Atlantis Highlights in Engineering, volume 5
International Conference on Precision Machining, Non-Traditional Machining and Intelligent Manufacturing (PNTIM 2019)

Research on Electric Power Emergency Warning Mechanism Based on Meteorological Big Data

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***Abstract*—In the context of climate change, power transmission and transformation equipment are experiencing increasingly severe weather disasters. Therefore, the theory and technology related to meteorological disaster warning and risk prevention have become important technologies for power system transmission equipment inspection operations. A regional grid security early warning mechanism affected by extreme meteorological conditions in the paper is established. Considering the meteorological elements that have an impact on grid security, a big data network failure probability model of meteorological elements is build. Taking the load reduction rate as the dominant consequence index, and taking the transmission line overload condition and the bus voltage deviation as the hidden consequence indicators, the failure probability and the fault impact are combined to evaluate the risk of failure under a certain meteorological condition. An early warning strategy, which includes the issuance of warning levels, warning time and warning areas, was established based on the degree of risk.**

Keywords-Meteorological Big Data; Electric Power Emergency Warning Mechanism; Network Failure Probability Model

I. INTRODUCTION

Power grid failures with frequent meteorological elements have caused huge economic losses. Therefore, it is of great significance to assess the risk of transmission operation under the influence of meteorological factors, which can achieve risk warning and avoid risks in advance. The operational risk is usually a comprehensive consideration of the likelihood and severity of uncertainties affecting grid operation. The risk assessment method comprehensively examines the possibility of accidents and the consequences of accidents. It is more objective than the probabilistic assessment method and the assessment method to assess the accidents, so that the dispatchers can understand the risk situation of the real-time accident and provide early warning information for taking measures. According to the influence of common meteorological conditions on grid operation, the five factors of wind, precipitation, ice coating, temperature and lightning as meteorological elements in the paper is selected. The grid operation risk of meteorological elements is defined as: a comprehensive measure of the probability of failure and the severity of failure of each transmission line of the system under the influence of meteorological elements. The empirical equation is

$$R_i = P_i D_i \tag{1}$$

In equation (1), P_i is the probability of failure of the i-th line under the influence of current meteorological elements; D_i is the consequences of the i-th line fault after disconnection; R_i is the risk value of the line under current weather conditions. Early warning information can be obtained by sorting quantified risks, which can provide decision support for dispatchers.

II. Determination of Risk Indicators Based on Big Data

Analysis of the transmission operation risk affected by meteorological elements is the risk generated by a single event. The load reduction rate is selected as the consequence evaluation indicator. Considering the grid protection measures in the actual situation, it is rare to cause load reduction after disconnecting one transmission line. If only the load reduction rate is used as the consequence review indicator, most of the risk values thus obtained will be zero, and the risk value cannot be reasonably compared. Disconnecting a line may not reduce the load, but it will still affect the grid. For example, it will increase the load of the relevant line or cause voltage deviation of other bus lines, which is not as obvious as the load reduction. Therefore, the load reduction rate can be selected as the explicit consequence comment indicator, and the line load condition and the bus voltage deviation are selected as the implicit consequence comment indicators. In equation (1), D_i is divided into the dominant consequence comment indicator D_{ix} and the recessive consequence comment indicator D_{iy}, which are correspond to the dominant risk R_{ix} and the recessive risk R_{iy}, respectively, as shown in equation (2).

$$R_i = R_{ix} + R_{iy} = P_i(D_{ix} + D_{iy}) \tag{2}$$

The dominant consequence comment indicator Dix is calculated, which is the load reduction rate caused by the disconnection of the i-th transmission line fault. The load reduction rate calculation flow chart is shown in Figure 1.

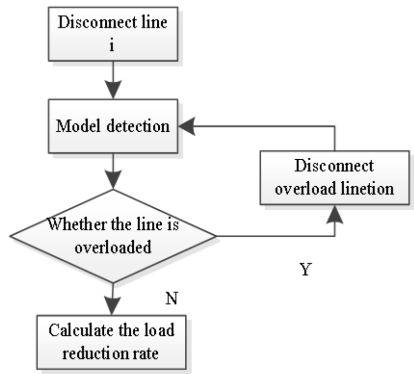

Figure 1. Load reduction rate calculation process

It can be concluded from Figure 1 that when the line load reaches 100%, the line is considered overloaded and the system is taken out of operation. The calculation of the implicit consequence comment indicator D_{iy} needs to separately evaluate the bus voltage deviation and the line load change after the i^{-th} line disconnection fault. The severity of the bus voltage deviation and load variation can be described by the severity membership degree. The severity membership ε_1 of the line load is subject to a large trend; the severity membership ε_2 of the bus bar deviation is intermediate. Severity membership of line load and bus voltage deviation is as shown in Figure 2[1-2].

