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RESEARCH ARTICLE

Huchang LIAO, Yinghan CHANG, Di WU, Xunjie GOU

Improved approach to quality function deployment based on Pythagorean fuzzy sets and application to assembly robot design evaluation

Abstract Quality function deployment (QFD) is an effective method that helps companies analyze customer requirements (CRs). These CRs are then turned into product or service characteristics, which are translated to other attributes. With the QFD method, companies could design or improve the quality of products or services close to CRs. To increase the effectiveness of QFD, we propose an improved method based on Pythagorean fuzzy sets (PFSs). We apply an extended method to obtain the group consensus evaluation matrix. We then use a combined weight determining method to integrate former weights to objective weights derived from the evaluation matrix. To determine the exact score of each PFS in the evaluation matrix, we develop an improved score function. Lastly, we apply the proposed method to a case study on assembly robot design evaluation.

Keywords quality function deployment, Pythagorean fuzzy sets, group consensus, combined weights, assembly robot design

1 Introduction

With rapid technological development and unstoppable economic globalization, the competition among companies has become increasingly fierce. With numerous copious products to choose from, customers become difficult to satisfy. These situations require companies to find an efficient tool for analyzing customer requirements (CR) and creating products that maximize customer satisfaction (Wu and Liao, 2018). Quality function deployment (QFD) (Cardoso et al., 2015; Wu and Ho, 2015; Yazdani et al., 2017) is a customer-oriented design tool that includes the consensus of cross-functional team members in developing new products or improving existing ones to increase customer satisfaction (Karsak et al., 2003). This method is particularly suitable for companies to apply in designing products.

Economic globalization has made China the largest automobile manufacturing country. When talking about the automobile manufacturing industry, efficiency and quality come to mind. To manufacture efficiently with high quality, industrial robots such as assembly robots have been widely used in factories. However, as technology becomes increasingly advanced, the applications of assembly robots have become imperative, and the requirements have become rigorous and novel. Thus, it is worthwhile to apply the QFD method to design assembly robots that meet current needs.

In the traditional QFD method, each design requirement and CR are evaluated with their outcomes expressed using crisp values fail to reflect imprecise information. To solve this problem, Khoo and Ho (1996) and Chan et al. (1999) introduced fuzzy sets into the QFD methods. Additionally, the Pythagorean fuzzy set (PFS) (Yager, 2013) was generalized from the intuitionistic fuzzy set (IFS) to consider the membership and non-membership pair (μ, ν) based on the condition $\mu^2+\nu^2\leqslant 1$. As IFSs need to satisfy the condition that $\mu+\nu\leqslant 1$, it can be observed that the space of Pythagorean membership grades is greater than that of intuitionistic membership grades (Yager, 2014). In this paper, we enhance the QFD method by using PFSs for solving decision-making problems given that PFSs can

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Huchang LIAO, Yinghan CHANG, Di WU, Xunjie GOU (✉)
Business School, Sichuan University, Chengdu 610064, China
E-mail: gou_xunjie@163.com

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express wide range evaluations and that they are more capable than IFSs in modeling vagueness in practical problems (Peng and Yang, 2015).

Many fuzzy QFD methods hardly considered how to integrate different expert evaluations into overall assessments (Wu and Liao, 2018). Thus, in this paper, we consider the situation with several experts and apply a method inspired by Zhang et al. (2014) to reach consensus. PFS is a ramification of IFS, and there has been no existing study that considers the combination of PFS and QFD. Therefore, we could extend the fuzzy QFD study in such direction. Many recent studies have been developed to achieve accurate weights and scores in the QFD method. However, fuzzy QFD has not been considered. Thus, it is valuable for us to study how to evaluate with increased precisions. To make the weights of the CRs and the final score accurate, we calculate the combined weights by the method proposed by Wu et al. (2018). This method helps us consider the objective weights derived by correlation coefficients, thereby avoiding the bias caused by highly correlated criteria (Wu et al., 2018). To obtain the final result, we propose a novel score function which overcomes the shortcoming of the score function proposed by Zhang and Xu (2014). We apply the proposed method to assembly robot design.

The rest of this paper is organized as follows. Section 2 reviews studies related to the QFD method and PFSs. Section 3 provides a consensus reaching method for a group with PFSs. A combinative weight determining method is discussed in Section 4. Section 5 introduces the proposed Pythagorean fuzzy QFD method and its stepwise algorithm. Section 6 presents a case study on assembly robot design. Section 7 concludes the paper.

