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Research Article

# Solving robot selection problem by a new interval-valued hesitant fuzzy multi-attributes group decision method

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**Abstract**

Selecting the most suitable robot among their wide range of specifications and capabilities is an important issue to perform the hazardous and repetitive jobs. Companies should take into consideration powerful group decision-making (GDM) methods to evaluate the candidates or potential robots versus the selected attributes (criteria). In this study, a new GDM method is proposed by utilizing the complex proportional assessment method under interval-valued hesitant fuzzy (IVHF)-environment. In the proposed method, a group of experts is established to evaluate the candidates or alternatives among the conflicted attributes. In addition, experts assign their preferences and judgments about the rating of alternatives and the relative importance of each attribute by linguistic terms which are converted to interval-valued hesitant fuzzy elements (IVHFEs). Also, the attributes weights and experts weights are applied in procedure of the proposed interval-valued hesitant fuzzy group decision-making (IVHF-GDM) method. Hence, the experts opinions about the relative importance of each attribute are considered in determination of attributes weights. Thus, we propose a hybrid maximizing deviation method under uncertainty. Finally, an illustrative example is presented to show the feasibility of the proposed IVHF-GDM method and also the obtained ranking results are compared with a recent method from the literature.

*Keywords* : Robot selection problem; Group decision making analysis; Interval-valued hesitant fuzzy sets.

## 1 Introduction

In a competitive marketing environment, selecting the most suitable robot is an important role to achieve the best quality product for some companies. In this respect, companies should be taken into account the best robot among some candidate robots versus their characteristics. Therefore, decision-making approaches are powerful tools to deal with this condition. Hence, some researchers are solved their robot selection problems based on the precise information [2, 21, 22].

In this regard, some decision methods and studies have been presented to solve the robot selection problems. Thus, Bhangale et al. [1] proposed a methodology based on the TOPSIS and graphical methods, and then compared the ranking results of two methods. Karsak and Ahiska [13] implemented an applicable common

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weight multi-attribute decision-making (MADM) methodology with an enhanced distinguishing power. Bhattacharya et al. [2] incorporated the quality function deployment and AHP methods to solve robot selection problem based on four candidates or alternatives and seven selected attributes (criteria). Chatterjee et al. [4] implemented two types of MADM methods, i.e. ELECTRE II and VIKOR methods. Also, Singh and Rao [25] extended a hybrid decision-making method based on incorporating the matrix approach and graph theory along with AHP method.

In real-life complex decision-making problems, the preferences and judgments of experts are difficult to be expressed precisely. In this case, the experts should defin their opinions under fuzzy environments. Fuzzy sets theory has been first defined by Zadeh [33]; this theory and its extension have been widely utilized in imprecise conditions to solve the decision-making problems [9, 10, 11, 16, 17, 18, 19, 26, 28, 29]. The fields can consist of management [3, 15], pattern recognition [6, 20] artificial intelligence [30] and robot selection problems [12, 14].

In this respect, to solve the industrial robot selection problem based on decision-making analysis under the fuzzy environment, Devi [7] developed VIKOR method under an intuitionistic fuzzy environment, in which the evaluating the candidate robots and the attributes weights are defined by triangular intuitionistic fuzzy sets. Samantra et al. [24] presented an interval-valued trapezoidal fuzzy VIKOR method to deal with uncertainty in solving the decision-making problems. Vahdani et al. [27] developed a complex proportional assessment method based on the interval-valued fuzzy sets regarding to the objective information and subjective judgments. Rashid et al. [23] proposed a generalized interval-valued trapezoidal fuzzy TOPSIS method according to the subjective judgment and objective information. In their method, the experts opinions are aggregated on different attributes.

The investigation of the literature shows that applying the extensions of fuzzy sets theories are the powerful tools to solve the industrial robot selection problems under uncertainty. In this respect, one of the most appropriate tools is the interval-valued hesitant fuzzy sets (IVHFSs) that first introduced by Chen et al. [5], which help experts to define their opinions by some interval-values for a candidate robot in terms of the conflicted attributes under a set to margin of errors.

In this paper, a new group decision-making (GDM) method is developed under an interval-valued hesitant fuzzy (IVHF)-environment by utilizing the complex proportional assessment method. The weight of each attribute is computed based on the hybridization of the extended maximizing deviation method and the experts judgments about the significance of each attribute (criterion). However, the main purposes of this study are outlined: (1) we propose a GDM method in an interval-valued hesitant fuzzy setting by regarding the complex proportional assessment method, (2) we consider a group of experts to rating the candidates or alternatives among the conflicted attributes based on linguistic variables, (3) we propose a hybrid maximizing deviation method to determine the weight of each attribute, and (4) we consider the attributes and experts weights in procedure of the proposed IVHF-GDM method.

