
%plots on the s-curve
        Cor_in, DOF_Cor(r,q), 'r+');
        title(['Correlation:      ',num2str(Cor_in),      '      with      Degree:
',num2str(DOF_Cor(r,q))]);
        grid;
        DOF_TS_Cust_Imp_Rate(l,q)=DOF_Cor(r,q);

%*****NEGATIVE CORRELATIONS*****

        elseif RS_Porch(g,k)==-1;%Loop when correlation is weak negative, i.e., =-1
        Cor_in = -Imp_Rating_update1(l+add,q);
        DOF_Cor(r,q) = (interp1(Z_correlation',Z_antecedent_correlation',Cor_in'))/3;
        plot(Z_correlation,Z_antecedent_correlation,... %plots on the z-curve
        Cor_in, DOF_Cor(r,q), 'r+');
        title(['Correlation:      ',num2str(Cor_in),      '      with      Degree:
',num2str(DOF_Cor(r,q))]);
        grid;
        DOF_TS_Cust_Imp_Rate(l,q)=DOF_Cor(r,q);
        else RS_Porch(g,k)==-2; %Loop when correlation is Strong negative, i.e.,
=-2
        Cor_in = -Imp_Rating_update1(l+add,q);
        DOF_Cor(r,q) = interp1(Z_correlation',Z_antecedent_correlation',Cor_in');
        plot(Z_correlation,Z_antecedent_correlation,...
        Cor_in, DOF_Cor(r,q), 'r+');
        title(['Correlation:      ',num2str(Cor_in),      '      with      Degree:
',num2str(DOF_Cor(r,q))]);
        grid;
        DOF_TS_Cust_Imp_Rate(l,q)=DOF_Cor(r,q);
        end
    else
        Cor_in = Imp_Rating_update1(l+add,q);
        DOF_TS_Cust_Imp_Rate(l,q)=0;
    end
    Cor_in =Cor_in; %Displays the differences
    DOF_TS_Cust_Imp_Rate =DOF_TS_Cust_Imp_Rate(l,q);
%Displays DOF corresponding to differences
    TS_Cust_Imp_Rate_num=Cor_in*DOF_TS_Cust_Imp_Rate(l,q);
%Displays the product of the DOF and its associated difference
    SUM_TS_Cust_Imp_Rate_num=SUM_TS_Cust_Imp_Rate_num+Cor_in*DOF_TS_Cus
t_Imp_Rate(l,q); %Sums the product of DOF*difference
    SUM_TS_Cust_Imp_Rate_den=SUM_TS_Cust_Imp_Rate_den+DOF_TS_Cust_Imp_Ra
te(l,q); %Sums the DOF

```

```

    end
    end
    if SUM_TS_Cust_Imp_Rate_den==0%If Sum of DOF is zero, then
    %TS_Cust_Imp_Rate is immediately zero.
        TS_Cust_Imp_Rate(q,r)=0;
    else
    %If only one input exists, it finds it and make the sum of
    %SUM_TS_Cust_Imp_Rate_den=1
        Imp_Rating_update1(:,loop);
        f=find(Imp_Rating_update1(:,loop)~=0);
        if size(f)==1
            SUM_TS_Cust_Imp_Rate_den=1;
        end
    TS_Cust_Imp_Rate(q,r)=SUM_TS_Cust_Imp_Rate_num/SUM_TS_Cust_Imp_Rate_den
    ; % Tagaki-Sugeno is the sum DOF*Diff divided by the sum of %DOF.
        TS_Cust_Imp_Rate_='TS_Cust_Imp_Rate'; %Changes the rows of
    TS_Cust_Imp_Rate into columns to match the desired output results.
        DOF_TS_Cust_Imp_Rate;
    end
        DOF_TS_Cust_Imp_Rate;
    end
    Imp_Rating_update2=[Imp_Rating_update2 DOF_TS_Cust_Imp_Rate];
end

Imp_Rating_update2=Imp_Rating_update2';
function [Rel_Matrix_Comb,Rel_Matrix_Comb_times_TS]=CombResults03

clear all

Imp_Rating_update_denorm=[];
RelShipMat_update_denorm=[];
%save Imp_Rating_update Imp_Rating_update -ascii

[xx1,xx2,xx3,xx4,xx5]=Input_RelShipMat;

for loop=1:size(xx2,1)
    loop_=loop;
    save loop loop -ascii
    save RelShipMat_update_denorm RelShipMat_update_denorm
    save Imp_Rating_update_denorm Imp_Rating_update_denorm

%Load
[Rel_Matrix_Porch,RS_Porch,Rel_Matrix_Roof,RS_Roof,Imp_Rating]=Input_RelShipMat;

