A weighted interval rough number based method to determine relative importance ratings of customer requirements in QFD product planning

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Abstract

Customer requirements (CRs) play a significant role in the product development process, especially in the early design stage. Quality function deployment (QFD), as a useful tool in customer-oriented product development, provides a systematic approach towards satisfying CRs. Customers are heterogeneous and their requirements are often vague, therefore, how to determine the relative importance ratings (RIRs) of CRs and eventually evaluate the final importance ratings is a critical step in the QFD product planning process. Aiming to improve the existing approaches by interpreting various CR preferences more objectively and accurately, this paper proposes a weighted *interval rough number* method. CRs are rated with interval numbers, rather than a crisp number, which is more flexible to adapt in real life; also, the fusion of customer heterogeneity is addressed by assigning different weights to customers based on several factors. The consistency of RIRs is maintained by the proposed procedures with design rules. A comparative study among fuzzy weighted average method, rough number method and the proposed method is conducted at last. The result shows that the proposed method is more suitable in determining the RIRs of CRs with vague information.

Keywords: Quality function deployment; rough set theory; fuzzy set theory; product planning; customer-centric design

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1. Introduction

In order to survive in the competitive market, companies strive to provide quality products that satisfy various customer needs and expectations to gain value-added profits (S. Q. Xie and Tu 2006; S. S. Xie and Tu 2011). To enable the customised product development process, our previous work (B. M. Li et al. 2011) gives a comprehensive review on its knowledge-based systems, methods and tools. Moreover, the tendency towards mass customisation and personalization (Tseng et al. 2010) requires companies to reveal latent customer requirements (CRs) (e.g. affective and cognitive ones) other than only explicit technical information (Wang and Tseng 2011), thus, the function-based methods need to be improved accordingly. Also, due to the customer heterogeneity with different opinions and various subjective information expressed, it inevitably contains much vagueness which needs to be interpreted into design specifications properly and rapidly.

Quality function deployment (QFD), which introduced by Akao (1972), has been a widely adopted methodology in assisting customer-oriented product development process (Zheng et al. 2015). It provides a systematic framework to analyse the customer need and to map them into design specifications all over the product development process (Goncalves-Coelho 2005). QFD has proven to have many advantages ever since its first application, such as: improve customer satisfaction, reduce product development cost, shorten the time-to-market, and enhance the multi-disciplined teamwork in the product development process (Cohen and Cohen 1995). The key element of QFD is a combined chart which is called the house of quality (HoQ) to map the CRs (the 'WHATs') into corresponding adjusted engineering characteristics (the 'HOWs') that fulfil the CRs in product planning stage, and subsequently into parts characteristics, process plans, and manufacture operations (Luo et al. ; Zheng et al. 2015). The major issue of QFD product planning is to determine the final importance ratings of CRs (Y.-L. Li et al. 2012), as its accuracy will largely affect the product success. In general, the determination process contains five steps: 1) identify CRs; 2) determine the relative importance ratings (RIRs) of CRs; 3) undertake competitive analysis of CRs; 4) set the suitable improvement ratio of CRs; and 5) determine the final importance ratings of CRs, among which the first two steps are particularly significant as they are directly related to the 'voice of customer' (VOC). Selection of representatives with reasonable knowledge of the product/service, and elicitation of their preferences of the CRs are a necessity (Franceschini et al. 2015).

This work introduces a way to determine the RIRs of CRs more accurately and effectively from the identified CRs by proposing a novel rough set based method, i.e. *interval rough numbers* method to manage the imprecise design information in product planning stage. The rest of the paper is organized as follows. Section 2 gives a comprehensive review of the typical RIR methods in QFD product planning process, and a comparison of two major approaches in dealing with imprecise information of

CRs: the fuzzy set theory method and the rough set theory method. Section 3 proposes a weighted *interval rough number* method and based on that, describes the detailed procedures of determining the RIRs correspondingly. Section 4 gives an illustrative example of mountain bicycle frameset product to validate the proposed method and procedures. Then, to validate its advantages, a comparative study of fuzzy weighted average method, rough number method and the proposed one is conducted with respect to preference ordering consistency and robustness in Section 5. Finally, discussions and the major contributions of this work are summarized in Section 6.

2. Literature review of RIR methods in QFD product planning

Relative importance, same as weightings, is usually defined by customers articulating their preferred trade-offs between the CRs. Customers can define the relative importance mainly through three ways: *direct assignment, pairwise comparison* and *preference ordering*, a comprehensive review of typical RIR methods in recent research work is given in Table 1.

For *direct assignment*, a user can directly evaluate the relative importance of one CR over the others in a certain scale, such as the point scoring scale (e.g. 1-5, 1-10) (Hauser and Clausing 1988; Griffin and Hauser 1993; Ramanathan and Jiang 2009). This technique is simple and straightforward. Customers who can precisely describe their preferences in this way will benefit from its simple input, otherwise they may face difficulties to choose correct values especially in the early design stage when information is limited. Also, as the priority rank is dependent on its rating scale, there is low robustness among variations (Chuang 2001; Nahm et al. 2013). Another problem is that customers have a tendency to rate every attribute (Lai et al. 2008; Chuang 2001) with the highest possible scores, which cannot assist the prioritizing process for final importance rating accurately. Despite the drawbacks, it is still a widely used way in marketing analysis, for its usability, small input effort and flexibility.

The *pairwise comparison* technique asks customers to compare a pair of CRs each time. It is based on the assumption that it is much easier for a customer to place a comparative value rather than an absolute one (Braglia and Petroni 1999). Conjoint analysis (Griffin and Hauser 1993; Jiang et al. 2005) is a typical way to determining the relative importance of CRs. Another similar method is Saaty's 1–9 scale in an analytic hierarchy process (AHP) approach (Saaty 1977). It has been widely used in determining the RIRs of CRs in the QFD product planning process (Ho 2008; Y. L. Li et al. 2010; H. Raharjo et al. 2011; Y. L. Li et al. 2011; Y.-L. Li et al. 2012). However, the relative importance matrix is inevitably arbitrary, subjective and inconsistent in judgments (Rao, Padmanabhan 2007). Besides, this approach is based on the hypothesis that the CRs are independent. The dependency implies a heavier weight of these joint attributes (Ishizaka, Nemery 2013). To overcome the limitation of interdependency, the analytic network process (ANP) method (Ertay et al. 2005; Hendry Raharjo et al. 2008; Geng et al. 2010) was utilized in a similar way. However, for all these methods, customers need to provide a comparison for each pair of attributes, which requires much detailed information from customers and sometimes beyond customer's knowledge capability (Chan et al. 1999).

