

# An integrated fuzzy multiple objective decision framework to optimal fulfillment of engineering characteristics in quality function development

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## ABSTRACT

Quality function development (QFD) is a planning tools used to fulfill customer expectation and QFD is a systematic process to translating customer requirement (WHATs) into technical description (HOWs). QFD aims to maximize customer satisfactions related to enterprise satisfaction. The inherent fuzziness of relationships in QFD modeling justifies the use of fuzzy regression for estimating the relationships between both customer needs and engineering characteristics, and among engineering characteristics. This paper present a fuzzy multiple objective method to fulfillment of technical description to maximize customer satisfactions and also maximization of extendibility and minimization of technical difficulty of engineering criteria are another object of this proposed method. In this paper fuzzy regression is used to estimating relationship between customer requirement and technical descriptions. Meanwhile, the fuzzy logic and triangular fuzzy numbers are utilized to deal with vagueness of human thought. Furthermore, a case study is conducted to illustrate the stages of ISP suppliers.

## Keywords

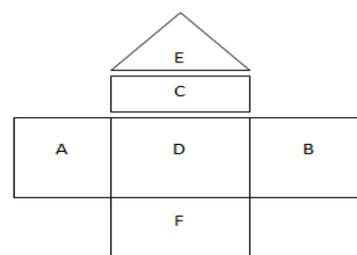
Quality Function Development, House of Quality, Fuzzy Multiple Objective Programming

## Introduction

Quality function deployment belongs to the sphere of quality management methods and use to fulfill customer expectations. It is disciplined approach to product design, engineering, and production and provides in-depth evaluation of a product. An organization that correctly implements QFD can improve engineering, productivity, and quality and reduce costs, product development time, and engineering changes. QFD focuses on customer expectations or requirements, often referred to as the voice of customer. It is

employed to translate customer expectations, in terms of specific requirements, into directions and actions, in terms of engineering or technical characteristics, that can be deployed through: product planning, part development, process planning, production planning, and service industries

(Besterfield, Michna, Besterfield, & Sacre, 2003). Further details on the benefits of using QFD can be found in (Griffin, 1992). The primary planning tool used in QFD is the House of Quality. The HOQ translates the voice of customer into design requirements that meet specific target values and matches those against how an organization will meet those requirements. The structure of HOQ can be thought of as a framework of a house, as shown in Fig. 1 (Wu, 2011).



A	Customer requirement (voice of customer) (WHATs)
B	Prioritized customer requirement
C	Technical descriptor (voice of organization) (HOWs)
D	Relationship between requirement and descriptor
E	International between technical descriptor
F	Prioritized technical descriptors

**Fig 1. House of quality.**

The process of quantifying the planning issues in the HOQ has received increasing attention within the past decade (Karsak, Sozer, & Alptekin, 2003; Wu2011). The methodologies presented in these works implicitly assumed

that the relationships between WHATs and HOWs and among HOWs can be identified using engineering knowledge. On the other hand, despite its numerous benefits, researchers have reported several problems concerning the QFD technique such as ambiguity in the voice of the customer, need to input and analyze large amounts of subjective data, impreciseness in the process of setting target values in the HOQ (Bouchereau & Rowlands, 2000 ; Na et al , 2012). The vagueness or imprecision arises mainly from the fact that WHATs, which tend to be subjective, qualitative, and nontechnical, need to be translated into HOWs that should be expressed in more quantitative and technical terms. Further, data available for product design is often limited, inaccurate, or vague at best (Kim, Moskowitz, Dhingra, & Evans, 2000). The inherent fuzziness of relationships in QFD modeling justifies the use of fuzzy regression to determine the functional relationships between WHATs and HOWs, and among HOWs. Several studies employed fuzzy regression to estimate the relationships in QFD. Kim et al. (2000) proposed fuzzy multi-criteria models for quality function deployment. They defined the major model components in a crisp or fuzzy way using multi-attribute value theory combined with fuzzy regression and fuzzy optimization without considering the cost factor. Chen, Tang, Fung, and Ren (2004) extended the fuzzy linear regression with symmetric triangular fuzzy coefficients to non-symmetric triangular fuzzy coefficients. The design budget is included in the model proposed for QFD product planning. Fung, Chen, Chen, and Tang (2005) proposed an asymmetric fuzzy linear regression approach to estimate the functional relationships for product planning based on QFD. Lately, QFD and fuzzy linear regression based framework has been used as an alternative approach for selection problems. Karsak (2008) employed QFD and fuzzy regression based optimization for robot selection. More recently, Karsak and zogul (2009) 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. Hashin and Dawaln (2012) use combination of Kano Model and fuzzy linear regression integration approach for Ergonomic Design Improvement characteristics. In all these studies, the target levels of engineering characteristics are determined by considering WHATs in a way to satisfy a single objective, which is maximizing overall customer satisfaction. In general, the satisfaction of WHATs is not the only consideration in product design. Other requirements such as cost budget, technical difficulty, and extendibility 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 HOWs, extendibility of HOWs, and cost of HOWs 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 fuzzy logic and triangular fuzzy numbers are utilized to deal with vagueness of human thought.