The rest of the paper is organized as follows: some basic operations and concepts of IVHFSs are defined in Section 2. The procedure of the proposed IVHF-GDM method is defined in Section 3. Hence, an illustrative example about the robot selection problem, and a comparative analysis are presented in Section 4. Finally, some concluding remarks are provided in Section 5.

## 2 Preliminaries

In this section, some operators in an interval-valued hesitant fuzzy setting are expressed which are applied in the proposed IVHF-GDM method.

**Definition 2.1** *Consider $X$ is a universe set, and then the IVHFS on this set is represented as follows:*

$$\tilde{E} = \left\{ \langle x_i, \tilde{h}_{\tilde{E}}(x_i) \rangle \mid x_i \in X, i = 1, 2, ..., n \right\} \quad (2.1)$$

*where $\tilde{h}_{\tilde{E}}(x_i)$ is defined as an interval membership degree for an object $x_i \in X$ under set $E$.*

**Definition 2.2** *[5], Consider three interval-valued hesitant fuzzy elements (IVHFE) as $\tilde{h}, \tilde{h}_1$ and $\tilde{h}_2$, then some basic relations are represented* *as follows:*

$$\tilde{h}^c = \left\{ \left[ 1 - \tilde{\gamma}^U, 1 - \tilde{\gamma}^L \right] \mid \tilde{\gamma} \in \tilde{h} \right\}; \qquad (2.2)$$

$$\tilde{h}^\lambda = \left\{ \left[ (\tilde{\gamma}^L)^\lambda, (\tilde{\gamma}^U)^\lambda \right] \mid \tilde{\gamma} \in \tilde{h} \right\}; \qquad (2.3)$$

$$\lambda\tilde{h} = \left\{ \left[ 1 - (1 - \tilde{\gamma}^L)^\lambda, 1 - (1 - \tilde{\gamma}^U)^\lambda \right] \mid \tilde{\gamma} \in \tilde{h} \right\}, \ \lambda > 0; \qquad (2.4)$$

$$\tilde{h}_1 \oplus \tilde{h}_2 = \left\{ \left[ \tilde{\gamma}_1^L + \tilde{\gamma}_2^L - \tilde{\gamma}_1^L \tilde{\gamma}_2^L, \tilde{\gamma}_1^U + \tilde{\gamma}_2^U - \tilde{\gamma}_1^U \tilde{\gamma}_2^U \right], \mid \tilde{\gamma}_1 \in \tilde{h}_1, \tilde{\gamma}_2 \in \tilde{h}_2 \right\}; \qquad (2.5)$$

$$\tilde{h}_1 \otimes \tilde{h}_2 = \left\{ \left[ \tilde{\gamma}_1^L \tilde{\gamma}_2^L, \tilde{\gamma}_1^U \tilde{\gamma}_2^U \right], \mid \tilde{\gamma}_1 \in \tilde{h}_1, \tilde{\gamma}_2 \in \tilde{h}_2 \right\}; \qquad (2.6)$$

**Definition 2.3** *[5], The hesitant interval-valued fuzzy geometric (HIVFG) aggregation operator is demonstrated as follows:*

$$\begin{aligned} &HIVFG(\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_n) \\ &= \left( \oplus_{j=1}^n (\tilde{h}_j)^{\frac{1}{n}} \right) \\ &= \cup_{\tilde{\gamma}_1 \in \tilde{h}_1, \tilde{\gamma}_2 \in \tilde{h}_2, \ldots \tilde{\gamma}_n \in \tilde{h}_n} \left\{ \left[ \Pi_{j=1}^n (\gamma_j^L)^{\frac{1}{n}}, \Pi_{j=1}^n (\gamma_j^U)^{\frac{1}{n}} \right] \right\} \end{aligned} \qquad (2.7)$$

**Definition 2.4** *[31], The hesitant interval-valued fuzzy weighted geometric (HIVFWG) aggregation operator is represented as follows:*

$$\begin{aligned} &HIVFWG(\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_n) \\ &= \left( \oplus_{j=1}^n (\tilde{h}_j)^{w_j} \right) \\ &= \cup_{\tilde{\gamma}_1 \in \tilde{h}_1, \tilde{\gamma}_2 \in \tilde{h}_2, \ldots \tilde{\gamma}_n \in \tilde{h}_n} \left\{ \left[ \Pi_{j=1}^n (\gamma_j^L)^{w_j}, \Pi_{j=1}^n (\gamma_j^U)^{w_j} \right] \right\} \end{aligned} \qquad (2.8)$$

where the weight vector of $\tilde{h}_j (j = 1, \ldots, n)$ is indicated by $w = (w_1, w_2, \ldots, w_n)^T$ and $w_j > 0$, $\sum_{j=1}^n = 1$.

