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Fuzzy linear regression models for QFD using optimized h values

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ABSTRACT

In recent years, the fuzzy linear regression (FLR) approach is widely applied in the quality function deployment (QFD) to identify the vague and inexact functional relationships between the customer requirements and the engineering characteristics on account of its advantages of objectiveness and reality. However, the h value, which is a vital parameter in the proceeding of the FLR model, is usually set by the design team subjectively. In this paper, we propose a systematic approach using the FLR models attached with optimized h values to identify the functional relationships in QFD, where the coefficients are assumed as symmetric triangular fuzzy numbers. The h values in the FLR models are determined according to the criterion of maximizing the system credibilities of the FLR models. Furthermore, an illustrative example is provided to demonstrate the performance of the proposed approach. Results of the numerical example show that the fuzzy coefficients obtained through the FLR models with optimized h values are more effective than those obtained through the FLR models with arbitrary h values selected by the design team.

1. Introduction

The quality function deployment (QFD), originated from Japan in 1960s Akao (1990), was firstly proposed to assist companies to proceed the product design planning and competitiveness analysis. So far, besides the design of new products, the methodology of QFD has been successfully applied in many other industries, including software development process (Barnett and Raja, 1995; Herzwurm and Schockert, 2003), supply chain management (Onut and Tosun, 2014; Prasad et al., 2014), project selection and assignment (Chen and Zhang, 2014; Jiang et al., 2014; Mohanty et al., 2005), investment (Celik et al., 2009; McLaughlin and Stratman, 1997), etc. The core idea of QFD suggests that the customer satisfaction is the main source of competitiveness of products (Chien and Su, 2003; Griffin and Hauser, 1993; Herrmann et al., 2000; Karsak et al., 2003; Liu et al., 2014; Zhong et al., 2014), and the producers should design or improve the performances of the products based on the detailed and quantitative requirements for the engineering characteristics of the products which are transferred from the ambiguous and qualitative voice of customers. This transformation is the key and foundation of QFD, and is usually achieved based on the identification of the functional relationships between the customer requirements (CRs) and the engineering characteristics (ECs) (Chen et al., 2005; Jiang et al., 2014; Ko and Chen, 2014; Kwong et al., 2011).

Until now, there are mainly two branches of methods to identify the functional relationships. The first one is determining the functional relationships with crisp or fuzzy numbers by product experienced specialists (Chen and Weng, 2006; Vanegas and Labib, 2001). Actually, in order to handle the uncertain information that the decision makers face, the fuzzy set theory has got a tremendous development in recent years, and has been applied in many areas, including product design (Liu et al., 2014; Zhong et al., 2014), product pricing (Zhao et al., 2012), game theory (Wang et al., 2008), etc. However, no matter the crisp or fuzzy numbers are used to express the relationship coefficients, although maybe the existence of the relationships between the CRs and the ECs is relatively simple to identify, the determination for the strength of the relationships is tough for the specialists, especially when the number of ECs of the product increases, e.g., there are usually hundreds of ECs in the design of a car. Meanwhile, the identification process is inevitably subjective. Apart from the method of determining by specialists, some regression approaches have also been introduced into QFD to identify the functional relationships, including the traditional statistical regression approach and the fuzzy regression approach. Nowadays, the fuzzy regression approach which was firstly proposed by Tanaka et al. (1982) using the fuzzy functions defined by the extension principle in Zadeh (1965) becomes to be a more and more common and adaptable method to handle the uncertain problems including QFD.

