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A Multi-Granularity 2-Tuple QFD Method and Application to Emergency Routes Evaluation

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Abstract: Quality function deployment (QFD) is an effective approach to satisfy the customer requirements (*CRs*). Furthermore, accurately prioritizing the engineering characteristics (*ECs*) as the core of QFD is considered as a group decision making (GDM) problem. In order to availably deal with various preferences and the vague information of different experts on a QFD team, multi-granularity 2-tuple linguistic representation is applied to elucidate the relationship and correlation between *CRs* and *ECs* without loss of information. In addition, the importance of *CRs* is determined using the best worst method (BWM), which is more applicable and has good consistency. Furthermore, we propose considering the relationship matrix and correlation matrix method to prioritize *ECs*. Finally, an example about evaluating emergency routes of metro station is proposed to illustrate the validity of the proposed methodology.

Keywords: quality function deployment; engineering characteristics; group decision making; 2-tuple; metro station; emergency routes

1. Introduction

In order to cope with intense global competitions, enterprises must design the highest quality products that satisfy the voice of customers (VOCs). Quality function deployment (QFD) is an effective method to map customer requirements (*CRs*) into engineering characteristics (*ECs*) in the area of product development [1] and construction industry [2]. The core of QFD is requirements conversion, moreover, the first phase in house of quality (HOQ) mapping *CRs* to *ECs* becomes an essential procedure of implementing QFD [3].

Aiming at implementing QFD successfully, plenty of *CRs* should be acquired, and group decision making (GDM) should be adopted [4]. QFD consists of two major steps: collecting the *CRs* and mapping it to *ECs*, both of which are performed [5,6]. This paper focuses on how the *ECs* in QFD can be prioritized.

There are plenty of methods to prioritize the *ECs*. Fuzzy set theory was widely employed to calculate the rankings of *ECs* under the circumstance of vagueness and impreciseness. Fuzzy multiple objective programming [7], fuzzy goal programming [8], fuzzy relationship and correlations [9], and expected value-based method [10] are proposed to prioritize *ECs*. In addition, Geng et al. [11] integrated the analytic network process to QFD to reflect the initial importance weights of *ECs*. However, the problem is that they paid little attention to the GDM method, which can aggregate different experts' preferences. For the purpose of reaching collective decisions, we combine GDM with QFD.

Kwong et al. [6] put forward the fuzzy GDM method integrated with a fuzzy weighted average to rank *ECs*. Wang [12] adopted the method of aggregating technical importance rather than *CRs* to prioritize *ECs*. With respect to consensus, modified fuzzy clustering was presented so as to reach the consensus of the QFD team [13]. A two-stage GDM was proposed to simultaneously solve the two types of uncertainties (i.e., human assessment on qualitative attributes as well as input information) underlying QFD [4]. However, due to varying personal experience and knowledge, the input information of experts presented with multi-format or multi-granular linguistic preferences makes prioritizing *ECs* more difficult. Therefore, some scholars have focused on the GDM approach based on multi-granularity linguistic environments [14–17]. Xu [18,19] analyzed multiple formats' preferences and provided an approach integrating information in the context of GDM. It is noteworthy that multi-granularity evaluation should be analyzed.

The correlation between *CRs* and *ECs* influencing on the relationship becomes ignored and simplified in the current study. In addition, the linguistic accuracy remains to be discussed. Considering that the 2-tuple linguistic representation can increase the information of precision [20,21]. In order to fill the gap, it is necessary that the QFD methodology is extended with a 2-tuple linguistic environment so as to lessen the loss of information and obtain accurate value of *ECs*. In addition, decision makers may have different knowledge and experience in the process of group decision making, and they may then adopt different linguistic labels to describe the same decision-making problems. This process is denoted as multi-granular linguistic information, which conforms to the actual decision-making process. Therefore, we allow decision makers to employ multi-granular linguistic information, i.e., the linguistic term set has different granularities.

A majority of methods deal with multi-granular linguistic information. Herrera et al. proposed the definition of a basic linguistic term set, and then different linguistic labels can be unified based on a basic linguistic term set [22]. In addition, some transformation methods based on the linguistic hierarchy and extended linguistic hierarchy were presented and applied to a plenty of decision-making problems [23,24]. Among these approaches, the method considering linguistic hierarchy is more flexible and convenient to carry out. In this paper, we adopt this method to deal with the problem of multi-granular linguistic evaluation. For determining the weight of *CRs*, we adopt the best–worst method (BWM) in this paper. This method has good consistency and is easier to implement [25,26]. Our contributions lie in using the BWM to determine the importance of *CRs* and integrate the correlations matrix with the relationship matrix based on a compromise idea, where experts can express their thoughts in different granularities.

In this paper, a GDM approach is integrated with QFD to solve different preferences and prioritize *ECs*. The multi-granularity 2-tuple linguistic information to reflect the attitudes of different experts is employed. This paper is organized as follows: In Section 2, a 2-tuple multi-granularity linguistic representation model, linguistic hierarchies, and a 2-tuple linguistic weighted geometric Bonferroni mean (2TLWGBM) operator are presented. In Section 3, the BWM is applied to compute the weight of *CRs*, and a novel GDM approach to prioritize *ECs* is proposed. An illustrated example about metro stations is provided in Section 4 to demonstrate the applicability of this method. Ultimately, conclusions and future research are marked in Section 5.

2. Preliminaries

In this section, we introduce some basic knowledge about QFD, 2-tuple representation and the 2TLWGBM Operator.

2.1. The Basic Knowledge on QFD

A four-phase QFD model is employed to translate the VOCs to *ECs*, which consists of Product Planning, Part Deployment, Process Planning, and Process and Quality control [3]. The first phase is to collect customer requirements for the product called WHATs and then to transform these needs into *ECs* called HOWs. This phase is so fundamental in product development that the corresponding QFD transformation matrix referred to the HOQ (Figure 1). The HOQ links customer needs to the development team's technical responses, so we focus on this phase in order to translate different preference of customers and experts to prioritize *ECs*. In this paper, we first take the relationship between *CRs* and *ECs* into consideration. In order to transform the importance of *CRs* into *ECs*, the correlation of *CRs* and *ECs* is introduced to modify the initial relationship afterward.

