Two uncertain chance-constrained programming models to setting target levels of design attributes in quality function deployment

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Abstract

Quality function deployment (QFD) is widely acknowledged as a customer-oriented product design tool, which is generated by translating consumer demands into design attributes of a product. In order to depict the internal ambiguous factors in the development process more appropriately, uncertain variables with a specialized kind of regular uncertainty distributions based on uncertainty theory are applied. Subsequently, two uncertain chance-constrained programming (CCP) models used for formulating the QFD procedure are set forth, whose objectives are maximizing the consumer satisfaction and minimizing the design cost, respectively. To demonstrate the feasibility of the proposed modelling approach, an example of the motorcycle design problem is illustrated, in which the new target levels of design attributes are selected and analyzed according to the decision-makers' subjectivity and preference at different confidence levels. Additionally, a comparative study between the uncertain CCP approach and another uncertain expected value modelling approach is conducted. The results indicate that uncertain CCP models are more suitable for optimization in the QFD procedure.

Keywords: Quality function deployment, Design attribute, Uncertain variable, Uncertain chance-constrained programming

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1　Introduction

Nowadays, the burgeoning demands of diversified and personalized products have pushed manufacturing industries to chase consumers' continuous and changeable needs in a faster pace. Therefore, dynamic and fierce competition emerges from the global market. To break this situation, many companies have adopted various product development tools to seek for permanent competence in seizing benefits. Quality function deployment (QFD) is a popular one among these tools, which can be traced back to the late 1960s [1]. It is a comprehensive method devoting to interpreting consumer demands (CDs) into design attributes (DAs) of the target product and ensuring the improved product to gain more customer support.

The house of quality (HoQ) is the core concept of QFD, which consists of several matrices based on "whats (CDs) - hows (DAs)" [11]. CDs and their relative importance weights are summarized on the left wall of an HoQ. The ceiling reflects each DA and the roof signifies correlations among DAs. And the body reveals relationships between CDs and DAs. In addition, the ground is furnished with the observed data of target levels for DAs, which is denoted by the quantitative technical specifications of DAs required to satisfy each CD.

As to a new or improved product, the QFD procedure aims at determining a series of target levels for DAs under resource constraints, whose overall consumer satisfaction is supposed to be equal to or larger than that of any other potential competitors in the market. In real-life applications, definitely multiple variables, trade-offs and contradictions will be involved. To deal with this complex operation course, an increasing number of programming models with different objectives have been arisen. Before establishing the optimization model, it is significant to confirm the relative importance weights of CDs and the internal relations and correlations in the HoQ. In the former literature, generally these elements were determined to be crisp, stochastic or fuzzy variables in a subjective way [7, 12, 27], or objectively determined from fuzzy linear regressions [3, 4, 19] or non-linear regressions [20].

As a crucial branch of the QFD research, abundant fuzzy modelling studies regarding how to get a series of target levels for DAs have been carried out. It seems quite reasonable to absorb fuzziness to express the inner indeterminate factors in HoQ with the aid of the fuzzy set theory. For example, Chen *et al.* [5] brought up a fuzzy expected value model to determine DAs' target levels,

which was separately in consideration of the maximum consumer satisfaction or the minimum development expense. Erginel [9] set forth a fuzzy multi-objective decision model which contains the information from design failure and effect analysis. The means-end chain notion was incorporated by Chen and Ko [4] to establish a fuzzy linear modelling approach in calculating the contribution of individual "how" to the whole consumer satisfaction. Sener and Karsak [24, 25] suggested some fuzzy mathematical programming models to determine target levels of DAs, including a fuzzy non-linear regression and optimization method, and an approach of combining a fuzzy linear regression and a fuzzy multiple objective programming. Liu *et al.* [20] embedded the compensation degree among CDs into QFD, which was realized by integrating the minimum fuzziness benchmark into a non-linear regression. A fuzzy least-square regression approach to depicting relationships in QFD was considered by Kwong *et al.* [14], which took both the fuzziness and randomness into account. Zhong *et al.* [29] set up a fuzzy chance-constrained programming in determining target levels of DAs, which was solved by a hybrid intelligent algorithm. Recently, Liu *et al.* [17] proposed an exact expected value-based method to prioritize DAs in fuzzy QFD, in which the expected values of the importance weights of DAs were obtained through the inverse credibility distribution of fuzzy numbers.

It is observed that the parameters involved in the QFD procedure are usually set as crisp or fuzzy values. Nevertheless, it is not very appropriate since either the probability theory or the fuzzy set theory may lead to counterintuitive outcomes under some circumstances [16]. Consequently, some researches based on uncertainty theory [16] were accomplished to mend this defect, such as uncertain finance [23], uncertain risk aversion [30], uncertain risk and reliability analysis [15], and uncertain minimum spanning tree problems [31], etc. Besides, uncertain chance-constrained programming (CCP) model was employed in project scheduling problems [13] and job shop scheduling problems [26] or other practical applications. With respect to the application of uncertainty theory to QFD, relevant studies are very limited. Liu *et al.* [18] utilized an uncertain expected value-based method to determine the importance weights of DAs. On this basis, Yang *et al.* [28] generalized it to the strategic management of logistics services in prioritizing several strategic actions. Miao *et al.* [21] proposed an uncertain expected value modelling (EVM) approach to setting target levels of DAs. It can be seen that uncertainty theory has gained extensive support and acknowledgement

from other fields as mentioned, but it has not been widely applied to QFD yet.

Therefore, a novel approach based on uncertainty theory and uncertain chance-constrained programming is put forward to formulate the QFD procedure in this paper. Analogous to fuzzy optimization, relative importance weights of CDs, relations between CDs and DAs, correlations among DAs, along with the variable fulfillment charge for each unit of DA, are predetermined as uncertain variables by experts. To vividly and specifically describe these vague information, uncertain variables with a certain kind of regular uncertainty distributions is applied. Afterwards, two uncertain chance-constrained programming models with two different considerations are proposed to determine target levels of DAs in actual manufacturing. For the sake of enhancing the company's competitiveness, the goal of the first model is to maximize the overall consumer satisfaction. In consideration of the company's current financial condition, the goal of the second model is to minimize the total design cost. It is noted that fuzzy CCP models are usually difficult to solve in many applications, whose results are usually obtained with the help of simulations and heuristic algorithms [8, 29]. However, we transform our models analytically into equivalent deterministic models through inverse uncertainty distributions and solve them by MATLAB, which largely simplifies the calculation procedure.

The rest of the article is arranged as follows. In regards to the imprecise factors in the QFD procedure, two uncertain CCP models in setting target levels of DAs are set forth in Section 2. Furthermore, Section 3 demonstrates a case study on a motorcycle design problem to address the effectiveness of the proposed method. And a comparison between uncertain CCP and EVM is also generated. Finally, some important conclusions and our major contributions are elaborated in Section 4.