[TS_Porch,Rel_Matrix_Porch_update2]=RelationShipMFPorch01(loop);
[TS_Roof,Rel_Matrix_Roof_update2]=RelationShipMFRoof01(loop);
[Imp_Rating_update2,TS_Cust_Imp_Rate]=RelationShipMF_Cust_Imp_Rate01(loop);
AveragePorchRoof=(TS_Porch+TS_Roof)/2;

%*****
% denormalisation of Rel_Matrix_Comb
%*****

```

```

[RelShipMat,RelShipMat_orig,Imp_Rating,Imp_Rating_orig]=Input_data;
%
%                               update RelShipMat
%
RelShipMat;
RelShipMat(loop,:)=RelShipMat(loop,:)+AveragePorchRoof(loop,:);
RelShipMat_update=RelShipMat;
%                               denormalisation of RelShipMat
%
RelShipMat_min=min(min(RelShipMat_orig));
RelShipMat_max=max(max(RelShipMat_orig));
for i=1:size(RelShipMat_update,1)
    for j=1:size(RelShipMat_update,2)
RelShipMat_update_denorm(i,j)=RelShipMat_update(i,j)*(RelShipMat_max-
RelShipMat_min)+RelShipMat_min;
    end
end

RelShipMat_update_denorm;

%
%                               update Imp_Rating
%
Imp_Rating(loop,1);
TS_Cust_Imp_Rate(loop,1);

Imp_Rating(loop,1)=Imp_Rating(loop,1)+TS_Cust_Imp_Rate(loop,1);
Imp_Rating_update=Imp_Rating;
%
%                               denormalisation of Imp_Rating
%

Imp_Rating_min=min(Imp_Rating_orig);
Imp_Rating_max=max(Imp_Rating_orig);
for i=1:size(Imp_Rating_update,1)
Imp_Rating_update_denorm(i,1)=Imp_Rating_update(i,1)*(Imp_Rating_max-
Imp_Rating_min)+Imp_Rating_min;
    end
    Imp_Rating_update_denorm
end

RelShipMat_update_denorm_ =RelShipMat_update_denorm;

save RelShipMat_update_denorm.txt RelShipMat_update_denorm -ascii
save Imp_Rating_update_denorm.txt Imp_Rating_update_denorm -ascii
for i=1:size(RelShipMat_update_denorm,2)
Scoring(1,i)=Imp_Rating_update_denorm(:,1)'*RelShipMat_update_denorm(:,i);
end
RelShipMat_update_denorm
Imp_Rating_update_denorm_ =Imp_Rating_update_denorm

Scoring % Calculates the scoring range

```

B.3 SPEARMAN'S RANK CORRELATION

Spearman rank correlation is a distribution-free way to discover the strength of a link between two sets of data (Clarke and Cooke, 1992). Unlike regression, it works on ranked (relative) data, rather than directly on the data itself. This test is useful to check whether matched pairs are really matched. If they are, their rank correlation should be statistically significant. The data is ranked with the highest score given a rank of 1 and so on. In mathematical notation:

$$r_s = 1 - \left(\frac{6 * (d_1^2 + d_2^2 + \dots + d_n^2)}{n(n^2 - 1)} \right) \quad (B.1)$$

The difference d between each paired rank is calculated for n number of data. The r_s statistic will be +1 if the two rankings are identical (complete agreement) or -1 if the rankings are opposite (complete disagreement). The significance of the agreement can be found by matching the r_s value with the corresponding n value on the Spearman's rank significance table (Clarke and Cooke, 1992).

The null hypothesis $H_0 = r_s = 0$, means that there is no relation between the two variables, whereas the alternative hypothesis, $H_1 = r_s \neq 0$, means that there is some relation, positive or negative between the rankings. In such a case the test must be a two-tail one.

B.3.1 Spearman's rank correlation for Independent Scoring vs. Fuzzy Range HOQ for toothpaste case study

Table B.1 shows the calculated Spearman's rank correlation and the significant of the results. Spearman's rank correlation, r_s , is greater than the Spearman's rank correlation value at $n = 10$, therefore the null hypothesis is rejected in favour of the alternative hypothesis. This means that there is high relation between these two sets of ranking.

Spearman's Rank Correlation for toothpaste case study				
Factor	Independent Scoring Rank	Fuzzy Range Rank	Rank Difference	Squared Rank Difference
A	3	3	0	0
B	5	5	0	0
C	10	9	1	1
D	11	7	4	16
E	8	6	2	4
F	7	10	3	9
G	6	8	2	4
H	4	4	0	0
I	1	1	0	0
J	2	2	0	0
K	8	11	3	9
Sum				43
Spearman's rank correlation r_s				0.807
Significance @ 99%				0.735
Exact significance computed by matlab file				99.40%

Table B.1 Spearman's rank correlation calculation for comparing the Independent Scoring HOQ rank data to the Fuzzy Range HOQ rank data

B.4 SENSITIVITY ANALYSIS

% Alterations in the roof correlation matrix

