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Using Fuzzy QFD for Design of Low-end Digital Camera

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Abstract: Quality Function Deployment (QFD) is an integrated product design process involving all members of designers and customers. It is a method for mapping and prioritizing customer requirements into functional features and technical modules to optimize market performance. Although the quality of a product can be dramatically improved through a QFD exercise, the traditional crisp scoring approach has a major drawback. A wrong conclusion can be easily produced since the fuzzy nature of linguistic correlation terms from evaluation members is ignored. To overcome this problem, fuzzy scoring for linguistic terms is proposed in this paper. The implementation case of a low-end digital camera design shows that the result of the proposed fuzzy QFD model can reflect the certainty level of an evaluation term, which is designated for each correlation of customer requirements and technical requirements considered in design.

Keywords: quality; function; deployment; fuzzy; set theory; penalty concept; camera design.

1. Introduction

Quality Function Deployment (QFD) is an effective tool for planning attributes of new products based on customer demands and involves all members of the producer or supplier organization (King 1989). QFD can be used to integrate an organization's diverse sources of information during product and process development, so that the goal of Total Quality Management (TQM) and Concurrent Engineering (CE) inside the organization can be facilitated.

In a QFD procedure, the product design team is forced to consider what the customer wants, then identify possible ways to achieve that end, instead of concentrating only on the design's aspects. Thus, QFD methodology provides a way to translate conceptual requirements into items that are workable, measurable, and capable of design enhancement.

The result is a better design, shorter product development cycles, better product quality, and lower costs. This process also enables organizations to be proactive rather than reac-

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tive to the market in product design.

A complete QFD exercise for a product design project consists of four phases, namely design, detail, process, and production. The four-phased scheme of QFD analysis can be accomplished by a series of matrix transformation, where each matrix is called “House of Quality” (HOQ). A HOQ consists of horizontal rows of *What*, representing customer requirements and vertical columns of *How*, denoting ways of achieving them (Guinta and Praizler 1993).

The customer requirements can then be translated into critical design characteristics, component characteristics, process control characteristics, and operational instructions. Table 1 depicts the basic structure of a HOQ including the major components of technical requirements, customer requirements, correlation (R_{ij}), importance, and resulted weight.

Table 1. A typical structure of a QFD

	Technical requirements					Importance
Customer requirements	R_{11}	R_{12}	…	…	R_{1m}	D_1
	R_{21}	R_{22}	⋱			D_2
	⋮					…
	⋮			⋱	⋮	…
	R_{n1}	R_{n2}	…	…	R_{nm}	D_n
Resulted weight	W_1	W_2	…	…	W_m	

Several studies concerning the improvement of QFD methodology, integration with other systems, and the automation of HOQ construction have been utilized in the past decade. Maier (1993) modified the traditional QFD model to connect the performance model with the structured method and managerial model. Chang (1989) proposed a general design of an integrated total quality information system involving QFD.

Dean (1992) extends QFD to large-scale systems that link QFD to system engineering process, concurrent engineering process, robust design process, and costing process. Perry (1992) presented a case study describing a consulting assignment undertaken for a computer system manufacturer in the midst of designing its next generation of high performance systems.

Generally, QFD software utilizes the relational database management system to enable the encapsulation of a consistent, company-standard product planning process while minimizing unnecessary complexity.

Locascio and Thurston (1993) used a multi-attribute utility theory and an optimization theory to determine the target values of technical requirements that can best achieve the overall objectives. Wasserman (1993) proposed a decision model that can be used to assist in cost tradeoff decisions during the QFD planning to prioritize design requirements.

2. Problems in using crisp QFD for design prioritization

In a traditional QFD exercise, the correlation between customer requirements and technical requirements as well as the importance for each customer requirement are determined by the members of a design team using linguistic expressions (e.g. weak, average, strong).

These linguistic terms are then scaled into crisp values (e.g. 1-3) for the ranking of each alternative. This crisp assessment for correlation evaluation in QFD analysis has difficulty coping with uncertainty among design team members (Masud and Dean 1993, Khoo and Ho 1996). The major problem is that the assignment of crisp values cannot reflect the imprecision or vagueness inherent in these types of assessments. Accordingly, the inconsistent ranking result could be generated due to the sensitivity of crisp evaluation where no imprecision or approximate concept is allowed.

