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Research Article

APPLYING EDAS AS AN APPLICABLE MCDM METHOD FOR INDUSTRIAL ROBOT SELECTION

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ABSTRACT

In order to stay an actual competitor in today's environment, it is essential for manufacturing organizations to make decisions promptly and correctly. In the real-time manufacturing decision making problems, some alternatives are more likely to be evaluated with respect to multiple conflicting criteria. Several multi-criteria decision-making (MCDM) methods have been available to help decision makers in choosing the best decisive course of actions. The aim of the study is to apply an efficient and relatively new method called Evaluation based on Distance from Average Solution (EDAS) as an applicable and useful MCDM method for robot selection problem (RSP). In order to examine the feasibility and effectiveness of the presented method, several numerical examples from the literature are considered. Comparing with other methods especially MCDM methods given in the literature for the industrial RSPs, the Spearman's rank correlations analysis indicates that this method is capable of accurately ranking selected robots.
Keywords: Industrial robot, robot selection problem, manufacturing, MCDM, EDAS.

1. INTRODUCTION

A competitive environment enforces managers to make immediate decisions. These decisions should be made accurately with high precision in a reasonable amount of time. In the manufacturing sector, managers usually face problems such as the selection of product design, manufacturing process, machine tool, industrial robot, material handling equipment, and etc. while evaluating some alternatives and selecting the best one based on conflicting criteria [1]. One of the challenging problems confronted by managers (decision makers) in a given industrial application is to select the most suitable industrial robot in order to achieve the desired output with minimum cost and specific application ability [2].

Robots are used extensively in many manufacturing companies since they are useful automated and reprogrammable machines with different features improved for handling specific tasks to increase efficiency and quality. The capability of moving on two or more axes and responding to various sensory inputs are the extensive features of robots. Many tasks such as assembly, welding, material handling, loading, packaging, inspection, and testing that require

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high endurance, speed, and precision are included in the applications of robots. Using and adapting inappropriate robots could decrease productivity and benefit, thus, it is crucial to decide the most appropriate robot for a particular task. Therefore, several attributes (criteria) including objective or subjective features in nature have to be considered for selecting a robot effectively. While the objective criteria are those that are quantitative in nature (such as load capacity, repeatability, memory capacity, manipulator reach, and degree of freedom, etc.), the subjective criteria are those that are qualitative in nature (such as service quality of vendor, and programming flexibility of a robot, etc.).

Due to the objective and/or subjective criteria in the selection of industrial robots, the robot selection problem (RSP) can be considered as a Multi-Criteria Decision-Making (MCDM) problem involving a large number of criteria with several alternative robots. Therefore, it is necessary to use an efficient MCDM method for selecting the best alternative robot. A number of MCDM methods are presented for solving different decision-making problems including RSP in the manufacturing environment. These methods are Graph Theory and Matrix Approach (GTMA), Simple Additive Weighting (SAW), Weighted Product Method (WPM), Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Data Envelopment Analysis (DEA), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), ELimination Et Choix Traduisant la REalité (ELECTRE), COmplex PRoportional ASsessment (COPRAS), Gray Relational Analysis (GRA), UTility Additive (UTA), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), Multi Objective Optimization by Ratio Analysis (MOORA), Ordered Weighted Averaging (OWA), and the Weighted Euclidean Distance Based Approach (WEDBA) [1, 3].

In this study, an efficient and relatively new MCDM method called Evaluation based on Distance from Average Solution (EDAS), firstly introduced by Keshavarz Ghorabaee et al. [4] to solve multi-criteria inventory ABC classification problem, is presented to apply for robot selection problem (RSP). This method has been recently applied to some engineering problems [5, 6]. The aim of this paper is to apply the EDAS method to show its applicability and effectiveness on RSPs which are one of the most important engineering problems as in other MCDM methods. In addition, it has been extended to handle MCDM problems in different uncertain environments [7-12]. The significant property of the EDAS method is to find the best alternative based on the distance from the average solution that makes it different from the compromise MCDM methods (e.g. VIKOR and TOPSIS). EDAS needs two measures to evaluate alternatives. These measures are positive distance from average (PDA) with its higher values and negative distance from average (NDA) with its lower values. Accordingly, a solution (alternative) is better than the average solution with respect to higher values of PDA and/or lower values of NDA. In the present study, some RSP examples from the related literature are taken into consideration to show the applicability of EDAS as an effective and suitable MCDM method by comparing with the results of other MCDM or various methods applied for the same examples. To the best of our knowledge, EDAS is firstly applied to industrial robot selection in this study. This paper unfolds as follows. A brief literature review including various MCDM methods and their applications to industrial robot selection problems is given in Section 2. EDAS method with its calculation steps an MCDM tool is presented in Section 3. Four robot selection examples are illustrated to provide a comparative analysis between the EDAS method and some relevant methods in Section 4. Finally, conclusions are given in the last section of the paper.

2. LITERATURE REVIEW

Since the existing robot selection literature is quite extensive over the last three decades, a brief literature review, especially including conventional MCDM methods and other some different methods, are provided in this section of the study. Seidmann et al. [13] implemented the AHP method in order to solve the complicated problem of robot selection. Jones et al. [14]

developed a decision support system (DSS) for RSP considering 22 numerical and seven discrete attributes. Nnaji [15] pres ented a mathematical model consisting of critical factors, objective factors (such as velocity, load capacity, repeatability error), and subjective factors (reliability) for the selection and evaluation of robots for any robot implementation. Nnaji and Yannacopoulou [16] used the utility theory for robot evaluation by specializing and referring to the case of electronic circuits industry, and introduced the concept of interaction among different parameters in RSPs by considering utility independence and mutual utility independence.

