The implementation of quality function deployment based on linguistic data

X. X. SHEN, K. C. TAN and M. XIE
Department of Industrial and Systems Engineering, National University of Singapore

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Quality function deployment (QFD) is a customer-driven quality management and product development system for achieving higher customer satisfaction. The QFD process involves various inputs in the form of linguistic data, e.g., human perception, judgment, and evaluation on importance or relationship strength. Such data are usually ambiguous and uncertain. An aim of this paper is to examine the implementation of QFD under a fuzzy environment and to develop corresponding procedures to deal with the fuzzy data. It presented a process model using linguistic variables, fuzzy arithmetic, and defuzzification techniques. Based on an example, this paper further examined the sensitivity of the ranking of technical characteristics to the defuzzification strategy and the degree of fuzziness of fuzzy numbers. Results indicated that selection of the defuzzification strategy and membership function are important. This proposed fuzzy approach allows QFD users to avoid subjective and arbitrary quantification of linguistic data. The paper also presents a scheme to represent and interpret the results.

Keywords: Quality function deployment, house of quality, fuzzy set theory, linguistic variable, fuzzy number, sensitivity analysis

1. Introduction

Quality is viewed as an essential means of competing in today’s rapidly changing global marketplace. Total quality management (TQM), a philosophy or approach to management, has emerged as an important aspect of overall quality improvement programs in many organizations. It is both a comprehensive managerial philosophy as well as a collection of tools and approaches for its implementation (Evans and Lindsay, 1996).

Focusing on listening to the voice of the customer (VOC), quality function deployment (QFD) is an essential tool for implementing TQM (Guinta and Praizer, 1993). QFD deploys the voice of the customer throughout the R&D, engineering, and manufacturing stages of product development (Griffin and Hauser, 1993). It is a powerful system for quality improvement and product development which assures that quality is built into new products and services.

Various techniques have been identified and studied with an aim to improving the QFD methodology. One emerging trend involves the use of artificial intelligence (AI) and related techniques. For example, Reich (1996) discussed the benefits that AI can bring to QFD. To avoid the need to input a large amount of data and the necessity of estimating values on a rather subjective basis, Zhang et al. (1996) suggested a machine learning approach. However, the QFD process involves various inputs in the form of linguistic data, e.g., human perception, judgment, and evaluation on importance of customer requirements or relationship strength, which are usually subjective and uncertain. In traditional QFD most of these input variables are assumed to be precise and are treated as numerical data. Linguistic data, however, is inherently vague and ambiguity. They can be treated to approximate exactness with the help of fuzzy set theory.

Some progress has been made along this line. Masud and Dean (1993) investigated how QFD analysis can be performed when input variables are
treated as linguistic variables with values expressed as fuzzy numbers. Bahrami (1994) introduced a method for performing routine design by using information content and fuzzy QFD based on the concept of linguistic variable. Kim et al. (1994) presented an integrated approach that allows a design team to mathematically consider tradeoffs among various customer attributes as well as the inherent fuzziness in the system by combining multi-attribute value theory with fuzzy linear regression and fuzzy optimization theory. Khoo and Ho (1996) developed an approach centered on applying possibility theory and fuzzy arithmetic to address the ambiguity involved in various relationships. Fung et al. (1998) proposed a hybrid system that incorporates the principles of QFD, analytic hierarchy process, and fuzzy set theory to tackle the complex and often imprecise problem domain encountered in customer requirement management.

When implementing QFD using linguistic data, some factors may affect the final results such as the ranking of technical characteristics. The factors include: the type of fuzzy numbers, defuzzification strategies, and the degree of fuzziness of fuzzy numbers. Little research, however, has been done on which factors influence the results and to what extent. This is despite realizing the necessity of knowing these information in order that use of the fuzzy approach is successful.

