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Practical common weights goal programming approach for technology selection

A. Alinezhad[a,1], **R. Kiani Mavi**[b]

[a]Department of Industrial Engineering, Islamic Azad University, Qazvin Branch, Qazvin, Iran.

[b]Department of Industrial Management, Islamic Azad University, Qazvin Branch, Qazvin, Iran.

Abstract

A practical common weight goal programming methodology with an improved discriminating power for technology selection is introduced. The proposed goal programming methodology enables the evaluation of the relative efficiency of decision-making units (DMUs) with respect to multiple outputs and a single exact input with common weights. Its robustness and discriminating power are illustrated via a previously reported robot evaluation problem by comparing the ranking obtained by the proposed goal programming framework with that obtained by the DEA classic model (CCR model) and Minimax method (Karsak and Ahiska (2005)).

Keywords: Technology selection, Robot selection, Goal programming approach, Discriminating power, Weight restriction, DEA, common set of weights.

1 Introduction

Rapid advances in computers and engineering science have resulted in a high range of available advanced manufacturing technologies (AMTs) among which industrial robots, computer numerical control (CNC) machines, flexible manufacturing systems and automated material handling (AMH) systems can be listed. Despite the acquisition and

[1]Corresponding Author. E-mail Address: alinezhad_ir@yahoo.com

the implementation of AMTs being very costly, manufacturers that compete in global markets seek to incorporate them into their manufacturing process due to their wide range of merits. However, the large number of available AMTs and numerous AMT performance attributes that should be considered in the decision process, make the evaluation and selection of AMTs a very complex decision-making process, which requires the use of a robust decision methodology capable of evaluating several AMT candidates based on a number of attributes.

Many studies report evaluation and selection of AMTs. The present paper proposes a robust practical common weight MOLP methodology for evaluating AMTs based on a single input and multiple outputs. The proposed methodology has two advantages compared with DEA-based approaches proposed in the literature for the similar problem. First, it evaluates all alternatives by common weights for performance attributes overcoming the unrealistic weighting scheme common to DEA resulting from the fact that each DMU selects its own factor weights to lie on the efficient frontier. Second, it identifies the best AMT by requiring fewer computations compared with DEA-based approaches.

The paper is organized as follows. Section 2 provides a concise literature review on the existing decision tools for AMT evaluation. In section 3, Karsak and Ahiska's methodology (2005) is presented briefly. Section 4 presents the proposed goal programming methodology. The robustness and convenience of the proposed goal programming methodology are illustrated through a comparison with the method of Karsak and Ahiska (2005) for a technology selection problem in sections 5. Finally, concluding remarks are provided in section 6.

2 Literature survey

Over the past several decades, manufacturers who have been faced with intense competition in the global marketplace, have invested in AMTs, 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. Table 1 provides a concise literature review on the existing decision tools for AMT evaluation. Meanwhile, Proctor and Canada (1992), Son (1992) and Raafat (2002) have provided comprehensive bibliographies on justification of AMTs.

3 Proposed MCDM model by Karsak and Ahiska

Karsak and Ahiska (2005) introduced an approach that differs from those approaches in that it does not necessitate a priori subjective assessments of the decision-maker on factor weights for further prioritization of DMUs. The proposed approach employs efficiency measures that are not specific to a particular DMU, but common to all DMUs. Proposed efficiency measures are a function of the deviation from efficiency. Let d_j be defined as the deviation of the efficiency of DMU_j, E_j, from the ideal efficiency of 1 (i.e. d_j=1-E_j). Then for DMU_o, we have:

$$\begin{array}{lllr} Min & d_o & & \\ s.t. & \dfrac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} + d_j = 1 & j = 1, 2, \ldots, n & (1) \\ & u_r \geq \varepsilon & r = 1, 2, \ldots, s & \\ & d_j \geq 0 & j = 1, 2, \ldots, n & \end{array}$$

The objective function of the above formulation is specific to a particular DMU. Therefore, to determine the efficiencies of all n DMUs, we need to formulate n models, each aiming to minimize the deviation from efficiency for a particular DMU. Furthermore, the maximum possible freedom in choosing the performance attribute weights in model (1) reduces the discriminating power of the model.

