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Research Issues in Robust QFD

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Abstract. Quality function deployment (QFD) provides a specific approach for ensuring quality throughout each stage of the product development and production process. Since the focus of QFD is placed on the early stage of product development, the uncertainty in the input information of QFD is inevitable. If the uncertainty is neglected, the QFD analysis results are likely to be misleading. It is necessary to equip practitioners with a new QFD methodology that can model, analyze, and dampen the effects of the uncertainty and variability in a systematic manner. Robust QFD is an extended version of QFD methodology, which is robust to the uncertainty of the input information and the resulting variability of the QFD output. This paper discusses recent research issues in Robust QFD. The major issues are related with the determination of overall priority, robustness evaluation, robust prioritization, and web-based Robust QFD optimizer. Our recent research results on the issues are presented, and some of future research topics are suggested.

Keywords: Quality Management, Product Design and Development

1. INTRODUCTION

Quality Function Deployment (QFD) is a concept and mechanism for translating the "voice of the customer" through the various stages of new product development. The basic concept of QFD is to translate the desires of the customer into product design or engineering characteristics, and subsequently into parts characteristics, process plans, and production requirements associated with its manufacture. Ideally, each translation uses a chart, called "house of quality (HOQ)".

The house of quality chart is the principal tool for QFD. There are a set of standard components of an HOQ, including customer attributes (CAs) and their relative weights, engineering characteristics (ECs), relationship matrix between CAs and ECs, correlation matrix among ECs, CA and EC benchmarking data, and EC importance values and their target levels.

The QFD analysis prioritizes the ECs by utilizing the information given in the HOQ. In typical QFD applications, a cell (i, j) in the relationship matrix (i-th row, j-th column) of an HOQ chart is assigned 1, 3, 9 (or 1, 3, 5) to represent a weak, medium, and strong relationship, respectively, between CA_i (i-th CA) and EC_j (j-th EC). The importance value of an EC is computed using the CA weights and the corresponding relationship coefficients. For each EC, the EC importance (ECI) value is computed as

$$ECI_j = \sum_{i=1}^{m} w_i f_{ij}\ , \tag{1}$$

where ECI_j is the ECI value of EC_j ($j = 1, \cdots, n$), w_i is the relative weight of CA_i ($I = 1, \cdots, m$), and f_{ij} is the relationship coefficient representing the strength of the relationship between CA_i and EC_j. Once the ECI values are computed, the ECs are prioritized by simply comparing the ECI values. The result of prioritization is used as the basis for making important decisions in the downstream phases

In the conventional QFD, the prioritization of ECs is conducted under an assumption that all the input information is certain. As a result, the ECI values are also treated as certain. However, since the focus of QFD is placed on the early stage of new product development, the uncertainty in the input information of QFD is inevi-

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table (Kim *et al*., 2000; Xie *et al*., 2003). If the uncertainty is neglected, the QFD analysis results can be misleading. In this view, a new QFD methodology that can model, analyze, and dampen the effects of the uncertainty in a systematic manner is warranted.

Robust QFD is an extended version of the QFD methodology, which is capable of considering the uncertainty of the input information (*e.g*., CA weights) and the resulting variability of the output (*e.g*., ECI values). In Robust QFD, the uncertainty of the input information is first modeled quantitatively. Utilizing the modeled uncertainty, the variability of the QFD output is formally analyzed. Given the variability of the QFD output, the ECs are prioritized. Finally, the robustness of the prioritization decision on ECs is evaluated and strategies for improving the robustness are devised (Kim *et al*., 2007).

The purpose of this paper is to introduce some of the recent research issues in Robust QFD and present the research progress to date. The research issues mentioned in this paper are as follows: determination of overall priority, robustness evaluation, robust prioritization, and development of web-based Robust QFD optimizer. These issues are mainly concerned with strengthening the methodological aspect of Robust QFD.

Section 2 briefly describes the Robust QFD methodology. Section 3 presents some recent research issues and briefly describes the progress on these issues. Section 4 presents some of future research topics. Finally, concluding remarks are given in Section 5.

2. ROBUST QFD METHODOLOGY

The Robust QFD methodology consists of four major steps-uncertainty modeling, variability derivation, EC prioritization, and robustness evaluation and improvement. The first three steps conceptually correspond to the three major tasks of the conventional QFD, namely, collecting HOQ input information, computing the ECI value of EC_j (ECI_j), and prioritizing the ECs, respectively. The difference is that we now consider the uncertainty and its effect on the decision process. The fourth step, which is new and did not exist in the conventional QFD, is introduced to evaluate and enhance the validity of the QFD decisions. For simplicity, the description is given assuming that uncertainty is allowed in the CA weights (w_i) only, and variability is considered only for the ECI value (The proposed model can be extended, if desired, to include uncertainty and variability in other parts of the HOQ) .