2 Preliminary

2.1 QFD

In the 1960s, QFD was developed by Yoji Akao and Shigeru Mizuno in Japan. It is a method that helps companies analyze CRs and enables them to become proactive in dealing with quality problems rather than be reactive by acting on customer complaints (Karsak et al., 2003). The QFD method could convey CRs into product or service characteristics, which are then translated to other attributes. With the QFD method, companies could design or improve the quality of the products or services close to CRs.

The American Supplier Institute (ASI) proposed a basic four-matrix method, including product, parts, process, and production planning matrices (Karsak et al., 2003). The ASI model is easily understood with a concise structure based on the fundamental of QFD.

In recent years, QFD has been adopted and improved to help decision makers make accurate decisions. It has been integrated with different theories and widely used in many fields. Most QFD applications are related to product development (Moğol Sever, 2018) in production processes and in industries. Dinçer et al. (2019) analyzed the European energy system investment policy with an improved QFD method. Pasawang et al. (2015) applied QFD to finish the conceptual design of an autonomous underwater robot. Many authors have focused on applying the QFD method to service fields recently. Sharma and Singhi (2018) adapted the QFD approach to analyze the importance of Vendor Managed Inventory in supply chain process improvement. Tunca and Bayhan (2012) implemented the QFD method to select the best supplier. Wang (2015) improved the medical service quality based on the QFD method.

Numerous studies have improved the QFD approach in different fields. As this paper focuses on improving the QFD method based on PFSs, we mainly discuss studies that used QFD with fuzzy theories. Khoo and Ho (1996) and Chan et al. (1999) introduced fuzzy sets into QFD to fit real situations. Chen and Ngai (2008) integrated fuzzy theory and QFD to optimize the values of engineering characteristics by considering design uncertainty and financial consideration. An integrated version of QFD and GRA was presented by Yazdani et al. (2019). The Grey relational coefficient was integrated into the fuzzy QFD to facilitate the decision-making process when big data are available in the study. Wu and Liao (2018) improved the QFD approach based on probabilistic linguistic term sets and the ORESTE (organísation, rangement et Synthèse de données relarionnelles, in French) method.

In traditional QFD, each step of deployment is linked to the House of Quality (HoQ). HoQ is paramount in QFD, and it has been studied by many experts. For example, the fuzzy set was introduced into the HoQ by Khoo and Ho (1996) and Chan et al. (1999). Karsak et al. (2003) combined the analytic network process and goal programming approach with HoQ. Only the first stage of traditional QFD, that is, how to use the HoQ to deploy CRs into product characteristics, is introduced in detail below. Note that this study only chose the most important part of the HoQ to introduce the concept and that the HoQ should be built properly according to real situations.

In the HoQ, the left wall is the CRs. This wall contains what customers want and the weight of each requirement. Usually, companies conduct questionnaire surveys to collect customers' opinions about the weight of every demand or use the analytic hierarchy process (AHP) to calculate the weights. These weights are also called the relative importance of customer needs.

The ceiling of the HoQ is the product technical requirements, also known as product features, product characteristics, and engineering attributes. The ceiling reflects the measurable and executable technical methods or requirements deployed from the CRs.

In the middle of the HoQ is the room containing a matrix that represents the relationships between the CRs and the product technical requirements. It is the main part of the HoQ. Some experts are invited to evaluate these relationships using symbols or numbers; the later is applied in this paper.

Finally, the priorities of product technical requirements, target values make up the basement of the HoQ. Priorities are calculated through the matrix mentioned above and the weights of CRs. In this part, companies can rank the product technical requirements and analyze them quantitatively and qualitatively.

2.2 PFSs

The concept of PFS was first proposed by Yager (2013, 2014), as well as Yager and Abbasov (2013).

Definition 1: (Yager, 2013). Let X be a non-empty and fixed set. A PFS P is an object in the form of

$$P = \{< x, P\left(\mu_p(x), \nu_p(x)\right)>|x \in X\}, \quad (1)$$

where the functions $\mu_p : X \longrightarrow [0, 1]$ and $\nu_p : X \longrightarrow [0, 1]$ define the degrees of membership and non-membership of the element $x \in X$ to P, respectively, with the condition of $0 \leqslant \left(\mu_p(x)\right)^2 + \left(\nu_p(x)\right)^2 \leqslant 1$. The hesitant degree of $x \in X$ is defined as $\pi_p(x) = \sqrt{1 - \left(\mu_p(x)\right)^2 - \left(\nu_p(x)\right)^2}$. For convenience, the element in P is called a Pythagorean fuzzy number (PFN) and denoted as $\beta = P(\mu_\beta, \nu_\beta)$, where $\mu_\beta, \nu_\beta \in [0, 1]$, $\pi_\beta = \sqrt{1 - (\mu_\beta)^2 - (\nu_\beta)^2}$, and $0 \leqslant (\mu_\beta)^2 + (\nu_\beta)^2 \leqslant 1$.