As a consequence, one objective of this paper is to propose a fuzzy process model that can be easily integrated into the traditional QFD process. This model considers the following two main inputs of QFD as linguistic variables: importance to customer and relationship strength. It is intended to produce the results in the form of either fuzzy or crisp numbers depending on request. Another aim of this paper is to examine the ability of the following two important factors that affect the ranking of technical characteristics: defuzzification strategies and the degree of fuzziness of fuzzy numbers.

This paper begins with an introduction to the use of fuzzy set theory and linguistic data and variables in QFD. A process model for implementing QFD under a fuzzy environment is proposed in Section 3. Particularly, the fuzzification of the input data and the defuzzification of the output data are presented. Section 4 presents an example for illustrating the use of a proposed fuzzy QFD model. Sensitivity analysis of the model is discussed in Section 5.

2. QFD based on linguistic data

2.1. Linguistic data in QFD

As an approach to design, QFD is a concept introduced by Akao (1990) in Japan in 1966. It was first put into use at Mitsubishi’s Kobe shipyard site in 1972. Later in 1983, it was introduced to the USA and it has since spread quickly to many other countries.

QFD converts consumers’ demands into ‘‘quality characteristics.’’ It develops a design quality for finished products by systematically deploying the relationships between the demands and the quality characteristics, starting with the quality of each functional component and extending the deployment to the quality of each part and process (Akao, 1990). Four key documents are commonly used in carrying out QFD, namely: the overall customer requirement planning matrix, the final product characteristic development matrix, the process plan and quality control charts, and the operating instructions (Sullivan, 1986).

As the primary element of QFD, the house of quality (HOQ) is a matrix style chart that correlates customer attributes called ‘‘Whats’’ with technical characteristics called ‘‘Hows.’’ The HOQ is a kind of conceptual map that provides the means for interfunctional planning and communication (Hauser and Clausing, 1988). It usually has six sub-matrices including customer attributes, technical characteristics, a relationship matrix, a planning matrix, technical correlations, and a technical matrix (see Fig. 1).
Most of the data that QFD uses are linguistic in nature. For example, customer requirements are often vague and loosely stated, such as: “easy to use,” “safe,” and “comfortable.” Capturing the elasticity of imprecise requirements is an important issue (Liu and Yen, 1996). Simonson (1993) stated that customers’ preferences are often fuzzy and imprecise, e.g., “very important” and “some important.” In addition, relationships between customer attributes and technical characteristics are identified qualitatively (Belhe and Kusiak, 1996). This is often ambiguous, e.g., “strong relationship.” Since linguistic data cannot be easily quantified, it may be more appropriate to treat them as fuzzy rather than precise.

2.2. Use of fuzzy theory and linguistic variables

Fuzzy set theory was developed for solving problems in which descriptions of activities and observations are imprecise, vague, and uncertain. It provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied. One area where fuzzy set theory has been useful is in quantifying the vagueness of human thought, cognition, and perception. Other areas of application include decision making, operations research, and production management (Lai and Hwang, 1994; Guiffrida and Nagi, 1998). The aim of applying fuzzy set theory to QFD is to translate vague and imprecise customer inputs into exact data.

To deal with the description about the vagueness of an object, Zadeh (1965) proposed a membership function associated with each object. He proposed a grade of membership belonging to the interval [0, 1]. A fuzzy set is designated as: \( \forall x \in X, \mu_A(x) \in [0, 1] \), where \( \mu_A(x) \) is the degree of membership, ranging from 0 to 1, of a vague predicate, \( A \), over the universe of objects, \( X \). \( X \) is a space set which can be real numbers, natural numbers, or integers. The membership function can be viewed as an opinion poll of human thoughts, perceptions, or expert opinions.

Linguistic variables differ from numerical variables in that their values are not numbers but are words or phrases (Zadeh, 1975). The use of linguistic variables allows precise modeling of imprecise statements such as “very important” or “some important.” The successful use of linguistic variables is highly dependent on the determination of a valid membership function. For example, where there is both a normal and a convex fuzzy set with membership functions that satisfy both normality and convexity, arithmetic operations can be performed to obtain fuzzy numbers (Kaufmann and Gupta, 1985).

