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New Approach for Quality Function Deployment Using Linguistic Z-Numbers and EDAS Method

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Abstract. Quality function deployment (QFD) is an effective product development and management tool, which has been broadly applied in various industries to develop and improve products or services. Nonetheless, when used in real situations, the traditional QFD method shows some important weaknesses, especially in describing experts' opinions, weighting customer requirements, and ranking engineering characteristics. In this study, a new QFD approach integrating linguistic Z-numbers and evaluation based on distance from average solution (EDAS) method is proposed to determine the prioritization of engineering characteristics. Specially, linguistic Z-numbers are adopted to deal with the vague evaluation information provided by experts on the relationships among customer requirements and engineering characteristics. Then, the EDAS method is extended to estimate the final priority ratings of engineering characteristics. Additionally, stepwise weight assessment ratio analysis (SWARA) method is employed to derive the relative weights of customer requirements. Finally, a practical case of Panda shared car design is introduced and a comparison is conducted to verify the feasibility and effectiveness of the proposed QFD approach. The results show that the proposed linguistic Z-EDAS method can not only represent experts' interrelation evaluation information flexibly, but also produce a more reasonable and reliable prioritization of engineering characteristics in QFD.

Key words: quality function deployment, linguistic Z-number, evaluation based on distance from average solution (EDAS), SWARA method, product development.

1. Introduction

Quality function deployment (QFD) was first introduced by Akao (1972) for designing new products systematically, which can translate customer requirements (CRs) into engineering characteristics (ECs) for maximum customer satisfaction (Bevilacqua *et al.*, 2006). Nowadays, the QFD has become a powerful tool for designing and developing products or services (Huang *et al.*, 2019). It can not only improve customer satisfaction, but also reduce cycle-time of product development, cut down production cost and enhance

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the performance of manufacturing process. Due to its effectiveness and benefits, the QFD method has been applied for product design and quality improvement in various areas, such as construction (Fargnoli *et al.*, 2020; Lapinskienė and Motuzienė, 2021), manufacturing (Neramballi *et al.*, 2020; Shi and Peng, 2020) and service (Lee *et al.*, 2020; Park *et al.*, 2021) industries.

When implementing QFD, house of quality (HOQ) occupies a central position, which assists designers in translating CRs into ECs through explicit assessment matrix of users and products. In this way, the QFD method serves as a valuable tool for managers or designers to develop products. However, when used in real situations, the traditional QFD method has some inherent deficiencies (Huang *et al.*, 2019; Jia *et al.*, 2016; Ping *et al.*, 2020; Wu *et al.*, 2020). On the one hand, crisp values are utilized to deal with the relationships between CRs and ECs in the traditional QFD. However, in the real world, it is often hard for experts to give accurate numerical values on the relationships between CRs and ECs due to the uncertainty and fuzziness of human perception (Aliev and Huseynov, 2014; Lorkowski *et al.*, 2014). Instead, they prefer to use linguistic terms to express their opinions (Liu *et al.*, 2019; Tian *et al.*, 2019; Liu *et al.*, 2021). Based on linguistic term sets (Zadeh, 1975) and Z-numbers (Zadeh, 2011), the concept of linguistic Z-numbers was introduced by Wang *et al.* (2017) to express both vagueness and randomness of uncertain linguistic information. For a linguistic Z-number, the two components (i.e. restriction and reliability measure) are represented with linguistic terms. Compared to other linguistic computing methods, the linguistic Z-numbers can not only describe decision-making information more flexibly, but also avoid the distortion and loss of original information effectively (Peng and Wang, 2017; Wang *et al.*, 2017). Hence, it is promising to employ the linguistic Z-numbers to represent experts' uncertain and vague evaluation information on the relationships between CRs and ECs in QFD.

On the other hand, the ranking of ECs in QFD can be considered as a multiple criteria decision making (MCDM) problem because it involves multiple and conflicting CRs (Ping *et al.*, 2020). Accordingly, many MCDM methods have been adopted to improve the performance of QFD in previous researches (Mistarihi *et al.*, 2020; Ocampo *et al.*, 2020; Yazdani *et al.*, 2016). As an effective MCDM method, the evaluation based on distance from average solution (EDAS) was put forward by Ghorabaee *et al.* (2015) to address MCDM problems. The EDAS includes two measures, i.e. positive distance from average (PDA) and negative distance from average (NDA), for dealing with the desirability of alternatives (Keshavarz-Ghorabaee *et al.*, 2018; Keshavarz Ghorabaee *et al.*, 2017). It has simple logic and is especially useful for decision making problems with conflicting criteria (Darko and Liang, 2020). Since its introduction, the EDAS method has been broadly adopted to solve MCDM problems in many areas, which include supplier selection (Ghorabaee *et al.*, 2016), manufacturer selection (Stević *et al.*, 2018), health-care waste disposal technology selection (Ju *et al.*, 2020), typhoon disaster assessment (Tan and Zhang, 2021), car selection (Yanmaz *et al.*, 2020) and logistics centre location (Özmen and Aydoğan, 2020). Therefore, it is of vital importance to adopt the EDAS method to determine the ranking of ECs in QFD analysis.

Based on the aforementioned discussions, an approach combining linguistic Z-numbers with EDAS method is presented in the study to improve the effectiveness of QFD.

Specifically, the linguistic Z-numbers are used to cope with the vague and uncertain assessments provided by experts on the relationships among CRs and ECs, and the EDAS method is utilized to acquire the priority orders of ECs in the process of product development. Moreover, the weights of CRs are obtained by the use of stepwise weight assessment ratio analysis (SWARA) method. Finally, a practical case of product design for Panda shared cars is introduced to testify the effectiveness and efficiency of the proposed QFD approach.