To compare two PFNs, Zhang and Xu (2014) developed a score function for calculating the magnitudes of PFNs.

There is another way to represent the PFS which was proposed by Yager and Abbasov (2013). A PFS could also be represented as $\beta = P(r_\beta, d_\beta)$, where r_β is named as the strength of β and d_β is named as the direction of the strength. r_β and d_β are associated with μ_β and ν_β. When r_β is large, the commitment is relatively large and the uncertainty is relatively small. d_β is a value between 0 and 1, which indicates the extent that how fully strength r_β is pointing to the membership. If $d_\beta = 1$, it means that r_β is completely pointing to the membership. Conversely, if $d_\beta = 0$, it means that r_β is completely pointing to the non-membership. $\beta = P(\mu_\beta, \nu_\beta)$ and $\beta = P(r_\beta, d_\beta)$ could be converted to each other because $\mu\beta = r_\beta(\cos\theta_\beta)$, $\nu_\beta = r_\beta(\sin\theta_\beta)$ and $d_\beta = 1 - 2\theta_\beta/\pi$ (Zhang and Xu, 2014).

Definition 2: Let $\beta = P(\mu_\beta, \nu_\beta)$, $\beta_1 = P(\mu_{\beta_1}, \nu_{\beta_1})$ and $\beta_2 = P(\mu_{\beta_2}, \nu_{\beta_2})$ be three PFNs. Then, we have

(1) $\beta_1 \cup \beta_2 = P(\max\{\mu_{\beta_1}, \mu_{\beta_2}\}, \min\{\nu_{\beta_1}, \nu_{\beta_2}\})$,
(2) $\beta_1 \cap \beta_2 = P(\min\{\mu_{\beta_1}, \mu_{\beta_2}\}, \max\{\nu_{\beta_1}, \nu_{\beta_2}\})$,
(3) $\beta^c = P(\nu_\beta, \mu_\beta)$.

Definition 3: (Zhang and Xu, 2014). Let $\beta = P(\mu_\beta, \nu_\beta)$ be a PFN. The score of β is then defined as

$$s(\beta) = (\mu_\beta)^2 - (\nu_\beta)^2. \quad (2)$$

According to the score function of PFN, two PFNs can be compared by using the following rules.

Definition 4: (Zhang and Xu, 2014). Let $\beta_j = P(\mu_{\beta_j}, \nu_{\beta_j})(j = 1, 2)$ be two PFNs, $s(\beta_1)$ and $s(\beta_2)$ be the scores of β_1 and β_2, respectively.

(1) If $s(\beta_1) > s(\beta_2)$, then $\beta_1 \succ \beta_2$;
(2) If $s(\beta_1) = s(\beta_2)$, then $\beta_1 \sim \beta_2$.

The proposed score function has some drawbacks in some situations. For example, for two PFNs $\beta_1 = (0.5, 0.5)$ and $\beta_2 = (0.8, 0.8)$, based on the score function, both have the same score value of zero, which means $\beta_1 \sim \beta_2$. However, this comparative result is apparently unreasonable and inaccurate. In this regard, scholars proposed new comparative rules based on other score functions.

Definition 5: Let $\beta = P(\mu_\beta, \nu_\beta)$ be a PFN. Then, the score of β can be defined as

$$s(\beta) = (\mu_\beta)^2\cos\theta - (\nu_\beta)^2\sin\theta - \pi^2, \quad (3)$$

where $\cos\theta = \mu_\beta/\sqrt{(\mu_\beta)^2 + (\nu_\beta)^2}$ and $\sin\theta = \nu_\beta/\sqrt{(\mu_\beta)^2 + (\nu_\beta)^2}$.

In Eq. (3), $\cos\theta$ and $\sin\theta$ are the weights of μ_β and ν_β, respectively. The non-membership value ν_β is regarded as a kind of punishment. If μ_β is constant and μ_β is relatively larger, then $\sin\theta$ is relatively larger, and the score function will deduct a relatively larger weight $(\nu_\beta)^2$. Similarly, μ_β is considered as a kind of reward. With a relatively larger μ_β, $(\mu_\beta)^2$ has a relatively larger weight.