Agrawal *et al.* [17] proposed a decision making approach for RSP by using an expert system, which defines the set of the most important attributes for the particular situation once the user has identified the required application. Then, they engaged an MCDM module (TOPSIS) to rank the feasible robot alternatives according to their closeness to the ideal solution. Boubekri et al. [18] developed an expert system containing most common robot attributes and applications, and determined the performance requirements by depending on the type of applications. Khouja and Offodile [19] reviewed comprehensive literature on RSP by referring to the publications in the field, categorizing the models by application, solution approach, robot attributes, and selection criteria. They categorized the robot selection models including MCDM, performance optimization, statistical, and computer-assisted models. Khouja [20] presented a two-phase robot selection model that involved the application of DEA to decide the technologies of robots according to their efficiencies and select efficient robots for the further phase in the first phase, and a multi-attribute decision-making model to select the best robot in the second phase. Baker and Talluri [21] used the DEA approach for technology selection by addressing some of the shortcomings in the methodology suggested in the study of Khouja [20] and presented a more robust analysis based on cross efficiencies in DEA. Goh et al. [22] proposed a revised weighted sum model including the values assigned by a group of experts on different factors for RSP. Goh [23] applied the AHP method to RSP under the evaluation of three different decision makers. Karsak [24] proposed a two-phase methodology for RSP that includes using DEA to determine the technically efficient robot alternatives, considering cost and technical performance parameters in the first phase, and applying a fuzzy robot selection algorithm to rank the technically efficient robots based on both predetermined objective criteria and additional vendor-related subjective criteria in the second phase. Parkan and Wu [25] presented TOPSIS as a decision-making model and Operational Competitiveness Rating Analysis (OCRA) performance measurement model with applications to robot selection. They made a final selection based on rankings obtained by averaging the results of TOPSIS, OCRA, and a utility model. They did not consider the subjective factors in these models and did not give any explanation about assigning of the weightings to various robot selection factors. Braglia and Petroni [26] proposed the DEA method for the selection of industrial robots to be able to identify optimal robot in a cost/benefit perspective by measuring the relative efficiency through the resolution of linear programming problems for each robot.

Talluri and Yoon [27] utilized a cone-ratio DEA method for robot selection by considering the preferences of decision makers. Ghrayeb et al. [28] used TOPSIS considering the assembly cycle time to replace the maximum speed of a robot as an attribute in the evaluation process. Bhangale et al. [29] illustrated a coded scheme for manipulator as an example and applied the TOPSIS method to find the weights of attributes of robot selection. They demonstrated the selected robots and their specifications on line graph plot and spider diagram polygon. Karsak and Ahiska [30] proposed a practical common weight MCDM method to evaluate the relative efficiency of decision-making units with respect to multiple outputs and a single exact input. Bhattacharya et al. [31] represented an integrated model combining AHP and Quality Function Deployment (QFD) for the industrial RSP. Their proposed integrated approach also identified the technical requirements followed by customer requirements. They also illustrated the performance of the integrated model with a case study including seven technical requirement factors. Rao and Padmanabhan [32] proposed a methodology based on digraph and matrix methods and solved two

RSPs and suggested a robot selection index to evaluate and rank the robots for a given industrial application. Rao (2007) used GTMA, SAW, WPM, AHP, TOPSIS, and their applications to different decision making situations of the manufacturing environment including RSP. Shih [33] evaluated the performance of candidate robots based on an incremental benefit-cost ratio model while ranking the robots using group TOPSIS method.

Kumar and Garg [34] proposed a distance-based approach for evaluation, selection, and ranking of robots. Chatterjee et al. [2] used two MCDM methods (VIKOR and ELECTRE II) for RSP, and applied these methods to two real cases and compared their results with respect to relative performance. Chakraborty [35] used the MOORA method for solving different common decision-making problems in the real-time manufacturing environment such as an industrial robot selection, a flexible manufacturing system selection, etc. Kentli and Kar [36] presented an MCDM model for an RSP using satisfaction function to convert various robot attributes into a unified scale and tested the model with an example case from the literature. Rao et al. [37] applied a subjective and objective-integrated MCDM method for the purpose of robot selection. Alinezhad et al. [38] integrated MCDM and DEA methods in order to evaluate the relative efficiency of alternative robots with respect to multiple outputs and a single input. Athawale and Chakraborty [39] compared the ranking performance of ten most popular MCDM methods for an industrial RSP. It was concluded that for a given RSP, more attention should be given on the proper selection of criteria and alternatives, not on choosing the most appropriate MCDM method to be employed. Koulouriotis and Ketipi [40] developed a digraph model for the evaluation of alternative robots and selection of the most appropriate one from the feasible alternatives. Bairagi et al. [41] proposed a novel multiplicative model of multi-criteria analysis (MMMCA) for RSP. Mondal and Chakraborty [42] applied four models of DEA to identify the feasible robots having the optimal performance measures, simultaneously satisfying the organizational objectives with respect to cost and process optimization. Furthermore, they also applied the weighted overall efficiency ranking method of multi-attribute decision-making theory for arriving at the best robot selection decision from the short-listed competent alternatives. In their study, they solved two real time industrial robot selection problems to demonstrate the relevance and distinctiveness of the adopted DEA-based approach. Chakraborty and Zavadskas [43] and Chakraborty *et al.* [44] have attempted to prove and validate the applicability of WASPAS method while considering different real time manufacturing problems including RSP in their examples. Koulouriotis and Ketipi [45] presented an extensive, aggregate, and detailed review for RSP, including a wide variety of models, ranging from the first attempts that have been developed in order to approach the issue to the most contemporary and flexible decision methodologies.

Keeping in view the above research works on robot selection, a novel MCDM method recently popular in the literature of multi-criteria analysis is presented in this paper for robot selection by giving four examples solved different MCDM methods and other mathematical methods in the literature. The purpose of this study is to show the effectiveness and applicability of the EDAS method in terms of the existing MCDM methods for the solution of the selection problems of industrial robots. In this respect, the most commonly used four sample problems in the literature were solved and the results obtained from the EDAS method were compared with the methods used in the solution of these samples.

3. EVALUATION BASED ON DISTANCE FROM AVERAGE SOLUTION (EDAS) METHOD

One of the most well-known branches of decision making, multi-criteria decision making (MCDM) can be described as a decision-making problem under the existence of a set of decision criteria [46]. EDAS method, one of the applicable MCDM methods, depends on the average solution for appraising the alternatives by considering two measures that are PDA (positive distance from average) and NDA (negative distance from average). In other words, this method determines the best alternative using the distance from average solution (AV) instead of calculating the distance from ideal and negative ideal solutions as in the compromise MCDM methods such as VIKOR, TOPSIS, etc. In this method, PDA and NDA are the two key necessary measures for the desirability of the alternatives since the higher values of PDA and/or lower values of NDA represent that the solution (alternative) is better than average solution. In this method, all the alternatives of a decision making problem can be evaluated according to multiple criteria often conflicting with each other in the presence of higher values of PDA and lower values of NDA.

Assuming *n* alternatives and *m* criteria, the calculation steps of EDAS method are given below [4]:

Step 1: Selecting the most important criteria that describe alternatives.
Step 2: Construct the decision-making matrix ($X = \left[X_{ij}\right]_{mxn}$), shown as follows:

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{1}$$

where X_{ij} denotes the performance value of *i*th alternative on *j*th criterion.

