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An MCDM-DEA approach for technology selection

***A. Alinezhad* [1*]*; A. Makui* [2]*; R. Kiani Mavi* [3]*; M. Zohrehbandian* [4]**

Assistant Prof., Dep. of Industrial Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran

Assistant Professor, Dep. of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran

Assistant Professor, Dep. of Industrial Management, Islamic Azad University, Qazvin Branch, Qazvin, Iran

Assistant Professor, Dep. of Mathematics, Islamic Azad University, Karaj Branch, Karaj, Iran

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Abstract: Technology selection is an important part of management of technology. Recently Karsak and Ahiska (2005) proposed a novel common weight multiple criteria decision making (MCDM) methodology for selection of the best Advanced Manufacturing Technology (AMT) candidates based on a number of attributes. However, Amin *et al*. (2006), by means of a numerical example demonstrated the convergence difficulty of the Karsak and Ahiska algorithms, and then introduced an improvement model to rectify that running problem. This paper presents an MCDM-DEA methodology in order to evaluate the relative efficiency of AMTs with respect to multiple outputs and a single exact input. Using displaced ideal methodology, a practical common weight is developed and its robustness and discriminating power are illustrated via a previously reported robot evaluation problem by comparing the ranking obtained by the proposed MCDM framework with that obtained by a data envelopment analysis (DEA) classic model.

Keywords: *AMT; Common weights; Displaced ideal; DEA; Technology selection; MCDM*

1. Introduction

Selection of technologies is one of the most challenging decision making areas that management of a company encounters. It is difficult to clarify the right technology alternatives because the number of technologies is increasing and the technologies are becoming more and more complex. The large number of available advanced manufacturing technologies (AMT), among which industrial robots, computer numerical control (CNC) machines, flexible manufacturing systems, automated material handling (AMH) systems can be listed, and numerous AMT performance attributes that should be considered in the decision making process require the use of a robust decision methodology capable of evaluating several AMT candidates. Several researchers have utilized a variety of DEA models to address the AMT evaluation and selection problem. Talluri *et al. (2000*) proposed innovative DEA frameworks for evaluating AMT considering qualitative and quantitative criteria as well as imprecision.

Recently Karsak and Ahiska (2005) proposed a novel common weight multi-criteria decision making (MCDM) methodology for selection of the best AMT candidates based on a number of attributes. Many justification methodologies for AMT selection necessitate the decision-maker to assign arbitrary importance weights to performance attributes. One problem with arbitrary weights is that they add subjectivity to the methodology. On the other hand, assigning weights is cumbersome since it is often quite difficult for the decision-maker to quantify their preferences on performance attributes. Furthermore, the task of assigning weights becomes more difficult as the number of performance attributes increases. Hence, a robust decision tool that does not require precise information on the importance of performance attributes from the decision maker would facilitate the AMT evaluation process.

The present paper proposes a multi-objective decision tool for industrial robot selection, which does not require subjective assessments of the decision maker to prioritize performance attributes. Hence, it can be named as objective decision techniques. The proposed methodology can be success-fully applied, but is not limited to technology selection problems such as the determination of the best industrial robot, CNC machine or flexible manufacturing system from a feasible set of mutually exclusive alternatives.

The plan for the rest of this paper is as follows: Section 2 provides a concise literature review on the existing decision tools for AMT. Section 3 presents a new multiple objective linear programming (MOLP) methodology for technology selection in seven steps. In Section 4, the robustness and convenience of the proposed MOLP me-

*Corresponding Author Email: alinezhad_ir@yahoo.com
Tel.: +98 9123342560

thodology are illustrated through a comparison with the results of CCR model. Finally concluding remarks are provided in Section 5.

2. Literature review

Over the past several decades, manufacturers who have been faced with intense competition in the global marketplace, have invested in AMTs, such as group technology, flexible manufacturing systems, industrial robots, etc., which enable high quality and customization in a cost-effective manner. The increased concern and importance attached to AMTs by the manufacturers have consequently oriented the researchers to develop models and methodologies for evaluation and selection of AMTs. Proctor and Canada (1992), Son (1992) and more recently, Raafat (2002) have provided comprehensive bibliographies on the justification of AMTs.