This paper proposes a novel approach for determining target levels of engineering characteristics by integrating

fuzzy linear regression and fuzzy multiple objective programming. Fuzzy regression is introduced in the model to identify relationships between WHATs and HOWs, and among HOWs. Due to the inherent fuzziness of relationships in QFD modeling, fuzzy regression is used as an effective tool for parameter estimation. Considering the multi-objective nature of the design problem, the highest possible fulfillment of HOWs to maximize overall customer satisfaction is used as an objective to be satisfied along with other objectives such as technical difficulty and extendibility of HOWs subject to a financial constraint. The rest of the paper is organized as follows: Section 2 presents fuzzy linear regression. In Section 3, fuzzy multiple objective programming approach for setting target levels of engineering characteristics in QFD is introduced. In Section 4, the proposed approach is illustrated using data from ISP supplier in IRAN. Conclusions and directions for future research are presented in the last section.

## 2. Fuzzy linear regression

According to Hauser and Clausing (1988), the HOQ, the primary tool for QFD, is a conceptual map that provides the means for inter functional planning and The HOQ translates the voice of customer into design requirements that meet specific target values and matches those against how an organization will meet those requirements . In general, maximizing overall customer satisfaction is the only objective considered in the process of setting target levels of HOWs. The process of determining target values for HOWs to maximize overall customer satisfaction can be formulated as an optimization problem as follows (Kim et al., 2000):

$$(1) \quad \text{Max } Z (y_1, y_2, \dots, y_m) = \sum_{i=1}^M W_i [(y_i - y_i^{\min}) / (y_i^{\max} - y_i^{\min})]$$

Subject to

$$\begin{aligned} y_i &= f_i (x_1, x_2, \dots, x_N) & i=1, 2, \dots, M \\ x_j &= g_j (x_1, x_2, \dots, x_{j-1}, x_{j+1}, \dots, x_N) & j=1, 2, \dots, N \\ y_i^{\min} &\leq y_i \leq y_i^{\max} \end{aligned}$$

where  $w_i$  represents the relative importance of customer need  $i$  such that  $0 < W_i \leq 1$  and  $\sum_{i=1}^M W_i = 1$  denotes the customer perception of the degree of satisfaction of customer need  $i$  ( $i = 1, 2, \dots, M$ ),  $x_j$  is the normalized target value of engineering characteristic  $j$  ( $j = 1, 2, \dots, N$ ),  $f_i$  represents the functional relationship between customer need  $i$  and engineering characteristics,  $g_j$  denotes the functional relationship between engineering characteristic  $j$  and other engineering characteristics, and  $y_i^{\min}$  and  $y_i^{\max}$  represent the minimum and the maximum possible values, respectively, for the customer need  $i$ .

The benchmarking data set available for product design in QFD is in general not sufficiently large to justify the assumptions of statistical regression analysis. Thus, the relationships between WHATs and HOWs and among HOWs cannot be quantified using classical statistical regression which makes rigid assumptions about the statistical properties of the model. Fuzzy regression, which was first introduced by Tanaka, Uejima, and Asai (1982), 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. The inherent fuzziness

in QFD modeling where human estimation is influential makes fuzzy

regression more appealing than classical statistical tools (Kim et al., 2000).