The remainder of the article is organized as follows: Section 2 briefly reviews research progress of the QFD method. The preliminaries of linguistic Z-numbers are presented in Section 3. Then the new integrated QFD approach combining linguistic Z-numbers and EDAS method is developed in Section 4. In Section 5, a practical example is given to demonstrate the proposed QFD framework. Lastly, conclusions of this study and outlines for future research are discussed in Section 6.

2. Literature Review

In the past decade, an increasing number of improved QFD methods have been developed to eliminate the deficiencies and enhance the performance of the traditional QFD. For instance, Li *et al.* (2014) introduced analytical network process (ANP) into QFD for deciding the importance of CRs and evaluating corresponding characteristics of software quality. Jia *et al.* (2016) proposed an integrated QFD method combining fuzzy evidence reasoning theory with fuzzy discrete Choquet integral to determine the importance value of design characteristics. Integrating QFD and decision-making trial and evaluation laboratory (DEMATEL) technique, Ramezankhani *et al.* (2018) designed a hybrid model and applied it to supply chain performance measurement. Liu *et al.* (2019) proposed a QFD approach by using partitioned Bonferroni mean operator and interval type-2 fuzzy sets to select a better solution from various green suppliers. Vats and Vaish (2019) employed QFD in combination with vlseKriterijumska optimisacija I kompromisno resenje (VIKOR) approach to select smart materials for thermal energy efficient architecture. Based on cloud model and grey relational analysis, Wang *et al.* (2020) put forward an integrated QFD model to control the quality of the rotor used in air compressor. Via integrating interval type-2 fuzzy sets and DEMATEL, Yazdani *et al.* (2020) designed a QFD approach to evaluate and rank sustainable supply chain drivers.

Recently, it has become a trend to integrate the advantages of different MCDM approaches for the improvement of traditional QFD. For example, by using DEMATEL and VIKOR, Wu *et al.* (2016) developed a QFD model for the product development of electric vehicle. Combining fuzzy BWM, fuzzy maximizing deviation method and fuzzy multi-objective optimization by ratio analysis plus the full multiplicative form (MULTI-MOORA), Tian *et al.* (2018) established a hybrid QFD model to assess the performance of a smart bike-sharing program. Huang *et al.* (2019) constructed a QFD technique to design manufacture system, in which the relationships between CRs and ECs were expressed by hesitant fuzzy linguistic term sets, the weights of CRs were derived by the best-worst method (BWM) and the ranking order of ECs were determined by the prospect theory. Lu *et al.* (2019) presented a QFD model by combining fuzzy analytic hierarchy process (AHP) with fuzzy ANP for the design of brand revitalization. A QFD model integrating TOPSIS and EDAS method was proposed by Ping *et al.* (2020) for a product-service system design.

As reviewed previously, many studies handled the uncertainty and vagueness of experts' assessments in QFD using fuzzy sets, interval type-2 fuzzy sets and hesitant fuzzy linguistic term sets. However, the reliability of experts' assessment information cannot be reflected in the processes of QFD. Besides, although different types of MCDM methods have been proposed to obtain the EC prioritization in QFD, they are extremely complex or not considering the conflict of CRs. To overcome these issues, in this paper, we develop a novel QFD approach integrating linguistic Z-numbers and an extended EDAS method to determine the priorities of ECs. Our proposed QFD model can not only represent experts' evaluation information flexibly, but also provide engineers more practical and reliable solutions for identifying critical ECs to improve product or service.

3. Preliminaries

In this section, some basic concepts of linguistic term sets and linguistic Z-numbers are introduced to aid in understanding the proposed QFD model.

Definition 1 (Duan *et al.* 2019). Let $S = \{s_0, s_1, \dots, s_{2t}\}$ be a finite and ordered linguistic term set with odd cardinality, where s_i is the possible value for a linguistic variable and t is a nonnegative integer. In this linguistic term set S, s_i and s_j are required to satisfy the following characteristics:

(1) The set is ordered: $s_i > s_j$, if and only if $i > j$;
(2) Negation operator: $neg(s_i) = s_j$, if $i + j = 2t$.

Definition 2 (Peng and Wang 2017). Let $S = \{s_0, s_1, \dots, s_{2t}\}$ be a linguistic term set. If $\theta_i \in [0, 1]$ is a numerical value, then the linguistic scale function is a mapping from s_i to θ_i $(i = 0, 1, \dots, 2t)$, and it is defined as:

$$F : s_i \to \theta_i \quad (i = 0, 1, \dots, 2t), \tag{1}$$

in which $0 \leqslant \theta_0 \leqslant \theta_1 \leqslant \cdots \leqslant \theta_{2t} \leqslant 1$.

A linguistic scale function is a monotonic increasing function. The following functions are two commonly used in the literature (Liu and Liu, 2017; Wang *et al.*, 2016).

$$F_1(\theta_i) = \theta_i = \frac{i}{2t}, \quad (0 \leqslant i \leqslant 2t), \tag{2}$$

$$F_2(\theta_i) = \theta_i = \begin{cases} \frac{a^t - a^{t-i}}{2a^t - 2}, & (0 \leqslant i \leqslant t), \\ \frac{a^t + a^{i-t} - 2}{2a^t - 2}, & (t + 1 \leqslant i \leqslant 2t), \end{cases} \tag{3}$$

where the variable a is a special value obtained from experiments or subjective methods.

Definition 3 (Wang *et al.* 2017). Let X be a universe of discourse, $S_1 = \{s_0, s_1, \dots, s_{2l}\}$, $S_2 = \{s'_0, s'_1, \dots, s'_{2k}\}$ are two finite and totally ordered uncontinuous linguistic term sets, with nonnegative integers l and k. Furthermore, let $A_{\phi(x)} \in S_1$ and $B_{\varphi(x)} \in S_2$. A linguistic Z-number set Z in X can be denoted in the following form:

$$Z = \{(x, A_{\phi(x)}, B_{\varphi(x)}) \,|\, x \in X\}, \tag{4}$$

where $A_{\phi(x)}$ is a fuzzy restriction on the values that uncertain variable x is allowed to take, and $B_{\varphi(x)}$ is a measure of reliability of $A_{\phi(x)}$.

