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Extension of PROMETHEE for robot selection decision making: Simultaneous exploration of objective data and subjective (fuzzy) data

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Simultaneous exploration of objective data and subjective (fuzzy) data

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Abstract

Purpose – Robot selection is basically a task of choosing appropriate robot among available alternatives with respect to some evaluation criteria. The task becomes much more complicated since apart from objective criteria a number of subjective criteria need to be evaluated simultaneously. Plenty of decision support systems have been well documented in existing literature which considers either objective or subjective data set; however, decision support module with simultaneous consideration of objective as well as subjective data has rarely been attempted before. The paper aims to discuss these issues.

Design/methodology/approach – Motivated by this, present work exhibits application potential of preference ranking organization method for enrichment evaluations (extended to operate under fuzzy environment) to solve decision-making problems which encounter both objective as well as subjective evaluation data.

Findings – An empirical case study has been demonstrated in the context of robot selection problem. Finally, a sensitivity analysis has been performed to make the robot selection process more robust. A trade-off between objective criteria measure and subjective criteria measure has been shown using sensitivity analysis.

Originality/value – Robot selection has long been viewed as an important decision-making scenario in the industrial context. Appropriate robot selection helps in enhancing value of the product and thereby, results in increased profitability for the manufacturing industries. The proposed decision support system considering simultaneous exploration of subjective as well as objective database is rarely attempted before.

Keywords Benchmarking, Decision support systems, PROMETHEE, Sensitivity analysis, Robot selection, Fuzzy

Paper type Research paper

1. Introduction

A robot is a power-driven self-controlled programmable machine made with mechanical, microelectronic and electrical components that can repeatedly perform often complicated and monotonous tasks. As per the American Robots Association, a robot can be characterized as a multi-functional structure, which can be better controlled by programs and commands (Mondal and Chakraborty, 2013). During the last decades, the use of robotic systems in commercial ventures and production units has been expanded considerably with a perspective to utilize the resources well in time for enhancing efficiency and and to improve product quality. Since robots are very expensive structures, so a detailed study for the pertinent robot selection must be

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carried out carefully. It is generally agreed from the literature that the maximum possible number of criteria both subjective and objective should be considered for authentic decision making.

Robot selection has dependably been a critical issue for assembling organizations in order to enhance part quality and to build profitability. The robot choice criteria may be objective, subjective or blending of both. Nowadays, several kind of robots which can perform repetitive, hazardous and difficult tasks are readily available in the marketplace with unique features and specification, presumably for all means of application like loading-unloading, assembly, material handling, welding, spray painting, etc. (Kumar and Garg, 2010). Apart from these, robotic packaging and robotic dispensing are some emerging applications of robots in manufacturing industries nowadays.

2. State of art

Robot selection is a complicated decision-making process in the multi-criteria decision-making (MCDM) framework. Hence, many of the past researchers have explored numerous ways to solve this complexity. Information available for this sort of selection may be objective or subjective in nature, and it is generally accepted that multi-criteria evaluation using objective information is quite handy than the subjective information-based analysis. Braglia and Petroni (1999) applied data envelopment analysis (DEA) toward selection of industrial robots. This methodology is based on a sequential dual use of DEA with restricted weights. The purpose of this research was to identify an optimal robot in a cost/benefit perspective, by measuring the relative efficiency of each robot through the resolution of linear programming problems. Bhangale *et al.* (2004) endeavored to produce a preserve reliable and comprehensive database of robot controllers based on their different pertinent attributes. This database could be utilized to standardize the robot choice strategy for a specific operation. Bhattacharya *et al.* (2005) delineated an integrated model combining analytic hierarchy process (AHP) and QFD for the industrial robot selection problem.

Rao and Padmanabhan (2006) added to a technique based on digraph and matrix methods for assessment of alternative industrial robots. A robot determination index was suggested that could evaluate and rank robots for a given industrial application. Chatterjee *et al.* (2010) proposed a dual approach to tackle the robot selection issue utilizing two most applicable multi-criteria choice making methods and equated their relative performance for a given industrial application. Initially "VIsekriterijumsko KOmpromisno Rangiranje" (VIKOR), a compromise ranking method was used followed by "ELimination and Et Choice Translating Reality" (ELECTRE), an outranking technique. Two real time examples were cited in order to demonstrate and validate the applicability and potentiality of both these MCDM methods so as to exhibit and accept the relevance and possibility of both these MCDM methods. Kumar and Garg (2010) developed a deterministic quantitative model based on distance-based approach technique for assessment, determination and ranking of robots. Kentli and Kar (2011) applied a MCDM model for a robot selection issue. The proposed model comprised a satisfaction function to transform various robot attributes into a unified scale. Further, a distance measure technique was used to determine the highest ranked candidate robot.

Due to the involvement subjective attributes, robot selection decision making often relies on the subjective judgment of the decision-making group. In the decision-making process, we usually confront with ambiguity and uncertainty for evaluating the criteria weights and alternatives of the problem (Ghorabaee, 2016). The subjectivity of linguistic human perception is often vague, imprecise and incomplete in nature. Fuzzy logic (Zadeh, 1965; Kapoor and Tak, 2005) has the capability of dealing with such inconsistent evaluation information efficiently.

Numerous studies have been done by the pioneers to extend traditional decision-making tools and techniques to operate under fuzzy environment so as to cope up with subjective evaluation information in the context of real world decision-making scenario. Fuzzy numbers set hypothesis, can be incorporated into traditional MCDM strategies to acquire the best acceptable preference order with the case where the data set is either subjective entirely or a combination of subjective and objective input. Past researchers utilized fuzzy set hypothesis intermittently with conventional MCDM approaches resulting Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy-MOORA, Fuzzy-ELECTRE, Fuzzy-preference ranking organization method for enrichment evaluations (PROMETHEE), etc.

In the context of robot selection, Wu (1990) developed a decision support system for robot selection using fuzzy set approach. Liang and Wang (1993) proposed a robot selection algorithm by combing the concepts of fuzzy set theory and hierarchical structure analysis. The stated methodology was used to aggregate the decision-makers' (DMs) fuzzy response about criteria weightings and the suitability ratings of a robot against various selection criteria to acquire fuzzy suitability indices. Parkan and Wu (1999) exhibited the aspects of multi-attribute decision making (MADM) and performance measurement methods through a robot selection problem. Emphasis was placed on a performance measurement procedure called operational competitiveness rating (OCRA), and an MADM tool called Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). A rank-relationship test demonstrated that the systems could produce comparable rankings for the robots, and final choice was made on the premise of the rankings obtained by averaging the consequences of OCRA, TOPSIS and a utility model.

Chu and Lin (2003) anticipated Fuzzy-TOPSIS method where the ratings of alternatives vs subjective criteria and the weights of all criteria were assessed in linguistic terms and characterized by fuzzy numbers. Kapoor and Tak (2005) executed fuzzy application along with an analytical hierarchy process for appropriate robot selection. This paper proposed an integrated methodology for solving common robot selection problems using a modification of the conventional AHP along with "Fuzzy Linguistic Variables" in place of numbers.

Rao *et al.* (2011) proposed a subjective and objective integrated multiple attribute decision-making method for the purpose of robot selection. The method considered objective weights of the attributes as well as the subjective preferences of the DMs to decide the integrated weight of importance of the attributes. The method used fuzzy logic to convert the qualitative attributes into the quantitative ones. Devi (2011) attempted to solve multiple criteria decision-making problems in relation to robot selection by exploring VIKOR method extended in intuitionistic fuzzy environment, in which the weights of criteria and ratings of alternatives were taken as triangular intuitionistic fuzzy set.

Koulouriotis and Ketipi (2011) attempted a fuzzy digraph method for robot evaluation and selection, rendering to a given industrial application. All the information about the objective and subjective attributes were articulated in linguistic terms and represented by fuzzy numbers. The methodology was resolved by converting the fuzzy output into a crisp value and estimating the selection index.

Bai and Wang (2013) proposed an effective weight estimation method in order to make objective and reliable approximation, and thereby, established a fuzzy multiple criteria decision-making (FMCDM) model to evaluate, identify and select an optimal robot system to perform the desired task from a large number of robotic systems. İç *et al.* (2013) developed a two-phase robot selection decision support system known as ROBSEL. In development of ROBSEL, an independent set of criteria was obtained first and arranged in the fuzzy analytical hierarchy process (FAHP) decision hierarchy. In the first elimination phase of the decision support system, the user could obtain the feasible set of robots by providing limited values for the requirements under consideration. ROBSEL could then use FAHP decision hierarchy to rank the feasible robots in the second phase.

Liu *et al.* (2014) proposed an interval 2-tuple linguistic TOPSIS method to handle the robot selection problem under uncertain and incomplete information environment. The major advantage of this method was that it could consider both subjective judgments and objective information in real-life applications. Rashid *et al.* (2014) suggested a robot selection approach by using generalized interval-valued fuzzy numbers with TOPSIS and reported that GITFN-TOPSIS produced satisfactory results by providing two ideal separation and anti-ideal separation matrices. Vahdani *et al.* (2014) applied a complex proportional assessment method (COPRAS) under an interval-valued fuzzy environment for robot selection. This method enhanced and extended the theory and concept of fuzzy compromise programming based on positive and negative ideal solutions as well as the fuzzy utility degree.

Bairagi *et al.* (2014) employed three FMCDM methodologies in the evaluation and selection of robots for automated foundry operations. In the methodologies, a FAHP was integrated individually with a Fuzzy Technique for Order Preference by Similarity to the Ideal Solution (FTOPSIS), a Fuzzy VIsekriterijumska optimizacija i KOmpromisno Resenje (FVIKOR) and a COPRAS method with the application of Grey systems theory.

A comparative analysis of the results obtained by the methodologies was carried out. Parameshwaran *et al.* (2015) constructed an integrated fuzzy MCDM-based approach for robot selection considering objective and subjective criteria. The approach utilized fuzzy Delphi method, FAHP; fuzzy modified TOPSIS or Fuzzy-VIKOR and Brown-Gibson model for robot selection.

