DECISION MAKING APPROACHES FOR SOFTWARE QUALITY FUNCTION DEPLOYMENT

(YAZILIM KALİTE FONKSİYONU YAYILIMI İÇİN
KARAR VERME YAKLAŞIMLARI)

by

Zeynep ŞENER, M.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

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Abstract

With the rapid development of software industry, improving software quality has gained increasing importance. Software development has been troubled by many problems, such as underestimation of cost, poor quality and customer dissatisfaction, since the inception of business computer systems in the 1950's. These problems are generally associated with incorrect or incomplete specification of customer needs, and still persist in spite of the technical advances in software engineering tools in the past two decades. Software manufacturers have recently applied quality improvement techniques to software development to respond to the needs for software quality. Quality function deployment (QFD) has been utilized to develop software that maximizes customer satisfaction.

QFD is a customer-oriented design tool for maximizing customer satisfaction. As an interdisciplinary team process, QFD is used to plan and design new or improved products or services that satisfy customer needs. The basic concept of QFD is to translate the desires of customers into engineering characteristics, and subsequently into parts characteristics, process plans and production requirements. In order to establish these relationships, QFD usually requires four matrices each corresponding to a stage of the product development cycle. These are product planning, part deployment, process planning, and production/operation planning matrices, respectively. The product planning matrix, called the house of quality (HOQ), which translates customer needs into engineering characteristics, is the most frequently employed matrix in QFD.

QFD allows for the company to allocate resources and to coordinate skills based on customer needs, and thus, helps to decrease production costs and to reduce the cycle time. It evaluates the necessary decisions for change and development at the beginning of the product design phase and minimizes the corrections during the entire development process.

Since its initial development in Japan in the late 1960s, QFD continues to be one of the most popular total quality management techniques. The QFD technique has been widely used successfully in the manufacturing industry for many years. However, it has been recently applied to software development.

Software quality function deployment (SQFD) represents a transfer of the technology of QFD from product manufacturing to software development. SQFD is a structured methodology which focuses on improving the quality of software development process to create products responsive to customer expectations by deploying the voice of customer throughout the development process. As a front-end technique, SQFD is an adaptation of the HOQ, the most commonly used matrix in the traditional QFD methodology. The objective of the HOQ is to determine the target levels of engineering characteristics of a product to maximize customer satisfaction.

The process of setting the target levels is, in general, accomplished in a subjective ad hoc manner, or in a heuristic way. Due to many tradeoffs that may exist among implicit or explicit relationships between customer needs and engineering characteristics and among engineering characteristics, these relationships cannot be identified using engineering knowledge. Moreover, such relationships are generally vague in practice. The vagueness arises mainly from the fact that the customer needs, which tend to be subjective and qualitative, need to be translated into engineering characteristics which are more quantitative and technical. Further, data available for product design is often limited and inaccurate. The inherent fuzziness of functional relationships in QFD modeling promotes fuzzy regression as an effective tool for parameter estimation.

The assumptions of classical statistical regression are difficult to justify unless a sufficiently large data set is available. The violation of these assumptions can adversely affect the performance of statistical regression model. Fuzzy regression has been reported as a more suitable tool than statistical regression when the data set is limited, human judgments are involved, and the degree of system fuzziness is high.

In this work, fuzzy regression is used to estimate the parameters of functional relationships between customer needs and engineering characteristics and among engineering characteristics. Then, target levels of engineering characteristics are determined using an optimization approach that employs parameters of functional relationships obtained by fuzzy regression. In order to build a model which employs crisp parameters, the center value estimates from fuzzy regression are used as the parameter estimates and the spread values are neglected. When the spread values of fuzzy parameters are also considered, a fuzzy mathematical programming formulation to maximize customer satisfaction is developed.

Although QFD aims to maximize customer satisfaction, requirements related to enterprise satisfaction such as extendibility and technical difficulty also need to be considered. In this work, a fuzzy multiple objective decision framework that includes not only fulfillment of engineering characteristics to maximize customer satisfaction, but also minimization of technical difficulty as an objective to determine target levels of engineering characteristics, is presented.

Customer needs obtained at the beginning of the QFD process are used to design new or improved products. Due to the time spent during the analysis and production, an innovative product cannot fully meet customer expectations when it is ready to market. In order to avoid this problem, the fuzzy multiple objective decision making approach presented in this paper is extended by considering future expectations to determine target levels of the new or improved software products that meet customer needs at the time when the product reaches the market. A search engine quality improvement problem is presented to illustrate the application of the proposed approaches.

Résumé

L'amélioration du processus du développement des nouveaux produits représente la clé du succès dans un monde compétitif. De nos jours, les entreprises utilisent différent techniques afin de pouvoir maintenir le niveau de qualité nécessaire pour continuer à survivre. Le déploiement de la fonction qualité (DFQ) est une des techniques de la gestion de la qualité totale qui est conçue pour satisfaire les attentes du client.

Le DFQ est une méthode de développement de produit visée sur les besoins du client. La méthode consiste à déployer les attributs d'un produit ou d'un service exigés par le client dans chaque étape de la production. Le DFQ est basé sur la traduction des besoins du client aux caractéristiques techniques de l'ingénierie. Comme les besoins du client sont considérés dès la première étape de la planification, le DFQ empêche l'augmentation des coûts de correction. Il permet à l'entreprise de faire la production en dépensant moins de ressources.

Le DFQ utilise des matrices correspondant aux étapes de la production pour traduire les attentes des clients aux exigences détaillées de production. La première matrice, appelée la maison de qualité, qui traduit les besoins du client aux caractéristiques techniques est la matrice la plus utilisée dans le DFQ.

Même si l'utilisation du DQF est très répandue dans certaines branches de l'industrie, la technique est assez rare utilisée pour le développement des logiciels. Suivant les changements rapides dans le domaine informatique, les producteurs des logiciels souffrent des problèmes de coût, de durée et de la qualité. Ces problèmes qui règnent sur l'industrie d'informatique sont souvent reliés au définition incomplet des besoins du client. Les entreprises d'informatique ont récemment commencé à utiliser les techniques d'amélioration de la qualité au processus du développement des logiciels afin de satisfaire la clientèle.

Le déploiement de la fonction qualité des logiciels (DFQL) consiste à l'application de la maison de qualité pour pouvoir améliorer la qualité du processus de développement des logiciels. L'objectif de la maison de qualité est de déterminer les valeurs cibles pour les caractéristiques techniques qui maximisent la satisfaction du client.

La détermination des valeurs cibles pour les caractéristiques techniques est accomplie en général de manière subjective. L'équipe de conception détermine les relations entre les besoins du client et les caractéristiques techniques et forme la matrice de corrélation de caractéristiques techniques selon leurs jugements. En effet, ces relations sont imprécises et les degrés des compromis existant entre elles sont difficiles à prédire. De plus, les données de production sont assez limitées. La régression floue qui a la capacité de modéliser les cas où les relations entre les paramètres du système ne sont pas bien définis, est une technique effective pour estimer les relations entre les besoins du client et les caractéristiques techniques et les relations entre les caractéristiques techniques elles-mêmes.

L'analyse de régression est considérée comme une technique indispensable dans la plupart des domaines scientifiques. Elle est utilisée pour modéliser les relations entre les variables. La technique est basée sur le calcul des coefficients (les paramètres du modèle) qui décrivent à quelle mesure les variables dites indépendantes sont liées à une variable qui dépend d'elles, nommée variable dépendante. L'analyse de régression permet de décrire les relations entre les variables par estimation des paramètres du système et de prédire les valeurs de la variable dépendante en utilisant les valeurs des variables indépendantes.

La régression classique fait des hypothèses strictes sur les propriétés statistiques du modèle qui ne sont pas facilement être justifiées si l'ensemble de données n'est pas suffisamment large. La violation des ces règles peut affecter la validité et la performance de la régression statistique. La régression floue est plus effective que la régression linéaire statistique quand les hypothèses ne peuvent pas être employées proprement, si par exemple les jugements humains ou des processus ambigus sont présents.

Dans ce travail, la régression floue est employée afin d'estimer les relations entre les besoins du client et les caractéristiques techniques et les relations entre les caractéristiques techniques elles-mêmes. Des approches de décision qui considèrent les objectifs du client et ceux de l'entreprise sont développées en utilisant les paramètres obtenues par la régression floue.

Les besoins du client forment la base et le point de départ du DFQ. Au fur et à mesure que l'équipe de conception définissent les valeurs cibles pour les caractéristiques du nouveau produit d'après les attentes du client obtenues précédemment, ces attentes peuvent se changer. Par conséquent, particulièrement pour les industries d'informatique, le produit conçu possède le risque de ne pas satisfaire le client quand il est prêt à être vendu. Afin d'éliminer ce risque, ce travail considère les besoins futures du client pour déterminer les valeurs cibles des caractéristiques techniques d'un logiciel nouveau ou amélioré. Les applications des approches proposées sont présentées à l'aide d'un exemple du développement d'un moteur de recherche sur web.

Özet

Yazılım endüstrisinin yakın geçmişte yaşadığı hızlı gelişmeler önemli kalite sorunlarını beraberinde getirmiştir. Artan rekabet ortamının etkisiyle, yazılım kalitesinin iyileştirilmesine daha fazla önem veren yazılım üreticileri, bilgisayar teknolojilerinin ortaya çıkmasından bu yana varolan müşteri memnuniyetsizliği, düşük kalite ve yanlış maliyetlendirme gibi sorunların çözümünde kalite iyileştirme yöntemlerinden yararlanmaya başlamışlardır. Günümüzde, kalite fonksiyonu yayılımı (KFY), müşteri beklentilerini karşılayan daha kaliteli tasarımlar oluşturmaya yardımcı bir yöntem olarak yazılım geliştirme sürecine uygulanmaktadır.

KFY, 1960'lı yıllarda Japonya'da, müşteri memnuniyetini sağlayacak ürün ve hizmetler geliştirmeyi amaçlayan müşteri odaklı bir kalite sistemi olarak tasarlanmıştır. KFY ürünün tasarım aşamasında müşteri isteklerinin karşılanmasını sağlamaktadır. KFY daha kısa sürede ve daha az maliyetle müşteri beklentilerini karşılayan ürünler geliştirmeye yardımcı olmaktadır. Üretim yapan işletmeler tarafından yaygın şekilde kullanılmasından uzun zaman sonra yazılım geliştirme sürecine uygulanmıştır. KFY yönteminin yazılım geliştirme sürecine uyarlaması yazılım kalite fonksiyonu yayılımı (YKFY) olarak adlandırılmaktadır.

Kalite fonksiyonun yayılımı yaklaşımında esas olan müşteri beklentilerinin teknik özelliklere dönüştürülmesidir. Bu şekilde sırasıyla teknik özellikler parça özelliklerine, süreç planlarına ve üretim gereksinimlerine dönüştürülmektedir. Sayılan ilişkilerin tanımlanmasında KFY, her biri ürün geliştirme döngüsünün farklı bir aşamasını belirten dört matristen yararlanmaktadır. Bu dört matristen ilki Kalite Evi olarak adlandırılmakta ve KFY uygulamalarının en sık kullanılan matrisi olma özelliğini taşımaktadır. Kalite evi, bölümler arası planlama ve iletişime yol gösteren kavramsal bir haritadır.

Müşteri beklentileri ile teknik özellikler arasındaki ilişkiler kalite evinin gövde kısmında, teknik özelliklerin kendi aralarındaki ilişkiler ise çatı matrisinde gösterilmektedir. Kalite evinin amacı müşteri memnuniyetini en büyükleyecek şekilde bir ürünün teknik özelliklerinin hedef değerlerinin belirlenmesidir.

Teknik özelliklerin hedef değerlerinin belirlenmesindeki zorluk, tanımlanan ilişkilerin genelde belirsizlik içermesinden kaynaklanmaktadır. Bu süreçteki belirsizliğin nedeni, öznel ve nitel şekilde elde edilen müşteri isteklerinin nicel ve teknik terimlerle ifade edilen teknik özelliklere dönüştürülmesidir. Ürünün tasarımı için gerekli olan veri kümesi çoğunlukla yetersizdir. Bulanık regresyon yönteminin sistem parametreleri arasındaki ilişkilerin kesin olarak tanımlanamadığı durumları modelleyebilme özelliği, kalite fonksiyonu yayılımı yaklaşımında müşteri beklentileri ile teknik özellikler arasındaki ilişkiler ile teknik özelliklerin kendi aralarındaki belirsizlik içeren ilişkilerin tahmin edilmesinde bulanık regresyonu etkin bir araç haline getirmektedir.

Klasik regresyon analizi modelin istatistiksel özellikleri hakkında bazı varsayımlar gerektirmektedir. Fakat bu varsayımların sağlanması, her koşulda kolay olmamaktadır. Sistem yapısındaki belirsizliğe bağlı olarak verilerin tamamının ya da bir kısmının kesin sayılar olarak elde edilememesi veya sistem yapısının değişkenler arasında kesin ilişkiler tanımlanmasına imkan vermemesi gibi durumlarda klasik regresyon analizinin uygulanması mümkün değildir.

Klasik regresyon analizinin gerektirdiği şartların sağlanamadığı ve belirsizliğin hakim olduğu durumlarda bulanık regresyon analizi etkili bir araç haline gelmektedir. Bulanık regresyonun, değişkenlerin bulanık sayılar olarak ifade edilmesi ya da sistem parametreleri arasındaki ilişkilerin net olarak tanımlanamaması halinde kullanılması önerilmektedir.

Bu çalışmada KFY yaklaşımında, müşteri beklentileri ile teknik özellikler arasındaki ilişkiler ve teknik özelliklerin kendi aralarındaki ilişkilerin belirlenmesinde bulanık regresyon yönteminden yararlanılmıştır. Bulanık regresyon sonucunda belirlenen parametrelerden yararlanılarak, teknik özelliklerin hedef değerlerinin belirlenmesi için karar verme yaklaşımları önerilmiştir.

Bulanık regresyon analizi ile elde edilen parametrelerin sadece merkez değerleri dikkate alınarak oluşturulan optimizasyon modeli, parametreleri bulanık şekilde içeren bulanık programlama modeli oluşturularak geliştirilmiş ve çözülmüştür. Müşteri memnuniyetinin enbüyüklenmesini amaçlayan bu modeller, teknik özelliklerin zorluk derecesinin enküçüklenmesi amacının da dikkate alınması ile çok amaçlı programlama modellerine dönüştürülmüştür. Bu şekilde, müşteri memnuniyetinin yanı sıra işletmenin beklentilerinin de sağlanması mümkün hale gelmektedir.

Yeni ürünlerin geliştirilmesinde, KFY sürecinin en başında elde edilen müşteri isteklerinden yararlanılmaktadır. KFY yaklaşımının uygulanması sırasında harcanan zaman nedeniyle, özellikle yenilikçi ürünler, piyasaya sunulduklarında mevcut müşteri beklentilerinin tamamını karşılayamama riski taşımaktadırlar. Bu nedenle, hızla değişen ihtiyaçların takip edilerek üretim sürecine dahil edilmesi gerekmektedir. Bu çalışmada, geliştirilen yazılım ürünlerinin satışa hazır hale geldiklerinde müşteri isteklerini tam olarak karşılamasını amaçlayan, gelecekte meydana gelebilecek değişimlerin dikkate alındığı yeni bir yaklaşım önerilmektedir. Geliştirilen karar verme yaklaşımlarının uygulaması internet arama motoru tasarımı örneğiyle incelenmektedir.

1. Introduction

During the past decade, the software industry has undergone a huge revolution. While the market has grown rapidly, competition has also intensified with an increase in the number of software firms. With heightened competition, the improvement of the quality of software development has gained increasing importance.

Software manufacturers have recently applied quality improvement techniques to software development to respond to the need for software quality. Total quality management (TQM) techniques helping software developers have received increasing attention parallel to the upward trend in the use of computer technology applications. Quality function deployment (QFD), as a technique for better quality designs that match customer needs, has been applied to software development to maximize customer satisfaction.

In the past, most software quality efforts have concentrated on minimizing customer dissatisfaction. Problems in the customer needs are typically not recognized until late in the software development process, where negative impacts are substantial and cost for correction has grown large [1]. Even worse, problems in the customer needs may go undetected through the development process, resulting in software systems not meeting customers' expectations. Therefore, methods that help software engineers to better understand software requirements are of great interest [2]. QFD is quite different from traditional quality improvement techniques that aim at minimizing defects. It concentrates on maximizing customer satisfaction from the software development process.

QFD is a customer-oriented design tool used to maximize customer satisfaction. According to Akao [3], who developed this technique with Katsuyo Ishihara in the mid 1960s, QFD is "a method for developing a design quality aimed at satisfying the customer and then translating the customer’s demands into design targets and major quality assurance points to be used throughout the production stage”.

QFD was originally proposed to develop products with higher quality to respond customer needs. Hence, the primary functions of QFD are product development, quality management, and customer needs analysis. Afterwards, functions of QFD have been expanded to planning, decision-making, engineering, management, timing, and costing [4]. QFD is widely used by manufacturing companies, and has been lately applied to software development.

Software quality function deployment (SQFD) represents a transfer of the technology of QFD from product manufacturing to software development [5]. SQFD is a structured methodology which focuses on improving the quality of software development process to create products responsive to customer expectations by deploying the voice of customer throughout the development process [6].

QFD incorporates satisfaction of customer requirements into every software development activity, and it has been applied in the development of many software products. Although QFD is now a well-defined discipline, SQFD lacks appropriate case study presentation and research.

Despite its numerous benefits, researchers have reported some problems with the QFD method. Several attempts have been made to cope with these difficulties such as ambiguity in the voice of costumer, need to input and analyze large amounts of subjective data, impreciseness in the process of setting target values [7]. QFD still has several limits in application, and therefore can be improved further.

The purpose of this thesis is to propose decision making approaches to attempt the solution of some of these problems. In particular, the focus is on the development of mathematical models, which incorporate imprecise and subjective information inherent in the SQFD planning process, to determine target levels of engineering characteristics of the new or improved products that meet customer needs at the time when the product reaches the market.

The rest of this study is organized as follows. In section 2, a brief description of QFD is presented and the existing work addressing the uncertainty in the QFD method is reviewed. Section 3 describes the SQFD process and contains a detailed literature review of SQFD. In section 4, fuzzy linear regression technique which is used to assess the relationships with incorporating both quantitative and qualitative information is presented. Decision making approaches are formulated in section 5. The decision framework to extend the concept of “listening to the voice of customer” into future is described in section 6. In section 7, a search engine quality improvement problem is presented to illustrate the proposed approaches. The results of the illustrative application are discussed in section 8. Finally, the conclusions are provided in the last section.

2. Quality Function Deployment

2.1. Introduction

Today, technological innovations and changing customer demands threaten the survival of companies in global markets. In order to cope with this problem these companies focus on product development, which is the key factor of success. Quality function deployment (QFD) is a strategic tool to help companies in developing products that satisfy the desires of customers.

QFD is used to develop better products and services responsive to customer needs. It employs a cross-functional team to identify the needs of the customer and translate them into design characteristics to plan new or improved products. QFD ensures a higher quality level that meets customer expectations throughout each stage of product planning.

According to the American Supplier Institute (ASI), QFD is “a system for translating customer or user requirements into appropriate company requirements at every stage from research, through product design and development, to manufacture, distribution, installation and marketing, sales, and service” [8].

Growth Opportunity Alliance of Lawrence, Massachusetts/Quality Productivity Center (GOAL/QPC) defines QFD as a system for designing products and services based on customer demand and involving all members of the producer or supplier organizations [8].

QFD allows for the company to allocate resources and to coordinate skills based on customer needs, and thus, helps to decrease production costs and to reduce the cycle time. It evaluates the necessary decisions for change and development at the beginning of the product design phase and minimizes the corrections during the entire development process.

QFD was originally proposed, through a well structured framework of analyzing the needs of the customer, to develop products with higher quality to meet or exceed customer expectations. Hence, at first, QFD was used for product development, quality management, and customer needs analysis. Later, quality function deployment's functions have been expanded to wider fields such as design, planning, decision-making, engineering, management, teamwork, timing, and costing. Essentially there is no definite boundary for quality function deployment's potential fields of applications [4].

Since its initial development in Japan in the late 1960s, QFD continues to be one of the most popular total quality management techniques. In order to improve the reliability of QFD methodology and to apply it in a more objective way, numerous quantitative methods have been presented. The extensions of QFD are now used by companies from a variety of industries all over the world as a part of their product development processes.

2.2. History

QFD's history began in Japan with a process assurance items chart created by Mr. Oshiumi of the Kurume Mant plant of Bridgestone Tire Corporation. This chart that contains some of the basic characteristics of QFD and the ideas of *functional deployment of business* developed by K. Ishihara formed the basis of the quality system called *hinshitsu tenkai* and conceptualized by Akao in the late 1960s in order to convert engineering characteristics of a product into quality control points in the quality control process charts prior to production startup [4].

QFD was first implemented at the Kobe Shipyards of Mitsubishi Heavy Industries Ltd. in 1972, and at the same time a quality table that showed correlations between the required quality functions and the engineering characteristics was created. Akao formulated all these into a technique called *hinshitsu kino tenkai* which translates the needs of customer into the production operations.

The term *quality function deployment* was originated from this Japanese phrase consisting of three words *hinshitsu kino tenkai* with the following meanings [8]:

- *hinshitsu* can mean quality, features, attributes, or qualities,
- *kino* can mean function or mechanism,
- *tenkai* can mean development, deployment, or evolution.

According to the meanings of these Japanese words, QFD means deploying the attributes of a product or service desired by the customer throughout all the appropriate functional components of an organization [9].

After the first implementation at the Kobe Shipyards of Mitsubishi Heavy Industries Ltd., QFD was introduced to Toyota and it has been used in many Japanese industries since then. Even though its application was followed by successful implementations throughout Japan, QFD was brought to the attention of the U.S. firms ten years later by an article by Kogure and Akao [10].