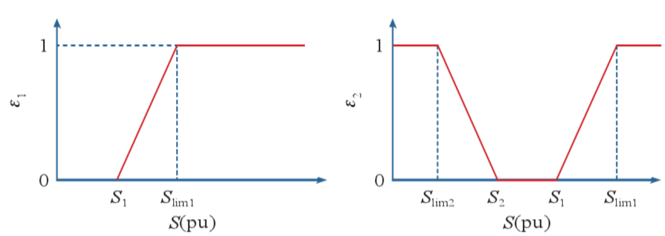

Figure 2. Membership of line load and bus voltage deviation

In Figure 2, S is the current state parameter of the component, and the trapezoidal distribution parameters S1, S2, Slim1, and Slim2 are thresholds for safe operation and failure of the component, respectively. The values in Figure 2 are all labeled. When calculating the line load severity membership degree here, the line with the load between 80% and 100% can only be considered, which S1 takes 0.8, and Slim takes 1. After the i-th line is disconnected[3], the line load severity of the whole network can be described by equation (3).

$$\mathrm{E}_{\mathrm{i1}} = \sum_{\mathrm{j=1,\,j\neq i}}^{\mathrm{n}} \varepsilon_{\mathrm{j1}} \tag{3}$$

In equation (3), n is the total number of lines in the entire network after the i-th transmission line is disconnected, and does not include the i-th transmission line and the line where the load reaches 100%. ε_{j1} is the subordinate degree of the load severity of the transmission line of the j-th. According to Figure 2, the same reason is obtained. After the fault of the i-th transmission line is disconnected, the voltage deviation of the bus voltage of the whole network is severe. It can be described by the equation (4).

$$Ei2 = \sum_{j=1}^{m} \varepsilon_{j2} \tag{4}$$

In equation (4), m is the number of bus bars in the whole network, and does not include the bus bar from which the disconnection is disconnected. ε_{j2} is the voltage deviation severity membership of the j-th bus. According to Fig. 2, the calculation formula is as shown in the equation (5).

$$\varepsilon_{j2} = \begin{cases} 1 & s_j < 0.9 \\ 20(0.95 - s_j) & 0.9 \le s_j \le 0.95 \\ 20(1.1 - s_j) & 1.05 \le s_j \le 1.1 \\ 1 & s_j > 1.1 \end{cases} \tag{5}$$

Therefore, the implicit consequence comment indicator D_{iy} can be obtained by calculating the seriousness of the line load of the whole network and the severity of the whole bus voltage deviation. Through the summation express the implicit consequences comment indicators, the specific calculation equation is as follows

$$\mathrm{D}_{\mathrm{iy}} = \mathrm{E}_{\mathrm{i1}} + \mathrm{E}_{\mathrm{i2}} \tag{6}$$

III. Establishment of Early Warning Strategy

A. *Meteorological big data model of extreme meteorological elements*

Since the five meteorological factors of precipitation, wind, ice, temperature and lightning are not independent of each other, for example, rainfall is accompanied by lightning, and ice coating often occurs below 0 ℃. Therefore, the probability of failure P_{i} in equation (1) cannot be calculated simply by using independent conditional probability calculations. There are not many weather data at the time of failure obtained in the actual operation of the power grid, and it is not necessarily accurate. The grade division is used to reduce the requirements on data and increase the number of samples[4-5], which is beneficial to the determination of weights and improve the accuracy of the model.

Meteorological big data builds models by adjusting the connections between big data. According to the complexity of different systems, theoretically, any nonlinear model can be approximated and adaptive. In the paper, the multi-layer feed forward network trained by the error back propagation algorithm, which is widely used, is used as the meteorological big data model. Meteorological big data can deeply explore the implicit relationship between predictive variables, and is applicable to situations where variables are not independent of each other. Therefore, the meteorological big data model in the paper is chosen to solve the problem of transmission line failure probability that multiple meteorological factors affect each other.