When X has only one element, the linguistic Z-number set Z is reduced to $(A_{\phi(\alpha)}, B_{\varphi(\alpha)})$. For convenience, $z_\alpha = (A_{\phi(\alpha)}, B_{\varphi(\alpha)})$ is called a linguistic Z-number.

Definition 4 (Wang *et al.* 2017). Let $z_i = (A_{\phi(i)}, B_{\varphi(i)})$ and $z_j = (A_{\phi(j)}, B_{\varphi(j)})$ be two linguistic Z-numbers; let f^* and g^* be the different linguistic scale functions and their inverse functions are f^{*-1} and g^{*-1}. Then, the basic operational rules of linguistic Z-numbers are defined as follows:

(1) $z_i \oplus z_j$
$$= \left(f^{*-1}(f^*(A_{\phi(i)}) + f^*(A_{\phi(j)})), g^{*-1}\left(\frac{f^*(A_{\phi(i)}) \times g^*(B_{\varphi(i)}) + f^*(A_{\phi(j)}) \times g^*(B_{\varphi(i)})}{f^*(A_{\phi(i)}) + f^*(A_{\phi(j)})}\right)\right);$$
(2) $\lambda z_i = (f^{*-1}(\lambda f^*(A_{\phi(i)})), B_{\varphi(i)})$, where $\lambda \geqslant 0$;
(3) $z_i \otimes z_j = (f^{*-1}(f^*(A_{\phi(i)}) f^*(A_{\phi(j)})), g^{*-1}(g^*(B_{\varphi(i)}) g^*(B_{\varphi(j)})))$;
(4) $z_i^\lambda = (f^{*-1}(f^*(A_{\phi(i)}) f^*(A_{\phi(j)})), g^{*-1}(g^*(B_{\varphi(i)})^\lambda))$, where $\lambda \geqslant 0$.

Definition 5 (Wang *et al.*, 2017). Let $z_i = (A_{\phi(i)}, B_{\varphi(i)})$ be linguistic Z-numbers. Then, the score function $S(z_i)$ of z_i is defined as:

$$S(z_i) = f^*(A_{\phi(i)}) \times g^*(B_{\varphi(i)}), \tag{5}$$

and the accuracy function $A(z_i)$ of z_i is defined as:

$$A(z_i) = f^*(A_{\phi(i)}) \times (1 - g^*(B_{\varphi(i)})). \tag{6}$$

Definition 6 (Wang *et al.*, 2017). Let $z_i = (A_{\phi(i)}, B_{\varphi(i)})$ and $z_j = (A_{\phi(j)}, B_{\varphi(j)})$ be two linguistic Z-numbers. Then the comparison rules of the two linguistic Z-numbers are listed below:

(1) If $A_{\phi(i)} > A_{\phi(j)}$ and $B_{\varphi(i)} > B_{\varphi(j)}$, then z_i is strictly greater than z_j, denoted by $z_i > z_j$;
(2) If $S(z_i) \geqslant S(z_j)$ and $A(z_i) > A(z_j)$, then z_i is greater than z_j, denoted by $z_i \succ z_j$;
(3) If $S(z_i) = S(z_j)$ and $A(z_i) = A(z_j)$, then z_i equals z_j, denoted by $z_i \sim z_j$;
(4) If $S(z_i) = S(z_j)$ and $A(z_i) < A(z_j)$ or $S(z_i) < S(z_j)$, then z_i is less than z_j, denoted by $z_i \prec z_j$.

Definition 7 (Wang *et al.*, 2017). For any two linguistic Z-numbers $z_i = (A_{\phi(i)}, B_{\varphi(i)})$ and $z_j = (A_{\phi(j)}, B_{\varphi(j)})$. The distance between z_i and z_j is calculated by:

$$d(z_i, z_j) = \frac{1}{2}\Big(\big|f^*(A_{\phi(i)}) \times g^*(B_{\varphi(i)}) - f^*(A_{\phi(j)}) \times g^*(B_{\varphi(j)})\big| + \max\big\{\big|f^*(A_{\phi(i)}) - f^*(A_{\phi(j)})\big|, \big|g^*(B_{\varphi(i)}) - g^*(B_{\varphi(j)})\big|\big\}\Big). \tag{7}$$

Definition 8 (Duan *et al.*, 2019). Let $z_i = (A_{\phi(i)}, B_{\varphi(i)})$, $(i = 1, 2, \dots, n)$ be a collection of linguistic Z-numbers. Then the linguistic Z-numbers weighted average (LZWA) operator is defined as:

$$\begin{aligned}\mathrm{LZWA}(z_i) &= \sum_{i=1}^{n} w_i z_i \\ &= \left(f^{*-1}\left(\sum_{i=1}^{n} w_i f^*(A_{\phi(i)})\right), g^{*-1}\left(\frac{\sum_{i=1}^{n} w_i f^*(A_{\phi(i)}) g^*(B_{\varphi(i)})}{\sum_{i=1}^{n} w_i f^*(A_{\phi(i)})}\right)\right),\end{aligned} \tag{8}$$

where $w = (w_1, w_2, \dots, w_n)^T$ is the weight vector of z_i $(i = 1, 2, \dots, n)$, satisfying $w_i \geqslant 0$ and $\sum_{i=1}^{n} w_i = 1$.

