Jestr
Journal of Engineering Science and Technology Review 7 (3) (2014) 141 – 150
JOURNAL OF
Engineering Science and Technology Review
www.jestr.org

Research Article

Investigating the Effect of Normalization Norms in Flexible Manufacturing Sytem Selection Using Multi-Criteria Decision-Making Methods

Prasenjit Chatterjee[*,1] and Shankar Chakraborty[2]

[1]Dept. of Mechanical Engineering, MCKV Institute of Engineering, Howrah, 711 204, West Begal, India
[2]Dept. of Production Engineering, Jadavpur University, Kolkata, 700 032, India

Received 3 January 2014; Accepted 30 July 2014

Abstract

The main objective of this paper is to assess the effect of different normalization norms within multi-criteria decision-making (MADM) models. Three well accepted MCDM tools, namely, preference ranking organization method for enrichment evaluation (PROMETHEE), grey relation analysis (GRA) and technique for order preference by similarity to ideal solution (TOPSIS) methods are applied for solving a flexible manufacturing system (FMS) selection problem in a discrete manufacturing environment. Finally, by the introduction of different normalization norms to the decision algorithms, its effct on the FMS selection problem using these MCDM models are also studied.

Keywords: FMS selection, MCDM, PROMETHEE, GRA, TOPSIS, normalization norm

1. Introduction

Remarkable development in human civilization has always been attained by the foundation of path-breaking technologies. The last few decades have witnessed exceptional advances in techno-commercial world. Survival of the manufacturing organizations in today's worldwide competitive environment centrally depends on their flexibility in adopting faster technological innovations and novelties to meet the set enterprise goals. Increasing demand for utmost products with shorter life cycles has motivated the entire manufacturing society to look for some progressive computerized automated processes and systems. Today many manufacturing organizations seek to maintain a competitive edge in the market place by exploiting the advantages of modern manufacturing technologies. One such technology which has become increasingly popular over the past few decades is flexible manufacturing system (FMS). An FMS is such a reprogrammable manufacturing system which is proficient in producing miscellaneous array of products without human intervention. An FMS is basically an advanced manufacturing system (AMS), consisting of a set of alike and complementary numerically controlled machines, interconnected through an automated transportation system. It is designed to fabricate a variety of products in a large volume at a lower cost. Each process in FMS is managed by a dedicated computer, known as FMS cell computer. Machine loading and unloading, part sequencing, route selection, tool changes and determination of spindle feed rate are conducted under the direct control of this FMS cell computer. Numerical control (NC) machine tools, automated material handling system (AMHS), automated guided vehicles (AGV), conveyors, automated storage and retrieval systems (AS/RS), industrial robots, control software, in-process storage inventories are the other main components of an FMS [1]. Several studies have been devoted to examine the potential benefits from implementing FMS in manufacturing industries. The main advantages of adopting FMS can be realized by its capability of producing a variety of items with superior product quality, reduced set-up time, improved product routing, reduced product completion time, increased machine and resource utilization, lesser floor space requirement, ability to handle changes and ability to quickly manage uncertain customer demands, leading to a highly efficient and focused approach towards manufacturing effectiveness. Due to these reasons, assessment, validation and selection of FMS have now been receiving noteworthy consideration in the manufacturing world. But FMS implementation is not an easy task to perform. It involves huge capital investment, administrative dedication, technological and organizational changes. It may leave a long term impact on the organization's survival to improve and maintain the competitive advantage. So the selection of the most appropriate FMS from a set of realistic configurations requires an extensive analysis and evaluation in the presence of multiple conflicting criteria with several performance measures. Thus, efforts need to be widened to recognize those criteria that influence an FMS selection decision for a given application using some simple and logical methods to eliminate the infeasible alternatives. These FMS selection criteria can be classified as cardinal and ordinal criteria, or beneficial and non-beneficial criteria. Cardinal criteria are those which can be numerically characterized, like capital and maintenance cost, floor space requirement, reduction in work-in-process (WIP) etc. On the other hand, ordinal criteria are qualitative in nature, including increase in market response, improvement in quality etc. In case of ordinal criteria, they are first expressed in linguistic terms, which are then transformed into corresponding fuzzy numbers and lastly converted to crisp scores using some fuzzy conversion scales [2]. Reduction in WIP, improvement in quality etc. are beneficial criteria for which

* E-mail address: prasenjit2007@gmail.com
ISSN: 1791-2377 © 2014 Kavala Institute of Technology. All rights reserved.

higher values are preferable, whereas, capital and maintenance cost, floor space requirement for FMS etc. are non-beneficial criteria, always targeting for lower values. Thus, the manufacturing organizations should follow a multi-stage evaluation process for assessment of FMS investment. In the first stage, the organizations should collect technical data for preliminary FMS design based on some detailed process analysis, production time study, group technology considerations and defining the basic requirements in terms of machines, supporting tools and other necessary accessories. The second stage deals with the validation of FMS implementation, taking into account both financial analysis and assessment of specific problems for which FMS is intended. In the third stage, the required capability of various FMS configurations and layouts are examined using some analytical capacity planning models. A detail description about this phase can be found in Solberg [4] and Suri [5]. This capacity planning stage initiates the bidding process and a request-for-proposal (RFP) is issued to the prospective vendors to collect a comprehensive list about the overall system performance of FMS alternatives. An effective RFP typically reflects the strategy and short/long term business objectives of the organization, depending upon which, the suppliers will be able to offer a similar perspective. Finally, a comparative performance evaluation analysis is conducted to select the best suitable FMS system, addressing organizational requirements, priorities, operational constraints and vendors' service quality etc. This stage involves critical examination about different FMS selection criteria and alternative configurations which form the heart of the present research work.

