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On Assembly Robotic Design Evaluation Problem Using Enhanced Quality Function Deployment with *q*-Rung Orthopair Fuzzy Set Theoretic Environment

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In view of the developing model of economic globalization, robots have been given a considerable amount of attention by various manufacturing companies. These companies are facing a significant challenge due to handling uncertain events and meeting customers' requirements. The notion of quality function deployment (QFD) strongly supports the companies in analyzing the customer's requirements and in improving the quality of products concerning customer's requirements. To improve the effectiveness and applicability of QFD, we propose *q*-rung orthopair oriented and revised QFD. The proposed methodology first obtains the group decision-making evaluation matrix and then utilizes the hybrid weight decider method for merging the prior weights with the objective weights obtained from the evaluation matrix. To find the accurate score of each *q*-rung orthopair fuzzy set (*q*-ROFS), we devise a modified score function. Based on the modified score function, the robotic machine assembly design evaluation problem has been technologically dealt with and analyzed with a proper methodology.

Keywords: quality function deployment, *q*-rung orthopair fuzzy set, group decision-making, hybrid weight, assembly robot design evaluation and selection

1. INTRODUCTION

In recent decades, robot design selection problems have gained significant popularity because of their application controlled by different types of manufacturing industries. The problem of appropriate selection of robots becomes more challenging and complex due to multiple interrelated criteria and decision-maker's linguistic opinions and inherited ambiguity in their thinking process. In literature, various precision-oriented methods for the selection of robots have been proposed [1-7]. It may be noted that these methods are based on the idea of accurate measurement and crisp evaluation. However, many subjective attributes such as man-machine interface, training, programming flexibility, *etc.* are not precise assignments by the decision-makers.

In comparison with humans, industrial robots can accomplish repetitious, rough/tough, and dangerous tasks with precision. This eventually brings improvement in product quality and a rise in production efficiency. For the sake of an increase in the production of manufacturing companies, the enhancement and improvement of product quality play a crucial role for which the robot design and selection are of utmost importance. The application of robots in technological development is increasing rapidly and very much diversified.

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Therefore, it becomes essential for the robots to have independent/autonomous mobility and decision-making capacity along with behavioral sensory awareness of the neighboring around for accomplishing the task in any complex situation. Accordingly, it becomes difficult for manufacturing companies to satisfy customer requirements & launches new products which maximally match customer satisfaction [8].

Yoji Akao and Shigeru Mizuno, in the year 1960, proposed the notion of quality function deployment (QFD) which effectively helped the companies to understand customer requirements and eventually enabled them to deal with customer complaints [9] based on the quality problems. With the development of QFD, manufacturing companies couldbe able to modify the products/services based on CRs. In recent years, the hybrid incorporation of QFD with various other existing theories has tremendously helped the decisionmakers to take precise decisions in many application fields related to product development [10] in manufacturing companies. Also, the European energy system investment policy has been mathematically dealt with the help of the improved QFD method proposed by Dincer *et al.* [11]. In literature, it has been observed that quality function deployment (QFD) [12, 13] is a customer-friendly technique that involves the decision-making structure with the diversification in the opinions for sake of launching a novel product or its improved version to match the customer satisfaction [9] at a higher level. Such a technique is specifically best for the industries to adopt for the better design of the products. In a conventional QFD method, design requirements and customer requirements go under evaluation individually along with their possible outcomes which can be represented with the help of precise values and this fails to address imprecise/inexact information. To overcome this limitation, Khoo and Ho [14] and Chan *et al.* [15] incorporated the concept of fuzziness in the conventional QFD methods.

Various fuzziness-oriented QFD methods have been suitably integrated into the evaluation process by experts and transformed into complete assessments [8]. Given the different decision-maker's opinions and the methodology proposed by Zhang *et al.* [16], the notion of the Pythagorean fuzzy set (PyFS), a generalized version of the intuitionistic fuzzy set has been successfully applied by Liao *et al.* [17], where the combination of PyFS and QFD has been proposed. Also, in the field of robot selection decision-making problems, Zhuo *et al.* [18] studied a different type of mobile robot selection problem as a VIKOR-MCDM in the healthcare pharmacy sector as utilized the fuzzy ranking technique based on the degree of possibility and minimized fuzzy comprehensive utility value. Rashid *et al.* [19] applied the TOPSIS method with generalized interval-valued trapezoidal fuzzy numbers in robot evaluation criteria for given alternatives under the varying opinions of experts.

