Decision Science Letters 11 (2022) 563–589

Contents lists available at GrowingScience

Decision Science Letters

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Technique of Accurate Ranking Order (TARO): A novel multi criteria analysis approach in performance evaluation of industrial robots for material handling

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C H R O N I C L E

Article history:
Received January 29, 2021
Received in revised format: July 20, 2021
Accepted May 4 2022
Available online May 4, 2022

Keywords:
MCDM
Technique of accurate ranking order (TARO)
Advanced version of entropy weighting method
Industrial robot selection

A B S T R A C T

Rank reversal in decision making is a common phenomenon resulting in confusion and ambiguity in selection procedure especially while multiple multi-criteria decision making (MCDM) techniques are independently applied. To eradicate this confusion, this paper proposes a novel MCDM methodology namely Technique of Accurate Ranking Order (TARO). The TARO method is an extension of conventional MCDM approaches. The proposed method commences at the end of conventional methodologies with the final selection values. The proposed technique, using an advanced version of entropy weighting method, initially measures weights of the final selection values. Subsequently, based on the final section values and their computed weights, TARO measures accurate selection indices that determine the accurate ranking order of the alternatives. The proposed technique is illustrated by three real life examples on robot selection problems. The results obtained by TARO justify the validity, applicability and requirements of the proposed techniques for proper decision making under the MCDM environment.

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1. Introduction

An industrial robot can be defined as a reprogrammable, self controlled, general purpose device consisting of an electrical, electronic or mechanical unit designed especially for certain desirable work functions. With advances in technology especially in robotics a number of manufacturing processes, entail fewer employees, are more efficient and can be continuously operated twenty fours a day without any rest. A company having the ability of affording industrial robots sees a dramatic growth in production, higher throughput and enhanced profitability.

Industrial robots can perform a wide range of work functions including assembly, finishing, machine loading, material handling, painting, pick and place type operation, palletizing, packaging and surface mount technology, product inspection, testing and welding. Accuracy, control resolution, cost, degrees of freedom, geometrical dexterity, life expectancy, load carrying capacity, man machine interfacing ability, maximum tip speed, memory capacity, path measuring system, programming flexibility, repeatability, rest time, stability, supplier's service quality, travelling time, types of drive, velocity, vertical reach and weight of robots are the most significant attributes for selecting an industrial robot for a specified industrial application. These criteria are classified in two ways; firstly, as objective (quantitative) subjective (qualitative), and critical criteria (that need to be satisfied before further processing) and secondly as benefit criteria (higher value is better) and cost criteria (lower value is better). Objective criteria are associated with certainty and subjective criteria are associated with fuzziness (Galetto et al., 2018, Samani et al., 2019). Past literature on robot selection are divided into four broad categories: multi-criteria decision making methods (MCDM), computer-assisted models, general category of

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doi: 10.5267/dsl.2022.5.001

solutions, and production system performance optimization models. Out of these four models, MCDM is chiefly used for ranking robots. Other models are rarely used.

Chodha et al. (2021) used entropy for measuring weight of criteria and TOPSIS for ranking of arc welding robots for industrial purposes. Narayanamoorthy et al. (2019) utilized interval valued intuitionistic hesitant fuzzy VIKOR method for selection of industrial robots and entropy for weight estimation. Li et al (2019) proposes a multiple criteria decision framework for assessment of robotic disassembly to maintain recycling and recovery. This framework is composed of three key phases: recycling options analysis, assessment criteria selection, and disassembly operations evaluation. Fu et al (2019) suggested industrial robot selection using stochastic multiple criteria acceptability analysis with group decision making process. Goswami and Beher (2021) solved a MHE selection Problem for industrial purposes using entropy weighting methods combined with ARAS and COPRAS techniques under MCDM. Nasrollahi et al. (2020) applied the FBWM based PROMETHEE method for ranking and selection of industrial robots. Ali and Rashid (2020) employed best–worst method for proper selection of robots for performing specific functions in industry. Yalcin and Uncu (2019) utilized the EDAS method for selection of industrial robots. Mathew et al., (2017) assessed and ranked alternatives in robot selection problem by applying weighted aggregated sum product. The authors also analyzed the consequences of normalization procedure on decision making. Rashid et al. (2021) adopted a BW based EDAS hybrid MCDM approach for the most favorable selection of robots used for industrial functionality. Liu et al. (2018) suggested a combined MCDM approach using Pythagorean interval-valued linguistic variables under uncertainty. Ahmad et al. (2020) selected the best robot by using an integrated MCDM approach in a flexible manufacturing system.

The analysis shows that, though the above papers can rank and select robots, these papers cannot rectify the rank reversal issues that arise when different MCDM techniques are applied to solve the same problem. Some of the abovementioned papers also suffer from the same problem but the authors did not address the way to fix the problems of rank reversal phenomenon.

Computer assisted models have been advocated by researchers to deal with a large number of robot attributes and a large number of robots (Boubekri, Shahou & Lakrib, 1991). Tansel, Yurdakul and Dengiz (2013) developed a two phase robot selection DSS, namely ROSEL, to assist the decision makers in their problems of robot ranking. In development of ROBSEL an independent set of criteria is first obtained and arranged in the Fuzzy Analytical Hierarchy Process (FAHP) decision hierarchy.

Statistical models, the general category of solution, are also proposed by some researchers. Layek and Lars (2000) developed a DSS based statistical model for robot selection. Khouja, Booth, Suh and Mahaney (2000) presented a statistical model for performance measuring, ranking, and selecting the best robots. Karsak, Senser and Dursun, (2012) developed and presented a fuzzy regression-based decision making approach performance evaluation and selection of robots considering multiple criteria viz. cost, velocity, repeatability and load carrying capacity. Parkan and Wu (1999) suggested a method that demonstrated and compared some of the current MADM and performance measurement procedures through a robot selection problem. Kahraman, Cevik, Ates, and Gulbay (2007) proposed a fuzzy hierarchical TOPSIS method for selection of industrial robotic systems. Shih (2008) proposed group TOPSIS to select robots using incremental benefit cost ratio. Chatterjee, Athwaale, and Chakraborty (2010) solved a robot selection problem using two MCDM methods and compared their relative importance.

Bairagi, Dey, Sarkar and Sanyal (2012) proposed a novel multiplicative model for multi criteria analysis (MMMCA) to solve the robot selection problem. In this approach, all performance ratings are converted into numerical values greater than or equal to unity and converting all non-benefit categories. Each normalized weight is considered as the index of related normalized rating to get the resulting score. The best alternative is related to the maximum resultant score. Bairagi, Dey Sarkar and Sanyal (2014) employed three FMCDM methodologies in the evaluation of robots for automatic foundry operations. In these methodologies, FAHP was integrated individually with FTOPSIS, FVIKOR (Fuzzy VIsekriterijumska optimizacija I KOmpromisno Resenje) and COPRAS-G. Pamuc and Cirovic (2015) presented DEMATEL–MABAC model in the procedure of making investment decisions on the acquisition of controlling transportation (Forklifts) in a logistics hub. Parameshwaran, Kumar and Saravanakumar (2015) developed an integrated method for the optimal selection of robots based on both objective and subjective criteria utilizing Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (FAHP), Fuzzy modified TOPSIS, Fuzzy VIKOR and Brown–Gibson model. Rashid, Beg and Husnine (2014) propose an approach to combine the judgment of several decision makers on diverse criteria for selection of robots employing generalized interval-valued trapezoidal fuzzy numbers. Bairagi et al. (2015) proposes an TOPSIS -based fuzzy multi criteria decision-making approach capable of selecting the best robotic system by considering tangible and intangible factors.

Bhangale, Aggarwal and Saha (2004) employed graphical method and the technique for order preference by similarity to ideal solution to compare the priority of the robots as obtained by applying the two methods. A coding system is used as well in support of different robot selection characteristics and a merit value is utilized to find the ranking order of the robots in the order of their fitness for a specified industrial purpose. Goh (1997) employed the well-known analytical hierarchy process (AHP) to select robots with both objective and subjective criteria. Rao and Padmanabhan (2006) employed the digraph and matrix method for the evaluation, ranking and selection of the robots for a particular industrial purpose, by means of similarity and dissimilarity coefficient values. Kahraman, Cevik, Ates Ulbayet (2007) presented a fuzzy TOPSIS approach for solving the multi criteria robot selection problems. Karsak (2008) suggested a decision algorithm for robot selection on the basis of quality function deployment (QFD) and fuzzy linear regression approach to combine the customer requirements with the technological attributes of the robots.

The above literature survey shows that a large number of various approaches have been proposed by the past researchers on robot selection problems. It is also seen that while multiple MCDM approaches are employed on the same robot selection problem, ranking order may differ giving rise to inconsistency and rank reversal (Chackraborty, 2010; Chatterjee et al., 2010; Rao, Patel and Parnichkun, 2011). Kir and Yazgan (2019) suggested a new hierarchical method for a problem associated with heterogeneous 3D pallet loading under delivery constraints and factual loading. In most of the cases rank reversal is a common phenomenon that makes the decision makers confused in proper selection of alternatives. This confusion and difficulty misleads the decision makers causing inappropriate choices that badly affects the profit and productivity of the business. This dilemma due to inconsistencies in robot ranking/selection motivates us to develop a new model that eliminates this contradiction and give a unanimous solution with a view to guide the decision makers to determine the precise ranking order. Therefore in this circumstance the introduction of the novel technique capable of providing accurate order preference of alternatives in a MCDM problem is essential in removing the ambiguity and confusion thus enhancing the state-of-the-art. The originality of the current paper can be pointed as follows. This study explores a new approach (TARO) for accurate order preference and selection of alternatives in MCDM. This study makes the advanced version of the entropy weighting method the integral parts of the proposed method TARO, which provides acceptable relative weights. Additionally this investigation makes group decisions using final selection values obtained by other conventional methods. This concept is new in literature. The objectives of the research paper are to assist and guide the decision makers by eliminating (a) rank reversal found using diverse conventional MCDM methods, (b) confusion and ambiguity in evaluation, ranking and selection of alternatives in MCDM environments. These objectives are achieved by exploring the new approach (TARO) for precise order preference and incorporating the advanced version of the entropy weighting method in the decision process.

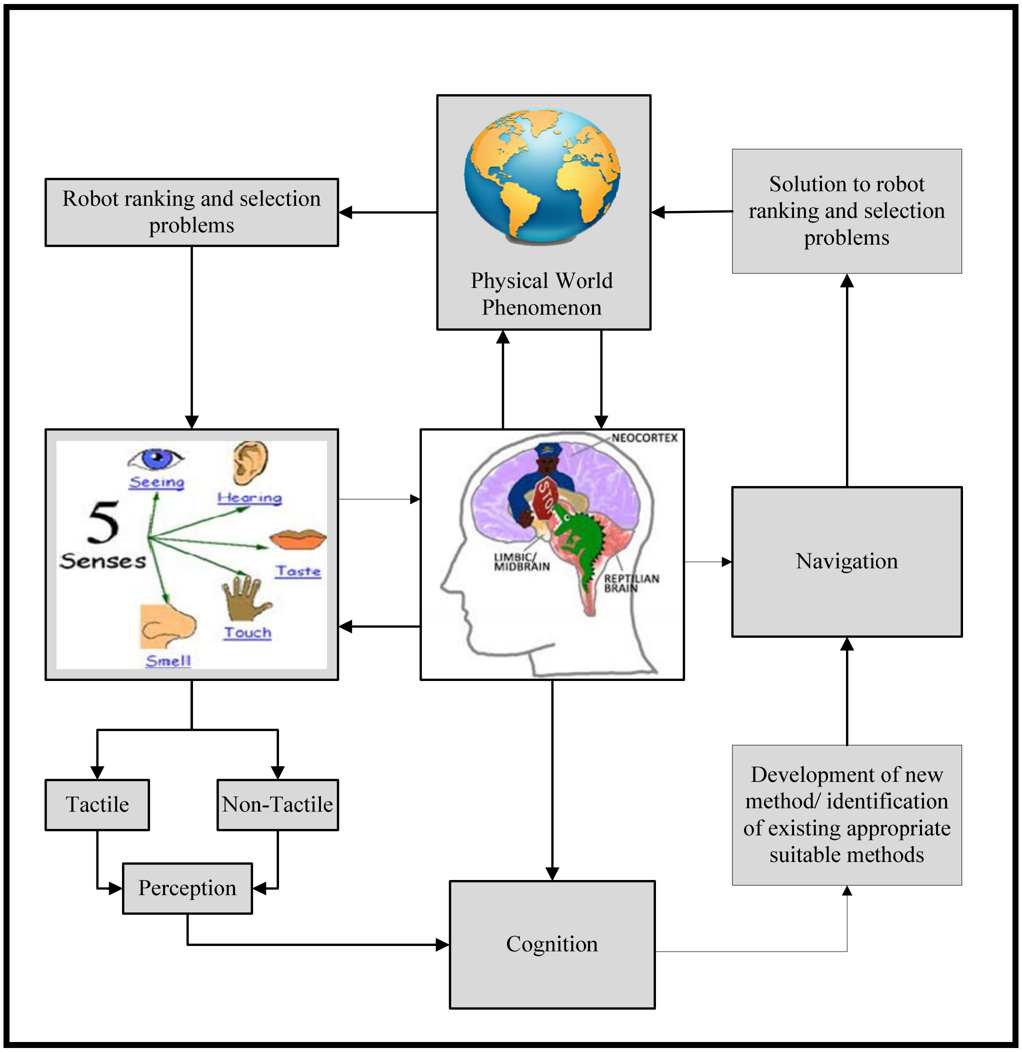

Fig. 1: Cognitive navigation of robot selection

Cognitive navigation regarding robot ranking and selection problems is diagrammatically depicted in Fig.1. This figure illustrates that the physical world phenomenon is the source of problems involving robot ranking and selection. Realizing the importance the human brain takes to evaluate the performance of robots. Using the sense organs of the human body the brain identifies the tactile and non-tactile attributes/criteria for the better perception of evaluation procedure. Thereafter the brain, with the mental abilities of judgment, evaluation, reasoning, decision making, comprehension and computation, develops a new method or applies an existing suitable methodology. Then the cognitive process is navigated to the domain of real/physical world phenomena in order to provide an appropriate solution to the robot ranking and selection problem.

