Personnel Selection Using an MCDM Approach that Integrates Numerical and Linguistic Information

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Abstract
A variety of factors that are considered in personnel selection such as oral communication skills, leadership, and self-confidence represent subjective and vague assessments. The fuzzy set theory appears as an effective tool to incorporate imprecise judgments inherent in the personnel selection process. This paper presents a multi-criteria decision making (MCDM) framework that enables the relative evaluation of a list of candidates with respect to a single input and multiple outputs where input and outputs can be assessed in exact numerical values or linguistic terms. The decision methodology consists of two major steps. First, a transformation procedure that is based on linguistic 2-tuple representation model is employed, which enables the numerical as well as linguistic data to be expressed on a common scale without loss of information. Next, a common weight MCDM methodology is applied to the scaled data in order to identify the best candidate. The proposed methodology is illustrated through a personnel selection problem, and its results are compared with those of data envelopment analysis (DEA).

Keywords: Multi-criteria decision making, Fuzzy linguistic approach, Minimax efficiency, Personnel selection.

1 Introduction
Personnel selection is the process of choosing individuals who match the qualifications required to perform a defined job in the best way [6]. Organizations differ with respect to the procedures and budgets for recruiting, selecting, and orienting people. Some firms make a strategic decision to choose the best candidate by utilizing rigorous and costly selection procedures, while others decide to fill positions quickly and inexpensively based only on the information stated on the application forms [1]. Nevertheless, there is an increasing trend in the use of analytical procedures in personnel selection.

A wide variety of tools have been proposed to select personnel in a complete and unbiased manner. Application blanks, biodata forms, reference checks, interviews, cognitive ability tests, personality tests, integrity tests, achievement tests, work sample tryouts, simulation, and group exercises can be listed among these tools [9]. In general, preliminary screening is the first step of the selection process. Preliminary screening enables the organization to eliminate a number of applicants who clearly do not meet the necessary qualifications of the job. Then, the organization reviews the application forms completed by the candidates to gather information regarding their past experience and personal characteristics. Further, interviews and tests are used to assess performance potential of the candidates. In addition to interviews, a wide range of testing
procedures, including tests of abilities, personality, skills and achievements, can be used to assess performance potential in an elaborate way.

After gathering all this information, the organization must make the employment decision considering both the requirements of the job, and the strategies and culture of the organization [6]. A variety of factors such as oral communication skills, leadership, self-confidence are subjective, and thus, exhibit imprecision and vagueness. The fuzzy set theory appears as an important tool to provide a decision framework that incorporates imprecise judgments inherent in the personnel selection process. Liang and Wang [8] developed a fuzzy multi-criteria decision making algorithm for personnel selection. Their approach employed fuzzy ranking methods to determine the most suitable candidate.

Subjective weighting of criteria which results in differences in selection results is a commonly encountered problem in personnel selection. In a recent paper, Jessop [5] addressed this problem and proposed a method based on the principle of maximum entropy to obtain minimally biased weight determination. In this paper, linear programming models that are derived from the original data envelopment analysis (DEA) model developed by Charnes, Cooper and Rhodes [2] by considering single input and multiple outputs, and different efficiency measures having an improved discriminating power compared with the DEA model have been proposed as an alternative decision aid. This methodology proves to be a robust objective decision tool since it does not require a priori subjective assessments of the decision-maker regarding the importance of performance attributes and allows the evaluation of all decision making units (DMUs) by common performance attribute weights. Moreover, this modeling framework has a practical structure with a substantial saving in computations compared with DEA-based approaches.

The rest of the paper is organized as follows. The next section provides a decision methodology that integrates both crisp and linguistic data for decision problems where alternatives are to be evaluated with respect to a single input and multiple outputs. Section 3 presents an illustration of the proposed multi-criteria decision making (MCDM) approach to a personnel selection problem, which consists of selecting the best among the short-listed candidates. Finally, concluding remarks and directions for future research are presented in the last section.