In the classical statistical regression model, which uses a linear function to express the relationship between a dependent variable  $y$  and the independent variables  $x_1, x_2, \dots, x_N$  the parameters are crisp

numbers and the error term is supposed to be due to measurement errors (Kim, Moskowitz, & Koksalan, 1996; Tanaka et al., 1982). On the other hand, 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. (1982) delineated a fuzzy linear regression function as:

$$Y_i^* = \tilde{A}_{i0} + \tilde{A}_{i1} x_1 + \tilde{A}_{i2} x_2 + \dots + \tilde{A}_{iN} x_N \quad (2)$$

The fuzzy parameter  $\tilde{A}_{ij}$  of fuzzy linear regression function can be represented as follows:

$$\mu_{\tilde{A}_{ij}}(a_{ij}) = \begin{cases} 1 - \frac{|m_{ij} - a_{ij}|}{s_{ij}} & m_{ij} - s_{ij} \leq a_{ij} \leq m_{ij} + s_{ij} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Where  $\tilde{A}_{ij}$  denotes a symmetric triangular fuzzy number with center  $m_{ij}$  and spread  $s_{ij}$ , respectively, and  $\mu_{\tilde{A}_{ij}}(a_{ij})$  represents the membership of  $a_{ij}$  in the fuzzy number  $\tilde{A}_{ij}$ . The use of fuzzy regression analysis in QFD is described as follows: Given a number of  $K$  crisp data points

$(X_1, y_{1i}), \dots, (X_r, y_{ir}), \dots, (X_k, y_{ik})$  fuzzy parameter estimates  $\tilde{A}_{ij} = \{(m_{i0}, m_{i1}, \dots, m_{iN}), (s_{i0}, s_{i1}, \dots, s_{iN})\}$  will be determined such that the membership value of  $y_{ir}$  to its fuzzy estimate  $Y_{ir}^*$  is at least  $H$ , whereby  $X_r = (x_{1r}, x_{2r}, \dots, x_{Nr})$  is the set of values of engineering characteristics of the  $r$ th competitor, and  $y_{ir}$  is the degree of customer satisfaction of the customer need  $i$  of the competitor  $r$ . The fuzzy regression approach 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, i.e. a higher  $H$  value, yields a wider spread, the resulting predicted intervals possess a higher fuzziness (Kim et al., 1996).  $H \in [0,1]$ , which is referred to as a measure of goodness of fit, is selected by the decision-maker.

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 adhoc, and  $H$  values in earlier studies vary widely ranging from 0 to 0.9. When the data set is sufficiently large  $H$  could be set to 0, whereas a higher  $H$  value is suggested as the size of the data set becomes smaller (Tanaka & Watada, 1988). The aim of fuzzy regression analysis is to minimize the total fuzziness of the predicted values for the dependent variables. The fuzzy regression approach to determine the functional relationships leads to the following linear programming model (Tanaka & Watada, 1988):

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

Subject to

$$\sum_{j=0}^N 1 m_{ij} x_{jr} + |L^{-1}(H)| \sum_{j=0}^N 1 s_{ij} | x_{jr} | \geq y_{ir} \quad r=1,2, \dots, K \quad (4)$$

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

$$\begin{aligned} X_{0i} &= 1 & r=1,2, \dots, K \\ X_{ij} &\geq 0 & j=1,2, \dots, N \end{aligned}$$

where  $L$  represents the membership function of a standardized fuzzy parameter, which is equal to

$$L(x) = \max(0, 1 - |x|) \rightarrow |L^{-1}(H)| = (1-H).$$

The coefficients of estimated functional relationships between WHATs and HOWs, and among HOWs can be obtained by solving formulation (4). The resulting equations are given as:

$$Y_i = f_i(x_1, x_2, \dots, x_N) = (m_{i0}, s_{i0}) + \sum_{j=1}^N 1(m_{ij}, s_{ij}) x_j \quad i=1,2, \dots, M \quad (5)$$

$$X_j = g_j(x_1, \dots, x_{j-1}, x_{j+1}, \dots, x_N) = (m_{ju}, s_{ju}) + \sum_{u=1, u \neq j}^N 1(m_{ju}, s_{ju}) x_u \quad j=1,2, \dots, N \quad (6)$$

When no fuzziness is considered in the system parameters, only the center value estimates obtained from formulation (4) are used while the spreads are disregarded (Chen et al., 2004). Therefore, the functional relationships are expressed in a more simple way, and the problem represented by (1) can be transformed to the formulation given below.

