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Nowadays selection of an optimal robot has become a challenging task for manufacturers with the increment of production demands and availability of more different robot models. Robot selection for a particular industrial application can be viewed as a complicated multi-criteria decision-making problem which requires consideration of a number of alternative robots and conflicting subjective and objective criteria. Furthermore, decision-makers tend to use multigranularity linguistic term sets to express their assessments on the subjective criteria, and there usually exists uncertain and incomplete assessment information. In this paper, an interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) method is proposed to handle the robot selection problem under uncertain and incomplete information environment. This method considers both subjective judgements and objective information in real-life applications, and models the uncertainty and diversity of decision-makers' assessments using interval 2-tuple linguistic variables. An example is cited for demonstrating the feasibility and practicability of the proposed method, and results show that the ITL-TOPSIS is an effective decision-making tool for robot evaluation and selection with uncertain and incomplete information.

Keywords: interval 2-tuple; multi-criteria decision-making (MCDM); robot selection; TOPSIS

1. Introduction

An industrial robot is a general purpose, reprogrammable machine with certain anthropometrical features (Chatterjee, Manikrao Athawale, and Chakraborty 2010; Rao, Patel, and Parnichkun 2011). The utilisation of robots has been greatly increased in diverse advanced manufacturing systems mainly due to the developments in information technologies and engineering sciences. Robots can perform repetitious, difficult and hazardous tasks with precision, and can improve quality and productivity dramatically if applied properly. Therefore, manufacturers prefer to use robots in a variety of industrial applications, such as assembly, material handling, finishing, loading and unloading, spray painting, welding, etc. During the past years, the available set of robots with vastly different capabilities and specifications is rapidly growing in both the range of applications and the number of robot systems. Improper selection of robots will adversely affect a company's competitiveness in terms of the productivity of its facilities and quality of its products (Kumar and Garg 2010; Rao, Patel, and Parnichkun 2011). As a result, the selection of robots to suit a particular application and production environment from the large number of robots available in the market today has become a challenging task for manufacturing companies.

In order to address the issue of robot selection, a number of precision-based methods have been reported in the literature. For example, Kumar and Garg (2010) developed a deterministic quantitative model based on distance-based approach (DBA) for evaluation, selection and ranking of robots. Chatterjee, Manikrao Athawale, and Chakraborty (2010) solved the robot selection problem using two multi-criteria decision-making (MCDM) methods and compared their relative performance for a given industrial application. The first MCDM method is VIKOR (VIsekriterijumsko KOmpromisno Rangiranje), a compromise ranking method and the other one is ELECTRE (ELimination and Et Choice Translating REality), an outranking method. In another work, Athawale, Chatterjee, and Chakraborty (2012) used VIKOR method to evaluate and rank the alternative candidate robots, while proposing a compromise solution to the robot selection problem. Rao and Padmanabhan (2006) suggested a methodology based on digraph and matrix methods for evaluation of alternative industrial robots. Agrawal, Kohli, and Gupta (1991) employed a MCDM method known as technique for order preference by similarity to ideal solution (TOPSIS) to evaluate, rank and select robots for a particular application according to the requirements of the users. Bhangale, Agrawal, and Saha (2004) identified a large number

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attributes needing to be considered for robot selection, and ranked the alternative robots using TOPSIS and graphical methods. Khouja (1995) presented a two-phase robot selection model, in which data envelopment analysis (DEA) is used for identifying robots with the best combination of performance parameters and a MCDM method is used to make a selection among those robots. In addition, Parkan and Wu (1999) used of and compared operational competitiveness rating (OCRA), TOPSIS and a utility-function model for the problem of robot selection, and the final selection was based on the averages of the rankings obtained by the three methods.

Under many conditions, however, exact data are inadequate to model real-life situations because of the complexity of robot selection problems. Therefore, fuzzy set theory was incorporated by many researchers to deal with the vagueness and ambiguity in decision-making process. For example, Rao, Patel, and Parnichkun (2011) proposed a subjective and objective integrated MCDM method for the purpose of robot selection and used fuzzy logic to convert the qualitative attributes into the quantitative attributes. Koulouriotis and Ketipi (2011) proposed a fuzzy digraph method for robot evaluation and selection, in which the appropriate data, quantitative and qualitative, are expressed by fuzzy numbers. Liang and Wang (1993) proposed a robot selection algorithm combing the concepts of fuzzy set theory and hierarchical structure analysis. To solve the limitations in Liang and Wang (1993), Chu and Lin (2003) proposed selecting a robot via a fuzzy TOPSIS method, where the ratings of various alternatives vs. various subjective criteria and the weights of all criteria are assessed in linguistic terms represented by fuzzy numbers. Vahdani, Mousavi, and Tavakkoli-Moghaddam (2011) also presented a fuzzy TOPSIS method for robot selection, which can select the best alternative by considering both subjective judgements and objective information. Kahraman et al. (2007) proposed a fuzzy hierarchical TOPSIS model with an application for the multi-criteria industrial robotic system selection problem. Tansel İç, Yurdakul, and Dengiz (2013) developed a two-phase robot selection model, namely ROBSEL, in which the robots which are not suitable for the user's specific application are eliminated in the first phase and the suitable ones are then ranked using the fuzzy analytical hierarchy process (FAHP) in the second phase. Wang, Singh, and Huang (1991) presented a decision support system which applies a fuzzy set method to the robot selection decision-making problem. Karsak (2008) introduced a decision model for robot selection based on quality function deployment (QFD) and fuzzy linear regression. In addition, Kavita (2011) extended VIKOR method in intuitionistic fuzzy environment for robot selection. Vahdani et al. (2013) proposed an interval-valued fuzzy modified TOPSIS (IVFM-TOPSIS) method for robot selection that can reflect both subjective judgements and objective information in realistic circumstances.

The literature review demonstrates that the majority of researchers concentrated on robot selection methods applying linguistic values by using fuzzy logic to handle the uncertainty in real situations. They usually deal with linguistic terms by using the extension principle (Klir and Yuan 1995) and the symbolic method (Yager 1981). As a result, an approximation process must be developed to express the result in the initial expression domain, since the computation results usually do not exactly match any of the initial linguistic terms. This produces a loss of information and hence a lack of precision in the final results (Herrera and Martínez 2000; Liu, Liu, and Wu 2013). On the other hand, decision-makers are often unsure of their preferences during the robot selection process because of time pressure, lack of experience and data. They often demonstrate different evaluations or opinions from one to another and produce different types of assessment information for a certain alternative concerning a given criterion, some of which may be precise or imprecise, certain or uncertain, and complete or incomplete. These different types of information are very hard to incorporate into the robot selection by fuzzy logic-based approaches. Whereas, the interval 2-tuple linguistic representation model (Zhang 2012, 2013) overcomes the above limitations. The advantages of this approach are that decision-makers can express their preferences by the use of linguistic term sets with different granularity of uncertainty, and their judgements can be expressed with interval 2-tuples from the predefined linguistic term sets. Therefore, the approach based on the interval 2-tuple linguistic representation model is more flexible and precise to deal with linguistic terms in solving robot selection problems.