The American Supplier Institute (ASI) and GOAL/QPC (Growth Opportunity Alliance of Lawrence, Massachusetts/Quality Productivity Center) have done an important job in publicizing QFD in the United States [11]. Early adopters of QFD in the U.S. included Ford, General Motors, Chrysler, AT&T, Procter and Gamble, Hewlett-Packard, Digital Equipment, ITT, Baxter Healthcare, 3M Company, Motorola, NASA, and Xerox [4, 11]. Recently, the U.S. companies have used QFD to a greater extent than Japanese companies and have reported deriving more significant product and process improvements. Management support and cross-functional involvement are also higher in the U.S. companies [12].

2.3. Overview

QFD focuses on delivering value by taking into account the desires of the customer and then using this information throughout the entire product development process. A key objective of QFD is to determine directly from the customer what they expect from a product or service. QFD translates the customer needs which tend to be subjective and qualitative into engineering characteristics which are expressed in technical and quantitative terms.

QFD is a systematic process for capturing customer needs and translating them into requirements that must be met throughout the supply chain. The result is a set of target values for designers, production people, and even suppliers to aim at, in order to produce the output desired by the customer [8].

The basic concept of QFD is to translate the desires of customers into engineering characteristics, and subsequently into parts characteristics, process plans and production requirements. In order to establish these relationships, QFD usually requires four matrices each corresponding to a stage of the product development cycle. These are product planning, part deployment, process planning, and production/operation planning matrices, respectively. The product planning matrix translates customer needs into engineering characteristics; the part deployment matrix translates important engineering characteristics into product/part characteristics; the process planning matrix translates important product/part characteristics into manufacturing operations; the production/operation planning matrix translates important manufacturing operations into day-to-day operations and controls [13].

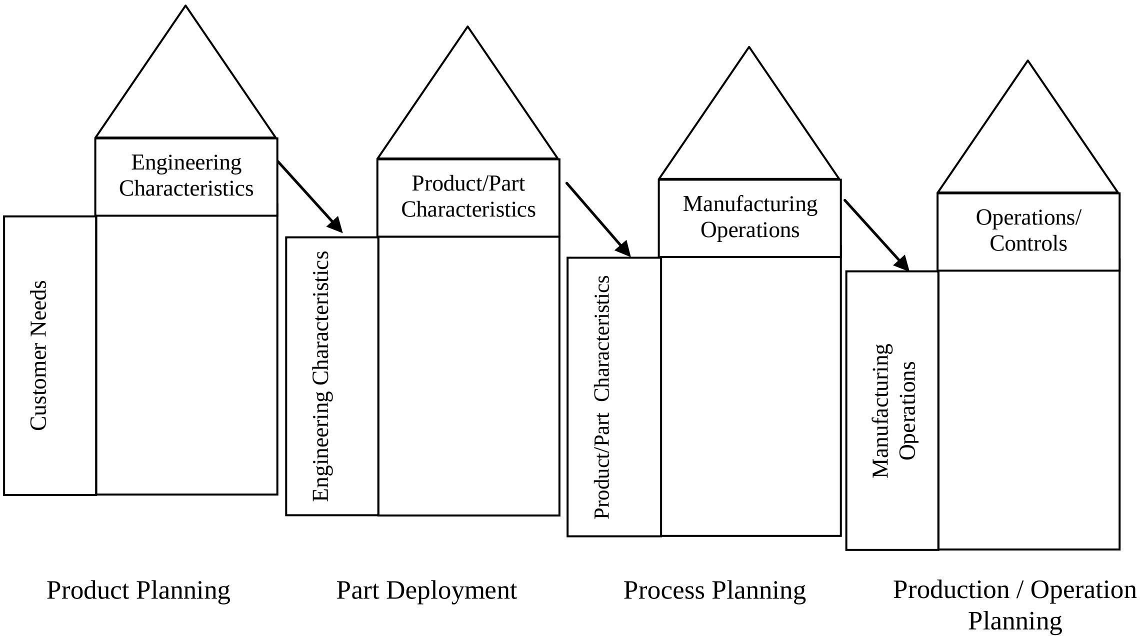

Figure 2.1. The four phases of QFD process

The first of the four matrices, called the house of quality (HOQ), is the most frequently employed matrix in QFD. The majority of the QFD applications end when the HOQ is built. Han et al. [14] state that many companies, such as Volvo, have found that a great deal of benefit can be achieved from just completing the first matrix. According to Cox [15], no more than five percent of companies go beyond the HOQ.

QFD allows for the company to enhance sales and profits while decreasing production costs and reducing the cycle time. It evaluates the necessary decisions for change and development at the beginning of the product design phase and minimizes the corrections during the entire development process. The implementation of QFD at companies encourages the teamwork to work for a common goal of maximizing customer satisfaction.

2.4. The House of Quality

The quality chart topped with a triangular peak, created by Toyota Auto Body, was for the first time referred by the name *house of quality* at a Japanese Society for Quality Control research presentation conference by Sawada in 1979 because of its shape [16]. This name was later introduced in the U.S. and it came to be popular.

The house of quality (HOQ) is a conceptual map that provides the means for interfunctional planning and communications [17]. It contains seven elements as shown in Figure 2.2.

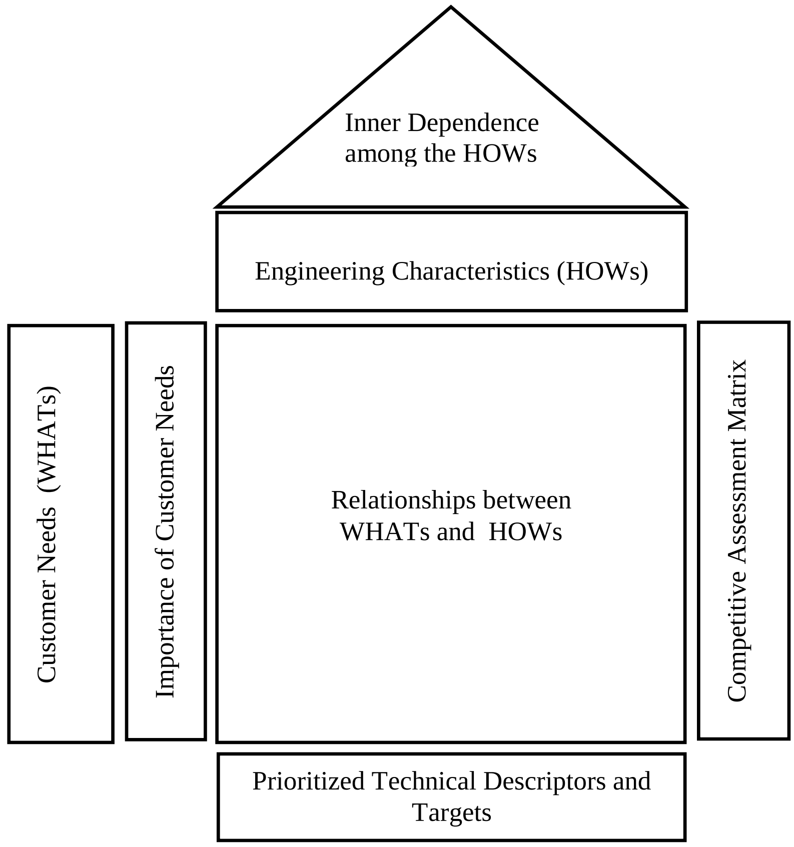

Figure 2.2. The House of Quality

1. Customer needs (WHATs). The process of building the HOQ begins with the collection of the needs of customers for the product or service concerned. Customers express what they want in their own words. The list of customer needs (CNs), also called the voice of customer (VOC), can be obtained through focus groups, individual interviews or mail and telephone surveys. All customers are not supposed to be end users. Customer needs can include the requirements of retailers or the needs of vendors.

2. Engineering characteristics (HOWs). Engineering characteristics (ECs), which are sometimes called the voice of company, describe the product in the language of the engineer. They are used to determine how well the company satisfies the customer needs. They tell the company how to do what the customers want. Engineering characteristics, which must be stated in measurable and benchmarkable terms, are defined by the QFD team using brainstorming technique or a tree analogy.

3. Importance of customer needs. The list of customer needs must be reviewed and must be rated by the company in order to determine the most important needs. The process of determining the weights is generally based on QFD team members' experience with customers or on surveys using 5-, 7-, 9- point scales. Innovative companies utilize more recent quantitative techniques such as analytic hierarchy process (AHP) in order to obtain the importance of customer needs.

4. Competitive assessment matrix. This matrix contains a competitive analysis of the company's product with main competitors' products for customer needs. Thus, the relative position of the company's product can be assessed in terms of customer needs. The information needed can be obtained by asking the customers, for each customer need, to rate the performance of the company's and its competitors' products using a scale.

5. Relationships between WHATs and HOWs. The relationship matrix indicates how much each engineering characteristic affects each customer need. The relationships between customer needs and engineering characteristics are generally expressed with graphic symbols which are translated in an appropriate rating scale.

6. Inner dependence among the HOWs. The roof matrix of the HOQ indicates how engineering characteristics affect each other. A positive relationship indicates that two engineering characteristics can improve each other, while a negative relationship indicates that a desirable change in one engineering characteristic adversely affects the improvement of another engineering characteristic.

7. Prioritized technical descriptors and targets. This part of the HOQ indicates the effects of all prior variables on each product feature. It may also contain target levels for engineering characteristics and a competitive analysis of other competitors' measures for the same variables [13].

The objective of the HOQ is to determine the target levels of engineering characteristics of a product to maximize customer satisfaction. The process of setting the target levels is currently accomplished in a subjective, ad hoc manner. In general, importance of customer needs, degree of relationship between customer needs and engineering characteristics, dependence among engineering characteristics, technical difficulty of changing or maintaining engineering characteristics, and cost of engineering characteristics cannot be assessed by either crisp values or random processes. Fuzzy set theory appears to be an effective means to represent imprecise design information [18].

2.5. Uncertainty in QFD

Despite its numerous benefits, researchers have reported some problems with the QFD method such as ambiguity in the VOC, need to input and analyze large amounts of subjective data, impreciseness in the process of setting target values in the HOQ [7].

The vagueness or imprecision arises mainly from the fact that the customer needs, which tend to be subjective, qualitative, and nontechnical, need to be translated into engineering characteristics which should be expressed in more quantitative and technical terms. Further, data available for product design is often limited, inaccurate, or vague at best [19].

Notwithstanding the rapid growth of the QFD literature, development of systematic procedures for handling uncertainty and variability has not received due attention. The degree of uncertainty in the input information becomes even more serious when developing an entirely new product that has a short life cycle. The effect of the uncertainty in the input information of QFD which may arise from four different sources; namely, fuzziness, heterogeneity, fluctuation, and incompleteness, is propagated into the output of QFD, leading the variability of QFD analysis results [20].

The uncertainty can be described in the context of the customer needs' weights. Fuzziness is associated with the imprecise and vague nature of the customer's understanding of the customer needs' relative weights. Different viewpoints of customers cause the heterogeneity, and the change of the desires of customers over time reveals the fluctuation. Incompleteness comes from limited information processing capabilities of customers.

Fuzzy methods are widely used in QFD to deal with the subjectivity and ambiguity of evaluations on the customer needs and engineering characteristics, and assessing the relationships between customer needs and engineering characteristics, and also among engineering characteristics.

There are a number of works applying fuzzy set theory to QFD. Masud and Dean [21] presented an approach for prioritizing engineering characteristics using the fuzzy weighted average method. Khoo and Ho [22] employed symmetric triangular fuzzy numbers for rating customer needs in a way that accounts for the interrelationships among customer needs. Chan et al. [23] employed fuzzy set theory and entropy concept for rating customer needs. Wang [24] presented a fuzzy outranking approach to prioritize engineering characteristics.

Although, previously reported studies developed fuzzy quantitative approaches for determining the importance weights of customer needs and prioritizing engineering characteristics, an optimization procedure is required in order to avoid sub-optimal or infeasible design solutions. Few researchers have proposed fuzzy decision procedures for setting target levels of engineering characteristics. Zhou [25] proposed an integer programming model that uses a fuzzy ranking procedure in order to optimize the improvement of target values. Fung et al. [26] suggested a fuzzy inference model to map the imprecise customer needs onto the relevant engineering characteristics in order to determine their target values. Vanegas and Labib [27] developed a fuzzy QFD model for deriving optimal target values of engineering characteristics. Piedras et al. [28] presented a mathematical programming technique to optimize the product development process. Recently, Chen and Ngai [29] proposed a fuzzy QFD modeling approach to optimize the values of engineering characteristics by taking into account the design uncertainty and financial considerations.

The fuzzy optimization models mentioned above implicitly assumed that the relationships between customer needs and engineering characteristics and among engineering characteristics could be identified through a team consensus. Due to many tradeoffs that may exist among implicit or explicit relationships between customer needs and engineering characteristics and among engineering characteristics, these relationships generally cannot be identified using engineering knowledge. Kim et al. [19] proposed fuzzy multi-criteria models for setting target levels of engineering characteristics. The relationships between customer needs and engineering characteristics and among engineering characteristics are determined using fuzzy regression with symmetric triangular fuzzy numbers in these models, and Chen et al. [30] extended this approach asymmetrically.

The single objective viewpoint of maximizing customer satisfaction is extended by considering the company's other design related objectives. Karsak [18, 31] proposed fuzzy multiple objective programming approach to determine the level of fulfillment of engineering characteristics. The relationships between customer needs and engineering characteristics, importance of customer needs, sales point data, extendibility and technical difficulty of the engineering characteristics are expressed using linguistic variables, and cost data are represented employing triangular fuzzy numbers.

Since the early applications of fuzzy set theory in QFD, a vast literature on fuzzy QFD has evolved. The interested reader may refer to review articles by Chan and Wu [4] and Carnevalli and Miguel [32] for a comprehensive review of QFD applications.

3. Software Quality Function Deployment

3.1. Introduction

Computer software can be defined as the stored machine readable code that instructs computers to perform specific tasks. The software industry can be classified into three main segments [33]:

- operating systems software that controls the operations of a computer,
- application tools, which include language compilers, network controllers, and tools that support applications in database management and other areas,
- application solutions which enable computer users to perform specific tasks such as accounting or shop floor scheduling.

The first two segments are often termed as systems software whereas the last segment is called applications software.

The software industry has recently undergone a huge revolution. While the market has grown rapidly, competition has also intensified with an increase in the number of software firms. With heightened competition, the improvement of the quality of software development has gained increasing importance.

Software manufacturers have recently applied quality improvement techniques to software development to respond to the need for software quality. Quality function deployment (QFD), which is referred to as the most advanced form of total quality control, has been applied to software development to maximize customer satisfaction [6, 34].

Today, the satisfaction of customer is considered as a strategic objective by many software developers. The reason for the growing emphasis on customer satisfaction is that fully satisfied customers lead to a stronger competitive position resulting in higher market share and profit [33]. Software firms can prioritize key drivers of customer satisfaction using feedback from customers. This aids software managers in allocating resources for product and service enhancements in an efficient manner [33].

QFD deployment (QFD) has been widely used successfully in the manufacturing industry for many years as a quality improvement tool to help companies in developing products that satisfy the desires of customers. However, it has been recently applied to software development.

Software quality function deployment (SQFD) represents a transfer of the technology of QFD from product manufacturing to software development [5]. SQFD is a structured methodology which focuses on improving the quality of software development process to create products responsive to customer expectations by deploying the voice of customer throughout the development process [6]. Although QFD is now a well-defined discipline, SQFD lacks appropriate case study presentation and research.

3.2. Problems Associated with Software Development

In the past, most software quality efforts have concentrated on minimizing customer dissatisfaction. The focus was on detecting and correcting defects by appraisal [35]. Problems in the customer needs are typically not recognized until late in the development process, where negative impacts are substantial and cost for correction has grown large [2]. Boehm [36] states that “It can easily cost ten times more to repair a piece of software that fails during testing than to correct that nonconformity during analysis and design”. Even worse, problems in the requirements may go undetected through the development process, resulting in software systems not meeting customers’ needs. Therefore, methods helping software developers to better manage software requirements are of great interest [2]. QFD is quite different from traditional quality systems that aim at minimizing defects. It concentrates on maximizing customer satisfaction from the software engineering process [35].

In the management of information systems, the quality improvement process at each step of the software development reduces the number of errors passed from one phase of the system development life cycle to the next, and resulting systems which satisfy customer needs. Then, the new software systems require less maintenance costs.

Software developers, when trying to capture market share with rapid software development, they suffer from poor quality of their software products. Software quality can be defined as conformance to software needs from customers.

The early institutional focus on software quality was primarily initiated by the U.S. Department of Defense. Its major 1974 standard, MIL-S-52779, "Software Quality Assurance Program Requirements", defined the objective of software quality assurance as "to assure that the software delivered under the contract meets the requirements of the contract". The major shortcoming of this approach is that software quality is purely based on the initial contract. If the contract specifies poor or incomplete quality requirements, you will get poor quality software [37]. In the 1980's, there began a trend away from the 1970's contract-oriented specification compliance toward service-oriented customer satisfaction as the primary quality objective. Thus, the 1990 definition of quality in the Institute of Electrical and Electronics Engineers (IEEE) Standard Glossary of Software Engineering Terminology (IEEE 1990) added "… meets customer or user needs or expectations" to its earlier definition of "… meets specified requirements" [37].

Software development has been troubled by many problems, such as underestimation of cost, project delays, poor quality and customer dissatisfaction, since the inception of business computer systems in the 1950's. These problems are generally associated with incorrect or incomplete specification of customer needs, and still persist in spite of the technical advances in software engineering tools in the past two decades.

According to the results of a survey conducted by Necco et al. [38] concerning key factors for improving the software development process, "improved user involvement" is the most important factor to develop improved systems. Thus, techniques, such as SQFD, which facilitate customer needs solicitation and specification, have a positive impact on developing improved computer-based information systems.

The leading edge practice in software industry is primarily driven by product quality, customer satisfaction and time to market. The objectives of quality management in leading software firms include meeting customer needs and delivering excellent solutions to customers through quality products. The economic effects of software defects and conformance quality in software are well recognized. Defects in software products can lead to enormous costs for software developers [33].

Practitioners in the software industry are still faced with the challenge of understanding the key tradeoffs in a software project in order to deliver quality products to customers on time and without cost overruns [33]. The cost and quality models in software have often considered one in the absence of the other. That is, most cost models ignore the quality of the delivered product and quality models often ignore the cost incurred in developing or maintaining the products [33].

3.3. Literature Review

SQFD originated in Japan in 1984, as a method to improve the quality of embedded software. Since then, SQFD has been used by many organizations, but because of the use of SQFD in software development process provides companies a competitive advantage in global markets, a few of them such as AT&T, Digital Equipment Corporation (DEC), Hewlett-Packard, IBM, Texas Instruments, and SAP have shared their knowledge [5, 39]. Despite the use of QFD in software development is gaining more attention, the number of published works on applying QFD to software industry is limited compared with the vast literature of QFD applications in manufacturing [6].

There has been some research on applying total quality management techniques, in particular QFD, to software development to respond to the need for software quality. Zultner [35] presented basic components of TQM, and then detailed the SQFD process as a quality improvement tool. Yilmaz and Chatterjee [40] explained how TQM techniques can be used to facilitate the continuous improvement of software quality.

A number of researchers proposed SQFD models in which QFD process is adapted to software development by taking into account the essential differences between classic QFD and SQFD that are listed by Herzwurm and Schockert [41]. Barnett and Raja [42] proposed a four stage model for performing SQFD. Elboushi and Sherif [43] used the QFD process with object-oriented design (OOD) software technology. Liu [44] adapted the four matrices of QFD that correspond to phases of product development cycle to software development. Pai [45] combined Goal-Question-Metrics approach and SQFD to help software developers produce higher quality software that not only meets customer requirements, but also achieves the goals of the project. Finally, Richardson [46] proposed a software process improvement model based on QFD for use in small software development companies.

Few researchers developed quantitative approaches for determining importance weights of customer requirements and prioritizing technical attributes in SQFD. Buyukozkan and Feyzioglu [47] proposed a group decision making approach in which the prioritization of customer needs is achieved by fusing multiple expression formats in one collaborative group decision with fuzzy logic. Ramires et al. [48] proposed a groupware tool supporting the SQFD approach to software requirements validation. Recently, Liu et al. [39] utilized linear and non-linear regression techniques for setting technical targets in SQFD, and Liu et al. [49] developed a method for setting target values of engineering attributes by incorporating the technical trend and time.

Several empirical studies reported applications of QFD in software development. Kekre et al. [34] analyzed the key determinants of customer satisfaction with software products. Haag et al. [6] reported the results of a survey of major software vendor firms that are using SQFD as an approach to software development quality improvement. Karlsson [2] discussed positive and negative experiences gained while using QFD in a commercial large scale software project. Herzwurm and Schockert [41] showed that QFD is suitable for planning e-business applications. They presented experiences in practice with certain software-specific QFD models as well. Finally, Ip and Jacobs [50] presented the outcomes from the application of QFD for interactive games development.

3.4. SQFD Process

The basis of QFD is to obtain and translate the needs of the customer in their own words, into a set of detailed design specifications that can be used to guide all phases of the production process. This same objective lies at the heart of the software development life-cycle [42]. QFD, in its classical form can be adapted to software development by taking into account a few differences. This adaptation is termed SQFD [6, 41].

SQFD represents a transfer of the technology of QFD from product manufacturing to software development. This transfer has been accompanied by modifications to the QFD process, such as adding, changing and/or deleting matrices, for successful implementation in software development. SQFD uses a set of matrices (or a single matrix) to obtain and translate the needs of the customer into a set of detailed design specifications [5].

SQFD is a structured methodology which focuses on improving the quality of software development process to create products responsive to customer expectations by deploying the voice of customer throughout the development process [6]. The reported benefits of SQFD include [6]:

- creating better communication among departments,
- fostering better attention to customers' perspectives,
- providing decision justification,
- quantifying qualitative customer requirements,
- representing data to facilitate the use of metrics,
- facilitating cross-checking,
- avoiding the loss of information,
- reaching consensus of features quicker,
- reducing product definition interval,
- ability to adapt to various SDLC methodologies.