2 Uncertain Chance-constrained Programming in QFD

In the process of setting target levels of DAs, some indeterminate elements are involved, like relative importance weights of CDs, relationships between CDs and DAs and correlations among DAs. These ambiguous factors are usually assumed to be random variables, whose probability distributions are mostly obtained via statistical estimation. Practically, due to the lack of comprehensive information, the evaluated probability distribution may significantly disagree with the accumula-

tive frequency [16]. In order to avoid this deficiency, with the aid of uncertainty theory [16], the internal indeterminate elements are viewed as uncertain variables in this paper according to their linguistic meanings.

It is known that the purposes of QFD design procedure are usually twofold. One is to obtain the maximal overall consumer satisfaction under limited resources. The other is to consume the minimal expense in terms of a desirable consumer satisfaction degree. To realize these targets, two uncertain CCP models with satisfaction or cost concerns are separately brought forward in this section to handle uncertain QFD issues.

2.1 Nomenclature

It is presumed that m CDs, n DAs and g companies are included in a QFD procedure, and the notion used in this paper is as follows:

- CD$_i$ is the ith consumer demand, $i = 1, 2, \cdots, m$;

- DA$_j$ is the jth design attribute, $j = 1, 2, \cdots, n$;

- w_i is the uncertain relative importance weight of CD$_i$, which is contained in matrix $W = (w_1, w_2, \cdots, w_m)^T$;

- r_{ik} is the uncertain relationship between CD$_i$ and DA$_k$, which is involved in matrix $R = (r_{ik})_{m \times n}$;

- p_{kj} is the uncertain correlation between DA$_k$ and DA$_j$, which is embodied in matrix $P = (p_{kj})_{n \times n}$;

- v_j is the uncertain importance weight of DA$_j$, which is contained in matrix $V = (v_1, v_2, \cdots, v_n)^T$;

- l_j is the target level of DA$_j$, $j = 1, 2, \cdots, n$;

- x_j is the fulfillment degree of DA$_j$, which is recorded in matrix $X = (x_1, x_2, \cdots, x_n)^T$;

- Comp$_h$ is the hth company in the market, $h = 1, 2, \cdots, g$;

- S_h is the achieved overall consumer satisfaction of the hth company, $h = 1, 2, \cdots, g$;

- C is the joint development expense combined by a fixed part C_f and a variable part C_v;

– C_j is the variable cost demanded for achieving x_j, $j = 1, 2, \cdots, n$;

– B is the budget for the whole design procedure.

2.2 Elicitation of the overall consumer satisfaction

Before computing the overall consumer satisfaction, it is critical to calculate the importance weights of DAs first. Through the multiplication of three matrices W, R and P in [22], the importance weight of DA_j denoted by v_j can be formulated as

$$v_j = \sum_{i=1}^{m}\sum_{k=1}^{n} w_i r_{ik} p_{kj}, \quad j = 1, 2, \cdots, n. \tag{1}$$

The obtained importance weights of DAs are illustrated in matrix V. When given a set of fulfillment degrees of DAs, the overall consumer satisfaction S can be acquired as

$$S = V^T X = \sum_{j=1}^{n} v_j x_j = \sum_{j=1}^{n} \left(\sum_{i=1}^{m}\sum_{k=1}^{n} w_i r_{ik} p_{kj} \right) x_j. \tag{2}$$

In Eq. (2), we characterize the vague linguistic terms w_i, r_{ik} and p_{kj} by uncertain variables on the basis of uncertainty theory proposed in [16]. More specifically, uncertain variables with the following regular uncertainty distributions (called regular uncertain variables) from [21] are suitable to be employed, i.e.,

$$\Phi(x) = \begin{cases} 0, & \text{if } x < 0 \\ x^a, & \text{if } 0 \leq x < 1 \\ 1, & \text{if } x \geq 1, \end{cases} \tag{3}$$

where parameter a is a positive real number. This kind of regular uncertainty distributions shares a similar philosophy with the utility functions in economics by considering marginal values, which is more consistent with human mentality and intuition.

Taking the assessment of uncertain relative importance weights of CDs in matrix W as an example, we suppose that there are three circumstances. If the parameter $a > 1$, Eq. (3) corresponds to the meaning of 'significant', which is illustrated like a concave pattern in Figure 1(a). When x increases in the interval $[0, 1]$, the value of $\Phi(x) = \mathcal{M}\{w_i \leq x\}$ increases quicker and quicker. Here w_i is the uncertain relative importance weight of CD_i, and $\mathcal{M}$ is the uncertain measure. Similarly, the translation of 'insignificant' can be reflected as a convex pattern in Figure 1(b) where the parameter $a < 1$ in Eq. (3). In this case, the increasing tendency of $\mathcal{M}\{w_i \leq x\}$ is slower and

slower as x rises in $[0, 1]$. Besides, the meaning of 'moderate significant' is depicted as a linear pattern in Figure 1(c) where the parameter a is set as 1 in Eq. (3).

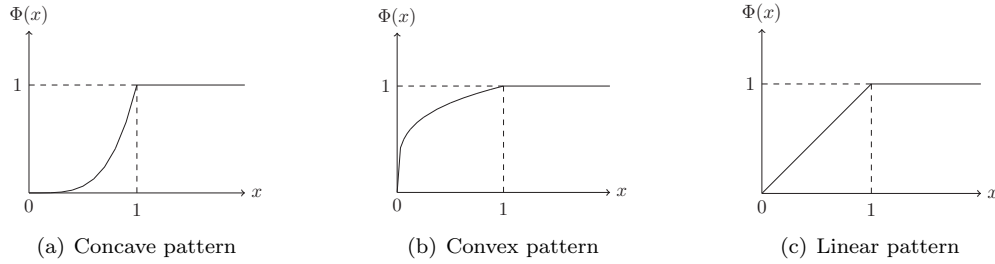(a) Concave pattern   (b) Convex pattern   (c) Linear pattern

Figure 1: Three patterns of regular uncertain variables

In the former applications, the rating of 1-2-3-4-5 or other grading systems are usually adopted to represent the importance degrees of CDs in matrix W and the strength of relations or correlations in matrices R and P. The higher the rating is, the more remarkable the importance or strength will be. Analogously, a new rating is set out in this paper by utilizing uncertain variables. As given in Table 1, there are nine specific types of regular uncertain variables along with their uncertainty distributions and linguistic meanings in matrices W, R and P.