$$\text{Max } z(y_1, y_2, \dots, y_M) = \sum_{j=0}^M 1(y_i - y_i^{\min}) / (y_i^{\max} - y_i^{\min})$$

$$Y_i - \sum_{j=0}^N 1 m_{ij} x_j = m_{i0} \quad i=1,2, \dots, M \quad (7)$$

$$X_j - \sum_{u=1, u \neq j}^N 1 m_{ju} x_u = m_{j0} \quad j=1,2, \dots, N$$

$$y_i^{\min} \leq y_i \leq y_i^{\max}$$

### 3. Fuzzy multiple objective decision making framework

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. This paper employs a fuzzy multiple objective decision making framework to incorporate the multi-objective nature of the design problem while also taking into consideration vague and imprecise information inherent in the QFD planning process. Employing a fuzzy multiple objective decision making approach broadens the perspective of considering a single objective of maximizing the fulfillment of HOWs by accounting for company's other design related objectives, and enables the consideration of specific financial and organizational constraints that may limit the extent of HOWs to be included while designing a

product. Hence, enterprise satisfaction is aimed along with customer satisfaction throughout the design phase. Karsak (2004) presented a fuzzy multiple objective programming approach for the QFD planning process to determine the level of fulfillment of HOWs, where relationship between WHATs and HOWs, extendibility of HOWs, and technical difficulty of HOWs are expressed using linguistic variables with predetermined membership functions. The decision framework proposed in this paper differs from the earlier work by employing fuzzy regression analysis to define these functional relationships rather than using subjective judgments. The proposed approach also enables to consider the dependencies among HOWs through fuzzy regression. 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

$$\begin{aligned} \text{Max } Z(x) &= (c_1x, c_2x, \dots, c_r x) \\ \text{Min } W(x) &= (c'_1x, c'_2x, \dots, c'_r x) \end{aligned} \tag{8}$$

Subject to  
 $x \in X = \{x \geq 0 \mid Ax = b\}$

where  $l$  is the number of objectives to be maximized,  $r$  is the number of objectives to be minimized,  $c_k$  ( $k=1, 2, \dots, l$ ) and  $c'_p$  ( $p=1, 2, \dots, r$ ) are  $n$ -dimensional vectors,  $b$  is an  $m$ -dimensional vector,  $A$  is an  $m \times n$

matrix  $c_k, c'_p, A$  and  $b$ 's elements are fuzzy numbers, and "\*" indicates " $\geq$ ", " $\leq$ " 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 (Perego & Rangone, 1998). In this paper, the fuzzy coefficients in the model are triangular fuzzy numbers represented by  $Q = (q_1, q_2, q_3)$  with the membership function given as:

$$\mu_Q(x) = \begin{cases} 0 & x < q_1 \\ (x - q_1) / (q_2 - q_1) & q_1 \leq x \leq q_2 \\ (q_3 - x) / (q_3 - q_2) & q_2 \leq x \leq q_3 \\ 0 & x > q_3 \end{cases} \tag{9}$$

If  $(Q)_a^L$  and  $(Q)_a^u$  are defined as the lower bound and the upper bound of the  $a$ -cut  $Q$ , respectively, the  $a$ -cut of  $Q$  can be expressed as

$$(Q)_a = [(Q)_a^L, (Q)_a^u] = [q_1 + (q_2 - q_1)a, q_3 - (q_3 - q_2)a] \tag{10}$$

The importance degree of each objective can be included in the formulation using fuzzy priorities (Narasimhan, 1981). The general representation for the membership function corresponding to the importance degrees can be given as:

$$\mu_1(x) = \begin{cases} 0 & x < i_1 \\ (x - i_1) / (i_2 - i_1) & i_1 \leq x \leq i_2 \\ 1 & x > i_2 \end{cases} \tag{11}$$

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

Max  $\beta$

Subject to

$$\begin{aligned} \beta &\leq \mu_1 \circ \mu_k^a(Z_k) \\ \beta &\leq \mu_1 \circ \mu_p^a(W_p) \\ \beta &\in [0, 1] \\ x &\in X_a \\ x_j &\geq 0 \quad j = 1, 2, \dots, N \end{aligned} \tag{12}$$

where "o" is the composition operator,  $b$  is the grade of compromise to which the solution satisfies all of the fuzzy objectives while the coefficients are at a feasible level  $a$ , and  $X_a$  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 un dominated solution (Lee & Li, 1993). Lee and Li (1993) proposed a two-phase approach, where in the first phase they solve the problem parametrically for a given value of  $a$ , and in the second phase, they obtain an un dominated solution using the value of  $a$  determined in phase I. In this paper, a modified version of the algorithm proposed by Lee and Li (1993) is employed as given below.