Step 1: Uncertainty Modeling

This step represents the degree and pattern of uncertainty in a quantitative manner. The w_i is considered a random variable. Hence, w_i has a probability distribution, rather than being a fixed point as in the conventional QFD model. The distribution of w_i can be assessed if the raw data on w_i are available. If the raw data on w_i are not available, the distribution of w_i needs to be assumed. The choice of the assumed distribution should be made based on various customer-related factors such as the size, attributes, and degree of homogeneity of the customer group.

Step 2: Variability Derivation

This step derives the variability of the ECI value, a major output of QFD, as a consequence of the input uncertainty. In the proposed model, w_i is a random variable, and hence ECI_j is another random variable. In general, the distribution of ECI_j is not identifiable analytically. A simulation approach can be employed to empirically derive the distribution of ECI_j (Law and Kelton, 2000). In this step, the variability of ECI is derived through a simulation experiment. In the k-th iteration of the simulation ($k = 1, \cdots, K$), a random number corresponding to w_i (denoted as $w_i(k)$) is generated using the estimated distribution function. The corresponding ECI_j (denoted as $ECI_j(k)$)is computed using Equation (1), with $w_i(k)$ substituted for w_i.

Step 3: EC Prioritization

This step prioritizes the ECs based on the distribution of ECI_j, *i.e*., $ECI_j(k)$, derived in Step 2. The prioritization can be conducted in various ways depending on the type of the ECI_j distributions. There are a few methods to prioritize the given alternatives based on their distributions. Examples include parametric or nonparametric tests (Montgomery and Runger, 2003), stochastic dominance (Hadar and Russell, 1969), and linear partial ordering (Kmietowicz and Pearman, 1984). Such methods can only provide the pairwise priorities.

However, an overall priority is needed for subsequent decisions in QFD because the pairwise priorities do not directly show the relative priority among more than two ECs. That is, the set of pairwise priorities has to be transformed into the overall priority. The determination of the overall priority will be described in Section 3.1.

Step 4: Robustness Evaluation and Improvement

The EC prioritization performed in Step 3 is not deterministic in nature. Hence, the possibility of making an error in prioritization always exists. Then, the stability of the prioritization decision is of concern, which is referred to as 'robustness' in this paper. Indices evaluating the degree of robustness can be developed. The robustness evaluation and robustness indices will be described in detail in Section 3.2. Using the robustness indices, various analyses can be performed to devise effective strategies to improve the robustness. As part of the robustness improvement, the notion of robust prioritization will be described in Section 3.3. The robust prioritization identifies a set of ECs or a priority relationship among ECs with a high level of robustness.

3. RECENT RESEARCH ISSUES

In this section, four recent research issues in Robust QFD are presented-(i) determination of overall priority, (ii) robustness evaluation, (iii) robust prioritization, and (iv) development of web-based Robust QFD Optimizer. A detail description for each issue is given next.

3.1 Determination of Overall Priority

The first issue is to determine the overall priority among ECs. Many authors studied on the determination of the overall priority from pairwise priorities (Brunk, 1960; Kendall, 1955; Saaty, 1977). The existing works have been focused on the case where the pairwise priorities are certain. As a result, the overall priority is also treated as stable. On the other hand, in Robust QFD, some degree of uncertainty is inevitably involved in the pairwise priorities. Hence, the existing methods cannot be directly applied to the situation of Robust QFD.

A new method to determine the overall priority among the ECs that is robust to the uncertainty of input information is under development (Kim and Kim, 2006). The method considers uncertainty by assigning a different or tie ranking flexibly. The flexible assignment of a different or tie ranking means that it assigns not only different ranking to ECs whose priorities are clearly different, but it also assigns tie ranking to ECs whose priorities are not clearly different.

This method determines the overall priority from a pairwise probability matrix, $\mathbf{P} = \{p_{ij}\}$, where p_{ij} is a pairwise probability of EC_i being favored over EC_j. The p_{ij} is computed by comparing $ECI_i(k)$ and $ECI_j(k)$. The portion that $ECI_i(k)$ is larger than $ECI_j(k)$ is obtained as p_{ij}. **P** is popularly used since it poses less burden on decision-makers than other types of pairwise comparisons (Cook and Kress, 1988).

Hypothetical example of overall priority from the method is given in Figure 1. In Figure 1, $G^{(r)}$ denotes r-th ranked group (*i.e.*, a set of ECs that have r-th ranking), $n(G^{(r)})$ denotes the size of $G,^{(r)}$ and N denotes the number of groups. From Figure 1, we can easily observe that highly robust overall priority should simultaneously have a large difference of priorities between groups and a large similarity of priorities within groups.

