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

Shuya Zhong, Jian Zhou, Yizeng Chen *

School of Management, Shanghai University, Shanghai 200444, China

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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.

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, Büyüközkan 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

* Corresponding author. Tel.: +86 21 66137931.
E-mail address: mfcyz@shu.edu.cn (Y. Chen).

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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 $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$ 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 $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$ 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 $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$. Then its membership function is derived from the possibility measure by

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

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 $\tilde{A} = (a^{\mathrm{L}}, a, a^{\mathrm{R}})$, 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 $a - a^{\mathrm{L}}$ and the upper limit $a + a^{\mathrm{R}}$, respectively.

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

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

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

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

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

$$\tilde{A}+\tilde{B}=(a^{\mathrm{L}}+b^{\mathrm{L}},\ a+b,\ a^{\mathrm{R}}+b^{\mathrm{R}}),$$
$$\tilde{A}-\tilde{B}=(a^{\mathrm{L}}-b^{\mathrm{R}},\ a-b,\ a^{\mathrm{R}}-b^{\mathrm{L}}), \tag{4}$$

respectively. What should be noted is that the results of the fuzzy multiplication and division of triangular fuzzy numbers are actually not triangular fuzzy numbers anymore, and the precise results can be obtained through many methodologies (see, e.g., [7,17]), or we can use fuzzy simulation to obtain the imprecise results according to the extension principle of Zadeh directly as used in this paper.

In order to measure the chance of fuzzy events, three measures, i.e., possibility, necessity, and credibility, have been presented. Suppose that x is a real number, then the possibility, necessity, and credibility of a fuzzy event $\{\tilde{\xi}\ge x\}$ can be defined by

$$\mathrm{Pos}\{\tilde{\xi}\ge x\}=\sup_{u\ge x}\mu_{\tilde{\xi}}(u),$$

$$\mathrm{Nec}\{\tilde{\xi}\ge x\}=1-\sup_{u<x}\mu_{\tilde{\xi}}(u),$$

$$\mathrm{Cr}\{\tilde{\xi}\ge x\}=\tfrac{1}{2}(\mathrm{Pos}\{\tilde{\xi}\ge x\}+\mathrm{Nec}\{\tilde{\xi}\ge x\}), \tag{5}$$

respectively.

The excepted value operator of random variable plays an extremely important role in probability theory. For fuzzy variables, there are many ways to define an expected value operator. In this paper, we use the definition of the expected value operator of fuzzy variable given by Liu and Liu [23].

Definition 3 (*Liu and Liu [23]*). Let $\tilde{\xi}$ be a fuzzy variable. Then the excepted value of $\tilde{\xi}$ is defined by

$$E[\tilde{\xi}]=\int_0^{+\infty}\mathrm{Cr}\{\tilde{\xi}\ge x\}\,dx-\int_{-\infty}^{0}\mathrm{Cr}\{\tilde{\xi}\le x\}\,dx \tag{6}$$

provided that at least one of the two integrals is finite.

As for a triangular fuzzy number $\tilde{A}=(a^{\mathrm{L}},a,a^{\mathrm{R}})$, to obtain the expected value $E[\tilde{A}]$, we need to calculate the credibility via the possibility and necessity as follows:

$$\mathrm{Pos}(\tilde{A}\ge x)=\begin{cases}1, & x\le a\\ \dfrac{-x+a+a^{\mathrm{R}}}{a^{\mathrm{R}}}, & a<x\le a+a^{\mathrm{R}}\\ 0, & x>a+a^{\mathrm{R}},\end{cases} \tag{7}$$

$$\mathrm{Pos}(\tilde{A}\le x)=\begin{cases}0, & x\le a-a^{\mathrm{L}}\\ \dfrac{x-a+a^{\mathrm{L}}}{a^{\mathrm{L}}}, & a-a^{\mathrm{L}}<x\le a\\ 1, & x>a,\end{cases} \tag{8}$$

$$\mathrm{Nec}(\tilde{A}\ge x)=\begin{cases}1, & x\le a-a^{\mathrm{L}}\\ \dfrac{-x+a}{a^{\mathrm{L}}}, & a-a^{\mathrm{L}}<x\le a\\ 0, & x>a,\end{cases} \tag{9}$$

$$\mathrm{Nec}(\tilde{A}\le x)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{a^{\mathrm{R}}}, & a<x\le a+a^{\mathrm{R}}\\ 1, & x>a+a^{\mathrm{R}},\end{cases} \tag{10}$$

$$\mathrm{Cr}(\tilde{A}\ge x)=\begin{cases}1, & x\le a-a^{\mathrm{L}}\\ \dfrac{-x+a+a^{\mathrm{L}}}{2a^{\mathrm{L}}}, & a-a^{\mathrm{L}}<x\le a\\ \dfrac{-x+a+a^{\mathrm{R}}}{2a^{\mathrm{R}}}, & a<x\le a+a^{\mathrm{R}}\\ 0, & x>a+a^{\mathrm{R}},\end{cases} \tag{11}$$

$$\mathrm{Cr}(\tilde{A}\le x)=\begin{cases}0, & x\le a-a^{\mathrm{L}}\\ \dfrac{x-a+a^{\mathrm{L}}}{2a^{\mathrm{L}}}, & a-a^{\mathrm{L}}<x\le a\\ \dfrac{x-a+a^{\mathrm{R}}}{2a^{\mathrm{R}}}, & a<x\le a+a^{\mathrm{R}}\\ 1, & x>a+a^{\mathrm{R}}.\end{cases} \tag{12}$$

Therefore, according to Eq. (6), we can get the fuzzy expected value of $\tilde{A}$ as

$$E[\tilde{A}]=\int_0^{+\infty}\mathrm{Cr}\left\{\tilde{A}\ge x\right\}dx-\int_{-\infty}^{0}\mathrm{Cr}\left\{\tilde{A}\le x\right\}dx=\frac{a^{\mathrm{R}}+4a-a^{\mathrm{L}}}{4}. \tag{13}$$

Considering the linearity of expected value operator, a relative theorem has been put forward.