Table 1: Linguistic meanings of different regular uncertain variables

Type	Distributions in $x \in [0, 1]$	$W = (w_i)_m$	$R = (r_{ik})_{m \times n}$	$P = (p_{kj})_{n \times n}$
1	$\Phi(x) = x^{1/9}$	extreme insignificant	extreme weak	strong negative
2	$\Phi(x) = x^{1/6}$	quite insignificant	quite weak	quite negative
3	$\Phi(x) = x^{1/4}$	rather insignificant	rather weak	rather negative
4	$\Phi(x) = x^{1/2}$	little significant	little strong	weak negative
5	$\Phi(x) = x$	moderate significant	medium	medium
6	$\Phi(x) = x^2$	significant	strong	weak positive
7	$\Phi(x) = x^4$	rather significant	rather strong	rather positive
8	$\Phi(x) = x^6$	quite signifitant	quite strong	quite positive
9	$\Phi(x) = x^9$	extreme significant	extreme strong	strong positive

2.3 Estimation of the total cost

In practice, a variety of resources are demanded in the product development procedure, such as technical personnel and sophisticated equipment. Generally, they are measured in financial units from a strategic perspective. The total development expense C consists of a fixed cost C_f and a

variable cost C_v as

$$C = C_f + C_v. \tag{4}$$

Here C_v merely depends on the fulfillment degrees of DAs, which can be obtained through the gathering of C_j required for accomplishing DA_j. To simplify, assume that C_j is scaled linearly to the fulfillment degree x_j. Thus, we can calculate the variable cost with

$$C_v = \sum_{j=1}^{n} C_j = \sum_{j=1}^{n} c_j x_j, \tag{5}$$

in which c_j is a cost coefficient indicating the unit charge needed for DA_j to be improved. A linear uncertain variable $\mathcal{L}(a_j, b_j)$ is utilized to denote c_j because of market fluctuations in raw material prices, whose uncertainty distribution (see Figure 2) is

$$\Phi(x) = \begin{cases} 0, & \text{if } x < a_j \\ (x - a_j)/(b_j - a_j), & \text{if } a_j \leq x < b_j \\ 1, & \text{if } x \geq b_j, \end{cases} \tag{6}$$

in which a_j and b_j represent the lowest and highest raw material prices in the market, respectively.
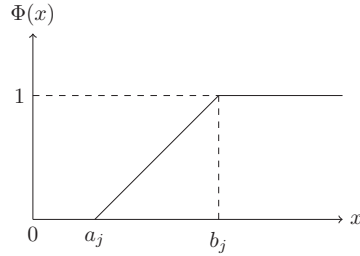

Figure 2: Uncertainty distribution of a linear uncertain variable $\mathcal{L}(a_j, b_j)$

Combining Eqs. (4) and (5), we can get the total development expense C as

$$C = C_f + C_v = C_f + \sum_{j=1}^{n} c_j x_j. \tag{7}$$

2.4   Two uncertain CCP models for QFD planning

For the sake of rubbing shoulders with the dominant company in the market, one scenario of QFD is to achieve the objective of maximizing the overall consumer satisfaction S under a cost constraint. Therefore, the expected value of the overall consumer satisfaction and the chance of the cost constraint are considered so as to build an uncertain CCP model to handle this issue.

In real applications, uncertain variables w_i, r_{ik} and p_{kj} are generally supposed to be mutually independent. Then, according to the linearity of the expected value operator of independent uncertain variables proved in [16], the expected value of the overall consumer satisfaction S in Eq. (2) is expressed to be

$$E[S] = E[V^T X] = E\left[\sum_{j=1}^{n} v_j x_j\right] = \sum_{j=1}^{n} E[v_j]x_j, \tag{8}$$

where $E[v_j]$ is the expected value of the uncertain importance weight of DA_j and can be further calculated in regards to Eq. (1) as

$$E[v_j] = E\left[\sum_{i=1}^{m}\sum_{k=1}^{n} w_i r_{ik} p_{kj}\right] = \sum_{i=1}^{m}\sum_{k=1}^{n} E[w_i r_{ik} p_{kj}], \quad j = 1, 2, \cdots, n. \tag{9}$$

Since uncertain variables w_i, r_{ik} and p_{kj} are assumed to follow regular uncertainty distributions in Eq. (3), the inverse uncertainty distributions of w_i, r_{ik} and p_{kj} are denoted by ϕ_i^{-1}, Ψ_{ik}^{-1} and Φ_{kj}^{-1} correspondingly. With respect to [16], the calculation of $E[v_j]$ in Eq. (9) can be transformed to

$$E[v_j] = \sum_{i=1}^{m}\sum_{k=1}^{n} E[w_i r_{ik} p_{kj}] = \sum_{i=1}^{m}\sum_{k=1}^{n}\left(\int_0^1 \phi_i^{-1}(\alpha)\Psi_{ik}^{-1}(\alpha)\Phi_{kj}^{-1}(\alpha)d\alpha\right), \quad j = 1, 2, \cdots, n. \tag{10}$$

The larger $E[v_j]$ is, the more significant DA_j is, which implies that DA with the largest expected value of importance will be progressed first. In addition, $E[v_j]$ can be standardized to the interval (0,1) by

$$\bar{E}[v_j] = \frac{E[v_j]}{\sum_{j=1}^{n} E[v_j]}, \quad j = 1, 2, \cdots, n, \tag{11}$$

in which $\bar{E}[v_j]$ is called the normalized expected value of the importance weight of DA_j. To facilitate the follow-up comparison, through the usage of $\bar{E}[v_j]$ we replace Eq. (8) by

$$\bar{E}[S] = \sum_{j=1}^{n} \bar{E}[v_j]x_j, \tag{12}$$

in which $\bar{E}[S]$ is called the normalized expected value of the overall consumer satisfaction and the range of the values for $\bar{E}[S]$ is (0,1).

When it comes to the cost constraint, in view of actual situations, we suppose that the overall expense C is constrained to a budget B. Then, it can be attained that

$$C_f + \sum_{j=1}^{n} c_j x_j \leq B. \tag{13}$$

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The overall expense C is an uncertain variable on the basis that c_j is an uncertain variable. Assume that the uncertain cost constraint in Eq. (13) will hold at the confidence level α_1, and then we can get

$$\mathcal{M}\left\{C_f + \sum_{j=1}^{n} c_j x_j \le B\right\} \ge \alpha_1, \tag{14}$$

where α_1 is regarded as the confidence level provided as an appropriate safety margin by the decision-makers. By means of the operational law, the chance constraint in Eq. (14) can be further converted into

$$C_f + \sum_{j=1}^{n} \varphi_j^{-1}(\alpha_1) x_j \le B, \tag{15}$$

in which φ_j^{-1} is the inverse uncertainty distribution of c_j (denoted by a linear uncertain variable $\mathcal{L}(a_j, b_j)$). Then $\varphi_j^{-1}(\alpha_1)$ can be further calculated by

$$\varphi_j^{-1}(\alpha_1) = (1 - \alpha_1)a_j + \alpha_1 b_j. \tag{16}$$

The first scenario indicates that the design group of the company wishes to maximize the normalized expected value of the overall consumer satisfaction under a chance constraint of cost. Based upon the underlying philosophy of uncertain programming, an uncertain CCP model (named UCCP-1) which aggregates Eqs. (12), (15) and (16) together is built as

$$\begin{cases} \max \sum_{j=1}^{n} \bar{E}[v_j] x_j \\ \text{subject to:} \\ C_f + \sum_{j=1}^{n} \Big((1 - \alpha_1)a_j + \alpha_1 b_j \Big) x_j \le B \\ 0 \le x_j \le 1, \quad j = 1, 2, \cdots, n, \end{cases} \tag{17}$$

in which the calculation of $\bar{E}[v_j]$ refers to Eqs. (10)-(11).

