Volume 3, Number 4, 2014

International Journal of Research in Industrial Engineering

www.nvlscience.com

Solving a Facility Location Problem by Three Multi-Criteria Decision Making Methods

M. Niyazi, R. Tavakkoli-Moghaddam*

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

A R T I C L E   I N F O

Article history :
Received:
June12, 2014
Revised:
September 15, 2014
Accepted:
November 10, 2014
Available online:
January 23, 2016

Keywords:

Facility location, MCDM methods, REGIME,ARAS,COPRAS, TOPSIS

A B S T R A C T

Selecting the most appropriate and optimal facility location for a new organization or expansion of an existing location is an important strategic issue. The location, which results in higher economic benefits through increased productivity and good distribution network, is the best location. It is necessary to compare the performance characteristics in a decisive way when a choice is to be made from among several alternative facility locations. While the facility location selection problem includes multiple conflicting criteria and a finite set of potential candidate alternatives, different multi-criteria decision making (MCDM) methods can be effectively applied to solve such type of problem. In this paper, we apply three MCDM methods on a facility location selection problem and their relative ranking performances are compared. Because of disagreement in the ranks obtained by the three different MCDM methods, a final ranking method based on REGIME is also proposed to facilitate the decision making process. Then, the results of this study are compared by the results of the same study.

1. Introduction

Facility layout is explained as the most effective physical arrangement of the manufacturing facilities (i.e., machines, processing equipment and service departments) of a plant and its different parts to achieve the best coordination and efficiency in the usage of machines, manpower and materials resulting in the smoothest and fastest production activities. Designing a facility layout is not necessary only at the time of establishing a new plant but also during the production process, because of various reasons, such as improvement in manufacturing procedure, introduction of new method, change in product and its design. Minimum material handling, providing safe working place leading to minimum accidents and hazards

* Corresponding author
E-mail address: tavakoli@ut.ac.ir

Please cite this article in press as: M. Niyazi, R. Tavakkoli-Moghaddam, Solving a Facility Location Problem by Three Multi-Criteria Decision Making Methods, Int. J. of Research in Industrial Engineering (2014)

to the personnel, providing sufficient place for maintenance as well as improve overall productivity are required for a good facility layout. A good placement of facilities can contribute to overall efficiency of operations and reduce almost 50% of the total operating expenses [1]. Designers can plan a good number of layout design alternatives considering multiple arrangements of the manufacturing facilities, leading to dissimilar advantages and disadvantages over each other. Need for continuous improvement in productivity results in the development of more efficient manufacturing facilities and processes, which subsequently considers additional evaluation criteria, to be considered for selecting the best facility layout. So, due to the involvement of several conflicting criteria, the decision for suitable selection of a facility layout now becomes more complicated.

Choosing the best facility layout for a given manufacturing organization from a finite set of feasible alternatives is an example of a multi-criteria decision making (MCDM) problem. The facility layout selection decision is based on evaluating the performance of alternatives expressed in qualitative and quantitative measures. In the past studies in a facility layout selection field, it is shown that qualitative performance measures of the alternatives should first be converted into quantitative scores before applying any decision-making method. Yang and Kuo [2] applied analytic hierarchy process (AHP) method, while Rao and Singh [3] adopted a fuzzy set theory to convert qualitative performance measures into the corresponding quantitative scores. The complexity of facility layout selection problems increases by converting the performance measures from qualitative to quantitative scores. Hence, a strong mathematical model, which is capable to deal with both qualitative and quantitative performance measures, is needed to solve facility layout design problems. Such an MCDM approach having advantage of taking into account the decision makers' subjective judgments about different alternatives with respect to several evaluation criteria and translating those attributes into relevant quantitative scores is Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). This ability of the MACBETH method verifies its applicability for solving facility layout selection problems.

The past studies have applied different mathematical approaches for solving facility layout selection problems. A facility layout ranking and selection model, based on linear assignment method for the single and group decision makers was developed by [4]. Enea et al. [5] implemented a genetic algorithm employing the concepts of evolutionary hybrid algorithms for facility layout selection. A combined data envelopment analysis (DEA) and AHP method-based approach for facility layout design selection and ranking of the alternatives was proposed by [6]. The design alternatives and performance measures on qualitative criteria were generated using a computer-aided layout planning tool (VisFactory), while the performance measures on quantitative criteria were developed by using the AHP method. Further, ranking of the alternatives was obtained using the DEA method. Grey relational analysis (GRA) for solving facility layout selection problems was adopted by [7]. Athawale and Chakraborty [8] applied a PROMETHEE-II (Preference Ranking Organization Method for Enrichment Evaluation) method for facility layout selection. Also, an ELECTRE-II (Elimination and Et Choice Translating Reality) method for ranking and selecting the best facility layout for a manufacturing environment was proposed by [9]. Maniya and Bhatt [10] proposed a method based on a preference selection index (PSI) method, for selection of facility layout and also performed a subjective cost benefit analysis to study the benefits to cost to the organization. An MCDM approach, in where a rough set theory was integrated with AHP to obtain the values of criteria weights, was applied by [11]. Further, the ranking of the alternative facility layout designs was obtained using a TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method.

