A Power Grid Comprehensive Evaluation Based on BP Neural Network

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Abstract. By building the index system for the evaluation target, the Power Grid comprehensive evaluation is to use corresponding evaluation model to get the evaluation results. In this paper, a multi-level power grid comprehensive evaluation index system including 7 first level indicators, 14 second level indicators and 28 third level indicators was built. Meanwhile, the AHP method was adopted to introduce game theory integration method, combined with fuzzy comprehensive evaluation method and entropy weight method, accordingly, the subjective and objective weight were determined and, the final weight was obtained and put into the neural network for training. Through the evaluations results for power grid satisfaction of 10 cities in a certain province, it can verify that this method will realize rapid, unanimous and accurate power grid evaluation.

Keywords: power grid comprehensive evaluation; satisfaction of electric power customers; BP neural network; genetic algorithm method; fuzzy comprehensive evaluation; entropy weight method; game theory

Introduction

Along with the reform of power marketing in China, the economic evaluation in the development of power enterprises is increasingly important. As a new economic indicator of economic quality, customer satisfaction is not only a measure of comprehensive indicator for a product quality or service quality, but also a measure of efficiency indicators of business performances [1]. The launch of the power grid comprehensive evaluation is to effectively supervise the problems existing in the power supply reliability and service and, further improve the power quality and service quality.

Fornell[2-7] introduced a logic model of econometrics including some factors, such as the customer expectations, the perception after buying and the purchase price, namely, the Fornell logic model is so called the customer satisfaction index (CSI) model.

Zeng[8] used the neural network method to analyze customer satisfaction evaluation. Although using of neural network evaluation has many advantages, its application is limited because of the slow convergence rate and it is easily trapped by local optimal values.

According to the power grid comprehensive evaluation questionnaire, in this paper a comprehensive evaluation index system including power grid construction, electric power business expansion etc. is set up. The evaluation index system contains 7 first level indicators, 14 second level indicators and 28 third level indicators. Based on the AHP method, we combine the fuzzy CE method and entropy weight method to determine the subjective and objective weight, then determine the
final weight by following the integration of game theory method and finally take the weight into the neural network training. Eventually, 10 cities Customer Satisfaction Evaluation data samples have been used as the original survey data, based on the result of the liner standardization of the data and together with the fuzzy mathematics’ results, we use neural networks and genetic algorithms to optimize neural network method of power grid customer satisfaction comprehensive evaluation. The results indicate that the genetic algorithm optimized BP neural network can make the power grid comprehensive evaluation rapid, unanimous and precise.

**Comprehensive evaluation index system**

Building an evaluation index system should be consistent with some of the following principles: science, purpose, hierarchy, operability, comprehensiveness, system and comparability.\(^ {9-12}\)

In this paper, the selected indicators come from the customers because the only basis for an enterprise to evaluate its customer satisfaction is the customers’ opinion. In order to set up a reasonable comprehensive evaluation index system as shown in Fig. 1, we adhere to the following principles. First, the system is built according to the characteristics of power supply enterprises. Second, the system is built based on clear selection of the important factors that influence the customer satisfaction. Third, we take the current exacting evaluation index system into consideration.\(^ {13-17}\).

![Power Grid Comprehensive Evaluation Index System](image)

**Figure 1. Index system of power customer satisfaction.**

**Power Grid Comprehensive Evaluation Model**

This paper establishes the comprehensive evaluation model by combining the AHP model and the method of genetic algorithm optimized BP neural network. We first build the AHP model and determine the index weight according to the model index system set up above.
The steps for determining the index weight are as follows: fuzzy comprehensive evaluation method is used to determine the subjective weights and then the entropy weight method is adopted to define the objective weights, then the game theory is introduced to determine the final weights.

The use of the fuzzy comprehensive evaluation method based on the AHP method can be divided into following steps. 1) Taking advantage of the 1-9 scale method to construct the judgment matrix $A$ according to the index system established above. 2) Single level sorting and consistency check. [18]

We solve the eigenvalue $\lambda_{\text{max}}$ of the judgment matrix $A$, and use the characteristic equation $AW = \lambda_{\text{max}}W$ we can work out the feature vector $W$, and by normalizing the vector $W$, we get the importance weights. Commonly $C$ is used to evaluate the extent of the inconsistency of the matrix $A$:

$$C = \frac{\lambda_{\text{max}} - n}{n-1}$$

(1)

When $C=0$, the judgment matrix is with great consistency. Along with the increasing of $C$, the degree of inconsistency of judgment matrix is more serious. $R$ is usually used to represent the coincidence indicator:

$$R = \frac{\lambda_{\text{max}} - n}{n-1}$$

(2)

When the random consistency ratio $C_R = C / R < 0.1$, the consistence of the matrix $A$ can be accepted.

