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*Research Article*

# The Extension of Quality Function Deployment Based on 2-Tuple Linguistic Representation Model for Product Design under Multigranularity Linguistic Environment

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Quality function deployment (QFD) is a customer-driven approach for product design and development. A QFD analysis process includes a series of subprocesses, such as determination of the importance of customer requirements (CRs), the correlation among engineering characteristics (ECs), and the relationship between CRs and ECs. Usually more than group of one decision makers are involved in the subprocesses to make the decision. In most decision making problems, they often provide their evaluation information in the linguistic form. Moreover, because of different knowledge, background, and discrimination ability, decision makers may express their linguistic preferences in multigranularity linguistic information. Therefore, an effective approach to deal with the multi-granularity linguistic information in QFD analysis process is highly needed. In this study, the QFD methodology is extended with 2-tuple linguistic representation model under multi-granularity linguistic environment. The extended QFD methodology can cope with multi-granularity linguistic evaluation information and avoid the loss of information. The applicability of the proposed approach is demonstrated with a numerical example.

## 1. Introduction

Due to the global competition and fast changing demands for product functions, product life cycle has markedly decreased. Enterprises have to develop new products that meet customer requirements in a shorter time to meet the challenge [1–4]. New product development according to customer requirements is not only for the success of the product but also for the company's survival in the market [5, 6]. Hence, analyzing customer requirements and responding to their needs have become the crucial task for the product development team.

Quality function deployment (QFD) is a useful tool that supports the planning and the realization of products for customer requirements-oriented product development [7]. The QFD is an approach to deploy the voice of customer into searching for the best solutions for the design and development of products. QFD has been used successfully by industries in both Japan [7] and USA [8]. With QFD, the gap between customers and development team is bridged, and customer satisfaction is bridged.

In the application of the QFD model, a typical four-phase QFD model is commonly used [9–12]. These phases consist of customer requirement planning (CRP), product characteristics deployment (PCD), process and quality control (PQC), and the operative instruction (OPI). The corresponding four successive matrices including customer requirement planning matrix, product characteristics deployment matrix, process and quality control matrix, and operative instruction matrix [13] are constructed in the four-phase QFD model to make a connection between the successive phases.

In this paper, we focus on the CRP phase, which is used to develop procedures for identifying priority of engineering characteristics [13–15]. In other words, the customer's requirements are transformed into engineering specifications, which are then evaluated to establish an impact ranking. Therefore, we concentrate on the first matrix (customer requirement planning matrix). The customer requirement planning matrix, also known as "house of quality" (HOQ), is the first step in investigating customer requirements [16]. The components of HOQ are shown in Figure 1. From the figure, we see that the HOQ is composed of six parts and the illustration of each part is shown as follows.

(i) Area A represents customer requirements, which is the voice of customer to be identified.

(ii) Area B represents the importance level of customer requirements (CRs).

(iii) Area C represents engineering characteristics (ECs). That is how to fulfill the customer requirements.

(iv) Area D represents relationship matrix, representing the relationship of customer requirements and engineering characteristics. This area is the core of the HOQ.

(v) Area E represents correlation matrix, which indicates how engineering characteristics affect each other.

(vi) Area F represents priority of engineering characteristics. In other words, this area determines which engineering characteristics have more influence on the customer satisfaction.

In order to construct HOQ, firstly, CRs are obtained from market survey or customer interview [1]. The acquired CRs are then translated into a list of measureable ECs. Afterwards, the correlations between ECs are identified. Based on the obtained CRs and ECs, the relationships between CRs and ECs can be determined. Finally, the importance of ECs is derived [14, 17].

In the construction of HOQ, group of decision makers are involved in each process, and they are required to give their opinions about the weights of customer requirement, correlations between ECs, and relationships between CRs and ECs. Therefore, the QFD analysis process is a typical group decision making problem. The data available in the early stage of new product design is often limited and inaccurate [18, 19]. Decisions are often made under circumstances with vague, imprecise, and uncertain information [20, 21]. Therefore, it is difficult for the decision makers to give their opinions in exact numerical values [22].

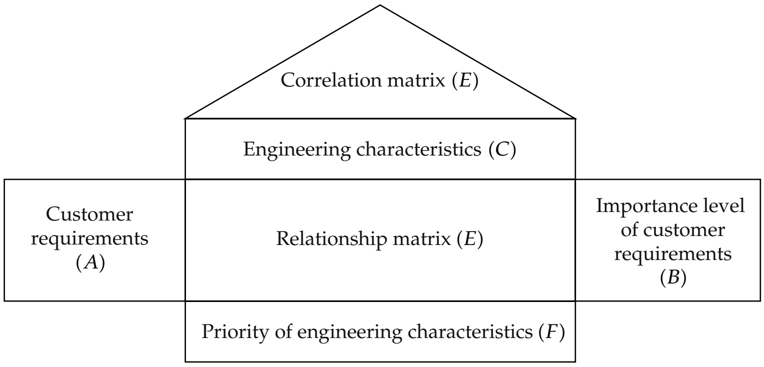


**Figure 1:** House of quality (HOQ).

Classical decision theory provides probabilistic models to manage uncertainty [23]. However, the use of numerical-based modeling to represent such uncertain information is not always adequate. These uncertainties are not of probabilistic nature because of imprecision and vagueness of meanings, and it is hard to provide numerical precise information when the knowledge is vague [24]. In the condition, it is more suitable for decision makers to provide their preferences by means of linguistic variables instead of numerical ones regarding the uncertain knowledge they have about the problem [24, 25]. Moreover, because of the different knowledge background and experience, the granularity of uncertainty, that is, the level of discrimination among different degrees of uncertainty is not consistent. The more knowledge the experts have about the problem, the more granularities they often can use to express their preferences [26]. Thus, the multiple granularities are often provided in the decision making processes.