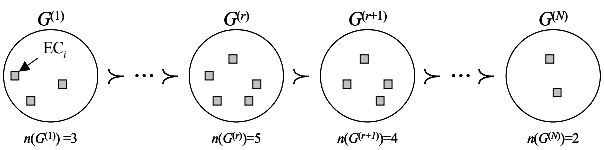

Figure 1. Example of an overall priority.

We shall call the difference of priorities between groups 'separation' between groups; and the similarity of priorities within groups 'homogeneity' within groups. That is, a highly robust overall priority should have a relatively large separation between groups and a relatively large homogeneity within groups simultaneously, similarly to rational subgroups in statistical process control (Montgomery, 1985). In this section, the separation between groups and the homogeneity within groups will be referred to as the separation and the homogeneity, respectively, for simplicity.

The separation and the homogeneity can be measured using **P**. First, the separation is represented as a geometric mean of p_{ij} where EC_i and EC_j have r-th and $(r+1)$-th ranking, respectively. The equation for the separation is expressed as

$$\begin{aligned}\text{Separation} &= \left[\prod_{r=1}^{N-1}\prod_{\substack{EC_i\in G^{(r)}\\ EC_j\in G^{(r+1)}}} p_{ij}\right]^{1/\sum_{r=1}^{N-1} n(G^{(r)})\times n(G^{(r+1)})} && \text{for } N>1 \\ &= 1 && \text{for } N=1.\end{aligned} \tag{2}$$

The separation is a larger-the-better type index, and it has a value between [0, 1]. Let the separation be defined as 1 if every EC has a tie ranking, *i.e.*, N is one. The separation becomes 0 when at least one p_{ij} is 0, where EC_i and EC_j are included in $G^{(r)}$ and $G^{(r+1)}$, respectively. That is, the probability of r-th ranked EC being favored over $(r+1)$-th ranked EC is 0. It indicates that the ranking between r-th and $(r+1)$-th is definitely reversed. The separation becomes 1 when every p_{ij} is 1 for EC_i and EC_j in $G^{(r)}$ and $G^{(r+1)}$, respectively. This case is the best case because no rank reversals occur.

Second, the homogeneity can be represented as a two fold of the geometric mean of the p_{ij} where both EC_i and EC_j have r-th ranking. The equation for the homogeneity is expressed as

$$\text{Homogeneity} = 2\left[\prod_{r=1}^{N}\prod_{EC_i,EC_j\in G^{(r)}}\sqrt{p_{ij}\cdot p_{ji}}\right]^{1/\sum_{r=1}^{N} n(G^{(r)})^2} \tag{3}$$

The homogeneity is a larger-the-better type index, and it has a value between [0, 1]. Let the homogeneity be defined as 1 if every EC has a different ranking, *i.e.*, every $n(G^{(r)})$ is one. The homogeneity also becomes 1 if every p_{ij} is 0.5 for EC_i and EC_j both in $G^{(r)}$. The p_{ij} being 0.5 means that the priorities of EC_i and EC_j are exactly the same. In such a case, the homogeneity should have the largest value, 1. On the other hand, the homogeneity becomes 0 if any p_{ij} of tie ranked ECs is 0. It represents a contradictory situation because a tie ranking is assigned to the ECs whose real priorities are clearly different.

There is a trade-off relationship between the separation and the homogeneity. When the every ECs has a tie ranking, the separation has the largest value, 1, but the homogeneity has a relatively low value. In contrast, the homogeneity has the largest value, 1, but the separation is low, when the every ECs has a different ranking.

In order to reach the overall priority, one needs to find a set of rankings where the separation and the homogeneity are reasonably high. Such a compromising point can be found using heuristic methods such as genetic algorithm.

3.2 Robustness Evaluation

The second issue is related to the evaluation of robustness of the prioritization decision (Step 4) in Robust QFD. Based on the pairwise or overall priority of ECs, a company would make a prioritization decision on the ECs. In order to justify the prioritization decision, a systematic method for checking its robustness is warranted. Robustness indices for this purpose are under development (Kim and Kim, 2008).

Two robustness indices for two types of prioritization decisions are considered: (i) *determining the absolute ranking of ECs* and (ii) *determining the priority relationship among ECs*. First, the robustness of the absolute ranking of ECs can be defined as the degree to which the ECs of interest have a higher or equal ranking than a pre-specified ranking (q) despite uncertainty. Here, the set of the ECs of interest will be referred to as **EC**. The robustness index on the absolute ranking of ECs is expressed as the likelihood that every EC in **EC** has a higher or equal ranking than q. The robustness index on the absolute ranking of EC, denoted as $\mathrm{RI}_1(\mathbf{EC}, q)$, can be calculated via simulation as

$$\mathrm{RI}_1(\mathbf{EC}, q) = \frac{\sum_k^K x(k)}{K}, \tag{4}$$

$$\text{where } \begin{cases} x(k) = 1, \text{ if } \mathit{ranking}(\mathrm{EC}_j, k) \le q \quad \forall\ \mathrm{EC}_j \in \mathbf{EC} \\ x(k) = 0, \text{ otherwise.} \end{cases}$$

where $\mathit{ranking}(\mathrm{EC}_j, k)$ denotes the ranking of EC_j in the k-th iteration of simulation and $x(k)$ is an indicator variable.