The remainder of the paper is organized as follows. Section 2 describes the proposed methodology TARO. Section 3 illustrates the new technique with three real life problems. Section 4 discusses and analyzes the results. Finally section 5 makes some essential conclusions encompassing the overall work along with few suggestions for possible direction of future research.

2. Technique of Accurate Ranking Order (TARO): The proposed methodology

This section presents the proposed methodology entitled Technique of Accurate Ranking Order (TARO) for finding the accurate ranking order of the alternatives. Past experience of the researchers says that while multiple MCDM approaches are individually applied to determine the proper ranking order of the alternatives, inconsistency in ranking orders is an ordinary trend (Bairagi, Dey, Sarkar, & Sanyal, 2014; Bairagi, Dey, Sarkar, and Sanyal, 2015; Chatterjee, Athawale, and Chakraborty, 2010; Rao, Patel and Parnichkun, 2011). The decision makers often fail to select appropriate alternatives being confused due to rank reversal. Hence it is essential to introduce a logical as well as a systematic technique in order to guide the decision makers in finding precise order preference and in selecting the most suitable alternative from a given set, because a wrong selection may often negatively contribute to the productivity and flexibility of the entire manufacturing process (Chatterjee, Athawale, & Chakraborty, 2010). Thus this paper proposes the new method TARO to find accurate ranking order of alternatives to eliminate confusion and ambiguity in ranking order.

Since each MCDM tool has its own functional and computational capability in evaluation, ranking and selection of alternatives, it is logical to consider different weights of the final selection values determined by the tools. Hence this investigation computes the importance/weights of the final selection values by advance entropy weighting method. Advanced entropy weighting method is logical extension of the conventional entropy method (Bairagi, Dey, Sarkar & Sanyal, 2015). The purpose of the advanced entropy method is to compute more rational and acceptable weights than those obtainedby conventional entropy methods. The steps of the proposed approach TARO are described below.

Step 1: *Construct a matrix comprising final selection values obtained by a number of suitable conventional MCDM approaches.* Let a decision problem, having $\boldsymbol{m}$ alternatives and $\boldsymbol{n}$ criteria ($\boldsymbol{m} \times \boldsymbol{p}$ final selection values) are solved by $\boldsymbol{p}$ conventional approaches. If the approaches give the alternatives inconsistent ranking orders to the alternatives then application of TARO may be initiated by constructing a matrix in the following way.

$$M = \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} \xi_{11} & \cdots & \xi_{1j} & \cdots & \xi_{1p} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ \xi_{i1} & \cdots & \xi_{ij} & \cdots & \xi_{ip} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ \xi_{m1} & \cdots & \xi_{mj} & \cdots & \xi_{mp} \end{bmatrix} \quad (1)$$

where, ξ_{ij} is the final selection value of i^{th} alternative (A_i) obtained by j^{th} conventional approach.

Step2: Normalize the final selection values for finding their weights. The magnitudes of the final selection values calculated by the diverse conventional methodologies may vary over an extensive range. Even the sign of the final selection values may differ in different methods. Consequently, the final selection values of the alternatives need normalization for attaining compatibility and removing biasness. For the purpose normalization, the following equation is recommended.

$$\lambda_{ij} = \frac{|\xi_{ij}|}{\sum_{i=1}^{m} |\xi_{ij}|}, \quad (2)$$

where, $0 \le \lambda_{ij} \le 1$, i=1, 2…m. j =1, 2...p. and $|\xi_{ij}|$ represents the absolute value of ξ_{ij} .

Step3: Compute the entropy of the final selection values using the following equation.

$$e_j = \frac{1}{\ln m}\left[\theta_{1j} + ... + \theta_{ij} + ... + \theta_{mj}\right] = \frac{1}{m}\left[\lambda_{1j} \ln \lambda_{1j} + ... + \lambda_{ij} \ln \lambda_{ij} + ... + \lambda_{mj} \ln \lambda_{mj}\right] = \frac{1}{\ln m} \sum_{i=1}^{m} \left|\lambda_{ij} \ln \lambda_{ij}\right|, \quad \lambda_{ij} \ne 0 \quad (3)$$

$\theta_{ij} = -1.382 \times 10^{-5}$, $\lambda_{ij} = 0$

where e_j represents the entropy of final selection value computed by j^{th} approach; Entropy is the measure of the degree of disorderliness of final selection values.

Step4: Estimate the pre-final weight (r_j) of j^{th} method using the g Eq. (4)

$$r_j = \frac{1 - e_j}{\sum_{j=1}^{p} (1 - e_j)} \quad (4)$$

where $(1 - e_j)$ may be treated as the complement of the entropy of final selection value determined by the j^{th} method whereas $\sum_{j=1}^{p} (1 - e_j)$ is treated as the sum of the complements of the entropies of all the final selection values. The value of r_j ranges from $0 \le r_{ij} \le 1$ and $\sum_{j=1}^{p} r_j = 1$. In the conventional entropy method this s_j value is considered as the weight.

In practice, the conventional entropy method usually gives excessively bulky weight to particular criteria that strongly govern over other criteria and thus control the decision. On the other hand conventional entropy weighting method grants very small weights to some criteria that the affect of the related criteria is negligible in the entire evaluation process. This paper attempts both to lessen the impact of the criteria with very large weights and to enlarge the affect of the criteria with insignificant weights. Therefore, steps 5-7 are rationally included for this reason, incorporating and employing advanced version of conventional entropy method in the work.

Step 5: Determine the value of r'_j using the following recommended equation.

$$r'_j = (1+\sqrt{r_j}) \tag{5}$$

where, $1 \le r'_j \le 2$ and $j = 1,2,..., p$. The reason of incorporation of Eq. (5) is to diminish the ratio of $\max(r'_j)$ to $\min(r'_j)$. As $0 \le r_j \le 1$ i.e., the maximum r_j value is 1 and the minimum r_j value is 0 (zero). Therefore the ratio of the maximum r_j to the minimum r_j may be infinite. This is not desirable because it may make some criteria insignificant in comparison with the others. As $r'_j = 1+\sqrt{r_j}$ is a parabolic function, it has minimum value 1 at r_j =0 and maximum value 2 at r_j =1, hence this function limits the ratio of maximum r_j to minimum r_j at 2/1=2, it can be considered as the acceptable range/limits.

Step 6: *compute the value of* R'_j *using the following equation*

$$R'_j = \sum_{j=1}^{p} r'_j = \sum_{j=1}^{p}(1+\sqrt{r_j}) = p + \sum_{j=1}^{p}\sqrt{r_j} \quad . \tag{6}$$

Here R'_j stands for the sum of all r'_j values, i.e., $\sum_{j=1}^{p} r'_j = R'_j$. It is noted that both r'_j and R'_j are dimensionless real numbers. It is noted that p (being number of conventional methods) be an integer and $p \ge 2$.

Step 7: *Calculate the final and accurate weight for the final selection values determined by the j*th *method.*

The final and accurate weight (w_j) of the final selection value is computed by the ratio of r'_j to R'_j as follows.

$$w_j = \frac{r'_j}{R'_j} = \frac{r'_j}{\sum_{j=1}^{p} r'_j} = \frac{1+\sqrt{r_j}}{\sum_{j=1}^{p}\left(1+\sqrt{r_j}\right)} = \frac{1+\sqrt{r_j}}{p+\sum_{j=1}^{p}\sqrt{r_j}}, \tag{7}$$

where w_j is the weight of the final selection values assessed by using jth method, and $\sum_{j=1}^{p} w_j = 1$. As shown in Step 4 that $\sum_{j=1}^{p} r_j = 1$, it can be proved that $\max\sum_{j=1}^{p}\sqrt{r_j} = \sqrt{p}$ and $\min\sum_{j=1}^{p}\sqrt{r_j} = 1$. Hence it can be easily shown that $\max\sum_{j=1}^{p}\left(1+\sqrt{r_j}\right) = p+\sqrt{p}$ and $\min\sum_{j=1}^{p}\left(1+\sqrt{r_j}\right) = p+1$. It can also be shown that $\min r'_j = \min(1+\sqrt{r_j}) = 1$ when $r_j = 0$ and $\max r'_j = \max(1+\sqrt{r_j}) = 2$ when $r_j = 1$. Thus the minimum and maximum value of w_j, denoted by $\min w_j$ and $\max w_j$ respectively, can be determined as follows.

$$\frac{1}{p+\sqrt{p}} \le w_j \le \frac{2}{p+1}.$$

Since zero weight of any individual final selection value means that the corresponding final selection value is insignificant whereas 1 or 100% weight of any individual final selection value implies that the corresponding final selection value alone completely governs the decision process making the others insignificant. That is why above constraint on w_j value implies that the weight of any individual final selection value under MCDM environment can be neither 0 (zero) nor 1.

Step 8: *Normalize the final selection values for evaluation of alternatives using the following equation.*

$$g_{ij}^{H} = \sin\left\{\frac{\xi_{ij} - \left(\xi_j\right)_{\min}}{\left(\xi_j\right)_{\max} - \left(\xi_j\right)_{\min}} \cdot \frac{\pi}{2}\right\}, \qquad \xi_{ij} \in H, \quad \left(\xi_j\right)_{\max} \in H, \quad \left(\xi_j\right)_{\min} \in H \tag{8}$$

$$g_{ij}^{L} = \sin\left\{\frac{\left(\xi_j\right)_{\max} - \xi_{ij}}{\left(\xi_j\right)_{\max} - \left(\xi_j\right)_{\min}} \cdot \frac{\pi}{2}\right\}, \qquad \xi_{ij} \in L, \quad \left(\xi_j\right)_{\max} \in L, \quad \left(\xi_j\right)_{\min} \in L \tag{9}$$

where $0 \le g_{ij} \le 1$ represents the normalized value of ξ_{ij}, $\left(\xi_j\right)_{\max}$ is maximum final selection value and $\left(\xi_j\right)_{\min}$ is minimum final selection value determined by jth approach. $\xi_{ij} \in H$ implies that higher value of ξ_{ij} is desirable and $\xi_{ij} \in L$ implies that lower value of ξ_{ij} is desirable. Higher value of ξ_{ij} indicates that the corresponding alternative is closer to the optimal solution and hence higher value of g_{ij} is desirable.

Step9: *Compute the exponentially weighted normalized final selection values (EWNFSV) using the following equations.*

$$h_{ij}^{H}=\exp(w_j+g_{ij}^{H})=\exp\left\{w_j+\sin\frac{\xi_{ij}-(\xi_j)_{\min}}{(\xi_j)_{\max}-(\xi_j)_{\min}}.\frac{\pi}{2}\right\} \tag{10}$$

$$h_{ij}^{L}=\exp(w_j+g_{ij}^{L})=\exp\left\{w_j+\sin\frac{(\xi_j)_{\max}-\xi_{ij}}{(\xi_j)_{\max}-(\xi_j)_{\min}}\frac{\pi}{2}\right\} \tag{11}$$

where h_{ij} is EWNFSV of i^{th} alternative with respect to j^{th} approach. Exponential function (monotonic increasing) is employed for weighted normalized final selection values. EWNFSV increases more than proportionate increase of the product of weight and normalized final selection value.