In other way, many objective and subjective criteria (or factors) should be taken into account when selecting an optimum robot for a particular application, including product design, production system, cost, positioning accuracy, repeatability, load capacity, degrees of freedom, man–machine interface, programming flexibility, maximum tip speed, memory capacity and supplier's service quality (Chu and Lin 2003; Bhangale, Agrawal, and Saha 2004; Chatterjee, Manikrao Athawale, and Chakraborty 2010; Rao, Patel, and Parnichkun 2011). In order to select the most suitable robot, it is necessary to make balance among these tangible and intangible factors some of which are conflicting in nature and have different units. Therefore, the selection of an optimal robot for a given industrial application can be regarded as a complex MCDM problem, and there is a need for systematic and efficient methods or mathematical tools to assist decision-makers in evaluating and selecting robots. The TOPSIS developed by Hwang and Yoon (1981) is one of the well-known classical MCDM methods for solving decision-making problems. The basic principle is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution concurrently (Hwang and Yoon 1981; Chen, Hwang, and Hwang 1992). If each criterion has a monotone

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increasing (or decreasing) effective function, the positive ideal solution, which consists of the best criteria values, and the negative ideal solution, which consists of the worst, are computed (Byun and Lee 2005). Due to its characteristics and capabilities, the TOPSIS has been extensively applied to engineering and management fields (Shanian and Savadogo 2006; Boran et al. 2009; Ekmekçioğlu, Kaya, and Kahraman 2010; Dursun, Karsak, and Karadayi 2011; Gupta 2011; Kelemenis, Ergazakis, and Askounis 2011; Liao and Kao 2011; Zouggari and Benyoucef 2012), and the use of TOPSIS method within the robot selection framework is practicable and can be accomplished (Agrawal, Kohli, and Gupta 1991; Chu and Lin 2003; Kahraman et al. 2007; Vahdani, Mousavi, and Tavakkoli-Moghaddam 2011; İç 2012; Vahdani et al. 2013).

The background introduced above shows that it may be inappropriate to use fuzzy logic-based methods for evaluation and selection of robots because of the loss of information in the linguistic information processing. Furthermore, decision-makers tend to use different linguistic term sets to express their judgements on the subjective criteria, and there usually exists uncertain and incomplete assessments. Therefore, this paper aims to develop a new MCDM method with interval 2-tuple linguistic information to solve the robot selection problem under uncertain and incomplete information environment. The method is an extended TOPSIS for group decision-making with interval 2-tuple linguistic variables. It can overcome both the drawbacks of the crisp and fuzzy robot section methods. Furthermore, both conflicting quantitative and qualitative evaluation criteria in real-life applications are considered simultaneously in the developed approach. In order to do so, the remainder of this paper is set out as follows. In Section 2, some basic concepts and operational laws of interval 2-tuple linguistic variables are briefly introduced. In Section 3, an extended TOPSIS for group decision-making is developed to solve the group multi-criteria robot selection problem with interval 2-tuple linguistic information. A numerical example is provided in Section 4 to illustrate the developed approach and some concluding remarks are offered in Section 5.

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2. Preliminaries

2.1 *2-tuple linguistic variables*

A linguistic variable is a variable whose values are expressed in linguistic terms. In other words, it is a variable whose values are not numbers but words or sentences in a natural or artificial language. The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described by traditional quantitative expressions (Zadeh 1975). For identifying the diversity of each evaluation item and facilitating the computation, linguistic terms often possess some characteristics such as finite set, odd cardinality, semantic symmetry, ordinal level and compensative operation (Tai and Chen 2009). Let $S = \{s_i | \, i = 0, 1, \ldots, g\}$ be a linguistic term set with odd cardinality, where s_i represents a possible value for a linguistic variable. It is required that the linguistic term set should satisfy the following characteristics (Herrera and Martínez 2000, 2001):

(1) Negation operator: Neg $(s_i) = s_j$ such that $j = g - i$;
(2) The set is ordered: $s_i > s_j$, if $i > j$;
(3) Max operator: $\max(s_i, s_j) = s_i$, if $s_i \geq s_j$;
(4) Min operator: $\min(s_i, s_j) = s_i$, if $s_i \leq s_j$.

For example, a set of seven linguistic terms S, could be defined as follows:

$$S = \{s_0 = \textit{Very poor},\ s_1 = \textit{Poor},\ s_2 = \textit{Medium poor},\ s_3 = \textit{Medium},\ s_4 = \textit{Medium good},\ s_5 = \textit{Good},\ s_6 = \textit{Very good}\}.$$

The 2-tuple linguistic representation model was firstly presented by Herrera and Martínez (2000) based on the concept of symbolic translation. It is used to represent the linguistic information by means of a linguistic 2-tuple (s, α), where s is a linguistic term from the predefined linguistic term set S and α is a numerical value representing the symbolic translation. That is, a 2-tuple linguistic variable can be denoted as (s_i, α_i), $s_i \in S$, where s_i represents the central value of the ith linguistic term and α_i indicates the distance to the central value of the ith linguistic term.

In the classical 2-tuple linguistic approach, the range of β is between 0 and g, which is relevant to the granularity of the linguistic term sets. Here, β is the result of an aggregation of the indices of a set of labels assessed in a linguistic term set S. In order to overcome the limitation, Chen and Tai (2005) proposed a generalised 2-tuple linguistic model.

Definition 1. Let $S = \{s_0, s_1, \ldots, s_g\}$ be a linguistic term set and $\beta \in [0, 1]$ a value representing the result of a symbolic aggregation operation. Then the generalised translation function Δ used to obtain the 2-tuple linguistic variable equivalent to β can be defined as follows (Chen and Tai 2005; Tai and Chen 2009):

$$\Delta : [0,1] \to S \times \left[-\frac{1}{2g}, \frac{1}{2g}\right), \tag{1}$$

$$\Delta(\beta) = (s_i, \alpha), \quad \text{with} \begin{cases} s_i, & i = \text{round}(\beta \cdot g) \\ \alpha = \beta - \frac{i}{g}, & \alpha \in \left[-\frac{1}{2g}, \frac{1}{2g}\right) \end{cases} \tag{2}$$

where round$(\cdot)$ is the usual rounding operation, s_i has the closest index label to β and α is the value of the symbolic translation. The interval of α is derived from the number of linguistic terms in S.