The conclusion from QFD analysis is sometimes questionable to product design teams. In addition, the certainty level of correlation during mapping of attributes from the decision-making team cannot be expressed in traditional QFD analysis. Sometimes, a design team is confident and clear with the decision-making environment, but many times it is not. With different certainty levels, the analysis could be distinct. However, certain levels of correlation terms are not a part of the input in using a crisp QFD analysis.

3. Fuzzy QFD model

To conquer the problems inherent in traditional crisp QFD analysis, we propose indices that can correct the aforementioned drawbacks through a consistent algorithm for a decision-making environment. Moreover, a display of changes of ranking according to different scenarios can provide a "what-if" analysis in product design. In this paper, we first briefly introduce fuzzy set theory related to the proposed tasks. Then, a fuzzy QFD model with a certainty-level index is proposed. An industrial case of re-designing a point-to-shoot camera is presented to demonstrate the benefit of the proposed model. Finally, a discussion and conclusion will follow.

3.1. Background information

To consider the uncertainty situations from the assessments of linguistic variables in a QFD analysis, fuzzy sets and the concept of linguistic variables introduced by Zadeh (1965) are adapted in this research. Fuzzy set theory has been proven as a useful tool in modeling the intuition, vagueness, and imprecision presented in descriptions of a decision-making or optimization problem.

Some of the mathematical background related to this research is introduced in this section.

Let X be a universe of discourse, and fuzzy subset $\tilde{A}$ of X is defined by a membership function $\mu_{\tilde{A}}(x)$ that maps each element x of a given universal set X to a real number in the unit interval [0,1]; that is $\mu_{\tilde{A}}(x): X \rightarrow [0,1]$. The function value $\mu_{\tilde{A}}(x)$ represents the grade of membership of x in $\tilde{A}$.

Fuzzy sets are defined on the set R of real numbers. Membership functions of these sets, which have the form $\mu_{\tilde{A}}(x): R \rightarrow [0,1]$, clearly have a quantitative meaning and can be viewed as fuzzy numbers. Specifically, $\tilde{A}$ is a fuzzy number if and only if its membership function is such that

$$\mu_{\tilde{A}}(x) = \begin{cases} l(x) & for \quad x \in (\alpha, \beta) \\ 1 & for \quad x \in [\beta, \gamma] \\ r(x) & for \quad x \in (\gamma, \delta) \\ 0 & otherwise \end{cases} \quad (1)$$

where $l(x)$ is a function from (α, β) to [0,1] that is monotonic increasing and continuous from the right; $r(x)$ is a function from (γ, δ) to [0,1] that is monotonic decreasing and continuous from the left.

Figure 1 shows a typical graph of a fuzzy number described in Equation (1).

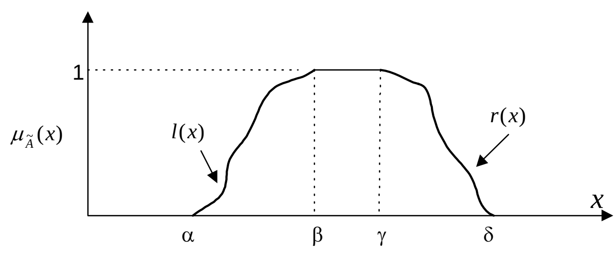


Figure 1. A typical fuzzy number

Most researchers use special fuzzy numbers, such as triangular fuzzy numbers, trapezoidal fuzzy numbers, and R-L fuzzy numbers, to satisfy the need of modeling fuzzy problems. For simplicity, the most commonly used trapezoidal fuzzy numbers are used for necessary illustrations in this paper. Let $x, \alpha, \beta, \gamma, \delta \in R$, where R is the set of real numbers. Then, we define that a fuzzy number $\tilde{A}$ is a trapezoidal fuzzy number if its membership function is

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-\alpha)/(\beta-\alpha) & for \quad x \in [\alpha, \beta] \\ 1 & for \quad x \in [\beta, \gamma] \\ (x-\delta)/(\gamma-\delta) & for \quad x \in [\gamma, \delta] \\ 0 & for \quad x \in (-\infty, \alpha) \; and \; x \in (\delta, \infty) \end{cases} \quad (2)$$

We also denote the trapezoidal fuzzy number $\tilde{A}$ as $(\alpha, \beta, \gamma, \delta)$. A fuzzy number $\tilde{A}$ is a triangular fuzzy number if $\beta = \gamma$ in its membership function.