Step 10: *Compute non-linear selection indices (NLSI) for each alternative using non-linear function of first kind.* TARO measures two pre-selection indices that find the precise order preference for each alternative. The first pre-selection index, termed as *Non-linear selection indices NLSI* of first kind, is computed using the following equation.

$$NLSI_i^{(1)}=\sum_{j=1}^{p}h_{ij}=\sum_{j\in H}\exp\left\{w_j+\sin\frac{\xi_{ij}-(\xi_j)_{\min}}{(\xi_j)_{\max}-(\xi_j)_{\min}}\frac{\pi}{2}\right\}+\sum_{j\in L}\exp\left\{w_j+\sin\frac{(\xi_j)_{\max}-\xi_{ij}}{(\xi_j)_{\max}-(\xi_j)_{\min}}\frac{\pi}{2}\right\} \tag{12}$$

Step 11: *Compute non-linear selection indices (NLSI) for each alternative using non-linear function of second kind.*

This paper proposes an algorithm which uses a nonlinear selection index (NLSI). NLSI is a nonlinear function of its both performance ratings of an alternative and weights of the associated criteria. The contribution of benefit criteria in the NLSI increases at an increasing rate and this contribution is determined by the exponential function of normalized performance rating. Normalized rating varies in the range 0 to 1. Hence, contribution of each benefit criteria varies from 1 to 2.7182. On the contrary, the contribution of non-benefit criteria in the final selection factor decreases at a decreasing rate, this is computed by the modulus of negative logarithm of the normalized performance ratings. Normalized performance rating $(\xi_{ij}\neq 0)$ varies in the range $0<\xi_{ij}\leq 1$. Hence, contribution of each non-benefit criterion inversely varies from 1 to below infinity ($\propto$). Thus the integration of the contributions of both benefit and non-benefit criteria measure the NLSI of second kind.

$$NLSI_i^{(2)}=\sum_{j\in H}\left[w_j\times\exp\left(\frac{\xi_{ij}}{\max_i \xi_{ij}}\right)\right]-\sum_{j\in L}\left(w_j\times\left|\ln\left\{\frac{1}{e}+\left|\frac{\xi_{ij}}{\max_i \xi_{ij}}\right|\right\}\right|\right) \tag{13}$$

Step 12: *Compute the accurate selection indices by integrating the non-linear selection indices of first and second kind.* Linear selection index varies linearly with the performance rating of alternatives. This linear evaluation of performance rating has the ability to rank and select alternatives but ignores additional benefit of its superiority as well as additional detriment of its inferiority. In contrast, the nonlinear selection index has the ability of evaluation, ranking and selection of robots at the same time it regards additional benefit for its superiority as well as additional detriment for its inferiority. Hence both the index should be integrated for their trade off by using Eq. (14).

$$ASI_i = \frac{\mu_1}{\mu_1+\mu_2} \times \frac{\sum_{j\in H} \exp\left\{w_j + \sin\frac{\xi_{ij} - (\xi_j)_{\min}}{(f_i)_{\max} - (f_j)_{\min}} \frac{\pi}{2}\right\} + \sum_{j\in L}\exp\left\{w_j + \sin\frac{(\xi_j)_{\max} - \xi_{ij}}{(f_j)_{\max} - (f_j)_{\min}}\frac{\pi}{2}\right\}}{\sum_{i=1}^{m}\left[\sum_{j\in H}\exp\left\{w_j+\sin\frac{\xi_{ij}-(\xi_j)_{\min}}{(\xi_j)_{\max}-(\xi)_{\min}}\frac{\pi}{2}\right\} + \sum_{j\in L}\exp\left\{w_j+\sin\frac{(\xi_j)_{\max}-\xi_{ij}}{(\xi_j)_{\max}-(\xi_j)_{\min}}\frac{\pi}{2}\right\}\right]}$$
$$+ \frac{\mu_2}{\mu_1+\mu_2}\times \frac{\sum_{j\in H}\left(w_j \times \exp\frac{\xi_{ij}}{\max_i \xi_{ij}}\right) - \sum_{j\in L} w_j \ln\left\{\frac{1}{e} + \left|\frac{\xi_{ij}}{\max_i\xi_{ij}}\right|\right\}}{\sum_{i=1}^{m}\left[\sum_{j\in H}\left(w_j\times\exp\frac{\xi_{ij}}{\max_i\xi_{ij}}\right) - \sum_{j\in L} w_j\left|\ln\left\{\frac{1}{e}+\left|\frac{\xi_{ij}}{\max_i\xi_{ij}}\right|\right\}\right|\right]} \quad (14)$$

where ASI_i is the non-linear accurate selection index for i[th] alternative. Here, $\mu_i\,(i=1,2)$ represents the decision making attitude/weight that ranges from 0 to1 and $\mu_1 + \mu_2 = 1$.

Arrange the alternatives in decreasing order of their ASI values. ASI resembles net benefit. Hence first rank is assigned to the alternative having the maximum ASI, second rank to the alternative having ASI just lower to the maximum ASI (i.e. second maximum) and so on. In other word, select the best alternative with the highest ASI and the worst alternative with the lowest ASI. The framework of the above algorithm is shown in Fig. 2.

The proposed technique TARO is demonstrated with three examples on industrial robot ranking and selection presented in section 3.

3. Case Study: Illustrations of the proposed method

In this section validity and applicability of the proposed technique are illustrated with three examples on robot ranking and selection.

3.1. Example 1: Robot ranking and selection

A set of seven industrial robots perform a certain pick-n-place operation. Many past researchers have solved the robot ranking problem using conventional or their own methodologies (Bhangale, Agrawal and Saha, 2004; Chatterjee, Athawale and Chakraborty, 2010; Rao, Patel and Parnichkun, 2011). In this problem, the seven robots are designated as R1, R2, R3, R4, R5, R6 and R7. The performance of an industrial robot is evaluated with respect to five conflicting criteria such as load carrying capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator reach (MR) and repeatability (R). Load capacity refers to the maximum load that a robot manipulator can bear without affecting its specified performance. Maximum tip speed of a robot refers to the highest speed at which it can move in an inertial reference frame. Memory capacity of a robot is expressed by the number of points or steps that it can store in its memory while traversing its specified path. Manipulator reach refers to the maximum distance that the robot manipulator can envelop for grasping the desired object. Repeatability of a robot can be defined as the ability to repeatedly return to the same position with same orientation.

Table 1 depicts the decision matrix consisting of robots' performance ratings that has directly been used by previous researcher in their works. The results found by the previous researchers with the application of conventional/their own approaches are analyzed for the realization of the relevance of the current proposed methods.

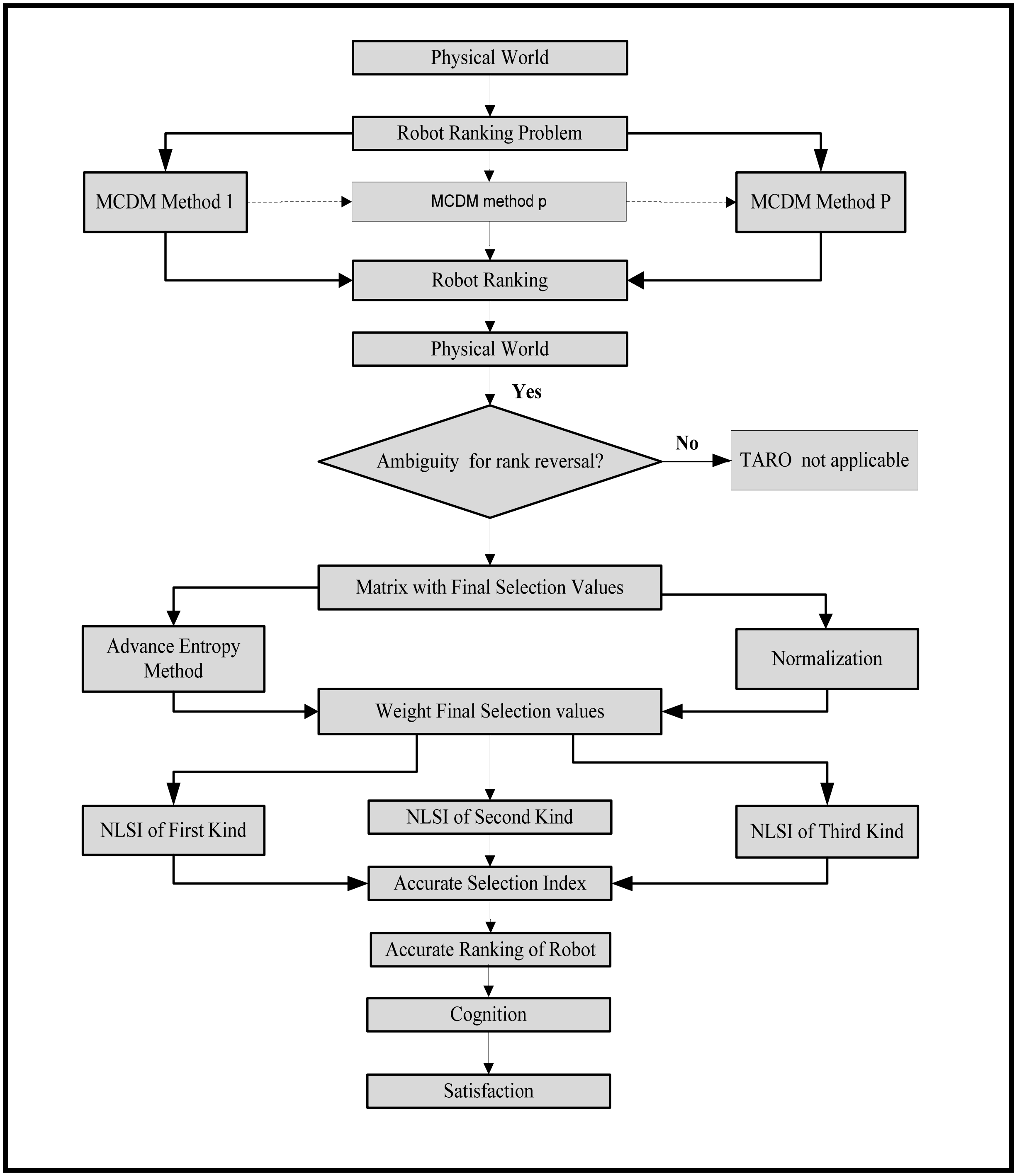

Fig. 2. Frame work of TARO for robot ranking and selection

Table 1
Decision matrix with performance scores of alternatives (example 1)

Robot	Load capacity (LC) (kg)	Maximum Tip Speed (MTS) (mm/s)	Memory Capacity (MC) (MB)	Manipulator Reach (MR) (mm)	Repeatability (R) (mm)
R1	60.00	2540	500	990	0.40
R2	6.35	1016	3000	1041	0.15
R3	6.80	1727	1500	1676	0.10
R4	10.00	1000	2000	965	0.20
R5	2.50	560	500	915	0.10
R6	4.50	1016	350	508	0.08
R7	3.00	177	1000	920	0.10

3.1.1. Results obtained by past researchers for the industrial robot selection problem(example 1)

The robot ranking and selection problem furnished in example 1 has been previously solved by several groups of past researchers using their own/conventional MCDM methods. The comparison of ranking orders obtained by the different past researchers for the industrial robots using five different methods is shown in Table 2. Chackraborty (2010) uses MOORA method and obtains the ranking order of the robots as 2-3-1-4-7-5-6. Preference order of the robots is R3>R1>R2>R4>R6>R7>R5. This ranking order indicates R3 is the first and the best choice and R5 is the last and the worst choice. Rao et al. (2011) determine the ranking order of the robots in the sequence 1-3-2-4-7-5-6 that gives the preference orders as R1>R3>R2>R4>R6>R7>R5. In these two methodologies, the researchers found that robot R1 and robot R3 exchange their ranking orders leading to ambiguity and confusion in the decision making process. Chaterjee et al (2010) apply two distinct conventional techniques ELECTRE and VIKOR for ranking the robots of the same problem. According to ELECTRE (Concordance) the ranking order is 4-2-1-5-7-6-3 that suggests the preference of alternative as R3>R2>R7>R1>R4>R7>R5 whereas as per ELECTRE (Discordance), the ranking order is 2-3-1-4-7-6-5 that indicates the preference order in the sequence R3>R1>R2>R4>R7>R6>R5. Continuation of inconsistency in ranking order is observed. Using VIKOR method the researchers determined the ranking order of the robots as 5-2-1-4-7-6-3 and the preference order R3>R2>R7>R4>R1>R6>R5. It is seen that ranking order in VIKOR method drastically changes that makes decision making procedure ambiguous and confusing.

Table 2

Comparison of ranking order obtained by the previous researchers using conventional techniques (example 1)

Robots	MOORA	Rao (2011)	ELECTRE (C)	ELECTRE(D)	VIKOR
R1	2	1	4	2	5
R2	3	3	2	3	2
R3	1	2	1	1	1
R4	4	4	5	4	4
R5	7	7	7	7	7
R6	5	5	6	6	6
R7	6	6	3	5	3

The authors found inconsistent ranking order of the alternative robots according to the final selection values obtained by respective methods. Fig.3 graphically shows the ranking orders of the robots obtained by the previous researchers using their own conventional MCDM approaches. It is evident that rank reversal is a common phenomenon in ranking and selection problems by conventional methods. Example 1 evidently explores that different MCDM techniques may give different ranking order to the same decision problem. For example 1 the rank reversal is clearly explained in sub-section 3.1.2.