### Phase I.

- Step 1. Define  $\lambda =$  step length,  $\delta =$  accuracy of tolerance,  $k =$  multiple of step length,  $c =$  iteration counter. Set  $k := 0, c := 0$ .
- Step 2. Set  $a = 1 - k \lambda$ .
- Step 3. Solve the problem for  $a_c$  to obtain  $\beta_c$  and  $x_c$ .
- Step 4a. If  $a_c - \beta_c > \delta$  then  $c := c + 1, k := k + 1$ , go to step 2.
- Step 4b. If  $a_c - \beta_c < -\delta$  then  $\lambda := \lambda / 2, k := 2k - 1$ , go to step 2.
- Step 4c. If  $|a_c - \beta_c| \leq \delta$  then go to step 5.
- Step 5. Output  $a_c, \beta_c$ , and  $x_c$ .

### Phase II.

After computing the values of  $a$  and  $b$  according to the procedure given in phase I, we can solve the following problem in order to obtain an un dominated solution for the situation where the solution is not unique.

$$\text{Max } \frac{1}{l+r} (\sum_{k=1}^l 1\beta_k + \sum_{p=1}^r 1\beta'_p) \tag{13}$$

Subject to

$$\beta \leq \beta_k = \frac{[(\sum_{j=1}^n 1[C_{kj3} - (C_{kj3} - C_{kj2})a]x_j - (Z_k)_a - i_{k1}(Z_k)_a^* - (Z_k)_a)] / [(Z_k)_a^* - (Z_k)_a] (i_{k2} - i_{k1})}{\beta \leq \beta'_p = \frac{[(W_p)_a - \sum_{j=1}^n 1[C_{pj1} - (C_{pj2} - C_{pj1})a]x_j - i_{p1}((W_p)_a - (W_p)_a^*)] / [(W_p)_a - (W_p)_a^*] (i_{p2} - i_{p1})}{p=1, \dots, r}$$

$$\beta_k, \beta'_p \in [0, 1], \quad k=1, \dots, l; p=1, \dots, r$$

$$x \in X_a$$

$$x_j \geq 0, \quad j=1, \dots, n$$

where  $(Z_k)_a^*$ ,  $(W_p)_a^*$  are the ideal solutions and  $(Z_k)_a$ ,  $(W_p)_a$  are the anti-ideal solutions, respectively, which can be obtained by solving formulation (8) for each objective separately subject to the constraints.

### 4. case review

This section presents an illustration of the proposed decision approach based on a real-world application. The decision making framework developed using fuzzy linear regression and fuzzy multiple objective programming is applied to determine target values of HOWs of a ISP server. In light of the fact that the use of QFD is expected to improve product quality and increase customer satisfaction, there are a number of reported QFD applications in the home appliances industry, including Yamashina, Ito, and Kawada (2002), Ozbayraktar (2005), Lai, Xie, and Tan (2005), Kobayashi (2006), Shimomura, Hara, and Arai (2008), Jin, Ji, Choi, and Cho (2009) and Li, Tang, Luo, and Xu (2009). In this study, the proposed approach is illustrated through an application concerning the process of determining target values of HOWs of a ISP supplier in IRAN . Manufacturers have aimed to maximize customer satisfaction, and thus, have focused on reaching a quality level that meets WHATs in every phase of design and production. The sector has also created solid brands with strong customer ties and has strengthened its existence in external markets.

The stepwise representation of the proposed decision making methodology is given below.

- Step 1. Identify the WHATs and the HOWs.
- Step 2. Determine the additional objectives related to enterprise satisfaction that should be considered along with customer satisfaction.
- Step 3. Determine the relative importance weights of WHATs employing the analytic hierarchy process.
- Step 4. Identify the relationships between WHATs and HOWs, and among HOWs.
- Step 5. Determine the performance ratings of competitors' products with respect to WHATs.
- Step 6. Obtain the related HOWs data for the existing situation.
- Step 7. Normalize the data concerning HOWs using a linear normalization procedure to avoid problems regarding scale differences.
- Step 8. Estimate the parameters of functional relationships between WHATs and HOWs, and among HOWs using fuzzy linear regression.

- Step 9. Determine the resource limitations and the importance degrees of the considered objectives.
- Step 10. Use fuzzy multiple objective programming to determine target values of HOWs of an enhanced product.