**Definition 2.5** *[8], Two types of ordering in an interval-valued hesitant fuzzy setting are defined. In this respect, the component-wise ordering and the total ordering are indicated, respectively, as follows. Let $\tilde{M}$ and $\tilde{N}$ consider as two IVHFSs on $X$.*

$$\begin{aligned} &\tilde{M} \leq \tilde{N} \text{ if } \ h_{\tilde{M}}^{\sigma(j)L}(x_i) \leq h_{\tilde{N}}^{\sigma(j)L}(x_i), \\ &h_{\tilde{N}}^{\sigma(j)U}(x_i) \leq h_{\tilde{M}}^{\sigma(j)U}(x_i), \\ &\forall i = 1, 2, \ldots, m \\ &\forall j = 1, 2, \ldots, n. \end{aligned} \qquad (2.9)$$

$$Score(\tilde{M}) = \frac{1}{n} \left( \frac{1}{l_{x_i}} \sum_{j=1}^{l_{x_i}} \left[ \frac{h_{\tilde{M}}^{\sigma(j)L}(x_i) + h_{\tilde{M}}^{\sigma(j)U}(x_i)}{2} \right] \right) \qquad (2.10)$$

$$\tilde{M} \preceq \tilde{N} \quad \text{if} \quad Score(\tilde{M}) \leq Score(\tilde{N})$$

**Definition 2.6** *[34], The normalized interval-valued hesitant fuzzy decision matrix can be obtained by applying the following relation:*

$$\begin{aligned} &b_{ij} = \cup_{t_{ij} \in b_{ij}} \\ &= \begin{cases} \left[ \gamma_{ij}^l, \gamma_{ij}^u \right] & \text{for posetive criteria} \\ \left[ 1 - \gamma_{ij}^u, 1 - \gamma_{ij}^l \right] & \text{for negative criteria} \end{cases} \\ &\forall i = 1, \ldots, m; \quad j = 1, \ldots, n \end{aligned} \qquad (2.11)$$

## 3 Proposed IVHF-GDM method

**Step 1**. Specify significant attributes (criteria) which satisfy the potential candidate or alternatives.

**Step 2**. Establish the interval-valued hesitant fuzzy decision matrix by utilizing a group of experts.

$$M = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \left[ \begin{array}{c} \left\{ \left[ \mu_{11}^{L1}, \mu_{11}^{U1} \right], \left[ \mu_{11}^{L2}, \mu_{11}^{U2} \right], \right. \\ \vdots \\ \left\{ \left[ \mu_{m1}^{L1}, \mu_{m1}^{U1} \right], \left[ \mu_{m1}^{L2}, \mu_{m1}^{U2} \right], \right. \end{array} \right.$$

$$, \ldots, \left[\mu_{11}^{Lk}, \mu_{11}^{Uk}\right]\Big\} \quad \cdots$$

$$\ddots$$

$$, \ldots, \left[\mu_{m1}^{Lk}, \mu_{m1}^{Uk}\right]\Big\} \quad \cdots$$

$$\Big\{\left[\mu_{1n}^{L1}, \mu_{1n}^{U1}\right], \left[\mu_{1n}^{L2}, \mu_{1n}^{U2}\right],$$

$$\vdots$$

$$\Big\{\left[\mu_{mn}^{L1}, \mu_{mn}^{U1}\right], \left[\mu_{mn}^{L2}, \mu_{mn}^{U2}\right],$$

$$\left.\begin{matrix} , \ldots, \left[\mu_{1n}^{Lk}, \mu_{1n}^{Uk}\right]\Big\} \\ \vdots \\ , \ldots, \left[\mu_{mn}^{Lk}, \mu_{mn}^{Uk}\right]\Big\} \end{matrix}\right] \tag{3.12}$$

