Reliability Assessment of Distribution Network with Distributed Generation based on BP Neural Network

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Abstract. The distributed power supply is developing rapidly to realize the energy conservation and consumption reduction of the whole society. But the development of distributed generation (DG) will affect the reliable operation of distribution network. A novel reliability assessment model for distribution network with DG was integrated. A series of essential criteria can be extracted by Principal Component Analysis (PCA). And their weights can be obtained based on the entropy method. The assessment results can be calculated by applying BP neural network. Example analysis were implemented to prove the validity of the comprehensive reliability assessment model.

1. Introduction

In order to construct the energy supply system of economic, clean, safe and sustainable development, a large amount of dispersed energy is gradually utilized. Distributed generation can offer short-term and continuous power for isolated island load in case of upstream distribution network failure. DG Large-scale development can improve the reliability of distribution network \cite{1}. But because of the climate and the environment, distributed generation shows strong randomness. Suitable load shedding strategies are adopted to ensure power balance in the case of island power supply shortage \cite{2}.

The reliability of distribution network system is closely related to the operating environment and the system operation planning. The relationship between the influencing factors and the reliability criteria is often complicated, dynamic and high-dimensional nonlinear. The traditional methods of deducing system reliability based on component reliability need a lot of historical statistical data and relatively stable system structure to ensure the accuracy of the correlation of random variables and the structure of deducing model\cite{3}. But because a lot of distributed power is absorbed into the distribution network, traditional system structure has been changed quickly. The traditional reliability prediction method based on statistical reasoning is difficult to implement effectively. Artificial Intelligence Algorithm has obvious advantages in simulating the internal law of things, determining the complex relationship between input and output, and dealing with uncertain parameter problems. Thus many researches on the reliability of distribution network were implemented based on the Artificial Intelligence Algorithm. T. Daemi and A. Ebrahimi\cite{4} proposed a reliability assessment process based on Bayesian Network, and took into account the effects of load level changes and weather conditions on the power grid. Duan, D.L. et al\cite{5} proposed a distribution network reconfiguration method for power loss reduction and reliability improvement. An enhanced genetic optimization algorithm is applied to handle the reconfiguration...
problem. Anteneh D. and Khan B.[6] focuses on enhancement of distribution network in Debre Berhan by using Intelligent Algorithm. The proposed method provides the minimum reliability cost while limiting the number of installed. Heidari A., Agelidis V. G., et al[7] proposed a comprehensive model based on the PDM cost. And a cascade correlation neural network (CCNN) were designed for simulation analysis.

Thus, a reliability assessment model of distribution network can be proposed by using BP neural network method. Principal Component Analysis was applied to choose the essential criteria for impacting on the reliability of distribute network with DG. Entropy method was introduced to determine criteria weights and perform the composite index. An empirical analysis was performed to validate the model.

2. Reliability evaluation model of Distribution Network based on BP Neural Network

2.1. Selecting the Input Criteria based on Principal Component Analysis

First, the factors influenced on the reliability of distribution network with DG are analyzed, some relation criteria were selected to form a preliminary evaluation index system. Then the selected criteria were analyzed by Principal Component Analysis (PCA) to simplify the dimension of variables and ensure the independence of the variables [8]. Much high-dimensional data can be transformed into low-dimensional data by the PCA to reflect the main features of the all data. According to statistics, the information contained in a characteristic variable can be described by its variance. The greater the variance, the greater the amount of information contained in these data. In principal component analysis, the weight of each principal component corresponds directly to its variance contribution rate. A principal component with more information has a larger weight.

There are many factors that affect the reliability of distribution network with DG. Based on the previous research, the preliminary criteria were selected, including system average power outage frequency, system average power outage duration, average power supply availability, system total power shortage degree, average length of overhead lines, average length of cable lines, average number of distribution and substation stations, cabling rate and looping rate. The essential criteria affecting the reliability of distribution network can be extracted by applying principal component analysis.

2.2. Processing input indicator based on the Entropy Method

Entropy method is a relatively objective method to determine the weight of the index. The importance of the index can be indicated through the variation of the index value. The smaller the information entropy of an index is, the greater the variation of the index value is, the more information it provides and the more valuable it is, the greater the weight of the index is. Otherwise, the weight of the index is smaller. The method can be used to integrate criteria values and avoid the subjectivity of artificial judgment.

