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Determination of target values of engineering characteristics in QFD using a fuzzy chance-constrained modelling approach

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ABSTRACT

Quality function deployment (QFD) is a method used for the manufacturing process of a product or service that is devoted to transforming customer requirements (CRs) into appropriate engineering characteristics (ECs) by specifying the importance of the ECs and then setting their target values. Confronting the inherent vagueness or impreciseness in the QFD process, we embed the fuzzy set theory into QFD. A fuzzy chance-constrained modelling approach with core philosophies of fuzzy expected value model and fuzzy chance-constrained programming is used in this paper. Thus, a novel fuzzy chance-constrained programming model whose objective is to minimize the fuzzy expected cost is proposed to determine the target values of the ECs with risk control to ensure satisfying CRs. Meanwhile, when considering the importance of the ECs, we adopt a more reasonable dispose which is to aggregate the relationships between the CRs and the ECs, and the correlations among the ECs. In order to solve the presented model, a hybrid intelligent algorithm is designed by integrating fuzzy simulation and genetic algorithm. Finally, an example of a motor car design is given to demonstrate the feasibility and effectiveness of the devised modelling approach and algorithm.

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1. Introduction

Quality function deployment (QFD), which was originally developed by Akao [1] in Japan in 1966, is a method used for the manufacturing process of a product or service that is devoted to transforming customer requirements (CRs) into appropriate engineering characteristics (ECs) by specifying the importance of the ECs and then setting their target values. Nowadays, QFD has been applied in a wide variety of areas such that quality control [13], decision-making [15], product design and improvement [16]. It is a customer-driven approach that can create a high level of ‘buy-in’ and reach a better control of the problem.

The typical and significant tool of QFD, House of Quality (HoQ) [14], which is a diagram that resembles a house, utilizes four sets of matrices linking *what* the CRs demand to *how* the ECs of a product or service meet these demands. The body of the HoQ is the relationship matrix of the *whats* and the *hows*, while the roof is the correlation matrix that shows the relevance among the *hows*. Besides, the importance vector of the CRs on the left side of the HoQ refers to the *whats*, and the matrix of target values of the ECs on the bottom gives the quantitative technical specifications for the ECs required to satisfy each CR.

As an important branch of QFD study, more and more systematic and rational methods for the targets setting of the ECs have received flourishing advances in the last decade, among which fuzzy modelling approaches were popular to be employed in order to get close to the fact. In this field, there are three main aspects, determining the importance of the ECs, rating the priority of the ECs and the CRs, and programming and solving the models to obtain target values that have much importance attached to them.

First and foremost, when mentioning the determination of the importance of the ECs, which is the prerequisite for deciding target values, the conventional meaning is the weighted sum of the fuzzy relation measures in the relationship matrix with the importance weights of the CRs, while the more reasonable way to present the importance of the ECs should be the aggregated importance of the ECs, which can be derived by simultaneously considering the conventional importance of the ECs as well as the impacts of an EC on other ECs, i.e., the fuzzy correlation measures in the correlation matrix among the ECs. In previous studies, many utilized the idea of the aggregated importance of the ECs. For instance, Büyükozkan et al. [3] used the analytic network process (ANP), the general form of the analytic hierarchy process (AHP), to prioritize the ECs by taking into account the aggregated importance. Chen and Weng [5] obtained the fuzzy normalized relationship matrix, with which

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fuzzy technical importance ratings for design requirements are determined. Kwong et al. [18] proposed a new methodology of determining aggregated importance of the ECs, in which fuzzy relation measures between the CRs and ECs as well as fuzzy correlation measures among the ECs were determined based on fuzzy expert systems approach.

Secondly, priority ratings of both the *whats* and the *hows* should also be concerned because they have an effect on the precedence order of the target values of the ECs getting improved. Chin et al. [8] presented an evidential reasoning based methodology which could be used to help the QFD team prioritize the ECs with customers' wants and preferences taken into account, for synthesizing various types of assessment information provided by a group of customers and multiple QFD team members. Kwong et al. [19] designed a novel fuzzy group decision-making method that integrated a fuzzy weighted average method with a consensus ordinal ranking technique for prioritizing the ECs in QFD under uncertainties. Except for the obtainment of the priority ratings of the ECs above, other elements in the HoQ, e.g., the CRs could also be given priority ratings, along with the customer satisfaction. Li et al. [20] developed a systematic and operational method based on the integration of a minimal deviation based method, balanced scorecard, AHP and scale method to determine the final priority ratings of the CRs, while Nepal et al. [26] constructed a fuzzy-AHP framework for prioritizing customer satisfaction attributes in target planning. To be thoughtful, Nahm et al. [25] proposed an approach to prioritize the CRs in the QFD process by developing two sets of new rating methods, called customer preference rating method and customer satisfaction rating method, for relative importance ratings and competitive priority ratings, respectively.

