Benchmarking: An International Journal

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Received 31 July 2015
Revised 26 October 2015
Accepted 11 November 2015

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Abstract

Purpose – Robot selection is a critical decision-making task frequently experienced in almost every industries. It has become increasingly complex due to availability of large variety of robotic system in the present market with varying configuration, specification and flexibility. Improper selection may yield loss for the company in terms of potential profit as well as productivity. Hence, selection of an appropriate robot to suit a particular industrial application is definitely a challenging task. The paper aims to discuss these issues.

Design/methodology/approach – During robot selection, different criteria-attributes need to be taken under consideration. Criteria may be subjective or objective or a combination of both, depending on the situation. Criteria many be conflicting, in the sense that some criteria may require to be of higher value (higher-is-better), i.e. beneficial; while, others should correspond to lower values (lower-is-better), i.e. adverse or non-beneficial. Hence, the situation can be articulated as a multi-criteria decision-making problem. The specialty of Tomada de Decisión Inerativa Multicritero (TODIM) method is that it explores a global measurement of value calculable by the application of the paradigm of non-linear cumulative prospect theory. The method is based on a description, proved by empirical evidence, of how decision makers' effectively make decisions in the face of risk.

Findings – Hence, the present work has aimed to explore the TODIM approach for industrial robot selection. Assuming all criteria have been quantitative in nature; the paper utilizes two different numeric data sets from available literature resource in perspectives of robot selection. Procedural hierarchy and application potential of the TODIM approach has been illustrated in detail in this reporting.

Originality/value – Variety of tools and techniques have already been documented in literature to solve different kinds of industrial decision-making problems; however, it seems that application of TODIM has got limited usage. Hence, application potential of TODIM has been demonstrated here in light of a robot selection problem.

Keywords Benchmarking, Multi-criteria decision making (MCDM), Decision support systems, Robot selection, TODIM (Tomada de Decisión Inerativa Multicritero)

Paper type Research paper

1. Introduction and state of art

The word ROBOT was first stated in 1920 by the Czech author K. Capek in his play *Rossum's Universal Robots*; it was derived from the Czech word robota, meaning worker. A robot is a power-driven self-controlled programmable device made with mechanical, microelectronic and electrical attachments which repeatedly performs complicated (often monotonous) tasks. According to the American Robots Association, a robot can be defined as a multi-functional operator, which can be

Authors gratefully acknowledge the support rendered by Professor A. Gunasekaran, Editor-in-Chief, *Benchmarking: An International Journal*. Special thanks to the anonymous reviewers for their valuable constructive comments and suggestions to prepare the paper a good contributor.

Benchmarking: An International Journal
Vol. 23 No. 7, 2016
pp. 1818-1833
© Emerald Group Publishing Limited
1463-5771
DOI 10.1108/BIJ-07-2015-0078

controlled by programs (Mondal and Chakraborty, 2013). During the last decades, the application of robotic system in industries has been increased substantially to ensure timely and economic utilization of the resources for improving product quality as well as business performance.

Now-a-days, different robotic systems capable of performing repetitive, hazardous and difficult tasks readily are available in the marketplace with a variety of features and specifications. Applications of industrial robots include loading and unloading, assembly, material handling, welding, spray painting, etc. (Kumar and Garg, 2010; Chatterjee *et al.*, 2010). Hence, selection of an appropriate robot in pursuit of a particular area of application is indeed a challenging task. It can, therefore, be viewed as a multi-criteria decision-making (MCDM) problem in which maximum possible criteria (both subjective and objective) should be considered for authentic decision making, failing which a company's competitiveness (in terms of productivity) may be affected adversely.

Goh *et al.* (1996) applied a revised weighted sum model that incorporated different values assigned by a group of experts on different factors in selecting robots. Parkan and Wu (1999) demonstrated exploration aspects of multi-attribute decision making (MADM) and performance measurement methods through a robot selection problem. Particular 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-correlation test showed that the methods could produce similar rankings for the robots. The final selection was made on the basis of the rankings as obtained by averaging the results of OCRA, TOPSIS, and a utility model. Braglia and Petroni (1999) proposed an efficient methodology for the selection of industrial robots using data envelopment analysis (DEA). The study aimed at the identification, in a cost/benefit perspective, of the optimal robot, by measuring, for each robot, the relative efficiency through the resolution of linear programming problems.

Bhangale *et al.* (2004) attempted to generate and maintain reliable and exhaustive database of robot manipulators based on their different pertinent attributes. This database could be used to standardize the robot selection procedure for a particular operation. Rao and Padmanabhan (2006) developed a methodology based on digraph and matrices methods for evaluation of alternative industrial robots. A robot selection index was proposed that evaluated and ranked robots for a given industrial application. Kumar and Garg (2010) developed a deterministic quantitative model based on distance-based approach method for evaluation and selection of alternative robots. Sensitivity analysis was also performed to analyze the critical and non-critical performance attributes for a robot. Athawale *et al.* (2010) focussed on solving the robot selection problem using VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje) method. Chatterjee *et al.* (2010) solved the robot selection problem using two most appropriate MCDM methods and compared their relative performance for a given industrial application. The first MCDM approach is "VIsekriterijumsko KOmpromisno Rangiranje" (VIKOR), a compromise ranking method and the other one is "ELimination and Et Choice Translating Reality" (ELECTRE), an outranking method. Two real time examples were cited in order to demonstrate and validate the applicability and potentiality of both these MCDM methods.

Kentli and Kar (2011) presented a MCDM model for a robot selection problem. The proposed model used satisfaction function to convert various robot attributes into a unified scale. Further, a distance measure technique was used to ascertain the highest ranked candidate robot. Rao *et al.* (2011) proposed a subjective and objective integrated MADM method for the purpose of robot selection. The method considered the objective weights of importance of the attributes as well as the subjective preferences of the decision maker to decide the integrated weights of importance of the attributes. Furthermore, the method used fuzzy logic to convert the qualitative attributes into the quantitative attributes. Chakraborty (2011) explored the application of an efficient multi-objective decision-making method, i.e., the multi-objective optimization on the basis of ratio analysis (MOORA) method to solve different decision-making problems as frequently encountered in the real time manufacturing environment. Here, the author cited an example of industrial robot selection.

In another reporting, Mondal and Chakraborty (2013) applied four models of DEA, i.e. Charnes, Cooper and Rhodes, Banker, Charnes and Cooper, additive, and cone-ratio models to identify feasible robots having the optimal performance measures, simultaneously satisfying the organizational objectives with respect to cost and process optimization. Furthermore, the weighted overall efficiency ranking method of MADM theory was also employed for arriving at the best robot selection decision from the short listed competent alternatives. In order to demonstrate the relevancy and distinctiveness of the adopted DEA-based approach, two real time industrial robot selection problems were also solved.