The network uses the NR-NY-1 structure, which includes an input layer, a hidden layer, and an output layer. Considering a variety of meteorological factors, the input layer uses wind level, precipitation intensity, ice thickness, temperature and lightning information as meteorological factors, and voltage level and line characteristics as electrical factors; hidden layer mapping function uses Sigmoid function; output layer uses Purelin function[6-7]. Therefore, a large amount of historical fault information caused by meteorological factors is input as a sample to the meteorological big data for training. After the training is completed, the weight is determined, and the meteorological big data model is determined. By inputting the current forecast weather information and line characteristics into the network, the probability P_i of failure of each node or transmission line in the area can be obtained.

B. *Transmission line fault risk matrix model of meteorological elements*

The risk matrix method is a classic structural approach to identify the importance of a risk or risk set. The main calculation process is to grade the risk occurrence probability and the impact, and then combine it into a risk level. When assessing the risk of transmission line failure considering meteorological elements, the probability of line failure is difficult to derive. The expert scoring method is generally used to describe the probability of failure and the impact of the fault, and to effectively assess the risks faced by the grid, which is a common method used by the staff.

According to the actual safety situation of the power grid, the line faults under the influence of meteorological conditions are divided into four levels: extremely low, low, high and extremely high. The consequences of the failure are divided into four levels: negligible, general, severe, and disaster. The risk is divided by the risk matrix, and the corresponding relationship is shown in table 1.

TABLE I. DIVISION OF RISK MATRIX RISK LEVELS OF METEOROLOGICAL ELEMENTS

probability	**extremely low**	**low**	**high**	**extremely high**
negligible	I	I	I	II
general	I	I	II	III
severe	I	II	III	IV
disaster	II	III	IV	V

IV. CASE ANALYSIS

The IEEE-30 bus system and the meteorological fault data of a certain place are combined to perform simulation analysis. The risk of transmission line safety failure caused by meteorological factors is calculated to conduct early warning exercises. The IEEE-30 bus system and regional conditions are shown in Figure 3.

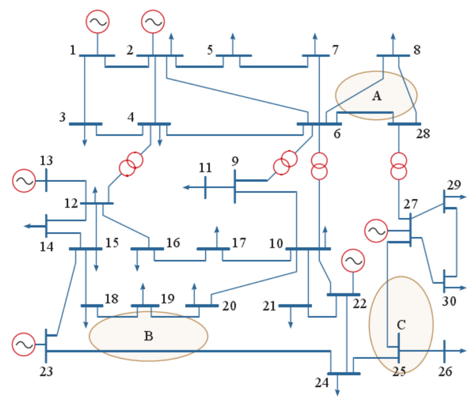

Figure 3. IEEE-30 bus system and regional conditions

It can be seen from Fig. 3 that at a certain moment, the regions A, B and C in the regional system may have transmission line faults due to meteorological factors. The specific weather and line conditions are shown in Table 2.

TABLE II. TRANSMISSION LINE RISK AND WARNING RESULTS

No	$P_i \cdot D_{ix} / 10^{-4}$	$P_i \cdot D_{iy} / 10^{-4}$	**Warning level**
6—8	4.4408	0	II
8—28	3.9016	0	II
25—26	2.3495	0	II
23—24	0.1301	0	I
19—20	0	2.5589	I
25—27	0	1.6629	I
6—28	0	0	I
18—19	0	0	I
24—25	0	0	I

In addition to the A, B and C areas, the weather conditions are good, the transmission lines are relatively safe, and they are not involved in the meteorological failure risk assessment. Comparing Table 2, the results of the warning strategy proposed in this paper show that the fault warning level of the transmission line obtained by using the risk matrix model is consistent with the warning level obtained by the warning strategy, which illustrates the effectiveness of the algorithm and the feasibility of the warning strategy. However, because this early warning strategy specifically calculates the risk value under the influence of meteorological factors, it can be seen that in the line of the early warning level Ⅰ, there is still a situation of transmission line overload and bus voltage deviation. The greater the hidden risk value, the greater the probability of causing an overload or voltage deviation. In the line of the warning level II, although it is the same as the early warning level, the risk value from large to small can still be seen, and the line with the largest risk value should be focused on.

V. CONCLUSIONS

The case analysis is carried out using the IEEE-30 bus bar system, thus the following conclusions are drawn.

1) The risk prediction results of the risk matrix method are compared and analyzed, and the effectiveness of the algorithm and the feasibility of the early warning strategy are verified.

2) The method of the paper reflects the practicality and provides support for the decision-making measures of the grid staff. The appropriate power grid disaster prevention measures is taken before the arrival of meteorological disasters to minimize their impact on operational safety.

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