3. Problem statement

Robot selection is basically a MCDM problem in which the most suitable robot is selected based on some evaluation criteria. Criteria may be objective or subjective or a combination of the both. Robot selection considering objective criteria can easily be tackled by traditional decision-making tools and techniques. Problem is faced in dealing with subjective criteria since they cannot be assessed by exact numeric score. These criteria are basically ill-defined and vague in nature. This creates uncertainty as well as inconsistency in the decision making as these criteria are assessed by the experts (DMs). Subjective human judgment often bears ambiguity and vagueness in the decision making; exploration of fuzzy set theory seems fruitful in this context. In fuzzy-based decision-making approaches, subjective criteria are judged by the experts and assessed in terms of linguistic variables. Linguistic data are further transformed into appropriate fuzzy numbers and finally by exploring fuzzy mathematics, a concrete decision is arrived. In order to tackle subjectivity of the evaluation criteria, traditional decision-making tools and techniques have been extended to work under fuzzy environment. A variety of fuzzy-based decision support systems have been proposed by pioneers to solve different decision-making problems in different fields of applications. The decision support systems thus reviewed in the existing literature either consider a consolidated objective database or a subjective database. However, rare attempt has been made to support a decision-making module considering subjective and objective database both. To fill up the existing research gap, present study attempts to conceptualize a decision support system considering objective as well as subjective (fuzzy) data in relation to a robot selection problem. The formulations of PROMETHEE I and II have been extended to support the said decision modeling.

In later phase of this work, a sensitivity analysis has been performed to make a trade-off between objective factor measures (OFM) as well as subjective factor measures. In this part of work, objective criteria and subjective criteria have been analyzed separately and a global selection score has been computed to select the most appropriate robot in view of variation of the DMs' risk-bearing attitude.

The research questions (objectives) of the present work are as follows:

RQ1. The research attempts to examine how PROMETHEE method can be explored to analyze objective as well as subjective (fuzzy) evaluation data simultaneously in industrial decision making.

RQ2. In traditional approaches, a decision-making database consisting of objective as well as subjective data cannot be evaluated simultaneously. To get rid of that, either objective data need to be fuzzified and combined with fuzzy data; or, fuzzy data need to be defuzzified (crisp) and analyzed with along with actual objective data. This research proposes an approach to achieve a reliable decision outcome through simultaneous utilization of objective as well as subjective data without changing their identity.

RQ3. The research also proposes a novel way (sensitivity analysis) to consider DMs' risk-bearing attitude in the selection of appropriate alternative.

4. Preliminaries of fuzzy mathematics

Decision making is very much perceived as an intellectual process, normally recognized to diminish the ambiguity and suspicion among the numbers of alternatives to make an enlightened choice. It is a conclusive strategic task of making an imperative decision, often executed by manufacturing unit, firms and business houses. To reach any result, DMs need to access the input response data/information that is of two types like subjective information and objective information. Subjective information can be expressed or communicated through natural language description only whereas objective information is a numerical measurement expressed in terms of numbers instead of a natural language description. Objective information can be accessed easily through conventional MCDM methods; however, dealing with the subjective information is a quite challenging task as this information does not acknowledge the explicit situation. Subjective information cannot be utilized until and unless they are converted into some scientific values. For doing so, fuzzy number set theory, was introduced through which subjective attributes can be assessed and represented (Chou *et al.*, 2008). Fuzzy set theory provides a strict scientific system through which precarious information can be converted into a unified scale precisely. Moreover, it can also be treated as a modeling terminology, strongly recommended for circumstances where fuzzy relationship, criteria and phenomena exist (Zimmermann, 2010). The fuzzy set hypothesis possibly may demonstrate to have a more extensive extent of appropriateness, particularly in the course of information transformation. Essentially, such a framework delivers a usual way of dealing with difficulties in which the source of fuzziness is inherent in the absence of sharply defined criteria of class membership rather than the presence of random variables (Zadeh 1965).

4.1 Definition of fuzzy sets

Definition 1. A fuzzy set $\tilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\tilde{A}}(x)$ which associates with each element x in X a real number in the interval [0, 1]. The function value $\mu_{\tilde{A}}(x)$ is termed the grade of membership of x in $\tilde{A}$ (Kaufmann and Gupta, 1991).

Definition 2. A fuzzy set $\tilde{A}$ in a universe of discourse X is convex if and only if:

$$\mu_{\tilde{A}}(\lambda x_1+(1-\lambda)x_2) \geqslant \min\left(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)\right) \tag{1}$$

For all x_1, x_2 in X and all $\lambda \in [0, 1]$, where "min" denotes the minimum operator (Klir and Yuan, 1995).

Definition 3. The height of a fuzzy set is the largest membership grade attained by any element in that set. A fuzzy set $\tilde{A}$ in the universe of discourse X is called normalized when the height of $\tilde{A}$ is equal to 1 (Klir and Yuan, 1995).

4.2 Definitions of fuzzy numbers

Definition 4. A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal. Figure 1 shows a fuzzy number $\tilde{n}$ in the universe of discourse X that conforms to this definition (Kaufmann and Gupta, 1991).

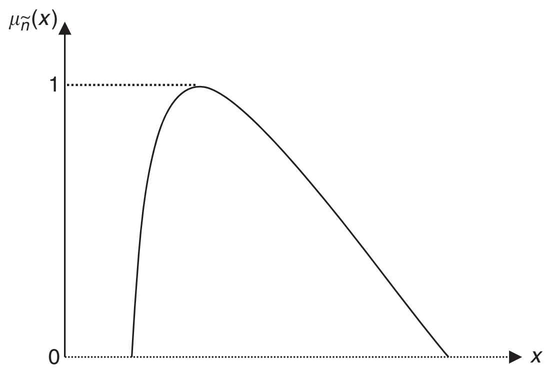

Figure 1.
A fuzzy number $\tilde{n}$

Definition 5. The α-cut of fuzzy number $\tilde{n}$ is defined as:

$$\tilde{n}^{\alpha} = \{x_i : \mu_{\tilde{n}}(x_i) \geqslant \alpha,\ x_i \in X\}, \tag{2}$$

here, $\alpha \in [0, 1]$.

The symbol $\tilde{n}^{\alpha}$ represents a non-empty bounded interval contained in X, which can be denoted by $\tilde{n}^{\alpha} = [n_l^{\alpha}, n_u^{\alpha}]$, n_l^{α} and n_u^{α} are the lower and upper bounds of the closed interval, respectively (Kaufmann and Gupta, 1991; Zimmermann, 1991). For a fuzzy number $\tilde{n}$, if $n_l^{\alpha} > 0$ and $n_u^{\alpha} \leqslant 1$ for all $\alpha \in [0, 1]$, then $\tilde{n}$ is called a standardized (normalized) positive fuzzy number (Negi, 1989).

Definition 6. Suppose, a positive triangular fuzzy number (PTFN) is $\tilde{A}$ and that can be defined as (a, b, c) shown in Figure 2. The membership function $\mu_{\tilde{n}}(x)$ is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-a)/(b-a), & \text{if } a \leqslant x \leqslant b, \\ (c-x)/(c-b), & \text{if } b \leqslant x \leqslant c, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

Based on extension principle, the fuzzy sum $\oplus$ and fuzzy subtraction Θ of any two triangular fuzzy numbers are also triangular fuzzy numbers; but the multiplication $\otimes$ of any two triangular fuzzy numbers is only approximate triangular fuzzy number (Zadeh, 1975). Let's have a two PTFNs, such as $\tilde{A}_1 = (a_1, b_1, c_1)$, and $\tilde{A}_2 = (a_2, b_2, c_2)$, and a positive real number $r = (r, r, r)$, some algebraic operations can be expressed as follows:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{4}$$

$$\tilde{A}_1 \Theta \tilde{A}_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2), \quad \tilde{A}_1 \otimes \tilde{A}_2 = (a_1 a_2, b_1 b_2, c_1 c_2), \tag{5}$$

$$r \otimes \tilde{A}_1 = (ra_1, rb_1, rc_1), \tag{6}$$

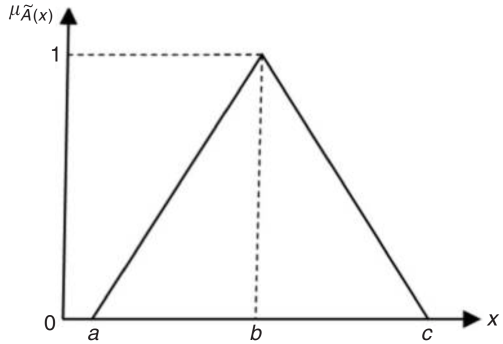

Figure 2. A triangular fuzzy number $\tilde{A}$

$$\tilde{A}_1 \phi \tilde{A}_2 = (a_1/c_2, b_1/b_2, c_1/a_2), \tag{7}$$

The operations of $\vee$(max) and $\wedge$(min) are defined as:

$$\tilde{A}_1(\vee)\tilde{A}_2 = (a_1 \vee a_2, b_1 \vee b_2, c_1 \vee c_2), \tag{8}$$

$$\tilde{A}_1(\wedge)\tilde{A}_2 = (a_1 \wedge a_2, b_1 \wedge b_2, c_1 \wedge c_2), \tag{9}$$

here, $r > 0$, and a_1, b_1, $c_1 > 0$.

Also the crisp value of triangular fuzzy number set $\tilde{A}_i$ can be determined by defuzzification which locates the Best Non-fuzzy Performance (BNP) value. Thus, the BNP values of fuzzy number are calculated by using the center of area method as follows (Moeinzadeh and Hajfathaliha, 2010):

$$\mathrm{BNP}_i = \frac{[(c-a)+(b-a)]}{3}+a, \quad \forall_i \tag{10}$$

Definition 7. A matrix $\tilde{\mathbf{D}}$ is called a fuzzy matrix if at least one element is a fuzzy number (Buckley, 1985).

5. Preference ranking organization method for enrichment evaluations

PROMETHEE is a well-known and widely used MCDM method. The PROMETHEE method incorporates pairwise comparison and outranking relationship for selection of the best alternatives. The PROMETHEE I (partial ranking) was developed by J.P. Brans (1982) and presented for the first time in a conference at the Université Laval, Québec, Canada (L'Ingéniérie de la Décision. Elaboration d'instruments d'Aide à la Décision). Further, Brans and Vincke (1985) introduced PROMETHEE II method (complete ranking) and constructed a valued outranking graph by using a preference index. Moreover, the authors considered two possibilities to resolve the ranking problem by using this valued graph and also mentioned the difference in the proposed two methods: PROMETHEE I is a partial ranking of the actions and based on the positive and negative flows. It includes indifferences, incomparability and preferences. PROMETHEE II is a complete ranking of the actions and based on the multi-evaluation net flow. It comprises preferences as well as indifferences. Few years later, Brans *et al.* (1986) developed PROMETHEE III (ranking based on intervals) and PROMETHEE IV (continuous case). After the development of PROMETHEE method up to the fourth level, Mareschal and Brans (1988) proposed the visual interactive module Geometrical Analysis for Interactive Assistance (GAIA) which is capable of providing a marvelous graphical representation supporting the PROMETHEE methodology. Later, Davignon and Mareschal (1989) presented numerous real world examples on the application of these methods in the field of healthcare.