Second, the robustness on the priority relationship among ECs is defined as the degree to which the relative priority relationship among ECs is kept despite uncertainty. For simplicity, the priority relationship among ECs will be denoted as **V**, an array of the EC indices. For example, $\mathbf{V}_{\mathrm{example}} = [a, b]$ means that EC_a has a higher priority than EC_b, or in short, $\mathrm{EC}_a \succ \mathrm{EC}_b$. The robustness index on the priority relationship among ECs is expressed as the likelihood that a priority relationship in **V** is kept. The robustness index on the priority relationship, denoted as $\mathrm{RI}_2(\mathbf{V})$, can be calculated via simulation as

$$\mathrm{RI}_2(\mathbf{V}) = \frac{\sum_k^K y(k)}{K} \tag{5}$$

$$\text{where } \begin{cases} y(k) = 1, \text{ if } \mathit{ranking}(\mathrm{EC}_{\mathbf{V}(v)}, k) \le \mathit{ranking}(\mathrm{EC}_{\mathbf{V}(v+1)}, k)\ \forall\ v \\ y(k) = 0, \text{ otherwise.} \end{cases}$$

where $\mathrm{EC}_{\mathbf{V}(v)}$ denotes the v-th EC in **V**, $n(\mathbf{V})$ denotes the array size of **V**, $y(k)$ is an indicator variable.

Both $\mathrm{RI}_1(\mathbf{EC}, q)$ and $\mathrm{RI}_2(\mathbf{V})$ have values between zero and one. A larger value of $\mathrm{RI}_1(\mathbf{EC}, q)$ or $\mathrm{RI}_2(\mathbf{V})$ means that the robustness of the absolute ranking of ECs in **EC** or the priority relationship in **V** is higher, respectively. As an extreme case, if $\mathrm{RI}_1(\mathbf{EC}^{※}, q)$ is equal to one, the absolute ranking of each EC in $\mathbf{EC}^{※}$ is always higher than or equal to q despite uncertainty. Similarly, the $\mathrm{RI}_2(\mathbf{V}^{※})$ value of one means that the priority relationship in $\mathbf{V}^{※}$ is always kept despite uncertainty.

Utilizing the robustness indices defined above, the robustness of prioritization decisions (namely, **EC** or **V**) can be evaluated. Depending upon the situation, $\mathrm{RI}_1(\mathbf{EC}, q)$, $\mathrm{RI}_2(\mathbf{V})$ or both may be utilized in the evaluation. One can consider three possible situations given next. The first situation is that a company is interested in the top q ECs, but not concerned with the priority relationship among them. In this situation, $\mathrm{RI}_1(\mathbf{EC}, q)$ will be used. This situation may happen when a company wishes to allocate its resources on some important ECs. This situation is analogous to the one of the project selection problem (Kim and Kim, 2008). In the second situation, a company is interested in finding out the priority relationship among the given ECs. Then, $\mathrm{RI}_2(\mathbf{V})$ will be used. It will be useful for a company that desires to prioritize the given investment options (Kim and Kim, 2008). The third situation is that a company is interested in identifying some important ECs, and also finding out the priority relationship among them. In this situation, both $\mathrm{RI}_1(\mathbf{EC}, q)$ and $\mathrm{RI}_2(\mathbf{V})$ will be used.

The role of q in $\mathrm{RI}_1(\mathbf{EC}, q)$ is comparable to that of the specification limit in a process capability study. As such, q should be predetermined by the company. As the probability of acceptance increases when the specification limit becomes wider, $\mathrm{RI}_1(\mathbf{EC}, q)$ generally increases when q increases. In general, the issue of robustness becomes more critical as q becomes small.

3.3 Robust Prioritization

A robust prioritization refers to the identification of a set of ECs ($\mathbf{EC}^*$) and/or a priority relationship among ECs ($\mathbf{V}^*$) with a high level of robustness. That is, a robust prioritization identifies the most robust $\mathbf{EC}^*$ or $\mathbf{V}^*$ that maximizes the robustness index, $\mathrm{RI}_1(\mathbf{EC}, q)$ or $\mathrm{RI}_2(\mathbf{V})$. As mentioned in Section 3.2, a company may wish to identify $\mathbf{EC}^*$ by maximizing $\mathrm{RI}_1(\mathbf{EC}^*, q)$, or identify $\mathbf{V}^*$ by maximizing $\mathrm{RI}_2(\mathbf{V}^*)$, identify not only $\mathbf{EC}^*$ but also $\mathbf{V}^*$ by considering both $\mathrm{RI}_1(\mathbf{EC}^*, q)$ and $\mathrm{RI}_2(\mathbf{V}^*)$.