Example 1. Assume $S = \{s_0, s_1, \ldots, s_6\}$ be a linguistic term set, then $g = 6$ and $\alpha \in [-0.083, 0.083)$. If the result of a symbolic aggregation operation $\beta = 0.6$, then the representation of this counting of information by means of a 2-tuple will be $\Delta(0.6) = (s_4, -0.067)$. Graphical representation of the transformation is shown in Figure 1.

Definition 2. Let $S = \{s_0, s_1, \ldots, s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There exists a function Δ^{-1}, which is able to convert a 2-tuple linguistic variable into its equivalent numerical value $\beta \in [0,1]$. The reverse function Δ^{-1} is defined as follows (Chen and Tai 2005; Tai and Chen 2009):

$$\Delta^{-1} : S \times \left[-\frac{1}{2g}, \frac{1}{2g}\right) \to [0,1], \tag{3}$$

$$\Delta^{-1}(s_i, \alpha) = \frac{i}{g} + \alpha = \beta. \tag{4}$$

It is obvious that the conversion of a linguistic term into a linguistic 2-tuple consists of adding a value 0 as symbolic translation (Herrera and Martínez 2000):

$$s_i \in S \Rightarrow (s_i, 0). \tag{5}$$

The comparison of linguistic information represented by 2-tuples is carried out according to an ordinary lexicographic order.

Definition 3. Let (s_k, α_k) and (s_l, α_l) be two 2-tuples, then (Herrera and Martínez 2000, 2001):

(1) If $k < l$ then (s_k, α_k) is smaller than (s_l, α_l);
(2) If $k = l$ then
    (a) if $\alpha_k = \alpha_l$, then (s_k, α_k) is equal to (s_l, α_l);
    (b) if $\alpha_k < \alpha_l$ then (s_k, α_k) is smaller than (s_l, α_l);
    (c) if $\alpha_k > \alpha_l$ then (s_k, α_k) is bigger than (s_l, α_l).

In the process of 2-tuple linguistic operation, both functions Δ and Δ^{-1} are used to ensure the operation of 2-tuple linguistic variables can be a 2-tuple without any information loss.

Definition 4. Let $X = \{(s_1, \alpha_1), (s_2, \alpha_2), \ldots, (s_n, \alpha_n)\}$ be a set of 2-tuples and $w = (w_1, w_2, \ldots, w_n)^T$ be their associated weights, with $w_i \in [0,1]$, $i = 1, 2, \ldots, n$, $\sum_{j=1}^{n} w_i = 1$. The 2-tuple weighted average (TWA) is defined as (Herrera and Martínez 2000):

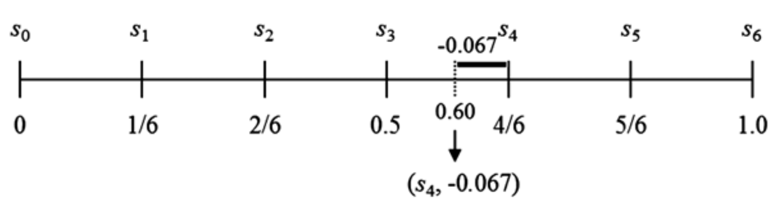

Figure 1. Example of a symbolic translation computation.

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$$\mathrm{TWA}(X)=\Delta\left(\frac{1}{n}\sum_{i=1}^{n}w_i\Delta^{-1}(s_i,\alpha_i)\right)=\Delta\left(\frac{1}{n}\sum_{i=1}^{n}w_i\beta_i\right). \tag{6}$$

2.2 *Interval 2-tuple linguistic variables*

Based on the definitions of Chen and Tai (2005), Zhang (2012) proposed an interval 2-tuple linguistic representation model, as a generalisation of the 2-tuple linguistic variables.

Definition 5. Let $S=\{s_0,s_1,\ldots,s_g\}$ be a linguistic term set. An interval 2-tuple linguistic variable is composed of two 2-tuples, denoted by $\left[(s_i,\alpha_i),(s_j,\alpha_j)\right]$, where $i\le j$ and $\alpha_i\le\alpha_j$, $s_i(s_j)$ and $\alpha_i(\alpha_j)$ represent the linguistic label of the predefined linguistic term set S and symbolic translation, respectively. The interval 2-tuple that expresses the equivalent information to an interval value $[\beta_1,\beta_2](\beta_1,\beta_2\in[0,1],\beta_1\le\beta_2)$ is derived by the following function (Zhang 2012, 2013):

$$\Delta[\beta_1,\beta_2]=\left[(s_i,\alpha_i),(s_j,\alpha_j)\right]\quad\text{with}\begin{cases}s_i, & i=\mathrm{round}(\beta_1\cdot g)\\ s_j, & j=\mathrm{round}(\beta_2\cdot g)\\ \alpha_i=\beta_1-\frac{i}{g}, & \alpha_i\in\left[-\frac{1}{2g},\frac{1}{2g}\right)\\ \alpha_j=\beta_2-\frac{j}{g}, & \alpha_j\in\left[-\frac{1}{2g},\frac{1}{2g}\right).\end{cases} \tag{7}$$

On the contrary, there is always a function Δ^{-1} such that an interval 2-tuple can be converted into an interval value $[\beta_1,\beta_2](\beta_1,\beta_2\in[0,1],\beta_1\le\beta_2)$ as follows:

$$\Delta^{-1}\left[(s_i,\alpha_i),(s_j,\alpha_j)\right]=\left[\frac{i}{g}+\alpha_i,\frac{j}{g}+\alpha_j\right]=[\beta_1,\beta_2]. \tag{8}$$

Specially, if $s_i=s_j$ and $\alpha_i=\alpha_j$, then the interval 2-tuple linguistic variable reduces to a 2-tuple linguistic variable.

