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APPLYING THE SUPERIOR IDENTIFICATION GROUP LINGUISTIC VARIABLE TO CONSTRUCT KANO MODEL ORIENTED QUALITY FUNCTION DEPLOYMENT

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Abstract. This study attempts to manipulate 2-tuple linguistic variables rather than pure linguistic variables in quality function deployment (QFD) in order to significantly improve the identification of the QFD model. The Kano model, a two-dimensional quality technique, is also integrated to recognize the degree of urgency in terms of enhancing and prioritizing quality-related requirements of customers via a fuzzy linguistic quantifier with a soft majority concept to fit the optimal aggregation weights. This study also retains the goodness on the usage of multi-granularity linguistic approach to facilitate the implementation of a group decision. Simultaneously, two-dimensional analysis is performed to explain the results synthetically between relationship matrix and correlation matrix from a management perspective, capable of providing comprehensive information for the decision process. Owing to the integration of several quality and management methods, results of this study demonstrate the capability of TRIZ.

Keywords: quality function deployment, linguistic variable, Kano model, group decision, fuzzy linguistic quantifier, linguistic aggregation operator.

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Introduction

Multinational enterprises heavily focus on competitiveness based on globalization. Meanwhile, to upgrade industrial practices and increase the number of value-added products, an effective business strategy closely aligns to the consumer marketplace and R&D to ensure that future high value-added products comply with consumer demand, rather than focus on the previous strategy of lowering retail prices. However, enterprises devote considerable resources to incorporate customer needs in the R&D process. Various product management and R&D schemes have subsequently been developed, especially TRIZ. TRIZ belongs to QFD, which considers customer needs and can be an effective medium for TRIZ to achieve quality improvement standards. Moreover, in addition to contributing to the conflict matrix for TRIZ in compliance with customer needs, QFD greatly facilitates an understanding of TRIZ (Verhaegen *et al.* 2009). Therefore, this study addresses how to reform the QFD approach to conform to TRIZ, allowing enterprises to upgrade their practices (Yamashina *et al.* 2002).

Nevertheless, the matrix analysis of TRIZ depends almost entirely on qualitative evaluation with linguistics, explaining why this study focuses on how to further improve the discrimination and sensitivity of linguistic evaluation. Furthermore, conventional computation models do not have the capability to deal with linguistic valuations hence this study develops reasoning mechanism that is able to map input words, perceptions, and propositions to decisions by computing with words (Martinez *et al.* 2010; Mendel *et al.* 2010). This study also attempts to distinguish between the order of priority among customer needs and expectation in order to promote quality improvement activities under limited resources. The soft majority concept, fuzzy linguistic quantifier, is thus adopted to guide the aggregation weights generated by the order of priority among customer needs. Meanwhile, entropy for the aggregation weights is also maximized to facilitate decision making during evaluation of qualitative linguistics (Chang *et al.* 2006, 2007; Wang *et al.* 2007, 2009). Additionally, the 2-tuple linguistic variable (Herrera, Martinez 2000), associated with linguistic and numerical information, is introduced to further improve the pure linguistic QFD model of Wang (2010) to increase the discrimination capability and sensitivity of qualitative linguistic information (Martinez *et al.* 2006; Wang 2008). This study also adopts the Kano model to validate the degree of eagerness and identify the order of priority among customer needs and expectations. According to our results, a finite resource can be incorporated in the most effective activities to facilitate quality improvement. This study first adopts the medium approach, House of Quality (HOQ) (Fig. 1), which can implement QFD activities and then be integrated with relevant approaches such as the Kano model, fuzzy linguistic quantifier, aggregation weights with maximum entropy, 2-tuple linguistic variable, group decision, multi-granularity linguistic uniformity, and linguistic aggregation operations.

The next section comments on the recent literature on fuzzy QFD. Section 2 details the construction of the proposed model, and Section 3 then interprets the algorithm of the proposed model interpreted by the flow chart. Subsequently, Section 4 presents a synthetic example illustrating the proposed model, and finally the last section presents conclusions and future research directions.

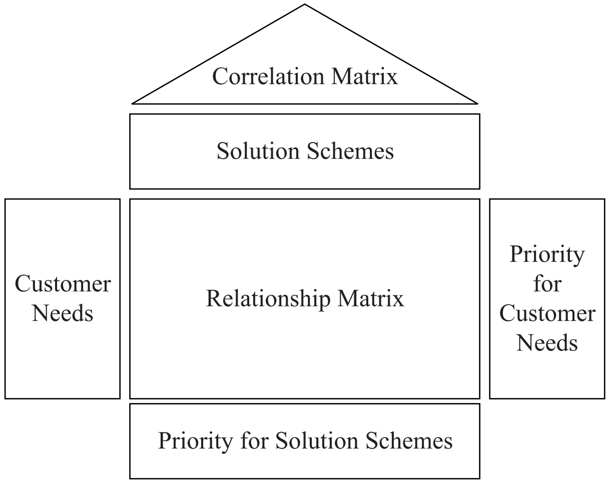


Fig. 1. House of quality

1. Literature review

This section describes relevant fuzzy QFD literature, especially with respect to linguistics, model integration, applications, and even group decision. Literature on the integration of Kano model and QFD is also discussed.

1.1. Fuzzy QFD

In research on the linguistics of Fuzzy QFD, Temponi *et al.* (1999) built a fuzzy logic–based linguistic evaluation matrix model. Chan and Wu (2005) presented the results of linguistic evaluations and HOQ operation on a crisp value and fuzzy number. Chen and Weng (2006) adopted the linguistic form to evaluate the weights of customer needs and a relationship matrix. Defuzzification results, cost and difficulty of solution schemes were then introduced into multiple objective fuzzy linear programming to determine the execution level of solution scenarios. Kahraman *et al.* (2006) combined defuzzification results obtained from a linguistic evaluation of customer needs using an analytical hierarchy process (AHP) to weight customer needs, and then used fuzzy linear programming (FLP) to determine the implementation level of the solution schemes. Büyüközkan *et al.* (2007) manipulated full linguistics to construct QFD, and also directly applied aggregation to linguistics. Chen and Weng (2003), and Chen and Ko (2008a, b, 2009) performed the HOQ operation by linguistic evaluation results with membership function and then via $\alpha - cut$ defuzzification.