```
RS_roof1=[0 WN 0 0 SP 0 WN SN WN 0 0;
           0 0 0 0 0 0 0 WP WP WN;
           0 0 0 0 WN 0 WN WN WN 0 0;
           0 0 0 0 0 0 0 0 0 0 0;
           0 0 0 0 0 0 WN SN SN 0 0;
           0 0 0 0 0 0 WN WN 0 0 0;
           0 0 0 0 0 0 0 WN WN 0 0;
           0 0 0 0 0 0 0 0 WP WP WN;
           0 0 0 0 0 0 0 0 0 SP WN;
           0 0 0 0 0 0 0 0 0 0 0;
           0 0 0 0 0 0 0 0 0 0 0];
```

Appendix C.

Least squares method

This Appendix reviews the Least Squares Method and lists some of the programs developed and used in the QFD-Taguchi approach in chapters 6 and 7. The average response table for thumtack example is also given.

C.1 LEAST SQUARES METHOD

The actual computations involved in solving regression problems can be expressed compactly and conveniently using matrix notation. The multiple regression model in matrix notation can be expressed as:

$$Y = Xb + e \quad (C.1)$$

where b is a column vector of 1 (for the intercept) + k unknown regression coefficients. The goal of multiple regression is to minimise the sum of the squared residuals. Regression coefficients that satisfy this criterion are found by solving the set of normal equations

$$\mathbf{X}^T \mathbf{X} b = \mathbf{X}^T \mathbf{Y} \quad (C.2)$$

When the X variables are linearly independent yielding an $X'X$ matrix there is a unique solution to the normal equations. Pre-multiplying both sides of the matrix formula for the normal equations by the inverse of $X'X$ gives

$$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{X} b = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (C.3)$$

or

$$b = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (C.4)$$

This last result is very satisfying in view of its simplicity and its generality. With regard to its simplicity, it expresses the solution for the regression equation in terms just 2 matrices (X and Y) and 3 basic matrix operations, (1) matrix transposition, which involves interchanging the elements in the rows and columns of a matrix, (2) matrix multiplication, which involves finding the sum of the products of the elements for each row and column, and (3) matrix inversion, which involves finding the matrix equivalent of a numeric reciprocal.

C.2 LISTING OF COMPUTER PROGRAMS

Matlab Programs for calculating the Least Square and hence the regression equation are outlined below.

C.2.1 Program: Thumbtack Example