Theorem 1 (*Liu and Liu [24]*). *Let $\tilde{\xi}$ and $\tilde{\eta}$ be independent fuzzy variables with finite expected values. Then for any real numbers λ and δ, we have*

$$E[\lambda\tilde{\xi}+\delta\tilde{\eta}]=\lambda E[\tilde{\xi}]+\delta E[\tilde{\eta}]. \tag{14}$$

Suppose that $\tilde{A}=(a^{\mathrm{L}},a,a^{\mathrm{R}})$ and $\tilde{B}=(b^{\mathrm{L}},b,b^{\mathrm{R}})$ are two independent triangular fuzzy numbers. By applying (Eqs. (13) and 14), it is easy to acquire

$$E[\lambda\tilde{A}+\delta\tilde{B}]=\lambda E[\tilde{A}]+\delta E[\tilde{B}]=\frac{\lambda}{4}(a^{\mathrm{R}}+4a-a^{\mathrm{L}})+\frac{\delta}{4}(b^{\mathrm{R}}+4b-b^{\mathrm{L}}). \tag{15}$$

3. Model formulations

In QFD, a more realistic objective of the product planning process than conventional ones is to find target values of the ECs to minimize the expected design cost under a preferred acceptable overall customer satisfaction holding at least with a predetermined confidence level, rather than to attain it without any risk. Practically, the product design is often carried out in the environments containing imprecise variables like the importance of the CRs or the ECs. Therefore, a fuzzy chance-constrained programming approach is presented in this section, and a fuzzy excepted cost minimization model with risk control for determining target values of the ECs in a fuzzy environment is proposed for indeterminate QFD planning.

3.1. Problem description and notations

Our problem is assumed to design a new product with m CRs, n ECs and p competitors. Before formulating this problem in the fuzzy environment, let us introduce the following indices, parameters, and decision variables used in this paper:

- $i=1,2,\ldots,m$: the index of customer requirements;
- $j=1,2,\ldots,n$: the index of engineering characteristics;
- $q=1,2,\ldots,p$: the index of competitors;
- CR_i : the ith customer requirement, $i=1,2,\ldots,m$;
- EC_j : the jth engineering characteristic, $j=1,2,\ldots,n$;
- Comp_q : the qth competitor, $q=1,2,\ldots,p$;
- $\tilde{\boldsymbol{R}}=(\tilde{r}_{ij})_{m\times n}$: the original fuzzy relationship matrix between the CRs and the ECs, in which $\tilde{r}_{ij}$ denotes the fuzzy relation measure between CR_i and EC_j, $i=1,2,\ldots,m,\ j=1,2,\ldots,n$;
- $\tilde{\boldsymbol{P}}=(\tilde{p}_{jk})_{n\times n}$: the fuzzy correlation matrix among the ECs, in which $\tilde{p}_{jk}$ denotes the correlation measure between EC_j and EC_k, $j,k=1,2,\ldots,n$;
- $\tilde{\boldsymbol{R}}'=(\tilde{r}'_{ij})_{m\times n}$: the modified fuzzy relationship matrix between the CRs and the ECs by integrating the fuzzy correlation matrix

$\tilde{\boldsymbol{P}}$, in which $\tilde{r}'_{ij}$ denotes the modified fuzzy relationship measure between CR_i and EC_j, $i=1,2,\ldots,m$, $j=1,2,\ldots,n$;

- $\boldsymbol{X}=(x_1,x_2,\ldots,x_n)^T$: the decision vector of the level of attainment of the ECs, in which x_j is the level of attainment of EC_j, $0\le x_j\le 1$, $j=1,2,\ldots,n$;
- $\tilde{\boldsymbol{Y}}=(\tilde{y}_1,\tilde{y}_2,\ldots,\tilde{y}_m)^T$: the fuzzy vector of customer perception of the CRs, in which $\tilde{y}_i$ is the customer perception of the satisfaction degree of CR_i, $i=1,2,\ldots,m$;
- $\tilde{\boldsymbol{W}}=(\tilde{w}_1,\tilde{w}_2,\ldots,\tilde{w}_m)^T$: the fuzzy relative importance vector of the CRs, in which $\tilde{w}_i$ is the fuzzy relative importance of CR_i, $i=1,2,\ldots,m$;
- $\tilde{\boldsymbol{V}}=(\tilde{v}_1,\tilde{v}_2,\ldots,\tilde{v}_n)^T$: the fuzzy importance vector of the ECs, in which $\tilde{v}_j$ is the fuzzy importance of EC_j, $j=1,2,\ldots,n$;
- $\tilde{\boldsymbol{V}}'=(\tilde{v}'_1,\tilde{v}'_2,\ldots,\tilde{v}'_n)^T$: the fuzzy relative importance vector of the ECs, in which $\tilde{v}'_j$ is the normalized fuzzy importance of EC_j, $j=1,2,\ldots,n$;
- $\tilde{S}$: the fuzzy overall customer satisfaction;
- $\tilde{S}'$: the fuzzy relative overall customer satisfaction;
- l_j : the target value of EC_j, $j=1,2,\ldots,n$;
- $\tilde{C}$: the fuzzy total cost of product development;
- $\tilde{C}_F$: the fixed part of the fuzzy development cost $\tilde{C}$;
- $\tilde{C}_V$: the variable part of the fuzzy development cost $\tilde{C}$;
- $\tilde{C}_j$: the fuzzy cost required for achieving x_j, $j=1,2,\ldots,n$;
- $\tilde{c}_j$: the fuzzy cost required to improve one unit of x_j, $j=1,2,\ldots,n$;
- ρ : the preferred acceptable overall customer satisfaction, $0\le\rho\le 1$;
- α : the predetermined confidence level, $0\le\alpha\le 1$.

3.2. Normalization of target values

As different ECs have different units of measurement, it is not reasonable to evaluate them synthetically by using their respective raw values. Thus, the normalization of target values of the ECs becomes a necessary step to transform the incommensurable data to commensurable ones. In our problem, $l_j(j=1,2,\ldots,n)$, which stands for the current target value of EC_j, is changed into the level of attainment $x_j(j=1,2,\ldots,n)$, such that $0\le x_j\le 1$. For the target value l_j, the performance of the EC is positively proportional to l_j when it pursues a positive goal, or negatively proportional to l_j when it seeks a passive goal. In the practical QFD process, such positive and passive goals often coexist to cater to different needs. For instance, in the motor car design, the organization usually pursues increasing the speed of airbag pop-up(positive goal), and reducing the time for windshield defogging(passive goal). The two categories of target values of the ECs can be normalized according to the following equations:

$$x_j=\frac{l_j-l_j^{\min}}{l_j^{\max}-l_j^{\min}}\quad \text{(positive type)} \tag{16}$$

$$x_j=\frac{l_j^{\max}-l_j}{l_j^{\max}-l_j^{\min}}\quad \text{(passive type)} \tag{17}$$

where $l_j^{\max}$ and $l_j^{\min}$ can be determined by the consideration of competition requirements and technology feasibility [32]. In Eq. (16), $l_j^{\max}$ is the maximum target value of EC_j to match competitors' performance, and $l_j^{\min}$ is the minimum physical limit, while in Eq. (17), $l_j^{\min}$ is the minimum target value of EC_j to match competitors' performance, and $l_j^{\max}$ is the maximum physical limit.