Except for the scenario discussed above, in some conditions, a corporation hopes to acquire an acceptable overall consumer satisfaction with the minimal design cost. Similar to the establishment process of UCCP-1, in terms of Section 2.3, the expected value of the total cost C is formulated as

$$E[C] = E[C_f + C_v] = C_f + E[C_v] = C_f + \sum_{j=1}^{n} E[c_j] x_j, \tag{18}$$

in which $E[c_j]$ is calculated by using the inverse uncertainty distribution of c_j as

$$E[c_j] = \int_0^1 \varphi_j^{-1}(\alpha) \, d\alpha = \int_0^1 \Big((1 - \alpha)a_j + \alpha b_j \Big) \, d\alpha = \frac{a_j + b_j}{2}, \quad j = 1, 2, \cdots, n. \tag{19}$$

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Thus we can rewrite the calculation of the expected cost $E[C]$ in Eq. (18) equivalently as

$$E[C] = C_f + E[C_v] = C_f + \sum_{j=1}^{n} \left(\frac{a_j + b_j}{2} \right) x_j. \tag{20}$$

Since C_f is a constant in the above equation, we just need to minimize the expected value of the variable cost $E[C_v]$.

The uncertain constraint of this scenario changes to a case that the overall consumer satisfaction of the target product ought to attain an acceptable degree S', which is expressed as

$$\sum_{j=1}^{n} \left(\sum_{i=1}^{m} \sum_{k=1}^{n} w_i r_{ik} p_{kj} \right) x_j \geq S'. \tag{21}$$

The chance of the uncertain constraint in Eq. (21) will hold at the confidence level α_2 as follows,

$$\mathcal{M} \left\{ \sum_{j=1}^{n} \left(\sum_{i=1}^{m} \sum_{k=1}^{n} w_i r_{ik} p_{kj} \right) x_j \geq S' \right\} \geq \alpha_2, \tag{22}$$

where the confidence level α_2 is also an appropriate safety margin predetermined by the decision-makers. On the basis of the operational law, the chance constraint in Eq. (22) can be transformed into

$$\sum_{j=1}^{n} \left(\sum_{i=1}^{m} \sum_{k=1}^{n} \phi_i^{-1}(1-\alpha_2) \Psi_{ik}^{-1}(1-\alpha_2) \Phi_{kj}^{-1}(1-\alpha_2) \right) x_j \geq S'. \tag{23}$$

As a consequence, another uncertain CCP model (named UCCP-2) can be obtained as

$$\begin{cases} \min E[C_v] = \sum_{j=1}^{n} \left(\dfrac{a_j + b_j}{2} \right) x_j \\[2ex] \text{subject to:} \\[1ex] \sum_{j=1}^{n} \left(\sum_{i=1}^{m} \sum_{k=1}^{n} \phi_i^{-1}(1-\alpha_2) \Psi_{ik}^{-1}(1-\alpha_2) \Phi_{kj}^{-1}(1-\alpha_2) \right) x_j \geq S' \\[2ex] 0 \leq x_j \leq 1, \quad j = 1, 2, \cdots, n, \end{cases} \tag{24}$$

where the determination of the values for S' and α_2 are up to the decision-makers' subjectivity and prediction on the market.

3 Case Study

The aim of incorporating QFD into the product design procedure is to measure the impacts of target levels of DAs on both consumer perception and product development expense. In order to illustrate the feasibility and performance of the proposed uncertain CCP models, an example of

the motorcycle design is introduced in this section. Based upon the solutions of these models, the design group will be equipped with a guide map in determining a new series of target levels for DAs to upgrade the product.

3.1 Building an HoQ for motorcycle design

Our enterprise is developing a new type of motorcycle to enhance its market share. According to the investigation statistics from the marketing department and the interview feedbacks from customers of different ages, genders, professions and salaries, five superior CDs are identified through a tree-like hierarchical structure approach employed from [2, 10]. Meanwhile, on the basis of the design group's expertise and knowledge on motorcycles, five crucial DAs are also recognized. All the five CDs and DAs are given in Figure 3.
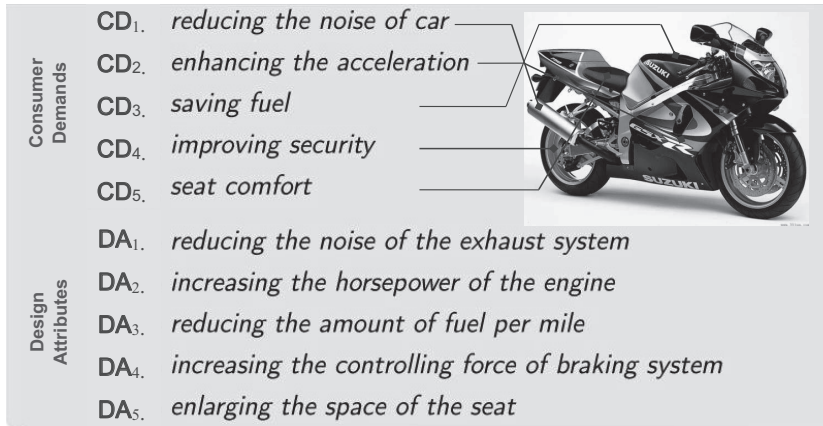

Figure 3: CDs and DAs of the motorcycle design

The relevant information about the HoQ of the motorcycle design is presented detailedly in Table 2. Through a comprehensive evaluation by experts utilizing the nine types of importance weights or relation strength enumerated in Table 1, matrices W, R and P in Table 2 are obtained. And their uncertainty distributions in $x \in [0, 1]$ are distinguished by using different lines in Figure 4. For example, the uncertainty distribution in $x \in [0, 1]$ of the relationship between CD_1 and DA_1 is assumed to be x^6 in Table 2, whose inverse uncertainty distribution is $\alpha^{1/6}$. It reveals the meaning of 'quite strong' and is depicted as Type 8 in Figure 4. Besides, there are five major companies in the motorcycle market, i.e., $Comp_1$ (our enterprise), $Comp_2$, $Comp_3$, $Comp_4$ and $Comp_5$. The observed data of these companies for the five DAs including their corresponding physical limits are investigated and recorded in the floor of the HoQ in Table 2, in which DAs are measured in units

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of dB, horsepower, gallon, kg and m^3, respectively. And the cost coefficient c_j of DA$_j$ is denoted by a linear uncertain variable $\mathcal{L}(a_j, b_j)$ as described in Section 2.3.