In real-world problems, there are many occurrences when the decision-makers have strong opinions in the context of providing grades in government administration megaprojects. For example, if the board of administration gives the project a high-end rating, say, the agreement membership degree $\mu = 0.8$, while people on contrary may have opposite opinions and assign the same effort as a wastage of money and say, they give the disagreement membership degree $\nu = 0.7$. In such cases, $\mu + \nu > 1$ and also $\mu^2 + \nu^2 > 1$, but $\mu^q + \nu^q < 1$ for $q \geq 2$, so that (μ, ν) is neither intuitionistic [22] and nor Pythagorean [2], but it comes to the category of q-rung orthopair fuzzy number (q-ROFN) [3] which are found to be more efficient to handle such kind of conflicting uncertainty. It may be noted that the Pythagorean fuzzy set (PyFS) was a kind of generalized form of the intuitionistic fuzzy set

(IFS) to consider the membership and non-membership pair based on the special condition. Various authors utilized the flexibility of q-rung orthopair fuzzy sets in many different application areas of soft computing, information measures, knowledge discovery, aggregation operators, *etc.*

In the present work, we propose the extended version of the quality function deployment method by incorporating the notion of q-ROFS for solving the decision-making structure and obtaining a revised hybrid score function. It can be well understood that this novel approach would be well capable to span a wide range of computational values and that these will be more appropriate than IFSs and PyFS in the process of formulating the vagueness in real-world problems. Thus, it is valuable for the research community to obtain higher precision. It has also been observed that to get the weights of the CRs and the final score value to be precise, we compute the combined/hybrid weights by the methodology developed by Wu *et al.* [20]. This methodology put forward to take the objective weights into account obtained by the correlation coefficients which somewhat handles the bias caused due to highly correlated criteria [20]. To accomplish the desired task, we propose a newly revised score function that can eliminate the drawback and limitations of the score function presented by Zhang and Xu [21].

The organization of the present manuscript is as follows: Section 2 presents the basic preliminaries related to the mathematical technique based on q-ROFSs with classifying definitions required for the evaluation purpose. In Section 3, the group decision-making method has been discussed in light of q-rung orthopair fuzzy sets. Further, in Section 4, the hybrid weights decider method has been explained and proposed. In Section 5, the q-ROFS quality function deployment method has been presented in detail along with the procedural steps. Also, the problem of assembly robot design evaluation problem has been solved with an illustrative example. The comparative remarks and advantages have been listed in Section 6 for understanding the novelty of the proposed method. Finally, the paper has been concluded in Section 7 with the possible scope of future work.

2. PRELIMINARIES

In this section, we are presenting the basic notions and definitions of various other fundamental sets which are available in the literature. These preliminaries would help to understand the proposed methodology based on the q-rung orthopair fuzzy sets:

Definition 1 Intuitionistic Fuzzy Set (IFS) [22]: An intuitionistic fuzzy set R in V is given by $R = \{v, \rho_R(v), \omega_R(v) | v \varepsilon V\}$; where $\rho_R : V \rightarrow [0, 1]$ is the degree of membership of v in R and $\omega_R : V \rightarrow [0, 1]$ is the degree of non-membership of v in R and ρ_R, ω_R satisfies the constraint $0 \leq \rho_R(v) + \omega_R(v) \leq 1$ $(\forall v \in V)$; and $\sqsupset_R(v) = 1 - (\rho_R(v) + \omega_R(v))$ is called the degree of indeterminacy v in R.

Definition 2 Picture Fuzzy Set (PFS) [23]: A picture fuzzy set R in V is given by $R = \{v, \rho_R(v), \tau_R(v), \omega_R(v) | v \varepsilon V\}$; where $\rho_R : V \rightarrow [0, 1]$ is the degree of membership of v in R and $\tau_R : V \rightarrow [0, 1]$ is the degree of non-membership of v in R and ρ_R, τ_R, ω_R satisfies the constraint $0 \leq \rho_R(v) + \omega_R(v) \leq 1$ $(\forall v \in V)$; and $\sqsupset_R(v) = 1 - (\rho_R(v) + \tau_R(v) + \omega_R(v))$ is called the degree of indeterminacy v in R.

Definition 3 Pythagorean Fuzzy Set (PyFS) [2]: A picture fuzzy set R in V is given by $R = \{v, \rho_R(v), \omega_R(v) | v \ \varepsilon \ V\}$; where $\rho_R : V \rightarrow [0, 1]$ is the degree of membership of v in R and $\omega_R : V \rightarrow [0, 1]$ is the degree of non-membership of v in R and ρ_R, ω_R satisfies the constraint $0 \le \rho_R^2(v) + \omega_R^2(v) \le 1$ $(\forall v \in V)$; and $\daleth_R(v) = \sqrt{(1-(\rho_R^2(v)+\omega_R^2(v)))}$ is called the degree of indeterminacy v in R.