We use the additional method to get the feature vector $W$ of the matrix $A$:

$$w_i = \sum_{j=1}^{n} b_{ij}, i = 1, 2, \cdots, n$$

(3)

in which:

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}, i = 1, 2, \cdots, n$$

(4)

The use of the entropy weight method to work out the subjective weights can be divided into following steps: 1) Get the standardized evaluation matrix $R = \left( r_{ij} \right)_{m \times n}$

$$r_{ij} = \frac{a_{ij} - \min_{j} \{a_{ij}\}}{\max_{j} \{a_{ij}\} - \min_{j} \{a_{ij}\}}$$

(5)

2) Calculate the specific weight of program $i$ under index $u$:

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}}, j = 1, 2, \cdots, n$$

(6)
3) According to the definition of entropy, calculate the information entropy of index $u_j$.

$$e_j = \frac{1}{\ln m} \sum_{i=1}^{m} P_{ij}, j = 1, 2, \ldots, n$$  \hfill (7)

4) On the basis of the entropy value, calculate the difference coefficient of index $u_j$:

$$\lambda_j = 1 - e_j, j = 1, 2, \ldots, n$$  \hfill (8)

5) Calculate the index weights:

$$w_j = \frac{\lambda_j}{n - \sum_{i=1}^{m} e_j}, j = 1, 2, \ldots, n$$  \hfill (9)

In order to improve the scientificness of the multi-attribute weights assignment and reduce the one-sidedness of the weights, assuming different methods are used to assign the weights, we build a basic weight vector set $W = \{w_1, w_2, \ldots, w_s\}$, the arbitrary linear combination of these weight vectors form a probable weight set:

$$W = \sum_{i=1}^{s} \alpha_i w_i^T (\alpha_i > 0),$$

in which: $\alpha_i$ is the coefficient of the weights.

Game rendezvous method can search the unanimousness or the compromise among different weights, minimize the deviations between the probable weights and every basic weights. Searching for the most satisfactory weight vector $\hat{w}$ is to minimize the deviation between $\hat{w}$ and every $w_i$:

$$\min \left\| \sum_{i=1}^{s} \alpha_i * w_j^T - w_i^T \right\|_2 (i = 1, 2, \ldots, s)$$  \hfill (10)

According to the differential properties of matrix, the qualification for the optimized first derivative is:

$$\sum_{j=1}^{s} \alpha_j * w_i^T * w_j^T = w_i * w_j^T, (i = 1, 2, \ldots, s)$$  \hfill (11)

The corresponding linear equations are:

$$\begin{bmatrix} w_1^T & w_1^T & \cdots & w_1^T \\ w_2^T & w_2^T & \cdots & w_2^T \\ \vdots & \vdots & \ddots & \vdots \\ w_s^T & w_s^T & \cdots & w_s^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_s \end{bmatrix} = \begin{bmatrix} w_1^T w_1^T \\ w_2^T w_2^T \\ \vdots \\ w_s^T w_s^T \end{bmatrix}$$  \hfill (12)

By solving the equations above and normalizing the solution vector $(\alpha_1, \ alpha_2, \ \cdots, \ \alpha_s)$:
\[ \alpha^* = \frac{\alpha_k}{\sum_{k=1}^{s} \alpha_k} \]  

(13)

Finally, the combination weight is obtained:

\[ w^* = \sum_{k=1}^{s} \alpha_k^* w_k^T \]  

(14)

Optimizing BP Neural Network by Genetic Algorithm

The Determination of the BP-NN Structure. Because of a three-layer neural network is sufficient to achieve the mapping of any dimension input layer to the output layer; this paper chooses a three-layer neural network as a model. The numbers of the input and output layers are set according to the specific requirements and, the hidden layer neurons are determined by the following formula:

\[ n_i = \sqrt{n + m + a} \]  

(15)

Where: \( n_i \) is the number of the hidden layer neurons, \( n \) is the number of the input layer neurons, \( m \) is the number of the output layer neurons and \( a \) is a constant number between \([1-10] \). In order to sort as much as the samples into the maximum gradient direction the samples need to be normalized. \([19] \)

According to the evaluation index system built above, the number of the input layer neurons is 16, corresponding to 7 first level indicators. For there is only one evaluation result, accordingly, there is only one output layer neuron. Because the normalized input vector value is within the range of \([-1, 1] \), but the value of the output vector is not in at the same time, so the transfer function between the hidden layer neurons is tansig and the transfer function between the output layer neurons is purelin.

