A Hybrid QFD Framework for New Product Development

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Abstract

Nowadays, new product development (NPD) is one of the most crucial factors for business success. The manufacturing firms cannot afford the resources in the long development cycle and the costly redesigns. Good product planning is crucial to ensure the success of NPD, while the Quality Function deployment (QFD) is an effective tool to help the decision makers to determine appropriate product specifications in the product planning stage. Traditionally, in the QFD, the product specifications are determined by a rather subjective evaluation, which is based on the knowledge and experience of the decision makers. In this paper, the traditional QFD methodology is firstly reviewed. An improved Hybrid Quality Function Deployment (HQFD) [MSOffice1]is then presented to tackle the shortcomings of traditional QFD methodologies in determining the engineering characteristics. A structured questionnaire to collect and analyze the customer requirements, a methodology to establish a QFD record base and effective case retrieval, and a model to more objectively determine the target values of engineering characteristics are also described.

Key words: Quality Function Deployment (QFD), Analytic Hierarchy Process, Case-based Reasoning, Fuzzy Linear Regression and optimization

1. Introduction

Successful New Product Development (NPD) is essential to manufacturing companies to make profit and even survive. However, NPD has been forged in the crucible of global competition, while the customer requirements become complicated. In order to increase the customer satisfaction, product planning is an important task to ensure the success of NPD. Good outcomes from product planning can reduce engineering changes throughout the entire product development cycle, and finally reduces the product development time and costs while increases the customer satisfactions. Quality Function Deployment (QFD) is a planning tool to translate customer requirements into product specifications [1, 12]. It has been applied in different industries, for examples, manufacturing, services and software development, since its first introduction by Prof. Yoji Akao in the late 1960s. QFD is usually represented in the House of Quality (HOQ). In HOQ, there are seven rooms showing the relationships between customer attributes (performance characteristics) and engineering characteristics (technical requirements), and the interrelationships among engineering characteristics. In this paper, we will examine the traditional QFD methodology and present our findings in section 2. In section 3, we will propose a Hybrid Quality Function Deployment (HQFD) framework to overcome the shortcomings stated in the traditional QFD methodology. In section 4, a structured design of the questionnaire to acquire the customer requirements is introduced. In section 5 and 6, a Case-based Reasoning (CBR) based method for determining the engineering characteristics is presented. The fuzzy logic based methodology in determining the target values of engineering characteristics is discussed with illustrated examples in section 7 and 8. Section 9 presents our conclusion.

2. Shortcomings of the Traditional QFD Methodology

Having examined the traditional QFD methodologies, several shortcomings have been found. The first one is the input of ambiguous voice of customers (VOC) into QFD. Decisions made in the design stage of product development are often made on the basis of incomplete, ill-structured and vague information [10]. As customer requirements is the input of QFD, it is very important to classify the customer requirements in a systematic way. However, there is a lack of systematic methods for companies. Secondly, the degrees of the relationships between customer attributes and engineering characteristics, and the interrelationships among engineering characteristics are usually fuzzy and vague [14]. In traditional QFD methodologies, the interrelationships among engineering characteristics is always ignored in the determination of the target values of engineering characteristics. It leads to the inaccuracy of the target values of the engineering characteristics, as each engineering characteristic is not an independent factor that is interrelated to other characteristics. In order to tackle the shortcomings of traditional QFD methodologies mentioned, a Hybrid Quality Function Deployment (HQFD) framework is proposed.

3. The HQFD Framework

In this section, a Hybrid Quality Function Deployment (HQFD) framework is proposed to overcome the shortcomings of traditional QFD methodologies. In the HQFD, Case-based Reasoning (CBR), Analytic Hierarchy Process (AHP) and fuzzy logic are applied in an integrated manner. CBR is a technique of artificial intelligence to seek solutions for new problems by making use of similar cases encountered in the past [15]. CBR can support QFD in a more structured way that similar QFD figures based on historical cases can be efficiently searched to initiate a new case. AHP is employed to determine the importance of customer requirements with pairwise comparisons [4]. Fuzzy logic is adopted to transfer linguistic data to crisp scores, which are then used to calculate overall customer satisfaction [3].

The HQFD framework can be divided into four sections, as shown in Figure 1. The first is to acquire customer attributes; the second is to retrieve the engineering characteristics using CBR; the third is to determine the relationships between customer requirements and engineering characteristics, and the interrelationships among engineering characteristics; and the fourth is to determine the target value of engineering characteristics.

When acquiring customer attributes, an AHP based questionnaire is introduced. This questionnaire integrates quality dimensions, critical incidents and satisfaction items. AHP is then used to calculate the relative importance (weightings) of each customer attribute. The second step of the proposed framework is to retrieve engineering characteristics corresponding to customer attributes. This step is based on the Performance Index Ration (PIR), which indicates how the engineering characteristics match the customer attributes. The third step and fourth steps can be achieved using fuzzy linear regression. The details are explained in the following sections.

