Research on risk prediction model for voltage sag based on Elman neural network

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Abstract. Voltage sag, as a prominent problem among many power quality problems, has always plagued power grids and users. To reduce the loss caused by the voltage sag and provide a basis for the prevention of the voltage sag, it is important to accurately and efficiently predict the risk of the voltage sag. This paper analyses the related factors of voltage sag risk from multi-directional and multi-dimensional, obtains the data of the influence factors of voltage sag risk in various information systems of the power grid, constructs voltage sag multi-source data, and uses Elman neural network to construct voltage sag risk prediction model. Through the training and learning of multi-source data, the model realizes the voltage sag risk assessment of each node in the power grid. Finally, the feasibility and validity of voltage sag risk prediction model are verified by case study of historical monitoring data in Fujian Province, which provides a method for voltage sag risk prediction.

1. Introduction
Voltage sag refers to a short-term disturbance event in which the root-mean-square value of the voltage drops suddenly and resumes normal after 0.5 cycles-1 minute. With the development of the power grid, more and more advanced devices are connected to the network. These devices tend to be integrated and precise, and they are very sensitive to voltage sag. After the voltage sag, the working state changes, causing downtime and faults, which will affect the production process and cause enormous economic losses. Therefore, in order to reduce the impact of voltage sag, it is essential to accurately predict the risk of voltage sag.

The current prediction and evaluation methods of voltage sag risk mainly include voltage sag risk prediction based on fault simulation and voltage sag risk prediction based on actual measurement data analysis. Most of the researches [1-4] on voltage sag risk prediction are based on fault simulation, and few [5-10] are based on the analysis of measured data. Reference [1] calculate the residual voltage through fault calculation to determine the vulnerable area and estimate the expected drop frequency of the voltage sag. Reference [2-3] uses the Monte Carlo method to randomly simulate the fault parameters
to estimate the frequency of voltage sag. Reference [4] consider experts' willingness and objective conditions of transmission line and use Monte Carlo method to analyse and realize voltage sag risk assessment. This method of voltage sag risk prediction based on fault simulation has complex calculation process, long calculation time, and is greatly affected by fault parameters, which has an impact on prediction accuracy. However, the method adopted in this paper is voltage sag risk prediction based on measured data, which avoids complex fault calculation, and the results obtained are closer to reality. Reference [5] introduces measured information to evaluate voltage sag. Reference [6] takes into account the influence of the power grid side and the user side. Compared with reference [6], two more factors, the basic information of voltage sags and environmental impacts are considered. When the voltage sag assessment is realized from four levels, the voltage sag risk prediction results are more comprehensive. Reference [7-8] are based on analytic hierarchy process (AHP) to calculate the weight of each index to evaluate voltage sag, but the factors considered are not specific enough. This paper obtains the data related to voltage sag risk from various information systems, and realizes voltage sag risk prediction through data mining. The results obtained are close to reality and more comprehensive and reliable. References [9-10] all use data mining methods to evaluate voltage sags. Reference [9] uses frequent pattern mining to generate association rules to achieve evaluation. Reference [10] first obtained the association rules by mining data, and then combined the grey target theory to calculate the approaching degree to evaluate the voltage sag. In this paper, Elman neural network is used for data mining to realize voltage sag risk prediction. Elman neural network has dynamic memory function, good stability and calculation ability, and is suitable for data prediction problems.

This paper provides a method for voltage sag risk prediction. In this paper, considering the influence factors of voltage sag risk from multiple dimensions, the information which can reflect the influencing factors of voltage sag risk is obtained from various power information systems, and multi-source data of voltage sag are generated. Based on the multi-source data and Elman neural network, a voltage sag risk prediction model is established. Then through the data of a certain area in Fujian, the feasibility and effectiveness of this method are verified. This method avoids complex calculation. And through analysing the measured data from various information systems, the results are closer to the reality and more accurate.

The rest of the paper is organized as follows: Influencing factors of voltage sag risk and multi-source data are presented in Section II. A risk prediction model based on Elman neural network is given in Section III. Sections IV displays the experimental results, and Section V concludes the paper.

2. Multi-source data related to voltage sag risk

2.1. Influencing factors of voltage sag risk
The occurrence of voltage sags is related to many factors. These influencing factors have certain influences on the occurrence of voltage sags. Mining these factors can screen useful information from massive power data more efficiently and pertinently, reduce the complexity of data and improve the efficiency of voltage sag risk prediction model. In addition, a variety of factors are considered in the voltage sag risk prediction, and the results are more reliable. Therefore, it is very important to obtain the influencing factors of voltage sag risk.

Weather is one of the important factors affecting the stable operation of the power system. There are many overhead lines in the power system. Faults are very easy to happen under severe weather on overhead lines. Then a voltage sag occurred. Therefore, weather is an important risk factor for voltage sags.