According to the hidden layer neurons number calculation formula, we find the number of the hidden layer neurons is between 7 and 12. Set the MSE (mean square error) as 0.001 and use MATLAB program to test the astringency of the BP-NN at different number of hidden layer neurons (7-12). The results are shown in the table 1 as below:

Table 1. Errors and training epochs at different hidden neurons.

<table>
<thead>
<tr>
<th>number of hidden layer neurons</th>
<th>MSE[\times 10^{-3}]</th>
<th>Epoches</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>0.993</td>
<td>836</td>
</tr>
<tr>
<td>8</td>
<td>0.965</td>
<td>465</td>
</tr>
<tr>
<td>9</td>
<td>0.996</td>
<td>1187</td>
</tr>
<tr>
<td>10</td>
<td>0.999</td>
<td>4728</td>
</tr>
<tr>
<td>11</td>
<td>0.997</td>
<td>560</td>
</tr>
<tr>
<td>12</td>
<td>0.986</td>
<td>907</td>
</tr>
</tbody>
</table>
We can conclude from Table 1 that when the number of hidden layer neurons is 8, the BP-NN has the fastest convergence speed. So the number of hidden layer neurons is selected as 8.

Take the combined weights in section 2.1 as the NN initial training data so that the speed and the accuracy of the NN training can be effectively increased.

Optimizing BP Neural Network by Genetic Algorithm. BP neural network can easily fall into local optimal values and has slow convergence when solving optimization problems. In view of the overall optimization ability, using genetic algorithms can overcome the shortcoming of the neural network algorithm, i.e., falling into local minimum values.

For BP neural network, the general genetic algorithm is always used to optimize the network weights.

The genetic algorithm designed in this paper is as the follows. We use the real code method to code the chromosome, use the inverse of the MSE as the fitness function and, based on the reserve one of the chromosome which has the highest fitness, we use roulette wheel selection method to select from the chromosomes left. The crossover strategy in this paper is to randomly choose 2 crossover points and change all the genes between these 2 crossover points, the crossover rate is $p_c = 0.5/n + 0.25$, the mutate mode and the mutate rate are: $K_{x+1} = K_x + \alpha$ and

$$p_m = \frac{0.01(f_{\text{max}} - f)}{f_{\text{max}} - f_{\text{min}}} + 0.001$$

Because low population number can not provide enough sampling points and an oversized population number will increase the amount of calculation and extend the convergence time, therefore, the population number is set as 50.

Model Validation

This paper verified the proposed method by analyzing the results based on the comprehensive evaluation questionnaire of a certain province in the year of 2014. During 2014 annual power grid comprehensive evaluation process, 500 questionnaires were selected from all the 5000 recovered questionnaires.

Index Weight Determination. The results from the evaluation questionnaires are transferred into the importance judgment matrix of different layers and different factors. The importance value is between 1 and 9, the higher the value is, the more the importance it is. The importance judgment matrix is:

$$A = \begin{bmatrix}
1 & 3.96 & 2.3 & 1.56 & 2.45 & 2.68 & 3.42 \\
0.25 & 1 & 0.34 & 0.25 & 0.28 & 0.33 & 0.81 \\
0.43 & 2.98 & 1 & 0.39 & 1.53 & 1.86 & 2.73 \\
0.64 & 4.01 & 2.56 & 1 & 2.85 & 2.89 & 3.88 \\
0.41 & 3.57 & 0.65 & 0.35 & 1 & 2.5 & 3.1 \\
0.37 & 3.05 & 0.54 & 0.35 & 0.4 & 1 & 1.22 \\
0.29 & 1.23 & 0.37 & 0.26 & 0.32 & 0.82 & 1
\end{bmatrix}$$

Normalize every column vector of matrix A, we get $W_f$. 

\begin{align*}
\end{align*}
sum $W_j$ by the rows, get $W_i$, normalize $W_i$, get $W = \begin{bmatrix} 0.2682 \\ 0.0482 \\ 0.1423 \\ 0.252 \\ 0.1402 \\ 0.0886 \\ 0.0606 \end{bmatrix}$, calculate the result of the equation $AW = \lambda_{max} W$, figure out $\lambda_{max} = 7.2466$.

After the calculation: $C_R = 0.0311 < 0.1$, we verify that it conforms to the consistency check.

Finally, the second level weights based on the fuzzy comprehensive evaluation method are obtained as: $(0.2682, 0.04819, 0.1423, 0.252, 0.1402, 0.0886, 0.0606)$.

