Performance Evaluation Model of Park Based on Intelligent Algorithm

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Abstract
Evaluation system of industrial park is a complex problem concerning multiple levels and multiple objectives and multiple evaluation indexes. Use all the evaluation indexes as input of neural network will result in complex structure of neural network affecting performance of quality evaluation stem of park. Propose a park performance evaluation method integrating intelligence algorithm and neural network. First, adopt analytic hierarchy process to sort evaluation index bodies in accordance with importance, and then screen out indexes with important effect on evaluation result as BP neural network input. Finally, adopt neural network to establish evaluation model. Take performance assessment of a logistics industrial park as example to conduct simulation experiment, which shows park performance evaluation method based on integrated intelligent algorithm and neural network not only simplifies structure of neural network but also improve accuracy and evaluation efficiency of performance and quality evaluation to be a feasible and effective method of performance evaluation.

Keywords: Performance evaluation; Industrial park; Index system; Intelligent algorithm; BP neural network

1. Introduction
Even though there are rich research achievements of performance evaluation for modern logistics enterprises at home and abroad, it is easy to see scholars in our country are still at a primary stage in the research field [1-3]. They mainly introduce and imitate advanced foreign theories, combining them with practical development situation of modern logistics enterprises in our country to conduct improved research. With inadequate innovation, there are some defects in terms of evaluation index setting, evaluation method selection, evaluation dimension expansion, evaluation standard establishment, evaluation result application, etc. Theories applicable to practice are rare. A whole set of recognized complete performance evaluation system for modern logistics enterprises has not formed so far with depth and breadth of research to be further expanded. Current standards of performance evaluation for modern logistics enterprises are not scientific and systematic enough. Commonly used evaluation standards lay one-sided emphasis on importance, quantifiability, procurability and understandability while connotation of relevance similar to strategy and relevance and levels of value enhancement and other principles as important as enterprise performance evaluation implementation are not accurately decided [4-7]. Even if these principles are considered in evaluation process to some extent, they are not implemented in position resulting in accuracy decrease in performance evaluation result [8-10].

2. Establish Evaluation Index Model

2.1. Build Index Judgment Matrix
17 middle layer indexes of the Research reflect innovative performance evaluation criterion of modern logistics enterprises. Universal indexes include policy environment index, competitor index, innovation investment index, management level index, innovative talents index, innovative efficiency index, resource integration index and basic business performance index. Special indexes include technical index, customer index, network environment performance index, innovative strategy index, knowledge management index, system index, brand performance index and cultural performance index [11-13].


<table>
<thead>
<tr>
<th>Table 1. Evaluation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qualitative evaluation index</td>
</tr>
<tr>
<td>Second-grade index</td>
</tr>
<tr>
<td>Policy environment index</td>
</tr>
<tr>
<td>Network environment</td>
</tr>
<tr>
<td>Customer index</td>
</tr>
<tr>
<td>Technical index</td>
</tr>
<tr>
<td>Management level index</td>
</tr>
<tr>
<td>Innovative investment index</td>
</tr>
<tr>
<td>System index</td>
</tr>
<tr>
<td>Organization structure index</td>
</tr>
<tr>
<td>Resources integration index</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Building index judgment matrix is the key step of analytic hierarchy process. In order to reduce subjective factor influence, conduct pairwise comparison for performance evaluation indexes to build judgment matrix A. Element values in matrix A show relative importance degree of evaluation index to performance evaluation result. The Thesis adopts enterprise competent departments and experts familiar with performance quality evaluation to score jointly to decide. Assignment standard of elements in judgment matrix is shown in Table 2.

