Hybrid Data Envelopment Analysis and Neural Networks for Suppliers Efficiency Prediction and Ranking

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Abstract

Supplier selection problem (SSP) is a problem to select the best among suppliers based on input and output data of the suppliers. Since different uncontrollable and unpredictable parameters are affecting selection, choosing the best supplier is a complicated process. Data Envelopment Analysis (DEA) is a method for measuring efficiency and inefficiencies of Decision Making Units (DMUs). While, the DEA has been employed by many researchers but it still has disadvantages. On the other hand, it has been widely used in SSP with inputs for supplier evaluation. Therefore, it seems need to provide models for further discrimination among these suppliers. Hence, in this paper, a combination of DEA and Neural Networks (NNs) model, DEA-NNs, has been improved based on Back-Propagation (BP) algorithm of NNs for complete ranking and prediction of supplier selection and performance.

Keywords. Supplier Selection Problem; Data Envelopment Analysis; Neural Networks

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Introduction

Supplier Selection Problem (SSP) is a problem to select the best among suppliers based on input and output data of the suppliers. Selection of the most appropriate suppliers is based on their ability to meet some criteria such as providing the right products for buyers, quality of services at the right time, price and quantities [27]. Since different uncontrollable and unpredictable parameters are affecting selection, choosing the best supplier is a complicated process. Data Envelopment Analysis (DEA) is a method for measuring efficiency and inefficiencies of Decision Making Units (DMUs) [7-8]. The multi-criteria decision making approaches are better than the traditional cost-based approaches, which aids the researchers and decision makers in applying the approaches effectively [15]. Several methods including Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Case-Based Reasoning (CBR), Fuzzy Set Theory (FST), Genetic Algorithm (GA), Mathematical Programming (MP) Models, Simple Multi-Attribute Rating Technique (SMART), Data Envelopment Analysis (DEA) and combination of the methods have been proposed for SSP [1-6],[8], [16], [18-19]. The DEA method, which is a linear programming technique for computing the efficiency DMUs, was first developed in [7]. DEA application in supplier evaluation has been presented in [21-26]. It has been widely used for efficiency estimation in both private and public sections of organizations such as banks, hospitals, airlines, universities, etc. and attract a great deal of researchers attention because of its ability in performance assessment. Recently, individual of DEA approaches have been presented for evaluation and selection process [15]. Also, supplier development strategies with DEA have been proposed in [14]. Various ranking approaches have been proposed in DEA in ranking of DMUs [13]. While, the DEA has been employed by several researchers but it still has disadvantages which are expressed as the following:

1- Inefficient units can be ranked according to their inefficiency, but efficient units (units with efficiency equal to 1) cannot be ranked. Also, with increasing number of input and output, the number of efficient units will increase. Obviously, without rank, it is not possible to choose the best among the efficient units.

2- DEA for a large dataset with many inputs or outputs would require an advanced computer with high resources in terms of memory and processing speed.

3- With addition of new units to old units, DEA cannot obtain efficiency of new units without recalculating the efficiency of all the units. In facts, DEA cannot be useful for predicting the efficiency new units.
According to the above literature, DEA has been widely used for applications with inputs and outputs; however, the approaches used in the prior researches have some drawbacks which include model infeasibility due to too small or too big values of input, suffer from obtaining complete ranking and non-generalization. Thus, in this paper, the combination of DEA and NNs is adopted and extended to evaluate different suppliers from two essential aspects, namely efficiency prediction and ranking. It is shown that the combined model can overcome the previously mentioned drawbacks of DEA.

The remainder of this paper is organized as follows. Section 2 provides research methodology and hybrid proposed model. Section 3 presents the experimental results and performance comparisons and finally, conclusions are presented in Section 4.

Methodology

In this section two traditionally used methods, namely DEA and NNs, and the combination of the two (DEA-NNs) for supplier selection process are presented. In our proposed model we combined two common methods of DEA, namely CCR and BCC, with NNs. We call our models CCR-NN and BCC-NN for the CCR and BCC models combined with NNs. The proposed models are used for ranking and efficiency prediction of suppliers. To evaluate the accuracy of the proposed models, the ranking data obtained from DEA and NNs are compared with CCR-NN and BCC-NN models.