The mathematical evaluation process of QFD matrices using fuzzy numbers involves the two basic fuzzy number operations of addition ($\oplus$) and multiplication ($\otimes$). These two fuzzy arithmetic operations are based on the extension principle introduced by Zadeh (1975). The extension principle is used to generalize non-fuzzy (crisp) mathematical concepts into fuzzy quantities.

3.2. Fuzzy QFD model with linguistic certainty index

In a QFD matrix, various inputs in the form of judgment and evaluations are required for quantitative analysis. Most of the time, these inputs are linguistic variables like IMPACT, IMPORTANCE, CORRELATION, INTERRELATION, etc. In general, the values of a linguistic variable are generated from a primary term (e.g. impact), its correlation weights (e.g. high, low, strong, weak), and a collection of modifiers (e.g. not, very, more, less).

To quantify the linguistic variables used in QFD, the fuzzy set theory is an excellent tool to help a design team to select proper alternatives in an uncertainty environment. As described in Table 1, building a complete QFD matrix includes the identification of technical requirements, customer requirements, correlation, importance, and interrelation.

Since interrelation between technical requirements does not affect the calculation of resulted weights, discussion of interrelation will not be included in our model.

In our fuzzy QFD model, two linguistic variables are defined as:

$\tilde{I}$ = "IMPORTANCE" for importance, and
$\tilde{C}$ = "CORRELATION" for correlation matrix.

Each linguistic variable is composed of a set of linguistic terms represented as fuzzy numbers. In this research, the universe for linguistic variables "IMPORTANCE" and "CORRELATION" are defined respectively as

$X_{\tilde{I}}$ = {"Very Low", "Low", "Medium Important", "High", "Very High"}.
$X_{\tilde{C}}$ = {"Very Weak", "Weak", "More-Or-Less Weak", "Medium", "More-Or-Less Strong", "Strong", "Very Strong"}.

Based on the design team's comprehension for linguistic terms of each linguistic variable, the trapezoidal fuzzy numbers for the linguistic variable "*IMPORTANCE*" and "*CORRELATION*" can be defined. After the selection of definitions for linguistic terms is completed, the resulting weight for each alternative can be calculated based on the fuzzy arithmetic operations described in Section 2. If there are m technical requirements and *n* customer requirements as depicted in Table 1, resulting weight $\tilde{W}_j$ can be evaluated as follows:

$$\tilde{W}_j = (\tilde{C}_{1j} \otimes \tilde{I}_1) \oplus (\tilde{C}_{2j} \otimes \tilde{I}_2) \oplus \cdots \oplus (\tilde{C}_{nj} \otimes \tilde{I}_n) \, , \; \forall j \in \{1, 2, \cdots, m\} \quad (3)$$

where $\tilde{W}_j$ = the resulting weight of the *j*th technical requirement,

$\tilde{C}_{ij}$ = the correlation of the *j*th technical requirement on *i*th customer requirement,

$\tilde{I}_i$ = the importance of the *i*th customer requirement,

$\oplus$ = fuzzy addition, and
$\otimes$ = fuzzy multiplication operation.

When incorporating fuzzy arithmetic operations in the QFD matrix, the resulting weight for each technical requirement is no longer a crisp number but a fuzzy number.

The fuzzy numbers must be interpreted in an appropriate way for people to understand. Researchers have proposed many fuzzy ranking methods to compare fuzzy numbers.

In this research, we adopt a ranking method proposed by Liou and Wang (1992). This method using integral values as fuzzy indexes has been proved as a very efficient and effective fuzzy ranking method (Liao 1996).