Definition 6. Let $\tilde{X}=\{[(s_1,\alpha_1),(t_1,\varepsilon_1)],[(s_2,\alpha_2),(t_2,\varepsilon_2)],\ldots,[(s_n,\alpha_n),(t_n,\varepsilon_n)]\}$ be a set of interval 2-tuples and $w=(w_1,w_2,\ldots,w_n)^T$ be their associated weights, with $w_i\in[0,1]$, $i=1,2,\ldots,n$, $\sum_{i=1}^{n}w_i=1$. The interval 2-tuple weighted average (ITWA) operator is defined as (Zhang 2012, 2013):

$$\mathrm{ITWA}(\tilde{X})=\Delta\left[\sum_{i=1}^{n}w_i\Delta^{-1}(s_i,\alpha_i),\sum_{i=1}^{n}w_i\Delta^{-1}(t_i,\varepsilon_i)\right]. \tag{9}$$

Definition 7. Let $\tilde{a}=\left[(s_i,\alpha_i),(s_j,\alpha_j)\right]$ and $\tilde{b}=[(s_k,\alpha_k),(s_l,\alpha_l)]$ be two interval 2-tuples, then:

$$\begin{aligned}\tilde{a}+\tilde{b}&=\left[(s_i,\alpha_i),(s_j,\alpha_j)\right]+[(s_k,\alpha_k),(s_l,\alpha_l)]\\&=\Delta\left[\Delta^{-1}(s_i,\alpha_i)+\Delta^{-1}(s_k,\alpha_k),\Delta^{-1}(s_j,\alpha_j)+\Delta^{-1}(s_l,\alpha_l)\right],\end{aligned} \tag{10}$$

$$\begin{aligned}\tilde{a}\times\tilde{b}&=[(s_i,\alpha_i),(s_j,\alpha_j)]\times[(s_k,\alpha_k),(s_l,\alpha_l)]\\&=\Delta[\Delta^{-1}(s_i,\alpha_i)\cdot\Delta^{-1}(s_k,\alpha_k),\Delta^{-1}(s_j,\alpha_j)\cdot\Delta^{-1}(s_l,\alpha_l)].\end{aligned} \tag{11}$$

Definition 8. Let $\tilde{a}=[(s_i,\alpha_i),(s_j,\alpha_j)]$ and $\tilde{b}=[(s_k,\alpha_k),(s_l,\alpha_l)]$ be two interval 2-tuples, then:

$$D(\tilde{a},\tilde{b})=\Delta\sqrt{\left(\Delta^{-1}(s_i,\alpha_i)-\Delta^{-1}(s_k,\alpha_k)\right)^2+\left(\Delta^{-1}(s_j,\alpha_j)-\Delta^{-1}(s_l,\alpha_l)\right)^2} \tag{12}$$

is called the Euclidean distance between $\tilde{a}$ and $\tilde{b}$.

Definition 9. Let $\tilde{X}_1=\{[(s_1,\alpha_1),(t_1,\varepsilon_1)],[(s_2,\alpha_2),(t_2,\varepsilon_2)],\ldots,[(s_n,\alpha_n),(t_n,\varepsilon_n)]\}$ and $\tilde{X}_2=\{[(s_1',\alpha_1'),(t_1',\varepsilon_1')],[(s_2',\alpha_2'),(t_2',\varepsilon_2')],\ldots,[(s_n',\alpha_n'),(t_n',\varepsilon_n')]\}$ be two sets of interval 2-tuples, then:

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$$D(\tilde{X}_1, \tilde{X}_2) = \Delta \sqrt{\sum_{i=1}^{n} \left[(\Delta^{-1}(s_i, \alpha_i) - \Delta^{-1}(s'_i, \alpha'_i))^2 + (\Delta^{-1}(t_i, \varepsilon_i) - \Delta^{-1}(t'_i, \varepsilon'_i))^2 \right]} \tag{13}$$

is called the Euclidean distance between $\tilde{X}_1$ and $\tilde{X}_2$.

3. Interval 2-tuple linguistic TOPSIS method

In this section, we present a modified TOPSIS method to solve linguistic MCDM problems in which the criteria weights take the form of 2-tuple linguistic variables, and the criteria values take the form of interval 2-tuple linguistic variables. The flow diagram of the proposed algorithm is illustrated in Figure 2.

Suppose that a MCDM problem has l decision-makers DM_k $(k = 1, 2, \ldots, l)$, m alternatives A_i $(i = 1, 2, \ldots, m)$, and n decision criteria C_j $(j = 1, 2, \ldots, n)$. Each decision-maker DM_k is given a weight $\lambda_k > 0$ $(k = 1, 2, \ldots, l)$ satisfying $\sum_{k=1}^{l} \lambda_k = 1$ to reflect his/her relative importance in the group decision-making process. Let $D_k = (d_{ij}^k)_{m \times n}$ be the linguistic decision matrix of the kth decision-maker, where d_{ij}^k is the linguistic information provided by DM_k on the assessment of A_i with respect to C_j. Let $w_k = (w_1^k, w_2^k, \ldots, w_n^k)^T$ be the linguistic weight vector given by the kth decision-maker, where w_j^k is the linguistic variable assigned to C_j by DM_k. In addition, decision-makers may use different linguistic term sets to express their assessments.