In the past few decades, a good number of researchers have proposed and applied many decision-making techniques to guide in dealing with the issue of evaluation and selection of advanced manufacturing technologies, like FMS for specific industrial applications. Analytic hierarchy process (AHP) [6-9], data envelopment analysis (DEA) [10-14], mixed integer linear programming model [15], intelligent tools and expert systems [16], decision algorithm based on fuzzy set theory [17], TOPSIS [18], fuzzy multi-objective programming [19], axiomatic design method [20], digraph and matrix approach [21], artificial neural network [22], combinatorial mathematics [23], PROMETHEE [24], analytic network process (ANP) [25], preference selection index (PSI) method [26], GRA [27], principal component analysis (PCA) [28] etc methods have been apllied to solve the FMS selection problems. Although, MCDM methods are observed to have immense potential to deal with such complex decision-making problems in conflicting situations, no effort yet been put to show the effet of normalization techniques on the ranking performance of MCDM methods while solving the FMS slection problems in discrete m,anufacturing environment. Also, very little attempt has been made to compare the relative performance of various MCDM methods employed under same decision-making situation. This paper mainly focuses on the applications of three popular MCDM tools, i.e. PROMETHEE, GRA and TOPSIS methods for effectively solving the FMS selection problems. The effet of various normalization techniques on the ranking performance of these MCDM methods have also been shown.

Sections 2, 3 and 4 of this paper deal with the detailed mathematical formulations of the three considered MCDM methods. In Section 5, a real time FMS selection problem is solved using these MCDM methods. A comparative study between these methods is shown in Section 6. The effects of normalization norms are presented in Section 7. Section 8 concludes the paper.

2. Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)

PROMETHEE method was developed by Brans in 1982, and further extended by Vincke and Brans in 1985 [4]. PROMETHEE is an preference function-based outranking method which can be effectively used for a finite set of alternatives to rank and select on the basis of some mutually independent and conflicting criteria. It is quite simpler in conception and application as compared to other MCDM methods. It is based on the pair-wise comparison of alternatives, considering the deviations that the alternatives show according to each criterion. PROMETHEE I method can provide the partial ordering of the decision alternatives, whereas, PROMETHEE II can derive the full ranking of the alternatives. The procedural steps as involved in PROMETHEE II method are enumerated as below [12,13]:

Step 1: Normalize the decision matrix using the following equation:

$$R_{ij} = [x_{ij} - \min(x_{ij})]/[\max(x_{ij}) - \min(x_{ij})] \quad (i = 1,2,\ldots,n;\ j = 1,2,\ldots,m) \tag{1}$$

For non-beneficial attributes, Eq. (2.28) can be rewritten as below:

$$R_{ij} = [\max(x_{ij}) - x_{ij}]/[\max(x_{ij}) - \min(x_{ij})] \tag{2}$$

Step 2: Calculate the evaluative differences of i^{th} alternative with respect to other alternatives. This step involves the calculation of differences in criteria values between different alternatives pair-wise.

Step 3: Calculate the preference function, $P_j(i,i')$.

The preference function is based on pair-wise comparisons. Here, the deviation between the evaluations of two alternatives on a particular criterion is considered. For small deviation, the decision maker will allocate a small preference to the best alternative and even possibly no preference if he/she considers that this deviation is negligible. The larger the deviation, the larger is the preference. There is no objection to consider that these preferences are real numbers varying between 0 and 1.

For each criterion, the preference function translates the difference between the evaluations obtained by two alternatives into a preference degree ranging from 0 to 1. In order to facilitate the selection of a specific preference function, the following six basic types are proposed by Brans and Mareschal [14], i.e. (a) Usual criterion, (b) U-shape criterion, (c) V-shape criterion, (d) Level criterion, (e) V-shape with indifference criterion, and (f) Gaussian criterion. But these preference functions require the definition of some preferential parameters, such as preference and indifference thresholds. However, in real time applications, it may be difficult for the decision maker to specify which specific form of preference function is suitable for each criterion and also to determine the parameters involved. To avoid this problem, the following simplified preference function is usually adopted:

$$P_j(i,i') = 0 \quad \text{if } R_{ij} \le R_{i'j} \tag{3}$$

$$P_j(i,i') = (R_{ij} - R_{i'j}) \quad \text{if } R_{ij} > R_{i'j} \tag{4}$$

Step 4: Calculate the aggregated preference function taking into account the criteria weights.

Aggregated preference function,

$$\pi(i,i') = \left[\sum_{j=1}^{n} w_j \, P_j(i,i')\right] \Big/ \sum_{j=1}^{n} w_j \tag{5}$$

Step 5: Determine the leaving and the entering outranking flows using the following equations:

Leaving (positive) flow for i[th] alternative,

$$\varphi^{+}(i) = \frac{1}{m-1}\sum_{i'=1}^{m} \pi(i,i') \quad (i \neq i') \tag{6}$$

Entering (negative) flow for i[th] alternative,

$$\varphi^{-}(i) = \frac{1}{m-1}\sum_{i'=1}^{m} \pi(i',i) \quad (i \neq i') \tag{7}$$

The leaving flow expresses how much an alternative dominates the other alternatives, while the entering flow denotes how much an alternative is dominated by the other alternatives.

Step 6: Calculate the net outranking flow for each alternative.

$$\varphi(i) = \varphi^{+}(i) - \varphi^{-}(i) \tag{8}$$

Step 7: Determine the ranking of all the considered alternatives depending on the values of $\varphi(i)$. Thus, the best alternative is the one having the highest $\varphi(i)$ value.

These procedural steps of PROMETHEE II are intended to provide a complete ranking of a finite set of feasible alternatives from the best to the worst.

3. Grey Relational Analysis (GRA) Method

The 'grey' means the primitive data with poor, incomplete and uncertain information in the grey system theory and the incomplete relation of information among this data is called the 'grey relation'. GRA is a part of grey system theory, which is suitable for solving problems with complicated interrelationships between multiple factors and variables. The GRA method can be used to effectively solve complex interrelationships among multiple performance characteristics through optimization of the grey relational grades. It makes use of grey relational generation and calculates the grey relational coefficients to solve uncertain systematic problems under the status of only partially known information. The grey relational coefficient can express the relationship between the desired and actual results, and the grey relational grade is simultaneously computed and used to select and rank the candidate alternatives. As most of the MCDM methods take into account multiple dimensions in criteria and a single dimension in alternatives, the concept of forming order pairs in the GRA method while considering multiple dimensions of criteria with multi-dimensional alternatives is a merit for this decision model to solve different selection problems.