2 Proposed MCDM Approach

This section describes a decision methodology for personnel selection where both numerical and linguistic input and outputs are to be evaluated. The methodology consists of first expressing all the numerical as well as linguistic assessments on a common scale through the use of transformation functions based on linguistic 2-tuple representation, and then, determining the best alternative using an MCDM approach.

The concept of a linguistic variable is useful for providing approximate characterization of phenomena that are too complex or ill-defined to be described in conventional quantitative terms [11]. The performance ratings of candidates with respect to qualitative attributes such as oral communication skills, self-confidence, etc. are mostly linguistic assessments rather than numerical values because of the difficulty in evaluating the imprecision or vagueness inherent in qualitative attributes using exact values. When a linguistic term set is used to represent the qualitative information, first the granularity of uncertainty, i.e. the level of discrimination among different counts of uncertainty should be determined. Typical values of cardinality mostly preferred are the odd ones, such as 5, 7 or 9 where the middle term represents approximately an assessment of 0.5 in the [0, 1] interval and the other terms are placed symmetrically around the middle term [4]. Once the granularity of the linguistic term set is determined, the linguistic terms and their corresponding semantics, i.e. the fuzzy numbers defined in the [0, 1] interval, should be established.

Herrera and Martínez [3] represented the linguistic information through the use of a 2-
tuple, \((s, \alpha)\), where \(s\) is a linguistic term and \(\alpha\) is a numerical value assessed in \([-0.5, 0.5]\) that represents the value of symbolic translation. The linguistic 2-tuple representation model has a number of advantages compared with classical linguistic models such as the ability to treat the linguistic domain as continuous as opposed to discrete, the ability to compute with words easily and without loss of information, and the ability to express the results of the process of computing with words in terms of the initial linguistic domain.

Herrera and Martinez \([4]\) introduced a transformation procedure that allows the conversion of a crisp number \(v \in [0,1]\) into a numerical value \(\beta \in [0,g]\) that represents the information from the crisp number \(v\) in terms of the linguistic term set \(S = \{s_0, s_1, \ldots, s_g\}\).

First, the crisp number \(v\) is converted into a fuzzy set in \(S\) using the following function:

\[
r : [0,1] \rightarrow F(S)
\]

\[
r(v) = (s_0, z_0), \ldots, (s_g, z_g),\ s_i \in S, and\ z_i \in [0,1].
\]

Here, \(z_i\) is defined as

\[
z_i = f_{s_i}(v) = \begin{cases} 
\frac{v - a_i}{b_i - a_i}, & a_i \leq v \leq b_i \\
\frac{c_i - v}{c_i - b_i}, & b_i \leq v \leq c_i \\
0, & otherwise
\end{cases}
\]

where \(a_i, b_i\) and \(c_i\) are the parameters of the triangular fuzzy number representing the linguistic term \(s_i \in S\). The main reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation \([6, 10]\).

Then, the resulting fuzzy set in \(S\) is transformed into a linguistic 2-tuple assessed in \(S\) using the following weighted average function:

\[
\chi : F(S_T) \rightarrow [0, g]
\]

\[
\chi(r(v)) = \chi((s_j, z_j), j = 0, \ldots, g) = \frac{\sum_{j=0}^{g} z_j}{\sum_{j=0}^{g} s_j} = \beta
\]

The value \(\beta \in [0, g]\) obtained by the function \(\chi\) is a numerical value that represents the information from the crisp number \(v\) in terms of the linguistic term set \(S\).

The present work proposes to solve the decision problems where numerical as well as linguistic outputs and a single input are to be evaluated by expressing first all the evaluation data on a common scale with respect to the linguistic term set \(S = \{s_0, \ldots, s_g\}\) that is used to represent the qualitative attributes. This is accomplished by assigning to the linguistic variables \(s_0, s_1, \ldots, s_g\), which represent the qualitative attributes, the numerical values \(0, 1, \ldots, g\), respectively, and converting the numerical data that represent the quantitative attributes into numerical values that belong to the interval \([0, g]\) using the transformation procedure described above. As a result, all evaluation data will be expressed on a common scale without any loss of information.