1.1 DEA models

DEA is a powerful method conventionally used for measuring the efficiency of DMUs using linear programming techniques [7]. DEA requires several inputs and outputs to be considered at the same time to measure DMU efficiency which is defined as:

\[
    \text{Efficiency} = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}} \quad \forall \text{ DMUs}
\]  

(1)
Assuming a set of observed DMUs \( \{ DMU_j \mid j = 1, 2, \ldots, n \} \) associated with \( m \) inputs \( \{ x_{ij} \mid i = 1, 2, \ldots, m \} \) and \( s \) outputs \( \{ y_{rj} \mid r = 1, 2, \ldots, s \} \) The two common DEA models, CCR and BCC models, are represented as follows [8]:

**CCR Model.** The CCR model is developed based on the assumption of Constant Returns to Scale (CRS) which can be applied in the production frontier with multiple input and output data. The CCR model is represented as follow [8]:

\[
\begin{align*}
\text{min} & \quad \theta \\
\text{subject to} & \quad \sum_j \lambda_j x_{ij} \leq \theta x_{ip}, \quad \forall i \\
& \quad \sum_j \lambda_j y_{rj} \geq y_{rp}, \quad \forall r \\
& \quad \lambda_j \geq 0, \quad \forall j
\end{align*}
\]  

(2)

where, \( \theta \) is the efficiency for each supplier \( p \), \( \lambda_j \) is the dual variables for the benchmarks of inefficient units and other variables are as previously defined. Assuming \( \theta^* \) as the optimum solution of the model, it can be said that if \( \theta^* = 1 \) then the unit is technical efficiency otherwise the unit is inefficient [8].

**BCC Model.** The BCC model, on the other hand, is based on Variable Returns to Scale (VRS). The condition considered in BCC and CCR models are the same except that the convexity condition of \( \sum_j \lambda_j = 1, \lambda_j \geq 0, \quad \forall j \). The BCC model is represented as follows [8]:

\[
\begin{align*}
\text{min} & \quad \theta \\
\text{subject to} & \quad \sum_j \lambda_j x_{ij} \leq \theta x_{ip}, \quad \forall i \\
& \quad \sum_j \lambda_j y_{rj} \geq y_{rp}, \quad \forall r \\
& \quad \sum_j \lambda_j = 1, \quad \forall j \\
& \quad \lambda_j \geq 0, \quad \forall j
\end{align*}
\]  

(3)

where, \( \theta \) is the efficiency for each supplier \( p \), \( \lambda_j \) is the dual variables for the benchmarks of inefficient units and other variables are as previously defined. The different between CCR and BCC is in the dual variable that is presented in the dual problem with the constraint \( \sum_j \lambda_j = 1, \lambda_j \geq 0, \quad \forall j \) which does not appear in the CCR model.

Also, the feasible region of the BCC model is a subset for feasible region of the
CCR model. Notice that $\theta^{*}_{\text{BCC}}$ is not less than $\theta^{*}_{\text{CCR}}$, so the feasible region of BCC model is a subset for feasible region of CCR model [8].

1.2 Hybrid Data Envelopment Analysis and Neural Networks for Supplier Selection

The Back-Propagation algorithm, which was proposed in the 1980s [17] is the most common algorithm of NNs. This algorithm can be applied on multilayer feed-forward NNs and perform the learning. Figure1 shows the Back-Propagation application in DMUs method and this combined method is called DEA-NN method. The data used for training the neural network includes input, output and efficiency of DEA [9-12],[20]. We consider input and output of DEA for suppliers as the neural network input and the efficiency as the output of neural networks. We compute the efficiencies of suppliers using CCR and BCC models and then use them as input to DEA-NN method. The Back-Propagation NN in DEA is trained by iteratively processing a training sample, comparing the network’s prediction of efficiency scores for each sample of DMUs with actual known efficiency scores.

2.2.1 Supplier Efficiency Prediction and Ranking

In the obtained results of CCR and BCC models, one can find some suppliers with the same efficiency. Therefore suppliers with equal efficiency cannot be ranked by CCR and BCC models. To overcome this problem, algorithms were developed which is a combination of CCR with NN (CCR-NN) and BCC with NN (BCC-NN).

In addition, the so called CCR-NN based efficiency prediction (CCR-NNP), and BCC-NN based efficiency prediction (BCC-NNP) models were also developed for prediction process of new suppliers. The algorithm for this model is illustrated in next section. The predicted results obtained from these two models are then compared against each other. We consider a supplier to be categorized as “Almost Efficient (AE)”, if the efficiency different (which is (1- the value of efficiency obtained by the model for the supplier)) is less than 0.001.

Figure 1 shows the general flow of steps in using CCR/BCC, CCR-NN/BCC-NN, and CCR-NNP/BCC-NNP for suppliers’ efficiency prediction and ranking.
Figure 1. Combined generally algorithm for ranking, prediction by CCR-NN, BCC-NN, CCR-NNP and BCC-NNP models.
Results and Discussion

In this section, the six different supplier selection models, CCR, BBC, CCR-NN, BBC-NN, CCR-NNP and BCC-NNP, were compared and evaluated based on the obtained efficiency measure of suppliers. A sample of 25 supplier’s data as in [14] was used. The sample includes 2 Inputs (X1: Quality management Practices & X2: Employee training) and 3 Outputs (Y1: Quality of the product, Y2: Price of the product and Y3: Delivery of the product). Furthermore, in our model, X1, X2, Y1, Y2 and Y3 are defined as the input data for DEA-NNs algorithm, and the network output as efficiency index. The efficiency of suppliers obtained by CCR, BCC, CCR-NN and BCC-NN models are shown in Table 1. Results of the experiments should be described and discussed in this section.

