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A COMPLEX PROPORTIONAL ASSESSMENT METHOD-BASED FRAMEWORK FOR INDUSTRIAL ROBOT SELECTION PROBLEM

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ABSTRACT

Today's manufacturing industries have become more customer-oriented which eventually requires to cater customer's demand in real time. The requirement of industrial robots turns into inevitable with increasing demand of complex products at higher production rate. Industrial robot selection is one of the tedious decision-making responsibilities regularly executed by various production houses in order to select the most suitable robot for specific industrial applications. It has become more and more intricate due to increase in complexity, addition of special features and facilities into the robots by the manufacturers. The decision makers need to identify and select the best suited robot in order to achieve the desired output with minimum cost and specific application ability. This paper focus on the application of a very potential multi-criteria approach, namely complex proportional assessment (COPRAS) for solving an industrial robot selection problem in a given manufacturing environment. One example is demonstrated to prove the suitability of the method in solving such complex industrial problems. It was experimental that the applied method is in good agreement with the rankings obtained by the past researchers.

Keywords: Robot Selection, complex proportional assessment method, MCDM

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1. INTRODUCTION

An industrial robot is commonly defined as a reprogrammable multifunctional manipulator, designed to move materials, parts, tools, or other devices by means of variable programmed motions, and to perform a variety of other tasks. In a broader context, the term robot also includes manipulators that are activated directly by an operator. Unimate first launched robot in the year of 1961 and it was first implemented by General Motors. From the very first day to present, there is a huge change in industrial robots in terms of incorporating newer features, technological advancements, artificial intelligence and so on. In the era of micro-electronics, automation and information technology, utilization of industrial robots in modern manufacturing organizations is increasing gradually. Very precise and cost effective products can be produced using different kinds of robots. To compete in today's high-technology environment, implementation of advanced manufacturing technologies, like robots has become the primary requirement for the manufacturing organizations. But proper execution of industrial robots for a useful manufacturing system is not an easy task to perform. Selection, evaluation and economic justification for an industrial robot for an application requires a widespread knowledge of different suitable alternative robots and identification of the most important robot selection attributes on the basis of which a proper decision can be made. Selection of industrial robots has now become a quite complicated and time consuming task due to the incorporation of various advanced features in robots by the manufacturers. An efficient robot selection decision-making methodology comprises of short listing of suitable robot alternatives and development of the decision matrix consisting of different robot selection attributes and their corresponding values for each of the short listed robot alternatives. According to the past researchers, there are several mutually conflicting robot selection attributes which may influence the entire robot selection process. Those attributes include repeatability, load capacity, speed, accuracy, handling coefficient, program flexibility, memory capacity and supplier's service quality. Repeatability can be defined as how well a robot can come back to a programmed location; load capacity indicates the weight (load) a robot can pick up; speed is defined as how quick a robot can position its arm end and accuracy can be measured as how closely a robot can attain a commended point. Among these attributes, some are beneficial in nature and some are non-beneficial. For beneficial criteria, like load capacity and program flexibility, higher values are always desirable, whereas, for non-beneficial criteria, like cost and repeatability, lower values are preferable. The application domains of robots comprise of welding, material handling, component assembling, painting and surface treatment etc. Due to availability of a wide range of industrial robots in the market, proper robot selection for a specific industrial application has become a very difficult assignment. Improper selection of robots may not only affect productivity and quality of products negatively, but also reputation of the organization is highly influenced. However, executing the application of a robot is a capital intensive job. So, prior to its implementation, a vigilant examination regarding its practicability and performance is needed, in which the impact of various selection factors should be assessed. While selecting the most suitable robot for a particular application, the decision maker requires to consider different robot selection attributes, which often involve the swapping between varieties of robot performance measures. Several approaches for robot selection have already been proposed by the past researchers. Various MCDM methods as well as numerous optimization techniques have been proposed by the past researchers to make the robot selection process simpler. Decision analysis is primarily concerned with those situations where a decision maker has to opt for the best alternative amongst several competent choices while considering a set of conflicting attributes.