For *preference ordering* method, each customer is asked to give his/her individual ranking of CR preferences instead of assigning different ratings by a certain rating scale or by elaborate pairwise comparison. The final importance ranking of CRs is determined by the aggregated weights of each customer's preference order. It overcomes the shortage of too much elaborate input effort from customers, and also it is capable of dealing with incomplete information (e.g. partial comparison). Nahm et al. (2013) proposed a preference-graph (PG) method which utilizes dominant matrix to represent customer's preference ordering. However, the ranking might not reflect final RIR accurately due to its questionable operations and lack of relative importance weights among CRs. Moreover, Franceschini et al. (2015) proposed a generalized Yager's method in determining the RIRs, which aims to fuse the preference orderings of different CRs by multiple interviewed customers into a consensus fused ordering.

On the other hand, in the development of a product planning HoQ, customers' perceptions of a product are elicited through marketing techniques and then categorized into a number of major CRs, which usually consists of linguistic expressions with ambiguity and multiple meanings, such as 'low importance', 'high performance'. In order to deal with imprecise or vague information, Zadeh's (1965) fuzzy set theory was widely used, such as fuzzy AHP (C. K. Kwong and Bai 2002; C. Kwong and Bai 2003), fuzzy ANP (Büyüközkan et al. 2004; Kahraman et al. 2006; Lee et al. 2010), fuzzy weighted average (Liu 2005; Chen et al. 2006). Furthermore, the variability of customer opinions, known as customer heterogeneity, causes vagueness in determining the consistency of RIRs. In such cases, fuzzy group decision-making methods were proposed to address it by fusing individual preferences into a consistent single order (Buyukozkan et al. 2007; Zhang and Chu 2009; C. K. Kwong et al. 2011).

Though fuzzy set theory is somewhat capable of handling vagueness, however, its selection of membership function lacks objectivity, which is usually determined based on engineers' experience and intuition subjectively (Jin 2003). Thus, rough set based methods, first proposed by Pawlak (1982), was utilized to deal with the subjective assessments in the product planning HoQ. In literature, the rough set (Y. Li et al. 2009; Y. Li et al. 2010) and rough number method (L.-Y. Zhai et al. 2008; L. Y. Zhai et al. 2009, 2010; Song et al. 2013) were proposed. Unlike fuzzy set theory which defines a set by a partial membership without clear boundary, the rough set theory utilizes the boundary region of a set to express vagueness (Pawlak 1982; L. Y. Zhai et al. 2009). Also, there is no need for it to require any external or additional subjective information to analyse data (L. Khoo et al. 1999; Pawlak 1982), the measurement of vagueness is computed based on the uncertainty already inherent in the data (L.-P. Khoo and Zhai 2001), which remains its objectivity. Moreover, rough set theory is suitable for small-sized data set which statistical methods are not (Pawlak 1991; L. Y. Zhai et al. 2009). A comparison of fuzzy set theory and rough set theory based methods in the QFD product planning RIR determination is given in Table 2.

Table 1 Literature review of typical types of RIR methods in QFD product planning

Table 2 Comparison of fuzzy set theory and rough set theory in determining RIRs of CRs

Though the existing rough number method (L. Y. Zhai et al. 2008, 2009) works well in determining the RIR of CRs, it has two shortages:

(1) Customers' perceptions are rated in crisp numbers, which is not flexible and might not be appropriate in real life, e.g. customers' feeling of 'low importance' should be defined by themselves in a predefined rating scale rather than designer's interpretation of '*low importance – 1*' in a crisp number or '*low importance – (0, 0, 2)*' in a fuzzy set.

(2) Customer heterogeneity is not considered. The hierarchical importance of each customer is not included. Also, the difference of customers' importance ratings (i.e. fluctuation) is regarded as the vagueness incorporated into the final calculation without consistency evaluation, which may not reflect customer preferences accurately.

3. Weighted interval rough number method

Aiming to enhance the existing rough set based methods and determine the RIRs more flexibly and accurately, this research proposes a weighted *interval rough number* method. It treats the fusion of customer heterogeneity by assigning different weights to each customer according to his/her 'performance'. Also, the flexibility of customer perception is defined as an interval number within a predefined rating scale. The detail information is introduced as follows.

3.1 Definition of interval rough number

In order to determine RIRs of CRs, the proposed method adopted some fundamental theories of Zhai et al. (2008, 2009) work to derive the definitions of *interval rough number*.

Assume there is a set of k classes of customer perceptions (e.g. expectation), $R = (J_1, J_2, \dots, J_k)$ ordered in a sequence of $J_1 < J_2 < \dots < J_k$, and another set of m classes, $R^* = \{I_1, I_2, \dots, I_m\}$ defined in the universe. In R^* each class is presented in an interval, as $I_i = \{I_{li}, I_{ui}\}$; $I_{li}, \leq I_{ui}$; $1 \leq i \leq m$; $I_{li},, I_{ui} \in R$. I_{li}, stands for the lower boundary and I_{ui} the upper of the ith class. Assume that U is the universe consisting of every object and Y stands for any object of U. If both the lower and upper boundary classes are ordered in the manner of $I_{l1}^* < I_{l2}^* < \dots I_{lj}^*$, $I_{u1}^* < I_{u2}^* < \dots I_{uk}^*$ $(1 \leq j, k \leq m)$, respectively, then define another two sets of lower classes $R_l^* = (I_{l1}^*, I_{l2}^* \dots, I_{lj}^*\}$ and upper classes as $R_u^* = \{I_{u1}^*, I_{u2}^* \dots, I_{uk}^*\}$, respectively. For any class $I_{li}^* \in R$, $1 \leq i \leq j$, and $I_{ui}^* \in R$, $1 \leq i \leq k$, the lower approximation of $I_{li}*$ and $I_{ui}*$ are defined as:

$$\underline{Apr}(I_{li}*) = \cup\left\{Y \in U / R_l*(Y) \leq I_{li}*\right\} \tag{1}$$

$$\underline{Apr}(I_{ui}*) = \cup\left\{Y \in U / R_u*(Y) \leq I_{ui}*\right\} \tag{2}$$

, and the upper approximation of I_{li}^* and I_{ui}^* are represented as:

$$\overline{Apr}\left(I_{li}*\right) = \cup\left\{Y \in U / R_l*(Y) \geq I_{li}*\right\} \tag{3}$$

$$\overline{Apr}\left(I_{ui}*\right) = \cup\left\{Y \in U / R_u*(Y) \geq I_{ui}*\right\} \tag{4}$$