Table 1. Efficiency of suppliers with different models

<table>
<thead>
<tr>
<th>Suppliers</th>
<th>Efficiency (CCR)</th>
<th>Efficiency (CCR-NN)</th>
<th>Efficiency (BCC)</th>
<th>Efficiency (BCC-NN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier 1</td>
<td>0.545418</td>
<td>0.545433</td>
<td>0.6509695</td>
<td>0.688982</td>
</tr>
<tr>
<td>Supplier 2</td>
<td>1</td>
<td>0.995619129</td>
<td>1</td>
<td>0.99778551</td>
</tr>
<tr>
<td>Supplier 3</td>
<td>0.601862</td>
<td>0.601862002</td>
<td>0.6889484</td>
<td>0.688881969</td>
</tr>
<tr>
<td>Supplier 4</td>
<td>1</td>
<td>0.99998511</td>
<td>1</td>
<td>0.99971368</td>
</tr>
<tr>
<td>Supplier 5</td>
<td>0.732617</td>
<td>0.73260836</td>
<td>0.7543066</td>
<td>0.766630574</td>
</tr>
<tr>
<td>Supplier 6</td>
<td>0.709511</td>
<td>0.709509656</td>
<td>0.7176225</td>
<td>0.725072151</td>
</tr>
<tr>
<td>Supplier 7</td>
<td>0.907325</td>
<td>0.907322904</td>
<td>1</td>
<td>0.766661621</td>
</tr>
<tr>
<td>Supplier 8</td>
<td>0.966631</td>
<td>0.97381182</td>
<td>0.9789644</td>
<td>0.979782335</td>
</tr>
<tr>
<td>Supplier 9</td>
<td>0.830973</td>
<td>0.830970899</td>
<td>0.8976391</td>
<td>0.99101061</td>
</tr>
<tr>
<td>Supplier 10</td>
<td>0.882817</td>
<td>0.882816113</td>
<td>1</td>
<td>0.99977623</td>
</tr>
<tr>
<td>Supplier 11</td>
<td>1</td>
<td>0.999985061</td>
<td>1</td>
<td>0.999756075</td>
</tr>
<tr>
<td>Supplier 12</td>
<td>0.797443</td>
<td>0.752767271</td>
<td>0.8136870</td>
<td>0.824588046</td>
</tr>
<tr>
<td>Supplier 13</td>
<td>0.723797</td>
<td>0.645963953</td>
<td>0.7637488</td>
<td>0.753191892</td>
</tr>
<tr>
<td>Supplier 14</td>
<td>0.898324</td>
<td>0.898321</td>
<td>0.9057548</td>
<td>0.940359</td>
</tr>
<tr>
<td>Supplier 15</td>
<td>0.937431</td>
<td>0.925610814</td>
<td>0.9569963</td>
<td>0.955291246</td>
</tr>
<tr>
<td>Supplier 16</td>
<td>1</td>
<td>0.980550588</td>
<td>1</td>
<td>0.999229412</td>
</tr>
<tr>
<td>Supplier 17</td>
<td>0.902665</td>
<td>0.864140233</td>
<td>1</td>
<td>0.975189832</td>
</tr>
<tr>
<td>Supplier 18</td>
<td>0.899932</td>
<td>0.917961434</td>
<td>0.9434356</td>
<td>0.947243516</td>
</tr>
<tr>
<td>Supplier 19</td>
<td>0.798203</td>
<td>0.798201</td>
<td>0.8180834</td>
<td>0.831961</td>
</tr>
<tr>
<td>Supplier 20</td>
<td>0.632663</td>
<td>0.632662</td>
<td>0.687500</td>
<td>0.689535</td>
</tr>
<tr>
<td>Supplier 21</td>
<td>0.72158</td>
<td>0.68511</td>
<td>1</td>
<td>0.999493</td>
</tr>
<tr>
<td>Supplier 22</td>
<td>0.816199</td>
<td>0.816196</td>
<td>0.8205705</td>
<td>0.832956</td>
</tr>
<tr>
<td>Supplier 23</td>
<td>0.810186</td>
<td>0.810183377</td>
<td>0.8102977</td>
<td>0.974117817</td>
</tr>
<tr>
<td>Supplier 24</td>
<td>0.775169</td>
<td>0.775166334</td>
<td>1</td>
<td>0.998732389</td>
</tr>
<tr>
<td>Supplier 25</td>
<td>0.872334</td>
<td>0.775184</td>
<td>0.9120176</td>
<td>0.919378</td>
</tr>
</tbody>
</table>

The ranking obtained by CCR and CCR-NN models are compared for efficient suppliers (efficiency equal to one) in Table 2. Based on CCR model alone, 4 suppliers (Supplier 2, 4, 11, and 16) have the same ranking (any rank between 1 to 4). With CCR-NN, on the other hand, it is possible to rank the best 4 suppliers and in this case Supplier 4 is the best supplier.