Definition 4 (q-Rung Orthopair Fuzzy Set) [3]: A picture fuzzy set R in V is given by $R = \{v, \rho_R(v), \omega_R(v) | v \ \varepsilon \ V\}$; where $\rho_R : V \rightarrow [0, 1]$ is the degree of membership of v in R and $\omega_R : V \rightarrow [0, 1]$ is the degree of non-membership of v in R and ω_R satisfies the constraint $0 \le \rho_R^2(v) + \omega_R^2(v) \le 1$ $(\forall v \in V)$; and, $\daleth_R|(v) = \sqrt{(1-(\rho_R^2(v)+\omega_R^2(v)))}$ is called the degree of indeterminacy v in R.

For the purpose of calculations, we define q-rung orthopair fuzzy number (q-ROFN), denoted by $\xi = (\rho_\xi, \omega_\xi)$, where ρ_ξ, $\omega_\xi \in [0, 1]$, and $\daleth_\xi = |\sqrt[q]{1-(\rho_\xi^q+\omega_\xi^q)}$ and $0 \le \rho_\xi^q + \omega_\xi^q \le 1$. On the basis of another representation of PyFS, given by Yager and Abbasov, we can represent q-ROFS in another form defined by $\xi = (r_\xi, d_\xi)$, r_ξ is the strength of ξ and d_ξ is the direction of strength of ξ. The parameters r_ξ and d_ξ are directly associated with ρ_ξ and ω_ξ. Further, r_ξ is inversely proportional to the uncertainty, *i.e.*, if the value of r_ξ is large, there is a large amount of commitment which results in a small amount of uncertainty. The value of d_ξ gives the extent that how strongly r_ξ is heading towards the membership and the value of d_ξ ranging between 0 and 1. The following two cases arise:

Case I: if $d_\xi = 1$, it means that r_ξ is heading towards the membership completely.
Case JI: if $d_\xi = 0$, it means that r_ξ is heading towards the non-membership completely.

Further, for the conversion of $\xi = (\rho_\xi, \omega_\xi)$ and $\xi = (r_\xi, d_\xi)$ into each other by making use of transformation $\rho_\xi = r_\xi(\cos\theta_\xi)$, $\omega_\xi = r_\xi(\sin\theta_\xi)$ and $d_\xi = 1 - 2\theta_\xi/\pi$.

Definition 5 [24]: Let $\xi = (\rho_\xi, \omega_\xi)$, $\xi_1 = (\rho_{\xi_1}, \omega_{\xi_1})$ and $\xi_2 = (\rho_{\xi_2}, \omega_{\xi_2})$ be three q-ROFNs. Then, we have

- $\xi^c = (\omega_\xi, \rho_\xi)$
- $\xi_1 \cup \xi_2 = (\max(\rho_{\xi_1}, \rho_{\xi_2}), \min(\omega_{\xi_1}, \omega_{\xi_2}))$
- $\xi_1 \cap \xi_2 = (\min(\rho_{\xi_1}, \rho_{\xi_2}), \max(\omega_{\xi_1}, \omega_{\xi_2}))$
- $\xi_1 \otimes \xi_2 = (\rho_{\xi_1} \cdot \rho_{\xi_2}, \sqrt[q]{(\omega_{\xi_1})^q + (\omega_{\xi_2})^q - (\omega_{\xi_1})^q \cdot (\omega_{\xi_2})^q}),$
- $\xi_1 \oplus \xi_2 = (\sqrt[q]{(\rho_{\xi_1})^q + (\rho_{\xi_2})^q - (\rho_{\xi_1})^q \cdot (\rho_{xi_2})^q}, \omega_{\xi_1} \cdot \omega_{\xi_2}),$
- $\xi^\alpha = (\rho_\xi^\alpha, \sqrt[q]{(1-(1-\omega_\xi)^\alpha)}),$
- $\alpha\xi = (\sqrt[q]{(1-(1-\rho_\xi)^\alpha)}, \omega_\xi^\alpha).$

Definition 6 [24]: Let $\xi_1 = (\rho_{\xi_1}, \omega_{\xi_1})$ and $\xi_2 = (\rho_{\xi_2}, \omega_{\xi_2})$ be two q-ROFNs. Then
- if $\rho_{\xi_1} \ge \rho_{\xi_2}$ and $\omega_{\xi_1} < \omega_{\xi_2}$, then $\xi_1 > \xi_2$,
- if $\rho_{\xi_1} < \rho_{\xi_2}$ and $\omega_{\xi_1} \ge \omega_{\xi_2}$, then $\xi_1 < \xi_2$.

