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Determining optimal levels of engineering characteristics in quality function deployment under multi-segment market

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ABSTRACT

Customers often have various requirements and preferences on a product. A product market can be partitioned into several market segments, each of which contains a number of customers with homogeneous preferences. In this paper, a methodology which mainly involves a market survey, fuzzy clustering, quality function deployment (QFD) and fuzzy optimization, is proposed to achieve the optimal target settings of engineering characteristics (ECs) of a new product under a multi-segment market. An integrated optimization model for partitioned market segments based on QFD technology is established to maximize the overall customer satisfaction (OCS) for the market considering the weights of importance of different segments. The weights of importance of market segments and development costs in the model are expressed as triangular fuzzy numbers in order to describe the imprecision caused by human subjective judgement. The solving approach for the fuzzy optimization model is provided. Finally, a case study is provided for illustrating the proposed methodology.

1. Introduction

Quality function deployment (QFD) is a widely adopted customer-oriented methodology in order to assist product design and development by analyzing customer requirements (CRs) (Akao, 1990). QFD provides a systematic method for translating the voice of the customer (VoC) into the complete specifications of a product, and thus lays a strong emphasis on satisfying the needs of customers. In QFD, customer's satisfaction to a new product is described by the degree of overall customer satisfaction (OCS), a percent-type number, to express how much the customer is satisfied. Determination of the target levels of the engineering characteristics (ECs) of a new product with a view to achieving a high level of OCS is an important activity in product design and development (Tang, Fung, & Xu, 2002).

The basic concept of QFD is to utilize a set of charts called the houses of quality (HoQ) (Hauser & Clausing, 1988) to translate CRs into engineering characteristics (ECs), and subsequently into parts characteristics, process plans, and manufacture operations. A HoQ typically contains information on "what to do" (*whats*), "how to do it" (*hows*), the integration of this information (relationship between CRs and ECs, and among ECs) and benchmarking data (Kim, Moskowitz, & Dhingra, 2000). Based upon the information contained in a HoQ, the target values for the ECs of a product can be determined to achieve a high level of OCS.

Although the amount of literature on QFD is vast, there are only a few research papers on the development of systematic procedures for setting the target EC values. The first prescriptive modelling approach to this subject was given by Wasserman (1993), who formulated the QFD planning process as a linear programming model to select the mix of design features and to obtain the highest level of customer satisfaction. Moskowitz and Kim (1997) proposed a decision support prototype for optimizing product designs based upon an integrated mathematical programming formulation and solution approach. Fung, Popplewell, and Xie (1998) suggested a fuzzy inference model to facilitate the design decision on target values for ECs with the use of a fuzzy rule base. Park and Kim (1998) presented an integrated decision model for selecting an optimal set of ECs using a modified HoQ model. Kim et al. (2000) proposed a fuzzy multicriteria modelling approach for QFD planning using fuzzy linear models with symmetric triangular fuzzy number coefficients. Tang et al. (2002) considered a fuzzy formulation combined with a genetic-based interactive approach to QFD planning and developed fuzzy optimization models for determining target values of ECs with financial consideration. Bai and Kwong (2003) proposed an optimization model with fuzzy equations and developed an inexact genetic algorithm approach to

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Nomenclature

CR	customer requirement
EC	engineering characteristics
OCS	overall customer satisfaction
CR_i	the ith CR
EC_j	the jth EC
MS_k	the kth market segment
l_j	the target value of EC_j
l_j^{max}, l_j^{min}	the maximum and minimum value of EC_j
x_j	the target level of attainment of EC_j
$w_{i,k}$	the weight of importance of the CR_i for MS_k
$y_{i,k}$	the customer perception of the degree of achievement of the CR_i for MS_k
$y_{i,k}^{max}$, $y_{i,k}^{min}$	the maximum and minimum value of $y_{i,k}$, respectively
S_k	the OCS for MS_k
S	the OCS for the product market
ξ_k, $\tilde{\xi}_k$	the crisp and fuzzy normalized weight of importance of MS_k, respectively
q_k, $\tilde{q}_k$	the crisp and fuzzy number of customers in MS_k
$f_{i,k}$	an individual value function for describing the relationship between $y_{i,k}$ and ECs
g_j	an individual value function for describing the relationship between the jth EC and other ECs
c_j	the development cost committed for the full attainment of the jth EC under the condition that no other costs are allocated to other ECs
B	the budget for the development of new product
ξ_k^p, ξ_k^m, ξ_k^o	the most pessimistic, most likely and most optimistic values of ξ_k, respectively
q_k^p, q_k^m, q_k^o	the most pessimistic, most likely and most optimistic values of $\tilde{q}_k$, respectively
c_j^p, c_j^m, c_j^o	the most pessimistic, most likely and most optimistic values of c_j, respectively
β	the minimal acceptable possibility given by decision maker
$z1$, $z2$, $z3$	the three objectives of the established multi-objective model
S^p, S^m, S^o	the most pessimistic, most likely and most optimistic values of S, respectively
μ_{z1}, μ_{z2}, μ_{z3}	the membership functions of $z1$, $z2$ and $z3$, respectively
γ	the degree of possibility for realizing the three objectives
α	the degree of membership of fuzzy numbers

solve the model that takes the mutation along the weighted gradient direction as a genetic operator. Chen, Fung, and Tang (2005) utilized the fuzzy expected value operator to model the QFD process in a fuzzy environment, and further proposed a modelling approach to determine the target value settings of ECs with the help of two fuzzy expected value models.

In the abovementioned research, one of the assumptions with regard to the QFD optimization problem is that, the requirements of heterogeneous customers in a market can be generalized. For example, in a HoQ, a set of weights of importance of CRs (left of the house) are given to express the preferences of all customers towards a new product; the competition benchmarking scores (right of the house) are regarded as the perceptions of all customer's satisfaction on the existing products. In other words, in these optimization models, the diversified CRs are simplified as shown in Fig. 1.

However, customers who have different beliefs with respect to social issues (e.g., religion, politics, work, drugs, women's right) or personal interests (e.g., family, home, job, food, self-achievement, health, clubs, friends, shopping) may have different purchasing behaviour or preferences (Urban & Hauser, 1993). Consequently, customers in a product market may have different responses towards a new product. Therefore, heterogeneity of customers should be introduced into QFD optimization models to describe the relationship between CRs and ECs and to model the OCS towards a product. Eventually, the maximum OCS for homogeneous customers in a market can be achieved in a more reasonable way.

