A new quant model to ensure successful QFD implementation in the increasingly uncertain environment

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Abstract - **QFD (Quality Function Deployment) can improve the quality of product and increase customer satisfaction, leading to superior performance of companies. But as global economy develops, the conditions wherein QFD is applied are becoming increasingly uncertain, which causes a lot of problems. Particularly, traditional techniques of QFD cannot deal with the vagueness, subjectivity and uncertainty of the linguistic information provided by customers as well as the R&D teams. This paper proposed a new model to solve such problems. We first integrate rough set theory into AHP (Analytic Hierarchy Process) to build one part of the model, which mainly deal with the uncertain information provided by customers. Then we applied linguistic information based GDM (Group Decision Making) theory to the expert assessment process to build another part of the model, which deal with the uncertain information within the R&D team.**

Keywords - **Quality Function Deployment, uncertain environment, rough set theory, linguistic information based group decision making theory**

I. INTRODUCTION

As global economy develops, customers are gaining clouts in the market. The powerful customers force companies pay more attention to the VOC (voice of customer), which is critical to customer satisfaction[1]. In order to gain competitive advantage, companies must rely on the sustainable product innovations that cater to the CNs (customer needs)[2]. That is the reason why QFD, a method to develop product and control the quality based on customer needs, is gaining attention in the literature[1, 3]

QFD is a "method to transform CNs into ECs (Engineering Characteristics), which can be easily monitored by the structured process (e.g. house of quality)"[1]. Previous researchers have demonstrated that QFD can shorten product development cycle [4], facilitate intern team communication[5], enhance quality of product and increase customer satisfaction, leading to superior performance of firms[6].

However, in the increasingly uncertain environment the traditional techniques used in QFD have showed a lot of drawbacks, especially its inability to deal with the vagueness, subjectivity and uncertainty of the linguistic information provided by customers as well as R&D teams[7].

Although scholars have tried hard to solve such problems [8-10], the methods they use might not be suitable in some conditions. For example, Kim et al. in [8] and Fung, R.Y.K., Y. Chen, and J. Tang in [10]applied fuzzy set theory and fuzzy regression in QFD, but the results might be unreliable to some extent because of the subjective selection of membership function used in their models.

To solve this problem we build a new model Fig. 1, integrating the rough set theory, which is a powerful knowledge discovery tool in uncertain conditions, the AHP and the linguistic information based GDM theory into QFD application.

The rest of this paper is organized as follows: Section 2 describes how we integrate rough set theory and AHP to get the RAHP method, which is used to analyze customer needs particularly to determine the comparative importance of different customer needs. In section 3, linguistic information based GDM theory is applied in the correlation determination process to determine the comparative importance of ECs. We conclude this paper in section 4.

II. THE R-AHP METHOD FOR CNS ANALYSIS

A. The vague, subjective and uncertain information of customers

Customers are the critical factor in the product development process, especially in the early stage. This makes the subjective judgments perceptions and

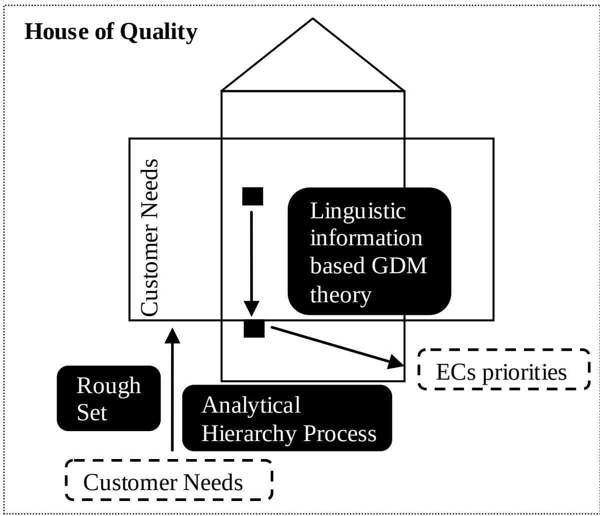

Figure 1. Quant model to tackle uncertainty

assessments unavoidable at the early stage of product development process. Therefore the QFD analysis of customers' needs is inherently subjective and uncertain[7]. Traditionally, analyses of customers' needs include two steps[11]: first, acquire initial customer needs by questionnaires; second, apply hierarchical method such as AHP (analysis of hierarchical process) to structuralize customers' needs and to determine the comparative importance of different customer needs. Currently the first step is relatively mature and certain. But the determination of the comparative importance of customer needs is much more difficult due to the large amount of ambiguous and vague information. To solve this problem we propose a new model that combines the rough set theory and AHP.