Selection of industrial robot has long been viewed as a MCDM problem. Literature depicts that a number of decision-making tools and techniques have been explored in facilitating appropriate robot selection. However, it has been noted that most of the existing MCDM tools are unable to capture or take into account the risk attitude/preferences of the decision maker. Prospect theory developed by Kahneman and Tversky (1979) is a descriptive model of individual decision making under condition of risk. Later, Tversky and Kahneman (1992) developed the cumulative prospect theory (CPT), which captures psychological aspects of decision making under risk. In the prospect theory, the outcomes are expressed by means of gains and losses with respect to a reference alternative (Salminen, 1994). The value function in prospect theory assumes the S-shape concave above the reference alternative, which reflects the aversion of risk in face of gains; and the convex part below the reference alternative reflects the propensity to risk in case of losses (Krohling and Souza, 2012). In Tomada de Decisión Inerativa Multicritero (TODIM), first, each shape characteristic of the value function models psychological processes; the concavity for gains describes a risk aversion attitude, the convexity describes a risk seeking attitude; second, the assumption that losses carry more weight than gains is represented by a steeper negative function side (Gomes *et al.*, 2013).

CPT is a model for descriptive decisions under risk. As ordinary prospect theory (OPT), CPT treats gains and losses, separately. Basically CPT considers: first, the evaluation of possible outcomes relative to a certain reference point (often the status quo); second, different risk attitudes toward gains (i.e. outcomes above the reference point) and losses (i.e. outcomes below the reference point) and care generally more about potential losses than potential gains (loss aversion); and third, a tendency to overweight extreme, but unlikely events, but underweight "average" events (Gomes *et al.*, 2013).

Existing literature supports that the prospect theory has successfully been used as behavioral model of decision making under risk mainly in economics and finance (Dhami and Al-Nowaihi, 2007; Gurevich *et al.*, 2009). Unfortunately, the application of prospect theory to MCDM problems has been rarely attempted. The first MCDM method based on prospect theory was proposed by Gomes and Lima (1992).

In the original mathematical formulation of TODIM (an acronym in Portuguese for iterative MCDM), the rating of alternatives, which composes the decision matrix, is represented by crisp values with the assumption that all criterions are beneficial. The TODIM method has many similarities with the PROMETHEE method; whereas, the preference function as computed in PROMETHEE is replaced by the prospect function. The TODIM method has been applied to rental evaluation of residential properties (Gomes and Rangel, 2009). In another reporting, Gomes *et al.* (2009) reported application of the TODIM-based MCDM approach for natural gas destination in Brazil.

Motivated by the application potential of TODIM approach; in the present reporting, MCDM problem toward selection of industrial robots has been articulated to examine decision outcome through logical exploration of TODIM approach.

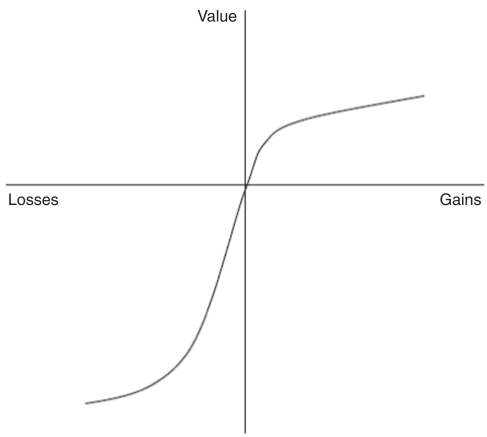
2. MCDM based on prospect theory

2.1 Preliminaries on prospect theory

The value function used in the prospect theory is described in form of a power law according to the following expression (Kahneman and Tversky, 1979):

$$v(x) = \begin{cases} x^{\alpha} & \text{If } x \geqslant 0 \\ -\theta(-x)^{\beta} & \text{If } x < 0 \end{cases} \quad (1)$$

Here α and β are parameters related to gains and losses, respectively. The parameter θ represents a characteristic of being steeper for losses than for gains. In case of risk aversion $\theta > 1$. Figure 1 shows a prospect value function with a concave and convex S-shaped for gains and losses, respectively. Kahneman and Tversky (1979) experimentally determined the values of $\alpha = \beta = 0.88$, and $\theta = 2.25$, which are consistent with empirical data. Further, they suggest that the value of θ is between 2.0 and 2.5.



Source: Gomes and Rangel (2009)

Figure 1. Value function of the prospect theory

2.2 MCDM: the TODIM method

Let us consider the decision matrix **A** which consists of alternatives and criteria, described by:

$$\mathbf{A} = \begin{array}{c} \\ A_1 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \dots & \dots & \dots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \end{array}$$

Here $A_1, A_2, \dots, A_m$ are viable alternatives, and $C_1, C_2, \dots, C_n$ are criteria, x_{ij} indicates the rating of the alternative A_i according to criteria C_j. The weight vector $\boldsymbol{W} = (w_1, w_2, \dots, w_n)$ composed of the individual weights $w_j (j = 1,2, \dots, n)$ for each criterion C_j satisfying $\sum_{j=1}^{n} w_j = 1$. The data of the decision matrix **A** come from different sources, so it is necessary to normalize it in order to transform it into a dimensionless matrix, which allow the comparison of the various criteria. Assume that the normalized decision matrix is $\boldsymbol{R} = [r_{ij}]_{m \times n}$ with $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$. After normalizing the decision matrix and the weight vector, TODIM begins with the calculation of the partial dominance matrices and the final dominance matrix. For such calculations the decision makers need to define first a reference criterion, which usually is the criterion with the height importance weight. So w_{rc} indicates the weight of the criterion c divided by the reference criterion r. Here, w_{rc} is also called the trade-off rate (or trade-off weighting factor).

Basically, TODIM is described in the following steps (Gomes and Lima, 1992; Gomes and Rangel, 2009).

Step 1: calculate the final measure of dominance of each alternative A_i over each alternative A_j using the following expression:

$$\delta(A_i, A_j) = \sum_{C=1}^{m} \phi_c(A_i, A_j) \quad \forall (i,j) \tag{2}$$

Here:

$$\phi_c(A_i, A_j) = \begin{cases} \sqrt{\dfrac{w_{rc}(r_{ic} - r_{jc})}{\sum_{c=1}^{m} w_{rc}}} & \text{If} (r_{ic} - r_{jc}) > 0 \\ 0 \quad \text{If} \ (r_{ic} - r_{jc}) = 0 \\ -\dfrac{1}{\theta} \sqrt{\dfrac{\left(\sum_{c=1}^{m} w_{rc}\right)(r_{jc} - r_{ic})}{w_{rc}}} & \text{If} (r_{ic} - r_{jc}) < 0 \end{cases} \tag{3}$$

Here r_{ic} and r_{jc} are, respectively, the performances (normalized) of the alternatives A_i and A_j in relation to the particular criterion c. The term $\phi_C(A_i, A_j)$ is a reference function and it represents the contribution of the criterion c to the function $\delta(A_i, A_j)$ when comparing the alternative i with alternative j. The parameter θ represents the attenuation factor of the losses, which can be tuned according to the problem at hand. In the present reporting θ value has been assumed 1.

Different kinds of decision makers can be understood in terms of their risk and loss attitude. Although the TODIM method does not deal with risk directly, the way the decision maker evaluates the outcomes of any decision can be expressed by their risk attitude: for instance, a cautious decision maker will under value a superior result more than a braver one (Gomes *et al.*, 2013). The attenuation factor θ in the TODIM method represents the risk aversion or propensity of the decision maker. It has been verified that fact that the three different values for θ led essentially to the same ranking order indicate robustness of the results (Gomes *et al.*, 2009).