Minimax efficiency measure can be briefly defined as the minimization of the maximum deviation from efficiency among all DMUs. Further discrimination among DMUs

Author	Year	Approach
Agrawal et al.	1991	Employed TOPSIS
Stam and Kula	1991	Developed a two-phase decision procedure that uses AHP and multi-objective programming
Chang and Tsou	1993	Formulated a chance-constraints LP model
Liang and Wang	1993	Used the concepts of fuzzy set theory
Khouja	1995	Proposed a two-phase methodology that uses DEA and multi-attribute utility theory
Shang and Sueyoshi	1995	Evaluated FMS alternatives by using AHP and DEA
Baker and Taluri	1997	Applied cross-efficiency analysis
Sambasivarao and Deshmukh	1997	Presented a decision support system
Karsak	1998	Integrated DEA with a fuzzy robot selection algorithm
Braglia and Petroni	1999	Applied DEA with restricted multiplier weights
Parkan and Wu	1999	Applied OCRA, TOPSIS and utility function model
Sarkis and Taluri	1999	Integrated DEA with cross-efficiency analysis.
Braglia and Gabbrieli	2000	Applied dimensional analysis theory
Parkan and Wu	2000	Applied OCRA, AHP and DEA
Taluri and Yoon	2000	Proposed a cone-ratio DEA approach
Karsak and Tolga	2001	Presented a fuzzy multi-criteria decision-making approach
Karsak	2002	Developed a distance-based fuzzy MCDM approach
Sun	2002	Proposed a cone-ratio DEA approach
Amin et. al.	2006	Introduced an improvement model of the Karsak and Ahiska algorithm

Table 1: Samples of AMT evaluation studies

can be allowed by replacing the objective function of formulation (1) with the Minimax efficiency measure, which yields the following MCDM model, namely the Minimax efficiency model.

$$\begin{array}{lll} Min & M & \\ s.t. & M \geq d_j & j=1,2,\ldots,n \\ & \dfrac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} + d_j = 1 & j=1,2,\ldots,n \\ & u_r \ \geq \varepsilon & r=1,2,\ldots,s \\ & d_j \ \geq 0 & j=1,2,\ldots,n \end{array} \quad (2)$$

where M is the maximum deviation from efficiency and $M \geq d_j$ are the constraints that are added to the model to assure that M=Max $\{d_j : j=1,2,\cdots,n\}$.

Minimax efficiency measure has a higher discriminating power than the classical efficiency measure, since it considers the favor of all DMUs simultaneously, which restricts the freedom of a particular DMU to choose the factor weights in its own favor. Furthermore, as the Minimax efficiency measure is an objective function not specific to a particular DMU but common to all DMUs, it does not necessitate solving n formulations to determine efficiencies of all DMUs. The efficiencies for all DMUs can be computed by a single formulation. When formulation (2) is solved, the efficiencies for al DMUs is determined by calculating 1-d_j, for j=1,$\cdots$,n. This one-step efficiency computation enables the evaluation of the relative efficiency of all DMUs based on common performance attribute weights, which contrasts with DEA models where each DMU is evaluated by different weights.

4 Practical common weight goal programming approach for technology selection

DEA model could be expressed as a multi-objective linear fractional programming problem. The objective function of the model is the same as in the CCR model but applied to maximize the efficiency of all DMUs, instead of one at a time, and the restrictions remaining unchanged. Therefore, consider the following MOLP:

$$\begin{array}{llll} Max & \{\frac{\sum_{r=1}^{s} u_r\, y_{r1}}{x_1},\dots,\frac{\sum_{r=1}^{s} u_r\, y_{rn}}{x_n}\} & & \\ s.t. & \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} \le 1 & j=1,2,\,\dots,\,n & \\ & u_r \ \ge \varepsilon & r=1,2,\,\dots,\,s & \end{array} \tag{3}$$

We can solve the above formulation by using goal programming, where all of the goals are equal to 1 (the maximum efficiency value). Therefore we have:

$$\begin{array}{lll} Min & \sum_{j=1}^{n}(d_j^- + d_j^+) & \\ s.t. & \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} + d_j^- - d_j^+ = 1 & j=1,2,\,\dots,\,n \\ & \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} \le 1 & j=1,2,\,\dots,\,n \\ & u_r \ \ge \varepsilon & r=1,2,\,\dots,\,s \\ & d_j^-, d_j^+ \ge 0 & j=1,2,\,\dots,\,n \end{array} \tag{4}$$

This model assured that $d_j^+=0$. However, by solving it, we have $u_r^* \ge \varepsilon$, that is common set of weights, and we can calculate the efficiency of all DMUs.