Thus, both the lower class I_{li}^* and upper class I_{ui}^* are defined by its lower limit $\underline{Lim}(I_{li}*)$ and $\underline{Lim}(I_{ui}*)$, and the upper limit $\overline{Lim}(I_{li}*)$ and $\overline{Lim}(I_{ui}*)$ respectively, where

$$\underline{Lim}\left(I_{li}*\right) = \in \frac{1}{M_L} \sum R_l*(Y) \mid Y \quad \underline{Apr}(I_{li}*) \tag{5}$$

$$\underline{Lim}\left(I_{ui}*\right) = \in \frac{1}{M_L*} \sum R_u*(Y) \mid Y \quad \underline{Apr}(I_{ui}*) \tag{6}$$

, where M_L, M_L* are the sum of containing objects in the lower approximation of I_{li}^* and I_{ui}^* respectively; and

$$\overline{Lim}\left(I_{li}*\right) = \in \frac{1}{M_U} \sum R_l*(Y) \mid Y \quad \overline{Apr}(I_{li}*) \tag{7}$$

$$\overline{Lim}\left(I_{ui}*\right) = \in \frac{1}{M_U*} \sum R_u*(Y) \mid Y \quad \overline{Apr}(I_{ui}*) \tag{8}$$

, where M_U, M_U* are the ones contained in the upper approximation of I_{li}^* and I_{ui}^*, respectively.

For the lower class, the rough boundary interval of $I_{li}*$ is the interval between the its lower and upper limit, which is represented as $RB(I_{li}*)$:

$$RB\left(I_{li}*\right) = \overline{Lim}\left(I_{li}*\right) - \underline{Lim}\left(I_{li}*\right) \tag{9}$$

, and for the upper class, rough boundary interval of I_{ui}^* is:

$$RB\left(I_{ui}*\right) = \overline{Lim}\left(I_{ui}*\right) - \underline{Lim}\left(I_{ui}*\right) \tag{10}$$

The vague class I_{li}^* and I_{ui}^* can be expressed by its lower limit and upper limit as follows:

$$RN\left(I_{li}*\right) = \lceil \underline{Lim}\left(I_{li}*\right), \overline{Lim}\left(I_{li}*\right) \rfloor \tag{11}$$

$$RN\left(I_{ui}*\right) = \lceil \underline{Lim}\left(I_{ui}*\right), \overline{Lim}\left(I_{ui}*\right) \rfloor \tag{12}$$

Since each class is defined by both its lower and upper boundaries rather than a crisp number defined by rough number method, it is called *interval rough number,* which is defined as:

$$IRN(I_i*) = [RN(I_{li}*),\ RN(I_{ui}*)] \tag{13}$$

3.2 Assignment of customer weight

Customers often have different ideas of CRs, and normally the existing RIR methods treat the customers as equally important, which is not flexible and sometimes cannot reflect the actual preferences in a segmented market. For example, the reliability of an anonymous online questionnaire is reasonably lower than a face-to-face interview with lead users. Despite marketing strategies, even utilizing the same method, it is assumed that customers who are more likely to provide accurate RIRs information of CRs should be considered as more important than other ones. It can depend on (Franceschini et al. 2015):

1) their level of participation and attention in the survey;
2) their degree of experience and familiarity regarding product related knowledge;
3) their level of education.

In this regard, assume that there are *M* customers participating in the determination of RIRs, each customer is assigned with a weight w_j, $(1 \leqslant j \leqslant M)$, *i* stands for the *ith* customer, and the total weights equals to:

$$\sum_{j=1}^{M} w_j = 1 \tag{14}$$

3.3 Procedures of determining the RIRs

Based on the proposed *interval rough number* method, the procedures of determining the RIRs of CRs contain 6 steps, as shown in Fig. 1.

Fig. 1 Procedures of determining RIRs of CRs

Step 1: Identification of CRs (WHATs)

In order to acquire the VOC, many marketing strategies have been proposed, such as: purchase history, focus group, lead user analysis, ethnography, brainstorm, etc. (Cooper and Dreher 2010). Also, many techniques were brought out in capturing the CRs, such as: virtual reality (VR) (Chryssolouris et al. 2007), product ecosystem (Zhou et al. 2011), recommender system (Fleder and Hosanagar 2009), co-design toolkits (Mugge et al. 2009) and human-computer interactions (Durka et al. 2012). Generally, these methodologies are combined to achieve more accurate information. Then, market analysts identify and categorize these raw information into the major high-level CRs by affinity diagram or tree diagrams.

Step 2: Customer weight and importance ratings of CRs

After eliciting the major CRs in Step 1, the customers are asked to give their preferences of each CR by direct assignment of ratings. The range of ratings is pre-determined by the marketing analysts which generally utilizes the discrete numbers in certain scale, such as: 1-5 and 1-9 points. It corresponds to the level of importance, i.e. a bigger number stands for a more important CR. Customers can either rate by a crisp number (e.g. 1, 3, 5) with certainty or by interval numbers in uncertainty (e.g. [1, 2], [3, 5]), which represents the flexibility of customer expression. Also, marketing analysts need to determine the 'reliability' of customers by assigning each customer with a certain weight (see Section 3.2).

Step 3: Quantification of ratings by interval rough number

According to the definition in Section 3.1, the customer interval importance ratings are calculated with its lower class and upper class, respectively. For example, 3 customers' (A, B, C) ratings of requirement R^* *is:* $R^* = \{(1, 3), (3, 3), (3, 5)\}$. Based on Eqs. (1) to (4):

Lower approximation of customer A's lower and upper class:

$$\underline{Apr}(I_{l1}^*) = \underline{Apr}(1) = \{1\} \qquad \underline{Apr}(I_{u1}^*) = \underline{Apr}(3) = \{3, \quad 3\}$$

Upper approximations of customer A's lower and upper class:

$$\overline{Apr}\left(I_{l1}^*\right) = \overline{Apr}\left(1\right) = \{1, \quad 3, \quad 3\} \qquad \overline{Apr}\left(I_{u1}^*\right) = \overline{Apr}\left(3\right) = \{3, \quad 3, \quad 5\}$$

, thus, according to Eqs. (5) to (8), A's lower limit and upper limit equals to:

$$\underline{Lim}\left(I_{l1}^*\right) = \underline{Lim}\left(1\right) = \frac{1}{1} \times (1) = 1 \qquad \underline{Lim}\left(I_{u1}^*\right) = \underline{Lim}\left(3\right) = \frac{1}{2} \times (3+3) = 3$$

$$\overline{Lim}\left(I_{l1}^*\right) = \overline{Lim}\left(1\right) = \frac{1}{3}(1+3+3) = \frac{7}{3} \qquad \overline{Lim}\left(I_{u1}^*\right) = \overline{Lim}\left(3\right) = \frac{1}{3}(3+3+5) = \frac{11}{3}$$