**Step 3**. Compute the experts weights by considering the following relations:

$$\lambda_k^L = \frac{\sum_i^m \sum_j^n \mu_{ij}^{kL}}{\sum_k^K \sum_i^m \sum_j^n \mu_{ij}^{kL}} \tag{3.13}$$

$$\lambda_k^U = \frac{\sum_i^m \sum_j^n \mu_{ij}^{kU}}{\sum_k^K \sum_i^m \sum_j^n \mu_{ij}^{kU}} \tag{3.14}$$

**Step 4**. Calculate the attributes weights based on a hybrid maximizing deviation method.
**Step 4.1**. Aggregate the relative significance of attributes weights which specified by linguistic variables regarding to the experts judgments.

$$\begin{aligned} \bar{v}_j &= HIVFG(\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_n) \\ &= \left( \oplus_{k=1}^K \left( \frac{\lambda_k^f \tilde{h}_k)}{2} \right)^{\frac{1}{k}} \right) \\ &= \cup_{\tilde{\gamma}_1 \in \tilde{h}_1, \tilde{\gamma}_2 \in \tilde{h}_2, \ldots \tilde{\gamma}_k \in \tilde{h}_k} \\ & \left\{ \frac{\Pi_{j=1}^K (\lambda_k^L \gamma_k^L)^{\frac{1}{k}} + \Pi_{j=1}^K (\lambda_k^U \gamma_k^U)^{\frac{1}{k}}}{2} \right\} \end{aligned} \tag{3.15}$$

where $\lambda_k^f = [\lambda_k^L, \lambda_k^U]$ is defined the weight of each expert.
**Step 4.2**. The maximizing deviation method for determining the attributes weights is defined by Xu and Zhang [32]. We specify the final weight of each attribute based on the extended maximizing deviation method and regarding to the experts opinions about the attributes weights.

$$\begin{aligned} \omega_j = & \Bigg[ \bar{v}_j . \sum_{i=1}^m \sum_{k=1}^m \Bigg( \frac{1}{2l} \sum_{\lambda=1}^l \Bigg( |h_{ij}^{\sigma(\lambda)^L} - h_{kj}^{\sigma(\lambda)^L}| \\ & + |h_{ij}^{\sigma(\lambda)^U} - h_{kj}^{\sigma(\lambda)^U}| \Bigg) \Bigg) \Bigg] \\ & \times \Bigg[ \sum_{j=1}^n \Bigg( \sum_{i=1}^m \sum_{k=1}^m \Bigg( \frac{1}{2l} \sum_{\lambda=1}^l \Bigg( |h_{ij}^{\sigma(\lambda)^L} - h_{kj}^{\sigma(\lambda)^L}| \\ & + |h_{ij}^{\sigma(\lambda)^U} - h_{kj}^{\sigma(\lambda)^U}| \Bigg) \Bigg) \Bigg)^2 \Bigg]^{-\frac{1}{2}} \end{aligned} \tag{3.16}$$

where the normalized optimal weight vector is computed as follows:

$$\omega_j^* = \frac{\omega_j}{\sum_{j=1}^n \omega_j}, \; j = 1, 2, \ldots, n. \tag{3.17}$$

**Step 5**. Establish the weighted normalized interval-valued decision matrix regarding to the attributes weights.
**Step 6**. Specify sums of positive attribute values ($R_i^P$) and sums of negative attribute values ($R_i^N$) by using the following relations, respectively:

$$\begin{aligned} R_i^P &= (1 - X_j) \Bigg[ \Pi_{k=1} \Bigg( 1 - \Pi_{j=1}^r (1 - \mu_{ij}^l \Bigg)^{\frac{1}{k}}, \\ & \quad \Pi_{k=1} \Bigg( 1 - \Pi_{j=1}^r (1 - \mu_{ij}^u \Bigg)^{\frac{1}{k}} \Bigg] \forall i, \\ R_i^N &= X_j \Bigg[ \Pi_{k=1} \Bigg( 1 - \Pi_{j=1}^r (1 - \mu_{ij}^l \Bigg)^{\frac{1}{k}}, \\ & \quad \Pi_{k=1} \Bigg( 1 - \Pi_{j=1}^r (1 - \mu_{ij}^u \Bigg)^{\frac{1}{k}} \Bigg] \forall i, \end{aligned} \tag{3.18}$$

$$R_i^P / R_i^N = \begin{cases} R_i^P & \forall X_j = 0 \quad \text{for positive attribute}(j) \\ R_i^N & \forall X_j = 0 \quad \text{for negative attribute}(j) \end{cases} \tag{3.19}$$