4. Customer Requirements Acquisitions

As the customer requirement is the baseline of the product development, the ability to correctly understand and address customer needs is key to the success of any product development effort, particularly in an environment of time-based competition [5,23]. The difficulty in understanding and defining customer needs is one of the common problems across the companies [6]. It is reported that in about 70 percents of the failure cases of NPD, the user needs are not carefully considered and correctly identified by the development team [6]. In order to reduce the failure, a systematic way to acquire and analyze the customer requirements must be developed during the product planning stage. The importance of customer requirements could be analyzed by

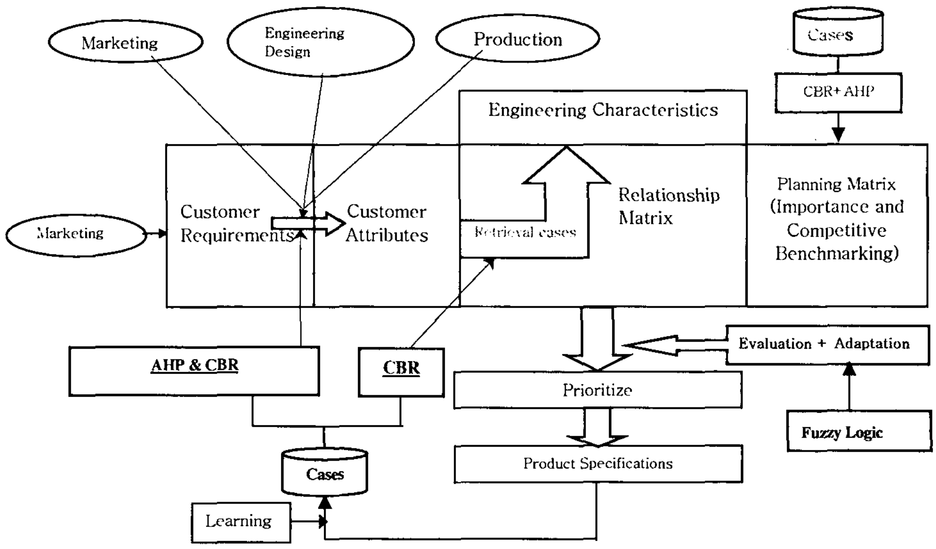


Figure 1. The proposed HQFD framework

the analytical hierarchy process (AHP) method. It, however, does need an effective mean to collect the data. In this paper, we propose to develop a systematic and structured design of a QFD questionnaire in a 4-step approach to understand the user needs, as shown in Figure 2.

In the first step, the internal focus group members are asked to identify the quality dimensions about the product. These quality dimensions can be determined according to the past similar cases from the case library. Table 1 shows the example of the quality dimensions.

The second step is to collect the critical incidents (CIs). The critical incident approach is used to obtain information from customers about the service or product they receive. The customer is asked to list out the positive and negative examples or elements of the product for the different quality dimensions. The positive and negative elements of the product are the critical incidents. The format to acquire the critical incidents is shown as Table 2.

Table 1. Examples of quality dimensions

Quality Dimensions	Meaning and example
Performance	Primary product characteristics, such as the brightness of the picture
Features	Secondary characteristics, added features, such as remote control
Conformance	Meeting specifications or industry standards, workmanship
Reliability	Consistency of performance over time, average time for the unit to fail
Aesthetics	Sensory characteristics, such as exterior finish

Table 2. A sample table to acquire the Critical Incidents from customers

Name of the Product: ____________ Propose of the product: ____________		
Quality Dimensions	Positive Critical Incidents/Examples	Negative Critical Incident /Examples
Performance	1. 2. 3	1. 2. 3.
Features	1. 2. 3.	1. 2. 3.
Other expectations about the product: ____________ ____________		

The third step is to group the CIs into satisfaction items (see Figure 3). For example, the CI1 and CI2 are group into the satisfaction item 1, while the CI3 and CI5 are grouped into satisfaction item 2. Both the positive and negative critical incidents are grouped to form the satisfaction items. The satisfaction items can be seen as the customer attributes, which are the input of the house of the quality.

The final step of the questionnaire is to put the satisfaction items into the AHP-based questionnaire in order to acquire the relative importance of different quality dimensions and also the lower hierarchical factors (satisfaction items). The example of the questionnaire is shown as Table 3.

One of the advantages of the AHP comparing with simple scoring is that AHP allows the customers give the direct comparison among the customer attributes. Simple scoring will cause excessive inaccuracy, as the customer tends to rate the all the attributes with higher scores. AHP thus provides a more objective judgment on the customer attributes.