, and A's lower and upper rating range is calculated by Eqs. (11) and (12) as interval rough numbers:

$$RN\left(I_{l1}^*\right) = \lceil \underline{Lim}\left(1\right), \overline{Lim}\left(1\right) \rfloor = \lceil 1, \frac{7}{3} \rfloor \qquad RN\left(I_{u1}^*\right) = \lceil \underline{Lim}\left(3\right), \overline{Lim}\left(3\right) \rfloor = \lceil 3, \frac{11}{3} \rfloor$$

According to Zhai et al. (2008), rough number uses boundary intervals to describe the imprecision of data. Therefore, the arithmetic operations defined in interval analysis (Kaufmann et al. 1985; Moore 1966) can be extended to the proposed *interval rough number* method. Thus, based on Eqs. (11) to (14), the overall average upper and lower importance ratings of each CR can be determined as follows:

$$AIR\left(CR_i\right) = \sum_{j=1}^{M} w_j RN\left(Ct_i\left(j\right)\right) \tag{15}$$

, where $AIR(CR_i)$ stands for the average importance rating of CR_i; M is the total number of customers involved in ratings; w_j is the weight of *jth* customer; and $RN(C_t(j))$ is the calculated interval rating range given by the *j*th customer for CR_i. Taking requirement $R*$ as an example, if the weights of customer A, B, C are (0.2, 0.3, 0.5), then based on Eq. (15), the lower class average importance ratings is:

$$AIR_l\left(R*\right)=0.2\times\left[1,\frac{7}{3}\right]+0.3\times\left[\frac{7}{3},3\right]+0.5\times\left[\frac{7}{3},3\right]=\left[\frac{31}{15},\frac{43}{15}\right]$$

, and the upper class average importance rating is:

$$AIR_u\left(R*\right)=0.2\times\left[3,\frac{11}{3}\right]+0.3\times\left[\frac{11}{3},5\right]+0.5\times\left[\frac{11}{3},5\right]=\left[\frac{53}{15},\frac{73}{15}\right]$$

Step 4: Determine if the design is consistent

In order to determine the rating is acceptable, the average importance ratings are first normalized and depicted in a bar graph, as shown in Fig. 2. The normalization process is represented as:

$$\overline{AIR\left(CR_i\right)}=\frac{AIR\left(CR_i\right)}{Max\ rating} \tag{16}$$

, in which $\overline{AIR\left(CR_i\right)}$ stands for the normalized average importance rating and *max rating* stands for the maximum number in the rating scale. In Fig. 2, if no intersection is found between upper and lower class, the red part shows the range of lower class, which stands for the customers' lower perceptions towards the importance ratings; and the purple part show the range of upper class, which stands for the customers' higher perceptions towards the importance ratings. If intersection is found, the green part shows the intersection part of upper class and lower class of importance ratings, which the lower range and upper range is defined by adding the green part to the red and purple part, respectively. Since the range of each class is determined by customers' various perceptions, it shows the fluctuation of customers' importance ratings of each CR. The larger the range of a class is, the more vague (or different) customers' perceptions of this CR are. For example, in Fig. 2, both the upper and lower class fluctuation of customer perceptions of CR_3 are smaller than any other CRs.

Fig. 2 Bar-graph of customer importance ratings of CRs

As shown in Fig. 3, if the upper range and lower range of customer importance rating has no intersection part, we call it *consensus rating* which means that customers are consistent towards the "WHATs". However, if the upper range and lower range has intersection, we call it *controversial rating* (Fig. 3). The intersection means customers have controversial attitude towards 'WHATs'. The larger intersection part overlaps, the more controversy it has.

In the scope of *controversial rating*, there are two types of rating, i.e. *acceptable rating* and *inconsistent rating.* It is determined by comparing the normalized range of intersection part with a threshold value *k* based on designer's experience. If the overlapping range is bigger than the threshold value, it means that customers' perception of the specific CR is controversial and further investigation needs to be conducted. Only *acceptable rating* and *consensus rating* are regarded as consistent and could be taken into further definition of relative importance range.

Fig. 3 Definition of consensus rating and controversial rating

Step 5: Define upper and lower class relative importance range

After Step 4, if the design is acceptable or consensus, we define the relative customer importance range of CR_i, represented by $RN(I_i*)$ is defined as:

$$RN\left(I_i*\right)=\begin{bmatrix}\min\left(AIR\left(\underline{Lim}\left(I_{ui}*\right)\right),AIR\left(\overline{Lim}\left(I_{li}*\right)\right)\right),\\ \max\left(AIR\left(\underline{Lim}\left(I_{ui}*\right)\right),AIR\left(\overline{Lim}\left(I_{li}*\right)\right)\right)\end{bmatrix} \tag{17}$$

, let

$$RN^{L}\left(I_i*\right)=\min\left(AIR\left(\underline{Lim}\left(I_{ui}*\right)\right),AIR\left(\overline{Lim}\left(I_{li}*\right)\right)\right) \tag{18}$$

$$RN^{U}\left(I_i*\right)=\max\left(AIR\left(\underline{Lim}\left(I_{ui}*\right)\right),AIR\left(\overline{Lim}\left(I_{li}*\right)\right)\right) \tag{19}$$

, where $RN^{L}\left(I_i*\right)$ stands for the lower boundary of relative customer importance range of CR_i, and $RN^{U}\left(I_i*\right)$ stands for its upper boundary, e.g. the relative customer importance range of *R** is:

$$RN\left(I_1\right)=\left[\frac{43}{15},\frac{53}{15}\right]$$

, and its lower boundary and upper boundary are:

$$RN^{L}\left(I_1\right)=\frac{43}{15};RN^{U}\left(I_1\right)\quad\frac{53}{15}$$

Step 6: Transform importance range into final RIR

To covert the relative importance range of each CR into crisp number of final RIR, we define an indicator λ_i *(*$0\leq \lambda_i \leq 1$*)* to transform the rough boundary interval into final $RIR(I_i*)$. Based on Eqs. (9), (10) and (15), the transformation calculation is as follows:

$$\lambda_i=\frac{RB\left(AIR\left(I_{ui}^{*}\right)\right)}{RB\left(AIR\left(I_{li}^{*}\right)\right)+RB\left(AIR\left(I_{ui}^{*}\right)\right)} \tag{20}$$

$$RIR\left(I_i*\right)=\lambda_i RN^{L}\left(I_i*\right)+(1-\lambda_i)RN^{U}\left(I_i*\right) \tag{21}$$

From Eqs. (20) and (21), one can find that λ_i is determined by the average lower and upper importance ratings. Take *R** as an example:

$$\lambda_{R^*} = \frac{20/15}{12/15+20/15} = \frac{5}{8}$$

$$RIR\left(R^*\right) = \frac{5}{8} \times \frac{43}{15} + (1 - \frac{5}{8}) \times \frac{53}{9} = 4$$