**Step 7**. Compute the minimum value of sums for negative attribute value as follows:

$$R_{\min}^N = \left[ \min_i (R_i^{lN}), \min_i (R_i^{uN}) \right] \forall k \tag{3.20}$$

**Step 8**. Determine the relative significance of each candidate potential alternative as follows:

$$Q_i = \left[ R_i^{lp} + (1 - R_i^{lp}) \times \left( \frac{1 - \left(\Pi_i^m (1 - R_i^{lN})\right)^{R_{\min}^{lN}}}{1 - \left(\Pi_i^m \left(1 - \frac{R_{\min}^{lN}}{R_i^{LN}}\right)\right)^{R_i^{lN}}} \right), P_i^{up} + (1 - P_i^{up}) \times \left( \frac{1 - \left(\Pi_i^m (1 - R_i^{uN})\right)^{R_{\min}^{uN}}}{1 - \left(\Pi_i^m \left(1 - \frac{R_{\min}^{uN}}{R_i^{uN}}\right)\right)^{R_i^{uN}}} \right) \right] \forall i \quad (3.21)$$

**Step 10**. The utility degree for each potential alternative is computed as below:

$$N_i = \left[ \frac{Q_i^l}{\max(Q_i^l)}, \frac{Q_i^u}{\max(Q_i^u)} \right] 100\% \quad (3.22)$$

**Step 11**. Select the best candidate alternative which has maximum value of utility degree regarding to ordering relation.

## 4 Illustrative example

In this section, an illustrative example which is adopted from Vahdani et al. [27] is presented to indicate the procedure of the proposed IVHF-multi-criteria group decision method. In addition, the proposed method is compared with Vahdani et al. [27] method to show the feasibility of the proposed method. In an illustrative example, there is a manufacturing company which requires a robot to perform the material handling. In this case, three robots ($R_i, i = 1, 2, 3$) are considered as alternatives and also sixth attributes are selected. In addition, the candidate robots versus the conflicted attributes are evaluated based on the fourth experts judgments. The selected attributes are expressed as follows:

- Man-machine interface ($C1$);
- Programming flexibility ($C2$);
- Vendors service contract ($C3$);
- Load capacity ($C4$);
- Positioning accuracy ($C5$); and
- Purchase cost ($C6$).

The group of experts defines their preferences and judgments about the attributes significance and the rating of candidate robots among the selected attribute by linguistic variables and then, the linguistic variables are converted to the IVHFEs. The linguistic terms and their hesitant fuzzy values about the attribute importance and evaluating the candidate robots are listed in Table 1 and 2, respectively. In addition, the opinions of each expert about the assessment of robots versus the attributes and the weight of each attribute are demonstrated by linguistic variables in Tables 3 and 4.

The weight of each expert is computed by using Eqs. (3.13) and (3.14). In addition, the relative importance of each attribute based on the experts opinions is determined by utilizing the Eq. (3.15). Then, the optimal attributes weight is obtained based on Eqs. (3.16) and (3.17). The computational results of determining the experts weights and attributes weights are demonstrated in Table 5. Hence, the normalized interval-valued hesitant fuzzy decision matrix is obtained based on definition 2.6. Then, the weighted normalized interval-valued hesitant fuzzy decision matrix is established.

Sums of positive/negative attributes values are assessed by using Eqs. (3.18) and (3.19), respectively. Thus, the smallest value of sums for negative attribute value is specified based on Eq. (3.20). The results are reported in Table 6. Finally, the relative importance and the utility degree of each candidate potential alternatives are computed by Eqs. (3.21) and (3.22), respectively. The potential alternatives are ranked based on the total ordering. The mentioned results are represented in Table 7. In this case, the worst and the best candidate robots are obtained (i.e., the first and the third robots). The ranking results of proposed method is compared with Vahdani et al. [27] method which have the same results. Consequently, the proposed IVHF-GDM method is feasible and powerful regarding to their considerable characteristics under uncertainty.