Definition 7 [24]: If ξ be a q-rung orthopair fuzzy number then the score function is given by $\mathbb{S}(\xi) = (\rho)^q - (\omega)^q$, where $q \in [1, \infty)$, $-1 \le \mathbb{S}(\xi) \le 1$; and the accuracy function is given by

$$\mathbb{A}(\xi) = (\rho)^q + (\omega)^q.$$

3. GROUP DECISION-MAKING METHOD WITH *Q*-ROFSS

In the past few years, various methods have been designed for the evaluation of experts' decisions in different types of decision-making problems under the environment of fuzzy information. Quality function deployment (QFD) is a cross-functional planning tool which works on translating the customers requirement/satisfaction into product design systematically [25, 26]. In particular, QFD converts customer requirements into engineering characteristics where inherited uncertainty gives a new variability in the outcomes. The incorporation of q-rung orthopair fuzzy sets gives the additional coverage to encounter the uncertainty mathematically. In this section, we first present a group decision-making framework for proposing the revised QFD methodology by utilizing the q-rung orthopair fuzzy sets and then outline the decisive steps to accomplish the defined task.

Let $B = \{B_1, B_2, ..., B_m\}$ be a set of alternatives, $D = \{D_1, D_2, ..., D_n\}$ be a set of criteria and $E = \{E_1, E_2, ..., E_k\}$ be a set of experts. Now, all the calculations carried out for each expert are given in the form of calculation matrices denoted by $C^k = (c_{ji}^k)_{n\times m}$, where $c_{ji}^k = (\rho_{ji}^k, \omega_{ji}^k)(j = 1, 2, ..., n;\ i = 1, 2, ..., m;\ k = 1, 2, ..., K)$. In this Method, after assessing the alternatives and criteria's. There is aggregation of all calculation matrices of experts, which results in combined matrix of the form $C^G = (c_{ji}^G)_{n\times m}$, where

$$c_{ji}^G = (\rho_{ji}^G, \omega_{ji}^G) = \left(\frac{1}{K}\sum_{k=1}^{K} \rho_{ji}^k, \frac{1}{K}\sum_{k=1}^{K} \omega_{ji}^k \right). \tag{3.1}$$

For every calculation value associated to each expert E_k, the distance between C^k and C^G is given by

$$C(\xi_1, \xi_2) = \tfrac{1}{5}(|\rho_{\xi_1} - \rho_{\xi_2}| + |\omega_{\xi_1} - \omega_{\xi_2}| + |\sqsupset_{\xi_1} - \sqsupset_{\xi_2}| + |r_{\xi_1} - r_{\xi_2}| + |d_{\xi_1} - d_{\xi_2}|).$$

Also, for every calculation value associated with each expert E_k, the degree of similarity between C^k and C^G is given by

$$S_{ji}^k = \begin{cases} 1; & \text{if } c_{ji}^k = c_{ji}^G = c_{ji}^{G_c}, \\ \dfrac{C(c_{ji}^k, c_{ji}^{G_c})}{C(c_{ji}^k, c_{ji}^G) + C(c_{ji}^k, c_{ji}^{G_c})}; & \text{otherwise.} \end{cases} \tag{3.2}$$

Similarly, the similarity degree for every alternative D_i corresponding to each expert E_k is given by $S_i^k = \sum_{i=1}^{n} v_j S_{ji}^k$. On the similar lines, the similarity degree of each alternative with respect to the combined matrix is given by

$$S_i^G = \frac{1}{K}\sum_{k=1}^{K} S_{ji}^k. \tag{3.3}$$

Now, between S_i^k and S_i^G the deviation in the two similarity degrees for each alternative D_i

with respect to the expert E_k is given by

$$S_i^k G = |S_i^k - S_i^G|. \tag{3.4}$$

Moreover, if κ is the threshold of $S_i^k G$. Then, if $S_i^k G \le \kappa$ the stage of taking the decision is reached, and if $S_i^k G > \kappa$, then calculations should be revised again.

4. HYBRID WEIGHTS DECIDER METHOD

To obtain the best suitable value of the criterion, the degree of variation under the same criterion must be high. For the comprehensive evaluation purpose, the role of the criterion is very important, and hence large objective weight should be assigned to the criterion. On the contrary, if the degree of variation under the criterion is small then the small objective weight should be assigned to the criterion. This assignment of weights would be very useful, which avoids deceptive results and prevents information loss. In this section, there is a calculation of the correlation coefficients with the combination of objective and subjective weights.

For the calculation of weighted correlation coefficients associated with the criteria, the distance between q-ROFSs should be evaluated. Further, for the cost and benefit type criteria, the best and the worst values of each criterion may be given by

$$c^{j+} = \begin{cases} \max_i \{c_{ji}\}; \text{ for benefit criterion,} \\ \max_i \{c_{ji}\}; \text{ for cost criterion.} \end{cases} \tag{4.1}$$

$$c^{j-} = \begin{cases} \max_i \{c_{ji}\}; \text{ for benefit criterion,} \\ \max_i \{c_{ji}\}; \text{ for cost criterion.} \end{cases} \tag{4.2}$$