3. A process model for QFD with linguistic input

As described earlier, the QFD process requires various input data which are fuzzy and vague in nature and are hence better represented as linguistic variables. To implement QFD based on linguistic data, a process model that includes the use of the concepts of linguistic variable, fuzzy number, fuzzy arithmetic, and defuzzification, is proposed here (see Fig. 2).

Step 0: Initialization. This step is basically concerned with preparation for the QFD project. Several issues are involved in this step, including: deciding the purpose of the QFD study (e.g., to design a new version of an existing product, to upgrade it, or simply to cut cost); defining the expected benefits; selecting the product or service to be studied; forming...
the QFD team to include people from R&D, engineering, manufacturing, marketing, finance, and customer service; and if necessary, training the team members.

**Step 1: Identification of linguistic data.** In this step, QFD team members collect customer requirements through brainstorming, focus groups, customer surveys, and other techniques. After the customer requirements have been substantially identified and developed, customers are asked to make judgment on the importance of each requirement. They may rank and categorize the customer requirements into several groups, each of which falls into one of several importance levels. After coming up with the technical characteristics, QFD team members identify the relationships between the customer attributes and the technical characteristics.

The difference between the proposed model and traditional QFD in this step is that the data are expressed and represented as linguistic variables rather than as crisp numbers. For example, for the importance of a customer attribute such as “interesting web pages,” instead of using the traditional numerical scale (e.g., 1–5 scale), customers may be asked to rank this requirement as not important at all, very important, or according to some other descriptor. The strength of relationship between customer attributes and technical characteristics may be categorized as either weak, moderate, or strong, as opposed to using the traditional numerical scale of $\{1,3,9\}$. The former, due to its reliance on natural language, is easier to use.

**Step 2: Fuzzification of input data.** In Step 2, the input data are further represented as fuzzy numbers. In this process model, two important input data are treated as linguistic variables and are fuzzified into fuzzy numbers, namely: the importance to customers, and the strength of relationship between the customer attributes and the technical characteristics.

One possible set of membership functions for the fuzzy numbers can be found in Fig. 3. Note that the choice of simple membership functions used in the figure is for illustrative purposes only. They may not represent the exact functions used in other situations. Throughout the paper, the triangular fuzzy number is used and all membership functions for linguistic input data are standardized in the interval $[0,1]$.

The relationship matrix indicates how much each technical characteristic affects each customer attribute (see Fig. 1). To numerically map the voice of the customer onto the voice of the engineer, two scales are traditionally adopted, i.e., $[1,3,5]$ and $[1,3,9]$. Occasionally other scale values are used. The literature, however, does not document any basis for choosing either value set (Sivaloganathan and Evbuomwan, 1997). The weighting schemes that represent the relationship strength are, thus, subjective and rather arbitrary (Kim, 1997).

*Fig. 3. Fuzzy numbers for “importance to customer”.*
To overcome the above difficulty, linguistic variables help QFD practitioners categorize relationships intuitively. In Step 1, the relationship strengths are judged as either none, weak, moderate, or strong. They can be further represented through fuzzy numbers. Figure 4 shows one possible set of fuzzy numbers for relationship strength with membership functions plotted.

Step 3: Applying fuzzy arithmetic. Fuzzy arithmetic, which is a direct application of the extension principle, can be used on fuzzy numbers. In this step, fuzzy arithmetic is applied to the calculation of the priorities of technical characteristics, i.e., the relative contributions of the technical characteristics to overall customer satisfaction. The technical priority is a key result of QFD since it guides QFD practitioners in decision-making, resource allocation, and the subsequent QFD phases. The addition and multiplication of fuzzy numbers will be performed for the calculation of technical priorities. Specifically, for each technical characteristic, its priority can be obtained by adding all the weighted relationships in the form of fuzzy numbers, each of which is calculated by multiplying the relationship strength by the importance of the corresponding customer attribute.