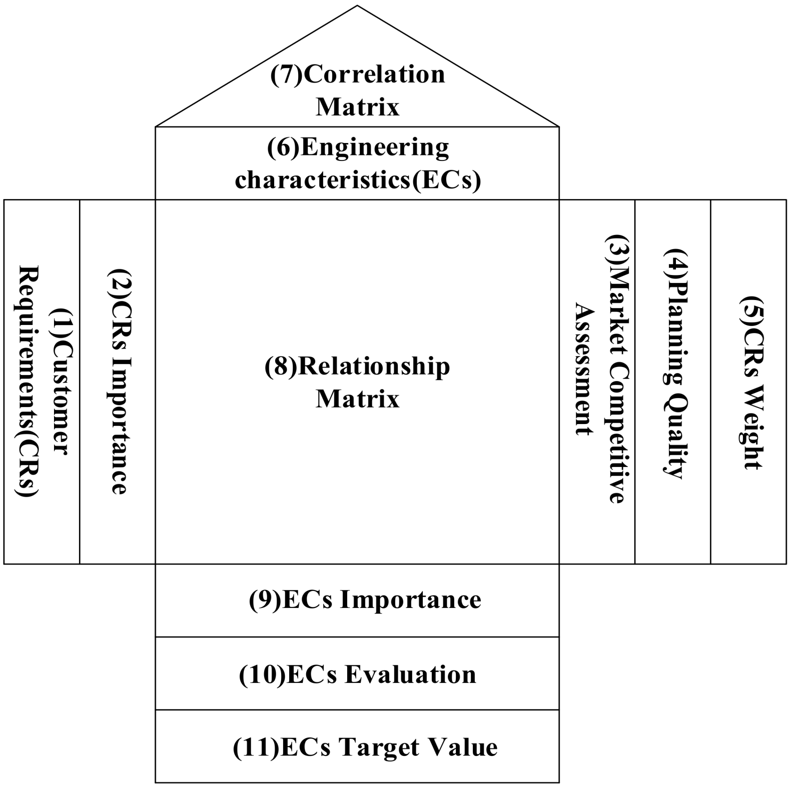


Figure 1. House of Quality (HOQ).

2.2. The 2-Tuple Linguistic Representation

There are numerous formats for representing preference such as linguistic, numerical and 2-tuple linguistic representation. Compared with other forms, 2-tuple linguistic representation makes the assessment more precise and without a loss of information [20]. Next, we will introduce some basic knowledge about 2-tuple representation.

Definition 1 [27]. *Assuming $S = \{s_1, s_2, \cdots, s_g\}$ is a linguistic term set and $\beta \in [0, g]$* represents the consequence of a symbolic aggregation operation. Afterwards, the 2-tuple is expressed as the equivalence to β as follows:

$$\Delta : [0, g] \to S \times [-0.5, 0.5) \tag{1}$$

$$\Delta(\beta) = (s_i, \alpha), \text{ with} \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha = [-0.5, 0.5) \end{cases} \tag{2}$$

where round $(\cdot)$ represents the usual round function, s_i has the closest index label to β, and α is the value of the symbolic translation.

Definition 2 [27]. *Let $S = \{s_1, s_2, \cdots, s_g\}$ be a linguistic term set and (s_i, α_i) be a 2-tuple. There is always a function Δ^{-1} that can be defined, such that, from a 2-tuple (s_i, α_i), its equivalent numerical value $\beta \in [0, g] \subset R$* can be obtained, which is described as follows:

$$\Delta^{-1} :\to S \times [-0.5, 0.5) \to [0, g] \tag{3}$$

$$\Delta^{-1}(s_i, \alpha_i) = i + \alpha_i = \beta \tag{4}$$

Definition 3 [28]. *There are 2-tuples $x = \{(s_1, \alpha_1), (s_2, \alpha_2), \cdots, (s_n, \alpha_n)\}$.* Their arithmetic mean is expressed as:

$$(\bar{s}, \bar{\alpha}) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n} \Delta^{-1}(r_i, \alpha_i)\right), \quad \bar{s} \in S, \quad \bar{\alpha} \in [-0.5, 0.5) \tag{5}$$

Definition 4 [28]. *Let (s_i, α_i) and (s_j, α_j) be two 2-tuple linguistic variables. Their granularities are both g,* and the distance between them is described as follows:

$$d((s_i, \alpha_i), (s_j, \alpha_j)) = \frac{\left|\Delta^{-1}(i + \alpha_i) - \Delta^{-1}(j + \alpha_j)\right|}{g} \tag{6}$$

Definition 5 [28]. *Let $x = \{(s_1, \alpha_1), (s_2, \alpha_2), \cdots, (s_n, \alpha_n)\}$ be a set of 2-tuples and $(\bar{s}, \bar{\alpha})$* be the arithmetic mean of these 2-tuples. The degree of similarity is expressed as

$$\text{sim}((s_{\pi(j)}, \alpha_{\pi(j)}), (\bar{s}, \bar{\alpha})) = 1 - \frac{d((s_{\pi(j)}, \alpha_{\pi(j)}), (\bar{s}, \bar{\alpha}))}{\sum\limits_{j=1}^{n} d((s_{\pi(j)}, \alpha_{\pi(j)}), (\bar{s}, \bar{\alpha}))}, \quad j = 1, 2, \cdots, n \tag{7}$$

Definition 6 [23]. *Let $LH = \bigcup\limits_t l(t, n(t))$, which is the union of all level t, a linguistic hierarchy whose linguistic term set is $S^{n(t)} = \left\{s_0^{n(t)}, s_1^{n(t)}, \cdots, s_{n(t)-1}^{n(t)}\right\}$.* Furthermore, different granularities reflect different preferences under the circumstance of evaluating. The transformation function (TF) between level t *and level* $t\prime$ is defined as

$$\begin{gathered} TF_{t\prime}^{t} : l(t, n(t)) \to l(t\prime, n(t\prime)) \\ TF_{t\prime}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t\prime) - 1)}{n(t) - 1}\right) \end{gathered} \tag{8}$$

where t and $t\prime$ represent different levels of linguistic hierarchy.

Note 1. The TF can implement the transformation between different granularities and further achieve a unified linguistic label. Without loss of generality, the transformation usually is carried out from the lower granularity to higher granularity in the process of transformation, i.e., the level $t\prime$ usually corresponds to the maximum granularity.