```
clear all
```

```
%%% The calculated OEC responses %%%%%%%%%%
```

	OEC
$Y_m =$	60.000
	67.840
	61.280
	63.360
	70.600
	65.360
	69.520
	78.080
	72.120
	51.920
	59.160
	53.920
	54.680
	63.240
	57.280
	62.160
	70.000
	63.440
	54.640
	63.200
	57.240
	58.720
	66.560
	60.000
	65.480
	72.720
	67.480

(C.5)

%%Using the coding Matrix for an L27 for thumbtack example %%%%%%%%%%

	Bo	HD	SJ	PS	PD
$X_m =$	1	-1	-1	-1	-1
	1	-1	-1	0	0
	1	-1	-1	1	1
	1	-1	0	-1	0
	1	-1	0	0	1
	1	-1	0	1	-1
	1	-1	1	-1	1
	1	-1	1	0	-1
	1	-1	1	1	0
	1	0	-1	-1	0
	1	0	-1	0	1
	1	0	-1	1	-1
	1	0	0	-1	1
	1	0	0	0	-1
	1	0	0	1	0
	1	0	1	-1	-1
	1	0	1	0	0
	1	0	1	1	1
	1	1	-1	-1	1
	1	1	-1	0	-1
	1	1	-1	1	0
	1	1	0	-1	-1
	1	1	0	0	0
	1	1	0	1	1
	1	1	1	-1	0
	1	1	1	0	1
	1	1	1	1	-1

(C.6)

Regression coefficient matrix $\hat{\beta}_m$

$$\hat{\beta}_m = \begin{bmatrix} 63.33 \\ -2.34 \\ 5.10 \\ 0.98 \\ -0.34 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{matrix} \quad (C.7)$$

Therefore the fitted regression model for the main factors Y_m , for this example is:

$$Y_m = 63.33 - 2.334HD + 5.10SJ + 0.98SP - 0.34PD \quad (C.8)$$

C.2.1.1 Adding the interaction coefficients

The interaction terms are then added to the regression model, where:

$HD \times SJ = 3/9 = 0.33$ and $SP \times PD = -9/9 = -1$ and the coefficients of the interaction are:

$$I = \begin{bmatrix} 0.33 \\ -1.0 \end{bmatrix} \quad (C.9)$$

Here $\beta_{\max} = 5.1$, $\beta_{\min} = -2.34$, $I_{\max} = 1$ and $I_{\min} = 0.33$. The mapping equation becomes $p = -6.003 + 11.10q$. And therefore the regression coefficient vector $\hat{\beta}_l$ including interaction is calculated from equation (C.10) and takes the form:

$$\hat{\beta}_1 = \begin{bmatrix} 63.33 \\ -2.34 \\ 5.10 \\ 0.98 \\ -0.34 \\ -2.34 \\ 5.10 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{34} \end{matrix} \quad (C.10)$$

The new regression equation Y_1 including interactions results in:

$$Y_1 = 63.33 - 2.34 \beta_1 + 5.10 \beta_2 + 0.98 \beta_3 - 0.34 \beta_4 - 2.34 \beta_{12} + 5.10 \beta_{34} \quad (C.11)$$

where β_{12} is the interaction between *Head Diameter (HD)* β_1 and *Strength of Join (SJ)* β_2 , whereas β_{34} is the interaction between *Pin Sharpness (PS)* β_3 and *Pin Diameter (PD)* β_4 . Using the new regression equation (C.11), new OEC responses are calculated using the least square method. The regression coefficient $\hat{\beta}_1$ from equation (C.10) and the coded factor level matrix for the main factors and interaction terms, X_i , from equation (C.12), are multiplied together to determine the new OEC Interaction with Regression Analysis (OEC Int_RA). The coding matrix with interactions is thus:

	Bo	HD	SJ	PS	PD	HD&SJ	PS&PD
X ₁ =	1	-1	-1	-1	-1	-1	-1
	1	-1	-1	0	0	-1	0
	1	-1	-1	1	1	-1	1
	1	-1	0	-1	0	0	1
	1	-1	0	0	1	0	-1
	1	-1	0	1	-1	0	0
	1	-1	1	-1	1	1	0
	1	-1	1	0	-1	1	1
	1	-1	1	1	0	1	-1
	1	0	-1	-1	0	1	1
	1	0	-1	0	1	1	-1
	1	0	-1	1	-1	1	0
	1	0	0	-1	1	-1	0
	1	0	0	0	-1	-1	1
	1	0	0	1	0	-1	-1
	1	0	1	-1	-1	0	-1
	1	0	1	0	0	0	0
	1	0	1	1	1	0	1
	1	1	-1	-1	1	0	0
	1	1	-1	0	-1	0	1
	1	1	-1	1	0	0	-1
	1	1	0	-1	-1	1	-1
	1	1	0	0	0	1	0
	1	1	0	1	1	1	1
	1	1	1	-1	0	-1	1
	1	1	1	0	1	-1	-1
	1	1	1	1	-1	-1	0

(C.12)

$$\text{OEC (Int_RA)} = X_I * \hat{\beta}_I$$

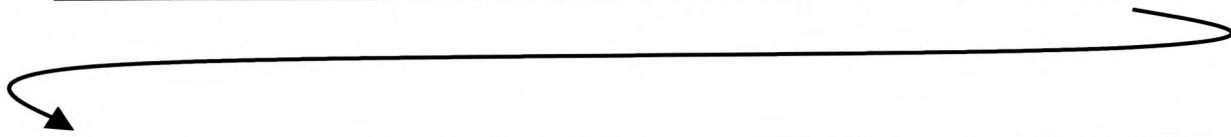
The final OEC (Int_RA) response is given in (C.13).