Step 4: Defuzzification of output data. As Fig. 2 shows, in this process model one decision needs to be made by the QFD team members. They should decide which type of output data is more useful and easy to interpret, i.e., whether crisp or fuzzy results are preferred. If fuzzy technical priorities are required, Step 4 will be skipped and the process goes directly to Step 5. On the other hand, if crisp output data are preferred, the fuzzy technical priorities based on fuzzy arithmetic will be defuzzified into crisp results for downstream activities. Defuzzification is defined as the mapping of a fuzzy set A to elements of the universe considered significant with respect to A. Various defuzzification techniques have been suggested. For more information on defuzzification strategies and their selection, see e.g., Zhao and Govind (1991) and Runkler (1997).

In this paper, two frequently used defuzzification methods are used, namely, the Mean of Maxima (MOM) and the Centroid methods. The MOM method selects a non-fuzzy output value corresponding to the maximum value of the membership function. The values are averaged when there is more than one such output value. This method results in a most probable solution, but does not take into account other information given by the fuzzy set.

The Centroid defuzzification method calculates the centroid or center of gravity (COG) of the area under the membership function \( \mu(x) \). Let \( x^* \) denotes the defuzzified value of fuzzy set \( A \). The Centroid method can be defined by

\[
x^* = \frac{\int x \mu_A(x) \, dx}{\int \mu_A(x) \, dx}
\]

Unlike the MOM method, the Centroid method makes
a compromise between all possible solutions. It does not, however, choose the most possible solution.

Step 5: Downstream QFD activities. In this step, the subsequent activities and operations involved in the QFD process are implemented based on the preceding steps. Two possible situations will occur here. One situation is that the HOQ is the only phase used in the QFD process. In this situation, downstream issues primarily include interpretation of the information that HOQ provides. The other situation is where the HOQ constitutes the first phase. Parts deployment, process planning, and/or production planning are incorporated into subsequent activities.

This process model is based mainly on the house of quality—the first phase of QFD. It shows the implementation process of HOQ under a fuzzy environment through the use of linguistic variables and fuzzy numbers. The HOQ is the most commonly used matrix in QFD. It contains many features seen also in subsequent QFD activities. The fuzzy approach can be easily integrated into the HOQ and extended to the whole QFD process.

4. An illustrative example

To help illustrate the use of the proposed fuzzy approach in dealing with linguistic data when implementing QFD, an example is presented in this section. It focuses on the application of QFD in defining and designing good web pages.

4.1. Scenario

In this example, the QFD technique using the HOQ method was employed to look into the human/user interface aspects of web pages. An analysis of general customer requirements identified a list of needs for good web pages, e.g., “interesting web page,” “good linkages.” QFD team members translated the requirements into technical characteristics, e.g., “use of graphics” and “number of updated links.” All of these customer requirements and technical characteristics are presented in the HOQ of Table 1, minus the roof portion for simplicity.

4.2. Applying the proposed model

Following Step 1, the importance of the customer needs and relationship strengths were identified as linguistic data. As Table 1 shows, the customer needs were categorized as either very important, important, moderately important, or some important. Similarly, the relationships between the customer needs and the technical characteristics were linguistically judged as either none, weak, moderate, or strong.

The linguistic data were further converted into fuzzy numbers as described previously in Step 2. The membership functions associated with the linguistic term “importance to customer” were defined as follows and they are plotted in Fig. 5:

\[
\mu_{\text{very}}(x) = 1 - 10x/3 \\
\mu_{\text{important}}(x) = 4x \\
\mu_{\text{moderately}}(x) = 5x - 1.5 \\
\mu_{\text{some}}(x) = 4x - 2 \\
\mu_{\text{not}}(x) = 10x/3 - 7/3
\]