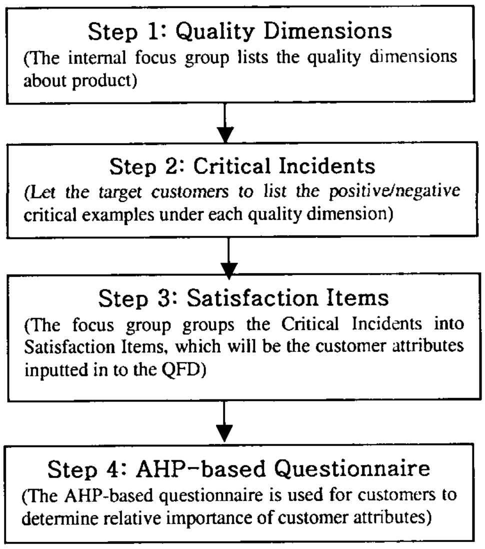


Figure 2. The flowchart to acquire the customer attributes

Table 3. A Sample AHP Questionnaire to get the relative importance with pair comparison

	Quality Dimension 1	**Quality Dimension 2**	**Quality Dimension 3**
Quality Dimension 1	1		
Quality Dimension 2		1	
Quality Dimension 3			1

After the relative importance of the customer attributes are collected, the product development team can analyze the results by the AHP software tool, Expert Choice. The result of the AHP rating illustrates the degree of importance to which these features influence customer satisfaction.

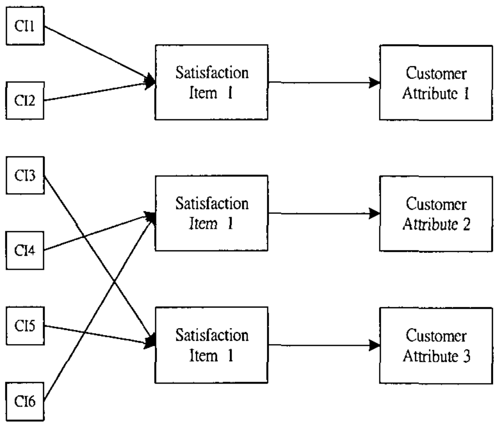


Figure 3. Generating the customer attributes

5. Engineering Characteristics Retrieval from Case Library

After determining the customer attributes and their relative importance, it is necessary to search and retrieve historical cases from the case library that are similar to the problems of a new case.

For example, when a manufacturing firm is developing a new technical drawing pencil, the product development team translates the customer requirements into customer attributes, which will be used as the search indexes to initiate the searching process. A coarse searching is done until the subgroup of technical drawing pencil is found. After matching all cases in the subgroup of technical drawing pencil, the highest score of the performance importance ratio (PIR) of each customer attribute is selected to choose the engineering characteristics, and then evaluate and adapt the exemplars to determine the optimized solution to the new case. After the product is developed, it will be added to the case bases, which can be considered as a self-learning feature of the system. The flowchart of the case retrieval process is shown in figure 4.

A common method to compare the similarity between two cases is the Nearest-Neighbour (NN) matching, which uses the numerical function to compute the degree of similarity (DOS) [20, 22, 25]. However, it is not suitable to implement DOS into the QFD framework because this rational comparison method is better for constant number of customer attributes [22]. By comparing the DOS of different historical cases, the highest DOS is used to choose the so-called most similar case, but there may be some new customer attributes that cannot be found in the most resemble case. However, it may be found in other cases. If a rational comparison is used, there is only one similar case found, which will lead to some information loss. Therefore, an object-oriented comparison is developed to tackle this difficulty.

In order to have a more objective comparison between the new customer attribute and past customer attribute, the performance importance ratio (PIR) is

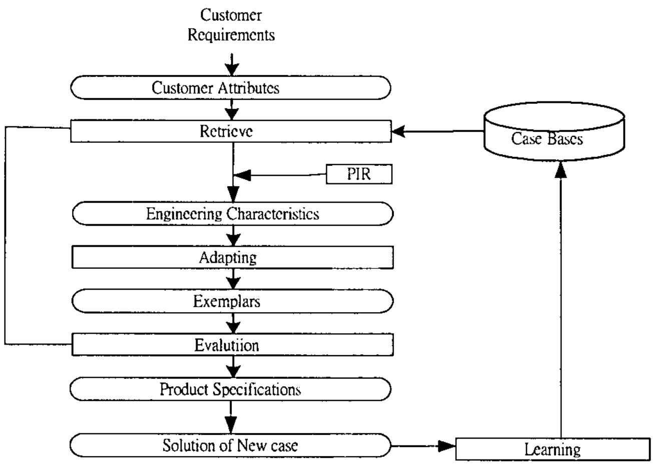


Figure 4. The Generated Process of CBR

developed. The PIR indicates the degree of satisfaction of the customer attributes by considering the performance of the corresponding engineering characteristics. PIR is calculated by the following equation:

$$PIR_i = \sum_{j=1}^{n} \left(\frac{S_{ij}}{\sum_{i}^{m} S_i} \times T_j \right) \times W_i \tag{3.1}$$

where S_{ij} is the weight of the jth engineering characteristic to the ith customer attribute, T_j is the target achieving level of jth engineering characteristic, and RI_i is the relative importance of ith customer attribute.