Lemma: If DMU$_j$ is efficient at formulation (4) then necessarily would be efficient by CCR model.

For complete ranking of all DMUs, we can define set A as follows:

A={j| DMU$_j$ is efficient by formulation (4)}

And then introduce the following formulation:

$$\begin{array}{lll} Min & \sum_{j\in A} d_j^- & \\ s.t. & \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} + d_j^- = 1 & j\in A \\ & \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{x_j} \le 1 & j\notin A \\ & u_r \ \ge \varepsilon & r=1,2,\,\dots,\,s \\ & d_j^-, d_j^+ \ge 0 & j=1,2,\,\dots,\,n \end{array} \tag{5}$$

5 Numerical Example

In this section, the proposed goal programming methodology that may be applied to a wide range of technology selection problems is used for robot selection, and its discriminating power is illustrated through a previously reported industrial robot selection problem (Karsak and Ahiska, 2005).

The robot selection problem addressed in Karsak and ahiska (2005) involves the evaluation of relative efficiency of 12 robots with respect to four engineering attributes including 'handling coefficient(HC)', 'load capacity(LC)', '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 2.

Formulations (3) and (4) for $\varepsilon = 0.00001$ are used to calculate DEA efficiency scores and Minimax efficiency scores and the new algorithm (goal programming approach) of robots, which are given in the second, third and fourth columns of table 3, respectively.

To test the robustness of the proposed goal programming methodology, the scores obtained are compared with Minimax efficiency scores in third column of table 3. To conclude whether there is a positive relationship between the sets of rankings of the two approaches (Minimax and goal programming efficiency scores), Spearman's rank correlation test is conducted.

The Spearman's rank correlation is 0.90 and means that there is a positive relationship between the set of rankings of the two approaches (Minimax and Goal programming efficiency scores). Because the number of efficient DMUs on a common weight basis is reduced so discriminating power of our approach is higher than previous approaches and because Spearman's rank correlation between the ranks obtained from our approach and Minimax approach (Karsak and Ahiska (2005)) is high therefore robustness of our approach is justified.

Robot (j)	Cost(US$)	HC	LC(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 2: Input and output data for 12 industrial robots.

Robot(j)	DEA efficiency scores	Minimax efficiency scores	GP efficiency scores
1	0.653(11)	0.653(9)	0.628(9)
2	0.821(7)	0.753(6)	0.821(5)
3	0.954(4)	0.883(4)	0.954(3)
4	0.950(5)	0.862(5)	0.951(4)
5	1.000(1)	1.000(1)	1.000(1)
6	0.563(12)	0.563(12)	0.508(12)
7	0.683(10)	0.683(8)	0.585(10)
8	1.000(1)	0.631(10)	0.746(8)
9	0.765(8)	0.687(7)	0.764(6)
10	0.714(9)	0.617(11)	0.549(11)
11	0.909(6)	0.890(3)	0.749(7)
12	1.000(1)	1.000(1)	0.998(2)
average	$\mu = 0.834$	$\mu = 0.768$	$\mu = 0.771$

Table 3: Efficiencies of robots for $\varepsilon = 0.00001$.

$$u_1 = 0.524280, \quad u_2 = 0.000010, \quad u_3 = 0.000010, \quad u_4 = 0.124319.$$

6 Conclusions

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. The proposed efficiency measurement technique uses a multi-objective linear programming method. Both the Minimax efficiency measure by Karsak and ahiska (2005) and the proposed efficiency measure (goal programming approach), being common to all DMUs, enable the computation of efficiency scores of all DMUs on a common weight basis. The comparison reveals that both analysis evaluate the same robot as the best one. Furthermore, the rankings obtained by the proposed methodology and Minimax 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. 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.