4. The Proposed QFD Approach

In this section, a new comprehensive QFD model combining linguistic Z-numbers and EDAS method is devised to acquire the ranking of ECs. Specially, linguistic Z-numbers are utilized to evaluate the relationships between CRs and ECs, the relative weights of CRs are computed by the SWARA method, and an extended EDAS method is employed to estimate the final priority ratings of ECs. Flowchart for the developed QFD model consisting of three phases is depicted in Fig. 1.

For a QFD analysis problem, suppose that there are m engineering characteristics EC_i $(i = 1, 2, \dots, m)$ and n customer requirements CR_j $(j = 1, 2, \dots, n)$. Meanwhile, l experts E_k $(k = 1, 2, \dots, l)$ are invited to provide their assessments for the relationships between CRs and ECs, and each expert is assigned a weight λ_k satisfying $\lambda_k > 0$ and $\sum_{k=1}^{l} \lambda_k = 1$ to describe his/her relative importance in the QFD analysis. Let $Z^k = [z_{ij}^k]_{m\times n}$ be the linguistic assessment matrix of E_k, where $z_{ij}^k = (A_{\phi(ijk)}, B_{\varphi(ijk)})$ is the linguistic Z-number evaluation EC_i with respect to CR_j provided by E_k. Based on the above assumptions, the proposed QFD model is described as follows:

Stage 1. Evaluate the relationships between ECs and CRs using linguistic Z-numbers.

Step 1: Establish the collective linguistic evaluation matrix Z.

By using the LZWA operator, the individual linguistic evaluation matrices Z^k $(k = 1, 2, \dots, l)$ can be aggregated to obtain the collective linguistic evaluation matrix $Z = (z_{ij})_{m\times n}$, in which

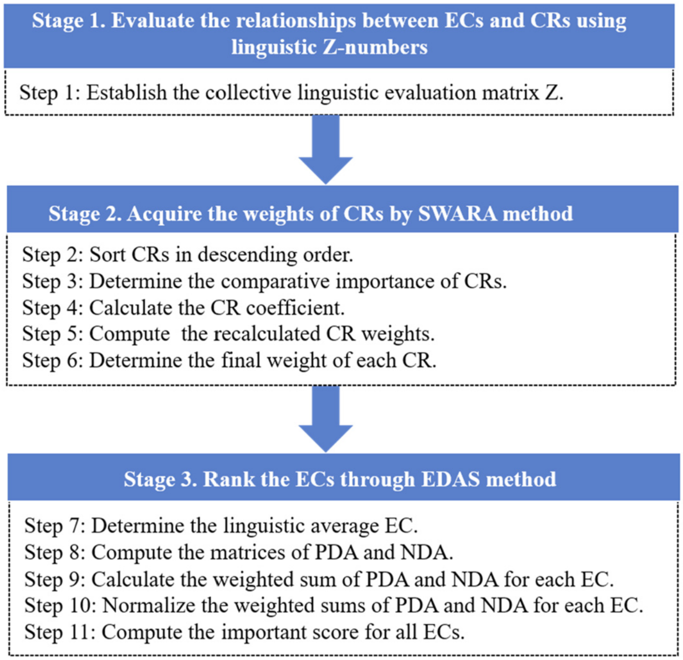

Fig. 1. Framework of the proposed QFD model.

$$
\begin{aligned}
z_{ij} &= \mathrm{LZWA}\big(z_{ij}^1, z_{ij}^2, \dots, z_{ij}^l\big) \\
&= \left(f^{*-1}\left(\sum_{k=1}^{l}\lambda_k f^*(A_{\phi(ijk)})\right), g^{*-1}\left(\frac{\sum_{k=1}^{l}\lambda_k f^*(A_{\phi(ijk)})g^*(B_{\varphi(ijk)})}{\sum_{k=1}^{l}\lambda_k f^*(A_{\phi(ijk)})}\right)\right). \qquad (9)
\end{aligned}
$$

Stage 2. Acquire the weights of CRs by the SWARA method.

The SWARA method proposed by Keršuliene *et al.* (2010) is a powerful weighting method in solving MCDM problems. The superiority of the SWARA is that it is uncomplicated, straightforward and involves less comparisons compared with other weighing methods (Hashemkhani Zolfani *et al.*, 2013; Karabasevic *et al.*, 2016; Ruzgys *et al.*, 2014; Stanujkic *et al.*, 2017). Given its strength, it has been used to find the relative weights of evaluation criteria in many researches (Duan *et al.*, 2019; Liu *et al.*, 2020; Naeini *et al.*, 2020). Therefore, the SWARA method is introduced to acquire the weights of CRs in this study. The detailed steps are listed as follows:

Step 2: Sort CRs in a descending order.

The n customer requirements CR_j $(j = 1, 2, \dots, n)$ are sorted in a descending order according to their expected importance. Then, newly ranked CRs are denoted as CR'_j $(j = 1, 2, \dots, n)$.

Step 3: Determine the comparative importance of CRs.

Starting from the second CR, experts are invited to assess the relative importance of CR'_j to CR'_{j-1} $(j = 2, 3, \dots, n)$. Then the comparative importance of CRs ρ_j is obtained.

Step 4: Calculate the CR coefficient k_j by

$$k_j = \begin{cases} 1, & j = 1, \\ \rho_j + 1, & j > 1. \end{cases} \tag{10}$$

Step 5: Compute the recalculated CR weights q_j by

$$q_j = \begin{cases} 1, & j = 1, \\ \frac{q_{j-1}}{k_j}, & j > 1. \end{cases} \tag{11}$$

Step 6: Determine the final weight of each CR w'_j by

$$w'_j = \frac{q_j}{\sum_{k=1}^{n} q_j}. \tag{12}$$

Finally, the weight vector of the n customer requirement CR_j $(j = 1, 2, \dots, n)$, i.e. $w = (w_1, w_2, \dots, w_n)$, can be derived by rearranging the weights w'_j $(j = 1, 2, \dots, n)$.