Although QFD is now a well-defined discipline, SQFD lacks appropriate case study presentation and research. Two schools of thought are present in software quality function deployment: macro and micro. One says that SQFD can be used as the entire system development life cycle (macro), and the other allows the system development life cycle to remain intact for the most part and is preceded by SQFD (micro) [5].

The macro point of view defines SQFD as "a systematic approach to capture the voice of the user from its earliest point, and visibly convert it throughout the system development life cycle" [51], and according to the micro point of view SQFD is "a systematic front-end technique adaptable to any software engineering methodology that quantifiably solicits and prioritizes critical customer requirements and deploys that value throughout the system development life cycle" [52].

While neither is better than the other, they do represent two distinct points of view. It is left to the individual organization to determine which point of view is more appropriate [5].

The QFD incorporates satisfaction of customer requirements into every software development activity, and it has been applied in the development of many software products. A framework for applying the QFD process in software development is shown in Figure 3.1 [44].

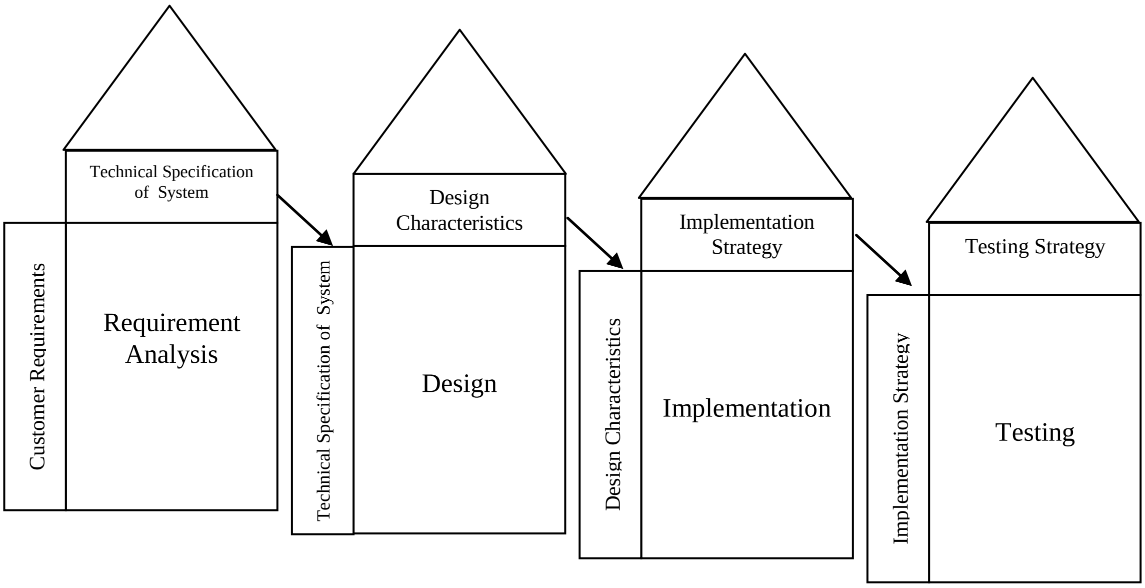

Figure 3.1. A framework for software quality function deployment

In requirement analysis, analysts must ensure that technical features of the system conform to the customer requirements. In software design, engineers develop software architecture, a module structure, data structures and user interface according to functional specification and non-functional constraints. In the implementation phase, programming language and tools are chosen. In the testing phase, test plans are developed and testing is done to remove defects in the programs [44].

3.5. The General Software Planning Problem Using QFD

SQFD focuses on improving the quality of the software development process by implementing quality improvement techniques during the requirements solicitation phase of the system development life cycle (SDLC). SQFD is a front-end requirements solicitation technique, adaptable to any software engineering methodology, which quantifiably solicits and defines critical customer requirements. SQFD precedes the SDLC process, allowing it to remain largely intact. As a front-end technique, SQFD is an adaptation of the HOQ, the most commonly used matrix in the traditional QFD methodology [6].

The HOQ, the basic tool of SQFD, translates customer needs into engineering characteristics. The relationships between customer needs and engineering characteristics are defined in each cell in the HOQ. Pairwise comparison of engineering characteristics is performed in the roof matrix, in order to incorporate the relationships among engineering characteristics. The objective of the HOQ is to determine the target levels of engineering characteristics of a product to maximize customer satisfaction [18, 30].

The process of determining target values for the engineering characteristics in SQFD can be formulated as an optimization problem.

Let

y_i = customer perception of the degree of satisfaction of customer need i
($i = 1, 2, \ldots, M$),
x_j = normalized target value of engineering characteristic j ($j = 1, 2, \ldots, N$),
f_i = functional relationship between customer need i and engineering characteristics, i.e.
$y_i = f_i(x_1, x_2, \ldots, x_N)$,
g_j = functional relationship between engineering characteristic j and other engineering characteristics, i.e. $x_j = g_j(x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_N)$,
z = degree of overall customer satisfaction.

The process of determining target values for the engineering characteristics can be formulated as an optimization problem as follows [19]:

Maximize overall customer satisfaction (3.1)

subject to

$y_i = f_i\ (x_1, x_2, \ldots, x_N),$ $\quad i = 1, 2, \ldots, M,$

$x_j = g_j\ (x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_N),$ $\quad j = 1, 2, \ldots, N.$

The objective function of formulation (3.1) can be expressed as

$$z\ (y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{3.2}$$

where w_i represents the relative importance of customer need i such that $0 < w_i \leq 1$ and $\sum_{i=1}^{M} w_i = 1$, and $y_i^{\min}$ and $y_i^{\max}$ represent the minimum and the maximum possible values, respectively, for the customer need i. Hence, formulation (3.1) can be rewritten as follows:

$$\text{Max}\ \ z\ (y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{3.3}$$

subject to

$y_i = f_i\ (x_1, x_2, \ldots, x_N),$ $\quad i = 1, 2, \ldots, M,$

$x_j = g_j\ (x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_N),$ $\quad j = 1, 2, \ldots, N,$

$y_i^{\min} \leq y_i \leq y_i^{\max}\ ,$ $\quad i = 1, 2, \ldots, M.$

The values for engineering characteristics, represented as l_j, can be normalized according to Eq. (3.4) for benefit characteristics where the greater the attribute value the more its preference, while the normalized values for engineering characteristics that offer decreasing monotonic utility, also named as cost characteristics, can be obtained by using Eq. (3.5) as

$$x_j = \frac{l_j^{\max}}{l_j}, \tag{3.4}$$

$$x_j = \frac{l_j}{l_j^{\min}}, \tag{3.5}$$

where x_j represents the normalized value for the *j*th engineering characteristic, and $l_j^{\max}$ and $l_j^{\min}$ denote the maximum and minimum target values for the *j*th engineering characteristic.

The process of setting the target levels is, in general, accomplished in a subjective ad hoc manner, or in a heuristic way. Many methods developed in the past decade for setting the target levels for engineering characteristics implicitly assumed that the relationship functions between customer needs and engineering characteristics and the interrelationships among the engineering characteristics could be identified using engineering knowledge. This assumption cannot be easily justified in a general case due to the fact that many tradeoffs may exist among the degrees of customer satisfaction as well as among many implicit or explicit relationships between engineering characteristics and customer needs and among engineering characteristics. Moreover, such relationships are generally vague in practice [30].

The vagueness or imprecision arises mainly from the fact that the customer needs, which tend to be subjective, qualitative, and nontechnical, need to be translated into engineering characteristics which should be expressed in more quantitative and technical terms. Further, data available for product design is often limited, inaccurate, or vague at best [19]. The inherent fuzziness of relationships in QFD modeling justifies the use of fuzzy regression to determine the functional relationships between customer needs and engineering characteristics, and among engineering characteristics.

4. Fuzzy Regression

4.1. Fuzzy Numbers

The concept of fuzziness that was first introduced by Zadeh [53] has been effectively employed in modeling systems where human estimation is influential. The fuzzy set theory is useful when there is no sharp distinction between the members and non-members of the classes of problems. A fuzzy set $\tilde{A}$ can be defined mathematically by assigning to each possible individual in the universe of discourse a value representing its grade of membership ($\mu_{\tilde{A}}(x)$) in the fuzzy set. The membership grade is frequently denoted by a real-number value ranging in the [0, 1] interval.

The set of elements that belong to the fuzzy set $\tilde{A}$ at least to the degree α is called the α-level set:

$$A_{\alpha} = \{ x \in X \mid \mu_{\tilde{A}}(x) \geq \alpha \}. \tag{4.1}$$

A fuzzy set is convex if

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda) x_2) \geq \min \left\{ \mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2) \right\},\ x_1, x_2 \in X, \lambda \in [0,1]. \tag{4.2}$$

A fuzzy set $\tilde{A}$ with a membership function $\mu_{\tilde{A}}(x)$ is said to be normalized if $\mu_{\tilde{A}}(x) = 1$, for at least one $x \in \Re$. A convex and normalized fuzzy set defined on $\Re$ whose membership function is piecewise continuous is called a fuzzy number.

A triangular fuzzy number $\tilde{A}$, which can be defined by a triplet (m, s_1, s_2), is represented by the membership function given below.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < (m - s_1) \\ [x - (m - s_1)]/s_1, & (m - s_1) \le x \le m \\ [(m + s_2) - x]/s_2, & m \le x \le (m + s_2) \\ 0, & x > m + s_2 \end{cases} \tag{4.3}$$

A symmetric triangular fuzzy number $\tilde{A} = (m, s)$ with center m and spread s is graphically depicted in Figure 4.1.

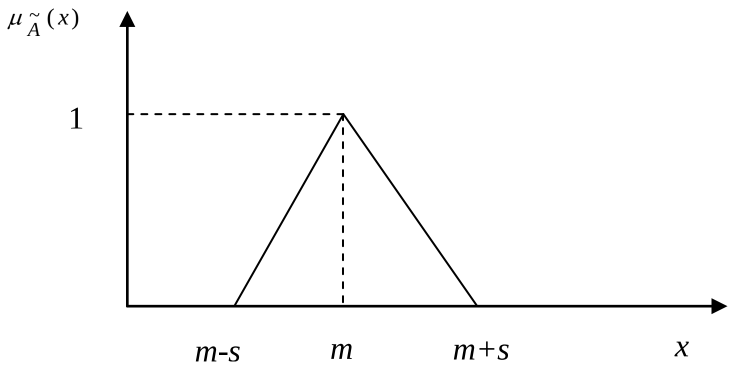

Figure 4.1. Symmetric triangular fuzzy number

The extended algebraic operations of the symmetric triangular fuzzy numbers $\tilde{A}_1 = (m_1, s_1)$ and $\tilde{A}_2 = (m_2, s_2)$ can be specified as follows:

Addition: If $\oplus$ denotes extended addition,

$$\tilde{A}_1 \oplus \tilde{A}_2 = (m_1 + m_2, s_1 + s_2)\,. \tag{4.4}$$

Substraction: If extended substraction is defined by Θ,

$$\tilde{A}_1 \Theta \tilde{A}_2 = (m_1 - m_2, s_1 + s_2)\,. \tag{4.5}$$

Multiplication: If k is a positive scalar constant and $\otimes$ denoted extended multiplication,

$$k \otimes \tilde{A}_1 = (km_1, ks_1)\,. \tag{4.6}$$

4.2. Fuzzy Linear Regression

Regression analysis, which aims to model relationship between variables, is a widely used tool in various fields of science. Statistical regression aims to describe how the dependent variable is related to the independent variables in a non-fuzzy environment. If a phenomenon under consideration does not have stochastic variability but is also uncertain in some sense, it is more natural to seek a fuzzy functional relationship for the given data that may be fuzzy or crisp. That is to say, a fuzzy phenomenon should be modeled by a fuzzy functional relationship. This is the prime motivation for fuzzy regression analysis [54]. A fuzzy linear relationship can be represented by a band with a centre line as in Figure 4.2.

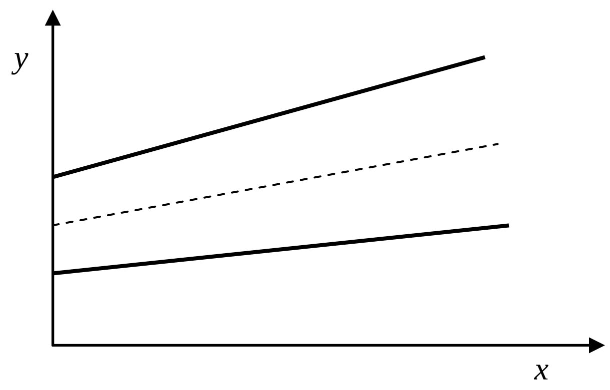

Figure 4.2. A fuzzy linear relationship

Fuzzy linear regression, which was first introduced by Tanaka et al. [55], provides an alternative approach for modeling situations where the relationships are not precisely defined or the data set cannot satisfy the assumptions of statistical regression. Hence, fuzzy regression can be applied to numerous real-life situations in which the assumptions of statistical regression cannot be satisfied. While statistical regression is based on probability theory, fuzzy regression is founded on possibility theory and fuzzy set theory [56].

There are three cases for input-output data to be analyzed in fuzzy regression:

- crisp input-output data,
- crisp input and fuzzy output data,
- fuzzy input-output data.

Corresponding to the type of data structures, several fuzzy regression models have been developed. In this study, we focus on only fuzzy regression analysis for crisp input-output data which is useful in QFD modeling.

The classical statistical regression model uses a linear function to express the relationship between a dependent variable y_i and the independent variables $x_{i1}, \ldots, x_{iN}$ as follows [57]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_N x_{iN} + e_i \tag{4.7}$$

The parameters are crisp numbers and the error term e_i, which is assumed to be a random variable with mean zero and constant variance, is supposed to be due to measurement errors [55, 58]. On the contrary, in fuzzy regression, regression residuals which denote the deviations between observed values and predicted values are assumed to be due to imprecise and vague nature of the system.

Tanaka et al. [55] delineated a fuzzy linear regression function as

$$\tilde{y}_i^* = \tilde{A}_0 + \tilde{A}_1 x_{i1} + \tilde{A}_2 x_{i2} + \ldots + \tilde{A}_N x_{iN} \tag{4.8}$$

For simplicity, it is assumed that the fuzzy parameter $\tilde{A}_j$ is a symmetrical fuzzy number defined by

$$\mu_{\tilde{A}_j}(a_j) = L((a_j - m_j)/s_j) \tag{4.9}$$

where m_j and s_j represent respectively the center and spread of fuzzy number $\tilde{A}_j$, and $\mu_{\tilde{A}_j}(a_j)$ represents the membership of a_j in the fuzzy number $\tilde{A}_j$. The reference function $L(x)$ satisfies [59]:

- $L(x) = L(-x)$,
- $L(0) = 1$,
- $L(x)$ is strictly decreasing on $[0, +\infty)$.

The H level set of $\tilde{y}_i^*$ can be obtained as follows [54]: Setting

$$L((y - \sum_{j=0}^{N} m_j x_{ij} \Big/ \sum_{j=0}^{N} s_j |x_{ij}|) = H \ , \tag{4.10}$$

and considering that $L(x)$ is a symmetrical function, equation (4.10) can be rewritten as

$$\pm (y - \sum_{j=0}^{N} m_j x_{ij} \Big/ \sum_{j=0}^{N} s_j |x_{ij}|) = L^{-1}(H) \tag{4.11}$$

Thus, the H level set of $\tilde{y}_i^*$ can be obtained as

$$\left[\sum_{j=0}^{N} m_j x_{ij} - \sum_{j=0}^{N} s_j |x_{ij}| \left|L^{-1}(H)\right|, \sum_{j=0}^{N} m_j x_{ij} + \sum_{j=0}^{N} s_j |x_{ij}| \left|L^{-1}(H)\right| \right] \tag{4.12}$$

Fuzzy linear regression uses the fuzzy parameters to model vague and imprecise phenomena. The problem addressed in the fuzzy linear regression model is to determine fuzzy parameters estimates $\tilde{A} = \{(m_0, m_1, \ldots, m_N), (s_0, s_1, \ldots, s_N)\}$ such that the membership value of y_i to its fuzzy estimate $\tilde{y}_i^*$ is at least H, where $H \in [0,1)$, which is referred to as a measure of goodness of fit, is selected by the decision-maker [58].

The aim of the fuzzy linear regression analysis is to minimize the total fuzziness of the predicted values for the dependent variables. This problem leads to the following linear programming model [59]:

$$\text{Min } Z = \sum_{j=0}^{N} \left(s_j \sum_{i=1}^{M} \left| x_{ij} \right| \right) \tag{4.13}$$

subject to

$$\sum_{j=0}^{N} m_j x_{ij} + \left| L^{-1}(H) \right| \sum_{j=0}^{N} s_j \left| x_{ij} \right| \geq y_i , \qquad i = 1, 2, ..., M,$$

$$\sum_{j=0}^{N} m_j x_{ij} - \left| L^{-1}(H) \right| \sum_{j=0}^{N} s_j \left| x_{ij} \right| \leq y_i , \qquad i = 1, 2, ..., M,$$

$$x_{i0} = 1 , \qquad i = 1, 2, ..., M,$$

$$s_j \geq 0, \qquad j = 0, 1, \ldots, N.$$

where L is equal to $L(x) = \max\left(0, 1 - |x|\right) \rightarrow \left| L^{-1}(H) \right| = (1 - H)$.

In fuzzy regression, the resulting possibility distribution of fuzzy parameters is dependent upon an H parameter value. A physical interpretation of H is that an observation y_i is contained in the support interval of the corresponding fuzzy estimate $\tilde{y}_i^*$, which has a degree of membership greater than or equal to H. Figure 4.3 is an interpretation of the fuzzy regression algorithm.

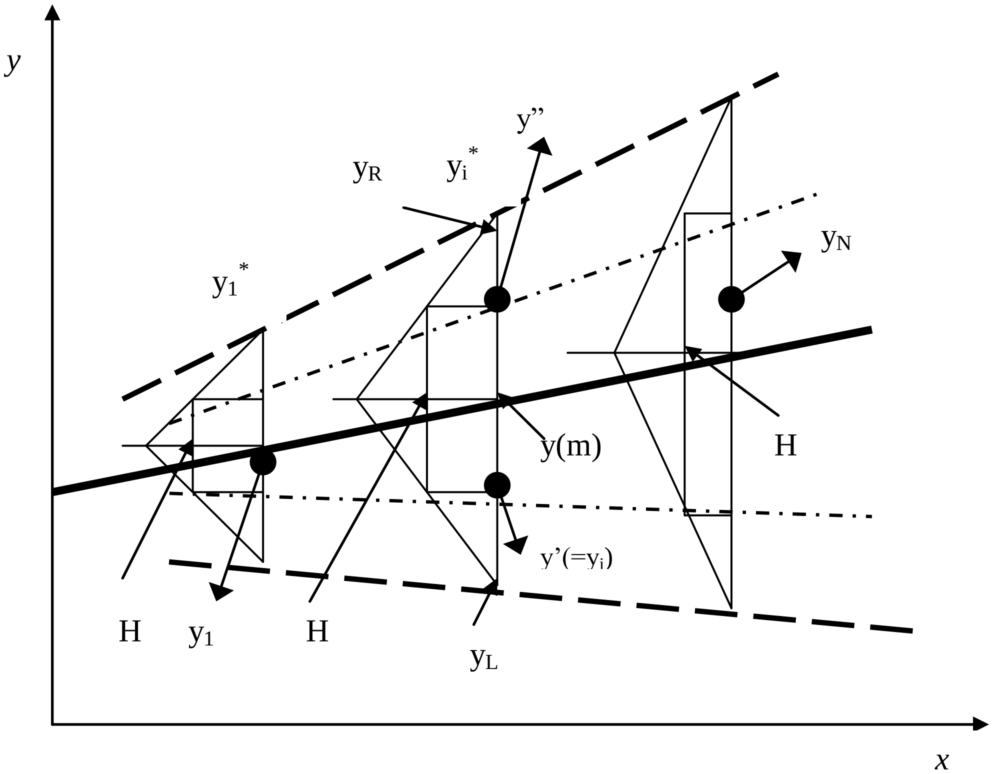

Figure 4.3. Interpretation of the fuzzy regression algorithm [58]

The selection of a proper value of *H* is important in fuzzy regression because it determines the range of the possibility distributions of fuzzy parameters. The criteria used to select the *H* value are generally ad hoc, and *H* values in previous research vary widely, ranging from 0 to 0.9 [60].

The fuzzy regression algorithm determines the spreads and the center values of the regression parameters to satisfy the *H* level, which denotes the level of credibility or confidence that the decision-maker desires. As a higher level of credibility (a higher *H* value) yields a wider spread, the resulting predicted intervals possess a higher fuzziness [58].

4.3. Review of the Literature on Fuzzy Regression Analysis

Fuzzy regression was first introduced by Tanaka et al. [55] to be used as an alternative approach for modeling situations where a source of vagueness is involved among system parameters. Since then, numerous fuzzy regression models have been proposed to estimate relationships among variables with incomplete information in different domains.

This section presents a review, analysis and classification of the literature on fuzzy regression. Through searching a number of databases, 66 works were identified over 18 different journals between 1982 and 2008. Table 4.1 shows the journals that published works on fuzzy regression in the 1982 - 2008 period. *Fuzzy Sets and Systems* published 40 articles (61% of the total) and *European Journal of Operational Research* published 8 articles (12%) between 1982 and 2008. In 21% of cases, the journals showed just one article on fuzzy regression during the 27-year period.

The basic concept for formulating fuzzy regression models is to use the fuzzy inclusion between observed and predicted values. The aim of the first model proposed by Tanaka et al. [55] was to minimize the total fuzziness of the predicted values for the dependent variables such that H-level sets of the observed values were covered by the estimated intervals. Several different versions of *min problem* have been developed. The methods proposed in this category include those of Tanaka [61], Tanaka and Watada [59], Tanaka et al. [62], Bardossy [63], Wang and Ha [64], Chang and Lee [65], Kim and Bishu [66], Yen et al. [67], and Hojati et al. [68]. Moskowitz and Kim [60] determined the relationship among the H value, membership function shape, and spreads of fuzzy parameters in the *min problem*, and Peters [69] extended Tanaka's model for crisp input/output to a fuzzy regression approach with fuzzy intervals which is robust in the presence of outliers. Later, Chen [70] focused on crisp input and fuzzy output data type and proposed approaches to handle the outlier problem.

