A Practical Common Weight Scaling Function Approach for Technology Selection

Mousa AMINI, Alireza ALINEZHAD

Abstract—A practical common weight scaling function methodology with an improved discriminating power for technology selection is introduced. The proposed scaling function 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 DEA classic model (CCR model) and Minimax method (Karsak & Ahiska, 2005). Because the number of efficient DMUs 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 is high therefore robustness of our approach is justified.

Keywords: Technology selection, Robot selection, scaling function approach, Discriminating power, weight restriction, DEA, common set of weights.

I. INTRODUCTION

For quality, productivity and safety reasons, the use of robots in industry has gained popularity in the past two decades. Robots can be programmed to keep a constant speed and a predetermined quality when performing a task repetitively. They can manage to work under conditions hazardous to human health such as excessive heat or noise, heavy load, toxic gases, etc. Therefore, manufacturers prefer to use robots in many industrial applications where repetitive, difficult or hazardous tasks need to be performed, such as assembly, machine loading, materials handling, spray painting and welding. However, the large number of existing robot options as well as the large number of attributes specifying robot performance for which industry-wide standards have not yet been determined result in a major impediment for potential robot users when deciding which robot to buy.

Many studies report that most widely considered performance attributes for industrial robots are load capacity, velocity, repeatability and accuracy. Repeatability and accuracy are the most easily confused attributes. Repeatability is a measure of the ability of the robot to return to the target point (the point where the robot is expected to go) and defined as the radius of the circle sufficiently large to include all points to which the robot actually goes on repeated trials. On the other hand, accuracy is a measure of closeness between the robot end effectors and the target point, and is defined as the distance between the target point and the centre of all points to which the robot goes on repeated trials. Manufacturers are more concerned with repeatability than accuracy since poor repeatability is more difficult to correct.

A robot with the capability of affording heavy load at high speed and low repeatability and accuracy will contribute positively to the productivity and flexibility of the manufacturing process, which are of vital importance where rapid changes in customer needs require the introduction of new products into the market very frequently. When product design changes need to be made repeatedly, owning a high-performing robot will avoid replacement or modification. Several works that address the development of a robust decision tool enabling the potential robot user to select a high performing robot have been reported so far. A brief survey on these previous works is given in section 2. This paper contributes to the AMT selection literature by introducing a novel multi-objective decision methodology that can integrate multiple outputs such as various technical characteristics with a single input such as cost. The proposed methodology can be successfully 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 paper is organized as follows. Section 2 provides a concise literature review on the existing decision tools for AMT evaluation. In section 3, a practical common weight MCDM methodology (Karsak & Ahiska, 2005) is presented. Section 4 presents the proposed scaling function methodology. The robustness and convenience of the proposed scaling function methodology are illustrated through a comparison with the method of Karsak and Ahiska (2005) for a technology selection problem in sections 5, 6. Finally, concluding remarks are provided in section 7.

II. 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-
A number of papers have focused on the use of MCDM techniques for AMT justification. Huang and Ghandforoush (1984) evaluated industrial robot vendors, and identified the best robot by assigning specific weights to those factors. Imany and Schlesinger (1989) compared linear goal programming and ordinary least-squares methods via a robot selection problem where robots are evaluated based on cost and technical performance measures including load capacity, velocity and repeatability. 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. Shang and Sueyoshi (1995) evaluated FMS alternatives using a decision framework that can integrate tangible and intangible benefits and financial factors. The proposed framework involved first the integrated use of AHP, simulation and an accounting procedure to determine the necessary outputs and inputs of FMS alternatives, and then, the application of DEA with restricted weights and cross-efficiency analysis to select the most efficient FMS. 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. Baker and Taluri (1997) addressed some limitations of the simple radial efficiency scores used in Khouja (1995) and suggested the use of cross-efficiency analysis for AMT selection. 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. Parkan and Wu (1999) studied the robot selection problem using OCRA, TOPSIS and utility function model, and proposed to rank the robots based on the averages of the rankings obtained by these there decision tools. Sarkis and Taluri (1999) evaluated FMS alternatives based on pair-wise efficiency comparisons made through a decision model that integrated the DEA model suggested by Cook et al. (1996) with cross-efficiency analysis. Parkan and Wu (2000) applied OCRA, AHP and DEA separately to an advanced automatic process evaluation problem and compared the results obtained by OCRA with those obtained by the other two methods to find out their similarities and differences. Braglia and Gabbieli (2000) proposed the use of a known mathematical method based on dimensional analysis theory for selection of the best robot when conflicting performance attributes are to be considered.