3.3. Formulation of the overall customer satisfaction

In reality, the inherent vagueness or impreciseness in QFD process of product development always leads to a special challenge for properly setting target values of the ECs, mainly because of the linguistic data used to describe the importance degree in HoQ, the subjective and qualitative way to translate CRs into ECs, and the limitation of sufficiently getting accurate data especially when an entirely new product is designed.

Owing to the uncertainties in the product design process, such as ill-defined or incomplete understanding of the importance of the CRs, the relationship between the CRs and the ECs, as well as the correlation among the ECs, these resources can be expressed in fuzzy terms [11,30]. Therefore, the relative importance vector of the CRs $\tilde{\boldsymbol{W}}$, the relationship matrix between the CRs and the ECs $\tilde{\boldsymbol{R}}$, and the correlation matrix among the ECs $\tilde{\boldsymbol{P}}$ are all assumed to be fuzzy. Accordingly, the deduced customer perception of the CRs $\tilde{\boldsymbol{Y}}$ and the importance of the ECs $\tilde{\boldsymbol{V}}$ are also fuzzy vectors.

Now let us consider the overall customer satisfaction $\tilde{S}$, which reflects the overall customer perception of a product. It is also fuzzy as it can be considered as a mathematical aggregation of $\tilde{y}_i$, $i=1,2,\ldots,m$, which can be represented as $\tilde{S}=f(\tilde{y}_1,\tilde{y}_2,\ldots,\tilde{y}_m)$. This aggregate function can usually be expressed as an additive, multiplicative or multi-linear operator depending on the customer preference. In this paper, a fuzzy weighted linear additive operator is adopted to express $\tilde{S}$ as follows:

$$\tilde{S}=\tilde{\boldsymbol{W}}^T\tilde{\boldsymbol{Y}}=\sum_{i=1}^{m}\tilde{w}_i\tilde{y}_i. \tag{18}$$

Along with the improvement of target values of the ECs, the satisfaction degree of each CR can get well promoted according to [27]. Thus we can obtain

$$\tilde{\boldsymbol{Y}}=\tilde{\boldsymbol{R}}'\boldsymbol{X} \tag{19}$$

where

$$\tilde{\boldsymbol{R}}'=\tilde{\boldsymbol{R}}\tilde{\boldsymbol{P}}, \tag{20}$$

i.e.,

$$\tilde{y}_i=\sum_{j=1}^{n}\sum_{k=1}^{n}\tilde{r}_{ik}\tilde{p}_{kj}x_j,\quad i=1,2,\ldots,m \tag{21}$$

where $\tilde{r}_{ik}$ denotes the strength of relationship between CR_i and EC_k, the correlation element $\tilde{p}_{kj}$ reflects the contribution to EC_j when EC_k is improved, and x_j represents the level of attainment of EC_j.

Thus, Eq. (18) can be rewritten as

$$\tilde{S}=\tilde{\boldsymbol{W}}^T\tilde{\boldsymbol{R}}'\boldsymbol{X}=\tilde{\boldsymbol{V}}^T\boldsymbol{X}=\sum_{j=1}^{n}\tilde{v}_jx_j \tag{22}$$

where $\tilde{\boldsymbol{V}}$ is the fuzzy importance vector of the ECs, which can be expressed as

$$\tilde{\boldsymbol{V}}=(\tilde{\boldsymbol{W}}^T\tilde{\boldsymbol{R}}')^T. \tag{23}$$

Therefore, the fuzzy importance of EC_j can be calculated by

$$\tilde{v}_j=\sum_{i=1}^{m}\sum_{k=1}^{n}\tilde{w}_i\tilde{r}_{ik}\tilde{p}_{kj},\quad j=1,2,\ldots,n. \tag{24}$$

From Eq. (24), it can be seen that not only the fuzziness in the relationships between the CRs and the ECs, but also the correlations among the ECs are aggregated to define the fuzzy importance of an individual EC, which can be regarded as a more reasonable way to deal with the uncertainties in the QFD process.

3.4. Formulation of the design cost

Apart from the consideration of customer satisfaction, there exist other multiple resources required for supporting the development of a new product, such as technical expertise, advanced equipment, tools and other facilities. These resources can be aggregated in financial terms at the level of strategic planning.

Due to the usual variations in supply and demand, all of the incurred costs in the QFD process are handled in fuzzy variables in this paper. Above all, the fuzzy total development cost $\tilde{C}$ can be viewed as a summation of a fixed part $\tilde{C}_F$ and a variable part $\tilde{C}_V$ as

$$\tilde{C} = \tilde{C}_F + \tilde{C}_V \tag{25}$$

where the fuzzy fixed cost $\tilde{C}_F$ is defined as the basic investment cost incurred when all the levels of attainment of the ECs are zero, i.e., $x_1 = x_2 = \cdots = x_n = 0$, which implies that all the target values of the ECs lie in the worst status and the overall customer satisfaction $\tilde{S}$ is zero. Since the fuzzy cost $\tilde{C}_V$ is the variable part of the total development cost $\tilde{C}$ only depending on the levels of attainment of the ECs x_j, $j = 1, 2, \ldots, n$, it can be acquired by the sum of costs required for achieving the level of individual EC, i.e.,

$$\tilde{C}_V = \sum_{j=1}^{n} \tilde{C}_j \tag{26}$$

where $\tilde{C}_j$ is the fuzzy cost incurred for improving EC_j. For simplicity, suppose that $\tilde{C}_j$ is scaled linearly to the level of attainment x_j, i.e.,

$$\tilde{C}_j = \tilde{c}_j x_j, \quad j = 1, 2, \ldots, n \tag{27}$$

where the fuzzy cost coefficient $\tilde{c}_j$ stands for the cost required for improving one unit of x_j. In other words, when one unit of attainment of EC_j is fulfilled, a cost item $\tilde{c}_j$ is incurred. Then according to (25)–(27), the fuzzy total cost for product development $\tilde{C}$ can be represented as

$$\tilde{C} = \tilde{C}_F + \tilde{C}_V = \tilde{C}_F + \sum_{j=1}^{n} \tilde{c}_j x_j. \tag{28}$$

3.5. Fuzzy expected cost minimization model with risk control

Standing on the perspective of enterprise, we assume that the product planning process based on QFD is to determine a set of levels of attainment $x_1, x_2, \ldots, x_n$ of the ECs for the new product to minimize the design cost $\tilde{C}$ under a preferred acceptable overall customer satisfaction. It seems very plausible to build such a fuzzy programming model for QFD planning as follows:

$$\begin{cases} \min\limits_{\boldsymbol{x}} \tilde{C} = \tilde{C}_F + \sum\limits_{j=1}^{n} \tilde{c}_j x_j \\ \text{subject to :} \\ \quad \sum\limits_{j=1}^{n} \tilde{v}_j x_j \ge \rho \\ \quad 0 \le x_j \le 1, \quad j = 1, 2, \ldots, n \end{cases} \tag{29}$$

where the first constraint means that the overall customer satisfaction $\tilde{S} = \sum_{j=1}^{n} \tilde{v}_j x_j$ for a product development is constrained to a preferred acceptable threshold value ρ as a control of the overall customer satisfaction. The determination of ρ usually depends on the decision-maker's preference and subjectivity.

