Robotics and Computer-Integrated Manufacturing 26 (2010) 483–489

Contents lists available at ScienceDirect

Robotics and Computer-Integrated Manufacturing

journal homepage: www.elsevier.com/locate/rcim

Selection of industrial robots using compromise ranking and outranking methods

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ARTICLE INFO

Article history:
Received 7 August 2009
Received in revised form
8 January 2010
Accepted 30 March 2010

Keywords:
Robot selection
Multi-criteria decision-making
VIKOR
ELECTRE
Concordance matrix
Discordance matrix

ABSTRACT

Selection of a robot for a specific industrial application is one of the most challenging problems in real time manufacturing environment. It has become more and more complicated due to increase in complexity, advanced features and facilities that are continuously being incorporated into the robots by different manufacturers. At present, different types of industrial robots with diverse capabilities, features, facilities and specifications are available in the market. Manufacturing environment, product design, production system and cost involved are some of the most influencing factors that directly affect the robot selection decision. The decision maker needs to identify and select the best suited robot in order to achieve the desired output with minimum cost and specific application ability. This paper attempts to solve the robot selection problem using two most appropriate multi-criteria decision-making (MCDM) methods and compares their relative performance for a given industrial application. The first MCDM approach is 'VIsekriterijumsko KOmpromisno Rangiranje' (VIKOR), a compromise ranking method and the other one is 'ELimination and Et Choice Translating REality' (ELECTRE), an outranking method. Two real time examples are cited in order to demonstrate and validate the applicability and potentiality of both these MCDM methods. It is observed that the relative rankings of the alternative robots as obtained using these two MCDM methods match quite well with those as derived by the past researchers.

1. Introduction

An industrial robot is a general purpose, reprogrammable machine with certain anthropometrical features. Its mechanical arm is the most important and vital anthropometrical component. Other less but still important features, like its decision-making capability, capacity of responding to various sensory inputs and communicating with other machines make it an important tool for diverse industrial applications, including material handling, assembly, finishing, machine loading, spray painting and welding. Control resolution, accuracy, repeatability, load carrying capacity, degrees of freedom, man–machine interfacing ability, programming flexibility, maximum tip speed, memory capacity and supplier's service quality are the most important attributes to be taken into consideration while selecting an industrial robot for a particular application. These attributes affecting the robot selection decision can be classified as objective and subjective attributes or beneficial and non-beneficial attributes. Objective attributes can be numerically defined, such as the cost and load carrying capacity of a robot, etc. On the other hand, subjective attributes are qualitative in nature, e.g. vendor's service quality, programming flexibility of a robot, etc. The beneficial attributes are those whose higher values are always desirable, e.g. load carrying capacity, programming flexibility and non-beneficial attributes are those whose lower values are preferable, e.g. cost, repeatability. While selecting an industrial robot for a given application, the decision maker needs to consider all these attributes, where a tradeoff between them and the robot performance measures is necessary. Several approaches for robot selection have already been proposed by the past researchers, which include the applications of multi-criteria decision-making (MCDM) methods, production system performance optimization models, computer-assisted models and statistical models.

Bhangale et al. [1] presented a robot selection methodology using the technique for order performance by similarity to ideal solution (TOPSIS) and graphical methods, and compared the relative rankings of the alternative robots as obtained using these two methods. A coding system is also employed for expressing various robot selection attributes and a merit value is used to rank the robots in the order of their suitability for a given industrial application. Goh et al. [2] proposed a revised weighted sum decision model that can take into account both the objective and subjective attributes while selecting an industrial robot. Khouja

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doi:10.1016/j.rcim.2010.03.007

and Booth [3] applied a statistical procedure, known as robust fuzzy cluster analysis that can identify the robots with the best combination of specifications based on various performance parameters. Khouja [4] developed a two-phase decision model for solving the industrial robot selection problems. In the first phase, data envelopment analysis (DEA) is employed for identifying the robots with the best combination of vendor specifications based on the robot performance parameters. In second phase, a multi-attribute decision-making (MADM) method is applied to select the best robot from those as identified in the previous phase. Zhao et al. [5] combined a multi-chromosome genetic algorithm with first-fit bin packing algorithm for the optimal robot selection and workstation assignment problem for a computer integrated manufacturing system. Baker and Talluri [6] proposed an industrial robot selection methodology based on cross efficiencies in DEA without considering the criteria weights or the decision maker's preferences. Goh [7] applied the analytic hierarchy process (AHP) for robot selection that can simultaneously consider both the objective and subjective attributes. Parkan and Wu [8] presented the applications and interrelationship of the operational competitiveness rating (OCRA) and TOPSIS methods in a robot selection problem and compared their performance with other approaches. It is observed that both these methods are strongly interrelated, and their performance measurements and decision-making processes involve the same mathematical treatment though they have their apparent structural differences. Rao and Padmanabhan [9] employed the diagraph and matrix methods for evaluating and ranking of the alternative robots for a given industrial application, using the similarity and dissimilarity coefficient values. Kahraman et al. [10] developed a hierarchical fuzzy TOPSIS method to solve the multi-attribute robot selection problems. Karsak [11] proposed a decision model for robot selection based on quality function deployment (QFD) and fuzzy linear regression methods while integrating the user demands with the technical characteristics of the robots.