The target achieving level of each engineering characteristics ranges from 0 to 1. It will be compared with the target level, where the target level is regarded as the best range for the product design. It is computed by the following equation:

$$T_j = 1 - \frac{RV_j - TR_j}{RV_{max} - TR_j} \tag{3.2}$$

where T_j is the target achieving level of jth engineering characteristic, RV_j is the real value of jth engineering characteristic, and TR_j is the target value of the jth engineering characteristic, and RV_{max} is the allowable maximum level of the real value.

The highest PIR for each case attribute is chosen for each new case. Therefore, if all the new customer attributes can be matched with those in the historical cases, at least one case will be chosen for further adaptation and evaluation to find the best solution for the new case. For each customer attribute, its importance of the major competitors can also be generated from the historical cases. If the new case is not exactly same as the historical cases, the adaptation is needed.

6. Case Adaptation and Evaluation to Determine the Target Value of Engineering Characteristics

Adaptation is the second step of the CBR approach. Since no historical case is ever exactly same as a new one, historical cases must usually be adapted to a new situation [15]. After the similar-case set is chosen, the adaptation process should be taken to evaluate the best engineering characteristic from the different cases. And if the new customer attributes cannot be found from the historical cases, it should be determined by judgment. After generating the technical requirements from the historical cases or by innovative judgment, the exemplars can be built up, and the evaluation is then done to determine the proper solutions so as to satisfy the customer attributes of the new case.

Evaluation is the process of judging the goodness of a proposed solution. Here, evaluation is to find out the most suitable engineering characteristics to the new case. Comparing and contrasting the proposed solution with other similar solutions, differences can be spotted. For example, if there are unsuccessful cases similar to the new case, the decision maker must consider whether the new situation has the same problems. Evaluation can point out the need for additional adaptation of the proposed solution. Fuzzy Logic will be used here to evaluate both the quantitative and qualitative data. The qualitative data is normalized into fuzzy term and then evaluated to choose the most suitable level of the engineering characteristics. The fuzzy linear regression will be applied in this research to determine the target value of the engineering characteristics. The details are shown in section 7.

7. Determination of the Target Values of Engineering characteristics

7.1 Current research in this area

Researchers have proposed several methods to improve the traditional QFD using different methods, for examples, AHP [17], Neural Network [3, 18, 24], knowledge-based system [18, 35], CBR [8, 9, 11, 13, 30] and expert systems [28,30]. Fuzzy logic is another popular method to help the decision makers determine the target values of engineering characteristics. Fuzzy logic can model vagueness. Usually, the voice of customers contains ambiguity and different meanings. Fuzzy logic can describe such information provided in terms of symbolic descriptions in linguistic variables by fuzzy numbers [3]. Many researchers have applied fuzzy logic to the determination of the target values of engineering characteristics. For examples, Vanegas and Labib [31], Kim et al. [14], Wang [32], Dawson and Askin [2], Fung et al. [7], Moskowitz and Kim [19], and

Schmidt [21] have applied fuzzy sets to decide the target engineering characteristics levels. But few researchers have attempted to develop a systematic approach to find the optimum engineering characteristics targets. Many researchers treat engineering characteristic as an independent factor and assume that they are not affected by each other. For example, Vanegas and Labib [31] applied fuzzy sets to determine the target values of engineering characteristics. They considered constraints on cost, technical difficulty and customer satisfaction, but treated each engineering characteristics as an independent factor. However, it is well known that engineering characteristics are always affected by each other. Some researches have addressed the issue of constructing quantitative models of customer preferences and translating these into optimal technical specifications [2]. Yoder and Mason [34] proposed using regression analysis to model the relationship between customer attributes and engineering characteristics. Other researchers modified Yoder and Mason's method for determining the target values of engineering characteristics; for examples, Kim et al [14] and Askin and Dawson [2]. They have applied linear regression to determine the target values of engineering characteristics.

Fuzzy linear regression was introduced by Tanaka et al., [26], which is based on the possibility distribution to model vague and imprecise phenomena using the fuzzy functions defined by Zadeh's extension principle [36]. Fuzzy linear regression is a useful tool to support the users in the application of QFD, since the users must incorporate both qualitative and quantitative information regarding relationships between customer attributes and engineering characteristics into the problem formulation.

7.2 Determination of target values by Fuzzy Linear Regression

In the proposed hybrid framework, a fuzzy regression model developed by Kim et al. [14] is basically followed to determine the relationship between customer attributes and engineering characteristics, and also the interrelationship among engineering characteristics. This model is formulated using Multiattribute value (MAV) theory. MAV is used to model the customer's preferences associated with multiple customer attributes. Three separate models are developed, namely, CCC model, FCC model and FFF model, as shown in Table 4. The common elements of customer attributes and engineering characteristics are broken into three major components, namely, system parameters that define the functional interrelationships between customer attributes and engineering characteristics and also among the engineering characteristics; objectives that are to maximize the customer satisfaction; and constraints that encapsulate design tradeoffs and tradeoffs between other parameters.