2. LITERATURE REVIEW

The past researchers have already applied different decision making methodologies to select industrial robots since the last two decades. Robot selection for different industrial applications has now become one of the major issues for the present and future research. A brief review on the significant contributions of the past researchers is depicted here. Braglia and Gabbrielli [2] considered the application of dimensional analysis for robot selection. The proposed approach would provide an easy, efficient and robust decision support system while overcoming all attributes dimension problems. Talluri and Yoon [3] utilized a decision maker's preference-based approach of DEA, i.e. CRDEA method for selecting industrial robots. The proposed model would integrate the decision maker's preferences and a new methodological extension in DEA. The applicability of the proposed model was explained with the real data set of industrial robots. Chu and Lin [4] applied a fuzzy TOPSIS method for robot selection problem where the ratings of various alternatives with respect to different subjective criteria and weights of all criteria were assessed in linguistic terms represented using fuzzy numbers. Bhangale et al. [5] developed a reliable and exhaustive database of robot manipulators to standardize the robot selection procedure, and help the robot users in selecting the most appropriate robotic system to meet the operational requirements. Bhattacharya et al. [6] proposed a combined model of AHP and QFD to justify the implementation of a robotic system in a manufacturing organization. The integrated approach could take into account the technical requirements as well as customer requirements. Karsak and Ahiska [7] solved the robot selection problems using cross efficiency analysis of DEA method. The proposed model would enable evaluation of the relative efficiency of DMUs considering multiple outputs and a single input. Rao and Padmanabhan [8] proposed a robot selection methodology based on digraph and matrix approach, and considered a robot selection index to evaluate and rank the candidate robots for a given industrial application. The index was obtained from a robot selection attributes function and the corresponding digraph. Kahraman et al. [9] proposed a fuzzy hierarchical TOPSIS model for multi-criteria evaluation of industrial robotic systems. Shih [10] applied an incremental benefit-cost ratio model for evaluating performance of the alternative robots and ranked them while using a group TOPSIS method. The applied model was observed to be quite robust and efficient under a group decision making scenario. Karsak [11] developed a decision model based on QFD and fuzzy linear regression analysis for robot selection. Kumar and Garg [12] proposed a distance-based approach for evaluation, selection and ranking of robots. Sensitivity analysis was also performed to analyze the critical and non-critical performance attributes for a robot. The proposed method could handle both quantitative and qualitative factors of complex MCDM problems. Chatterjee et al. [13] solved two real time robot selection problems using VIKOR and ELECTRE methods, and compared their relative performance. Rao et al. [14] applied a subjective and objective-integrated MCDM method for robot selection. The proposed model could consider objective weights of importance of the attributes as well as subjective preferences of the decision makers to decide the integrated weights of importance of the attributes. Alinezhad et al. [15] integrated an MCDM approach with DEA method for evaluating the relative efficiencies of some alternative robots with respect to multiple outputs and a single input. Using displaced ideal methodology, a practical common weight was developed, and its robustness and discriminating power were illustrated through a robot evaluation problem while comparing the ranking preorder of the proposed decision making framework with that as obtained using the classical DEA model. Koulouriotis and Ketipi [16] developed a digraph-based approach for evaluation and selection of the candidate robots from a set of feasible alternatives. Karsak et al. [17] presented a decision model based on fuzzy linear regression for industrial robot selection. Fuzzy linear regression would provide an alternative approach to statistical regression for modeling situations where the relationships were vague or the data set could not satisfy the assumptions of statistical regression. The results obtained employing fuzzy linear regression were compared with those of earlier studies applying different analytical methods to a previously reported robot selection problem. Devi [18] applied an extended VIKOR method in intuitionistic fuzzy environment for solving robot selection problems. Athawale et al. [19] solved industrial robot selection problems using VIKOR method which had become a popular MCDM tool for evaluating and ranking of alternative robots. Ic et al. [20] proposed a two-phase robot selection decision support system (ROBSEL) to help decision makers in robot selection decisions. While developing ROBSEL, an independent set of criteria was first obtained and arranged in the fuzzy AHP decision hierarchy. In the elimination phase of the proposed decision support system, the user could obtain the feasible set of robots while providing values for 15 requirements. ROBSEL would then employ fuzzy AHP decision hierarchy to rank the feasible robots in the second phase. Mondal and Chakraborty [21] applied a two phase methodology based on data envelopment analysis (DEA). In the first phase Charnes, Cooper and Rhodes (CCR), Banker, Charnes and Cooper (BCC), additive, and cone-ratio models are applied to identify the feasible robots having the optimal performance measures, simultaneously satisfying the organizational objectives with respect to cost and process optimization. Furthermore, the weighted overall efficiency ranking method of multi-attribute decision-making theory is also employed for arriving at the best robot selection decision from the short-listed competent alternatives. Shahrabi [23] introduced FAHP (Fuzzy Analytical Hierarchy Process) and FTOPSIS (Fuzzy Technique for Order Preference by Similarity to Ideal Solution) methods to solve the robot selection problems. Azimia et al. [24] solved robot selection problems with Polygons Area Method (PAM). In this method the maximum polygons area obtained from the attributes of an alternative robot on the radar chart is introduced as a decision making criterion. Obtained results were compared with the well known MCDM techniques. Parameshwaran et al. [25] presented an integrated approach, Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (FAHP), Fuzzy modified TOPSIS or Fuzzy VIKOR and Brown–Gibson model for the optimal selection of robots by considering both objective and subjective criteria. Sen et al. [26] utilized preference ranking organization method for enrichment evaluation (PROMETHEE) II method which provides complete ranking order of all available robot alternatives prudently, thus avoiding errors in decision making. Xue et al. [27] proposed an integrated model based on hesitant 2-tuple linguistic term sets and an extended QUALIFLEX approach for handling robot selection problems with incomplete weight information. The new model can not only manage uncertain and imprecise assessment information of decision-makers with the aid of hesitant 2-tuple linguistic term sets, but also derive the important weights of criteria objectively when the weight information is incompletely known. Moreover, based on the extended QUALIFLEX algorithm, the priority orders of robots can be clearly determined and a more reasonable and credible solution can be yielded in a particular industrial application.

