An Investment Decision Model of Distribution Network Planning Based on Correlation Mining of Reconstruction Measures and Loss Load Index

Jun Xiong1, Zhixuan Liu2, Yue Xiang3, Yanxin Chai3, Junyong Liu3 and Youbo Liu3

1. State Grid Xiamen electric power supply company, Xiamen, 361000, China
2. State Grid Fujian Electric Power Research Institute, Fuzhou, 350007, China
3. Sichuan University, Chengdu 610065 China

The corresponding author’s e-mail address: ziqi_chai@163.com

Abstract. In recent years, how to build a reliable, high-efficient, high-tech and environmental-friendly distribution network infrastructure and service system, especially to accurately assess the reliability impact of various technical measures and establish optimal investment decision model for the future distribution network planning, has great theoretical and practical significance. However, the traditional analysis of investment decision model of distribution network is based on complex power flow calculation, which is not suitable for current construction of large and smart distribution network with multi-agent interaction under electrical market environment. Therefore, in this paper, based on the sample data, the correlation mining methods of the reconstruction measures and loss load index, such as neural network method, are applied to analyse the relationship between different types of reconstruction measures and loss load index. Based on the correlation mining methods, the relationship between the reconstruction measures and loss load index can be obtained and the value of loss load can be fast predicted. Through the comparison the relationship between reconstruction measures and loss load index, the optimal reconstruction measures can be chosen, and the data relationship based accurate investment decision model can be built. Experimental result shows the accuracy and effectiveness of the presented methodology.

1. Introduction

With the increasing permeability of clean energy, the transformation and investment decision of distribution network is the need of the development of smart distribution network in the future. [1-2]. However, traditional way of extensive investment projects has been unable to meet the accurate investment demand of the future active distribution network.

To establish the precise investment decision model, the relationship between the transformation reconstruction measures and performance indexes is crucial. However, the traditional correlation analysis involves complicated power flow calculation. Therefore, common data correlation mining methods [3-8] seem to be better choices. Based on the artificial neural network prediction method, the reliability index of the operation reliability of a certain time scale could be predicted [9].

At present, the investment decision has evolved into a large scale dynamic combinatorial optimization problem. Taking the maximization of the project portfolio as the target, establish the investment decision model [10-11]. Besides, the analytic hierarchy process and the principal
component and set pair analysis were also used to analyze the comprehensive investment decision based on the evaluation index system [12-14]. Moreover, an investment evaluation model based on triangular fuzzy number is put forward [15]. Correlation analysis is also widely used. The investment evaluation model based on the improved grey relational degree and TOPSIS was constructed, and the investment benefit is evaluated and compared according to the degree of relevance of the sample and the ideal solution [16-17].

In this paper, the artificial neural network algorithm is applied to obtain the association expressions between the reconstruction measures and loss load index. And then the investment decision model of distribution network planning based on correlation mining is established, taking the optimal performance indexes as the target. The IEEE 33 node distribution network is used as an example to verify the effectiveness of the proposed investment decision model in the paper.

2. Distribution network index correlation mining based in BP neural network

In this paper, considering the complex relationship between the loss load index and reconstruction measures, BP Neural Network is used to achieve correlation mining.

2.1. BP neural network principle

BP Neural Network (Back Propagation Neural Network, the BPNN) is a kind of multilayer feedforward Neural Network based on error Back Propagation algorithm. The training process of BP neural network includes two parts. The structure is shown in the Figure 1 below.

![Figure 1. The structure of BP Neural Network](image)

2.2. BP neural network training

According to the structure of BPNN in Figure. 1, signal forward propagation can be described as formula (1-2). \( x_i \) represents the input sample. \( y_j \) represents the hidden layer output. \( o_k \) represents the output layer output. \( w \) represents the weight. \( b \) represents the threshold.

\[
y_j = f[\sum_{i=1}^{m} w_{ij} x_i + b_j], \quad j = 1,2,\ldots, p
\]

\[
o_k = f[\sum_{j=1}^{p} w_{jk} y_j + b_{jk}], \quad k = 1,2,\ldots,l
\]

Error back propagation can be described as formula (3-5). The gradient descent method is applied. \( e \) represents the output error. \( d_k \) represents the expected output. \( \Delta w \) and \( \Delta b \) represent the weight and threshold of the adjustment. \( \eta \) represents the learning rate, which is an important factor impacting the convergence rate of the algorithm.

\[
e = \frac{1}{2} (\text{D} - \text{O})^2 = \frac{1}{2} \sum_{k=1}^{l} (d_k - o_k)^2
\]

\[
e = \frac{1}{2} \sum_{k=1}^{l} \left[ d_k - f[\sum_{j=1}^{p} w_{jk} y_j + b_{jk}] \right]^2
\]
\[
\frac{1}{2} \sum_{i=1}^{n} [d_i - f(\sum_{j=1}^{n} w_{ij} f(\sum_{k=1}^{m} w_{jk} x_k + b_j) + b_{ij})]^2
\]  
(3)

\[
\nabla w = -\eta \frac{\partial e}{\partial w}
\]  
(4)

\[
\nabla b = -\eta \frac{\partial e}{\partial b}
\]  
(5)

3. The investment decision model based on the correlation mining

3.1. Reconstruction measure set of distribution network

Generally speaking, the optional plan of reconstruction measure can be expanded from the following three aspects:

1) Reconstruction of infrastructure;
2) Deployment of modern facilities;
3) Improvement of technology and management level.