Yang and Deuse [12] integrated AHP with the PROMETHEE-II method for ranking and selecting the best facility layout. A weighted Euclidean distance-based approach was applied to deal with plant layout design selection problems by [3]. To represent the qualitative performance scores, a ranked value judgment on a fuzzy conversion scale was suggested. Mohamadghasemi and Hadi-Vencheh [13] presented an integrated approach for incorporating qualitative judgments of criteria in a facility layout design problem as well as ranking of the alternatives. To determine the performance measures related to qualitative criteria, the synthetic value of a fuzzy judgment approach was applied, while non-linear programming (NLP) was employed to derive the final ranking of the alternatives. Also, an integrated AHP-NLP approach for facility layout design selection was presented by [13]. Alternative facility layout designs generated by the use of Spiral software were selected using NLP, while the AHP method was adopted for obtaining the criteria weight values.

In this paper, data have been collected from a facility location selection problem by [14] consisting of multiple conflicting criteria and having a finite set of potential candidate alternatives. Then, an attempt has been made to solve it with the help of three well-known MCDM methods. Very little attempt has been made to compare the relative performances of the MCDM methods while solving the decision making problems. Although in the literature, there are many studies on solving facility layout selection problems using different mathematical approaches, specially employing MCDM methods. The main focus area of this paper is to compare the relative performances of three well-known MCDM methods.

This paper includes the following structure. The related literature is reviewed in the first section. Three MCDM methods are presented in Section 2. Then in Section 3, a case study is presented and the computational results of this study are presented in Section 4. Finally, the conclusion of this study is provided in Section 5.

2. Multi-Criteria Decision Making Methods

Multi-criteria decision making (MCDM) refers to making decisions while there are multiple, usually conflicting criteria. Now, various MCDM methods are being applied in strategic planning that can also be effectively used to select the most suitable facility layout for a given industrial organization. As there are a large number of available MCDM methods, varying complexity and possibly solutions, the decision maker also faces the problem of selecting the most suitable MCDM method among several feasible alternatives. Any MCDM problem can be represented by a matrix (X) consisting of m alternatives and n criteria.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

where *xij* is the performance measure of the *i*-th alternative on the *j*-th criterion. In MCDM methods, it is also required to determine the priority weight (*wj*) of each criterion such that the sum of weights for all the criteria equals to one. By using AHP or entropy method, these priority weights can be determined. In this paper, we use the following MCDM methods in order to compare the ranking performances of different MCDM methods while solving a facility location selection problem.

2.1. ARAS Method

The typical MCDM problem is to deal with the task of ranking a finite number of decision alternatives, which each of them is explicitly described in terms of different decision criteria that should be taken into account simultaneously. The Additive Ratio Assessment (ARAS) method was introduced by [15]. In the ARAS method, a utility function value which determines the complex relative efficiency of a feasible alternative is directly proportional to the relative effect of values and weights of the main criteria considered in a project.

The first stage of this method is to form the decision-making matrix (DMM). In the MCDM of the discrete optimization problem, each problem is represented by the following DMM of preferences for m feasible alternatives (i.e., in rows) rated on n sign full criteria (i.e., in columns):

$$X = \begin{pmatrix} x_{01} & x_{0j} & x_{0n} \\ \vdots & \ddots & \vdots \\ x_{i1} & x_{ij} & x_{in} \\ \vdots & \ddots & \vdots \\ x_{m1} & x_{mj} & x_{mn} \end{pmatrix}; \quad i = 0,\dots,\mathrm{m};\ j = 1,\dots,\mathrm{n} \tag{1}$$

where *m* is the number of alternatives, *n* is the number of criteria describing each alternative, *xijis* the value that represents the performance value of the *i*-th alternative in terms of the *j*-th criterion, and *x0jis* the optimal value of the *j*-th criterion. If an optimal value of the *j*-th criterion is unknown, then we have:

$$\begin{aligned} &\mathrm{x0j} = \max_i x_{ij}, \text{ if } \max_i x_{ij} \text{ is preferable;} \\ &\mathrm{x0j} = \min_i x_{ij}^*, \text{ if } \min_i x_{ij}^* \text{ is preferable;} \end{aligned} \tag{2}$$