Table 4.1. Journals that published articles on fuzzy regression in the study period

Journals	**Number of Articles**
Fuzzy Sets and Systems	40
European Journal of Operational Research	8
Computers & Mathematics with Applications	2
International Journal of Production Resarch	2
Applied Mathematics and Computation	1
Applied Soft Computing	1
Chemical Engineering Communications	1
Computational Statistics & Data Analysis	1
Computers & Operations Research	1
Engineering Optimization	1
IEEE Transactions on Systems, Man, and Cybernetics	1
Information Sciences	1
International Journal of Advanced Manufacturing Technology	1
International Journal of Technology Management	1
Jounal of Materials Processing Technology	1
Mathematical Modeling	1
Statistics	1
Water Resources Research	1

The fuzzy linear regression model, called the *max problem*, which implies that all observed values contain the estimated intervals, is presented in Tanaka [61], Tanaka and Watada [59], and Tanaka et al. [62].

Alternatively, a number of methods based on a fuzzy extension of the classical least-squares regression have been presented. "Fuzzy least squares regression" approaches developed for this category include those of Jajuga [71], Celmins [72, 73], Diamond [74], Nather and Albrecht [75], Savic and Pedrycz [76], Chang and Lee [77, 78], D'Urso and Gastaldi [79], Wang and Tsaur [80], Chang [81], Wünsche and Nather [82], Yang and Lin [83], D'Urso [84], Kao and Chyu [85], and Yang and Liu [86]. Redden and Woodall [57] reviewed some of *min* models and fuzzy least squares regression approaches and discussed their strengths and weaknesses relative to each other. Later, Kim et al. [58] described the conceptual and methodological differences between statistical linear regression and fuzzy linear regression and compared their descriptive and predictive capabilities. Finally, Chang and Ayyub [87] illustrated different fuzzy regression methods using numerical examples.

Moreover, multiobjective programming approaches for obtaining fuzzy regression models have been proposed by Sakawa and Yano [88], Özelkan and Duckstein [89, 90], Tran and Duckstein [91], Nasrabadi et al. [92].

Furthermore, hybrid methods that combine neural networks and fuzzy regression have been presented in Ishibuchi and Tanaka [93], Ishibuchi et al. [94], Dunyak and Wunsch [95], Ishibuchi and Nii [96], and Khaskei et al. [97].

The objectives of the regression analysis are to describe the relationship among variables by estimating the model parameters and predict the dependent variables' values given the levels of independent variables. Thus, primary functions of fuzzy regression are system modeling and forecasting.

Different fuzzy regression approaches presented above have been used for modeling various phenomena such as price mechanism [55, 63], exchange rate [59, 60, 98], costing [99].

Fuzzy regression has been also applied as an effective tool for researchers in decision making problems to estimate relationships among variables with fuzzy information. Several studies [19, 30, 100-102] utilized fuzzy regression to assess the relationships between both customer needs and engineering characteristics, and among engineering characteristics in QFD modeling. Lately, a fuzzy regression based decision making approach is presented by Karsak [103] for robot selection.

A number of authors used fuzzy regression technique to make predictions. Reported examples include sales forecasting [73, 104-107], manpower forecasting [108], water temperature prediction [109], and financial forecasting [110].

There have been other interesting application domains of fuzzy regression such as cellulose hydrolysis [111], hydrology [112], economic indicators [69], ergonomics [113], life cycle assessment [114], pattern recognition [115], soil erosion [116], business cycle analysis [117], process modeling [118], replacement analysis [119], and research and development project evaluation [120].

4.4. Use of Fuzzy Regression in QFD

4.4.1. Problem Statement

The HOQ, which is also considered as the basic tool for QFD, translates customer needs into engineering characteristics. According to Hauser and Clausing [17], the HOQ is a conceptual map that provides the means for interfunctional planning and communications.

There has been some research on quantifying the planning issues in HOQ within the past decade. Although, several authors developed quantitative approaches using for prioritizing engineering characteristics [23, 24, 121] development of an optimization procedure is required to avoid sub-optimal design solutions. Wasserman [122] formulated the process of prioritizing engineering characteristics in QFD as a linear programming model. Karsak et al. [123] proposed a combined analytic network process (ANP) and goal programming approach to determine the set of engineering characteristics to be considered in the design process. The optimization models presented in these articles focus on prioritiziting or determining the engineering characteristics, rather than setting their target levels.

The process of determining target levels of engineering characteristics using the information contained in a HOQ is a complex decision process. In general, it is accomplished in a subjective ad hoc manner, or in a heuristic way. Few researchers addressed the development of systematic procedures for setting target levels in QFD using fuzzy decision techniques to deal with the subjectivity and ambiguity of evaluations regarding the customer requirements and engineering characteristics, and to assess the relationships between both customer requirements and engineering characteristics, and among engineering characteristics. Fung et al. [26] proposed a fuzzy inference model to map the customer requirements onto the relevant engineering characteristics and determine their corresponding target values. Vanegas and Labib [27] presented a fuzzy QFD model to derive optimum targets of engineering characteristics which considers constraints such as cost, technical difficulty, and market position. Karsak [18] proposed a fuzzy multiple objective programming framework that incorporates imprecise and subjective design information inherent in the QFD planning process to determine the level of fulfillment of engineering characteristics.

The models mentioned above implicitly assumed that the relationships between customer needs and engineering characteristics and interrelationships among engineering characteristics could be identified through a team consensus. The conventional HOQ employs a rating scale to indicate the degree of relationships between customer needs and engineering characteristics. The relationship ratings used in the HOQ prioritization process have a strong impact on the technical importance ratings of engineering characteristics. Thus, the choice of a relationship rating scheme is critical in QFD applications; however, none of the applications in the literature provided a justification for the choice of such a rating scale. Moreover, due to many tradeoffs that may exist among implicit or explicit relationships between customer needs and engineering characteristics and among engineering characteristics, these relationships generally cannot be identified using engineering knowledge.

Furthermore, relationships between customer needs and engineering characteristics and among engineering characteristics are generally vague in practice. The vagueness arises mainly from the fact that the customer needs, which tend to be subjective and qualitative, need to be translated into engineering characteristics which are more quantitative and technical [19]. The inherent fuzziness of relationships in QFD modeling justifies the use of fuzzy regression.

Likewise, data available for product design is often limited and inaccurate [19]. The assumptions of classical statistical regression such as the normality of error terms are difficult to justify unless a sufficiently large data set is available. The violation of these assumptions can adversely affect the performance of statistical regression model. Fuzzy regression has been reported as a more effective tool than statistical regression when the data set is insufficient to support statistical regression, human judgments are involved, and the degree of system fuzziness is high [55].

4.4.2. Related Work

Several studies utilized fuzzy regression to estimate the relationships in QFD. Kim et al. [19] employed fuzzy regression to determine the functional relationships between customer needs and engineering characteristics and among engineering characteristics in QFD. They defined the major components of their multicriteria models in a crisp or fuzzy way using multiattribute value theory combined with fuzzy regression and fuzzy optimization without considering the cost factor.

Following this pioneering work, a number of researchers proposed more sophisticated fuzzy regression models for use in QFD. Chen et al. [30] extended the fuzzy linear regression with symmetric triangular fuzzy coefficients to non-symmetric triangular fuzzy coefficients. The parameters estimated by fuzzy regression in both symmetric and non-symmetric cases are used in a linear programming model which maximizes customer satisfaction in order to determine the target values of engineering characteristics taking into consideration the design budget. When fuzzy regression approaches based on LP are used to identify the relationships in QFD, a significant number of regression coefficients are estimated as crisp numbers. In order to rectify the crisp characteristics of LP-based approach, Chen and Chen [102] used non-linear programming based fuzzy regression to model functional relationships in product planning.

There has been some research on integrating the least squares regression into fuzzy linear regression. Fung et al. [100] proposed a hybrid algorithm to estimate the functional relationships for product planning based on QFD. In their study, a fuzzy expected value-based goal programming model is developed to determine target values of technical attributes. Fung et al. [101] proposed a hybrid linear programming model with asymmetric triangular fuzzy coefficients by incorporating the least squares method into fuzzy linear regression approach. Then, asymmetric triangular fuzzy coefficients are extended to asymmetric trapezoidal fuzzy coefficients.

Lately, QFD and fuzzy linear regression based framework has been used as an alternative approach for selection problems. Karsak [103] employed QFD and fuzzy regression based optimization for robot selection. The functional relationships between customer needs and robot characteristics and among the robot characteristics are estimated employing fuzzy linear regression, and then, the estimated parameters are used in the linear programming model to determine the target robot characteristic values. More recently, Karsak and Özogul [124] have proposed a decision model for enterprise resource planning (ERP) system selection based on QFD, fuzzy linear regression, and goal programming. In their work, fuzzy linear regression is used to express the vague relationships between customer requirements and ERP characteristics, and the interrelationships among ERP characteristics.

4.4.3. Fuzzy Regression Analysis in QFD Modeling

The use of fuzzy regression analysis in QFD is outlined as follows: given a number of K crisp data points ($\mathbf{x}_1$, y_{i1}), …, ($\mathbf{x}_r$, y_{ir}), …, ($\mathbf{x}_K$, y_{iK}), fuzzy parameter estimates $\tilde{A}_{ij}$ = {(m_{i0}, m_{i1}, …, m_{iN}), (s_{i0}, s_{i1},…, s_{iN})} will be determined such that the membership value of y_{ir} to its fuzzy estimate $\tilde{y}^*_{ir}$ is at least H, whereby $\mathbf{x}_r = (x_{1r}, \ldots, x_{jr}, \ldots, x_{Nr})$ is the set of values of engineering characteristics of the rth competitor, and y_{ir} is the degree of customer satisfaction of the customer need i of the competitor r. The fuzzy regression problem to determine the functional relationships f_i (i = 1, 2, …, M) leads to the following LP model [59]:

$$\text{Min } Z = \sum_{j=0}^{N}\left(s_{ij} \sum_{r=1}^{K} \left| x_{jr} \right| \right) \tag{4.14}$$

subject to

$$\sum_{j=0}^{N} m_{ij} x_{jr} + \left| L^{-1}(H) \right| \sum_{j=0}^{N} s_{ij} \left| x_{jr} \right| \geq y_{ir}, \qquad r = 1, 2, ..., K,$$

$$\sum_{j=0}^{N} m_{ij} x_{jr} - \left| L^{-1}(H) \right| \sum_{j=0}^{N} s_{ij} \left| x_{jr} \right| \leq y_{ir}, \qquad r = 1, 2, ..., K,$$

$$x_{0r} = 1, \qquad r = 1, 2, ..., K,$$

$$s_{ij} \geq 0, \qquad j = 0, 1, \ldots, N,$$

where m_{ij} represents the center and s_{ij} represents the spread of the fuzzy parameter estimates of the functional relationship between customer need i and engineering characteristic j, respectively. L is the membership function of a standardized fuzzy parameter, which is equal to $L(x) = \max\left(0, 1 - |x|\right) \rightarrow \left| L^{-1}(H) \right| = (1 - H)$.

5. Decision Making Models for SQFD

5.1. Preliminaries

Many design tasks take place in an environment in which the model components are not known precisely. Fuzzy methods can be used to deal with such imprecision. The fuzzy mathematical programming can be classified into three categories in view of the kinds of uncertainties treated in the method [125]:

- fuzzy mathematical programming with vagueness,
- fuzzy mathematical programming with ambiguity,
- fuzzy mathematical programming with vagueness and ambiguity.

The fuzzy mathematical programming in the first category treats decision making problem under fuzzy goals and constraints. The fuzzy goals and constraints represent the flexibility of the target values of objective functions and elasticity of constraints. From this point of view, this type of fuzzy mathematical programming is called the *flexible programming* [125].

The second category in fuzzy mathematical programming treats ambiguous coefficients of objective functions and constraints but does not treat fuzzy goals and constraints. This type of fuzzy mathematical programming is called the *possibilistic programming* [125].

The last type of fuzzy mathematical programming treats ambiguous coefficients as well as vague decision-maker's preference [125]. Numerous papers were devoted to the development of fuzzy mathematical programming techniques.

Fuzziness can be expressed in different ways in the general model given in (3.1):

- system parameters of functional relationships are fuzzy,
- objective functions are fuzzy,
- constraints are not hard, so that some leeway can be provided on the equality relationships [19].

Various crisp/fuzzy optimization models for SQFD can be defined by combining each model component (system parameters, objective function, and constraints) which is suited for the design situation.

5.2. System Parameters

The coefficients of estimated functional relationships between customer needs and engineering characteristics, and among engineering characteristics can be obtained by solving model (4.14). The resulting equations are given as:

$$\tilde{y}_i = \tilde{f}_i(x_1, x_2, ..., x_N) = (m_{i0}, s_{i0}) + \sum_{j=1}^{N} (m_{ij}, s_{ij}) x_j \ , \qquad i = 1, 2, \ldots, M, \qquad (5.1)$$

$$\tilde{x}_j = \tilde{g}_j(x_1, x_{j-1}, x_{j+1}, ..., x_N) = (m_{j0}, s_{j0}) + \sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju}) x_u \ , \qquad j = 1, 2, \ldots, N. \qquad (5.2)$$

In order to build a model which employs crisp parameters, the center value estimates from fuzzy regression can be used as the parameter estimates and the spread values can be neglected. Thus, the constraints of the optimization problem represented by (3.3) can be transformed to the following equations:

$$\sum_{j=1}^{N} m_{ij} x_j - y_i = -m_{i0}, \qquad i = 1, 2, \ldots, M, \tag{5.3}$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} m_{ju} x_u - x_j = -m_{j0}, \qquad j = 1, 2, \ldots, N, \tag{5.4}$$

If the spread values of fuzzy parameters are also considered, formulation (3.3) becomes a fuzzy mathematical programming problem with constraints having fuzzy coefficients.

$$\sum_{j=1}^{N} (m_{ij}, s_{ij}) x_j - y_i = (-m_{i0}, s_{i0}), \qquad i = 1, 2, \ldots, M, \tag{5.5}$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju}) x_u - x_j = (-m_{j0}, s_{j0}), \qquad j = 1, 2, \ldots, N. \tag{5.6}$$

Numerous methods for solving fuzzy mathematical programming problems have been developed. Following Lee and Li [126], the fuzzy equality constraints can be converted into an equivalent system of two inequality constraints using the lower bound and the upper bound of the α-cut of fuzzy parameters. For a given value of α, the equality constraints (5.5) and (5.6) can be transformed to the following systems of inequality constraints (5.7) and (5.8), respectively;

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{L} x_j - y_i \leq (-m_{i0}, s_{i0})_{\alpha}^{U}, \qquad i = 1, 2, \ldots, M, \tag{5.7}$$

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{U} x_j - y_i \geq (-m_{i0}, s_{i0})_{\alpha}^{L}, \qquad i = 1, 2, \ldots, M,$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{L} x_u - x_j \leq (-m_{j0}, s_{j0})_{\alpha}^{U}, \qquad j = 1, 2, \ldots, N, \tag{5.8}$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{U} x_u - x_j \geq (-m_{j0}, s_{j0})_{\alpha}^{L}, \qquad j = 1, 2, \ldots, N.$$

5.3. Objective Function

In general, maximizing overall customer satisfaction is the only objective considered in the process of setting target levels of engineering characteristics. The objective function of the optimization problem formulated to determine target values for engineering characteristics can be expressed as:

$$z\,(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{5.9}$$

where w_i represents the relative importance of customer need i such that $0<w_i\leq 1$ and $\sum_{i=1}^{M} w_i = 1$, and $y_i^{\min}$ and $y_i^{\max}$ represent the minimum and the maximum possible values, respectively, for the customer need i.

Albeit QFD aims to maximize customer satisfaction, requirements related to enterprise satisfaction such as cost budget, extendibility, and technical difficulty also need to be considered. In other words, enterprise satisfaction along with customer satisfaction should be included in the modeling framework, thus the decision problem requires to be addressed using a multiple objective programming approach.

Moreover, technical difficulty of changing or maintaining engineering characteristics or extendibility of engineering characteristics cannot be assessed by either crisp values or random processes. Linguistic variables and triangular fuzzy numbers are effective means to represent the imprecise design information. The value of a linguistic variable can be quantified and extended to mathematical operations using fuzzy set theory. This study proposes a fuzzy multiple objective programming framework for setting target levels of engineering characteristics in QFD.

Let X be the set of alternatives and C be the set of objectives that has to be satisfied by X. The objectives to be maximized and the ones to be minimized are denoted by Z_k and W_p, respectively. Considering these definitions, the model formulation is as

$$\text{Max } \tilde{Z}(\mathbf{x}) = (\tilde{\mathbf{c}}_1\mathbf{x}, \tilde{\mathbf{c}}_2\mathbf{x}, \ldots, \tilde{\mathbf{c}}_l\mathbf{x}) \tag{5.10}$$

$$\text{Min } \tilde{W}(\mathbf{x}) = (\tilde{\mathbf{c}}'_1\mathbf{x}, \tilde{\mathbf{c}}'_2\mathbf{x}, \ldots, \tilde{\mathbf{c}}'_r\mathbf{x})$$

subject to

$$\mathbf{x} \in X = \left\{ \mathbf{x} \geq \mathbf{0} \,\middle|\, \tilde{\mathbf{A}}\mathbf{x} * \tilde{\mathbf{b}} \right\},$$

where l is the number of objectives to be maximized, r is the number of objectives to be minimized, $\tilde{\mathbf{c}}_\mathbf{k}$ (k =1, …, l) and $\tilde{\mathbf{c}}'_\mathbf{p}$ (p = 1, …, r) are n-dimensional vectors, $\tilde{\mathbf{b}}$ is an m-dimensional vector, $\tilde{\mathbf{A}}$ is an m x n matrix, $\tilde{\mathbf{c}}_\mathbf{k}$, $\tilde{\mathbf{c}}'_\mathbf{p}$, $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{b}}$'s elements are fuzzy numbers, and "*" indicates "≤", "≥" and "=" operators. The formulation given above is a multiple objective linear programming model. Here, the coefficients of the constraints and the objective functions are triangular fuzzy numbers, which are useful means in quantifying the uncertainty in decision making due to their intuitive appeal and computational-efficient representation [127]. The membership function of triangular fuzzy number coefficients represented by $\tilde{Q} = (q_1, q_2, q_3)$ is given as

$$\mu_{\tilde{Q}}(x) = \begin{cases} 0 & , \quad x < q_1 \\ (x - q_1)/(q_2 - q_1), & q_1 \leq x \leq q_2 \\ (q_3 - x)/(q_3 - q_2), & q_2 \leq x \leq q_3 \\ 0 & , \quad x > q_3. \end{cases} \tag{5.11}$$

The importance degree of each objective can be included in the formulation using fuzzy priorities [128]. The general representation for the membership function corresponding to the importance degrees can be given as

$$\mu_I(x) = \begin{cases} 0 & , \quad x < i_1 \\ (x - i_1)/(i_2 - i_1) & , i_1 \le x \le i_2 \\ 1 & , \quad x > i_2 . \end{cases} \tag{5.12}$$

For a given value of α, using the maxmin approach, the formulation that incorporates fuzzy priorities of the objectives is stated as a deterministic linear problem with multiple objectives as follows:

$$\text{Max } \beta \tag{5.13}$$

subject to

$$\beta \le \mu_I \circ \mu_k^{\alpha}(Z_k)$$

$$\beta \le \mu_I \circ \mu_p^{\alpha}(W_p)$$

$$\beta \in [0,1]$$

$$x \in X_\alpha$$

$$x_j \ge 0, \quad j = 1, \ldots, n$$

where "$\circ$" is the composition operator, β is the grade of compromise to which the solution satisfies all of the fuzzy objectives while the coefficients are at a feasible level α, and X_α denotes the set of system constraints.

The "min" operator is non-compensatory, and thus, the results obtained by the "min" operator indicate the worst situation and cannot be compensated by other members that may be very good. A dominated solution can be obtained due to the non-compensatory nature of the "min" operator. This problem can be overcome by applying a two-phase approach employing the arithmetic mean operator in the second phase to assure an undominated solution [126].

Lee and Li [126] proposed a two-phase approach, where in the first phase they solve the problem parametrically for a given value of α, and in the second phase, they obtain an undominated solution using the value of α determined in phase I. In this study, a modified version of the algorithm proposed by Lee and Li [126] is employed as given below.

Phase I.

Step 1. Define λ = step length, τ = accuracy of tolerance, k = multiple of step length, c = iteration counter. Set k:=0, c:=0.

Step 2. Set $\alpha_c := 1 - k\lambda$.

Step 3. Solve the problem for α_c to obtain β_c and x_c .

Step 4a. If $\alpha_c - \beta_c > \tau$ then c := c + 1, k := k + 1, go to step 2.

Step 4b. If $\alpha_c - \beta_c < -\tau$ then λ := λ/2, k := 2k - 1, go to step 2.

Step 4c. If $|\alpha_c - \beta_c| \leq \tau$ then go to step 5.

Step 5. Output α_c , β_c , and x_c .