Table 2. Assignment standard of elements in judgment matrix

<table>
<thead>
<tr>
<th>Assignment (wi/wj)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>It shows two indexes have the same importance</td>
</tr>
<tr>
<td>3</td>
<td>It shows index Vi is slightly more important than Vj</td>
</tr>
<tr>
<td>5</td>
<td>It shows index Vi is obviously more important than Vj</td>
</tr>
<tr>
<td>7</td>
<td>It shows index Vi is highly more important than Vj</td>
</tr>
<tr>
<td>9</td>
<td>It shows index Vi is extremely more important than Vj</td>
</tr>
</tbody>
</table>

2.2. Weight Calculation and Consistency Test of Evaluation Index

According to evaluation index factor matrix, first W can be determined by $\lambda W = \lambda_{\text{max}}W$ and then conduct normalization to obtain importance weight value of corresponding index to the previous level. Finally conduct consistency test for judgment matrix. Conduct relative importance of the same level to overall performance evaluation result to obtain comprehensive weight. Conduct consistency test for judgment matrix from high level to low level. Finally, sort evaluation indexes according to weight of performance evaluation indexes. Remove unimportant indexes and screen out relatively important evaluation indexes as BP neural network input according to weight value order of influence of all the evaluation indexes on final performance evaluation results to reduce input dimension for neural network, simplify network result, accelerate learning rate of neural network and improve evaluation accuracy and evaluation efficiency of performance.

3. Park Performance Evaluation Model Based on BP Neural Network

3.1. BP Neural Network Model Design

BP neural network is a kind of nerve net with error back propagation which consists of input layer, hide layer and output layer, becoming the most widely used artificial neural network.
Output of input layer in BP neural network is:

\[ O^{(1)}(j) = x(j) \]  \hspace{1cm} (1)

Input and output of hide layer in neural network are:

\[
\begin{align*}
net_i^{(2)}(k) &= \sum_{j=0}^{M} w_{i,j}^{(2)} O_j^{(1)} \\
O_i^{(2)}(k) &= f\left(net_i^{(2)}(k)\right)
\end{align*}
\]  \hspace{1cm} (2)

Activation function in neuron in hide layer uses Sigmoid function with positive and negative symmetry:

\[ f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \]  \hspace{1cm} (3)

Input and output of network output layer are:

\[
\begin{align*}
net_i^{(3)}(k) &= \sum_{j=0}^{Q} w_{i,j}^{(3)} O_j^{(2)}(k) \\
O_i^{(3)}(k) &= g\left(net_i^{(3)}(k)\right)
\end{align*}
\]  \hspace{1cm} (4)

Activation function in neuron in output layer is a non-negative Sigmoid function:

\[ g(x) = \frac{e^x}{e^x + e^{-x}} \]  \hspace{1cm} (5)

Adopt gradient descent algorithm to decide threshold value and weight value to minimize mean squared error index of performance evaluation.

BP (Back Propagation) neural network is a kind of multilayer feed forward network trained in error back propagation algorithm and is a mathematical equation which is able to learn and store plenty of mapping relations for input-output model without prior disclosure and description of this kind of mapping relation. Its learning rule is to use steepest descent method to continuously adjust weight value and threshold value by back propagation to minimize error sum of squares of network. Topological structure of BP neural network model contains input layer, hide layer and output layer. G. Cybenyo and others have proved that neural network with one hide layer can express any continuous function in any accuracy and can reduce error and improve accuracy but with increased network complexity and longer training time in the case of more than two hide layers. By comparative analysis, the model selects three-layer network model with multiple inputs, single output and one hide layer. The structure chart is shown in Figure 1.
(1) Determination of input nodes
According to established index system, regard 16 key reflecting ELS timeliness, flexibility, quality and cost as input nodes of BP neural network, represented by \( I_i \) respectively.

(2) Determination of output nodes
Number of output nodes is generally decided by type of output data and magnitude of data required to represent the type. Model established in the Thesis is an evaluation model which outputs one evaluation value. Therefore, 1 output node is decided represented by \( O \).