4. An illustrative example

To validate the proposed method, this work gives an illustrative example on a mountain bicycle frameset from a local bicycle company in New Zealand. The company intends to develop a customized frameset with multiple options for customers' selection. The initial marketing analysis has already been conducted by the company's marketing team, and 8 major CRs are elicited and refined by online questionnaire and after sale feedback. Affinity diagram is utilized to organize these CRs into 3 categories (*Step 1*), i.e.:

Functional group:

CR_1: the frameset need to be robust for mountain road (reliable)

CR_2: the frameset should be light-weighted and easy to carry (light weight)

CR_3: the frameset need to consider speed issues when assembling with headset and wheels (sporty)

CR_4: the shape of the frameset can be adjustable to fit multi-use (flexible)

CR_8: the frameset need to be waterproof (rust resistance)

Affective group:

CR_5: the frameset should look great with personalized options (e.g. painting, shape) (aesthetic)

CR_6: the frameset should be comfortable to ride on (comfortable)

Cost-related group:

CR_7: the frameset should be economical (low cost)

In this example, the importance rating scale of CRs is defined in 1-9 scores, of which: 1 – not at all; 3 – little; 5 – medium important; 7 – important; 9 – extreme important. Also, for simplicity and to compare the ranking result with existing methods (i.e. rough number method, fuzzy weighted average method) which do not distinguish customers' relative importance, the rating process (*Step 2*) was conducted twice by focus group from 9 lead customers (Ct) with equal importance. They were introduced about the prospective product with CRs, and had an interactive discussion with other members before they were asked to give the RIRs of the CRs both in crisp number and in interval numbers respectively, as shown in Table 3.

Table 3 Importance ratings towards WHATs (CRs) in both crisp and interval number

Based on the definitions described in Section 3.1, the rough approximations and interval rough numbers of importance ratings towards WHATs (see Table 3) can be easily calculated. In such case, the 9 lead customers' perceptions of importance ratings are defined by interval numbers rather than a crisp number. Take CR_1 in Table 3 as an example: 9 customers provided four lower classes and four upper classes for the importance rating of CR_1. In the lower classes: class "4" rated by customer 5 and 6 (Ct_5, Ct_6); class "5" rated by customer 3 and 7 (Ct_3, Ct_7); class "6" rated by customer 1, 4, 8 and 9 (Ct_1, Ct_4 Ct_8, Ct_9); and class "7" rated by customer 2 (Ct_2). In the upper class: class "4" rated by customer 6 (Ct_6); class "6" rated by customer 5 (Ct_5); class "7" rated by customer 4, 7 and 8 (Ct_4, Ct_7, Ct_8); and class "8" rated by customer 1, 2, 3 and 9 (Ct_1, Ct_2, Ct_3, Ct_9). Using Eqs. (1) to (8), the lower and upper limits, the rough boundary interval, and the interval rough number of both lower class and upper class can be calculated, as shown in Table 4 and Table 5, respectively. Then, following Eqs. (15) and (16), the average rating range of each CR is normalized and depicted in bar graph, as shown in Fig. 2 (*Step 3*).

Table 4 Calculation result of importance ratings of lower interval rough numbers

Table 5 Calculation result of importance ratings of upper interval rough numbers

From Fig. 2, one can find that CR_1, CR_3, CR_5, CR_6, CR_8 has no intersection part, which means that the importance ratings from customers are consistent, known as *consensus rating*; and CR_2, CR_4, CR_7 has an intersection part, respectively. It shows the vagueness among customers towards the importance ratings, known as *controversial rating*. Assuming the threshold value $k = 0.2$, thus, CR_7 (0.078) is acceptable for further product planning process, i.e.: *acceptable rating*, while CR_2 (0.267), CR_4 (0.267) are *inconsistent ratings*, which needs to be re-investigated by marketing team for consistency *(Step 4).*

For the later comparison with rough number method and fuzzy weighted average method (Section 5), it is assumed that data in *Step 4* are all acceptable. Thus, according to Eqs. (17) to (19), the upper and lower class relative importance range are calculated *(Step 5)*, as shown in Table 6. For example, customers' perceptions towards *CR_7: low cost* is: [6.0, 7.6] for lower class and [6.9, 8.4] for upper class, respectively. Finally, according to *Step 6*, the indicator and its corresponding final RIR is calculated based on Eqs. (21) and (22), as shown in Table 7. From the table, one can find that the importance ranking of the CRs is: $CR_3 > CR_7 > CR_5 > CR_1 > CR_8 > CR_2 > CR_4 > CR_6$.

Table 6 The calculation results of average importance ratings of CRs in lower and upper classes

Table 7 The calculation result of relative importance ratings of CRs

5. A comparative study

A comparative study among Zhai et al. (2008, 2009) rough number method, Chen et al. (2006) fuzzy average weighted method and the proposed one is conducted based on two concerns: consistency of the fused ordering and the robustness of evaluation.

5.1 Ranking result of existing methods

5.1.1 Rough number method

The customers' importance ratings of CRs using *rough number* method are calculated based on the crisp ratings of customers (Table 8). Since it follows the same arithmetic operation rules as *interval rough number*, the normalized results of customer importance ratings of CRs (WHATs) using *rough number* method is depicted in Fig. 4. According to the ranking rules of Zhai et al. (2008, 2009), in such cases, the preference order of CRs is: $CR_3 > CR_7 > CR_5 > CR_1 > CR_8 > CR_2 > CR_4 > CR_6$, which is the same as the proposed method.

Table 8 Calculation result of importance ratings of WHATs using rough number

Fig. 4 Normalized customer importance ratings of CRs using rough number method

5.1.2 Fuzzy weighted average method

According to Chen et al. (2006), customers' vague expressions are represented by triangular fuzzy numbers (TFNs) in the fuzzy sets, and the fuzzy boundary interval is defined by designer's interpretation as a number "2" constantly, as shown in Table 9. For example, in fuzzy cases, customer's perception of *medium importance* is defined as a TFN *(3, 5, 7)* within the predefined fuzzy set. In such case, the weight of each CR is determined by:

$$\overline{w_i} = \frac{1}{n}\sum_{k=1}^{n} w_i^k \tag{22}$$

where w_i^k stands for the *kth* customer's normalized rating of *ith* CR and n stands for the number of customers. In this case, the normalized RIRs of CRs is depicted in Fig. 6, which the ranking result can be derived as: $CR_3 > CR_7 > CR_5 > CR_1 > CR_8 > CR_2 > CR_4 > CR_6$, which also matches the proposed method.

