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# Using fuzzy non-linear regression to identify the degree of compensation among customer requirements in QFD

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ABSTRACT

As an effective customer-driven approach, the quality function deployment (QFD) takes numbers of customer requirements (CRs) into account in the process of the initial product design and the competitive analysis. It is a traditional multi-attribute decision making problem, and the trade-off strategy among CRs which is interpreted as decision parameters, is crucial for resulting the overall customer satisfaction. Although the general trade-off strategies concern about the importance weights of CRs, which are specified with a variety of methods, they ignore the influence of the degree of compensation among them. In this paper, we embed the degree of compensation among CRs into QFD, which is expressed as a symmetric triangular fuzzy number, and develop a fuzzy non-linear regression model using the minimum fuzziness criterion to identify it. Furthermore, an illustrative example is provided to demonstrate the application and the performance of the modeling approach. It can be verified from the experimental results that the overall customer satisfaction as well as the prioritization of products are affected by the degree of compensation among CRs. Meanwhile, against to the products in example, the overall customer satisfaction obtained with the traditional weighted-sum method is confirmed to be underestimated.



## 1. Introduction

To improve the competitiveness and market shares, the worldwide companies increasingly concern about the voice of customers. The quality function deployment (QFD) was originated from Japan in the late 1960s [1]. As an effective customer-driven approach, QFD integrates customer requirements (CRs) into the product design to maximize the customer satisfaction with limited technical and resource constraints. The manipulation of QFD data can be expressed graphically in a matrix-like configuration called the House of Quality (HoQ) presented by Hauser and Clausing [11]. Until now, it has been successfully applied in many industries, such as software development process [5], supplier selection [3,4], electronics [15], R&D projects [34] and so on.

Generally, a number of CRs constituting the overall customer satisfaction for the product are taken into account in QFD, and the trade-off strategy among them that is finally reflected on the objective function is vital for the evaluation of the products and the acquirement of the optimal values of engineering characteristics (ECs). So far, the weighted-sum method has been one of the most commonly used trade-off strategies performing with the direct specification on different importance weights of CRs. Based on this idea, many methods have been developed, for example, AHP [2], FAHP [12,22], ANP [18] and FANP [16,27]. Besides, the fuzzy entropy method was also used to assess the importance weights of CRs [6,14]. Considering the differences in backgrounds, education, domain knowledge, etc., of the investigated customers, Wang [38] suggested that customers should express their preferences on the relative importance weights of CRs in their preferred or familiar formats.

However, as a typical multi-attribute decision making (MADM) problem, the trade-off strategies that are established in the above methods are incomplete. They only rely on the specification of importance weights of CRs and ignore other important decision parameters, e.g., the degree of compensation among them. Compensation refers to a willingness to allow high performance on one attribute to compensate for low performance on another and it is a property of a decision rather than a design [31]. In general, the degree of compensation is denoted with $s$. It has long been certified that the weighted-sum aggregation of preferences cannot always identify all the Pareto points for a design and runs the risk of missing 'optimal' options with a default $s=1$. A family of aggregation operators $\mathcal{P}_s$ that governs the decision parameters involving both the importance weights of attributes and the degree of compensation among them

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was first proposed by Scott and Antonsson in 1998 [29] as follows, which spans an entire range of possible operators between min and max

$$\mathcal{P}_s(\mu_1,\mu_2,\ldots,\mu_n;\omega_1,\omega_2,\ldots,\omega_n)=\left(\frac{\omega_1\mu_1^s+\omega_2\mu_2^s+\cdots+\omega_n\mu_n^s}{\omega_1+\omega_2+\cdots+\omega_n}\right)^{1/s}, \quad (1)$$

where $\mu_1,\mu_2,\ldots,\mu_n$ are the attributes in the MADM problems, $\omega_1,\omega_2,\ldots,\omega_n$ are the importance weights of attributes with $\omega_1,\omega,\ldots,\omega_n\geq 0$, and $s$ indicates the degree of compensation among attributes and ranges from $-\infty$ to $+\infty$. The aggregation operator $\mathcal{P}_s$ possesses the property that every Pareto point could be the optimal solution through the different combination settings of decision parameters, $s$ and $\omega_i, i=1,2,\ldots,n$, which collectively determine how to distribute the resources in the attributions to obtain the optimal objective with constraints. Meanwhile, four special situations are as follows:

$$\mathcal{P}_{-\infty}=\lim_{s\to-\infty}\mathcal{P}_s=\min(\mu_1,\mu_2,\ldots,\mu_n), \quad (2)$$

$$\mathcal{P}_0=\lim_{s\to 0}\mathcal{P}_s=(\mu_1^{\omega_1}\mu_2^{\omega_2},\ldots,\mu_n^{\omega_n})^{1/(\omega_1+\omega_2+\cdots+\omega_n)}, \quad (3)$$

$$\mathcal{P}_1=\lim_{s\to 1}\mathcal{P}_s=\frac{\omega_1\mu_1+\omega_2\mu_2+\cdots+\omega_n\mu_n}{\omega_1+\omega_2+\cdots+\omega_n}, \quad (4)$$

$$\mathcal{P}_{+\infty}=\lim_{s\to+\infty}\mathcal{P}_s=\max(\mu_1,\mu_2,\ldots,\mu_n). \quad (5)$$

Note that $\mathcal{P}_0$ and $\mathcal{P}_1$ are the forms of the geometric mean and the arithmetic mean, respectively, that we often used in the MADM problems.