The main procedure of GRA method starts by translating the performance of all the alternatives into a comparability sequence. This step is called grey relational generation. Based on this sequence, a reference sequence (ideal target sequence) is defined. Then, the grey relational coefficients between all the comparability sequences and the reference sequence are computed. Finally, based on these grey relational coefficients, the grey relational grade between the reference sequence and every comparability sequence is calculated. If a comparability sequence translated from an alternative has the highest grey relational grade between the reference sequence and itself, that alternative will be the best choice. The procedural steps of GRA method are presented as below [15]:

Step 1: Grey relation generation (normalization).

When the units of various selection criteria are different, then it is required to process all the performance values for every alternative into a comparability sequence, called normalization, i.e. grey relational generation or data pre-processing. In a decision-making problem, if there are m alternatives and n criteria, the i[th] alternative can be expressed as $Y_i = (y_{i1}, y_{i2}, \ldots, y_{ij}, \ldots, y_{in})$, where y_{ij} is the performance value of criterion j of alternative i. The term Y_i can be translated into the corresponding comparability sequence, $X_i = (x_{i1}, x_{i2}, \ldots, x_{ij}, \ldots, x_{in})$ using Eq. (9) or Eq. (10). If the criterion is beneficial in nature, i.e. higher value is desirable, then the decision matrix can be normalized using Eq. (9). For non-beneficial criteria, Eq. (10) can be used for normalization.

$$x_{ij} = \frac{y_{ij} - \min\{y_{ij}, i = 1,2,\ldots,m\}}{\max\{y_{ij}, i = 1,2,\ldots,m\} - \min\{y_{ij}, i = 1,2,\ldots,m\}} \tag{9}$$

$$x_{ij} = \frac{\max\{y_{ij}, i = 1,2,\ldots,m\} - y_{ij}}{\max\{y_{ij}, i = 1,2,\ldots,m\} - \min\{y_{ij}, i = 1,2,\ldots,m\}} \tag{10}$$

Step 2: Define the reference sequence.

After the grey relation generation procedure, the performance values will lie between 0 and 1. For a criterion j of alternative i, if the value x_{ij} which is normalized using grey relation generation procedure, is equal to 1, or nearer to 1 than the value of the other alternative, it means that the performance of alternative i is the best one for that criterion j. Therefore, an alternative will be the best choice if all of its performance values are closest to or equal to 1. The reference alternative is defined as $X_0 = (x_{01}, x_{02}, \ldots, x_{0j}, \ldots, x_{0n}) = (1,1,\ldots,1,\ldots,\ldots,1)$ and it aims to find the alternative whose comparability sequence is the closest to the reference sequence.

Step 3: Calculate the grey relational coefficient (γ).

Grey relational coefficient is used to determine how close x_{ij} is to x_{0j}. The grey relational coefficient can be calculated using Eq. (11). The larger the value of γ, the closer x_{ij} and x_{0i} are.

$$\gamma(x_{0i}, x_{ij}) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{ij} + \zeta\Delta_{max}} \tag{11}$$

$$for\ i = 1,2,\ldots,m\ and\ j = 1,2,\ldots,n$$

where $\gamma(x_{0i}, x_{ij})$ is the grey relational coefficient between x_{ij} and x_{oj}, $\Delta_{ij} = |x_{0j} - x_{ij}|$,

$$\Delta_{\min} = \min\{\Delta_{ij}, 1,2,...,m; j = 1,2,...,n\},$$
$$\Delta_{\max} = \max\{\Delta_{ij}, i = 1,2,...,m; j = 1,2,...,n\}$$

and ζ is the distinguishing coefficient (ζ Є [0,1]), generally taken as 0.5.

The purpose of the distinguishing coefficient is to expand or compress the range of the grey relational coefficient. Step 4 Compute the grey relational grade.

After calculating the grey relational coefficient $\gamma(x_{0i}, x_{ij})$, the grey relational grade can be calculated using the following equation:

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(x_i, x_{ij}) \qquad \text{for } i = 1,2,..., m \tag{12}$$

where $\sum_{j=1}^{n} w_j = 1$ and w_j is the weight of j^{th} criterion which generally depends on the decision maker. The grey relational grade represents the level of correlation between the reference sequence and the comparability sequence. If the comparability sequence for an alternative gets the highest grey relational grade with the reference sequence, it means that the comparability sequence is most similar to the reference sequence and that alternative will be the best choice to select.

4. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Method

In 1981, Yoon and Hwang [3] developed TOPSIS method based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. The positive-ideal solution is a hypothetical solution for which all the criteria values correspond to the maximum criteria values in the database comprising the satisfying solutions and the negative-ideal solution is a hypothetical solution for which all the criteria values correspond to the minimum criteria values in the database. The TOPSIS method thus gives a solution that is not only closest to the hypothetically best, but also the farthest from the hypothetically worst. This method defines an index called 'similarity index' (or relative closeness) to the positive-ideal solution by combining the proximity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then, it chooses an alternative with the maximum similarity to the positive-ideal solution. The TOPSIS method assumes that each criterion takes either monotonically increasing or monotonically decreasing utility, i.e. the larger the criteria outcome, the greater the preference for benefit attributes and the less the preference for cost attributes. Figure 1 shows that the locations of the positive-ideal (A^+) and the negative-ideal (A^-) solutions in a two-dimensional Euclidean space. The main steps involved in TOPSIS method are enlisted as follows:

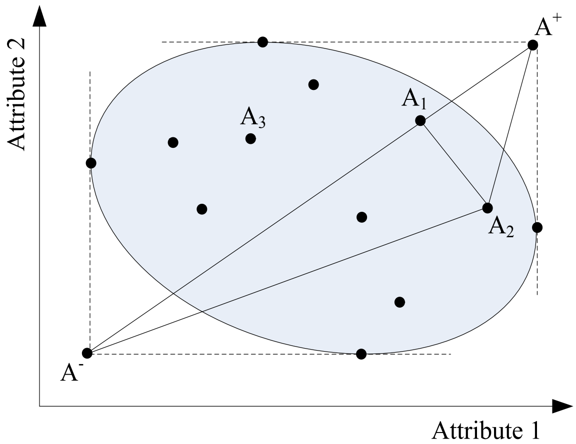

Fig. 1. Euclidean distances to positive-ideal and negative-ideal solutions

Step 1: Determine the goal or objective of the problem and identify the pertinent decision criteria.