All in all, from the perspective of ranking results, it can be inferred that the proposed method can perform as well as the existing methods. Moreover, from the perspective of ranking objectivity, the rough number method and proposed method outperforms the fuzzy weighted average method by computing within the inherent data from customers' own information rather than subjectively selecting the fuzzy membership function by designers. Thus, the calculation result of rough set based methods is more objective and somehow reliable than fuzzy one. Also, in rough set based methods, the more vagueness of customers' perceptions will result in a bigger rough boundary interval (see Fig. 2 and Fig. 5), while it is not reflected in fuzzy weighted average method due to its rigid fuzzy boundary interval selection. This again, outperforms fuzzy weighted average by displaying the customer heterogeneity more straightforward. Besides, the proposed *interval rough number* method enables the flexibility of customer ratings, and also takes the relative importance of customers into the RIR decision making process, which excels the existing rough number method as well.

Table 9 Calculation result of importance ratings of WHATs using TFNs

Fig. 5 Normalized customer importance ratings of CRs using fuzzy weighted average method

5.2 Consistency of the fused ordering

The consistency of the fused ordering here is defined as the consistency between the output ranking result of the proposed *interval rough number* method and the input customer preference orderings. It can be demonstrated in a simple way, which the fused ordering and the customers' preference orderings are pairwise compared between CRs (Franceschini et al. 2015).

For simplicity, we take the *consensus ratings* from the first 4 rankings (i.e.: $CR_3 > CR_5 > CR_1$), and the last 4 rankings containing *controversial ratings* of the fused ordering into consideration. For example, from $CR_3 > CR_5 > CR_1$, we can obtain the information $CR_3 > CR_5$, $CR_3 > CR_1$, $CR_5 > CR_1$. Following this, the pairwise comparison relations are depicted in Table 10 and Table 11, respectively. It can be seen that, in the ranking only with *consensus ratings*, for each pairwise comparison, the relation gained from the fused ordering is always the most frequent in customers' preference orderings, while in the ranking with *controversial ratings*, due to the large fluctuation of customer perceptions, it may not be consistent with customers' preference orderings (e.g. CR_8 and CR_2).

In the existing methods, such as rough number method and fuzzy weighted average method, they do not take this controversy into consideration when fusing the customer information, and thus sometimes they cannot reflect customer preferences accurately. In our method, we outperformed those methods by setting a threshold value *k* regarding the *controversial ratings* of customers. If the fluctuation range is bigger than *k*, it is suggested that the customers' importance ratings of the CR be re-investigated rather than just fused with little care. In such case, the consistency of the ranking can be guaranteed by re-determining the ratings that are inconsistent (e.g. $CR_{2,}$ CR_4)

Table 10 Pairwise comparison between the consensus ratings among first 4 rankings of the fused ordering and the customer's preference orderings

Table 11 Pairwise comparison between the last 4 rankings of the fused ordering and the customer's preference orderings

5.3 Sensitivity analysis

Since the proposed method is based on a direct assignment of ratings, the rating scale needs to be stable all along the rating process (Chuang 2001; Nahm et al. 2013). In such case, the evaluation of robustness is performed by a sensitivity analysis of the proposed method and the other two existing methods with respect to a slight variation of the sample size. We select only the first 8 customers as another sample, and compare the result with the original one in Tables 6 and 7.

On one hand, following the proposed procedures of determining the RIRs, the calculation results of the 8 customers' sample are derived in Table 12. It can be found that the ranking of 8 customers' preference is represented as: $CR_3 > CR_7 > CR_5 > CR_8 > CR_1 > CR_2 > CR_4 > CR_6$, which only CR_8 and CR_1 exchange the ranking positions with respect to Table 7, and the importance rating difference of these two CRs remains very small, which somehow maintains its robustness in analysing CRs with limited information. Moreover, in Table 12, both the upper and lower class average ranges are different from the original ones. This is due to the calculation process based on Eqs. (1) to (8), which instead of having the same boundary intervals as fuzzy weighted average method, the intervals in *interval rough number* method are calculated by the inputs from the customer and their stability are determined by the *consistent ratings* from customers.

On the other hand, the results of RIRs based on rough number method and fuzzy weighted average method are also calculated based on the previous work, as shown in Table 13. For the rough number method, the ranking can be derived as: $CR_3 > CR_7 > CR_5 > CR_8 > CR_1 > CR_2 > CR_4 > CR_6$, which is the same as the proposed method. Compared with the 9-customer sample, again, only the CR_8 and CR_1 exchange the ranking positions with a small importance rating difference as well. As both methods share the similar calculation process, it is convincible that the proposed method can perform as well as the rough number method in robustness concerns. For the fuzzy weighted average method, the ranking is: $CR_3 > CR_7 > CR_5 > CR_1 = CR_8 > CR_2 > CR_4 > CR_{6,}$ which only the ranking position between CR_8 and CR_1 has been changed due to the scale down of sample size. Also, it can be found that in Table 13, the interval boundary of fuzzy weighted average method is kept the same by designer's own membership function selection.

From the comparison result, one can conclude that the proposed method perform equally well as, if not better than the rough number method and fuzzy weighted average method in regards to the robustness of determining RIRs.

Table 12 The preference rating result of each CR in the sample size of 8 customers

Table 13 The RIR result based on an 8-customer sample by rough number method and fuzzy weighted average method

6. Conclusion

Determination of the RIRs and correspondingly the final importance ratings of CRs is a critical step in QFD product planning process. Due to the vagueness of CRs, in literature, both fuzzy numbers and rough numbers methods were utilized to quantify them so as to identify engineering characteristics in the QFD product planning phase. However, for fuzzy numbers methods, the selection of membership functions is normally subjective and remains unsolved. For the rough numbers method, though the measure of vagueness is computed based on the uncertainty already inherent in the data, the existing method lacks flexibility in customer rating and did not take customer heterogeneity into consideration, which may not truly reflect customer preferences in the RIR process.

Aiming to improve the existing approaches by evaluating CRs more objectively and accurately, this paper proposed a weighted *interval rough number* method. CRs are rated with interval numbers, rather than a crisp number, which is more truthful and flexible in real life. The definition and analytical algorithms of the proposed method were introduced in details. Also, for customer heterogeneity concerns, the ‘reliability’ of fused ratings is determined by assigning each customer a weight. Then, the design rules and procedures of determining the RIRs of CRs are described. According to its design rules, in product planning stage, customer-oriented design could be classified into three categories: *consensus design*, *acceptable design* and *confusing design*. Only *consensus design* and *acceptable design* could be carried out in further design process, while *confusing design* should be re-investigated.