The total integral value for fuzzy number $\tilde{A}$ with highest optimistic attitude is defined as:

$$I_T^{\omega}(\tilde{A}) = \int_0^1 g_{\tilde{A}}^R(y)dy \tag{4}$$

where $g_{\tilde{A}}^R(y)$ are the inverse functions of $r(x)$ defined as Equation (1).

If $I_T^{\omega}(\tilde{A}_1) > I_T^{\omega}(\tilde{A}_2)$, then the ranking of $\tilde{A}_1$ is higher than that of $\tilde{A}_2$

3.3. Adjustment with a linguistic certainty index

A fuzzy QFD model should not only reflect a design team's optimistic degree but also its linguistic certainty level for the decision problem. We have developed an index to include different spreads of a fuzzy number for a linguistic variable.

By using this index, fuzzy numbers for assessment can be adjusted according to the linguistic certainty level of a design team. Since certainty level is a relative concept, a neutral fuzzy number is needed as a reference.

The shape of the neutral fuzzy number can be derived from the understanding of linguistic expression and the scale used in linguistic variables.

Let $\tilde{A}$ be a neutral fuzzy number. Therefore, a fuzzy number $\tilde{B}$ is defined as λ levels of linguistic certainty relative to $\tilde{A}$ such that

$$\begin{cases} \alpha_{\tilde{B}} = \beta_{\tilde{A}} - (\beta_{\tilde{A}} - \alpha_{\tilde{A}})/\lambda \\ \beta_{\tilde{B}} = \beta_{\tilde{A}} \\ \gamma_{\tilde{B}} = \gamma_{\tilde{A}} \\ \delta_{\tilde{B}} = \gamma_{\tilde{A}} + (\delta_{\tilde{A}} - \gamma_{\tilde{A}})/\lambda \end{cases} \tag{5}$$

where $\alpha_{\tilde{A}}, \beta_{\tilde{A}}, \lambda_{\tilde{A}}, \delta_{\tilde{A}}$ are the parameters defined in Equation (1) for $\tilde{A}$, and $\alpha_{\tilde{B}}, \beta_{\tilde{B}}, \lambda_{\tilde{B}}, \delta_{\tilde{B}}$ are the parameters defined in Equation (1) for $\tilde{B}$.

If the linguistic certainty index is $0 < \lambda < 1$, we claim that the fuzzy number $\tilde{B}$ has lower linguistic certainty than the fuzzy number $\tilde{A}$ does. Oppositely, when the linguistic certainty index is $\lambda > 1$, we say that $\tilde{B}$ has higher linguistic certainty than $\tilde{A}$ does.

To show the proposed linguistic certainty index at work, let us take an example of three trapezoidal fuzzy numbers $\tilde{A}_1$, $\tilde{B}_1$, and $\tilde{B}_2$ shown in Figure 2(a) to 2(c). Let $\tilde{A}_1$ be the neutral fuzzy number.

If a design team is uncertain about the problem at hand, a fuzzy number with a lower level of linguistic certainty is recommended.

As shown in Figure 2(b), a fuzzy number $\tilde{B}_1$ possesses a lower level linguistic certainty than a fuzzy number $\tilde{A}_1$ does when the linguistic certainty index $\lambda = 1/2$. On the other hand, a fuzzy number with a higher level of linguistic certainty is suggested for a design team who is more certain or clear about its decision environment.