3.2. Loss load index

Loss load index can be described as formula (6-7).

\[ I_D = \lambda D (T_1 + \beta_2 T_2 + \beta_3 T_3) \]  
(6)

\[ I_E = I_D P_L \]  
(7)

The loss of load index can be represented by EENS (expected energy not supplied) index \( I_E \). And \( P_L \) is the total quantity of load of the feeders.

3.3. The investment decision model of distribution network

The traditional correlation analysis of the reconstruction measures and performance indexes involves the constraints of the complex power flow, which can be described as follow:

\[
\max (\tilde{I} - I)
\]  
(8)

\[
\text{s.t. } \sum_{i=1}^{n} K(X_i) \leq K_{\text{max}}
\]  
(9)

\[
X_i \in \{0,1\}
\]  
(10)

\[
\phi_i (I_i, X_i, y) = 0
\]  
(11)

The objective of the model is maximizing the index as formula (11). Investment cost constraint, reconstruction measures inseparable constraint and correlation constraint are respectively shown in formula (9-11). \( \tilde{I} \) and \( I \) represent the index after and before the implementation of the reconstruction measures. \( X_i \) is the reconstruction measure type and \( K(X_i) \) is the investment cost. Besides, \( \phi_i \) expresses the relationship between \( X_i \) and \( I_i \). In particular, \( y \) in formula (11) represent the network and power flow condition.

Compared with the traditional and complicated power flow calculation shown as formula (11), the investment decision model proposed in this paper introduces the BP NN described as formula (12). \( w \) and \( b \) represents the weight and threshold of the applied BP neural network.

\[
\max (\tilde{I} - I)
\]  
(12)

\[
\text{s.t. } \sum_{i=1}^{n} K(X_i) \leq K_{\text{max}}
\]
\( X_i \in \{0, 1\} \)
\[ \varphi(I, X', w, b) = 0 \]  

(12)

4. Case study
In this paper, the offline BP neural network is trained based on a large number of reconstruction measures and performance indexes data of distribution network, and then the sensitivity of each reconstruction measure to each performance index can be obtained, based on which the optimal combination of reconstruction scheme can also be gained. The initial distribution network applied in the paper is shown in Figure 2, and the reconstruction measures implemented are listed in Table 1.

Table 1. Reconstruction measures of distribution network

| Serial Number | Measure                                                                 | Cost(¥) |
|---------------|-------------------------------------------------------------------------|---------|
| P1            | additional remote terminals at node 9                                   | 100,000 |
| P2            | additional remote terminals at node 26                                  | 100,000 |
| P3            | new construction of DG at node 14: Photovoltaic 0.5MW                    | 1000,000|
| P4            | existing DG expansion at node 14: Photovoltaic 1MW                       | 1500,000|

At the same load level, as the result is shown in Table 2, all the four measures have influence on the loss load index. For example, the quantity of lost load of initial network reaches 1.4194MW, while the quantity of lost load of the network with 1.5MW additional photovoltaic at node 14 and remote terminals at node 9 and 26 is 1.2725MW, which has reduced 10.35%.

Table 2. The EENS index with reconstruction measures

| Terminal Lost load(PV) | P1 | P2 | P1 | P2 | P1 | P2 | P1 | P2 |
|------------------------|----|----|----|----|----|----|----|----|
| 0 MW                   | 1.4194 | 1.3569 | 1.3674 | 1.3141 |
| 0.5 MW(P3)             | 1.3965 | 1.3390 | 1.3324 | 1.2864 |
| 1.5 MW(P4)             | 1.3288 | 1.3127 | 1.3118 | 1.2725 |

Figure 2. The initial distribution network with DGs and switches

In order to make optimal investment decision, the cost-effectiveness ratio which can be described in formula (13) is introduced to measure the various reconstruction measures. The cost-index ratio of measures P1, P2, P3 and P4 are shown in Figure 3.

\[ BCR = \frac{|I - I'|}{\text{cost}} \times 100\% \]  

(13)
In this paper, based on the calculation of the cost-effectiveness ratio above, the optimal reconstruction process can be presented as Figure 4 with the decrease of EENS index of the distribution network as the target.

As shown in Table 3, when setting the reduction of lost load as the target, the optimal investment process of distribution network is adding the remote terminals at node 9 and 26 in turn, and finally constructing new photovoltaic at node 14 with the maximum investment cost of ¥2000,000. At this time, the quantity of lost load is 1.2864MW and the reduction is 9.37%.

5. Conclusion
In this paper, BP neural network is utilized to realize the correlation mining of the reconstruction measures and loss load index of distribution network, which replaces the complex power flow calculation in distribution network planning. And the optimal investment process and scheme can be obtained. Therefore, the planning schemes decided by this method have more practical guidance.

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