The performance values *xij* and the criteria weights *wj* are usually considered as the entries of a DMM. The system determination of criteria as well as the values and initial weights of criteria are done by experts. The information can be corrected by the interested parties by taking into account their goals and opportunities. Then in several stages, the determination of the priorities of alternatives is carried out. Usually, the criteria have different dimensions. In the next stage, the dimensionless weighted values are received from the comparative criteria. The ratio to the optimal value is used in order to avoid the difficulties caused by different dimensions of the criteria. There are various theories that describe the ratio to the optimal value. However, by applying the normalization of a DMM, the values are mapped either on the interval [0, 1] or the interval [0, ∞]. In the second stage, the initial values of all the criteria are normalized - defining values $\overline{x_{ij}}$ of a normalized decision-making matrix $\overline{X}$.

$$\overline{X} = \begin{pmatrix} \overline{x}_{01} & \overline{x}_{0j} & \overline{x}_{0n} \\ \vdots & \ddots & \vdots \\ \overline{x}_{i1} & \overline{x}_{ij} & \overline{x}_{in} \\ \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \overline{x}_{mj} & \overline{x}_{mn} \end{pmatrix}; \quad i = 0,\ldots,\mathrm{m};\ j = 1,\ldots,\mathrm{n} \tag{3}$$

The normalization of criteria, whose preferable values are maxima, is done by applying a two-stage procedure as follows:

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{4}$$

All the criteria having different dimensions can be compared when the dimensionless values of the criteria are known. Defining a normalized-weighted matrix $-\hat{x}$ - is the third stage. We can evaluate the criteria with weights 0 < w_j < 1. As weights are always subjective and influence the solution, only well-founded weights should be used because. Usually determination of the values of weight w_j is done by the expert evaluation method. The sum of weights w_j will be limited as follows:

$$\sum_{j=1}^{n} w_j = 1 \tag{5}$$

$$\hat{X} = \begin{pmatrix} \hat{x}_{01} & \hat{x}_{0j} & \hat{x}_{0n} \\ \vdots & \ddots & \vdots \\ \hat{x}_{i1} & \hat{x}_{ij} & \hat{x}_{in} \\ \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \hat{x}_{mj} & \hat{x}_{mn} \end{pmatrix}; \quad i = 0,\ldots,\mathrm{m};\ j = 1,\ldots,\mathrm{n} \tag{6}$$

Normalized-weighted values of all the criteria are calculated by:

$$\hat{x}_{ij} = \overline{x}_{ij} w_j \ ; \ i = 0,\ldots,m \tag{7}$$

where w_j is the weight (importance) of the j-th criterion and $\overline{x_{ij}}$ is the normalized rating of the j-th criterion. The optimality function values are computed by:

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}\ ; i = 0,...,m \tag{8}$$

where S_i is the value of optimality function of the i-th alternative.

The best and least ones are the biggest and worst values, respectively. Considering the calculation process, the optimality function Si has a direct and proportional relationship with the values x_{ij} and weights w_j of the investigated criteria and their relative influence on the final result. Therefore, the greater the value of the optimality function Si, the more effective the alternative. According to the value Si, the priorities of alternatives can be determined. As a result, evaluating and ranking decision alternatives will be convenient when this method is used.

The alternative utility degree is determined by a comparison of the variant, which is analyzed with the ideally best one $S0$. The equation used for the calculation of the utility degree K_i of an alternative A_i is given below:

$$K_i = \frac{S_i}{S_0}; i = 0,...,m \tag{9}$$

where S_i and S_0 are the optimality criterion values obtained from Eq. (8).

It is obvious that the calculated values K_i are in the interval [0, 1] and can be ordered in an increasing sequence, which is the wanted order of precedence. According to the utility function values, the complex relative efficiency of the feasible alternative can be determined.

2.2. COPRAS Method

Zavadskas et al. [16] developed the preference ranking method of Complex Proportional Assessment (COPRAS). Under the presence of mutually conflicting criteria, this method assumes the direct and proportional dependences of the priority and utility degree of the available alternatives. With respect to different criteria and corresponding criteria weights, it considers the performance of the alternatives. Evaluating the direct and proportional dependence of the significance and utility degree of alternatives in a system of attributes, weights, and values of the attributes is allowed by the decision approach. A solution with the ratio to the ideal solution and the ratio with the ideal–worst solution is determined by this method [16], which is simply the best and worst solution. By comparing the analyzed alternatives with the best one, the degree of utility is determined. The values of the utility degree are from 0 to 100% between the worst and best alternatives. This method has already been applied successfully to solve various problems in the field of construction [16-18], property management, economics, etc. The steps of the COPRAS method are noted as follows [19]:

Step 1: Develop the decision matrix, X (objectives).

$$X = [X_{ij}]_{m\times n} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & \cdots & \cdots & x_{mn} \end{pmatrix} \tag{10}$$

where x_{ij} is the performance value of the i-th alternative on the j-th criterion, m is the number of alternatives, and n is the number of criteria.