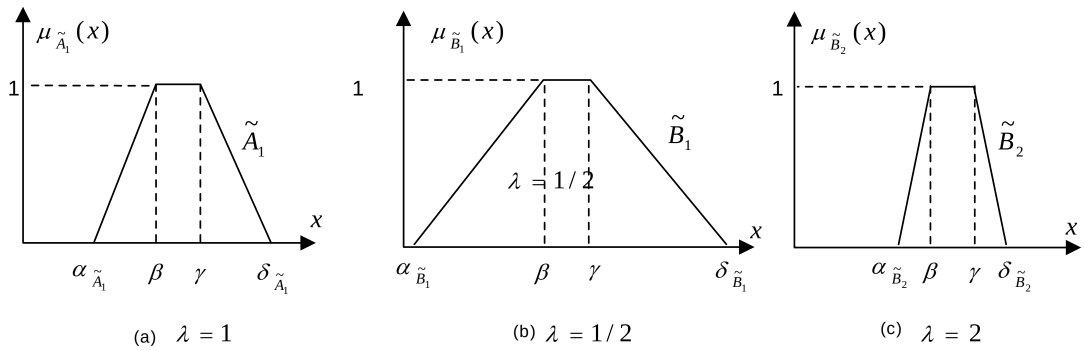


Figure 2. Different fuzzy numbers revealing different linguistic certainty levels

For instance, a fuzzy number $\tilde{B}_2$ possesses a higher-level of linguistic certainty than a fuzzy number $\tilde{A}_1$ does when the linguistic certainty index $\lambda = 2$; that is, $\tilde{B}_2$ is "less fuzzy" or "more crisp" than $\tilde{A}_1$. By using a changing linguistic certainty index λ, the certainty level of the design team is a part of the decision input.

4. Implementation

While film cameras have been designed and manufactured for the past 160 years, the development of more sophisticated digital cameras is still in an early stage. Although high-end digital cameras have been adopted in studio businesses for two decades, low-end digital cameras have become practical and popular in substituting film cameras for common use only within the past five years (Boydston 2000) (Yoshida 2004).

Although its market is enlarging quickly, the market competition is also very harsh. The pace of redesigning products to enhance performance and lower prices has been accelerated in a dizzying speed. Due to the small product differentiation among different makes of digital cameras, a wrong step in newer models may lose big market shares for several seasons.

Thus, a better tool in determining design features that integrates customer requirements and product developers is critical. Traditional crisp QFD models that do not reflect fuzzy judgment of designers in determining certainty of linguistic evaluations are not sufficient for this situation.

The proposed fuzzy QFD model was experimented with the design of a low-end digital camera. The target product is a fairly popular model in which the camera company wants to improve the product and develop a more competitive model to increase its market share for the coming season. The first thing to do for this design project was to search for the customers' desires regarding the product we are going to offer (Sugikubo 2002).

Figures of a prototype design are shown in Figure 3. With the help of market surveys, interviews, sales records, and the marketing members of the design team, seven customer requirements were identified from the analysis. They are 1) Lower price; 2) Wider range zoom function; 3) Lightness; 4) Compactness; 5) Durability of battery life; 6) High quality picture; and 7) Fast focus function.

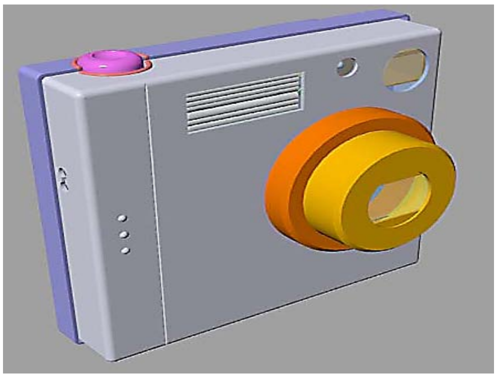
To determine what technical requirements the desired new camera must have in order to match the customer requirements, an analysis for the current low-end cameras and other competitive products already in the market was conducted (Henshall 1998) (Grottta 2001) (Harrison 2003). The result yields the following technical requirements to plan a new product:

A. Increase the diameter of the zoom lens and enhance digital zoom,
B. Redesign the body configuration to a much smaller size,
C. Replace the material of the body and components to reduce product weight,
D. Improve the speed of the motor drive,
E. Change to a small motor drive, and
F. Use a lighter lens set.

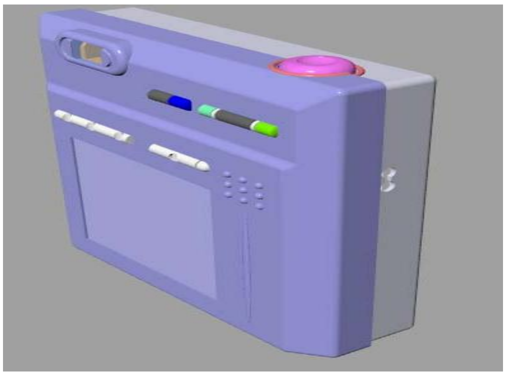
Surprisingly, much effort of most companies in increasing pixel numbers for each image is not a technical factor in improving camera quality in a review.