In addition, several studies contribute to the non-deterministic MCDM literature on evaluation, justification and selection of AMTs. Chang and Tsou (1993) formulated a chance-constraints linear programming model for economic evaluation of FMSs. Liang and Wang (1993) proposed a robot selection procedure using the concepts of fuzzy set theory. Perego and Rangone (1998) analyzed and compared fuzzy set theory-based multi-attribute decision-making techniques for AMT justification. Karsak (1998) proposed a two-phase robot selection procedure that integrated DEA with a fuzzy robot selection algorithm, which enabled the decision-maker to fully rank robot alternatives. Khouja and Kumar (1999) proposed a methodology for robot selection, which integrated technical considerations with real options theory. 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. Despite many fuzzy MCDM methods involve the use of a fuzzy number ranking method to handle imprecision and vagueness existing in decision problems, fuzzy number ranking methods is criticized for not producing consistent outcomes. Furthermore, there is no consensus on the best 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. Taluri and Yoon (2000) proposed a cone-ratio DEA approach for AMT justification, which made use of weight restriction constraints to incorporate a priori information on the priorities of factors, and illustrated the proposed model via a robot selection problem. A similar decision problem has recently been addressed by Sun (2002).

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 possesses two advantages compared with DEA-based approaches proposed in the literature for the similar problem. First, the proposed approach 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. One other similarity between the proposed methodology and DEA-based approaches is that they do not demand a priori importance weights from the decision-maker for performance attributes under consideration, and thus, they can be named as objective decision techniques.

### III. PROPOSED MCDM MODEL BY KARSAK AND AHISKA

Data envelopment analysis is a mathematical programming-based decision-making technique, which has
been widely used to treat decision problems that necessitate the consideration of multiple outputs and multiple inputs to evaluate the relative efficiency of DMUs. While considering multiple inputs in efficiency analysis, DEA makes an implicit assumption that any input can act as a substitute for any other because it uses weighted combination of all the inputs (Tofalis 1997). This critical assumption does not hold for cases where the inputs are not substitutes for each other. Tofalis (1997) states that considering one input at a time eliminates the problem of extreme or unrealistic weights on the inputs since they are not weighted at all.

When multiple exact outputs and a single input are to be considered in the evaluation process, the conventional DEA formulation takes the following form:

\[
\begin{align*}
\text{max} & \quad E_0 = \sum_{r} y_{rj} \mu_r \\
\text{subject to} & \quad \sum_{r} y_{rj} \mu_r \leq 1, \quad j = 1, 2, \ldots, n \\
& \quad \mu_r \geq \epsilon, \quad r = 1, 2, \ldots, s \\
& \quad w \geq \epsilon
\end{align*}
\]

where \(E_0\) is the efficiency of the evaluated DMU, \(\mu_r\) is the weight assigned to output \(r\), \(w\) is the weight assigned to the single input, \(y_{rj}\) is the amount of output \(r\) produced by DMU\(j\), \(x_j\) is the amount of the single input consumed by DMU\(j\), and \(\epsilon\) is a small positive scalar.

Formulation (1) is non-linear; however, it is possible to convert it into a linear program through a straightforward variable alternation. Replacing the term \(\frac{\mu_r}{w}\) with \(u_r\), for \(\forall r\), yields the following linear formulation:

\[
\begin{align*}
\text{max} & \quad E_0 = \sum_{r} u_r y_{rj} \\
\text{subject to} & \quad \sum_{r} u_r y_{rj} \leq 1, \quad j = 1, 2, \ldots, n \\
& \quad u_r \geq \epsilon, \quad r = 1, 2, \ldots, s
\end{align*}
\]

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., \(d_j = 1 - E_j\)). As minimizing \(d_0\), the deviation from efficiency for DMU\(0\), is equivalent to maximizing its efficiency, \(E_0\), an equivalent of formulation (2) can be written as (3).

\[
\begin{align*}
\text{min} & \quad d_0 \\
\text{subject to} & \quad \sum_{r} u_r y_{rj} + d_j = 1, \quad j = 1, 2, \ldots, n \\
& \quad u_r \geq \epsilon, \quad r = 1, 2, \ldots, s \\
& \quad d_j \geq 0, \quad j = 1, 2, \ldots, n
\end{align*}
\]
attribute weights, which 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 can be allowed by replacing the objective function of formulation (3) with the Minimax efficiency measure, which yields the following MCDM model, namely the Minimax efficiency model.

\[
\begin{align*}
\min & \quad M

\text{s.t.} & \quad M \geq d_j, \quad j = 1, 2, \ldots, n

\sum_{i=1}^{s} u_i y_{i,j} + d_j = 1, \quad j = 1, 2, \ldots, n

u_j \geq \varepsilon, \quad r = 1, 2, \ldots, s

d_j \geq 0, \quad j = 1, 2, \ldots, n
\end{align*}
\]

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 \( M = \max_j d_j \).