In research on the application and integration of fuzzy QFD, Kim *et al.* (2000), and Fung *et al.* (2006) developed a fuzzy multiple criteria model for HOQ operation and presented the results via fuzzy numbers that became the parameters of fuzzy regression in prioritizing solution scenarios. Chen and Ko (2008a, b) and Lee *et al.* (2008) introduced the Kano model into QFD. Yang *et al.* (2003) utilized linguistic variables defined in fuzzy numbers to weight customer needs and identify the relationship matrix in architectural design. Fuzzy number–based aggregation results were compared with the definition of linguistic variables to assess the eventual linguistic result. Karsak (2004) employed linguistic variables to weight customer needs and relationship matrix in a clothing design context. After obtaining the defuzzification results, cost and difficulty of solution schemes were incorporated into multi-objective FLP to resolve the fulfilled rate of solution schemes. Büyüközkan and Feyzioğlu (2005) developed the ordered weighted geometric (OWG) operator to aggregate the information from the group-decision QFD model on the application of software design. Moreover, seven calculations for weighting are proposed to construct a complete numerical HOQ. Fuzzy linguistic quantifiers are then introduced to aggregate and prioritize solution scenarios. Bevilacquaa *et al.* (2006), Bottani and Rizzi (2006) constructed the HOQ using a linguistic variable defined by fuzzy numbers to deal with issues of supplier selection and strategy management for logistics services. Karsak and Özogul (2009) combined QFD, fuzzy regression and zero-one goal programming to select enterprise resource planning (ERP) system. The data collected via QFD is used for fuzzy regression and then solved by zero-one goal programming. Celik *et al.* (2009) evaluated shipping investment by introducing fuzzy theory in QFD and AHP. By using FLP, Chen and Ko (2010) developed a new product by expanding QFD into four phases.

In research on group decision-making on fuzzy QFD, Büyüközkan and Feyzioğlu (2005), Chin *et al.* (2009), and Kuo *et al.* (2009) constructed the numeric HOQ based on group decision-making, and Büyüközkan *et al.* (2007) constructed the linguistic HOQ based on group decision-making.

Carnevalli and Miguel (2008) reviewed and analyzed 157 studies on QFD published from 2000 to 2006. Although lots of the literature touched upon fuzzy QFD and usage of linguistics, most of the literature on practical calculation adopts a numeric approach together with defuzzification (Kwong *et al.* 2007; Lai *et al.* 2008; Celik *et al.* 2009; Chen, Ko 2010) and thus differs significantly from this study. Notwithstanding Büyüközkan *et al.* (2007) constructed a complete linguistic QFD based on group decision; the usage of multi-granularity linguistics and the integration utility of correlation matrix have still not been discussed. This study cites the example of a previous case by introducing 2-tuple linguistic variable with superior discriminability and the Kano model to understand how customer needs information in a previous study differs from that in this study and, in doing so, expands the extent and depth of application to QFD. In addition to its comprehensiveness, this study differs from conventional representations of the results of HOQ based on two-dimensional analysis. Moreover, decision makers can also clearly understand the order of executive priority and conflicting severity.

1.2. Kano model within QFD

While investigating the application and integration between the Kano model and QFD, Matzler and Hinterhuber (1998) introduced the Kano model in QFD to provide decision makers with satisfactory information on the association with customer needs and quality improvements. Chen and Chuang (2008) utilized robust product design to increase customer satisfaction via the Kano model. Chen and Ko (2008a, b) associated fuzzy linear and non-linear programming with the Kano model to incorporate QFD in product design. In addition to adopting the Kano model and fuzzy theory to implement QFD, Lee *et al.* (2008) expanded QFD based on a product life cycle oriented concept. Li *et al.* (2009) determined the importance of customer needs within HOQ via the Kano model and AHP. While reviewing 18 studies on the integration between the Kano model and QFD, Delice and Güngör (2009) developed a method related to the Kano model and integer linear programming in order to optimize the solution schemes in QFD. Xu *et al.* (2009) adopted the Kano model to analyze customer needs in HOQ and implement the specifications for parameters design and quality improvement.

To sum up the above studies on the Kano model and QFD, this study determines the weights of customer needs, based on direct use of linguistics, which significantly differs from previous studies, yet is similar to the human decision making process.

2. 2-tuple linguistic model and multi-granular information

This section introduces in detail the modeling procedures used in this study. This section also demonstrates how to apply fuzzy linguistic quantifier, 2-tuple multi-granularity linguistic variable, aggregation weights with maximum entropy, linguistic aggregation, and solution schemes analysis for synergy. Fortunately, Martinez and Herrera (2012) pointed out the extensions, applications and challenges on the 2-tuple linguistic model for computing with words in decision making. Besides, Espinilla *et al.* (2011) proposed an extended hierarchical linguistic model for decision-making problems. Hence this study integrates the features on Fusion I and LH approaches reviewed by Espinilla *et al.* (2011) to construct the model that would possess accurate 2-tuple linguistic term with unlimited term sets.

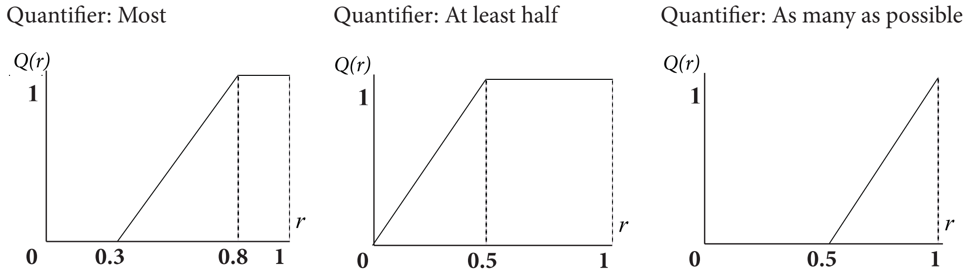
2.1. Fuzzy linguistic quantifier

The aggregation weighted vector W is a mapping to membership function $Q(r)$ guided by a monotonically non-decreasing fuzzy linguistic quantifier, Q, repersented as Eqs. (1) to (2). The membership function $Q(r)$. represents the membership grade on r that belongs to Q. The membership function also differs from Q (Herrera *et al.* 2000). This study illustrats three quantifiers in Fig. 2.

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right), \ j = 1,\ldots,n; \tag{1}$$

$$Q(r) = \begin{cases} 0 & if \quad r < a \\ \dfrac{r-a}{b-a} & if \quad a \le r \le b \\ 1 & if \quad r > b \end{cases}, \ a, b, r \in [0,1]. \tag{2}$$

According to the Kano model, quality is divided into five features: 1) Attrative Quality; 2) One-dimensional Quality; 3) Must-be Quality; 4) Indifferent Quality; and 5) Reverse Quality. Customer needs belonging to “Must-be Quality” and “Attractive Quality” are similar to “Hygiene Factor” and “Motivator Factor” in “Herzberg’s Two Factor Theory”, respectively.



$$Q(r)=\begin{cases}0 & \text{if } r<0.3\\ \dfrac{r-0.3}{0.8-0.3} & \text{if } 0.3\le r\le 0.8\\ 1 & \text{if } r>0.8\end{cases}$$
$a,b,r\in[0,1]$

$$Q(r)=\begin{cases}0 & \text{if } r<0\\ \dfrac{r-0}{0.5-0} & \text{if } 0\le r\le 0.5\\ 1 & \text{if } r>0.5\end{cases}$$
$a,b,r\in[0,1]$

$$Q(r)=\begin{cases}0 & \text{if } r<0.5\\ \dfrac{r-0.5}{1-0.5} & \text{if } 0.5\le r\le 1\\ 1 & \text{if } r>1\end{cases}$$
$a,b,r\in[0,1]$