It was found that most low-end users were printing pictures in 3x5 or 4x6 and using one mega-byte images (with a maximal capability up to three mega-byte). Meanwhile, the correlation between customer requirements and technical requirements, as well as the importance for each customer requirement, is determined by the design team and recorded into a QFD matrix.

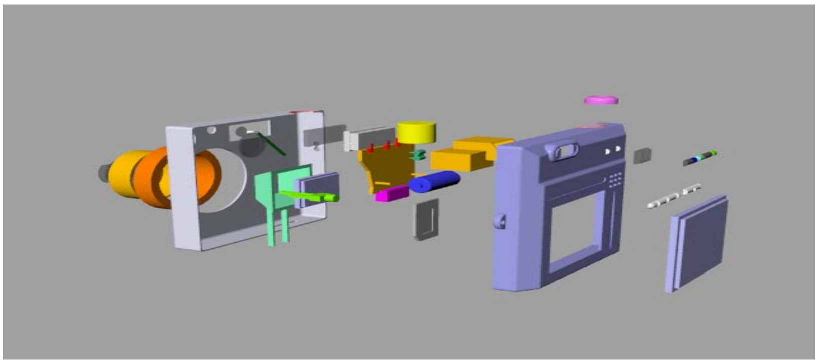
A traditional QFD model that uses crisp scoring is then established in Table 2 where the design team receives the conclusion $C > E > A > D = F > B$



(a) Front design



(b) Back design



(c) Explosion diagram

Figure 3. A prototype

Table 2. A traditional QFD matrix

Customer requirements \ Technical requirements	Increase the diameter of the zoom lens and enhance digital zoom	Redesign the body configuration to a much smaller size	Replace the material of the body and component to reduce weight	Improve the speed of the motor drive	Change to a smaller motor drive	Use a lighter lens set	Importance
	A	B	C	D	E	F	
Lower price		2	5		1	1	3
Wider range of the zoom	6	1					5
Lightness		7	7	2	6	4	5
Compactness		1	3		6	6	4
Durability of battery	1		2	1	1		3
High quality picture	5		2	6			4
Fast focus function	3			7		1	2
Resulting weight	59	50	82	51	60	51	

5. Prioritizing factors using fuzzy QFD model

To increase the discriminating ability for QFD analysis, a fuzzy QFD matrix is construed and depicted in Table 3. For simplifying, we use trapezoidal fuzzy numbers to represent all the fuzzy numbers in this implementation case. However, the proposed fuzzy QFD model is not limited to trapezoidal fuzzy numbers only. The linguistic terms defined for "CORRELATION" and "IMPORTANCE" are defined and represented in Figure 4 and Figure 5 respectively.

Since only trapezoidal fuzzy numbers are applied, a fuzzy addition operation ($\oplus$) and fuzzy multiplication operation ($\otimes$) can be generalized into formulas described in the Appendix.

After conducting Equation (3) for each technical requirement candidate, the resulting weights can also be represented as trapezoidal fuzzy numbers and shown in Table 4.