Table 2: The HoQ of the motorcycle design

	Design Attributes	− DA$_1$ x_1	+ DA$_2$ x_2	− DA$_3$ x_3	+ DA$_4$ x_4	+ DA$_5$ x_5
Uncertain Correlation Matrix P	DA$_1$	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)
	DA$_2$	$x^{1/9}$ (α^9)	x^6 ($\alpha^{1/6}$)	x^2 ($\alpha^{1/2}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)
	DA$_3$	$x^{1/9}$ (α^9)	x^2 ($\alpha^{1/2}$)	x^6 ($\alpha^{1/6}$)	x^4 ($\alpha^{1/4}$)	$x^{1/9}$ (α^9)
	DA$_4$	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	x^4 ($\alpha^{1/4}$)	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)
	DA$_5$	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	x^6 ($\alpha^{1/6}$)
Consumer Demands	**Uncertain Weights of Consumer Demands W**	**Uncertain Relationship Matrix between Consumer Demands and Design Attributes R**				
CD$_1$	x^4 ($\alpha^{1/4}$)	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)	x^2 ($\alpha^{1/2}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)
CD$_2$	x^2 ($\alpha^{1/2}$)	$x^{1/9}$ (α^9)	x^4 ($\alpha^{1/4}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)
CD$_3$	x^2 ($\alpha^{1/2}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)
CD$_4$	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	x^6 ($\alpha^{1/6}$)	$x^{1/9}$ (α^9)
CD$_5$	$x^{1/4}$ (α^4)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	$x^{1/9}$ (α^9)	x^4 ($\alpha^{1/4}$)
Technical Measures	Units	dB	horsepower	gallon	kg	m^3
	Comp$_1$	80	75	0.042	23	0.18
	Comp$_2$	65	70	0.034	24	0.20
	Comp$_3$	65	80	0.028	23	0.18
	Comp$_4$	75	60	0.032	15	0.14
	Comp$_5$	95	80	0.030	20	0.19
	Min	60	60	0.027	15	0.14
	Max	95	90	0.042	25	0.21
	Cost coefficients c_j	$\mathcal{L}(8,12)$	$\mathcal{L}(9,12)$	$\mathcal{L}(24,26)$	$\mathcal{L}(14,16)$	$\mathcal{L}(7,10)$

3.2 Standardizing target levels of DAs

It can be seen that DAs are classified into two categories in Table 2, in which the positive mark indicates 'Larger-the-better type' (*L-type*) and the negative mark indicates 'Smaller-the-better type' (*S-type*). The performance of an *L-type* DA is positively proportional to its target level, whereas the performance of an *S-type* DA is negatively proportional to its target level.

Mostly, target levels of DAs are accumulated in units and they usually have wide ranges. To eliminate the influence of multiple measurements, in terms of Chen *et al.* [6], the target level of the jth DA l_j can be converted into the fulfillment degree x_j, $j = 1, 2, \cdots, n$, as

$$
x_j = \begin{cases} \dfrac{l_j^{max} - l_j}{l_j^{max} - l_j^{min}} & (S\text{-}type) \\[2mm] \dfrac{l_j - l_j^{min}}{l_j^{max} - l_j^{min}} & (L\text{-}type) \end{cases} \tag{25}
$$

where $0 \leq x_j \leq 1$. For *S-type* DAs, $l_j^{\max}$ is the maximum target level of DA that matches the performance of the competitors and $l_j^{\min}$ is the minimum physical limit. On the contrary, for *L-type*
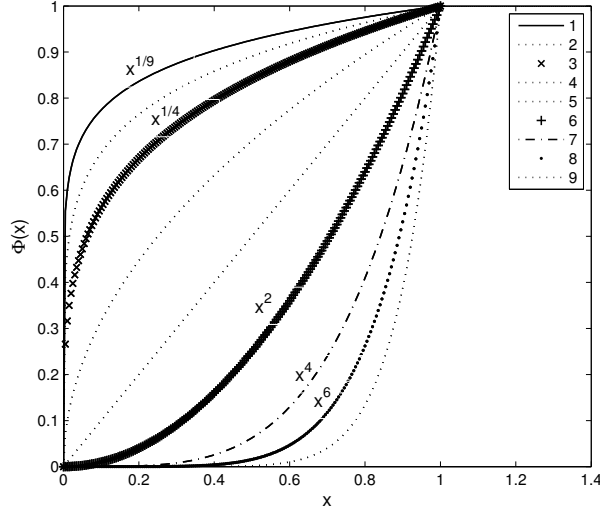
Figure 4: Regular uncertain variables listed in the HoQ of the motorcycle design

DAs, $l_j^{\min}$ is the minimum target level of DA that matches the performance of the competitors and $l_j^{\max}$ is the maximum physical limit.

Then, by utilizing Eq. (25), the observed data matrix of DAs of the five companies in Table 2 can be standardized to fulfillment degree matrix X as

$$X = (x_{hj})_{g \times n} = \begin{bmatrix} 0.43 & 0.50 & 0 & 0.80 & 0.57 \\ 0.86 & 0.33 & 0.53 & 0.90 & 0.86 \\ 0.86 & 0.67 & 0.93 & 0.80 & 0.57 \\ 0.57 & 0 & 0.67 & 0 & 0 \\ 0 & 0.83 & 0.80 & 0.50 & 0.71 \end{bmatrix}, \tag{26}$$

where x_{hj} is the fulfillment degree of DA$_j$ of Comp$_h$, and $0 \le x_{hj} \le 1$.

3.3 The solutions of UCCP-1

Before optimizing the target product, an evaluation of the five companies about their current overall consumer satisfaction S_h is generated so as to determine the position of our enterprise. Firstly, according to Eqs. (10)-(11), the expected values of the importance weights $E[v_j]$ for the five DAs, their normalized values $\bar{E}[v_j]$ and priorities can be obtained, which are demonstrated in Table 3. We can see that the importance weight of DA$_3$ 0.27 is the largest, which implies that the increase of the fulfillment degree of DA$_3$ will greatly help improve the consumer satisfaction.

Secondly, in regards to $\bar{E}[v_j]$ displayed in Table 3 and the present fulfillment degrees of DAs x_{hj} in Eq. (26), we can attain the normalized expected values of the overall consumer satisfaction

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Table 3: $E[v_j]$, $\bar{E}[v_j]$ and priorities for the five DAs

	DA$_1$	DA$_2$	DA$_3$	DA$_4$	DA$_5$
$E[v_j]$	2.18	2.91	3.67	3.17	1.78
$\bar{E}[v_j]$	0.16	0.21	0.27	0.23	0.13
Priorities	4	3	1	2	5

$\bar{E}[S_h]$ of our enterprise (Comp$_1$) and each competitor company via Eq. (12). The results are listed in Table 4 together with the rankings of five companies. Our enterprise scores 0.4319 and ranks the 4th, whereas Comp$_3$ occupies the highest overall consumer satisfaction 0.7875. It is clear that our enterprise lacks competitiveness in the market and the weakness of the existing design is urgent to be enhanced to chase the other three rivals except Comp$_4$.