Step 3: Determine the average solution according to all criteria, shown as follows:

$$AV = \left[AV_j\right]_{1xn} \tag{2}$$

where,

$$AV_j = \frac{\sum_{i=1}^{m} x_{ij}}{m} \tag{3}$$

Step 4: Calculate the positive distance from average (PDA) and the negative distance from average (NDA) matrixes according to the type of criteria (benefit and cost), shown as follows:

$$PDA = \left[PDA_{ij}\right]_{mxn} \tag{4}$$

$$NDA = \left[NDA_{ij}\right]_{mxn} \tag{5}$$

if *j*th criterion is beneficial,

$$PDA_{ij} = \frac{\max\left(0, \left(x_{ij} - AV_j\right)\right)}{AV_j}, \tag{6}$$

$$NDA_{ij} = \frac{\max\left(0, \left(AV_j - x_{ij}\right)\right)}{AV_j}, \tag{7}$$

if *j*th criterion is cost,

$$PDA_{ij} = \frac{\max\left(0, \left(AV_j - x_{ij}\right)\right)}{AV_j}, \tag{8}$$

$$NDA_{ij} = \frac{\max\left(0, \left(x_{ij} - AV_j\right)\right)}{AV_j} \tag{9}$$

where PDA_{ij} and NDA_{ij} denote the positive and negative distance of *i*th alternative from average solution in terms of *j*th criterion, respectively.

Step 5: Determine the weighted sum of PDA and NDA (SP_i and SN_i) for all alternatives, shown as follows:

$$SP_i = \sum_{j=1}^{n} w_j PDA_{ij} \tag{10}$$

$$SN_i = \sum_{j=1}^{n} w_j NDA_{ij} \tag{11}$$

where w_j is the weight of *j*th criterion.

Step 6: Normalize the values of *SP* and *SN* for all alternatives, shown as follows:

$$NSP_i = \frac{SP_i}{\max_i(SP_i)}, \tag{12}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)}, \tag{13}$$

Step 7: Calculate the appraisal score (*AS*) for all alternatives, shown as follows:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i), \tag{14}$$

where $0 \le AS_i \le 1$.

4. ILLUSTRATIVE EXAMPLES

In this paper, an attempt is made to prove and validate the applicability of the EDAS method while considering the following four examples taken from the literature of industrial robot evaluation and selection problems.

4.1. Example 1

The first robot selection example is quoted from Agrawal et al. [17] who proposed TOPSIS as an MCDM technique for the selection of a robot for an industrial application. This problem considers four robot performance criteria that are load capacity (LC), repeatability error (R), vertical reach (VR), and degrees of freedom (DF), and five alternative robots. The quantitative data related to these criteria for alternative robots are shown in Table 1. Among these four criteria, LC, VR, and DF are beneficial (i.e. higher values are desirable), one criterion (R) is a non-beneficial (i.e. lower value is desirable).

Table 1. Quantitative data for example 1 [17]

Robot	LC (kg)	R (mm)	VR (cm)	DF
1	60	0.40	125	5
2	60	0.40	125	6
3	68	0.13	75	6
4	50	1.00	100	6
5	30	0.60	55	5
AV_j	53.6	0.51	96	5.6

While solving the same example by the EDAS method, the quantitative data (decision matrix) given in Table 1 is used for steps 1 and 2. Then, the corresponding average solution (AV) for all evaluation criteria is calculated for step 3 which can be seen at the last row of Table 1. The results of the remaining steps (4 to 7) and the ranking of the robots are given in Table 2.

Table 2. Results of calculation steps and ranking of EDAS method for example 1

	Step 4							
Robot	PDA j =1	PDA j =2	PDA j =3	PDA j =4	NDA j =1	NDA j =2	NDA j =3	NDA j =4
1	0.1194	0.2095	0.3021	0.0000	0.0000	0.0000	0.0000	0.1071
2	0.1194	0.2095	0.3021	0.0714	0.0000	0.0000	0.0000	0.0000
3	0.2687	0.7431	0.0000	0.0714	0.0000	0.0000	0.2188	0.0000
4	0.0000	0.0000	0.0417	0.0714	0.0672	0.9763	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.4403	0.1858	0.4271	0.1071

	Step 5		*Step 6*		*Step 7*	
Robot	SP_i	SN_i	NSP_i	NSN_i	AS_i	Ranking
1	0.2109	0.0017	0.3883	0.9974	0.6929	3
2	0.2121	0.0000	0.3904	1.0000	0.6952	2
3	0.5432	0.0381	1.0000	0.9436	0.9718	1
4	0.0084	0.6762	0.0155	0.0000	0.0077	5
5	0.0000	0.2585	0.0000	0.6177	0.3088	4

Rao and Padmanabhan [32] also used this same example to demonstrate and validate the proposed procedure of robot selection through digraph and matrix methods. They used the AHP method to determine the relative normalized weight (w_i) of each criterion. The criteria weights were obtained as follows: w_{LC} = 0.0963; w_R = 0.5579; w_{VR} = 0.0963; and w_{DF} = 0.2495. Kumar and Garg [34] employed Distance Based Approach (DBA) method using these normalized weights of the criteria and suggested same the robot rankings. Rao *et al.* [37] solved the same example using their proposed MCDM method considering objective criteria weights obtained from statistical variance. Chakraborty *et al.* [44] applied WASPAS method for this robot selection problem by varying λ values to exhibit the ranking performance of the method. To show the calculation steps of the EDAS method for this example, the same aforementioned subjective criteria weights are used.

In order to demonstrate the aptness of using EDAS method as an MCDM tool, the results drawn by EDAS are compared with those obtained by the proposed methods in the literature (Table 3). Based on the results attained through EDAS method-based analysis, the rank ordering of robots is derived as 3-2-1-5-4 with respect to all different criteria weights. When the rank orderings are compared, the Spearman's rank correlation coefficient (r_S) value 0.90 proves the applicability of EDAS method as a well-known decision tool for solving complex decision-making problems.

4.2. Example 2

Bhangale et al. [29] used TOPSIS and graphical methods as comparatively to select the most suitable robot for some pick-n-place operations and illustrated the comparison of the methods with an example. This example problem including five criteria that are load capacity (LC), repeatability (RE), maximum tip speed (MTS), memory capacity (MC) and manipulator reach (MR), and seven robot alternatives are shown in Table 4. Among these five criteria of robot selection, four criteria (LC, MTS, MC and MR) are beneficial, and only one (RE) is non-beneficial.