Step 1: standardize valued to reduce the influence of criterion dimension on incommensurability.

For benefit-type criteria, the standardization process is:

\[ \hat{u}_j = \frac{u_j - \min u_j}{\max u_j - \min u_j} \]  \hspace{1cm} (1)

For cost-type criteria, the standardization process is:

\[ \hat{u}_j = \frac{\max u_j - u_j}{\max u_j - \min u_j} \]  \hspace{1cm} (2)

Step 2: determine the entropy value \( h_i \) for all criteria, as is
\[ f_y = \frac{\tilde{u}_y}{\sum_{j=1}^{n} \tilde{u}_y} \]  

(3)

\[ h_i = -\frac{\sum_{j=1}^{n} f_y \ln f_y}{\ln n} \]  

(4)

Step 3: obtain the weights \( w_i \) according to the entropy values, as is:

\[ w_i = \frac{1 - h_i}{m - \sum_{i=1}^{m} h_i} \]  

(5)

2.3. BP neural network model

Neural network method is a multi-layer feed forward network trained on the basis of the error Backpropagation. The objective function of the algorithm is the square error of the actual output value and the expected output value [9]. The minimum value of the objective function can be calculated by the gradient descent method.

BP Neural Network consists of three layers: input layer, hidden layer and output layer. The neurons in each layer are connected with each other by connecting weights. The neurons in the same layer are independent of each other. The input signal is first transmitted from the input layer to the hidden layer, and then processed layer by layer to the output layer. If the desired output isn’t obtained in the output layer, the reverse propagation process begins. The error signal is returned from the originally connected channel and be eliminated by automatically correcting the weights of each neuron. Its topological structure diagram is shown in Figure 1. BP Neural Network model has the advantages of fast calculation speed, high efficiency of solution, strong self-learning ability, excellent fault-tolerance ability, wide adaptability, etc. The model is suitable to evaluation the reliability of power systems dynamically. Newff function in the MATLAB R2014a software was introduced to solve the model.

Figure 1. Topological Structure Diagram of BP neural network

3. Example analysis

3.1. Criteria and data

Based on the reliability assessment method proposed in this paper, a city distribution network is selected for assessment and analysis.
Table 1. Reliability criteria data of urban distribution network in a city from 2012 to 2018

| Criteria                                      | Unit          | 2012       | 2013       | 2014       | 2015       | 2016       | 2017       | 2018       |
|-----------------------------------------------|---------------|------------|------------|------------|------------|------------|------------|------------|
| system average power outage frequency (C1)   | time/household| 1.132      | 1.118      | 1.109      | 1.102      | 1.097      | 1.089      | 1.085      |
| system average power outage duration (C2)    | h/year        | 3.14       | 2.94       | 2.73       | 2.41       | 2.24       | 1.92       | 1.71       |
| average power supply availability (C3)       | %             | 99.929     | 99.935     | 99.943     | 99.951     | 99.962     | 99.972     | 99.981     |
| system total power shortage degree (C4)      | kW·h          | 31.823     | 31.682     | 31.376     | 31.228     | 31.192     | 31.034     | 29.984     |
| average length of overhead lines (C5)        | km            | 5.722      | 5.145      | 4.968      | 4.784      | 4.248      | 3.996      | 3.875      |
| average length of cable lines (C6)           | km            | 4.753      | 4.587      | 4.297      | 4.073      | 3.843      | 3.572      | 3.142      |
| average number of distribution and substation stations (C7) | table/bar | 9.35 | 9.84 | 10.62 | 11.23 | 12.69 | 13.39 | 14.46 |
| cabling rate (C8)                            | %             | 6.68       | 9.29       | 16.34      | 24.88      | 46.61      | 59.06      | 79.21      |
| looping rate (C9)                            | %             | 24.84      | 39.42      | 51.78      | 56.52      | 60.53      | 64.71      | 69.29      |

3.2. Data processing
First, the criteria data was standardized by software SPSS 22.0. Then the PCA method was implemented to select the important criteria. The KMO statistic is 0.773, which is greater than the minimum standard 0.6. And the P value of Bartlet spherical test is 0.000 and is less than 0.001. The two principal components with cumulative variance contribution 98.6% are extracted. C1, C5, C9, C2, C3, C7 and C6 belong to principal components 1. And C8 and C4 are classified as principal component 2. Contribution of variance for principal components 1 is 89.853%, which means that the factor contains almost 90% of the data information. Final, the criteria belonging to principal components 1 were considered as the essential criteria, including C1, C2, C3, C5, C6, C7, C9.