In order to cope with the linguistic evaluation information in QFD activity process, some extensions of QFD have been made under fuzzy linguistic environment. For example, Wang and Xiong [3] proposed the approach to aggregate the linguistic judgments using linguistic symbolic computational models based on ordinal scales in QFD activity process. Zhang and Chu [27] proposed the method to cope with the linguistic assessments by the linguistic computational model based on membership functions in the construction of HOQ. The previous methods have an important weakness that is the consequent loss of information and hence the lack of precision when expressing the result in the initial expression domain by an approximation process. The 2-tuple linguistic representation model is proposed to overcome the drawback of the previous linguistic computational models [24]. Since the 2-tuple linguistic representation model takes the advantage of the minimization of the loss of information and the lack of precision [24], the use of it in the construction of HOQ can make multigranularity linguistic evaluation information be processed more accurately. However, few researches put on the extension of QFD based on 2-tuple linguistic representation model.

Therefore, in this paper, 2-tuple linguistic representation model is applied for MCDM problems in the construction of HOQ to help the development of products. To do that, the rest of this paper is organized as follows. The next section reviews the necessary linguistic concepts and methods for the study. Section 3 makes the extension of quality function deployment based on 2-tuple linguistic representation model. In the fourth section, an example is given to illustrate the applicability of the proposed method. The final section makes conclusions.

## 2. Linguistic Background

Many linguistic computational models are proposed to deal with the linguistic information [24, 25, 28, 29], as follows.

> The linguistic computational model based on membership functions [28]. It is based on the fuzzy linguistic approach and makes the computations directly on the membership functions of the linguistic terms.
>
> The linguistic symbolic computational models based on ordinal scales [29]. It represents the information according to the fuzzy linguistic approach and uses the ordered structure of the linguistic term set to accomplish symbolic computations in such ordered linguistic scales.

Many MCDM methods based on the previous two models have been proposed. For example, the LOWA (linguistic ordered weighted averaging) operator and the LWA (linguistic weighted averaging) operator are used to evaluate website quality [30] and informative quality of documents [31]. MLIOWA (majority guided linguistic induced ordered weighted averaging) and weighted MLIOWA operators are proposed to evaluate the information quality of websites [32].

The previous linguistic computational models present an important weakness. Since the results usually do not exactly match any of the initial linguistic terms, an approximation process must be developed to express the result in the initial expression domain, and as a result, the consequent loss of information and hence the lack of precision are produced.

In order to overcome the drawback of the previous linguistic computational models, the 2-tuple linguistic representation model is proposed [24]. The model represents the linguistic evaluation information with a pair of values which is composed by a linguistic term and a number. The main advantages of this method include that (1) the representation model is continuous in its domain, so it can express any counting of information in the universe of the discourse; (2) the results match the initial linguistic terms, which is more understandable than numeric numbers; (3) it does not need the approximation process, and as a result, the loss of information and the lack of precision are avoided. The use of the 2-tuple linguistic representation model has produced successful results in different fields. For example, it has been used in the evaluation of quality of health-related websites [33], collaboration satisfaction of NPD team [34], knowledge management capability [35], fuzzy risk [25], researching resources [30], document category [36], knowledge [37], the company [38], and the industry [39].

In the following, we briefly review the 2-tuple fuzzy linguistic representation model [24] and linguistic hierarchies [26, 40].

### *2.1. 2-Tuple Linguistic Representation Model*

The 2-tuple linguistic representation model is based on the concept of symbolic translation. It is used for representing the linguistic evaluation information by means of a 2-tuple that is composed of a linguistic term and a number. It can be denoted as $(s_i, \alpha)$ where $s_i$ represents the linguistic label of the predefined linguistic term set $S$, and $\alpha$ indicates the distance to the central value of the $i$th linguistic term. For example, a set of seven terms $S$ could be given as follows:

$$\begin{aligned} S = \{&S_0 = \text{Definitely Low}, S_1 = \text{Very Low}, \\ &S_2 = \text{Low}, S_3 = \text{Average}, S_4 = \text{High}, \quad S_5 = \text{Very High}, \quad S_6 = \text{Definitely High}\}. \end{aligned} \tag{2.1}$$

*Definition 2.1.* Let $s_i \in S$ be a linguistic label. Then, the function $\Delta$ used to obtain the corresponding 2-tuple linguistic information of $s_i$ is defined as

$$\begin{aligned} &\Delta : \mathrm{S} \longrightarrow \mathrm{S} \times [-0.5, 0.5), \\ &\Delta(s_i) = (s_i, 0), \quad s_i \in S. \end{aligned} \tag{2.2}$$

*Definition 2.2.* Let $S = \{S_0, S_1, \ldots, S_T\}$ be a linguistic term set and $\beta \in [0, T]$ a number value representing the aggregation result of linguistic symbolic. Then, the symbolic translation process is applied to translate $\beta$ into a 2-tuple linguistic variable. The generalized translation function $(\Delta)$ can be represented as

$$\begin{gathered} \Delta : [0, T] \longrightarrow S \times [-0.5, 0.5), \\ \Delta(\beta) = (S_i, \alpha) = \begin{cases} S_i, & i = \operatorname{Round}(\beta), \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5), \end{cases} \end{gathered} \tag{2.3}$$

where $\operatorname{Round}(\cdot)$ is the usual round operation, $s_i$ has the closest index label to $\beta$, and $\alpha$ is the value of the symbolic translation.