## 5 Conclusions

The robot selection problem is a complex issue for some companies that reduce the production cost and increase the product quality. This paper proposed a group decision-making (GDM) method in an interval-valued hesitant fuzzy (IVHF)-setting by the complex proportional assessment to se-

**Table 1:** Linguistic variables for rating the importance of attributes

| Linguistic variables | Hesitant interval-valued fuzzy elements |
|---|---|
| Very high (VH) | [0.90, 0.90] |
| High (H) | [0.75, 0.80] |
| Medium (M) | [0.50, 0.55] |
| Low (L) | [0.35, 0.40] |
| Very low (VL) | [0.10, 0.10] |

**Table 2:** Linguistic variables for rating the potential alternatives

| Linguistic variables | Hesitant interval-valued fuzzy elements |
|---|---|
| Extremely good (EG) | [1.00, 1.00] |
| Very very good (VVG) | [0.90, 0.90] |
| Very good (VG) | [0.80, 0.90] |
| Good (G) | [0.70, 0.80] |
| Moderately good (MG) | [0.60, 0.70] |
| Fair (F) | [0.50, 0.60] |
| Moderately poor (MP) | [0.40, 0.50] |
| Poor (P) | [0.25, 0.40] |
| Very poor (VP) | [0.10, 0.25] |
| Very very poor (VVP) | [0.10, 0.10] |

**Table 3:** Performance ratings of the alternatives in linguistic variables

| Criteria | Alternatives | Decision makers | | | |
|---|---|---|---|---|---|
| | | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ |
| | $R_1$ | F | F | G | VG |
| $C_1$ | $R_2$ | F | G | F | F |
| | $R_3$ | G | F | VG | G |
| | $R_1$ | G | P | G | F |
| $C_2$ | $R_2$ | VG | G | VG | F |
| | $R_3$ | G F | VG | G | |
| | $R_1$ | F | F | G | F |
| $C_3$ | $R_2$ | G | F | VG | G |
| | $R_3$ | G | G | G | VG |
| | $R_1$ | G | MG | F | F |
| $C_4$ | $R_2$ | MG | G | MG | MG |
| | $R_3$ | F | F | G | G |
| | $R_1$ | F | P | MP | F |
| $C_5$ | $R_2$ | MG | F | F | MG |
| | $R_3$ | G | G | MG | G |
| | $R_1$ | G | G | G | MG |
| $C_6$ | $R_2$ | MG | MG | F | F |
| | $R_3$ | F | F | P | MP |

lect the best candidate robot. In the proposed method, the preferences and judgments of decision makers were defined by linguistic terms which were transformed to interval-valued hesitant fuzzy elements (IVHFEs). In addition, a hybrid maximizing deviation method was presented by incorporating the extended maximizing deviation method and the opinions of each decision maker about the relative significance of each attribute. In this respect, the optimal at-

**Table 4:** Decision makers judgments about attributes weights

| Criteria | Decision makers | | | |
|---|---|---|---|---|
| | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ |
| $C_2$ | H | VH | VH | H |
| $C_2$ | VH | H | VH | M |
| $C_2$ | M | L | M | L |
| $C_2$ | VH | VH | H | VH |
| $C_2$ | VH | H | H | H |
| $C_2$ | M | M | M | L |

**Table 5:** Experts weights and the attributes weights

| | $\lambda_k^f$ | | $\bar{v}_j$ | $\omega_j^*$ |
|---|---|---|---|---|
| $\lambda_1^f$ | [0.259560, 0.257426] | $\bar{v}_1$ | [0.205130, 0.211954] | $\omega_1^*$ |
| 0.225080 | | | | |
| $\lambda_2^f$ | [0.229432, 0.233663] | $\bar{v}_2$ | [0.185356, 0.193001] | $\omega_2^*$ |
| 0.191442 | | | | |
| $\lambda_3^f$ | [0.260718, 0.259406] | $\bar{v}_3$ | [0.104447, 0.117162] | $\omega_3^*$ |
| 0.067535 | | | | |
| $\lambda_4^f$ | [0.250290, 0.249505] | $\bar{v}_4$ | [0.214696, 0.218288] | $\omega_4^*$ |
| 0.237524 | | | | |
| | | $\bar{v}_5$ | [0.195990, 0.205804] | $\omega_5^*$ |
| 0.204737 | | | | |
| | | $\bar{v}_6$ | [0.114188, 0.126871] | $\omega_6^*$ |
| 0.073680 | | | | |

**Table 6:** Positive/negative attributes values and the minimum negative attributes value

| Robots | $R_i^P$ | $R_i^N$ | $R_{\min}^N$ |
|---|---|---|---|
| $R_1$ | [0.394022, 0.455495] | [0.024919, 0.036293] | |
| $R_2$ | [0.439182, 0.493126] | [0.039000, 0.050348] | [0.024919, 0.036293] |
| $R_3$ | [0.464669, 0.516782] | [0.052696, 0.065202] | |