2.3. The 2TLWGBM Operator

There are numerous operators to aggregate information in different linguistic environments, such as hesitant fuzzy Maclaurin symmetric mean Operators [29], 2-tuple linguistic Muirhead mean operators [30], 2-tuple linguistic Neutrosophic number Bonferroni mean operators [31], and hesitant 2-tuple linguistic prioritized weighted averaging aggregation operator [32] in the context of the 2-tuple environment. In view of the Bonferroni mean (BM) operator capturing the interrelationship between input information and ranking *ECs* under a 2-tuple environment, so the 2TLWGBM operator [33] will be applied to prioritize the sequence of *ECs*. BM is defined as follows:

Definition 7 [33]. *Let $p, q \geq 0$ and $a_i (i = 1, 2, \cdots, n)$ be a series of non-negative numbers. Then the BM operator is defined as*

$$BM^{p,q}(a_1, a_2, \cdots, a_n) = \left(\frac{1}{n(n-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{n} a_i^p a_j^q\right)^{\frac{1}{p+q}} \tag{9}$$

Definition 8 [33]. *Let $\mathbf{x} = \{(r_1, a_1), (r_2, a_2), \cdots, (r_n, a_n)\}$ be a set of 2-tuple and $p, q \geq 0$. In addition, $\mathbf{w} = (w_1, w_2, \cdots, w_n)^T$ is the weight vector of $\mathbf{x}$, where $w_i > 0\, (i = 1, 2, \cdots, n)$ represents the importance degree of $(r_i, a_i)\, (i = 1, 2, \cdots, n)$, and $\sum_{i=1}^{n} w_i = 1$.* The 2TLWGBM operator is then expressed as

$$2TLWGBM_w^{p,q}((r_1,a_1),(r_2,a_2),\cdots,(r_n,a_n)) = \Delta\left(\frac{1}{p+q}\left(\prod_{\substack{i,j=1\\ i\neq j}}^{n}\left(p\left(\Delta^{-1}(r_i,a_i)\right)^{w_i}+q\left(\Delta^{-1}(r_j,a_j)\right)^{w_j}\right)\right)^{\frac{1}{n(n-1)}}\right) \tag{10}$$

For the sake of simplicity, it can be set $p = q = 1$, the aggregation operator is indicated as

$$2TLWGBM_w^{1,1}((r_1,a_1),(r_2,a_2),\cdots,(r_n,a_n)) = \Delta\left(\frac{1}{2}\left(\prod_{\substack{i,j=1\\ i\neq j}}^{n}\left(\left(\Delta^{-1}(r_i,a_i)\right)^{w_i}+\left(\Delta^{-1}(r_j,a_j)\right)^{w_j}\right)\right)^{\frac{1}{n(n-1)}}\right) \tag{11}$$

Note 2. Although a majority of aggregation operators have been proposed in recent years, the 2TLWGBM operator has some merits in prioritizing *ECs*. On the one hand, this operator considers the relevance, which accords with the relationship and correlation between *CRs* and *ECs*. On the other hand, it is more flexible owing to the parameter p and q, which makes it more suitable for different decision makers.

3. A Group Decision-Making Approach to Prioritize *ECs*

3.1. Determine the Importance of CRs Based on BWM

Best worst method (BWM) is a MCDM method possessing the advantages in aspects of reaching the consistency and simplifying the calculation with respect to AHP. The core idea of BWM is constructing comparisons relationships between the best attribute (and the worst attribute) to the other attributes. Additionally, an optimization model established ground on consistency is solved to obtain the optical weights. Owing to simple operation and calculation, the BWM is synthesized to determine the importance of *CRs*. The steps are listed as follows:

Step 1. *CRs* $\{CR_1, CR_2, \cdots, CR_n\}$ are chosen, as are the best and the worst CR. The best CR is then compared with the other *CRs* using Number 1–9 is constructed. The best-to-others (BO) vector A_B = (α_{B1}, α_{B2}, $\cdots$, α_{Bn}) is represented where α_{Bj} describes the preference of the best CR over CR_j. Similarly, the Others-to-worst (OW) vector A_W = $(\alpha_{1W}, \alpha_{2W}, \cdots, \alpha_{nW})^{\mathrm{T}}$ is represented where α_{jW} describes the preference of CR_j over the worst CR.

Step 2. The optimal weights of *CRs* are obtained. The optimization model is established to minimize the maximum the difference $\{\,|\, w_B - \alpha_{Bj}\, w_j \,|\,\}$ and $\{\,|\, w_j - \alpha_{jW}\, \omega_W \,|\,\}$.

$$\begin{aligned} &\min\max{}_j\left\{\left|w_B - a_{Bj}w_j\right|,\left|w_j - a_{jW}w_W\right|\right\}\\ &s.t.\sum_j w_j = 1 \qquad\qquad \text{(Model 1)}\\ &w_j \geq 0,\ j = 1,2,\cdots,n \end{aligned}$$

Model 1 can be transformed into a linear programming model as follows:

$$
\begin{aligned}
& \min \xi \\
& s.t. \left| w_B - a_{Bj} w_j \right| \le \xi,\ j = 1, 2, \cdots, n \\
& \left| w_j - a_{jW} w_W \right| \le \xi,\ j = 1, 2, \cdots, n \quad \text{(Model 2)} \\
& \sum_j w_j = 1 \\
& w_j \ge 0,\ j = 1, 2, \cdots, n
\end{aligned}
$$

Model 2 is solved to obtain the optimal importance of *CRs* ($w_1^*, w_2^*, \cdots, w_n^*$) and ξ^*. Alternatively, the bigger ξ^* demonstrates the higher consistency ratio provided by customers. The consistency ratio can be calculated by the proportion between ξ^* and max ξ (Consistency Index).

$$
\text{Consistency Ratio} = \frac{\xi^*}{\max \xi} = \frac{\xi^*}{\text{Consistency Index}} \tag{12}
$$

where the max ξ is determined according to $(\alpha_{BW} - \xi) \times (\alpha_{BW} - \xi) = (\alpha_{BW} + \xi)$ and $\alpha_{BW} \in \{1, 2, \cdots, 9\}$. The consistency index is listed in Table 1.

Table 1. Consistency index.

α_{BW}	1	2	3	4	5	6	7	8	9
Consistency index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

3.2. A Group Decision-Making Approach to Prioritize ECs

In this section, the steps of GDM for multi-granularity 2-tuple linguistic preference to prioritize *ECs* in QFD are given as follows:

Step 3. Different multi-granularity linguistic preferences are obtained.

Suppose the experts $EP_k\,(k = 1, 2, \cdots, t)$ in QFD product research or design team give the relationship between $CR_i(i = 1, 2, \cdots, n)$ and $EC_j(j = 1, 2, \cdots, s)$ based on different multi-granularities. The *k*th expert's linguistic term set and evaluation matrix respectively denoted as $S^{n(t)_k} = \left\{ s_i^{n(t)_k} | i = 0, 1, \cdots, n(t) - 1 \right\}$ and $R^k = \left(r_{ij} \right)_{n \times s} r_{ij} \in S^{n(t)_k}$, which is transformed into 2-tuple linguistic evaluation matrix $\widetilde{R}^k = \left(r_{ij}^{n(t)_k}, 0 \right)_{n \times s}, r_{ij}^{n(t)_k} \in S^{n(t)_k}$.

Step 4. Different multi-granularity linguistic preferences are unified.