Phase II. After computing the values of α and β according to the procedure given in phase I, we can solve the following problem in order to obtain an undominated solution for the situation where the solution is not unique.

$$\text{Max}\ \frac{1}{l+r}\left(\sum_{k=1}^{l}\beta_k+\sum_{p=1}^{r}\beta_p{}'\right) \tag{5.14}$$

subject to

$$\beta \le \beta_k = \frac{\left[\sum_{j=1}^{n}\left[c_{kj_3}-(c_{kj_3}-c_{kj_2})\alpha\right]x_j-(\tilde{Z}_k)_\alpha^- - i_{k1}((\tilde{Z}_k)_\alpha^* - (\tilde{Z}_k)_\alpha^-)\right]}{\left[((\tilde{Z}_k)_\alpha^* - (\tilde{Z}_k)_\alpha^-)(i_{k2}-i_{k1})\right]},\ k = 1,\ \ldots,\ l$$

$$\beta \le \beta_p{}' = \frac{\left[(\tilde{W}_p)_\alpha^- - \sum_{j=1}^{n}\left[c'_{pj_1}+(c'_{pj_2}-c'_{pj_1})\alpha\right]x_j - i_{p1}((\tilde{W}_p)_\alpha^- - (\tilde{W}_p)_\alpha^*)\right]}{\left[((\tilde{W}_p)_\alpha^- - (\tilde{W}_p)_\alpha^*)(i_{p2}-i_{p1})\right]},\ p = 1,\ldots,\ r$$

$$\beta_k,\beta_p{}' \in [0,1],\ k = 1,\ \ldots,\ l;\ p = 1,\ldots,\ r$$

$$x \in X_\alpha$$

$$x_j \ge 0, \qquad j = 1,\ \ldots,\ n$$

where $(\tilde{Z}_k)_\alpha^*$, $(\tilde{W}_p)_\alpha^*$ are the ideal solutions and $(\tilde{Z}_k)_\alpha^-$, $(\tilde{W}_p)_\alpha^-$ are the anti-ideal solutions, respectively, which can be obtained by solving formulation (5.10) for each objective separately subject to the constraints.

5.4. Definition of Models

This work considers four decision making models for QFD obtained by combining each model components (objective function - system parameters) described above.

The first model called SINGLE-CRISP refers to a single objective model in which the parameters are crisp.

$$\text{Max } z\,(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{5.15}$$

subject to

$$\sum_{j=1}^{N} m_{ij} x_j - y_i = -m_{i0}, \qquad i = 1, 2, \ldots, M,$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} m_{ju} x_u - x_j = -m_{j0}, \qquad j = 1, 2, \ldots, N,$$

$$y_i^{\min} \leq y_i \leq y_i^{\max}, \qquad i = 1, 2, \ldots, M.$$

The SINGLE-FUZZY model uses a single objective function when the system parameters are fuzzy.

$$\text{Max } z\,(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{5.16}$$

subject to

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{L} x_j - y_i \leq (-m_{i0}, s_{i0})_{\alpha}^{U}, \qquad i = 1, 2, \ldots, M,$$

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{U} x_j - y_i \geq (-m_{i0}, s_{i0})_{\alpha}^{L}, \qquad i = 1, 2, \ldots, M,$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{L} x_u - x_j \leq (-m_{j0}, s_{j0})_{\alpha}^{U}, \qquad j = 1, 2, \ldots, N,$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{U} x_u - x_j \geq (-m_{j0}, s_{j0})_{\alpha}^{L}, \qquad j = 1, 2, \ldots, N,$$

$$y_i^{\min} \leq y_i \leq y_i^{\max}, \qquad i = 1, 2, \ldots, M.$$

The MULTI-I model uses multiple objective functions when the center value estimates from fuzzy regression are employed as the crisp parameter estimates.

$$\text{Max } z\,(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{5.17}$$

$$\text{Min } T\,(x_1, x_2, \ldots, x_N) = \sum_{j=1}^{N} \tilde{t}_j x_j$$

subject to

$$\sum_{j=1}^{N} m_{ij} x_j - y_i = -m_{i0}\,, \qquad i = 1, 2, \ldots, M,$$

$$\sum_{\substack{u=1 \\ u \neq j}}^{N} m_{ju} x_u - x_j = -m_{j0}\,, \qquad j = 1, 2, \ldots, N,$$

$$y_i^{\min} \leq y_i \leq y_i^{\max}\,, \qquad i = 1, 2, \ldots, M.$$

where T represents overall technical difficulty for engineering characteristics.

The MULTI-II model is a multiple objective programming approach using the fuzzy coefficients of estimated functional relationships between customer needs and engineering characteristics, and among engineering characteristics.

$$\text{Max } z\,(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \tag{5.18}$$

$$\text{Min } T\,(x_1, x_2, \ldots, x_N) = \sum_{j=1}^{N} \tilde{t}_j x_j$$

subject to

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{L} x_j - y_i \le (-m_{i0}, s_{i0})_{\alpha}^{U}, \qquad i = 1, 2, \dots, M,$$

$$\sum_{j=1}^{N} (m_{ij}, s_{ij})_{\alpha}^{U} x_j - y_i \ge (-m_{i0}, s_{i0})_{\alpha}^{L}, \qquad i = 1, 2, \dots, M,$$

$$\sum_{\substack{u=1 \\ u \ne j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{L} x_u - x_j \le (-m_{j0}, s_{j0})_{\alpha}^{U}, \qquad j = 1, 2, \dots, N,$$

$$\sum_{\substack{u=1 \\ u \ne j}}^{N} (m_{ju}, s_{ju})_{\alpha}^{U} x_u - x_j \ge (-m_{j0}, s_{j0})_{\alpha}^{L}, \qquad j = 1, 2, \dots, N,$$

$$y_i^{\min} \le y_i \le y_i^{\max}, \qquad i = 1, 2, \dots, M.$$

6. Future Voice of the Customer

6.1. Listening to the Future Voice of the Customer

Most of the optimization techniques in the QFD only used the VOC obtained previously, which is the past voice of customer. This strategy will not work for strongly innovative products, especially when there is no predecessor product [7]. Under rapidly changing environments, customers change their opinions and thus have requirements that are more dynamic than static [8]. There is a time lag from the collection of the VOC to the marketing of the final product. Therefore, it is possible that the final product cannot fully meet customer needs at the time when the product reaches the market [129].

The voice of the customer can be divided into two types: qualitative VOC and quantitative VOC. The qualitative VOC defines what customers want and the quantitative VOC represents the importance of customer needs. Both of these two types of VOCs are shown in the HOQ [8]. This work focuses on the quantitative VOC.

Traditional QFD collects customer needs and their importance degrees in the present tense. However, the importance of each customer need might be the same as before or it might have increased or decreased after a product is designed and manufactured. In order to deal with the changing a proactive approach is a time-based extension by listening to the future voice of the customer (FVOC). Quantitatively, the FVOC contains the new prioritization of customer needs [8]. As Shillito [13] pointed out, little attention has been paid to the time dimension of the VOC, especially for very novel products or in rapidly changing industries like the information technology (IT) industry.

To maintain a competitive edge in today's marketplace, it is necessary to extend the concept of listening to the VOC into the future. Some forecasting techniques can be used to obtain the future voice of customer (FVOC). In QFD, the importance degrees of the customer needs usually follow trends. When it is assumed that the company has sufficient historical data for an effective forecasting, the QFD team can use exponential smoothing technique to predict the importance of the VOC.

In general, the available data set is insufficient to obtain accurate forecasts. Or, there is no historical data for each customer need. This situation can occur when companies just start to use the QFD technique or use it for a new product development. In this case, the quantitative VOC can be extended into the future by using the trend of importance. Practically, it is difficult to use all of the information about the trend because usually they are linguistic variables that cannot be quantified. The linguistic trend of importance can be quantified through the use of fuzzy trend of importance rather than a crisp number [8]. Thus, the obtained importance values are fuzzy numbers.

To date, number of works concerning the use of FVOC is very limited in the published literature. Shillito [13] was the first to point out the importance of this major problem in QFD and stated that VOC information related to the future can be collected using the Delphi questionnaire. Shen et al. [129] used fuzzy trend analysis to extend the VOC into the future. Xie et al. [8] detailed the use of double exponential smoothing and fuzzy trend analysis techniques to project the FVOC. Lately, Raharjo et al. [130] proposed a mathematical model based on the quality loss function and the zero-one goal programming to prioritize engineering characteristics that meet the FVOC.

In QFD analysis, a single HOQ can be used with the integrated VOC obtained by combining the current and future VOCs. Consequently, the QFD team wants to know how much attention should be paid to listening to the future VOC. Xie et al. [8] remarked that "the issue of the future VOC versus the present VOC is one risk versus benefit and that the decision between the future versus present orientations is critical since there are no clear-cut measures, criteria or benchmarks to act as indicators".

Different methods should be applied to different situations. Numerous factors such as competitiveness, technical capability, etc. should be considered when making decisions.

In this work, we are concerned with the problem of formulating an overall decision function of importance degree such that for any customer need, the score obtained by the decision function indicates the integrated importance degree to which the desired requirements with respect to present and forthcoming periods are satisfied.

In decision processes with multiple information sources, generally, the final decision is made according to the majority of performance profiles given by different sources [131]. Thus, rather than requiring all the criteria to be satisfied, only some portion of the criteria need to be satisfied. This portion of the criteria can be specified in terms of a linguistic quantifier such as *most* [132]. This work proposes to employ ordered weighted averaging (OWA) operators to implement quantifier guided aggregations which allow to calculate the integrated importance degrees for each customer need.

6.2. Quantifier Guided Aggregations Using OWA Operators

6.2.1. Preliminaries

Yager [133] formulated the aggregation problem as it follows: Assume A_1, A_2, …, A_n criteria of concern in a multiple criteria problem. For each criteria A_j, $A_j(x) \in [0, 1]$ denotes the degree to which an alternative x satisfies that criteria. The problem in multiple criteria decision making is to formulate a decision function that finds some overall single value for each alternative by aggregating its scores to the individual criteria. In order to obtain this aggregation, some information must be provided on the relationship between the criteria.

At one extreme is the situation of requiring all the criteria to be satisfied. This requirement leads to the use of *and* operator to combine the criteria functions to form an overall decision function. At the other extreme is the situation in which we desire that any of the criteria be satisfied. Thus, the requirement that at least one of the criteria be satisfied is manifested by the use of *or* operator. In many cases the type of aggregation operator desired lies between these two cases of wanting *all* or *at least one*. A decision-maker can desire *most* or *many* or *at least half* of the criteria to be satisfied. Yager [133] suggested a generalization of this type of situation which he called *quantifier guided aggregation*.

6.2.2. Linguistic Quantifiers

The classic logic uses only two linguistic quantifiers: the existential quantifier, *there exists*, and the universal quantifier, *all*, in forming logical propositions. In natural language, there are many additional quantifiers such as *many*, *most*, and *few*.

Zadeh [134] suggested a formal representation of these linguistic quantifiers using fuzzy sets. The quantifiers can be represented as fuzzy subsets of either the unit interval or the real line. The distinction is based upon whether the quantifier relates to an absolute or is a proportion type statement. Thus, if Q is relative a quantity such as *most*, the Q can be represented as a fuzzy subset of the unit interval I such that for each $y \in I$, $Q(y)$ indicates the degree to which y portion of the objects satisfies the concept denoted by Q. The quantifier *for all* can be represented as a fuzzy subset of I such that $Q(1) = 1$, and $Q(y) = 0$, when $y \neq 1$ [133].

A fuzzy subset Q quantifier is called a regular increasing monotone (RIM) quantifier if $Q(0)=0$, $Q(1)=1$, and $Q(y_1) \geq Q(y_2)$ if $y_1 > y_2$.

6.2.3. OWA Operators

The ordered weighted averaging (OWA) operators were introduced by Yager [133] in order to provide aggregations which lie between two extreme cases of multiple criteria decision making problems that lead to the use of *and* and *or* operators to combine the criteria functions.

An OWA operator of dimension n is a mapping $F : R^n \to R$ which has an associated weighting vector $\mathbf{w} = [w_1, w_2, ..., w_n]^T$ such that $\sum_{j=1}^{n} w_j = 1$; $w_j \in [0, 1]$ and where $F(a_1, a_2, ..., a_n) = \sum_{j=1}^{n} w_j b_j$ with b_j being the jth largest of the a_i.

A key aspect of the OWA operator is the ordering of arguments by value, in particular a_i is not associated with a particular weight w_i but rather a weight w_i is associated with a particular ordered position i of the arguments. It can be shown that the OWA operator is commutative, monotonic, and idempotent. It can also be shown that for any weighting vector **w**, the OWA aggregation is bounded by the Min and Max of the arguments [135].

Its generality lies in the fact that by selecting the weights we can implement different aggregation operators. Specifically, by appropriately selecting the weights in **w** we can emphasize different arguments based upon their position in the ordering. If we place most of the weights near the top of **w,** we can emphasize the higher scores while placing the weights near bottom of **w** emphasizes the lower scores in the aggregation [136].

A known property of the OWA operators is that they include the Max, Min, and arithmetic mean operators. Each of these special cases can be obtained by the appropriate selection of the vector **w** respectively $\mathbf{w} = [1, 0, 0, ..., 0]^T$, $\mathbf{w} = [0, 0, ..., 0, 1]^T$, and $\mathbf{w} = [1/n, 1/n, ..., 1/n]^T$. Thus, the two extreme cases of OWA operators are the *and* and *or* operators. In particular, the largest OWA operator is the smallest *or* operator, Max, while the smallest OWA operator is the largest *and* operator, Min [133].

Since this class of operators runs between Max (*or*) and Min (*and*), Yager [133] introduced a measure called *orness* to characterize the type of aggregation being performed for a weighting vector. The degree of *orness* associated with an OWA operator guided by the vector **w** is defined as

$$orness\ (\mathbf{w}) = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i \tag{6.1}$$

This measure which lies between 0 and 1, characterizes the degree to which the aggregation is like an *or* (Max) operation. It can be shown that Max, Min, and arithmetic mean operators are OWA operators with degree of orness respectively 1, 0, and 0.5.

Yager [133] introduced a second measure called the dispersion or entropy to calculate how much of the information in the arguments is used during an aggregation based on **w**.

$$Disp\ (\mathbf{w}) = \sum_{i=1}^{n} w_i \ln w_i \tag{6.2}$$

In order to apply an OWA operator for decision making, a key issue is the determination of the weights of the operators. A number of approaches have been suggested in the literature for determining the weights of OWA operators. One of the first approaches, suggested by O'Hagan [137], determines a special class of OWA operators having maximal entropy of the OWA weights for a given level of orness. Filev and Yager [135] presented a learning approach using observed data and an exponential smoothing method to obtain weights of a class of OWA operators called exponential OWA operators. Later, Fullér and Majlender [138] suggested a minimum variance method to obtain the minimal variability OWA operator weights. Recently, Wang and Parkan [139] proposed a minimax disparity approach, which minimizes the maximum disparity between two adjacent weights under a given level of orness. The interested reader can refer to Fullér [140] for a survey of recent developments on obtaining OWA operator weights.

6.2.4. Quantifiers and OWA Operators

Consider a decision-maker has n criteria, A_1, A_2, …, A_n. For each criteria A_j, $A_j(x) \in [0, 1]$ denotes the degree to which an alternative x satisfies that criteria. The decision-maker provides a linguistic quantifier Q which indicates the proportion of criteria he feels is necessary for a good solution. This quantifier can be used to generate the weighting vector **w** of an OWA aggregation operator to determine the overall evaluation for each alternative [132].

The weights from a RIM quantifier such as *most* are generated as [132]:

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right), \quad i = 1, 2, \ldots, n\,. \tag{6.3}$$

Due to the nondecreasing nature of Q, the weights are positive. Furthermore, because of the regularity of Q, $Q(0) = 0$ and $Q(1) = 1$, it follows that $\sum_{i=1}^{n} w_i = 1$. Thus, the weights generated are an acceptable class of OWA weights.

7. Search Engine Design Using the Proposed Decision Framework

Search engines are widely used tools to find information on the Internet. In spite of the development of information technology, most search engines were created without consideration for customer expectations. In practice, information technology service companies generally lack a suitable process to achieve high-quality services [141]. Although the quality of search engines is important in our daily lives, customer satisfaction regarding the quality of search engines are very low [142]. SQFD can be used for the quality improvement problem of a search engine.

7.1. Web Search Engines

7.1.1. Introduction

The storage and retrieval of information has always required the development of access mechanisms, whether for use by the information specialists, or by end users [143]. In the past, access was generally in the form of lists. The use of electronic databases made access mechanisms more complex. With the development of the Internet, the efficient retrieval of information has gained new importance [143]. A hudge number of institutions and individuals make information available; however, because there is no single controlling entity over the Internet, there is no controlled structure or means of access to the information. Consequently, a number of programs have been designed to make access to the information in easier and more efficient way [143].

The Internet became widely available to the scholarly, business and consumer communities as a research and communication tool towards the end of the 1980s [144]. The year 1991 saw the first general release of www line mode browsers at CERN

(European Organization for Nuclear Research). In 1994, as the number of http resources increased the services that we now know as search engines began to appear. Like the web, the world of search engines is now complex and rich [144].

Search engines are widely used tools to find information on the Internet. Internet users are confused by the need to choose from an increasing number of tools, each of them with their own advantages, disadvantages, and use protocols [143].

It is of considerable importance for the designer to develop quality search engines and for the users to select the most appropriate ones for the use. In fact, most search engines are developed mainly for better technical performance and there would be a lack of quality attributes from the customers' perspective [142]. The development of search engines would require knowledge and skills drawn from a variety of disciplines. In addition to the technical knowledge of computer science, the designer of such search tools should have an understanding of information organization and management, including indexing and vocabulary control; cognitive approaches to information retrieval, such as formulation of search queries and use of hypertext links; the psychology of the potential users and their approaches and responses to search problems; and the social environment in which the search engine is likely to be used [143].

There are numerous search engines today, usually developed by commercial firms or academic institutions. As more search engines become available, selection of a suitable search engine becomes an important and urgent task [142]. In spite of the development of information technology, most search engines were created on the basis of technical requirements and without consideration for customer expectations. In practice, information technology service companies generally lack a suitable process to achieve high-quality services [141]. The quality of the search engines is seldom considered from the user's point of view. Many customer-oriented quality aspects may not have been taken into serious consideration or given sufficient recognition. Although the quality of search engines is important in our daily lives, customer satisfaction regarding the quality of search engines are very low [142].

Reviews of search engines have been carried out by other researchers in their effort to identify the advantages and disadvantages of each search engine. Most comparative studies focus only on comparison of the characteristics and technical part of the search engines, thus ignoring quality considerations from the users' point of view [142].

SQFD can be used for the quality improvement problem of a search engine. Listening to the requirements from the customers is the first and most important part of improving search engine quality. To satisfy the customers and improve the quality of search engines, accurate analysis of true customer expectations is extremely important.

Xie et al. [142] applied a widely used service quality model to identify the important quality dimensions of search engines. The SERVQUAL model was developed by Parasuraman et al. [145] to measure the gap between customer expectations and perception of services received. In their work, five service quality dimensions - tangibles, reliability, responsiveness, assurance and empathy - were identified. Empirical research confirmed that service quality dimensions are not the same across different sectors of service industry. Each sector of the service industries has its own features which contribute to different groupings of the service quality dimensions. In order to make it suitable for the quality of search engines, the five SERVQUAL dimensions are redefined as the dimensions in Table 7.1 by Xie et al. [142].

In order to obtain a list of customer expectations on quality search engines, Xie et al. [142] studied available articles, reviews relating to the quality of search engines and a survey using the Internet is conducted to gather the needs of customers. The fourteen customer requirements that they obtained are divided into five quality dimensions defined in Table 7.1. The fourteen customer requirements considered important for the design and service of the search engines are given in Table 7.2.

Table 7.1. Redefinition of the dimensions in service quality [142]

	Definitions in Service Quality	Definitions for Search Engines
Tangible	Appearance of physical facilities, equipment, personnel, and communication materials	The existing characteristics and functions of the search engines
Reliability	Ability to perform the promised service dependably and accurately	Ability to provide relevant and useful information to the query
Responsiveness	Willingness to help customers and provide prompt service	Ability to provide prompt response to the query
Assurance	Knowledge and courtesy of employees and their ability to convey trust and confidence	Ability to ensure that the results given to the query are accurate, recent and on target
Empathy	Caring, individualized attention the firm provides its customers	Caring, individualized attention the search engines provide to their customers

Table 7.2. Customer expectations on quality search engines

	Customer Needs
Tangible	- Information is well organized - Different search methods available - A large amount of information available - Can narrow search topic
Reliability	- Good syntax - consistency for the keywords in searching - Search results are relevant to the query
Responsiveness	- Search results are provided quickly
Assurance	- No repetitions of pages/sites - No dead links - Information is up to date
Empathy	- The layout upon first impression is easy to understand - Offers natural language searching - There are help screens, etc, to guide users - Offers language selection

The technical aspects of search engines can be retrieved from several sources [144, 146, www.searchengineshowdown.com]. The engineering characteristics determined in order to satisfy customer needs are *response time, total database size, unique hits, dead links, update time, number of languages,* and *number of formats.*

SQFD will be applied to link customer needs with the engineering characteristics. The HOQ will provide information on the relationships between customer needs and engineering characteristics and among engineering characteristics, along with the benchmarking data set. Such information will be used to estimate the parameters of the functional relationships.

7.1.2. House of Quality

In this study, applications of the proposed models are presented for determining target values of engineering characteristics of a search engine which is aimed to satisfy customer needs. The illustrative example uses a HOQ shown in Figure 7.1, which is adapted from Liu et al. [39], for the design of a search engine.