Karsak and Ahiska \([7]\) proposed a practical common weight MCDM approach for decision problems with a single exact input and multiple exact/ordinal outputs, which consists of successive application of linear programming models until the best decision alternative is identified. The proposed efficiency models are originally derived from the non-linear DEA model \([2]\), which is given as

\[
\begin{align*}
\max E_{j_0} &= \frac{\sum r \mu_r y_{rj_0}}{\sum_i w_i x_{ij_0}} \\
\text{subject to} & \quad \sum_i w_i x_{ij} = 1, \forall j \\
& \quad \sum_r \frac{r \mu_r y_{rj}}{\sum_i w_i x_{ij}} \leq 1, \forall j \\
& \quad \mu_r \geq 0, \forall r \\
& \quad w_i \geq 0, \forall i
\end{align*}
\]

where \(E_{j_0}\) is the efficiency value of the evaluated decision making unit, \(\mu_r\) is the weight assigned to output \(r\), \(w_i\) indicates the weight assigned to input \(i\), \(y_{rj}\) is the amount of output \(r\) produced by DMU \(j\), and \(x_{ij}\) is the amount of input \(i\) consumed by DMU \(j\).
Formulation (1) can be rewritten for the case where a single input and multiple outputs are to be considered in the evaluation process, by simply replacing the weighted input summation term by \( w x_j \). Then, the non-linearity is eliminated through a simple variable alternation, \( \mu_r / w \rightarrow u_r \), and the model can be rewritten as follows:

\[
\begin{align*}
\text{max } E_{j_0} &= \frac{\sum u_r y_{rj_0}}{x_{j_0}} \\
\text{subject to} & \quad \frac{\sum u_r y_{rj}}{x_{j}} \leq 1, \forall j \\
& \quad u_r \geq 0, \forall r \\
& \quad d_j \geq 0, \forall j
\end{align*}
\]

subject to

\[
\begin{align*}
\sum u_r y_{rj} &+ d_j = 1, \forall j \\
u_r &\geq 0, \forall r \\
d_j &\geq 0, \forall j
\end{align*}
\]

Let \( d_j \) be defined as the deviation of the efficiency of DMU \( j \) from the ideal efficiency value of 1 (i.e. \( d_j = 1 - E_j \)). As minimizing the deviation from efficiency for DMU \( j_0 \) \( (d_{j_0}) \) is equivalent to maximizing its efficiency value, \( E_{j_0} \), the resulting formulation can be represented as

\[
\begin{align*}
\text{min } d_{j_0} \\
\text{subject to} & \quad \frac{\sum u_r y_{rj}}{x_{j}} + d_j = 1, \forall j \\
& \quad u_r \geq 0, \forall r \\
& \quad d_j \geq 0, \forall j
\end{align*}
\]

where \( x_{j} \) is the amount of the single input consumed by DMU \( j \).

To avoid unrealistic weight distribution and improve the discriminating power of DEA, the minimax efficiency measure that is not specific to a particular DMU, but common to all DMUs is proposed. Using the minimax efficiency measure, which can be briefly defined as the minimization of the maximum deviation from efficiency among all DMUs, formulation (3) is transformed into a common weight MCDM model with an improved discriminating power, namely the minimax efficiency model, represented as

\[
\begin{align*}
\text{min } M \\
\text{subject to} & \quad M \geq d_j, \forall j \\
& \quad \frac{\sum u_r y_{rj}}{x_{j}} + d_j = 1, \forall j \\
& \quad u_r \geq 0, \forall r \\
& \quad d_j \geq 0, \forall j
\end{align*}
\]

where \( M \) represents the maximum deviation from efficiency.

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 select the factor weights in a way to maximize its own efficiency score. Moreover, since the efficiency values for all DMUs can be computed by a single formulation, the minimax efficiency measure is more practical to implement. When formulation (4) is solved, the efficiency values for all DMUs is determined by computing \( 1 - d_j \), for \( j = 1, \ldots, n \). This one-step efficiency computation enables the evaluation of the relative efficiency of all DMUs based on the same performance attribute weights, which contrasts with DEA models where each DMU is evaluated by different weights.