To solve the shortcoming above, we add π^2 to the score function. In this manner, the scores of the two PFNs $\beta_1 = (0.5, 0.5)$ and $\beta_2 = (0.8, 0.8)$ are different.

3 Consensus reaching method for a group with PFSs

In recent years, numerous methods have been developed to integrate expert evaluations in group decision making under fuzzy environment. Zhang et al. (2014) proposed a method to integrate expert evaluations in IFSs. Inspired by this method, we developed a consensus-reaching method for group decision making with PFSs.

Let $C = \{C_1, C_2,..., C_n\}$ be a set of criteria, $A = \{A_1, A_2,..., A_m\}$ be a set of alternatives, and $E = \{e_1, e_2,..., e_K\}$ be a set of experts. All the evaluations of each expert are given in PFNs, which establish the evaluation matrices denoted as $D^k = (p_{ji}^k)_{n\times m}$ with $p_{ji}^k = P(u_{ji}^k, \nu_{ji}^k)$ $(k = 1, 2,..., K)$. In the QFD method, the criteria are the CRs, and the alternatives are the designing requirements.

Aggregating all evaluation matrices of experts, we can obtain an integrated matrix $D^G = (p_{ji}^G)_{n\times m}$ where

$$p_{ji}^G = P\left(u_{ji}^G, \nu_{ji}^G\right) = P\left(\frac{1}{K}\sum_{k=1}^{K} u_{ji}^k, \frac{1}{K}\sum_{k=1}^{K} \nu_{ji}^k\right). \quad (4)$$

For each evaluation value associated to expert e_k, the distance between D'^k and the integrated matrix D^G can be calculated by

$$D(\beta_1, \beta_2) = \frac{1}{5}(|\mu_{\beta_1} - \mu_{\beta_2}| + |\nu_{\beta_1} - \nu_{\beta_2}|$$

$$+|\pi_{\beta_1} - \pi_{\beta_2}| + |r_{\beta_1} - r_{\beta_2}| + |d_{\beta_1} - d_{\beta_2}|).$$

For each evaluation value associated to expert e_k, the similarity degree between D'^k and the integrated matrix D^G can be calculated by

$$S_{ji}^k = \begin{cases} 1, & \text{if } p'^k_{ji} = p_{ji}^G = p_{ji}^{G_c}; \\ \dfrac{D(p'^k_{ji}, p_{ji}^{G_c})}{D(p'^k_{ji}, p_{ji}^G) + D(p'^k_{ji}, p_{ji}^{G_c})}, & \text{otherwise.} \end{cases} \quad (5)$$

For each alternative A_i associated to expert e_k, the similarity degree is

$$S_i^k = \sum_{j=1}^{n} \omega_j S_{ji}^k. \quad (6)$$

The group similarity degree of each alternative is then obtained by

$$S_i^G = \frac{1}{K}\sum_{k=1}^{K} S_i^k. \quad (7)$$

The deviation of expert e_k for alternative A_i is obtained by

$$S_i^{kG} = |S_i^k - S_i^G|. \quad (8)$$

Additionally, let σ be the threshold of S_i^{kG}. Then,

(1) if all deviations $S_i^{kG} \leqslant \sigma$ $(i = 1, 2,..., m;\ k = 1, 2, ..., K)$, then all experts reach the consensus;

(2) if there is $S_i^{kG} > \sigma$ $(i = 1, 2,..., m;\ k = 1, 2,..., K)$, then expert e_k is asked to revise evaluations until all $S_i^{kG} \leqslant \sigma$ $(i = 1, 2,..., m)$.

4 Novel weight determining method

If the variation degree of a criterion is high, then the information provided by the evaluation value under this criterion will be great. In this regard, this criterion plays an important role in the comprehensive evaluation, and thus, a large objective weight should be given to it. By contrast, if the variation degree of a criterion is small, the criterion with small variation degree should be given a small weight. This weight assignment not only avoids the loss of evaluation information, but also prevents misleading results. Thus, this section applies the method proposed by Wu et al. (2018) for calculating the correlation coefficients to represent the variation degrees of criteria. The objective weights are combined with the subjective weights.

To calculate the weighted correlation coefficients of criteria, the distance between PFSs should be calculated. In addition, as for the cost and benefit criteria, we calculate them separately.