**Table 7:** Final $Q_i$ values regarding to each DM

| Robots | $Q_i$ | $N_i$ | Total ordering | Ranked by the proposed IVHF-GDM method | Ranked by Vahdani et al. [27] method |
|---|---|---|---|---|---|
| $R_1$ | [0.395818, 0.458570] | [84.8929, 88.2695] | 86.5812% | 3 | 3 |
| $R_2$ | [0.440844, 0.495989] | [94.5498, 95.4722] | 95.011% | 2 | 2 |
| $R_3$ | [0.466256, 0.519511] | [100,100] | 100% | 1 | 1 |

tributes weight and the importance of each decision maker were applied in the proposed IVHF-GDM method. Finally, the proposed approach was implemented in an illustrative example. The results showed that the third robot was selected as the best robot and the worst robot was the first robot. Also, the comparative analysis which indicated the same ranking results was presented the feasibility and applicability of the proposed IVHF-GDM method. For future direction, the proposed method can be enhanced by proposing a method to determine the experts weights precisely. Also, the preferences and judgments of experts should be aggregated in last steps to prevent the loss of data.

## References

[1] P. Bhangale, V. Agrawal, S. Saha, *Attribute based specification, comparison and selection of a robot*, Mechanism and Machine Theory 39 (2004) 1345-1366.

[2] A. Bhattacharya, B. Sarkar, S. K. Mukherjee, *Integrating AHP with QFD for robot selection under requirement perspective*, International Journal of Production Research 43 (2005) 3671-3685.

[3] T. H. Chang, T. C. Wang, *Using the fuzzy multi-criteria decision making approach for measuring the possibility of successful knowledge management*, Information Sciences 179 (2009) 355-370.

[4] P. Chatterjee, V. Manikrao Athawale, S. Chakraborty, *Selection of industrial robots using compromise ranking and outranking methods*, Robotics and Computer-Integrated Manufacturing 26 (2010) 483-489.

[5] N. Chen, Z. Xu, M. Xia, *Interval-valued hesitant preference relations and their applications to group decision making*, Knowledge-Based Systems 37 (2013) 528-540.

[6] A. Chohra, N. Kanaoui, V. Amarger, K. Madani, *Hybrid Intelligent Diagnosis Approach Based On Neural Pattern Recognition and Fuzzy Decision-Making*, Knowledge-based Intelligent System Advancements: Systemic and Cybernetic Approaches 6 (2011) 444-450.

[7] K. Devi, *Extension of VIKOR method in intuitionistic fuzzy environment for robot selection*, Expert Systems with Applications 38 (2011) 14163-14168.

[8] B. Farhadinia, *Information measures for hesitant fuzzy sets and interval-valued hesitant fuzzy sets*, Information Sciences 240 (2013) 129-144.

[9] H. Gitinavard, S. Mousavi, B. Vahdani, *A new balancing and ranking method based on hesitant fuzzy sets for solving decision-making problems under uncertainty*, International Journal of Engineering-Transactions B: Applications 28 (2014) 214-223.

[10] H. Gitinavard, S. M. Mousavi, B. Vahdani, *A new multi-criteria weighting and ranking model for group decision-making analysis based on interval-valued hesitant fuzzy sets to selection problems*, Neural Computing and Applications 27 (2015) 1593-1605.

[11] H. Hashemi, J. Bazargan, S. M. Mousavi, *A Compromise Ratio Method with an Application to Water Resources Management: An Intuitionistic Fuzzy Set* , Water resources management 27 (2013) 2029-2051.

[12] E. E. Karsak, *Robot selection using an integrated approach based on quality function deployment and fuzzy regression*, International Journal of Production Research 46 (2008) 723-738.

[13] E. Karsak, S. Ahiska, *Practical common weight multi-criteria decision-making approach with an improved discriminating power for technology selection*, International Journal of Production Research 43 (2005) 1537-1554.

[14] D. E. Koulouriotis, M. K. Ketipi, *A fuzzy digraph method for robot evaluation and selection*, Expert Systems with Applications 38 (2011) 11901-11910.

[15] E. C. Man Hui, O. M. Fai Lau, K. K. Lo, *A fuzzy decisionmaking approach for portfolio management with direct real estate investment*, International Journal of Strategic Property Management 13 (2009) 191-204.