PROMETHEE I and II are appropriate if one of the recognized alternatives needs to be selected; but in the case, where identification of a subset of alternatives is indeed needed under the set of certain constraints, then PROMETHEE series developed yet fails to resolve such sort of problem. In order to fulfill that PROMETHEE V is developed for that particular case. Brans and Mareschal (1992, 1995) further suggested two nice extensions: PROMETHEE V (MCDA including segmentation constraints) and

PROMETHEE VI (representation of the human brain), in addition to that (Brans and Mareschal, 1994) presented GAIA approach, a visual interactive modulation which characterizes a graphic interpretation of the PROMETHEE method. Using GAIA many effective applications of PROMETHEE method to numerous fields were marked. After the development of PROMETHEE methods in series a considerable number of successful applications were conducted in various fields such as banking, industrial location, manpower planning, water resources, investments, medicine, Chemistry, healthcare, tourism, ethics in operations research, dynamic management, the success of the methodology is basically due to its mathematical properties and to its friendliness of usage (Brans and Vincke, 1985; Tomic *et al.*, 2011; Velasquez and Hester, 2013).

The PROMETHEE family includes PROMETHEE I, II, III, IV, V, VI, PROMETHEE GDSS and PROMETHEE TRI methods. PROMETHEE I provides a partial ranking of the alternatives, Extension II provides a complete ranking with the net flows. Extension III gives the preference and indifference relations using the means and deviations for preference indices. Extension IV accords with a set of infinite alternatives. Extension V is a technique for several selections of alternatives under segmentation constraints (Brans and Mareschal, 1992) and version VI provides representations of the human brain (Brans and Mareschal, 1995). Recently, Behzadian *et al.* (2010) highlighted two extended approaches on PROMETHEE, called as the PROMETHEE TRI for dealing with sorting problems and the PROMETHEE CLUSTER for nominal classification problems. In addition to that (Behzadian *et al.*, 2013) applied PROMETHEE group decision support system for selection and ranking of the technical requirements in the house of quality. Further, (Motlagh *et al.*, 2015) proposed Fuzzy-PROMETHEE GDSS for technical requirements ranking in HOQ. The methods of PROMETHEE were effectively applied in many fields, and a number of researchers used these two extensions of PROMETHEE method in decision making. Macharis *et al.* (2004) revealed the advantage and disadvantage of the PROMETHEE methodology (outranking methods) over other approaches. First and foremost the PROMETHEE I method evades trade-offs between scores on criteria, which is expected to happen in AHP. Though, when the partial ranking is forced into a complete ranking of the alternatives (PROMETHEE II), detailed information might also get misplaced. Second, PROMETHEE attains a synthesis indirectly and only requires evaluations to be accomplished on each alternative for each criterion. Equally, in fuzzy AHP, the synthesis builds directly on the information included in the evaluation matrix that might lead to a substantial amount of pairwise comparisons to be completed (Brucker *et al.*, 2004). Finally, outranking methods like PROMETHEE are better suited to perform an extensive sensitivity analysis (Turcksin *et al.*, 2011). Espinilla *et al.* (2015) concluded that among the PROMETHEE family PROMETHEE I and II methods are the mostly used and well-known in the context of the complex decision-making scenario.

Zhang *et al.* (2009) coupled the concepts of fuzzy sets to represent uncertain site information with the PROMETHEE method. Chen *et al.* (2011) established a strategic decision-making elucidation using fuzzy-PROMETHEE for the case of information system outsourcing. Kuang *et al.* (2015) established a grey-based PROMETHEE II for evaluation of source water protection strategies. Taillandier and Stinckwich (2011) attempted robot selection using PROMETHEE. The authors concluded that PROMETHEE II method allowed establishing a complete ranking between possible movements based on outranking relations. Experimental results showed that this method could be used to combine effectively the different criteria and outperform several classic exploration strategies. Sen *et al.* (2015) highlighted application potential of PROMETHEE II method in relation to robot selection problem subjected to a set of quantitative (objective) evaluation data. Advantages and disadvantages of PROMETHEE II method have also been reported in comparison to other existing MCDM approaches.

6. Proposed decision support system: extended PROMETHEE

In this section, the formulations of traditional PROMETHEE approach have been modified so that objective as well as subjective criteria can be utilized simultaneously in course of decision making. First, the procedural hierarchies of two approaches have been documented below (Section 6.1 and 6.2, respectively) in which one considers subjective weight and objective rating of criteria and another considers subjective weight and subjective rating of criteria. In later phase, by utilizing aforesaid two approaches a robot selection decision-making problem has been articulated which involves objective as well as subjective evaluation data; weight of each criteria has been expressed subjectively rather than crisp representation. In practice, assignment of exact priority weight is very difficult and therefore, this study assumes that weights are to be given by the DMs. Linguistic weights can be transferred into appropriate fuzzy numbers and by using fuzzy aggregation operator; aggregated fuzzy weight against each criterion can be obtained.

6.1 Consideration of subjective weight and objective rating of criteria

In this approach, it has been assumed that the decision-making problem involves a set of quantitative (objective) criteria with respect to a finite set of alternatives. Also, criteria weights have been assessed subjectively by the DMs. The procedural steps of proposed PROMETHEE approach have been depicted as follows.

Step 1: generate a set of feasible alternatives, determine evaluation criteria, and form a group of DMs. Suppose m alternatives, k criteria and n DMs are involved in the decision making.

Step 2: define a set of linguistic variables and their corresponding triangular fuzzy numbers. Linguistic variables are used to evaluate the importance (weight) of criteria.

A seven-scale linguistic variable fuzzy number has been used to assess the importance of evaluation criteria with a fuzzy set. Table I shows the linguistic scale and corresponding triangular fuzzy numbers for weight of criteria.

Step 3: aggregate DMs evaluations. A decision is derived by aggregating the fuzzy weights of criteria from n DMs as calculated by Equation (11):

$$\tilde{w}_j = \frac{1}{n}\left[\sum_{e=1}^{n} \tilde{w}_j^e\right] = \frac{1}{n}\left[\tilde{w}_j^1 + \tilde{w}_j^2 + \ldots + \tilde{w}_j^n\right] \tag{11}$$

Table I.
Linguistic scales and corresponding fuzzy representation for criteria weight and criteria rating with respect to alternatives

Performance rating	Importance weight	Triangular fuzzy numbers
Very poor (VP)	Very low (VL)	(0, 0, 0.15)
Poor (P)	Low (L)	(0, 0.15, 0.3)
Medium poor (MP)	Medium low (ML)	(0.15, 0.3 0.5)
Medium (M)	Medium (M)	(0.3, 0.5, 0.65)
Medium good (MG)	Medium high (MH)	(0.5, 0.65, 0.8)
Good (G)	High (H)	(0.65, 0.8, 1.0)
Very good (VG)	Very high (VH)	(0.8, 1.0, 1.0)

Step 4: construct a decision matrix **D** and compute the aggregated fuzzy weight of criterion:

$$\mathbf{D} = \left[x_{ij}\right]_{m\times k} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{ik} \\ x_{21} & x_{22} & \dots & x_{2k} \\ . & . & . & . \\ x_{m1} & x_{m2} & \dots & x_{mk} \end{bmatrix} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, k) \tag{12}$$

$$\tilde{\mathbf{W}} = [\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_k] \tag{13}$$

here x_{ij} is the crisp rating of alternative A_i with respect to criterion C_j, and $\tilde{w}_j$ is the aggregated fuzzy weight (computed from Equation (1)) of the jth criterion. This study, therefore, denotes $\tilde{w}_j$ as triangular fuzzy number.

Step 5: normalize the decision-making matrix denoted by **R** is shown as:

$$\mathbf{R} = \left[r_{ij}\right]_{m\times k} \tag{14}$$

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{i1} \\ r_{21} & r_{22} & \dots & r_{2k} \\ . & . & . & . \\ r_{m1} & r_{m2} & \dots & r_{mk} \end{bmatrix} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, k) \tag{15}$$

The normalization process can be performed by following two Equations (6)-(7):

$$r_{ij} = \frac{x_{ij}}{\underset{i}{Max}\left(x_{ij}\right)}, \quad i = 1, 2, \dots, m; \; j = 1, 2, \dots, n. \quad \text{(for benefit criteria)} \tag{16}$$

$$r_{ij} = \frac{\underset{i}{Min}\left(x_{ij}\right)}{x_{ij}}, \quad i = 1, 2, \dots, m; \; j = 1, 2, \dots, n. \quad \text{(for cost criteria)} \tag{17}$$

here, r_{ij} is the normalized value of ith alternative for jth criterion.

Step 6: construct the preference function.

Let A be a set of alternatives; a and b re two alternatives of set A. Preference function $P_j(a, b)$ can be defined as follows:

$$P_j(a,b) = \begin{cases} 0, & r_{aj} \leqslant r_{bj}, \\ r_{aj} - r_{bj}, & r_{aj} > r_{bj}, \end{cases} \quad j = 1, 2, \dots, k. \tag{18}$$

here, the preference function $P_j(a, b)$ is the outranking intensity indicating that a is superior to b.

Also r_{ij} indicates the normalized rating of the ith alternative with respect to jth criterion. The preference function $P_j(a, b)$ for a criterion j derives, for the difference measures between two evaluations on that particular criterion. The outranking relational constructs from pairwise comparison of alternatives rates:

$$\begin{cases} r_{aj} > r_{bj} \Leftrightarrow aPb \; (a\ outranks\ b), \\ r_{aj} = r_{bj} \Leftrightarrow aIb \; (a\ is\ indifferent\ to\ b). \end{cases} \tag{19}$$

Step 7: generate the multi-criteria preference index to determine the value of the outranking relation.

If each criterion C_j ($j=1, 2, ..., k$) with preference function P_j, the multi-criteria preference index $\tilde{\pi}(a, b)$ can be derived as:

$$\tilde{\pi}(a, b) = \frac{\sum_{j=1}^{k} \tilde{w}_j P_j(a, b)}{\sum_{j=1}^{k} \tilde{w}_j} \tag{20}$$

here $\tilde{\pi}(a, b)$ be the multi-criteria preference index expressed in triangular fuzzy number. Also $\tilde{w}_j$ is the aggregated fuzzy weight of jth criterion, i.e. C_j.