A number of papers have focused on the use of MCDM techniques for AMT justification. Stam and Kuula (1991) developed a two-phase decision procedure that uses AHP and multi-objective mathematical programming for the problem of flexible manufacturing system (FMS) selection. Agrawal *et al.* (1991) employed TOPSIS for robot selection whereas Agrawal *et al.* (1992) applied TOPSIS for optimum gripper selection. Khouja (1995) addressed the robot evaluation problem and proposed a two-phase methodology that consisted of first using DEA to identify the technically efficient robots from a list of feasible robots, and then, using multi-attribute utility theory to further discriminate among efficient robots and select the best alternative. Sambasivarao and Deshmukh (1997) presented a decision support system that employed economic analysis, multi-attribute analysis including AHP, TOPSIS and linear additive utility model, and risk analysis.

In addition, several studies contribute to the non-deterministic MCDM literature on evaluation, justification and selection of AMTs. Perego and Rangone (1998) analyzed and compared fuzzy set theory-based multi-attribute decision-making techniques for AMT justification. Karsak and Tolga (2001) presented a fuzzy multi-criteria decision-making approach for evaluating AMT investments, which integrated both economic and strategic selection criteria using a decision algorithm based on a fuzzy number ranking method. Karsak (2002) has recently developed a distance-based fuzzy MCDM approach for evaluating FMS alternatives that eliminates the need for using a fuzzy number ranking method.

3. Practical common weight displaced ideal approach for technology selection

In DEA, the measure of efficiency of a DMU is defined as a ratio of a weighted sum of outputs to a weighted sum of inputs subject to the condition that corresponding ratios for each DMU be less than or equal to one. A standard formulation of DEA creates a separate linear program for each DMU. The model chooses nonnegative weights for a DMU in a way that is most favorable for it and that DMU achieve the maximal relative efficiency index value. This flexibility in selecting the weights, on the other hand, deters the comparison among DMUs on a common base. For dealing with this difficulty and assessment of all the DMUs on the same scale, the DEA model could be expressed as a multi-objective linear fractional programming problem. The idea behind this approach and identification of the common weights is formulated as the simultaneously maximizing the ratio of outputs to inputs for all DMUs. Hence, the objective function of the model is the same as in the conventional DEA model but applied to maximize efficiency of all DMUs, instead of one at a time, and the restrictions remaining unchanged.

In technology selection problems, when multiple exact outputs and a single input are to be considered in the evaluation process, this approach produces the following MOLP problem:

$$\text{Max} \left\{ \frac{\sum_{r=1}^{s} u_r y_{r1}}{x_1}, \frac{\sum_{r=1}^{s} u_r y_{r2}}{x_2}, \ldots, \frac{\sum_{r=1}^{s} u_r y_{rn}}{x_n} \right\} \tag{1}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j} \le 1, \qquad j = 1,2,\ldots,n$$

$$u_r \ge \varepsilon, \qquad r = 1,2,\ldots,s$$

Each preferred solution (preferred common set of weight), of Model (1) produce efficiency measures that is not specific to a particular DMU, but common to all DMUs. For solving the above MOLP problem and presenting a preferred solution, we employ the displaced ideal approach as follows:

Step 1: All DMUs are evaluated in input-oriented CCR model as follows:

$$\text{Max}\,\theta_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{x_0}, \qquad j = 1,2,...,n \tag{2}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j} \le 1, \qquad j = 1,2,...,n$$

$$u_r \ge \varepsilon, \qquad r = 1,2,...,s$$

where, DMU_o is under evaluation and

$$\frac{\sum_{r=1}^{s} u_r^* y_{r0}}{x_0} = \theta_0^* \tag{3}$$

The optimal solution of Model (2) u_r^* is used for assessment of the efficiency of the other DMUs. Hence, we calculate:

$$\theta_{0j} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j}, \quad j = 1,2,...,n\,(j \ne 0) \tag{4}$$

In other words, θ_{Oj} represents the score given to unit j in the DEA run of unit k, i.e. unit j is evaluated by the optimal weights of unit k and according to Model (4) we have:

$$\theta_{oo} = \frac{\sum_{r=1}^{s} u_r^* y_{ro}}{x_o} = \theta_0^* \tag{5}$$

Step 2: The results of step 1 are used to form an n by n payoff matrix; see Table 1, where $\underline{u}^{*o}$ is the vector of optimal output weights when DMU_o is under evaluation. Note that all the elements in the matrix are between zero and one, i.e. $0 < \theta_{oj} \le 1$, and the elements in the diagonal, θ_{jj} represent the standard DEA efficiency score, which are the highest values that the DMUs can attain. In other words, a diagonal element of the payoff matrix introduces an ideal solution. Furthermore, if the optimal weights of the LP Model (2) are not unique, a technique e.g. goal programming, can be applied to choose between the optimal solutions. In this manner, each column of the table is associated to an efficient solution of Model (1).