B. Rough set theory and rough number

AHP is easy to implement in the second stage of customer needs analysis, but it cannot deal with the vague and subjective linguistic-information. On the other hand the rough set theory can solve the vagueness and subjectivity without any preliminary information (e.g. the membership function in fuzzy theory)[12]. This provides with the solid foundation to the combination.

Before we propose our model, we give some basic definition used in the model.

Definition 1: U is a set of real numbers, according to rough set theory[12] $B_*(c_i)$ and $B^*(c_i)$ are the B-lower and B-upper approximation of number C_i, wherein B is the attributes of the objects in U (here B has one object: 'value'). $BN_B(c_i) = B^*(c_i) - B_*(c_i)$ is the boundary of $B(c_i)$. Define:

$$\underline{\mathrm{Lim}}(c_i) = \frac{1}{|B_*(c_i)|}\sum x|x \in B_*(c_i)$$

$$\overline{\mathrm{Lim}}(c_i) = \frac{1}{|B^*(c_i)|}\sum x|x \in B^*(c_i)$$

as the maximum approximation and minimum approximation of set $B(c_i)$, wherein c_i is an object of U and satisfies $c_i < c_j$ ($i < j$). We further define the rough number as follows:

$$\mathrm{RN}(c_i) = [\underline{\mathrm{Lim}}(c_i), \overline{\mathrm{Lim}}(c_i)]$$

$\underline{\mathrm{Lim}}(c_i)$ and $\overline{\mathrm{Lim}}(c_i)$ are denoted as c_i^- and c_i^+ for short

C. Integrate rough number and AHP to assess CNs

Now we can present the model proposed to assess CNs in Fig 2

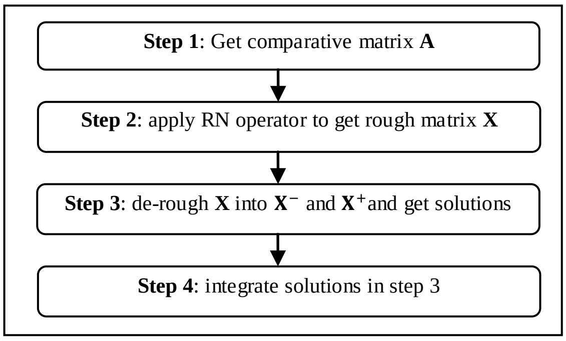

Figure 2. R-AHP model for CNs analysis

Step 1: determine and structuralize CNs, and use AHP questionnaire to get comparative matrix A. Suppose we have *s* customers to assess *n* CNs. We get comparative matrix $\mathbf{A^i}$ (i=1,2,…,s) as follows:

$$\mathbf{A^i} = \begin{bmatrix} \mathbf{1} & \mathbf{x_{12}^i} & \cdots & \mathbf{x_{1n}^i} \\ \mathbf{x_{21}^i} & \mathbf{1} & \cdots & \mathbf{x_{2n}^i} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x_{n1}^i} & \mathbf{x_{n2}^i} & \cdots & \mathbf{1} \end{bmatrix}$$

Step 2: in order to construct the rough number matrix, we first integrate $\mathbf{A^i}$ into $\mathbf{A}^*$

$$\mathbf{A}^* = \begin{bmatrix} \mathbf{1} & \mathbf{X_{12}^*} & \cdots & \mathbf{X_{1n}^*} \\ \mathbf{X_{21}^*} & \mathbf{1} & \cdots & \mathbf{X_{2n}^*} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{X_{n1}^*} & \mathbf{X_{n2}^*} & \cdots & \mathbf{1} \end{bmatrix}$$

wherein $\mathbf{X_{ij}^*} = (\mathbf{x_{ij}^1}, \mathbf{x_{ij}^2}, \ldots, \mathbf{x_{ij}^s})$.