Step 2: This step represents a decision matrix based on all the information available on the alternatives and criteria. Each row of this matrix is allocated to one alternative and each column to one criterion. Therefore, an element x_{ij} of the decision matrix gives the value of j^{th} criterion in original non-normalized form and unit for i^{th} alternative. From this decision matrix, obtain the normalized decision matrix, D_{ij} using the following equation:

$$D_{ij} = x_{ij} \Bigg/ \left[\sum_{i=1}^{m} x_{ij}^2\right]^{1/2} \tag{13}$$

Step 3: Obtain the weighted normalized matrix, V_{ij}, by multiplying each element of the column of the matrix D_{ij} with its associated weight w_j.

$$V_{ij} = w_j D_{ij} \tag{14}$$

Step 4: Derive the positive-ideal (best) and the negative-ideal (worst) solutions using following expressions:

$$V^+ = \left\{ \begin{array}{l} \left[\sum_i^{\max} V_{ij} \Big/ j \in J\right], \\ \left[\sum_i^{\min} V_{ij} \Big/ j \in J'\right] / \, i = 1,2,....,m \end{array} \right\} \tag{15}$$
$$= \left(V_1^+, V_2^+, V_3^+, ..., V_n^+\right)$$

$$V^- = \left\{ \begin{array}{l} \left[\sum_i^{\min} V_{ij} \Big/ j \in J\right], \left[\sum_i^{\max} V_{ij} \Big/ j \in J'\right] / \\ i = 1,2,....,m \end{array} \right\} \tag{16}$$
$$= \left(V_1^-, V_2^-, V_3^-, ..., V_n^-\right)$$

where J = (j = 1,2,...,n)/j is associated with beneficial criteria and J′ = (j = 1,2,...,n)/j is associated with non-beneficial criteria.

V_j^+ indicates the positive-ideal (best) value of the considered criteria among all the criteria for different alternatives. In case of beneficial attributes, V_j^+ indicates the higher value of the criterion and on the other hand, for non-beneficial attributes, V_j^+ indicates the lower value of the criterion. On the other hand, V_j^- indicates the negative-ideal (worst) value of the considered criteria among all the criteria for different alternatives. In case of beneficial attributes, V_j^- indicates the lower value of the criterion and the higher value of the criterion for non-beneficial attributes respectively.

Step 5: Calculate the separation measures of each alternative from the positive-ideal and the negative-ideal solutions using the following equations:

$$S_i^+ = \left\{ \sum_{j=1}^{n} \left(V_{ij} - V_j^+\right)^2 \right\}^{0.5}, i = 1,2,\ldots,m \quad (17)$$

$$S_i^- = \left\{ \sum_{j=1}^{n} \left(V_{ij} - V_j^-\right)^2 \right\}^{0.5}, i = 1,2,\ldots,m \quad (18)$$

Step 6: The relative closeness of an alternative to the positive-ideal solution can be computed as follows:

$$P_i = S_i^- / \left(S_i^+ + S_i^-\right) \quad (19)$$

where P_i is the overall performance score for i^{th} alternative.

Step 7: Based on the overall performance scores, the alternatives are ranked in descending order.

5. FMS selection problem

To demonstrate the computational flexibility and applicability of PROMETHEE II, GRA and TOPSIS methods, the FMS selection problem of Karsak and Kuzgunkaya [19] is considered here. This FMS selection problem consists of eight FMS alternatives with seven FMS selection criteria and a fuzzy multi-objective programming approach was adopted by Karsak and Kuzgunkaya [19] to solve that problem. Rao and Parnichkun [23] solved the same FMS selection problem using a combinatorial mathematics (CM)-based decision-making method. In this present research work, the attributes considered are same as those of Karsak and Kuzgunkaya [19] and they are reduction in labour cost (RLC), reduction in WIP (RWP), reduction in set up cost (RSC), increase in market response (IMR), increase in quality (IQ), capital and maintenance cost (CMC) and floor space used (FSU). Among those, five criteria were expressed quantitatively and two criteria (IMR and IQ) were expressed qualitatively. In this FMS selection problem, RLC, RWP, RSC, IMR and IQ are beneficial in nature, so higher values are desirable. On the other hand, CMC and FSU are non-beneficial criteria, and their lower values are preferable. Rao and Parnichkun [23] applied AHP method to calculate the normalized weights of the criteria as $w_{RLC} = 0.1129$, $w_{RWP} = 0.1129$, $w_{RSC} = 0.0445$, $w_{IMR} = 0.1129$, $w_{IQ} = 0.2861$, $w_{CMC} = 0.2861$ and $w_{FSU} = 0.0445$. These criteria weights are used here for the subsequent analyses using the eight preference ranking-based methods. Table 1 presents the decision matrix as considered by Karsak and Kuzgunkaya [19]. The qualitative measures of IMR and IQ criteria are converted into appropriate quantitative data using an 11-point fuzzy conversion scale, as proposed by Rao and Parnichkun [23], and are given in Table 2.