To begin with, a basic linguistic term set $S^{n(t)_u} = \left\{ s_i^{n(t)_u} | i = 0, 1, \cdots, n(t) - 1 \right\}$ can be chosen, and the relationship matrix can then be transformed applying Equation (8) so as to make 2-tuple linguistic representation reach the same granularity. For instance, the *k*th expert's judgement matrix is transformed as $\widetilde{R}^{k\prime} = \left(r_{ij}^{n(t)_u}, \alpha_{ij}^{n(t)_u} \right)_{n \times s}, r_{ij}^{n(t)_u} \in S^{n(t)_u}$.

Step 5. All the evaluation matrices are aggregated.

All the evaluation matrices uniformed are aggregated with 2TLWGBM operator in virtue of Equation (10) into $R_{ij}(i = 1, 2, \cdots, n; j = 1, 2, \cdots, s)$. Furthermore, the new matrix represents ultimate relationship matrix between *CRs* and *ECs* in essence.

Step 6. The relationship between *CRs* and *ECs* is modified based on a compromise idea.

After establishing the aggregation matrix, experts give the correlations among *CRs* and *ECs* and the initial HOQ can be obtained, which reflects the relationship R_{ij} between CR_i and

EC_j,$i = 1, 2, \cdots, n$; $j = 1, 2, \cdots, s$.It is indispensable that the QFD team estimates the correlations between *CRs* (i.e., $L_{i\xi}(\xi \neq i, \xi = 1, 2, \cdots, n)$) and *ECs* (i.e., $T_{i\theta}(\theta \neq i, \theta = 1, 2, \cdots, s)$) using 2-tuple based on the basic linguistic set $S_i^{n(t)_u}$. Considering that the assessment result of $L_{i\xi}(\xi \neq i, \xi = 1, 2, \cdots, n)$ and $T_{i\theta}(\theta \neq i, \theta = 1, 2, \cdots, s)$ has an effect on the initial aggregation matrix of relationship R_{ij} with respect to *CRs* and *ECs*, a higher $L_{i\xi}(\xi \neq i, \xi = 1, 2, \cdots, n)$ or $T_{i\theta}(\theta \neq i, \theta = 1, 2, \cdots, s)$ implies a benefit to R_{ij}. Consequently, the correlations are taken into account when modifying the relationships between *CRs* and *ECs*. In the process of adjustment, Equation (13) is applied to integrate $L_{i\xi}(\xi \neq i, \xi = 1, 2, \cdots, n)$ and $T_{i\theta}(\theta \neq i, \theta = 1, 2, \cdots, s)$ into R_{ij}. Furthermore, the modified relationship is computed using the formula as follows:

$$R'_{ij} = \Delta\left(\prod_{v=1}^{V} \Delta^{-1}(s_m, \alpha_m)^{\gamma_v}\right), i = 1, 2, \cdots, n; j = 1, 2, \cdots, s \tag{13}$$

where $\Delta^{-1}(r_m, a_m)$ is stemming from the set $S = \left\{\Delta^{-1}R_{ij}(r_{ij}^{n(t)_u}, \alpha_{ij}^{n(t)_u}), \Delta^{-1}L_{i\xi}\left(r_{i\xi}^{n(t)_u}, \alpha_{i\xi}^{n(t)_u}\right), \Delta^{-1}T_{j\theta}(r_{j\theta}^{n(t)_u}, \alpha_{j\theta}^{n(t)_u})\right\}$ $\xi \neq i, \theta \neq j$. In addition, the weight of γ_v is corresponding to the proportion of $\Delta^{-1}(r_m, a_m)$. For the sake of reducing the impact from subjectivity, unduly high or unduly low preference values in the correlation matrices are supposed to possess a low weight under the circumstances. That means only moderated assessment giving a higher weight has a small deviation from the true value, which might be advocated in the process of evaluation. Therefore, the weight can be determined by Equation (14).

$$\gamma_v = \frac{\mathrm{sim}((s_m, \alpha_m), (\bar{s}, \bar{\alpha}))}{\sum\limits_{v=1}^{V} sim((s_m, \alpha_m), (\bar{s}, \bar{\alpha}))} \tag{14}$$

Step 7. Integrated *ECs* priorities are determined.

On account of the inconformity of representation, the 2-tuple linguistic form of the relationship matrix, and the numerical value of *CRs* importance, the integrated *ECs* priority $S_{TC_j}(j = 1, 2, \cdots, s)$ is calculated by Equation (11).

Step 8. Basic priority of ECs is confirmed.

The linguistic distance $d((s_{TC_j}^{n(t)}, \alpha^{n(t)})(s_{\min}^{n(t)}, \alpha^{n(t)}))$ can be adopted to measure the importance degree, where $(s_{\min}^{n(t)}, \alpha^{n(t)})$ is the minimum value of linguistic term set. Furthermore, the measurement of 2-tuple linguistic distance decides the importance of $EC_j(j = 1, 2, \cdots, s)$. Therefore, the normative value of basic priority bpr_j is computed as follows:

$$bpr_j = \frac{d((s_{EC_j}^{n(t)}, \alpha^{n(t)})(s_{\min}^{n(t)}, \alpha^{n(t)}))}{\sum\limits_{j=1}^{s} d((s_{EC_j}^{n(t)}, \alpha^{n(t)})(s_{\min}^{n(t)}, \alpha^{n(t)}))} \tag{13}$$

Step 9. End.

The flow chart of the whole procedures is shown in Figure 2.