$$OEC(Int_RA) = \begin{array}{|l} 57.17 \\ 62.91 \\ 68.65 \\ 69.79 \\ 60.23 \\ 66.99 \\ 67.11 \\ 73.87 \\ 64.31 \\ 60.01 \\ 50.45 \\ 57.21 \\ 64.35 \\ 71.11 \\ 61.55 \\ 62.69 \\ 68.43 \\ 74.17 \\ 54.57 \\ 61.33 \\ 51.77 \\ 52.91 \\ 58.65 \\ 64.39 \\ 72.55 \\ 62.99 \\ 69.75 \end{array} \quad (C.13)$$

Programs for the Paper roll example for the QFD-Taguchi approach are developed in the same way.

C.3 AVERAGE RESPONSE TABLE FOR THUMTACK EXAMPLE

Exp	Response	Column 1 HD			Column 2 SJ			Column 3 HDxSJ & PSxPD			Column 4 HDxSJ			Column 5 PS			Column 6		
		Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3
1	57.17	57.170			57.170			57.170			57.170			57.170			57.170		
2	62.91	62.910			62.910			62.910			62.910			62.910			62.910		
3	68.65	68.650			68.650			68.650			68.650			68.650			68.650		
4	69.79	69.790			69.790			69.790			69.790			69.790			69.790		
5	60.23	60.230			60.230			60.230			60.230			60.230			60.230		
6	66.99	66.990			66.990			66.990			66.990			66.990			66.990		
7	67.11	67.110			67.110			67.110			67.110			67.110			67.110		
8	73.87	73.870			73.870			73.870			73.870			73.870			73.870		
9	64.31	64.310			64.310			64.310			64.310			64.310			64.310		
10	60.01	60.010			60.010			60.010			60.010			60.010			60.010		
11	50.45	50.450			50.450			50.450			50.450			50.450			50.450		
12	57.21	57.210			57.210			57.210			57.210			57.210			57.210		
13	64.35	64.350			64.350			64.350			64.350			64.350			64.350		
14	71.11	71.110			71.110			71.110			71.110			71.110			71.110		
15	61.55	61.550			61.550			61.550			61.550			61.550			61.550		
16	62.69	62.690			62.690			62.690			62.690			62.690			62.690		
17	68.43	68.430			68.430			68.430			68.430			68.430			68.430		
18	74.17	74.170			74.170			74.170			74.170			74.170			74.170		
19	54.57	54.570			54.570			54.570			54.570			54.570			54.570		
20	61.33	61.330			61.330			61.330			61.330			61.330			61.330		
21	51.77	51.770			51.770			51.770			51.770			51.770			51.770		
22	52.91	52.910			52.910			52.910			52.910			52.910			52.910		
23	58.65	58.650			58.650			58.650			58.650			58.650			58.650		
24	64.39	64.390			64.390			64.390			64.390			64.390			64.390		
25	72.55	72.550			72.550			72.550			72.550			72.550			72.550		
26	62.99	62.990			62.990			62.990			62.990			62.990			62.990		
27	69.75	69.750			69.750			69.750			69.750			69.750			69.750		
Total	1709.91	591.03	569.97	548.91	524.07	569.97	615.87	569.97	569.97	569.97	591.03	569.97	548.91	561.15	569.97	578.79	569.97	569.97	569.97
No. of values	27	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
Average	63.33	65.670	63.33	60.99	58.23	63.33	68.43	63.33	63.33	63.33	65.67	63.33	60.99	62.35	63.33	64.31	63.33	63.33	63.33
Effect		4.680			10.200			0.000			4.680			1.960			0.000		
Rank		3			1			7			3			5			7		



Column 7 HDxPS			Column 8			Column 9 PD			Column 10			Column 11			Column 12			Column 13 PSxPD		
Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3	Level1	Level2	Level3
57.170			57.170			57.170			57.170			57.170			57.170			57.170		
	62.910		62.910			62.910			62.910			62.910			62.910			62.910		
		68.650	68.650			68.650			68.650			68.650			68.650			68.650		68.650
69.790			69.790			69.790			69.790			69.790			69.790			69.790		69.790
	60.230		60.230			60.230			60.230			60.230			60.230			60.230		
		66.990	66.990			66.990			66.990			66.990			66.990			66.990		
67.110			67.110			67.110			67.110			67.110			67.110			67.110		
	73.870		73.870			73.870			73.870			73.870			73.870			73.870		
		64.310	64.310			64.310			64.310			64.310			64.310			64.310		
		60.010	60.010			60.010			60.010			60.010			60.010			60.010		