Table 4. The comparison of different models

Model	CCC	FCC	FFF
System Parameters	Crisp	Fuzzy	Fuzzy (with 10%, 20% and 30% flexibility)
Objectives	Crisp	Crisp	Fuzzy
Constraints	Crisp	Crisp	Fuzzy

In the CCC Model, it is assumed that there is no fuzziness and vagueness. Instead, this model requires that all customer attributes are optimized and the design tradeoffs are seen as hard constraints with no leeway. The FCC model incorporates fuzziness in the system by defining the model components using fuzzy system parameters, where the spread of each system parameter is introduced to the system parameters. In the FFF model, it is assumed that there are fuzziness in the system parameters, objectives and constrains, and the fuzzy flexibility is applied to the constraints of engineering characteristics. Details of these models are elaborated below.

Model 1: CCC model

In this model, all the system parameters, objectives and constraints are assumed to be crisp. It means that there is no fuzzy data in the components in this model, all the data inputted into the QFD are well defined, the decision believe that there does not include vagueness in the data.

The process of determining target values for engineering characteristics in QFD can be formulated as an optimization problem. Let

y_i = customer perception of the degree of achievement of customer attribute i, i = 1,...m,

x_j = the target value of engineering characteristic j, j = 1,...n

f_i = functional relationship between customer attribute i and engineering characteristics, i = 1;...;m, i.e., $y_i = f_i (x_1;...; x_n)$,

g_j = functional relationship between engineering characteristic j and other engineering characteristics, j= 1;...; n, i.e., $x_j = g_j (x_1;...; x_{j-1}; x_{j+1};...; x_n)$:

In the crisp case, there is an essential assumption that the system parameters and constraints all have crisp linear relationships. All the functions are assumed to be of the following format.

$$Y = \alpha_1 x_1 + \alpha_2 x_2 + ... + \alpha_n x_n + \alpha_0 \qquad (7.1)$$

Based on this assumption, total linear regression methods are used to determine the linear functional relationships, i.e. determine the values of $\alpha_0, ..., \alpha_n$.

Once the parameters are estimated, Multiattribute value (MAV) theory is used to define the crisp objectives. MAV function is used to generate the overall level of customer satisfaction.

$$Z = \sum_{i=1}^{m} w_i V_i(y_i) \tag{7.2}$$

where w_i are scaling constants representing the relative importance of customer attributes, $V_i(y_i)$ is the individual value function for customer attribute i. Subject to

$$y_i = f_i(x_1, \ldots\ldots, x_n) \tag{7.3}$$

$$x_j = g_i(x_1, \ldots\ldots x_n) \tag{7.4}$$

Model 2: FCC Model

In this model, the inputs are fuzzy parameters, but the objectives and the constraints are crisp. In the model, we assume that there is some vagueness in the system parameters. Let,

$$\overline{y_i} = \overline{f_i}(x_1, \ldots\ldots, x_m),\ i = 1, \ldots\ldots, m$$

$$\overline{x_j} = \overline{g}_j(x_1, \ldots\ldots, x_n),\ j = 1, \ldots\ldots, n$$

The bar over a symbol indicates that the expression or variable is fuzzy.

The first major source of vagueness is between engineering characteristics and customer attributes, and also the interrelationships among engineering characteristics. This can be accounted for by altering the crip equation into a fuzzy linear function:

$$Y = \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_n x_n + \alpha_0 = \alpha X$$

Where Y is the dependent variable and X a vector of the independent variables. $\alpha = (\alpha_1, \alpha_2, \ldots \alpha_n)$ are fuzzy parameters, and can be denoted in vector form as $\alpha = \{(\alpha_{m1}, \alpha_{m2}, \ldots \alpha_{mn}), (\alpha_{s1}, \alpha_{s2}, \ldots \alpha_{sn})\}$. Here, α_{mj} is the center value of α_j, and α_{sj} is the width (or spread) of α_j around α_{mj}.

A symmetric triangle membership function is employed for fuzzy parameters in this paper. The centre value describes the most possible value of α_j while the spread represents the precision of α_j. This allows for vagueness in the functional relationships. The spread can be found using Tanaka's linear programming formulation [26].