ECs	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Response Time (x_1)		■						
Database Size (x_2)	■			■		■		■
Precision (x_3)					■			
# of Languages (x_4)		■						
Unique Hits (x_5)			■					
Dead Links (x_6)		■						
Update Time (x_7)								
# of Formats (x_8)		■						

CNs	**Relative Importance**	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**min**	**max**
Scalability (y_1)	2.0		■		■				■	3.3	5.3	3.2	3.5	5.5	3.6	1.0	6.0
Reliability (y_2)	3.0			■			■	■		5.0	3.7	3.6	4.7	3.7	4.8	1.0	5.5
Speed (y_3)	4.0	■								4.2	2.7	3.2	3.4	4.5	3.0	1.0	5.0
Accuracy (y_4)	1.0			■		■		■		4.4	3.6	4.7	3.6	5.0	4.3	1.0	5.5
Easy to Use (y_5)	5.0	■				■	■		■	3.4	4.1	5.6	4.6	5.8	4.2	1.0	6.0

Competitors	sec	millions	-	-	%	%	-	-
C1	2.70	346.0	0.80	15.0	18.0	13.7	10.0	2.0
C2	4.20	552.0	0.40	23.0	13.0	8.7	7.0	4.0
C3	3.00	334.0	0.60	20.0	23.0	1.9	7.0	3.0
C4	3.50	364.0	0.60	12.0	14.0	23.0	8.0	2.0
C5	2.30	730.0	0.60	26.0	29.0	1.7	14.0	5.0
C6 (Our Product)	3.80	369.0	0.70	24.0	18.0	5.7	9.0	3.0
Targets	2.07	1093.0	0.86	27.0	31.5	1.7	6.0	7.0
Technical Difficulty	H	M	VH	VL	VH	H	L	M

Figure 7.1. House of quality for a search engine

The five customer needs obtained through requirement analysis are *scalability* (y_1), *reliability* (y_2), *speed* (y_3), *accuracy* (y_4), and *easy to use* (y_5). The eight engineering characteristics determined in order to satisfy customer needs are *response time* (x_1), *database size* (x_2), *precision* (x_3), *number of languages* (x_4), *unique hits* (x_5), *dead links* (x_6), *update time* (x_7), and *number of formats* (x_8).

The design team identified the relationships between customer needs and engineering characteristics. The interrelationships among the engineering characteristics are indicated in the roof of the HOQ. The engineering data set for customer and technical analysis is collected from the company (C6) and its five main competitors, C1 through C5. Assume that customer perception of the degree of satisfaction of each customer requirement has been scaled from 1 to the corresponding quality goal denoted in the HOQ, where 1 and the corresponding quality goal represent the worst and best values, respectively. Technical difficulty of engineering characteristics are expressed using linguistic variables 'very low (VL)', 'low (L)', 'medium (M)', 'high (H)' and 'very high (VH)', which possess membership functions depicted in Figure 7.2.

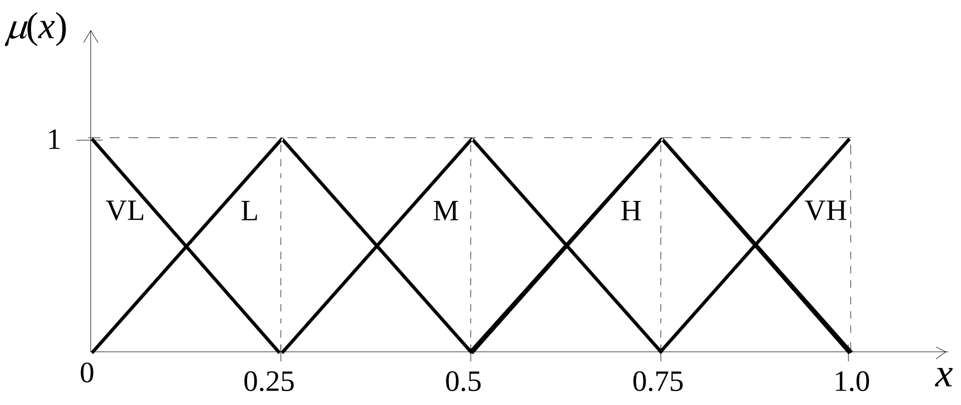

Figure 7.2. Membership functions for linguistic variables regarding technical difficulty of engineering characteristics:
(VL: (0, 0, 0.25), L: (0, 0.25, 0.5), M: (0.25, 0.5, 0.75), H: (0.5, 0.75, 1), VH: (0.75, 1, 1))

7.2. Parameter Estimation and Model Formulation

In this study, fuzzy linear regression is used to estimate the relationship functions between customer needs and engineering characteristics, i.e. $y_i = f_i\ (x_1, x_2, \ldots, x_N)$, and among the engineering characteristics, i.e. $x_j = g_j\ (x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_N)$. The data set needed for this analysis is contained in the HOQ.

For *database size* (x_2), *precision* (x_3), *number of languages* (x_4), *unique hits* (x_5), and *number of formats* (x_8), the greater the performance value the more its preference, and thus they are named benefit characteristics. On the contrary, for *response time* (x_1), *dead links* (x_6), and *update time* (x_7), the greater the performance value the less its preference, and thus they are considered cost characteristics. The normalized values obtained by using Eq. (3.4) and Eq. (3.5) are given as follows:

$$X = \begin{bmatrix} 0.766667 & 0.316560 & 0.930233 & 0.555556 & 0.571429 & 0.124088 & 0.600000 & 0.285714 \\ 0.492857 & 0.505032 & 0.465116 & 0.851852 & 0.412698 & 0.195402 & 0.857143 & 0.571429 \\ 0.690000 & 0.305581 & 0.697674 & 0.740741 & 0.730159 & 0.894737 & 0.857143 & 0.428571 \\ 0.591429 & 0.333028 & 0.697674 & 0.444444 & 0.444444 & 0.073913 & 0.750000 & 0.285714 \\ 0.900000 & 0.667887 & 0.697674 & 0.962963 & 0.920635 & 1.000000 & 0.428571 & 0.714286 \\ 0.544737 & 0.337603 & 0.813953 & 0.888889 & 0.571429 & 0.298246 & 0.666667 & 0.428571 \end{bmatrix}$$

Fuzzy linear regression model (4.13) is used to estimate the parameters of the functional relationships f_i and g_j. The H value is set to 0.5 as in a number of earlier applications [19, 30, 55]. The results of the fuzzy linear regression model are shown in Table 7.3. The values in parentheses represent the spread values for parameter estimates.

Table 7.3. Fuzzy linear regression centre and spread values m_j (s_j) for H = 0.5

	Intercept	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
y_1	0.920604		6.966369		1.194231				-0.992978 (1.439427)
y_2	2.611275			2.809242 (0.281402)			-1.030394	0.099707 (0.085349)	
y_3	0.699997	4.094207 (0.942027)							
y_4	0.555619			1.186404		3.524993		1.038718 (0.344115)	
y_5	6.217503	-1.271864 (1.251269)				-2.361978	3.437693		-1.538697
x_1	0.646529		0.037616 (0.683793)						
x_2	-0.061846 (0.024748)	0.274351			-0.289965		-0.151024		1.260969
x_3	0.472384 (0.392442)					0.457848			
x_4	0.147441 (0.437361)		1.548470						
x_5	0.301586 (0.476191)			0.546033					
x_6	0.391555 (0.828798)		0.290536						
x_8	0.105339 (0.164502)		0.788601						

For example as can be observed from Figure 7.1, y_2 is associated with x_3, x_6, and x_7. When the normalized data for the web search engine design are considered, fuzzy linear regression model for y_2 is given as

$$\text{Min } Z = 6.000000\, s_{20} + 4.302324\, s_{23} + 2.586386\, s_{26} + 4.159524\, s_{27} \tag{7.1}$$

subject to

$m_{20} + 0.930233\, m_{23} + 0.124088\, m_{26} + 0.600000\, m_{27} + 0.500000\, s_{20} + 0.465117\, s_{23} + 0.062044\, s_{26} + 0.300000\, s_{27} \geq 5$

$m_{20} + 0.465116\, m_{23} + 0.195402\, m_{26} + 0.857143\, m_{27} + 0.500000\, s_{20} + 0.232558\, s_{23} + 0.097701\, s_{26} + 0.428572\, s_{27} \geq 3.7$

$m_{20} + 0.697674\, m_{23} + 0.894737\, m_{26} + 0.857143\, m_{27} + 0.500000\, s_{20} + 0.348837\, s_{23} + 0.447369\, s_{26} + 0.428572\, s_{27} \geq 3.6$

$m_{20} + 0.697674\, m_{23} + 0.073913\, m_{26} + 0.750000\, m_{27} + 0.500000\, s_{20} + 0.348837\, s_{23} + 0.036957\, s_{26} + 0.375000\, s_{27} \geq 4.7$

$m_{20} + 0.697674\, m_{23} + m_{26} + 0.428571\, m_{27} + 0.500000\, s_{20} + 0.348837\, s_{23} + 0.500000\, s_{26} + 0.214286\, s_{27} \geq 3.7$

$m_{20} + 0.813953\, m_{23} + 0.298246\, m_{26} + 0.666667\, m_{27} + 0.500000\, s_{20} + 0.406977\, s_{23} + 0.149123\, s_{26} + 0.333334\, s_{27} \geq 4.8$

$m_{20} + 0.930233\, m_{23} + 0.124088\, m_{26} + 0.600000\, m_{27} - 0.500000\, s_{20} - 0.465117\, s_{23} - 0.062044\, s_{26} - 0.300000\, s_{27} \leq 5$

$m_{20} + 0.465116\, m_{23} + 0.195402\, m_{26} + 0.857143\, m_{27} - 0.500000\, s_{20} - 0.232558\, s_{23} - 0.097701\, s_{26} - 0.428572\, s_{27} \leq 3.7$

$m_{20} + 0.697674\, m_{23} + 0.894737\, m_{26} + 0.857143\, m_{27} - 0.500000\, s_{20} - 0.348837\, s_{23} - 0.447369\, s_{26} - 0.428572\, s_{27} \leq 3.6$

$m_{20} + 0.697674\, m_{23} + 0.073913\, m_{26} + 0.750000\, m_{27} - 0.500000\, s_{20} - 0.348837\, s_{23} - 0.036957\, s_{26} - 0.375000\, s_{27} \leq 4.7$

$m_{20} + 0.697674\, m_{23} + m_{26} + 0.428571\, m_{27} - 0.500000\, s_{20} - 0.348837\, s_{23} - 0.500000\, s_{26} - 0.214286\, s_{27} \leq 3.7$

$m_{20} + 0.813953\, m_{23} + 0.298246\, m_{26} + 0.666667\, m_{27} - 0.500000\, s_{20} - 0.406977\, s_{23} - 0.149123\, s_{26} - 0.333334\, s_{27} \leq 4.8$

$s_{20}, s_{23}, s_{26}, s_{27} \geq 0$

The solution for this linear program is $m^*_{20} = 2.611275$, $m^*_{23} = 2.809242$, $m^*_{26} = -1.030394$, $m^*_{27} = 0.099707$, $s^*_{23} = 0.281402$, and $s^*_{27} = 0.085349$.

The relationships between the *H* value, membership function shape and the spreads of fuzzy parameters in fuzzy linear regression model have been examined by Moskowitz and Kim [60]. In order to analyse the effect of varying the *H* value on the solution for y_2, formulation (7.1) is solved for *H* values ranging from 0 to 0.9 increasing by a step size of 0.1. The results given in Table 7.4 indicates that the *H* value does not change the centre values but influences the spread values, and a higher *H* value results in a larger spread of fuzzy parameters.

Table 7.4. Effect of the *H* value on the solutions for y_2

H	s_{20}	s_{23}	s_{26}	s_{27}	m_{20}	m_{23}	m_{26}	m_{27}	Z
0	0	0.140701	0	0.042674	2.611275	2.809242	-1.030394	0.099707	0.782846
0.1	0	0.156334	0	0.047416	2.611275	2.809242	-1.030394	0.099707	0.869829
0.2	0	0.175876	0	0.053343	2.611275	2.809242	-1.030394	0.099707	0.978558
0.3	0	0.201001	0	0.060963	2.611275	2.809242	-1.030394	0.099707	1.118352
0.4	0	0.234502	0	0.071124	2.611275	2.809242	-1.030394	0.099707	1.304744
0.5	0	0.281402	0	0.085349	2.611275	2.809242	-1.030394	0.099707	1.565693
0.6	0	0.351752	0	0.106686	2.611275	2.809242	-1.030394	0.099707	1.957116
0.7	0	0.469003	0	0.142248	2.611275	2.809242	-1.030394	0.099707	2.609488
0.8	0	0.703505	0	0.213372	2.611275	2.809242	-1.030394	0.099707	3.914232
0.9	0	1.407009	0	0.426744	2.611275	2.809242	-1.030394	0.099707	7.828464

In order to build a model which employs crisp parameters with a single objective function which is *maximizing customer satisfaction*, the center value estimates from fuzzy regression can be used as the parameter estimates and the spread values can be neglected.

The model SINGLE-CRISP (5.15) can be rewritten as:

$$\text{Max } z = 0.026667\, y_1 + 0.044444\, y_2 + 0.066667\, y_3 + 0.014815\, y_4 + 0.066667\, y_5 \qquad (7.2)$$

subject to

$6.966369\, x_2 + 1.194231\, x_4 - 0.992978\, x_8 - y_1 = -\,0.920604$

$2.809242\, x_3 - 1.030394\, x_6 + 0.099707\, x_7 - y_2 = -2.611275$

$4.094207\, x_1 - y_3 = -0.699997$

$1.186404\, x_3 + 3.524993\, x_5 + 1.038718\, x_7 - y_4 = -0.555619$

$-1.271864\, x_1 - 2.361978\, x_5 + 3.437693\, x_6 - 1.538697\, x_8 - y_5 = -6.217503$

$0.037616\, x_2 - x_1 = -0.646529$

$0.274351\, x_1 - 0.289965\, x_4 - 0.151024\, x_6 + 1.260969\, x_8 - x_2 = 0.061846$

$0.457848\, x_5 - x_3 = -0.472384$

$1.548470\, x_2 - x_4 = -0.147441$

$0.546033\, x_3 - x_5 = -0.301586$

$0.290536\, x_2 - x_6 = -0.391555$

$0.788601\, x_2 - x_8 = -0.105339$

$1 \le y_1 \le 6,$

$1 \le y_2 \le 5.5,$

$1 \le y_3 \le 5,$

$1 \le y_4 \le 5.5,$

$1 \le y_5 \le 6,$

$0 \le x_j \le 1, \qquad j = 1, 2, 3, 4, 5, 6, 7,$

The results of the SINGLE-CRISP model are given in Table 7.5. The fuzzy regression based optimization model considers all interactions between customer needs and engineering characteristics as well as among engineering characteristics simultaneously. Consequently, it determines the target values of engineering characteristics which maximize customer satisfaction for the improved search engine.

Table 7.5. Results of the SINGLE-CRISP model

z	y_1	y_2	y_3	y_4	y_5	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
0.690648	3.402249	4.504292	3.393231	5.189768	4.738299	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	1.000000	0.341959

If the spread values of fuzzy parameters are also considered, formulation (7.2) can be rewritten as:

$$\text{Max } z = 0.026667\, y_1 + 0.044444\, y_2 + 0.066667\, y_3 + 0.014815\, y_4 + 0.066667\, y_5 \quad (7.3)$$

subject to

$6.966369\, x_2 + 1.194231\, x_4 + (-0.992978, 1.439427)\, x_8 - y_1 = -\ 0.920604$

$(2.809242, 0.281402)\, x_3 - 1.030394\, x_6 + (0.099707, 0.085349)\, x_7 - y_2 = -2.611275$

$(4.094207, 0.942027)\, x_1 - y_3 = -0.699997$

$1.186404\, x_3 + 3.524993\, x_5 + (1.038718, 0.344115)\, x_7 - y_4 = -0.555619$

$(-1.271864, 1.251269)\, x_1 - 2.361978\, x_5 + 3.437693\, x_6 - 1.538697\, x_8 - y_5 = -6.217503$

$(0.037616, 0.683793)\, x_2 - x_1 = -0.646529$

$0.274351\, x_1 - 0.289965\, x_4 - 0.151024\, x_6 + 1.260969\, x_8 - x_2 = (0.061846, 0.024748)$

$0.457848\, x_5 - x_3 = (-0.472384, 0.392442)$

$1.548470\, x_2 - x_4 = (-0.147441, 0.437361)$

$0.546033\, x_3 - x_5 = (-0.301586, 0.476191)$

$0.290536\, x_2 - x_6 = (-0.391555, 0.828798)$

$0.788601\, x_2 - x_8 = (-0.105339, 0.164502)$

$1 \le y_1 \le 6,$

$1 \le y_2 \le 5.5,$

$1 \le y_3 \le 5,$

$1 \le y_4 \le 5.5,$

$1 \le y_5 \le 6,$

$0 \le x_j \le 1, \qquad j = 1, 2, 3, 4, 5, 6, 7, 8.$

Following to Lee and Li [126], each fuzzy equality constraint is converted into an equivalent system of two inequality constraints to solve this fuzzy mathematical programming model.

$$\text{Max } z = 0.026667\, y_1 + 0.044444\, y_2 + 0.066667\, y_3 + 0.014815\, y_4 + 0.066667\, y_5 \qquad (7.4)$$

subject to

$$6.966369\, x_2 + 1.194231\, x_4 + (-0.992978\ , 1.439427\ )_\alpha^L\ x_8 - y_1 \le -\ 0.920604$$

$$6.966369\, x_2 + 1.194231\, x_4 + (-0.992978\ , 1.439427\ )_\alpha^U\ x_8 - y_1 \ge -\ 0.920604$$

$$(2.809242\ , 0.281402\ )_\alpha^L\ x_3 - 1.030394\, x_6 + (0.099707\ , 0.085349\ )_\alpha^L\ x_7 - y_2 \le -2.611275$$

$$(2.809242\ , 0.281402\ )_\alpha^U\ x_3 - 1.030394\, x_6 + (0.099707\ , 0.085349\ )_\alpha^U\ x_7 - y_2 \ge -2.611275$$

$$(4.094207\ , 0.942027\ )_\alpha^L\ x_1 - y_3 \le -0.699997$$

$$(4.094207\ , 0.942027\ )_\alpha^U\ x_1 - y_3 \ge -0.699997$$

$$1.186404\, x_3 + 3.524993\, x_5 + (1.038718\ , 0.344115\ )_\alpha^L\ x_7 - y_4 \le -0.555619$$

$$1.186404\, x_3 + 3.524993\, x_5 + (1.038718\ , 0.344115\ )_\alpha^U\ x_7 - y_4 \ge -0.555619$$

$$(-1.271864\ , 1.251269\ )_\alpha^L\ x_1 - 2.361978\, x_5 + 3.437693\, x_6 - 1.538697\, x_8 - y_5 \le -6.217503$$

$$(-1.271864\ , 1.251269\ )_\alpha^U\ x_1 - 2.361978\, x_5 + 3.437693\, x_6 - 1.538697\, x_8 - y_5 \ge -6.217503$$

$$(0.037616\ , 0.683793\ )_\alpha^L\ x_2 - x_1 \le -0.646529$$

$$(0.037616\ , 0.683793\ )_\alpha^U\ x_2 - x_1 \ge -0.646529$$

$$0.274351\, x_1 - 0.289965\, x_4 - 0.151024\, x_6 + 1.260969\, x_8 - x_2 \le (0.061846\ , 0.024748\ )_\alpha^U$$

$$0.274351\, x_1 - 0.289965\, x_4 - 0.151024\, x_6 + 1.260969\, x_8 - x_2 \ge (0.061846\ , 0.024748\ )_\alpha^L$$

$$0.457848\, x_5 - x_3 \le (-0.472384\ , 0.392442\ )_\alpha^U$$

$$0.457848\, x_5 - x_3 \ge (-0.472384\ , 0.392442\ )_\alpha^L$$

$1.548470\, x_2 - x_4 \leq (-0.147441 \ , 0.437361 \ )_{\alpha}^{U}$

$1.548470\, x_2 - x_4 \geq (-0.147441 \ , 0.437361 \ )_{\alpha}^{L}$

$0.546033\, x_3 - x_5 \leq (-0.301586 \ , 0.476191 \ )_{\alpha}^{U}$

$0.546033\, x_3 - x_5 \geq (-0.301586 \ , 0.476191 \ )_{\alpha}^{L}$

$0.290536\, x_2 - x_6 \leq (-0.391555 \ , 0.828798 \ )_{\alpha}^{U}$

$0.290536\, x_2 - x_6 \geq (-0.391555 \ , 0.828798 \ )_{\alpha}^{L}$

$0.788601\, x_2 - x_8 \leq (-0.105339 \ , 0.164502 \ )_{\alpha}^{U}$

$0.788601\, x_2 - x_8 \geq (-0.105339 \ , 0.164502 \ )_{\alpha}^{L}$

$1 \leq y_1 \leq 6,$

$1 \leq y_2 \leq 5.5,$

$1 \leq y_3 \leq 5,$

$1 \leq y_4 \leq 5.5,$

$1 \leq y_5 \leq 6,$

$0 \leq x_j \leq 1, \qquad j = 1, 2, 3, 4, 5, 6, 7, 8.$

The results obtained by solving the SINGLE-FUZZY model (7.4) for different α levels are summarized in Table 7.6. According to the results, z value increases as α decreases, i.e. as more fuzziness in the system parameters is considered in the optimization model.

Table 7.6. Results of the SINGLE-FUZZY model

α	z	y_1	y_2	y_3	y_4	y_5	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1	0.690648	3.402249	4.504292	3.393231	5.189768	4.738299	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	1.000000	0.341959
0.7	0.851071	5.052949	4.483970	4.062658	5.006494	5.869187	0.768289	0.501579	0.883721	0.792914	0.641270	0.785921	1.000000	0.550236
0.5	0.956361	6.000000	4.742812	4.850140	5.500000	6.000000	0.909078	0.691805	1.000000	1.000000	0.723810	0.932447	1.000000	0.731705
0.3	0.976394	6.000000	4.968766	5.000000	5.500000	6.000000	0.904573	0.596718	1.000000	0.765289	0.703087	0.784344	1.000000	0.581641
0	0.988403	6.000000	5.238960	5.000000	5.500000	6.000000	1.000000	0.590201	1.000000	0.623989	0.673801	0.628900	1.000000	0.498713

Albeit QFD aims to maximize customer satisfaction, requirements related to enterprise satisfaction such as extendibility, and technical difficulty also need to be considered. In other words, enterprise satisfaction along with customer satisfaction should be included in the modeling framework, thus the decision problem requires to be addressed using a multiple objective programming approach. This work presents a fuzzy multiple objective decision framework that includes not only fulfillment of engineering characteristics to maximize customer satisfaction, but also minimization of technical difficulty of engineering characteristics as objectives.