Then use $\mathbf{RN(C_i)}$ operator on $\mathbf{X_{ij}^*}$, denote as $\mathbf{RN}(\mathbf{X_{ij}^*}) = [\mathbf{x_{ij}^-}, \mathbf{x_{ij}^+}]$. And therefore

$$\mathbf{RN}(\mathbf{A}^*) = \mathbf{X} = \begin{bmatrix} [\mathbf{1},\mathbf{1}] & [\mathbf{x_{12}^-}, \mathbf{x_{12}^+}] & \cdots & [\mathbf{x_{1n}^-}, \mathbf{x_{1n}^+}] \\ [\mathbf{x_{21}^-}, \mathbf{x_{21}^+}] & [\mathbf{1},\mathbf{1}] & \cdots & [\mathbf{x_{2n}^-}, \mathbf{x_{2n}^+}] \\ \vdots & \vdots & \ddots & \vdots \\ [\mathbf{x_{n1}^-}, \mathbf{x_{n1}^+}] & [\mathbf{x_{n2}^-}, \mathbf{x_{n2}^+}] & \cdots & [\mathbf{1},\mathbf{1}] \end{bmatrix}$$

Step 3: to get the comparative importance of CNs, we can break the rough AHP matrix X into $\mathbf{X}^-$ and $\mathbf{X}^+$, and calculate respectively.

$$\mathbf{X}^- = \begin{bmatrix} \mathbf{1} & \mathbf{x_{12}^-} & \cdots & \mathbf{x_{1n}^-} \\ \mathbf{x_{21}^-} & \mathbf{1} & \cdots & \mathbf{x_{2n}^-} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x_{n1}^-} & \mathbf{x_{n2}^-} & \cdots & \mathbf{1} \end{bmatrix}$$

$$\mathbf{X}^+ = \begin{bmatrix} \mathbf{1} & \mathbf{x_{12}^+} & \cdots & \mathbf{x_{1n}^+} \\ \mathbf{x_{21}^+} & \mathbf{1} & \cdots & \mathbf{x_{2n}^+} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x_{n1}^+} & \mathbf{x_{n2}^+} & \cdots & \mathbf{1} \end{bmatrix}$$

We can obtain the comparative importance of CNs from $\mathbf{X}^-$ and $\mathbf{X}^+$ [11, 13]

$$\mathbf{W}^- = (\mathbf{w_1^-}, \mathbf{w_2^-}, \ldots, \mathbf{w_n^-})$$

$$\mathbf{W}^+ = (\mathbf{w_1^+}, \mathbf{w_2^+}, \ldots, \mathbf{w_n^+})$$

Step 4: standardize and integrate the results in step 3 to get the comparative importance of CNs.

$$w_i^* = \frac{1}{2}\left(\frac{w_i^-}{\sum_{k=1}^{n} w_k^-} + \frac{w_i^+}{\sum_{k=1}^{n} w_k^+}\right)$$

III. LINGUISTIC INFORMATION BASED METHOD FOR ECs ASSESSMENT

A. Linguistic information theory

One of the most important steps to determine ECs is to figure out the preliminary priority of them by analyzing the relationships between customer requirements and ECs. In previous literatures the essential methods to determine such relationships is expert interviews and decisions[14]. But due to the complex and ambiguous decision making situation and uncertain judgment process of human, the experts often cannot give accurate quantitative assessment when they evaluate the situation. In order to solve this problem, we apply linguistic information group decision making theory into the experts' decision.