Now, to find the objective weights, the correlation coefficients Y_{jt} between the criteria D_j and $D_t(j, t = 1, 2, ..., n)$ is given by

$$Y_{jt} = \frac{\sum_{i=1}^{m}((\frac{y_{ji}}{y_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{y_{ji}}{y_j}) \times (\frac{y_{ji}}{y_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{y_{ji}}{y_j}))}{\sqrt{\sum_{i=1}^{m}(\frac{y_{ji}}{y_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{y_{ji}}{y_j})^2} \times \sqrt{\sum_{i=1}^{m}(\frac{y_{ji}}{y_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{y_{ji}}{y_j})^2}}, \tag{4.3}$$

where $y_{ji} = y(c_{ji}, c^{j+})$ is the distance between c_{ji} and c^{j+}, and $y_j = y(c^{j-}, c^{j+})$ is the distance between c^{j-} and c^{j+}.

The distance between two q-ROFNs $c_1 = (\rho_1, \omega_1)$ and $c_1 = (\rho_1, \omega_1)$ is given by

$$d(c_1, c_2) = ½(|(\rho_1)^q - (\rho_2)^q| + |(\omega_1)^q - (\omega_2)^q| + |(\square_1)^q - (\square_2)^q|). \tag{4.4}$$

By combining the $v'(j = 1, 2, ..., n)$ (objective weights) and $v''_j(j = 1, 2, ..., n)$ (subjective weights), the final weights v_j is given by

$$v'_j = \sum_{t=1}^{n} \frac{(1 - Y_{jt})}{\sum_{j=1}^{n}(\sum_{t=1}^{n}(1 - Y_{jt}))}. \tag{4.6}$$

Now, the objective weights of criteria can be given by

$$v_j = \frac{\sqrt{v'_j v''_j}}{\sum_{j=1}^{n} \sqrt{v'_j v''_j}}. \tag{4.5}$$

5. ASSEMBLY ROBOT DESIGN EVALUATION PROCEDURE BASED ON *Q*-ROFS QFD METHOD

In this section, we first discuss and propose all the procedural steps ofthe q-ROFS QFD method for the assembly robot design evaluation problem. Suppose there are m alternatives $B = \{B_1, B_2, ..., B_m\}$ under the n criterion, say, $D = \{D_1, D_2, ..., D_n\}$ which are to be evaluated by a set of k experts $E = \{E_1, E_2, ..., E_K\}$. In the matrix of QFD, the columns represent the multiple criteria and the rows denote the different alternatives. The expert's weights or the weights provided by experts (subjective weights) are denoted by v''_j according to the different criteria. The algorithm of the q-ROFS involves the following steps:

Step 1: The information provided by every expert regarding alternatives by keeping in mind the different criteria and then formulate the calculation matrix $C^k = [c^k_{ji}]_{n\times m}$, where $c^k_{ji} = (\rho^k_{ji}, \omega^k_{ji})(j = 1, 2, ..., n; i = 1, 2, ..., m; k = 1, 2, ..., K)$.
Step 2: By making use of Eq. (3.1), we get the combined matrix $C^G = (c^G_{ji})_{n\times m}$.
Step 3: In the next step, evaluate the degree of similarity $S^k(i = 1, 2, ..., m; k = 1, 2, ..., K)$ between C^k and C^G by Eq. (3.2). Further, calculate the degree of similarity S^G with respect to each alternative by Eq. (3.3) and the deviations between S^k_i and S^G_i, *i.e.*, S^k_iG of every expert with respect to alternative B_i by Eq. (3.4).
Step 4: In this step, we have to fix the threshold value κ of S^{kG}_i. Now, at this stage, there will be two cases which are as follows:
Case I – If $S^{kG}_i \le \kappa$, then the decision-maker will reach a stage of consensus.
Case II – If $S^{kG}_i > \kappa$, then the decision-maker has to revise the computations and has go back to Step 2.
Step 5: By making use of the score function formula, compute the score value $\mathbb{S}_{ji}$ of every element of the combined matrix $C^G = (c^G_{ji})_{n\times m}$ and we get the matrix C^G_s. Further, c^{j+} and c^{j-} of every criterion can be calculated.
Step 6: Now, making use of Eqs. (4.3) and (4.4), the correlation coefficients Y_{jt} between the criteria D_j and $D_t(j, t = 1, 2,..., n)$ can be obtained.
Step 7: In the next step, with the help of Eq. (4.5) the objective weights, are obtained and from Eq. (4.6) the final weights are obtained.
Step 8: In the final step, the ranking of the available alternatives can be done by using $R_i = \sum_{j=1}^{n} \mathbb{S}_{ji} v_j (i = 1, 2, ..., m)$.