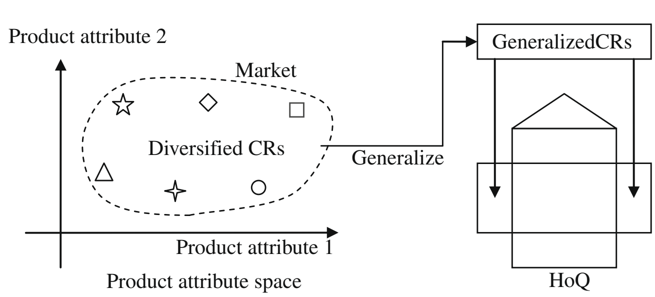

Fig. 1. The diversified CRs in market and the CRs in HoQ.

In this research, we propose a new methodology for determining the optimal levels of ECs in QFD under a product market with heterogeneous customers. The basic idea of this methodology is described as follows: (1) a market survey towards the product is performed; (2) the market is partitioned into several segments based on the survey data by using fuzzy C-means clustering analysis; (3) a fuzzy optimization model for all market segments is established to obtain the optimal value settings of ECs. The objective of the model is to maximize the OCS of the whole market considering the weights of importance of the market segments; (4) the fuzzy optimization model is transformed into a linear programming model and eventually solved by simplex methods.

The rest of this paper is organized as follows. Section 2 proposes a QFD-based methodology for determining optimal levels of ECs in QFD under a multi-segment market. In Section 3, a mathematical model using QFD optimization technology is derived to maximize the OCS for the market. Imprecision of parameters in the model is also considered and the solving approach of the fuzzy linear programming model is described. Section 4 provides a case study to illustrate the proposed methodology. Finally, conclusions are drawn in Section 5.

2. A methodology for determining the optimal levels of ECs in QFD under a multi-segment market

The proposed methodology for determining the optimal levels of ECs in QFD under a multi-segment market consists of six steps as shown in Fig. 2. The detailed procedures of these steps are described as follows:

Step 1: Market survey. First of all, the key CRs and ECs of a product are elicited and some customers from product market are invited as respondents. Then market survey is carried out to investigate customers' preferences. By applying techniques such as scale rating or analytic hierarchy process, the weights of importance of CRs towards a new product and the competition benchmarking scores towards the existing products are determined for each respondent.

Step 2: Market segmentation. Based on the collected survey data, fuzzy C-means clustering analysis (Miyamoto, Ichihashi,

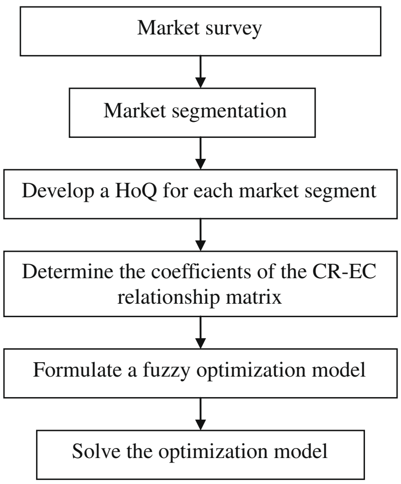

Fig. 2. The six steps of the proposed methodology.

& Honda, 2008) is carried out to partition the respondents into several clusters so that inside each cluster the respondents have similar purchasing preferences. After clustering analysis, a cluster is defined as a segment of the product market, and the identified center of a cluster is regarded as the location of the representative weights of importance of CRs and benchmarking scores of the corresponding market segment.

A convenient way to estimate the weight of importance of a market segment is to estimate the number of customers in each segment according to historical sales data of the firm and salesmen's knowledge, and then compare the number of customers in a segment with that in other segments.

Step 3: Develop a HoQ for each market segment. The HoQs of the market segments have the same house structure, house roof (ECs correlation matrix), binary relationship between CRs and ECs, and values of ECs of the competitors' products and the firm's existing products. Therefore, we define a HoQ only containing these items as a *HoQ template* of the product. Fig. 3 shows a schematic diagram of *HoQ template*.

The coefficients of ECs correlation matrix in a *HoQ template* can be determined by a human expert familiar with the design of this product. An alternative quantitative approach is to estimate these values by using least square regression based on the values of ECs of the existing products (Fung, Chen, & Tang, 2006; Kim et al., 2000).

The binary relationship between the CRs and ECs of a HoQ template can also be determined by an expert. If a CR has relationship with a EC, a dot is marked in the corresponding cell in the HoQ; otherwise this cell leaves blank.

The HoQ of a market segment may be different from that of another segment in the following aspects:

(1) the weights of importance of CRs (on the left side of the house), representing the priorities information of CRs;
(2) the benchmarking scores of the existing products (on the right side of the house), representing the customer perception of the competitors' product and the firm's existing products on CRs;
(3) the CRs–ECs relationship matrix (in middle of the house), in which an element represents the quantitative level of strength of the relationship between a CR and a EC.

Among these three items, the first two item are obtained directly from the result of Steps 1 and 2, and the last item can be obtained by the approach explained in Step 4.

Step 4: Determine the coefficients of the CRs–ECs relationships matrix. In this step, the coefficients of the CRs–ECs matrix of each HoQ, i.e., the levels of strength of functional relationships between CRs and ECs, are estimated by using a least square regression method. The set of data points for regression can be extracted from the benchmarking scores in the HoQ. The detailed example of this technique is given in Section 4.

Step 5: Formulate a fuzzy optimization model. A QFD-based optimization model is formulated to achieve the optimal target value settings of ECs with the objective of maximizing the OCS for the product market. Imprecision caused by human subjective judgement and financial constraint are considered in the model. The modelling process is described in Section 3.

Step 6: Solve the optimization model. An equivalent auxiliary multi-objective linear programming model is developed for the established fuzzy model. Fuzzy programming method is applied to solve this multi-objective model and the optimal target value settings of ECs are obtained. Details of the solving approach are provided in Section 3.7.

3. Developing the optimization model

The process of determining the target levels of the ECs in QFD under a multi-segment product market can be formulated as an optimization problem. Assume that a product has m CRs and n ECs involved, and the product market is partitioned into p segments. Based on the information provided in HoQs, an optimization model can be established with the objective of maximizing the OCS under limited budget in a multi-segment market.