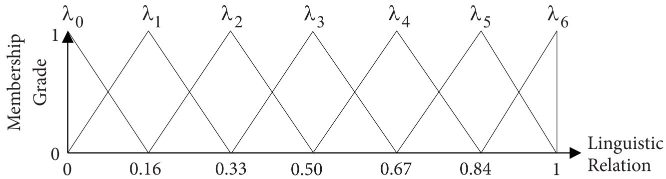
Fig. 2. Monotonically non-decreasing fuzzy linguistic quantifier

"One-dimensional Quality" is situated between "Must-be Quality" and "Attractive Quality". From the perspective of avoiding customer dissatisfaction, "Must-be Quality" is the top priority, followed by "One-dimensional Quality" and finally "Attractive Quality". Customer needs belonging to "Indifferent Quality" can be disregarded from the aggregation weighted vector due to the lack of significant improvement in customer satisfaction. "Reverse Quality" can then be eliminated directly by considering customer needs, without a positive improvement in customer satisfaction. Customer needs are further sorted according to the features of "Must-be Quality", "One-dimensional Quality", and "Attractive Quality" in sequence, which depend on the analysis results of the Kano model. The sorted customer needs are then fitted with an aggregation weighted vector based on the fuzzy linguistic quantifier "At least half" to reflect the eagerness degree of quality improvement for all customer needs.

2.2. 2-tuple multi-granularity linguistic variable

The 2-tuple multi-granularity linguistic variable is formed by combining 2-tuple linguistic variable (s_t,α) (Herrera, Martinez 2000) and multi-granularity linguistic information (Herrera *et al.* 2000), where the semantic element s_t is assessed by the linguistic variable *S* defined in the linguistic term set $S=\{s_0,s_1,\ldots,s_d\}$ and $t\in\{0,1,\ldots,d\}$; meanwhile, $\alpha\in[-0.5,+0.5)$ is employed to represent the degree of conformation regarding the semantic element s_t based on actual supply behavior. The characteristic value $\Delta(\theta)$ is applied rather than 2-tuple linguistic variable (s_t,α) to implement the mathematical calculations in follow-up sections, where $\theta=t+\alpha$. The 2-tuple multi-granularity linguistic variable used in this investigation is constructed by the linguistic variable (linguistic scale), which comprises two linguistic term sets with several semantic elements, as shown in Fig. 3. Linguistic results are assessed based on a selected linguistic scale. Furthermore, multi-granularity information is expressed via 2-tuple rather than single linguistic information to increase the sensitivity of the identification.

Label	Semantic	(x_L, x_m, x_R)
λ_0	None	(0,0,0.16)
λ_1	Very Low	(0,0.16,0.33)
λ_2	Low	(0.16,0.33,0.5)
λ_3	Medium	(0.33,0.5,0.67)
λ_4	High	(0.5,0.67,0.84)
λ_5	Very High	(0.67,0.84,1)
λ_6	Perfect	(0.84,1,1)



Label	Semantic	(x_L, x_m, x_R)
δ_0	None	(0,0,0.12)
δ_1	Very Low	(0,0.12,0.25)
δ_2	Low	(0.12,0.25,0.37)
δ_3	Almost Low	(0.25,0.37,0.5)
δ_4	Medium	(0.37,0.5,0.62)
δ_5	Almost High	(0.5,0.62,0.75)
δ_6	High	(0.62,0.75,0.87)
δ_7	Very High	(0.75,0.87,1)
δ_8	Perfect	(0.87,1,1)

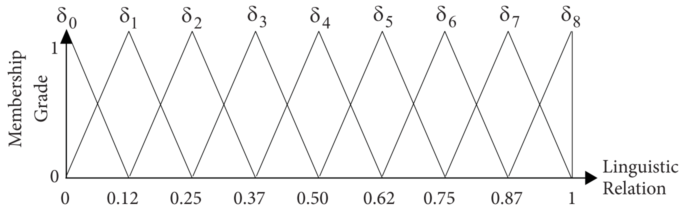


Fig. 3. The definition of linguistic variable λ and δ

Furthermore, the semantic element (SE) used in the linguistic term set (LTS) is constructed using the triangular membership function with fuzzy relation, which is defined in the unit interval [0, 1] by the fuzzy number (x_L, x_m, x_R), where x_L and x_R represent the left and right limits of the triangular membership function, and x_m indicates the value at which equals to 1.

2.3. Aggregation weighted vector optimization

Optimizing the aggregation weighted vector requires calculating the degree of "Orness" and "Entropy" (Dispersion). The calculation is based on the aggregation weighted vector *W*, displayed in Eqs. (3) to (4). Orness, which lies in the unit interval, is a good measurement for characterizing the degree to which the aggregation is an Or-like (Max-like) or And-like (Min-like) operation. When Orness equals 1, the aggregation equals the maximum operation; when Orness equals 0, the aggregation equals the minimum operation; and when Orness equals 0.5, the aggregation equals the arithmetic mean operation. Simultaneously, Entropy represents the measurement for characterizing the degree to which information on the individual behaviours in the aggregation process is used (Yager 1988).

$$Orness(W) = \frac{1}{n-1}\sum_{j=1}^{n}(n-j)w_j\ ; \tag{3}$$

$$Entropy(W) = -\sum_{j=1}^{n} w_j \ln w_j\ . \tag{4}$$

The concept and purpose of optimization is based on the premise that the current Orness should be kept constant to implement an amendment process for maximizing the Entropy. Eq. (5) illustrates the approach to proceed (Filev, Yager 1995).

Maximize $$-\sum_{j=1}^{n} w_j \ln w_j \,. \tag{5}$$

Subject to $$Orness(W) = \frac{1}{n-1}\sum_{j=1}^{n}(n-j)w_j \,; \tag{5a}$$

$$\sum_{j=1}^{n} w_j = 1\,,\ w_j \in [0,1]\,,\ j = 1,\ldots,n\,. \tag{5b}$$

Furthermore, the Lagrange multiplier method can be used to obtain the maximum entropy aggregation weighted vector W^*, which can aggregate the maximum information from supplier behaviors. Filev and Yager (1995) presented the detailed information. Equation (5) can be further simplified as Eqs. (6) and (7). Moreover, the numerical analysis approach can be used to obtain *h* from Eq. (6), and *h* can be substituted into Eq. (7) to obtain W^*. The initial vector of *W* thus is replaced by the new W^* implicated the maximum entropy.

$$\sum_{j=1}^{n}\left(\frac{n-j}{n-1} - Orness(W)\right) h^{n-j} = 0\,; \tag{6}$$

$$w_j^* = \frac{h^{n-j}}{\sum_{j=1}^{n} h^{n-j}}\,. \tag{7}$$

2.4. Linguistic aggregation

The proposed model in this study allows for a group decision that should have different LTSs adopted by individuals within a group during the decision process that would cause multi-granularity linguistic information. Hence, the uniformity of linguistic scale should be executed via a basic linguistic term set (BLTS) before linguistic aggregation, if necessary. BLTS is defined as being the same as LTS, only the number of SEs in BLTS must contain all of the SEs in LTS to avoid reducing semantic discrimination in the uniformity process (Chang *et al.* 2007). The transformation function of linguistic scale uniformity τ_{AS_T} is defined as follows (Herrera *et al.* 2000):