However, the above model (29) is not well defined due to the fuzzy return function $\tilde{C}$ and the first fuzzy constraint. In fact, the form of fuzzy programming like (29) appears frequently in the literature. Fuzzy programming constructs a class of mathematical models, which should be given an explicit explanation. From this point of view, model (29) does not have a mathematical meaning because it can have different interpretations. In order to build an unambiguous fuzzy programming model for QFD planning, we integrate core philosophies of fuzzy expected value model and fuzzy chance-constrained programming appropriately.

Firstly, as for the fuzzy objective function, it is natural to minimize the expected value of the fuzzy total design cost $\tilde{C}$, which can be calculated according to (14) as

$$\begin{aligned} E(\tilde{C}) &= E(\tilde{C}_F + \tilde{C}_V) = E(\tilde{C}_F) + E(\tilde{C}_V) \\ &= E(\tilde{C}_F) + E\left(\sum_{j=1}^{n} \tilde{c}_j x_j\right) = E(\tilde{C}_F) + \sum_{j=1}^{n} E(\tilde{c}_j) x_j \end{aligned} \tag{30}$$

where E is the expected operator defined in (6). Since $E(\tilde{C}_F)$ is a constant, which implies $\min E(\tilde{C})$ is equivalent to $\min E(\tilde{C}_V)$ essentially, then the objective function (30) can be replaced as

$$E(\tilde{C}_V) = \sum_{j=1}^{n} E(\tilde{c}_j) x_j. \tag{31}$$

Secondly, referring to the first constraint of model (29), as $0 \le \rho \le 1$, it is necessary to normalize $\tilde{v}_j$ to $\tilde{v}'_j$ as

$$\tilde{v}'_j = \frac{\tilde{v}_j}{\sum_{j=1}^{n} \tilde{v}_j}, \quad j = 1, 2, \ldots, n, \tag{32}$$

so that an appropriate threshold ρ can be acquired. Here $\tilde{v}'_j$ is referred to as the fuzzy relative importance of EC_j.

Thirdly, since the first constraint $\sum_{j=1}^{n} \tilde{v}_j x_j \ge \rho$ does not define a crisp feasible set, the fuzzy chance-constrained programming method developed by Liu and Iwamura [21,22] is utilized, the underlying philosophy of which is to model fuzzy decision systems with assumptions that the chance constraints hold at least with some predetermined confidence levels, which are provided as appropriate safety margins by the decision-maker. Thus, the constraint $\sum_{j=1}^{n} \tilde{v}_j x_j \ge \rho$ can be substituted to a chance constraint based on the above idea as

$$\text{Cr}\left\{\sum_{j=1}^{n} \tilde{v}'_j x_j \ge \rho\right\} \ge \alpha \tag{33}$$

where α is the predetermined confidence level generally interpreted as the constraint reliability for the overall customer satisfaction threshold ρ, and Cr is the credibility measure defined in (5).

Consequently, we formulate the QFD planning problem based on (Eqs. (31) and 33) as follows:

$$\begin{cases} \min\limits_{\boldsymbol{x}} E(\tilde{C}_V) = \sum\limits_{j=1}^{n} E(\tilde{c}_j) x_j \\ \text{subject to :} \\ \quad \text{Cr}\left\{\sum\limits_{j=1}^{n} \tilde{v}'_j x_j \ge \rho\right\} \ge \alpha \\ \quad 0 \le x_j \le 1, \quad j = 1, 2, \ldots, n \end{cases} . \tag{34}$$

This fuzzy programming model is built for the purpose of minimizing the expected design cost in the QFD planning process of a new product development, under a preferred acceptable overall customer satisfaction with an assurance to achieve a predetermined confidence level so as to control risks.

The uncertainty of fuzzy objective and constraint can cause a considerable risk of the design cost failing to satisfy the customer requirements for the final product, so we suggest the fuzzy chance-constrained programming model (34) to overcome this difficulty, which makes a good tradeoff between the design cost and the failure risk of not sufficiently meeting the demands of customers. The risk can be managed by proper combinations of the satisfaction limitations ρ and the confidence levels α, and the constraint to the risk guarantees that the failure rate is less than the predetermined level $1-\alpha$.

4. Hybrid intelligent algorithm

It is often difficult to obtain results from fuzzy programming models by traditional methods. A good way is to design some hybrid intelligent algorithms for figuring them out. In this section, we introduce the design of a hybrid intelligent algorithm integrating fuzzy simulation and genetic algorithm for solving the proposed model (34).

First, we suppose that all the fuzzy numbers including $\tilde{w}_i=(w_i^L, w_i, w_i^R)$, $\tilde{r}_{ik}=(r_{ik}^L, r_{ik}, r_{ik}^R)$, and $\tilde{p}_{kj}=(p_{kj}^L, p_{kj}, p_{kj}^R)$ are triangular fuzzy numbers, which are the most widely used form of fuzzy variables and can be easily handled arithmetically as referred to in Section 2. When considering the first type of fuzzy function $\sum_{j=1}^n E(\tilde{c}_j)x_j$, i.e., the objective function of model (34), we can easily obtain its value by utilizing Eq. (13) for calculating fuzzy expected values of triangular fuzzy numbers $\tilde{c}_j=(c_j^L, c_j, c_j^R)$, $j=1,2,\ldots,n$, as follows:

$$E(\tilde{c}_j)=\frac{c_j^R+4c_j-c_j^L}{4}, \tag{35}$$

so that the expected cost $E(\tilde{C}_V)$ can be calculated as

$$E(\tilde{C}_V)=\sum_{j=1}^n\frac{(c_j^R+4c_j-c_j^L)x_j}{4}. \tag{36}$$

The second type of fuzzy function is

$$U: \boldsymbol{X}\to \mathrm{Cr}\left\{\sum_{j=1}^n \tilde{v}_j' x_j \ge \rho\right\}, \tag{37}$$

which is the credibility of fuzzy event $\{\sum_{j=1}^n \tilde{v}_j' x_j \ge \rho\}$. According to the definition of credibility given in Eq. (5) as well as Eqs. (24) and (32), we design a fuzzy simulation to approximatively compute U as follows.