*Definition 2.3.* The 2-tuple linguistic variable can be converted into an equivalent numerical value $\beta$ ($\beta \in [0, T]$) by the following formula:

$$\Delta^{-1}(S_i, \alpha) = i + \alpha = \beta, \tag{2.4}$$

where $\Delta^{-1}(S_i, \alpha)$ signifies a reverse equation for converting the 2-tuple linguistic variable into a crisp value, $\beta$ is a number value representing the aggregation result of linguistic symbolic, and $\alpha$ is a numerical value which represents the symbolic translation.

*Definition 2.4* (negative operator).

$$\operatorname{Neg}(S_i, \alpha) = \Delta\left(T - \left(\Delta^{-1}(S_i, \alpha)\right)\right). \tag{2.5}$$

*Definition 2.5.* Letting $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a 2-tuple linguistic variable set, their arithmetic mean $\overline{x}$ can be calculated as

$$\overline{x} = \Delta\left[\frac{1}{n}\sum_{i=1}^{n}\Delta^{-1}(r_i, \alpha_i)\right] = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right). \tag{2.6}$$

*Definition 2.6.* When $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ is a 2-tuple linguistic variable set and $W = \{w_1, \ldots, w_n\}$ is the weight set of linguistic terms, the 2-tuple linguistic weighted average $\overline{x}^w$ can be computed as

$$\overline{x}^w = \Delta\left[\frac{\sum_{i=1}^n \Delta^{-1}(r_i, \alpha_i) \times w_i}{\sum_{i=1}^n w_i}\right] = \Delta\left(\frac{\sum_{i=1}^n \beta_i \times w_i}{\sum_{i=1}^n w_i}\right). \tag{2.7}$$

*Definition 2.7.* Let $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a 2-tuple linguistic variable set and let $W = \{(w_1, \alpha_1^w), \ldots, (w_n, \alpha_n^w)\}$ be their linguistic 2-tuple-associated weights. This linguistic weighted average operator can be computed as

$$\overline{x}_l^w = \Delta\left(\frac{\sum_{i=1}^n \left[\Delta^{-1}(r_i, \alpha_i) \times \Delta^{-1}(w_i, \alpha_i^w)\right]}{\sum_{i=1}^n \Delta^{-1}(w_i, \alpha_i^w)}\right). \tag{2.8}$$

*Definition 2.8.* If $(S_i, \alpha_i)$ and $(S_j, \alpha_j)$ are two 2-tuple linguistic variables, with each one of them representing a counting of information as follows:

(1) when $i > j$, $(S_i, \alpha_i)$ is better than $(S_j, \alpha_j)$;

(2) if $i = j$ and $\alpha_i > \alpha_j$, then $(S_i, \alpha_i)$ is better than $(S_j, \alpha_j)$;

(3) if $i = j$ and $\alpha_i < \alpha_j$, then$(S_i, \alpha_i)$ is worse than $(S_j, \alpha_j)$;

(4) if $i = j$ and $\alpha_i = \alpha_j$, then $(S_i, \alpha_i)$ is equal to $(S_j, \alpha_j)$.

## *2.2. Linguistic Hierarchies*

There are kinds of approaches to deal with multiple linguistic scales [26]. Since the approach proposed by Herrera and Martínez [40] overcomes the drawbacks related to the accuracy and to the expression domain for the computed results that exist in the other approaches, it is used to deal with the multiple linguistic scales in the study.

A linguistic hierarchy is a set of levels, where each level is a linguistic term set with different granularities to the rest of levels of the hierarchy, as shown in Figure 2. Each level belonging to a linguistic hierarchy is denoted as

$$l(t, n(t)), \tag{2.9}$$

being

(1) $t$, a number that indicates the level of the hierarchy;

(2) $n(t)$, the granularity of the linguistic term set of the level.

The levels belonging to a linguistic hierarchy are ordered according to their granularity, that is, for two consecutive levels $t$ and $t+1, n(t+1) > n(t)$.

For example, the linguistic hierarchies in Figure 2 are denoted as $l(1,3)$ and $l(2,5)$, and $l(2,5) > \ l(1,3)$.

The most important step in dealing with multi-granularity linguistic information is transforming the multi-granularity linguistic information into the same granularity linguistic

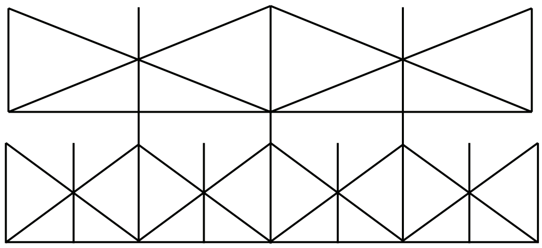

**Figure 2:** Linguistic hierarchies of three and five.

information without loss of information. In the contexts of 2-tuple linguistic representation model, the transformation functions are as follows.