Table 1. Decision matrix of FMS selection problem [19]

FMS	RLC (%)	RWP (%)	RSC (%)	IMR	IQ	CMC ($000)	FSU (sq. ft.)
1	30	23	5	Good	Good	1500	5000
2	18	13	15	Good	Good	1300	6000
3	15	12	10	Fair	Fair	950	7000
4	25	20	13	Good	Good	1200	4000
5	14	18	14	Worst	Good	950	3500
6	17	15	9	Good	Fair	1250	5250
7	23	18	20	Fair	Good	1100	3000
8	16	8	14	Worst	Fair	1500	3000

Table 2. Modified decision matrix

FMS	RLC	RWP	RSC	IMR	IQ	CMC	FSU
1	30	23	5	0.745	0.745	1500	5000
2	18	13	15	0.745	0.745	1300	6000
3	15	12	10	0.5	0.5	950	7000
4	25	20	13	0.745	0.745	1200	4000
5	14	18	14	0.255	0.745	950	3500
6	17	15	9	0.745	0.5	1250	5250
7	23	18	20	0.5	0.745	1100	3000
8	16	8	14	0.255	0.5	1500	3000

5.1 PROMETHEE II method

At first, this FMS selection problem is solved using PROMETHEE II method. For this, the decision matrix, as given in Table 2, is first normalized using Eq. (1) or (2) depending on the nature of the considered attributes. The normalized decision matrix is shown in Table 3.

Table 3. Normalized decision matrix

FMS	RLC	RWP	RSC	IMR	IQ	CMC	FSU
1	1.0000	1.0000	0.0000	1.0000	1.0000	0.0000	0.5000
2	0.2500	0.3333	0.6667	1.0000	1.0000	0.3636	0.2500
3	0.0625	0.2667	0.3333	0.5000	0.0000	1.0000	0.0000
4	0.6875	0.8000	0.5333	1.0000	1.0000	0.5455	0.7500
5	0.0000	0.6667	0.6000	0.0000	1.0000	1.0000	0.8750
6	0.1875	0.4667	0.2667	1.0000	0.0000	0.4545	0.4375
7	0.5625	0.6667	1.0000	0.5000	1.0000	0.7273	1.0000
8	0.1250	0.0000	0.6000	0.0000	0.0000	0.0000	1.0000

The preference function and aggregated preference function values are calculated for all the pairs of alternatives, using Eq. (3) or (4) and (5) respectively. Now, the leaving and the entering flows for different FMS alternatives are computed using Eq. (6) and Eq. (7) respectively, and are given in Table 4. Then applying Eq. (8), the net outranking flow values for different FMS alternatives are calculated, as shown in Table 5. The FMS alternatives are now ranked according to the values of the net outranking flow as also exhibited in Table 5. The best choice of FMS for the given application is FMS 7, whereas, FMS 8 is the worst choice.

Table 4. Leaving and entering flows for different FMS alternatives

FMS	$\varphi^+(i)$	$\varphi^-(i)$
1	0.3201	0.2030
2	0.2294	0.1550
3	0.1838	0.3552
4	0.3307	0.0615
5	0.3292	0.1391
6	0.1139	0.3383
7	0.3384	0.0686
8	0.0313	0.5562

Table 5. Net outranking flow values for FMS alternatives

FMS	$\varphi(i)$	Rank
1	0.1172	4
2	0.0745	5
3	-0.1714	6
4	0.2692	2
5	0.1901	3
6	-0.2245	7
7	0.2698	1
8	-0.5248	8

5.2 GRA method

The modified decision matrix, as shown in Table 2, is first normalized using Eq. (9) or (10). The grey relational coefficients are now calculated using Eq. (11) and are shown in Table 6. Here, the value of the distinguishing coefficient (ζ) is considered as 0.5. Based on the grey relational coefficient values, the corresponding grey relational grade (GRG) for each FMS alternative is computed using Eq. (12), as given in Table 7. The alternative with the highest grey relational grade with the reference sequence is the best choice. From Table 7, it is observed that the grey relational grade for alternative FMS 7 is the highest and the ranking of the FMS alternatives is 7 > 4 > 5 > 1 > 2 > 3 > 6 > 8. Thus, FMS 7 is the best choice to select followed by FMS 4. FMS 8 is the worst choice.

Table 6. Grey relational coefficients

FMS	RLC	RWP	RSC	IMR	IQ	CMC	FSU
1	1.0000	1.0000	0.3333	1.0000	1.0000	0.3333	0.5000
2	0.4000	0.4286	0.6000	1.0000	1.0000	0.4400	0.4000
3	0.3478	0.4054	0.4286	0.5000	0.3333	1.0000	0.3333
4	0.6154	0.7143	0.5172	1.0000	1.0000	0.5238	0.6667
5	0.3333	0.6000	0.5556	0.3333	1.0000	1.0000	0.8000
6	0.3810	0.4839	0.4054	1.0000	0.3333	0.4783	0.4706
7	0.5333	0.6000	1.0000	0.5000	1.0000	0.6471	1.0000
8	0.3636	0.3333	0.5556	0.3333	0.3333	0.3333	1.0000

Table 7. Grey relational grades

FMS	GRG	Rank
1	0.7573	4
2	0.6629	5
3	0.5569	6
4	0.7870	2
5	0.7755	3
6	0.4817	7
7	0.8130	1
8	0.3763	8

5.3 TOPSIS method

As the seven considered FMS selection criteria are having different units, it is necessary to normalize their values using Eq. (13) and obtain the normalized decision matrix. The weighted normalized decision matrix is developed using Eq. (14), as shown in Table 8. The positive-ideal and the negative-ideal solutions are determined by choosing the maximum and minimum criteria values in Table 9 depending on whether the criterion is beneficial or non-beneficial in nature. The separation measures are computed using Eq. (17) and Eq. (18), as given in Table 10.