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In the QFD programming, due to the characteristic of ambiguous and imprecise in the relationships, fuzzy numbers are frequently utilized to express the relationship coefficients. Besides, in practice, the relationships are usually assumed to be linear for simplicity. Kim et al. (2000) first introduced the FLR model into QFD to estimate functional relationships, and they proposed a fuzzy multi-criteria modeling approach for product planning. Since then, the fuzzy linear regression (FLR) model has been widely applied in QFD (see, e.g., Chen et al., 2004; Karsak, 2008; Sener and Karsak, 2011; Wu, 2011). In the FLR model, there is a vital parameter, i.e., the h value, which is used to constrain that the observed crisp output values should be included in the h intervals of the fuzzy outputs obtained through the regression model. Moskowitz and Kim (1993) and Kim et al. (1996) studied the relations among the h value, the shapes of the membership functions, and the spreads of fuzzy parameters in the FLR model with symmetric triangular fuzzy numbers, which were extended to general fuzzy numbers with a decreasingly concave or increasingly convex membership function. The studies showed that whether an h value is appropriate or not would affect the effectiveness of the obtained fuzzy relationship expression directly. However, in practical situations, the h value in the FLR model is usually pre-selected by a design team subjectively (Chen and Ngai, 2008). The concepts of credibility and system credibility were initially proposed by Liu and Chen (2013), and subsequently a systematic method was presented to determine the optimized h value with a maximum system credibility of the FLR model with symmetric triangular fuzzy coefficients.

In this paper, we introduce the FLR model with an optimized h value in Liu and Chen (2013) into QFD, and propose a systematic approach to identifying the functional relationships between the CRs and the ECs. The fuzzy coefficients of the functional relationships are assumed as symmetric triangular fuzzy numbers, which are the most commonly used fuzzy numbers. An example of packing machine is also provided to show that the fuzzy coefficients obtained through the FLR models with optimized h values are more effective than those through the FLR models with arbitrary h values selected by the design team.

The rest of the paper is organized as follows. Section 2 briefly introduces the FLR model and the solution procedure of the optimized h value. Then Section 3 describes the systematic approach to identifying the functional relationships between the CRs and the ECs in a QFD programming through FLR models with optimized h values. Section 4 gives an illustrative example about the packing machine, and some analysis on the corresponding results of the obtained fuzzy functional relationships is also presented.

2. Preliminaries

In this section, we give a brief introduction about the FLR model together with a systematic method proposed by Liu and Chen (2013) for determining an optimized h value with a maximum system credibility.

2.1. Fuzzy linear regression model

In a traditional FLR model, n observations $(y_1, \boldsymbol{x}_1)$, $(y_2, \boldsymbol{x}_2)$, …, $(y_i, \boldsymbol{x}_i), \dots, (y_n, \boldsymbol{x}_n)$ are given, where y_i is the ith observed crisp output, and $\boldsymbol{x}_i = (x_{i0}, x_{i1}, \dots, x_{ij}, \dots, x_{im})^T$ is the ith observed crisp input vector with the setting of $x_{i0} = 1$ for $i = 1, 2, \dots, n$. Generally, the fuzzy relationship between the dependent variable y and independent variables $x_1, x_2, \dots, x_m$ is usually expressed as follows:

$$\tilde{y} = f(\boldsymbol{x}) = \tilde{A}_0 + \tilde{A}_1 x_1 + \cdots + \tilde{A}_j x_j + \cdots + \tilde{A}_m x_m. \quad (1)$$

Here, the fuzzy coefficients $\tilde{A}_j$, $j = 0, 1, \dots, m$, are set as symmetric

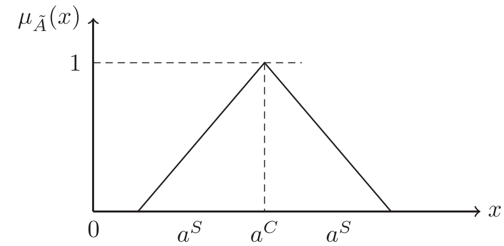

Fig. 1. The membership function of a symmetric triangular fuzzy number $\tilde{A} = (a^C, a^S)$.

triangular fuzzy numbers in Fig. 1, denoted as $\tilde{A}_j = (a_j^C, a_j^S)$, where a_j^C and a_j^S representing the center and spread values of the jth fuzzy coefficient $\tilde{A}_j$, respectively.