For the sake of better understanding and readability, we present the methodology to solve the decision-making problem under consideration in Fig. 1. To well understand the implementation of the proposed methodology, we choose some important requirements and the corresponding requirements of designing based on available literature in this application area. Suppose that the selected customer requirements are

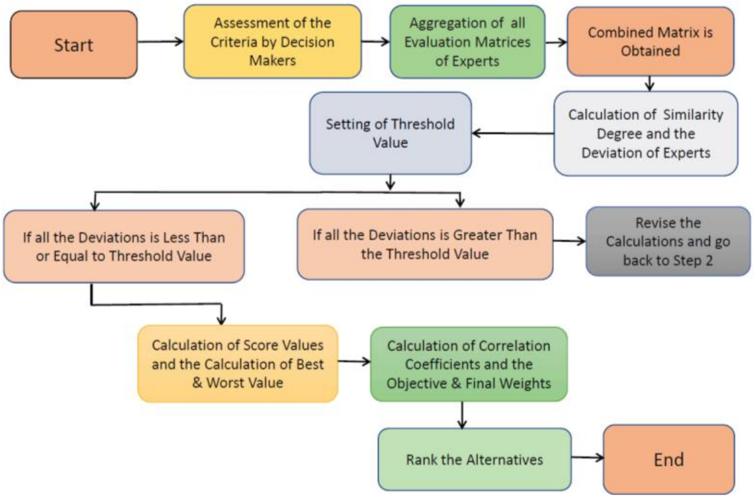

Fig. 1. Procedural steps of q-ROFS quality function deployment.

- Long Term Execution Precision (B_1),
- Fairly Adequate Intellectual Level (B_2),
- Fairly Adequate Recognizing Feature (B_3),
- Fairly fast Speed (B_4),
- Having Adequate Comprehensiveness (B_5),
- Suitable & Right Cost (B_6).

Further, suppose that the corresponding designing requirements are listed as follows:
- Fundamental Technique/Tool (D_1),
- Structure of Controlling Mechanism (D_2),
- Automated Driving System (D_3),
- Simulated Transmission Feature (D_4),
- Sensor System (D_5),
- Robot Programming Feature (D_6),
- Modular Architecture of Robot (D_7).

For the derivation of the subjective weights v_j'' of the designing requirements and for the calculation of the information, situation is evaluated by the set of three experts $E = \{E_1, E_2, E_3\}$. The situation consists of alternatives $B = \{B_1, B_2, ..., B_6\}$ under the criterion $D = \{D_1, D_2, ..., D_7\}$ as discussed above. Now, based on q-ROFSs, there is an evaluation of each alternative under every criterion followed by the subjective weights v_j''. We consider hypothetical example data for the sake of carrying out the necessary calculation. The procedural steps have been computed step-wise as follows:

Step 1: Further, the three experts $E = \{E_1, E_2, E_3\}$ are assigned for evaluation, and the resultant matrices given by the three experts have been tabulated as follows (Tables 1-3):
Step 2: Using Eq. (3.1), we get the combined matrix $C^G = (c_{ji}^G)_{6\times 7}$ as shown in Table 4.
Step 3: In the next step, evaluate the degree of similarity $S_i^k (i = 1, 2, ..., 7; k = 1, 2, 3)$

between C^k and C^G by Eq. (3.2). Further, calculate the degree of similarity S_i^G with respect to each alternative by Eq. (3.3) and the deviations between S^k and S^G, *i.e.*, S^kG of every expert with respect to alternative B_i by Eq. (3.4) as shown in Table 5.

Table 1. Matrix of evaluation values by expert E_1.

		D_1	D_2	D_3	D_4	D_5	D_6	D_7
0.14	B_1	(0.7, 0.2)	(0.6, 0.2)	(0.9, 0.2)	(0.9, 0.1)	(0.2, 0.7)	(0, 1)	(0.2, 0.6)
0.16	B_2	(0.4, 0.6)	(0.7, 0.6)	(0.5, 0.5)	(0, 1)	(0.8, 0.4)	(0.6, 0.6)	(1, 0)
0.2	B_3	(0, 1)	(1, 0)	(0, 1)	(0, 1)	(0.8, 0.1)	(0.9, 0.3)	(0.2, 0.9)
0.15	B_4	(0.6, 0.4)	(0.7, 0.4)	(0.7, 0.3)	(0.7, 0.2)	(0.9, 0.3)	(0.7, 0.4)	(1, 0)
0.2	B_5	(0, 1)	(0.9, 0.2)	(0, 1)	(0, 1)	(1, 0)	(0.1, 0.8)	(0.2, 0.9)
0.15	B_6	(0.8, 0.3)	(0.8, 0.3)	(0.7, 0.2)	(0.8, 0.2)	(1, 0)	(0.8, 0.5)	(0.5, 0.8)