3.1. Normalizing the target values of ECs to target levels

Following the method proposed by Chen et al. (2005), we normalize the target values of ECs of a product into the target levels of attainment of ECs as

$$x_j = \left(l_j^{\max} - l_j\right) \Big/ \left(l_j^{\max} - l_j^{\min}\right) \quad (1)$$

$$x_j = \left(l_j - l_j^{\min}\right) / \left(l_j^{\max} - l_j^{\min}\right) \quad (2)$$

where x_j is the target level of attainment of the jth EC (denoted as EC_j), l_j is the target value of EC_j, $l_j^{\max}$ and $l_j^{\min}$ are the maximum and minimum value of EC_j ($j = 1, 2, \ldots, n$), respectively. $l_j^{\max}$ and $l_j^{\min}$ can be determined by the consideration of competition requirements and technology feasibility (Zhou, 1998). If a design team's objective

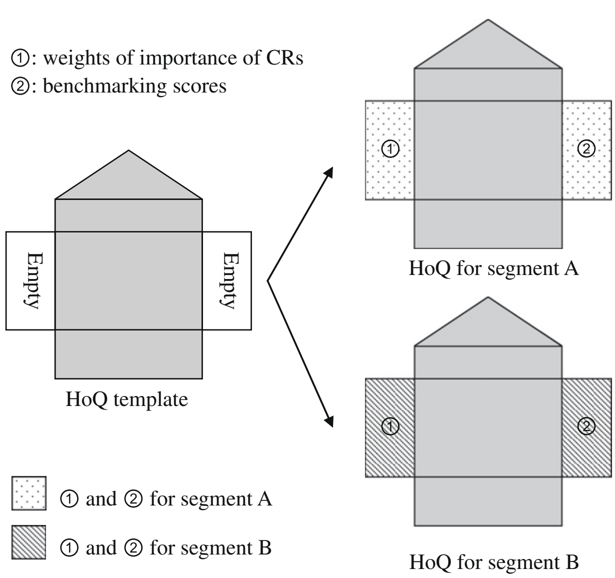

Fig. 3. An example of HoQ template.

is to increase l_j, e.g., the memory size of a computer, then Eq. (2) is applied; otherwise, if a design team's objective is to decrease l_j, e.g., the noise index of a machine, then Eq. (1) is applied. Therefore, in either case, the larger x_j is pursued in optimization model.

3.2. Modelling the OCS for the product market

After market survey and segmentation are accomplished, the OCS for the customers in MS_k, denoted as S_k, can be derived by applying the linear weighted sum method (Fung, Tang, & Tu, 2003). The linear weighted sum method is based on the assumption that OCS can be described as the linear aggregation of the degrees of satisfaction of CRs with scaled weight importance. The method has a simple mathematical expression and has been adopted by many research papers to formulate OCS (Chen et al., 2005; Fung et al., 2003; Tang, Zhang, & Tu, 2005). It can be expressed as

$$S_k = \sum_{i=1}^{m} w_{i,k} s_i(y_{i,k}) \tag{3}$$

where $w_{i,k}$ is the scaled weight of importance of the ith CR (denoted as CR_i) for MS_k ($0 \leqslant w_{i,k} \leqslant 1$ and $\sum_{i=1}^{m} w_{i,k} = 1$), $y_{i,k}$ is the customer perception of the degree of achievement of CR_i for MS_k, and s_i is an individual value function on CR_i. For each CR in MS_k, $y_{i,k}$ can be assigned as a numerical value to indicate the degree of satisfaction of CR_i in comparison with the competitors' products. This numerical value can be chosen from a positive scale $[a,b]$ (e.g. 1–5). Therefore, $s_i\ (y_{i,k})$ can be scaled in such a way that $s_i\left(y_{i,k}^{\min}\right) = 0$ and $s_i\left(y_{i,k}^{\max}\right) = 1$ and can be configured as

$$s_i(y_{i,k}) = \left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{4}$$

where $y_{i,k}^{\max}$ and $y_{i,k}^{\min}$ are the maximum and minimum value of $y_{i,k}$, respectively, and hence Eq. (3) can be rewritten as

$$S_k = \sum_{i=1}^{m} w_{i,k} \left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{5}$$

and thus S_k is also a value between 0 and 1, with 0 being the worst and 1 the best.

Because the number of customers and the expected profit of a market segment are different from those of other segments, in order to satisfy the CRs for the whole market, a trade-off of OCS is required among the market segments. Assume that the OCS of the market (denoted as S) is the weighted sum of the OCS of the individual market segments, the objective function of this optimization problem can be formatted as

$$S = \sum_{k=1}^{p} \sum_{i=1}^{m} \xi_k w_{i,k} \left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{6}$$

where ξ_k is the normalized weight of importance of the kth segment ($0 \leqslant \xi_k \leqslant 1$ and $\sum_{i=1}^{m} \xi_k = 1$). If the number of customers in a market segment is estimated according to historical sales data of the firm and salesmen's knowledge, ξ_k can be obtained as

$$\xi_k = q_k \Bigg/ \sum_{k'=1}^{p} q_{k'} \tag{7}$$

where q_k is the estimated number of customers in the kth market segment.

3.3. Parameter estimation of functional relationships between CRs and ECs

The functional relationship between the customer perception of the degree of achievement of a CR and the determined the target level of ECs can be described as

$$y_{i,k} = f_{i,k}(x_1, x_2, \ldots, x_n) \tag{8}$$

where $f_{i,k}$ is an individual value function for describing this relationship.

A widely used method for formulating this function is to apply regression-based methods (Chen, Tang, & Fung, 2004; Fung et al., 2006; Kim et al., 2000). Usually for simplicity, the functional relationship can be considered as a linear function as

$$y_{i,k} = a_{i,k,0} + \sum_{j=1}^{n} a_{i,k,j} x_j = a_{i,k,0} + a_{i,k,1} x_1 + a_{i,k,2} x_2 + \cdots + a_{i,k,n} x_n \tag{9}$$

where $A_{i,k} = (a_{i,k,0}, a_{i,k,1}, a_{i,k,2}, \ldots, a_{i,k,n})$ is the vector of coefficients to be estimated. If a CR does not have any relationship with a EC in the *HoQ template*, which means that the improvement of the EC do not have any contribution to the customer perception of the degree of achievement of the CR, then the coefficients corresponding to this EC in Eq. (9) is set to zero directly.