Table 2. The principal components matrix after rotation

| Sub-criteria | principal components 1 | principal components 2 |
|--------------|------------------------|------------------------|
| C1           | 0.949                  | 0.299                  |
| C5           | 0.944                  | 0.305                  |
| C9           | -0.944                 | -0.253                 |
| C2           | 0.906                  | 0.411                  |
| C3           | -0.893                 | -0.437                 |
| C7           | -0.879                 | -0.456                 |
| C6           | 0.859                  | 0.508                  |
| C8           | -0.246                 | -0.968                 |
| C4           | 0.653                  | 0.751                  |

| Contribution of variance | 89.853% | 8.725% |

3.3. Criteria weights calculations
According to the characteristics of the criteria, the important criteria can be divided into distribution system factors and distribution equipment factors. Based on the Entropy weight method, the weight of the important criteria under the two attributes can be determined as equations (1) to (5). The results were shown as the table 3.

Table 3. The entropy values and weights of the important criteria based on the entropy method

| Attribute | distribution system | distribution equipment |
|-----------|---------------------|------------------------|
| Criteria  | C1                  | C2                     | C3 | C5 | C6 | C7 | C9 |
| $h_i$     | 0.887               | 0.843                  | 0.831 | 0.878 | 0.832 | 0.819 | 0.895 |
| $w_i$     | 0.258               | 0.357                  | 0.385 | 0.211 | 0.293 | 0.314 | 0.182 |
3.4. Reliability assessment results

The reliability evaluation can be processed by BP Neural Network. The criteria data from 2012 to 2017 were selected as training samples to evaluate the reliability in 2018. The true value of distribution network reliability from 2012 to 2017 is shown in Table 4. The input data is normalized and reduced to two dimensions, which are system factor and equipment factor. The output data is reduced to one dimension.

| Criteria Unit                                    | Criteria Unit                                    | year |
|-------------------------------------------------|-------------------------------------------------|------|
|                                                 |                                                 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
| distribution network reliability %              | 99.933                                          | 99.951 | 99.962 | 99.967 | 99.972 | 99.984 | 99.988 |
| distribution system factor                      | 0                                               | 0.171 | 0.332 | 0.51 | 0.661 | 0.859 | 1 |
| distribution equipment factor                   | 0                                               | 0.186 | 0.357 | 0.476 | 0.685 | 0.824 | 1 |

The number of neurons in the hidden layer was three by some tests. The training samples are trained by the common neural networks including standard BP, elastic BP, Conjugate gradient and Levenberg-Marquardt methods. The results of reliability evaluation, average relative error and response time are compared in Table 5. The calculation results by Levenberg-Marquardt method is the minimum mean relative error and should be applied to evaluate distribution network reliability assessment based on BP neural network.

| Algorithm                          | Unit                  | Mean relative error |
|------------------------------------|-----------------------|---------------------|
| standard BP                        | %                     | 0.0624              | 0.0442 | 0.0330 | 0.0276 | 0.0224 | 0.0099 | 0.0047 | 0.0292 |
| elastic BP                         | %                     | -0.0164             | -0.0122 | -0.0100 | -0.0115 | -0.0140 | -0.0141 | -0.0139 | -0.0132 |
| Conjugate gradient                 | %                     | -0.0179             | -0.0215 | -0.0203 | -0.0062 | 0.0113 | 0.0145 | 0.0159 | -0.0035 |
| Levenberg-Marquardt                | %                     | 0.0149              | 0.0199 | 0.0191 | 0.0058 | -0.0107 | -0.0149 | -0.0177 | 0.0023 |

4. Conclusion

To improve the reliability of distribution network under the DG development, a comprehensive assessment method for distribution network reliability was proposed based on the PCA, entropy weighting method and BP Neural Network. First, the PCA methods was applied to select the essential criteria. Then the weights of the essential criteria were calculated by the entropy weighting method, which can avoid the subjectivity of human decision. Finally, the BP Neural Network was introduced to evaluate reliability. Example analysis was implemented to verify the validity of the model. Levenberg-Marquardt method was selected because of the minimum mean relative error compared with other algorithms.

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