*Definition 2.9.* Let $LH = U_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{S_0^{n(t)}, S_1^{n(t)}, \ldots, S_{n(t)-1}^{n(t)}\}$ and let us consider the 2-tuple linguistic representation. The transformation function from a linguistic label in level $t$ to a label in level $t+1$, satisfying the linguistic hierarchy basic rules, is defined as

$$TF_{t+1}^{t} : l(t, n(t)) \longrightarrow l(t+1, n(t+1)),$$

$$TF_{t+1}^{t}\left(S_i^{n(t)}, \alpha^{n(t)}\right) = \Delta\left(\frac{\Delta^{-1}\left(S_i^{n(t)}, \alpha^{n(t)}\right) \cdot (n(t+1)-1)}{n(t)-1}\right). \tag{2.10}$$

*Definition 2.10.* Let $LH = U_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{S_0^{n(t)}, S_1^{n(t)}, \ldots, S_{n(t)-1}^{n(t)}\}$ and let us consider the 2-tuple linguistic representation. The transformation function from a linguistic label in level $t$ to a label in level $t-1$, satisfying the linguistic hierarchy basic rules, is defined as

$$TF_{t-1}^{t} : l(t, n(t)) \longrightarrow l(t+1, n(t-1)),$$

$$TF_{t-1}^{t}\left(S_i^{n(t)}, \alpha^{n(t)}\right) = \Delta\left(\frac{\Delta^{-1}\left(S_i^{n(t)}, \alpha^{n(t)}\right) \cdot (n(t-1)-1)}{n(t)-1}\right). \tag{2.11}$$

## 3. The Extension of Quality Function Deployment Based on 2-Tuple Linguistic Representation Model under Multigranularity Linguistic Environment

In most actual situations, many decision makers are involved in the decision making of new product development. These decision makers usually include customers and experts from various departments, such as marketing, R&D, and manufacturing. Because of the limited and inaccurate data in the early stage of new product design, decision makers can only provide fuzzy linguistic values. Moreover, decision makers have different knowledge background and experience the level of discrimination among different degrees of uncertainty is not consistent [3, 27]. The more knowledge they have about the problem, the more accurate evaluation information can be provided, and as a result, the more granularities they need to use to express their preferences. Therefore, the multi-granularity linguistic terms are required for the decision making problem.

In the section, we extend the quality function deployment based on 2-tuple linguistic representation model to deal with the multi-granularity linguistic information. The proposed method consists of ten steps in total. The detailed explanations for the procedure are presented as follows.

*Step 1* (identify CRs). In this step, CRs are identified and placed on the left side of the house. These requirements can be identified with the aid of questionnaires to customers, the literature surveys, or expert views. We use $\mathrm{CR} = \{\mathrm{CR}_1, \mathrm{CR}_2, \ldots, \mathrm{CR}_m\}$ for representing the discrete set of customer requirements.

*Step 2* (identify ECs). In this step, CRs are transformed to technical attributes. ECs are specified on the basis of the company's design plans in order to satisfy the customers. We use $\mathrm{EC} = \{\mathrm{EC}_1, \mathrm{EC}_2, \ldots, \mathrm{EC}_n\}$ for representing the discrete set of engineering characteristics.

*Step 3* (measure the importance level of CRs). Decision makers give their preference to the importance level of the CRs, which are derived in Step 1. They use different linguistic term sets to express their opinions. Suppose that $U_k = (u_i^{(k)})_{m\times 1}$ is the linguistic decision making matrix of CRs, where $u_i^{(k)} \in S^k$ is the evaluation value, which is represented by the label in the linguistic term set $S^k = \{S_0^k, S_1^k, \ldots, S_f^k\}$ and is given by decision maker $D_k \in D_{t1}$, for customer requirement $\mathrm{CR}_i \in \mathrm{CR}$. In the evaluation process, experts express their preferences depending on their knowledge over them. Therefore, the linguistic term sets $S^k$ may be different.

*Step 4* (define the correlation among ECs). ECs may have influence on each other. Also, we ask the decision makers to give their preferences to the relationship among the ECs. Suppose that $C_k = (c_{ij}^{(k)})_{n\times n}$ is the linguistic decision making matrix of correlations. Since the relationship is undirected, the matrix is symmetric matrix. $c_{ij}^{(k)} \in S^k$ represents the correlation between $\mathrm{DR}_i$ and $\mathrm{DR}_j$. It is the evaluation value, which is represented by the label in the linguistic term set $S^k = \{S_0^k, S_1^k, \ldots, S_2^k\}$, given by decision maker $D_k \in D_{t2}$. Likewise, in evaluation process, each expert expresses his/her preferences using different linguistic term sets.

*Step 5* (identify the relationship between CRs and ECs). Relation matrix is the matrix of relationship between CRs and ECs. Each of the ECs is correlated individually to each of the CRs by considering to what extent a EC contributes to meeting customer requirement. Suppose that $R_k = (r_{ij}^{(k)})_{m\times n}$ is the linguistic decision making matrix of relationship, where $r_{ij}^{(k)} \in S^k$ is the evaluation value of the impact of $\mathrm{DR}_i$ in meeting $\mathrm{CR}_j$, which is represented by the label in the linguistic term set $S^k = \{S_0^k, S_1^k, \ldots, S_2^k\}$, given by decision maker $D_k \in D_{t3}$. In evaluation process, each expert expresses the preferences using different linguistic terms depending on his preference.