Subject to,

Minimize $(\alpha_{s1}, \alpha_{s2}, \ldots \alpha_{sn})$,

$$y_i = fi(x_1, \ldots x_n),$$

$$y_i^L \le f_i^L(x_1, \ldots x_n), \quad i = 1, \ldots, m \tag{7.5}$$

$$y_i^R \le f_i^R(x_1, \ldots x_n), \quad i = 1, \ldots, m \tag{7.6}$$

$$x_j = g_j(x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad i = 1, \ldots, m \tag{7.7}$$

$$\quad j = 1, \ldots, n \tag{7.8}$$

$$x_j^L \le g_j^L(x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1, \ldots, n \tag{7.9}$$

$$x_j^R \le g_j^R(x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1, \ldots, n \tag{7.10}$$

Where f_i, f_i^L, f_i^R (and g_j, g_j^L, g_j^R) are real linear vectors of mean values and left and right spreads of the estimated fuzzy parameters $\overline{f_i}$ of (and $\overline{g_j}$), and f_i, f_i^L, f_i^R (and g_j, g_j^L, g_j^R) are also real linear vectors of mean values and left and right spreads of $\overline{y_i}$ (and $\overline{x_j}$).

Model 3: FFF Model

In this model, the system parameters, objectives and constraints are fuzzy, which indicates that there is some vagueness or imprecision in system parameters, objectives and constraints. The fuzzy flexibility is introduced into the system parameters. The flexibility is a number set between 0% and 100%, which signifying the flexibility allowed by widening the solution set. The model employs a fuzzy objective function and attempts to optimize the overall degree of customer satisfaction derived from multiple performance characteristics. The fuzzy optimization scheme has been proven to be usually in modeling multiple criteria decision-making problems involving human perception, and can be posed as an equivalent crisp optimization problem as follows [37,38].

Find $x_1, x_2, \ldots, x_n$, which maximize λ (7.11) subject to each membership function $\lambda \le \mu_{Y_i}(X)$, i= 1,...,m, Where $\lambda\,(0 \le \lambda \le 1)$ represents the overall membership function value. Subject to,

$$
\begin{array}{lll}
\lambda \le \mu_{f_i}(X,Y), & i=1,\ldots,m & (7.12) \\
\lambda \le \mu_{Gj}(X,Y), & j=1,\ldots,n & (7.13) \\
y_i^L \le f_i^L(x_1,\ldots x_n), & i=1,\ldots,m & (7.14) \\
y_i^R \le f_i^R(x_1,\ldots x_n), & j=1,\ldots,m & (7.15) \\
x_j^L \le g_j^L(x_1,\ldots,x_{j-1},x_{j+1},\ldots,x_n), & j=1,\ldots,n & (7.16) \\
x_j^R \le g_j^R(x_1,\ldots,x_{j-1},x_{j+1},\ldots,x_n), & j=1,\ldots,n & (7.17)
\end{array}
$$

The functional relationships may be used as strict (crisp) or flexible (fuzzy) constraints. When the constraints are strict, the violation of any constraint by any amount renders the solution infeasible. Considering the fact that, in practice, the estimated functional relationships would probably be imprecise, permitting small violations would be more realistic. This can be done by employing fuzzy (flexible) constraints. The membership function of a fuzzy constraint arising from "$S_j(X)=b_j$" is constructed as (assuming a linear form):

$$\mu_{S_j}(X) = 1 - \frac{|S_j(X) - b_j|}{d_j}$$

Where b_j is the average of the jth engineering characteristics, and d_j=assigned flexibility $*b_j$.

We could obtain different levels of flexibility between engineering constrains (i.e. 10% and 20%) and optimum solutions are found after carrying out a MINIMAX formulization whereby the spreads are minimized by maximizing the overall satisfaction. In the fuzzy model, λ denotes the overall degree of customer satisfaction when a fuzzy objective function is employed and the whole objective of the formulation is to maximize this quantity.

8. Illustrated Example

8.1 Customer Requirements Acquisition

ABC Stationery Company is going to develop a technical drawing pencil. The product development team is formed for this project. They are from different functional departments, namely, marketing, engineering design, production department, and etc. They are also the members of the internal focus group. They list out all the quality dimensions related to the new product in both performance and aesthetics aspects.

A semi-opened questionnaire is used to collect the customer expectations on the new product. The customers are asked to list out the critical incidents (both positive and negative cases) about the product. They are listed as shown in Table 5. According to the customer requirements, the product development team translates the critical incidents to the satisfaction items, and then to customer attributes. In this illustration, under the performance dimension, we get four customer attributes, namely, "easy to hold", "does not smear", "point lasts", and "does not roll".

8.2 Customer Importance determination

In this step, the customer requirements are built into a hierarchy structure (see Figure 5).

The AHP-based questionnaire is then developed to determine the customer importance. Table 6 indicates the ratings between the quality dimensions of aesthetic and performance attributes. Table 7 shows the AHP ratings results of the customer attributes of the performance dimension.