Algorithm 1 (*Fuzzy simulation for the credibility*).

Step 1: Randomly generate $w_i^t, r_{ik}^t, p_{kj}^t$ from the t/M-cuts $(\tilde{w}_i)_{t/M}$, $(\tilde{r}_{ik})_{t/M}$, $(\tilde{p}_{kj})_{t/M}$, $i=1,2,\ldots, m, k, j=1,2,\ldots,n$, $t=1,2,\ldots,M$, respectively, where M is a sufficiently large number (see Eq. (3) in Section 2 for the calculation of the t/M-cuts of triangular fuzzy numbers).

Step 2: Compute

$$S_t'=\sum_{j=1}^n\frac{\sum_{i=1}^m\sum_{k=1}^n w_i^t r_{ik}^t p_{kj}^t}{\sum_{j=1}^n\sum_{i=1}^m\sum_{k=1}^n w_i^t r_{ik}^t p_{kj}^t}x_j$$

for $t=1,2,\ldots,M$.

Step 3: Return L as the credibility calculated, where

$$L=\frac{1}{2}\left(\max_{1\le t\le M}\{t/M|S_t'\ge\rho\}+\min_{1\le t\le M}\{1-t/M|S_t'<\rho\}\right).$$

Successively, the above fuzzy simulation which can simulate the credibility is embedded into a genetic algorithm to design a hybrid intelligent algorithm for searching the optimal solutions of model (34). The detailed procedures of the hybrid intelligent algorithm presented in this paper are described as follows.

Algorithm 2 (*Hybrid intelligent algorithm*).

Step 1: Initialize chromosomes $V_i=(x_1, x_2, \ldots, x_n)$ for $i=1,2,\ldots,$ *pop_size*, from the domain $[0,1]^n$, and the feasibility of chromosomes can be checked by the proposed fuzzy simulation (Algorithm 1).

Step 2: Calculate the objective values $E(\tilde{C}_V)$ according to Eq. (36) for all chromosomes V_i, $i=1,2,\ldots,pop\_size$.

Step 3: Compute the fitness of all chromosomes V_i, $i=1,2,\ldots,$ *pop_size*, by the rank-based evaluation function $Eval(V_i)=a(1-a)^{i-1}$, $i=1,2,\ldots,pop\_size$.

Step 4: Select *pop_size* chromosomes for a new population by spinning the roulette wheel.

Step 5: Update chromosomes V_i, $i=1,2,\ldots,pop\_size$, by crossover and mutation operations, and the feasibility should also be checked by the proposed fuzzy simulation (Algorithm 1).

Step 6: Repeat the second to fifth steps for a given number of iterations.

Step 7: Report the best chromosome $V^*=(x_1^*, x_2^*, \ldots, x_n^*)$ found according to the fitness values as the optimal levels of attainment of the ECs.

5. Numerical example

In order to verify the feasibility and effectiveness of the proposed fuzzy chance-constrained modelling approach and the corresponding hybrid intelligent algorithm, the development of a new type of motor car is illustrated as a numerical example, and the results are also presented and analyzed in this section.

An automobile enterprise is developing a new type of motor car. The purpose of applying QFD is to explore the effects of both the overall customer satisfaction and the confidence level on the target values of the ECs and the total development cost. Thereby, a dynamic selection approach can be provided to guide the design team to flexibly determine target values of the ECs for motor car designing and manufacturing in different environments by reconciling tradeoffs among the competition requirements, the technical feasibility and the financial factors.

In the first place, an investigation has been conducted into the potential target market, and we get some feedback from customers, whose results are displayed in the HoQ in Fig. 1. From the HoQ, we can see that five major CRs can be identified as the biggest concerns of the customers, of which the relative fuzzy importance is classified into five levels to describe the difference of importance. Five sets of triangular fuzzy numbers, $\tilde{w}_1=(0,0,0.25)$, $\tilde{w}_2=(0.25,0.25,0.25)$, $\tilde{w}_3=(0.25,0.5,0.25)$, $\tilde{w}_4=(0.25,0.75,0.25)$, and $\tilde{w}_5=(0.25,1,0)$, are used to quantize these five linguistic terms (see Fig. 2).

And then, the detailed contents in the HoQ in Fig. 1 are determined one after another. The design team first recognizes five most important ECs related to the CRs based on their professional knowledge and experience of this product, which are measured in units of dB, horsepower, gallon, kg and m^3. The positive/negative signs on the ECs indicate that the design team wishes to increase/reduce the target values of each EC. To identify the fuzzy importance of the five ECs, the strength of the fuzzy relationship measures between the CRs and ECs as well as the correlation measures among the ECs is linguistically judged as four levels, which can also be represented by triangular fuzzy numbers $\tilde{u}_1=(0,0,0.1)$, $\tilde{u}_1=(0.2,0.2,0.2)$, $\tilde{u}_3=(0.3,0.5,0.3)$, and $\tilde{u}_4=(0.3,\ 1,0)$ (see Fig. 3). Besides, five competitors are taken into consideration and their corresponding target values of the ECs are set by the design teams on the basis of enterprise environments and strategies. The limit values and the fuzzy cost coefficients of the ECs are confirmed according to industry standards and shown in Fig. 1.