The value settings of ECs and benchmarking scores of competitors' products in a HoQ can be used as data points for regression. Suppose that there are h competitors involved in HoQ and $X^{(l)} = \left(x_1^{(l)}, x_2^{(l)}, \ldots, x_n^{(l)}\right)^T$ ($l = 1,2,\ldots,h$) is the real-valued input vector of the target levels of ECs of the lth competitor, the set of data points for the regression can be defined as

$$P = \left\{ \left(X^{(l)}, y_{i,k}^{(l)}\right) \Big| l = 1, 2, \ldots, h \right\} \tag{10}$$

where $y_{i,k}^{(l)}$ is the degree of customer satisfaction of the lth competitor on CR_i.

3.4. Modelling the correlations among ECs

The functional relationship between a EC and other ECs can be described as

$$x_j = g_j(x_1, x_2, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n) \tag{11}$$

where g_j is an individual value function. Similarly to the relationship function (8), g_j is considered linear and least square regression method can be used to estimate the parameters (Chen et al., 2005). The value settings of ECs of the competitors' products in the *HoQ template* are used as the data points for regression.

3.5. Formulating the development budget constraint

Multiple resources are required to support the design of a new product, including technical engineers, advanced equipment, tools and other facilities. At the level of strategic planning, these types of resources can be represented in financial terms. Assume that the cost committed for the full attainment of the jth EC under the condition that no other costs are allocated to other ECs is c_j, and the cost function for achieving the degree of attainment of the jth EC is scaled linearly to the degree of attainment x_j, the budget constraint can be described as (Tang et al., 2002)

$$\sum_{j=1}^{n} x_j c_j < B \tag{12}$$

where c_j is the development cost committed for the full attainment of the jth EC under the condition that no other costs are allocated to other ECs, B is the budget for the development of the new product.

3.6. Optimization model

The optimization model can thus be formulated as the follows (Model I):

$$\text{Max} \quad S = \sum_{k=1}^{p} \sum_{i=1}^{m} \xi_k w_{i,k} \left(y_{i,k} - y_{i,k}^{\min}\right) \bigg/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{13}$$

$$\text{s.t.} \quad y_{i,k} = f_{i,k}(x_1, x_2, \ldots, x_n), \quad i = 1,2,\ldots,m; \ k = 1,2,\ldots,p \tag{14}$$

$$x_j = g_j(x_1, x_2, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1,2,\ldots,n \tag{15}$$

$$\sum_{j=1}^{n} x_j c_j < B \tag{16}$$

$$0 \leqslant x_j \leqslant 1, \quad j = 1,2,\ldots,n \tag{17}$$

where $f_{i,k}$ and g_j can be simplified as linear equations as suggested in Sections 3.3 and 3.4. Additional engineering constraints may be added to the above formulation as appropriate.

Model I is a standard linear programming (LP) model, which can be solved by many LP software packages, such as Matlab, ILOG CPLEX, Lingo.

3.7. Optimization model with fuzzy parameters

In practical scenarios, due to the imprecision caused by human subjective judgement, the estimated numbers of customers in market segments and development costs coefficients can be expressed by fuzzy numbers. Let $\tilde{q}_k$ be a triangular fuzzy number denoted by $\tilde{q}_k = (q_k^p, q_k^m, q_k^o)$, where q_k^p, q_k^m and q_k^o are the most pessimistic, most likely and most optimistic values of q_k, respectively. The fuzzy weight of importance of the kth segment, $\tilde{\xi}_k$, can be formulated as

$$\tilde{\xi}_k = \tilde{q}_k \bigg/ \sum_{k'=1}^{p} \tilde{q}_{k'} \tag{18}$$

According to fuzzy arithmetic, $\tilde{\xi}_k$ is a triangular fuzzy number denoted as (ξ^p, ξ^m, ξ^o), and

$$\xi_k^p = q_k^p \bigg/ \sum_{k'=1}^{p} q_{k'}^o \tag{19}$$

$$\xi_k^m = q_k^m \bigg/ \sum_{k'=1}^{p} q_{k'}^m \tag{20}$$

$$\xi_k^o = q_k^o \bigg/ \sum_{k'=1}^{p} q_{k'}^p \tag{21}$$

The sum of all fuzzy weights of importance of segments, $\psi = \sum_{k=1}^{p} \tilde{\xi}_k$, is also a triangular fuzzy number denoted as $\psi = (\psi^p, \psi^m, \psi^o)$, and

$$\psi^p = \sum_{k=1}^{p} \xi_k^p = \sum_{k=1}^{p} q_k^p \bigg/ \sum_{k=1}^{p} q_k^o \leqslant 1 \tag{22}$$

$$\psi^m = \sum_{k=1}^{p} \xi_k^m = \sum_{k=1}^{p} q_k^m \bigg/ \sum_{k=1}^{p} q_k^m = 1 \tag{23}$$

$$\psi^o = \sum_{k=1}^{p} \xi_k^o = \sum_{k=1}^{p} q_k^o \bigg/ \sum_{k=1}^{p} q_k^p \geqslant 1 \tag{24}$$

It can be seen that the most optimistic value of ψ can be larger than one as indicated in Eq. (24). If we directly replace ξ_k with $\tilde{\xi}_k$ in Model I, the value of the objective function, the OCS, may be larger than one. For a given degree of membership of fuzzy numbers, α, the optimization model can be formulated as (Model II)

$$\text{Max} \quad S = \sum_{k=1}^{p} \sum_{i=1}^{m} z_k w_{i,k} \left(y_{i,k} - y_{i,k}^{\min}\right) \bigg/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{25}$$

$$\text{s.t.} \quad \sum_{k=1}^{p} z_k = 1 \tag{26}$$

$$\xi_k^p + \alpha\left(\xi_k^m - \xi_k^p\right) \leqslant z_k \leqslant \xi_k^o - \alpha\left(\xi_k^o - \xi_k^m\right), \quad k = 1,2,\ldots,p \tag{27}$$

$$y_{i,k} = f_{i,k}(x_1, x_2, \ldots, x_n), \quad i = 1,2,\ldots,m; \ k = 1,2,\ldots,p \tag{28}$$

$$x_j = g_j(x_1, x_2, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1,2,\ldots,n \tag{29}$$

$$\sum_{j=1}^{n} x_j c_j < B \tag{30}$$

$$0 \leqslant x_j \leqslant 1, \quad j = 1,2,\ldots,n \tag{31}$$

where z_k is a decision variable representing a possible value of fuzzy weight of importance of the kth market segment. Constraint (26) ensures that the sum of the weights equals to one. Constraint (27) confines the z_k to the range of the α level set of $\tilde{\xi}_k$.