Karande et al. [28] applied six most popular and easily comprehensive multi-criteria decision-making (MCDM) methods, i.e. weighted sum method (WSM), weighted product method (WPM), weighted aggregated sum product assessment (WASPAS) method, multi-objective optimization on the basis of ratio analysis and reference point approach (MOORA) method, and multiplicative form of MOORA method (MULTIMOORA) to solve the industrial robot selection problems. Both single dimensional and high dimensional weight sensitivity analyses were performed to study the effects of weight variations of the most important as well as the most critical criterion on the ranking stability of all the six considered MCDM methods. Sen et al. [29] aimed to explore the TODIM (Tomada de Decisión Inerativa Multicritero) approach to solve two different numeric data sets from available literature resource in perspectives of industrial robot selection. Sen et al. [30] exhibited application potential of preference ranking organization method for enrichment evaluations (extended to operate under fuzzy environment) to solve decision-making problems which encounter both objective as well as subjective evaluation data

From the literature survey as presented above, it is well understood that although numerous research works have already been reported in the past on solving various industrial robot selection problems using different mathematical and MCDM-based methods, any prior study has not demonstrated the application of complex proportional assessment (COPRAS) method, for solving machine tool selection problems.

3. COMPLEX PROPORTIONAL ASSESMENT METHOD

The complex proportional assessment (COPRAS) method assumes direct and proportional dependences of the significance and utility degree of the available alternatives under the presence of mutually conflicting criteria [31-33]. It takes into account the performance of the alternatives with respect to different criteria and also the corresponding criteria weights. This method selects the best decision considering both the ideal and the ideal-worst solutions. The COPRAS method which is used here for decision-making in manufacturing environment adopts a six stage procedure for ranking and evaluating alternatives in terms of their significance and utility degree. COPRAS has the ability to account for both positive (beneficial) and negative (non-beneficial) criteria, which can be assessed separately within the evaluation process. The most important feature that makes COPRAS method superior to other methods is that it can be used to calculate the utility degree of alternatives indicating the extent to which one alternative is better or worse than other alternatives taken for comparison. The steps for COPRAS method are presented as below:

Step 1: Normalize the decision matrix using linear normalization procedure [31]. The purpose of normalization is to obtain dimensionless values of different criteria so that all of them can be compared.