Step 8: Calculate the flow to preorder alternatives.

PROMETHEE I: the usage of partial preorder reveals the message which the comparison between some alternatives cannot show.

Outgoing/leaving flow is given in Equation (11):

$$\tilde{\varphi}^+(a) = \sum_{y \neq a} \tilde{\pi}(a, y), \quad \forall a, y \in A, \tag{21}$$

where$\tilde{\phi}^+(a)$ is the sum of preferences, indicating that a is superior to other alternatives. As the value$\tilde{\phi}^+(a)$increases, the suitability of alternative a increases.

Incoming/entering flow is given in Equation (12):

$$\tilde{\varphi}^-(a) = \sum_{y \neq a} \tilde{\pi}(y, a), \quad \forall a, y \in A, \tag{22}$$

where $\tilde{\varphi}^-(a)$ is the sum of preferences, indicating that other alternatives are superior to a. As the value of $\tilde{\varphi}^-(a)$ is smaller, the suitability of alternative a increases.

The fuzzy values of $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$ need to be defuzzified to get the net flow $\phi(a)$ as depicted in Equation (16):

Then, the preference relation and partial preorder ($P^{(\mathrm{I})}$, $I^{(\mathrm{I})}$, R) are derived as follows:

$$aP^+b : \begin{cases} P \ if \ \phi^+(a) > \phi^+(b), & \forall a, b \in A, \\ I \ if \ \phi^+(a) = \phi^+(b), & \forall a, b \in A, \end{cases} \tag{23}$$

$$aP^-b : \begin{cases} P \ if \ \phi^-(a) < \phi^-(b), & \forall a, b \in A, \\ I \ if \ \phi^-(a) = \phi^-(b), & \forall a, b \in A, \end{cases} \tag{24}$$

here $\phi^+(a)$ and $\phi^-(a)$ are the defuzzified values of $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$, respectively.

Based on the intersection between Equations (13) and (14), one can obtain the outranking relation and partial preorder as follows:

$$\begin{cases} aP^{(\mathrm{I})}(a \ outranks \ b), \begin{cases} aP^+b : P \ and \ aP^-b : P, \\ aP^+b : P \ and \ aP^-b : I, \\ aP^+b : I \ and \ aP^-b : P, \end{cases} \\ aI^{(\mathrm{I})}b(a \ is \ indifferent \ to \ b), \quad aP^+b : I \text{ and } aP^-b : I, \\ aRb(a \ and \ b \ are \ incomparable), \ otherwise \end{cases} \tag{25}$$

PROMETHEE II: compare and rank all alternatives using the complete preorder. This model ranks the alternatives according to their net flows. The definition of net flows

$\phi(a)$ is:

$$\varphi(a) = \varphi^{+}(a) - \phi^{-}(a), \quad \forall a \in A. \tag{26}$$

As the value of $\phi(a)$ increases, the suitability of alternative a increase. The preference relation is defined as follows:

$$\begin{cases} aP^{(\mathrm{II})}b(a\ outranks\ b)\ \ If\ \ \phi(a) > \phi(b), \quad \forall a, b \in A, \\ aI^{(\mathrm{II})}b(a\ is\ indifferent\ to\ b)\ If\ \ \phi(a) = \phi(b), \quad \forall a, b \in A. \end{cases} \tag{27}$$

Additionally, in PROMETHEE I, the partial preorder can be obtained from leaving and entering flows. In PROMETHEE II, the consideration of net flow leads to a complete ranking.

Step 9: construct a value outranking graph to evaluate the preference rank of each alternative.

6.2 Consideration of subjective weight and subjective rating of criteria

In this section, it has been assumed that the decision-making problem is involved with a set of qualitative (subjective) criteria and the importance weight of each criterion is subjectively assessed rather than crisp representation. The procedural steps of the said decision-making module have been described below.

Step 1: same as in Section 6.1.

Step 2: define two separate linguistic terms set and their corresponding triangular fuzzy numbers representation to evaluate the importance (weight) of criteria and ratings of alternatives with respect to various criteria. Table I shows the linguistic scales and corresponding triangular fuzzy numbers for weight of criteria and rating of alternatives, respectively.

Step 3: aggregate DMs evaluations. A decision is derived by aggregating the fuzzy weights of criteria and fuzzy appropriateness rating of alternatives from n DMs as calculated by Equation (11). Additionally, the rating n DMs with respect to jth criterion (C_j) of each alternative in the ith alterative (A_i) can be calculated using: following equation:

$$\tilde{x}_{ij} = \frac{1}{n}\left[\sum_{e=1}^{n} \tilde{x}_{ij}^{e}\right] = \frac{1}{n}\left[\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{n}\right] \tag{28}$$

Step 4: construct a fuzzy decision matrix $\tilde{\mathbf{D}}$ and compute the aggregated fuzzy weight of criterion:

$$\tilde{\mathbf{D}} = \left[\tilde{x}_{ij}\right]_{m\times k} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \tilde{x}_{ik} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots & \tilde{x}_{2k} \\ . & . & . & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \ldots & \tilde{x}_{mk} \end{bmatrix} \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, k) \tag{29}$$

$$\tilde{\mathbf{W}} = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_k]$$

here $\tilde{x}_{ij}$ is the aggregated fuzzy rating of alternative A_i with respect to criterion C_j, and

$\tilde{w}_j$ is the aggregated fuzzy weight of the jth criterion. This study, therefore, denotes linguistic variables $\tilde{x}_{ij}$ and $\tilde{w}_j$ as triangular fuzzy numbers.

Step 5: normalize the fuzzy decision-making matrix denoted by $\tilde{\mathbf{R}}$ is shown as:

$$\tilde{\mathbf{R}} = \left[\tilde{r}_{ij}\right]_{m\times k} \tag{30}$$

$$\tilde{\mathbf{R}} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \dots & \tilde{r}_{ik} \\ \tilde{r}_{21} & \tilde{r}_{22} & \dots & \tilde{r}_{2k} \\ . & . & . & . \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \dots & \tilde{r}_{mk} \end{bmatrix} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, k) \tag{31}$$

If $\tilde{x}_{ij}, i = 1, 2, \dots, m; j = 1, 2, \dots, k$ are triangular fuzzy numbers, then the normalization process can be performed by assuming $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \quad (i = 1, 2, \dots, m, j \in B,) \tag{32}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \quad (i = 1, 2, \dots, m, j \in C,) \tag{33}$$

where, B and C are the set of benefit criteria B and cost criteria C, respectively, and:

$$c_j^* = \max_i c_{ij}\ j \in B, \tag{34}$$

$$a_j^- = \min_i a_{ij}\ j \in C. \tag{35}$$

Step 6: construct the preference function.

Let A be a set of alternatives; a and b re two alternatives of set A. Preference function $\tilde{P}_j(a, b)$ can be defined as follows:

$$\tilde{P}_j(a, b) = \begin{cases} 0, & \tilde{r}_{aj} \leqslant \tilde{r}_{bj}, \\ \tilde{r}_{aj} - \tilde{r}_{bj}, & \tilde{r}_{aj} > \tilde{r}_{bj}, \end{cases} j = 1, 2, \dots, k. \tag{36}$$

here, the preference function $\tilde{P}_j(a, b)$ is the outranking intensity indicating that a is superior to b.

The preference function $\tilde{P}_j(a, b)$ for a criterion j derives, for the difference measures between two evaluations on that particular criterion. The outranking relational constructs from pairwise comparison of alternatives rates:

$$\begin{cases} \tilde{x}_{aj} > \tilde{x}_{bj} \Leftrightarrow aPb(a\ outranks\ b), \\ \tilde{x}_{aj} = \tilde{x}_{bj} \Leftrightarrow aIb(a\ is\ indifferent\ to\ b). \end{cases} \tag{37}$$

Step 7: generate the multi-criteria preference index to determine the value of the outranking relation.

If each criterion C_j ($j = 1, 2, \dots, k$) with preference function $\tilde{P}_j$, the multi-criteria preference index $\tilde{\pi}(a, b)$ can be derived as:

$$\tilde{\pi}(a, b) = \frac{\sum_{j=1}^{k} \tilde{w}_j \tilde{P}_j(a, b)}{\sum_{j=1}^{k} \tilde{w}_j} \tag{38}$$

here $\tilde{\pi}(a,b)$ be the multi-criteria preference index expressed in triangular fuzzy number. Also $\tilde{w}_j$ is the aggregated fuzzy weight of jth criterion, i.e. C_j.

Steps 8-9: same as in Section 6.1.

7. Case empirical research

In this empirical illustration, a decision-making scenario has been generated for evaluation and selection of industrial robots. For this specific sort of study, a consolidated database considering information in relation to objective criteria as well as subjective criteria have been explored.

Based on exhaustive literature review, the criteria list has been selected. Basically, the paper articulates a framework on exploration of extended PROMETHEE with simultaneous consideration of objective as well as subjective data. The application potential of the said approach has been case empirically demonstrated through a robot selection decision-making view point. Therefore, the criteria lists as well the data sets explored here are empirical in nature. However, companies may go through detailed survey regarding necessity and importance of the criteria to be considered for a realistic decision making.