When formulation (4) does not enable the determination of the best DMU by identifying more than one efficient DMU, the common weight MCDM model given below is used.

\[
\begin{align*}
\text{min } M - k \sum_{j \in EF} d_j \\
\text{subject to} & \quad M \geq d_j, \forall j \\
& \quad \frac{\sum u_r y_{rj}}{x_{j}} + d_j = 1, \forall j
\end{align*}
\]

where \( EF \) is the set of efficient DMUs. When formulation (5) is solved, the efficiency values for all DMUs is determined by computing \( 1 - d_j \), for \( j = 1, \ldots, n \).
where $EF$ is the set of DMUs which are minimax efficient, and $k \in [0,1]$ is a discriminating step size parameter whose value is to be determined by the analyst.

The value of $k$ will be increased from 0 to 1 with a predetermined step size until the model results in a single efficient DMU. One shall note that, for $k = 0$, formulation (5) is equivalent to the minimax efficiency model.

In summary, the proposed model has several advantages compared with the DEA model. First, it discriminates better among DMUs, allowing the determination of the best DMU. Second, it calculates the efficiency values of all DMUs by solving a single formulation, which enables the evaluation of relative efficiency of DMUs on a common weights basis and with a significant saving in computations. Last, its intuitive common weight structure enables its results to be more easily acknowledged and adopted by management.

### 3 Personnel Selection Example

In this section, the proposed decision framework is illustrated through a personnel selection example and its robustness is tested via a comparison with DEA.

The personnel selection problem involves the evaluation of 15 short-listed candidates with respect to a single input, namely “salary request on a yearly basis”; two crisp outputs, namely “general aptitude test score” and “professional knowledge test score”, and three subjective outputs, which are “oral communication skills”, “planning & organizing ability” and “self-confidence”. The selected input and outputs are commonly employed factors in personnel selection.

The crisp attributes are assessed by exact numerical values while the subjective attributes are assessed using the linguistic term set depicted in Figure 1. In Figure 1, the granularity of the linguistic term set is 5, with $s_0 = $ very low (VL), $s_1 = $ low (L), $s_2 = $ moderate (M), $s_3 = $ high (H), and $s_4 = $ very high (VH).

![Figure 1: A linguistic term set $S = \{s_0=VL, s_1=L, s_2=M, s_3=H, s_4=VH\}$ with granularity of 5.](image)

Input and output data related to the short-listed candidates are given in Table 1.

<table>
<thead>
<tr>
<th>Ci</th>
<th>Salary req. ($)</th>
<th>General apt. test score</th>
<th>Prof. know. test score</th>
<th>Oral com. skills</th>
<th>Plan.&amp; organ. ability</th>
<th>Self-conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>52000</td>
<td>67</td>
<td>81</td>
<td>H</td>
<td>M</td>
<td>VH</td>
</tr>
<tr>
<td>C2</td>
<td>64000</td>
<td>58</td>
<td>49</td>
<td>VH</td>
<td>H</td>
<td>M</td>
</tr>
<tr>
<td>C3</td>
<td>50000</td>
<td>62</td>
<td>76</td>
<td>H</td>
<td>M</td>
<td>VH</td>
</tr>
<tr>
<td>C4</td>
<td>56000</td>
<td>100</td>
<td>82</td>
<td>H</td>
<td>VH</td>
<td>VH</td>
</tr>
<tr>
<td>C5</td>
<td>67000</td>
<td>82</td>
<td>64</td>
<td>H</td>
<td>H</td>
<td>VH</td>
</tr>
<tr>
<td>C6</td>
<td>45000</td>
<td>67</td>
<td>76</td>
<td>M</td>
<td>M</td>
<td>H</td>
</tr>
<tr>
<td>C7</td>
<td>62000</td>
<td>93</td>
<td>91</td>
<td>M</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>C8</td>
<td>55000</td>
<td>58</td>
<td>58</td>
<td>H</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>C9</td>
<td>63000</td>
<td>89</td>
<td>78</td>
<td>M</td>
<td>H</td>
<td>M</td>
</tr>
<tr>
<td>C10</td>
<td>70000</td>
<td>53</td>
<td>56</td>
<td>M</td>
<td>VH</td>
<td>H</td>
</tr>
<tr>
<td>C11</td>
<td>51000</td>
<td>82</td>
<td>100</td>
<td>H</td>
<td>VH</td>
<td>H</td>
</tr>
<tr>
<td>C12</td>
<td>48000</td>
<td>56</td>
<td>91</td>
<td>M</td>
<td>M</td>
<td>VH</td>
</tr>
<tr>
<td>C13</td>
<td>67000</td>
<td>49</td>
<td>52</td>
<td>VH</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>C14</td>
<td>49000</td>
<td>57</td>
<td>87</td>
<td>H</td>
<td>M</td>
<td>VH</td>
</tr>
<tr>
<td>C15</td>
<td>63000</td>
<td>80</td>
<td>67</td>
<td>VH</td>
<td>M</td>
<td>H</td>
</tr>
</tbody>
</table>