In Equation (3), it can occur three cases: first, if the value ($r_{ic}-r_{jc}$) is positive, it represents a gain; second, if the value ($r_{ic}-r_{jc}$) is 0, it represents neither gain nor loss; third, if the value ($r_{ic}-r_{jc}$) is negative, it represents a loss. The final matrix of dominance is obtained by summing up the partial matrices of dominance for each criterion. The relative measure of dominance of one alternative over another is found for each pair of alternatives. This measure is computed as the sum over all criteria of both relative gain/loss values for these alternatives. The parts in this sum will be either gains, losses or zeros, depending on the performance of each alternative with respect to every criterion (Gomes *et al.*, 2009).

The function ϕ_c reproduces the value function of OPT and replicates the most relevant shape characteristics. That function fulfils the concavity for positive outcomes (convexity for negative outcomes), and second, it enlarges the perception of negative values for losses than positive values for gains, both value functions are steeper for negative outcomes than for positive ones (Gomes *et al.*, 2013).

Step 2: calculate the global value of the alternative i by normalizing the final matrix of dominance according to the following expression:

$$\xi_i = \frac{\sum \delta(i,j) - \min \sum \delta(i,j)}{\max \sum \delta(i,j) - \min \sum \delta(i,j)} \tag{4}$$

Ordering the values ξ_i provides the rank of each alternative. The best alternatives are those that have higher value ξ_i.

In real world decision-making scenario, an important aspect is the criteria conflict. That is why criteria can be classified as benefit and adverse criteria. Benefit criteria are those whose higher values are always preferred (higher-is-better, HB type). On the contrary, adverse criteria corresponds to (lower-is-better, LB) type; whose lower values are always preferred. Before, applying any MCDM tool it is necessary to normalize criteria values (decision-making data) to avoid effect of different dimensions (units) of different criteria and to avoid criteria conflict. However, the formula for linear normalization (Equation (5)) as proposed by Gomes and Rangel (2009), Gomes *et al.* (2009) can overcome dimensional effects of criteria but it does not take care of criteria conflict:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n. \tag{5}$$

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

The formula was found suitable to solve the decision-making problem as attempted by Gomes and Rangel (2009), Gomes *et al.* (2009), because all criteria were beneficial in nature. In presence of criteria conflict, aforesaid normalization procedure does not work. Hence, in this paper, the following linear normalization formulae have been explored to the decision-making problem containing benefit as well as adverse criteria both. The normalized data lies in the interval [0, 1] and its maximum value is 1. Upon normalization, the normalized criteria values become beneficial in nature, i.e. HB characteristic.

The formulae for normalization for benefit and adverse criteria have been in Equations (6) and (7), respectively:

$$r_{ij} = \frac{x_{ij}}{\underset{i}{\text{Max}}\,(x_{ij})},\ \ i = 1, 2, ..., m;\ \ j = 1, 2, ..., n.\ \text{(For benefit criteria)} \qquad (6)$$

$$r_{ij} = \frac{\underset{i}{\text{Min}}\,(x_{ij})}{x_{ij}},\ \ i = 1, 2, ..., m;\ \ j = 1, 2, ..., n.\ \text{(For adverse criteria)} \qquad (7)$$

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

3. Numerical illustrations

In this section, two numerical case studies have been attempted exploring robot selection data set collected from the past literature. Application potential of TODIM approach has been compared to that of other existing MCDM approaches.

3.1 Case 1

Considering the data set (Table I) adapted from the reporting of Bhangale *et al.* (2004), Chatterjee *et al.* (2010) in relation to industrial robot selection; the same problem has been solved herewith through TODIM. Among various robot selection criteria (namely, load capacity, LC; repeatability, RE; maximum tip speed, MTS; memory capacity, MC; and manipulator reach, MR); only repeatability has been considered as a non-beneficial criterion while rests as beneficial ones.

The criteria weights as used by Chatterjee *et al.* (2010) have also been explored here. Criteria weights have been given as follows: $W_{LC}=0.036$, $W_{RE}=0.192$, $W_{MTS}=0.326$, $W_{MC}=0.326$ and $W_{MR}=0.120$.

The objective data, as furnished in Table I, have been normalized using Equations (6-7) and the normalized data have been furnished in Table II.

The initial decision-making matrix as shown in Table I has been normalized as follows.

By using Equation (6) for beneficial attributes: $r_{11} = x_{ic}/\underset{i}{\text{Max}}\,(x_{ic}) = 60/60 = 1$, and similar for all alternatives with respect to the particular criterion; while Equation (7) has been used to normalize non-beneficial criterion values (repeatability, in the present case). $r_{12} = \underset{i}{\text{Min}}\,(x_{ic})/x_{ic} = 0.08/0.4 = 0.2$, and similar for all alternatives with respect to the particular criterion.

Table I.
Numeric data set for robot selection (case 1)

Robot (s)	Load capacity (LC) (kg)	Repeatability (RE) (mm)	Maxim tip speed (MTS) (mm/sec)	Memory capacity (MC) (points or steps)	Manipulator reach (MR) (mm)
A_1	60	0.4	2,540	500	990
A_2	6.35	0.15	1,016	3,000	1,041
A_3	6.8	0.10	1,727.2	1,500	1,676
A_4	10	0.2	1,000	2,000	965
A_5	2.5	0.10	560	500	915
A_6	4.5	0.08	1,016	350	508
A_7	3	0.1	1,778	1,000	920

Now, the values of w_{rc} have been determined as follows:

$$w_{r_1} = 0.036/0.326 = 0.11, \;\; w_{r_2} = 0.192/0.326 = 0.589, \;\; w_{r_3} = 0.326/0.326 = 1.0,$$

$$w_{r_4} = 0.326/0.326 = 1.0 \;\; w_{r_5} = 0.120/0.326 = 0.368$$

Here, $w_r = 0.326$ is the maximum weight in the group and:

$$\sum\nolimits_{c=1}^{n} w_{rc} = 0.11 + 0.589 + 1 + 1 + 0.368 = 3.07$$

Now, from Table II, the evaluative difference $(r_{ic} - r_{jc}) | i = 1,2, \ldots, m$ of ith alternative with respect to jth alternative has been computed (as shown in Table III) as discussed earlier in the procedural steps of TODIM.

For example, pair $(A_1, A_2) = 1 - 0.106 = 0.89$, and similar for all individual alternative with respect to other alternatives.