Step 2: Normalize the decision matrix using the following equation to obtain dimensionless values of different criteria so that all of them can be compared [17].

$$R = [r_{ij}]_{m\times n} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{11}$$

Step 3: Determination of the weighted normalized decision matrix, D:

$$D = [y_{ij}]_{m\times n} = r_{ij} \times w_j \, ; i = 1, 2, ..., m \, ; j = 1, 2, ..., n \tag{12}$$

where r_{ij} is the normalized performance value of the i-th alternative on the j-th criterion and w_j is the weight of j-th criterion. The sum of dimensionless weighted normalized values of each criterion is always equal to the weight of that criterion.

$$\sum_{i=1}^{m} y_{ij} = w_j \tag{13}$$

It can be said that the weight, w_j of the investigated criterion is proportionally distributed among all the alternatives according to their weighted normalized value, y_{ij}.

Step 4: For both the beneficial attributes and non-beneficial attributes, the sums of weighted normalized values are calculated. The better is the attainment of a goal; the lower is the value of a non-beneficial attribute (e.g., price). On the other hand, the greater is the value of a beneficial attribute (e.g., quality), the better is the attainment of a goal. These sums are calculated using the following equations:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \tag{14}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \tag{15}$$

where y_{+ij} and y_{-ij} are the weighted normalized values for the 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 degree of goals attained by each alternative is express by the S_{+i} and S_{-i} values. The sums of 'pluses' S_{+i} and 'minuses' S_{-i} of the alternatives are always, respectively, equal to the sums of weights of the beneficial and non-beneficial attributes as expressed by:

$$S_{+} = \sum_{j=1}^{n} S_{+i} = \sum_{i=1}^{m} \sum_{j=1}^{n} y_{+ij} \tag{16}$$

$$S_{-} = \sum_{j=1}^{n} S_{-i} = \sum_{i=1}^{m} \sum_{j=1}^{n} y_{-ij} \tag{17}$$

In this way, Equations (16) and (17) can be used to verify the calculations.

Step 5: Determine the preferences of the alternatives on the basis of defining the positive alternatives S_{+i} and negative alternatives S_{-i} characteristics.

Step 6: Determine the relative preferences or priorities of the alternatives. The priorities of the candidate alternatives are calculated on the basis of Qi. The greater the value of Qi, the higher is the priority of the alternative. The relative preference value of an alternative shows the degree of satisfaction attained by that alternative. The alternative with the highest relative preference value (Q_{max}) is the best choice among the candidate alternatives. The relative preference value (priority), Q_i of the i-th alternative can be obtained by:

$$Q_i = S_{+i} + \frac{S_{-\min} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \left(S_{-\min} / S_{-i} \right)} \tag{18}$$

where S_{-min} is the minimum value of S_{-i}.

Step 7: Calculate the quantitative utility (U_i) for the i-th alternative. The degree of an alternative's utility is directly associated with its relative preference value (Q_i). By comparing the priorities of all the alternatives with the most efficient one, the degree of an alternative's utility, leading to a complete ranking of the candidate alternatives, is determined and can be denoted by:

$$U_i = \left[\frac{Q_i}{Q_{\max}} \right] \times 100\% \tag{19}$$

where Q_{max} is the maximum relative preference value. It is observed that with the increase or decrease in the value of the relative preference for an alternative, its degree of utility also increases or decreases [16]. Candidate alternatives utility values, range from 0 to 100%. Therefore, this approach allows for evaluating the direct and proportional dependence of preference and utility degree of the considered alternatives in a decision-making problem involving multiple criteria, their weights, and preference values of the alternatives with respect to all the criteria.

2.3. TOPSIS Method

A TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is a multi-criteria decision analysis method, which was originally developed by [20] with further developments by [21 and 22]. This method considers three types of attributes or criteria:

- Qualitative benefit attributes/criteria
- Quantitative benefit attributes
- Cost attributes or criteria

In this method, two artificial alternatives are hypothesized:

Ideal alternative: the one that has the best level for all attributes considered; and negative ideal alternative: the one that has the worst attribute values.

TOPSIS selects the alternative that is the closest to the ideal solution and farthest from negative ideal alternative. TOPSIS assumes that we have m alternatives (options) and n attributes/criteria and we have the score of each option with respect to each criterion. Let x_{ij} be the score of option i with respect to criterion j. We have a matrix $X = (x_{ij})m\times n$. Let J be the set of benefit attributes or criteria (more is better) and let J' be the set of negative attributes or criteria (less is better). The steps of the TOPSIS method are as follows:

Step 1: Construct the normalized decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria.

Normalize scores or data as follows:

$$r_{ij} = x_{ij} \;/\; (\sum_i x_{ij}^2) \quad i = 1,\ldots,m,\ j = 1,\ldots,n \tag{20}$$

Step 2: Construct the weighted normalized decision matrix.

Assume that we have a set of weights for each criteria wj for $j = 1,\ldots n$. Multiply each column of the normalized decision matrix by its associated weight. An element of the new matrix is as follows:

$$v_{ij} = w_j r_{ij} \quad i = 1,\ldots,m \;,\; j = 1,\ldots,n \tag{21}$$

Step 3: Determine the ideal and negative ideal solutions.