Table 3. Ranking results of EDAS and other methods for example 1

Author(s)	Different criteria weights	Ranking results			r_S
		Method		EDAS	
Agrawal et al. [17]	w_{LC} = 0.0963, w_R = 0.5579, w_{VR} = 0.0963, w_{DF} = 0.2495	TOPSIS	3-2-1-4-5	3-2-1-5-4	0,90
Rao and Padmanabhan [32]		Digraph and matrix methods	3-2-1-4-5		0,90
Kumar and Garg [34]		DBA	3-2-1-5-4		1,00
Rao et al. [37]		A proposed MCDM	3-2-1-4-5		0,90
Chakraborty et al. [44]		WASPAS	3-2-1-5-4 (λ<0,5)		1,00
			3-2-1-4-5 (λ>=0,5)		0,90
Rao et al. [37]	w_{LC} = 0.1257, w_R = 0.6840, w_{VR} = 0.1742, w_{DF} = 0.0161	A proposed MCDM	3-2-1-4-5	3-2-1-5-4	0,90
	w_{LC} = 0.1198, w_R = 0.6588, w_{VR} = 0.1586, w_{DF} = 0.0628		3-2-1-4-5	3-2-1-5-4	0,90
	w_{LC} = 0.1139, w_R = 0.6336, w_{VR} = 0.1431, w_{DF} = 0.1094		3-2-1-4-5	3-2-1-5-4	0,90
	w_{LC} = 0.1110, w_R = 0.6209, w_{VR} = 0.1353, w_{DF} = 0.1328		3-2-1-4-5	3-2-1-5-4	0,90
	w_{LC} = 0.1081, w_R = 0.6083, w_{VR} = 0.1275, w_{DF} = 0.1561		3-2-1-4-5	3-2-1-5-4	0,90
	w_{LC} = 0.1022, w_R = 0.5831, w_{VR} = 0.1119, w_{DF} = 0.2028		3-2-1-4-5	3-2-1-5-4	0,90

Table 4. Quantitative data for example 2 [29]

Robot no.	Robots	LC (kg)	RE (mm)	MTS (mm/s)	MC	MR (mm)
1	ASEA-IRB 60/2	60	0.40	2540	500	990
2	Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
3	CybotechV15Electric Robot	6.8	0.10	1727.2	1500	1676
4	Hitachi America Process Robot	10	0.20	1000	2000	965
5	Unimation PUMA500/600	2.5	0.10	560	500	915
6	United States Robots Maker 110	4.5	0.08	1016	350	508
7	Yaskawa Electric Motoman L3C	3	0.10	177	1000	920

In the related literature, several MCDM methods for different combinations of criteria weights applied to the robot selection problem were shown in Table 5. In this example, Bhangale *et al.* [29] determined the weights of the relative importance of the criteria weights as w_{LC} = 0.1761, w_{RE} = 0.2042, w_{MTS} = 0.2668, w_{MC} = 0.2430, and w_{MR}=0.2286 using AHP method, but the sum of these criteria weights exceeded one. The weights of these five criteria were renormalized by Chakraborty [35] as w_{LC} = 0.1574, w_{RE} = 0.1825, w_{MTS} = 0.2385, w_{MC} = 0.2172, and w_{MR} = 0.2043 to select these seven robots by using MOORA method.

Table 5. Ranking results of EDAS and other methods for example 2

Author(s)	Different criteria weights	Ranking results			r_S
		Method		EDAS	
Bhangale et al. [29]	w_{LC} = 0.1761, w_{RE} = 0.2042, w_{MTS} = 0.2668 w_{MC} = 0.1243, w_{MR} = 0.2286	TOPSIS	2-5-3-1-7-6-4	2-3-1-5-7-6-4	0,571
Sen et al. [47]		PROMETHEE II	1-3-2-4-6-7-5		0,857
Rao [3]	w_{LC} = 0.0360, w_{RE} = 0.1920, w_{MTS} = .3260, w_{MC} = 0.3260, w_{MR} = 0.1200	AHP	4-2-1-5-7-6-3	5-1-2-4-7-6-3	0,929
Chatterjee et al. [2]		VIKOR	5-2-1-4-7-6-3		0,964
Chatterjee et al. [2]		ELECTRE II	3-2-1-5-7-6-4		0,857
Rao et al. [37]		A proposed MCDM	4-2-1-5-7-6-3		0,929
Chakraborty and Zavadskas [43]		WASPAS	5-2-1-4-7-6-3		0,964
Rao et al. [37]	w_{LC} = 0.6282, w_{RE} = 0.1264, w_{MTS} =0.0615, w_{MC} = 0.1532, w_{MR}=0.0307	A proposed MCDM	1-2-3-4-7-5-6	1-4-3-2-7-6-5	0,821
	w_{LC} = 0.5098, w_{RE} = 0.1395, w_{MTS} = 0.1144, w_{MC} = 0.1877, w_{MR}=0.0486		1-2-3-4-7-5-6	1-4-3-2-7-6-5	0,821
	w_{LC} = 0.3913, w_{RE} = 0.1527, w_{MTS} = 0.1673, w_{MC} = 0.2223, w_{MR} = 0.0664		1-3-2-4-7-5-6	1-3-2-4-7-6-5	0,964