Table 8. Weighted normalized decision matrix

FMS	RLC	RWP	RSC	IMR	IQ	CMC	FSU
1	0.0586	0.0556	0.0060	0.0498	0.1135	0.1228	0.0164
2	0.0351	0.0314	0.0179	0.0498	0.1135	0.1065	0.0197
3	0.0293	0.0290	0.0119	0.0334	0.0762	0.0778	0.0230
4	0.0488	0.0484	0.0155	0.0498	0.1135	0.0983	0.0131
5	0.0273	0.0435	0.0167	0.0171	0.1135	0.0778	0.0115
6	0.0332	0.0363	0.0107	0.0498	0.0762	0.1024	0.0172
7	0.0449	0.0435	0.0239	0.0334	0.1135	0.0901	0.0098
8	0.0312	0.0193	0.0167	0.0171	0.0762	0.1228	0.0098

Table 9. Positive-ideal and negative-ideal solutions

Criteria	RLC	RWP	RSC	IMR	IQ	CMC	FSU
V_i^+	0.0586	0.0556	0.0239	0.0498	0.1135	0.0778	0.0098
V_i^-	0.0273	0.0193	0.0060	0.0171	0.0762	0.1228	0.0230

Table 10. Separation measures

FMS	S_i^+	S_i^-
1	0.0551	0.0693
2	0.0535	0.0556
3	0.0667	0.0493
4	0.0341	0.0675
5	0.0520	0.0652
6	0.0626	0.0432
7	0.0338	0.0642
8	0.0837	0.0174

Using these separation measures, the relative closeness (P_i) values of all the FMS alternatives to the positive-ideal solution are estimated using Eq. (19) and are shown in Table 11. The FMS with the highest P_i value is the best choice. Table 11 shows the ranking preorders of the FMS alternatives as 4 > 7 > 1 > 5 > 2 > 3 > 6 > 8, indicating FMS 4 as the best choice, followed by FMS 7 for the given application.

Table 11. Relative closeness values for FMS alternatives

FMS	P_i	Rank
1	0.5570	3
2	0.5098	5
3	0.4250	6
4	0.6644	1
5	0.5565	4
6	0.4085	7
7	0.6553	2
8	0.1722	8

6. Comparative analysis

The aim of the comparative analysis is to test the level of ranking agreement between the three MCDM methods for the considered FMS selection problem. Weights and performance measures in the evaluation matrix are held constant for each of these methods. Three tests are performed to measure the level of ranking agreement:

a) In the first test, similarity of rankings produced by all the considered MCDM methods is determined by Kendall's coefficient of concordance (z) value using Eq. (20). The z value ranges from 0 to 1. Higher the value of z, better is the rank similarity between the considered methods. A z value of one indicates a perfect match between the results obtained by the available methods.

$$z = \frac{\sum_{i=1}^{m}\left(S_i - \frac{\sum_{i=1}^{m} S_i}{m}\right)^2}{\frac{1}{12}k^2\left(m^3 - m\right)} \quad (20)$$

where, m denotes number of alternatives and k is the number of MCDM methods, which equals 3 for this paper and
S_i is the sum of ranks assigned to a decision alternative i across all k MCDM methods.

b) In the second test, similarity between two sets of rankings is validated using Spearman's rank correlation coefficient (r_s), as given by Eq. (21). Usually, r_s value lies between –1 and +1, where the value of +1 indicates a perfect match between two sets of rank orderings and a –1 value indicates a strong negative correlation between the methods.

$$r_s = 1 - 6\frac{\sum_{i=1}^{m} D_i^2}{m(m^2 - 1)} \quad (21)$$

where, D_i is the difference between ranks R_i and R'_i and n is the number of alternatives.

c) Average r_s value between these MCDM methods is also computed to determine the mean ranking agreement among themselves.

In order to compare the relative performances of the three MCDM methods with respect to the CM-based decision-making approach, as adopted by Rao and Parnichkun [23] for solving this FMS selection problem, the results of the three performance tests are now discussed. Fig. 2 and Table 12 show the ranking preorders of the FMS alternatives as obtained using different MCDM methods.

The overall ranking agreement between all the considered methods is first determined using z value. For this FMS selection problem, the z value is obtained as 0.9554, which indicates an almost perfect rank conformity between these methods.

The r_s values are then calculated for all the pairs of these methods. Table 13 exhibits that the r_s values between different pairs of methods lie in a range of 0.9047 and 1.0000 signifying almost perfect agreement between these methods.

Average r_s value between these MCDM methods, as shown in Table 13, is also computed to determine the mean ranking agreement among themselves.

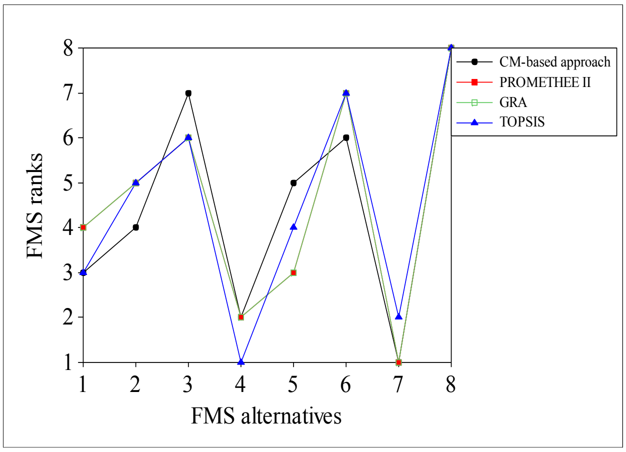

Fig. 2. Comparative rankings for FMS selection problem

Table 12. Ranking preorders obtained from different MCDM methods

FMS	CM-based approach [23]	PROMETHEE II	GRA	TOPSIS
1	3	4	4	3
2	4	5	5	5
3	7	6	6	6
4	2	2	2	1
5	5	3	3	4
6	6	7	7	7
7	1	1	1	2
8	8	8	8	8

Table 13. Spearman's rank correlation coefficient values

Method	PROMETHEE II	GRA	TOPSIS	Mean r_s value
Rao and Parnichkun [23]	0.9047	0.9047	0.9285	0.9126
PROMETHEE II		1.0000	0.9667	0.98335
GRA			0.9667	0.98335

7. Effect of normalization norm

It is a well known fact that any MCDM model may lack in the delivery of the absolute optimum solution, although, they are capable of deciding over the best options among some predetermined alternatives. Also, if not properly assigned, normalization norms within the solution methods may fail to reveal the actual decision. In fact, while the normalization process scales the criteria values to be approximately of the same magnitude, different normalization techniques may yield different solutions and, therefore, may cause deviation from the originally recommended solutions. This paper particularly concentrates on the effect of different normalization methods in the context of MCDM models, with specific concentration to the domain of FMS selection problem.