To validate the proposed method, an example of bicycle frameset was undertaken in a local company, and both the ranking consistency and sensitivity of it had been analysed. A comparative study among fuzzy weighted average method, rough number method and the proposed one was conducted. The result showed that the *interval rough number* method can perform as well as the other two methods with regards to the robustness and consistency of RIRs calculation. Moreover, it has some advantages compared to the rough number method in two aspects. First, it provides a solution for treating hierarchical importance rating of CRs (customer heterogeneity) to engineers and marketing analysts, which makes the rating process more accurately. Second, it gives customers more flexibility in determining the importance rating, which reflects the nature of customer perception vagueness. On the other hand, compared to fuzzy weighted average method, the result showed that the *interval rough number* method provides a more objective way in processing linguistic assessments and is more suitable for customised product planning process, especially when customer information is limited.

The proposed method can be applied in "engineer-to-order" mode industries with a focus on customer-centric product development with limited CR information initially. However, the proposed method has its own limitations, as the large fluctuation of customer heterogeneity may result in *inconsistency* of RIRs. Therefore, it might not be applicable for product development which customer perceptions on each CR are significantly different.

References

Akao, Y. (1972). New product development and quality assurance–quality deployment system. *Standardization and Quality Control*, *25*(4), 7-14.

Büyüközkan, G., Ertay, T., Kahraman, C., & Ruan, D. (2004). Determining the importance weights for the design requirements in the house of quality using the fuzzy analytic network approach. *International Journal of Intelligent Systems, 19*(5), 443-461.

Braglia, M., & Petroni, A. (1999). A management-support technique for the selection of rapid prototyping technologies. *Journal of Industrial Technology, 15*(4), 1-6.

Buyukozkan, G., Feyzioglu, O., & Ruan, D. (2007). Fuzzy group decision-making to multiple preference formats in quality function deployment. *Computers in Industry, 58*(5), 392-402, doi:10.1016/j.compind.2006.07.002.

Chan, L., Kao, H., & Wu, M. (1999). Rating the importance of customer needs in quality function deployment by fuzzy and entropy methods. *International Journal of Production Research, 37*(11), 2499-2518.

Chen, Y. Z., Fung, R. Y. K., & Tang, J. F. (2006). Rating technical attributes in fuzzy QFD by integrating fuzzy weighted average method and fuzzy expected value operator. *European Journal of Operational Research, 174*(3), 1553-1566, doi:10.1016/j.ejor.2004.12.026.

Chryssolouris, G., Pappas, M., Karabatsou, V., Mavrikios, D., & Alexopoulos, K. (2007). A Shared VE for Collaborative Product Development in Manufacturing Enterprises. In *Collaborative Product Design and Manufacturing Methodologies and Applications* (pp. 59-70): Springer.

Chuang, P.-T. (2001). Combining the analytic hierarchy process and quality function deployment for a location decision from a requirement perspective. *The International Journal of Advanced Manufacturing Technology, 18*(11), 842-849.

Cohen, L., & Cohen, L. (1995). *Quality function deployment: how to make QFD work for you*: Addison-Wesley Reading, MA.

Cooper, R. G., & Dreher, A. (2010). Voice-of-Customer Methods. *Marketing Management, 19*, 38-43.

Durka, P. J., Kus, R., Zygierewicz, J., Michalska, M., Milanowski, P., Labecki, M., et al. (2012). User-centered design of brain-computer interfaces: OpenBCI.pl and BCI Appliance. [Article]. *Bulletin of the Polish Academy of Sciences-Technical Sciences, 60*(3), 427-431, doi:10.2478/v10175-012-0054-1.

Ertay, T., Büyüközkan, G., Kahraman, C., & Ruan, D. (2005). Quality function deployment implementation based on analytic network process with linguistic data: An application in automotive industry. *Journal of Intelligent & Fuzzy Systems, 16*(3), 221-232.

Fleder, D., & Hosanagar, K. (2009). Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity. *Management Science, 55*(5), 697-712, doi:10.1287/mnsc.1080.0974.

Franceschini, F., Maisano, D., & Mastrogiacomo, L. (2015). Customer requirement prioritization on QFD: a new proposal based on the generalized Yager's algorithm. *Research in Engineering Design, 26*(2), 171-187, doi:10.1007/s00163-015-0191-2.

Geng, X., Chu, X., Xue, D., & Zhang, Z. (2010). An integrated approach for rating engineering characteristics' final importance in product-service system development. *Computers & Industrial Engineering, 59*(4), 585-594.

Goncalves-Coelho, A. M. (2005). Improving the use of QFD with Axiomatic Design. *Concurrent Engineering, 13*(3), 233-239, doi:10.1177/1063293x05056787.

Griffin, A., & Hauser, J. R. (1993). The voice of the customer. *Marketing science, 12*(1), 1-27.

Hauser, J. R., & Clausing, D. (1988). The house of quality.

Ho, W. (2008). Integrated analytic hierarchy process and its applications–A literature review. *European Journal of Operational Research, 186*(1), 211-228.

Jiang, J. D., Xu, F., Zhao, Y. D., Zhang, L. B., & Sun, X. J. (2005). *QFD in design for small agricultural machinery under mass customization* (Proceedings of the 12th International Conference on Industrial Engineering and Engineering Management, Vols 1 and 2: Modern Industrial Engineering and Innovation in Enterprise Management).

Jin, Y. (2003). *Advanced fuzzy systems design and applications* (Vol. 112): Springer.

Kahraman, C., Ertay, T., & Buyukozkan, G. (2006). A fuzzy optimization model for QFD planning process using analytic network approach. *European Journal of Operational Research, 171*(2), 390-411, doi:10.1016/j.ejor.2004.09.016.

Kaufmann, A., Gupta, M. M., & Kaufmann, A. (1985). *Introduction to fuzzy arithmetic: theory and applications*: Van Nostrand Reinhold Company New York.

Khoo, L.-P., & Zhai, L.-Y. (2001). A prototype genetic algorithm-enhanced rough set-based rule induction system. *Computers in Industry, 46*(1), 95-106.

Khoo, L., Tor, S., & Zhai, L. (1999). A rough-set-based approach for classification and rule induction. *The International Journal of Advanced Manufacturing Technology, 15*(6), 438-444.

Kwong, C., & Bai, H. (2003). Determining the importance weights for the customer requirements in QFD using a fuzzy AHP with an extent analysis approach. *Iie Transactions, 35*(7), 619-626.

Kwong, C. K., & Bai, H. (2002). A fuzzy AHP approach to the determination of importance weights of customer requirements in quality function deployment. *Journal of Intelligent Manufacturing, 13*(5), 367-377, doi:10.1023/a:1019984626631.

Kwong, C. K., Ye, Y., Chen, Y., & Choy, K. L. (2011). A novel fuzzy group decision-making approach to prioritising engineering characteristics in QFD under uncertainties. *International Journal of Production Research, 49*(19), 5801-5820, doi:10.1080/00207543.2010.520043.

Lai, X., Xie, M., Tan, K.-C., & Yang, B. (2008). Ranking of customer requirements in a competitive environment. *Computers & Industrial Engineering, 54*(2), 202-214.