Robot(s)	LC	RE	MTS	MC	MR
A_1	1.000	0.200	1.000	0.167	0.591
A_2	0.106	0.533	0.400	1.000	0.621
A_3	0.113	0.800	0.680	0.500	1.000
A_4	0.167	0.400	0.394	0.667	0.576
A_5	0.042	0.800	0.220	0.167	0.546
A_6	0.075	1.000	0.400	0.117	0.303
A_7	0.050	0.800	0.700	0.333	0.549

Table II. Normalized decision matrix

Pair	LC	RE	MTS	MC	MR	Pair	LC	RE	MTS	MC	MR
(A_1, A_2)	0.89	−0.33	0.60	−0.83	−0.03	(A_4, A_5)	0.13	−0.40	0.17	0.50	0.03
(A_1, A_3)	0.89	−0.60	0.32	−0.33	−0.41	(A_4, A_6)	0.09	−0.60	−0.01	0.55	0.27
(A_1, A_4)	0.83	−0.20	0.61	−0.50	0.01	(A_4, A_7)	0.12	−0.40	−0.31	0.33	0.03
(A_1, A_5)	0.96	−0.60	0.78	0.00	0.04	(A_5, A_1)	−0.96	0.60	−0.78	0.00	−0.04
(A_1, A_6)	0.93	−0.80	0.60	0.05	0.29	(A_5, A_2)	−0.06	0.27	−0.18	−0.83	−0.08
(A_1, A_7)	0.95	−0.60	0.30	−0.17	0.04	(A_5, A_3)	−0.07	0.00	−0.46	−0.33	−0.45
(A_2, A_1)	−0.89	0.33	−0.60	0.83	0.03	(A_5, A_4)	−0.13	0.40	−0.17	−0.50	−0.03
(A_2, A_3)	−0.01	−0.27	−0.28	0.50	−0.38	(A_5, A_6)	−0.03	−0.20	−0.18	0.05	0.24
(A_2, A_4)	−0.06	0.13	0.01	0.33	0.05	(A_5, A_7)	−0.01	0.00	−0.48	−0.17	0.00
(A_2, A_5)	0.06	−0.27	0.18	0.83	0.08	(A_6, A_1)	−0.93	0.80	−0.60	−0.05	−0.29
(A_2, A_6)	0.03	−0.47	0.00	0.88	0.32	(A_6, A_2)	−0.03	0.47	0.00	−0.88	−0.32
(A_2, A_7)	0.06	−0.27	−0.30	0.67	0.07	(A_6, A_3)	−0.04	0.20	−0.28	−0.38	−0.70
(A_3, A_1)	−0.89	0.60	−0.32	0.33	0.41	(A_6, A_4)	−0.09	0.60	0.01	−0.55	−0.27
(A_3, A_2)	0.01	0.27	0.28	−0.50	0.38	(A_6, A_5)	0.03	0.20	0.18	−0.05	−0.24
(A_3, A_4)	−0.05	0.40	0.29	−0.17	0.42	(A_6, A_7)	0.03	0.20	−0.30	−0.22	−0.25
(A_3, A_5)	0.07	0.00	0.46	0.33	0.45	(A_7, A_1)	−0.95	0.60	−0.30	0.17	−0.04
(A_3, A_6)	0.04	−0.20	0.28	0.38	0.70	(A_7, A_2)	−0.06	0.27	0.30	−0.67	−0.07
(A_3, A_7)	0.06	0.00	−0.02	0.17	0.45	(A_7, A_3)	−0.06	0.00	0.02	−0.17	−0.45
(A_4, A_1)	−0.83	0.20	−0.61	0.50	−0.01	(A_7, A_4)	−0.12	0.40	0.31	−0.33	−0.03
(A_4, A_2)	0.06	−0.13	−0.01	−0.33	−0.05	(A_7, A_5)	0.01	0.00	0.48	0.17	0.00
(A_4, A_3)	0.05	−0.40	−0.29	0.17	−0.42	(A_7, A_6)	−0.03	−0.20	0.30	0.22	0.25

Table III. Evaluative differences $(r_{ic} - r_{jc})$

After determining evaluative differences, preference function $\Phi_c(A_i,A_j)$ has been calculated by using Equation (3). Table IV shows the partial matrices of dominance for all pairs of alternatives.

For example, partial dominance for the pair $(A_1, A_2) = 0.89$, which is > 0; so preference functions must be calculated as follows:

$$\Phi_c(A_i, A_j) = \sqrt{\frac{w_{rc}(r_{ic} - r_{jc})}{\sum_{c=1}^{m} w_{rc}}} = \sqrt{(0.11 \times 0.89)/3.07} = 0.18$$

Here $i = 1$ and $c = 1$ (for load capacity).

Now using Equation (2), the measurement of dominance of alternative A_i over alternative A_j has been computed. Next, the final dominance matrix has been constructed. Table V exhibits final dominance matrix for all paired alternatives.

Table IV. Partial matrices of dominance

Pair	LC	RE	MTS	MC	MR	Pair	LC	RE	MTS	MC	MR
(A_1, A_2)	0.18	−1.32	0.44	−1.60	−0.50	(A_4, A_5)	0.07	−1.44	0.24	0.40	0.06
(A_1, A_3)	0.18	−1.77	0.32	−1.01	−1.85	(A_4, A_6)	0.06	−1.77	−0.14	0.42	0.18
(A_1, A_4)	0.17	−1.02	0.44	−1.24	0.04	(A_4, A_7)	0.06	−1.44	−0.97	0.33	0.06
(A_1, A_5)	0.19	−1.77	0.50	0.00	0.07	(A_5, A_1)	−5.17	0.34	−1.55	0.00	−0.61
(A_1, A_6)	0.18	−2.04	0.44	0.13	0.19	(A_5, A_2)	−1.34	0.23	−0.74	−1.60	−0.79
(A_1, A_7)	0.18	−1.77	0.31	−0.72	0.07	(A_5, A_3)	−1.41	0.00	−1.19	−1.01	−1.95
(A_2, A_1)	−5.00	0.25	−1.36	0.52	0.06	(A_5, A_4)	−1.87	0.28	−0.73	−1.24	−0.50
(A_2, A_3)	−0.46	−1.18	−0.93	0.40	−1.78	(A_5, A_6)	−0.96	−1.02	−0.74	0.13	0.17
(A_2, A_4)	−1.30	0.16	0.05	0.33	0.07	(A_5, A_7)	−0.48	0.00	−1.21	−0.72	−0.16
(A_2, A_5)	0.05	−1.18	0.24	0.52	0.09	(A_6, A_1)	−5.08	0.39	−1.36	−0.39	−1.55
(A_2, A_6)	0.03	−1.56	0.00	0.54	0.20	(A_6, A_2)	−0.93	0.30	0.00	−1.65	−1.63
(A_2, A_7)	0.04	−1.18	−0.96	0.47	0.09	(A_6, A_3)	−1.03	0.20	−0.93	−1.08	−2.41
(A_3, A_1)	−4.97	0.34	−0.99	0.33	0.22	(A_6, A_4)	−1.60	0.34	0.05	−1.30	−1.51
(A_3, A_2)	0.02	0.23	0.30	−1.24	0.21	(A_6, A_5)	0.03	0.20	0.24	−0.39	−1.42
(A_3, A_4)	−1.22	0.28	0.31	−0.72	0.23	(A_6, A_7)	0.03	0.20	−0.96	−0.82	−1.43
(A_3, A_5)	0.05	0.00	0.39	0.33	0.23	(A_7, A_1)	−5.15	0.34	−0.96	0.23	−0.59
(A_3, A_6)	0.04	−1.02	0.30	0.35	0.29	(A_7, A_2)	−1.25	0.23	0.31	−1.43	−0.78
(A_3, A_7)	0.05	0.00	−0.25	0.23	0.23	(A_7, A_3)	−1.33	0.00	0.08	−0.72	−1.94
(A_4, A_1)	−4.82	0.20	−1.36	0.40	−0.35	(A_7, A_4)	−1.80	0.28	0.32	−1.01	−0.47
(A_4, A_2)	0.05	−0.83	−0.14	−1.01	−0.62	(A_7, A_5)	0.02	0.00	0.40	0.23	0.02
(A_4, A_3)	0.04	−1.44	−0.94	0.23	−1.88	(A_7, A_6)	−0.84	−1.02	0.31	0.27	0.17