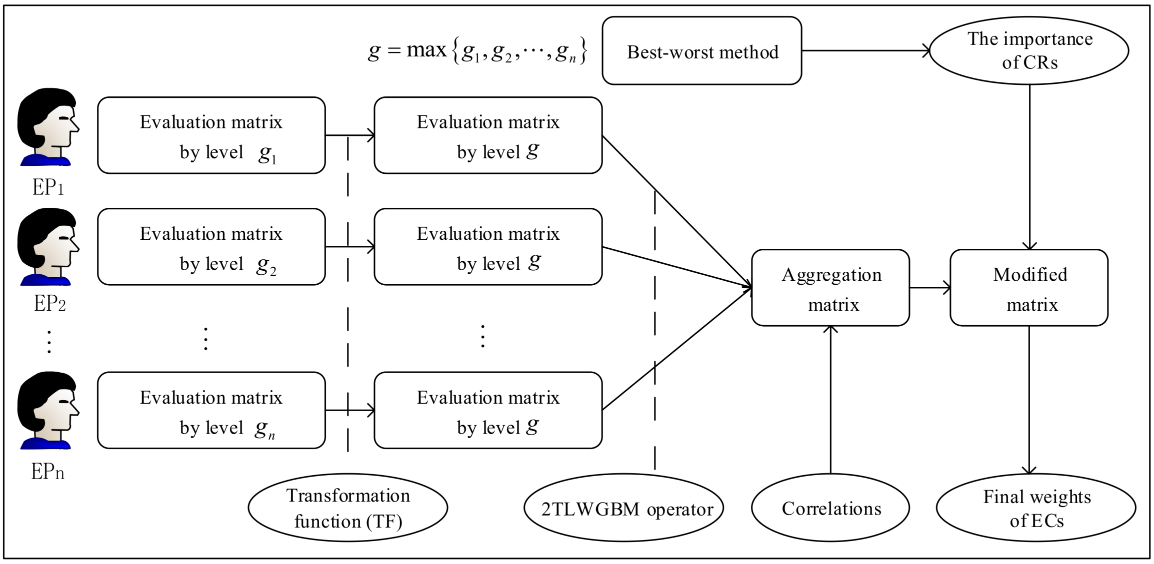
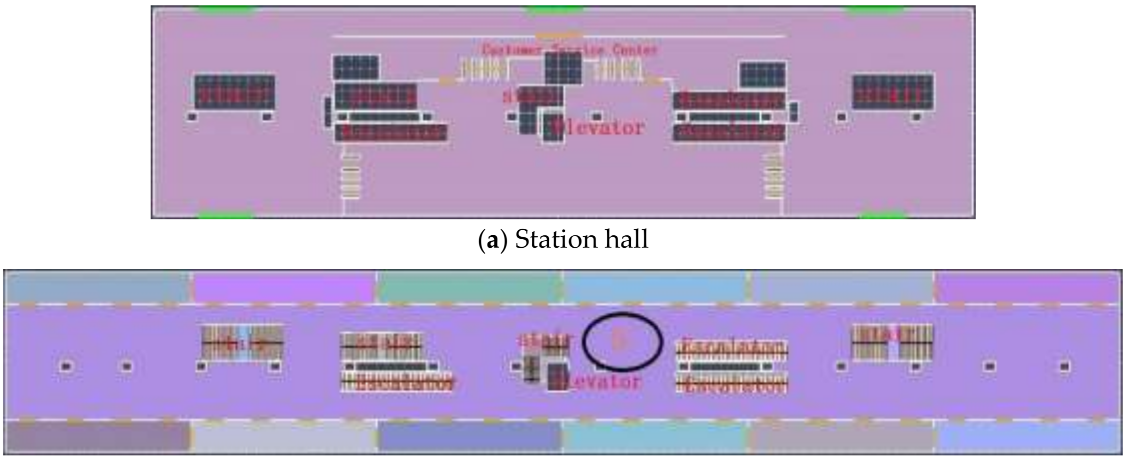


Figure 2. Group decision making for multi-granularity 2-tuple linguistic preference to prioritize engineering characteristics in quality function deployment.

4. Case Study

4.1. Background

The Wuhan metro station is the most common two-floor island structure, which consists mainly of a platform and a station hall. The underground floor is the station hall floor. As shown in Figure 3, the metro station has four main exits and one reserved outlet for docking with the shopping mall and fire curtains are installed at each exit. Therefore, when a crowd passes through the fire curtain in the emergency evacuation process, they have reached the safe area. The station hall floor has four automatic ticket checkers and two emergency dedicated channels. In emergency situations, an automatic ticket checking machine and emergency dedicated channels are in open state. The second underground floor is the platform layer. When an emergency occurs on the platform layer, the crowd must first ascend to the station hall layer and then evacuate through the safety exit.



(**a**) Station hall

(**b**) Platform

Figure 3. The structure of metro station in Wuhan.

Taking regional *S* as an example, we analyze the influence factors that have an effect on the evacuation route planning in this area. Five *CRs* and *ECs* are selected in order to determine the weight degree of *ECs*, which can be a basic of evaluating emergency routes.

$CR_1:$ Expected evacuation time $EC_1:$ Number of evacuees per unit time
$CR_2:$ Crowd density $EC_2:$ Managerial capability
$CR_3:$ Risk level in the region $EC_3:$ Risk level of disaster
$CR_4:$ Possibility of congestion $EC_4:$ Organizational situation
$CR_5:$ Evacuation capability $EC_5:$ Evacuation equipment

4.2. Implementation

Step 1. The evaluation *CRs* relationships by passengers are shown in Tables 2 and 3.

Table 2. Best-to-others (BO) vector for passengers.

Passengers	Best	CR_1	CR_2	CR_3	CR_4	CR_5
1	CR_2	3	1	5	9	7
2	CR_2	5	1	4	9	8
3	CR_1	1	2	7	5	9
4	CR_3	4	3	1	7	9
5	CR_1	1	3	9	6	8

Table 3. Others-to-worst (OW) vector for passengers.

Passengers	1	2	3	4	5
Worst	CR_4	CR_4	CR_5	CR_5	CR_3
CR_1	6	4	9	4	9
CR_2	9	9	8	7	7
CR_3	5	7	2	9	1
CR_4	1	1	5	2	6
CR_5	4	3	1	1	3

Step 2. The importance of *CRs* is respectively computed as 0.302, 0.359, 0.187, 0.082 and 0.070, which is determined by the average value by passengers. For example, the model by first passenger is established as follows:

$$
\begin{aligned}
& \min \xi \\
& s.t.\ |w_2 - 3w_1| \leq \xi, |w_2 - 5w_3| \leq \xi, \\
& |w_2 - 9w_4| \leq \xi, |w_2 - 7w_5| \leq \xi, \\
& |w_1 - 6w_4| \leq \xi, |w_3 - 5w_4| \leq \xi, \\
& |w_5 - 4w_4| \leq \xi, \sum_{5} w_j = 1, \\
& w_j \geq 0,\ j = 1, 2, \cdots, 5.
\end{aligned}
$$

The parameter ξ is obtained as 0.12, and the consistency ratio can be then computed using Equation (12) as 0.023, which indicates it has good consistency.

Step 3. In order to determine the basic priority of these *ECs*, three experts EP_1, EP_2, EP_3 evaluate the importance of *ECs* according to *CRs* given as below (Tables 4–6). They represent preference by using the different linguistic term sets $S_i^{7_1} = \{s_0^7, s_1^7, s_2^7, s_3^7, s_4^7, s_5^7, s_6^7\}$ $S_i^{5_2} = \{s_0^5, s_1^5, s_2^5, s_3^5, s_4^5\} S_i^{9_3} = \{s_0^9, s_1^9, s_2^9, s_3^9, s_4^9, s_5^9, s_6^9, s_7^9, s_8^9\}$.