Ideal solution:

$$A^* = \left\{v_1^*, \ldots, v_n^*\right\} \tag{22}$$

where $v_j^* = \{\max_i(v_{ij}) \text{ if } j \hat{I} J; \min_i(v_{ij}) \text{ if } j \hat{I} J'\}$

Negative ideal solution:

$$A^- = \left\{v_1^-, \ldots, v_n^-\right\} \tag{23}$$

where $v^- = \{\min_i(v_{ij}) \text{ if } j \in J; \max_i(v_{ij}) \text{ if } j \in J'\} \}$

Step 4: Calculate the separation measures for each alternative. The separation from the ideal alternative is as follows:

$$S_i^{*} = [\Sigma_j \left(v_j^{*} - v_{ij}\right)^2]^{½} \quad i = 1, \ldots, m \tag{24}$$

Similarly, the separation from the negative ideal alternative is as follows:

$$S_i^{-} = [\Sigma_j \left(v_j^{-} - v_{ij}\right)^2]^{½} \quad i = 1, \ldots, m \tag{25}$$

Step 5: Calculate the relative closeness to the ideal solution *Ci** as follows:

$$C_i^{*} = S_i^{-} / \left(S_i^{*} + S_i^{-}\right) \quad 0 < C_i^{*} < 1 \tag{26}$$

A set of alternatives can now be preference ranked according to the descending order of *Ci**.

2.4. Final Ranking Method (REGIME)

The REGIME method was described by [23 and 24], which is an ordinal generalization of pairwise comparison methods, such as concordance analysis. The steps of REGIME are explained as follows:

Step 1: Computing the concordance c_{il}using the following equation:

$$C_{il} = \sum_{j \in \hat{c}_{il}} \pi_j \tag{27}$$

$\widehat{Cil}$ is the set of concordance that reflects the set of attributes for which $a_i$is at least as good as $a_l \in A$, where $a_i$and $a_l \in A$. π_j is the weight of the attribute $g_i \in F$.

Step 2: Construction of the regime matrix by pair-wise comparison of alternatives in the multi-criteria evaluation table. For every criterion, it is examined whether *a* has a better rank than *b*, then on the corresponding place in the regime matrix the number *+1* is noted, while if *a* is a better position than *b*, then *–1* will be placed in the regime matrix.

Step 3: Next, for each criterion g_j an indicator c_{il}, *j* for each pair of alternatives (a_i, a_l) can be defined by:

$$C_{il,j} C_{il} \begin{cases} +1 if \;\; r_{ij} < r_{lj} \\ 0 if \;\; r_{ij} = r_{lj} \\ -1 if \;\; r_{ij} > r_{lj} \end{cases} \tag{28}$$

where $r_{ij}\left(r_{lj}\right)$is the rank of the alternative $a_i(a_l)$ with respect to attribute g_i

The elements of the regime matrix are called regimes and they are used to determine the rank order of alternatives. The concordance index, for the alternative a_i is given by:

$$C_{il} = \sum_j \pi_j C_{il,j} \tag{29}$$

Step 4: Construction of a pair-wise comparison matrix V_{il}, defined as:

$$V_{il}\begin{cases}+1 \text{ if } C_{il}>0\\ -1 \text{ if } C_{il}<0\end{cases} \tag{30}$$

This matrix consists of elements equal to 1 or -1, and zeroes on main diagonal. A final ranking can be achieved on the basis of matrixV_{il}. The alternative that has a maximum number of positive elements (i.e., +1 in the matrixV_{il}) is considered as the best alternative.

3. Case Study

In this paper, we consider the layout design proposed by Shahanaghi and Yazdian [14]. A two-phase approach is employed by them to deal with this problem. The decision maker scores and ranks all potential distribution centers (DC) locations with regard to a set of criteria in the first phase. In the second phase through a multi-objective mixed-integer programming (MOMIP) model, final location and distribution decisions are made, which incorporate selection of transportation modes and their associated loads. They have used AHP and TOPSIS to determine the relative importance of each criterion and to do the final ranking, respectively. This example considers six facility location selection criteria and four alternatives DC. The six criteria considered in this problem are, Fire history (F); Access to infrastructures (I); Reliability in operations (R); Closeness to market (M); Expert personnel availability (P); Earthquake possibility (E).

Following, we consider the same example to demonstrate the applicability and effectiveness of our three other well-known MCDM methods used in this paper. The hierarchy structure of the facility location problem is shown in Figure 1 [15].