Subsequently, we can start to utilize QFD by the proposed model and the algorithm. The current target values of the ECs of all competitors can be normalized by Eqs. (16) and (17) as follows:

$$(\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots, \boldsymbol{X_5})^T=\begin{pmatrix} 0.85 & 0.71 & 0.62 & 0 & 0.34\\ 0.78 & 0 & 0.62 & 0.76 & 0.45\\ 0.67 & 0.37 & 0.59 & 0.42 & 0.89\\ 0 & 0.88 & 0.55 & 0.76 & 0\\ 0.37 & 0.90 & 0.84 & 0.50 & 0.70 \end{pmatrix}. \tag{38}$$

The fuzzy function (37), i.e., the credibility of the fuzzy relative overall customer satisfaction $\tilde{S}'=\sum_{j=1}^5 \tilde{v}_j' x_j$ exceeding a preferred acceptable value, say 0.6, can be acquired via the fuzzy simulation

Fuzzy Correlation among the ECs

Engineering Characteristics	- EC_1 x_1	+ EC_2 x_2	- EC_3 x_3	+ EC_4 x_4	+ EC_5 x_5
EC_1	$\tilde{u}_4$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$
EC_2	$\tilde{u}_1$	$\tilde{u}_4$	$\tilde{u}_2$	$\tilde{u}_1$	$\tilde{u}_1$
EC_3	$\tilde{u}_1$	$\tilde{u}_2$	$\tilde{u}_4$	$\tilde{u}_1$	$\tilde{u}_1$
EC_4	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_4$	$\tilde{u}_1$
EC_5	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_4$

Customer Requirements	Fuzzy Relative Importance	Fuzzy Relationship between the CRs and the ECs				
CR_1 $\tilde{y}_1$	$\tilde{w}_5$	$\tilde{u}_4$	$\tilde{u}_1$	$\tilde{u}_2$	$\tilde{u}_1$	$\tilde{u}_1$
CR_2 $\tilde{y}_2$	$\tilde{w}_4$	$\tilde{u}_1$	$\tilde{u}_3$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$
CR_3 $\tilde{y}_3$	$\tilde{w}_3$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_4$	$\tilde{u}_1$	$\tilde{u}_1$
CR_4 $\tilde{y}_4$	$\tilde{w}_3$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_4$	$\tilde{u}_1$
CR_5 $\tilde{y}_5$	$\tilde{w}_2$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_1$	$\tilde{u}_3$

Competitors	Target Values of the ECs				
	dB	horsepower	gallon	kg	m^3
$Comp_1$	65.3	81.3	0.0327	15	0.164
$Comp_2$	67.7	60	0.0327	22.6	0.172
$Comp_3$	71.6	71.1	0.0332	19.2	0.202
$Comp_4$	95	86.4	0.0338	22.6	0.14
$Comp_5$	82.1	87	0.0294	20	0.189
Min	60	60	0.027	15	0.14
Max	95	90	0.042	25	0.21
Fuzzy Cost Coefficients	(3, 25, 5)	(1, 10, 2)	(2, 15, 3)	(0, 10, 2)	(1, 8, 2)

CR_1: Reducing the noise of car CR_2: Enhancing the acceleration CR_3: Saving fuel

CR_4: Improving security CR_5: Raising the seat comfort

EC_1: Reducing the noise of the exhaust system

EC_2: Increasing the horsepower of the engine

EC_3: Reducing the amount of fuel per mile

EC_4: Increasing the controlling force of the braking system

EC_5: Enlarging the space of the seat

Fig. 1. The house of quality of a motor car.

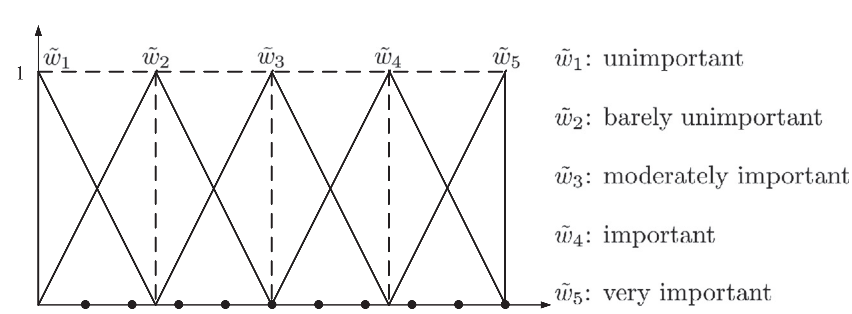

Fig. 2. Relative fuzzy importance of the CRs.

method which is introduced in Algorithm 1. The current credibility of the fuzzy relative overall customer satisfaction of all competitors exceeding the basic satisfaction level $\rho = 0.6$ is shown in Table 1. Table 1 indicates that the existing design of Comp_5 currently has the highest score of $\text{Cr}\{\tilde{S}_5' \geq 0.6\} = 0.61$, which means it is a relatively competitive one with lower risk, while Comp_3 and Comp_4 reach relatively poor results with higher risks. Therefore, there is especially a need for Comp_3 and Comp_4 to rationalize their existing design in order to outstand their competitiveness.

It can be verified that the simultaneous variations on both the preferred acceptable overall customer satisfaction ρ and the confidence level α will have effects on the attainment of the target values of the ECs, and a further impact on the expected design cost, of which the optimal solutions are obtained by employing the designed hybrid intelligent algorithm (see Algorithm 2). Such influences are shown in Table 2, and it can be concluded from Table 2 that the optimal value of the expected cost $E(\tilde{C}_V)$ increases along with the enlarging of the preferred acceptable overall customer satisfaction ρ and the confidence level α. To put it simply, pursuit of a low cost must bring high risk and low satisfaction. Along with the reducing of the development cost from the bottom to top and the right to left in Table 2, the risk level $1-\alpha$ increases and the satisfaction level ρ decreases. Besides, notably, when the confidence level $\alpha = 1$, the constraint of model (34) degenerates to $\text{Cr}\{\sum_{j=1}^{5} \tilde{v}_j' x_j \geq \rho\} = 1$, i.e., $\sum_{j=1}^{5} \tilde{v}_j' x_j \geq \rho$ must be achieved with zero risk.

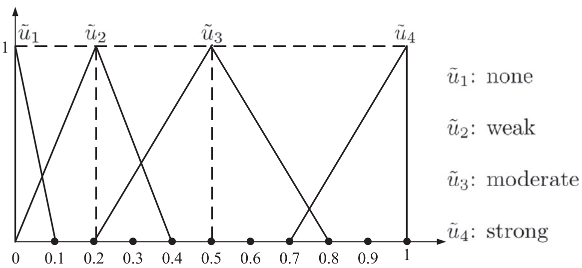

Fig. 3. Fuzzy relationship measures and correlation measures.

Table 1
Credibility of $\{\tilde{S}' \geq 0.6\}$ of five competitors.

Competitor	Comp_1	Comp_2	Comp_3	Comp_4	Comp_5
$\text{Cr}\{\tilde{S}' \geq 0.6\}$	0.50	0.46	0.38	0.23	0.61
Ranking	2	3	4	5	1

Table 2
Impacts on expected cost $E(\tilde{C}_V)$ while ρ and α change.