Table 2. Comparison of ranking between efficient suppliers with CCR and CCR-NN models

<table>
<thead>
<tr>
<th>Suppliers</th>
<th>2</th>
<th>4</th>
<th>11</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranking of Suppliers obtained using CCR</td>
<td>1,2,3,4</td>
<td>1,2,3,4</td>
<td>1,2,3,4</td>
<td>1,2,3,4</td>
</tr>
<tr>
<td>Ranking of Suppliers obtained using CCR-NN</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
Similarly when the BCC model is used, it shows that the BBC model alone is unable to give definite ranking to individual supplier. In fact, it is more indecisive here since, as shown in Table 3, the number of suppliers with seemingly equal ranking is larger (that is 9 suppliers compared to 4 suppliers with CCR model). With BCC-NN, the 9 suppliers can be distinctively ranked.

Table 3. Comparison of ranking between efficient suppliers with BCC and BCC-NN models

<table>
<thead>
<tr>
<th>Suppliers</th>
<th>2</th>
<th>4</th>
<th>7</th>
<th>10</th>
<th>11</th>
<th>16</th>
<th>17</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranking of Suppliers obtained using BCC</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
<td>1,2,...,9</td>
</tr>
<tr>
<td>Ranking of Suppliers obtained using BCC-NN</td>
<td>9</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>7</td>
<td>8</td>
</tr>
</tbody>
</table>

It can be seen that CCR-NN and BCC-NN models outperform the traditional models in the accuracy of the efficiency estimation. The predicted data for five new suppliers obtained from CCR-NNP and BCC-NNP are shown in Table 4. It can be seen that four of suppliers are efficient.

To design our network we adopted training iteration for the optimum number of hidden nodes in hidden layers. In our simulation, we consider the number of hidden layers as 4 and 8. To design the optimum NNs, we used the iteration method of training to obtain the optimum numbers of layers and nodes. The score of difference in the CCR-NN model is obtained for 5 new suppliers in Figure 2.

Table 4. Efficiency and ranking with models of Eff-CCRNNP and Eff-BCCP for new suppliers (AE and IE are almost efficient and inefficient respectively)

<table>
<thead>
<tr>
<th>New Suppliers</th>
<th>X1</th>
<th>X2</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Efficiency (CCR-NNP)</th>
<th>Rank (CCR-NNP)</th>
<th>Efficiency (BCC-NNP)</th>
<th>Rank (BCC-NNP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S 26</td>
<td>56</td>
<td>73</td>
<td>61</td>
<td>98</td>
<td>78</td>
<td>0.999999347(AE)</td>
<td>1</td>
<td>0.999788667(AE)</td>
<td>3</td>
</tr>
<tr>
<td>S 27</td>
<td>64</td>
<td>53</td>
<td>49</td>
<td>76</td>
<td>70</td>
<td>0.998608271(AE)</td>
<td>2</td>
<td>0.99829813(AE)</td>
<td>1</td>
</tr>
<tr>
<td>S 28</td>
<td>82</td>
<td>73</td>
<td>61</td>
<td>52</td>
<td>66</td>
<td>0.596543046(EI)</td>
<td>5</td>
<td>0.690622256(EI)</td>
<td>5</td>
</tr>
<tr>
<td>S 29</td>
<td>64</td>
<td>53</td>
<td>69</td>
<td>85</td>
<td>70</td>
<td>0.998448658(EI)</td>
<td>3</td>
<td>0.998279298(AE)</td>
<td>2</td>
</tr>
<tr>
<td>S 30</td>
<td>45</td>
<td>67</td>
<td>87</td>
<td>45</td>
<td>50</td>
<td>0.995619129(EI)</td>
<td>4</td>
<td>0.998778551(EI)</td>
<td>4</td>
</tr>
</tbody>
</table>
Conclusion

In this paper, several methods for Ranking and Prediction of suppliers have been proposed and their performance compared. The results show that these models can be used to solve the related problems of traditional models, in the case of equal efficiency. Two other models i.e. CCR-NNP and BCC-NNP have been proposed for efficiency prediction of new supplier selection. These models applied to evaluate the new suppliers which were not possible by traditional models like DEA. The most efficient suppliers which are called “Almost Efficient (AE)”, in this research, have been determined by applying these prediction models.

References