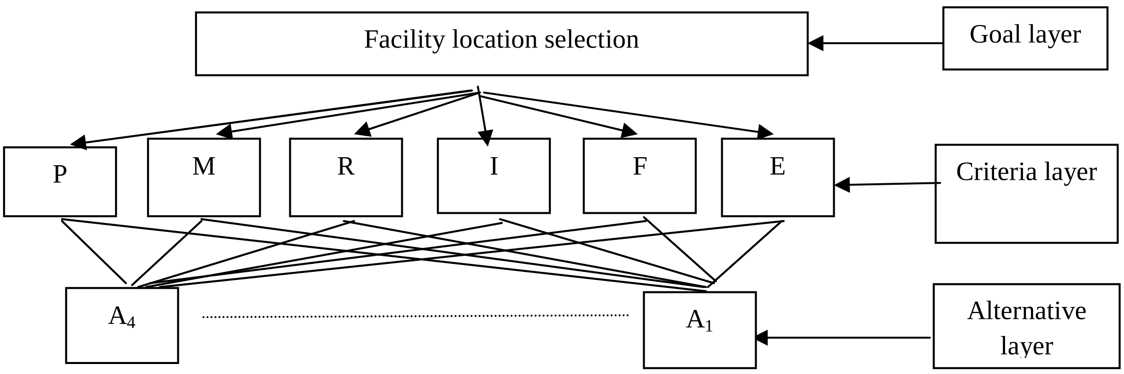

FIGURE 1. Hierarchy structure of a facility location problem

4. Computational Results

First of all, we need the decision matrix for rank calculation, as shown in Table 1. Following, we present the results for three MCDM methods.

4.1. TOPSIS Method

The normalized decision matrix (R= [r_{ij}]) by using Equation 20 is presented in Table 2. The weighted normalized decision matrix (V= [v_{ij}]) is shown in Table 3, in which each element is calculated by Equation 21.

The ideal solution (A*) and negative-ideal solution (A-) are calculated by using Equations 22 and 23, respectively.

A* ={0.028, 0.066, 0.032, 0.072, 0.022, 0.110},

A- ={0.195, 0.328, 0.018, 0.031, 0.007, 0.047}.

Table 4 presents the separation measures for each alternative by using Equation 24, the separation from the negative ideal alternative by using Equation 25, and the final ranking of the TOPSIS method according to the relative closeness to the ideal solution calculated by using Equation 26.

4.2. ARAS Method

The value of optimality function of each alternative (*Si*) calculated by using Equation 8 and final ranking according to these values are presented in Table 5 as follows.

TABLE 1. Decision matrix for rank evaluation

Alternatives	E	F	I	R	M	P
Criteria weights	0.255	0.394	0.047	0.107	0.034	0.164
A_1	3	1	7	3	7	5
A_2	1	5	5	5	9	3
A_3	7	1	5	5	3	7
A_4	5	3	9	7	7	5

TABLE 2. Normalized decision matrix

Alternative	E	F	I	R	M	P
A_1	0.327	0.167	0.522	0.289	0.511	0.481
A_2	0.109	0.833	0.373	0.481	0.656	0.289
A_3	0.764	0.167	0.373	0.481	0.219	0.674
A_4	0.546	0.5	0.671	0.674	0.511	0.481

TABLE 3. Weighted normalized decision matrix

	E	F	I	R	M	P
A_1	0.083	0.066	0.025	0.031	0.017	0.079
A_2	0.028	0.328	0.018	0.051	0.022	0.047
A_3	0.195	0.066	0.018	0.051	0.007	0.110
A_4	0.139	0.197	0.032	0.072	0.017	0.079

TABLE 4. Final ranking and closeness coefficients of potential DC locations

Alternatives	S_i^*	S^-_i	Closeness coefficient	Rank
A_1	0.076	0.278	0.791	1
A_2	0.271	0.169	0.384	4
A_3	0.169	0.271	0.616	2
A_4	0.175	0.153	0.476	3

TABLE 5. Final Ranking of ARAS

Alternatives	S_i	Rank
A_1	0.0993	2
A_2	0.0757	4
A_3	0.1099	1
A_4	0.0919	3

Please cite this article in press as: M. Niyazi, R. Tavakkoli-Moghaddam, Solving a Facility Location Problem by Three Multi-Criteria Decision Making Methods, Int. J. of Research in Industrial Engineering (2014)

4.3. COPRAS Method

Table 6 presents the relative preference value (i.e., priority), *Qi*, and the degree of an alternative's utility that are calculated by using Equations 18 and 19, respectively. It also shows the final ranking according to these values.

TABLE 6. Final Ranking and closeness coefficients of potential DC locations

Alternatives	Q_i	U_i	Rank
A_1	0.7279	0.9667	3
A_2	0.7212	0.9578	4
A_3	0.7461	0.9910	2
A_4	0.7529	1	1

4.4. REGIME Method

A ranking method is proposed by [25], which combines the ranking results of the three MCDM methods. This ranking method is very similar to the REGIME method and is different only in place of criteria used in REGIME. We take into account three MCDM methods as criteria. Obtaining a composite final rank, which combines the ranking results of all the other methods, is the main objective behind this. The impact matrix is shown in Table 7. The REGIME matrix is presented in Table 8.