The HOQ shown in table1 illustrates the WHATs and HOWs data related to the four ISP server in IRAN. These company are represented as supplier 1, supplie2, supplier3, and supplier4. The WHATs obtained through requirement analysis are Effective marketing promotion (y1), Experience (y2), Financial strength (y3), Management stability (y4), Strategic alliance (y5), Support resource (y6). The HOWs determined in order to satisfy WHATs are Accessibility (x1), Reliability (x2), security (x3), Speed (x4), Monthly fee (x5), Supply variety (x6), Installation fee (x7), Service (x8). The relationship matrix in the HOQ is used to identify the relationships between WHATs and HOWs, and the roof matrix is employed to specify the interactions among HOWs. The aim of the study is to determine target values for the engineering characteristics of the ISP server in a way to satisfy the set of objectives. Overall customer satisfaction and extendibility of HOWs are the objectives to be maximized, whereas technical difficulty of HOWs is the objective to be minimized. In this paper, extendibility and technical difficulty of HOWs are expressed using linguistic variables which possess membership functions depicted in Fig. 2.

**Table1. House of quality for ISP server.**

HOWs	x <sub>1</sub>	x <sub>2</sub>	x <sub>3</sub>	x <sub>4</sub>	x <sub>5</sub>	x <sub>6</sub>	x <sub>7</sub>	x <sub>8</sub>
Accessibility (x <sub>1</sub> )								
Reliability (x <sub>2</sub> )								
security (x <sub>3</sub> )				*		*		
Speed (x <sub>4</sub> )			*			*		
Monthly fee (x <sub>5</sub> )								
Supply variety (x <sub>6</sub> )			*	*				
Installation fee(x <sub>7</sub> )								
Service (x <sub>8</sub> )								

The relative importance weights of WHATs are determined using the pair wise comparisons of the analytic hierarchy process (AHP) (Saaty, 1980). In AHP, the relative importance values are determined using pair wise comparisons with a scale of 1–9, where a score of 1 indicates equal importance between the two elements and 9 represents the extreme importance of one element compared to the other one. The values in between signify varying degrees of importance between these two extremes. After obtaining the pair wise comparisons of HOWs, the formal AHP procedure was conducted to compute the relative importance weights is shown in table 1. A 5-point scale has been used to represent performance of competitors with respect to WHATs, where 1 and 5 represent the worst and the best values, respectively. In order to avoid problems regarding scale differences for HOWs, a linear normalization scheme is employed. Data related to Accessibility (x1), Reliability (x2), security (x3), Speed (x4), Supply variety (x6), , for which the greater the attribute value the more its preference, are normalized as  $x_{jr}/x_j^{\max}$  On the other hand, Monthly fee (x5), Installation fee

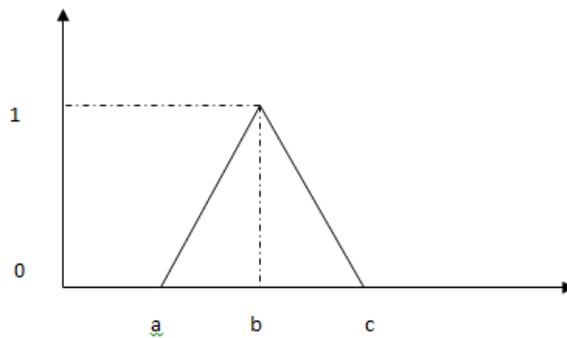
(x7), Service (x8) for which the greater the attribute value the less its preference, are normalized as  $x_j^{min}/x_{jr}$ . Here,  $x_{jr}$  denotes the jth HOWs value for the rth competitor prior to normalization, and  $x_j^{max}$  and  $x_j^{min}$  represent the maximum value and the minimum value for the jth HOWs, respectively. The normalized data lie in the [0, 1] interval, and the HOWs is considered more favorable as the normalized data

approaches 1. The normalized values for the HOWs are given as follows:

$$X = \begin{bmatrix} 0.61 & 0.75 & 0.88 & 0.9 & 0.4 & 0.8 & 0.67 & 0.5 \\ 0.65 & 0.88 & 0.87 & 0.83 & 0.66 & 1 & 0.7 & 0.8 \\ 0.7 & 0.6 & 0.92 & 0.69 & 0.33 & 0.8 & 0.76 & 0.66 \\ 0.67 & 0.94 & 0.92 & 0.76 & 0.73 & 1 & 0.84 & 1 \end{bmatrix}$$