The best value of each criterion can be defined as:

$$p^{j+} = \begin{cases} \max\limits_i\{p_{ji}\} & \text{for benefit criterion,} \\ \min\limits_i\{p_{ji}\} & \text{for cost criterion.} \end{cases} \quad (9)$$

The worst value of each criterion can be defined as:

$$p^{j-} = \begin{cases} \min\{p_{ji}\} & \text{for benefit criterion,} \\ \max\{p_{ji}\} & \text{for cost criterion.} \end{cases} \quad (10)$$

To determine the objective weights, the correlation coefficients of two criteria C_j and C_t $(j, t = 1, 2,..., n)$ can be obtained as:

$$R_{jt} = \frac{\sum\limits_{i=1}^{m}\left(\left(\frac{d_{ji}}{d_j} - \frac{1}{m}\sum\limits_{i=1}^{m}\frac{d_{ji}}{d_j}\right)\times\left(\frac{d_{ti}}{d_t} - \frac{1}{m}\sum\limits_{i=1}^{m}\frac{d_{ti}}{d_t}\right)\right)}{\sqrt{\sum\limits_{i=1}^{m}\left(\frac{d_{ji}}{d_j} - \frac{1}{m}\sum\limits_{i=1}^{m}\frac{d_{ji}}{d_j}\right)^2}\times\sqrt{\sum\limits_{i=1}^{m}\left(\frac{d_{ti}}{d_t} - \frac{1}{m}\sum\limits_{i=1}^{m}\frac{d_{ti}}{d_t}\right)^2}}, \quad (11)$$

where $d_{ji} = d(p_{ji}, p^{j+})$ is the distance between the evaluation p_{ji} and the best value p^{j+}, and $d_j = d(p^{j-}, p^{j+})$ is the distance between the worst value p^{j-} and the best value p^{j+}.

The distance between two PFNs $p_1 = (u_1, v_1)$ and $p_2 = (u_2, v_2)$ is defined as

$$d(p_1, p_2) = \frac{1}{2}\big(|(u_1)^2 - (u_2)^2|$$

$$+|(v_1)^2 - (v_2)^2| + |(\pi_1)^2 - (\pi_2)^2|\big). \quad (12)$$

The objective weights of criteria can then be calculated by the following formula:

$$\omega_j' = \sum_{t=1}^{n} (1-R_{jt}) / \sum_{j=1}^{n} \left(\sum_{t=1}^{n} (1-R_{jt}) \right),$$

$$j = 1, 2,..., n. \quad (13)$$

Combining the objective ω_j' $(j = 1, 2,..., n)$ and subjective weights ω_j'' $(j = 1, 2,..., n)$, the final weights ω_j $(j = 1, 2,..., n)$ of criteria are through

$$\omega_j = \sqrt{\omega_j'\omega_j''} / \sum_{j=1}^{n} \sqrt{\omega_j'\omega_j''}. \quad (13)$$

5 Procedure of the Pythagorean fuzzy QFD method

Based on the above analysis, this section discusses the procedure of the Pythagorean fuzzy QFD method.

Suppose that experts $E = \{e_1, e_2,..., e_K\}$ are invited to evaluate m alternatives $A = \{A_1, A_2,..., A_m\}$ under n customer demands $C = \{C_1, C_2,..., C_n\}$. In the QFD matrix, the rows represent different alternatives to be evaluated, whereas the different columns denote multiple criteria. The subjective weights of all demands ω_j'' $(j = 1, 2,..., n)$ are provided by experts according to customers' opinions. The Pythagorean fuzzy QFD method includes the following steps:

Step 1. Each expert provides the evaluation information of alternatives under customer demands and then establishes the evaluation matrix $D^k = (p_{ji}^k)_{n\times m}$, where $p_{ji}^k = P(u_{ji}^k, \nu_{ji}^k)$ $(k = 1, 2,..., K)$.

Step 2. Based on Eq. (4), the integrated matrix $D^G = (p_{ji}^G)_{n\times m}$ is obtained.

Step 3. Calculate the similarity degree S_i^k $(i = 1, 2,..., m;\ k = 1, 2,..., K)$ between D^k and the integrated matrix D^G by Eq. (5). Next, compute the group similarity degree S_i^G of each alternative by Eq. (7) and the deviation S_i^{kG} of expert e_k for alternative A_i by Eq. (8).

Step 4. Set the threshold value σ of S_i^{kG}. If all deviations $S_i^{kG} \leqslant \sigma$ $(i = 1, 2,..., m;\ k = 1, 2,..., K)$ then the experts reached a consensus. Therefore, proceed to the next step. If $S_i^{kG} > \sigma$ $(i = 1, 2,..., m;\ k = 1, 2,..., K)$, then the expert e_k is asked to revise evaluations. Go back to Step 2.