Let $A = \{l_0, l_1, \ldots, l_p\}$ be a LTS for the linguistic variable, and $S_T = \{c_0, c_1, \ldots, c_g\}$ be a BLTS for the linguistic variable to uniform the linguistic scale, where $g \geq p$, such that $\tau_{AS_T} : A \to F(S_T)$.

$$\tau_{AS_T}(l_e) = \{(c_u, \psi_{c_u}^{l_e}) \mid u \in \{0,1,\ldots,g\}\}\,, \quad \forall l_e \in A\,;$$

$$\psi_{c_u}^{l_e} = \max_x \ \min\{\mu_{l_e}(x), \mu_{c_u}(x)\}\,.$$

The result of uniformity τ_{AS_T} for any SE of A is a fuzzy set defined in S_T, where $\mu_{l_e}(x)$ and $\mu_{c_u}(x)$ are the membership functions of the fuzzy sets associated with the SEs l_e and c_u, respectively. The uniformity generates a new fuzzy set $\tau_{AS_T}(l_e) = \{(c_u, \psi_{c_u}^{l_e}) \mid u \in \{0,1,\ldots,g\}\}$, where $(c_u, \psi_{c_u}^{l_e})$ indicates the membership grade $\psi_{c_u}^{l_e}$ of each SE c_u in BLTS associated with the original SE l_e. Subsequently the characteristic value of the unidirectional uniformed

2-tuple linguistic information is determined by $\Delta\left(\frac{\sum_{u=0}^{g} u\psi_{c_u}^{l_e}}{\sum_{u=0}^{g} \psi_{c_u}^{l_e}}\right) = \Delta(\theta)$ (Herrera *et al.* 2005).

The aggregation of 2-tuple linguistic information is performed using the modified linguistic ordered weighted averaging (M-LOWA) operator based on the maximum entropy aggregation weighted vector W^*. Let $E = \{\Delta(\theta_1), \Delta(\theta_2), \ldots, \Delta(\theta_m)\}$ denote a set of characteristic value of 2-tuple linguistic information assessed by the linguistic variable $S = \{s_0, s_1, \ldots, s_d\}$ to be aggregated, then the M-LOWA operator F_Q has to modify slightly from Herrera *et al.* (1996) and is defined as follows (Wang 2008):

$$F_Q(\Delta(\theta_1), \Delta(\theta_2), \ldots, \Delta(\theta_m)) = W^* \cdot B^T = C^m\{w_k^*, b_k, k = 1,2,\ldots,m\} =$$
$$w_1^* \otimes b_1 \oplus (1 - w_1^*) \otimes C^{m-1}\{\beta_h, b_h, h = 2,3,\ldots,m\},$$

where: $W^* = [w_1^*, w_2^*, \ldots, w_m^*]$, is a maximum entropy aggregation weighted vector, such that, $w_i^* \in [0,1]$ and $\sum_i w_i^* = 1$; $\beta_h = \frac{w_h^*}{\sum_{k=2}^{m} w_k^*}$, $h = 2,3,\ldots,m$; and B is the associated ordered set from $E = \{\Delta(\theta_1), \Delta(\theta_2), \ldots, \Delta(\theta_m)\}$. Each $b_i \in B$ is the ith largest characteristic value in the collection $\Delta(\theta_1), \Delta(\theta_2), \ldots, \Delta(\theta_m)$. C^m is the convex combination operator of m characteristic value, $\otimes$ is the general product of a characteristic value by a positive real number and $\oplus$ is the general additional of characteristic value (Delgado *et al.* 1992). If $m = 2$, then F_Q is defined as below (Wang 2008):

$$F_Q(\Delta(\theta_1), \Delta(\theta_2)) = W^* \cdot B^T = C^2\{w_i^*, b_i, i = 1,2\} = w_1^* \otimes \Delta(\theta_j) \oplus (1 - w_1^*) \otimes \Delta(\theta_i) = \Delta(\theta),$$

such that $\theta = \min\{d, i + w_1^* \cdot (j - i)\}$, where: $b_1 = \Delta(\theta_j)$ and $b_2 = \Delta(\theta_i)$. If $w_j = 1$ and $w_i = 0$ with $i \neq j$ $\forall i$, then the convex combination is defined as $C^m = \{w_i^*, b_i, i = 1,2,\ldots,m\} = b_j$. The M-LOWA operator can retain more information from the aggregation through omitted the round operation from the LOWA operator.

Finally, the aggregated result can be reversed from characteristic value $\Delta(\theta)$ to 2-tuple linguistic information (s_t, α) by $t = round(\theta)$ and $\alpha = \theta - t$, where *round* is the usual round operation (Herrera, Martinez 2000).

2.5. Synergistic analysis for solution schemes

The interworking formed with 2-tuple between the priority and correlation among solution schemes displayed in Fig. 4 would be further demonstrated synergistic analysis via two-dimensional coordinates where the priority showed on horizontal axis and the correlation showed on vertical axis. The solution scheme located within phase I will possess higher superiority than other phases due to the solution scheme held not only higher priority but also augmentation impression on correlation concurrently. On the contrary, the solution scheme located within phase III will possess lower superiority than other phases due to lower priority and conflict impression. Although the solution scheme located within phase IV is lower than within phase II on correlation, the solution scheme is still slightly superior to the priority. However based on customer needs, the solution scheme located within phase IV will be superior to phase II. Decision makers can further consider other factors such as cost to distinguish the superiority between phase II and IV.

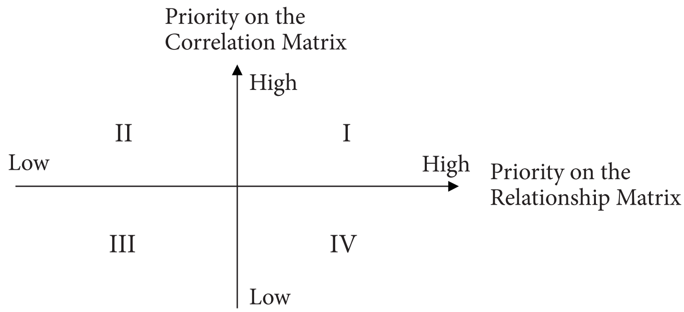


Fig. 4. Synergistic analysis for solution schemes

3. Algorithm

The methodology proposed from this study can be divided into 9 steps which are displayed below in sequence. The flow chart of algorithm can also refer to Fig. 5.

Step 1. Identify customer needs. Understand and cognize practical customer needs through general surveys and investigations.

Step 2. Analysis customer needs. Apply Kano model to differentiate and confirm the properties of customer needs.

Step 3. Fit fuzzy linguistic quantifier to the priority of customer needs. Sort the customer needs accordance the priorities of "Must-be Quality", "One-dimensional Quality", and "Attractive Quality" in sequence which depended on the result of analysis from Kano model. Thereupon fit the fuzzy linguistic quantifier "At least half" and calculate the aggregation weighted vector through by Eqs. (1) and (2).

Step 4. Optimize the priority of customer needs. Due to avoiding of lack customer needs, the procedure of maximizing entropy is adopted to mine the maximum information for aggregation via Eqs. (3) to (7).