A total number of thirteen criteria have been evaluated with respect to seven choices (alternatives). The criteria includes load capacity (C_1) (Goh *et al.*, 1996; Parkan and Wu, 1999; Khouja and Booth, 1995; Bhangale *et al.*, 2004; Rao and Padmanabhan, 2006; Kumar and Garg, 2010; Chatterjee *et al.*, 2010; Rao *et al.*, 2011; Chakraborty, 2011; Karsak *et al.*, 2012), repeatability (C_2) (Goh *et al.*, 1996; Parkan and Wu, 1999; Khouja and Booth, 1995; Bhangale *et al.*, 2004; Rao and Padmanabhan, 2006; Kumar and Garg, 2010; Chatterjee *et al.*, 2010; Rao *et al.*, 2011; Karsak *et al.*, 2012; Chakraborty, 2011), maximum tip speed (C_3) (Bhangale *et al.*, 2004; Chatterjee *et al.*, 2010; Rao *et al.*, 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011), memory capacity (C_4) (Bhangale *et al.*, 2004; Chatterjee *et al.*, 2010; Rao *et al.*, 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011), manipulator reach (C_5) (Bhangale *et al.*, 2004; Chatterjee *et al.*, 2010; Rao *et al.*, 2011; Mondal and Chakraborty, 2013; Chakraborty, 2011), man-machine interface (C_6) (Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani *et al.*, 2014; Rashid *et al.*, 2014), programming flexibility (C_7) (Goh *et al.*, 1996; Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani *et al.*, 2014; Rashid *et al.*, 2014), vendor's service contract (C_8) (Goh *et al.*, 1996; Chu and Lin, 2003; Rao and Padmanabhan, 2006; Devi, 2011; Vahdani *et al.*, 2014; Rashid *et al.*, 2014), positioning accuracy (C_9) (Chu and Lin, 2003; Bhangale *et al.*, 2004; Devi, 2011; Vahdani *et al.*, 2014; Rashid *et al.*, 2014) safety (C_{10}) (Bhangale *et al.*, 2004), environmental performance (C_{11}) (Rossetti and Selandari, 2001; Choudhury *et al.*, 2006), reliability (C_{12}) (Bhangale *et al.*, 2004; Choudhury *et al.*, 2006) and maintainability (C_{13}) (Bhangale *et al.*, 2004; Choudhury *et al.*, 2006). Out of 13 considered criteria, first five criteria, i.e. C_1-C_5 have been objective in nature and corresponding numeric values have been collected from past literature (Mondal and Chakraborty, 2013; Omoniwa, 2014). The remaining eight criteria, i.e. C_6-C_{13} have been assessed subjectively by the DMs'. In the known set of attributes (objective criteria) only repeatability has been considered as the non-beneficial attribute while other attributes treated as beneficial in nature. All the subjective criteria have been considered as beneficial in nature.

A seven-member linguistic term set has been chosen for assigning priority weight of the criteria. The linguistic terms set is: {Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H) and Very High (VH)}. Moreover, a separate linguistic term set (seven-member) has been adapted for assessing appropriateness rating of various robot alternatives with respect to the subjective criteria. The linguistic term set for rating of subjective criteria is: {Very Poor (VP), Poor (P), Medium Poor (MP), Medium (M), Medium Good (MG), Good (G), and Very Good (VG)}. The linguistic terms and corresponding fuzzy representations have been tabulated in Table I.

In this paper, an empirical decision-making scenario has been provided to focus application potential of the proposed extended PROMETHEE in consideration with both objective as well as subjective data. The expert team exploited has been basically hypothetical one. The group members (presumed as four members) are supposed to be the respondents to fill up the questionnaire. In practice, industries may select the DMs based on their own policy. Respondents may include industry personnel, management consultant as well as academician. They must possess enough knowledge and experience in industrial decision making, more precisely in robot selection in the present context.

The decision-making committee which consists of four DMs have been instructed to provide their consent in order to determine the priority weight against individual criterion (C_1-C_{13}), and appropriateness rating for each subjective criterion (C_6-C_{13}) over each alternatives as shown in Tables II and III, respectively. Table IV exhibits data in relation to the objective criteria for individual alternative robots. DMs expert judgment expressed in linguistic terminology has been transformed into appropriate triangular fuzzy numbers in accordance with Table I. Based on Equation (11), aggregated fuzzy weights against criteria C_1-C_{13} have been computed and shown in Table II. Similarly, aggregated fuzzy ratings against subjective criteria C_6-C_{13} have been computed by using Equation (28) and shown in Table III. Considering objective data collected from Table IV and aggregated fuzzy ratings with respect to subjective criteria from Table III, the initial decision-making matrix has been formed (Table V).

Normalization of the initial decision matrix has been carried out in two ways as mentioned below. The normalized decision matrix has been represented in Table VI. Objective data have been normalized by using Equation (16) for beneficial attributes (C_1-C_5) and Equation (17) for non-beneficial attribute(s) (C_6-C_{13}). Aggregated fuzzy ratings for subjective criteria have been normalized by using Equation (32), assuming all criteria have been beneficial in nature. After normalizing the initial decision matrix, multi-criteria preference index for all pair of alternatives has been calculated. The multi-criteria preference function $P_j(a, b)$ between two alternatives a and b for the objective criterion C_j has been computed by using Equation (18); and the multi-criteria

Table II. Subjective weights for robot selection attributes as given by the DMs

	Weights given by DMs				
Criteria	DM1	DM2	DM3	DM4	Aggregated fuzzy weight
C_1	VH	VH	H	H	(0.725, 0.900, 1.000)
C_2	H	H	H	VH	(0.688, 0.850, 1.000)
C_3	H	VH	VH	VH	(0.763, 0.950, 1.000)
C_4	MH	H	H	H	(0.613, 0.763, 0.950)
C_5	H	VH	VH	VH	(0.763, 0.950, 1.000)
C_6	VH	VH	H	H	(0.725, 0.900, 1.000)
C_7	H	VH	VH	H	(0.725, 0.900, 1.000)
C_8	MH	MH	H	H	(0.575, 0.725, 0.900)
C_9	H	MH	H	MH	(0.575, 0.725, 0.900)
C_{10}	MH	MH	MH	MH	(0.500, 0.650, 0.800)
C_{11}	H	MH	MH	H	(0.575, 0.725, 0.900)
C_{12}	H	H	H	H	(0.650, 0.80, 1.000)
C_{13}	MH	MH	H	H	(0.575, 0.725, 0.900)

Criteria	Alternatives	Ratings given by DMs DM1	DM2	DM3	DM4	Aggregated fuzzy rating
C_6	R_1	VG	VG	G	G	(0.725, 0.900, 1.000)
C_7		G	MG	G	G	(0.613, 0.763, 0.950)
C_8		G	G	G	G	(0.650, 0.800, 1.000)
C_9		MG	G	G	G	(0.613, 0.763, 0.950)
C_{10}		G	G	G	G	(0.650, 0.800, 1.000)
C_{11}		MG	G	MG	G	(0.575, 0.725, 0.900)
C_{12}		G	G	G	G	(0.650, 0.800, 1.000)
C_{13}		MG	G	MG	MG	(0.538, 0.688, 0.850)
C_6	R_2	VG	G	G	G	(0.613, 0.763, 0.950)
C_7		VG	G	VG	G	(0.650, 0.813, 0.950)
C_8		MG	MG	G	G	(0.575, 0.725, 0.900)
C_9		G	G	G	G	(0.650, 0.800, 1.000)
C_{10}		VG	G	VG	G	(0.725, 0.900, 1.000)
C_{11}		MG	MG	MG	MG	(0.500, 0.650, 0.800)
C_{12}		G	VG	VG	VG	(0.763, 0.950, 1.000)
C_{13}		G	G	G	G	(0.650, 0.800, 1.000)
C_6	R_3	M	M	MG	MG	(0.400, 0.575, 0.725)
C_7		M	M	MG	G	(0.438, 0.613, 0.775)
C_8		MG	G	G	G	(0.613, 0.763, 0.950)
C_9		G	G	MG	G	(0.613, 0.763, 0.950)
C_{10}		MG	G	MG	G	(0.575, 0.725, 0.900)
C_{11}		G	G	G	MG	(0.613, 0.763, 0.950)
C_{12}		MG	MG	MG	MG	(0.500, 0.650, 0.800)
C_{13}		G	G	G	MG	(0.613, 0.763, 0.950)
C_6	R_4	P	P	MP	MP	(0.075, 0.225, 0.400)
C_7		M	M	M	M	(0.300, 0.500, 0.650)
C_8		MP	P	M	M	(0.188, 0.363, 0.525)
C_9		M	M	M	M	(0.300, 0.500, 0.650)
C_{10}		P	MP	VP	MP	(0.113, 0.238, 0.400)
C_{11}		M	M	M	M	(0.300, 0.500, 0.650)
C_{12}		MP	MP	MP	M	(0.188, 0.350, 0.538)
C_{13}		M	M	M	M	(0.300, 0.500, 0.650)
C_6	R_5	G	MG	MG	MG	(0.538, 0.688, 0.850)
C_7		MG	MG	MG	MG	(0.500, 0.650, 0.800)
C_8		G	VG	G	G	(0.688, 0.850, 1.000)
C_9		MG	MG	G	G	(0.575, 0.725, 0.900)
C_{10}		G	G	G	G	(0.650, 0.800, 1.000)
C_{11}		MG	MG	MG	MG	(0.500, 0.650, 0.800)
C_{12}		G	G	G	G	(0.650, 0.800, 1.000)
C_{13}		MG	G	MG	G	(0.575, 0.725, 0.900)
C_6	R_6	P	P	P	P	(0.000, 0.150, 0.300)
C_7		VP	P	VP	P	(0.000, 0.075, 0.225)
C_8		P	P	P	P	(0.000, 0.150, 0.300)
C_9		VP	VP	VP	VP	(0.000, 0.000, 0.150)
C_{10}		P	P	P	VP	(0.000, 0.113, 0.263)
C_{11}		P	P	P	P	(0.000, 0.150, 0.300)
C_{12}		MP	MP	M	M	(0.225, 0.400, 0.575)
C_{13}		M	M	M	M	(0.300, 0.500, 0.650)
C_6	R_7	M	MG	MG	MG	(0.450, 0.613, 0.763)

(*continued*)

Table III. Ratings for subjective attributes as given by the DMs and corresponding aggregated fuzzy representation

Table III.

Criteria	Alternatives	Ratings given by DMs DM1	DM2	DM3	DM4	Aggregated fuzzy rating
C_7		M	MG	MG	M	(0.400, 0.575, 0.725)
C_8		M	M	M	M	(0.300, 0.500, 0.650)
C_9		MG	M	M	MG	(0.400, 0.575, 0.725)
C_{10}		MG	MG	M	MG	(0.450, 0.613, 0.763)
C_{11}		M	MG	MG	MG	(0.450, 0.613, 0.763)
C_{12}		MG	MG	MG	M	(0.450, 0.613, 0.763)
C_{13}		MG	M	MG	M	(0.400, 0.575, 0.725)

Table IV.
Objective data for robot selection

Sl. No.	LC (Kg), C_1	RE (mm), C_2	MTS (mm/sec), C_3	MC (steps), C_4	MR (mm), C_5
R_1	60	0.4	2,540	500	990
R_2	6.35	0.15	1,016	3,000	1,041
R_3	6.8	0.1	1,727.2	1,500	1,676
R_4	10	0.2	1,000	2,000	965
R_5	2.5	0.1	560	500	915
R_6	4.5	0.08	1,016	350	508
R_7	3	0.1	1,778	1,000	920

preference function $\tilde{P}_j(a, b)$ between two alternatives a and b for the subjective criterion C_j has been computed by using Equation (36). The preference function values ($P_j(a, b)$ when j is objective criterion and $\tilde{P}_j(a, b)$ when j is subjective criterion) thus computed have been furnished in Table VII. Now, the preference function $\tilde{\pi}(a, b)$ between two alternatives a and b have been computed (by using Equations 20 and 38) and furnished in Table VIII. Outgoing/leaving flow $\tilde{\phi}^+(a)$, incoming/entering flow $\tilde{\phi}^-(a)$ for different robot alternatives have been computed by using Equations (21) and (22) and shown in Table IX. The defuzzified values of $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$ have been computed to get the net flow $\phi(a)$using Equation (26). Based on net flow $\phi(a)$ alternative robots have been ranked. The ranking order appears as: $R_1 > R_2 > R_3 > R_5 > R_7 > R_4 > R_6$.

