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A combined fuzzy linear regression and fuzzy multiple objective programming approach for setting target levels in quality function deployment

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ABSTRACT

Quality function deployment (QFD) is a systematic process for translating customer needs into engineering characteristics, and then communicating them throughout the enterprise in a way to ensure that details are quantified and controlled. 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. 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. This paper presents a fuzzy multiple objective decision framework that includes not only fulfillment of engineering characteristics to maximize customer satisfaction, but also maximization of extendibility and minimization of technical difficulty of engineering characteristics as objectives subject to a financial budget constraint to determine target levels of engineering characteristics in product design. A real-world quality improvement problem is presented to illustrate the application of the decision approach.

1. Introduction

In today's global markets, companies need to develop enhanced products and services responsive to customer expectations to remain competitive. Quality function deployment (QFD) is a customer-oriented design tool that aims to satisfy the desires of customers while maximizing company goals. QFD ensures a quality level that meets customer needs throughout each stage of product planning and design. Its use helps to design new or improved products or services in a shorter period with a lower cost. The basis of QFD is to obtain and translate customer needs into engineering characteristics, and subsequently into part characteristics, process plans and production requirements. In order to establish these relationships, QFD usually requires four matrices: product planning, part deployment, process planning, and production/operation planning matrices, respectively. The product planning matrix, also called the house of quality (HOQ), 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 (Shillito, 1994). In this paper, we focus on the HOQ, the most commonly used matrix in QFD.

The objective of the HOQ, which converts feedback from customers into information for engineers, is to determine the target levels of engineering characteristics of a product to maximize customer satisfaction. Customer needs (CNs), also referred to as voice of the customer, present a guideline for the providers on attributes that the product should possess. Engineering characteristics (ECs) are also known as technical attributes, product technical requirements or design requirements. They describe the product in the language of the engineer; therefore, they are sometimes called the voice of the company. The ECs are used to determine how well the company satisfies the CNs. The relationships between CNs and ECs are defined in each cell in the relationship matrix of the HOQ. The roof matrix is used to perform pairwise comparison of ECs to incorporate the inner dependencies among them.

The process of quantifying the planning issues in the HOQ has received increasing attention within the past decade (Karsak, Sozer, & Alptekin, 2003; Lai, Tan, & Xie, 2007). The methodologies presented in these works implicitly assumed that the relationships between CNs and ECs and among ECs 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

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and analyze large amounts of subjective data, impreciseness in the process of setting target values in the HOQ (Bouchereau & Rowlands, 2000). The vagueness or imprecision arises mainly from the fact that CNs, which tend to be subjective, qualitative, and non-technical, need to be translated into ECs 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 CNs and ECs, and among ECs. 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 Özogul (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 characteristics.

In all these studies, the target levels of engineering characteristics are determined by considering CNs in a way to satisfy a single objective, which is maximizing overall customer satisfaction. In general, the satisfaction of CNs 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 ECs, extendibility of ECs, and cost of ECs 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 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 the functional relationships between CNs and ECs, and among ECs. Due to the inherent fuzziness of relationships in QFD modeling, fuzzy regression emerges as an effective tool for parameter estimation. Considering the multi-objective nature of the design problem, the highest possible fulfillment of ECs to maximize overall customer satisfaction is used as an objective to be satisfied along with other objectives such as technical difficulty and extendibility of ECs subject to a budget constraint.

The rest of the paper is organized as follows: Section 2 presents the preliminaries of fuzzy linear regression. In Section 3, fuzzy multiple objective programming framework for setting target levels of engineering characteristics in QFD is introduced. In Section 4, the proposed approach is illustrated using data from washing machine manufacturers in Turkey. 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 basic tool for QFD, is a conceptual map that provides the means for inter-functional planning and communications. In general, maximizing overall customer satisfaction is the only objective considered in the process of setting target levels of ECs. The process of determining target values for ECs to maximize overall customer satisfaction can be formulated as an optimization problem as follows (Kim et al., 2000):

$$\begin{aligned} &\text{Max } z(y_1, y_2, \ldots, y_M) = \sum_{i=1}^{M} w_i \frac{y_i - y_i^{\min}}{y_i^{\max} - y_i^{\min}} \\ &\text{subject to} \\ &\quad y_i = f_i(x_1, x_2, \ldots, x_N), \quad i = 1, 2, \ldots, M, \\ &\quad x_j = g_j(x1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_N), \quad j = 1, 2, \ldots, N, \\ &\quad y_i^{\min} \leqslant y_i \leqslant y_i^{\max}, \quad i = 1, 2, \ldots, M, \end{aligned} \tag{1}$$

where w_i represents the relative importance of customer need i such that $0 < w_i \leqslant 1$ and $\sum_{i=1}^{M} w_i = 1$, y_i denotes the customer perception of the degree of satisfaction of customer need i ($i = 1, 2, \ldots, M$), x_j is the normalized target value of engineering characteristic j ($j = 1, 2, \ldots, N$), 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 CNs and ECs and among ECs 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 $x_1, \ldots, x_N$, 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

$$\tilde{y}_i^* = \widetilde{A}_{i0} + \widetilde{A}_{i1} x_1 + \widetilde{A}_{i2} x_2 + \cdots + \widetilde{A}_{iN} x_N. \tag{2}$$

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

$$\mu_{\widetilde{A}_{ij}}(a_{ij}) = \begin{cases} 1 - \frac{|m_{ij} - a_{ij}|}{s_{ij}}, & m_{ij} - s_{ij} \leqslant a_{ij} \leqslant m_{ij} + s_{ij}, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$