Tables 9 and 10 show the paired comparison matrix for composite rank calculation and the final ranking obtained by this method, respectively.

Also the same study has been done by Turskis and Zavadskas [15], who employed four well-known MCDM methods, namely GRA, MOORA, ELECTRE-II and OCRA. The results are shown in Tables 11 to 13. We can see from these results that the final rank is different from our study and it is due to the different methods that employed in order to rank the alternatives.

TABLE 7. Impact matrix

Alternatives	TOPSIS	ARAS	CORPAS
A_1	1	2	3
A_2	4	4	4
A_3	2	1	2
A_4	3	3	1

TABLE 8. REGIME matrix

Alternatives	TOPSIS	ARAS	CORPAS
A_1, A_2	1	1	1
A_1, A_3	1	-1	-1
A_1, A_4	1	1	-1
A_2, A_1	-1	-1	-1
A_2, A_3	-1	-1	-1
A_2, A_4	-1	-1	-1
A_3, A_1	-1	1	1
A_3, A_2	1	1	1
A_3, A_4	1	1	-1
A_4, A_1	-1	-1	1
A_4, A_2	1	1	1
A_4, A_3	-1	-1	1

TABLE 9. Paired comparison matrix

Alternatives	A_1	A_2	A_3	A_4
A_1	0	1	-1	1
A_2	-1	0	-1	-1
A_3	1	1	0	1
A_4	-1	1	-1	0

TABLE 10. Final rank of alternatives

Alternatives	Total no. of positive elements (+1)	Final rank
A_1	2	2
A_2	0	4
A_3	3	1
A_4	1	3

TABLE 11. REGIME matrix

Alternatives	GRA	MOORA	ELECTRE II	OCRA
A_1, A_2	1	1	1	1
A_1, A_3	1	1	1	1
A_1, A_4	1	1	1	1
A_2, A_1	-1	-1	-1	-1
A_2, A_3	-1	-1	-1	-1
A_2, A_4	-1	-1	-1	1
A_3, A_1	-1	-1	-1	-1
A_3, A_2	1	1	1	1
A_3, A_4	1	1	-1	1
A_4, A_1	1	-1	-1	-1
A_4, A_2	1	1	1	-1
A_4, A_3	-1	-1	1	-1

Table 12. Paired comparison matrix

Alternatives	A_1	A_2	A_3	A_4
A_1	0	1	1	1
A_2	-1	0	-1	-1
A_3	-1	1	0	1
A_4	-1	1	-1	0

TABLE 13. Final rank of alternatives

Alternatives	Total no. of positive elements (+1)	Final rank
A_1	3	1
A_2	0	4
A_3	2	2
A_4	1	3

5. Conclusion

Solving a facility location selection problem while ranking the performance of three most well-known MCDM methods (i.e., ARAS, COPRAS and TOPSIS) was investigated in this paper. It was shown that by the choice of the MCDM methods employed, the rankings were significantly influenced. Due to the difference in the mathematical modeling, the discrepancy appeared between the rankings obtained by various MCDM methods while solving a decision

Please cite this article in press as: M. Niyazi, R. Tavakkoli-Moghaddam, Solving a Facility Location Problem by Three Multi-Criteria Decision Making Methods, Int. J. of Research in Industrial Engineering (2014)

problem. Hence, deciding which ranking method was best suited for the problem became so difficult for the decision maker. Thus, a final ranking model based on REGIME method was used in this paper. As, instead of depending on the results of just one or two MCDM methods, this model combined the ranking results obtained by three different methods. Additionally, the model could be considered more reliable for the decision problems. Furthermore, the results of this study were compared by the results of the same study employed four well known MCDM methods (i.e., GRA, MOORA, ELECTRE-II and OCRA). The results showed that the final rank was different.

References

[1] Drira, A., Pierreval, H. and Hajri-Gabouj, S. (2007). Facility layout problems: A survey.*Annual Reviews in Control*, Vol. 31, No. 2, pp. 255-267.

[2] Yang, T. and Kuo, C. (2003). A hierarchical AHP/DEA methodology for the facilities layout design problem.*European Journal of Operational Research*, Vol. 147, No. 1, pp. 128-136.

[3] Rao, R. V. and Singh, D. (2012). Weighted Euclidean distance based approach as a multiple attribute decision making method for plant or facility layout design selection.*International Journal of Industrial Engineering Computations*, Vol. 3, No. 3, pp. 365-382.

[4] Lin, S. S., Lee, R. H., Perng, C., Chiou, W. C. and Tsai, J. T. (2004). A decision support model for selecting facility layout alternatives. Proceedings of 5th Asia Pacific Industrial Engineering and Management Systems Conference, Australia, pp. 24.1.1- 24.1.17.