Table V. Final matrices of dominance for all the pairs of alternatives

Robot	A_1	A_2	A_3	A_4	A_5	A_6	A_7
A_1	–	−2.80	−4.13	−1.60	−1.01	−1.10	−1.92
A_2	−5.52	–	−3.94	−0.69	−0.27	−0.79	−1.53
A_3	−5.08	−0.48	–	−1.13	1.00	−0.04	0.27
A_4	−5.94	−2.55	−3.99	–	−0.68	−1.25	−1.96
A_5	−6.99	−4.25	−5.56	−4.06	–	−2.43	−2.57
A_6	−7.99	−3.90	−5.26	−4.02	−1.34	–	−2.98
A_7	−6.13	−2.92	−3.90	−2.70	0.66	−1.11	–

Measurement of dominance of alternative A_1 over alternative A_1 $\delta(A_1,A_1)$ has been calculated as:

$$\delta(A_1, A_2) = (0.18 - 1.32 + 0.44 - 1.60 - 0.50) = -2.8$$

$$\delta(A_1, A_3) = (0.18 - 1.77 + 0.32 - 1.01 - 1.85) = -4.13 \text{ and so on up to}$$

$$\delta(A_7, A_6) = -1.11$$

Now, the global measures $(\xi_i)|i = 1,2, \ldots, m$ of each alternative have been determined through normalization of the corresponding dominance measurements by using Equation (4). The value of $\sum_{j=1}^{n} \delta(A_i, A_j)$ and the value of global measures (ξ_i) have been calculated and shown in Table VI. Ranking order has been derived on the basis of HB criterion:

$\sum_{j=1}^{n} \delta(A_i, A_j) = (-2.80 - 4.13 - 1.60 - 1.01 - 1.10 - 1.92) = -12.55$ for $i = 1$ and $j = 1 \ldots n$ and so on.

$$\xi_1 = \frac{\{(-12.55) - (-25.85)\}}{[(-5.46) - (-25.85)]} = 0.65$$

According to TODIM, robot A_3 appears at the most appropriate choice; whereas, robot A_5 is the worst. Bhangale *et al.* (2004) also suggested that robot A_3 and robot A_5 as the best and worst choice of selection, respectively, by using coefficient of similarity approach based on spider diagram. Furthermore, Chakraborty (2011) considered the same case illustration using MOORA method and recommended that robot A_3 as the wise choice of selection; while robot A_5 remains as a worst choice in their approach. Chatterjee *et al.* (2010) also reported the same decision data set and found that robot A_3 as a most favorable candidate robot and robot A_5 as the worst one by using a compromise ranking and outranking method.

3.2 Case 2

In this case example, the numeric data set as used by Imany and Shlesinger (1989), Khouja (1995) has been considered here to solve the robot selection problem through TODIM method. In this computation, the criteria weights as determined by Khouja (1995) have been reutilized here. Quantitative decision data have been highlighted in Table VII; which involves beneficial as well as non-beneficial criteria/attributes. Among these criteria, cost and repeatability have been treated here as non-beneficial; while the remaining as beneficial in nature. Khouja (1995) determined the criteria weights as $W_{Vel} = 0.35$, $W_{LC} = 0.20$, $W_C = 0.15$, $W_{RE} = 0.30$ for the same robot selection problem. The same weight set has been reutilized here for computational part of TODIM approach.

Robot(s)	$\sum_{j=1}^{n} \delta(A_i, A_j)$	ξ	Ranking order
A_1	−12.55	0.65	2
A_2	−12.75	0.64	3
A_3	−5.46	1.00	1
A_4	−16.36	0.47	4
A_5	−25.85	0.00	7
A_6	−25.50	0.02	6
A_7	−16.09	0.48	5

Table VI. Global measure of alternatives

Robot (s)	Velocity (Vel) (m/s)	Load capacity (LC) (kg)	Cost (C) ($)	Repeatability (RE) (mm)	Robot (s)	Velocity (Vel) (m/s)	Load capacity (LC) (kg)	Cost (C) ($)	Repeatability (RE) (mm)
A_1	1.35	60.0	7.20	0.150	A_{15}	1.00	47.0	3.68	1.00
A_2	1.10	6.0	4.80	0.050	A_{16}	1.00	80.0	6.88	1.00
A_3	1.27	45.0	5.0	1.270	A_{17}	2.00	15.0	8.0	2.00
A_4	0.66	1.5	7.20	0.025	A_{18}	1.00	10.0	6.30	0.200
A_5	0.05	50.0	9.60	0.250	A_{19}	0.30	10.0	0.94	0.050
A_6	0.30	1.0	1.07	0.100	A_{20}	0.80	1.5	0.16	2.00
A_7	1.00	5.0	1.76	0.100	A_{21}	1.70	27.0	2.81	2.00
A_8	1.00	15.0	3.20	0.100	A_{22}	1.00	0.9	3.80	0.050
A_9	1.10	10.0	6.72	0.200	A_{23}	0.50	2.5	1.25	0.100
A_{10}	1.00	6.0	2.40	0.050	A_{24}	0.50	2.5	1.37	0.100
A_{11}	0.90	30.0	2.88	0.500	A_{25}	1.00	10.0	3.63	0.200
A_{12}	0.15	13.6	6.90	1.00	A_{26}	1.25	70.0	5.30	1.270
A_{13}	1.20	10.0	3.20	0.050	A_{27}	0.75	205.0	4.0	2.030
A_{14}	1.20	30.0	4.00	0.050					

Table VII. Numerical data for robot selection (case 2)

The objective data, as given in Table VII, have been normalized using Equations (6-7) and provided in Table VIII. Now, after computing w_{rc} the partial matrices of dominance has been calculated for all the pairs of alternatives using Equation (3); and results have been furnished in Table IX.

Now using Equation (2), the measurement of dominance of alternative A_i over alternative A_j has been evaluated followed by the construction of the final dominance matrix. Table X exhibits the final matrices of dominance for all the paired alternatives.

Now, the global measure of dominance $(\xi_i)|i=1,2,\ldots,m$ for the alternative i has been determined through normalization of the corresponding dominance measurements by using Equation (4). The computed value of $\sum_{j=1}^{n}\delta(A_i,A_j)$ and the value of global measures (ξ) have been shown in Table XI. Alternative ranking order has been evaluated on the basis of HB.