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 (4) is solved, the efficiencies for al DMUs is determined by calculating \( f_j(x) \), for \( j = 1, 2, \ldots, n \). 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.

IV. SCALING FUNCTION APPROACH

Consider the multi-objective problem in (5), where X is the region of solutions.

\[
\begin{align*}
\max & \quad \{ f_1, f_2, \ldots, f_k \}

\text{s.t.} & \quad z \in X, \quad X = \left\{ x \in R \mid g_i(x) \leq \varepsilon, \quad i = 1, 2, \ldots, m \right\}
\end{align*}
\]

For solving this MODM, we can use scaling function approach (Wiersbicki method) that assumes the optimal solution of the following problem is efficient for the above MODM problem.

\[
\begin{align*}
\min & \quad \left\{ \max_{j=1}^{n} (f_j(x)) \right\} + \delta \sum_{j=1}^{n} (f_j(x) - f_j(x))

\text{s.t.} & \quad x \in X
\end{align*}
\]

In formulation (6), \( b_j \) are the goals of objective functions \( f_j \) and \( \delta \) is a very small positive number. In one special case if \( f_j = f_j^*(x) \), \( j = 1, 2, \ldots, n \) then, \( f_j^*(x) \) is optimal for all objective functions that calculated from the following formulation.

\[
\begin{align*}
\max & \quad f_j(x), \quad j = 1, 2, \ldots, n

\text{s.t.} & \quad x \in X
\end{align*}
\]

Therefore, formulation (7) is rewritten as

\[
\begin{align*}
\min & \quad \left\{ \max_{j=1}^{n} \left( f_j(x) - f_j(x) \right) + \delta \sum_{j=1}^{n} \left( f_j(x) - f_j(x) \right) \right\}

\text{s.t.} & \quad x \in X
\end{align*}
\]

V. PRACTICAL COMMON WEIGHT SCALING FUNCTION APPROACH FOR TECHNOLOGY SELECTION

Consider the following MOLP:

\[
\begin{align*}
\max & \quad \left\{ \sum_{i=1}^{s} u_i y_{i,j} \right\}

\text{s.t.} & \quad \sum_{i=1}^{s} u_i y_{i,j} \leq 1, \quad j = 1, 2, \ldots, n

u_j \geq \varepsilon, \quad r = 1, 2, \ldots, s
\end{align*}
\]

We can solve the above formulation by using (8). That is

\[
\begin{align*}
\min & \quad \left\{ \max_{j=1}^{n} \left( \theta_j - \sum_{i=1}^{s} u_i y_{i,j} \right) \right\} + \delta \sum_{j=1}^{n} \left( \theta_j - \sum_{i=1}^{s} u_i y_{i,j} \right)

\text{s.t.} & \quad \sum_{i=1}^{s} u_i y_{i,j} \leq 1, \quad j = 1, 2, \ldots, n

u_j \geq \varepsilon, \quad r = 1, 2, \ldots, s
\end{align*}
\]

Formulation (10) is nonlinear so by defining variable Z, model (10) becomes a linear one.

\[
\begin{align*}
\min & \quad Z + \delta \sum_{j=1}^{n} \left( \theta_j - \sum_{i=1}^{s} u_i y_{i,j} \right)

\text{s.t.} & \quad Z \geq \theta_j - \sum_{i=1}^{s} u_i y_{i,j}, \quad j = 1, 2, \ldots, n

\sum_{i=1}^{s} u_i y_{i,j} \leq 1, \quad j = 1, 2, \ldots, n

u_j \geq \varepsilon, \quad r = 1, 2, \ldots, s

Z \geq 0
\end{align*}
\]
In formulation (11) we calculate \( \theta^*_j \) from the following model.

\[
\begin{align*}
\max & \sum_{r,s} u_{rs} y_{rs} = \theta^*_j, & j \in \{1, 2, \ldots, n\} \\
\text{s.t.} & \sum_{j=1}^{n} u_{rs} y_{rs} \leq 1, & j = 1, 2, \ldots, n, \\
& u_r \geq \varepsilon, & r = 1, 2, \ldots, s, \\
& Z \geq \theta^*_j - \sum_{r=1}^{s} u_{r} y_{rj}, & j \in A, \\
& \sum_{j=1}^{n} u_{rj} y_{rj} \leq 1, & j \notin A, \\
& u_r \geq \varepsilon, & r = 1, 2, \ldots, s, \\
& Z \geq 0.
\end{align*}
\]

By solving formulation (11), \( \theta^*_j \) are calculated that are a CSW and we can calculate efficiency of all DMUs.

Theorem: If \( DMU_j \) is efficient in formulation (11) then necessarily would be efficient by model CCR.