Since ELS performance under earthquake disaster is a qualitative concept, it is difficult to represent simply using data. Therefore, the Thesis divides ELS performance conditions into four grades, namely, excellent, good, common and poor according to scores, as shown in Table 3:

<table>
<thead>
<tr>
<th>Grade</th>
<th>Score</th>
<th>Level</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>(0.75,1]</td>
<td>Excellent</td>
<td>All the aspects of ELS perform well so that performance is excellent</td>
</tr>
<tr>
<td>II</td>
<td>(0.5,0.75]</td>
<td>Good</td>
<td>Overall performance of ELS is good with small part of index to be improved so that performance is good</td>
</tr>
<tr>
<td>III</td>
<td>(0.25,0.5]</td>
<td>Average</td>
<td>A few indexes of ELS perform well with most indexes to be improved so that performance is average</td>
</tr>
<tr>
<td>IV</td>
<td>(0,0.25]</td>
<td>Poor</td>
<td>Overall ELS does not perform well with all the aspects to be enhanced and improved so that performance is poor</td>
</tr>
</tbody>
</table>

(3) Determination of nodes in hide layer
Determination of nodes number in hide layer of the model is a very important link which directly relates to number of both input nodes and output nodes of model, which may refer to the following three equations:

\[
n_1 = \sqrt{n + m + a} \quad (6)
\]

Where \( n \) is number of output nodes; \( m \) is number of input nodes and \( a \) is a constant within 1-10.

\[
n_1 = \frac{3\sqrt{nm}}{2} \quad (7)
\]

Where \( n \) is number of output nodes and \( m \) is number of input nodes.

\[
n_1 = \log_2 n \quad (8)
\]
With comprehensive consideration of complexity of network structure and error magnitude, the model selects 16 as number of hidden nodes, represented by $H_i$.

(4) Transition function
The model selects logsig()S type logarithmic function as transition function between input layer and hide layer as well as transition function between hide layer and output layer:

$$y = f(x) = 1 / (1 + e^{-x}), y \in [0,1]$$

(9)

3.2. Parameter Setting
According to characteristics of evaluation model, the Thesis selects the following parameters for BP neural network model:

(1) Network training function: the Thesis adopt batch processing mode to select traingd as training function;
(2) Network learning function: select learngdm function;
(3) Performance function: select mse function of which mse (Mean Squared Error) represents mean squared error;
(4) Learning rate: learning rate use 0.0001;
(5) Expected error: $S=0.0001$;
(6) Maximum training times: 10000 times;
(7) One learning process is indicated for every 50 times of operation;
(8) Other parameters are all default values.

Conduct standardization for original data of indexes in accordance with the following principles, the method of which is as follows:

Positive type index (the larger it is, the better evaluation is):

$$F_j = (x_j - x_{j, \text{min}}) / (x_{j, \text{max}} - x_{j, \text{min}})$$

(10)

Negative type index (the smaller it is, the better evaluation is):

$$F_j = 1 - (x_j - x_{j, \text{min}}) / (x_{j, \text{max}} - x_{j, \text{min}})$$

(11)

Where $x_j$ is original value, $F_j$ standardized value, $x_{j, \text{min}}$ the minimum value of the sample data of first $j$ index, $x_{j, \text{max}}$ the maximum value of the sample data of first $j$ index and $j$ the ordinal number of index.

4. Example Verification

4.1. Model Implementation
First, adopt analytic hierarchy process to decide weight for evaluation index of park performance quality and screen out according to weight value to obtain 5 indexes including performance evaluation objective, enterprise production efficiency, completing government plans and its own healthy development. Then conduct normalization for these 5 indexes and form new data sets by normalized data and actual evaluation result to input training sample into BP neural network for training. Training process is shown in Table 2.
Adopt the best performance quality evaluation model established to evaluate test data of performance quality of logistics parks. The evaluation accuracy obtained is up to 98.5%, which is rather high. The result shows the park performance quality evaluation method in the Thesis combining analytic hierarchy process with BP neural network is effective and feasible.

4.2. Performance Comparison

To test advantages and disadvantages of evaluation performance of models, conduct contrast experiment for single BP neural network (BPNN), analytic hierarchy process (AHP), multiple linear regression (MLR), analytic hierarchy process +multivariate linear regression model (AHP - MLR) models, and adopt evaluation accuracy as measure standard of models. The comparison result is shown in Table 4.