Step 2: Determine the weighted normalized decision matrix, D.

$$D = [y_{ij}]_{mxn} = r_{ij} \, x \, w_j \qquad (i = 1,2,\ldots,m;\ j = 1,2,\ldots,n) \qquad (1)$$

The sum of dimensionless weighted normalized values of each criterion is always equal to the weight for that criterion.

$$\sum_{i=1}^{m} y_{ij} = w_j \qquad (2)$$

Thus, it can be said that the weight, w_j of j^{th} criterion is proportionally distributed among all the alternatives according to their weighted normalized value, y_{ij}.

Step 3: The sums of weighted normalized values are calculated for both the beneficial and non-beneficial attributes using the following equations:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \qquad (3)$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \qquad (4)$$

where y_{+ij} and y_{-ij} are the weighted normalized values for beneficial and non-beneficial attributes respectively.

The greater the value of S_{+i}, the better is the alternative; and the lower the value of S_{-i}, the better is the alternative. The S_{+i} and S_{-i} values express the degree of goals attained by each alternative. In any case, the sums of 'pluses' S_{+i} and 'minuses' S_{-i} of the alternatives are always respectively equal to the sums of weights for the beneficial and non-beneficial attributes as expressed by the following equations:

$$S_{+} = \sum_{i=1}^{m} S_{+i} = \sum_{i=1}^{m}\sum_{j=1}^{n} y_{+ij} \qquad (5)$$

$$S_{-} = \sum_{i=1}^{m} S_{-i} = \sum_{i=1}^{m}\sum_{j=1}^{n} y_{-ij} \qquad (6)$$

Step 4: Determine the significances of the alternatives on the basis of defining the positive alternatives S_{+i} and negative alternatives S_{-i} characteristics.
Step 5: Determine the relative significances or priorities (Q_i) of the alternatives.

$$Q_i = S_{+i} + \frac{S_{-\min}\sum_{i=1}^{m} S_{-i}}{S_{-i}\sum_{i=1}^{m}(S_{-\min}/S_{-i})} \qquad (i = 1,2,\ldots,m) \tag{7}$$

where S_{-min} is the minimum value of S_{-i}. The greater the value of Q_i, the higher is the priority of the alternative. The relative significance value of an alternative shows the degree of satisfaction attained by that alternative. The alternative with the highest relative significance value (Q_{max}) is the best choice among the candidate alternatives.
Step 6: Calculate the quantitative utility (U_i) for i^{th} alternative. The degree of an alternative's utility which leads to a complete ranking of the candidate alternatives is determined by comparing the priorities of all the alternatives with the most efficient one and can be denoted as below:

$$U_i = \left[\frac{Q_i}{Q_{max}}\right] x100\% \tag{8}$$

where Q_{max} is the maximum relative significance value. These utility values of the alternatives range from 0% to 100%. Thus, this approach allows for evaluating the direct and proportional dependence of significance and utility degree of the considered alternatives in a decision-making problem having multiple criteria, their weights and performance values of the alternatives with respect to all the criteria.

4. ILLUSTRATIVE EXAMPLE

This example deals with selection of the best industrial robot for a pick-n-place operation in a discrete manufacturing environment. Bhangale et al. [5] applied TOPSIS and some graphical approaches for solving this robot selection problem, considering repeatability error (RE), load capacity (LC), maximum tip speed (MTS), memory capacity (MC) and manipulator reach (MR) as the predominant robot selection attributes. RE is defined as the returning ability of a robot manipulator to its original position after a certain period of time. LC is the maximum load that can be carried by a manipulator. MTS is the speed at which a robot can move in an intertial reference frame. MC is the capacity to store the steps of a predefined program in memory by a robot. MR is the maximum distance to be covered by a manipulator to grasp objects for a given industrial application. Among these, LC, MTS, MC and MR are beneficial in nature, where higher values are desirable and RE is the only non-beneficial attribute requiring lower values. The criteria weights, as estimated by Rao [1] using AHP method, are used for all the preference ranking-based analyses, and these weights are w_{LC} = 0.036, w_{RE} = 0.192, w_{MTS} = 0.326, w_{MC} = 0.326 and w_{MR} = 0.120. Rao [1] solved the same robot selection problem using AHP method and obtained a ranking of the alternative robots as $A_3 > A_2 > A_7 > A_1 > A_4 > A_6 > A_5$