Step 5. Propose solution schemes. Look for appropriate solution schemes and assess the practicability.

Step 6. Assess the relationship and correlation matrices based on group decision process. Allow decision makers to choose preferred linguistic variables to perform the relationship matrix assessments according to strong or weak relations between each customer need and solution scheme pair, and thus make correlation matrix assessments according to the positive or negative relevance between each pair of solution schemes.

Step 7. Uniform linguistic scale for relationship and correlation matrices. If the relationship and correlation matrices are assessed using different linguistic variables, the uniformity

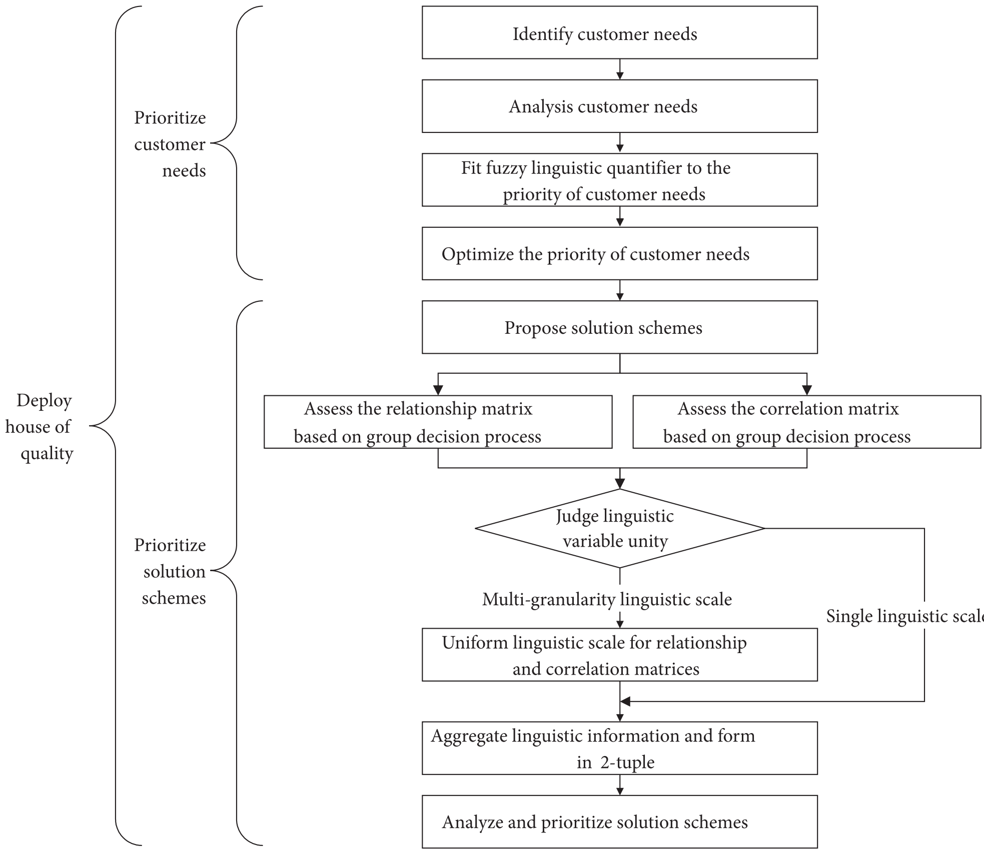


Fig. 5. The flow chart of the algorithm

procedure should be performed via BLTS before aggregation that is illustrated in the beginning of Subsection 3.4.

Step 8. Aggregate linguistic information and form in 2-tuple. The M-LOWA operator with maximum entropy aggregates group based linguistic information from the relationship and correlation matrices. Then, the M-LOWA operator with maximum entropy also employs to aggregate the relationship matrix of customer needs to prioritize each solution scheme as well as the correlation matrix and finally forms the results in 2-tuples.

Step 9. Analyse and prioritize solution schemes. Manipulate the two-dimensional coordinates to synthetically demonstrate the priority of solution schemes and the result of linguistic aggregation on the correlation matrix.

4. Demonstrative example

The focal company, which specializes in fabricating notebook computers, wants to upgrade one of their products using QFD improving activities. Five customer needs (convenience for carry-on, artistic modelling, sustaining power, multi-function integration, and reception of vision) are obtained after a serial survey from the marketplace. Based on the order of priority, Table 1 lists the differentiation results from the Kano model for each customer need.

Table 1. The priority of customer needs with differentiation from Kano model

Customer needs	Convenience for carry-on	Artistic modeling	Sustaining power	Multi-function integration	Reception of vision
Differentiation	Must-be quality	Must-be quality	One-dimensional quality	Attractive quality	Attractive quality

According to the order of customer needs guided by an appropriate fuzzy linguistic quantifier "At least half" involved the eagerness degree, the aggregation weighted vector W and maximum entropy aggregation weighted vector W^* are calculated through Eqs. (1) to (2) and Eqs. (3) to (7) respectively, as listed in Table 2. The computing process dealing with the fuzzy linguistic quantifier "At least half" and involving five customer needs is displayed below:

$$w_1 = Q\left(\frac{1}{5}\right) - Q\left(\frac{0}{5}\right) = 0.4 - 0 = 0.4\,;\; w_2 = Q\left(\frac{2}{5}\right) - Q\left(\frac{1}{5}\right) = 0.8 - 0.4 = 0.4\,;$$

$$w_3 = Q\left(\frac{3}{5}\right) - Q\left(\frac{2}{5}\right) = 1 - 0.8 = 0.2\,;\; w_4 = Q\left(\frac{4}{5}\right) - Q\left(\frac{3}{5}\right) = 1 - 1 = 0\,;$$

$$w_5 = Q\left(\frac{5}{5}\right) - Q\left(\frac{4}{5}\right) = 1 - 1 = 0\,;$$

$$Orness(W) = \frac{1}{5-1}\sum_{j=1}^{5}(5-j)w_j = \frac{1}{4}(4w_1 + 3w_2 + 2w_3 + w_4) = 0.8\,;$$

$$\sum_{j=1}^{5}\left(\frac{5-j}{5-1} - 0.8\right)h^{5-j} = (\frac{4}{4} - 0.8)\,h^4 + (\frac{3}{4} - 0.8)\,h^3 + (\frac{2}{4} - 0.8)\,h^2 + (\frac{1}{4} - 0.8)\,h - 0.8 = 0\,;$$

$$h = 2.0690085\,;$$

$$w_1{}^* = \frac{h^4}{\sum_{j=1}^{5} h^{5-j}} = \frac{h^4}{h^4 + h^3 + h^2 + h + 1} = 0.53067\,;$$

$$w_2{}^* = \frac{h^3}{\sum_{j=1}^{5} h^{5-j}} = \frac{h^3}{h^4 + h^3 + h^2 + h + 1} = 0.25649\,;$$

$$w_3{}^* = \frac{h^2}{\sum_{j=1}^{5} h^{5-j}} = \frac{h^2}{h^4 + h^3 + h^2 + h + 1} = 0.12397\,;$$

$$w_4{}^* = \frac{h}{\sum_{j=1}^{5} h^{5-j}} = \frac{h}{h^4 + h^3 + h^2 + h + 1} = 0.05992\,;$$

$$w_5{}^* = \frac{1}{\sum_{j=1}^{5} h^{5-j}} = \frac{1}{h^4 + h^3 + h^2 + h + 1} = 0.02896\,.$$

The quality improvement project team proposed five feasible schemes in an attempt to meet customer needs. Linguistic variable φ shown in Table 3 is employed to demonstrate assessment results for the relationship matrix (refer to Table 4); linguistic variables λ and δ shown in Table 3 and Fig. 3 are employed by different team members to demonstrate assessment results for the correlation matrix (refer to Fig. 6). The assessment and aggregation results are both formed in 2-tuple.