50.450			50.450			50.450			50.450			50.450			50.450			50.450		
	57.210		57.210			57.210			57.210			57.210			57.210			57.210		
		64.350	64.350			64.350			64.350			64.350			64.350			64.350		
71.110			71.110			71.110			71.110			71.110			71.110			71.110		
	61.550		61.550			61.550			61.550			61.550			61.550			61.550		
		62.690	62.690			62.690			62.690			62.690			62.690			62.690		
68.430			68.430			68.430			68.430			68.430			68.430			68.430		
	74.170		74.170			74.170			74.170			74.170			74.170			74.170		
		54.570	54.570			54.570			54.570			54.570			54.570			54.570		
		61.330	61.330			61.330			61.330			61.330			61.330			61.330		
51.770			51.770			51.770			51.770			51.770			51.770			51.770		
	52.910		52.910			52.910			52.910			52.910			52.910			52.910		
		58.650	58.650			58.650			58.650			58.650			58.650			58.650		
64.390			64.390			64.390			64.390			64.390			64.390			64.390		
	72.550		72.550			72.550			72.550			72.550			72.550			72.550		
		62.990	62.990			62.990			62.990			62.990			62.990			62.990		
69.750			69.750			69.750			69.750			69.750			69.750			69.750		
569.97	569.97	569.97	569.97	569.97	569.97	573.03	569.97	566.91	569.97	569.97	569.97	569.97	569.97	569.97	569.97	569.97	569.97	524.07	569.97	615.87
9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
63.33	63.33	63.33	63.33	63.33	63.33	63.67	63.33	62.99	63.33	63.33	63.33	63.33	63.33	63.33	63.33	63.33	63.33	58.23	63.33	68.43
0.000			0.000			0.680			0.000			0.000			0.000			10.200		
7			7			6			7			7			7			1		

C.4 RESULTS FOR THE INTEGRATED SYSTEMS APPROACH TO QFD

C.4.1 Paper roll example

The calculated Fuzzy OEC Responses are:

	OEC
$Y_m =$	59.53
	63.46
	71.02
	64.69
	67.65
	69.48
	67.90
	65.13
	73.66
	61.57
	64.53
	66.36
	65.76
	62.99
	71.52
	61.59
	67.17
	74.72
	65.50
	61.08
	69.61
	66.25
	62.31
	73.80
	66.49
	65.51
	75.21

(C.14)

The coded factor level matrix X_m is given in equation (C.15) and the calculated regression coefficients are given in equation (C.16):

$$\begin{array}{c}
 \mathbf{X}_m = \\
 \left[\begin{array}{ccccc}
 \text{Bo} & \text{PT} & \text{RR} & \text{CT} & \text{TS} \\
 1 & -1 & -1 & -1 & -1 \\
 1 & -1 & -1 & 0 & 0 \\
 1 & -1 & -1 & 1 & 1 \\
 1 & -1 & 0 & -1 & 0 \\
 1 & -1 & 0 & 0 & 1 \\
 1 & -1 & 0 & 1 & -1 \\
 1 & -1 & 1 & -1 & 1 \\
 1 & -1 & 1 & 0 & -1 \\
 1 & -1 & 1 & 1 & 0 \\
 1 & 0 & -1 & -1 & -1 \\
 1 & 0 & -1 & 0 & 0 \\
 1 & 0 & -1 & 1 & 1 \\
 1 & 0 & 0 & -1 & 0 \\
 1 & 0 & 0 & 0 & 1 \\
 1 & 0 & 0 & 1 & -1 \\
 1 & 0 & 1 & -1 & 1 \\
 1 & 0 & 1 & 0 & -1 \\
 1 & 0 & 1 & 1 & 0 \\
 1 & 1 & -1 & -1 & -1 \\
 1 & 1 & -1 & 0 & 0 \\
 1 & 1 & -1 & 1 & 1 \\
 1 & 1 & 0 & -1 & 0 \\
 1 & 1 & 0 & 0 & 1 \\
 1 & 1 & 0 & 1 & -1 \\
 1 & 1 & 1 & -1 & 1 \\
 1 & 1 & 1 & 0 & -1 \\
 1 & 1 & 1 & 1 & 0
 \end{array} \right]
 \end{array} \tag{C.15}$$

$$\hat{\underline{\beta}}_m = \begin{bmatrix} 66.83 \\ 0.18 \\ 0.93 \\ 3.67 \\ 1.60 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{matrix} \tag{C.16}$$

Therefore the fitted regression model for only the main factors, Y_m , for this example is:

$$Y_m = 66.83 + 0.18PT + 0.93RR + 3.67CT + 1.60TS \quad (C.17)$$

The interaction terms are now added, where:

$PT \times RR = -9/9 = -1$, $PT \times CT = 3/9 = 0.33$ and $PT \times TS = 9/9 = 1$. The interaction coefficients are therefore:

$$I = \begin{bmatrix} -1.0 \\ 0.33 \\ 1.0 \end{bmatrix} \quad (C.18)$$