Table 1 Quantitative data for robot selection problem

Robot	LC	RE	MTS	MC	MR
ASEA-IRB 60/2 (A_1)	60	0.4	2540	500	990

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Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
Cybotech V15 Electric Robot	6.8	0.1	1727.	1500	1676
Hitachi America Process Robot	10	0.2	1000	2000	965
Unimation PUMA 500/600	2.5	0.1	560	500	915
United States Robots Maker	4.5	0.08	1016	350	508
Yaskawa Electric Motoman	3	0.1	177	1000	920

4.1 COPRAS method

While solving this robot selection problem using COPRAS method, the decision matrix, as shown in Table 1, is first normalized to obtain the comparable dimensionless criteria values. Then each element of the normalized decision matrix is multiplied by the corresponding criteria weight to derive the weighted normalized matrix, as given in Table 2.

Table 2 Weighted normalized matrix

Robot	LC	RE	MTS	MC	MR
A_1	0.0232	0.0680	0.1030	0.0184	0.0169
A_2	0.0025	0.0255	0.0412	0.1105	0.0178
A_3	0.0026	0.0170	0.0701	0.0553	0.0287
A_4	0.0039	0.0340	0.0406	0.0737	0.0165
A_5	0.0010	0.0170	0.0227	0.0184	0.0157
A_6	0.0017	0.0136	0.0412	0.0129	0.0087
A_7	0.0012	0.0170	0.0072	0.0368	0.0157

Now, the sums of the weighted normalized values are estimated for both beneficial and non-beneficial attributes respectively, as given in Table 3. Then, the relative significance or priority value for each robot is determined and is shown in Table 4.

Table 3 Sums of the weighted normalized values

Robot	S_{+i}	Value	S_{-i}	Value
A_1	S_{+1}	0.1616	S_{-1}	0.0680
A_2	S_{+2}	0.1720	S_{-2}	0.0255

A_3	S_{+3}	0.1566	S_{-3}	0.0170
A_4	S_{+4}	0.1346	S_{-4}	0.0340
A_5	S_{+5}	0.0578	S_{-5}	0.0170
A_6	S_{+6}	0.0645	S_{-6}	0.0136
A_7	S_{+7}	0.0609	S_{-7}	0.0170

Next, the quantitative utility for each robot alternative is calculated, as exhibited in Table 4 and the descending order of these utility values yields a complete ranking of the robot alternatives as $A_2 > A_3 > A_1 > A_4 > A_6 > A_7 > A_5$. The best choice is Robot A_2 (Cincinnati Milacrone T3-726) and the last choice is Robot A_5 (Unimation PUMA 500/600).

Table 4 Q_i and U_i values

Robot	Q_i	U_i	Rank
A_1	0.1701	87.3966	3
A_2	0.1946	100.0000	1
A_3	0.1905	97.9067	2
A_4	0.1516	77.8893	4
A_5	0.0916	47.0957	7
A_6	0.1069	54.9355	5
A_7	0.0948	48.7197	6

5. CONCLUSIONS

Selecting the best robot is an important problem in industrial context due to the involvement of various performance attributes. This paper presents the COPRAS method for solving the robot selection problem. One real time cast study has been presented to validate the applied method. It is observed that the proposed method almost corroborate with the rankings of the previous researchers. The COPRAS method can also be used for any type of decision-making problem. Furthermore, the selection of industrial robots to suit a particular job essentially depends on profile of the job and concerned attributes required in the robot. A selection method thereafter is solely responsible for using attributes data of robots to evaluate.

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