Since the two indices are considered simultaneously in the last case, there are many compromising alternative combinations of **EC** and **V**. For example, suppose two prioritization decisions $\mathbf{D}_1 = (\mathbf{EC}_1, \mathbf{V}_1)$ and $\mathbf{D}_2 = (\mathbf{EC}_2, \mathbf{V}_2)$. If $\mathrm{RI}_1(\mathbf{EC}_1, q)$ is larger than $\mathrm{RI}_1(\mathbf{EC}_2, q)$ and $\mathrm{RI}_2(\mathbf{V}_1)$ is less than $\mathrm{RI}_2(\mathbf{V}_2)$, neither $\mathbf{D}_1$ nor $\mathbf{D}_2$ dominates the other, and thus one cannot conclude which prioritization is more robust. Hence, such combinations would form an efficient frontier of **EC** and **V**. Here an efficient frontier is defined as a set of compromising alternative combinations of **EC** and **V** that cannot be identified to be less robust than the others. The final $\mathbf{EC}^*$ and $\mathbf{V}^*$ should be selected from the alternatives on the efficient frontier based on the company's preference trade-off.

In order to identify $\mathbf{EC}^*$ or $\mathbf{V}^*$ that maximizes the corresponding robustness index, a full enumeration method or various heuristic algorithms can be used. Although the full enumeration method requires much computational burden, it can be used when the number of ECs is relatively small. Heuristic algorithms such as genetic algorithm can also be used (Rardin, 1998).

3.4 Development of Web-based Robust QFD Optimizer

The Robust QFD methodology involves much computation such as the estimation of a distribution function in Step 1, the generation of random numbers in Step 2, prioritization in Step 3, and robustness evaluation in Step 4. In order to facilitate the practical application of Robust QFD, a systematic support is necessary.

In this view, a software system for Robust QFD, called 'web-based Robust QFD Optimizer (Web-RQO)' has been developed. Web-RQO, developed in Windows and World-Wide-Web (WWW) environment, is designed to collect the input information from distributed customers and practitioners through WWW and conduct the Robust QFD analysis at the practitioner's site.

Web-RQO consists of the web part and the application part. First, the web part, developed using ASP (Active Server Pages) in WWW environment, collects the input information from distributed QFD practitioners and customers. The web part provides four functions, namely, evaluation function, user management function, project management function, and information view function. Second, the application part, developed using Microsoft Visual Basic, conducts the Robust QFD analysis at the QFD practitioner's site. The application part provides four functions, namely, data loading function, graphical interface function, variability analysis function, and robustness evaluation function. The hierarchical structure of Web-RQO is given in Figure 2.

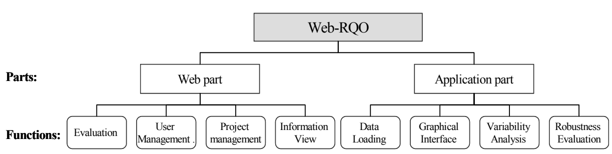

Figure 2. Structure of Web-RQO.

Figure 3 shows the process of activities associated with the execution of Web-RQO. QFD practitioners access the web part, and input CA and EC items. Then, customers access the web part and evaluate the CA weights and CA-EC relationships using the evaluation function. The evaluation information is saved in the database. During this process, QFD practitioners can monitor the information evaluated by customers. From the database, the application part fetches the input information. When the application part is executed, the application connects to the database in the web server, and obtains the information. Using the information, the Robust QFD analysis is conducted. Web-RQO allows QFD practitioners to collect information from distributed customers easily and analyze the effect of input information uncertainty in an effective and efficient manner.

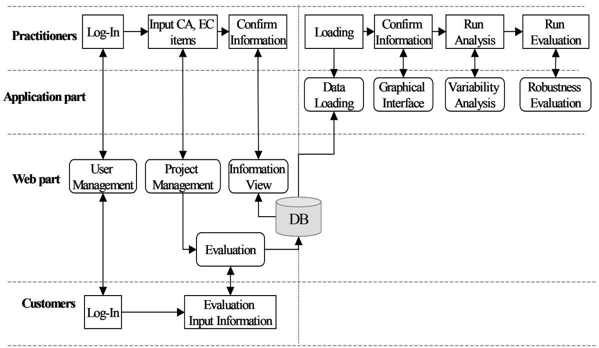

Figure 3. Process of Activities in Web-RQO Application.