Step 5. Based on Eq. (3), calculate the score value s_{ji} of each element of the integrated matrix $D^G = (p_{ji}^G)_{n\times m}$ and obtain the matrix D_s^G. Based on Eqs. (9) and (10), the best value p^{j+} and the worst value p^{j-} of each criterion can be obtained, respectively.

Step 6. By Eqs. (11) and (12), the correlation coefficient R_{jt} between different criteria C_j and C_t $(j, t = 1, 2,..., n)$ can be obtained.

Step 7. The objective weights of demands are obtained by Eq. (13), and the final weights ω_j are calculated by Eq. (14).

Step 8. All alternatives can be ranked by the values of $r_i = \sum_{j=1}^{n} s_{ji}\omega_j$ $(i = 1, 2,..., m)$.

6 Case study on the assembly robot design

In this section, we employ the proposed Pythagorean fuzzy QFD method to design the mechanical structure of an assembly robot. The weight of each part is calculated to determine paramount designing requirements when designing the robot based on the CRs.

An assembly robot is a kind of industrial robot, and it is the central equipment of a flexible automatic assembly system. As the industry is developing rapidly, the bottleneck of manufacturing emerges gradually. The appearance of the assembly robot can solve this problem well due to its high efficiency and accuracy. By utilizing assembly robots, heavy parts could be assembled easily, and dangerous tasks could be accomplished without undertaking the risks that workers originally bore. Assembly robots can also eliminate the influence of turnover and assemble products with high quality and consistency, which will enhance a company's competitive ability.

Assembly robots are currently applied massively in the automobile manufacturing industry. As the largest automobile manufacturing country, the demand for assembly robots in the automobile manufacturing industry in China is extremely high. Considering this situation and the demands of China's automobile and industrial robot industries, we focus on studying the assembly robot that assembles the windshield and investigate an automobile manufacturing factory. We use the proposed method to design the mechanical structure and determine the weight of each part.

The whole process of designing an assembly robot is highly complex. The process requires the calculation of the mechanical property of each part and the kinematical equations of the robot, as well as the design of the software of the control system. These details are technical, and their design is not the main purpose of this paper. This study limits its focus on the application of the Pythagorean fuzzy QFD in analyzing the design requirements of assembly robots.

Step 1. The first step of designing an assembly robot is to find the CRs. This step is important because the design of a robot is customer-oriented. In this case study, the customer is the automobile manufacturing factory. Requirements are determined by consulting the historical documents in the field of assembly robots, asking factory employees of the factory, and considering expert suggestions.

To simplify the calculation, we select the most important requirements and the corresponding designing requirements. The chosen CRs are high sustained working accuracy (C_1), relatively high intelligence level (C_2), relatively high sensing ability (C_3), high working speed (C_4), having some universality (C_5), and appropriate cost (C_6). The corresponding designing requirements are constituent mechanism (A_1), control system (A_2), driving system (A_3), transmission structure (A_4), sensing system (A_5), programming mode (A_6), and modular design (A_7). To derive the subjective weights ω''_{ij} of these requirements and the evaluation information, we design a questionnaire and deliver it to factory experts. The questionnaire mainly consists of the criteria $\{C_1, C_2,..., C_6\}$ and alternatives $\{A_1, A_2,..., A_7\}$ discussed above. Based on the PFSs and real numbers, experts can evaluate each alternative with respect to each criterion and the subjective weights ω''_{ij}.

Three experts $E = \{e_1, e_2, e_3\}$ are invited to evaluate, and three evaluated matrices are obtained, as shown in Tables 1–3.

Step 2. Based on Eq. (4), the integrated matrix $D^G = (p^G_{ji})_{6\times 7}$ is obtained and shown in Table 4.

Step 3. Calculate the similarity degree S^k_i ($i = 1, 2, ..., 7$; $k = 1, 2, 3$) between D^k and integrated matrix D^G, and the deviation S^{kG}_i of expert e_k for function A_i. The results are shown in Table 5.

Step 4. Set the threshold value $\sigma = 0.1$. All deviations are clearly smaller than the threshold value. Therefore, it is not necessary to change the evaluations.

Step 5. Calculate the score value s_{ji} of each element of the integrated matrix $D^G = (p^G_{ji})_{n\times m}$ and obtain the matrix D^G_s, as shown in Table 6.

We can find the best and worst values of all demands. For instance, $p^{1+} = \max_i\{s_{1i}\} = 0.626$.

Step 6. Calculate the correlation coefficients between each pair of different demands. Results are shown in Table 7.