<table>
<thead>
<tr>
<th>Evaluation models</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLR</td>
<td>75.6%</td>
</tr>
<tr>
<td>AHP</td>
<td>90.1%</td>
</tr>
<tr>
<td>BPNN</td>
<td>93.6%</td>
</tr>
<tr>
<td>AHP-MLR</td>
<td>89.68%</td>
</tr>
<tr>
<td>Method in the Thesis</td>
<td>98.74%</td>
</tr>
</tbody>
</table>

From the comparison result in Table 3, evaluation accuracy of combined model AHP-MLR and park performance quality in the Thesis is higher than that of single model, which is mainly because combination model uses advantages of single model to complement each other’s advantages and effectively improve evaluation accuracy for park performance quality. Meanwhile, from Figure 3, evaluation result of BP neural network is superior to that of MLR and AHP. This is mainly because neural network is based on nonlinear modeling, having intelligent learning and classifying capacity, while MLR and AHP are based on linear modeling which fails to reflect nonlinear relation between park performance quality evaluation index and evaluation grades well. Therefore BP neural network is better than other linear models. Moreover, evaluation accuracy of the method in the Thesis is the highest which shows adopting AHP to analyze evaluation index, screening out the most important index for evaluation result and then adopting BP neural network with strong nonlinear predictive capacity have fully made use of advantages of both to enhance park performance quality evaluation efficiency and evaluation accuracy, which may conduct effective classification and evaluation for park performance quality.
4.3. Result Analysis

Input sample data into the program to operate on Matlab software. After 2000 times of operation, the accuracy satisfies requirements. Error change conditions are shown in Figure 3:

![Figure 3. Error change curve of network training](image)

Comparison between operation result and actual value assessed by experts is shown in Table 5.

From Table 5, network training, error square and mse are controlled within expected error. Thus park performance evaluation model of BP neural network has been established. At the time of performance evaluation for logistics parks, only a set of normalized index data are needed to be input into program to obtain park performance evaluation value so as to grade logistics park performance.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Actual value</th>
<th>Training Value</th>
<th>Absolute error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.41</td>
<td>0.50123</td>
<td>-0.00200</td>
</tr>
<tr>
<td>2</td>
<td>0.52</td>
<td>0.5552</td>
<td>0.00018</td>
</tr>
<tr>
<td>3</td>
<td>0.62</td>
<td>0.65234</td>
<td>-0.00159</td>
</tr>
<tr>
<td>4</td>
<td>0.82</td>
<td>0.79842</td>
<td>0.00452</td>
</tr>
<tr>
<td>5</td>
<td>0.43</td>
<td>0.56392</td>
<td>0.00689</td>
</tr>
<tr>
<td>6</td>
<td>0.24</td>
<td>0.23659</td>
<td>-0.00651</td>
</tr>
<tr>
<td>7</td>
<td>0.73</td>
<td>0.72862</td>
<td>0.03659</td>
</tr>
<tr>
<td>8</td>
<td>0.53</td>
<td>0.49882</td>
<td>-0.00245</td>
</tr>
<tr>
<td>9</td>
<td>0.67</td>
<td>0.59686</td>
<td>-0.01884</td>
</tr>
<tr>
<td>10</td>
<td>0.44</td>
<td>0.45851</td>
<td>0.00055</td>
</tr>
</tbody>
</table>

5. Conclusion

In previous research for logistics park performance evaluation, the method combining traditional analytic hierarchy process with fuzzy comprehensive evaluation method is mainly adopted. Calculation amount of this method is great and have strong subjectivity at the time of deciding index weigh vector. Besides, when performance evaluation index system is relatively large and under the restriction that weight vector sum shall be 1, membership degree coefficient is relatively small with weight vector mismatching fuzzy matrix resulting in super fuzzy
phenomenon and even failure to judge. The Thesis adopts exploratory method combing intelligent algorithm with BP neural network to evaluate park performance. Intelligent algorithm integrating BP artificial neural network evaluation has solved dynamic solution due to multiple indexes problem with variable weight to overcome subjective factors during weight decision process to add to scientificity for evaluation result. Moreover, during practical application, application of knowledge storage and self-adaptive characteristics of BP neural network, dynamic evaluation can be conducted for logistics park system performance for users to correct parameters according to practical condition if necessary, making the whole process easier for operation.

Acknowledgements

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References