Table 4: $\bar{E}[S_h]$ and rankings for the five companies

	Comp$_1$	Comp$_2$	Comp$_3$	Comp$_4$	Comp$_5$
$\bar{E}[S_h]$	0.4319	0.6688	0.7875	0.2721	0.5976
Ranking	4	2	1	5	3

The first objective is to progress the current design procedure in the perspective of maximizing the overall consumer satisfaction with a limited budget. After taking the financial situation of our enterprise into account, the budget B is set by project managers as 100 units and the steady part of the design cost C_f is set as 50 units. In the variable cost C_j of DA$_j$, we adopt five linear uncertain variables to denote the cost coefficient c_j as expressed in Table 2.

Afterwards, through substituting the values of $\bar{E}[v_j]$, the budget B, the fixed cost C_f and the lower and upper limits (a_j, b_j) in the cost coefficient c_j into UCCP-1 in Eq. (17), we obtain

$$\begin{cases} \max \bar{E}[S] = 0.16x_1 + 0.21x_2 + 0.27x_3 + 0.23x_4 + 0.13x_5 \\ \text{subject to:} \\ \quad (8 + 4\alpha_1)x_1 + (9 + 3\alpha_1)x_2 + (24 + 2\alpha_1)x_3 + (14 + 2\alpha_1)x_4 + (7 + 3\alpha_1)x_5 \leq 50 \\ \quad 0 \leq x_j \leq 1, \quad j = 1, 2, \cdots, 5. \end{cases} \quad (27)$$

In model (27), the confidence level α_1 decides the level of attainment of the uncertain event that the total design cost C is constrained to the budget B, which is an important parameter predetermined by the decision-makers. So as to assist the decision-makers in choosing a proper confidence level, we divide the values of α_1 from 0 to 1 by the scale 0.1 to study the three relationships between

α_1 and fulfillment degrees of DAs, target levels of DAs and the normalized expected values of the overall consumer satisfaction, respectively. First, we draw the relationship between different values of α_1 and the fulfillment degree x_j of DA_j, which is illustrated in Figure 5. Next, through the reverse transformation in Eq. (25), we are able to obtain target levels of DAs from their fulfillment degrees. Consequently, target levels of DAs and the normalized expected values of the overall consumer satisfaction $\bar{E}[S]$ at different confidence levels are listed in Table 5.
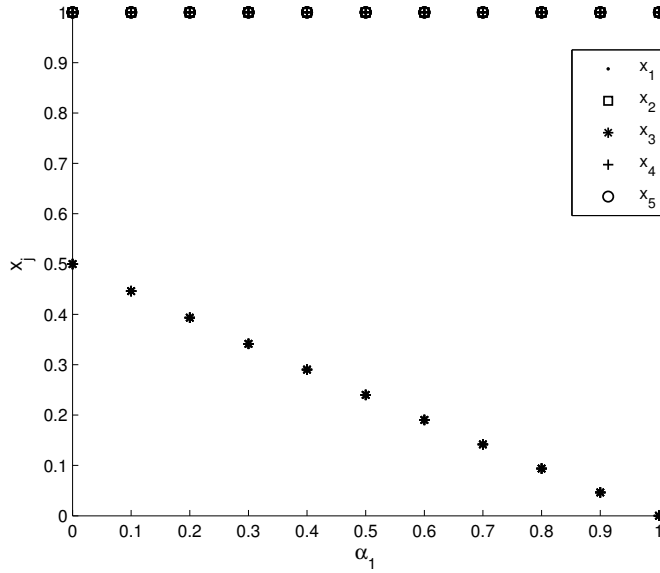

Figure 5: The relationship between α_1 and x_j in model (27)

Table 5: Target levels of DAs and relevant $\bar{E}[S]$ at different confidence levels in model (27)

α_1	l_1	l_2	l_3	l_4	l_5	$\bar{E}[S]$
0	60	90	0.0345	25	0.21	0.8650
0.1	60	90	0.0353	25	0.21	0.8505
0.2	60	90	0.0361	25	0.21	0.8362
0.3	60	90	0.0369	25	0.21	0.8222
0.4	60	90	0.0376	25	0.21	0.8084
0.5	60	90	0.0384	25	0.21	0.7948
0.6	60	90	0.0391	25	0.21	0.7814
0.7	60	90	0.0399	25	0.21	0.7683
0.8	60	90	0.0406	25	0.21	0.7553
0.9	60	90	0.0413	25	0.21	0.7426
1	60	90	0.0420	25	0.21	0.7300

From Figure 5 and Table 5, it is obvious that the fulfillment degrees and target levels of DA_1, DA_2, DA_4 and DA_5 stay unchanged as the increasing of α_1, whereas the fulfillment degree and target level of DA_3 vary in a decreasing or increasing tendency, respectively. The reason of this inconsistent trend between DA_3 and other DAs lies in the relationship of the input cost and the output benefit. Taking the confidence level $\alpha_1 = 0.8$ as an example, this cost/benefit analysis about DAs is calculated by the ratios between parameters of x_j in the first constraint and the objective function in model (27), and the results are listed in Table 6. It is explicit that the score of $\varphi_3^{-1}(\alpha_1)/\bar{E}[v_3]$ is much larger than others, which means the extent of the cost increase of DA_3 is much higher than that of benefit and explains why DA_3 is the only one to be optimized. Moreover, it is observed in Table 5 that the normalized expected values of the overall consumer satisfaction $\bar{E}[S]$ at all confidence levels have been enhanced a lot compared with the previous satisfaction degree 0.4319. Additionally, as the value of α_1 increases, the relevant $\bar{E}[S]$ decreases, which is very intuitive in terms of the mathematical meaning of α_1 as a safety margin.

Table 6: Cost/benefit analysis at the confidence level $\alpha_1 = 0.8$ in model (27)

	DA_1	DA_2	DA_3	DA_4	DA_5
$\varphi_j^{-1}(\alpha_1)$	11.2	11.4	25.6	15.6	9.4
$\bar{E}[v_j]$	0.16	0.21	0.27	0.23	0.13
$\varphi_j^{-1}(\alpha_1)/\bar{E}[v_j]$	70.0000	54.2857	94.8148	67.8261	72.3077
Ranking	3	5	1	4	2

Through the above results, some suggestions are provided for the decision-makers in our enterprise. Since the cost constraint is critical in UCCP-1, the solutions of model (27) at higher confidence levels are more rational in view of its meaning. On this basis, target levels of DAs at confidence levels 0.8, 0.9 and 1 for our enterprise (Comp$_1$) in Table 5 are selected and summarized in Table 7 together with the calculations of respective $E[C_v]$. The original target levels of DAs for Comp$_1$ and Comp$_3$ are extracted from Table 2, and both of their $E[C_v]$ are also calculated and displayed in Table 7. We can see that the prior-period investment of Comp$_1$'s 26.3950 is not enough compared with Comp$_3$'s 55.7300, which may be the key reason leading to its low consumer satisfaction. After applying target levels of DAs at confidence levels 0.8, 0.9 and 1 to the upgraded motorcycle, Comp$_1$ is able to beat Comp$_2$ and becomes the second place among the five companies

from the perspective of satisfaction degree. Meanwhile, the variable expenses invested at higher confidence levels are lower than $Comp_3$. The above analysis implies that by using UCCP-1 we can realize pretty good satisfaction degrees and greatly enhance the market position of our enterprise under a tight financial budget. As far as a situation that if the decision-makers want to be dominant in the market, a larger budget is necessary.