Table 4. Evaluation matrix R^1 for EP_1.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$s_5^{7_1}$	$s_6^{7_1}$	$s_0^{7_1}$	$s_4^{7_1}$	$s_0^{7_1}$
CR_2	$s_1^{7_1}$	$s_5^{7_1}$	$s_1^{7_1}$	$s_3^{7_1}$	$s_4^{7_1}$
CR_3	$s_2^{7_1}$	$s_4^{7_1}$	$s_4^{7_1}$	$s_1^{7_1}$	$s_1^{7_1}$
CR_4	$s_3^{7_1}$	$s_5^{7_1}$	$s_1^{7_1}$	$s_6^{7_1}$	$s_5^{7_1}$
CR_5	$s_1^{7_1}$	$s_4^{7_1}$	$s_1^{7_1}$	$s_4^{7_1}$	$s_5^{7_1}$

Table 5. Evaluation matrix R^2 for EP_2.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$s_3^{5_2}$	$s_4^{5_2}$	$s_0^{5_2}$	$s_3^{5_2}$	$s_1^{5_2}$
CR_2	$s_1^{5_2}$	$s_3^{5_2}$	$s_2^{5_2}$	$s_2^{5_2}$	$s_3^{5_2}$
CR_3	$s_1^{5_2}$	$s_2^{5_2}$	$s_3^{5_2}$	$s_1^{5_2}$	$s_1^{5_2}$
CR_4	$s_2^{5_2}$	$s_3^{5_2}$	$s_1^{5_2}$	$s_4^{5_2}$	$s_3^{5_2}$
CR_5	$s_0^{5_2}$	$s_3^{5_2}$	$s_1^{5_2}$	$s_2^{5_2}$	$s_3^{5_2}$

Table 6. Evaluation matrix R^3 for EP_3.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$s_6^{9_3}$	$s_8^{9_3}$	$s_1^{9_3}$	$s_5^{9_3}$	$s_0^{9_3}$
CR_2	$s_2^{9_3}$	$s_7^{9_3}$	$s_2^{9_3}$	$s_6^{9_3}$	$s_6^{9_3}$
CR_3	$s_0^{9_3}$	$s_6^{9_3}$	$s_6^{9_3}$	$s_2^{9_3}$	$s_4^{9_3}$
CR_4	$s_3^{9_3}$	$s_7^{9_3}$	$s_2^{9_3}$	$s_8^{9_3}$	$s_6^{9_3}$
CR_5	$s_1^{9_3}$	$s_7^{9_3}$	$s_1^{9_3}$	$s_7^{9_3}$	$s_7^{9_3}$

Step 4. Three evaluation matrices are transformed into 2-tuple representation in Tables 7–9.

Table 7. 2-tuple linguistic evaluation matrix $\widetilde{R}^1$ for EP_1.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$(s_5^{7_1}, 0)$	$(s_6^{7_1}, 0)$	$(s_0^{7_1}, 0)$	$(s_4^{7_1}, 0)$	$(s_0^{7_1}, 0)$
CR_2	$(s_1^{7_1}, 0)$	$(s_5^{7_1}, 0)$	$(s_1^{7_1}, 0)$	$(s_3^{7_1}, 0)$	$(s_4^{7_1}, 0)$
CR_3	$(s_2^{7_1}, 0)$	$(s_4^{7_1}, 0)$	$(s_4^{7_1}, 0)$	$(s_1^{7_1}, 0)$	$(s_1^{7_1}, 0)$
CR_4	$(s_3^{7_1}, 0)$	$(s_5^{7_1}, 0)$	$(s_1^{7_1}, 0)$	$(s_6^{7_1}, 0)$	$(s_5^{7_1}, 0)$
CR_5	$(s_1^{7_1}, 0)$	$(s_4^{7_1}, 0)$	$(s_1^{7_1}, 0)$	$(s_4^{7_1}, 0)$	$(s_5^{7_1}, 0)$

Table 8. 2-tuple linguistic evaluation matrix $\widetilde{R}^2$ for EP_2.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$(s_3^{5_2}, 0)$	$(s_4^{5_2}, 0)$	$(s_0^{5_2}, 0)$	$(s_3^{5_2}, 0)$	$(s_1^{5_2}, 0)$
CR_2	$(s_1^{5_2}, 0)$	$(s_3^{5_2}, 0)$	$(s_2^{5_2}, 0)$	$(s_2^{5_2}, 0)$	$(s_3^{5_2}, 0)$
CR_3	$(s_1^{5_2}, 0)$	$(s_2^{5_2}, 0)$	$(s_3^{5_2}, 0)$	$(s_1^{5_2}, 0)$	$(s_1^{5_2}, 0)$
CR_4	$(s_2^{5_2}, 0)$	$(s_3^{5_2}, 0)$	$(s_1^{5_2}, 0)$	$(s_4^{5_2}, 0)$	$(s_3^{5_2}, 0)$
CR_5	$(s_0^{5_2}, 0)$	$(s_3^{5_2}, 0)$	$(s_1^{5_2}, 0)$	$(s_2^{5_2}, 0)$	$(s_3^{5_2}, 0)$

Table 9. 2-tuple linguistic evaluation matrix $\widetilde{R}^3$ for EP_3.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$\left(s_6^{9_3},0\right)$	$\left(s_8^{9_3},0\right)$	$\left(s_1^{9_3},0\right)$	$\left(s_5^{9_3},0\right)$	$\left(s_0^{9_3},0\right)$
CR_2	$\left(s_2^{9_3},0\right)$	$\left(s_7^{9_3},0\right)$	$\left(s_2^{9_3},0\right)$	$\left(s_6^{9_3},0\right)$	$\left(s_6^{9_3},0\right)$
CR_3	$\left(s_0^{9_3},0\right)$	$\left(s_6^{9_3},0\right)$	$\left(s_6^{9_3},0\right)$	$\left(s_2^{9_3},0\right)$	$\left(s_4^{9_3},0\right)$
CR_4	$s_3^{9_3}$	$\left(s_7^{9_3},0\right)$	$\left(s_2^{9_3},0\right)$	$\left(s_8^{9_3},0\right)$	$\left(s_6^{9_3},0\right)$
CR_5	$\left(s_1^{9_3},0\right)$	$\left(s_7^{9_3},0\right)$	$\left(s_1^{9_3},0\right)$	$\left(s_7^{9_3},0\right)$	$\left(s_7^{9_3},0\right)$

Step 5. The aggregation of all the evaluation matrices in Tables 9–11 applying 2TLWGBM operator in Equation (11) into R_{ij} is shown in Table 12.