WHATs	Relative importance	x <sub>1</sub>	x <sub>2</sub>	x <sub>3</sub>	x <sub>4</sub>	x <sub>5</sub>	x <sub>6</sub>	x <sub>7</sub>	x <sub>8</sub>	Competitive assessment					
										S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	max	min
Effective marketing promotion (y <sub>1</sub> )	0.431	*					*		*	2	3	4	4	1	5
Experience (y <sub>2</sub> )	0.097		*	*	*			*		3	4	2	4	1	5
Financial strength (y <sub>3</sub> )	0.173		*	*	*					4	4	3	5	1	5
Management stability (y <sub>4</sub> )	0.186		*	*				*		3	4	3	5	1	5
Strategic alliance (y <sub>5</sub> )	0.041	*					*		*	2	4	3	4	1	5
Support resource (y <sub>6</sub> )	0.072									2	4	3	4	1	5

WHATs	x <sub>1</sub>	x <sub>2</sub>	x <sub>3</sub>	x <sub>4</sub>	x <sub>5</sub>	x <sub>6</sub>	x <sub>7</sub>	x <sub>8</sub>
Supplier 1 (s <sub>1</sub> )	75	1.2	54	55	6	4	82	8
Supplier 2 (s <sub>2</sub> )	70	1.02	55	60	10	5	78	5
Supplier 3 (s <sub>3</sub> )	65	1.5	52	72	5	4	72	6
Supplier 4 (s <sub>4</sub> )	68	0.95	52	65	11	5	65	4
target	46	0.9	48	50	15	5	55	4
cost	(27,30,32)	(23,27,32)	(3,6,10)	(5,7,9)	(20,30,40)	(40,50,55)	(27,30,32)	(2,4,5)
Extendibility	VH	H	H	M	VH	H	M	VL
Technical difficulty	H	H	L	L	H	H	H	L



VL	L	M	H	VH
(0,0,0.25)	(0,0.25,0.5)	(0.25,0.5,0.75)	(0.5,0.75,1)	(0.75,1,1)

Figure 2. A triangular fuzzy numbers

The parameters of the functional relationships  $f_i$  and  $g_j$  can be obtained using fuzzy linear regression. The H value is set to 0.5 as in a number of earlier applications (Chen et al., 2004; Karsak & Ozogul, 2009; Kim et al., 2000; Tanaka et al., 1982). The results obtained using formulation (4) are shown in Table2.

The values in parentheses denote the spread values for parameter estimates. Budget constraint

$\sum_{j=1}^N k_j x_j \leq 150$  where  $k_j$  denotes the cost of the jth HOWs and 150\$ is the budget estimated by industry experts, is incorporated into the fuzzy multiple objective programming model which maximizes overall customer

satisfaction and extendibility of HOWs while minimizing technical difficulty of HOWs. In addition, the normalized values for HOWs are constrained to values between minimum normalized value for the respective HOWs and the highest possible value, i.e. 1.0. After introducing the importance degrees of the objectives given in Table3, formula (12) is employed.

The step length ( $\lambda$ ) and the accuracy of tolerance ( $\delta$ ) are set to be 0.05 and 0.005, respectively, as in Karsak (2004). The algorithm presented in the preceding section yields the results given in Table3. In order to ensure an un dominated solution, formulation (13) is solved using the a value determined at the end of phase I and the arithmetic mean operator. The results given in Table 4 show that the grade of compromise obtained by the arithmetic mean operator is 0.917. According to the results given in Table5, the optimal values of HOWs indicate 100% fulfillment in Reliability , while the fulfillment Service are 77.88% in Accessibility, 90.27% in security, 79.86% in Speed, 41.19% Monthly fee, 90.04% in Supply variety, 71.33% in Installation fee, and 81.98% in Service.