	w_{LC} = 0.3321, w_{RE} = 0.1592, w_{MTS} = 0.1938, w_{MC} = 0.2396, w_{MR} = 0.0753		1-3-2-5-7-6-4	1-3-2-4-7-6-5	0,964
	w_{LC} = 0.2729, w_{RE} = 0.1658, w_{MTS} = 0.2202, w_{MC} = 0.2569, w_{MR}=0.0843		1-3-2-5-7-6-4	1-3-2-4-7-6-5	0,964
	w_{LC} = 0.1544, w_{RE} = 0.1789, w_{MTS} = 0.2731, w_{MC} = 0.2914, w_{MR} = 0.1021		3-2-1-5-7-6-4	3-1-2-4-7-6-5	0,929
Chakraborty [35]		MOORA	2-3-1-4-7-5-6		0,929
Athawale and Chakraborty [39]	w_{LC} = 0.1574, w_{RE} = 0.1825, w_{MTS} = 0.2385, w_{MC} = 0.2172, w_{MR} = 0.2043	SAW	2-3-1-5-7-6-4	3-2-1-4-7-6-5	0,929
		WPM	2-3-1-4-7-6-5		0,964
		AHP	3-2-1-5-7-6-4		0,964
		TOPSIS	1-3-2-5-7-6-4		0,857
		GTMA	2-3-1-5-7-6-4		0,929
		VIKOR	4-3-1-5-7-6-2		0,786
		ELECTRE II	2-3-1-6-7-5-4		0,857
		PROMETHEE II	3-2-1-5-6-7-4		0,964
		GRA	2-3-1-5-7-6-4		0,929
		ROV	3-2-1-5-6-7-4		0,929
Rao [11]	w_{LC} = 0.5515, w_{RE} = 0.1370, w_{MTS} = 0.0792, w_{MC} = 0.1932, w_{MR} = 0.0391	WEDBA	1-2-3-4-7-5-6	1-3-4-2-7-6-5	0,857
	w_{LC} = 0.1391, w_{RE} = 0.1810, w_{MTS} = 0.2766, w_{MC} =0.2994, w_{MR} = 0.1038		3-2-1-5-7-6-4	3-1-2-4-7-6-5	0,929
	w_{LC} = 0.2422, w_{RE} = 0.1700, $_{MTS}$ = 0.2273, w_{MC} = 0.2729, w_{MR} = 0.0877		1-2-3-5-7-6-4	1-2-3-4-7-6-5	0,964
	w_{LC} = 0.2937, w_{RE} = 0.1645, w_{MTS} = 0.2026, w_{MC} = 0.2596, w_{MR}=0.0796		1-2-3-5-7-6-4	1-2-3-4-7-6-5	0,964
	w_{LC} = 0.3453, w_{RE} = 0.1590, w_{MTS} = 0.1779, w_{MC} = 0.2463, w_{MR}=0.0715		1-2-3-4-7-6-5	1-2-3-4-7-6-5	1,000

	w_{LC} = 0.4484, w_{RE} = 0.1480, w_{MTS} = 0.1285, w_{MC} = 0.2198, w_{MR}=0.0553		1-2-3-4-7-6-5	1-3-4-2-7-6-5	0,893
	w_{LC} = 0.4484, w_{RE} = 0.1480, w_{MTS} = 0.1285, w_{MC} = 0.2198, w_{MR}=0.0553		5-1-3-2-7-6-4	4-1-2-3-7-6-5	0,929
Sen et al. [47]	w_{LC} = 0.2000, w_{RE} = 0.2000, w_{MTS} = 0.2000, w_{MC} = 0.2000, w_{MR}=0.2000	PROMETHEE II	1-3-2-4-6-7-5	2-3-1-4-7-6-5	0,929

Athawale and Chakraborty [39] also used the same renormalized criteria weights and solved the example using SAW, WPM, AHP, TOPSIS, GTMA, VIKOR, ELECTRE II, PROMETHEE II, GRA and Range of Value (ROV) methods. Rao [1] used the Weighted Euclidean Distance Based Approach (WEDBA) with different criteria weights. Sen *et al.* [47] applied the PROMETHEE II for the same example by considering the equal criteria weights.

In this study, all different criteria weights are used in the calculation procedure of the EDAS method and the ranking results are given in Table 5. The Spearman's rank correlation (r_S) coefficients calculated between EDAS and each method are quite high to confirm the applicability of EDAS.

4.3. Example 3

Rao and Padmanabhan [32] developed a methodology based on digraph and matrix methods to evaluate alternative industrial robots. In their study, a robot selection index evaluating and ranking robots for a given industrial application was proposed and two examples were solved. One of these examples presented by Agrawal et al. [17] is also used in the present study as the first example. The other example of their study is handed here and its related data is illustrated in Table 6.

Table 6. Quantitative data for example 4 [32]

Robot	PC ($\$\times1000$)	LC (kg)	R (mm)	MI	PF	SC
1	70	45	0,16	AA (0,6818)	H (0,8636)	VH (1)
2	68	45	0,17	AA (0,6818)	VH (1)	AA(0,6818)
3	73	50	0,12	H (0,8636)	H (0,8636)	AA (0,6818)

As can be seen in Table 6, three robot alternatives are evaluated with six criteria. These criteria are classified into beneficial and non-beneficial. While load capacity (LC), man–machine interface (MI), programming flexibility (PF), and vendor's service contract (SC) are beneficial criteria, purchase cost (PC) and repeatability error (R) are non-beneficial. In addition, while three criteria (PC, LC and R) have quantitative information, the remaining three criteria (MI, PF and SC) have qualitative information. In the related literature, Rao and Padmanabhan [32] solved the same example by using AHP to assign the subjective weights to the criteria. In addition, Rao et al. [37] used these same subjective weights and the integrated weights of the criteria obtained from the statistical variance for different weightings.

Table 7. Ranking results of EDAS and other methods for example 3

Author(s)	Different criteria weights	Ranking results: Method		Ranking results: EDAS	r_S
Rao and Padmanabhan [32]	w_{PC} = 0.1830, w_{LC} = 0.1009, w_R = 0.3833, w_{MI} = 0.0555, w_{PF} = 0.1027, w_{SC} = 0.1745	Digraph and matrix methods	2-3-1	2-3-1	1,00
Rao et al. [37]		A proposed MCDM	2-3-1		1,00
Rao et al. [37]	w_{PC} = 0.0159, w_{LC} = 0.0474, w_R = 0.3854, w_{MI} = 0.1029, w_{PF} = 0.0768, w_{SC} = 0.3716	A proposed MCDM	1-3-2	1-3-2	1,00
	w_{PC} = 0.0503, w_{LC} = 0.0611, w_R = 0.4097, w_{MI} = 0.0875, w_{PF} = 0.0787, w_{SC} = 0.3127		1-3-2	2-3-1	0,50
	w_{PC} = 0.0835, w_{LC} = 0.0711, w_R = 0.4031, w_{MI} = 0.0795, w_{PF} = 0.0847, w_{SC} = 0.2781		1-3-2	2-3-1	0,50
	w_{PC} = 0.1001, w_{LC} = 0.0761, w_R = 0.3998, w_{MI} = 0.0755, w_{PF} = 0.0877, w_{SC} = 0.2609		2-3-1	2-3-1	1,00
	w_{PC} = 0.1167, w_{LC} = 0.0810, w_R = 0.3965, w_{MI} = 0.0715, w_{PF} = 0.0907, w_{SC} = 0.2436		2-3-1	2-3-1	1,00
	w_{PC} = 0.1498, w_{LC} = 0.0910, w_R = 0.3899, w_{MI} = 0.0635, w_{PF} = 0.0967, w_{SC} = 0.2090		2-3-1	2-3-1	1,00

The ranking results of three alternative robots with respect to different criteria weights obtained by various methods and EDAS are given in Table 7. According to Spearman's rank correlation values given in Table 7, the ranking results show that the EDAS method can find similar solutions compared with other methods.