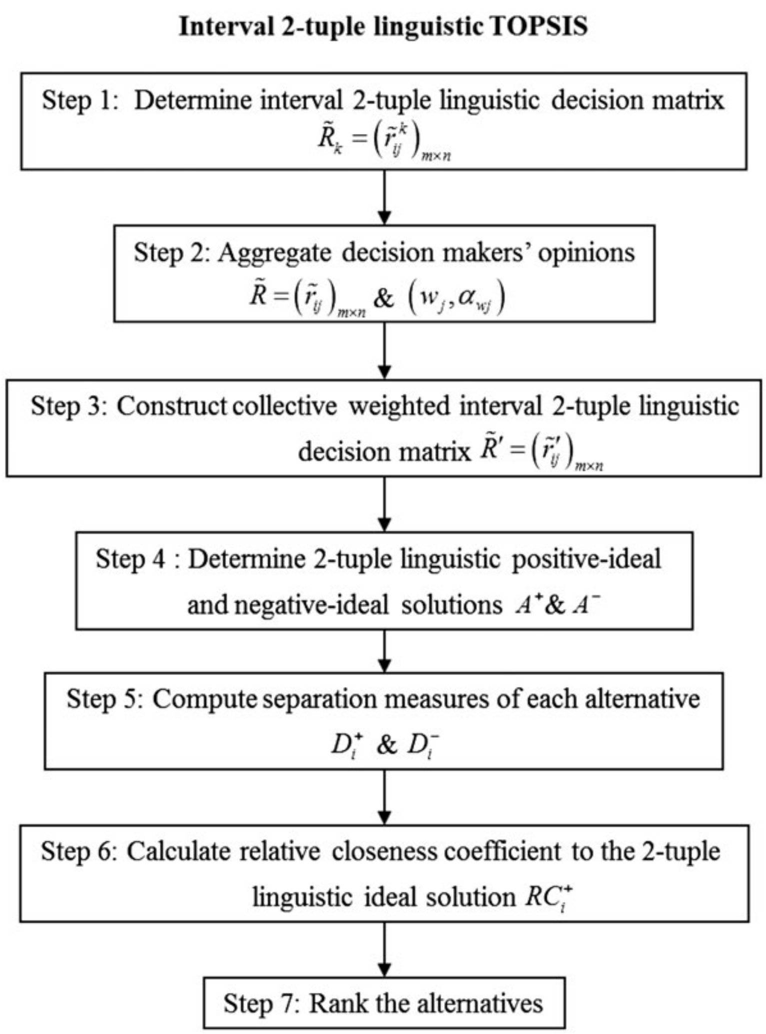

Figure 2. Flow diagram of the proposed algorithm.

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Based upon above assumptions or notations, the procedure of interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) method can be described as the follows:

Step 1: Convert the linguistic decision matrix $D_k = (d_{ij}^k)_{m\times n}$ into interval 2-tuple linguistic decision matrix $\tilde{R}_k = \left(\tilde{r}_{ij}^k\right)_{m\times n} = \left(\left[\left(s_{ij}^k, 0\right), \left(t_{ij}^k, 0\right)\right]\right)_{m\times n}$, where $s_{ij}^k, t_{ij}^k \in S,\ S = \{s_i | i = 0, 1, 2, \ldots, g\}$ and $s_{ij}^k \le t_{ij}^k$.

Suppose that DM_k provides his assessments in a set of five linguistic terms and the linguistic term set is denoted as

$$S = \{s_0 = Very\ poor,\ s_1 = Poor,\ s_2 = Medium,\ s_3 = Good,\ s_4 = Very\ good\}.$$

The linguistic information provided in the linguistic decision matrix D_k can be converted into its corresponding interval 2-tuple linguistic assessments according to the following ways:

- A certain grade such as *Poor*, which can be written as [(s_1, 0), (s_1, 0)].
- An interval such as *Poor-Medium*, which means that the assessment of an alternative with respect to the criterion under consideration is between *Poor* and *Medium*. This can be written as [(s_1, 0), (s_2, 0)].
- No judgement, which means the decision-maker is not willing to or cannot provide an assessment for an alternative with respect to the criterion under consideration. In other words, the assessment by this decision-maker could be anywhere between *Very poor* and *Very good,* and can be expressed as [(s_0, 0), (s_4, 0)].

Step 2: Aggregate the decision-makers' opinions to construct a collective interval 2-tuple linguistic decision matrix $\tilde{R} = (\tilde{r}_{ij})_{m\times n}$ and get the aggregated 2-tuple linguistic weight of each criterion (w_j, α_{wj}), where

$$\begin{aligned}\tilde{r}_{ij} &= \left[(s_{ij}, \alpha_{ij}), (t_{ij}, \varepsilon_{ij})\right] \\ &= \mathrm{ITWA}\left(\left[(s_{ij}^1, 0), (t_{ij}^1, 0)\right], \left[(s_{ij}^2, 0), (t_{ij}^2, 0)\right], \ldots, \left[(s_{ij}^l, 0), (t_{ij}^l, 0)\right]\right) \\ &= \Delta\left[\sum_{k=1}^{l} \lambda_k \Delta^{-1}(s_{ij}^k, 0), \sum_{k=1}^{l} \lambda_k \Delta^{-1}(t_{ij}^k, 0)\right], \quad i = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n.\end{aligned} \tag{14}$$

$$\begin{aligned}(w_j, \alpha_{wj}) &= \mathrm{TWA}\left[(w_j^1, 0), (w_j^2, 0), \ldots, (w_j^l, 0)\right] \\ &= \Delta\left[\sum_{k=1}^{l} \lambda_k \Delta^{-1}(w_j^k, 0)\right], \quad j = 1, 2, \ldots, n.\end{aligned} \tag{15}$$

Step 3: Construct a collective weighted interval 2-tuple linguistic decision matrix.

After the weights of criteria and the collective interval 2-tuple linguistic decision matrix are determined, the collective weighted interval 2-tuple linguistic decision matrix $\tilde{R}' = (\tilde{r}'_{ij})_{m\times n}$ can be constructed, where

$$\begin{aligned}\tilde{r}'_{ij} &= \left[(s'_{ij}, \alpha'_{ij}), (t'_{ij}, \varepsilon'_{ij})\right] = (w_j, \alpha_{wj}) \times \left[(s_{ij}, \alpha_{ij}), (t_{ij}, \varepsilon_{ij})\right] \\ &= \Delta\left[\Delta^{-1}(w_j, \alpha_{wj}) \cdot \Delta^{-1}(s_{ij}, \alpha_{ij}), \Delta^{-1}(w_j, \alpha_{wj}) \cdot \Delta^{-1}(t_{ij}, \varepsilon_{ij})\right], \\ &\qquad i = 1, 2, \ \ldots, m,\ j = 1, 2, \ldots, n.\end{aligned} \tag{16}$$

Step 4: Determine the 2-tuple linguistic positive-ideal solution A^+ and the 2-tuple linguistic negative-ideal solution A^- as:

$$A^+ = \left[(r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \ldots, (r_n^+, \alpha_n^+)\right], \tag{17}$$

$$A^- = \left[(r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \ldots, (r_n^-, \alpha_n^-)\right], \tag{18}$$

where

$$(r_j^+, \alpha_j^+) = \left\{\begin{array}{l}\max\limits_i\left\{(t_{ij}, \varepsilon_{ij})\right\},\ \text{for benefit criteria} \\ \min\limits_i\left\{(s_{ij}, \alpha_{ij})\right\},\ \text{for cost criteria}\end{array}\right\}, \quad j = 1, 2, \ldots, n, \tag{19}$$

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$$(r_j^-, \alpha_j^-) = \left\{ \begin{array}{l} \min_i \{(s_{ij}, \alpha_{ij})\}, \text{ for benefit criteria} \\ \max_i \{(t_{ij}, \varepsilon_{ij})\}, \text{ for cost criteria} \end{array} \right\}, \quad j = 1, 2, \ldots, n. \tag{20}$$

Step 5: Compute the separation measures.