Model II is a quadratic programming model. Since the Hessian matrix of the quadratic objective function is not necessarily positive semi-definite, it is difficult to obtain the global optimal solution of the model (Pillo & Giannessi, 2000). Therefore, we propose an approximation for the weight of importance of a segment by defining ξ^p, ξ^m and ξ^o as shown below.

$$\xi_k^p = q_k^p \bigg/ \sum_{k'=1}^{p} q_{k'}^o \tag{32}$$

$$\xi_k^m = q_k^m \bigg/ \sum_{k'=1}^{p} q_{k'}^o \tag{33}$$

$$\xi_k^o = q_k^o \bigg/ \sum_{k'=1}^{p} q_{k'}^o \tag{34}$$

Accordingly, ψ^p, ψ^m and ψ^o are calculated as

$$\psi^p = \sum_{k=1}^{p} \xi_k^p = \sum_{k=1}^{p} q_k^p \bigg/ \sum_{k=1}^{p} q_k^o \leqslant 1 \tag{35}$$

$$\psi^m = \sum_{k=1}^{p} \xi_k^m = \sum_{k=1}^{p} q_k^m \bigg/ \sum_{k=1}^{p} q_k^o \leqslant 1 \tag{36}$$

$$\psi^o = \sum_{k=1}^{p} \xi_k^o = \sum_{k=1}^{p} q_k^o \bigg/ \sum_{k=1}^{p} q_k^o \leqslant 1 \tag{37}$$

Based on the above formulation, $\tilde{\xi}_k$ can be used to replace ξ_k in Model I and the value of the objective function with fuzzy coefficients is within the value range of OCS.

Let $\tilde{c}_j$ be a triangular fuzzy number denoted by $\tilde{c}_j = \left(c_j^p, c_j^m, c_j^o\right)$, where c_j^p, c_j^m and c_j^o are the most pessimistic, most likely and most optimistic values of c_j, respectively. The possibility distribution functions $\pi_{\tilde{\xi}_k}(t)$ and $\pi_{\tilde{c}_j}(t)$ are shown in Fig. 4a and c. Accordingly, Model I can be reformulated as a fuzzy optimization model (Model III) as follows:

$$\text{Max} \quad \tilde{S} = \sum_{k=1}^{p} \sum_{i=1}^{m} \tilde{\xi}_k w_{i,k} \left(y_{i,k} - y_{i,k}^{\min}\right) \bigg/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{38}$$

$$\text{s.t.} \quad y_{i,k} = f_{i,k}(x_1, x_2, \ldots, x_n), \quad i = 1,2,\ldots,m; \ k = 1,2,\ldots,p \tag{39}$$

$$x_j = g_j(x_1, x_2, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1,2,\ldots,n \tag{40}$$

$$\sum_{j=1}^{n} x_j \tilde{c}_j \leqslant B \tag{41}$$

$$0 \leqslant x_j \leqslant 1, \quad j = 1,2,\ldots,n \tag{42}$$

Suppose that $f_{i,k}$ and g_j are in linear form, then Model III is a linear programming model with fuzzy coefficients. There are many approaches available for solving this type of problems, e.g., the

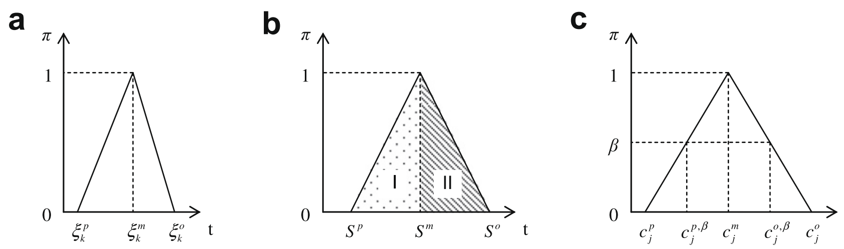

Fig. 4. The possibility formulation of $\tilde{\xi}_k$, $\tilde{S}$ and $\tilde{c}_j$.

approaches by Lai and Hwang (1992), Luhandjula (1987), Rommelfanger (1989). In the follows, we use Lai and Hwang's approach, which is easy to implement and has been adopted by many researchers (Hsu & Wang, 2001; Torabi & Hassini, 2008; Wang & Liang, 2005), to solve Model III.

First, according to fuzzy arithmetic, the value of objective function of Model III, is a triangular fuzzy number with possibility distribution, which can be denoted as $\tilde{S} = (S^p, S^m, S^o)$, where S^p, S^m, S^o are the most pessimistic, most likely and most optimistic values of S, and they can be calculated as

$$S^p = \sum_{k=1}^{p}\sum_{i=1}^{m} \xi_k^p w_{i,k}\left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{43}$$

$$S^m = \sum_{k=1}^{p}\sum_{i=1}^{m} \xi_k^m w_{i,k}\left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{44}$$

$$S^o = \sum_{k=1}^{p}\sum_{i=1}^{m} \xi_k^o w_{i,k}\left(y_{i,k} - y_{i,k}^{\min}\right) \Big/ \left(y_{i,k}^{\max} - y_{i,k}^{\min}\right) \tag{45}$$

The fuzzy objective of Model III can be considered as maximizing the most possible value of the degree of OCS at the point of possibility degree = 1, minimizing the risk of obtaining lower OCS (i.e., minimize the region I in Fig. 4b), and maximizing the possibility of obtaining higher OCS (i.e., maximize the region II in Fig. 4b). Thus the objective of Model III can be expressed as the following multiple objectives:

$$\mathrm{Max} S^m \tag{46}$$
$$\mathrm{Min} S^m - S^p \tag{47}$$
$$\mathrm{Max} S^o - S^m \tag{48}$$

On the other hand, to compare the crisp budget to the aggregated fuzzy cost as indicated by Eq. (41), Lai and Hwang (1992) suggested using the weighted average of the most possible value, and the pessimistic and optimistic values to represent a fuzzy development cost. Usually the weights of these values can be set to 4, 1, and 1, respectively, to emphasize that the most possible values is often the most important one (Krajewski, Ritzman, & Malhotra, 2004). Hence Eq. (41) can be rewritten as

$$\sum_{j=1}^{n} x_j\left(c_j^{p,\beta} + 4c_j^{m,\beta} + c_j^{o,\beta}\right) \Big/ 6 \leqslant B \tag{49}$$

where β is the minimal acceptable possibility, which can be initially given by decision maker; $c_j^{p,\beta}$, $c_j^{m,\beta}$ and $c_j^{o,\beta}$ are c_j^p, c_j^m and c_j^o under β, respectively.