$E(\tilde{C}_V)$	$\rho=0.1$	$\rho=0.2$	$\rho=0.3$	$\rho=0.4$	$\rho=0.5$	$\rho=0.6$	$\rho=0.7$	$\rho=0.8$	$\rho=0.9$	$\rho=1.0$
$\alpha=0.1$	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25
$\alpha=0.2$	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25
$\alpha=0.3$	8.25	8.25	8.25	10.25	15.25	20.75	33.75	36.00	58.43	69.75
$\alpha=0.4$	8.25	8.25	10.25	10.25	20.75	25.50	36.00	53.51	63.09	69.75
$\alpha=0.5$	8.25	10.25	10.25	20.75	20.75	33.75	44.80	54.93	69.75	69.75
$\alpha=0.6$	8.25	10.25	15.25	23.50	33.75	36.00	50.39	56.94	69.75	69.75
$\alpha=0.7$	10.25	17.34	22.12	28.42	31.66	43.12	51.60	63.09	69.75	69.75
$\alpha=0.8$	11.22	17.49	23.71	31.04	37.77	47.01	56.70	63.09	69.75	69.75
$\alpha=0.9$	17.15	30.04	30.04	37.77	37.77	69.75	69.75	69.75	69.75	69.75
$\alpha=1.0$	69.75	69.75	69.75	69.75	69.75	69.75	69.75	69.75	69.75	69.75

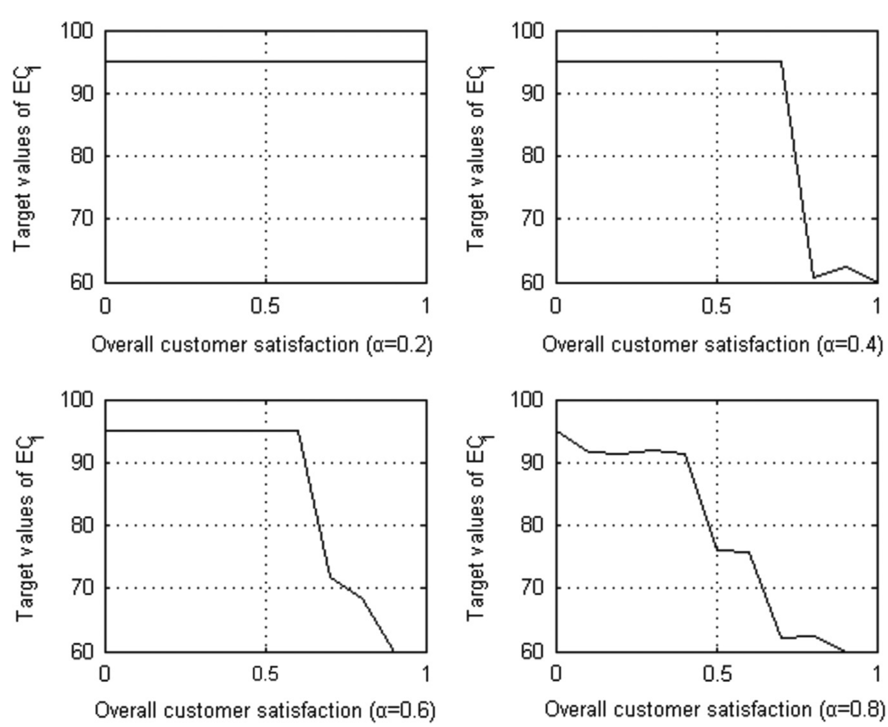

Fig. 4. Relationship between ρ and target values of EC_1 with different α values.

Furthermore, using the invertible functions of Eqs. (16) and (17), the target values of an individual EC for different values of ρ and α can be obtained. By employing Eq. (27), the fuzzy variable development cost required for improving each EC, i.e., $\tilde{C}_j=(C_j^L, C_j, C_j^R),\ j=1,2,\ldots,5$, can be calculated. The relationships between the overall customer satisfaction ρ and the target values of the five ECs while the confidence level α changes are described in Figs. 4–8.

It can be concluded from Figs. 4–8 that for a fixed risk level $1-\alpha$, the increasing of the satisfaction level ρ makes the target value of an EC approach its optimal goal, i.e., makes the EC have a high level of attainment. According to the internal and external environments the enterprise lies in, the design team can adjust their strategic direction by choosing different pairs of ρ and α. For example, suppose that the design team decides to fix their risk level on $1-\alpha=0.4$ in a long term. When the company is in its initial stage of development, the design

Fig. 5. Relationship between ρ and target values of EC_2 with different α values.

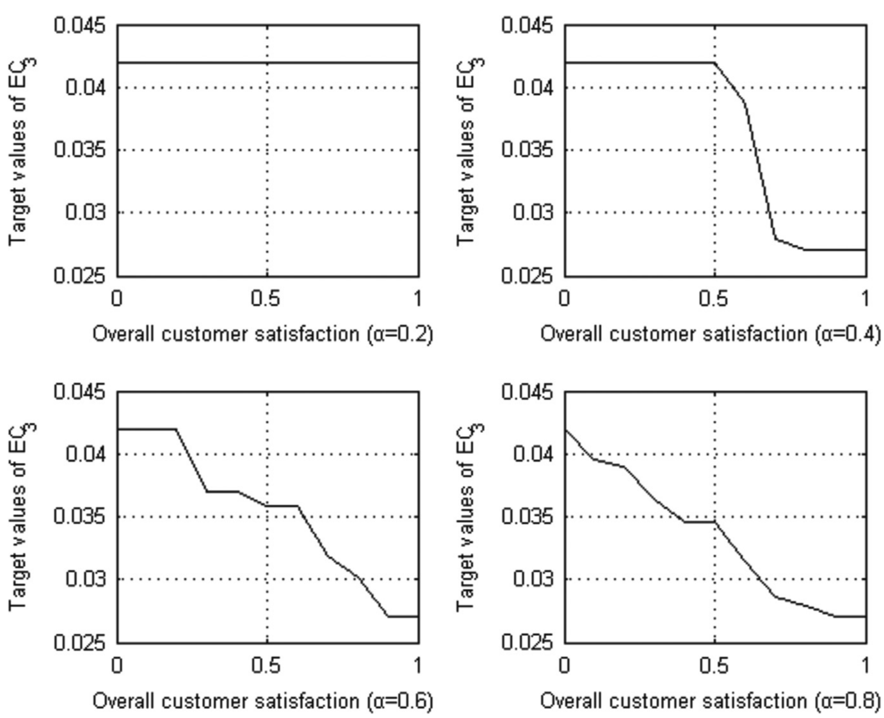

Fig. 6. Relationship between ρ and target values of EC_3 with different α values.