To investigate the influences of different normalization procedures on the ranking performance of the considered MCDM methods while solving the given FMS selection problem, the following five different normalization approaches are considered [154] here.

a) Vector normalization (VN) method

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{ for beneficial criteria} \tag{22}$$

$$r_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{ for non-beneficial criteria} \tag{23}$$

b) Weitendorf's linear normalization (WLN) method

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \text{ for beneficial criteria} \tag{24}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \text{ for non-beneficial criteria} \tag{25}$$

c) Jüttler's-Körth's normalization (JKN) method

$$r_{ij} = 1 - \left| \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij}} \right| \text{ for beneficial criteria} \tag{26}$$

$$r_{ij} = 1 - \left| \frac{\min_i x_{ij} - x_{ij}}{\min_i x_{ij}} \right| \text{ for non-beneficial criteria} \tag{27}$$

d) Non-linear normalization (NLN) method

$$r_{ij} = \left(\frac{x_{ij}}{\max_i x_{ij}} \right)^2 \text{ for beneficial criteria} \tag{28}$$

$$r_{ij} = \left(\frac{\min_i x_{ij}}{x_{ij}} \right)^2 \text{ for non-beneficial criteria} \tag{29}$$

where x_{ij} is the performance of i^{th} alternative with respect to j^{th} criterion and r_{ij} is the normalized x_{ij} value.

Table 14 shows the ranking performance for the three MCDM methods with respect to different normalization procedures. From this table, it is clearly revealed that the PROMETHEE II method remains less affected by different normalization procedures with the highest mean rs value of 0.9167, on the other hand, TOPSIS is the most sensitive MCDM method with the least mean rs value of 0.5654.

When the mean r_s values for the four normalization procedures are computed separately for different MCDM methods as showm in Fig. 3 (a) and (b), it is highlighted that the vector normalization (VN) is the most preferred procedure. The effectiveness of the remaining normalization procedures are more or less the same.

Table 14. Ranking performance for different normalization procedures

MCDM method	Normalization norm	Alternative								r_s	Mean r_s
		FMS 1	FMS 2	FMS 3	FMS 4	FMS 5	FMS 6	FMS 7	FMS 8		
TOPSIS	VN	1	3	8	2	6	5	4	7	0.6905	0.5654
	WLN	1	2	8	3	5	7	4	6	0.6429	
	JKN	1	2	8	3	7	6	5	4	0.3333	
	NLN	1	3	8	2	7	5	4	6	0.5952	
PROMETHEE II	VN	3	5	7	1	4	6	2	8	0.9762	0.9167
	WLN	5	4	6	3	1	7	2	8	0.7857	
	JKN	4	5	6	2	3	7	1	8	0.9524	
	NLN	4	5	6	2	3	7	1	8	0.9524	
GRA	VN	3	5	7	1	4	6	2	8	0.9762	0.880
	WLN	2	5	6	3	1	7	4	8	0.7857	
	JKN	4	5	6	2	3	7	1	8	0.9524	
	NLN	1	5	6	3	2	7	4	8	0.8095	

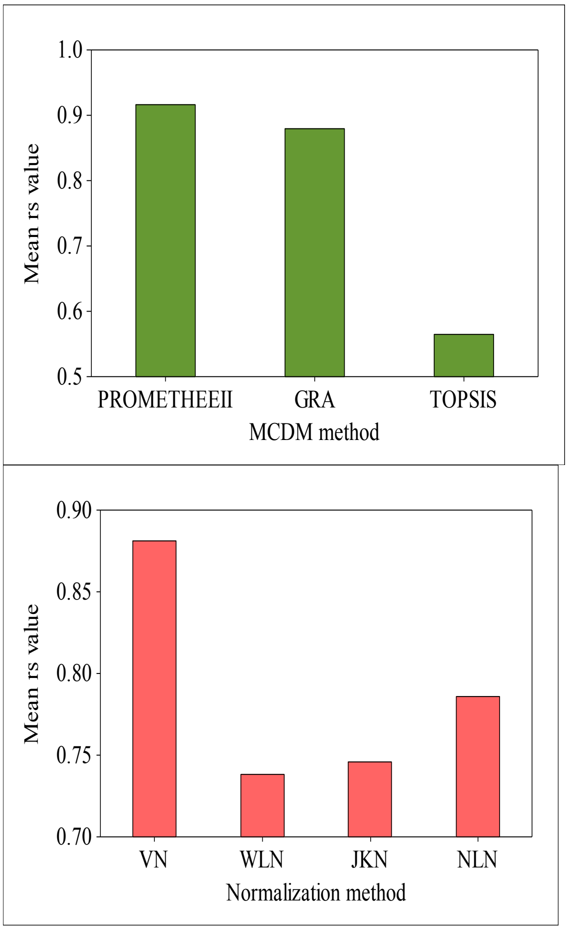

Fig. 3. Mean r_s values of different MCDM and normalization methods

8. Conclusion and discussion

All the three considered MCDM methods are quite capable in solving real time FMS selection decision-making problems and the rankings of the FMS alternatives as obtained by these methods are almost similar to those observed by the past researchers. The r_s values are considered here as a measure to check the similarity between two set of orderings. High r_s values suggest that any of these MCDM methods may be applied to solve any of the decision-making problems. Hence, it is advisable that the decision makers should focus more on the development of the related decision matrix by choosing the appropriate criteria values, and not on selecting a particular MCDM method to implement. Among the four methods as adopted to normalize the criteria values in the decision matrices, it is observed that the vector normalization procedure is the most preferred choice. PROMETHEE II method remains lessaffected by different normalization procedures, on the other hand, TOPSIS is the most sensitive MCDM method. The average r_s values for the four normalization procedures also highlight that the vector normalization (VN) is the most preferred procedure.