Until now, the aggregation operator $\mathcal{P}_s$ has attracted much attentions, especially from the area of engineering design. For example, in [31], the idea that both the degree of compensation and the distribution of importance weights among attributes must be considered to capture all potential acceptable decisions was illustrated by a simple truss design example. Kulok and Lewis [21] and See and Lewis [32] investigated the effect of different aggregation function formulations on multi-attribute group decision making. Scott [28] put forward an improved AHP method to quantify uncertainty in measurement error and different degree of compensation in trade-offs among criteria. The concept of the operator $\mathcal{P}_s$ has been also used in the context of physical programming [25,26] that can successfully be integrated into both collaborative and multidisciplinary design optimizations [24].

Since the concept of the degree of compensation was proposed, the identification of $s$ value is always the main problem that needs to be solved at first. In 2000, Scott and Antonsson [30] applied indifference points to identify the value of $s$, but the selection of the indifference points is subjective, and finding two designs that are of exact equivalent value to a decision maker can be a challenging and time-consuming task [36]. Two attributes were included in the above application, so only three indifference points were needed for identifying the value of importance weights and the degree of compensation. Once the number of attributes increases, the process is hard to carry on. Besides, Chen and Ngai [9] presented a methodology combining the fuzzy set theory and the compensation strategy to optimize the target values of ECs and control the distribution of the development budget by varying the value of $s$. In [9], the degree of compensation $s$ was expressed as a crisp number and its determination which was on the basis of the engineering knowledge and experience of the decision makers was arbitrary and ad hoc. However, in our paper, considering that the degree of compensation among CRs is uncertain and imprecise, we would like to express it as a triangular fuzzy number, which is one of the most commonly used fuzzy numbers, in order to show how the overall customer satisfaction changes along with the change of the level of attainment for each customer requirement objectively. Meanwhile, utilizing the investigation of the overall customer satisfaction from customers, we develop a fuzzy non-linear regression model on the basis of the traditional fuzzy linear regression method, in which we set the minimization of the fuzziness as the objective function, constraining that all the observed values of overall customer satisfaction for the products must be involved in the $h$-level sets of the corresponding fuzzy outputs.

The rest of the paper is organized as follows. In the next section, the concept of the degree of compensation is embedded into QFD, and we build a fuzzy non-linear regression model to identify the degree of compensation $s$ among different CRs. In Section 3, an illustrative example is presented to demonstrate the proposed approach and a result analysis is given. Finally, some conclusions are drawn in Section 4.

## 2. Fuzzy non-linear regression model

Considering the deficiencies of the traditional weighted-sum method, which is usually set as the trade-off strategy in QFD, we introduce the concept of the degree of compensation among CRs into QFD and set the trade-off strategy as a combination together with the relative importance weights of them. In order to perform the uncertainty of the degree of compensation from customers, we express it as a fuzzy number. Furthermore, for ease of calculation, we set it as a symmetric triangular fuzzy number and then develop a fuzzy non-linear regression model to establish it.

### 2.1. Problem description and notation

As an effective and widely applied method that transforms the CRs to the ECs, the main function of QFD is to assist the enterprises to proceed competition analysis and product preliminary design, the objective and principle of which are to improve the overall customer satisfaction of products as much as possible. Since the effectiveness of the objective function will directly impact on the products' competitive analysis and market strategy, it is always an important issue in QFD. Based on the analysis of the deficiencies of the traditional weighted-sum method, we introduce the degree of compensation $s$ among CRs into QFD. Moreover, we express it as a symmetric triangular fuzzy number. And in order to establish the value of $s$ with the fuzzy non-linear regression method, the issues below need to be processed at first: (1) identification of CRs and their relative importance weights; (2) calculation and normalization of relationship matrix; (3) normalization of the values of ECs; (4) investigation of the overall customer satisfaction for given products; and (5) derivation of overall customer satisfaction, which will be described in the following subsections successively.

Before that, the notions that will be used are summarized as follows for reference:

| | |
|---|---|
| $CR_i$ | the $i$ th customer requirement, $i=1,2,\ldots,m$; |
| $EC_j$ | the $j$th engineering characteristic, $j=1,2,\ldots,n$; |
| $Pro_p$ | the $p$th product, $p=1,2,\ldots,k$; |
| $l_{pj}$ | the value of $EC_j$ of $Pro_p$, $p=1,2,\ldots,k,\ j=1,2,\ldots,n$; |
| $x_{pj}$ | the level of attainment of $EC_j$ of $Pro_p$ with $0\leq x_{pj}\leq 1$, $p=1,2,\ldots,k, j=1,2,\ldots,n$; |
| $r'_{ij}$ | the strength of the relation measure between $CR_i$ and $EC_j$, $i=1,2,\ldots,m, j=1,2,\ldots,n$; |
| $r_{ij}$ | the normalized strength of the relation measure between $CR_i$ and $EC_j$, $i=1,2,\ldots,m,\ j=1,2,\ldots,n$; |
| $R$ | the relationship matrix between CRs and ECs with $R=(r_{ij})_{m\times n}$; |