4.4. Example 4

The last illustrated example for RSP in this study is the robot selection example of Khouja [20] who was taken this sample from the study of Imany and Schlesinger [48] which contains four specifications for 27 industrial robots (Table 10). The specifications of this example are Cost (C), Load Capacity (LC), Velocity (V) and Repeatability (R) that are the criteria taken into account to determine the most suitable robot. The quantitative decision data involving beneficial criteria (LC and V) as well as non-beneficial criteria (C and R) is depicted in Table 8.

This example was solved through various different methods by some authors in the literature. Imany and Shlesinger [48] used the least square and linear goal programming methods. Khouja [20] explored DEA for solving a particular RSP and solved this example by using the criteria weights as w_C = 0.20, w_{LC} = 0.15, w_V = 0.30, w_R = 0.35. Parkan and Wu [25] applied four different methods using TOPSIS, OCRA, Khouja's two-phase model and the single utility model for the same problem, and thus generated four different sets of preference ranks for the 27 robots. Sen et al. [47] solved this problem by using PROMETHEE II method considering two different criteria weights (unequal criteria weights determined by Khouja [20] and equal criteria weights) to rank the alternative robots.

Table 8. Quantitative data for example 3 [48]

Robot no.	C ($10,000)	LC (kg)	V (m/s)	R (mm)	Robot no.	C ($10,000)	LC (kg)	V (m/s)	R (mm)
1	7.20	60.0	1.35	0.150	15	3.68	47.0	1.00	1.000
2	4.80	6.0	1.1	0.050	16	6.88	80.0	1.00	1.000
3	5.00	45.0	1.27	1.270	17	8.00	15.0	2.00	2.000
4	7.20	1.5	0.66	0.025	18	6.30	10.0	1.00	0.200
5	9.60	50.0	0.05	0.250	19	0.94	10.0	0.30	0.050
6	1.07	1.0	0.3	0.100	20	0.16	1.50	0.80	2.000
7	1.76	5.0	1.00	0.100	21	2.81	27.0	1.70	2.000
8	3.20	15.0	1.00	0.100	22	3.80	0.90	1.00	0.050
9	6.72	10.0	1.10	0.200	23	1.25	2.50	0.50	0.100
10	2.40	6.0	1.00	0.050	24	1.37	2.50	0.50	0. 100
11	2.88	30.0	0.90	0.500	25	3.63	10.0	1.00	0.200
12	6.90	13.6	0.15	1.000	26	5.30	70.0	1.25	1.270
13	3.20	10.0	1.20	0.050	27	4.00	205.0	0.75	2.030
14	4.00	30.0	1.20	0.050					

In this paper, this problem has been solved here considering equal criteria weights and different criteria weights determined by Khouja [20] to demonstrate the applicability and effectiveness of the EDAS method as an MCDM tool. The ranking results of the 27 industrial robots with respect to equal and different criteria weights obtained by various methods and EDAS are given in Table 9. According to Spearman's rank correlation values given in Table 9, the ranking results show that the EDAS method could find similar solutions compared with especially other MCDM methods.

Table 9. Ranking results of EDAS and other methods for example 4

Robot no.	Different criteria weight (w_V = 0.3000, w_{LC} = 0.1500, w_C = 0.2000, w_{RE} = 0.3500) Ranking results: TOPSIS	OCRA	Khouja's model	Utility model	PROMETHEE II	EDAS	($w_V = w_{LC} = w_C = w_{RE}$ = 0.2500) Ranking results: PROMETHEE II	EDAS
1	1	1	5	6	4	1	6	3
2	7	9	10	7	7	7	13	12
3	23	23	22	21	19	23	21	21
4	17	20	7	18	21	18	23	22
5	18	22	19	25	25	22	26	23
6	16	15	23	16	17	14	15	19
7	6	6	3	3	1	5	1	7
8	5	7	13	5	6	6	5	6
9	10	16	25	14	11	16	17	20
10	4	5	4	4	5	4	4	8
11	15	14	15	13	10	15	12	4
12	26	25	27	27	27	26	27	25
13	3	4	2	2	3	3	3	5
14	2	2	1	1	2	2	2	2
15	20	19	17	17	18	20	16	10
16	19	18	18	20	20	19	22	11
17	25	27	24	26	24	25	25	27
18	14	17	26	15	12	17	19	18
19	13	8	6	12	15	9	10	13
20	27	26	9	24	26	27	24	26
21	24	24	11	22	22	24	20	24
22	8	10	12	9	8	8	9	14
23	11	11	14	10	13	11	7	16
24	12	13	16	11	14	12	11	17
25	9	12	21	8	9	10	8	9
26	22	21	20	19	16	21	18	15
27	21	3	8	23	23	13	14	1
r_S	0.954	0.960	0.647	0.937	0.900		0.792	

4.5. Results and Discussion

In this paper, four decision-making problems are considered from the selection of industrial robots, which is a kind of real-time manufacturing environment issue. The decision matrices of these four problems are taken from the well-known published studies in the literature. These mentioned four problems have already been solved and approved using other mathematical approaches (especially different MCDM methods) by past researches. As stated in the calculation steps of the EDAS method, it requires criteria importance weights. In order to compare the ranking results of EDAS with other methods used to solve the same example, different sets of criteria weights is utilized as proposed by previous researchers in this study. It could be concluded that the ranking order may appear almost same for the four problems according to Spearman's rank-correlation test a technique for determining whether there is significant rank-correlation between two sets of values. As seen in the first example [17], when the EDAS is compared with the different MCDM methods (such as TOPSIS, WASPAS), the highest and the lowest rank-correlation coefficients of 1.00 and 0.90, respectively. In the second example [29], when the EDAS is compared with the different MCDM methods (such as TOPSIS, VIKOR, ELECTRE), the highest and the lowest rank-correlation coefficients of 1.00 and 0.571., respectively. In this example, the lowest correlation coefficient belongs to the two sets of preference rankings obtained by EDAS and TOPSIS. In the third example [32], when the EDAS is compared with the different methods (such as a proposed MCDM), the highest and the lowest rank-correlation coefficients of 1.00 and 0.50, respectively. In the third example, the lowest correlation coefficient belongs to the two sets of preference rankings obtained by EDAS and MCDM method proposed by the researches [37]. Since this problem has been solved with different criteria sets by the researchers, it can be said that different benchmark weights have an effect on the difference of ranking results. In the fourth example, when the EDAS is compared with the different methods (such as TOPSIS, PROMEETHE II), the highest and the lowest rank-correlation coefficients of 0.960 and 0.647, respectively. In the fourth example, the lowest correlation coefficient belongs to the two sets of preference rankings obtained by EDAS and the two-phase model of Khouja [20] that involves the application of DEA. Considering all four examples, there is no so much difference in the ranking orders which may result from the difference in the working principle of different MCDM methods and also the assigning criteria weights. Accordingly, the four cited examples demonstrate the potentiality, applicability, efficiency, and simplicity of the EDAS method in solving industrial robot selection decision-making problems.