Table 2. Matrix of evaluation by expert E_2

		D_1	D_2	D_3	D_4	D_5	D_6	D_7
0.14	B_1	(0.9, 0.2)	(0.5, 0.3)	(1, 0)	(1, 0)	(0.2, 0.7)	(0, 1)	(0.2, 0.8)
0.16	B_2	(0.6, 0.5)	(0.4, 0.6)	(0.4, 0.6)	(0.2, 0.8)	(0.7, 0.4)	(0.6, 0.6)	(1, 0)
0.2	B_3	(0, 1)	(1, 0)	(0, 1)	(0, 1)	(1, 0)	(0.8, 0.3)	(0, 1)
0.15	B_4	(0.5, 0.6)	(0.8, 0.4)	(0.8, 0.3)	(0.6, 0.3)	(0.9, 0.2)	(0.8, 0.5)	(0.9, 0.1)
0.2	B_5	(0, 1)	(0.7, 0.2)	(0, 1)	(0, 1)	(1, 0)	(0.1, 0.8)	(0.1, 0.9)
0.15	B_6	(0.7, 0.2)	(0.9, 0.3)	(0.7, 0.1)	(0.9, 0.1)	(0.8, 0.2)	(0.6, 0.5)	(0.6, 0.7)

Table 3. Matrix of evaluation by expert E_3.

		D_1	D_2	D_3	D_4	D_5	D_6	D_7
0.14	B_1	(0.8, 0.3)	(0.6, 0.3)	(0.9, 0.1)	(1, 0)	(0.2, 0.9)	(0, 1)	(0.4, 0.7)
0.16	B_2	(0.6, 0.3)	(0.6, 0.4)	(0.5, 0.6)	(0.1, 0.8)	(0.6, 0.3)	(0.4, 0.7)	(1, 0)
0.2	B_3	(0, 1)	(1, 0)	(0, 1)	(0, 1)	(0.9, 0.1)	(0.8, 0.2)	(0.1, 0.9)
0.15	B_4	(0.5, 0.4)	(0.8, 0.2)	(0.8, 0.2)	(0.7, 0.3)	(0.8, 0.2)	(0.8, 0.3)	(0.9, 0.2)
0.2	B_5	(0, 1)	(0.8, 0.4)	(0, 1)	(0, 1)	(1, 0)	(0.2, 0.9)	(0.3, 0.9)
0.15	B_6	(0.9, 0.2)	(0.8, 0.2)	(0.8, 0.3)	(0.9, 0.2)	(0.9, 0.2)	(0.6, 0.6)	(0.4, 0.7)

Table 4. Combined matrix.

		D_1	D_2	D_3	D_4	D_5	D_6	D_7
0.14	B_1	(0.80, 0.23)	(0.57, 0.27)	(0.93, 0.1)	(0.97, 0.03)	(0.20, 0.77)	(0, 1)	(0.27, 0.70)
0.16	B_2	(0.53, 0.47)	(0.57, 0.53)	(0.47, 0.57)	(0.10, 0.87)	(0.70, 0.37)	(0.57, 0.63)	(1, 0)
0.2	B_3	(0, 1)	(1, 0)	(0, 1)	(0, 1)	(0.90, 0.07)	(0.83, 0.27)	(0.10, 0.93)
0.15	B_4	(0.53, 0.47)	(0.77, 0.33)	(0.77, 0.27)	(0.67, 0.27)	(0.87, 0.23)	(0.77, 0.40)	(0.93, 0.10)
0.2	B_5	(0, 1)	(0.80, 0.27)	(0, 1)	(0, 1)	(1, 0)	(0.13, 0.83)	(0.20, 0.90)

Table 5. Degree of similarity and deviations of experts.

		D_1	D_2	D_3	D_4	D_5	D_6	D_7
SimilarityDegree	E_1	0.8401	0.8322	0.9024	0.9417	0.9010	0.7930	0.8799
	E_2	0.7991	0.7963	0.8969	0.9255	0.8995	0.7979	0.8644
	E_3	0.8072	0.8289	0.8758	0.9135	0.8702	0.7967	0.8933
Deviation	E_1	0.0244	0.0132	0.0108	0.0151	0.0111	0.0028	0.0006
	E_2	0.0163	0.0228	0.0055	0.0017	0.0092	0.0023	0.0149

The correlation between the degree of similarity and degree of deviations given the individual experts can be graphically observed with the help of Fig. 2:

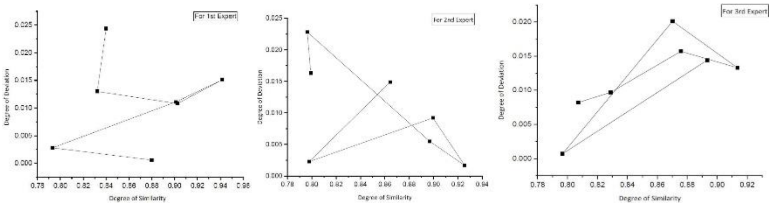

Fig. 2. Correlation between degree of similarity and deviations given the experts.