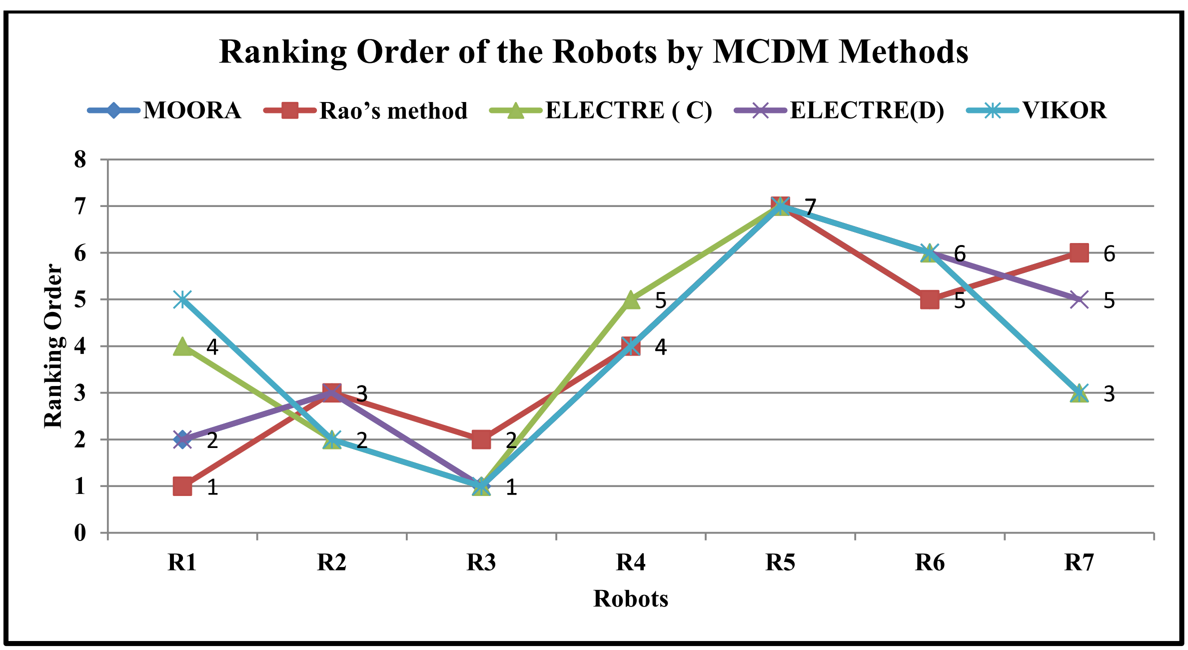

Fig 3: Ranking order of the robots by various MCDM methods (Example 1)

3.1. 2. Rank reversal in example 1

In example 1 four out of five alternative robots have been provided distinct ranks by the past researchers using their own conventional ranking methods. Industrial robot R1 is assigned four diverse ranks viz.1, 2, 4 and 5. Industrial robot R2 is given two distinct ranks viz. 2 and 3 whereas R3 also has two distinct ranks viz. 1 and 2. Industrial robot R4 is provided two distinct ranks viz. 4 and 5 though the robot R5 is unanimously granted rank 7. Industrial robot R6 is given two distinct ranks viz. 5 and 6 whereas R7 is assigned by three distinct ranks viz. 3, 5 and 6. Since industrial robots R1, R2, R3, R4, R6 and R7 are assigned with reversed ranking orders, consequently this is an example of MCDM problem with rank reversal that is eradicated by the application of TARO in section 3.1.3.

3.1.3. Application of proposed method (TARO) on example 1 for the elimination of rank reversal

In the above analysis it is observed that the conventional MCDM methods fail to determine the unique ranking order of the industrial robots. Now, in this circumstance to get rid of ambiguity and confusion one can apply TARO for unique and accurate ranking order of the industrial robots. For the purpose, the alternative robots with final selection values and the corresponding methodologies are summarized in Table 3. To determine the accurate ranking order of the alternative robots, TARO exploits the final selection values obtained by previous researchers with their own methods. The higher final selection values in MOORA, Rao's method and ELECTRE (Concordance) are better and desirable because they are beneficial. Whereas the lower final selection values in VIKOR and ELECTRE (Discordance) are better and desirable because they are in non-benefit/cost sense. Therefore normalization of these final selection values for the estimation of the weights of the methodologies is carried out with an advanced entropy weighting method, using Eq. (2).

Table 3

Final selection values obtained by past researchers for industrial robots (example 1)

Robots	MOORA[1]	Rao (2011)[2]	ELECTRE(C)[3]	ELECTRA(D)[3]	VIKOR[3]
R1	0.3104	0.64215	0.282	-2.6271	0.6953
R2	0.2965	0.48394	1.726	-2.3735	0.2701
R3	0.3341	0.49188	2.480	-2.9277	0
R4	0.2202	0.39842	-0.624	-2.2070	0.4829
R5	0.1134	0.26497	-3.246	5.5282	1
R6	0.1188	0.31240	-1.922	4.4478	0.9646
R7	0.1163	0.27867	1.304	0.1593	0.3855
Max	0.3341	0.64215	2.480	5.5282	1
Min	0.1134	0.26497	-3.246	-2.9277	0

Source: [1]Chackraborty (2010), [2]Rao (2011), [3]Chatterjee et al. (2010)

The normalization process for the final selection value 0.3104 (determined by MOORA) is illustrated as follows.

$$\lambda_{11} = \frac{|0.3104|}{|0.3104|+|0.2965|+|0.3341|+|0.2202|+|0.1134|+|0.1188|+|0.1163|} = 0.2056$$

Similarly, the normalized final selection value of each remaining alternative by each conventional approach is calculated. For robot R1, the final selection values in normalized form are $\lambda_{11} = 0.2056$, $\lambda_{21} = 0.1964$ $\lambda_{31} = 0.2213$, $\lambda_{41} = 0.1459$ and $\lambda_{51} = 0.0751$, $\lambda_{61} = 0.0787$, $\lambda_{71} = 0.0770$. Calculation of entropy e_1 for the method 1 (MOORA) is demonstrated as follows.

$$e_1 = (\ln 7)^{-1} \times \ln\left(0.2056^{0.2056} \times 0.1964^{0.1964} \times 0.2213^{0.2213} \times 0.1459^{0.1459} \times 0.0751^{0.0751} \times 0.0787^{0.0787} \times 0.0770^{0.0770}\right) = 0.9515.$$

Similarly, the entropy values $e_{j(j=2,3,4,5)}$ for the other remaining methods are computed and found as $e_2 = 0.9757$, $e_3 = 0.9054$, $e_4 = 0.9055$ and $e_5 = 0.8698$. The values r_1, $\sqrt{r_1}$ and r_1' for alternative robot R1 is calculated as follows.

$$r_1 = (1-e_1)/\sum_{j=1}^{5}(1-e_j) = (1-0.9515)/\{(1-0.9515)+(1-0.9757)+(1-0.9054)+(1-0.9055)+(1-0.8698)\} = 0.1238$$

$\sqrt{r_1} = \sqrt{0.1238} = 0.3519$, $r_1' = (1+\sqrt{r_1}) = 1 + 0.3519 = 1.3519$. The others $r'_{j(j=2,3,4,5)}$ values are $r_2' = 1.2490$, $r_3' = 1.4912$, $r_4' = 1.4908$, and $r_5' = 1.5760$, R_j' is computed as follows.

$$R_j' = \sum_{j=1}^{5}(1+\sqrt{r_j}) = (1.3519+1.2490+1.4912+1.4908+1.5760) = 7.1590$$

So, quantitative weight (w_1) for the method1 (MOORA) is measured using Eq. (7) as follows

$$w_1 = r_1'/R_j' = (1+\sqrt{r_1})/\sum_{j=1}^{5}(1+\sqrt{r_j}) = 1.3519/7.1590 = 0.1888.$$

Table 4

Normalized final selection values for weights of the approaches in example 1

		MOORA	Rao (2011)	ELECTRE (C)	ELECTRE (D)	VIKOR	Sum
Normalized final selection values	R1	0.2056	0.2236	0.0243	0.1296	0.1831	---
	R2	0.1964	0.1685	0.1490	0.1171	0.0711	---
	R3	0.2213	0.1712	0.2141	0.1444	0	---
	R4	0.1459	0.1387	0.0539	0.1089	0.1271	---
	R5	0.0751	0.0922	0.2802	0.2727	0.2633	---
	R6	0.0787	0.1088	0.1659	0.2194	0.2539	---
	R7	0.0770	0.0970	0.1126	0.0079	0.1015	---
	e_j (entropy)	0.9515	0.9757	0.9054	0.9055	0.8698	---
	$1-e_j$	0.0485	0.0243	0.0946	0.0945	0.1302	0.3921
	r_j	0.1238	0.0620	0.2412	0.2409	0.3320	1.0000
	$\sqrt{r}_j$	0.3519	0.2490	0.4912	0.4908	0.5762	2.1590
	$1+\sqrt{r}_j$	1.3519	1.2490	1.4912	1.4908	1.5760	7.1590
	w_j (weight)	0.1888	0.1745	0.2082	0.2082	0.2203	1.0000

Similarly, remaining weights are obtained as $w_2 = 0.1745$, $w_3 = 0.2082$, $w_4 = 0.2082$ and $w_5 = 0.2203$ for the respective conventional techniques used in example1 viz. Rao's method, ELECTRE(C), ELECTRE (D) and VIKOR. These weights of the methods of example 1 are presented in Table 4. Eq. (3) – (7) are used for the measurement of the weights. It is noted that VIKOR method is assigned the maximum importance weight and Rao's (2011) method the minimum importance weight based on the industrial robot selection problem of example 1.

In the example 1, the MOORA method, Rao's (2011) method and VIKOR method have non-negative final selection values whereas ELECTRE (C) and ELECTRE (D) methods have some negative final selection values (though remaining are non-negative). The proposed method TARO uses two different normalization techniques, one for weight estimation, whereas another for final selection values evaluation.

Final selection values having the positive sense (higher value is desirable) are normalized using same course of action. The technique of normalization for the evaluation of final selection value $\xi_{11} = 0.3104$ (with positive sense) is illustrated as follows.

$$g_{11} = g_{11}^{H} = \sin\left\{\frac{\xi_{11} - (\xi_1)_{\min}}{(\xi_1)_{\max} - (\xi_1)_{\min}}.\frac{\pi}{2}\right\} = \sin\left\{\frac{0.3104 - 0.1134}{0.3341 - 0.1134}.\frac{\pi}{2}\right\} = 0.9858.$$

All the final selection values determined by MOORA, Rao (2011) and ELECTRE(C) have the same (positive) sense. Therefore they are calculated using same formula. Normalized value of $\xi_{21} = 0.6122$ is $g_{12} = g_{12}^{H} = 1.0000$ and that of $\xi_{31} = 0.282$ is $g_{13} = g_{13}^{H} = 0.0.8236$.

Therefore these values are normalized using Eq. (9) to convert them to positive sense. For example normalization procedure of $\xi_{41} = -2.2672$ is demonstrated by calculating g_{41}^{L} as follows.

$$g_{14} = g_{14}^{L} = \sin\left\{\frac{(\xi_1)_{\max} - \xi_{11}}{(\xi_1)_{\max} - (\xi_1)_{\min}}.\frac{\pi}{2}\right\} = \sin\left\{\frac{5.5282 - (-2.6271)}{5.5282 - (-2.9277)}.\frac{\pi}{2}\right\} = 0.9984.$$

For $\xi_{51} = 0.6953$ normalized final selection value is $g_{15}^{L} = 0.4605$. Normalized final selection values computed for performance evaluation of alternative robots of example 1is shown in Table 5.

Table 5

Normalized final selection values computed for performance evaluation of alternative robots (example 1)

	MOORA	Rao (2011)	ELECTRE (C)	ELECTRE(D)	VIKOR
R1	0.9858	1.0000	0.8236	0.9984	0.4605
R2	0.9644	0.7906	0.9787	0.9947	0.9113
R3	1.0000	0.8105	1.0000	1.0000	1.0000
R4	0.6890	0.5276	0.6588	0.9910	0.7258
R5	0.0000	0.0000	0.0000	0.0000	0.0000
R6	0.0384	0.1962	0.3553	0.1993	0.0556
R7	0.0206	0.0570	0.9484	0.8400	0.8222

Calculation procedure of exponentially weighted normalized final selection values (EWNFSV) for g_{11}^H and g_{41}^L are shown by determining h_{11}^H and h_{41}^L using Eq. (10) and Eq. (11) as follows.

$$h_{11}^H = \exp\left(w_1 + g_{11}^H\right) = \exp(0.1888 + 0.9895) = 3.2368$$

$$h_{41}^L = \exp\left(w_1 + g_{11}^L\right) = \exp(0.2082 + 0.9984) = 3.3422$$

Non-linear selection indices of first kind $\left(NLSI_i^{(1)}\right)$ for the alternatives are calculated using Eq. (12). Calculation procedure for $NLSI_1^{(1)}$ is illustrated as follows.

$$NLSI_1^{(1)} = \exp\ (0.1888 + 0.9858) + \exp(0.1745 + 1.0000) + \exp(0.2082 + 0.8236) + \exp(0.2082 + 0.9984) + \exp(0.2203 + 0.4605) = 14.5970$$

Similarly, $NLSI_2^{(1)} = 15.5004$, $NLSI_3^{(1)} = 16.0439$, $NLSI_4^{(1)} = 12.6965$, $NLSI_5^{(1)} = 6.1078$, $NLSI_6^{(1)} = 7.2814$, and $NLSI_7^{(1)} = 11.3613$ are computed by same procedure and using same equation. All EWNFSVs and NLSIs of first kind are presented in Table 6.