5. CONCLUSION

In today's competitive market, managers have to make very important decisions for their organization, especially in the areas where the technical decision is required such as robot selection problem. When considering all sectors of the world, since customers are becoming more diverse in their demands and are putting more pressure on companies to produce products and services that respond to these demands, competition is getting more and more intense day by day. As manufacturing organizations face world-class intensified competition carried out by customers with more complex needs, manufacturers are constantly working to meet and balance customer-focused performance measures. The managers applying advanced manufacturing technology in their organizations face difficulties in robot selection due to the number of robots with a wide range of performance with different technical features.

In the selection of industrial robots, the selection criterion defined as a factor that influences the selection of a robot for a given industrial application. Therefore, the goal of a robot selection procedure is to identify the robot selection criteria and obtain the most appropriate combination of the criteria, which are objectively and subjectively considered, in conjunction with the real requirements. The selection of a suitable robot for a particular application is a critical process in manufacturing industries to improve product quality and increase productivity. Since several criteria have to be considered for selecting the best-suited robot from several alternative robots, RSP can be considered as an MCDM problem. Although a number of mathematical approaches have been proposed by past researchers to solve RSPs, a simple and systematic tool is needed for decision makers/managers to identify and select the most appropriate robot from a set of industrial robot alternatives. Since a wrong choice can often make a negative contribution to the efficiency and flexibility of the entire manufacturing process, managers have to be careful at this point.

The purpose of this paper is to apply an efficient and relatively new method called Evaluation based on Distance from Average Solution (EDAS) as an applicable and useful MCDM method for the robot selection problem (RSP). In order to examine the feasibility and effectiveness of the presented method, several numerical examples from the literature are considered. Comparing the existing ranking results of various methods with the results of EDAS for the industrial RSPs, the Spearman's rank correlations analysis indicate that EDAS is capable of accurately ranking selected robots. It is observed that in comparison to other MCDM methods (such as AHP, TOPSIS, VIKOR, ELECTRE, PROMETHEE, MOORA, WASPAS, GRA, ROV, OCRA), EDAS method is quite comprehensible and easy to apply in selection of industrial robots. In the light of the results obtained from the samples solved by using EDAS method in this study, this method may be one of the methods expected to provide managers with good guidance and insight in robot selection problems as well as other MCDM methods. In summary, managers can think of the presented methodology as a robust alternative decision aid for RSPs that can be used with quantitative and also qualitative data on robot characteristics. However, the limitation of this study is that if the selection of robots contains a set of criteria that are inherently subjective, this problem cannot be solved by using this method. Therefore, it is necessary to use fuzzy-based MCDM tools for solving this kind of problem. Further research may compare the results obtained from the EDAS and other MCDM tools in a fuzzy environment. In addition, since this method is computationally very simple and easily comprehensible, it can be applied in a wider range of selection problems in real-time manufacturing environment for further research.

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REFERENCES

[1] Rao R.V., (2013) Decision Making in Manufacturing Environment Using Graph Theory and Fuzzy Multiple Attribute Decision Making Methods, *Springer Series in Advanced Manufacturing Volume 2*, London: Springer-Verlag.
[2] Chatterjee P., Athawale V.M., Chakraborty S., (2010) Selection of industrial robot using compromise ranking and outranking methods, *Robotics and Computer Integrating Manufacturing* 26(5), 483-489.
[3] Rao R.V., (2007) Decision Making in the Manufacturing Environment: Using Graph Theory and Fuzzy Multiple Attribute Decision Making Methods. London: Springer.
[4] Keshavarz Ghorabaee M., Zavadskas E.K., Olfat L., Turskis Z., (2015) Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS), *Informatica* 26(3), 435-451.
[5] Stević Ž., Vasiljević M., Vesković S., (2016) Evaluation in logistics using combined AHP and EDAS method. *XLIII International Symposium on Operational Research*, Serbia.
[6] Turskis Z., Juodagalvienė B., (2016) A novel hybrid multicriteria decision-making model to assess a stairs shape for dwelling houses, *Journal of Civil Engineering and Management* 22(8), 1078-1087.
[7] Keshavarz Ghorabaee M., Zavadskas E.K., Amiri M., Turskis Z., (2016) Extended EDAS method for fuzzy multi-criteria decision-making: An application to supplier selection, *International Journal of Computers Communications & Control* 11(3), 358-371.
[8] Kahraman C., Keshavarz Ghorabaee M., Zavadskas E.K., Cevik Onar S., Yazdani M., Oztaysi B., (2017) Intuitionistic fuzzy EDAS method: An application to solid waste disposal site selection, *Journal of Environmental Engineering and Landscape Management* 25(1), 1-12.
[9] Keshavarz Ghorabaee M., Amiri M., Zavadskas E.K., Turskis Z., (2017a) Multi-criteria group decision-making using an extended EDAS method with interval type-2 fuzzy sets. *E&M Ekonomie a Management* 20(1), 48–68.
[10] Keshavarz Ghorabaee M., Amiri M., Zavadskas E.K., Turskis Z., Antucheviciene J., (2017b) Stochastic EDAS method for multi-criteria decision-making with normally distributed data, *Journal of Intelligent & Fuzzy Systems* 33(3), 1627-1638.
[11] Peng X., Liu C., (2017) Algorithms for neutrosophic soft decision making based on EDAS, new similarity measure and level soft set, *Journal of Intelligent & Fuzzy Systems* 32(1), 955-968.