For complete ranking of DMUs, we have A as follow:

\[ A = \{ j | DMU_j \text{ is efficient by formulation (11)} \} \]

Now, we have

\[
\begin{align*}
\min & \{ Z + \delta \sum_{j \in A} \left( \theta^*_j - \sum_{r,s} u_{rs} y_{rs} \right) \} \\
\text{s.t.} & Z \geq \sum_{j=1}^{n} \left( \theta^*_j - \sum_{r,s} u_{rs} y_{rs} \right), & j \in A, \\
& \sum_{j=1}^{n} u_{rj} y_{rj} \leq 1, & j \notin A, \\
& u_r \geq \varepsilon, & r = 1, 2, \ldots, s, \\
& Z \geq 0.
\end{align*}
\]

VI. EXAMPLE PROBLEM

In this section, the proposed scaling function 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 & 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 Karsak and Ahiska.

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 1.

Formulations (3) and (4) for \( \varepsilon = 0.00001 \) are used to calculate DEA efficiency scores and Minimax efficiency scores and the new algorithm (scaling function approach) of robots, which are given in the second, third and fourth columns of table 2, respectively.

To test the robustness of the proposed scaling function methodology, the scores obtained are compared with Minimax efficiency scores in third column of table 2. To conclude whether there is a positive relationship between the sets of rankings of the two approaches (Minimax and scaling function efficiency scores), Spearman’s rank correlation test is conducted.

### Table 1. Input and output data for 12 industrial robots

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

### Table 2. Efficiencies of robots for \( \varepsilon = 0.00001 \)

<table>
<thead>
<tr>
<th>Robot (j)</th>
<th>DEA efficiency scores</th>
<th>Minimax efficiency scores</th>
<th>Scaling function efficiency scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.653(11)</td>
<td>0.653(9)</td>
<td>0.586(9)</td>
</tr>
<tr>
<td>2</td>
<td>0.821(7)</td>
<td>0.753(6)</td>
<td>0.767(6)</td>
</tr>
<tr>
<td>3</td>
<td>0.954(4)</td>
<td>0.883(4)</td>
<td>0.940(3)</td>
</tr>
<tr>
<td>4</td>
<td>0.959(5)</td>
<td>0.863(5)</td>
<td>0.909(4)</td>
</tr>
<tr>
<td>5</td>
<td>1.000(1)</td>
<td>1.000(1)</td>
<td>1.000(1)</td>
</tr>
<tr>
<td>6</td>
<td>0.563(12)</td>
<td>0.563(12)</td>
<td>0.487(12)</td>
</tr>
<tr>
<td>7</td>
<td>0.683(10)</td>
<td>0.683(8)</td>
<td>0.549(10)</td>
</tr>
<tr>
<td>8</td>
<td>1.000(1)</td>
<td>0.631(10)</td>
<td>0.798(5)</td>
</tr>
<tr>
<td>9</td>
<td>0.765(8)</td>
<td>0.687(7)</td>
<td>0.751(7)</td>
</tr>
<tr>
<td>10</td>
<td>0.714(9)</td>
<td>0.617(11)</td>
<td>0.514(11)</td>
</tr>
<tr>
<td>11</td>
<td>0.909(6)</td>
<td>0.890(3)</td>
<td>0.729(8)</td>
</tr>
<tr>
<td>12</td>
<td>1.000(1)</td>
<td>1.000(1)</td>
<td>0.998(2)</td>
</tr>
<tr>
<td>average</td>
<td>( \mu = 0.834 )</td>
<td>( \mu = 0.768 )</td>
<td>( \mu = 0.751 )</td>
</tr>
</tbody>
</table>

We can also use correlation to obtain Spearman’s \( \rho \) (rank correlation coefficient). Like the Pearson product moment correlation coefficient, Spearman’s \( \rho \) is a measure of the relationship between two variables. However, Spearman’s \( \rho \) is calculated on ranked data.

For calculating spearman’s we can use the below formulation that is the difference between ranks for the same observation (DMU). And \( n \) is the number of DMUs.

\[
r_s = 1 - \frac{\sum_{i,j=1}^{n} (r_i - r_j)^2}{n(n^2 - 1)}
\]

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. In this formulation \( x_{ij} \) are the ranks for the same DMU. And \( i = 1, 2, 3, \ldots, n \)
Spearman’s rank correlation is 0.808 and means that there is a positive relationship between the sets of rankings of the two approaches (Minimax and scaling function 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 & Ahiska, 2005) is high therefore robustness of our approach is justified.

VII. 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 & ahiska (2005) and the proposed efficiency measure (scaling function approach), being common to all DMUs, enable the computation of efficiency scores of all DMUs on a common weight basis.

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 Minimax analysis, which is proposed by Karsak and Ahiska (2005). The comparison reveals that both analyses 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.

VIII. REFERENCES


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