Step 3: Define efficiency distance index as follows:

$$d_j\left(\underline{u}^{*o}\right) = \frac{\theta_j^* - \theta_{oj}}{\theta_j^* - \theta_j^{\min}} = d_{oj}, \; o, j \in \{1,2,...,n\} \tag{6}$$

The efficiency distance index of DMU_j measures the distance of efficiency of DMU_j, when using optimal weights of DMU_o, from optimal efficiency of DMU_j ($0 \le d_{oj} \le 1$, and d_{jj}=0).

Step 4: The results of Step 3 form the distance matrix as follows, where the elements on the diagonal are zero.

Step 5: We define general norm as follows:

$$L - P\left(\underline{u}^{*o}\right) = \left\{\sum_{j=1}^{n}\left[d_j\left(\underline{u}^{*o}\right)\right]^P\right\}^{1/P} = \left\{\sum_{j=1}^{n} d_{oj}^P\right\}^{1/P}$$

$$1 \le P \le \infty \quad o \in \{1,2,...,n\} \tag{7}$$

For P=2, the results form the Table (3) (Euclidean norm).

Step 6: Find out the minimum amount of the results in Step 5 as:

$$\text{Min}\,\{L\text{-}2[\underline{u}^{*j}] \mid j=1,\ldots,n\} \tag{8}$$

Assume that the minimum is obtained by DMU_o as:

$$L\text{-}2[\underline{u}^{*o}],\; o \in \{1,\ldots, n\} \tag{9}$$

Step 7: $\underline{u}^{*o}$ is a superior common set of weights of outputs and we can calculate the efficiency score of all DMUs with these weights.

4. Numerical example

In this section, the proposed MOLP methodology is used for robot selection and its discriminating power is illustrated through a previously reported industrial robot selection problem (Karsak & Ahiska, 2005). The robustness of the methodology proposed in this paper is tested via comparing the ranking obtained by the proposed methodology with that obtained by the CCR model. The robot selection problem addressed in Karsak & Ahiska (2005) involves the evaluation of relative efficiency of 12 robots with respect to four engineering attributes including 'handling coefficient', 'load capacity', 'repeatability' and 'velocity', which are considered as outputs, and 'cost', which is considered as the single input. Since lower values of repeatability indicate better performance, the reciprocal values of repeatability are used in efficiency computation of robots. Input and output data regarding the robots are given in Table 4.

The results obtained by execution of the proposed approach in this paper, are depicted in Tables 5, 6 and 7. According to the results of Table 7, the minimum of L-2[$\underline{u}^{*j}$], equals to 0.5676, is obtained for, $\underline{u}^{*1}$, $\underline{u}^{*6}$ and $\underline{u}^{*7}$. Therefore, $\underline{u}^{*1}$, $\underline{u}^{*6}$ and $\underline{u}^{*7}$ are superior common set of weights and we can calculate the efficiency score of all DMUs with these weights. These common weights are u_1=0.537483, u_2=0.135944, u_3=0.000010 and u_4=0.000010. Final results are shown in Table 8.

To test the robustness of the proposed methodology, the obtained scores are compared with DEA efficiency scores (CCR model) by Spearman's rank correlation test. Like the Pearson product moment correlation coefficient, Spearman's ρ is a measure of the relationship between two variables. However, Spearman's ρ is calculated on ranked data. For calculating spearman's ρ we can use the formulation:

$$r_s = 1 - \frac{\sum_{j=1}^{n} d_j^2}{n(n^2-1)} \tag{10}$$

that d_j (j=1,2, …,n) is the difference between ranks for the same observations (DMUs), and n is the number of DMUs.

Or we can compute the Pearson's correlation on the columns of ranked data. The result of this formulation is too close to the exact Spearman's ρ. In this formulation:

$$r = \frac{\sum_{j=1}^{n} x_j y_j - n\overline{xy}}{\sqrt{\sum_{j=1}^{n} x_j^2 - n\overline{x}^2} \cdot \sqrt{\sum_{j=1}^{n} y_j^2 - n\overline{y}^2}} \tag{11}$$

and x_j and y_j are the ranks for the same DMU_j (j=1,2, …,n).

Spearman's rank correlation, in this example, is 0.67, which means that there is a positive relationship between the rankings of the proposed approach and CCR model. However, the number of efficient DMUs of the proposed approach has been reduced. Hence, discriminating power of the approach is higher than conventional DEA models.