In these 500 questionnaires, 7 second level index can be described by 5 level fuzzy languages: $S = (s_0, s_1, s_2, s_3, s_4, s_5) = (20, 40, 60, 80, 100)$. According to the steps of the entropy weight method, the final weight based on this method is: $(0.0948, 0.1798, 0.0772, 0.1012, 0.1631, 0.2605, 0.1233)$.

The objective and subjective weights are given by the fuzzy comprehensive evaluation method and the entropy weight method shown as the above. Gather them to the game rendezvous vector set and conclude a linear equation:

$$\begin{bmatrix} 0.1892 & 0.1240 \\ 0.1240 & 0.1672 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} 0.1892 \\ 0.1672 \end{bmatrix}$$

Solve this equation, the final weight vector is: $(0.1938, 0.1046, 0.1144, 0.1874, 0.1500, 0.1623, 0.0875)$.

BP-NN Model Validation. Take advantage of the genetic algorithm, the weights and threshold of the neural network above are optimized, we set the encoding length as $S = R \times S_1 + S_1 \times S_2 + S_1 + S_2 = 201$, the popular number is 50; genetic algebra is 50; NN input layer neural number is 24; one hidden layer, the hidden layer neural number is 8; there is only one output layer neural; the input data is 500 questionnaire results of 2014 annual satisfaction survey; the desired output is the satisfaction result.

Compare the results shown in Fig. 2 between BP-NN and the genetic algorithm optimized BP-NN.
From these two charts, we can figure out that taking MES=0.001, the BP-NN spends 1227 epoches to get convergence, but the genetic algorithm optimizing BP-NN spends just 488 epoches at the same time. The latter one has a better convergence feature. We can conclude from the chart that the genetic algorithm optimizing BP-NN convergence to the target error is at a larger slope. Although there appear local minimum, but the residence time is very short, the convergence efficient is increased. It can be seen that the genetic algorithm optimized BP-NN can effectively overcome the BP-NN easily to fall into local optimum, getting more accurate results under the same training time.

Take the research result into the neural network; the simulation fitting curve is shown as the table below:

<table>
<thead>
<tr>
<th>City Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target Results</td>
<td>78.62</td>
<td>73.82</td>
<td>81.24</td>
<td>83.65</td>
<td>76.36</td>
</tr>
<tr>
<td>BP Results</td>
<td>76.3</td>
<td>72.16</td>
<td>79.63</td>
<td>79.35</td>
<td>78.23</td>
</tr>
<tr>
<td>BP-GA Results</td>
<td>79.63</td>
<td>74.25</td>
<td>81.96</td>
<td>84.13</td>
<td>77.28</td>
</tr>
<tr>
<td>BP Error</td>
<td>2.32</td>
<td>1.66</td>
<td>1.61</td>
<td>4.3</td>
<td>1.87</td>
</tr>
<tr>
<td>BP-GA Error</td>
<td>1.01</td>
<td>0.43</td>
<td>0.72</td>
<td>0.48</td>
<td>0.92</td>
</tr>
<tr>
<td>City Number</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Target Results</td>
<td>73.86</td>
<td>75.85</td>
<td>72.53</td>
<td>74.11</td>
<td>75.81</td>
</tr>
<tr>
<td>BP Results</td>
<td>70.69</td>
<td>72.25</td>
<td>75.1</td>
<td>71.92</td>
<td>73.23</td>
</tr>
<tr>
<td>BP-GA Results</td>
<td>74.36</td>
<td>76.76</td>
<td>72.63</td>
<td>74.75</td>
<td>76.71</td>
</tr>
</tbody>
</table>
We can conclude from the chart above that the simulation error of the BP-NN is greatly bigger than the genetic algorithm optimized BP-NN. The average error is 2.587 and 0.661, the maximum error of BP-NN is 4.3, but the genetic algorithm optimized BP-NN only has a 1.01 maximum error at the same time. It is obvious that the genetic algorithm optimized BP-NN has a highly fitting degree and it can insure a stable and consistent power grid comprehensive evaluation.

**Summary**

Based on the AHP method, a method which is combined with fuzzy comprehensive evaluation method and entropy weight method to determine the subjective and objective weight has been introduced in the paper. The research adheres to the integration of game theory method to determine the final weight, and take this weight into the neural network training to approach the power grid comprehensive evaluation. This procedure can effectively ensure the accuracy of evaluation and produce the evaluation results rapidly after the initial data is input. Simultaneously, the proposed method can avoid the tedious process of the weights calculation. This certain method can fulfill the power grid comprehensive evaluation rapidly, accurately and concordantly, accordingly, the method will provide an accurate decision-making for the State Grid to effectively improve the service quality and company efficiency.

**References**