Formulation (5.13) is employed after introducing the importance degrees of the objectives given in Table 7.7. The step length (λ) and the accuracy of tolerance (τ) are set to be 0.05 and 0.005, respectively, as in [31].

Table 7.7. Importance degrees of the objectives

Objective	Type	Importance degree	Membership function
Fulfillment of overall customer satisfaction	Max	Very high (VH)	(0.7, 1, 1)
Technical difficulty of engineering characteristics	Min	Medium (M)	(0.2, 0.5, 0.5)

The algorithm presented in subsection 5.3 using crisp parameters yields the results given in Table 7.8. In order to ensure an undominated solution, formulation (5.14) is solved using the α value determined at the end of phase I and the arithmetic mean operator. According to the results given in Table 7.9, the grade of compromise obtained by the arithmetic mean operator is 0.899293. The same algorithm considering the spreads of fuzzy linear coefficients yields the results shown in Tables 7.10 and 7.11. The results given in Table 7.11 show that the grade of compromise for the MULTI-II model obtained by the arithmetic mean operator is 0.852715.

Table 7.8. Results of the phase I of the decision algorithm applied to MULTI-I model

α_c	β_c	α_c-β_c	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1.00	0.166637	0.833363	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.750008	0.341959
0.95	0.589194	0.360806	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.876775	0.341959
0.90	0.917657	-0.017657	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.975314	0.341959
0.925	0.763112	0.161888	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.928950	0.341959
0.9125	0.842596	0.069904	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.952795	0.341959
0.90625	0.880653	0.025597	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.964212	0.341959
0.903125	0.899293	0.003832	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.969804	0.341959

Table 7.9. Undominated solution for the MULTI-I model

α	β	$\lvert\alpha - \beta\rvert$	x_1^*	x_2^*	x_3^*	x_4^*	x_5^*	x_6^*	x_7^*	x_8^*	β_1 Fulfillment of overall customer satisfaction	β_2 Technical difficulty	$\overline{\beta}$
0.903125	0.899293	0.003832	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.969804	0.341959	0.899293	0.899293	0.899293

Table 7.10. Results of the phase I of the decision algorithm applied to MULTI-II model

α_c	β_c	α_c-β_c	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1.00	0.166637	0.833363	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.750008	0.341959
0.95	0.773367	0.176633	0.670250	0.330347	0.773255	0.637106	0.699999	0.528973	0.998630	0.374076
0.90	0.830875	0.069125	0.684884	0.361857	0.770753	0.664029	0.674824	0.579567	1.000000	0.407150
0.85	0.855128	-0.005128	0.701853	0.394649	0.768818	0.692940	0.649957	0.630535	1.000000	0.441235
0.875	0.844581	0.030419	0.693068	0.378088	0.769548	0.678229	0.662261	0.605003	1.000000	0.424063
0.8625	0.851353	0.011147	0.697384	0.386328	0.769738	0.685521	0.656412	0.617757	1.000000	0.432617
0.85625	0.852715	0.003535	0.699599	0.390479	0.768955	0.689216	0.653009	0.624143	1.000000	0.436918

Table 7.11. Undominated solution for the MULTI-II model

α	β	$\lvert\alpha - \beta\rvert$	x_1^*	x_2^*	x_3^*	x_4^*	x_5^*	x_6^*	x_7^*	x_8^*	β_1 Fulfillment of overall customer satisfaction	β_2 Technical difficulty	$\overline{\beta}$
0.85625	0.852715	0.003535	0.699599	0.390479	0.768955	0.689216	0.653009	0.624143	1.000000	0.436918	0.852715	0.852715	0.852715

The multiple criteria models presented in Section 5 use the VOC obtained previously, which is the past voice of customer. In rapidly changing industries like the information technology (IT) industry, customers can change their opinions. Thus, the importance of each customer need might have increased or decreased after a product is designed and manufactured.

In this work, to extend the concept of listening to the VOC into the future, an expert on the design of web pages is asked to estimate what the future importance of customer needs could be in a numerical sense for years 2009 (period 1) and 2012 (period 2). Table 7.12 shows the obtained information about the importance degrees of the customer needs.

Table 7.12. Importance degrees of the customer needs

Customer needs	**Period 0 (Liu et al., 2006a)**	**Period 1**	**Period 2**
Scalability	2	1	3
Reliability	3	4	4
Speed	4	3	1
Accuracy	1	2	2
Easy to use	5	5	5

In this work, we are concerned with the problem of formulating an overall decision function of importance degree such that for any customer need, the score obtained by the decision function indicates the integrated importance degree to which the desired requirements with respect to present and future periods (period 1 and period 2) are satisfied.

In decision processes with multiple information sources, in general, the final decision is made according to the majority of performance profiles given by different sources [131]. Thus, rather than requiring all the criteria be satisfied, only some portion of the criteria need to be satisfied. This portion of the criteria can be specified in terms of a linguistic quantifier such as *most* [132]. This quantifier can be used to generate the weighting vector **w** of an OWA aggregation operator to determine the overall evaluation for each customer need.

This work uses the RIM quantifier *most* which is shown in Figure 7.3.

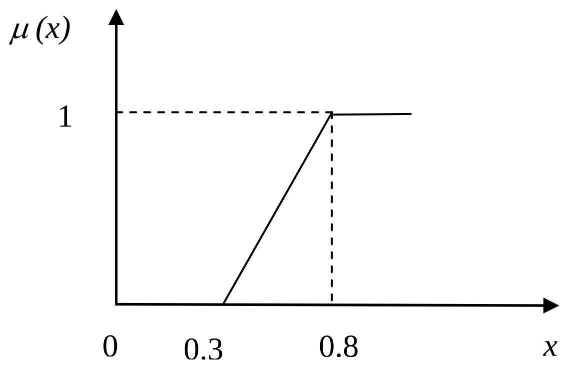

Figure 7.3. Regular increasing monotone quantifier *most* [131].

The weights obtained for each criteria (period 0, period 1 and period 2) from this linguistic quantifier Q by using the equation (6.3) are w_1 = 0.066667, w_2 = 0.666667, and w_3 = 0.266667.

The integrated importance degree of each customer need by combining the importance degrees of the three periods are calculated using an OWA operator which has an associated weighting vector **w** = [0.066667, 0.666667, 0.266667]. The MULTI-II model is solved employing new importance degrees. The results are given in Tables 7.13 and 7.14.

Table 7.13. Results of the phase I of the decision algorithm applied to MULTI-II model with FVOC

α_c	β_c	α_c-β_c	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1.00	0.166664	0.833336	0.657816	0.300050	0.813953	0.612060	0.746031	0.478730	0.749999	0.341959
0.95	0.687994	0.262006	0.667139	0.287023	0.822073	0.570019	0.726655	0.516365	1.000000	0.323460
0.90	0.741096	0.158904	0.679082	0.307122	0.837209	0.579274	0.711110	0.563665	1.000000	0.343610
0.85	0.771674	0.078326	0.701853	0.394649	0.792390	0.692940	0.662828	0.630535	1.000000	0.441235
0.80	0.793671	0.006329	0.721303	0.428809	0.796256	0.723968	0.641130	0.681900	1.000000	0.476399
0.75	0.808831	-0.058831	0.743391	0.464422	0.800488	0.757245	0.619631	0.733686	1.000000	0.512709
0.775	0.802116	-0.027116	0.734509	0.447805	0.798240	0.742447	0.630309	0.708138	1.000000	0.495491
0.7875	0.798291	-0.010791	0.726571	0.437574	0.797429	0.732072	0.635818	0.694806	1.000000	0.485367
0.79375	0.796013	-0.002263	0.723916	0.433181	0.796832	0.728002	0.638469	0.688350	1.000000	0.480875

Table 7.14. Undominated solution for the MULTI-II model with FVOC

α	β	$\lvert\alpha - \beta\rvert$	x_1^*	x_2^*	x_3^*	x_4^*	x_5^*	x_6^*	x_7^*	x_8^*	β_1 Fulfillment of overall customer satisfaction	β_2 Technical difficulty	$\overline{\beta}$
0.79375	0.796013	0.002263	0.723916	0.433181	0.796832	0.728002	0.638469	0.688350	1.000000	0.480875	0.796013	0.796013	0.796013

8. Results and Discussion

The z values for the competitors (i.e. Company 1 to Company 6) that are computed employing formulation (2) can be utilized to compare the results. Using the customer competitive assessment information contained in the HOQ given in Figure 7.1, the z values for Company 1, Company 2, Company 3, Company 4, Company 5, and Company 6 are computed as 0.662816, 0.593188, 0.682373, 0.669631, 0.852596, and 0.633779, respectively. Our product (C6) which has a low z value is ranked the fifth among all six competitors. It is currently weak in characteristics y_1, y_3, and y_5, moderate in y_4, and strong in y_2.

The z value of the design from the SINGLE-CRISP model (= 0.690648) is relatively high compared with our current z value (= 0.633779), and C6 ranks second among six competitors considering the outcomes of the optimization model. Compared with our current design, the optimization model improved y_3, y_4, and y_5 by trading off y_1 and y_2. The engineering characteristic values are determined to achieve such a value trade-off in the most efficient way.

For instance, the result of the optimization model yields a significantly higher y_5 than in our current design because y_5 is the most important customer need. According to Table 7.3, the value of y_5 is positively correlated with x_6 and negatively correlated with x_1, x_5, and x_8. In order to increase y_5, the resulting design improves the level of x_6 from 0.298246 to 0.478730, and lowers the level of x_8 from 0.428571 to 0.341959. The value of x_1 does not decrease in here (in fact, x_1 increases from 0.544737 to 0.657816) since the correlation between y_5 and x_1 is rather weak and making x_1 lower would significantly decrease the satisfaction on y_3, which is the customer need with the second highest relative importance. The value of y_3 is only positively correlated with x_1, and thus, the higher value of x_1 leads to an increase in y_3 from 3 to 3.393231. Likewise, in lieu of a decline in x_5, an increase from 0.571429 to 0.746031 is observed because the correlation between y_5 and x_5 is relatively weak and making x_5 lower would decrease the satisfaction on y_4. The model considers all such interactions between customer needs and engineering characteristics, as well as those among engineering characteristics simultaneously, and determines the optimal engineering characteristic values.

According to the results of the SINGLE-FUZZY model, when spread of the fuzzy parameters are considered (i.e. $\alpha < 1$), the z values exceed that of SINGLE-CRISP model. Table 7.6 shows that z value increases as α decreases, i.e. as more fuzziness in the system parameters is considered in the optimization model. When total fuzziness is allowed ($\alpha = 0$), the z value obtained for the SINGLE-FUZZY model, which is 0.988403, is much higher compared to the z value of the SINGLE-CRISP model, which is calculated as 0.690648, and exceeds that of C5 which has the highest z value among all six competitors.

The results of the SINGLE-FUZZY model enable the design team to concentrate on the engineering characteristics that would maximize overall customer satisfaction. For example, considering the optimal values of engineering characteristics for the improved search engine obtained using fuzzy regression and optimization framework with $\alpha = 0.3$, C6 has to improve its design performance in response time (x_1) from 0.544737 to 0.904573, database size (x_2) from 0.337603 to 0.596718, precision (x_3) from 0.813953 to 1, unique hits (x_5) from 0.571429 to 0.703087, dead links (x_6) from 0.298246 to 0.784344, update time (x_7) from 0.666667 to 1, number of formats (x_8) from 0.428571 to 0.581641 by trading off performance value in number of languages (x_4).

The results of the MULTI-I and MULTI-II approaches enable the company to concentrate on the engineering characteristics that would maximize overall customer satisfaction while also minimizing technical difficulty. The results given in Table 7.11 show that the grade of compromise obtained by the arithmetic mean operator is 0.852715 when the spreads of fuzzy parameters are considered. According to the results given in Table 7.11, the optimal values of ECs for the search engine indicate

100% fulfillment in *update time*, while the fulfillment degrees are 69.96% in *response time*, 39.05% in *database size*, 76.90% in *precision*, 68.92% in *number of languages*, 65.30% in *unique hits*, 62.41% in *dead links*, and 43.69% in *number of formats*.

9. Conclusion

The process of determining target levels of engineering characteristics using the information contained in a HOQ is a complex decision process which is generally accomplished in a subjective ad hoc manner in SQFD. Due to many tradeoffs that may exist among implicit or explicit relationships between customer needs and engineering characteristics and among engineering characteristics, these relationships cannot be identified using engineering knowledge through a team consensus. Moreover, relationships between customer needs and engineering characteristics and among engineering characteristics are generally vague in practice. The inherent fuzziness of functional relationships in QFD modeling promotes fuzzy regression as an effective tool for parameter estimation. In this work, fuzzy regression is used to estimate the parameters of functional relationships between customer needs and engineering characteristics and interrelationships among engineering characteristics. Fuzzy regression does not require the stringent assumptions of statistical regression and it is more suitable in addressing product design problems where the data set is limited and the degree of system fuzziness is high.

This work proposes multiple criteria decision approaches based on fuzzy regression that incorporate imprecise and subjective information inherent in the SQFD planning process to determine the target levels of engineering characteristics. First, a linear programming model that maximizes overall customer satisfaction is developed for setting target values of engineering characteristics using the functional relationships obtained by fuzzy regression. This primary model considers only the center value estimates from fuzzy regression as the parameter estimates and neglects the spread values. The degrees of satisfaction of customer needs and the target values of engineering characteristics are not set subjectively using engineering knowledge, but obtained employing the fuzzy regression and optimization approach. The proposed approach enables the design team to consider the tradeoffs among the degrees of satisfaction of customer needs to determine engineering characteristics values which maximize overall customer satisfaction.

The fuzzy regression and optimization approach with crisp parameters is extended to the fuzzy case by taking into account not only the center values but also spread values of fuzzy parameters obtained by fuzzy regression. The fuzzy mathematical programming model, which is developed to determine target levels of engineering characteristics, avoids loss of information in the design phase, and thus improves the optimal design.

QFD aims to maximize customer satisfaction; however, other requirements such as extendibility, and technical difficulty also need to be considered. The resulting decision problem needs to be addressed using a multiple objective decision making approach. The fuzzy multiple objective decision making framework proposed in this work enables the highest possible fulfillment of engineering characteristics to maximize overall customer satisfaction as an objective to be satisfied along with another enterprise related objective which is minimizing technical difficulty of engineering characteristics. The proposed approach can also distinguish between the importance of the objectives that are taken into account in QFD planning process by integrating the objective's membership function and the membership function corresponding to its importance degree employing the composition operator.

Quantitative approaches for determining target levels in QFD consider customer requirements obtained previously. Therefore, an innovative product cannot fully meet customer expectations when it is ready to market. In order to avoid this problem, it is necessary to forecast the changes on customers' future preferences. Finally, the fuzzy multiple objective decision making approach presented in this study is extended by considering future requirements to determine target levels of the new or improved software products that meet customer needs at the time when the product reaches the market.

The fuzzy multiple objective decision making framework presented in this work includes fulfillment of engineering characteristics to maximize overall customer satisfaction as an objective to be satisfied along with the company's another design related objective which is minimization of technical difficulty to determine target levels of ECs in product design. In fact, financial budget for meeting these targets is limited. Therefore, consideration of the design budget enables to preclude an unrealistic QFD planning in practice. In order to improve the proposed decision making approaches, a budget constraint can be incorporated into the formulations.

Due to the QFD's team-oriented characteristic, QFD process may involve information provided by many people. As a result, considering opinions of multiple decision-makers rather than a single decision-maker is more appropriate in making decisions. For further study, multiple decision-makers' viewpoints regarding the future importance of customer needs can be taken into account in QFD planning process. Thus, the determination of importance degree of customer needs in the fuzzy multiple objective decision making approach which considers FVOC can be addressed using group decision making.

References

[1] Davis, A.M., *Software Requirements: Objects, Functions, and States*, Prentice-Hall, Englewood Cliffs, NJ, (1993).

[2] Karlsson, J., “Managing Software Requirements Using Quality Function Deployment”, *Software Quality Journal*, 6, 311-325, (1997).

[3] Akao, Y., *Quality Function Deployment: Integrating Customer Requirements into Product Design*, Productivity Press, Cambridge MA, (1990).

[4] Chan, L-K., Wu, M-L., “Quality Function Deployment: A Literature Review”, *European Journal of Operational Research*, 143, 463-497, (2002).

[5] Haag, S.E., *A Field Study of the Use of Quality Function Deployment as Applied to Software Development*, Ph.D. Thesis, University of Texas at Arlington, (1992).

[6] Haag, S., Raja, M.K., Schkade, L.L., “Quality Function Deployment Usage in Software Development”, *Communications of the ACM*, 39 (1), 41-49, (1996).

[7] Bouchereau V., Rowlands, H., “Methods and Techniques Help Quality Function Deployment (QFD)”, *Benchmarking: An International Journal*, 7, 8-20, (2000).

[8] Xie, M., Tan, K.C., Goh, T.N., *Advanced QFD Applications*, ASQ Quality Press, Milwaukee, Wisconsin, (2003).

[9] ReVelle, J.B., Moran, J.W., Cox, C.A., *The QFD Handbook*, Wiley, New York, (1998).

[10] Kogure, M., Akao, Y., "Quality Function Deployment and Company Wide Quality Control in Japan: A Strategy for Assuring that Quality is Built into Products", *Quality Progress*, 25-29, (1983).

[11] Prasad, B., "Review of QFD and Related Deployment Techniques", *Journal of Manufacturing Systems*, 17, 221-234, (1998).

[12] Cristiano, J.J., Liker, J.K., White, C.C., "Customer-Driven Product Development through Quality Function Deployment in the U.S. and Japan", *Journal of Product Innovative Management*, 17, 286-308, (2000).

[13] Shillito, M.L., *Advanced QFD – Linking Technology to Market and Company Needs*, Wiley, New York, (1994).

[14] Han, S.B., Chen, S.K., Ebrahimpour, M., Sohdi, M.S., "A Conceptual QFD Planning Model", *International Journal of Quality & Reliability Management*, 18 (8), 796-812, (2001).

[15] Cox, C.A., "Key to Success in Quality Function Deployment", *APICS-The Performance Advantage*, 25-8, (1992).

[16] Akao, Y., "QFD: Past, Present, and Future", *Proceedings of the International Symposium on QFD'97*, Linköping, (1997).

[17] Hauser, J.R., Clausing, D., "The House of Quality", Harvard Business Review, 66, 63-73, (1988).

[18] Karsak, E.E., "Fuzzy Multiple Objective Decision Making Approach to Prioritize Design Requirements in Quality Function Deployment", *International Journal of Production Research*, 15, 3957-3974, (2004).

[19] Kim, K.J., Moskowitz, H., Dhingra, A., Evans, G., “Fuzzy Multicriteria Models for Quality Function Deployment”, *European Journal of Operational Research,* 121, 504-518, (2000).

[20] Kim, K.J., Kim, D.H., Min, D.K., “Robust QFD: Framework and a Case Study”, *Quality and Reliability Engineering International*, 23, 31-44, (2007).

[21] Masud, A.S.M., Dean, E.B., “Using Fuzzy Sets in Quality Function Deployment”, *Proceedings of the Second Industrial Engineering Research Conference,* Los Angeles, (1993).

[22] Khoo, L.P., Ho, N.C., “Framework of a Fuzzy Quality Function Deployment System”, *International Journal of Production Research,* 34 (2), 299-311, (1996).

[23] Chan, L., Kao, H., Ng, A., Wu, M., “Rating the Importance of Customer Needs in Quality Function Deployment by Fuzzy and Entropy Methods”, *International Journal of Production Research,* 37 (11), 2499-2518, (1999).

[24] Wang, J., “Fuzzy Outranking Approach to Prioritize Design Requirements in Quality Function Deployment”, *International Journal of Production Research,* 37 (4), 899-916, (1999).

[25] Zhou, M., “Fuzzy Logic and Optimization Models for Implementing QFD”, *Computers and Industrial Engineering,* 35, 237-240, (1998).

[26] Fung, R.Y.K., Law, D.S.T., Ip, W.H., “Design Targets Determination for Inter-Dependent Product Attributes in QFD Using Fuzzy Inference”, *Integrated Manufacturing Systems,* 10 (6), 376-383, (1999).

[27] Vanegas, L.V., Labib, A.W., "A Fuzzy Quality Function Deployment (FQFD) Model for Deriving Optimum Targets", *International Journal of Production Research*, 39 (1), 99-120, (2001).

[28] Piedras, H., Yacout, S., Savard, G., "Concurrent Optimization of Customer Requirements and the Design of a New Product", *International Journal of Production Research*, 44 (20), 4401-4416, (2006).

[29] Chen, Y.Z., Ngai, E.W.T., "A Fuzzy QFD Program Modelling Approach Using the Method of Imprecision", *International Journal of Production Research,* 46 (24), 6823-6840, (2008).

[30] Chen, Y., Tang, J., Fung, R.Y.K., Ren, Z., "Fuzzy Regression-Based Mathematical Programming Model for Quality Function Deployment", *International Journal of Production Research*, 42 (5), 1009-1027, (2004).

[31] Karsak, E.E., "Fuzzy Multiple Objective Programming Framework to Prioritize Design Requirements in Quality Function Deployment", *Computers & Industrial Engineering*, 47, 149-163, (2004).

[32] Carnevalli, J.A., Miguel, P.C., "Review, Analysis and Classification of the Literature on QFD – Types of Research, Difficulties and Benefits", *International Journal of Production Economics*, 114, 737-754, (2008).

[33] Krishnan, M.S., *Cost and Quality Considerations in Software Product Management*, Ph.D. Thesis, Carnegie Mellon University, Pittsburgh, (1996).

[34] Kekre, S., Krishnan, M.S., Srinivasan, K., "Drivers of Customer Satisfaction for Software Products: Implications for Design and Service Support", *Management Science*, 41 (9), 1456-1470, (1995).

[35] Zultner, R.E., “TQM for Technical Teams”, *Communications of the ACM*, 36 (10), 78-91, (1993).

[36] Boehm, B.W., *Software Engineering Economics*, Prentice-Hall Publishing Company, New Jersey, (1981).