Therefore, Model III can be transformed into the following auxiliary crisp multi-objective programming model (Model IV)

$$\mathrm{Max} z_1 = S^m \tag{50}$$
$$\mathrm{Min} z_2 = S^m - S^p \tag{51}$$
$$\mathrm{Max} z_3 = S^o - S^m \tag{52}$$

$$\text{s.t.}\quad y_{i,k} = f_{i,k}(x_1, x_2, \ldots, x_n), \quad i = 1, 2, \ldots, m;\ k = 1, 2, \ldots, p \tag{53}$$

$$x_j = g_j(x_1, x_2, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n), \quad j = 1, 2, \ldots, n \tag{54}$$

$$\sum_{j=1}^{n} x_j\left(c_j^{p,\beta} + 4c_j^{m,\beta} + c_j^{o,\beta}\right) \Big/ 6 \leqslant B \tag{55}$$

$$0 \leqslant x_j \leqslant 1, \quad j = 1, 2, \ldots, n \tag{56}$$

The positive ideal solutions (PIS) and negative ideal solutions (NIS) of the these three objectives (Eqs. (50)–(52)) can be achieved as

$$z_1^{\mathrm{PIS}} = \max S^m, \quad z_1^{\mathrm{NIS}} = \min S^m \tag{57}$$
$$z_2^{\mathrm{PIS}} = \min S^m - S^p, \quad z_2^{\mathrm{NIS}} = \max S^m - S^p \tag{58}$$
$$z_3^{\mathrm{PIS}} = \max S^o - S^m, \quad z_3^{\mathrm{NIS}} = \min S^o - S^m \tag{59}$$

The linear membership functions of these objective functions are formulated as

$$\mu_{z1} = \begin{cases} 1 & \text{if } z_1 > z_1^{\mathrm{PIS}} \\ \frac{z_1 - z_1^{\mathrm{NIS}}}{z_1^{\mathrm{PIS}} - z_1^{\mathrm{NIS}}} & \text{if } z_1^{\mathrm{PIS}} \geqslant z_1 \geqslant z_1^{\mathrm{NIS}} \\ 0 & \text{if } z_1 < z_1^{\mathrm{NIS}} \end{cases} \tag{60}$$

$$\mu_{z2} = \begin{cases} 1 & \text{if } z_2 < z_2^{\mathrm{PIS}} \\ \frac{z_2^{\mathrm{NIS}} - z_2}{z_2^{\mathrm{NIS}} - z_2^{\mathrm{PIS}}} & \text{if } z_2^{\mathrm{NIS}} \geqslant z_2 \geqslant z_2^{\mathrm{PIS}} \\ 0 & \text{if } z_2 > z_2^{\mathrm{NIS}} \end{cases} \tag{61}$$

$$\mu_{z3} = \begin{cases} 1 & \text{if } z_3 > z_3^{\mathrm{PIS}} \\ \frac{z_3 - z_3^{\mathrm{NIS}}}{z_3^{\mathrm{PIS}} - z_3^{\mathrm{NIS}}} & \text{if } z_3^{\mathrm{PIS}} \geqslant z_3 \geqslant z_3^{\mathrm{NIS}} \\ 0 & \text{if } z_3 < z_3^{\mathrm{NIS}} \end{cases} \tag{62}$$

Finally, according to Zimmermann's fuzzy programming method (Zimmermann, 1978), the equivalent single-objective linear programming model for Model IV can be formulated as follows (Model V):

$$\mathrm{Max}\quad \gamma \tag{63}$$
$$\text{s.t.}\quad \mu_{z1} \geqslant \gamma, \quad \mu_{z2} \geqslant \gamma \quad \text{and} \quad \mu_{z3} \geqslant \gamma \tag{64}$$

where γ is the degree of possibility for realizing the three objectives.

The optimal solution of Model V provides a satisfying set of target levels of ECs under the abovementioned strategy of maximizing the most possible value of the degree of OCS, maximizing the possibility of obtaining higher OCS, and minimizing the risk of obtaining lower OCS.

4. Illustrative example

An example of an industrial pincers, which is a product of an oil equipment corporation in Jiangsu province, China, is introduced in this section to illustrate the application of the proposed methodology. The schematic diagram of the industrial pincers is shown in Fig. 5. Four major CRs were identified to represent the biggest

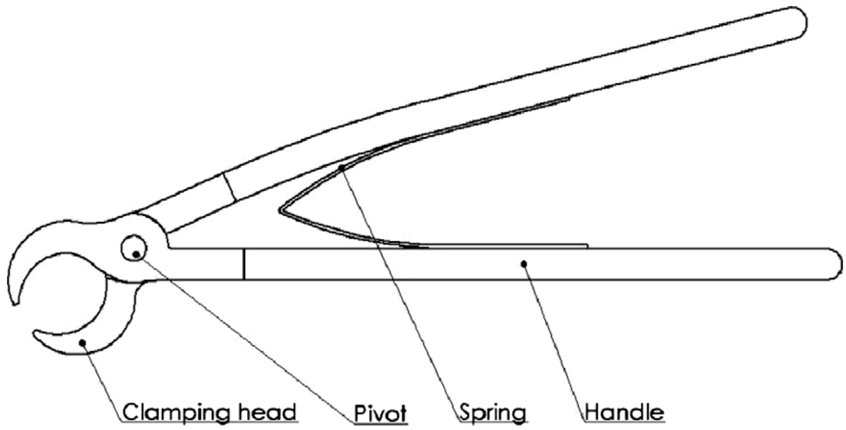

Fig. 5. The schematic diagram of an industrial pincers.