Step 4: In this step, we have fixed the threshold value $\kappa = 0.1$ (which may vary as per the need). Since all the deviation values are not greater than the threshold value. Hence, we can go to the next step.
Step 5: By making use of the score function formula, we have computed the score value $\mathbb{S}_{ji}$ of every element of the combined matrix $C^G = (c^G)_{6\times 7}$ and we get the matrix C^G as shown in Table 6. Further, we can calculate the best and worst values of all criteria For example, $c^{1+} = \max\{c_{1i}\} = 0.625$.

Table 6. Score values of the combined matrix.

	D_2	D_3	D_4	D_5	D_6	D_7	
B_1	−0.294	−0.348	0.746	0.869	−0.931	−1.000	−0.871
B_2	−0.427	−0.356	−0.571	−0.984	−0.004	−0.438	1.000
B_3	−1.000	1.000	−1.000	−1.000	0.622	0.405	−0.984
B_4	−0.427	0.194	0.191	−0.098	0.517	0.195	0.746
B_5	−1.000	0.296	−1.000	−1.000	1.000	−0.971	−0.932
B_6	0.294	0.405	0.086	0.511	0.626	−0.102	−0.516

Step 6: Compute the correlation coefficients Y_{jt} between the different criterion as shown by Table 7.

Table 7. Correlation coefficients between different criterion.

	B_1	B_2	B_3	B_4	B_5	B_6
B_1	1	0.336	0.568	0.342	–0.644	0.444
B_2		1	0.692	–0.566	–0.012	–0.234
B_3			1	–0.433	0.141	–0.372
B_4				1	–0.636	0.635
B_5					1	–0.773
B_6						1

Step 7: In the next step, with the help of Eqs. (4.5) and (4.6), the objective and final weights of different criterion are

$v_j' = (0.183, 0.221, 0.153, 0.170, 0.141, 0.127)^t$
$v_j = (0.160, 0.192, 0.176, 0.166, 0.172, 0.138)^t$

Step 8: In the final step, the ranking of alternatives on the basis of following weighted score values $R = (-0.338, 0.192, -0.233, -0.294, 0.301, -0.322, -0.408)$.

Therefore, $D_5 > D_2 > D_3 > D_4 > D_6 > D_1 > D_7$.

6. COMPARATIVE REMARKS AND ADVANTAGES

Given the computations carried as per the proposed method and having a comparative observation, we find that the proposed method has the following advantages:

- For the sake of handling uncertainties in the evaluation process, the incorporation of *q*-ROFSs increases the performance of the process in terms of intuitionistic hesitancy and Pythagorean wider space to have more appropriate results. The consistency of the analysis results can further be verified by making additional analysis with intuitionistic and Pythagorean fuzzy sets.
- The modified score function based on the *q*-rung orthopair fuzzy set has the additional capability which overcomes the limitation of the existing method [21] by taking the weights of agreement and non-agreement together.
- Also, the correlation coefficients of the criteria have been taken into consideration to fix the objective weights of the criteria. This score finding hybrid weights decider method proves to be more optimal than those methods based on similarity and distance measures. It may be noted that the coefficient of correlation can better address the inter-relationships between criteria from all aspects.
- Therefore, the purpose of the proposed manuscript is not to have a loss of useful information that has been served by obtaining the final hybrid weights of the criteria by superposition of objective and subjective weights. It can be mentioned that objective attributes (cost, reliability, load capacity, position accuracy, *etc*.) are numerically defined while the subjective attributes (vendor's service contract, training, man-machine interface, *etc.*) are qualitatively defined.
- The work presented deals with impreciseness in terms of linguistic evaluations, not exact quantitative values. The ratings and global importance of QFD in terms of Spherical fuzzy aggregation operators and information [27] may further be referred to for understanding the complexity prospects.

7. CONCLUSIONS

Based on various specifications of robots and multiple conflicting criteria, the selection and design evaluation process of the best robot design can be a complex decision-making problem. This study proposes a new QFD method based on the *q*-ROFSs which evaluates various assembly robot designs successfully. The proposed q-Rung Orthopair Fuzzy QFD technique strongly supports the companies in analyzing the customer's requirements and in improving the quality of products concerning the customer's requirements. The modified score function has been effectively applied for assembling the robotic designs. This score function is very much flexible because it is in its generalized form and can be calculated for different values of q (here $q = 2$). The proposed methodology is very much reliable because it strongly meets the customer's requirements and significant challenges of the companies. While designing the methodology, it should be kept in mind that the customer's requirements should be of high priority. The proposed methodology has the advantage of increased accuracy with the increasing value of q. In the future, the problem-solving technique can be analyzed with golden cut-oriented bipolar q-ROFS in prioritizing to make the method more robust and hybrid.

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