Table 10. The transformed 2-tuple linguistic evaluation matrix $\widetilde{R}^{1\prime}$ for EP_1.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$(s_7^{9_1},-0.33)$	$(s_8^{9_1},0)$	$(s_0^{9_1},0)$	$(s_5^{9_1},0.33)$	$(s_0^{9_1},0)$
CR_2	$(s_1^{9_1},0.33)$	$(s_7^{9_1},-0.33)$	$(s_1^{9_1},0.33)$	$(s_4^{9_1},0)$	$(s_5^{9_1},0.33)$
CR_3	$(s_3^{9_1},-0.33)$	$(s_5^{9_1},0.33)$	$(s_5^{9_1},0.33)$	$(s_1^{9_1},0.33)$	$(s_1^{9_1},0.33)$
CR_4	$(s_4^{9_1},0)$	$(s_7^{9_1},-0.33)$	$(s_1^{9_1},0.33)$	$\left(s_8^{9_3},0\right)$	$(s_7^{9_1},-0.33)$
CR_5	$(s_1^{9_1},0.33)$	$(s_5^{9_1},0.33)$	$(s_1^{9_1},0.33)$	$(s_5^{9_1},0.33)$	$(s_7^{9_1},-0.33)$

Table 11. The transformed 2-tuple linguistic evaluation matrix $\widetilde{R}^{2\prime}$ for EP_2.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$(s_6^{9_2},0)$	$(s_8^{9_2},0)$	$(s_0^{9_1},0)$	$(s_6^{9_2},0)$	$(s_2^{9_2},0)$
CR_2	$(s_2^{9_2},0)$	$(s_6^{9_2},0)$	$(s_4^{9_2},0)$	$(s_4^{9_1},0)$	$(s_6^{9_2},0)$
CR_3	$(s_2^{9_2},0)$	$(s_4^{9_2},0)$	$(s_6^{9_2},0)$	$(s_2^{9_2},0)$	$(s_2^{9_2},0)$
CR_4	$(s_4^{9_2},0)$	$(s_6^{9_2},0)$	$(s_2^{9_2},0)$	$(s_8^{9_2},0)$	$(s_6^{9_2},0)$
CR_5	$(s_0^{9_2},0)$	$(s_6^{9_2},0)$	$(s_2^{9_2},0)$	$(s_4^{9_2},0)$	$(s_6^{9_2},0)$

Table 12. The aggregation of all the evaluation matrices.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	$(s_2^9,-0.14)$	$(s_2^9,0.05)$	$(s_0^9,0)$	$(s_2^9,-0.23)$	$(s_0^9,0)$
CR_2	$(s_1^9,0.23)$	$(s_2^9,-0.08)$	$(s_1^9,0.33)$	$(s_2^9,-0.26)$	$(s_2^9,-0.16)$
CR_3	$(s_1^9,-0.23)$	$(s_2^9,-0.23)$	$(s_2^9,-0.16)$	$(s_1^9,0.23)$	$(s_1^9,0.41)$
CR_4	$(s_2^9,-0.48)$	$(s_2^9,-0.08)$	$(s_1^9,0.23)$	$(s_2^9,0.05)$	$(s_2^9,-0.14)$
CR_5	$(s_1^9,-0.35)$	$(s_2^9,-0.1)$	$(s_1^9,0.1)$	$(s_2^9,-0.17)$	$(s_2^9,-0.08)$

Step 6. On the basic of different knowledge and experience, three experts adopt their own linguistic representations to evaluate correlations between *CRs* and *ECs*. These matrices are then aggregated in the same way as the fourth step. Consequently, the initial HOQ is shown in Figure 4.

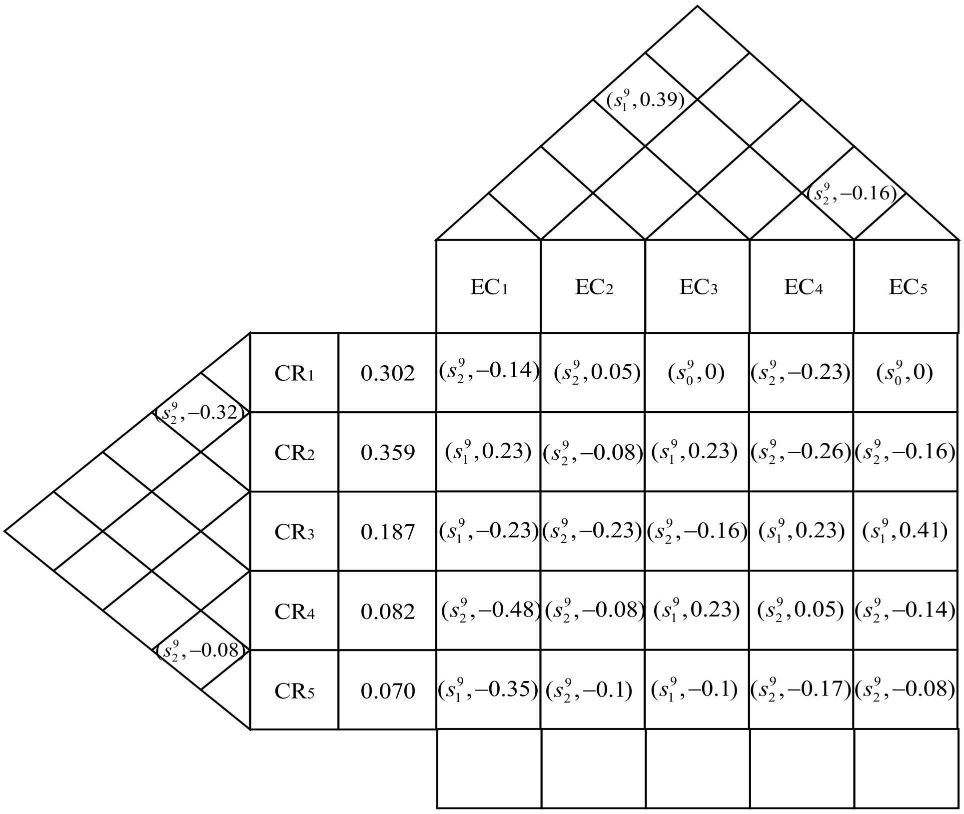


Figure 4. The 2-tuple initial HOQ.

In Figure 4, the correlations between *CRs* and *ECs* are computed in the same way as the relationships between *CRs* and *ECs* are treated. Apparently, an appropriate relationship matrix should take correlations into account, so the modified relationship in virtue of Equations (5)–(7), (12), and (13) is obtained. The result is illustrated in Figure 5.