*Step 6* (unify the linguistic evaluation information). In this context, the linguistic term sets $S^k$ may have different granularities. In order to manage such linguistic evaluation information, we must make it uniform; that is, the multi-granularity linguistic evaluation information provided by all decision makers must be transformed into unified linguistic term set, that is, basic linguistic term set (BLTS). BLTS denoted as $S_T$ is a basic linguistic term set with a larger number of terms than the number of terms that a decision maker is able to discriminate,

$$S_T = \left\{ S^k \mid \max_k f,\ \forall S_f^k \in S^k \right\}. \tag{3.1}$$

After $S_T$ is chosen, each linguistic evaluation term set $S^k$ can be transformed by the transformation function equation (2.10). The transformed matrix of importance level of CRs, correlation among ECs and relationship between CRs, and ECs are shown as follows:

$$U'_k = \left(u_i^{'(k)}\right)_{m\times 1}, \qquad C'_k = \left(c_{ij}^{'(k)}\right)_{n\times n}, \qquad R'_k = \left(r_{ij}^{'(k)}\right)_{m\times n}. \tag{3.2}$$

*Step 7* (calculate the collective importance level of customer requirements)

*Substep 7.1.* Transform the linguistic decision matrix $U'_k = (u_i^{\prime(k)})_{m\times 1}$ into 2-tuple linguistic decision matrix $U'_k = (u_i^{\prime(k)}, 0)_{m\times 1}$.

*Substep* 7.2. Utilize the decision information given in matrix $U'_k$ to derive the collective overall 2-tuple linguistic decision matrix $U' = (u'_i, \alpha'_i)_{m\times 1}$:

$$\left(u'_i, \alpha'_i\right) = \Delta\left(\frac{1}{t}\sum_{k=1}^{t}\Delta^{-1}\left(u_i^{'(k)}, a_i^{'(k)}\right)\right), \quad i = 1, 2, \ldots, m. \tag{3.3}$$

*Step 8* (calculate the collective correlation among ECs)

*Substep 8.1.* Transform linguistic decision matrix $C'_k = (c_{ij}^{\prime(k)})_{n\times n}$ into 2-tuple linguistic decision matrix $C'_k = (c_{ij}^{\prime(k)}, 0)_{n\times n}$.

*Substep 8.2.* Utilize the decision information given in matrix $C'_k$ to derive the collective overall 2-tuple linguistic decision matrix $C' = (c'_{ij}, \alpha'_{ij})_{n\times n}$:

$$\left(c'_{ij}, \alpha'_{ij}\right) = \Delta\left(\frac{1}{t}\sum_{k=1}^{t}\Delta^{-1}\left(c_{ij}^{'(k)}, a_{ij}^{'(k)}\right)\right), \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, n. \tag{3.4}$$

*Step 9* (calculate the collective relationship between CRs and ECs). The collective relationship is calculated based on the correlation matrix and relationship matrix.

*Substep 9.1.* Transform linguistic decision matrix $R'_k = (r_{ij}^{\prime(k)})_{n\times n}$ into 2-tuple linguistic decision matrix $R'_k = (r_{ij}^{\prime(k)}, 0)_{m\times n}$.

*Substep 9.2.* Utilize the decision information given in matrix $R'_k$ to derive the collective overall 2-tuple linguistic decision matrix $R' = (r'_{ij}, \alpha'_{ij})_{m\times n}$:

$$\left(r'_{ij}, \alpha'_{ij}\right) = \Delta\left(\frac{1}{t}\sum_{k=1}^{t}\Delta^{-1}\left(r_{ij}^{'(k)}, a_{ij}^{'(k)}\right)\right), \quad i = 1,2,\ldots,m, \quad j = 1,2,\ldots,n. \tag{3.5}$$

*Step 9.3*. For obtaining relative relationship degrees of ECs with respect to some CR and dealing with the dependence among ECs, the normalized transform on the relationship values contained in the relationship matrix is used and expressed as follows [14]:

$$\left(\mathrm{EC}_{ij}^{'}, \alpha'_{ij}\right) = \frac{(T-1)\times\sum_{h=1}^{n}\Delta^{-1}(r'_{ih}, \alpha'_{ih})\times\Delta^{-1}\left(c'_{hj}, \alpha'_{hj}\right)}{\sum_{j=1}^{n}\sum_{h=1}^{n}\Delta^{-1}\left(r'_{ih}, \alpha'_{hj}\right)\times\Delta^{-1}\left(c'_{ij}, \alpha'_{ij}\right)}, \tag{3.6}$$

where $T$ is the cardinality of the set $S_T$ and $\mathrm{EC}_{ij}^{'}$ is the relationship value between customer requirement $\mathrm{CR}_i$ and engineering characteristic $\mathrm{EC}_j$, $i = 1,2,\ldots,m$, $j = 1,2,\ldots,n$.

*Step 10* (calculate the importance of the engineering characteristics). The importance of rating $w_j$ for the $j$th EC is obtained by the sum of multiplying the importance degree of each customer requirement by the corresponding normalized relationship as

$$\left(w_j, \beta'_j\right) = \frac{1}{m}\sum_{i=1}^{m}\Delta^{-1}\left(\mathrm{EC}_{ij}^{'}, \alpha'_{ij}\right)\times\Delta^{-1}(u'_i, \alpha'_i). \tag{3.7}$$

The importance rating is the measure for one engineering characteristic on the overall impact of customer satisfaction. The EC that gets the highest rate should be paid the most attention in designing and developing the products, since it is the most probable to improve the customer satisfaction.

## 4. Empirical Analysis

In this section, the fully automatic washing machine development case is used to illustrate the proposed approach [41]. QFD is used to obtain a conceptual design, that is, determining customer requirements concerning washing machines, determining new engineering characteristics that satisfy the customer requirements, and deriving the importance level of engineering characteristics for customer satisfaction. Our main focus is to determine the importance ratings of CRs and ECs under a group decision setting with multi-granularity linguistic evaluation in QFD. The steps of the case to be taken are described in the following.