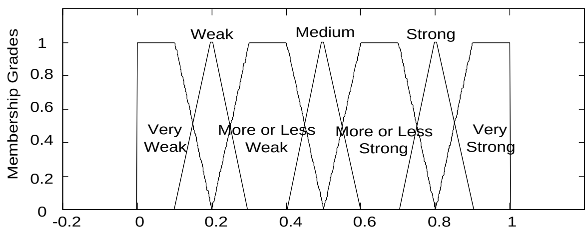


Figure 4. Linguistic terms for CORRELATION

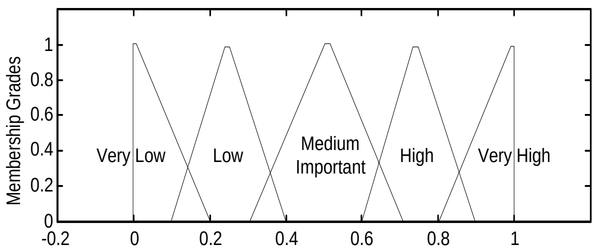


Figure 5. Linguistic terms for *IMPORTANCE*

Table 3. A fuzzy QFD matrix

Technical requirements / Customer requirements	Increase the diameter of the zoom lens and enhance digital zoom	Redesign the body configuration to a much smaller size	Replace the material of the body and component to reduce weight	Improve the speed of the motor drive	Change to a smaller motor drive	Use a lighter lens set	Importance
	A	B	C	D	E	F	
Lower price		W	MS		VW	VW	MI
Wider range of the zoom	S	VW					VH
Lightness		VS	VS	W	S	M	VH
Compactness		VW	MW		S	S	H
Durability of battery	VW		W	VW	VW		MI
High quality picture	MS		MW	S			H
Fast focus function	MW			VS		VW	L
Resulting weight	W_A	W_B	W_C	W_D	W_E	W_F	

Legend:
CORRELATION: VW: Very Weak, W: Weak, MW: More-Or-Less Weak, M: Medium, MS: More-Or-Less Strong, S: Strong, VS: Very Strong.
IMPORTANCE: VL: Very Low, L: Low, MI: Medium Important, H: High, VH: Very High.

Table 4. Trapezoidal fuzzy numbers

	W_A	W_B	W_C	W_D	W_E	W_F
α	0.8800	0.6700	1.1800	0.5800	0.9800	0.7400
β	1.3250	1.0000	1.9000	1.0250	1.4000	1.1000
γ	1.4750	1.2750	2.1250	1.1000	1.5000	1.1750
δ	1.9600	1.5900	2.7600	1.6500	1.9900	1.6300

Since the membership function of a trapezoidal fuzzy number is denoted in Equation (2), the inverse functions of $r(x)$ described in Equation (4) can then be represented as $g_{\tilde{A}}^{R}(y) = \delta + (\gamma - \delta)y$. Thus, the total integral value of the trapezoidal fuzzy number $\tilde{A}$ can be modified as

$$I_T^{\omega}(\tilde{A}) = \int_0^1 [\alpha + (\beta - \alpha)y]\,dy = \frac{1}{2}(\gamma + \delta)$$

When evaluating the total integral value for every technical requirement by Equation (6), we have the ranking result of $C > E > A > B > F > D$ by comparing their total integral value. It is found that the fuzzy QFD model can distinguish the subtle difference between D and F while the traditional QFD model cannot.

6. Changing linguistic certainty level

The proposed fuzzy QFD model provides the ability for changing the level of linguistic certainty for the problem by altering the proposed linguistic certainty index. That is, selecting different spreads of fuzzy numbers will reveal different levels of linguistic certainty.

A fuzzy number with a wider spread possesses a more ambiguous decision-making condition where the design team is uncertain with the evaluation.

Conversely, a fuzzy number with a shorter spread represents a more clear and confident decision-making environment.

For example, if the certainty level index for all linguistic terms defined in "IMPORTANCE" of Figure 5 is simultaneously changed to the value between 1.000 and 0.686, we found that the ranking result is $C > E > A > B > F > D$. However, if we change the index to the value between 0.685 and 0.672, we found that the ranking result is $C>E>A>B>D>F$. That is, if the design team possesses less confidence about the QFD construction process including survey and investigation, technical requirement D would be a better choice than technical requirement F. On the other hand, if the design team is quite certain with evaluation of the QFD matrix, then technical requirement F is suggested rather than D. Due to cost constraint, top managers would like to pursue five technical requirements instead of six for the next stage of QFD analysis. To fulfill this goal, a complete experiment with different linguistic certainty levels is conducted for all the linguistic terms defined in "IMPORTANCE."