Table 6

Weighted normalized final selection values (EWNFSV) and non-linear selection indices of first kind (example 1)

	MOORA*	Rao (2011)	ELECTRE (C)	ELECTRE (D)	VIKOR	$NLSI_i^{(1)}$
R1	3.2368	3.2365	2.8062	3.3422	1.9755	14.597
R2	3.1683	2.6252	3.2768	3.3297	3.1006	15.5006
R3	3.2831	2.6777	3.3475	3.3475	3.3882	16.0439
R4	2.4056	2.0179	2.3798	3.3176	2.5757	12.6965
R5	1.2078	1.1907	1.2315	1.2315	1.2465	6.1078
R6	1.2551	1.4488	1.7567	1.5031	1.3179	7.2814
R7	1.2330	1.2605	3.1791	2.8525	2.8362	11.3613
					$\sum NLSI_i^{(1)}$	83.5889

Non-linear selection indices of second kind $\left(NLSI_i^{(2)}\right)$ are calculated using Eq. (12). Calculation procedure for $NLSI_1^{(2)}$, is demonstrated as follows.

$$NLSI_1^{(2)} = 0.1888\exp\left(\frac{0.3104}{0.3341}\right) + 0.1745\exp\left(\frac{0.6422}{0.6422}\right) + 0.2082\exp\left(\frac{0.282}{0.2480}\right) - 0.2082\left|\ln\left(\frac{1}{e} + \left|\frac{-2.6271}{5.5282}\right|\right)\right| - 0.2203\left|\ln\left(\frac{1}{e} + \left|\frac{0.6953}{1}\right|\right)\right| = 1.2616$$

Non-linear selection indices of second kind $\left(NLSI_i^{(2)}\right)$ for the remaining alternative are similarly computed and the values are found as

$NLSI_2^{(2)} = 1.4217$, $NLSI_3^{(2)} = 1.6545$, $NLSI_4^{(2)} = 0.9990$, $NLSI_5^{(2)} = 0.3784$, $NLSI_6^{(2)} = 0.4423$, $NLSI_7^{(2)} = 0.9196$.

$\sum_{i=1}^{7} NLSI_i^{(2)} = 0.70474$, EWNFSVs and NLSIs of second kind are shown in Table 7.

Non-linear selection indices of first kind $\left(NLSI_i^{(1)}\right)$ and non-linear selection indices of second kind $\left(NLSI_i^{(2)}\right)$ are integrated to find accurate selection indices using Eq. (14). The calculation of the accurate selection index for the alternative robot 1 is illustrated as follows.

$$\frac{NLSI_1^{(1)}}{\sum_{i=1}^{7} NLSI_i^{(1)}} = \frac{14.5970}{14.5970 + 15.5004 + 16.0439 + 12.6965 + 6.1078 + 7.2814 + 11.3613} = 0.1746$$

$$\frac{NLSI_1^{(2)}}{\sum_{i=1}^{7} NLSI_i^{(2)}} = \frac{1.2616}{1.2616 + 1.42176 + 1.6545 + 0.9990 + 0.3487 + 0.4423 + 0.9196} = 0.1790$$

$$ASI_1 = \frac{\mu_1}{\mu_1+\mu_2}\left(\frac{NLSI_1^{(1)}}{\sum_{i=1}^{7} NLSI_i^{(1)}}\right) + \frac{\mu_2}{\mu_1+\mu_2}\left(\frac{NLSI_1^{(2)}}{\sum_{i=1}^{7} NLSI_i^{(2)}}\right) = \frac{0.5}{0.5+0.5}(0.1746) + \frac{0.5}{0.5+0.5}(0.1790) = 0.1768$$

Table 7

Weighted normalized final selection values (EWNFSV) and non-linear selection indices of second kind (exam ple 1)

	MOORA	Rao (2011)	ELECTRE(C)	ELECTRA(D)	VIKOR	$NLSI_i^{(2)}$
R1	0.4781*	0.4743	0.2333	-0.1549	0.0790	1.2616
R2	0.4586	0.3707	0.4176	-0.1761	0.0013	1.4217
R3	0.5132	0.3754	0.5659	-0.1324	-0.0676	1.6545
R4	0.3650	0.3245	0.1619	-0.1912	0.0436	0.9990
R5	0.2651	0.2636	0.0563	0.1148	0.1215	0.3487
R6	0.2694	0.2838	0.0960	0.0900	0.1170	0.4423
R7	0.2674	0.2693	0.3522	-0.0559	0.0252	0.9196
					$\sum NLSI_i^{(2)}$	7.0474

Table 8

Accurate selection indices and accurate ranking order (example 1)

Robots	$\frac{NLSI_i^{(1)}}{\sum NLSI_i^{(1)}}$	$\frac{NLSI_i^{(2)}}{\sum NLSI_i^{(2)}}$	ASI_i	Rank
R1	0.1746	0.1790	0.1768	3
R2	0.1854	0.2017	0.1936	2
R3	0.1919	0.2348	0.2134	1
R4	0.1519	0.1417	0.1468	4
R5	0.0730	0.0495	0.0613	7
R6	0.0871	0.0627	0.0749	6
R7	0.1359	0.1305	0.1332	5

Similarly, using Eq. (14) remaining ASIs are calculated as $ASI_2 = 0.1936$, $ASI_3 = 0.2134$, $ASI_4 = 0.1468$, $ASI_5 = 0.0613$, $ASI_6 = 0.0749$ and $ASI_7 = 0.1332$. Since, the higher ASI values are better; hence ASIs are arranged in the descending order of their values. Obviously ASIs in descending order are $ASI_3 > ASI_2 > ASI_1 > ASI_4 > ASI_7 > ASI_6 > ASI_5$ that suggests ranks of the robots in the order of $R_3 > R_2 > R_1 > R_4 > R_7 > R_6 > R_5$. The alternative robots along with corresponding ASIs values and accurate ranking orders are presented in Table 8. The ranking order of the robots in example 1 obtained by the proposed TARO methods is also graphically represented in Fig. 4**.** It clearly shows that TARO is capable of removing the rank reversal, confusion and ambiguity generated by conventional MCDM approaches.

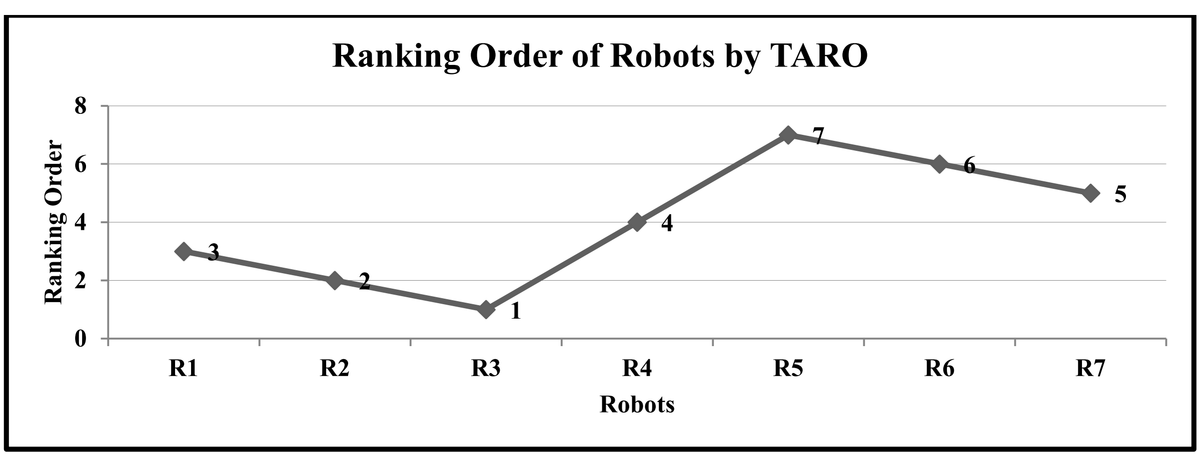

Fig 4: Ranking order of the robots by TARO method (Example 1)

3.2. *Example 2: Robot ranking and selection*

Example 2 is robot ranking and selection problem for industrial application, which is taken from Chatterjee, Athawale, Chakraborty (2010). This example considers four robots and seven selection criteria. The robots are designated as R1, R2, R3 and R4. The seven criteria are velocity, load capacity, vendor's service quality, robot's programming flexibility, cost and repeatability. The first four are benefit criteria and the last two are cost/non-benefit criteria. The attributes vendor's service quality and robot's programming flexibility are subjective criteria whereas the remaining are objective criteria. The subjective measure of vendor's service quality and robot's programming flexibility are assigned by a group of experts using a 10-point judgment scale. A summary of the subjective and objective performance measure of the criteria for alternate robots is presented in Table 9. The result of this industrial robot selection problem of example 2, determined by the previous researchers using conventional approaches, is elucidated in sub-section 3. 2.1.

Table 9

Decision matrix comprising of performance ratings of alternative robots (Example 2)

	C1	C2	C3	C4	C5	C6
R1	1.8	90	9500	0.45	6	4
R2	1.4	80	5500	0.3	7	5
R3	0.8	70	4000	0.2	6	6
R4	0.8	60	4000	0.15	4	7
Max	1.8	90	9500	0.45	7	7
Min	0.8	60	4000	0.15	4	4

3.2.1. *Results of the industrial robot selection problem (example 2) using conventional approaches*

The robot ranking and selection problem described in example 2 is solved by Chaterjee et al. (2010) using the ELECTRE and VIKOR method. The same problem is also solved using MOORA, TOPSIS and SAW in the current research work. The final selection values for alternative robots by various MCDM methods are shown in Table 10. The corresponding ranking orders of the alternative robots are presented in Table 11. Ranking order using MOORA and SAW method is 4-1-2-3 that indicates preference should be given in the sequence R2>R3>R4>R1. Ranking order using the TOPSIS, ELECTRE and VIKOR method is 2-1-3-4 that shows preference in the sequence of R2>R1>R3>R4. Fig. 5 compares the ranking order of the robots obtained by various MCDM methods. This comparison clearly shows the difference in ranking order of the alternative industrial robots as per various conventional MCDM approaches.

Table 10

Final selection values for alternative robots by various MCDM methods (Example 2)

	MOORA	TOPSIS	SAW	ELECTRE(C)	ELECTRE(D)	VIKOR
R1	0.3453	0.5248	0.7298	0.3480	-0.3283	0.4848
R2	0.4384	0.6313	0.7836	0.4416	-1.6868	0.0000
R3	0.4055	0.5139	0.7706	-0.1624	0.7730	0.7559
R4	0.3704	0.4427	0.7550	-0.6272	1.2421	1.0000
Max	0.4384	0.6313	0.7836	0.4416	1.2421	1.0000
Min	0.3453	0.4427	0.7298	-0.6272	-1.6868	0.0000

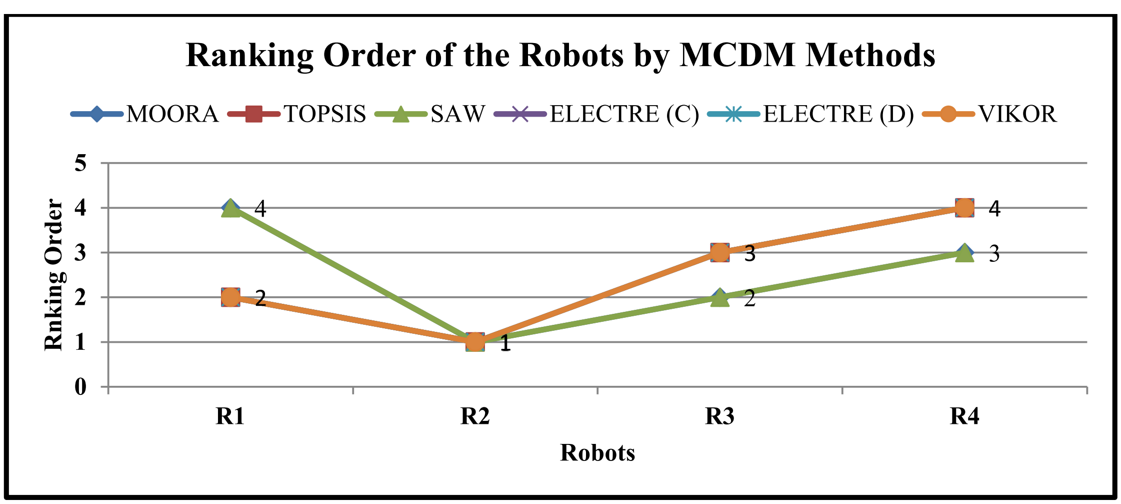

Fig 5: Ranking order of the robots by various MCDM methods (Example 2)

Table 11

Ranking order of the robots by conventional MCDM methods (Example 2)

Robots	MOORA	TOPSIS	SAW	ELECTRE(C)	ELECTRE(D)	VIKOR
R1	4	2	4	2	2	2
R2	1	1	1	1	1	1
R3	2	3	2	3	3	3
R4	3	4	3	4	4	4

3.2.2. Rank reversal in example 2

The analysis shows that industrial robot R1 receives two different preference orders, ranks 2 (four times) and rank 4 (twice). Robot R3 attains two different ranks 3 (twice) and 4 (four times) though robot R3 has the ranking order 1 in each method. Ambiguity arises when a comparison between the performances of two distinct robots is essential. Due to this ambiguity decision makers often suffer from uncertainty.