ECs	EC_1	EC_2	EC_3	EC_4	Correlation
EC_1		•			
EC_2	•				
EC_3					
EC_4					

		Relation				Benchmark information						
CRs	Weights					Ours	Co1	Co2	Co3	Co4	Min	Max
CR_1		•	•								1	5
CR_2		•		•	•						1	5
CR_3		•	•								1	5
CR_4		•	•		•						1	5
	Units	mm	mm	mm	μm						Satisf.(%)	

Engineering Measrues	EC_1	EC_2	EC_3	EC_4
Units	mm	mm	mm	μm
Ours	185	860	24	40
Co1	198	890	28	20
Co2	195	885	27	30
Co3	192	875	26	60
Co4	188	865	25	20
Min	180	850	20	20
Max	220	950	40	60

Fig. 6. The HoQ template of pincers.

concern of the customers of this pincers. They are: "strong clamping force" (CR1), "long durability" (CR2), "light weight" (CR3) and "low cost" (CR4). In light of engineer's design experiences of this product, four ECs were identified, i.e., "size of clamping head" (EC1), "length of handle" (EC2), "diameter of pivot" (EC3) and "thickness of antirust coat" (EC4). Four main competitors of the corporation, i.e. Co1, Co2, Co3 and Co4, were considered. The binary relationship between CRs and ECs, the binary correlation between ECs, and technical measure data collected from the corporation and its main competitors are illustrated in the *HoQ template* in Fig. 6.

A total number of 32 companies were invited to act as respondents in the market survey. Each respondent was asked to evaluate: (1) the preference on each CR of the new product by giving a mark on a 9-point scale (Tang et al., 2005), where "9" means strongest weight of importance and "1" lowest; (2) the perception of customer satisfaction on each CR towards the competitors' products and the firm's existing products by giving a numeric value ranged from 1 to 5, where "5" means "fully satisfied" and "1" means "very unsatisfied". Then the preference marks on CRs were normalized to form a vector of weight of importance of CRs, and the perceptions on CRs towards the products form a benchmarking value matrix.

The fuzzy C-means clustering model proposed by Bezdek (1981) was used to partition the respondents into groups. The compactness and separation validity function defined by Xie and Beni (1991) was adopted to determine the number of clusters. Experiment results show that when the number of clusters is two, the compactness and separation validity value has a minimum value of 0.039. Accordingly, two market segments were formed: S1 (containing 20 respondents) and S2 (containing 12 respondents), suggesting customers from large companies and small companies, respectively. According to the locations of cluster centers, the representative weights of importance and the benchmarking scores of CRs in each market segment were obtained as shown in Table 1.

For each segment, four regression equations were established to formulate the relationships between CRs and ECs. The benchmarking scores in Table 1 and EC values of competitors' products were

Table 1
The representative weights of importance of CRs and benchmarking scores.

Market segment	Weights of importance of CRs	Benchmarking scores				
		Ours	Co1	Co2	Co3	Co4
S1	0.37	2.68	4.53	4.15	3.64	3.05
	0.30	3.53	2.55	3.06	4.64	2.49
	0.12	4.56	4.18	4.26	4.35	4.41
	0.21	4.11	4.07	3.94	3.86	4.23
S2	0.18	4.28	4.61	4.55	4.47	4.32
	0.16	4.46	4.25	4.35	4.59	4.21
	0.31	3.09	2.40	2.54	2.73	2.94
	0.35	2.54	2.45	2.21	1.11	3.24

Table 2
The obtained regression coefficients of the relationship functions.

		Intercept	x_1	x_2	x_3	x_4
	x_1	0.04		1.02		
S1	y_1	2.02	2.67	3.25		
	y_2	2.37	−0.08		0.56	2.13
	y_3	4.59	1.00	−2.13		
	y_4	4.44	−2.73	2.02		−0.30
S2	y_1	4.14	0.88	0.22		
	y_2	4.55	1.44		−2.40	0.34
	y_3	3.32	−0.90	−1.30		
	y_4	3.79	−1.08	−2.10		−1.82

Table 3
The costs and budget for the development of the new product.

	EC1	EC2	EC3	EC4
Cost (k$)	(4.5,5,6)	(6,7,8)	(2.6,3,3.2)	(5.5,6,6.5)

Total budget for the new product is 15 k$.

used as data points for regression. Table 2 shows the obtained regression coefficients of these equations and the equations for ECs correlations.

Based on the judgments and experience of the marketing personnel of the company, the numbers of customers in two market segments, $\tilde{q}_1$ and $\tilde{q}_2$, were estimated as (6,7,7.5) and (2.5,3,4) millions, respectively. By referring to Eqs. (32)–(34), $\tilde{\xi}_1$ and $\tilde{\xi}_2$ were calculated as (0.52,0.61,0.65) and (0.22,0.26,0.35), respectively. The budget for the development of the new product and the costs committed for the full attainment of the ECs were estimated by the R&D department as listed in Table 3.

Based on the obtained regression coefficients, Eqs. (39) and (40) of Model III, i.e., the functional relationships between CRs and ECs and the correlations among ECs, can be instantiated by the following linear equations:

$$
\begin{aligned}
y_{11} &= 2.02 + 2.67^* x_1 + 3.25^* x_2,\\
y_{12} &= 2.37 - 0.08^* x_1 + 0.56^* x_3 + 2.13^* x_4,\\
y_{13} &= 4.59 + 1.00^* x_1 - 2.13^* x_2,\\
y_{14} &= 4.44 - 2.73^* x_1 + 2.02^* x_2 - 0.30^* x_4,\\
y_{21} &= 4.14 + 0.88^* x_1 + 0.22^* x_2,\\
y_{22} &= 4.55 + 1.44^* x_1 - 2.40^* x_3 + 0.34^* x_4,\\
y_{23} &= 3.32 - 0.90^* x_1 - 1.30^* x_2,\\
y_{24} &= 3.79 - 1.08^* x_1 - 2.10^* x_2 - 1.82^* x_4,\\
x_1 &= 0.04 + 1.02^* x_2.
\end{aligned}
$$