By the aid of the software tool, EXPERT CHOICE, we can get the relative importance (weightings) of the four customer attributes

Table 5. The questionnaire to acquire the Critical Incidents

Name of the product: Pencil Model 123

Propose of the product: Technical Drawing

Quality Dimension	Positive cases	Negative cases
Performance	1. easy to hold 2. doesnt roll 3. Does not smear 4. Point lasts	1 Need to sharpen the pencil frequently 2 Easy to get dirty
Aesthetics	1. beautiful 2. Modern 3.	1. 2. 3.
...	...	...

Another requirement about the product:

____

____

of performance dimension, as shown in Table 8.

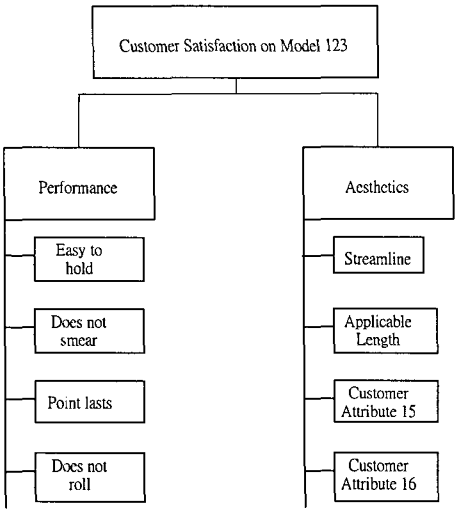


Figure 5. The hierarchy structure of customer requirements

Table 6. AHP ratings of the quality dimensions to product (Model 123)

	Performance	Aesthetics
Performance	1	7
Aesthetics	1/7	1

8.3 Determination of the engineering characteristics and its symbols

After the determined customer attributes are then used as the searching index to search the best fit from the historical cases in order to find the corresponding engineering characteristics. In this research, the Performance Index Ration (PIR) method is used. The PIR indicates the degree of satisfaction of the customer attributes by considering the performance of the related engineering characteristics. Each PIR of customer attribute is calculated by Equation 3.1, From the previous section, we got four customer attributes to retrieve the engineering characteristics from the case library. According to the PIR, we find two engineering characteristics from case 1 (Easy to Hold, and Point Lasts), and one engineering characteristic from case 2 (Does not Roll). However, we cannot find the same customer attribute (Does not Smear) from the historical cases (see Table 9). The corresponding engineering characteristics found from each case are shown as Table 10.

Table 7. AHP ratings of the customer attributes of performance

	Easy to Hold	Does not Smear	Point Lasts	Does not Roll
Easy to Hold	1	4	7	5
Does not Smear	1/4	1	9	3
Point Lasts	1/7	1/9	1	5
Does not Roll	1/5	1/3	1/5	1

Now, by integrating the two cases and the new customer requirement, we can generate an exemplar to show the relation between the new customer attributes and the engineering characteristics, which is shown in Figure 6. In the proposed framework, the relationship between the customer attributes and engineering characteristics, and the interrelationship between the engineering characteristics are shown by the symbol "√".

Table 8. Relative importance (weightings) of each customer attribute of the performance dimension

Customer attributes	Easy to Hold	Does not Smear	Point Lasts	Does not Roll
Weight	0.3	0.1	0.4	0.2

Table 9. The PIR of the four customer attributes

Customer attribute	**Easy to Hold**	**Does not Smear**	**Point Lasts**	**Does not Roll**
PIR	0.925	--	0.97	0.99
Case No.	1	Not found in the historical cases.	1	2

Table 10. Corresponding engineering characteristics and its symbols

Case 1	Time between sharpening	Lead dust generated	Shape	Minimal erasure residue
CA1: Point last	✓	✓		
CA2: Does not Roll	✓	✓	✓	✓
Case 2	Length of pencil	Time between sharpening	Shape	Minimal erasure residue
CA1: Easy to hold	✓	✓	✓	✓

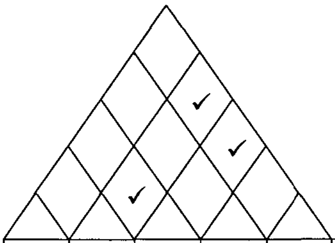
Now, we determine the target value of each system parameter, and the overall customer satisfaction of the different models. By applying the different optimization functions of the overall customer satisfaction, and constraints to the equations, we can get the overall customer satisfaction. The definitions and the formulas used in the models can be summarized as in Tables 11 and 12.