Stage 3. Rank the ECs through EDAS method.

In this part, we extend the EDAS method with linguistic Z-numbers, and adopt the linguistic Z-EDAS to obtain the ranking of ECs. The detail steps for ranking ECs are as follows.

Step 7: Determine the linguistic average EC.

The linguistic average engineering characteristics EC is defined as $z_A = (z_{A1}, z_{A2}, \dots, z_{An})$, which can be derived by

$$z_{Aj} = \frac{1}{m} \bigoplus_{i=1}^{m} z_{ij}. \tag{13}$$

Step 8: Compute the matrices of PDA and NDA.

The PDA matrix $D^+ = [d_{ij}^+]_{m\times n}$ and the NDA matrix $D^- = [d_{ij}^-]_{m\times n}$ are, respectively, computed by

$$d_{ij}^+ = \begin{cases} \frac{\max\{0, (s(z_{ij}) - s(z_{Aj}))\}}{s(z_{Aj})}, & \text{if } z_{ij} > z_{Aj}, \\ 0, & \text{if } z_{ij} \leqslant z_{Aj}, \end{cases} \tag{14}$$

$$d_{ij}^- = \begin{cases} \frac{\max\{0, (s(z_{ij}) - s(z_{Aj}))\}}{s(z_{Aj})}, & \text{if } z_{ij} < z_{Aj}, \\ 0, & \text{if } z_{ij} \geqslant z_{Aj}. \end{cases} \tag{15}$$

Step 9: Calculate the weighted sum of PDA and NDA for each EC.

Considering the weight of each customer requirement w, the weighted sums of PDA and NDA for each EC are calculated by

$$SP_i = \sum_{j=1}^{n} w_j d_{ij}^{+}, \quad i = 1, 2, \dots, m, \tag{16}$$

$$SN_i = \sum_{j=1}^{n} w_j d_{ij}^{-}, \quad i = 1, 2, \dots, m. \tag{17}$$

Step 10: Normalize the weighted sums of PDA and NDA for each EC.

The normalized values of SP_i and SN_i for each EC can be derived by

$$\overline{SP}_i = \frac{SP_i}{\max_i SP_i}, \quad i = 1, 2, \dots, m, \tag{18}$$

$$\overline{SN}_i = 1 - \frac{SN_i}{\max_i SN_i}, \quad i = 1, 2, \dots, m. \tag{19}$$

Step 11. Compute the important score for all ECs.

The importance scores for the m ECs can be computed by

$$IS_i = \frac{1}{2}(\overline{SP}_i + \overline{SN}_i), \quad i = 1, 2, \dots, m. \tag{20}$$

In the process of QFD analysis, the larger the important score IS_i, the higher the importance of the engineering characteristics EC_i is. Therefore, the priority of all the ECs can be obtained according to the descending order of the values of IS_i $(i = 1, 2, \dots, m)$.

5. Case Study

In this section, the designing process of Panda shared cars (Wu and Liao, 2018) is provided to illustrate the feasibility and applicability of our proposed QFD approach.

5.1. *Implementation and Results*

In the past several years, "shared economy" has profoundly influenced people's daily life, and has been strongly advocated at the national level. Recently, as a most representative form of "shared economy", "shared cars" began to appear in Chinese market to improve the efficiency of transport and solve the problem of scarcity of transportation resources. The "Panda" is a travel platform of shared new energy cars, which focuses on the form of "internetwork + vehicle networking + energy economy + auto service". Due to its unique mode of electric vehicles and excellent smart travel experience, "Panda" has become the fastest time sharing leasing business and the largest shared project of new energy vehicles in a single city in China. Nowadays, more and more shared car brands are appearing in the market, therefore the expansion of the market and success in the competition of the "shared

Table 1
CRs and ECs identified in the case.

CRs	Customer requirements	ECs	Engineering characteristics
CR_1	Price	EC_1	Cost
CR_2	Comfortability	EC_2	Car body material
CR_3	Safety	EC_3	Seat material
CR_4	Convenience	EC_4	Car internal decoration
CR_5	Space	EC_5	On-board system
		EC_6	Air-conditioning system

cars" market is a big challenge. Thus, it is urgent for "Panda" to design new products that satisfy people's travel needs at low prices.

Through interviews and surveys of users and specialists, five CRs (CR_j, $j = 1, 2, \dots, 5$) and six ECs (EC_i, $i = 1, 2, \dots, 6$) are identified for the product design of "Panda", as shown in Table 1. For the QFD problem, five experts (E_k, $k = 1, 2, \dots, 5$) are organized to express their evaluations on the interrelations between the ECs and CRs. The weights of experts are assumed the same in this study. The evaluations are conducted by using the following linguistic term sets:

$$S = \left\{ \begin{array}{l} s_0 = None,\ s_1 = Extremely\ weak,\ s_2 = Weak,\ s_3 = Medium, \\ s_4 = Strong,\ s_5 = Extremely\ strong,\ s_6 = Perfect \end{array} \right\},$$

$$S' = \left\{ \begin{array}{l} s'_0 = Uncertain,\ s'_1 = Slightly\ uncertain,\ s'_2 = Medium, \\ s'_3 = Slightly\ sure,\ s'_4 = Sure \end{array} \right\}.$$

As a result, the evaluation results of the five experts toward the relationships between ECs and CRs are obtained, and shown in Table 2.

In what follows, the steps of the proposed QFD model were implemented to determine the ranking orders of ECs for the given case study.