The numerical data regarding the quantitative input and outputs are first normalized using a max-value normalization scheme in order to obtain numerical values that belong to the $[0,1]$ interval. The linguistic terms that are used to assess subjective outputs are replaced by their corresponding index. Then, in order to combine numerical and linguistic data without loss of information and in a reliable way, the transformation functions given in Section 2 are
applied successively to the numerical values regarding quantitative assessments, which result in values $\beta \in [0, g]$, where $g$ is the index of the last linguistic term in $S$, i.e. 4 in our case. As a result, all quantitative as well as linguistic assessments have a common scale, which is a numerical value belonging to $[0, 4]$, as shown in Table 2.

### Table 2: Data for the list of candidates (C_i) converted to common linguistic scale

<table>
<thead>
<tr>
<th>C_i</th>
<th>Salary req. ($)</th>
<th>General apt. test score</th>
<th>Prof. know. test score</th>
<th>Oral com. skills</th>
<th>Plan.&amp; organ. ability</th>
<th>Self-conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_1</td>
<td>2.97</td>
<td>2.68</td>
<td>3.24</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>C_2</td>
<td>3.66</td>
<td>2.32</td>
<td>1.96</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>C_3</td>
<td>2.86</td>
<td>2.48</td>
<td>3.04</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>C_4</td>
<td>3.20</td>
<td>4.00</td>
<td>3.28</td>
<td>3</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>C_5</td>
<td>3.83</td>
<td>3.28</td>
<td>2.56</td>
<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>C_6</td>
<td>2.57</td>
<td>2.68</td>
<td>3.04</td>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>C_7</td>
<td>3.54</td>
<td>3.72</td>
<td>3.64</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>C_8</td>
<td>3.14</td>
<td>3.92</td>
<td>2.32</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>C_9</td>
<td>3.60</td>
<td>3.56</td>
<td>3.12</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>C_{10}</td>
<td>4.00</td>
<td>2.12</td>
<td>2.24</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>C_{11}</td>
<td>2.91</td>
<td>3.28</td>
<td>4.00</td>
<td>3</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>C_{12}</td>
<td>2.74</td>
<td>2.24</td>
<td>3.64</td>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>C_{13}</td>
<td>3.83</td>
<td>1.96</td>
<td>2.08</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>C_{14}</td>
<td>2.80</td>
<td>2.28</td>
<td>3.48</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>C_{15}</td>
<td>3.60</td>
<td>3.20</td>
<td>2.68</td>
<td>4</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

The formulations (3), (4) and (5) are employed successively to evaluate the short-listed candidates in a comparative way. Formulation (3) gives the DEA efficiency scores of the candidates, which are shown in the second column of Table 3. According to DEA efficiency scores, six candidates, namely C_2, C_4, C_{11}, C_{12}, C_{14} and C_{15}, turn out to be efficient. On the other hand, formulation (4), which gives the minimax efficiency scores of candidates reported in the third column of Table 3, reduces the number of candidates to two, C_4 and C_{11} being the minimax efficient candidates. This result illustrates higher discriminating power of the minimax efficiency measure. Since the minimax efficiency scores do not enable the determination of the best candidate, formulation (5) that considers the $\min M - k \sum_{j=EF} d_j$ efficiency measure is employed by setting the discriminating parameter $k$ equal to 0.1. As shown in the last column of Table 3, C_{11} is determined as the best candidate.