In aforesaid section, alternatives robots have been evaluated based on objective as well as subjective criteria. In later part of this work, a sensitivity analysis has been carried out to make a compromise between objective factor (criteria) measure (OFM) and subjective factor (criteria) measure (SCM). In this section, initially, ranking order of candidate robots has been evaluated by considering objective and subjective criteria separately. Then a compromise selection procedure has been demonstrated to make a trade-off between objective criteria and subjective criteria.

In course of sensitivity analysis, the first part is to evaluate robot alternatives by considering objective criteria only. The preference function values ($P_j(a, b)$ when j is objective criterion) from Table VII have been explored to compute the multi-criteria preference index $\tilde{\pi}(a, b)$ between two alternatives a and b (considering objective criteria only, i.e. C_1-C_5) by using Equation (20). (Table X). Table XI shows $\tilde{\phi}^+(a)$ and $\tilde{\phi}^-(a)$(computed from Equations (21) and (22)) and net flow $\phi(a)$ for individual alternatives. The ranking order of alternative robots appears as (Table XIV): $R_3 > R_1 > R_2 > R_7 > R_4 > R_6 > R_5$.

A separate analysis has been carried out in order to determine the ranking order of candidate robots by considering subjective criteria only. Exploring the preference

Table V. Initial decision-making matrix (combination of objective and subjective data)

Alternatives	Objective criteria (in appropriate units)					Subjective criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
R_1	60	0.4	2,540	500	990	(0.725,0.900,1.000)	(0.613,0.763,0.950)	(0.650,0.800,1.000)	(0.613,0.763,0.950)	(0.650,0.800,1.000)	(0.575,0.725,0.900)	(0.650,0.800,1.000)	(0.538,0.688,0.850)
R_2	6.35	0.15	1,016	3,000	1,041	(0.613,0.763,0.950)	(0.650,0.813,0.950)	(0.575,0.725,0.900)	(0.650,0.800,1.000)	(0.725,0.900,1.000)	(0.500,0.650,0.800)	(0.763,0.950,1.000)	(0.650,0.800,1.000)
R_3	6.8	0.1	17,27.2	1,500	1,676	(0.400,0.575,0.725)	(0.438,0.613,0.775	(0.613,0.763,0.950)	(0.613,0.763,0.950)	(0.575,0.725,0.900)	(0.613,0.763,0.950)	(0.500,0.650,0.800)	(0.613,0.763,0.950)
R_4	10	0.2	1,000	2,000	965	(0.075,0.225,0.400)	(0.300,0.500,0.650)	(0.188,0.363,0.525)	(0.300,0.500,0.650)	(0.113,0.238,0.400)	(0.300,0.500,0.650)	(0.188,0.350,0.538)	(0.300,0.500,0.650)
R_5	2.5	0.1	560	500	915	(0.538,0.688,0.850)	(0.500,0.650,0.800)	(0.688,0.850,1.000)	(0.575,0.725,0.900)	(0.650,0.800,1.000)	(0.500,0.650,0.800)	(0.650,0.800,1.000)	(0.575,0.725,0.900)
R_6	4.5	0.08	1,016	350	508	(0.000,0.150,0.300)	(0.000,0.075,0.225)	(0.000,0.150,0.300)	(0.000,0.000,0.150)	(0.000,0.113,0.263)	(0.000,0.150,0.300)	(0.225,0.400,0.575)	(0.300,0.500,0.650)
R_7	3	0.1	1,778	1,000	920	(0.450,0.613,0.763)	(0.400,0.575,0.725)	(0.300,0.500,0.650)	(0.400,0.575,0.725	(0.450,0.613,0.763)	(0.450,0.613,0.763)	(0.450,0.613,0.763)	(0.400,0.575,0.725)

Table VI. Normalized decision matrix

Alternatives	Objective criteria					Subjective criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
R_1	1.000	0.200	1.000	0.167	0.591	(0.725,0.900,1.000)	(0.645,0.803,1.000)	(0.650,0.800,1.000)	(0.613,0.763,0.950)	(0.650,0.800,1.000)	(0.605,0.763,0.947)	(0.650,0.800,1.000)	(0.538,0.688,0.850)
R_2	0.106	0.533	0.400	1.000	0.621	(0.613,0.763,0.950)	(0.684,0.855,1.000)	(0.575,0.725,0.900)	(0.650,0.800,1.000)	(0.725,0.900,1.000)	(0.526,0.684,0.842)	(0.763,0.950,1.000)	(0.650,0.800,1.000)
R_3	0.113	0.800	0.680	0.500	1.000	(0.400,0.575,0.725	(0.461,0.645,0.816)	0.613,0.763,0.950)	(0.613,0.763,0.950)	(0.575,0.725,0.900)	(0.645,0.803,1.000)	(0.500,0.650,0.800)	(0.613,0.763,0.950)
R_4	0.167	0.400	0.394	0.667	0.576	(0.075,0.225,0.400)	(0.316,0.526,0.684)	(0.188,0.363,0.525)	(0.300,0.500,0.650)	(0.113,0.238,0.400)	(0.316,0.526,0.684)	(0.188,0.350,0.538)	(0.300,0.500,0.650)
R_5	0.042	0.800	0.220	0.167	0.546	(0.538,0.688,0.850)	(0.526,0.684,0.842)	(0.688,0.850,1.000)	(0.575,0.725,0.900)	(0.650,0.800,1.000)	(0.526,0.684,0.842)	(0.650,0.800,1.000)	(0.575,0.725,0.900)
R_6	0.075	1.000	0.400	0.117	0.303	(0.000,0.150,0.300)	(0.000,0.079,0.237)	(0.000,0.150,0.300)	(0.000,0.000,0.150)	(0.000,0.113,0.263)	(0.000,0.158,0.316)	(0.225,0.400,0.575)	(0.300,0.500,0.650)
R_7	0.050	0.800	0.700	0.333	0.549	(0.450,0.613,0.763)	(0.421,0.605,0.763)	(0.300,0.500,0.650)	(0.400,0.575,0.725)	(0.450,0.613,0.763)	(0.474,0.645,0.803)	(0.450,0.613,0.763)	(0.400,0.575,0.725)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
R_1, R_1	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_1, R_2	0.894	0.000	0.600	0.000	0.000	(0.113,0.138,0.050)	(0.000,0.000,0.000)	(0.075,0.075,0.100)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.079,0.079,0.105)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_1, R_3	0.887	0.000	0.320	0.000	0.000	(0.325,0.325,0.275)	(0.184,0.158,0.184)	(0.038,0.038,0.050)	(0.000,0.000,0.000)	(0.075,0.075,0.100)	(0.000,0.000,0.000)	(0.150,0.150,0.200)	(0.000,0.000,0.000)
R_1, R_4	0.833	0.000	0.606	0.000	0.015	(0.650,0.675,0.600)	(0.329,0.276,0.316)	(0.463,0.438,0.475)	(0.313,0.263,0.300)	(0.538,0.563,0.600)	(0.289,0.237,0.263)	(0.463,0.450,0.463)	(0.238,0.188,0.200)
R_1, R_5	0.958	0.000	0.780	0.000	0.045	(0.188,0.213,0.150)	(0.118,0.118,0.158)	(0.000,0.000,0.000)	(0.038,0.037,0.050)	(0.000,0.000,0.000)	(0.079,0.079,0.105)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_1, R_6	0.925	0.000	0.600	0.050	0.288	(0.725,0.750,0.700)	(0.645,0.724,0.763)	(0.650,0.650,0.700)	(0.613,0.763,0.800)	(0.650,0.688,0.738)	(0.605,0.605,0.632)	(0.425,0.400,0.425)	(0.238,0.188,0.200)
R_1, R_7	0.950	0.000	0.300	0.000	0.042	(0.275,0.288,0.238)	(0.224,0.197,0.237)	(0.350,0.300,0.350)	(0.213,0.188,0.225)	(0.200,0.188,0.238)	(0.132,0.118,0.145)	(0.200,0.188,0.238)	(0.138,0.113,0.125)
R_2, R_1	0.000	0.333	0.000	0.833	0.030	(0.000,0.000,0.000)	(0.039,0.053,0.000)	(0.000,0.000,0.000)	(0.038,0.038,0.050)	(0.075,0.100,0.000)	(0.000,0.000,0.000)	(0.113,0.150,0.000)	(0.113,0.113,0.150)
R_2, R_2	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_2, R_3	0.000	0.000	0.000	0.500	0.000	(0.213,0.188,0.225)	(0.224,0.211,0.184)	(0.000,0.000,0.000)	(0.038,0.038,0.050)	(0.150,0.175,0.100)	(0.000,0.000,0.000)	(0.263,0.300,0.200)	(0.038,0.038,0.050)
R_2, R_4	0.000	0.133	0.006	0.333	0.045	(0.538,0.538,0.550)	(0.368,0.329,0.316)	(0.388,0.363,0.375)	(0.350,0.300,0.350)	(0.613,0.663,0.600)	(0.211,0.158,0.158)	(0.575,0.600,0.463)	(0.350,0.300,0.350)
R_2, R_5	0.064	0.000	0.180	0.833	0.075	(0.075,0.075,0.100)	(0.158,0.171,0.158)	(0.000,0.000,0.000)	(0.075,0.075,0.100)	(0.075,0.100,0.000)	(0.000,0.000,0.000)	(0.113,0.150,0.000)	(0.075,0.075,0.100)
R_2, R_6	0.031	0.000	0.000	0.883	0.318	(0.613,0.613,0.650)	(0.684,0.776,0.763)	(0.575,0.575,0.600)	(0.650,0.800,0.850)	(0.725,0.788,0.738)	(0.526,0.526,0.526)	(0.538,0.550,0.425)	(0.350,0.300,0.350)
R_2, R_7	0.056	0.000	0.000	0.667	0.072	(0.163,0.150,0.188)	(0.263,0.250,0.237)	(0.275,0.225,0.250)	(0.250,0.225,0.275)	(0.275,0.288,0.238)	(0.053,0.039,0.039)	(0.313,0.338,0.238)	(0.250,0.225,0.275)
R_3, R_1	0.000	0.600	0.000	0.333	0.409	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.039,0.039,0.053)	(0.000,0.000,0.000)	(0.075,0.075,0.100)
R_3, R_2	0.008	0.267	0.280	0.000	0.379	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.038,0.037,0.050)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.118,0.118,0.158)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_3, R_3	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_3, R_4	0.000	0.400	0.286	0.000	0.424	(0.325,0.350,0.325)	(0.145,0.118,0.132)	(0.425,0.400,0.425)	(0.313,0.263,0.300)	(0.463,0.488,0.500)	(0.329,0.276,0.316)	(0.313,0.300,0.263)	(0.313,0.263,0.300)
R_3, R_5	0.072	0.000	0.460	0.333	0.454	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.038,0.037,0.050)	(0.000,0.000,0.000)	(0.118,0.118,0.158)	(0.000,0.000,0.000)	(0.038,0.038,0.050)
R_3, R_6	0.038	0.000	0.280	0.383	0.697	(0.400,0.425,0.425)	(0.461,0.566,0.579)	(0.613,0.613,0.650)	(0.613,0.763,0.800)	(0.575,0.613,0.638)	(0.645,0.645,0.684)	(0.275,0.250,0.225)	(0.313,0.263,0.300)
R_3, R_7	0.063	0.000	0.000	0.167	0.451	(0.000,0.000,0.000)	(0.039,0.039,0.053)	(0.313,0.263,0.300)	(0.213,0.188,0.225)	(0.125,0.113,0.138)	(0.171,0.158,0.197)	(0.050,0.038,0.038)	(0.213,0.188,0.225)
R_4, R_1	0.000	0.200	0.000	0.500	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.0000.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_2	0.061	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_3	0.053	0.000	0.000	0.167	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.0000.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000))	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_4	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.0000.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_5	0.125	0.000	0.173	0.500	0.030	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_6	0.092	0.000	0.000	0.550	0.273	(0.075,0.075,0.100)	(0.316,0.447,0.447)	(0.188,0.213,0.225)	(0.300,0.500,0.500)	(0.113,0.125,0.138)	(0.316,0.368,0.368)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_4, R_7	0.117	0.000	0.000	0.333	0.027	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_5, R_1	0.000	0.600	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.038,0.050,0.000	(0.000,0.000,0.000)	(0.000,0.0000.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.038,0.038,0.050)
R_5, R_2	0.000	0.267	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.113,0.125,0.100)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_5, R_3	0.000	0.000	0.000	0.000	0.000	(0.138,0.113,0.125)	(0.066,0.039,0.026)	(0.075,0.088,0.050)	(0.000,0.000,0.000)	(0.075,0.075,0.100)	(0.000,0.000,0.000)	(0.150,0.150,0.200)	(0.000,0.000,0.000)
R_5, R_4	0.000	0.400	0.000	0.000	0.000	(0.463,0.463,0.450)	(0.211,0.158,0.158)	(0.500,0.488,0.475)	(0.275,0.225,0.250)	(0.538,0.563,0.600)	(0.211,0.158,0.158)	(0.463,0.450,0.463)	(0.275,0.225,0.250)
R_5, R_5	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_5, R_6	0.000	0.000	0.000	0.050	0.243	(0.538,0.538,0.550)	(0.526,0.605,0.605)	(0.688,0.700,0.700)	(0.575,0.725,0.750)	(0.650,0.688,0.738)	(0.526,0.526,0.526)	(0.425,0.400,0.425)	(0.275,0.225,0.250)