Step 1: By using Eq. (9), the individual evaluation matrices Z^k ($k = 1, 2, \dots, 5$) are aggregated to obtain the collective linguistic evaluation matrix $Z = (z_{ij})_{6\times 5}$, as shown below

$$Z = \begin{bmatrix} (s_{5.40}, s'_{4.00}) & (s_{1.00}, s'_{1.00}) & (s_{5.40}, s'_{3.22}) & (s_{2.00}, s'_{3.00}) & (s_{0.20}, s'_{2.00}) \\ (s_{2.00}, s'_{4.00}) & (s_{0.00}, s'_{1.00}) & (s_{5.20}, s'_{3.19}) & (s_{0.00}, s'_{3.20}) & (s_{0.60}, s'_{2.00}) \\ (s_{3.00}, s'_{3.80}) & (s_{3.00}, s'_{3.80}) & (s_{1.00}, s'_{2.00}) & (s_{0.00}, s'_{3.20}) & (s_{0.20}, s'_{1.00}) \\ (s_{0.00}, s'_{3.00}) & (s_{3.00}, s'_{2.20}) & (s_{0.00}, s'_{3.80}) & (s_{0.00}, s'_{3.20}) & (s_{0.00}, s'_{3.20}) \\ (s_{2.00}, s'_{3.00}) & (s_{0.00}, s'_{3.20}) & (s_{0.00}, s'_{3.80}) & (s_{0.80}, s'_{3.25}) & (s_{0.20}, s'_{1.00}) \\ (s_{3.00}, s'_{3.80}) & (s_{4.00}, s'_{0.80}) & (s_{0.80}, s'_{3.00}) & (s_{0.00}, s'_{3.20}) & (s_{0.00}, s'_{1.60}) \end{bmatrix}.$$

Step 2: According to the opinions of experts, the five customer requirements are sorted in a descending order. As a result, we can determine the newly ranked customer requirements as: $CR'_1 = CR_1$, $CR'_2 = CR_3$, $CR'_3 = CR_4$, $CR'_4 = CR_2$, $CR'_5 = CR_5$.

Step 3: Starting from the second customer requirement, experts are invited to assess the relative importance of the customer requirement CR'_j with respect to the previous cus-

Table 2
Evaluation results provided by the five experts.

Experts	CRs	EC_1	EC_2	EC_3	EC_4	EC_5	EC_6
E_1	CR_1	(s_5, s'_4)	(s_2, s'_4)	(s_3, s'_3)	(s_0, s'_3)	(s_2, s'_3)	(s_3, s'_4)
	CR_2	(s_1, s'_1)	(s_0, s'_1)	(s_4, s'_1)	(s_3, s'_2)	(s_4, s'_2)	(s_4, s'_1)
	CR_3	(s_5, s'_3)	(s_5, s'_3)	(s_1, s'_2)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)
	CR_4	(s_2, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)
	CR_5	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_3, s'_1)	(s_0, s'_1)	(s_0, s'_1)
E_2	CR_1	(s_6, s'_4)	(s_2, s'_4)	(s_3, s'_4)	(s_0, s'_3)	(s_2, s'_3)	(s_3, s'_4)
	CR_2	(s_1, s'_1)	(s_0, s'_1)	(s_4, s'_1)	(s_3, s'_2)	(s_4, s'_2)	(s_4, s'_1)
	CR_3	(s_5, s'_3)	(s_5, s'_3)	(s_1, s'_2)	(s_0, s'_4)	(s_0, s'_4)	(s_1, s'_3)
	CR_4	(s_2, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_1, s'_3)	(s_0, s'_3)
	CR_5	(s_0, s'_2)	(s_1, s'_2)	(s_0, s'_1)	(s_3, s'_1)	(s_0, s'_1)	(s_0, s'_2)
E_3	CR_1	(s_5, s'_4)	(s_2, s'_4)	(s_3, s'_4)	(s_0, s'_3)	(s_2, s'_3)	(s_3, s'_4)
	CR_2	(s_1, s'_1)	(s_0, s'_1)	(s_4, s'_1)	(s_3, s'_2)	(s_4, s'_2)	(s_4, s'_1)
	CR_3	(s_5, s'_3)	(s_5, s'_3)	(s_1, s'_2)	(s_0, s'_4)	(s_0, s'_4)	(s_1, s'_3)
	CR_4	(s_2, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_1, s'_3)	(s_0, s'_3)
	CR_5	(s_0, s'_0)	(s_0, s'_0)	(s_0, s'_1)	(s_3, s'_2)	(s_0, s'_2)	(s_0, s'_1)
E_4	CR_1	(s_5, s'_4)	(s_2, s'_4)	(s_3, s'_4)	(s_0, s'_3)	(s_2, s'_3)	(s_3, s'_3)
	CR_2	(s_1, s'_1)	(s_0, s'_1)	(s_4, s'_0)	(s_3, s'_3)	(s_4, s'_2)	(s_4, s'_1)
	CR_3	(s_6, s'_3)	(s_6, s'_3)	(s_1, s'_2)	(s_0, s'_4)	(s_0, s'_4)	(s_1, s'_3)
	CR_4	(s_2, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_0, s'_3)	(s_1, s'_3)	(s_0, s'_3)
	CR_5	(s_0, s'_2)	(s_1, s'_2)	(s_0, s'_3)	(s_3, s'_3)	(s_0, s'_1)	(s_0, s'_2)
E_5	CR_1	(s_6, s'_4)	(s_2, s'_4)	(s_3, s'_4)	(s_0, s'_3)	(s_2, s'_3)	(s_3, s'_4)
	CR_2	(s_1, s'_1)	(s_0, s'_1)	(s_4, s'_1)	(s_3, s'_2)	(s_4, s'_2)	(s_4, s'_0)
	CR_3	(s_6, s'_4)	(s_5, s'_4)	(s_1, s'_2)	(s_0, s'_4)	(s_0, s'_4)	(s_1, s'_3)
	CR_4	(s_2, s'_3)	(s_0, s'_4)	(s_0, s'_4)	(s_0, s'_4)	(s_1, s'_4)	(s_0, s'_4)
	CR_5	(s_1, s'_2)	(s_1, s'_2)	(s_1, s'_1)	(s_3, s'_1)	(s_1, s'_0)	(s_0, s'_2)

Table 3
Computation results of the SWARA method.