Similarly, the membership functions associated with the linguistic term “relationship strength” are defined as follows and these are plotted in Fig. 6:

\[
\mu_{\text{none}}(x) = 1 - 10x \\
\mu_{\text{weak}}(x) = 5x \\
\mu_{\text{weak}}(x) = 2 - 5x \\
\mu_{\text{moderate}}(x) = 10x/3 - 2/3 \\
\mu_{\text{strong}}(x) = 2.5x - 1.5
\]
Table 1. The HOQ with linguistic inputs and defuzzified technical priorities

<table>
<thead>
<tr>
<th>Importance H1: Use of graphics information</th>
<th>Importance H2: Amount of text and formatting</th>
<th>Importance H3: Text formatting and grammar</th>
<th>Importance H4: Spelling and grammar</th>
<th>Importance H5: Standard page design</th>
<th>Importance H6: Integration of links into text</th>
<th>Importance H7: Provision of links for downloaded information</th>
<th>Importance H8: Provision of Organization link back to home page</th>
<th>Importance H9: Number of updated links of page communications</th>
<th>Importance H10: Number of important web pages</th>
<th>Importance H11: Size of web pages</th>
<th>Importance H12: Speed of computers and communications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Important</td>
<td>Moderate</td>
<td>Important</td>
<td>Some</td>
<td></td>
<td>Important</td>
<td>Moderate</td>
<td>Strong</td>
<td>Moderate</td>
<td>Important</td>
<td>Weak</td>
<td>None</td>
</tr>
<tr>
<td>Interesting web pages</td>
<td>Easy-to-read text</td>
<td>Uniform &amp; standardized page design</td>
<td>Sufficient information</td>
<td>Easy-to-locate information</td>
<td>Good linkages</td>
<td>Good integration of links</td>
<td>Fast in loading</td>
<td>Technical importance (crisp)</td>
<td>Relative importance (%)</td>
<td>Ranking</td>
<td></td>
</tr>
<tr>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>1.32</td>
<td>12.5</td>
<td>1</td>
<td>Weak</td>
</tr>
<tr>
<td>Interest in reading text</td>
<td>Uniform &amp; standardized page design</td>
<td>Sufficient information</td>
<td>Easy-to-locate information</td>
<td>Good linkages</td>
<td>Good integration of links</td>
<td>Fast in loading</td>
<td>Technical importance (crisp)</td>
<td>Relative importance (%)</td>
<td>Ranking</td>
<td></td>
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</tr>
<tr>
<td>Important</td>
<td>Moderate</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>1.21</td>
<td>11.5</td>
<td>2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Uniform &amp; standardized page design</td>
<td>Sufficient information</td>
<td>Easy-to-locate information</td>
<td>Good linkages</td>
<td>Good integration of links</td>
<td>Fast in loading</td>
<td>Technical importance (crisp)</td>
<td>Relative importance (%)</td>
<td>Ranking</td>
<td></td>
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<tr>
<td>Important</td>
<td>Moderate</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>0.72</td>
<td>6.9</td>
<td>8</td>
<td>Moderate</td>
</tr>
<tr>
<td>Sufficient information</td>
<td>Easy-to-locate information</td>
<td>Good linkages</td>
<td>Good integration of links</td>
<td>Fast in loading</td>
<td>Technical importance (crisp)</td>
<td>Relative importance (%)</td>
<td>Ranking</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>0.49</td>
<td>4.6</td>
<td>12</td>
<td>Moderate</td>
</tr>
<tr>
<td>Easy-to-locate information</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>0.87</td>
<td>8.3</td>
<td>6</td>
<td>Moderate</td>
</tr>
<tr>
<td>Good linkages</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>0.87</td>
<td>8.3</td>
<td>6</td>
<td>Moderate</td>
</tr>
<tr>
<td>Good integration of links</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>1.06</td>
<td>10.1</td>
<td>3</td>
<td>Moderate</td>
</tr>
<tr>
<td>Fast in loading</td>
<td>Very</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Important</td>
<td>Very</td>
<td>0.67</td>
<td>6.3</td>
<td>9</td>
<td>Moderate</td>
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<tr>
<td>Technical importance (crisp)</td>
<td>Relative importance (%)</td>
<td>Ranking</td>
<td>1</td>
<td>2</td>
<td>8</td>
<td>12</td>
<td>6</td>
<td>6</td>
<td>3</td>
<td>4</td>
<td>11</td>
</tr>
</tbody>
</table>