References

[1] V.Malhotra, T. Raj and A.Arora, Excellent techniques of manufacturing systems: RMS and FMS, International Journal of Engineering Science and Technology, **2**, 137, (2010).
[2] R.V. Rao, Decision Making in the Manufacturing Environment using Graph Theory and Fuzzy Multi Attribute Decision Making Methods, Springer-Verlag, London, (2007).
[3] A. Arbel and A. Seidmann, Performance evaluation of flexible manufacturing systems, IEEE Transactions on Systems, Man, and Cybernetics, **14**, 606, (1984).
[4] J.J. Solberg, Capacity planning with a stochastic work flow model, AIIE Transactions, **13**, 116, (1981).
[5] R. Suri, New techniques for modelling and control flexible automated manufacturing systems, Proc. IFAC 8th Triennial World Congress, (Kyoto), **175**, (1981).
[6] V. Srinivasan and R.A. Millen, Evaluating flexible manufacturing systems as a strategic investment, Proc. 2nd ORSA/TIMS Conference on Flexible Manufacturing Systems: Operations Research Models and Applications, University of Michigan, (U.S.A.), **83**, (1986).
[7] R.N. Wabalickis, Justification of FMS with the analytic hierarchy process, Journal of Manufacturing Systems, **7**, 175, (1988).
[8] A. Stam and M. Kuula, Selecting a flexible manufacturing system using multiple criteria analysis, International Journal of Production Research, **29**, 803, (1991).
[9] O. Bayazit, Use of AHP in decision-making for flexible manufacturing systems, Journal of Manufacturing Technology Management, **16**, 808, (2005).
[10] J. Shang and T. Sueyoshi, A unified framework for the selection of a flexible manufacturing system, European Journal of Operational Research, **85**, 297, (1995).
[11] J. Sarkis, Evaluating flexible manufacturing systems alternatives using data envelopment analysis, The Engineering Economist, **43**, 25, (1997).
[12] S. Talluri, M.M. Whiteside and S.J. Seipel, A nonparametric stochastic procedure for FMS evaluation, European Journal of Operational Research, **124**, 529, (2000).
[13] E.E. Karsak, Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data, International Journal of Advanced Manufacturing Technology, **35**, 867, (2008).
[14] S-T. Liu, A fuzzy DEA/AR approach to the selection of flexible manufacturing systems, Computers & Industrial Engineering, **54**, 66, (2008).
[15] V. Lotfi, Implementing flexible automation: A multiple criteria decision making approach, International Journal of Production Economics, **38**, 255, (1995).
[16] F.T.S. Chan, B. Jiang and N.K.H. Tang, The development of intelligent decision support tools to aid the design of flexible manufacturing systems, International Journal of Production Economics, **65**, 73, (2000).
[17] E.E. Karsak and E. Tolga, Fuzzy multi-criteria decision-making procedure for evaluating advanced manufacturing system investments, International Journal of Production Economics, **69**, 49, (2001).
[18] E.E. Karsak, Distance-based fuzzy MCDM approach for evaluating flexible manufacturing system alternatives, International Journal of Production Research, **40**, 3167, (2002).
[19] E.E. Karsak and O. Kuzgunkaya, A fuzzy multiple objective programming approach for the selection of a flexible manufacturing system, International Journal of Production Economics, **79**, 101, (2002).
[20] O. Kulak and C. Kahraman, Multi-attribute comparison of advanced manufacturing systems using fuzzy vs. crisp axiomatic design approach, International Journal of Production Economics, **95**, 415, (2005).
[21] R.V. Rao, A decision-making framework model for evaluating flexible manufacturing systems using digraph and matrix methods, International Journal of Advanced Manufacturing Technology, **30**, 1101, (2006).
[22] A. Bhattacharya, A. Abraham, P. Vasant and C. Grosan, Evolutionary artificial neural network for selecting flexible manufacturing systems under disparate level-of-satisfaction of decision maker, International Journal of Innovative Computing, Information and Control, **3**,131, (2007).
[23] R.V. Rao and M. Parnichkun, Flexible manufacturing system selection using a combinatorial mathematics-based decision-making method, International Journal of Production Research, **47**, 6981, (2009).
[24] M.S. Mehrabad and M. Anvari, Provident decision making by considering dynamic and fuzzy environment for FMS evaluation, International Journal of Production Research, **48**, 4555, (2010).
[25] R. Kodali and G. Anand, Application of analytic network process for the design of flexible manufacturing systems, Global Journal of Flexible Systems Management, **11**, 39, (2010).
[26] K.D. Maniya and M.G. Bhatt, The selection of flexible manufacturing system using preference selection index method, International Journal of Industrial and Systems Engineering, **9**, 330, (2011).
[27] P.R. Dhal, S. Datta and S.S. Mahapatra, Flexible Manufacturing System selection based on grey relation under uncertainty, International Journal of Services and Operations Management, **8**, 516, (2011).
[28] K. Rezaie and A. Haeri, Using PCA and Pareto optimality to select flexible manufacturing systems, Proc. IEEE International Systems Conference (SysCon), (Iran), **538**, (2011).
[29] J. Figueira, S. Greco and M. Ehrgott, Multiple criteria decision making analysis: State of the art surveys, Springer Science and Business Media Inc., Bostan, (2005).
[30] M. Doumpos and C. Zopounidis, A multicriteria classification approach based on pairwise comparisons, European Journal of Operational Research, **158**, 378, (2004).
[31] S. Hajkowicz and A. Higgins, A comparison of multiple criteria analysis techniques for water resource management, European Journal of Operational Research, **184**, 255, (2008).
[32] S.J. Chen and C.L. Hwang, Fuzzy multiple attribute decision making: Methods and applications, Springer-Verlag, New York, (1992).
[33] Y. Kuo, T. Yang and G.W. Huang, The use of grey relational analysis in solving multiple attribute decision making problems, Computers & Industrial Engineering, **55**, 80, (2008).
[34] K.P. Yoon and C-L. Hwang, Multiple attribute decision making - An introduction, SAGE Publications Inc., California, (1995).
[35] Z. Turskis, E.K. Zavadskas and F. Peldschus, Multi-criteria optimization system for decision making in construction design and management, Engineering Economics, **61**, 7, (2009).