In this implementation, we conduct $\lambda = 1.000 \sim 0.600$ for the set of linguistic terms in "IMPORTANCE" and get a ranking result shown in Table 5. Figure 6 shows the shapes of linguistic terms of "IMPORTANCE" when $\lambda = 2/3$. While the ranking result for technical requirements A, C, and E is consistent, it is not for B, D, and F.

If top managers are confident with the evaluation and investigation of the QFD matrix, a higher linguistic certainty index is recommended. We found that technical requirement D would not be considered in this case. On the other hand, if the top managers possess a higher degree of uncertainty for the problem at hand, a lower certainty index is suggested; that is, technical requirement B would be rejected. While some top managers tend to be extremely certain or uncertain for the environment they are in, most top managers will possess a medium level of certainty. Therefore, technical requirement F would not be further considered.

Table 5. Fuzzy ranking results when $\omega = 1$

Linguistic certainty in λ applied for *CORR-ELATION*	Fuzzy ranking result
1.000~0.686	$C > E > A > B > F > D$
0.685~0.672	$C > E > A > B > D > F$
0.671~0.658	$C > E > A > D > B > F$
0.657~0.600	$C > E > A > D > F > B$

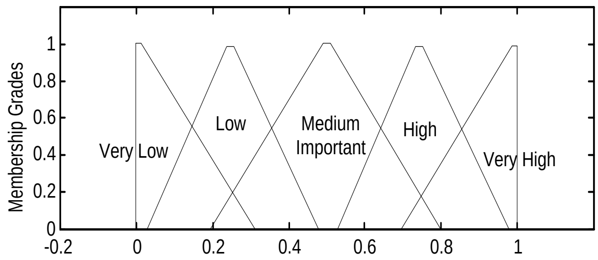


Figure 6. $\lambda = 2/3$ for all linguistic terms defined in *IMPORTANCE*

7. Conclusion

Customer-oriented product design process is critical to survive in today's business world. Quality Function Deployment (QFD) is a systematic tool for planning attributes of new products based on customer demands to achieve the goal of Total Quality Management (TQM) and Concurrent Engineering (CE). Although QFD has been suggested for this purpose, its traditional crisp evaluation process causes several implementation problems.

To eliminate the shortcomings in a traditional QFD model, a fuzzy QFD model with a linguistic certainty index is proposed in this research. Fuzzy evaluation procedures can reflect the uncertain issues inherent from common linguistic assessment. Subtle differences among candidates can also be easily discriminated. The proposed fuzzy QFD model also provides flexibility that can adopt different linguistic certainty levels by altering an index. Changing the linguistic certainty index will generate different spreads of fuzzy numbers so that a different level of linguistic certainty can be revealed. When the index is greater than one, a generated fuzzy number with a wider spread expresses a lower level of certainty in the assessment. If the index is less than one, the generated fuzzy number with a narrower spread exhibits a higher level of certainty. Thus, the group bias of a QFD assessment team can be properly adjusted without using unequal weights that would derail the systematic approach of QFD models.

Appendix

The fuzzy arithmetic operations for trapezoidal fuzzy numbers are introduced as follows.

Let $\tilde{X} = (\alpha_1, \beta_1, \gamma_1, \delta_1)$ and $\tilde{Y} = (\alpha_2, \beta_2, \gamma_2, \delta_2)$ denote two fuzzy numbers in the real number domain, R. The following result can be readily verified when $\tilde{X} > 0$ and $\tilde{Y} > 0$:

1. Addition

$$\tilde{X} \oplus \tilde{Y} = (\alpha_1 + \alpha_2, \beta_1 + \beta_2, \gamma_1 + \gamma_2, \delta_1 + \delta_2) \qquad \text{(A-1)}$$

2. Multiplication

$$\tilde{X} \otimes \tilde{Y} \approx \{(\alpha_1 \times \alpha_2, \beta_1 \times \beta_2, \gamma_1 \times \gamma_2, \delta_1 \times \delta_2) \qquad \text{(A-2)}$$

Note that when performing multiplication of two trapezoidal fuzzy numbers, the outcome is not a trapezoidal shape but actually quadric curves. However, we use this trapezoidal shape to approximate the exact solution for convenience (Chen et al. 1992).

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