**Table 2. Fuzzy linear regression center and spread values  $m_i (s_i)$  for  $H = 0.5$ .**

	Intercept	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
$y_1$	-11.61	16.92				0.376		4.59	
$y_2$			4.03	-3.59	1.26		2.52		
$y_3$	-20.59		4.82	19.15	4.33				
$y_4$	-16.4		3.49	15.34			3.92		
$y_5$	-8.35	19.05				5.01		-4.98	
$y_6$									4.5(1)
$x_3$	1.16								
$x_4$	3.89			3.28(0.11)			0.147		
$x_6$	1.08			0.16 (0.23)	- 0.04		-0.14		

**Table 3. Importance degrees of the objectives.**

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

**Table 4. Results of the phase I of the decision algorithm.**

$a_c$	$\beta_c$	$a_c - \beta_c$	$X_1$	$X_2$	$X_3$	$X_4$	$X_5$	$X_6$	$X_7$	$X_8$
1	0.6117	0.3882	0.7716	1.0	0.90274	0.79859	0.4089	0.9004	0.6830	0.5
0.95	0.8324	0.1175	0.7793	1.0	0.90274	0.79859	0.4089	0.9004	0.7114	0.634
0.9	0.9603	-0.0603	0.7784	1.0	0.90274	0.79859	0.4089	0.9004	0.7143	0.913
0.925	0.8973	0.0276	0.7788	1.0	0.90274	0.79859	0.4089	0.9004	0.7128	0.776
0.912	0.9291	-0.0166	0.7786	1.0	0.90274	0.79859	0.4089	0.9004	0.7135	0.845
0.918	0.9133	0.0054	0.7787	1.0	0.90274	0.79859	0.4089	0.9004	0.7131	0.811
0.915	0.9212	-0.0056	0.7787	1.0	0.90274	0.79859	0.4089	0.9004	0.7133	0.828
0.971	0.9172	-0.0008	0.7787	1.0	0.90274	0.79859	0.4089	0.9004	0.7132	0.819

**Table 5. Un dominated solution.**

$a$	$\beta$	$a-\beta$	$X_1^*$	$X_2^*$	$X_3^*$	$X_4^*$	$X_5^*$	$X_6^*$	$X_7^*$	$X_8^*$	$\beta_1$	$\beta_2$	$\beta_1'$	$\beta'$
0.917188	0.917268	0.000080	0.778751	1.000000	0.902744	0.798598	0.411915	0.900440	0.713283	0.819751	0.917268	0.917268	0.917268	0.917268

$\beta_1$  : Fulfillment of overall customer satisfaction

$\beta_2$  : Extendibility

$\beta_1'$  : Technical difficulty

The results of the proposed approach enable the company to concentrate on the HOWs that would maximize overall customer satisfaction while also accounting for other design objectives as well as availability of financial resources. For example, considering the optimal values of HOWs for the ISP server obtained from the fuzzy multiple objective decision framework, Company 1 has to improve its performance in

‘Accessibility ( $x_1$ )’, ‘Reliability ( $x_2$ )’, ‘security ( $x_3$ )’, ‘Monthly fee ( $x_5$ )’, ‘Supply variety ( $x_6$ )’, ‘Installation fee( $x_7$ )’ and ‘Service ( $x_8$ )’. Similar evaluations could be made for other companies using the normalized values of HOWs given in X for the respective ISP server. Furthermore, one shall note that, given the grade of compromise of 0.917268, HOWs values of supplier 4 does not yield a

feasible solution since the resulting cost of 155.94\$ exceeds the cost budget of 150\$. Thus, although Company 4 appears to outperform other ISP server according to competitive assessment matrix given in table 1, it falls short of satisfying the cost budget. Hence, its HOWs values shall not be regarded as benchmark for improving the design performance of other companies.

## 5. Conclusions

This paper proposes a novel approach for determining target levels of engineering characteristics by integrating fuzzy linear regression and fuzzy multiple objective programming. The inherent fuzziness of functional relationships in QFD modeling promotes fuzzy regression as an effective tool for parameter

estimation. Fuzzy regression is introduced in the model to estimate the parameters of functional relationships between WHATs and HOWs, and among HOWs. In QFD planning process, the single objective point of view that focuses on maximizing customer satisfaction needs to be extended by considering the company's other design related objectives. Considering the multi-objective nature of the design problem, the decision framework proposed in this paper enables the highest possible fulfillment of HOWs to maximize overall customer satisfaction as an objective to be satisfied along with other enterprise related objectives such as minimizing technical difficulty and maximizing extendibility of HOWs subject to a budget constraint. Another contribution of the proposed approach is that one can 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 of HOWs consider customer requirements obtained previously. A wider perspective on the QFD methodology that considers the changes on customers' future preferences is needed to overcome this problem. For future study, target levels of the new or enhanced products that satisfy WHATs at the time when the product reaches the market can be determined by extending the decision framework proposed in this paper in a way to account for future WHATs. Moreover, other strategic objectives and organizational constraints could be considered in the modeling framework.

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