Step 7. Based on Eqs. (11) and (12), the objective and

Table 1 Evaluation matrix of expert e_1

ω''_j		A_1	A_2	A_3	A_4	A_5	A_6	A_7
0.15	C_1	P(0.8,0.3)	P(0.8,0.3)	P(0.7,0.2)	P(0.8,0.2)	P(1,0)	P(0.8,0.5)	P(0.5,0.8)
0.2	C_2	P(0,1)	P(1,0)	P(0,1)	P(0,1)	P(0.8,0.1)	P(0.9,0.3)	P(0.2,0.9)
0.2	C_3	P(0,1)	P(0.9,0.2)	P(0,1)	P(0,1)	P(1,0)	P(0.1,0.8)	P(0.2,0.9)
0.14	C_4	P(0.7,0.2)	P(0.6,0.2)	P(0.9,0.2)	P(0.9,0.1)	P(0.2,0.7)	P(0,1)	P(0.2,0.6)
0.16	C_5	P(0.4,0.6)	P(0.7,0.6)	P(0.5,0.5)	P(0,1)	P(0.8,0.4)	P(0.6,0.6)	P(1,0)
0.15	C_6	P(0.6,0.4)	P(0.7,0.4)	P(0.7,0.3)	P(0.7,0.2)	P(0.9,0.3)	P(0.7,0.4)	P(1,0)

Table 2 Evaluation matrix of expert e_2

ω''_j		A_1	A_2	A_3	A_4	A_5	A_6	A_7
0.15	C_1	P(0.7,0.2)	P(0.9,0.3)	P(0.7,0.1)	P(0.9,0.1)	P(0.8,0.2)	P(0.6,0.5)	P(0.6,0.7)
0.2	C_2	P(0,1)	P(1,0)	P(0,1)	P(0,1)	P(1,0)	P(0.8,0.3)	P(0,1)
0.2	C_3	P(0,1)	P(0.7,0.2)	P(0,1)	P(0,1)	P(1,0)	P(0.1,0.8)	P(0.1,0.9)
0.14	C_4	P(0.9,0.2)	P(0.5,0.3)	P(1,0)	P(1,0)	P(0.2,0.7)	P(0,1)	P(0.2,0.8)
0.16	C_5	P(0.6,0.5)	P(0.4,0.6)	P(0.4,0.6)	P(0.2,0.8)	P(0.7,0.4)	P(0.6,0.6)	P(1,0)
0.15	C_6	P(0.5,0.6)	P(0.8,0.4)	P(0.8,0.3)	P(0.6,0.3)	P(0.9,0.2)	P(0.8,0.5)	P(0.9,0.1)

Table 3 Evaluation matrix of expert e_3

ω''_j		A_1	A_2	A_3	A_4	A_5	A_6	A_7
0.15	C_1	P(0.9,0.2)	P(0.8,0.2)	P(0.8,0.3)	P(0.9,0.2)	P(0.9,0.2)	P(0.6,0.6)	P(0.4,0.7)
0.2	C_2	P(0,1)	P(1,0)	P(0,1)	P(0,1)	P(0.9,0.1)	P(0.8,0.2)	P(0.1,0.9)
0.2	C_3	P(0,1)	P(0.8,0.4)	P(0,1)	P(0,1)	P(1,0)	P(0.2,0.9)	P(0.3,0.9)
0.14	C_4	P(0.8,0.3)	P(0.6,0.3)	P(0.9,0.1)	P(1,0)	P(0.2,0.9)	P(0,1)	P(0.4,0.7)
0.16	C_5	P(0.6,0.3)	P(0.6,0.4)	P(0.5,0.6)	P(0.1,0.8)	P(0.6,0.3)	P(0.4,0.7)	P(1,0)
0.15	C_6	P(0.5,0.4)	P(0.8,0.2)	P(0.8,0.2)	P(0.7,0.3)	P(0.8,0.2)	P(0.8,0.3)	P(0.9,0.2)