CRs	ρ_j	k_j	q_j	w_j
CR'_1		1.00	1.00	0.47
CR'_2	0.90	1.90	0.53	0.25
CR'_3	0.80	1.80	0.29	0.14
CR'_4	0.50	1.50	0.19	0.09
CR'_5	0.90	1.90	0.10	0.05

tomer requirement CR'_{j-1}. Then the comparative importance ρ_j of CRs is derived as shown in Table 3.

Steps 4–6: Via Eqs. (10)–(12), the CR coefficient k_j $(j = 1, 2, \dots, 5)$, the recalculated CR weights q_j $(j = 1, 2, \dots, 5)$ and the final weights of CRs w'_j $(j = 1, 2, \dots, 5)$ are calculated, respectively. The results are listed in Table 3.

Finally, the weight vector of the five CRs CR_j $(j = 1, 2, \dots, 5)$ is determined as:

$$w = (0.47, 0.09, 0.25, 0.14, 0.05).$$

Table 4
The calculate results using the linguistic Z-EDAS method.

ECs	SP_i	SN_i	$\overline{SP_i}$	$\overline{SN_i}$	IS_i
EC_1	1.45	0.57	1.00	0.69	0.85
EC_2	0.40	1.04	0.28	0.43	0.36
EC_3	0.08	0.70	0.06	0.62	0.34
EC_4	0.26	1.84	0.18	0.00	0.09
EC_5	0.18	1.23	0.12	0.33	0.23
EC_6	0.08	0.65	0.06	0.65	0.35

Step 7: Through Eq. (13), the linguistic average EC ($\mathrm{EC_A}$) is computed as:

$$Z_A = \{(s_{2.57}, s'_{3.79}), (s_{2.67}, s'_{1.23}), (s_{2.07}, s'_{3.10}), (s_{0.47}, s'_{3.07}), (s_{0.70}, s'_{1.57})\}.$$

Step 8: Utilizing Eqs. (14) and (15) the PDA matrix $D^+ = [d^+_{ij}]_{6\times5}$ and the NDA matrix $D^- = [d^-_{ij}]_{6\times5}$ are required as:

$$D^+ = \begin{bmatrix} 1.22 & 0.00 & 1.72 & 3.19 & 0.00 \\ 0.00 & 0.00 & 1.59 & 0.00 & 0.09 \\ 0.17 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.02 & 0.00 & 0.00 & 3.36 \\ 0.00 & 0.71 & 0.00 & 0.81 & 0.00 \\ 0.17 & 0.00 & 0.00 & 0.00 & 0.00 \end{bmatrix},$$

$$D^- = \begin{bmatrix} 0.00 & 2.27 & 0.00 & 0.00 & 0.70 \\ 1.73 & 3.27 & 0.00 & 1.43 & 0.00 \\ 0.00 & 0.07 & 4.40 & 1.43 & 0.90 \\ 9.73 & 0.00 & 6.40 & 1.43 & 0.00 \\ 3.73 & 0.00 & 6.40 & 0.00 & 0.90 \\ 0.00 & 0.07 & 4.00 & 1.43 & 1.10 \end{bmatrix}.$$

Step 9: Based on Eqs. (16) and (17) the weighted sum of PDA and NDA for each EC SP_i $(i = 1, 2, \dots, 6)$ and SN_i $(i = 1, 2, \dots, 6)$ are derived as presented in Table 4.

Step 10: The normalized values of SP_i $(i = 1, 2, \dots, 6)$ and SN_i $(i = 1, 2, \dots, 6)$ for each EC are calculated by Eqs. (18) and (19) The results are displayed in Table 4.

Step 11: Applying Eq. (20) the importance scores for the ECs IS_i $(i = 1, 2, \dots, 6)$ are obtained as shown in Table 4.

According to the descending order of the important scores, the ranking of the considered six ECs is determined as: $EC_1 \succ EC_2 \succ EC_6 \succ EC_3 \succ EC_5 \succ EC_4$. Therefore, the design engineer should pay more attention to EC_1, which is the most important EC for reducing costs and improving customer satisfaction.

Table 5
Sensitivity analysis with different weight values to CRs.

ECs	Case 0	Case 1	Case 2	Case 3
	$w_j = (0.47, 0.09, 0.25, 0.14, 0.05)$	$w_j = (0.2, 0.2, 0.2, 0.2, 0.2)$	$w_j = (0.1, 0.35, 0.1, 0.1, 0.35)$	$w_j = (0.35, 0.35, 0.1, 0.1, 0.1)$
EC_1	1	1	1	1
EC_2	2	2	4	3
EC_3	4	5	5	4
EC_4	6	3	2	6
EC_5	5	6	6	5
EC_6	3	4	3	2

5.2. *Sensitivity Analysis*

In this section, to explore the influence of CRs weights on the obtained results, a sensitivity analysis is conducted by assigning different weight values to CRs. Four cases, as listed in Table 5, are considered in the sensitivity analysis. Case 0 describes the original weights of CRs derived by the SWARA method, and other three cases are different sets of CRs weights in a possible range of value. By using the proposed QFD method, the ranking results for the six ECs in four cases are obtained, as presented in Table 5.