Group of decision makers including customers and engineers is invited to give their preferences. Considering the different background and discrimination ability of decision makers, the following two different linguistic term sets $S_1$ and $S_2$ are used, as shown in Table 1.

*Step 1* (identify CRs). It is based on the assumption that the machine will be used by housewives in families. From the analysis of the questionnaire results, five customer

**Table 1:** Linguistic labels for rating of criteria and grade of importance.

| Linguistic term sets $S_1$ | Linguistic term sets $S_2$ |
|---|---|
| $S_0^1$ = DL: definitely low | $S_0^2$ = $VL^2$: very low |
| $S_1^1$ = VL: very low | $S_1^2$ = $L^2$: low |
| $S_2^1$ = L: low | $S_2^2$ = $M^2$: middle |
| $S_3^1$ = M: middle | $S_3^2$ = $H^2$: high |
| $S_4^1$ = H: high | $S_4^2$ = $VH^2$: very high |
| $S_5^1$ = VH: very high | |
| $S_6^1$ = DH: definitely high | |

**Table 2:** The evaluation information of the importance level of CRs.

| | $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|---|
| $D_1$ | DH | VL | H | DH | L |
| $D_2$ | VH | L | M | DH | L |
| $D_3$ | $H^2$ | $VL^2$ | $M^2$ | $VH^2$ | $L^2$ |
| $D_4$ | $H^2$ | $L^2$ | $L^2$ | $H^2$ | $L^2$ |

**Table 3:** The evaluation information of the correlation among ECs given by the first expert.

| | $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|---|
| $CR_1$ | DH | L | H | VL | VH |
| $CR_2$ | | DH | VL | VL | L |
| $CR_3$ | | | DH | L | H |
| $CR_4$ | | | | DH | M |
| $CR_5$ | | | | | DH |

requirements are identified. These CRs include "thorough washing" ($CR_1$), "quiet washing" ($CR_2$), "thorough rinsing" ($CR_3$), "no damage to clothes" ($CR_4$) and "short washing time" ($CR_5$).

*Step 2* (identify ECs). In this step, CRs in Step 1 are transformed to five technical attributes. ECs include "washing quality" ($EC_1$), "noise level" ($EC_2$), "washing time" ($EC_3$), "rinsing quality" ($EC_4$), and "clothes damage rate" ($EC_5$).

*Step 3* (measure the importance level of CRs). In the step, decision makers give their preferences to the importance level of the CRs. There are four customer representatives involved in determining the weight for each CR. The linguistic evaluations provided by the four customers are shown in Table 2. The first two customer representatives give their opinions using the linguistic set $S_1$, and the other two customer representatives use the linguistic set $S_2$.

*Step 4* (define the correlation among ECs). Three product designers and development experts are invited to evaluate the relationships between CRs and ECs. They use the linguistic term from the set $S_1$ to express their preferences. The linguistic evaluations information provided by the three experts is shown in Tables 3, 4, and 5, respectively.

**Table 4:** The evaluation information of the correlation among ECs given by the second expert.

| | $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|---|
| $CR_1$ | DH | VL | H | DL | DH |
| $CR_2$ | | DH | VL | L | L |
| $CR_3$ | | | DH | M | VH |
| $CR_4$ | | | | DH | M |
| $CR_5$ | | | | | DH |

**Table 5:** The evaluation information of the correlation among ECs given by the third expert.

| | $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|---|
| $CR_1$ | DH | VL | M | DL | VH |
| $CR_2$ | | DH | VL | VL | L |
| $CR_3$ | | | DH | VL | M |
| $CR_4$ | | | | DH | H |
| $CR_5$ | | | | | DH |

**Table 6:** The evaluation information of the relationships between CRs and ECs given by the first expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | DH | H | H | L | H |
| $CR_2$ | M | DH | H | M | M |
| $CR_3$ | L | M | L | DH | H |
| $CR_4$ | VH | M | M | L | DH |
| $CR_5$ | VH | L | DH | VH | H |

**Table 7:** The evaluation information of the relationships between CRs and ECs given by the second expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | VH | M | M | L | H |
| $CR_2$ | M | DH | H | L | M |
| $CR_3$ | VL | L | VL | VH | H |
| $CR_4$ | H | VL | L | L | DH |
| $CR_5$ | VH | L | VH | H | M |

*Step 5* (identify the relationship between the CRs and ECs). The experts in Step 4 also identify the relationships between CRs and ECs. They all use the linguistic term from the set $S_1$ to express their preferences. The linguistic evaluations provided by the three experts are shown in Tables 6, 7, and 8.

*Step 6* (unify the linguistic evaluation information). Since the customer representatives give their preference to the importance level of the CRs using different linguistic term sets in Step 1, we unify the evaluation information of the importance level of CRs. Because the linguistic term set $S_1$ includes a larger number of terms, it is selected as the BLTS. The unified result is shown in Table 9.