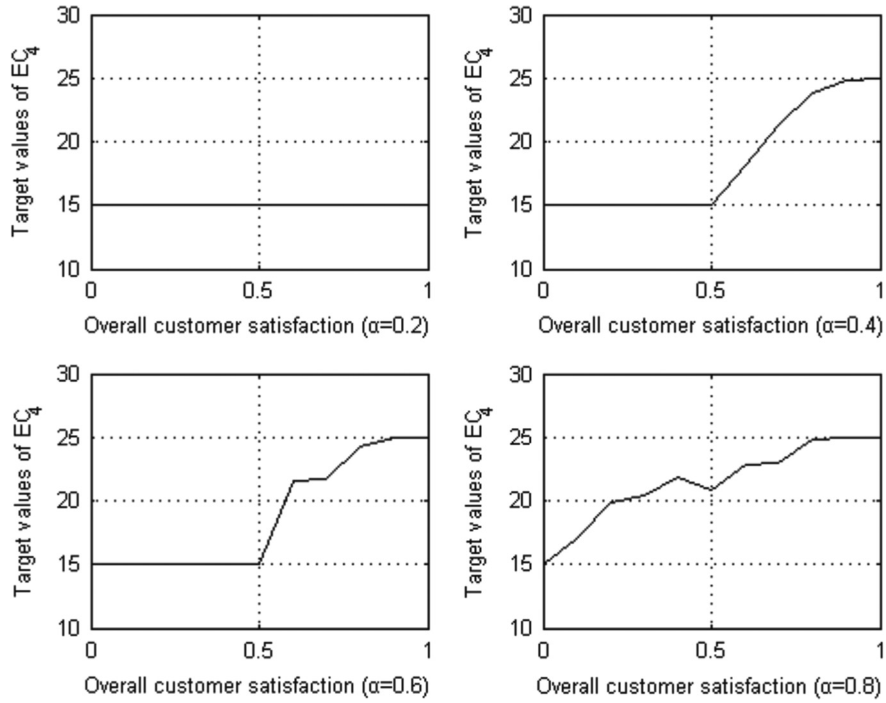

Fig. 7. Relationship between ρ and target values of EC_4 with different α values.

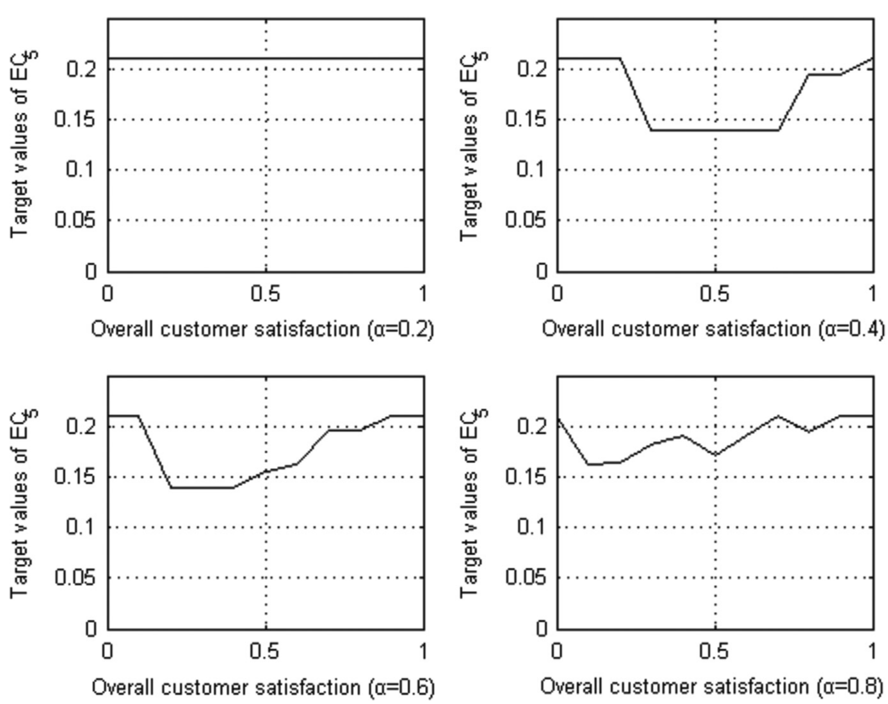

Fig. 8. Relationship between ρ and target values of EC_5 with different α values.

team focuses more on minimizing the total development cost, which makes him formulate a relatively low satisfaction level, e.g., $\rho = 0.4$, to just ensure the customer requirements. If the company has fully grown, the design team considers to put effort into maintaining customer loyalty and is able to undertake the incurred cost, that makes him adopt a relatively high satisfaction level, e.g., $\rho = 0.8$, to perfectly attain the customer requirements. Therefore, the five plots provide a dynamic roadmap to help the design team easily determine the target values of the five ECs of the motor car by selecting different pairs of customer satisfaction ρ and confidence level α, taking account of the competition requirements, the technical feasibility, the financial factors, etc.

6. Conclusions

In this paper, we have contributed to the research area of the targets setting of the ECs in QFD in the following three aspects: (i) we utilized a fuzzy chance-constrained modelling approach to determine the target values of the ECs with risk control in the fuzzy environment; (ii) regarding the importance of the ECs, we considered not only the relationships between the CRs and the ECs, but also the correlations among the ECs, i.e., made an aggregation of them; and (iii) in order to solve the proposed model efficiently, we integrated fuzzy simulation and genetic algorithm to design a hybrid intelligent algorithm, which was illustrated by a numerical example about a motor car design.

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Shuya Zhong received a B.D. degree in information management and system from Zhejiang University of Technology, in 2011, and M.D. degree in logistics engineering from Shanghai University, in 2013. She is currently a doctoral student at Shanghai University, working towards her Ph.D. degree in management science and engineering. Her current research interests include QFD, computational intelligence, and uncertainty theory.

Jian Zhou received a B.S. degree in applied mathematics, the M.S. and Ph.D. degrees in computational mathematics from Tsinghua University, Beijing, China, in 1998 and 2003, respectively. She joined the school of management at Shanghai University, in May 2011, as an associate professor. Her research interests include supply chain finance, network optimization, computational intelligence, and uncertainty theory. She has published more than 40 papers in national and international conferences and journals. For the other information, please visit her personal webpage at http://zhou-jian.jimdo.com.

Yizeng Chen is now in the Management School of Shanghai University, Shanghai, PR China. His research interest falls in the field of Fuzzy and Stochastic optimization, hybrid regression method and their applications in product planning and manufacturing process modelling. Up to now, he has taken part in more than ten research projects and published/accepted more than thirty academic papers in reputed international journals.