As can be seen from Table 5, the ranking results of the ECs vary with the change of CRs weights. Except for EC_1, the remaining ECs have inconsistent ranking orders in the four cases. In case 0, EC_2 is ranked the second when the weight of CR_1 is the highest and the weight of CR_5 is the lowest. In Case 2, EC_4 is at the second position when the weight of CR_1 is the lowest whereas the weight of CR_5 is the highest. In contrast, EC_6 is the second important engineering characteristic in Case 3. The sensitivity analysis shows that the weights of CRs have a great impact on the final priorities of ECs. Therefore, it is of vital importance to determine suitable CR weights for the ranking of ECs in the practical situations.

5.3. *Comparative Analysis*

To verify the effectiveness of our developed QFD model, a comparative analysis is performed with the probabilistic linguistic ORESTE (PL-ORESTE) method (Wu and Liao, 2018), the hesitant fuzzy VIKOR (HF-VIKOR) method (Wu *et al.*, 2016) and the classical EDAS method (Ghorabaee *et al.*, 2015). The ranking results of the six ECs derived by the considered methods are exhibited in Fig. 2. It can be observed from Fig. 2 that the most vital EC for the considered problem remains the same (i.e. EC_1) for the proposed method and the other three methods. Thus, the proposed QFD model is validated.

There are some differences between the ranking results derived by the proposed method and the PL-ORESTE method. Apart from EC_1 and EC_4, the ranking orders for the other ECs obtained by the proposed method are different from those by the PL-ORESTE method. The big difference happens in EC_6, which ranks the third, in the proposed model. Nevertheless, based on the PL-ORESTE, EC_6 ranks in the fifth position. This difference

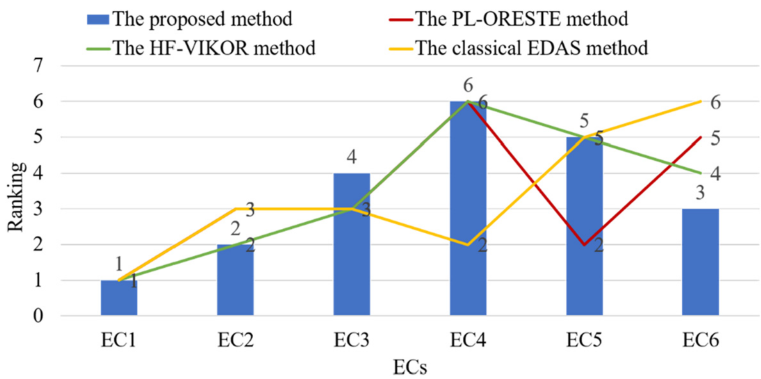

Fig. 2. The EC ranking results of comparative analysis.

can be attributed to the fact that the PL-ORESTE does not consider the reliability of the evaluation information provided by experts, which results in the distortion of initial information. Moreover, EC_5 is the second critical EC with the PL-ORESTE method, while by using the proposed QFD, it ranks in the fifth position. Giving the fifth position to EC_5 can also be validated by the HF-VIKOR and the classical EDAS methods.

The ranking orders of EC_3 and EC_6 determined by the HF-VIKOR are different from those yielded by the proposed method. More specifically, EC_6 is ranked behind EC_3 according to the HF-VIKOR method. However, in the reality, the former is more important, because it has a higher comfortability. Thus, the result of the proposed model is more reasonable, which suggests that EC_6 has a higher priority in comparison with EC_3.

In comparison to the classical EDAS method, the proposed method gives different ranking orders for EC_2, EC_3, EC_4 and EC_6. These differences can be explained by the different evaluation and prioritization mechanisms of the two methods. First, crisp values are utilized by experts to evaluate the relationships between ECs and CRs. It is not efficient to express the uncertain and fuzzy evaluation information provided by experts. Second, the classical EDAS method determines the ranking orders of ECs based on the EDAS algorithm, while the proposed model obtains the prioritization of ECs based on the linguistic Z-EDAS method.

5.4. *Managerial Implications*

Considering the findings related to this study, the proposed QFD model has some practical implications for engineers to design new products for reducing costs and improving customer satisfaction. First, the proposed model is performed in the uncertain linguistic environment where experts can flexibly and conveniently evaluate ECs by using linguistic rating. In this way, the proposed model can offer a convenient and flexible technique to obtain more comprehensive and reliable evaluation information about ECs in real-world application. Second, the SWARA method, a powerful weighting method, is adopted to derive the weights of CRs in the proposed QFD. Via this method, the proposed model is able to obtain a more reasonable weights of CRs easily, since expert's opinions about the importance ratios of CRs are taken into account. Finally, an extended EDAS method is employed to determine the ranking orders of ECs in QFD. Hence, the proposed approach can derive a more credible and reasonable ranking of ECs with a straightforward computational procedure, and help product engineers get a final solution efficiently.

6. Conclusions

In this paper, we presented a novel systematic QFD method based on linguistic Z-numbers and EDAS method to improve the performance of QFD. First, linguistic Z-numbers were used by experts to assess the relationships between ECs and CRs. Second, an extended EDAS method was proposed to determine the prioritization of ECs. Besides, the SWARA method was adopted to derive the weights of CRs. Finally, the effectiveness and reliability of the proposed method were testified by a shared cars' product design case. The results indicate that the proposed QFD model can not only represent experts' interrelation evaluation information flexibly, but also produce a more reasonable and reliable prioritization of ECs in QFD.

Future studies will focus on the following aspects. First, the relationships among ECs are not considered in the proposed QFD model. Thus, in future research, effort can be devoted to incorporate the correlations among ECs into the proposed QFD. Second, in practice, there are some situations in which the weight information of CRs is completely unknown. Hence, the extension of the proposed model can be developed to solve the QFD problems with unknown CR weights. Lastly, an intelligent information system can be constructed to help product managers and designers to reduce the task of QFD analysis in real-life applications.

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