The separation measures, D_i^+ and D_i^-, of each alternative from 2-tuple linguistic positive-ideal and 2-tuple linguistic negative-ideal solutions are calculated based on the n-dimensional Euclidean distance of interval 2-tuples:

$$D_i^+ = \Delta \sqrt{\sum_{j=1}^{n} \left[\left(\Delta^{-1}(s'_{ij}, \alpha'_{ij}) - \Delta^{-1}(r_j^+, \alpha_j^+) \right)^2 + \left(\Delta^{-1}(t'_{ij}, \varepsilon'_{ij}) - \Delta^{-1}(r_j^+, \alpha_j^+) \right)^2 \right]}, \quad i = 1, 2, \ldots, m, \tag{21}$$

$$D_i^- = \Delta \sqrt{\sum_{j=1}^{n} \left[\left(\Delta^{-1}(s'_{ij}, \alpha'_{ij}) - \Delta^{-1}(r_j^-, \alpha_j^-) \right)^2 + \left(\Delta^{-1}(t'_{ij}, \varepsilon'_{ij}) - \Delta^{-1}(r_j^-, \alpha_j^-) \right)^2 \right]}, \quad i = 1, 2, \ldots, m. \tag{22}$$

Step 6: Calculate the relative closeness coefficient to the 2-tuple linguistic ideal solution.

The relative closeness coefficient of each alternative A_i with respect to the 2-tuple linguistic positive-ideal solution A^+ is defined as follows:

$$RC_i^+ = \Delta \left(\frac{\Delta^{-1}(D_i^-)}{\Delta^{-1}(D_i^+) + \Delta^{-1}(D_i^-)} \right), \tag{23}$$

where $0 \leq \Delta^{-1}(RC_i^+) \leq 1$.

Step 7: Rank the alternatives.

According to the relative closeness coefficient to the ideal alternative, the bigger the RC_i^+, the better is the alternative A_i. Thus, all the alternatives A_i ($i = 1, 2, \ldots, m$) can be ranked according to descending order of their relative closeness values.

4. An illustrative example

In this section, the robot selection problem from (Liang and Wang 1993; Vahdani et al. 2013) is adopted to illustrate the computation and applicability of the proposed ITL-TOPSIS method. Suppose that a manufacturing company requires a robot to perform a material handling task, and that the prospective robot buyer can afford to spend at most \$75,000. After a task analysis, it has been identified that the desired load capacity should be at least 30 lb and the positioning accuracy should be within 0.2 in. Moreover, man–machine interface, programming flexibility and vendor's service contract are also considered as important evaluation criteria. After initial selection, three robots (A_1, A_2 and A_3) that satisfy the requirements of the particular problem are chosen for further evaluation. In order to select the most suitable robot, an expert committee of four decision-makers (DM_1, DM_2, DM_3 and DM_4) has been formed. The six criteria C_j ($j = 1, 2, \ldots, 6$), which are critical for the robot selection, are as follows:

C_1: Man–machine interface;
C_2: Programming flexibility;
C_3: Vendor's service contract;
C_4: Purchase cost;
C_5: Load capacity;
C_6: Positioning accuracy.

The four decision-makers employ different linguistic term sets to evaluate the alternative robots with respect to the subjective criteria (C_1, C_2 and C_3). Specifically, DM_1 provides his assessments in the set of 5 labels, A; DM_2 provides his assessments in the set of 7 labels, B; DM_3 provides her assessments in the set of 9 labels, C; DM_4 provides his assessments in the set of 7 labels, D. In addition, the relative importance of the six criteria was rated by the decision-makers with a set of 7 linguistic terms, E. These linguistic term sets are denoted as follows:

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$$A = \{a_0 = Very\ poor(VP),\ a_1 = Poor(P),\ a_2 = Fair(F),\ a_3 = Good(G),\ a_4 = Very\ good(VG)\},$$

$$B = \{b_0 = Very\ poor(VP),\ b_1 = Poor(P),\ b_2 = Moderately\ poor\ (MP),\ b_3 = Fair(F),\ b_4 = Moderately\ good(MG),\ b_5 = Good(G),\ b_6 = Very\ Good(VG)\}.$$

$$C = \{c_0 = Extreme\ poor(EP),\ c_1 = Very\ poor(VP),\ c_2 = Poor(P),\ c_3 = Moderately\ poor(MP),\ c_4 = Fair(F),\ c_5 = Moderately\ good(MG),\ c_6 = Good(G),\ c_7 = Very\ good(VG),\ c_8 = Extreme\ good(EG)\},$$

$$D = \{d_0 = Very\ poor(VP),\ d_1 = Poor(P),\ d_2 = Moderately\ \ poor(MP),\ d_3 = Fair(F),\ d_4 = Moderately\ \ good(MG),\ d_5 = Good(G),\ d_6 = Very\ good(VG)\},$$

$$E = \{e_0 = Very\ low(VL),\ e_1 = Low(L),\ e_2 = Medium\ low(ML),\ e_3 = Medium(M),\ e_4 = Medium\ high(MH),\ e_5 = High(H),\ e_6 = Very\ high(VH)\}.$$

The assessments of the three alternatives vs. each subjective criterion and the criteria weights provided by the four decision-makers are presented in Tables 1 and 2, respectively, where ignorance information is highlighted and shaded. Also, the data of objective criteria is obtained from vendors and presented in Table 3. In this example, it is assumed that degrees of the importance for the four decision-makers are equal.

Next, we utilise the ITL-TOPSIS method to derive the most desirable alternative, which consists of the following steps:

Step 1: The linguistic evaluations shown in Tables 1 and 2 are converted into interval 2-tuple linguistic variables and 2-tuple linguistic variables, respectively. The results are shown in Tables 4 and 5. For example, for the expert DM_2, the evaluations of the three alternative robots on criterion C_1, MG-G (interval grade), unknown and VG (certain grade), can be converted into their corresponding interval 2-tuple linguistic variables, $[(b_4, 0), (b_5, 0)]$, $[(b_0, 0), (b_6, 0)]$ and $[(b_6, 0),$

Table 1. Decision-makers' evaluation of the three robots under subjective criteria.