The interaction terms are taken from the roof of the HOQ. Note that only the magnitude of the interactions will be used as coefficients. The mapping equation becomes $p = -0.015 + 0.052q$. And therefore the regression coefficient vector $\hat{\beta}_1$ including interaction takes the form:

$$\hat{\beta}_1 = \begin{bmatrix} 66.83 \\ 0.18 \\ 0.93 \\ 3.67 \\ 1.60 \\ 3.67 \\ 0.18 \\ 3.67 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{13} \\ \beta_{14} \end{matrix} \quad (C.19)$$

The new regression equation including interaction results in:

$$Y_i = 66.83 + 0.18\beta_1 + 0.93\beta_2 + 3.67\beta_3 + 1.60\beta_4 + 3.67\beta_{12} + 0.18\beta_{13} + 3.67\beta_{14} \quad (C.20)$$

where β_{12} is the interaction between *Paper Thickness* (PT) β_1 and *Roll Roundness* (RR) β_2 , whereas β_{13} is the interaction between *Paper Thickness* (PT) β_1 and *Coating*

Thickness (CT) β_3 . β_4 is the interaction between Paper Thickness (PT) β_1 and Tensile Strength (TS) β_4 . Using the regression equation in equation (C.20), new Fuzzy OEC responses are determined. The values of the response YI can be calculated based on the regression model in equation (C.20) by multiplying the regression coefficient matrix $\hat{\beta}_j$ in equation (C.19) with X_i in equation (C.21). The final Fuzzy OEC (Int_RA) after using the Fuzzy-QFD-Taguchi method is shown in equation (C.22).

	Bo	PT	RR	CT	TS	PTxRR	PTxCT	CTxTS
$X_1 =$	1	-1	-1	-1	-1	-1	-1	-1
	1	-1	-1	0	0	-1	0	0
	1	-1	-1	1	1	-1	1	1
	1	-1	0	-1	0	0	-1	1
	1	-1	0	0	1	0	0	-1
	1	-1	0	1	-1	0	1	0
	1	-1	1	-1	1	1	-1	0
	1	-1	1	0	-1	1	0	1
	1	-1	1	1	0	1	1	-1
	1	0	-1	-1	-1	1	1	-1
	1	0	-1	0	0	1	-1	0
	1	0	-1	1	1	1	0	1
	1	0	0	-1	0	-1	1	1
	1	0	0	0	1	-1	-1	-1
	1	0	0	1	-1	-1	0	0
	1	0	1	-1	1	0	1	0
	1	0	1	0	-1	0	-1	1
	1	0	1	1	0	0	0	-1
	1	1	-1	-1	-1	0	0	-1
	1	1	-1	0	0	0	1	0
	1	1	-1	1	1	0	-1	1
	1	1	0	-1	0	1	0	1
	1	1	0	0	1	1	1	-1
	1	1	0	1	-1	1	-1	0
	1	1	1	-1	1	-1	0	0
	1	1	1	0	-1	-1	1	1
	1	1	1	1	0	-1	-1	-1

(C.21)

$$Y_i = \begin{array}{|c} \text{OEC} \\ \hline 52.9 \\ 62.1 \\ 71.2 \\ 62.8 \\ 71.9 \\ 65.2 \\ 72.7 \\ 65.9 \\ 75.1 \\ 69.8 \\ 67.3 \\ 71.6 \\ 57.6 \\ 61.4 \\ 70.5 \\ 62.7 \\ 71.3 \\ 69.4 \\ 64.0 \\ 68.3 \\ 65.9 \\ 69.1 \\ 67.2 \\ 75.8 \\ 56.9 \\ 66.1 \\ 69.8 \\ \hline \end{array} \quad (C.22)$$

C.4.2 Thumbtack example

The calculation of the regression model requires the response matrix Y_m (equation (C.23)) and the coded factor level matrix X_m (equation (C.24)). The calculated regression coefficients are given in equation (C.25).

	Fuzzy_OEC
$Y_m =$	57.376
	61.900
	59.307
	67.071
	65.572
	63.918
	72.288
	71.727
	75.157
	55.798
	54.299
	52.645
	59.470
	58.910
	62.340
	65.625
	70.149
	67.556
	57.223
	56.663
	60.093
	61.834
	66.358
	63.765
	73.073
	71.574
	69.920

(C.23)

$$\begin{array}{c}
 X_m = \\
 \left[\begin{array}{ccccc}
 \text{Bo} & \text{HD} & \text{SJ} & \text{PS} & \text{PD} \\
 1 & -1 & -1 & -1 & -1 \\
 1 & -1 & -1 & 0 & 0 \\
 1 & -1 & -1 & 1 & 1 \\
 1 & -1 & 0 & -1 & 0 \\
 1 & -1 & 0 & 0 & 1 \\
 1 & -1 & 0 & 1 & -1 \\
 1 & -1 & 1 & -1 & 1 \\
 1 & -1 & 1 & 0 & -1 \\
 1 & -1 & 1 & 1 & 0 \\
 1 & 0 & -1 & -1 & 0 \\
 1 & 0 & -1 & 0 & 1 \\
 1 & 0 & -1 & 1 & -1 \\
 1 & 0 & 0 & -1 & 1 \\
 1 & 0 & 0 & 0 & -1 \\
 1 & 0 & 0 & 1 & 0 \\
 1 & 0 & 1 & -1 & -1 \\
 1 & 0 & 1 & 0 & 0 \\
 1 & 0 & 1 & 1 & 1 \\
 1 & 1 & -1 & -1 & 1 \\
 1 & 1 & -1 & 0 & -1 \\
 1 & 1 & -1 & 1 & 0 \\
 1 & 1 & 0 & -1 & -1 \\
 1 & 1 & 0 & 0 & 0 \\
 1 & 1 & 0 & 1 & 1 \\
 1 & 1 & 1 & -1 & 0 \\
 1 & 1 & 1 & 0 & 1 \\