[12] Stanujkic D., Zavadskas E.K., Keshavarz Ghorabaee M., Turskis Z., (2017) An extension of the EDAS method based on the use of interval grey numbers, *Studies in Informatics and Control* 26(1), 5-12.

[13] Seidmann A., Arbel A., Shapira R., (1984) A two-phase analytic approach to robotic system design, *Robotics and Computer-Integrated Manufacturing* 1(2), 181-190.

[14] Jones M.S., Malmborg C.J., Agee M.H., (1985) Decision support system used for robot selection, *Industrial Engineering* 17, 66-73.

[15] Nnaji B.O., (1988) Evaluation methodology for performance and system economics for robotic devices, *Computers and Industrial Engineering* 14, 27-39.

[16] Nnaji B.O., Yannacopoulou M., (1989) A utility theory based robot selection and evaluation for electronics assembly, *Computers & Industrial Engineering* 14(4), 477-493.

[17] Agrawal V.P., Kohli V., Gupta S., (1991) Computer aided robot selection: the multiple attribute decision making approach, *International Journal of Production Research* 29(8), 1629-1644.

[18] Boubekri N., Sahoui M., Lakrib C., (1991) Development of an expert system for industrial robot selection, *Computers & Industrial Engineering* 20, 119-127.

[19] Khouja M., Offodile O.F., (1994) The industrial robots selection problem: literature review and directions for future research, *IIE Transactions* 26(4), 50-61.

[20] Khouja M., (1995). The use of data envelopment analysis for technology selection, *Computers & Industrial Engineering* 28(1), 123-132.

[21] Baker R.C., Talluri S., (1996) A closer look at the use of data envelopment analysis for technology selection, *Computers & Industrial Engineering* 32(1), 101-108.

[22] Goh C.-H., Tung Y.C.A., Cheng C.H., (1996) A revised weighted sum decision model for robot selection, *Computers & Industrial Engineering* 30, 193-199.

[23] Goh C.H., (1997) Analytic Hierarchy Process for robot selection, *Journal of Manufacturing Systems* 16(5), 381-386.

[24] Karsak E.E., (1998) A two-phase robot selection procedure, *Production Planning & Control* 9(7), 675-684.

[25] Parkan C., Wu M. L., (1999) Decision making and performance measurement models with application to robot selection, *Computers & Industrial Engineering* 36, 503-523.

[26] Braglia M., Petroni A., (1999) Evaluating and selecting investments in industrial robot, *International Journal of Production Research* 37(18), 4157-4178.

[27] Talluri S., Yoon K.P., (2000) A cone-ratio DEA approach for AMT justification, *International Journal of Production Economics* 66(2), 119-129.

[28] Ghrayeb O., Phojanamongkolkij N., Marcellus R., Zhao W., (2004) A practical framework to evaluate and select robots for assembly operations, *Journal of Advanced Manufacturing Systems* 3(2), 151-167.

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

[30] Karsak E.E., Ahiska S.S., (2005) Practical common weight multi-criteria decision-making approach with an improved discriminating power for technology selection, *International Journal of Production Research* 43(8), 1537-1554.

[31] Bhattacharya A., Sarkar B., Mukherjee S.K., (2005) Integrating AHP with QFD for robot selection under requirement perspective, *International Journal of Production Research* 43(17), 3671-3685.

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

[33] Shih H.-S., (2008) Incremental analysis for MCDM with an application to group TOPSIS, *European Journal of Operational Research* 186(2), 720-734.

[34] Kumar R., Garg R.K., (2010) Optimal selection of robots by using distance based approach method, *Robotics and Computer-Integrated Manufacturing* 26(5), 500-506.

[35] Chakraborty S. (2011) Application of the MOORA method for decision making in manufacturing environment, *International Journal of Advanced Manufacturing Technology* 54(9/12), 1155-1166.

[36] Kentli A., Kar A.K., (2011) A satisfaction function and distance measure based multi-criteria robot selection procedure, *International Journal of Production Research* 49, 5821–5832.

[37] Rao R.V., Patel B.K., Parnichkun M., (2011) Industrial robot selection using a novel decision making method considering objective and subjective preferences, *Robotics and Autonomous Systems* 59(6), 367-375.

[38] Alinezhad A., Makui A., Mavi R.K., Zohrehbandian M., (2011) An MCDM-DEA approach for technology selection, *Journal of Industrial Engineering International* 7(12), 32-38.

[39] Athawale V.M., Chakraborty S., (2011) A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection, *International Journal of Industrial Engineering Computations* 2(4), 831-850.

[40] Koulouriotis D.E., Ketipi M. K., (2011) A fuzzy digraph method for robot evaluation and selection, *Expert Systems with Applications* 38(9), 11901-11910.

[41] Bairagi B., Balaram D., Sarkar B., Sanyal S., (2012) A Novel Mutiplicative Model of Multi Criteria Analysis for Robot Selection, *International Journal on Soft Computing, Artificial Intelligence and Applications* 1(3), 1-9.

[42] Mondal S., Chakraborty S., (2013) A solution to robot selection problems using data envelopment analysis, *International Journal of Industrial Engineering Computation* 4(3), 355-372.

[43] Chakraborty S., Zavadskas E.K., (2014) Applications of WASPAS Method in Manufacturing Decision Making, *Informatica* 25(1), 1-20.

[44] Chakraborty S., Zavadskas E.K., Antucheviciene J., (2015) Applications of WASPAS Method as A Multi-Criteria Decision-Making Tool, *Economic Computation and Economic Cybernetics Studies and Research* 49(1), 5-22.

[45] Koulouriotis D.E., Ketipi M.K., (2014) Robot evaluation and selection Part A: an integrated review and annotated taxonomy, *The International Journal of Advanced Manufacturing Technology* 71, 1371-1394.

[46] Şenyiğit E., Demirel B., (2018) The selection of material in dental implant with entropy based simple additive weighting and analytic hierarchy process methods, *Sigma Journal of Engineering and Natural Sciences* 36(3), 2018, 731-740.

[47] Sen D.K., Datta S., Patel S.K., Mahapatra S.S., (2015) Multi-criteria decision making towards selection of industrial robot: Exploration of PROMETHEE II method, *Benchmarking: An International Journal* 22(3), 465-487.

[48] Imany M.M., Shlesinger R. J., (1989) Decision models for robot selection: a comparison of ordinary least squares and linear goal programming methods, *Decision Sciences* 20(1), 40-53.