5. Conclusion

This paper introduces a new efficiency measure with an improved discriminating power that can be successfully applied for AMT evaluation based on multiple exact outputs and a single exact input. Using the proposed efficiency measure, a practical common weight MOLP methodology is developed and illustrated through a robot selection problem. The convenience and robustness of the proposed methodology are tested via a comparison with CCR model. The comparison reveals that both analyses evaluate the same robot as the best one. Furthermore, the rankings obtained by the proposed methodology and CCR analysis are shown to be positively correlated.

The merits of the proposed framework compared with DEA-based approaches that have previously been used for technology selection can be listed as follows. First, this methodology allows the computation of the efficiency scores of all DMUs by a single formulation, i.e. all DMUs are evaluated by common performance attribute weights and on a common base. Second, it identifies the best alternative by using fewer formulations compared with DEA-based approaches. Further, its practical formulation structure enables its results to be more easily adopted by management who may not poses advanced mathematical programming skills. On the other hand, one similarity between the proposed methodology and DEA-based approaches is that they are both objective decision tools since they do not demand a priori importance weights from the decision-maker for performance attributes.

For further study, useful extensions of the proposed methodology may be developed, which enables the decision-maker to consider imprecise output data denoted by fuzzy numbers.

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Table 1: Payoff matrix.

$\underline{u}^{*j}$ / θ_j	$\underline{u}^{*1}$	$\underline{u}^{*2}$	…	$\underline{u}^{*o}$	…	$\underline{u}^{*n}$	$\theta_j^{\min}$
θ_1	θ_1^*	θ_{21}	…	θ_{o1}	…	θ_{n1}	$\min_{1\le j\le n}\{\theta_{j1}\}$
θ_2	θ_{12}	θ_2^*	…	θ_{o2}	…	θ_{n2}	$\min_{1\le j\le n}\{\theta_{j2}\}$
⋮	⋮	⋮	…	⋮	…	⋮	⋮
θ_n	θ_{1n}	θ_{2n}	…	θ_{on}	…	θ_n^*	$\min_{1\le j\le n}\{\theta_{jn}\}$

Table 2: Distance matrix.

$\underline{u}^{*j}$ / d_j	$\underline{u}^{*1}$	$\underline{u}^{*2}$	…	$\underline{u}^{*o}$	…	$\underline{u}^{*n}$
d_1	0	d_{21}	…	d_{o1}	…	d_{n1}
d_2	d_{12}	0	…	d_{o2}	…	d_{n2}
⋮	⋮	⋮	⋮	⋮	⋮	⋮
d_n	d_{1n}	d_{2n}	…	d_{on}	…	0

Table 3: Final results for P=2.

	$\underline{\mathbf{u}}^{*1}$	$\underline{\mathbf{u}}^{*2}$	…	$\underline{\mathbf{u}}^{*o}$	…	$\underline{\mathbf{u}}^{*n}$
L-2[$\underline{u}^{*j}$]	$\left\{\sum_{j=1}^{n} d_{1j}^2\right\}^{1/2}$	$\left\{\sum_{j=1}^{n} d_{2j}^2\right\}^{1/2}$	…	$\left\{\sum_{j=1}^{n} d_{oj}^2\right\}^{1/2}$	…	$\left\{\sum_{j=1}^{n} d_{nj}^2\right\}^{1/2}$

Table 4: Input and output data for 12 industrial robots.

Robot (j)	Cost(US$)	Handling coeffi-cient	Load capacity(kg)	1/Repeatability (mm^{-1})	Velocity (m/s)
1	100000	0.995	85	1.70	3.00
2	75000	0.933	45	2.50	3.60
3	56250	0.875	18	5.00	2.20
4	28125	0.409	16	1.70	1.50
5	46875	0.818	20	5.00	1.10
6	78125	0.664	60	2.50	1.35
7	87500	0.880	90	2.00	1.40
8	56250	0.633	10	8.00	2.50
9	56250	0.653	25	4.00	2.50
10	87500	0.747	100	2.00	2.50
11	68750	0.880	100	4.00	1.50
12	43750	0.633	70	5.00	3.00

Table 5: Payoff matrix.