Table 2. The aggregation weighted vector W and W^* for fuzzy linguistic quantifier "At least half"

Customer needs	**Convenience for carry-on**	**Artistic modeling**	**Sustaining power**	**Multi-function integration**	**Reception of vision**	
W	w_1	w_2	w_3	w_4	w_5	$Orness(W)$
	0.4	0.4	0.2	0	0	0.8
W^*	$w_1{}^*$	$w_2{}^*$	$w_3{}^*$	$w_4{}^*$	$w_5{}^*$	$Orness(W^*)$
	0.53067	0.25649	0.12397	0.05992	0.02896	0.8

Table 3. Linguistic variables ϕ, λ, and δ

Linguistic variable ϕ (Relationship Matrix)		**Linguistic variable λ (Correlation Matrix)**		**Linguistic variable δ (Correlation Matrix)**	
Label	**Semantic Element**	**Label**	**Semantic Element**	**Label**	**Semantic Element**
ϕ_0	Absolute Harmful	λ_0	Absolute Negative Correlation	δ_0	Absolute Negative Correlation
ϕ_1	Very High Harmful	λ_1	Very High Negative Correlation	δ_1	Very High Negative Correlation
ϕ_2	High Harmful	λ_2	High Negative Correlation	δ_2	High Negative Correlation
ϕ_3	Almost High Harmful	λ_3	No Correlation	δ_3	Almost High Negative Correlation
ϕ_4	No Relationship	λ_4	High Positive Correlation	δ_4	No Correlation
ϕ_5	Almost High Useful	λ_5	Very High Positive Correlation	δ_5	Almost High Positive Correlation
ϕ_6	High Useful	λ_6	Absolute Positive Correlation	δ_6	High Positive Correlation
ϕ_7	Very High Useful			δ_7	Very High Positive Correlation
ϕ_8	Absolute Useful			δ_8	Absolute Positive Correlation

Table 4. Aggregation results for the relationship matrix with the order of priority

Need \ Scheme	Power Subsystem	Graphics & TV Tuner	Display	Commu-nication	Storage Subsystem
Sustaining power	$(\phi_7,0)$	$(\phi_3,0)$	$(\phi_3,0)$	$(\phi_4,0)$	$(\phi_5,0)$
Convenience for carry-on	$(\phi_2,0)$	$(\phi_3,0)$	$(\phi_3,0)$	$(\phi_4,0)$	$(\phi_7,0)$
Multi-function Integration	$(\phi_4,0)$	$(\phi_7,0)$	$(\phi_6,0)$	$(\phi_6,0)$	$(\phi_6,0)$
Large size monitor	$(\phi_4,0)$	$(\phi_4,0)$	$(\phi_7,0)$	$(\phi_4,0)$	$(\phi_4,0)$
Artistic modeling	$(\phi_3,0)$	$(\phi_4,0)$	$(\phi_6,0)$	$(\phi_4,0)$	$(\phi_6,0)$
Aggregation results	$(\phi_3,0.054)$	$(\phi_4,-0.475)$	$(\phi_4,0.065)$	$(\phi_5,-0.349)$	$(\phi_6,0.349)$

Power Subsystem: High watt Li-ion battery pack
Graphics & TV Tuner: Advanced graphic card & Built-in digital and analog hybrid TV tuner
Display: 15.4 inch WXGA crystalbrite color TFT LCD
Communication: Wireless techniques (LAN & Bluetooth)
Storage Subsystem: Slot-load DVD-dual double-layer

Table 4 clearly indicates that various schemes can exert different yet related influences on single customer needs. For instance, although the scheme "Power Subsystem" enhances the customer need "Sustaining Power", the scheme "Graphics and TV Tuner" subjects the power supply to increased loading and negatively impacts the customer need "Sustaining Power". The schemes "Power Subsystem" and "Graphics and TV Tuner" thus conflict with each other. Acording to aggregation results for the relationship matrix, the scheme "Storage Subsystem" has the highest piority, followed by "Commucation", "Display", "Graphics and TV Tuner", and finally "Power Subsystem". The following example describes the aggregation process for the scheme "Power Subsystem":

$$F_Q((\varphi_7,0),(\varphi_2,0),(\varphi_4,0),(\varphi_4,0),(\varphi_3,0)) = F_Q(\Delta(7),\Delta(2),\Delta(4),\Delta(4),\Delta(3)) =$$
$$W^* \cdot B^T = [0.124, 0.060, 0.029, 0.256, 0.531] \cdot [\Delta(7),\Delta(4),\Delta(4),\Delta(3),\Delta(2)]^T =$$
$$C^5\{(0.124,\Delta(7)),(0.060,\Delta(4)),(0.029,\Delta(4)),(0.256,\Delta(3)),(0.531,\Delta(2))\} =$$
$$0.124 \otimes \Delta(7) \oplus (1-0.124) \otimes C^4\{(0.068,\Delta(4)),(0.033,\Delta(4)),(0.293,\Delta(3)),(0.606,\Delta(2))\};$$

$$C^4\{(0.068,\Delta(4)),(0.033,\Delta(4)),(0.293,\Delta(3)),(0.606,\Delta(2))\} =$$
$$0.068 \otimes \Delta(4) \oplus (1-0.068) \otimes C^3\{(0.035,\Delta(4)),(0.314,\Delta(3)),(0.650,\Delta(2))\};$$

$$C^3\{(0.035,\Delta(4)),(0.314,\Delta(3)),(0.650,\Delta(2))\} =$$
$$0.035 \otimes \Delta(4) \oplus (1-0.035) \otimes C^2\{(0.326,\Delta(3)),(0.674,\Delta(2))\};$$

$$C^2\{(0.326,\Delta(3)),(0.674,\Delta(2))\} = 0.326 \otimes \Delta(3) \oplus (1-0.326) \otimes \Delta(2) = \Delta(\theta);$$

$$\theta = \min\{8, 2 + [0.326 \times (3-2)]\} = \min\{8, 2.326\} = 2.326;$$

$$C^2\{(0.326,\Delta(3)),(0.674,\Delta(2))\} = \Delta(2.326);$$

$$C^3\{(0.035,\Delta(4)),(0.314,\Delta(3)),(0.650,\Delta(2))\}=0.035\otimes\Delta(4)\oplus(1-0.035)\otimes\Delta(2.326)=\Delta(\theta);$$