4. CASE STUDY: ROBUST QFD STUDY FOR ADSL QUALITY IMPROVEMENT

This case study was conducted to improve the high-speed internet service based on the asymmetric digital subscriber line (ADSL) technology of Company K in Korea. Company K has provided the ADSL service for domestic customers since 1999. Currently, Company K has more than six million ADSL service subscribers, and is considered the leader in this market. As part of the quality improvement efforts, Company K conducted this QFD study.

The HOQ in this study includes eleven CA items and fourteen EC items. The CA weights were obtained from a group of thirty customers-ten customers from Company K and ten customers each from two of its major competitors. For each of the thirty respondents, an interview was conducted to solicit pairwise comparisons of the CAs for an AHP analysis. As a result, thirty sets of CA weights, one set for each respondent, were obtained. The relationship matrix of the HOQ was developed by a focus group, which consisted of several staff members of Company K and several researchers specializing in customer satisfaction management in telecommunication industry. The relationship between a CA and an EC was evaluated using the conventional 'Strong-Medium-Weak' scale. The completed HOQ is shown in Figure 4. The CA weight given in Figure 4 indicates the average value of the thirty sets of the CA weights.

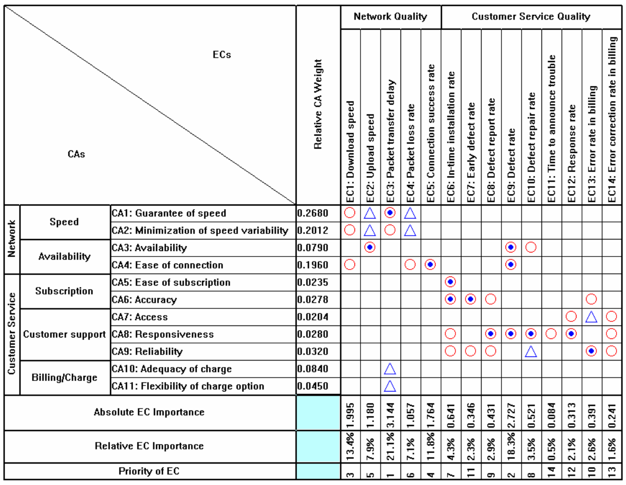

Figure 4. HOQ of the case study.

This case study includes the uncertainty in the w_i, because all the thirty customers do not have the same weights on the CA items. Other input information is assumed to be certain for simplicity in this case study.

Step 1: Uncertainty Modeling

Step 1 estimates the distribution of w_i based on the thirty sets of w_i from thirty customers. The distribution function is estimated using a linear interpolation as in Figure 5.

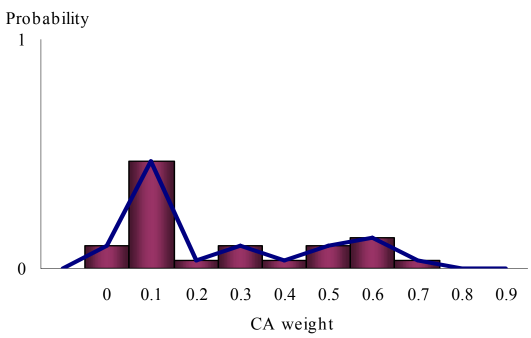

Figure 5. Estimation of the distribution of w_1.

Step 2: Variability Derivation

Step 2 derives the variability of ECI via a simulation experiment. One thousand sets of $ECI_j(k)$ are obtained from the simulation. Figure 6 shows the histogram of $ECI_j(k)$, which demonstrates the variability of each ECI.

Step 3: EC Prioritization

Step 3 prioritizes the ECs considering the derived variability of ECI. This case study identifies the stochastic dominance relationships and pairwise probability, p_{ij}. The result of the prioritization is given in Table 1.

The symbol '$\succ$' (or '$\prec$') in the cell (i, j) denotes that EC_i has a higher (or a lower) priority than EC_j, respectively. The symbol '$\approx$' in the cell (i, j) denotes that the priority between EC_i and EC_j cannot be differentiated. The value in parentheses in each cell indicates p_{ij}, computed by comparing $ECI_i(k)$ and $ECI_j(k)$.