**Table 8:** The evaluation information of the relationships between CRs and ECs given by the third expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | VH | H | M | L | H |
| $CR_2$ | H | DH | VH | H | M |
| $CR_3$ | M | H | VL | DH | VH |
| $CR_4$ | VH | H | M | L | DH |
| $CR_5$ | DH | L | H | M | L |

**Table 9:** The unified evaluation information of the importance level of CRs.

| | $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|---|
| $D_1$ | (DH, 0) | (VL, 0) | (H, 0) | (DH, 0) | (L, 0) |
| $D_2$ | (VH, 0) | (L, 0) | (M, 0) | (DH, 0) | (L, 0) |
| $D_3$ | (VH, −0.5) | (DL, 0) | (M, 0) | (DH, 0) | (L, −0.5) |
| $D_4$ | (VH, −0.5) | (L, −0.5) | (L, −0.5) | (VH, −0.5) | (L, −0.5) |

**Table 10:** The collective overall importance level of CRs.

| $CR_1$ | $CR_2$ | $CR_3$ | $CR_4$ | $CR_5$ |
|---|---|---|---|---|
| (VH, 0) | (VL, 0.13) | (M, −0.13) | (DH, −0.38) | (L, −0.25) |

The evaluation information of the correlation among ECs and the relationships between CRs and ECs are expressed using the same linguistic term set $S_1$, which is also the BLTS; therefore, the evaluation information does not need unification and is kept as original.

*Step 7* (calculate the collective importance level of customer requirements). Firstly, linguistic decision matrix in Table 9 is transformed into 2-tuple linguistic decision matrix. Then, the 2-tuple linguistic decision matrix is used to derive the collective overall 2-tuple linguistic decision matrix by (3.3). The calculated results are shown in Table 10.

Then, we can prioritize the customer requirements: $CR_4 \succ CR_1 \succ CR_3 \succ CR_5 \succ CR_2$. Thus, $CR_4$ has the highest potential contribution to customer satisfaction and should be paid more attention during the following product development process.

*Step 8* (calculate the collective correlation among ECs)

*Substep 8.1*. Transform linguistic decision matrixes in Tables 3–5 into 2-tuple linguistic decision matrix. The results are shown in Tables 11, 12, and 13.

*Substep 8.2*. Utilize the decision information given in Tables 11–13 to derive the collective overall 2-tuple linguistic decision matrix. The results are shown in Table 14.

*Step 9* (calculate the collective relationship between the CRs and ECs)

*Substep 9.1.* Transform linguistic decision matrixes in Tables 6–8 into 2-tuple linguistic decision matrix. The results are shown in Tables 15, 16, and 17.

**Table 11:** The transformed evaluation information of the correlation among ECs given by the first expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $EC_1$ | (DH, 0) | (L, 0) | (H, 0) | (VL, 0) | (VH, 0) |
| $EC_2$ | | (DH, 0) | (VL, 0) | (VL, 0) | (L, 0) |
| $EC_3$ | | | (DH, 0) | (L, 0) | (H, 0) |
| $EC_4$ | | | | (DH, 0) | (M, 0) |
| $EC_5$ | | | | | (DH, 0) |

**Table 12:** The transformed evaluation information of the correlation among ECs given by the second expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $EC_1$ | (DH, 0) | (VL, 0) | (H, 0) | (DL, 0) | (DH,0) |
| $EC_2$ | | (DH, 0) | (VL, 0) | (L, 0) | (L, 0) |
| $EC_3$ | | | (DH, 0) | (M, 0) | (VH, 0) |
| $EC_4$ | | | | (DH, 0) | (M, 0) |
| $EC_5$ | | | | | (DH, 0) |

**Table 13:** The transformed evaluation information of the correlation among ECs given by the third expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $EC_1$ | (DH, 0) | (VL, 0) | (M, 0) | (DL, 0) | (VH, 0) |
| $EC_2$ | | (DH, 0) | (VL, 0) | (VL, 0) | (L, 0) |
| $EC_3$ | | | (DH, 0) | (VL, 0) | (M, 0) |
| $EC_4$ | | | | (DH, 0) | (H, 0) |
| $EC_5$ | | | | | (DH, 0) |

*Substep 9.2.* Utilize the decision information given in Tables 15–17 to derive the collective overall 2-tuple linguistic decision matrix. The results shown in Table 18.

*Substep 9.3.* We use (3.6) to derive the collective relationship between the CRs and ECs. The calculated results are shown in Table 19.

*Step 10* (calculate the importance of the engineering characteristics). The importance of rating is the measure for one engineering characteristic on the overall impact of customer satisfaction. Based on evaluation information in Tables 10, 14 and 19, the importance of the engineering characteristics can be got by (3.7). The results are shown in Table 20.

From Table 20, we get the final priority of ECs: $EC_5 \succ EC_1 \succ EC_3 \succ EC_4 \succ EC_2$. $EC_5$ has the highest potential contribution to the achievement of CRs and should be given the highest attention in the product design and development process. $EC_5$ is followed by $EC_1$, $EC_3$ and $EC_4$, while $EC_2$ is considered as the least important.

The method can differentiate between the ECs clearly and well reflect the customer requirements. It is rational and effective. From the evaluation information of the importance level of CRs in Table 2, we see that most decision makers concerned more about the "thorough washing" ($CR_1$) and "no damage to clothes" ($CR_4$) and concerned less about the "quiet washing" ($CR_2$) and "short washing time" ($CR_5$). In Tables 15–17, "clothes damage rate" ($EC_5$) and "washing quality" ($EC_1$) have great influence on the "thorough washing" ($CR_1$) and "no damage to clothes" ($CR_4$), and "noise level" ($EC_2$) and "rinsing quality" ($EC_4$) have

**Table 14:** The collective overall correlation among ECs.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $EC_1$ | (DH, 0.00) | (VL, 0.33) | (H, −0.33) | (DL, 0.33) | (VH, 0.33) |
| $EC_2$ | | (DH, 0.00) | (VL, 0.00) | (VL, 0.33) | (L, 0.00) |
| $EC_3$ | | | (DH, 0.00) | (L, 0.00) | (H, 0.00) |
| $EC_4$ | | | | (DH, 0.00) | (M, 0.33) |
| $EC_5$ | | | | | (DH, 0.00) |