$$\theta=\min\{8,2.326+[0.035\times(4-2.326)]\}=\min\{8,2.385\}=2.385;$$

$$C^3\{(0.273,\Delta(4)),(0.364,\Delta(3)),(0.364,\Delta(2))\}=\Delta(2.385);$$

$$C^4\{(0.068,\Delta(4)),(0.033,\Delta(4)),(0.293,\Delta(3)),(0.606,\Delta(2))\}= \\ 0.068\otimes\Delta(4)\oplus(1-0.068)\otimes\Delta(2.385)=\Delta(\theta);$$

$$\theta=\min\{8,2.385+[0.068\times(4-2.385)]\}=\min\{8,2.496\}=2.496;$$

$$C^4\{(0.068,\Delta(4)),(0.033,\Delta(4)),(0.293,\Delta(3)),(0.606,\Delta(2))\}=\Delta(2.496);$$

$$C^5\{(0.124,\Delta(7)),(0.060,\Delta(4)),(0.029,\Delta(4)),(0.256,\Delta(3)),(0.531,\Delta(2))\}= \\ 0.124\otimes\Delta(7)\oplus(1-0.124)\otimes\Delta(2.496)=\Delta(\theta);$$

$$\theta=\min\{8,2.496+[0.124\times(7-2.496)]\}=\min\{8,3.054\}=3.054;$$

$$C^5\{(0.124,\Delta(7)),(0.060,\Delta(4)),(0.029,\Delta(4)),(0.256,\Delta(3)),(0.531,\Delta(2))\}=\Delta(3.054)=(\varphi_3,0.054).$$

Thus the quality improvement project team further considered the technique correlation and resource competitiveness among schemes in performing the assessment and aggregation of the correlation matrix, as mentioned for the relationship matrix. However, the assessments are performed via two different linguistic variables λ and δ by the team members (refer to Fig. 6) that should achieve further uniformity, as mentioned in Subsection 3.4, before aggregation. Table 5 illustrates the uniformity matrix associated with linguistic variable λ and δ, where the contained data indicate the fuzzy preference relation (horizontal coordinate) and the membership grade (vertical coordinate) of the corresponding SE. The corresponding SE with the highest membership grade is exhibited within gray background. The LTS of linguistic variable δ is used to represent BLTS, and the uniformity results in Fig. 6 can be referred to Table 5. The deduction process is shown in Fig. 7 to illustrate how to obtain the uniformity membership grade $\psi_{\delta_7}^{\lambda_5}$ of SE δ_7 in BLTS from the initial assessment of SE λ_5. An example of the uniformity process for the SE "λ_5" is displayed below:

$$A=\{l_0,l_1,\ldots,l_p\}=\left\{\lambda_0,\lambda_1,\lambda_2,\lambda_3,\lambda_4,\lambda_5,\lambda_6\right\};$$

$$S_T=\{c_0,c_1,\ldots,c_g\}=BLTS=\left\{\delta_0,\delta_1,\delta_2,\delta_3,\delta_4,\delta_5,\delta_6,\delta_7,\delta_8\right\};$$

$$\psi_{\delta_0}^{\lambda_5}=\alpha_{\delta_1}^{\lambda_5}=\alpha_{\delta_2}^{\lambda_5}=\alpha_{\delta_3}^{\lambda_5}=\alpha_{\delta_4}^{\lambda_5}=0;\quad \psi_{\delta_5}^{\lambda_5}=\max_x\ \min\{\mu_{\lambda_5}(x),\mu_{\delta_5}(x)\}=0.267;$$

$$\psi_{\delta_6}^{\lambda_5}=\max_x\ \min\{\mu_{\lambda_5}(x),\mu_{\delta_6}(x)\}=0.690;\quad \psi_{\delta_7}^{\lambda_5}=\max_x\ \min\{\mu_{\lambda_5}(x),\mu_{\delta_7}(x)\}=0.893;$$

$$\psi_{\delta_8}^{\lambda_5}=\max_x\ \min\{\mu_{\lambda_5}(x),\mu_{\delta_8}(x)\}=0.448;$$

$$\tau_{AS_T}(\lambda_5)=\{(\delta_0,0),(\delta_1,0),(\delta_2,0),(\delta_3,0),(\delta_4,0),(\delta_5,0.267),(\delta_6,0.690),(\delta_7,0.893),(\delta_8,0.448)\};$$

$$\Delta(\theta)=\Delta\left(\frac{\sum_{u=0}^{8} u\psi_{\delta_u}^{\lambda_5}}{\sum_{u=0}^{8} \psi_{\delta_u}^{\lambda_5}}\right)=$$

$$\Delta\left(\frac{0\times 0+1\times 0+2\times 0+3\times 0+4\times 0+5\times 0.267+6\times 0.690+7\times 0.893+8\times 0.448}{0+0+0+0+0+0.267+0.690+0.893+0.448}\right)=\Delta(6.662)=(\delta_7,-0.338).$$

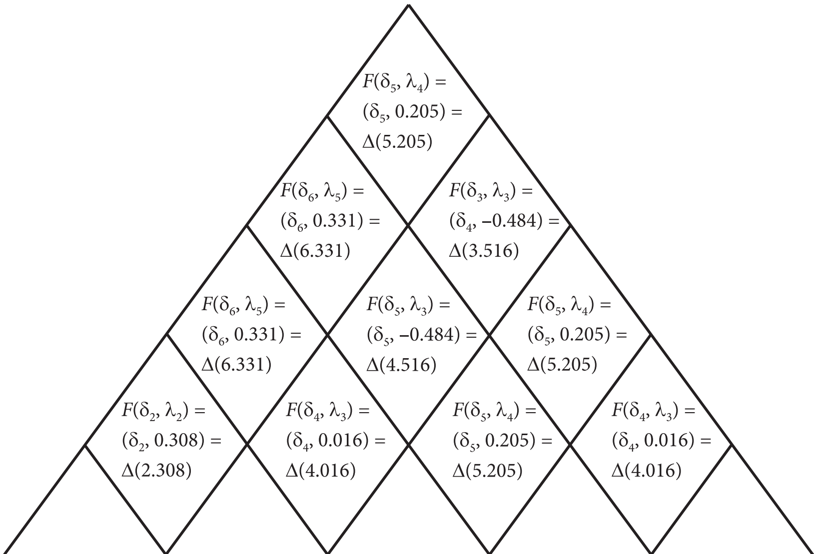
The membership grade of corresponding SEs in BLTS from initial assessed SE can be determined by simultaneous linear equations. The result of the uniformity set $\tau_{AS_T}(\lambda_5)$ illustrates that the initial SE λ_5 has the highest membership grade "0.893" in the SE δ_7 of BLTS at horizontal coordinate "0.857" (fuzzy preference relation). Therefore, the characteristic value $\Delta(\theta)=\Delta(6.662)$ in 2-tuple form $(\delta_7,-0.338)$ replaces $(\lambda_5,0)$ to represent the uniformity result.