Relationship Key
- Strong ★
- Moderate ○
- Weak △
- None blank
and “provision of links for downloaded information” were the three most important features for satisfying customer needs.

4.3. Comparison of the fuzzy approach with traditional approach

The above example illustrated the use of the proposed fuzzy approach. Two important inputs for the HOQ, importance to customer and relationship strength, were identified as linguistic rather than as numerical variables. Compared with the traditional approach, we may conclude that this fuzzy approach has at least two advantages. The first advantage is that the treatment of input data as linguistic variables appears intuitive and reasonable. In fact, the above example suggests that subjective and arbitrary quantification of input data can be avoided.
The second advantage is that the fuzzy model can provide a flexible data output scheme. For QFD practitioners, both fuzzy and crisp technical priorities can be obtained with the use of this approach. Thus, the traditional approach can be viewed as a special form of the fuzzy approach where the linguistic variables can be quantified and represented as crisp numbers instead of as fuzzy numbers. Such a flexible scheme makes for easy interpretation of results. Crisp results are desirable as decision-makers may have difficulty in analyzing fuzzy results. At other times, the results may be required in the form of fuzzy numbers for downstream QFD processes.

5. Sensitivity analysis

The technical priorities provide guidelines for allocating limited resources, and also direct the downstream activities involved in the QFD process. This section examines the sensitivity of the ranking of technical characteristics to the factors involved in the implementation of QFD based on linguistic data. Two factors of interest in this paper are: (1) the defuzzification strategy used to obtain the crisp results, and (2) the degree of fuzziness of fuzzy numbers. As described previously, two defuzzification strategies considered here are the MOM and Centroid methods.

Measures of fuzziness estimate the average amount of ambiguity embedded in fuzzy sets in some well-defined sense. Various methods have been developed for measuring the amount of fuzziness, see, e.g., Pal and Bezdek (1994). In this paper, the degree of fuzziness is measured by the linear index of fuzziness $\nu(A)$ proposed by Kaufmann (1975, p. 23). The linear index of fuzziness $\nu(A)$ is defined as the generalized relative Hamming distance between $A$ and $\hat{A}$, the crisp set nearest to $A$, i.e.,

$$\mu_{\hat{A}}(x) = \begin{cases} 1 & \mu_A(x) \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$$

When the support of $A$ is the continuous interval $[a, b]$, the linear index of fuzziness is:

$$\nu(A) = \frac{2}{b-a} \int_a^b |\mu_A(x) - \mu_{\hat{A}}(x)| \, dx \tag{2}$$

With respect to the degree of fuzziness, two different sets of fuzzy numbers were considered in the sensitivity analysis. The membership functions for Set 1 are plotted in Figs. 5 and 6 while the membership functions for Set 2 are plotted in Figs. 3 and 4. The degree of fuzziness associated with each fuzzy number in Set 2 was designed to be 80% of the ones in Set 1. For example, according to Formula (2), the degrees of fuzziness associated with linguistic term “important” in Figs. 3 and 5 are 0.25 and 0.2 respectively.