By taking the crisp input vector $\boldsymbol{x}_i$ into (1), we can get the fuzzy output $\tilde{y}_i$, which can be deduced as a symmetric triangular fuzzy number through the basic fuzzy arithmetics. Denote the fuzzy output by $\tilde{y}_i = (y_i^C, y_i^S)$, where y_i^C and y_i^S indicate the center and spread values of $\tilde{y}_i$, respectively, and can be calculated as

$$y_i^C = a_0^C x_{i0} + a_1^C x_{i1} + \cdots + a_m^C x_{im} = \sum_{j=0}^{m} a_j^C x_{ij},$$
$$y_i^S = a_0^S |x_{i0}| + a_1^S |x_{i1}| + \cdots + a_m^S |x_{im}| = \sum_{j=0}^{m} a_j^S |x_{ij}|. \quad (2)$$

According to Tanaka et al. (1982) and Tanaka and Watada (1988), the center and spread values of fuzzy coefficients $\tilde{A}_j = (a_j^C, a_j^S), j = 0, 1, \dots, m$, which are in the forms of symmetric triangular fuzzy numbers, can be determined by solving the following FLR model:

$$\begin{cases} \min \Delta = \sum_{i=1}^{n} \sum_{j=0}^{m} a_j^S |x_{ij}| \\ \text{s.t. :} \\ \quad (1-h) \sum_{j=0}^{m} a_j^S |x_{ij}| - \sum_{j=0}^{m} a_j^C x_{ij} \ge -y_i, \quad i = 1, 2, \dots, n \\ \quad (1-h) \sum_{j=0}^{m} a_j^S |x_{ij}| + \sum_{j=0}^{m} a_j^C x_{ij} \ge y_i, \quad i = 1, 2, \dots, n \\ \quad a_j^S \ge 0, \quad j = 0, 1, \dots, m. \end{cases} \quad (3)$$

The goal of model (3) is to minimize the system fuzziness Δ with the constraints that each observed crisp output y_i should be included in the h interval of the fuzzy outputs $\tilde{y}_i$, i.e., the membership degree $\mu_{\tilde{y}_i}(y_i)$ of each crisp output y_i should be greater than or equal to h.

As for the solution of model (3), according to the conclusions presented by Moskowitz and Kim (1993), the optimal center values of $\tilde{A}_j$ keep constant with the changes of the value of h, denoted by $\hat{a}_j^C, j = 0, 1, \dots, m$. In addition, let us denote the obtained optimal fuzzy coefficients through the FLR model (3) with the setting of $h = h_1$ as $\tilde{A}_j^{h_1} = (\hat{a}_j^C, (a_j^S)^{h_1})$ for $j = 0, 1, \dots, m$, and denote the corresponding fuzzy outputs as $\tilde{y}_i^{h_1} = (\hat{y}_i^C, (y_i^S)^{h_1})$ for $i = 1, 2, \dots, n$. Moskowitz and Kim (1993) proved that the optimal fuzzy coefficients and the related fuzzy outputs with respect to h_2 can be deduced through the corresponding results $\tilde{A}_j^{h_1}, \tilde{y}_i^{h_1}$ with respect to h_1 as

$$\tilde{A}_j^{h_2} = (\hat{a}_j^C, (a_j^S)^{h_2}) = \left(\hat{a}_j^C, \frac{1-h_1}{1-h_2} (a_j^S)^{h_1} \right), \quad (4)$$

$$\tilde{y}_i^{h_2} = (\hat{y}_i^C, (y_i^S)^{h_2}) = \left(\hat{y}_i^C, \frac{1-h_1}{1-h_2} (y_i^S)^{h_1} \right). \quad (5)$$

2.2. An optimized h value

In the FLR model (3), the setting of the h value is crucial since it influences the solution directly, i.e., the fuzzy regression coefficients