3.2.3. Application of proposed method (TARO) on example 2 for the elimination of rank reversal

The rank reversal in example 2 creates ambiguity; ambiguity causes uncertainty, which leads to the application of proposed method TARO. The final selection values obtained by MOORA, TOPSIS, SAW, ELECTRE and VIKOR method for the alternatives are normalized through Eq. (1) to Eq. (7) with a view to attain importance of these methods. Table 12 shows that the weights of the methodologies are in the normalized ratio of $w_{MOORA} = 0.1268$, $w_{TOPSIS} = 0.1494$, $w_{SAW} = 0.1296$, $w_{ELECTRE\ (C)} = 0.1853$, $w_{ELECTRE\ (D)} = 0.1931$, $w_{VIKOR} = 0.2158$. The final selection values of the alternative robots are normalized using Eq. (8) and is presented in Table 13. Non-linear selection indices (NLSI) for each alternative using non-linear function of first kind is measured using Eq. (9) and is presented in Table 14. Non-linear selection indices (NLSI) of second kind for each alternative robot are shown in Table 15. Accurate selection index is calculated using Eq. (15), as given in Table 16. These accurate selection indices are found as $ASI_1 = 0.8071$ $ASI_2 = 1.0219$ $ASI_3 = 0.6755$ and $ASI_4 = 0.4955$. ASIs in descending order are $ASI_2 > ASI_1 > ASI_3 > ASI_4$. Obviously the accurate ranking order achieved by using the proposed method for the robots is 2-1-3-4. This ranks indicate the preference order in the sequence R2>R1>R3>R4, which is compatible with that as derived by previous researchers. Fig. 6 exhibits the ranking orders of the alternative robots as achieved using the proposed method.

Table 12

Weights of the methodologies (example 2)

		MOORA	TOPSIS	SAW	ELECTRE (C)	ELECTRE(D)	VIKOR	Sum
Normalization	R1	0.2214	0.2484	0.2401	0.2204	0.0815	0.2164	---
	R2	0.2811	0.2988	0.2578	0.2796	0.4185	0.0000	---
	R3	0.2600	0.2432	0.2536	0.1028	0.1918	0.3373	---
	R4	0.2375	0.2095	0.2484	0.3972	0.3082	0.4463	---
$\theta_i = \xi_{ij} \ln \xi_{ij}$	R1	-0.3338	-0.3460	-0.3426	-0.3333	-0.2043	-0.3312	---
	R2	-0.3567	-0.3609	-0.3495	-0.3563	-0.3645	0.0000	---
	R3	-0.3502	-0.3439	-0.3479	-0.2339	-0.3167	-0.3666	---
	R4	-0.3414	-0.3275	-0.3460	-0.3667	-0.3628	-0.3601	---
sum		-1.3822	-1.3782	-1.3859	-1.2903	-1.2483	-1.0579	---
e_j (entropy)		0.9971	0.9942	0.9997	0.9307	0.9004	0.7631	---
$1-e_j$		0.0029	0.0058	0.0003	0.0693	0.0996	0.2369	0.4147
r_j		0.0071	0.0140	0.0006	0.1670	0.2400	0.5713	1.0000
$\sqrt{r_j}$		0.0842	0.1183	0.0246	0.4087	0.4899	0.7558	1.8816
$1+\sqrt{r_j}$		1.0842	1.1183	1.0246	1.4087	1.4899	1.7558	7.8816
w_j (weight)		**0.1376**	**0.1419**	**0.1300**	**0.1787**	**0.1890**	**0.2228**	1.0000

Table 13

Normalization of the final selection values (example 2)

	MOORA	TOPSIS	SAW	ELECTRE(C)	ELECTRE(D)	VIKOR
R1	0.0000	0.4356	0.0000	0.9124	0.5362	0.5152
R2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
R3	0.6466	0.3774	0.7584	0.4349	0.1602	0.2441
R4	0.2696	0.0000	0.4684	0.0000	0.0000	0.0000

Table 14
Non-linear selection indices (NLSI) of first kind for each alternative robot (Example 2)

	MOORA	TOPSIS	SAW	ELECTRE (C)	ELECTRE (D)	VIKOR	$NLSI_i^{(1)}$
R1	1.1475	2.1677	1.1388	3.2194	2.5469	2.5761	12.7963
R2	3.1192	3.1327	3.0957	3.2502	3.2839	3.3966	19.2783
R3	2.6836	2.0144	2.8824	2.2472	1.5494	1.8161	13.1930
R4	1.7303	1.1524	2.2275	1.1957	1.2081	1.2495	8.7636
						$\sum NLSI_i^{(1)}$	54.0312

Table 15
Non-linear selection indices (NLSI) of second kind for each alternative robot (Example 2)

	MOORA	TOPSIS	SAW	ELECTRE (C)	ELECTRE (D)	VIKOR	$NLSI_i^{(2)}$
R1	0.3024	0.3258	0.3299	0.3930	-0.0867	-0.0355	1.4734
R2	0.3739	0.3857	0.3534	0.4858	0.1032	-0.2228	1.7185
R3	0.3469	0.3202	0.3476	0.1237	-0.0019	0.0260	1.1143
R4	0.3202	0.2861	0.3407	0.0432	0.0592	0.0698	0.8612
						$\sum NLSI_i^{(2)}$	5.1673

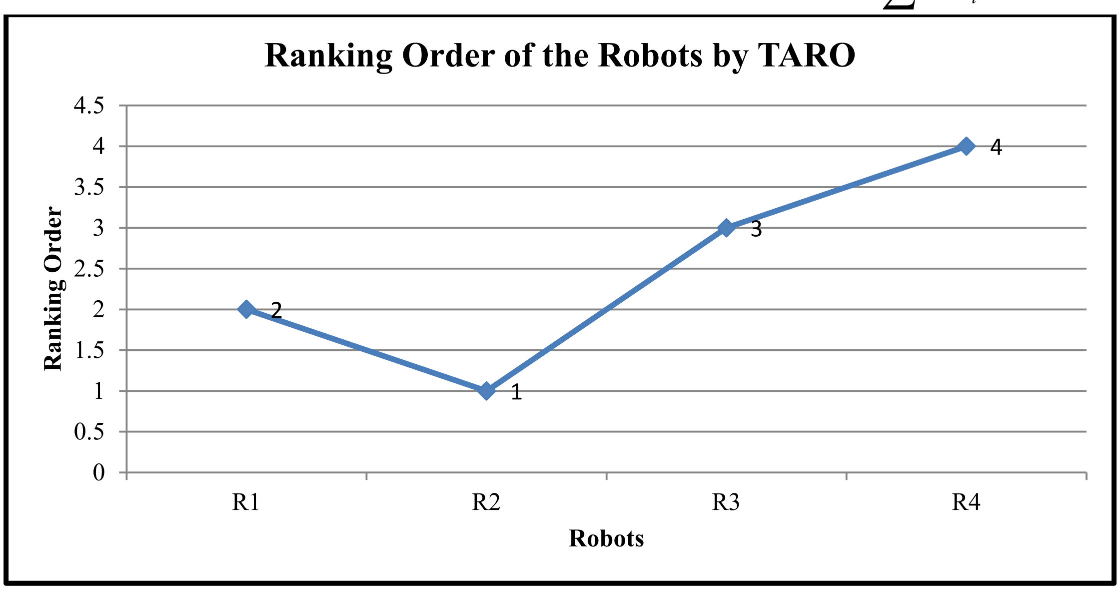

Fig 6: Ranking order of the robots by TARO method (Example 2)

Table 16

Accurate selection index and ranking order of the alternative robots (Example 2)

Robots	$\frac{NLSI_i^{(1)}}{\sum NLSI_i^{(1)}}$	$\frac{NLSI_i^{(2)}}{\sum NLSI_i^{(2)}}$	ASI	Accurate Rank
R1	0.5220	0.2851	0.8071	2
R2	0.6894	0.3326	1.0219	1
R3	0.4598	0.2156	0.6755	3
R4	0.3289	0.1667	0.4955	4

3.3. *Example 3: Robot ranking and selection problem 3*

Example 3 is a robot ranking and selection problem cited from Tansel, Yurdakul and Dengiz (2013). This problem involves a set of nine robots and a group of seven criteria. The models of robots are MA1400, EA1400N, HP-20-6, HP-6, MA1900, UP20MN, MH6, KR16 and KR5ARC. The criteria are Vertical reach (VR), S-axis motion range (S-AMR), L-axis motion range (L-AMR), T-axis motion range (T-AMR), Payload (P), Repeatability(R) and B-axis motion range (B-AMR). The decision matrix consisting of performance rating with respect to criteria for the alternative robots along with the criteria weights are furnished in Table 17.

3.3.1. *Results of the industrial robot selection problem (example 3) using conventional approaches*

The industrial robot ranking and selection problem cited in example-3 is solved using six conventional approaches viz. MOORA, SAW, TOPSIS, Buckley's FAHP, ELECTRE, and VIKOR. The final selection values of the alternative robots using these methods are presented in Table 18. The final selection values of MOORA, SAW, TOPSIS, Buckley's FAHP and ELECTRE (C) have the benefit i.e. positive sense, whereas, that of ELECTRE (D) and VIKOR have the cost i.e. non-benefit sense. These final selection values obtained by various conventional methods determine the ranking orders of the alternative robots as shown in Table 19. The result shows the ranking order as per the result found is ambiguous, except the models EA1400N and MA 1900 having the rank 9 and 7 respectively. Ranking order of the industrial robots by various conventional MCDM methods for example 3 is graphically presented in Fig.7.

Table 17

Assessment of robot selection criteria (Example 3)

	VR (mm)	S-AMR (^{0})	L-AMR (^{0})	T-AMR (^{0})	P (kg)	R (1/100 mm)	B-AMR (^{0})
Weight	0.0894	0.0275	0.0069	0.5183	0.1766	0.133	0.0482
MA1400	2511	170	155	200	3	8	180
EA1400N	1390	170	155	180	3	8	210
HP-20-6	1915	180	155	360	6	6	220
HP-6	1378	170	155	360	6	8	225
MA1900	3437	180	155	200	3	8	180
UP20MN	3106	180	135	360	20	15	130
MH6	2486	170	155	360	6	8	235
KR16	2412	185	35	350	16	10	130
KR5ARC	2207	155	65	350	5	10	130
sum	20842	1560	1165	2720	68	81	1640
Max	3437	185	155	360	20	15	235
Min	1378	155	35	180	3	6	130

Table 18

Final selection values for alternative robots by various MCDM methods (Example 3)

Model	MOORA	SAW	TOPSIS	Buckley's FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR
MA1400	0.3779	0.5486	0.2141	0.31	-3.8422	5.8638	0.4607
EA1400N	0.3261	0.4968	0.1746	0.23	-6.0838	7.4065	0.5183
HP-20-6	0.6467	0.8329	0. 6781	0.83	1.2456	0.5669	0.1454
HP-6	0.6145	0.7852	0. 6640	0.79	1.4208	0.6349	0.1454
MA 1900	0.4035	0.5742	0.2414	0.37	-3.4312	2.5202	0.4607
UP20MN	0.7021	0.8883	0.7847	0.88	4.4224	-7.2756	0.0482
MH6	0.6454	0.8161	0.6797	0.84	1.7266	-3.4007	0.1454
KR16	0.6750	0.8434	0.8148	0.85	0.0818	-5.1488	0.0739
KR5ARC	0.5694	0.7379	0.6359	0.71	0.0257	-1.1672	0.1558
max	0.7021	0.8883	0.8148	0.88	4.4224	7.4065	0.5183
Min	0.3261	0.4968	0.1746	0.23	-6.0838	-7.2756	0.0482

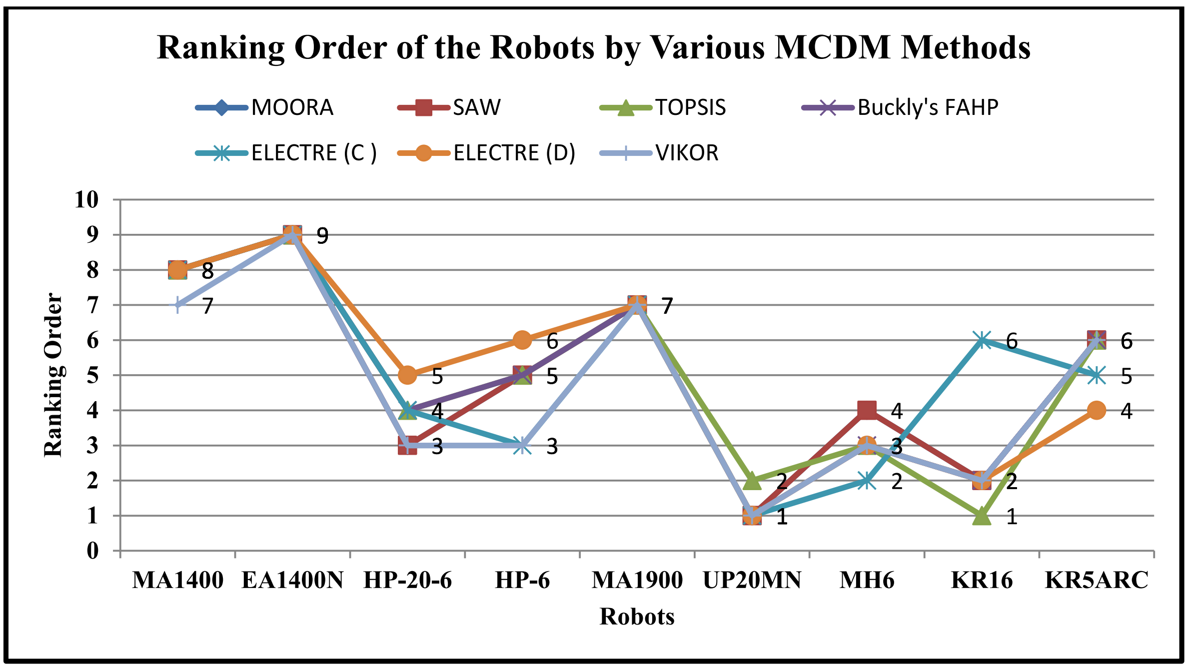

Fig 7: Ranking order of the robots by various MCDM methods (Example 3)

3.3.2. Rank reversal in example 3

The study shows that rank reversal occurs in case of example 3. Table 19 depicts that the model of industrial robot MA1400 gets two different ranks 7(once) and 8 (6 times). Model HP-20-6 receives three different preference orders, rank 3 (thrice), rank 4 (thrice) and 5(once).