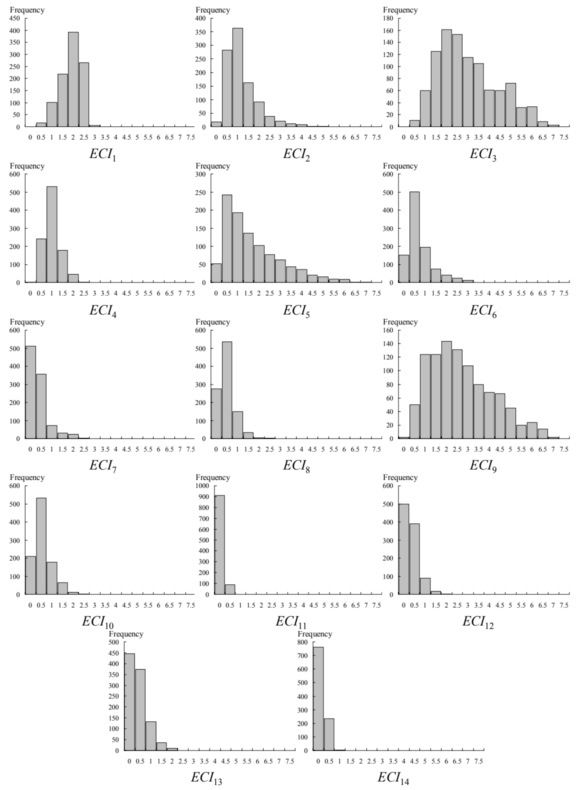

Figure 6. Histogram of $ECI_j(k)$.

Table 1. Pairwise priorities among ECs.

	EC_2	EC_3	EC_4	EC_5	EC_6	EC_7	EC_8	EC_9	EC_{10}	EC_{11}	EC_{12}	EC_{13}	EC_{14}
EC_1	$\approx$ (0.848)	$\approx$ (0.227)	$\succ$ (1.000)	$\approx$ (0.606)	$\approx$ (0.918)	$\approx$ (0.972)	$\approx$ (0.971)	$\approx$ (0.429)	$\approx$ (0.977)	$\succ$ (1.000)	$\approx$ (0.986)	$\succ$ (0.967)	$\succ$ (1.000)
EC_2		$\prec$ (0.128)	$\approx$ (0.522)	$\approx$ (0.435)	$\succ$ (0.775)	$\succ$ (0.908)	$\succ$ (0.828)	$\prec$ (0.143)	$\succ$ (0.878)	$\succ$ (0.993)	$\succ$ (0.889)	$\succ$ (0.849)	$\succ$ (0.976)
EC_3			$\succ$ (0.868)	$\succ$ (0.726)	$\succ$ (0.943)	$\succ$ (0.979)	$\succ$ (0.979)	$\approx$ (0.586)	$\succ$ (0.975)	$\succ$ (1.000)	$\succ$ (0.990)	$\succ$ (0.982)	$\succ$ (1.000)
EC_4				$\approx$ (0.351)	$\approx$ (0.776)	$\approx$ (0.926)	$\approx$ (0.849)	$\approx$ (0.112)	$\approx$ (0.847)	$\succ$ (0.999)	$\approx$ (0.913)	$\approx$ (0.861)	$\succ$ (0.988)
EC_5					$\approx$ (0.747)	$\succ$ (0.881)	$\succ$ (0.815)	$\prec$ (0.000)	$\succ$ (0.810)	$\succ$ (0.969)	$\succ$ (0.851)	$\succ$ (0.837)	$\succ$ (0.931)
EC_6						$\succ$ (1.000)	$\succ$ (0.665)	$\prec$ (0.088)	$\succ$ (0.500)	$\succ$ (1.000)	$\succ$ (0.766)	$\succ$ (0.779)	$\succ$ (0.999)
EC_7							$\approx$ (0.334)	$\prec$ (0.034)	$\approx$ (0.24)	$\succ$ (0.845)	$\approx$ (0.486)	$\approx$ (0.449)	$\succ$ (0.952)
EC_8								$\prec$ (0.040)	$\approx$ (0.405)	$\succ$ (1.000)	$\approx$ (0.883)	$\approx$ (0.608)	$\succ$ (0.966)
EC_9									$\succ$ (1.000)	$\succ$ (1.000)	$\succ$ (0.994)	$\succ$ (0.957)	$\succ$ (0.993)
EC_{10}										$\succ$ (1.000)	$\approx$ (0.864)	$\approx$ (0.678)	$\succ$ (0.934)
EC_{11}											$\prec$ (0.000)	$\prec$ (0.152)	$\prec$ (0.310)
EC_{12}												$\approx$ (0.481)	$\succ$ (0.809)
EC_{13}													$\succ$ (0.968)

In this case study, a heuristic method is introduced to determine the overall priority with high level of separation and homogeneity. The method consists of two tasks-(i) grouping ECs and (ii) prioritizing groups. Task 1 groups ECs whose relative rankings cannot be clearly differentiated, and Task 2 prioritizes the groups formed in Task 1. That is, Task 1 seeks to join two groups whose merger leads to the largest homogeneity and Task 2 finds the order of the groups to maximize the separation. The determined overall priority is shown in Figure 7, where the separation and the homogeneity are 0.82414 and 0.97926, respectively.