Lee, A. H. I., Kang, H. Y., Yang, C. Y., & Lin, C. Y. (2010). An evaluation framework for product

planning using FANP, QFD and multi-choice goal programming. *International Journal of Production Research, 48*(13), 3977-3997, doi:10.1080/00207540902950845.
Li, B. M., Xie, S. Q., & Xu, X. (2011). Recent development of knowledge-based systems, methods and tools for One-of-a-Kind Production. *Knowledge-Based Systems, 24*(7), 1108-1119, doi:10.1016/j.knosys.2011.05.005.
Li, Y.-L., Chin, K.-S., & Luo, X.-G. (2012). Determining the final priority ratings of customer requirements in product planning by MDBM and BSC. *Expert Systems with Applications, 39*(1), 1243-1255.
Li, Y., Tang, J., Luo, X., & Xu, J. (2009). An integrated method of rough set, Kano's model and AHP for rating customer requirements' final importance. *Expert Systems with Applications, 36*(3), 7045-7053.
Li, Y., Tang, J., Luo, X., Yao, J., & Xu, J. (2010). A quantitative methodology for acquiring engineering characteristics in PPHOQ. *Expert Systems with Applications, 37*(1), 187-193, doi:10.1016/j.eswa.2009.05.006.
Li, Y. L., Tang, J. F., Chin, K. S., Jiang, Y. S., Han, Y., & Pu, Y. (2011). Estimating the final priority ratings of engineering characteristics in mature-period product improvement by MDBA and AHP. *International Journal of Production Economics, 131*(2), 575-586, doi:10.1016/j.ijpe.2011.02.003.
Li, Y. L., Tang, J. F., & Luo, X. G. (2010). An ECI-based methodology for determining the final importance ratings of customer requirements in MP product improvement. [Article]. *Expert Systems with Applications, 37*(9), 6240-6250, doi:10.1016/j.eswa.2010.02.100.
Liu, S. T. (2005). Rating design requirements in fuzzy quality function deployment via a mathematical programming approach. [Article]. *International Journal of Production Research, 43*(3), 497-513, doi:10.1080/0020754042000270395.
Luo, X., Kwong, C., Tang, J., & Sun, F. QFD-Based Product Planning With Consumer Choice Analysis.
Moore, R. E. (1966). *Interval analysis* (Vol. 4): Prentice-Hall Englewood Cliffs.
Mugge, R., Schoormans, J. P. L., & Schifferstein, H. N. J. (2009). Incorporating consumers in the design of their own products. The dimensions of product personalisation. [Article]. *Codesign-International Journal of Cocreation in Design and the Arts, 5*(2), 79-97, doi:10.1080/15710880802666416.
Nahm, Y. E., Ishikawa, H., & Inoue, M. (2013). New rating methods to prioritize customer requirements in QFD with incomplete customer preferences. *International Journal of Advanced Manufacturing Technology, 65*(9-12), 1587-1604, doi:10.1007/s00170-012-4282-1.
Pawlak, Z. (1982). Rough sets. *International Journal of Computer & Information Sciences, 11*(5), 341-356.
Pawlak, Z. (1991). *Rough sets: Theoretical aspects of reasoning about data* (Vol. 9): Springer.
Raharjo, H., Brombacher, A. C., & Xie, M. (2008). Dealing with subjectivity in early product design phase: A systematic approach to exploit Quality Function Deployment potentials. *Computers & Industrial Engineering, 55*(1), 253-278.
Raharjo, H., Xie, M., & Brombacher, A. C. (2011). A systematic methodology to deal with the dynamics of customer needs in Quality Function Deployment. [Article]. *Expert Systems with Applications, 38*(4), 3653-3662, doi:10.1016/j.eswa.2010.09.021.
Ramanathan, R., & Jiang, Y. (2009). Incorporating cost and environmental factors in quality function

deployment using data envelopment analysis. *Omega-International Journal of Management Science, 37*(3), 711-723, doi:10.1016/j.omega.2007.12.003.

Song, W., Ming, X., Han, Y., & Wu, Z. (2013). A rough set approach for evaluating vague customer requirement of industrial product-service system. *International Journal of Production Research, 51*(22), 6681-6701, doi:10.1080/00207543.2013.832435.

Tseng, M. M., Jiao, R. J., & Wang, C. (2010). Design for mass personalization. [Article; Proceedings Paper]. *Cirp Annals-Manufacturing Technology, 59*(1), 175-178, doi:10.1016/j.cirp.2010.03.097.

Wang, Y., & Tseng, M. M. (2011). Integrating comprehensive customer requirements into product design. *Cirp Annals-Manufacturing Technology, 60*(1), 175-178.

Xie, S. Q., & Tu, Y. L. (2006). Rapid one-of-a-kind product development. *International Journal of Advanced Manufacturing Technology, 27*(5-6), 421-430, doi:10.1007/s00170-004-2225-1.

Xie, S. S., & Tu, Y. (2011). *Rapid One-of-a-kind Product Development: Strategies, Algorithms and Tools*: Springer Science & Business Media.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control, 8*(3), 338-353.

Zhai, L.-Y., Khoo, L.-P., & Zhong, Z.-W. (2008). A rough set enhanced fuzzy approach to quality function deployment. *International Journal of Advanced Manufacturing Technology, 37*(5-6), 613-624, doi:10.1007/s00170-007-0989-9.

Zhai, L. Y., Khoo, L. P., & Zhong, Z. W. (2009). A rough set based QFD approach to the management of imprecise design information in product development. *Advanced Engineering Informatics, 23*(2), 222-228, doi:10.1016/j.aei.2008.10.010.

Zhai, L. Y., Khoo, L. P., & Zhong, Z. W. (2010). Towards a QFD-based expert system: A novel extension to fuzzy QFD methodology using rough set theory. *Expert Systems with Applications, 37*(12), 8888-8896, doi:10.1016/j.eswa.2010.06.007.

Zhang, Z., & Chu, X. (2009). Fuzzy group decision-making for multi-format and multi-granularity linguistic judgments in quality function deployment. *Expert Systems with Applications, 36*(5), 9150-9158, doi:10.1016/j.eswa.2008.12.027.

Zheng, P., Xu, X., & Xie, S. Q. (2015). Integrate Product Planning Process of OKP Companies in the Cloud Manufacturing Environment. In *Advances in Production Management Systems: Innovative Production Management Towards Sustainable Growth* (pp. 420-426): Springer.

Zhou, F., Xu, Q., & Jiao, R. J. (2011). Fundamentals of product ecosystem design for user experience. *Research in Engineering Design, 22*(1), 43-61, doi:10.1007/s00163-010-0096-z.