		Criteria		
Decision-makers	Alternatives	C_1	C_2	C_3
DM_1	A_1	VG	F	P-F
	A_2	F-VG	F-G	G
	A_3	G	G-VG	VG
DM_2	A_1	MG-G	G	MG-G
	A_2	–	G-VG	VG
	A_3	VG	VG	G
DM_3	A_1	F	P-F	MP-MG
	A_2	G-VG	G	F
	A_3	MG	F-MG	G
DM_4	A_1	MP-F	G	–
	A_2	F	VG	MG
	A_3	G	MG-VG	G-VG

Table 2. Weights of criteria determined by the decision-makers.

	Decision-makers			
Criteria	DM_1	DM_2	DM_3	DM_4
C_1	H	VH	VH	H
C_2	M	VH	H	VH
C_3	L	M	L	M
C_4	L	M	M	M
C_5	VH	VH	H	VH
C_6	H	VH	H	VH

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Table 3. Data of objective criteria for the three robots.

Alternatives	Criteria		
	Purchase cost ($ × 1000), C_4	Load capacity (lb), C_5	Positioning accuracy (±), C_6
A_1	73	50	0.12
A_2	70	45	0.16
A_3	68	45	0.17

Table 4. Interval 2-tuple linguistic decision matrices of the four decision-makers.

Decision-makers	Alternatives	Criteria		
		C_1	C_2	C_3
DM_1	A_1	$[(a_4,0), (a_4,0)]$	$[(a_2,0), (a_2,0)]$	$[(a_1,0), (a_2,0)]$
	A_2	$[(a_2,0), (a_4,0)]$	$[(a_2,0), (a_3,0)]$	$[(a_3,0), (a_3,0)]$
	A_3	$[(a_3,0), (a_3,0)]$	$[(a_3,0), (a_4,0)]$	$[(a_4,0), (a_4,0)]$
DM_2	A_1	$[(b_4,0), (b_5,0)]$	$[(b_5,0), (b_5,0)]$	$[(b_4,0), (b_5,0)]$
	A_2	$[(b_0,0), (b_6,0)]$	$[(b_5,0), (b_6,0)]$	$[(b_6,0), (b_6,0)]$
	A_3	$[(b_6,0), (b_6,0)]$	$[(b_6,0), (b_6,0)]$	$[(b_5,0), (b_5,0)]$
DM_3	A_1	$[(c_4,0), (c_4,0)]$	$[(c_2,0), (c_4,0)]$	$[(c_3,0), (c_5,0)]$
	A_2	$[(c_6,0), (c_7,0)]$	$[(c_6,0), (c_6,0)]$	$[(c_4,0), (c_4,0)]$
	A_3	$[(c_5,0), (c_5,0)]$	$[(c_4,0), (c_5,0)]$	$[(c_6,0), (c_6,0)]$
DM_4	A_1	$[(d_2,0), (d_3,0)]$	$[(d_5,0), (d_5,0)]$	$[(d_0,0), (d_6,0)]$
	A_2	$[(d_3,0), (d_3,0)]$	$[(d_6,0), (d_6,0)]$	$[(d_4,0), (d_4,0)]$
	A_3	$[(d_5,0), (d_5,0)]$	$[(d_4,0), (d_6,0)]$	$[(d_5,0), (d_6,0)]$

$(b_6, 0)]$, based on the linguistic term set B. It may be mentioned here that the 2-tuple linguistic variables are special cases of the interval 2-tuple linguistic variables. In this example, the relative importance weights of robot selection criteria are expressed by 2-tuple linguistic variables. This is mainly because they are relatively easier to be assessed than the criteria themselves. If they are also difficult to be determined, the criteria weights can be transformed into the interval 2-tuple linguistic variables and processed by the proposed method.

Step 2: The aggregated linguistic ratings of alternatives and aggregated weights of criteria are calculated by Equations (14) and (15), and are presented in Tables 5–6. In addition, the data of objective criteria are normalised according to the traditional TOPSIS method (Hwang and Yoon 1981) as shown in Table 6.

Step 3: The collective weighted interval 2-tuple linguistic decision matrix is constructed by Equation (16) and is given in Table 7.

Step 4: The 2-tuple linguistic positive-ideal solution A^+ and the 2-tuple linguistic negative-ideal solution A^- are determined using Equations (17)–(20) and are shown below.

$$A^+ = [\Delta(0.773), \Delta(0.755), \Delta(0.299), \Delta(0.232), \Delta(0.592), \Delta(0.419)],$$

$$A^- = [\Delta(0.401), \Delta(0.503), \Delta(0.108), \Delta(0.250), \Delta(0.533), \Delta(0.594)].$$

Table 5. 2-Tuple linguistic criteria weights and the aggregated weights.

Criteria	Decision-makers				Aggregated weights
	DM_1	DM_2	DM_3	DM_4	
C_1	$(e_5, 0)$	$(e_6, 0)$	$(e_6, 0)$	$(e_5, 0)$	$\Delta(0.917)$
C_2	$(e_3, 0)$	$(e_6, 0)$	$(e_5, 0)$	$(e_6, 0)$	$\Delta(0.833)$
C_3	$(e_1, 0)$	$(e_3, 0)$	$(e_1, 0)$	$(e_3, 0)$	$\Delta(0.333)$
C_4	$(e_1, 0)$	$(e_3, 0)$	$(e_3, 0)$	$(e_3, 0)$	$\Delta(0.417)$
C_5	$(e_6, 0)$	$(e_6, 0)$	$(e_5, 0)$	$(e_6, 0)$	$\Delta(0.958)$
C_6	$(e_5, 0)$	$(e_6, 0)$	$(e_5, 0)$	$(e_6, 0)$	$\Delta(0.917)$

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Table 6. Aggregated linguistic assessments under subjective criteria and normalised values under objective criteria.

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	$\Delta[0.625, 0.708]$	$\Delta[0.604, 0.667]$	$\Delta[0.323, 0.740]$	0.599	0.618	0.457
A_2	$\Delta[0.438, 0.844]$	$\Delta[0.771, 0.875]$	$\Delta[0.729, 0.729]$	0.574	0.556	0.610
A_3	$\Delta[0.802, 0.802]$	$\Delta[0.729, 0.906]$	$\Delta[0.854, 0.896]$	0.558	0.556	0.648

Table 7. Collective weighted interval 2-tuple linguistic decision matrix.

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	$\Delta[0.573, 0.649]$	$\Delta[0.503, 0.556]$	$\Delta[0.108, 0.247]$	$\Delta(0.250)$	$\Delta(0.592)$	$\Delta(0.419)$
A_2	$\Delta[0.401, 0.773]$	$\Delta[0.642, 0.729]$	$\Delta[0.243, 0.243]$	$\Delta(0.239)$	$\Delta(0.533)$	$\Delta(0.559)$
A_3	$\Delta[0.735, 0.735]$	$\Delta[0.608, 0.755]$	$\Delta[0.285, 0.299]$	$\Delta(0.232)$	$\Delta(0.533)$	$\Delta(0.594)$

Table 8. Results of the proposed ITL-TOPSIS method.