Table 11. The equations applied in different Models

Model	**Objectives**	**Constraints**
CCC	Eqs. (7.2)	(7.3), (7.4)
FCC	Eqs. (7.2)	(7.5)-(7.10)
FFF	Eqs. (7.11)	(7.12)-(7.17)

Table 12. Result of different models

	Models			
Characteristic	**CCC**	**FCC**	**FFF (10%)**	**FFF (20%)**
Y1	2.8383	1.09	2.55	4.72
Y2	2.14042	2.22	2.14	3.85
Y3	2.1756	1.09	2.58	3.83
Y4	3	4	3.91	3.8
X1	150	140	140.94	172
X2	60	31.3306	16.7637	16.2441
X3	0.76468	0.501	0.362	0.105
X4	1	1	1	3
X5	0.8070	0.6625	0.45	0.15
Z	0.7874	0.311	0.4489	0.78
λ	-	-	0.3	0.71



		Length of pencil	Time between sharpening	Lead dust generated	Shape	Minimal erasure residue	Degree of Importance (Customer)	Our Companys	Company A's	Company B's	Company C's	Min	Max
		EC1	EC2	EC3	EC4	EC5							
CA1	Easy to hold	✓			✓		0.3	2	4	5	3	1	5
CA2	Does not smear		✓	✓		✓	0.1	4	1	4.5	1	1	5
CA3	Point lasts	✓	✓	✓		✓	0.4	1	2	3	3	1	5
CA4	Does not roll	✓			✓		0.2	3	4	1	2	1	5

Measurement Units	mm	Mins	g		g
Our past similar product	150	30	0.3	1	0.4
Company As Product	160	20	0.4	2	0.5
Company Bs Product	170	15	0.1	3	0.1
Company Cs Product	180	25	0.2	3	0.3
Minimum	140	15	0.1	1	0.1
Maximum	190	60	1	5	1

For the EC4, the shape of the pencil, where
1 indicates hexagon,
2 indicates round, and
3 indicates octagon.

Figure 6. Example of QFD figure

From the results, the highest Z (overall customer satisfaction) can be obtained in CCC model. However, in determining the target value of the CCC model, we found that we have to determine five target values of the five engineering characteristics respectively, but there are only three constraints functions. The results may be fluctuated, and it is difficult to the decision maker to decide which one is the most optimistic solution to the model. On the other hand, if the number of constraints is greater than the number of engineering characteristics, the optimistic solution can be determined, as proved by Kim [14] and Kumar [16]. Since the solutions in the CCC model, the relationships among the engineering characteristics and the relationships between the customer attributes and the engineering characteristics have uncertainties and imprecision, fuzzy set is more appropriate to be used to determine the target values of the engineering characteristics. After allowing for 10% flexibility in the engineering constraints in FFF model, λ is assessed using the SOLVER in Microsoft Excel. As shown in Table 12, this resulted in an increase in overall satisfaction levels. Flexibility levels are set on the parameters subjectively, depending on the credibility of the assessed parameters, technological feasibility and engineering tolerances. Flexibility allows for vagueness to be accounted but too much flexibility may deteriorate the validity of the system. Hence if the marginal rate of increase in customer satisfaction falls on increasing flexibility, it is revealed that the flexibility is too much (Kumar, 2001). In this illustration, it was deemed that 20% was the maximum level of flexibility. The best result obtained was at 20% flexibility and by counter checking the values. it can be said that the optimized design values can be achieved in practice.

By comparing the results generated using the FCC and FFF models, the results generated from the FFF model are better as expected because there is a high degree of vagueness in the system. Taking account of the fuzziness in uncertain environments where relationships are not very discrete, using fuzzy regression yields more reliable parameter estimates thereby allowing for better optimization results.

On the other hand, comparing the methodologies introduced in this paper in determining the target values of the engineering characteristics and the traditional QFD methodology, we can conclude that the main advantage is that the traditional QFD methodology treats all the parameters of the HOQ as crisp variables (the CCC Model), however, if the data are fuzzy and imprecise, the result will not reflect the real situation. If the decision maker thinks that there is sufficient and reliable information to determine the product specifications, then the CCC model is appropriate to use. However, a certain degree of fuzziness and imprecision always exist in the data input to the QFD, and thus the fuzzy approach is recommended to determine the product specifications.

9. Conclusion

QFD is widely used in the different manufacturing companies, but the traditional methodology has shortcomings. In this paper, a hybrid approach is proposed as a modification to the QFD. A systematic questionnaire approach is introduced to acquire the customer requirements. This questionnaire can help the manufacturing companies to acquire the customer requirements more effectively. The product development team is recommended to determine the engineering characteristics by the aid of case based reasoning approach. An efficient case retrieval methodology is also developed.

Fuzzy linear regression is proposed in the paper to determine the degree of the target value of the engineering characteristics, with an illustrated example. The fuzzy optimization models provide for better results for the QFD model than the crisp multiattribute value theory as expected. This confirms that the vagueness does exist in the relationship between linguistic customer attributes and engineering characteristics. Also the analysis shows how accounting for uncertainties introduced by customer perception and other imprecise quantities can improve the method of analysis and produce optimum target value.

To conclude, the proposed hybrid QFD approach can allow designers to specify the design problem more accurately and imaginatively allowing for a funnel like design process to develop where the number of possibilities reduce in time until one final design is left. This can have significant implications on design costs and design time and also reduce the number of revisions to the final design.

Acknowledgement

This work was partly supported by the UK EPSRC under grant No. GR/R96187/01.

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