[37] Huang, L., *Software Quality Analysis: A Value-Based Approach*, Ph.D. Thesis, University of Southern California, (2006).

[38] Necco, C.R., Gordon, C.L., Tsai N.W., “Systems Analysis and Design Current Practices”, *MIS Quarterly*, December, 460-475, (1987).

[39] Liu, F., Noguchi, K., Dhungana, A., Srirangam A., V.V.N.S.N., Inuganti, P., “A Quantitative Approach for Setting Technical Targets Based on Impact Analysis in Software Quality Function Deployment (SQFD)”, *Software Quality Journal*, 14, 113-134, (2006).

[40] Yilmaz, M.R., Chatterjee, S., “Deming and the Quality of Software Development”, *Business Horizons*, 40 (6), 51-58, (1997).

[41] Herzwurm, G., Schockert, S., “The Leading Edge in QFD for Software and Electronic Business”, *The International Journal of Quality & Reliability Management*, 20 (1), 36-55, (2003).

[42] Barnett, W.D., Raja, M.K., “Application of QFD to the Software Development Process”, *The International Journal of Quality & Reliability Management*, 12 (6), 24-42, (1995).

[43] Elboushi, M.I., Sherif, J.S., “Object – Oriented Software Design Utilizing Quality Function Deployment”, *Journal of Systems and Software*, 38, 133-143, (1997).

[44] Liu, X.F., “Software Quality Function Deployment”, *IEEE Potentials*, 19 (5), 14-16, (2000).

[45] Pai, W.C., “A Quality-Enhancing Software Function Deployment Model”, *Information Systems Management*, 19 (3), 20-24, (2002).

[46] Richardson, I., “SPI Models: What Characteristics Are Required for Small Software Development Companies?”, *Software Quality Journal*, 10, 101-114, (2002).

[47] Buyukozkan, G, Feyzioglu, O., “Group Decision Making to Better Respond Customer Needs in Software Development” *Computers & Industrial Engineering*, 48, 427-441, (2005).

[48] Ramires, J., Antunes, P., Respício, A., “Software Requirements Negotiation Using the Software Quality Function Deployment”, *Lecture Notes in Computer Science*, 3706, 308-324, (2005).

[49] Liu, X., Inuganti, P., Noguchi, K., “Technical Target Setting in Time-Stamped Quality Function Deployment”, *Total Quality Management*, 12 (2), 149-177, (2006).

[50] Ip, B., Jacobs, G., “Quality Function Deployment for the Games Industry: Results from a Practical Application”, *Total Quality Management*, 17 (7), 835-856, (2006).

[51] Zultner, R.E., *Software Quality Deployment Basic Seminar: Applying QFD to Software*, Methuen, Massachusetts, (1991).

[52] Haag, S.E., *Software Quality Function Deployment: A New Beginning for Software Engineering Methodologies*, Presentation to Electronic Data Systems, Plano, Texas, (1991).

[53] Zadeh, L.A., “Fuzzy Sets”, *Information and Control*, 8, 338-353, (1965).

[54] Tanaka, H., Guo, P., *Possibilistic Data Analysis for Operations Research,* Physica-Verlag Heidelberg, New York, (1999).

[55] Tanaka, H., Uejima, S., Asai, K., “Linear Regression Analysis with Fuzzy Model”, *IEEE Transactions on Systems, Man, and Cybernetics*, 12 (6), 903-907, (1982).

[56] Sener, Z., Karsak, E.E., “A Decision Model for Advanced Manufacturing Technology Selection Using Fuzzy Regression and Fuzzy Optimization”, *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, Montréal, 565-569, (2007).

[57] Redden, D.T., Woodall W. H., “Properties of Certain Fuzzy Linear Regression Methods”, *Fuzzy Sets and Systems*, 64, 361-375, (1994).

[58] Kim, K.J., Moskowitz, H., Koksalan, M., “Fuzzy versus Statistical Linear Regression”, *European Journal of Operational Research*, 92, 417-434, (1996).

[59] Tanaka, H., Watada, J., “Possibilistic Linear Systems and Their Application to the Linear Regression Model”, *Fuzzy Sets and Systems*, 27, 275-289, (1988).

[60] Moskowitz, H., Kim, K., “On Assessing the H Value in Fuzzy Linear Regression”, *Fuzzy Sets and Systems*, 58, 303-327, (1993).

[61] Tanaka, H., “Fuzzy Data Analysis by Possibilistic Linear Models”, *Fuzzy Sets and Systems*, 24, 363-375, (1987).

[62] Tanaka, H., Hayashi, I., Watada, J., “Possibilistic Linear Regression Analysis for Fuzzy Data”, *European Journal of Operational Research*, 40, 389-396, (1989).

[63] Bardossy, A., “Note on Fuzzy Regression”, *Fuzzy Sets and Systems*, 37, 65-75, (1990).

[64] Wang, X., Ha, M., “Fuzzy Linear Regression Analysis”, *Fuzzy Sets and Systems*, 51, 179-188, (1992).

[65] Chang, P.T., Lee, E.S., “Fuzzy Linear Regression with Spread Unrestricted in Sign”, *Computers & Mathematics with Applications*, 28, 61-70, (1994).

[66] Kim, B., Bishu, R.R., “Evaluation of Fuzzy Linear Regression Models by Comparing Membership Functions”, *Fuzzy Sets and Systems*, 100 (1-3), 343-352, (1998).

[67] Yen, K.K., Ghoshray, S., Roig, G., “A Linear Regression Model Using Triangular Fuzzy Number Coefficients”, *Fuzzy Sets and Systems*, 106, 167-177, (1999).

[68] Hojati, M., Bector, C.R., Smimou, K., “A Simple Method for Computation of Fuzzy Linear Regression”, *European Journal of Operational Research*, 166 (1), 172-184, (2005).

[69] Peters, G., “Fuzzy Linear Regression with Fuzzy Intervals”, *Fuzzy Sets and Systems*, 63, 45-55, (1994).

[70] Chen, Y-S., “Outliers Detection and Confidence Interval Modification in Fuzzy Regression”, *Fuzzy Sets and Systems*, 119, 259-272, (2001).

[71] Jajuga, K., “Linear Fuzzy Regression”, *Fuzzy Sets and Systems*, 343-353, (1986).

[72] Celmins, A., “Multidimensional Least-Squares Fitting of Fuzzy Models”, *Mathematical Modeling*, 9, 669-690, (1987).

[73] Celmins, A., “Least Squares Model Fitting to Fuzzy Vector Data”, *Fuzzy Sets and Systems*, 22, 2455-269, (1987).

[74] Diamond, P., “Fuzzy Least Squares”, *Information Sciences*, 46, 141-157, (1988).

[75] Nather, W., Albrecht, M., “Linear Regression with Random Fuzzy Observations”, *Statistics*, 21, 521-531, (1990).

[76] Savic, D.A., Pedrycz, W., “Evaluation of Fuzzy Linear Regression Models”, *Fuzzy Sets and Systems*, 39, 51-63, (1991).

[77] Chang, P.T., Lee, E.S., “Fuzzy Least Absolute Deviations Regression and the Conflicting Trends in Fuzzy Parameters”, *Computers & Mathematics with Applications*, 28, 89-101, (1994).

[78] Chang, P.T., Lee, E.S., “A Generalized Fuzzy Weighted Least-Squares Regression”, *Fuzzy Sets and Systems*, 82 (3), 289-298, (1996).

[79] D’Urso, P., Gastaldi, T., “A Least-Squares Approach to Fuzzy Linear Regression Analysis”, *Computational Statistics & Data Analysis*, 34 (4), 427-440, (2000).

[80] Wang, H-F., Tsaur, R-C., “Resolution of Fuzzy Regression Model”, *European Journal of Operational Research*, 126, 637-650, (2000).

[81] Chang, Y-H.O., “Hybrid Fuzzy Least-Squares Regression Analysis and Its Reliability Measures”, *Fuzzy Sets and Systems*, 119 (2), 225-246, (2001).

[82] Wünsche, A., Nather, W., “Least-Square Fuzzy Regression with Fuzzy Random Variables”, *Fuzzy Sets and Systems*, 130, 43-50, (2002).

[83] Yang, M-S., Lin, T-S., "Fuzzy Least-Squares Linear Regression Analysis for Fuzzy Input-Output Data", *Fuzzy Sets and Systems*, 126 (3), 389-399, (2002).

[84] D'Urso, P., "Linear Regression Analysis for Fuzzy/Crisp Input and Fuzzy/Crisp Output Data", *Computational Statistics & Data Analysis*, 42 (1-2), 47-72, (2003).

[85] Kao, C., Chyu, C-L., "Least-Squares Estimates in Fuzzy Regression Analysis", *European Journal of Operational Research*, 148, 426-435, (2003).

[86] Yang, M-S., Liu, H-H., "Fuzzy Least-Squares Algorithms for Interactive Fuzzy Linear Regression Models", *Fuzzy Sets and Systems*, 135 (2), 305-316, (2003).

[87] Chang, Y., Ayyub, B.M., "Fuzzy Regression Methods – A Comparative Assessment", Fuzzy Sets and Systems, 119, 187-203, (2001).

[88] Sakawa, M.,Yano, H., "Multiobjective Fuzzy Linear Regression Analysis for Fuzzy Input-Output Data", *Fuzzy Sets and Systems,* 47, 173-181, (1992).

[89] Özelkan, E.C., Duckstein, L., "Multi-Objective Fuzzy Regression: A General Framework", *Computers & Operations Research*, 27, 635-652, (2000).

[90] Özelkan, E.C., Duckstein, L., "Fuzzy Conceptual Rainfall–Runoff Models", *Journal of Hydrology*, 253 (1-4), 41-68, (2001).

[91] Tran, L., Duckstein, L., "Multiobjective Fuzzy Regression with Central Tendency and Possibilistic Properties", *Fuzzy Sets and Systems*, 130, 21-31, (2002).

[92] Nasrabadi, M.M., Nasrabadi, E., Nasrabady, A.R., "Fuzzy Linear Regression Analysis: A Multi-Objective Programming Approach", *Applied Mathematics and Computation*, 163 (1), 245-251, (2005).

[93] Ishibuchi, H., Tanaka, H., “Fuzzy Regression Analysis Using Neural Networks”, *Fuzzy Sets and Systems,* 50, 257-365, (1992).

[94] Ishibuchi, I., Tanaka, H., Okada, H., “An Architecture of Neural Networks with Interval Weights and Its Application to Fuzzy Regression Analysis”, *Fuzzy Sets and Systems*, 57, 27-39, (1993).

[95] Dunyak, J.P., Wunsch, D., “Fuzzy Regression by Fuzzy Number Neural Networks”, *Fuzzy Sets and Systems,* 112 (3), 371-380, (2000).

[96] Ishibuchi, H., Nii, M., “Fuzzy Regression Using Asymmetric Fuzzy Coefficients and Fuzzified Neural Networks”, *Fuzzy Sets and Systems*, 119(2), 273-290, (2001).

[97] Khaskei, M., Hejazi, S.R., Bijari, M., “A New Hybrid Artificial Neural Networks and Fuzzy Regression Model for Time Series Forecasting”, *Fuzzy Sets and Systems*, 159, 769-786, (2008).

[98] Sánchez, J., Gomez, A.T., “Estimating a Fuzzy Term Structure of Interest Rates Using Fuzzy Regression Techniques”, *European Journal of Operational Research,* 154 (3), 804-818, (2004).

[99] Wen, C.-G., Lee, C.-S., “Development of a Cost Function for Wastewater Treatment Systems with Fuzzy Regression”, *Fuzzy Sets and Systems,* 106, 143-153, (1999).

[100] Fung, R.Y.K., Chen, Y., Chen, L., Tang, J., “A Fuzzy Expected Value-Based Goal Programing Model for Product Planning Using Quality Function Deployment”, *Engineering Optimization,* 37 (7), 1-15, (2005).

[101] Fung, R.Y.K., Chen, Y., Tang, J., "Estimating the Functional Relationships for Quality Function Deployment Under Uncertainties", *Fuzzy Sets and Systems*, 157, 98-120, (2006).

[102] Chen, Y., Chen, L., "A Non-Linear Possibilistic Regression Approach to Model Functional Relationships in Product Planning", *International Journal of Advanced Manufacturing Technology*, 28, 1175-1181, (2006).

[103] Karsak, E.E., "Robot Selection Using an Integrated Approach Based on Quality Function Deployment and Fuzzy Regression", *International Journal of Production Research*, 46 (3), 723-738, (2008).

[104] Heshmaty, B., Kandel, A., "Fuzzy Linear Regression and its Applications to Forecasting in Uncertain Environment", *Fuzzy Sets and Systems*, 15, 159-191, (1985).

[105] Sakawa, M., Yano, H., "Fuzzy Linear Regression and Its Application to the Sales Forecasting", *International Journal of Policy and Information*, 13, 111-125, (1989).

[106] Chang, P-T., "Fuzzy Seasonality Forecasting", *Fuzzy Sets and Systems*, 90 (1), 1-10, (1997).

[107] Kahraman, C., "An Application of Fuzzy Linear Regression to the Information Technology in Turkey", *International Journal of Technology Management*, 24, 330-339, (2002).

[108] Lee, H.T., Chen, S.H., "Fuzzy Regression Model with Fuzzy Input and Output Data for Manpower Forecasting", *Fuzzy Sets and Systems*, 119 (2), 205-213, (2001).

[109] Hayashi, I., Tanaka, H., "The Fuzzy GMDH Algorithm by Possibility Models and Its Application", *Fuzzy Sets and Systems*, 36, 245-258 (1990).

[110] Oh, S.-B., Kim, W., Lee, J.K., "An Approach to Causal Modeling in Fuzzy Environment and Its Application", *Fuzzy Sets and Systems*, 35, 43-55, (1990).

[111] Gharpuray, M.M., Tanaka, H., Fan, L.T., Lai, F.S., "Fuzzy Linear Regression Analysis of Cellulose Hydrolysis", *Chemical Engineering Communications*, 41, 299-314, (1986).

[112] Bardossy, A., Bogardi, I., Duckstein, L., "Fuzzy Regression in Hydrology", *Water Resources Research*, 26, 1497-1508, (1990).

[113] Chang, P.-T., Lee, E.S., Konz, S.A., "Applying Fuzzy Linear Regression to VDT Legibility, Fuzzy Sets and Systems, 80, 197-204, (1996).

[114] Chang, P-T., "Fuzzy Stage Characteristic-Preserving Product Life Cycle Modeling", *Fuzzy Sets and Systems*, 126 (1), 33-47, (2002).

[115] Cron, G., Dubuisson, B., "Pattern Characteristics of an Evolution between Two Classes", *Fuzzy Sets and Systems*, 126 (3), 293-310, (2002).

[116] Tran, L.T., Ridgley, M.A., Duckstein, L., Sutherland, R., "Application of Fuzzy-Logic Based Modeling to Improve the Performance of the Revised Universal Soil Loss Equation", *Catena*, 47 (3), 203-226, (2002).

[117] Wu, B., Tseng, N-F., "A New Approach to Fuzzy Regression Models with Application to Business Cycle Analysis", *Fuzzy Sets and Systems*, 130, 33-42, (2002).

[118] Ip, K.W., Kwong, C.K., Wong, Y.W., "Fuzzy Regression Approach to Modelling Transfer Moulding for Microchip Encapsulation", *Journal of Materials Processing Technology*, 140 (1-3), 147-151, (2003).

[119] Chang, P-T., “Fuzzy Strategic Replacement Analysis”, *European Journal of Operational Research*, 160 (2), 532-559, (2005).

[120] Imoto, S., Yabuuchi, Y., Watada, J., “Fuzzy Regression Model of R&D Project Evaluation”, *Applied Soft Computing*, 8, 1266-1273, (2008).

[121] Wang, H., Xie, M., Goh, T.N., “A Comparative Study of the Prioritization Matrix Method and the Analytic Hierarchy Process Technique in Quality Function Deployment”, *Total Quality Management*, 9 (6), 421-430, (1998).

[122] Wasserman, G.S., “On How to Prioritize Design Requirements During the QFD Planning Process”, *IIE Transactions*, 25, 59-65, (1993).

[123] Karsak, E.E., Sozer, S., Alptekin, S.E., “Product Planning in Quality Function Deployment Using a Combined Analytic Network Process and Goal Programming Approach”, *Computers & Industrial Engineering*, 44 , 171-190, (2003).

[124] Karsak, E.E, Özogul, C.O., “An Integrated Decision Making Approach for ERP System Selection”, *Expert Systems with Applications*, 36 (1), 660-667, (2009).

[125] Inuiguchi, M., Ramik, J., “Possibilistic Linear Programming: A Brief Review of Fuzzy Mathematical Programming and a Comparison with Stochastic Programming in Portfolio Selection Problem”, *Fuzzy Sets and Systems*, 111, 3-28, (2000).

[126] Lee, E.S., Li, R.J., “Fuzzy Multiple Objective Programming and Compromise Programming with Pareto Optimum”, *Fuzzy Sets and Systems*, 53, 275-288, (1993).

[127] Perego, A., Rangone, A., “A Reference Framework for the Application of MADM Fuzzy Techniques to Selecting AMTS”, *International Journal of Production Research*, 36 (2), 437-458, (1998).

[128] Narasimhan, R., “On Fuzzy Goal Programming – Some Comments”, *Decision Sciences*, 12, 532-537, (1981).

[129] Shen, X., Xie, M., Tan, K., “Listening to the Voice of Customer Using Fuzzy Trend Analysis in QFD”, *Quality Engineering*, 13 (3), 419-425, (2001).

[130] Raharjo, H., Xie, M., Brombacher, A.C., “Prioritizing Quality Characteristics in the Dynamic QFD”, *International Journal of Production Research*, 44 (23), 5005-5018, (2006).

[131] Herrera, F., Herrera-Viedma, E., Martinez, L., “A Fusion Approach for Managing Multi-Granularity Linguistic Term Sets in Decision Making”, *Fuzzy Sets and Systems*, 114, 43-58, (2000).

[132] Yager, R.R., “Quantifier Guided Aggregation Using OWA Operators”, *International Journal of Intelligent Systems*, 11, 49-73, (1996).

[133] Yager, R.R., “On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decision Making”, *IEEE Transactions on Systems, Man and Cybernetics*, 18, 183-190, (1988).

[134] Zadeh, L.A., “A Computational Approach to Fuzzy Quantifiers in Natural Languages”, *Computers and Mathematics with Applications*, 9, 149-184, (1983).

[135] Filev, D., Yager, R.R., “Learning OWA Operator Weights From Data”, *Proceedings of the Third IEEE Conference on Fuzzy Systems*, Orlando, FL, 468-473, (1994).

[136] Yager, R.R., “Criteria Importances in OWA Aggregation: An Application of Fuzzy Modeling”, *Proceedings of the Sixth IEEE International Conference on Fuzzy Systems*, 1677-1682, (1997).

[137] O'Hagan, M., "Aggregating Template or Rule Antecedents in Real-Time Expert Systems with Fuzzy Set Logic", *Proceedings of the 22nd Annual IEEE Asilomar Conference on Signals, Systems, Computers*, Pacific Grove, CA, 681-689, (1988).

[138] Fullér, R., Majlender, P., "On Obtaining Minimal Variability OWA Operator Weights", *Fuzzy Sets and Systems*, 136, 203-215, (2003).

[139] Wang, Y.-M., Parkan, C., "A Minimax Disparity Approach for Obtaining OWA Operator Weights", *Information Sciences*, 175, 20-29, (2005).

[140] Fullér, R., "On Obtaining OWA Operator Weights: A Short Survey of Recent Developments", *Proceedings of the 5th IEEE International Conference on Computational Cybernetics*, Tunisia, 241-244, (2007).

[141] Wang, H., Xie, M., Goh, T.N., "Service Quality of Internet Search Engines", *Journal of Information Science,* 25 (6), 499-507, (1999).

[142] Xie, M., Wang, H., Goh, T.N., "Quality Dimensions of Internet Search Engines", *Journal of Information Science,* 24 (5), 87-94, (1998).

[143] Herring, S.D., "The Value of Interdisciplinarity: A Study Based on the Design of Internet Search Engines", *Journal of the American Society for Information Science,* 50 (4), 358-365, (1999).

[144] Schwartz, C., "Web Search Engines", *Journal of the American Society for Information Science*, 49 (11), 973-982, (1998).

[145] Parasuraman, A., Zeithaml, V.A., Berry, L.L., "SERVQUAL: A Multiple–Item Scale for Measuring Consumer Perceptions of Service Quality", *Journal of Retailing*, 64 (1), 12-40, (1988).

[146] Chu, H., Rosenthal, M., “Search Engines for the World Wide Web: A Comparative Study and Evaluation Methodology”, *ASIS 1996 Annual Conference Proceedings,* (1996).

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Selected Publications

Sener Z., Karsak, E.E. (2010). A Fuzzy Regression and Optimization Approach for Setting Target Levels in Software Quality Function Deployment. Software Quality Journal, DOI: 10.1007/s11219-010-9095-6.

Sener Z., Karsak, E.E. (2009). A Decision Model for Setting Target Levels in Quality Function Deployment Using Nonlinear Programming-Based Fuzzy Regression and Optimization. International Journal of Advanced Manufacturing Technology, DOI: 10.1007/s00170-009-2330-2.

Sener, Z., Karsak, E.E. (2008). A Decision Making Approach Based on Fuzzy Regression and Fuzzy Multiple Objective Programming for Advanced Manufacturing Technology Selection. Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM 2008), Singapore, 964-968. **(Honorable Mention Award)**

Sener, Z., Karsak, E.E. (2007). A Decision Model for Advanced Manufacturing Technology Selection Using Fuzzy Regression and Fuzzy Optimization. Proceedings of the 2007 IEEE International Conference on Systems, Man and Cybernetics (SMC 2007), Montréal, Canada, 565-569.

Karsak, E.E., Yilmaz, Z. (2005). Fuzzy Linear Regression-Based Decision Model for Robot Selection. Proceedings of the 35th International Conference on Computers and Industrial Engineering (ICC&IE), Istanbul, Turkey, 1085-1090.