[5] Enea, M., Galante, G. and Panascia, E. (2005). The facility layout problem approached using a fuzzy model and a genetic search.*Journal of Intelligent Manufacturing*, Vol. 16, No. 3, pp. 303-316.

[6] Ertay, T., Ruan, D. and Tuzkaya, U. R. (2006). Integrating data envelopment analysis and analytic hierarchy for the facility layout design in manufacturing systems.*Information Sciences*, Vol. 176, No. 3, pp. 237-262.

[7] Kuo, Y., Yang, T. and Huang, G. W. (2008). The use of grey relational analysis in solving multiple attribute decision making problems.*Computers & Industrial Engineering*, Vol. 55. No. 1, pp. 80-93.

[8] Athawale, V. M. and Chakraborty, S. (2010). Facility layout selection using PROMETHEE II method.*The IUP Journal of Operations Management*, Vol. 9, Nos. 1 & 2, pp. 81-98.

[9] Chatterjee, P., Athawale, V.M. and Chakraborty, S. (2010). Selection of facility layouts using ELECTRE II method.*International Journal of Advanced Manufacturing Systems*, Vol. 1, No. 1, pp. 41-53.

[10] Maniya, K.D. and Bhatt, M. G. (2011). An alternative multiple attribute decision making methodology for solving optimal facility layout design selection problems.*Computers & Industrial Engineering*, Vol. 61, No. 3, pp. 542-549.

[11] Yang, L., Deuse, J. and Jiang, P. (2013). Multiple-attribute decision-making approach for an energy-efficient facility layout design.*The International Journal of Advanced Manufacturing Technology*, Vol. 66, No. 5-8, pp. 795-807.

[12] Yang, L. and Deuse, J. (2012). Multiple-attribute decision making for an energy efficient facility layout design. Proceedings of 45th CIRP Conference on Manufacturing Systems, Athens, pp. 149-154.

[13] Mohamadghasemi, A. and Hadi-Vencheh, A. (2012). An integrated synthetic value of fuzzy judgments and nonlinear programming methodology for ranking the facility layout patterns.*Computers & Industrial Engineering*, Vol. 62, No. 1, pp. 342-348.

[14] Shahanaghi, K. and Yazdian, S. A. (2010). Facility location and distribution decisions in supply chains with fleet sizing considering both tangible and intangible criteria. *International Journal of Management Science and Engineering Management*, Vol. 5, No. 4, pp. 303-309.

[15] Turskis, Z. and Zavadskas, E. K. (2010). A new additive ratio assessment (ARAS) method in multicriteria decision-making.*Technological and Economic Development of Economy*, Vol. 16, No. 2, pp. 159-172.

[16] Zavadskas, E. K., Kaklauskas, A., Turskis, Z. and Tamošaitiene, J. (2008). Selection of the effective dwelling house walls by applying attributes values determined at intervals.*Journal of Civil Engineering and Management*, Vol. 14, No. 2, pp. 85-93.

[17] Kaklauskas, A., Zavadskas, E.K., Raslanas, S., Ginevicius, R., Komka, A. and Malinauskas, P. (2006). Selection of low e-windows in retrofit of public buildings by applying multiple criteria method COPRAS: A Lithuanian case.*Energy and Buildings*, Vol. 38, No. 5, pp. 454-462.

[18] Kaklauskas, A., Zavadskas, E. K., and Trinkunas, V. (2007). A multiple criteria decision support on-line system for construction.*Engineering Applications of Artificial Intelligence*, Vol. 20, No. 2, pp. 163-175.

[19] Chatterjee, P. and Chakraborty, S. (2010), Selection of Flexible Manufacturing System using Complex Proportional Assessment Method. Proceedings of the 4th International Conference on Advances in Mechanical Engineering. Surat, Gujarat: SVNIT.

[20] Hwang, C. L. and Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications*. New York: Springer-Verlag.

[21] Yoon, K. (1987). A reconciliation among discrete compromise situations.*Journal of Operational Research Society*, Vol. 38. No. 3 pp. 277-286.

[22] Hwang, C. L., Lai, Y. J. and Liu, T. Y. (1993). A new approach for multiple objective decision making.*Computers & operations research*, Vol. 20, No. 8, pp. 889-899.

[23] Hinloopen, E., Nijkamp, P. and Rietveld, P. (1983). Qualitative discrete multiple criteria choice models in regional planning.*Regional Science and Urban Economics*, Vol. 13, No. 1, pp. 77-102.

[24] Hinloopen, E., Nijkamp, P. and Rietveld, P. (1983). *The regime method: A new multicriteria technique*. In Essays and surveys on multiple criteria decision making, Springer Berlin Heidelberg.

[25] Chakraborty, R., Ray, A. and Dan, P. (2013). Multi criteria decision making methods for location selection of distribution centers.*International Journal of Industrial Engineering Computations*, Vol. 4, No. 4, pp. 491-504.