Alternatives	D_i^+	D_i^-	RC_i^+	2-tuples	Ranking
A_1	$\Delta(0.726)$	$\Delta(0.637)$	$\Delta(0.467)$	$(b_3, -0.0328)$	3
A_2	$\Delta(0.743)$	$\Delta(0.773)$	$\Delta(0.510)$	$(b_3, 0.0100)$	2
A_3	$\Delta(0.683)$	$\Delta(0.874)$	$\Delta(0.561)$	$(b_3, 0.0613)$	1

Step 5: The separation measures, D_i^+ and D_i^-, of each alternative from 2-tuple linguistic positive-ideal and 2-tuple linguistic negative-ideal solutions are computed by Equations (21)–(22) as in Table 8.

Step 6: The relative closeness coefficients $RC_i^+(i = 1, 2, 3)$ are computed by Equation (23) and the results are shown in Table 8. In addition, by Equations (1)–(2), we can express the final results in the initial expression domain used by each expert. Taking the expert DM_2 as an example, the final results can be expressed by 2-tuples derived from the linguistic term set B with 7 labels, which are also listed in Table 8.

Step 7: According to Table 8, the ranking of the three alternative robots is $A_3 \succ A_2 \succ A_1$ for the robot selection problem. Hence, the most suitable alternative for the given industrial application vs. the six selected criteria is robot A_3.

To illustrate the effectiveness of the proposed ITL-TOPSIS, we used the above case study to analyse some existing robot selection methods, which include the fuzzy hierarchical structure analysis (HSA) (Liang and Wang 1993), the fuzzy TOPSIS (Chu and Lin 2003), the interval-valued fuzzy modified TOPSIS (IVFM-TOPSIS) (Vahdani et al. 2013), the intuitionistic fuzzy VIKOR (IF-VIKOR) (Kavita 2011) and the ELECTRE (Chatterjee, Manikrao Athawale, and Chakraborty 2010) methods. In addition, the comparison with one of the most commonly used interval number-based methods, i.e., the complex proportional assessment of alternatives with grey relations (COPRAS-G) (Chatterjee and Chakraborty 2012a, 2012b), is also conducted. Table 9 exhibits the ranking results of all the alternative robots as derived using these approaches. Based on the results in Table 9, the advantages that the proposed method has over other methods can be identified.

From Table 9, it can be observed that five of the seven methods suggest robot A_3 as the first choice for the given industrial application. Moreover, the ranking orders of the three robots obtained using the proposed method are exactly matched with those derived by the fuzzy HSA, the IVFM-TOPSIS and the ELECTRE methods. Therefore, the present method is validated. However, the COPRAS-G utilises grey numbers to evaluate the robots with respect to each criterion; but in some situations decision-makers are hard to express their evaluations in this way especially for the qualita-

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Table 9. Rankings of the alternative robots.

Alternatives	ITL-TOPSIS	Fuzzy HSA	Fuzzy TOPSIS	IVFM-TOPSIS	IF-VIKOR	ELECTRE	COPRAS-G
A_1	3	3	1	3	1	3	2
A_2	2	2	3	2	3	2	3
A_3	1	1	2	1	2	1	1

tive selection criteria. The COPRAS-G method did not explain clearly how to quantify the qualitative criteria. By using the fuzzy TOPSIS, the ranking of the alternative robots is obtained as $A_1 \succ A_3 \succ A_2$, which is total different from the one given by the proposed method. This inconsistency can be explained by fact that the fuzzy TOPSIS method is based on the extension principle, which produces the consequent loss of information and hence the lack of precision in the final results (Herrera and Martínez 2000). According to the IF-VIKOR method, both robots A_1 and A_2 are compromise solutions for this robot selection problem because the condition C1 is not satisfied: $Q_3 - Q_1 < 1/(3-1)$. That is, the best choice of robot for the considered industrial application cannot be determined by the IF-VIKOR method. Furthermore, the proposed method makes a provision to deal with the quantitative selection criteria in the problem. But this was missing in the IF-VIKOR method suggested by Kavita (2011).

From the above analysis, it can be concluded that the ranking of the three robots given by the proposed method is more accurate and reliable. Compared with other robot selection methods, the proposed ITL-TOPSIS has the following advantages:

- The proposed method has exact characteristic in linguistic information processing. It can effectively avoid the loss and distortion of information which occur formerly in the linguistic information processing.
- Both quantitative and qualitative evaluation criteria are taken into consideration in the process of prioritisation of alternative robots, which makes the proposed robot selection model more realistic, more practical and more flexible.
- The selection criteria of robots and their relative importance weights are evaluated in a linguistic manner rather than in precise numerical values. This enables the decision-makers to express their judgements more realistically and makes the assessment easier to be carried out.
- The uncertainty and diversity of decision-makers' assessment information can be well reflected and modelled using interval 2-tuple linguistic variables. And it provides an organised method to combine expert knowledge and experience for use in selecting the best-suited robot for a given industrial application.

5. Conclusions

Selection of appropriate robots for different industrial applications is one of the most challenging tasks in real-time manufacturing environment. It has become more difficult and complicated for manufacturing firms owing to the increase in complexity, advanced features and facilities and the large number of available industrial robots in the market. In this paper, we study the robot selection problem in the advanced manufacturing process under uncertain and incomplete information environment. And an extended TOPSIS method for group decision-making with interval 2-tuple linguistic variables was developed to deal with the decision-making situation of the robot selection. The methodology developed in this paper helps the decision-maker in selecting a suitable robot by considering both conflicting quantitative and qualitative selection criteria in real-life applications. Furthermore, a numerical example has demonstrated analytically the computational process of the proposed method. The results derived using the ITL-TOPSIS exactly match with those as obtained by the past researchers in the literature, and further prove that the extended TOPSIS method for group decision-making with interval 2-tuple linguistic information can cope with the robot selection problem under uncertain and incomplete information environment effectively.

The decision model presented here for selecting robots with interval 2-tuple linguistic variables is a general method. It can be utilised for making a best decision in any other areas of engineering and management problems, such as rapid prototyping process selection, plant layout design, supply chain management, and failure mode and effects analysis.

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