Table 7: Before and after target levels of DAs for $Comp_1$ by using UCCP-1

UCCP-1	l_1	l_2	l_3	l_4	l_5	$\bar{E}[S]$	$E[C_v]$
$Comp_1$ (before)	80	75	0.0420	23	0.18	0.4319	26.3950
$Comp_3$ (current leader)	65	80	0.0280	23	0.18	0.7875	55.7300
$Comp_1$ (after, $\alpha_1 = 0.8$)	60	90	0.0406	25	0.21	0.7553	46.3426
$Comp_1$ (after, $\alpha_1 = 0.9$)	60	90	0.0413	25	0.21	0.7426	45.1667
$Comp_1$ (after, $\alpha_1 = 1$)	60	90	0.0420	25	0.21	0.7300	44.0000

3.4 The solutions of UCCP-2

Different from UCCP-1 considering the maximum overall consumer satisfaction under the cost constraint, UCCP-2 aims at minimizing the variable cost C_v and getting a desirable overall consumer satisfaction S'. There exist two predetermined parameters in UCCP-2, the confidence level α_2 and the preferred consumer satisfaction S'. In this section, by fixing the confidence level α_2 to be a higher value 0.9 and substituting the relevant known values of UCCP-2 in Eq. (24), we obtain the following model,

$$\begin{cases} \min E[C_v] = 10x_1 + 10.5x_2 + 25x_3 + 15x_4 + 8.5x_5 \\ \text{subject to:} \\ \quad 0.17x_1 + 0.21x_2 + 0.25x_3 + 0.21x_4 + 0.16x_5 \geq S^* \\ \quad 0 \leq x_j \leq 1, \quad j = 1, 2, \cdots, 5. \end{cases} \quad (28)$$

In model (28), the parameter before each x_j (called $parameter_j$) in the first constraint is normalized artificially for the sake of standardizing S' into S^* in the interval (0,1). This normalization is convenient for the decision-makers to choose a proper S^* in the follow-up process. Similarly, through varying S^* from 0.1 to 1 by the scale 0.1, it allows us to observe the relationship between S^* and the fulfillment degrees of DAs in model (28), the results of which are demonstrated in Table 8 as well as the corresponding values of $E[C_v]$ and $\bar{E}[S]$.

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Table 8: The fulfillment degrees of DAs and relevant $E[C_v]$ in model (28) when S^* alters

S^*	x_1	x_2	x_3	x_4	x_5	$E[C_v]$	$\bar{E}[S]$
0.1	0	0.4762	0	0	0	5.0000	0.1000
0.2	0	0.9524	0	0	0	10.0000	0.2000
0.3	0	1	0	0	0.5625	15.2813	0.2831
0.4	0.1765	1	0	0	1	20.7647	0.3682
0.5	0.7647	1	0	0	1	26.6471	0.4624
0.6	1	1	0	0.2857	1	33.2857	0.5657
0.7	1	1	0	0.7619	1	40.4286	0.6752
0.8	1	1	0.2000	1	1	49.0000	0.7840
0.9	1	1	0.6000	1	1	59.0000	0.8920
1	1	1	1	1	1	69.0000	1.0000

From Table 8, undoubtedly the larger S^* is, the more the design cost is consumed. It is noted that the calculated normalized expected values of the overall consumer satisfaction $\bar{E}[S]$ is a little lower than S^* in most cases, which is attained by the combination of $\bar{E}[v_j]$ and x_j through Eq. (12). Furthermore, there is a changing order of the five DAs being fulfilled, which is more explicit for visualization in Figure 6. The reason of this priority is also explained by the benefit/cost analysis in Table 9, in which DA$_2$ is on the top of the ranking. It is optimized first in Table 8 and Figure 6, while other DAs are optimized in accordance with the rankings in Table 9. Besides, we can see that the extent of variation among $parameter_j/E[c_j]$ in Table 9 is much smaller in contrast to that among $\varphi_j^{-1}(\alpha_1)/\bar{E}[v_j]$ in Table 6, which leads all DAs in model (28) to be optimized orderly when S^* increases.

Table 9: Benefit/cost analysis at the confidence level $\alpha_2 = 0.9$ in model (28)

	DA$_1$	DA$_2$	DA$_3$	DA$_4$	DA$_5$
$parameter_j$	0.17	0.21	0.25	0.21	0.16
$E[c_j]$	10	10.5	25	15	8.5
$parameter_j/E[c_j]$	0.0170	0.0200	0.0100	0.0140	0.0188
Ranking	3	1	5	4	2

By utilizing model (28), the before and after target levels, the normalized expected values of the overall consumer satisfaction, together with the variable cost of our enterprise Comp$_1$ and the current leader Comp$_3$ are calculated and listed in Table 10. If our enterprise intends to play
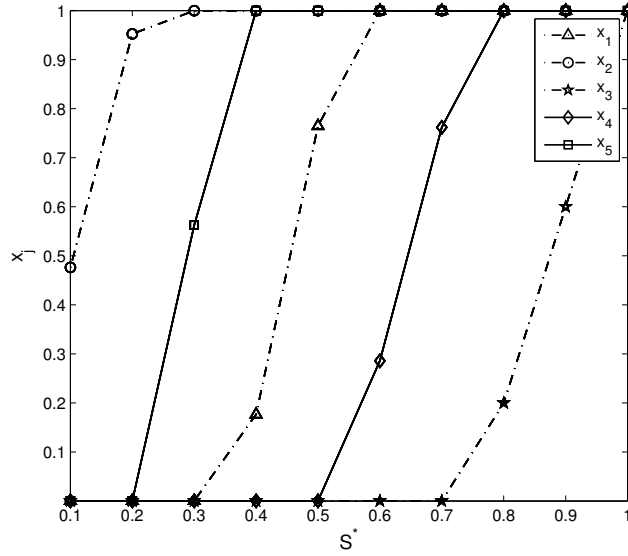
Figure 6: The fulfillment degrees of DAs with respect to different S^* in model (28)

a dominant role in the market defeating all rivals, the desirable overall consumer expectation is meant to be greater than that of $Comp_3$ (0.7875), who is the present leader from the aspect of gaining consumer satisfaction. That is to say, we should choose the solutions of model (28) with at least $\bar{E}[S] = 0.7875$ in Table 8. It can be seen that our expected satisfaction degree 0.7840 at $S^* = 0.8$ is approaching $Comp_3$, but still cannot reach the target of being the leader. For further efforts of realizing this, after implementing model (28) in the design procedure of our enterprise with $\bar{E}[S] = 0.7875$ or $S^* = 0.8032$, the variable cost of our company is 49.3241, which is lower than 55.7300 of $Comp_3$.