The fuzzy cost constraint based on Eq. (41) can be formulated as

$$(4.5, 5, 6)^* x_1 + (6, 7, 8)^* x_2 + (2.6, 3, 3.2)^* x_3 + (5.5, 6, 6.5)^* x_4 <= 15$$

Table 4
The PIS and NIS of the three objectives (z_1, z_2 and z_3).

	z_1	z_2	z_3
Maximal	$z_1^{PIS} = 0.612$	$z_2^{NIS} = 0.091$	$z_3^{PIS} = 0.083$
Minimal	$z_1^{NIS} = 0.482$	$z_2^{PIS} = 0.072$	$z_3^{NIS} = 0.065$
$z_i^{PIS} - z_i^{NIS}$	0.13	−0.019	0.018

and the objective function of Model III can be formulated as

$$
\begin{aligned}
&\text{Max } (0.52, 0.61, 0.65)^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14})\\
&\quad + (0.22, 0.26, 0.35)^*(0.18^* y_{21} + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24})
\end{aligned}
$$

By following the procedure described in Section 3.7 and assuming that any possibility is acceptable, the fuzzy optimization model was then transformed into a multiple objective optimization model (Model IV) with the following three crisp objective functions based on the Eqs. (50)–(52), respectively.

$$
\begin{aligned}
\text{Max}\quad z_1 &= 0.61^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14})\\
&\quad + 0.26^*(0.18^* y_{21} + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24})\\
\text{Min}\quad z_2 &= 0.09^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14})\\
&\quad + 0.04^*(0.18^* y_{21} + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24})\\
\text{Max}\quad z_3 &= 0.04^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14})\\
&\quad + 0.09^*(0.18^* y_{21} + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24})
\end{aligned}
$$

The PIS and NIS of the three objectives (z_1, z_2 and z_3) were determined by solving the corresponding single objective model as listed in Table 4. ILOG CPLEX was applied to solve these linear programming models. Eq. (64) of the derived equivalent single-objective linear programming model (Model V) was formulated as

$$
\begin{aligned}
&(0.61^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14}) + 0.26^*(0.18^* y_{21}\\
&\quad + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24}) - 0.482)/0.13 >= \gamma\\
&(0.091 - 0.09^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14})\\
&\quad - 0.04^*(0.18^* y_{21} + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24}))/0.019 >= \gamma\\
&(0.04^*(0.37^* y_{11} + 0.3^* y_{12} + 0.12^* y_{13} + 0.21^* y_{14}) + 0.09^*(0.18^* y_{21}\\
&\quad + 0.16^* y_{22} + 0.31^* y_{23} + 0.35^* y_{24}) - 0.065)/0.018 >= \gamma
\end{aligned}
$$

Table 5
The achieved optimal solution of the example.

	EC1	EC2	EC3	EC4
The optimal EC levels	0.481	0.438	0.103	0
The optimal EC values	199.3 mm	893.8 mm	22.1 mm	20.0 μm

The maximal degree of possibility (α) is 0.671 the optimal OCS has a triangular possibility distribution of (0.484,0.569,0.646).

Table 6
The average weights of importance of CRs and benchmarking scores of respondents.

Weights of importance of CRs	Benchmarking scores				
	Ours	Co1	Co2	Co3	Co4
0.28	3.48	4.57	4.35	4.06	3.69
0.23	4.00	3.40	3.71	4.62	3.35
0.22	3.83	3.29	3.40	3.54	3.68
0.28	3.33	3.26	3.08	2.49	3.74

Table 7
The optimal solutions under unpartitioned market and partitioned market.

		EC1	EC2	EC3	EC4
Under the unpartitioned case	The optimal EC levels	0.527	0.483	0.130	0
	The optimal EC values	201.1 mm	898.3 mm	22.6 mm	20.0 μm
	The maximal OCS is 0.681				
Under the partitioned case	The optimal EC levels	0.527	0.483	0.928	0.661
	The optimal EC values	201.1 mm	898.3 mm	38.6 mm	46.5 μm
	The maximal OCS is 0.703				

Again, ILOG CPLEX was applied to solve Model V. The achieved optimal levels and values of ECs are listed in Table 5. The maximal degree of possibility is 0.671, and the obtained OCS for the market is also imprecise and has a triangular possibility distribution of $(0.484, 0.569, 0.646)$.

To explore the necessity of considering multi-segment market, an experiment was performed to compare the results under the two scenarios, partitioned and unpartitioned markets. Since there is no fuzzy weight of importance of segment in the unpartitioned case, Model I with crisp parameters was used in the experiment. For the unpartitioned case, the average weights of importance of the CRs and benchmarking scores were calculated according to the corresponding average values of all respondents as listed in Table 6. By applying Chen's optimization model (Chen et al., 2005), the obtained optimal solution and maximal OCS are listed in the second row of Table 7. For the partitioned case, the most likes values of $\tilde{q}_1$ and $\tilde{q}_2$, 7 and 3 millions, were used as the crisp estimated numbers of customers of S1 and S2, respectively. ξ_1 and ξ_2 were calculated as 0.7 and 0.3 respectively according to Eq. (7). The obtained optimal solution and maximal OCS are listed in the third row of Table 7. It can be observed that the maximal OCS under the partitioned case is 0.022 $(0.703 - 0.681)$ higher than that under the unpartitioned case. Therefore, segmentation of product market is necessary and better value settings of ECs of new product can be achieved based on the proposed approach.

5. Conclusions

In this research, a methodology for determining the optimal levels of ECs in QFD under a multi-segment market is proposed. Based on the discussions made in this paper, the following points can be summarized and concluded:

(1) Different from the existing QFD approaches, the proposed methodology suggests partitioning the product market into several segments, each of which contains a number of customers with homogeneous preferences. Therefore, the methodology can be applied to a product market with diversified customer requirements. It can be considered as a necessary extension of the existing QFD optimization approaches.
(2) A mathematical model is established to obtain the optimal levels of ECs in QFD under a multi-segment market. Each segment has individual contribution to the OCS for the whole market; hence hopefully a more reasonable set of value settings of ECs can be achieved.
(3) Due to the imprecision caused by the human subjective judgement, the numbers of customers in market segments and development costs are expressed as triangular fuzzy numbers in the mathematical model. Lai and Hwang's (1992) approach is used to transform the possibilistic linear programming model to a crisp model. The consideration of fuzziness in modeling increases the usability of the proposed methodology in practical scenario.

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