Table 2 shows the results of sensitivity analysis on the defuzzification strategy and the degree of fuzziness. The rankings of technical characteristics resulting from two defuzzification strategies were different. For instance, for the set of fuzzy numbers that have fixed degrees of fuzziness, e.g., Set 1, the technical characteristic H7 “provision of links for downloaded information” ranked fifth under the MOM defuzzification method, while it ranked third using the Centroid defuzzification technique. Although it should be noted that the difference is not significant, it seems that the technical priority is generally sensitive to the two defuzzification strategies used. Hence, when crisp results are required, the

<table>
<thead>
<tr>
<th>Degree of fuzziness</th>
<th>Defuzz. strategy</th>
<th>Technical importance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MOM</td>
<td>Relative(%)</td>
</tr>
<tr>
<td>Set 1</td>
<td></td>
<td>H1 14.0 H2 12.3 H3 6.2 H4 2.8 H5 7.3 H6 8.4 H7 9.8 H8 5.6 H9 5.6 H10 11.2 H11 5.6 H12 11.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ranking 1 2 8 12 7 6 5 9 9 3 9 3</td>
</tr>
<tr>
<td></td>
<td>Centroid</td>
<td>Relative(%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H1 12.5 H2 11.5 H3 6.9 H4 4.6 H5 8.3 H6 8.3 H7 10.1 H8 6.3 H9 6.2 H10 9.5 H11 6.3 H12 9.5</td>
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<tr>
<td></td>
<td></td>
<td>Ranking 1 2 8 12 6 6 3 9 11 4 9 4</td>
</tr>
<tr>
<td></td>
<td>MOM</td>
<td>Relative(%)</td>
</tr>
<tr>
<td>Set 2</td>
<td></td>
<td>H1 14.0 H2 12.3 H3 6.2 H4 2.8 H5 7.3 H6 8.4 H7 9.8 H8 5.6 H9 5.6 H10 11.2 H11 5.6 H12 11.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ranking 1 2 8 12 7 6 5 9 9 3 9 3</td>
</tr>
<tr>
<td></td>
<td>Centroid</td>
<td>Relative(%)</td>
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<td></td>
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<td>H1 12.8 H2 11.6 H3 6.7 H4 4.3 H5 8.0 H6 8.3 H7 10.0 H8 6.2 H9 6.1 H10 9.8 H11 6.2 H12 9.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ranking 1 2 8 12 7 6 3 9 11 4 9 4</td>
</tr>
</tbody>
</table>
selection of a suitable defuzzification strategy is important.

Table 2 also indicated that the degree of fuzziness had a slight influence on the ranking of technical characteristics when the Centroid defuzzification method was used, but it had no effect on the technical ranking when using the MOM defuzzification method. Specifically, when using Centroid defuzzification, the technical importances changed slightly due to the use of different degrees of fuzziness. However, both the relative importance and the ranking of technical characteristics were the same under the two different sets of fuzzy numbers when using the MOM method. This is possibly due to the nature of MOM defuzzification in that it selects the non-fuzzy output value corresponding to the maximum value of the membership function. In this example, although the degrees of fuzziness of fuzzy numbers in Sets 1 and 2 are different, the maximum values of the membership functions are kept the same.

6. Conclusions

As a customer-driven quality management system, QFD involves numerous input data from both customers and QFD team members. This paper attempted to treat the main inputs of QFD as linguistic data on the basis of a proposed process model. Furthermore, sensitivity analysis was carried out by examining the possible influence of the defuzzification strategy and the degree of fuzziness of fuzzy numbers associated with each linguistic term on the ranking of technical characteristics.

By using a web page design example, it was indicated that the proposed fuzzy-based QFD model allows the avoidance of subjective and even arbitrary quantification of linguistic data by utilizing the fuzzy theory related concepts, e.g., linguistic variable, fuzzy arithmetic, and defuzzification. It was also shown that technical importance values could be flexibly represented as either fuzzy or crisp numbers. Overall, the sensitivity analysis suggest that determination of the proper defuzzification strategy to use, and the membership functions are important for the use of this method.

For future research, it would be beneficial to extend the proposed method to subsequent HOQs. It should also be worth while to incorporate other related factors into the sensitivity analysis, e.g., the number of fuzzy numbers. Due to the relative sensitivity of the technical importance, further research efforts should focus on the defuzzification method and the membership functions.

References