Table 19
Ranking orders of the robots by various MCDM techniques (Example 3)

Model	MOORA	SAW	TOPSIS	Buckley's FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR
MA1400	8	8	8	8	8	8	7
EA1400N	9	9	9	9	9	9	9
HP-20-6	3	3	4	4	4	5	3
HP-6	5	5	5	3	3	6	3
MA 1900	7	7	7	7	7	7	7
UP20MN	1	1	2	1	1	1	1
MH6	4	4	3	2	2	3	3
KR16	2	2	1	5	5	2	2
KR5ARC	6	6	6	6	6	4	6

Model HP-6 attains three different ranks, 3 (thrice), 5 (thrice) and 6 (once). UP20MN gets two distinct ranks, 1 (six times) and 2(once). MH6 obtains ranks 2 (twice), 3(thrice) and 4(twice). The model KR16 also receives three different ranking orders, 1(once), 2(four times) and 5(twice). The model KR5ARC gets two different ranks 4(once) and 6(six times). The models of robot EA1400N and MA 1900 unanimously obtain the rank 9 and rank 7 respectively. The fact of rank reversal causes ambiguity that makes decision makers fail to rank and select the alternative properly. The detrimental phenomenon of rank reversal in example 3 leads to the application of proposed method TARO for finding the accurate ranking orders of the alternatives that is described in section 3.3.3.

3.3.3. Application of proposed method (TARO)on example 3 for the elimination of rank reversal

The final selection values determined by conventional MCDM techniques for the alternative industrial robots are used as the basis or raw material of the proposed TARO method. This raw data are normalized for measuring weights of the conventional methodology and performance assessment of alternative. For example, normalization of the final selection values for measuring weights of the MCDM techniques are carried out and presented in Table 20. Exponentially weighted normalized final selection values for evaluation of alternatives are computed and shown in Table 21. Non-linear selection indices of first kind $\left(NLSI_i^{(1)}\right)$ for each alternative industrial robot of example 3 are computed and presented in Table 22. Non-linear selection indices of second kind $\left(NLSI_i^{(2)}\right)$ for each alternative industrial robot are computed and presented in Table 23. Accurate selection index (ASI_i) and accurate ranking order of the industrial robots are determined and shown in Table 24. It is seen that accurate selection indices for the models of the robots are found as $ASI_{MA1400} = 0.0652$, $ASI_{EA1400N} = 0.0545$, $ASI_{HP-20-6} = 0.1344$, $ASI_{HP-6} = 0.1314$, $ASI_{MA1900} = 0.0740$, $ASI_{UP20MN} = 0.1488$, $ASI_{MH-6} = 0.1337$, $ASI_{KR-16} = 0.1350$ and $ASI_{KR5ARC} = 0.1230$. Therefore the ranking order of the industrial robots is 8-9-3-5-7-1-4-2-6. The preference order of the models of robots is UP20MN> KR-16> HP-20-6> MH-6> HP-6> KR5ARC > MA1900> MA1400> EA1400N. Fig. 8 exhibits the ranking orders of the alternative industrial robots as achieved by using the proposed method TARO. It clearly implies that UP20MN is the best option and EA1400N is the worst option and so on.

Table 20

Normalized final selection values, entropy, and weight of the MCDM techniques (Example 3)

	Model	MOORA	SAW	TOPSIS	Buckley's FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR	Sum
Normalization	MA1400	0.0762	0.0841	0.0438	0.0534	0.1707	0.1725	0.2139	---
	EA1400N	0.0657	0.0762	0.0357	0.0396	0.2703	0.2179	0.2406	---
	HP-20-6	0.1304	0.1277	0.1387	0.1429	0.0553	0.0167	0.0675	---
	HP-6	0.1239	0.1204	0.1359	0.1360	0.0631	0.0187	0.0675	---
	MA1900	0.0813	0.0880	0.0494	0.0637	0.1524	0.0742	0.2139	---
	UP20MN*	0.1415	0.1362	0.1606	0.1515	0.1965	0.2141	0.0224	---
	MH-6	0.1301	0.1251	0.1391	0.1446	0.0767	0.1001	0.0675	---
	KR-16	0.1361	0.1293	0.1667	0.1463	0.0036	0.1515	0.0343	---
	KR5ARC	0.1148	0.1131	0.1301	0.1222	0.0114	0.0343	0.0723	---
	e_j	0.9855	0.9914	0.9475	0.9614	0.8487	0.8797	0.8826	---
	$1-e_j$	0.0145	0.0086	0.0525	0.0386	0.1513	0.1203	0.1174	0.5032
	r_j	0.0287	0.0170	0.1043	0.0767	0.3007	0.2392	0.2334	1.0000
	$\sqrt{r_j}$	0.1695	0.1305	0.3229	0.2769	0.5484	0.4890	0.4831	2.4204
	$1+\sqrt{r_j}$	1.1695	1.1305	1.3229	1.2769	1.5484	1.4890	1.4831	9.4204
	w_j (weight)	0.1241	0.1200	0.1404	0.1355	0.1644	0.1581	0.1574	1.0000

Table 21

Exponentially weighted normalized final selection values for evaluation of alternatives (Example 3)

Model	MOORA	SAW	TOPSIS	Buckley's AHP	ELECTRE (C)	ELECTRE (D)	VIKOR
MA1400	0.2166	0.2062	0.0968	0.1920	0.3287	0.1642	0.1911
EA1400N	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HP-20-6	0.9731	0.9752	0.9441	0.9926	0.8891	0.6679	0.9475
HP-6	0.9335	0.9154	0.9321	0.9763	0.9007	0.6625	0.9475
MA1900	0.3175	0.3053	0.1630	0.3317	0.3861	0.4991	0.1911
UP20MN	1.0000	1.0000	0.9972	1.0000	1.0000	1.0000	1.0000
MH-6	0.9719	0.9581	0.9454	0.9953	0.9196	0.9151	0.9475
KR-16	0.9935	0.9837	1.0000	0.9973	0.7964	0.9741	0.9963
KR5ARC	0.8499	0.8230	0.9050	0.9166	0.8120	0.7937	0.9358

Table 22

Non-linear selection indices ($NLSI_i^{(1)}$) of first kind for each alternative robot (exam ple3)

Model	MOORA	SAW	TOPSIS	Buckley's FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR	$NLSI_i^{(1)}$
MA1400	1.4032	1.3857	1.2677	1.3876	1.6374	1.3803	1.4171	9.8790
EA1400N	1.1322	1.1275	1.1508	1.1452	1.1786	1.1712	1.1705	8.0760
HP-20-6	2.9960	2.9898	2.9580	3.0900	2.8674	2.2841	3.0190	20.2043
HP-6	2.8797	2.8162	2.9227	3.0400	2.9011	2.2717	3.0190	19.8504
MA1900	1.5552	1.5301	1.3545	1.5957	1.7341	1.9292	1.4171	11.1158
UP20MN	3.0776	3.0649	3.1194	3.1129	3.2039	3.1838	3.1817	21.9442
MH-6	2.9923	2.9391	2.9619	3.0982	2.9565	2.9245	3.0190	20.8913
KR-16	3.0576	3.0153	3.1281	3.1045	2.6138	3.1023	3.1699	21.1915
KR5ARC	2.6487	2.5677	2.8446	2.8637	2.6547	2.5902	2.9839	19.1535

Table 23

Non-linear selection indices ($NLSI_i^{(2)}$) of second kind (Example 3)

Model	MOORA	SAW	TOPSIS	Buckley's FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR	$NLSI_i^{(2)}$
MA1400	0.2127	0.2225	0.1826	0.1928	0.0689	0.02341	0.0359	0.8202
EA1400N	0.1975	0.2099	0.1740	0.1760	0.0415	0.04952	0.0493	0.7002
HP-20-6	0.3118	0.3065	0.3228	0.3481	0.2178	-0.1282	-0.0681	1.7034
HP-6	0.2979	0.2905	0.3172	0.3326	0.2266	-0.1249	-0.0681	1.6580
MA1900	0.2206	0.2290	0.1889	0.2064	0.0757	-0.0545	0.0359	0.9391
UP20MN	0.3375	0.3262	0.3679	0.3685	0.4468	0.04746	-0.1219	1.9213
MH-6	0.3113	0.3007	0.3234	0.3521	0.2429	-0.03	-0.0681	1.6286
KR-16	0.3247	0.3101	0.3817	0.3561	0.1674	0.00967	-0.1058	1.6363
KR5ARC	0.2793	0.2754	0.3065	0.3037	0.1742	-0.1017	-0.0633	1.5042

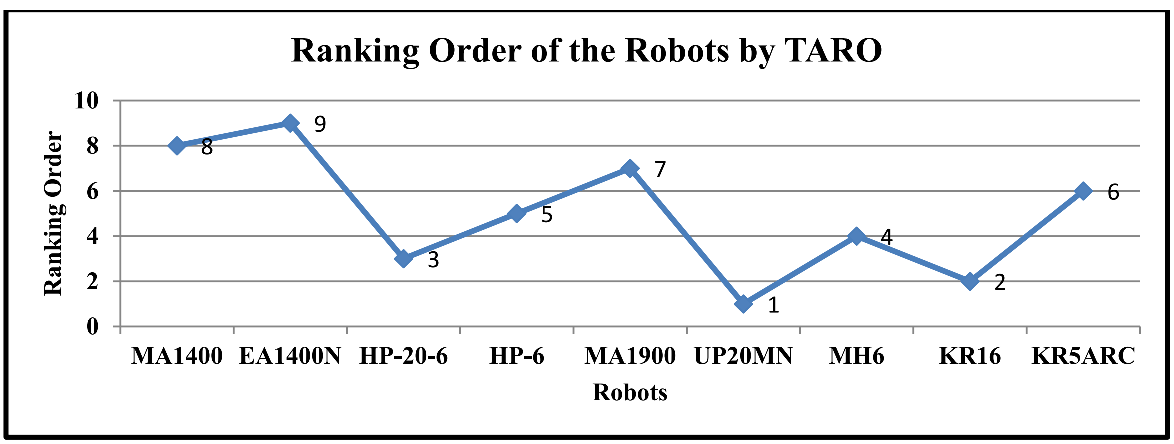

Fig 8: Ranking order of the robots by TARO method (Example 3

Table 24
Accurate selection index (ASI_i) (Example 3)

Model	$\frac{NLSI_i^{(1)}}{\sum_{i=1}^{9} NLSI_i^{(1)}}$	$\frac{NLSI_i^{(2)}}{\sum_{i=1}^{9} NLSI_i^{(2)}}$	ASI_i	Rank
MA1400	0.0649	0.0656	0.0652	8
EA1400N	0.0530	0.0559	0.0545	9
HP-20-6	0.1327	0.1361	0.1344	3
HP-6	0.1303	0.1325	0.1314	5
MA1900	0.0730	0.0751	0.0740	7
UP20MN*	0.1441	0.1536	0.1488	1
MH-6	0.1372	0.1302	0.1337	4
KR-16	0.1391	0.1308	0.1350	2
KR5ARC	0.1258	0.1202	0.1230	6

4. Discussions

Applicability and validity of the proposed technique are illustrated with the solutions of ranking and selection problems of robots. It is noted that for application of the proposed technique TARO, a number of conventional MCDM methods need to be used to determine the final selection values on which TARO acts upon.