We take the relationship between CR_1 and EC_1 for an example, the process of calculation is demonstrated as follow

$$\begin{aligned}(\bar{s},\bar{\alpha}) &= \triangle(\tfrac{1}{3}(\triangle^{-1}(s_2^9,-0.14)+(\triangle^{-1}(s_2^9,-0.32)+(\triangle^{-1}(s_1^9,0.39))\\ &= (s_2^9,-0.36)\end{aligned}$$

$$d((s_2^9,-0.14),(s_2^9,-0.36)) = \frac{\left|\triangle^{-1}(2-0.14)-\triangle^{-1}(2-0.36)\right|}{9} = 0.024$$

Similarly, $d((s_2^9,-0.32),(s_2^9,-0.36)) = 0.004, d((s_1^9,0.39),(s_2^9,-0.36)) = 0.028$

$$sim((s_2^9,-0.14),(s_2^9,-0.36)) = 1-\frac{0.024}{0.024+0.004+0.028} = 0.571$$

Similarly, $sim((s_2^9,-0.32),(s_2^9,-0.36)) = 0.928, sim((s_1^9,0.39),(s_2^9,-0.36)) = 0.5$
We then compute the weight γ_v by Equation (13)

$$\gamma(s_2^9,-0.14) = \frac{0.571}{0.571+0.928+0.5} = 0.286$$

In the same way, $\gamma(s_2^9,-0.32) = 0.464, \gamma(s_1^9,0.39) = 0.25$

The modified relationship is expressed

$$R'_{11} = \triangle(\triangle^{-1}(s_2^9,-0.14)^{0.286} * \triangle^{-1}(s_2^9,-0.32)^{0.464} * \triangle^{-1}(s_1^9,0.39)^{0.25}) = (s_2^9,-0.35)$$

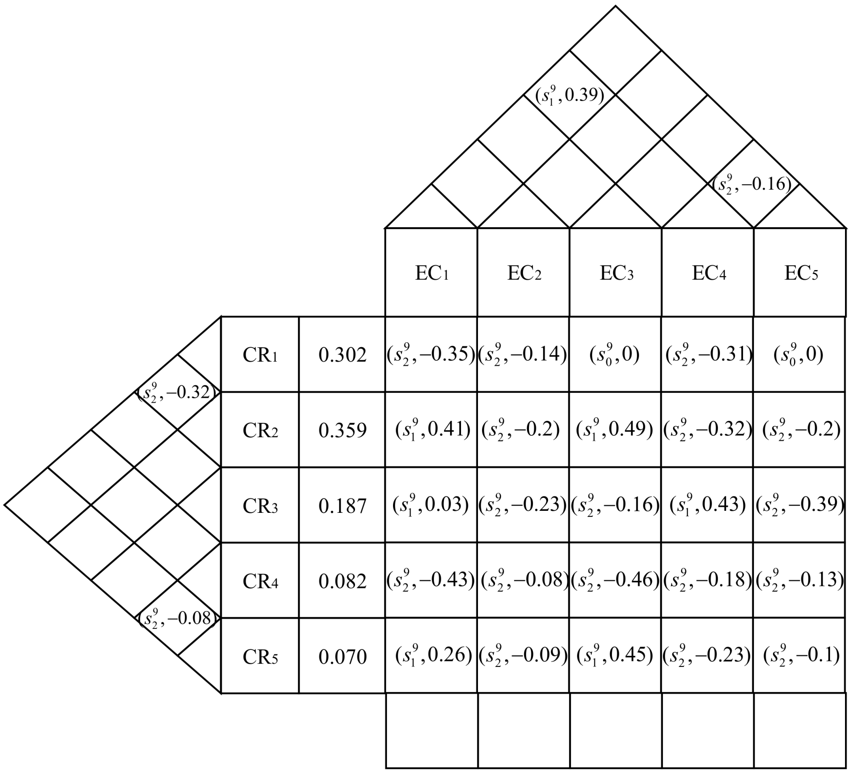


Figure 5. The 2-tuple modified HOQ.

Step 7. After obtaining the modified matrix, the importance of *CRs* should be integrated to reach the final relationships between *CRs* and *ECs*. The result is presented in Table 13. Therefore, the rank of integrated *ECs* priority is $EC_2 \succ EC_4 \succ EC_1 \succ EC_5 \succ EC_3$.

Table 13. The integrated *ECs* priority.

	EC_1	EC_2	EC_3	EC_4	EC_5
Priority	$(s_1^9, 0.07)$	$(s_1^9, 0.13)$	$(s_1^9, -0.18)$	$(s_1^9, 0.11)$	$(s_1^9, -0.16)$

Step 8. The basic priority of *ECs* is computed according to Equations (7) and (14) and Table 13. The minimum value of linguistic term set is $(s_{\min}^{n(t)}, \alpha^{n(t)}) = (s_0^9, 0)$. The ultimate weights of *ECs* are $(s_0^9, 0.215)$ $(s_0^9, 0.228)$ $(s_0^9, 0.165)$ $(s_0^9, 0.223)$ $(s_0^9, 0.169)$.

Step 9. End.

4.3. Managerial Tips

The outcomes of this study are beneficial to planning and selecting the appropriate emergency routes. Moreover, the ranking result can be outlined that decision makers should be paid more attention to management ability. The result indicates that crowd density has a significant influence on emergency route evaluation. Subsequently decision makers should concentrate on these two aspects in order to design and select emergency routes.

In addition, the proposed model is sufficient robust and could be easily implemented in practices for GDM problems. DMs can choose their linguistic preference to evaluate the correlation and relationship between *CRs* and *ECs*. Furthermore, the importance of *ECs* can be adjusted appropriately according to the actual circumstance.

5. Conclusions and Future Research

A systematic GDM approach for prioritizing *ECs* in QFD under the multi-granularity 2-tuple linguistic environment is proposed in this paper. The provided method allows experts from QFD team to evaluate the relationship and correlations between *CRs* and *ECs* in accordance with their experience and preference. For the sake of guaranteeing accurate information, the 2-tuple linguistic representation addressing the vague and imprecise information is utilized. Based on the linguistic hierarchy, different granularities originating from different experts are translated into a basic linguistic term we set in advance. The BWM is applied to determine the importance of *CRs*, which is simple and quick to represent customers' advice.

BM can capture inter-relationships among the aggregated information by taking the conjunction among each pairs of aggregated arguments, for instance, correlations among *CRs*. Therefore, the 2TLWGBM operator is applied to aggregate the evaluation matrix and the importance of *CRs*. In addition, correlations could have an impact on relationship between *CRs* and *ECs.* A modified matrix reflecting the influence is determined in this paper. Compared with other approaches in terms of calculating weight, a method that can lessen the subjectivity of assessment is put forward. Finally, a case study has been calculated and is presented to verify the effectiveness of the proposed method.

In this study, prioritizing *ECs* in QFD is extended to 2-tuple linguistic environment, in which all evaluation matrices from experts are represented by 2-tuple. For one thing, an appropriate and applicable BM operator is employed to deal with the aggregation problem, which should be suitable for accurately prioritizing *ECs* in QFD. Moreover, the degree of similarity is introduced to determine the weight that responds to the effect of correlations, which could obtain a more objective modified matrix.

In future research, the proposed method can be applied to supplier selection, green buildings and new product development. In addition, other GDM approaches can be integrated into QFD to rank the *ECs*, and consensus can be considered. A more reasonable aggregation operator should be developed and applied to QFD. In real life, plenty of problems might be complex and changeful. Establishing a dynamic HOQ is necessary.

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