(*continued*)

Table VII.
Computation of preference function

Table VII.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
R_5, R_7	0.000	0.000	0.000	0.000	0.000	(0.088,0.075,0.088)	(0.105,0.079,0.079)	(0.388,0.350,0.350)	(0.175,0.150,0.175)	(0.200,0.188,0.238)	(0.053,0.039,0.039)	(0.200,0.188,0.238)	(0.175,0.1500.175)
R_6, R_1	0.000	0.800	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_6, R_2	0.000	0.467	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.0000.000,0.000)
R_6, R_3	0.000	0.200	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_6, R_4	0.000	0.600	0.006	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.038,0.050,0.038)	(0.000,0.000,0.000)
R_6, R_5	0.033	0.200	0.180	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_6, R_6	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_6, R_7	0.025	0.200	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_7, R_1	0.000	0.600	0.000	0.167	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_7, R_2	0.000	0.267	0.300	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_7, R_3	0.000	0.000	0.020	0.000	0.000	(0.050,0.038,0.037)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.0000.000)
R_7, R_4	0.000	0.400	0.306	0.000	0.000	(0.375,0.388,0.363)	(0.105,0.079,0.079)	(0.113,0.138,0.125)	(0.100,0.075,0.075)	(0.338,0.375,0.363)	(0.158,0.118,0.118)	(0.263,0.263,0.225)	(0.100,0.075,0.075)
R_7, R_5	0.008	0.000	0.480	0.167	0.003	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_7, R_6	0.000	0.000	0.300	0.217	0.246	(0.450,0.463,0.463)	(0.421,0.526,0.526)	(0.300,0.350,0.350)	(0.400,0.575,0.575)	(0.450,0.500,0.500)	(0.474,0.487,0.487)	(0.225,0.213,0.188)	(0.100,0.075,0.075)
R_7, R_7	0.000	0.000	0.000	0.000	0.000	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)

Note: $P_j(a, b)$ when j is objective criterion and $\tilde{P}_j(a,b)$ when j is subjective criterion

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
R_1	(0.000,0.000,0.000)	(0.103,0.152,0.210)	(0.115,0.167,0.226)	(0.259,0.365,0.487)	(0.131,0.192,0.269)	(0.349,0.525,0.733)	(0.165,0.234,0.336)
R_2	(0.082,0.116,0.158)	(0.000,0.000,0.000)	(0.077,0.105,0.139)	(0.206,0.281,0.362)	(0.093,0.131,0.183)	(0.309,0.462,0.642)	(0.136,0.186,0.261)
R_3	(0.081,0.117,0.176)	(0.063,0.092,0.141)	(0.000,0.000,0.000)	(0.200,0.279,0.382)	(0.086,0.126,0.190)	(0.280,0.427,0.612)	(0.093,0.129,0.203)
R_4	(0.036,0.052,0.080)	(0.004,0.005,0.007)	(0.011,0.017,0.025)	(0.000,0.000,0.000)	(0.045,0.065,0.095)	(0.116,0.201,0.308)	(0.025,0.036,0.054)
R_5	(0.037,0.054,0.076)	(0.020,0.030,0.042)	(0.027,0.038,0.047)	(0.174,0.240,0.309)	(0.000,0.000,0.000)	(0.235,0.358,0.494)	(0.068,0.093,0.130)
R_6	(0.045,0.064,0.095)	(0.026,0.038,0.055)	(0.011,0.016,0.024)	(0.036,0.053,0.076)	(0.024,0.035,0.049)	(0.000,0.000,0.000)	(0.013,0.018,0.027)
R_7	(0.042,0.060,0.090)	(0.033,0.048,0.067)	(0.004,0.005,0.007)	(0.125,0.175,0.215)	(0.039,0.056,0.077)	(0.193,0.305,0.419)	(0.000,0.000,0.000)

Table VIII. Computation of multi-criteria preference index $\tilde{\pi}(a, b)$

function values ($\tilde{P}_j(a,b)$ when j is subjective criterion) obtained from Table VII, the multi-criteria preference index $\tilde{\pi}(a,b)$ between two alternatives a and b (considering subjective criteria only, i.e. C_6-C_{13}) has been computed (by using Equation (38)) and furnished in Table XII. Table XIII shows $\tilde{\phi}^+(a)$and $\tilde{\phi}^-(a)$(computed from Equations (21) and (22)) and net flow $\phi(a)$ for individual alternatives. The ranking order of alternative robots appears as (Table XIV): $R_2 > R_1 > R_5 > R_3 > R_7 > R_4 > R_6$.

Finally, a robot selection score (RSS) has been obtained by using Equation 39, for alternative robots. Sensitivity analysis plot shows how DMS' perception (risk-bearing attitude) influences choice of the most appropriate robot (Ray *et al.*, 2010):

$$(RSS)_i = [\alpha \times SFM_i + (1-\alpha)OFM_i] \tag{39}$$

In Equation 39, $(RSS)_i$ is the overall RSS for ith robot considering both subjective as well as objective criteria. SFM_i be the subjective factor measure for ith robot, i.e. normalized value of $\phi(a)$; whereas, OFM_i be the OFM for ith robot, i.e. normalized value of $\phi(a)$ (Table XIV). In this expression, α is the decision-maker's risk-bearing attitude $(0 \leqslant \alpha \leqslant 1)$.

Considering objective criteria, the net flow $\phi(a)$ values for alternative robots obtained from Table XI have been normalized and treated as OFM in Table XIV. Similarly, by considering subjective criteria, the net flow $\phi(a)$values for alternative robots obtained from Table XIII have been normalized and treated as OFM in Table XIV. Finally, RSS has been computed based on Equation (39), for determining appropriate ranking order of candidate robots.

Sensitivity analysis plot (Figure 3) reflects that when DMs' risk-bearing attitude α is approximately up to 0.4, robot R_3 is the best. When α varies approximately in between 0.4 and 0.8, robot R_1 is the best; and, for the case when α is greater than 0.8, robot R_2 appears as the best choice.