### Table 3: Ranking scores for the candidates

<table>
<thead>
<tr>
<th>Candidate (C_i)</th>
<th>DEA efficiency scores</th>
<th>Minimax efficiency scores</th>
<th>$\min M - 0.1 \sum_{j=EF} d_j$ efficiency scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_1</td>
<td>0.974</td>
<td>0.801</td>
<td>0.686</td>
</tr>
<tr>
<td>C_2</td>
<td>1.000</td>
<td>0.680</td>
<td>0.721</td>
</tr>
<tr>
<td>C_3</td>
<td>0.995</td>
<td>0.821</td>
<td>0.703</td>
</tr>
<tr>
<td>C_4</td>
<td>1.000</td>
<td>1.000</td>
<td>0.942</td>
</tr>
<tr>
<td>C_5</td>
<td>0.792</td>
<td>0.726</td>
<td>0.658</td>
</tr>
<tr>
<td>C_6</td>
<td>0.956</td>
<td>0.775</td>
<td>0.679</td>
</tr>
<tr>
<td>C_7</td>
<td>0.877</td>
<td>0.695</td>
<td>0.644</td>
</tr>
<tr>
<td>C_8</td>
<td>0.873</td>
<td>0.628</td>
<td>0.623</td>
</tr>
<tr>
<td>C_9</td>
<td>0.803</td>
<td>0.628</td>
<td>0.623</td>
</tr>
<tr>
<td>C_{10}</td>
<td>0.728</td>
<td>0.628</td>
<td>0.623</td>
</tr>
<tr>
<td>C_{11}</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>C_{12}</td>
<td>1.000</td>
<td>0.765</td>
<td>0.623</td>
</tr>
<tr>
<td>C_{13}</td>
<td>0.960</td>
<td>0.681</td>
<td>0.682</td>
</tr>
<tr>
<td>C_{14}</td>
<td>1.000</td>
<td>0.827</td>
<td>0.710</td>
</tr>
<tr>
<td>C_{15}</td>
<td>1.000</td>
<td>0.695</td>
<td>0.655</td>
</tr>
</tbody>
</table>

### 4 Conclusion

This paper proposes a decision methodology that allows the consideration of both crisp and linguistic assessments in personnel selection based on multiple outputs and a single input. Initially, all the numerical data representing exact attributes are transformed to represent the original data in terms of the linguistic variables used to assess the subjective attributes, so that all exact as well as subjective assessments have a common scale. The transformation procedure used for this data conversion is based on linguistic 2-tuple representation, and it eliminates the shortcomings such as loss of information or complexity related to other fuzzy linguistic methodologies. After that, practical linear programming models based on the
minimax efficiency measure are successively applied until a single candidate is determined.

The robustness of this evaluation procedure is tested via a comparison with the DEA results. DEA that determines six efficient alternatives, among which there is also the candidate selected using the proposed approach, does not enable to identify the best candidate. The use of the proposed efficiency models for personnel selection has other advantages compared with DEA-based methodologies such as the ability to compute the efficiency scores of all DMUs by a single formulation, which allows the evaluation of all DMUs by common performance attribute weights, and a practical formulation structure that assures the convenience in application. Furthermore, the proposed framework enables input and output data to be represented using linguistic terms.

One should note that the proposed methodology can be successfully applied, but is not limited to personnel selection problems. Extending the proposed approach to multi-expert evaluation where experts may consider linguistic term sets with different granularity remains as a future research objective.

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References