Definition 1: define linguistic information measurement

$$S^{(k)} = \left\{ S_\alpha^{(k)} \middle| \begin{array}{c} \alpha = 1-k, \frac{2}{3}(2-k), \ldots, 0, \ldots, \frac{2}{3}(k-2) \\ , \ldots, k-1 \end{array} \right\} \quad (1)$$

Wherein k is positive integer, and $S_\alpha^{(k)}$ satisfies:
(1) if $\alpha > \beta$, *then* $S_\alpha^{(k)} > S_\beta^{(k)}$;
(2) It has negative operator $\mathrm{neg}(S_\alpha^{(k)}) = S_{-\alpha}^{(k)}$

For calculation purpose, we further extend discrete set $S^{(k)}$ to continuous set $\bar{S}^{(k)} = \left\{ S_\alpha^{(k)} \middle| \alpha \in [-t, t] \right\}, t(\, t \geq k)$ is a nature number.

Definition 2: for any two linguistic terms, $S_{\alpha_1}^{(k)}, S_{\alpha_2}^{(k)} \in \bar{S}^{(k)}, \lambda \in [0,1]$ we have following algorithm

$$S_{\alpha_1}^{(k)} \oplus S_{\alpha_2}^{(k)} = S_{\alpha_2}^{(k)} \oplus S_{\alpha_1}^{(k)} = S_{\alpha_1+\alpha_2}^{(k)}$$

$$\lambda S_{\alpha_1}^{(k)} = S_{\lambda\alpha_1}^{(k)}$$

Definition 3[15]: a projection from n dimensions vector to single dimension vector, $\bar{S}^n \to \bar{S}$, we define LWA (Linguistic Weighted Algorithm) as:

$$\begin{aligned} \mathrm{LWA}(\, S_{\alpha_1}, S_{\alpha_2}, \ldots, S_{\alpha_n}) &= w_1 S_{\alpha_1} \oplus w_2 S_{\alpha_2} \oplus \ldots \oplus w_n S_{\alpha_n} \\ &= S_{\bar{\alpha}} \end{aligned} \quad (2)$$

Wherein $\bar{\alpha} = \sum_{j=1}^{n} w_j \alpha_j$ and $w_j \in [0,1], \sum_{j=1}^{n} w_j = 1$

Definition 3[16]: a projection from n dimensions vector to single dimension vector $\bar{S}^n \to \bar{S}$; and $\boldsymbol{\nu} = (\nu_1, \nu_2, \ldots, \nu_n)$ is the weighted location vector, $\nu_j \in [0,1], \sum_{j=1}^{n} \nu_j = 1$. We define LHA (Linguistic Hybrid Algorithm) as:

$$\mathrm{LHA}(\, S_{\alpha_1}, S_{\alpha_2}, \ldots, S_{\alpha_n}) = \nu_1 S_{\beta_1} \oplus \nu_2 S_{\beta_2} \oplus \ldots \oplus \nu_1 S_{\beta_n} \quad (3)$$

Wherein S_{β_j} is the j^{th} factor in weighted average set $\bar{S}' = \left\{ S'_{\alpha_i} \middle| S'_{\alpha_i} = n w_i S_{\alpha_i}, i = 1,2,\ldots,n \right\}$, here n is the balance coefficient; $\mathbf{w} = (w_1, w_2, \ldots, w_n)$ is the weight vector of $S_{\alpha_i} (i = 1,2,\ldots,n), \sum_{i=1}^{n} w_i = 1$.

Often in time, the experts give linguistic information assessment with different granular, due to their different experience and knowledge base. To make the calculation of linguistic information consistent we should standardize the linguistic information assessments that have different granular. Assume we have continuous linguistic information assessment $\bar{S}^{(k_1)} = \left\{ S_\alpha^{(k_1)} \middle| \alpha \in [1-k_1, k_1-1] \right\}$ and $\bar{S}^{(k_1)} = \{ S_\beta^{(k_2)} | \beta \in [1-k_2, k_2-1] \}$, define the transfer function[17] F as:

$$F: S^{(k_1)} \to S^{(k_2)} \quad (4)$$

$$\boldsymbol{\beta} = F(\boldsymbol{\alpha}) = \boldsymbol{\alpha} \frac{k_2 - 1}{k_1 - 1} \quad (5)$$

$$F^{-1}: S^{(k_2)} \to S^{(k_1)} \quad (6)$$

$$\boldsymbol{\alpha} = \mathbf{F}^{-1}(\boldsymbol{\beta}) = \boldsymbol{\beta} \frac{\mathbf{k_1 - 1}}{\mathbf{k_2 - 1}} \quad \mathbf{(7)}$$