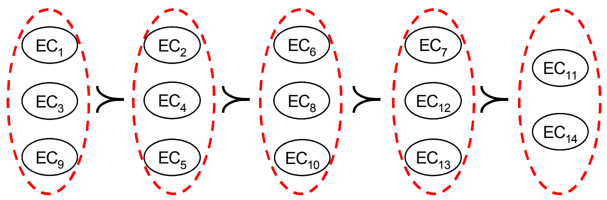

Figure 7. Overall priority.

Step 4: Robustness Evaluation and Improvement

In this case study, QFD practitioners make two decisions. First, they decide to monitor ECs in **EC** = {EC_1, EC_3, EC_9, EC_2, EC_4, EC_5} for quality control. Second, they also decide to invest on the equipment related to EC_3, EC_9, and EC_1 with relative priority as **V** = [3 9 1], where the order is based on the conventional QFD. Before the execution of the decisions, the robustness on the decision-makings should be checked.

The result of the robustness evaluation on the first decision-making is that $RI_1(\mathbf{EC}, q = 6) = 0.4940$. It indicates that EC_1, EC_3, EC_9, EC_2, EC_4, and EC_5 have higher rankings than the sixth ranking in about half cases. Second, the robustness on **V** is that $RI_2(\mathbf{V}) = 0.1570$. In indicates that the priority relationship, $EC_3 \succ EC_9 \succ EC_1$ is kept with a probability 15.7%. The second decision-making seems very sensitive to uncertainty.

To improve robustness, QFD practitioners try to search for more robust **EC** or **V** as mentioned in Section 3.3. For the first decision-making, unfortunately, there is no more robust **EC,** which includes six ECs. However, one can find more robust **V** for the second decision-making. The **V'** = [3 1 9] with $RI_2(\mathbf{V'}) = 0.4260$ is more robust than V = [3 9 1] with $RI_2(\mathbf{V}) = 0.1570$. This is a different result to the conventional QFD. It implies that the conventional QFD can mislead decision-makings because it cannot consider the uncertainty.

5. FUTURE RESEARCH TOPICS

This section describes some of future research topics in Robust QFD. Currently, Robust QFD is focused on the situation where the given uncertainty in input information is unchangeable; the uncertainty only in CA weights and CA-EC relationship matrix are considered; and the uncertainty is due to the heterogeneity of multiple customers. Three research topics are suggested to resolve the aforementioned limitations, namely, robustness improvement, consideration of uncertainty in other parts of input information, and consideration of multiple types of uncertainty. A brief description for each issue is given next.

First, the uncertainty can be reduced under certain situations by, for example, collecting more information. In such a case, the robustness can be improved by reducing uncertainty. However, the reduction of uncertainty in an *ad-hoc* manner would be inefficient. In order to improve robustness efficiently, the critical uncertainty, which is most responsible for the low robustness, should be identified and reduced. For this purpose, the following three questions should be answered. "Which uncertainty should be reduced?"; "How much of the uncertainty should be reduced?"; and "How to reduce the uncertainty?" A further research on these issues is warranted in future studies.

Second, the input information of QFD other than CA weights and CA-EC relationship, may have uncertainty. As an example, the correlation matrix is likely to have uncertainty in its assessed entries. Such uncertainty would affect the QFD analysis. Hence, a systematic method is desired to incorporate the uncertainty in various parts of input information in QFD. One possible approach is to transfer the uncertainty in the correlation matrix (or any other input information) into the CA-EC relationship matrix and then focus on handling the uncertainty of the CA-EC relationship matrix, similarly to the normalization idea proposed by Wasserman (1993).

Third, multiple types of uncertainties may be present at the same moment. For example, the CA weights may be fuzzy and incomplete as well as heterogeneous among customers. Such a case is often encountered in practice when, for instance, developing highly innovative products. While the four-step framework of Robust QFD is generic enough to accommodate any type of uncertainty, the detailed strategies regarding how to perform the steps with multiple types of uncertainties are yet to be desired. In particular, the uncertainty modeling in Step 1 (*i.e.*, how to represent the different types of uncertainties in an aggregated, common random variable form) would be a challenging task. A more in-depth study on this interesting issue is necessary.

6. CONCLUDING REMARKS

In the conventional QFD, it is assumed that all the input information is certain. As a result, the EC importance values, a major output of QFD, are also treated as certain. However, since the focus of QFD is placed on the early stage of new product development, the uncertainty in the input information of QFD is inevitable.

This paper has briefly described an extended version of QFD methodology, called Robust QFD, which is capable of considering the uncertainty of the input information and the resulting variability of the QFD output. Then, four recent research issues are presented, namely, determination of overall priority, robustness evaluation, robust prioritization, and development of Web-based Robust QFD Optimizer. These research issues are still in their early phases and more in-depth studies are called for. In order for Robust QFD to be pervasively and usefully applied in practice, future research endeavors are expected.

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