**Table 15:** The transformed evaluation information of the relationships between CRs and ECs given by the first expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | (DH, 0) | (H, 0) | (H, 0) | (L, 0) | (H, 0) |
| $CR_2$ | (M, 0) | (DH, 0) | (H, 0) | (M, 0) | (M, 0) |
| $CR_3$ | (L, 0) | (M, 0) | (L, 0) | (DH, 0) | (H, 0) |
| $CR_4$ | (VH, 0) | (M, 0) | (M, 0) | (L, 0) | (DH, 0) |
| $CR_5$ | (VH, 0) | (L, 0) | (DH, 0) | (VH, 0) | (H, 0) |

**Table 16:** The transformed evaluation information of the relationships between CRs and ECs given by the second expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | (VH, 0) | (M, 0) | (M, 0) | (L, 0) | (H, 0) |
| $CR_2$ | (M, 0) | (DH, 0) | (H, 0) | (L, 0) | (M, 0) |
| $CR_3$ | (VL, 0) | (L, 0) | (VL, 0) | (VH, 0) | (H, 0) |
| $CR_4$ | (H, 0) | (VL, 0) | (L, 0) | (L, 0) | (DH, 0) |
| $CR_5$ | (VH, 0) | (L, 0) | (VH, 0) | (H, 0) | (M, 0) |

**Table 17:** The transformed evaluation information of the relationships between CRs and ECs given by the third expert.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | (VH, 0) | (H, 0) | (M, 0) | (L, 0) | (H, 0) |
| $CR_2$ | (H, 0) | (DH, 0) | (VH, 0) | (H, 0) | (M, 0) |
| $CR_3$ | (M, 0) | (H, 0) | (VL, 0) | (DH, 0) | (VH, 0) |
| $CR_4$ | (VH, 0) | (H, 0) | (M, 0) | (L, 0) | (DH, 0) |
| $CR_5$ | (DH, 0) | (L, 0) | (H, 0) | (M, 0) | (L, 0) |

great influence on “quiet washing” ($CR_2$) and “short washing time” ($CR_5$). According to the final priority of ECs, “clothes damage rate” ($EC_5$) and “washing quality” ($EC_1$) rank the first, and “noise level” ($EC_2$) and “rinsing quality” ($EC_4$) rank the last, which are consistent with the customer requirements.

In the calculation process of the example, we see that the result matches the initial linguistic terms rather than only numeric values. It makes the results more understandable. The method does not need the approximation process to express the result in the initial expression domain, and as a result, the consequent loss of information and the lack of

**Table 18:** The collective overall 2-tuple linguistic decision matrix between CRs and ECs.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | (VH, 0.33) | (H, −0.33) | (M, 0.33) | (L, 0.00) | (H, 0.00) |
| $CR_2$ | (M, 0.33) | (DH, 0.00) | (H, 0.33) | (M, 0.00) | (M, 0.00) |
| $CR_3$ | (L, 0.00) | (M, 0.00) | (VL, 0.33) | (DH, −0.33) | (H, 0.33) |
| $CR_4$ | (H, −0.33) | (M, −0.33) | (M, −0.33) | (L, 0.00) | (DH, 0.00) |
| $CR_5$ | (VH, 0.33) | (L, 0.00) | (VH, 0.00) | (H, 0.00) | (M, 0.00) |

**Table 19:** The overall collective relationships between CRs and ECs.

| | $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|---|
| $CR_1$ | (VL, 0.45) | (VL, −0.12) | (VL, 0.29) | (VL, −0.25) | (L, −0.37) |
| $CR_2$ | (VL, 0.23) | (VL, 0.10) | (VL, 0.25) | (VL, −0.1) | (L, −0.49) |
| $CR_3$ | (VL, 0.09) | (VL, −0.09) | (VL, 0.11) | (VL, 0.31) | (L, −0.41) |
| $CR_4$ | (VL, 0.47) | (VL, −0.21) | (VL, 0.27) | (VL, −0.19) | (L, −0.34) |
| $CR_5$ | (VL, 0.37) | (VL, −0.31) | (VL, 0.39) | (VL, −0.09) | (L, −0.37) |

**Table 20:** The importance of the engineering characteristics for washing machine.

| $EC_1$ | $EC_2$ | $EC_3$ | $EC_4$ | $EC_5$ |
|---|---|---|---|---|
| (H, 0.49) | (M, −0.22) | (H, 0.13 ) | (M, −0.06) | (VH, 0.32) |

precision are avoided. Therefore, the method is more convenient and precise when dealing with fuzzy linguistic evaluation information.

## 5. Conclusions

As a customer-driven product development tool, QFD is usually used in the early phase of new or improved products design process. QFD involves numerous linguistic information provided by a group of decision makers including customers and product developers. Because of the different background and discrimination ability, decision makers may express their linguistic preferences using different linguistic term sets. Therefore, this study proposes a new QFD method to deal with the multi-granularity linguistic information. In the new method, the traditional quality function deployment is extended based on 2-tuple linguistic representation model under multi-granularity linguistic environment. With the new method, decision makers can freely give their opinions using different linguistic term sets in each step in QFD. It facilitates decision making in product design and development. When computing the linguistic information, the loss of evaluation information is avoided by taking the advantage of 2-tuple linguistic representation model in the new method. The illustrated example shows the applicability of the proposed method.

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