θ_1	.65304	.62788	.62788	.62788	.35932	.65304	.65304	.39868	.62788	.53064	.53064	.43718	.35932
θ_2	.75356	.82124	.82124	.82124	.50746	.75356	.75356	.56323	.82124	.37457	.37457	.69948	.37457
θ_3	.88300	.95386	.95386	.95386	.86132	.88300	.88300	.88514	.95386	.19959	.19959	.56944	.19959
θ_4	.86365	.95127	.95127	.95127	.69736	.86365	.86365	.74950	.95127	.35547	.35547	.77789	.35547
θ_5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	.26622	.26622	.34179	.26622
θ_6	.56370	.50767	.50767	.50767	.39130	.56370	.56370	.40723	.50767	.47961	.47961	.25189	.25189
θ_7	.68310	.58518	.58518	.58518	.39054	.68310	.68310	.41116	.58518	.64212	.64212	.23316	.23316
θ_8	.63149	.74577	.74577	.74577	.99831	.63149	.63149	.99835	.74577	.11089	.11089	.64709	.11089
θ_9	.68690	.76449	.76449	.76449	.66578	.68690	.68690	.69897	.76449	.27721	.27721	.64709	.27721
θ_{10}	.61653	.54850	.54850	.54850	.34816	.61653	.61653	.38140	.54850	.71347	.71347	.41636	.34816
θ_{11}	.88853	.74925	.74925	.74925	.63680	.88853	.88853	.65132	.74925	.90739	.90739	.31771	.31771
θ_{12}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table 6: Distance matrix.

	$\underline{u}^{*1}$	$\underline{u}^{*2}$	$\underline{u}^{*3}$	$\underline{u}^{*4}$	$\underline{u}^{*5}$	$\underline{u}^{*6}$	$\underline{u}^{*7}$	$\underline{u}^{*8}$	$\underline{u}^{*9}$	$\underline{u}^{*10}$	$\underline{u}^{*11}$	$\underline{u}^{*12}$
d_1	.00000	.08565	.08565	.08565	1.0000	.00000	.00000	.86600	.08565	.41670	.41670	.73493
d_2	.15153	.00000	.00000	.00000	.70245	.15153	.15153	.57760	.00000	.99995	.99995	.27258
d_3	.09394	.00000	.00000	.00000	.12269	.09394	.09394	.09111	.00000	1.0000	1.0000	.50966
d_4	.14706	.00000	.00000	.00000	.42617	.14706	.14706	.33866	.00000	1.0000	1.0000	.29100
d_5	.00000	.00016	.00016	.00016	.00000	.00000	.00000	.00013	.00016	1.0000	1.0000	.89704
d_6	.00000	.17969	.17969	.17969	.55291	.00000	.00000	.50181	.17969	.26970	.26970	1.0000
d_7	.00000	.21763	.21763	.21763	.65022	.00000	.00000	.60440	.21763	.09107	.09107	1.0000
d_8	.41464	.28548	.28548	.28548	.00004	.41464	.41464	.00000	.28548	1.0031	1.0031	.39701
d_9	.15923	.00000	.00000	.00000	.20258	.15923	.15923	.13445	.00000	1.0000	1.0000	.24093
d_{10}	.26537	.45159	.45159	.45159	1.0000	.26537	.26537	.90903	.45159	.00000	.00000	.81333
d_{11}	.03199	.26818	.26818	.26818	.45888	.03199	.03199	.43426	.26818	.00000	.00000	1.0000
d_{12}	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000	.00000

Table 7: Final results for P=2.

$\underline{u}^{*2}$	$\underline{u}^{*1}$	$\underline{u}^{*3}$	$\underline{u}^{*4}$	$\underline{u}^{*5}$	$\underline{u}^{*6}$	$\underline{u}^{*7}$	$\underline{u}^{*8}$	$\underline{u}^{*9}$	$\underline{u}^{*10}$	$\underline{u}^{*11}$	$\underline{u}^{*12}$
.6666	.5676	.6666	.6666	2.1611	.5676	.5676	1.6902	.6666	2.5022	2.5022	2.3750

Table 8: Efficiency scores and the associated rankings (in parentheses).

Robot(j)	CCR efficiency scores	Displaced ideal efficiency scores
1	0.653(11)	0.653(9)
2	0.821(7)	0.754(6)
3	0.954(4)	0.883(4)
4	0.950(5)	0.864(5)
5	1.000(1)	1.000(1)
6	0.563(12)	0.564(12)
7	0.683(10)	0.683(8)
8	1.000(1)	0.631(10)
9	0.765(8)	0.687(7)
10	0.714(9)	0.617(11)
11	0.909(6)	0.889(3)
12	1.000(1)	0.998(2)
average	$\mu = 0.834$	$\mu = 0.768$

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