Table 4 Integrated matrix

ω_j''		A_1	A_2	A_3	A_4	A_5	A_6	A_7
0.15	C_1	P(0.80,0.23)	P(0.83,0.27)	P(0.73,0.20)	P(0.87,0.17)	P(0.90,0.13)	P(0.67,0.53)	P(0.50,0.73)
0.2	C_2	P(0.00,1.00)	P(1.00,0.00)	P(0.00,1.00)	P(0.00,1.00)	P(0.90,0.07)	P(0.83,0.27)	P(0.10,0.93)
0.2	C_3	P(0.00,1.00)	P(0.80,0.27)	P(0.00,1.00)	P(0.00,1.00)	P(1.00,0.00)	P(0.13,0.83)	P(0.20,0.90)
0.14	C_4	P(0.80,0.23)	P(0.57,0.27)	P(0.93,0.1)	P(0.97,0.03)	P(0.20,0.77)	P(0.00,1.00)	P(0.27,0.70)
0.16	C_5	P(0.53,0.47)	P(0.57,0.53)	P(0.47,0.57)	P(0.10,0.87)	P(0.70,0.37)	P(0.57,0.63)	P(1.00,0.00)
0.15	C_6	P(0.53,0.47)	P(0.77,0.33)	P(0.77,0.27)	P(0.67,0.27)	P(0.87,0.23)	P(0.77,0.40)	P(0.93,0.10)

Table 5 Similarity degrees and deviations of experts

		A_1	A_2	A_3	A_4	A_5	A_6	A_7
Similarity degree	e_1	0.8074	0.8280	0.8757	0.9134	0.8701	0.7966	0.8930
	e_2	0.7990	0.7961	0.8968	0.9254	0.8991	0.7979	0.8643
	e_3	0.8400	0.8321	0.9023	0.9419	0.9011	0.7930	0.8796
Deviation	e_1	0.0081	0.0093	0.0159	0.0135	0.0200	0.0008	0.0140
	e_2	0.0164	0.0226	0.0052	0.0015	0.0090	0.0021	0.0147
	e_3	0.0245	0.0133	0.0107	0.0150	0.0110	0.0029	0.0007

Table 6 Score values of all elements of the integrated matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.294	0.405	0.086	0.511	0.626	−0.102	−0.516
C_2	−1.000	1.000	−1.000	−1.000	0.622	0.405	−0.984
C_3	−1.000	0.296	−1.000	−1.000	1.000	−0.971	−0.932
C_4	0.294	−0.348	0.746	0.869	−0.931	−1.000	−0.871
C_5	−0.427	−0.356	−0.571	−0.984	−0.004	−0.438	1.000
C_6	−0.427	0.194	0.191	−0.098	0.517	0.195	0.746

Table 7 Correlation coefficients between each pair of different demands

	C_1	C_2	C_3	C_4	C_5	C_6
C_1	1	0.338	0.569	0.343	–0.646	0.442
C_2		1	0.693	–0.562	–0.012	–0.234
C_3			1	–0.430	0.142	–0.373
C_4				1	–0.637	0.635
C_5					1	–0.772
C_6						1

final weights of demands are obtained, $\omega' = (0.128, 0.154, 0.142, 0.182, 0.223, 0.171)^{\mathrm{T}}$ and $\omega_j = (0.139, 0.177, 0.170, 0.161, 0.191, 0.162)^{\mathrm{T}}$, respectively.

Step 8. We can finally calculate the weighed score of each design requirement and obtain $r = (-0.409, 0.191, -0.293, -0.339, 0.300, -0.321, -0.234)$. Thus, the ranking is

$$A_5 \succ A_2 \succ A_7 \succ A_3 \succ A_6 \succ A_4 \succ A_1.$$

Comparative analysis: Based on the above calculation process and a comparison with other methods, we can determine that the proposed method mainly involves three advantages.

First, the score function defined in this paper can overcome the shortcoming of the existing method (Zhang and Xu, 2014) by considering the weights of both membership and non-membership.

Second, the correlation coefficients of the criteria are introduced to determine the objective weights of the criteria. This process is more reasonable than that of the weight determining methods based on distance and similarity measures because the correlation coefficient can reflect the relationships between two criteria from positive and negative angles.

Third, this paper calculates the final weights of the criteria by combining the objective and subjective weights, which will not lose any useful information.

7 Conclusions

The proposed Pythagorean fuzzy QFD method effectively evaluates different assembly robot designs. The score of each design requirement indicates that we should pay increased attention to the design of the control system. This result is reasonable because the current equipment in automobile manufacturing factories should be intelligible and should be able to flexibly handle different situations. Assembly accuracy, which can be improved by good sensing and control systems, is also important. In the following design of assembly robots, it is worthwhile to carefully consider how to meet the customers' demands better, such as using the composite control system, setting a force sensor in every joint, and applying optic vision sensors. Computer programs can also simplify calculations and obtain results effectively. The proposed method can help analyze the product with increased precision, and this method also has some room for improvement. For example, when applying this method in the multistep QFD analysis, the final scores of the advanced chart should be converted into positive weights of the criteria in the next chart.

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