 1 & 1 & 1 & 1 & -1
 \end{array} \right]
 \end{array}
 \tag{C.24}$$

$$\hat{\beta}_m = \begin{bmatrix} 63.76 \\ -0.77 \\ 6.77 \\ 0.27 \\ 0.69 \end{bmatrix} \begin{array}{l} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{array}
 \tag{C.25}$$

Therefore the fitted regression model for the main factors Y_m , for this example is:

$$Y_m = 63.76 - 0.77 HD + 6.77 SJ + 0.27 SP + 0.69 PD \quad (C.26)$$

The interaction terms are then added to the regression model, where:

$HD \times SJ = 3/9 = 0.33$ and $SP \times PD = -9/9 = -1$ and the coefficients of the interaction are:

$$I = \begin{bmatrix} 0.33 \\ -1.0 \end{bmatrix} \quad (C.27)$$

The interaction terms are taken from the roof of the original HOQ. The mapping equation becomes $p = -4.484 + 11.254q$. Therefore the regression coefficient matrix $\hat{\beta}_I$ including interaction takes the form:

$$\hat{\beta}_I = \begin{bmatrix} 63.76 \\ -0.77 \\ 6.77 \\ 0.27 \\ 0.69 \\ -0.77 \\ 6.77 \end{bmatrix} \begin{matrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{34} \end{matrix} \quad (C.28)$$

The new regression equation Y_I including interactions results in:

$$Y_I = 63.76 - 0.77 \beta_1 + 6.77 \beta_2 + 0.27 \beta_3 + 0.69 \beta_4 - 0.77 \beta_{12} + 6.77 \beta_{34} \quad (C.29)$$

where β_{12} is the interaction between *Head Diameter (HD)*, β_1 and *Strength of Join (SJ)*, β_2 , whereas β_{34} is the interaction between *Pin Sharpness (PS)*, β_3 and *Pin Diameter (PD)*, β_4 . Using the new regression equation (C.29), new Fuzzy_OEC responses are determined. The regression coefficient, $\hat{\beta}_I$, from equation (C.28) and the coded factor level matrix, X_b (equation (C.30)) are multiplied together to determine the new response, Fuzzy_OEC_Interaction_Regression Analysis (equation (C.31)).

	B ₀	HD	SJ	PS	PD	HD&SJ	PS&PD
X ₁	1	-1	-1	-1	-1	-1	-1
	1	-1	-1	0	0	-1	0
	1	-1	-1	1	1	-1	1
	1	-1	0	-1	0	0	1
	1	-1	0	0	1	0	-1
	1	-1	0	1	-1	0	0
	1	-1	1	-1	1	1	0
	1	-1	1	0	-1	1	1
	1	-1	1	1	0	1	-1
	1	0	-1	-1	0	1	1
	1	0	-1	0	1	1	-1
	1	0	-1	1	-1	1	0
	1	0	0	-1	1	-1	0
	1	0	0	0	-1	-1	1
	1	0	0	1	0	-1	-1
	1	0	1	-1	-1	0	-1
	1	0	1	0	0	0	0
	1	0	1	1	1	0	1
	1	1	-1	-1	1	0	0
	1	1	-1	0	-1	0	1
	1	1	-1	1	0	0	-1
	1	1	0	-1	-1	1	-1
	1	1	0	0	0	1	0
	1	1	0	1	1	1	1
	1	1	1	-1	0	-1	1
	1	1	1	0	1	-1	-1
	1	1	1	1	-1	-1	0

(C.30)

$$\begin{aligned} & 50.80 \\ & 58.53 \\ & 66.26 \\ & 71.72 \\ & 57.07 \\ & 64.80 \\ & 70.26 \\ & 77.99 \\ & 63.34 \\ & 62.03 \\ & 49.45 \\ & 57.18 \\ & 64.95 \\ \text{Fuzzy_OEC(Int_RA)} = & 70.61 \\ & 58.03 \\ & 63.49 \\ & 71.22 \\ & 76.88 \\ & 55.26 \\ & 62.99 \\ & 50.41 \\ & 55.87 \\ & 61.53 \\ & 69.26 \\ & 77.03 \\ & 64.45 \\ & 70.11 \end{aligned} \tag{C.31}$$

Appendix D.

List of papers resulting from the research

This Appendix lists papers published during the course of this research.

Bouchereau, V. and Rowlands, H. (June 2000). A helping hand for QFD. *Transactions of the 44th European Quality Congress, Budapest, Hungary* **2**, pp. 282-289.

Bouchereau, V. and Rowlands, H. (Mar 2000). Methods and techniques to help QFD. *Benchmarking: An International Journal* **7**, (1), pp.8-19.

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Bouchereau, V. and Rowlands, H. (Sept 99). Artificial Intelligence: a helping hand for Quality Function Deployment (QFD). *Workshop on European Scientific and Industrial Collaboration (WESIC '99), UK*, pp. 383-390.

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