A matrix consisting of final selection values determined by a set of conventional approaches for the alternatives is constructed. Final selection value is used as the basis of evaluation because it is more fundamental than the ranks of the alternatives. Final selection values are infinite and continuous over a range whereas ranks are discrete and finite in number. Final selection values can take any values- positive, negative or zero whereas ranks are some fixed natural number starting from unity. Besides final selection values are also the basis of ranks of the alternatives. These are the reasons for using final selection values in lieu of ranks as the basic raw data in proposed technique TARO.

The final selection values obtained by different conventional techniques have significant differences due to which they give distinct ranks to an alternative though the conventional techniques use the same information regarding performance rating and weights of criteria. This significant difference deserves distinct weights to the different set of final selection values as per some logical basis. The current paper employs the advanced entropy weighting method proposed by Bairagi et al. (2015).

To assimilate the final selection values, weights are granted to the methods using an advanced version of the entropy method introduced in the paper. It is observed in example 1 the methods in descending order of their importance weights are VIKOR, ELECTRE(C) or ELECTRE (D), MOORA and Rao et al. (2011) respectively. Obviously the VIKOR method attains the highest importance and the method of Rao et al. (2011) the least importance, where ELECTRE (C) and ELECTRE (D) possess equal amounts of importance. In example 2 the methods in increasing order of their importance weights are VIKOR, ELECTRE (D), ELECTRE (C), TOPSIS, SAW and MOORA respectively. Obviously VIKOR once again attains the highest importance weight and MOORA the least one. Unlike the example 1 ELECTRE (C) and ELECTRE (D) obtain unequal importance weights. In example 3, the methods in increasing order of their importance weights are ELECTRE(C), ELECTRE (D), VIKOR, TOPSIS, Buckley's AHP, MOORA and SAW respectively. In this case ELECTRE(C) attains the highest importance weight, ELECTRE (D) the second highest. Next important method is VIKOR. MOORA attains the least important weight. The analysis clearly shows that relative importance of different conventional approaches vary from decision problem to decision problem. Naturally accuracy of the results depends on the number of the conventional methods used. Accuracy increases with increase of the number of conventional methods and decreases with decrease of the same.

For accurate ranking order of the alternative final selection values determined by the other conventional MCDM methodologies are assessed twice by the new technique TARO using two independent Eqs. (11) and (12) for higher accuracy and robustness of the approaches. An average assessed value is taken assuming . One may consider unequal values of and with reasonable basis. TARO integrates final selection values with corresponding weights to measure accurate selection index (ASI). ASI is the proportional distance of an alternative from the ideal reference point.

Advantages of the proposed TARO method can be furnished as follows.

- In TARO, final selection values obtained by past research for the alternatives may be directly used.
- TARO can determine the weight of the FSV as well as the conventional MCDM/FMCDM approaches. Weight measuring external methods such as AHP, ANP, and conventional entropy is not necessary.
- TARO makes group decisions. Each conventional MCDM/FMCDM approach has an implicit effect in measuring the accurate ranking by using the proposed method TARO.
- TARO is capable of distinguishing the alternatives by evaluating performance and assigning distinct rank. No iteration of the method to the same problem is required for ranking or selecting the alternatives.
- Estimation of the weight for the conventional methods is based on the crisp data of the final selection values that leads to accuracy avoiding subjective measure through use of linguistic variables.

Main disadvantages of TARO are the prerequisite of the application of multiple MCDM approaches to obtain distinguished sets of final selection values. Besides, the proposed method is not compatible with the decision matrix consisting of performance ratings or with the weight matrix consisting of weights of the criteria. Comparisons of the proposed method with the conventional MCDM approaches are depicted in Table 25.

Table 25
Comparisons of conventional methods with the proposed method

Conventional methods		Proposed TARO method	
1.	Inputs are performance ratings of alternatives and weights of decision criteria.	**1.**	Inputs are final selection values determined by different conventional MCDM methods.
2.	Outputs are final selection values and ranking orders of the alternatives.	**2.**	are accurate selection indices and ranks of the alternatives.
3.	Important entities are alternatives, criteria. In some cases decision makers are also considered an entity.	**3.**	Important entities are alternatives and conventional methodologies.
4.	Weight measuring method is an external to the performance evaluation procedure.	**4.**	Weight measuring method is an integral part of the performance evaluation procedure of the proposed technique.
5.	Individual technique cannot take the account of the results obtained by other methods.	**5.**	TARO takes the account of the results obtained by the others conventional methods.
6.	Application of multiple MCDM techniques may generate rank reversal.	**6.**	A single application of TARO on the results obtained by multiple MCDM techniques removes the rank reversal.

Limitation of the proposed TARO method is that it cannot incorporate the conventional methods incapable of generating final selection value for each individual alternative (Shih, 2008). Moreover, TARO cannot take account of experts' opinion for estimation of criteria weights.

5. Case Study

To conduct a case study for the proposed approach I was searching for an automotive manufacturing organization which uses robotic systems for its Material handling purpose. Having received the information from a reliable source that a Kolkata based automotive automobile company (the authority does not want to disclose the name of the organization) are seeking a solution to the selection problem on robots, I personally communicated with the manager of the manufacturing unit through email. After several communications, he became convinced and interested to consult decision making problems on collaborative robot selection for assembly operation for manufacturing of the organization.

At a scheduled date and time, a meeting was held with the managers and other two personnel associated with the decision making process. Through long discussions with the manager and his colleagues, the decision making problem is defined and stated as below.

The automobile company has an automotive manufacturing unit which the manager and his decision making team wants to extend by installing collaborative robots. After an extensive market survey the company came to the decision to buy the robots from FANUC robot manufacturing company. FANUC has eight different collaborative robots. Two of the robots do not have minimum information to be considered. Therefore only six robots out of eight are taken into consideration for further assessment. The six robots are: CR- 4iA, CR- 7iA, CR- 7iA/L, CR- 14iA/L, CR-15iA, and CR- 35iA. A decision making committee is formed including managers and two experts to take important decisions on the selection process. The committee chooses eight selection criteria: cost, repeatability, maximum payload, reach, speed, control, flexibility and reliability. Cost and repeatability are of the cost category and the remaining six criteria viz. maximum payload, reach, speed, control, flexibility and reliability are of benefit category. Moreover four criteria namely repeatability, maximum payload, and speed are quantitative criteria and considered as qualitative criteria due to lack of precise information. Alternatives regarding qualitative criteria are assessed by five degrees of linguistic terms. The importance of criteria is unanimously assessed by the experience, knowledge and opinion of the members of the decision making committee with five degrees of linguistic terms. The linguistic terms for performance ratings as well as weights of criteria are converted to respective fuzzy numbers. The decision matrix for collaborative robots is shown in Table 26.

Now as per the proposed approach, each of the methods MOORA, SAW, TOPSIS, AHP, ELECTRE(C), ELECTRE (D) and VIKOR is individually applied for finding the rank of the alternatives. The final selection values of the above mentioned techniques are used in the entropy weighting method for calculating the weights of the respective techniques. Now, the respective final selection values and the corresponding weights are integrated to compute the selection index of the proposed method. The rank reversal by the conventional methods and rectification are shown in Table 27. Respective graphical representations of the same are in Fig. 9 and Fig.10.

From the above analysis of the case study it is evident that the proposed method is capable of rectifying the rank reversal phenomenon that occurred in the decision making process. Thus, this method can assist decision makers in removing confusion as well as ambiguity and in taking appropriate decisions with confidence.

Table 26
Decision matrix collaborative robots

Robots	Cost	Repeatability (mm)	Maximum Payload (kg)	Reach (mm)	Speed mm/sec	Control	Flexibility	Reliability
CR- 4iA	L	±0.01	4	550	1000	VH	H	H
CR- 7iA	H	±0.03	7	717	1000	H	L	VH
CR- 7iA/L	VH	±0.03	7	911	1000	L	VH	H
CR- 14iA/L	VH	±0.01	14	911	500	VH	H	L
CR-15iA	H	±0.02	15	1441	800-15000	H	VH	VH
CR- 35iA	VH	±0.01	35	1813	750	H	H	VH
Criteria Weight	Low Important	Important	Extremely Important	Important	Extremely Important	Important	High Important	Important

Table 27
Rank reversal by conventional methodologies and rectification by proposed method

Robots	MOORA	SAW	TOPSIS	FAHP	ELECTRE (C)	ELECTRE (D)	VIKOR	Proposed Method
CR- 4iA	3	4	4	2	4	4	5	4
CR- 7iA	6	6	6	6	5	5	6	6
CR- 7iA/L	5	5	5	5	6	6	4	5
CR- 14iA/L	4	3	3	4	2	2	3	3
CR-15iA	2	2	2	3	3	3	1	2
CR- 35iA	1	1	1	1	1	1	2	1

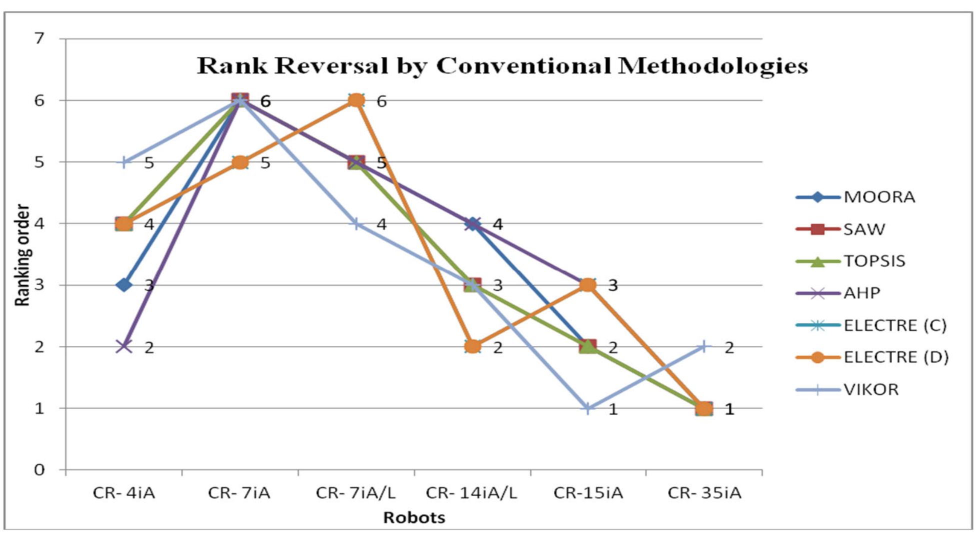

Fig.9. Rank reversal by conventional methodology

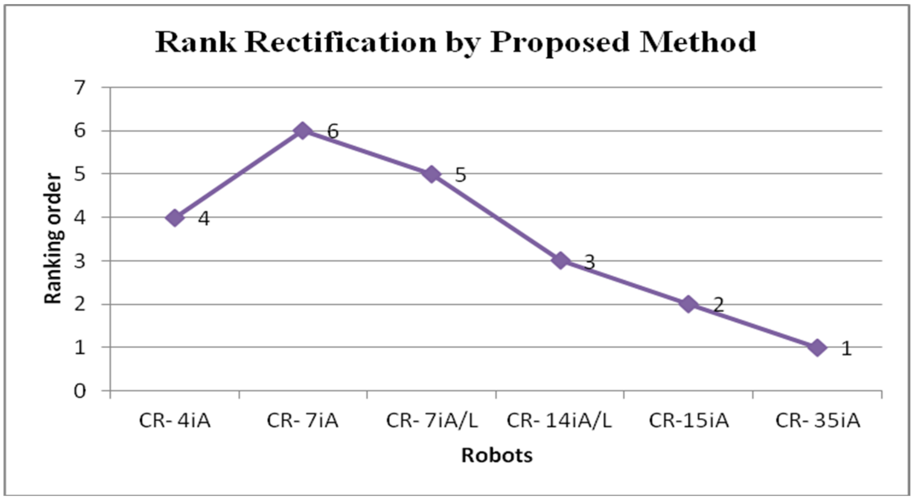

Fig. 10. Rectification of rank reversal by proposed method (TARO).

6. Conclusions

This paper proposes a multi-approach multi-criteria technique named TARO for eclectic decisions in industrial robot ranking and selection. TARO uses final selection values determined by conventional MCDM methods. TARO incorporates an advanced version of entropy weighting method for measuring weights of the final selection values/conventional MCDM techniques. The proposed technique assigns unique ranking order by removing rank. This technique clearly eradicates the ambiguity from the decision making process and ensures the certainty regarding the ranking order of alternative robots in the MCDM environment.

In the past decade various MCDM techniques have been developed and proposed by many researchers. Application of these different conventional MCDM techniques to rank a set of industrial robots commonly shows inconsistency/ rank reversal giving rise to a new problem of ambiguity and confusion. In this case TARO can be suitably applied to remove the rank reversal as well as confusion for making accurate decisions.

Though TARO is employed only on robot ranking problems, this technique is equally effective for finding accurate ranking order alternatives in any other field provided that inconsistency in ranking order is found. The limitation of the techniques is that it can be employed in those cases where conventional methods generate final selection values. Incorporation of methods having no capability of providing final selection values and inclusion of decision makers opinion in estimating importance weights of conventional methods may be the important directions of future research.

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