Table 10: Before and after target levels of DAs for $Comp_1$ by using UCCP-2

UCCP-2 ($\alpha_2 = 0.9$)	l_1	l_2	l_3	l_4	l_5	$E[C_v]$	$\bar{E}[S]$
$Comp_1$ (before)	80	75	0.0420	23	0.18	26.3950	0.4319
$Comp_3$ (current leader)	65	80	0.0280	23	0.18	55.7300	0.7875
$Comp_1$ (after, $S^* = 0.8$)	60	90	0.0390	25	0.21	49.0000	0.7840
$Comp_1$ (after, $S^* = 0.8032$)	60	90	0.0388	25	0.21	49.3241	0.7875

In summary, QFD is a useful tool that helps enhance competitiveness or save money. The applications of the aforementioned two uncertain CCP models in this QFD procedure have given the decision-makers some advice on choosing an appropriate model in particular cases. By comparing

the solutions of the two models, firstly, if the company is on a tight budget, UCCP-1 is more suitable to help improve the overall consumer satisfaction under a cost constraint. Secondly, if the budget is sufficient, the decision-makers are suggested to adopt UCCP-2 to compete with rivals in expanding the market share of the target product. In addition, through the adjustment of the confidence levels in these uncertain CCP models, the decision-makers could make reasonable tradeoffs according to the risk tolerances of their companies.

3.5 Comparative study

Except for demonstrating the solutions of UCCP-1 and UCCP-2, a comparative study is also generated between our work and another work, an uncertain expected value modelling (EVM) approach for setting target levels of DAs in QFD planning, which was brought up by Miao *et al.* [21].

Firstly, for the purpose of obtaining the maximum expected overall consumer satisfaction subject to an expected cost constraint, an EVM model (named UP-1) was set forth in [21], which is expressed as

$$
\begin{cases}
\max \sum_{j=1}^{n} \bar{E}[v_j]x_j \\
\text{subject to:} \\
\quad C_f + \sum_{j=1}^{n} E[c_j]x_j \leq B \\
\quad 0 \leq x_j \leq 1, \quad j = 1, 2, \cdots, n.
\end{cases}
\tag{29}
$$

By setting the same parameters, the solution of Eq. (29) to improving the current motorcycle design of our enterprise (Comp$_1$) is displayed in Table 11. Likewise, when the confidence level $\alpha_1 = 0.5$, we can figure out the same result by using UCCP-1. It is not a coincidence since we can get the following equation about a linear uncertain variable $c_j \sim \mathcal{L}(a_j, b_j)$ as

$$
E[c_j] = \int_0^1 \varphi_j^{-1}(\alpha)\mathrm{d}\alpha = \frac{(a_j + b_j)}{2} = \varphi_j^{-1}(0.5),
\tag{30}
$$

the calculation of which can be found in [16]. It is explicit that the form of model (27) at the confidence level $\alpha_1 = 0.5$ via Eq. (30) will be identical to Eq. (29) numerically. Even so, the inner meanings they represent are not the same. UP-1 is designed out of a risk-neutral consideration, which is constrained to an expected cost limit, while UCCP-1 makes decisions under the chance constraint of the design cost with a safety margin. Moreover, as depicted in Table 5, model (27)

can achieve different combinations of target levels of DAs and satisfaction degrees with the altering of the confidence level α_1, which provides the decision-makers with more choices.

Table 11: Comparison between UCCP-1 and UP-1

Comp$_1$	l_1	l_2	l_3	l_4	l_5	$\bar{E}[S]$
UCCP-1 ($\alpha_1 = 0.5$)	60	90	0.0384	25	0.21	0.7948
UP-1	60	90	0.0384	25	0.21	0.7948

Secondly, when switching to the goal of obtaining the expected minimum variable design cost, another EVM model (named UP-2) was put forward in [21] as follows,

$$\begin{cases} \min E[C_v] = \sum_{j=1}^{n} E[c_j]x_j \\ \text{subject to:} \\ \quad \sum_{j=1}^{n} \bar{E}[v_j]x_j \geq S'' \\ \quad 0 \leq x_j \leq 1, \quad j = 1, 2, \cdots, n, \end{cases} \tag{31}$$

in which the overall consumer satisfaction S'' is divided from 0 to 1 by 0.1. With respect to UCCP-2 in model (28), the confidence level α_2 is set to be 0.9 and the altering of S^* is similar to S'' in UP-2. The comparison results of UCCP-2 and UP-2 with the same satisfaction degree $\bar{E}[S] = 0.7875$ defeating all rivals are presented in Table 12. It is observed that UP-2 consumes the same variable cost 49.3241 with UCCP-2 due to the identical objective functions. Additionally, apart from the confidence level $\alpha_2 = 0.9$, the decision-makers can set it to be other crisp values from 0 to 1 in UCCP-2, which will lead to various results.

Table 12: Comparison between UCCP-2 and UP-2 with $\bar{E}[S] = 0.7875$

Comp$_1$	l_1	l_2	l_3	l_4	l_5	$\bar{E}[S]$	$E[C_v]$
UCCP-2 ($\alpha_2 = 0.9$, $S^* = 0.8032$)	60	90	0.0388	25	0.21	0.7875	49.3241
UP-2($S'' = 0.7875$)	60	90	0.0388	25	0.21	0.7875	49.3241

The relations and differences between uncertain CCP and EVM are elaborated as follows. Both of them are feasible solutions for optimizing the QFD procedure. Although these two approaches

share the same objective functions, they are based upon distinct modelling ideas and risk decisions. Expected value models are designed on the basis that the decision-makers are neutral, whose target is to obtain the mean values of objective functions and constraints. In our chance-constrained programming models, it is very natural and intuitive to consider the levels of attainment of different constraints in practice. From the above comparison results, it is more suitable to adopt uncertain CCP models in QFD because the outcomes of them not only cover the results of uncertain EVM models but also have a wider selection range. The decision-makers can choose their preferred decisions out of diversified results at different confidence levels according to individual subjective evaluations and preferences.

4   Conclusions

In this paper, an uncertain CCP approach based on uncertainty theory was applied to formulating the QFD development procedure under uncertain circumstances. Two novel models with separate considerations were set forth in determining target levels of DAs, endeavoring to make trade-offs between the overall consumer satisfaction and the design cost.

To sum up, our major contributions lay in several parts as follows. Firstly, from the strategic management perspective, we considered both the competitiveness and the financial condition of a company, formulating two uncertain CCP models to assist the decision-makers in making proper decisions in product development. Secondly, the case of a motorcycle design demonstrated that the proposed method was able to model the product design procedure effectively and efficiently. By altering the confidence levels or the acceptable overall consumer satisfaction in uncertain CCP models, diversified solutions were figured out. Finally, we conducted a comparative analysis between our proposed uncertain CCP approach and a former uncertain expected value modelling approach. It was concluded that although they had different application ranges, uncertain CCP model was more suitable to deal with the QFD optimization procedure owing to its underlying philosophy and various choices provided for the decision-makers.

Acknowledgements

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