Although a number of mathematical approaches have already been proposed by the past researchers on solving the robot selection problems, still there is a need for a simple as well as systematic tool to guide the decision maker to identify and select the most suitable industrial robot from a given set of alternatives, because a wrong selection may often negatively contribute to the productivity and flexibility of the entire manufacturing process. Taking decision in the presence of multiple conflicting attributes is known as the multi-criteria decision-making (MCDM) problem. A typical MCDM problem usually consists of three main components, i.e. (a) alternatives, (b) criteria/attributes and (c) relative importance (weight) for each criterion. All the elements of a MCDM problem are to be normalized to the same units so that all the possible criteria can be considered in the decision-making process. Various mathematical models, like simple additive weighting (SAW), weighted product method (WPM), AHP, TOPSIS, DEA, etc. are now available to tackle and solve these MCDM problems. The main advantage of any MCDM method lies in its consideration of a large number of attributes and alternatives. In this paper, an attempt is made to discover the applicability and potentiality of another two yet to be popular MCDM methods while selecting the most suitable industrial robot for a given application. The first MCDM method is VIKOR (a compromise ranking method) and the other one is ELECTRE (an outranking method). Two real time examples are cited to demonstrate and compare the performance of both these MCDM methods.

2. Compromise ranking method

The VIKOR (the Serbian name is 'VIsekriterijumsko KOmpromisno Rangiranje', which means multi-criteria optimization (MCO) and compromise solution) method was first established by Zeleny [12] and later promoted by Opricovic and Tzeng [13,14]. This method is developed to solve the MCDM problems with conflicting and non-commensurable (criteria with different units) attributes, assuming that compromise can be acceptable for conflict resolution, when the decision maker wants a solution that is the closest to the ideal solution and the alternatives can be evaluated with respect to all the established attributes. It focuses on ranking and selecting the best alternative from a finite set of alternatives with conflicting criteria, and on proposing the compromise solution (one or more). The compromise solution is a feasible solution, which is the closest to the ideal solution, and a compromise means an agreement established by mutual concessions made between the alternatives. The following multiple attribute merit for compromise ranking is developed from the L_p-metric used in the compromise programming method [15]

$$L_{p,i}=\left\{\sum_{j=1}^{M}\left(w_j\left[(m_{ij})_{\max}-m_{ij}\right]/\left[(m_{ij})_{\max}-(m_{ij})_{\min}\right]\right)^p\right\}^{1/p} \quad (1)$$

$1\le p\le\infty;\quad i=1,2,\ldots,N$

where M is the number of criteria and N is the number of alternatives. The m_{ij} values (for $i=1,2,\ldots,N$; $j=1,2,\ldots,M$) denote the values of criteria for different alternatives. In the VIKOR method, $L_{1,i}$ and $L_{\infty,i}$ are used to formulate the ranking measures.

The procedural steps for the VIKOR method are highlighted as below:

Step 1: Identify the major robot selection criteria for a given industrial application and short-list the robots on the basis of the identified criteria satisfying the requirements. A quantitative or qualitative value is assigned to each criterion to develop the related decision matrix.

Step 2: (a) After short-listing the robots and development of the decision matrix, determine the best, $(m_{ij})_{\max}$ and the worst, $(m_{ij})_{\min}$ values for all the criteria.

(b) The weights or relative importance of the considered criteria are estimated using analytic hierarchy process (AHP) or any other method (entropy method).

(c) Calculate E_i and F_i values

$$E_i=L_{1,i}=\sum_{j=1}^{M}w_j\left[(m_{ij})_{\max}-m_{ij}\right]/\left[(m_{ij})_{\max}-(m_{ij})_{\min}\right] \quad (2)$$

$$F_i=L_{\infty,i}=\mathrm{Max}^m\mathrm{of}\left\{w_j\left[(m_{ij})_{\max}-m_{ij}\right]/\left[(m_{ij})_{\max}-(m_{ij})_{\min}\right]\right\} \quad j=1,2,\ldots,M \quad (3)$$

Eq. (2) is only applicable to beneficial attributes (whose higher values are desirable). For non-beneficial attributes (whose lower values are preferable), the term $[(m_{ij})_{\max}-m_{ij}]$ in Eq. (2), is to be replaced by $[m_{ij}-(m_{ij})_{\min}]$. Hence, for non-beneficial attributes, Eq. (2) can be rewritten as

$$E_i=L_{1,i}=\sum_{j=1}^{M}w_j\left[m_{ij}-(m_{ij})_{\min}\right]/\left[(m_{ij})_{\max}-(m_{ij})_{\min}\right] \quad (4)$$

(d) Calculate P_i values as follows:

$$P_i=v((E_i-E_{i-\min})/(E_{i-\max}-E_{i-\min}))+(1-v)((F_i-F_{i-\min})/(F_{i-\max}-F_{i-\min})) \quad (5)$$

where $E_{i-\max}$ and $E_{i-\min}$ are the maximum and minimum values of E_i, respectively, and $F_{i-\max}$ and $F_{i-\min}$ are the maximum and minimum values of F_i, respectively. v is introduced as weight of the strategy of 'the majority of attributes' (or 'the maximum group utility'). The value of v lies between 0 and 1. Normally, the value of v is taken as 0.5. The compromise can be selected with