Thirdly, when a given HoQ contains a large number of CRs and ECs, determining the target values of the ECs would be a very complex and difficult decision process. Currently, different programming models with different functions and the corresponding algorithms have been exploited by researchers for targets setting. Cristiano et al. [9] developed a formal, numerically based process for targets setting by combining ideas from multiattribute decision analysis, set inclusion, and QFD. Chen et al. [6] proposed a fuzzy expected value modelling approach for determining target values, which simultaneously took minimizing the design cost and maximizing the customer satisfaction into account. Sener and Karsak [28,29] developed some fuzzy mathematical programming models to determine target values of the ECs not only by using the functional relationships obtained from a nonlinear-programming-based fuzzy regression, but also by an integrated fuzzy linear regression and fuzzy multiple objective programming approach. Moreover, Delice and Güngor [10] proposed a fuzzy mixed-integer goal programming model that determined a composition of optimal discrete EC values, following a new decision support system which integrated QFD and mathematical programming. Chen and Ko [4] considered the close link between the four sequential phases in a complete QFD process in the new product development using the means-end chain concept to build up a series of fuzzy nonlinear programming models with risk constraint for determining the attainment levels of each decision outcome for customer satisfaction. Fung et al. [12] considered a fuzzy formulation combined with a genetic-based interactive approach to determine target values of the ECs. Bai and Kwong [2] proposed an inexact genetic algorithm approach to set target values of the ECs.

In this paper, the basic philosophy of fuzzy chance-constrained programming is used to model the QFD process in a fuzzy environment in order to determine target values of the ECs for making different practical decisions. As a result, a fuzzy chance-constrained programming model with the objective of minimizing the fuzzy expected cost and the chance constraint of overall customer satisfaction is constructed. To consider not only the inherent fuzziness in the relationships between the CRs and the ECs, but also those among the ECs, these two kinds of fuzzy relationships are aggregated to derive the fuzzy importance of the ECs. So as to effectively solve the proposed model, we design a hybrid intelligent algorithm, which incorporates fuzzy simulation and genetic algorithm.

The rest of the paper is organized as follows. In the next section, some specific aspects of fuzzy variables and fuzzy expected value operator are discussed. In Section 3, a fuzzy chance-constrained modelling approach for QFD planning in a fuzzy environment is presented, and a fuzzy chance-constrained programming model is then developed to determine the target values of the ECs with risk control for making different practical decisions of product design. In order to solve the model, a hybrid intelligent algorithm integrating fuzzy simulation and genetic algorithm is presented in Section 4. Finally, an example of motor car design is used to demonstrate the performance of the proposed approach and algorithm in Section 5.

2. Fuzzy set theory

In the following, we briefly review the concepts of fuzzy variable, membership function, and expected value operator of fuzzy variable. Let Θ be a nonempty set, $\mathcal{P}(\Theta)$ the power set of Θ, and Pos a possibility measure. Then the triplet $(\Theta, \mathcal{P}(\Theta), \text{Pos})$ is called a possibility space. We use the following mathematical definition of fuzzy variable in our problem.

Definition 1. A fuzzy variable is defined as a function from a possibility space $(\Theta, \mathcal{P}(\Theta), \text{Pos})$ to the set of real numbers.

Therewith, the membership function of a fuzzy variable can be defined as follows.

Definition 2. Let $\tilde{\xi}$ be a fuzzy variable defined on the possibility space $(\Theta, \mathcal{P}(\Theta), \text{Pos})$. Then its membership function is derived from the possibility measure by

$$\mu_{\tilde{\xi}}(x) = \text{Pos}\{\theta \in \Theta | \tilde{\xi}(\theta) = x\}, \quad x \in \Re. \tag{1}$$

Practically, triangular fuzzy numbers, which are the most widely used form of fuzzy variables and can be easily handled arithmetically, are adopted to interpret the fuzziness of CRs and ECs in this paper. Let $\tilde{A}$ be a triangular fuzzy number with membership function $\mu_{\tilde{A}}(x)$, and be fully determined by a triplet of crisp numbers as $\tilde{A} = (a^L, a, a^R)$, where a is the central value that satisfies $\mu_{\tilde{A}}(a) = 1$ describing the most possible value of $\tilde{A}$, and a^L and a^R are the left and right spreads representing the precision of $\tilde{A}$ which make the lower limit $a - a^L$ and the upper limit $a + a^R$, respectively.

Hence, the triangular fuzzy number $\tilde{A}$ can be characterized by its membership function $\mu_{\tilde{A}}(x)$ as

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{a^L - (a-x)}{a^L}, & a - a^L \le x \le a \\ \dfrac{a^R - (x-a)}{a^R}, & a \le x \le a + a^R \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

or alternatively by its h-cuts $\tilde{A}_h$ as

$$\tilde{A}_h = \{x | \mu_{\tilde{A}}(x) \ge h\} = [\underline{A}(h), \overline{A}(h)] = [a - a^L(1-h), a + a^R(1-h)]. \tag{3}$$

The arithmetic of fuzzy variables is a direct application of the extension principle of Zadeh in [31]. For arbitrary triangular fuzzy numbers $\tilde{A} = (a^L, a, a^R)$ and $\tilde{B} = (b^L, b, b^R)$, we have the addition and

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