Table 5. Linguistic scale uniformity matrix for linguistic variable λ and δ

Horizontal/vertical	λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
δ_0	0.000 / 1.000	0.069 / 0.429	–	–	–	–	–
δ_1	0.069 / 0.571	0.138 / 0.862	0.211 / 0.300	–	–	–	–
δ_2	0.138 / 0.001	0.211 / 0.700	0.283 / 0.724	0.353 / 0.138	–	–	–
δ_3	–	0.283 / 0.276	0.353 / 0.862	0.426 / 0.567	–	–	–
δ_4	–	–	0.426 / 0.433	0.500 / 1.000	0.570 / 0.414	–	–
δ_5	–	–	–	0.570 / 0.586	0.642 / 0.833	0.715 / 0.267	–
δ_6	–	–	–	0.642 / 0.167	0.715 / 0.733	0.787 / 0.690	0.857 / 0.107
δ_7	–	–	–	–	0.787 / 0.310	0.857 / 0.893	0.928 / 0.552
δ_8	–	–	–	–	–	0.928 / 0.448	1.000 / 1.000
Uniformity result	$(\delta_0,0.365)$	$(\delta_1,0.363)$	$(\delta_3,-0.384)$	$(\delta_4,0.031)$	$(\delta_5,0.410)$	$(\delta_7,-0.338)$	$(\delta_8,-0.462)$

After uniformity is achieved, the group based aggregation weights for the assessment results based on two different linguistic variables (λ and δ) are equal to 0.5 (Intra-aggregation for each pair-wise scheme). Next, the correlation based aggregation weights for the group based aggregation results are equal to 0.25 (Inter-aggregation for four pair-wise schemes). Figure 6 displays the results of intra-aggregation and inter-aggregation for the correlation matrix.

Although "Power Subsystem" facilitated the performance of the other four schemes, it occupied space. Hence the quality improvement project team was concerned with space requirement and weight factors associated with the request for portability.



Aggregation results	$\Delta(5.044) = (\delta_5, 0.044)$	$\Delta(3.589) = (\delta_4, 0.411)$	$\Delta(5.189) = (\delta_5, 0.189)$	$\Delta(5.314) = (\delta_5, 0.314)$	$\Delta(4.486) = (\delta_4, 0.486)$
Scheme	Power Subsystem	Graphics & TV Tuner	Display	Communication	Storage Subsystem

Intra-aggregation: aggregation for each pair-wise scheme by equal weights “0.5”

Inter-aggregation: aggregation for four pair-wise schemes by equal weights “0.25”

Fig. 6. Aggregation results for the correlation matrix with the order of priority

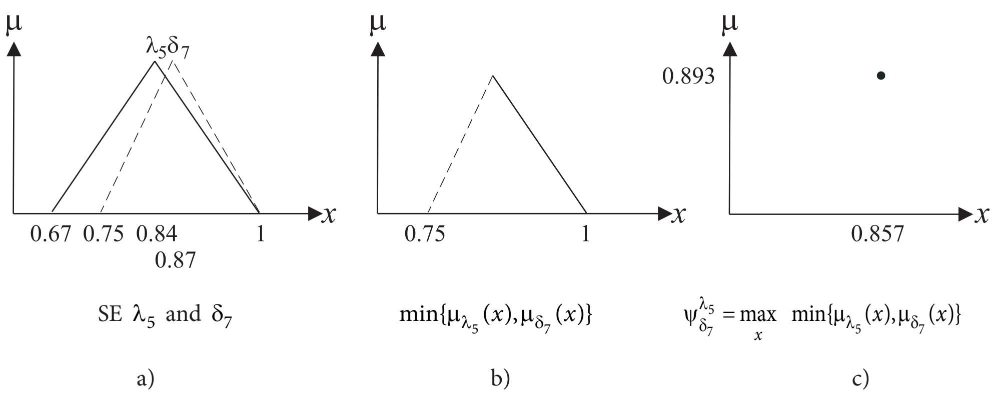


Fig. 7. The deducing process of uniformity about the membership grade $\psi_{\delta_7}^{\lambda_5}$

Furthermore, this study performed two-dimensional analysis with 2-tuple linguistic information, as shown in Fig. 8, to clarify scheme priorities in the relationship and correlation matrices. Obviously, the scheme "Storage Subsystem" ranks first based on customer needs in the relationship matrix, and is followed sequentially by "Communication", "Display", "Graphics & TV Tuner", and finally "Power Subsystem". However, the scheme "Communication" ranks first based on conflict analysis in the correlation matrix, followed sequentially by "Display", "Power Subsystem", "Storage Subsystem" and, finally, "Graphics & TV Tuner". According to the synergistic analysis of this study, the scheme "Graphics & TV Tuner" can be excluded first to reduce the complexity of the decision process as well as focus the quality improvement activities on the remaining schemes. Otherwise, the schemes "Communication", "Storage Subsystem", and "Display" can be adopted first.

Conclusion

The QFD model developed in this study incorporates the Kano model to handle the priority of customer needs, which differs from the common mode. Additionally, the differentiation ability of 2-tuple linguistic information is further enhanced more than the singleton. Simultaneously, the implication of information from the relationship and correlation matrices is re-annotated well by synergistic analysis to provide decision makers with more comprehensive information. The multi-granularity linguistic variable is also incorporated in the QFD model to premeditate the possibility of a group decision. Integrating the result of this investigation with other management techniques such as cost-benefit analysis and analytic hierarchy process (AHP) represents a further achievement of this study.

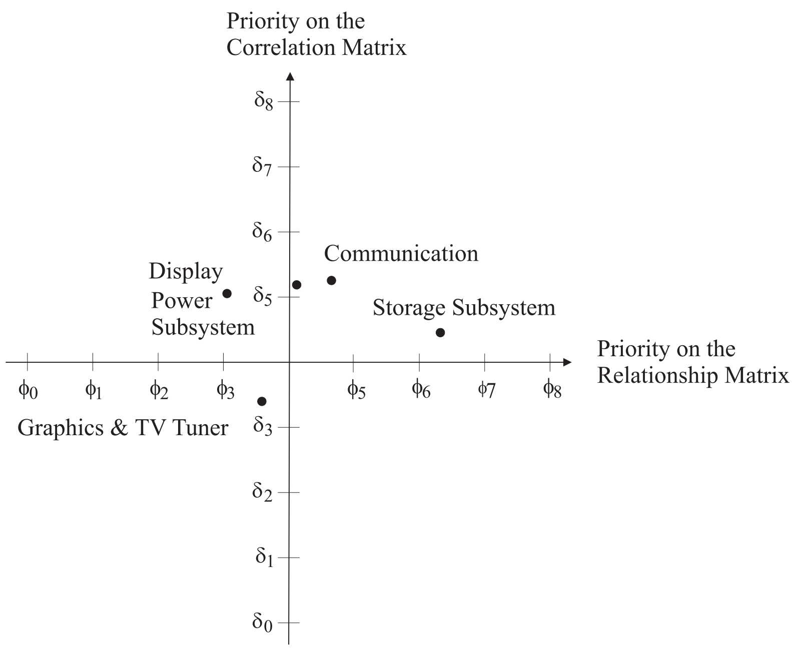


Fig. 8. Synergistic analysis for the relationship and correlation matrices

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