In aforesaid case illustration, using the TODIM method, 27 robot alternatives have been ranked by considering criteria weight as proposed by Khouja (1995). The ranking

Robot	Vel	LC	C	RE	Robot	Vel	LC	C	RE
A_1	0.675	0.293	0.022	0.167	A_{15}	0.500	0.229	0.043	0.025
A_2	0.550	0.029	0.033	0.500	A_{16}	0.500	0.390	0.023	0.025
A_3	0.635	0.220	0.032	0.020	A_{17}	1.000	0.073	0.020	0.013
A_4	0.330	0.007	0.022	1.000	A_{18}	0.500	0.049	0.025	0.125
A_5	0.025	0.244	0.017	0.100	A_{19}	0.150	0.049	0.170	0.500
A_6	0.150	0.005	0.150	0.250	A_{20}	0.400	0.007	1.000	0.013
A_7	0.500	0.024	0.091	0.250	A_{21}	0.850	0.132	0.057	0.013
A_8	0.500	0.073	0.050	0.250	A_{22}	0.500	0.004	0.042	0.500
A_9	0.550	0.049	0.024	0.125	A_{23}	0.250	0.012	0.128	0.250
A_{10}	0.500	0.029	0.067	0.500	A_{24}	0.250	0.012	0.117	0.250
A_{11}	0.450	0.146	0.056	0.050	A_{25}	0.500	0.049	0.044	0.125
A_{12}	0.075	0.066	0.023	0.025	A_{26}	0.625	0.341	0.030	0.020
A_{13}	0.600	0.049	0.050	0.500	A_{27}	0.375	1.000	0.040	0.012
A_{14}	0.600	0.146	0.040	0.500					

Table VIII. Normalized decision matrix

Pair	Vel	LC	C	RE	Pair	Vel	LC	C	RE
(A_1, A_1)	00	00	00	00	(A_1, A_{17})	−0.96	0.21	0.02	0.22
(A_1, A_2)	0.21	0.23	−0.27	−1.05	(A_1, A_{18})	0.25	0.22	−0.15	0.11
(A_1, A_3)	0.12	0.12	−0.26	0.21	(A_1, A_{19})	0.43	0.22	−0.99	−1.05
(A_1, A_4)	0.35	0.24	0.00	−1.66	(A_1, A_{20})	0.31	0.24	−2.55	0.22
(A_1, A_5)	0.48	0.10	0.03	0.14	(A_1, A_{21})	−0.71	0.18	−0.48	0.22
(A_1, A_6)	0.43	0.24	−0.92	−0.53	(A_1, A_{22})	0.25	0.24	−0.37	−1.05
(A_1, A_7)	0.25	0.23	−0.68	−0.53	(A_1, A_{23})	0.39	0.24	−0.84	−0.53
(A_1, A_8)	0.25	0.21	−0.43	−0.53	(A_1, A_{24})	0.39	0.24	−0.79	−0.53
(A_1, A_9)	0.21	0.22	−0.11	0.11	(A_1, A_{25})	0.25	0.22	−0.38	0.11
(A_1, A_{10})	0.25	0.23	−0.55	−1.05	(A_1, A_{26})	0.13	−0.49	−0.23	0.21
(A_1, A_{11})	0.28	0.17	−0.47	0.19	(A_1, A_{27})	0.32	−1.88	−0.35	0.22
(A_1, A_{12})	0.46	0.21	−0.09	−0.69	(A_2, A_1)	−0.60	−1.15	0.04	0.32
(A_1, A_{13})	0.16	0.22	−0.43	−1.05	–	–	–	–	–
(A_1, A_{14})	0.16	0.17	−0.35	−1.05	–	–	–	–	–
(A_1, A_{15})	0.25	0.11	−0.38	0.21	(A_{27}, A_{26})	−0.85	0.36	0.04	−0.16
(A_1, A_{16})	0.25	−0.70	−0.09	0.21	(A_{27}, A_{27})	00	00	00	00

Table IX. Partial matrices of dominance for all the pairs of alternatives

order of robot alternatives shows that robot A_{14} is the highest ranked robot followed by robot A_{13}; while robot A_{12} is the worst choice for this particular robot selection problem. A separate analysis was made through the criteria weight as suggested by Khouja (1995) who proposed a DEA approach and applied it on the same robot selection data set; also found robot A_{14} as the most suitable alternative. In a relatively recent work, Kentli and Kar (2011) established a decision model for robot selection based on the concepts of the satisfaction function and distance measure; explored the same data set and also determined A_{14} as the best robot. In addition to this, Karsak *et al.* (2012) used a fuzzy regression-based decision-making approach and recommended robot A_{14} as best choice and robot A_{20} as the last choice.

4. Conclusion

Aforesaid two case illustration reveals application potential of TODIM in relation to solve decision-making problems for industrial robot selection. The alternative ranking order as obtained by TODIM has been compared to that of existing MCDM approaches. It has been found that in all the case, the most appropriate choice appears the same. The worst choice is also appeared same for many cases. However, it has been noticed that apart from best and worst choices, intermediate ranking orders slightly deferred. This is quite obvious due to fact that different MCDM approaches explore their own philosophy and also the procedure to normalize raw data is different.

Industries may adopt this decision making come appraisement module as a test-kit toward performance assessment and selection of appropriate robot to satisfy specific functional requirements and suitable for specific area of application. This may also help in benchmarking of robot manufactures with respect to product variety, reliable and safe functionality – performance and robustness – flexibility in usage.

In this reporting, it has been assumed that all evaluation criterions are objective (quantitative) in nature. In many real world decision-making situations, apart from objective data, subjective attributes need to be considered simultaneously. As subjective decision-making data invites some kind of ambiguity and vagueness in the