8. Managerial implication

The work bears significant managerial implication. Appropriate robot selection improves overall firm's efficiency and thereby enhances profitability. During robot selection, apart from objective criteria, a number of subjective criteria need to be evaluated simultaneously. As subjective criteria are ill-defined and vague in nature, there evaluation is based on linguistic assessment of the experts which is further transformed into appropriate fuzzy numbers. An integrated decision-making module with the capability of simultaneously considering known (crisp) set of objective data as well as fuzzy database of subjective criteria has been proposed

Table IX. Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives

Alternatives	$\tilde{\phi}^+(a)$	$\phi^+(a)$	$\tilde{\phi}^-(a)$	$\phi^-(a)$	$\phi(a)$	Ranking order
R_1	(1.122, 1.636, 2.261)	1.673	(0.322, 0.464, 0.675)	0.487	1.186	1
R_2	(0.903, 1.282, 1.746)	1.310	(0.250, 0.366, 0.522)	0.379	0.931	2
R_3	(0.804, 1.170, 1.702)	1.225	(0.246, 0.348, 0.468)	0.354	0.871	3
R_4	(0.237, 0.377, 0.569)	0.394	(1.000, 1.392, 1.831)	1.408	−1.013	6
R_5	(0.562, 0.813, 1.099)	0.825	(0.417, 0.605, 0.863)	0.628	0.196	4
R_6	(0.154, 0.224, 0.325)	0.235	(1.482, 2.279, 3.207)	2.323	−2.088	7
R_7	(0.436, 0.650, 0.874)	0.653	(0.500, 0.697, 1.012)	0.736	−0.083	5

Table X. Multi-criteria preference index $\tilde{\pi}(a, b)$ between two alternatives a and b (considering objective criteria only, i.e. C_1-C_5)

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
R_1	(0.000,0.000,0.000)	(0.223,0.312,0.421)	(0.179,0.250,0.340)	(0.218,0.304,0.410)	(0.267,0.373,0.502)	(0.278,0.388,0.524)	(0.192,0.267,0.364)
R_2	(0.154,0.215,0.325)	(0.000,0.000,0.000)	(0.062,0.086,0.134)	(0.068,0.094,0.141)	(0.152,0.212,0.313)	(0.163,0.227,0.335)	(0.102,0.142,0.214)
R_3	(0.188,0.261,0.374)	(0.140,0.195,0.263)	(0.000,0.000,0.000)	(0.165,0.230,0.313)	(0.193,0.269,0.367)	(0.204,0.284,0.389)	(0.099,0.139,0.190)
R_4	(0.090,0.125,0.190)	(0.009,0.012,0.017)	(0.028,0.040,0.060)	(0.000,0.000,0.000)	(0.112,0.156,0.226)	(0.124,0.172,0.250)	(0.063,0.087,0.130)
R_5	(0.083,0.116,0.169)	(0.037,0.051,0.075)	(0.000,0.000,0.000)	(0.056,0.077,0.113)	(0.000,0.000,0.000)	(0.044,0.061,0.082)	(0.000,0.000,0.000)
R_6	(0.111,0.154,0.225)	(0.065,0.090,0.131)	(0.028,0.039,0.056)	(0.084,0.117,0.171)	(0.060,0.084,0.116)	(0.000,0.000,0.000)	(0.031,0.044,0.063)
R_7	(0.104,0.144,0.214)	(0.083,0.116,0.160)	(0.003,0.004,0.006)	(0.103,0.143,0.199)	(0.096,0.134,0.183)	(0.111,0.155,0.212)	(0.000,0.000,0.000

in this paper. The PROMETHHE I and II method have been extended to work under fuzzy environment facilitating the said decision making in relation to a robot selection problem. Industries may adopt this decision support system for effective evaluation and selection of industrial robot. The same procedure may also be helpful to solve other decision-making problems in industrial context.

In any real world decision-making problem (e.g. robot selection, in the present case), situation arises in which we have to consider objective as well as subjective data set. If the case is involved with objective data set only, traditional MCDM tools and techniques can solve the problem. If the case is associated with subjective data set only, fuzzy-based decision-making approaches like Fuzzy-TOPSIS, Fuzzy-VIKOR, Fuzzy-MOORA may be applied. But the case, where objective as well as subjective data set need to be explored and analyzed simultaneously, it becomes a tough job. As we look into previous literature, we find that attempts have been made to use objective and subjective data, but in a different way. Here, objective data are transformed into subjective (fuzzy) data and analyzed along with actual subjective data. On the other hand, subjective data are defuzzified to get equivalent objective (crisp) score and analyzed along with actual objective data set. Literature seems rare in proposing such a decision-making module which could simultaneously tackle both objective and subjective data without allowing changing their identity. This aspect has been articulated in this reporting.

9. Conclusion

In this paper, PROMETHHE approach has been extended to solve a robot selection decision-making problem by considering objective as well as subjective criteria. The procedural hierarchy of the proposed decision support system has been case empirically illustrated. Sensitivity analysis has also been performed to make a compatible balance (compromise) between OFM and subjective factor measure. Finally, a compromise selection preference has been demonstrated by using RSS. Sensitivity analysis plot reflects how variations of DMs' perception influence the most favorable choice. The proposed decision-making module can also be applied in a variety of industrial decision-making situations involving objective as well as subjective evaluation criteria.

Table XI. Net flow values of different robot alternatives for objective criteria only

Robots	$\tilde{\phi}^{+}(a)$	$\phi^{+}(a)$	$\tilde{\phi}^{-}(a)$	$\phi^{-}(a)$	$\phi(a)$
R_1	(1.358,1.893,2.561)	1.937	(0.730,1.015,1.497)	1.081	0.857
R_2	(0.701,0.977,1.463)	1.047	(0.557,0.776,1.067)	0.800	0.247
R_3	(0.988,1.378,1.894)	1.420	(0.300,0.419,0.595)	0.438	0.982
R_4	(0.425,0.592,0.873)	0.630	(0.693,0.965,1.346)	1.002	−0.372
R_5	(0.220,0.305,0.439)	0.321	(0.880,1.228,1.707)	1.272	−0.951
R_6	(0.380,0.527,0.764)	0.557	(0.923,1.289,1.791)	1.334	−0.777
R_7	(0.500,0.697,0.972)	0.723	(0.487,0.679,0.961)	0.709	0.014

Notes: Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives (considering objective criteria only, i.e. C_1-C_5)

Table XII. Preference index for subjective criteria

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
R_1	(0.000,0.000,0.000)	(0.023,0.038,0.048)	(0.071,0.103,0.160)	(0.274,0.390,0.607)	(0.039,0.062,0.091)	(0.379,0.600,0.934)	(0.145,0.200,0.339)
R_2	(0.030,0.550,0.037)	(0.000,0.000,0.000)	(0.082,0.125,0.159)	(0.282,0.407,0.595)	(0.049,0.084,0.089)	(0.387,0.618,0.923)	(0.152,0.217,0.328)
R_3	(0.009,0.013,0.028)	(0.012,0.018,0.038)	(0.000,0.000,0.000)	(0.212,0.301,0.475)	(0.015,0.023,0.047)	(0.317,0.511,0.802)	(0.087,0.116,0.215)
R_4	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.108,0.217,0.335)	(0.000,0.000,0.000)
R_5	(0.006,0.010,0.009)	(0.009,0.015,0.018)	(0.044,0.060,0.097)	(0.241,0.338,0.524)	(0.000,0.000,0.000)	(0.346,0.548,0.852)	(0.111,0.148,0.257)
R_6	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.003,0.007,0.008)	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.000,0.000,0.000)
R_7	(0.000,0.000,0.000)	(0.000,0.000,0.000)	(0.005,0.005,0.008)	(0.129,0.190,0.267)	(0.000,0.000,0.000)	(0.234,0.400,0.595)	(0.000,0.000, 0.000)

Table XIII. Net flow values of different robot alternatives for subjective criteria only

Robots	$\tilde{\phi}^{+}(a)$	$\phi^{+}(a)$	$\tilde{\phi}^{-}(a)$	$\phi^{-}(a)$	$\phi(a)$
R_1	(0.931,1.393,2.179)	1.501	(0.045,0.574,0.074)	0.231	1.270
R_2	(0.982,2.000,2.132)	1.704	(0.044,0.071,0.104)	0.073	1.631
R_3	(0.652,0.983,1.605)	1.080	(0.202,0.293,0.424)	0.306	0.774
R_4	(0.108,0.217,0.335)	0.220	(1.141,1.632,2.476)	1.750	−1.530
R_5	(0.757,1.119,1.758)	1.211	(0.103,0.169,0.228)	0.167	1.045
R_6	(0.003,0.007,0.008)	0.006	(1.771,2.895,4.440)	3.036	−3.030
R_7	(0.369,0.596,0.870)	0.612	(0.495,0.681,1.139)	0.772	−0.160

Notes: Outgoing/leaving flows, incoming/entering flows and net flow values for different robot alternatives (considering subjective criteria only, i.e. C_6-C_{13})

Table XIV. Computation of robot selection scores (RSSs) (combining two different selections)

Alternatives	$\phi(a)$ (considering objective criteria)	OFM (normalized $\phi(a)$)	Ranking order (considering objective criteria only)	$\phi(a)$ (considering subjective criteria)	SFM (normalized $\phi(a)$)	Ranking order (considering subjective criteria only)
R_1	0.857	0.935	2	1.270	0.923	2
R_2	0.247	0.620	3	1.631	1.000	1
R_3	0.982	1.000	1	0.774	0.816	4
R_4	−0.372	0.300	5	−1.530	0.322	6
R_5	−0.951	0.000	7	1.045	0.874	3
R_6	−0.777	0.090	6	−3.030	0.000	7
R_7	0.014	0.499	4	−0.160	0.616	5

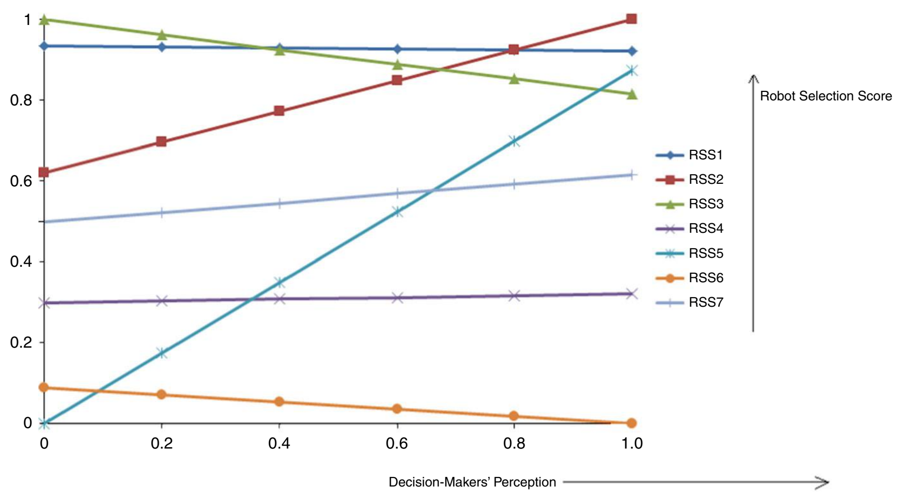

Figure 3. Sensitivity analysis plot

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