In short, the proposed methodology can be considered as a sound as well as practical alternative decision aid that can be used for justification and selection problems accounting for multiple exact outputs and a single input that can be applied in a wide range of AMT's selection activities. For further study, useful extensions of the proposed methodology can be developed, which enables the decision-maker to consider imprecise output data denoted by fuzzy numbers.

References

[1] Agrawal V.P., Kohli V. and Gupta S. (1991) "Computer aided robot selection: The 'multiple attribute decision-making' approach," Int. J. Prod. Res., 29, 1629-164.

[2] Amin G.R., Toloo M. and Sohrabi B. (2006) "An improved MCDM DEA model for technology selection," International Journal of Production Research., 44, 2681-2686.

[3] Baker R.C. and Taluri S., (1997) "A closer look at the use of data envelopment analysis for technology selection," Comput. Ind. Eng., 32, 101-108.

[4] Braglia M. and Gabbrieli R., (2000) "Dimensional analysis for investment selection in industrial robots," Int. J. Prod. Res., 38, 4843-4848.

[5] Braglia M. and Petroni A. (1999) "Evaluating and selecting investments in industrial robots," Int. J. Prod. Res., 37, 4157-4178.

[6] Chang D.S. and Tsou C.S. (1993) "A chance-constraints linear programming model on the economic evaluation of flexible manufacturing systems," Prod. Plan. Contr., 4, 159-165.

[7] Karsak E.E. (1998) "A two-phase robot selection procedure," Prod. Plan. Contr., 9, 675-684.

[8] Karsak E.E. and Tolga E. (2001) "Fuzzy multi-criteria decision-making procedure for evaluating advanced manufacturing system investments," Int. J. Prod. Econ., 69, 49-64.

[9] Karsak E.E. and Ahiska s.s. (2005) "Practical common weight multi-criteria decision-making approach with an improved discriminating power for technology selection," Int. J. Prod. Res., 43, 1537-1554.

[10] Khouja M. (1995) "The use of data envelopment analysis for technology selection," Comput. Ind. Eng., 28, 123-132.

[11] Liang G.S. and Wang M.J.J. (1993) "A fuzzy multi-criteria decision-making approach for robot selection," Comput. Integr. Manuf., 10, 267-274.

[12] Parkan C. and Wu M.L. (1999) "Decision-making and performance measurement models with applications to robot selection," Comput. Ind. Eng., 36, 503-523.

[13] Parkan C. and Wu M.L. (2000) "Comparison of three modern multi-criteria decision-making tools," Int. J. Sys. Sci., 31, 497-517.

[14] Proctor M.D. and Canada J.R. (1992) "Past and present methods of manufacturing investment evaluation: A review of the empirical and theoretical literature," Eng. Economist, 38, 45-58.

[15] Raafat F. (2002) "A comprehensive bibliography on justification of advanced manufacturing systems," Int. J. Prod. Econ., 79, 197-208.

[16] Sambasivarao K.V. and Deshmukh S.G., (1997) "A decision support system for selection and justifcation of advanced manufacturing technologies," Prod. Plan. Contr., 8, 270-284.

[17] Sarkis J. and Taluri S. (1999) "A decision model for evaluation of flexible manufacturing systems in the presence of both cardinal and ordinal factors," Int. J. Prod. Res., 37, 2927-2938.

[18] Shang J. and Sueyoshi T. (1995) "A unified framework for the selection of a flexible manufacturing system," Eur. J. Oper. Res, 85, 297-315.

[19] Son Y.K. (1992) "A comprehensive bibliography on justification of advanced manufacturing technologies," Eng. Economist, 38, 59-71.

[20] Stam A. and Kula M. (1991) "Selecting a flexible manufacturing system using multiple criteria analysis," Int. J. Prod. Res., 29, 803-820.

[21] Sun S. (2002) "Assessing computer numerical control machines using data envelopment analysis," Int. J. Prod. Res., 40, 201-2039.

[22] Taluri S. and Yoon K.P. (2000) "A cone-ratio DEA approach for AMT justification," Int. J. Prod. Econ., 66, 19-129.