Table X.
Final matrices of dominance for all the pairs of alternatives

Robot	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{26}	A_{27}
A_1	–	−0.89	0.19	−1.08	0.75	−0.78	−0.72	−0.50	0.43	−1.12	0.17	−0.11	−1.10	−1.07	0.19	−0.34	−0.52	0.43	−1.40	−1.79	−0.79	−0.93	−0.74	−0.70	0.20	−0.38	−1.69
A_2	−1.39	–	0.09	−0.91	−0.21	−0.16	−0.18	−0.40	−0.23	−0.34	−0.60	0.39	−0.80	−1.21	−0.58	−0.80	−1.18	0.19	−0.90	−1.86	−1.66	−0.04	−0.14	−0.09	−0.12	−1.31	−1.79
A_3	−1.60	−0.99	–	−1.23	−0.35	−1.14	−1.09	−0.83	−0.20	−1.33	−0.33	0.52	−1.31	−1.26	−0.40	−0.80	−0.76	−0.16	−1.63	−2.00	−1.01	−1.10	−1.10	−1.06	−0.47	−0.70	−1.86
A_4	−1.69	−1.01	−1.68	–	−0.22	−0.17	−1.19	−1.23	−0.85	−1.19	−1.36	0.76	−1.38	−1.67	−1.59	−1.63	−1.40	−0.79	−0.81	−2.45	−1.95	−0.65	−0.36	−0.31	−1.03	−1.90	−2.39
A_5	−2.77	−2.62	−1.75	−2.72	–	−2.21	−2.55	−2.34	−1.86	−2.81	−1.83	−0.62	−2.83	−2.81	−1.75	−2.45	−1.72	−1.82	−2.69	−3.47	−1.99	−2.63	−2.34	−2.30	−2.01	−2.48	−3.43
A_6	−2.13	−2.20	−1.82	−2.27	−0.53	–	−1.22	−1.46	−1.21	−2.15	−1.40	0.01	−2.39	−2.76	−1.67	−1.99	−1.74	−1.14	−1.75	−3.06	−1.83	−1.77	−0.67	−0.65	−1.15	−2.07	−2.64
A_7	−2.45	−1.70	−1.48	−1.40	−1.04	−1.08	–	−1.28	−1.21	−1.36	−0.87	0.03	−2.07	−2.49	−0.93	−1.25	−1.53	−0.83	−1.99	−2.15	−1.60	−0.54	−0.63	−0.54	−0.58	−1.72	−1.85
A_8	−1.53	−1.15	−1.16	−1.16	−0.24	−0.35	−0.42	–	−0.05	−1.15	−0.42	0.75	−1.38	−2.01	−0.59	−0.94	−0.86	0.32	−1.39	−1.95	−1.49	−0.76	−0.31	−0.26	0.29	−1.44	−1.64
A_9	−2.06	−1.30	−1.47	−1.32	−0.44	−1.09	−1.11	−1.28	–	−1.45	−0.82	0.30	−1.91	−2.52	−1.01	−0.99	−1.27	0.04	−1.73	−2.04	−1.85	−1.24	−1.07	−1.02	−0.23	−1.70	−2.08
A_{10}	−1.46	−0.31	−1.15	−0.90	−0.20	−0.05	−0.09	−0.15	−0.28	–	−0.23	0.41	−0.80	−1.24	−0.57	−0.89	−1.20	0.10	−0.79	−1.86	−1.30	0.13	−0.01	0.05	0.08	−1.40	−1.55
A_{11}	−2.21	−1.55	−1.18	−1.34	−0.65	−1.11	−1.52	−1.04	−0.83	−1.72	–	0.65	−1.71	−1.83	−0.89	−1.33	−0.95	−0.67	−1.63	−2.10	−0.99	−1.39	−1.08	−1.02	−0.70	−1.54	−1.75
A_{12}	−3.05	−2.60	−2.35	−2.54	−1.28	−2.14	−2.55	−2.58	−1.76	−2.81	−2.42	–	−2.85	−3.45	−2.38	−2.38	−1.73	−1.75	−2.65	−3.34	−2.48	−2.61	−2.30	−2.26	−2.00	−2.61	−3.37
A_{13}	−1.19	0.24	−0.81	−0.83	−0.12	−0.05	0.01	0.11	0.53	−0.08	−0.29	0.57	–	−0.66	−0.35	−0.68	−0.97	0.58	−0.50	−1.78	−1.32	0.32	−0.01	0.04	0.56	−1.04	−1.48
A_{14}	−0.95	0.32	−0.51	−0.76	0.15	−0.01	0.03	0.32	0.66	−0.08	0.28	0.98	−0.12	–	−0.23	−0.49	−0.51	0.71	−0.39	−1.71	−0.74	0.24	0.02	0.07	0.50	−0.84	−1.41
A_{15}	−1.90	−1.40	−0.50	−1.29	−0.30	−1.15	−1.23	−0.90	−0.71	−1.45	−0.32	0.62	−1.82	−1.64	–	−0.84	−0.90	−0.34	−1.64	−2.06	−1.10	−1.03	−1.11	−1.06	−0.47	−1.27	−1.67
A_{16}	−1.24	−1.63	−0.64	−1.27	0.11	−1.16	−1.27	−1.04	−0.77	−1.53	−0.40	0.60	−1.95	−1.91	−0.19	–	−0.86	−0.44	−1.64	−2.02	−1.19	−1.34	−1.13	−1.08	−0.69	−0.68	−1.81
A_{17}	−1.55	−1.08	−0.93	−1.33	−0.86	−1.15	−1.06	−0.92	−0.30	−1.32	−1.01	0.26	−1.28	−1.87	−1.06	−1.19	–	−0.31	−1.66	−1.98	−0.81	−1.12	−1.11	−1.07	−0.52	−1.21	−2.04
A_{18}	−2.14	−1.66	−1.56	−1.35	−0.46	−1.11	−1.24	−1.40	−0.36	−1.58	−0.87	0.28	−2.06	−2.67	−1.13	−1.12	−1.33	–	−1.75	−2.08	−1.92	−1.36	−1.09	−1.04	−0.36	−1.82	−2.11
A_{19}	−1.87	−0.86	−1.58	−1.77	−0.28	0.42	−0.55	−0.94	−0.59	−0.81	−1.13	0.39	−1.03	−1.69	−1.44	−1.78	−1.37	−0.52	–	−2.72	−1.55	−0.77	−0.10	−0.09	−0.52	−1.85	−2.46
A_{20}	−2.42	−1.88	−1.62	−1.27	−0.88	−0.21	−1.35	−1.62	−1.34	−1.77	−1.19	−0.03	−2.11	−2.49	−1.41	−1.74	−1.50	−1.22	−1.08	–	−1.55	−1.41	−0.46	−0.46	−1.22	−1.86	−1.74
A_{21}	−1.29	−0.75	−0.48	−1.16	−0.67	−1.02	−0.87	−0.40	−0.09	−1.03	−0.23	0.51	−0.82	−1.19	−0.50	−0.92	−0.47	−0.06	−1.52	−1.95	–	−0.72	−0.96	−0.91	−0.09	−0.83	−1.61
A_{22}	−1.54	−0.70	−1.24	−1.12	−0.28	−0.29	−0.62	−0.55	−0.86	−0.76	−0.65	0.26	−1.24	−1.36	−0.78	−0.96	−1.34	−0.09	−1.05	−2.08	−1.73	–	−0.39	−0.34	−0.26	−1.48	−1.63
A_{23}	−2.00	−2.01	−1.69	−1.90	−0.46	−0.15	−1.02	−1.29	−1.04	−1.96	−1.23	0.11	−2.23	−2.62	−1.52	−1.84	−1.62	−0.96	−1.68	−2.77	−1.71	−1.60	–	0.04	−0.97	−1.94	−2.44
A_{24}	−2.01	−2.02	−1.69	−1.91	−0.29	−0.24	−1.03	−1.30	−0.88	−1.96	−1.24	0.10	−2.24	−2.63	−1.52	−1.84	−1.63	−0.96	−1.75	−2.78	−1.72	−1.61	−0.27	–	−0.98	−1.94	−2.45
A_{25}	−2.13	−1.39	−1.33	−1.31	−0.43	−1.04	−1.13	−1.19	−0.32	−1.44	−0.69	0.32	−1.85	−2.33	−0.77	−1.08	−1.30	0.06	−1.03	−1.71	−1.75	−1.01	−1.00	−0.95	–	−1.59	−1.76
A_{26}	−0.94	−1.00	−0.13	−1.19	0.13	−1.10	−1.05	−0.80	−0.16	−1.30	−0.28	0.58	−1.29	−1.23	−0.07	−0.39	−0.72	0.07	−1.18	−1.95	−0.97	−1.08	−1.06	−1.02	−0.45	–	−1.73
A_{27}	−1.22	−1.51	−0.59	−1.19	0.26	−1.02	−1.63	−1.32	−0.84	−1.85	−0.73	0.60	−1.90	−1.66	−0.57	−0.41	−0.89	−0.73	−1.49	−2.39	−1.13	−1.54	−1.00	−0.95	−0.94	−0.60	–