B. Apply Linguistic information theory into ECs analysis

Now that we have basic tool for linguistic information assessment, we can build up our linguistic information based model in Fig 3

Step 1: Assume we have m ECs, EC_i $(i = 1,2,\ldots,m)$, which can be determined by current product standards or cause-effect analysis such as DOE (Design of Experiment)

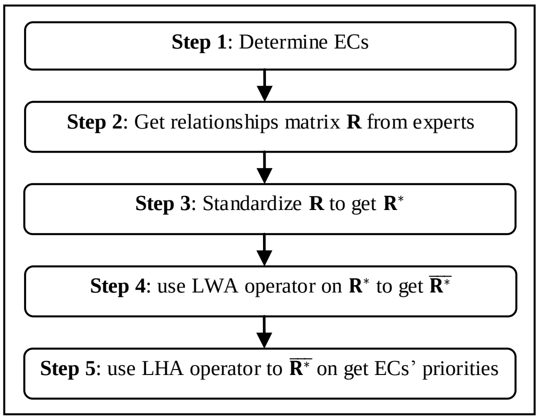

Figure 3. Linguistic information based model for ECs correlation analysis

Step 2: Assume that we have t experts to determine the relationships $Ex_\xi(\xi = 1,2,\dots,t)$. The weight of Ex_ξ is $\mathbf{w} = (w_1, w_2, \dots, w_t)^T$, which satisfies $w_\xi \geq 0$, and $\sum_{\xi=1}^{t} w_\xi = 1$. They consider n CNs of relationships for each EC CN_ξ $(\xi = 1,2,\dots,n)$ and its weights vector $= (d_1, d_2, \dots, d_n)^T d_j \geq 0$, $\sum_{j=1}^{n} d_j = 1$. This generates relationships values $r_{i,j}^{(k^\xi)}(\xi = 1,2,\dots,t; i = 1,2,\dots,m; j = 1,2,\dots,n)$.

We define expert matrix $\mathbf{R} = (R_{i,j})$ wherein $R_{i,j} = \{r_{i,j}^{k^1}, r_{i,j}^{k^2}, \dots, r_{i,j}^{k^t}\}$.

Note that the matrix **R** is a three-dimension matrix and $\mathbf{k^\xi}(\boldsymbol{\xi} = \mathbf{1}, \mathbf{2}, \dots, \mathbf{t})$ indicate the different granular the decision maker uses.

Step 3: To get the ultimate priorities of ECs we should standardize k^ξ, using algorithm (4) – (7) mentioned above to get a unified-granular decision making matrix $\mathbf{R}^* = (R_{i,j}{}^*)$.

Step 4: Then we can apply LWA operator (2) to $\mathbf{R}^*$ to get $\overline{\mathbf{R}^*} = (r_{i,j})_{m\times n}$.

Note, here LWA operator makes the three-dimensional matrix $\mathbf{R}^*$ a two-dimension matrix $\overline{\mathbf{R}^*}$, which indicate the relationships between CNs and ECs.

Step 5: We finally apply LHA operator (3) to $\overline{\mathbf{R}^*}$ to calculate the ultimate priorities value $(P_i(i = 1,2,\dots,m))$ of each EC.

IV. DISCUSSION AND CONCLUSION

Firstly, compared with traditional methods to analyze CNs, our R-AHP method does not need any preliminary information such as subjective pre-judgment, hypothesis or membership function. All the calculations are based on the data acquired through AHP questionnaire. This ensures the objectivity of original data. On the other hand, the rough number, which is based on rough set theory, considers accordingly the vague subjective and uncertain information provided by customer. Therefore, the model has much more validity and effectiveness than traditional methods.

Secondly, the method proposed for correlation analysis between ECs and CNs is integrated with linguistic information based GDM theory, which ensures the better understanding and description of the experts' survey than traditional methods. Firstly, it can properly deal with the different linguistic information granular used by experts. Secondly it also appropriately leverages the knowledge base of different experts, by assigning importance weights and location weights when conducting calculation.

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