[16] S. Mousavi, H. Gitinavard, B. Vahdani, *Evaluating construction projects by a new group decision-making model based on intuitionistic fuzzy logic concepts*, International Journal of Engineering-Transactions C: Aspects 28 (2015) 1312-1321.

[17] S. M. Mousavi, H. Gitinavard, A. Siadat. *A new hesitant fuzzy analytical hierarchy process method for decision-making problems under uncertainty*, in 2014 IEEE International Conference on Industrial Engineer-

ing and Engineering Management. (2014) : IEEE.

[18] S. M. Mousavi, F. Jolai, R. Tavakkoli-Moghaddam, *A fuzzy stochastic multi-attribute group decision-making approach for selection problems*, Group Decision and Negotiation 22 (2013) 207-233.

[19] S. M. Mousavi, S. A. Torabi, R. Tavakkoli-Moghaddam, *A hierarchical group decision-making approach for new product selection in a fuzzy environment*, Arabian Journal for Science and Engineering 38 (2013) 3233-3248.

[20] D. R. Pathak, A. Hiratsuka, *An integrated GIS based fuzzy pattern recognition model to compute groundwater vulnerability index for decision making*, Journal of Hydro-Environment Research 5 (2011) 63-77.

[21] R. Rao, B. Patel, M. Parnichkun, *Industrial robot selection using a novel decision making method considering objective and subjective preferences*, Robotics and Autonomous Systems 59 (2011) 367-375.

[22] R. V. Rao, K. Padmanabhan, Selection, *identification and comparison of industrial robots using digraph and matrix methods*, Robotics and Computer-Integrated Manufacturing 22 (2006) 373-383.

[23] T. Rashid, I. Beg, S. M. Husnine, *Robot selection by using generalized interval-valued fuzzy numbers with TOPSIS*, Applied Soft Computing 21 (2014) 462-468.

[24] C. Samantra, S. Datta, S. S. Mahapatra, *Selection of industrial robot using intervalvalued trapezoidal fuzzy numbers set combined with VIKOR method*, International Journal of Technology Intelligence and Planning 7 (2011) 344-360.

[25] D. Singh, R. Rao, *A hybrid multiple attribute decision making method for solving problems of industrial environment*, International Journal of Industrial Engineering Computations 2 (2011) 631-644.

[26] R. Tavakkoli-Moghaddam, H. Gitinavard, S. M. Mousavi, A. Siadat. *An interval-valued hesitant fuzzy TOPSIS method to determine the criteria weights*, in International Conference on Group Decision and Negotiation. (2015) : Springer.

[27] B. Vahdani, S. M. Mousavi, R. Tavakkoli-Moghaddam, A. Ghodratnama, M. Mohammadi, *Robot selection by a multiple criteria complex proportional assessment method under an interval-valued fuzzy environment*, The International Journal of Advanced Manufacturing Technology 73 (2014) 687-697.

[28] B. Vahdani, S. M. Mousavi, R. Tavakkoli-Moghaddam, H. Hashemi, *A new design of the elimination and choice translating reality method for multi-criteria group decision-making in an intuitionistic fuzzy environment*, Applied Mathematical Modelling 37 (2013) 1781-1799.

[29] B. Vahdani, R. Tavakkoli-Moghaddam, S. M. Mousavi, A. Ghodratnama, *Soft computing based on new interval-valued fuzzy modified multi-criteria decision-making method*, Applied Soft Computing 13 (2013) 165-172.

[30] N. Wakefield, K. Bryant, P. Knight, H. Azzam. *FUMS$^{TM}$ artificial intelligence technologies including fuzzy logic for automatic decision making. in Fuzzy Information Processing Society*, 2005. NAFIPS 2005. Annual Meeting of the North American. (2005) : IEEE.

[31] G. Wei, X. Zhao, R. Lin, *Some hesitant interval-valued fuzzy aggregation operators and their applications to multiple attribute decision making*, Knowledge-Based Systems 46 (2013) 43-53.

[32] Z. Xu, X. Zhang, *Hesitant fuzzy multi-attribute decision making based on TOPSIS with incomplete weight information*, Knowledge-Based Systems 52 (2013) 53-64.

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

[34] Z. Zhang, C. Wang, D. Tian, K. Li, *Induced generalized hesitant fuzzy operators and their application to multiple attribute group decision making*, Computers & Industrial Engineering 67 (2014) 116-138.

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