Robot	$\sum_{j=1}^{n} \delta(A_i, A_j)$	ξ	Rank	Robot	$\sum_{j=1}^{n} \delta(A_i, A_j)$	ξ	Rank
A_1	−14.29	0.84	3	A_{15}	−27.50	0.61	14
A_2	−16.23	0.80	5	A_{16}	−27.17	0.62	11
A_3	−24.19	0.67	10	A_{17}	−28.48	0.60	15
A_4	−30.16	0.57	17	A_{18}	−35.28	0.48	21
A_5	−61.34	0.05	26	A_{19}	−27.44	0.62	13
A_6	−43.67	0.34	25	A_{20}	−35.82	0.48	22
A_7	−34.55	0.50	20	A_{21}	−20.02	0.74	6
A_8	−21.29	0.72	8	A_{22}	−23.08	0.69	9
A_9	−32.68	0.53	19	A_{23}	−38.50	0.43	23
A_{10}	−15.62	0.81	4	A_{24}	−38.81	0.43	24
A_{11}	−32.08	0.54	18	A_{25}	−30.16	0.57	16
A_{12}	−64.22	0.00	27	A_{26}	−20.32	0.74	7
A_{13}	−9.19	0.92	2	A_{27}	−27.24	0.62	12
A_{14}	−4.50	1.00	1				

Tablee XI. Overall value (global measures) of alternatives

decision making; application of fuzzy set theory, grey numbers set theory, etc., may be fruitful in this context. However, crisp-TODIM fails to solve decision-making problems involving subjective data. Hence, there exists scope for extending traditional TODIM approach by integrating with fuzzy and grey set theory. Work may be extended in this particular direction.

References

Athawale, V.M., Chatterjee, P. and Chakraborty, S. (2010), "Selection of industrial robots using compromise ranking method", *Proceedings of the 2010 International Conference on Industrial Engineering and Operations Management, Dhaka, January 9-10*.

Bhangale, P.P., Agrawal, V.P. and Saha, S.K. (2004), "Attribute based specification, comparison and selection of a robot", *Mechanism and Machine Theory*, Vol. 39 No. 12, pp. 1345-1366.

Braglia, M. and Petroni, A. (1999), "Evaluating and selecting investments in industrial robots", *International Journal of Production Research*, Vol. 37 No. 18, pp. 4157-4178.

Chakraborty, S. (2011), "Applications of the MOORA method for decision making in manufacturing environment", *International Journal of Advanced Manufacturing Technology*, Vol. 54 Nos 9-12, pp. 1155-1166.

Chatterjee, P., Athawale, V.M. and Chakraborty, S. (2010), "Selection of industrial robot using compromise ranking and outranking methods", *Robotics and Computer Integrating Manufacturing*, Vol. 26 No. 5, pp. 483-489.

Dhami, S. and Al-Nowaihi, A. (2007), "Why do people pay taxes? Prospect theory versus expected utility theory", *Journal of Economic Behavior & Organization*, Vol. 64 No. 1, pp. 171-192.

Goh, C.H., Tung, Y.C.A. and Cheng, C.H. (1996), "A revised weighted sum decision model for robot selection", *Computers & Industrial Engineering*, Vol. 30 No. 2, pp. 193-199.

Gomes, L.F.A.M. and Lima, M.M.P.P. (1992), "TODIM: basics and application to multi-criteria ranking of projects with environmental impacts", *Foundations of Computing and Decision Sciences*, Vol. 16 No. 4, pp. 113-127.

Gomes, L.F.A.M. and Rangel, L.A.D. (2009), "An application of the TODIM method to the multi-criteria rental evaluation of residential properties", *European Journal of Operational Research*, Vol. 193 No. 1, pp. 204-211.

Gomes, L.F.A.M., Machado, M.A.S. and Rangel, L.A.D. (2013), "Behavioral multi-criteria decision analysis: the TODIM method with criteria interactions", *Annals of Operations Research Springer Science Business Media New York*, Vol. 211 No. 1, pp. 531-548.

Gomes, L.F.A.M., Rangel, L.A.D. and Maranhãoc, F.J.C. (2009), "Multi-criteria analysis of natural gas destination in Brazil: an application of the TODIM method", *Mathematical and Computer Modelling*, Vol. 50 Nos 1-2, pp. 92-100.

Gurevich, G., Kliger, D. and Levy, O. (2009), "Decision-making under uncertainty – a field study of cumulative prospect theory", *Journal of Banking & Finance*, Vol. 33 No. 7, pp. 1221-1229.

Imany, M.M. and Shlesinger, R.J. (1989), "Decision models for robot selection: a comparison of ordinary least squares and linear goal programming methods", *Decision Sciences*, Vol. 20 No. 1, pp. 40-53.

Kahneman, D. and Tversky, A. (1979), "Prospect theory: an analysis of decision under risk", *Econometrica*, Vol. 47 No. 2, pp. 263-292.

Karsak, E.E., Sener, Z. and Dursun, M. (2012), "Robot selection using a fuzzy regression-based decision-making approach", *International Journal of Production Research*, Vol. 50 No. 23, pp. 6826-6834.

Kentli, A. and Kar, A.K. (2011), "A satisfaction function and distance measure based multi-criteria robot", *International Journal of Production Research*, Vol. 49 No. 19, pp. 5821-5832.

Khouja, M. (1995), "The use of data envelopment analysis for technology selection", *Computers & Industrial Engineering*, Vol. 28 No. 1, pp. 123-132.

Krohling, R.A. and Souza, T.T.M.D. (2012), "Combining prospect theory and fuzzy numbers to multi-criteria decision making", *Expert Systems with Applications*, Vol. 39 No. 13, pp. 11487-11493.

Kumar, R. and Garg, R.K. (2010), "Optimal selection of robots by using distance based approach method", *Robotics and Computer-Integrated Manufacturing*, Vol. 26 No. 5, pp. 500-506.

Mondal, S. and Chakraborty, S. (2013), "A solution to robot selection problems using data envelopment analysis", *International Journal of Industrial Engineering Computations*, Vol. 4 No. 3, pp. 355-372.

Parkan, C. and Wu, M.L. (1999), "Decision-making and performance measurement models with applications to robot selection", *Computers & Industrial Engineering*, Vol. 36 No. 3, pp. 503-523.

Rao, R.V. and Padmanabhan, K.K. (2006), "Selection, identification and comparison of industrial robots using digraph and matrices methods", *Robotics and Computer-Integrated Manufacturing*, Vol. 22 No. 4, pp. 373-383.

Rao, R.V., Patel, B.K. and Parnichkun, M. (2011), "Industrial robot selection using a novel decision making method considering objective and subjective preferences", *Robotics and Autonomous Systems*, Vol. 59 No. 6, pp. 367-375.

Salminen, P. (1994), "Solving the discrete multiple criteria problem using linear prospect theory", *European Journal of Operational Research*, Vol. 72 No. 1, pp. 146-154.

Tversky, A. and Kahneman, D. (1992), "Advances in prospect theory: cumulative representation of uncertainty", *Journal of Risk and Uncertainty*, Vol. 5 No. 4, pp. 297-323.

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