Voltage sags generally use residual voltage amplitude to characterize its severity. The residual voltage amplitude is closely related to the monitoring position. As shown in Fig.1, when a fault occurs at point K, the expression of residual voltage amplitude V1 at monitoring point J. The formula is as follows (1).

$$V_1 = \frac{R_1}{R_1 + R_2} \ast V$$

(1)
(R1 is the equivalent resistance from the power supply to the monitoring point J, and R2 is the equivalent resistance from the monitoring point J to K.)

![System topology](image)

Fig. 1. System topology

Therefore, considering the monitoring position as the risk factor of voltage sag can help to accurately predict the risk of subsequent voltage sags that occur near the monitoring point.

Voltage level is also a key factor affecting voltage sag risk. The protection of power system and the proportion of overhead lines is different in different voltage levels. Thus, the failure rate has the difference in different voltage levels. Therefore, it is necessary to consider the voltage level as the risk factor of voltage sag.

Voltage sags are mostly caused by faults, and the occurrence of faults is related to the operation conditions of lines to a great extent. Generally speaking, the longer the operating years and length of the line, the higher the fault rate, and the greater the possibility of voltage sag. Therefore, the line operation status should also be included in the influencing factors of voltage sag risk.

The number of sag phases is also one of the important factors affecting voltage sag. Considering the number of sag phases as the risk factors of voltage sag is convenient to distinguish the relevant data of voltage sag and to predict and evaluate the voltage sag risk more accurately.

### 2.2. Multi-source data

Multi-source data is the data from different information systems through investigation and analysis. According to the above analysis, this paper extracts the relevant data which can reflect the influencing factors of voltage sag risk from several information systems, and these data are used to construct multi-source data of voltage sag. The dimension attributes corresponding to each influencing factor in the constructed multi-source data are shown in Table 2.

| Influencing factor          | The name of the dimension attribute                                      |
|-----------------------------|--------------------------------------------------------------------------|
| Basic Information           | Residual voltage amplitude, fault cause, fault location                  |
| Weather                     | Meteorological data                                                      |
| Monitoring location         | Geographical location of the monitoring point                            |
| Voltage level               | Voltage level of monitoring point                                        |
| The number of sag phases    | The number of sag phases                                                 |
| The operation status of the line | The length of the line 、 The operating years 、 Line trip rate |

After the construction of multi-source data, the multi-source data will be used as the data support and input data of the voltage sag risk prediction model. The model will carry out data mining and analysis on the multi-source data to realize the function of voltage sag risk prediction.

### 3. Risk prediction model based on Elman neural network

#### 3.1. Elman neural network

Elman neural network is a kind of dynamic recurrent neural network with excellent performance. Its basic structure is composed of input layer, hidden layer, connection layer and output layer. Compared with BP neural network, Elman neural network has an extra connection layer. In this layer, a delay unit is added as a delay operator, which makes it have the ability of dynamic memory, makes the system have the ability to adapt to the time-varying characteristics, and enhances the computing ability and stability of the network. Considering the characteristics of Elman neural network, this paper uses Elman neural network to predict voltage sag risk. The structure of Elman neural network is shown in Fig.2.
3.2. Multi-source data processing
Multi-source data is used as the data support of the voltage sag risk prediction model, which contains data reflecting the influencing factors of the voltage sag risk, and also serves as the input and training set of the risk prediction model. However, it cannot be directly input into the model. It needs to be quantified and normalized to ensure that the multi-source data can be recognized by the model. Quantification is the conversion of non-numerical data into numerical data. Normalization is to change the range of values of the data to between [0,1]. The normalization formula is shown in the following formula (2).

$$X^* = \frac{X - \text{min}}{\text{max} - \text{min}}$$  \hspace{1cm} (2)

(X* represents the normalized value of the data, X represents the value before the normalization of the data, min represents the minimum value in the data, and max represents the maximum value in the data.)

3.3. Risk prediction model
The risk prediction model uses multi-source data to realize the function of voltage sag risk prediction for each node of power grid. The data source is the multi-source data which is constructed by using the data from different information systems that reflect the influencing factors of voltage sag risk. After processing the multi-source data, it can be used as the input and training set of the model. After that, a risk prediction model based on Elman neural network is established, and the model is trained by the multi-source data. The model takes mean square error (MSE) as the loss function to debug the model. After training and debugging, the model can output the residual voltage amplitude of the node. The work flow chart of the model is shown in Fig.3:

Fig. 2. Elman neural network structure

Fig. 3. Model workflow diagram
4. Case study
This article uses monitoring data from a certain area in Fujian. And there is no clear record of line trip rate in each information system, therefore the line trip rate is quoted from literature [11,12].
Firstly, process 75 pieces of data to generate a voltage sag multi-source database. After that, 65 pieces of data were randomly selected as the training set of the model, and the remaining 10 pieces were used as the test set of the model. Then, establish a voltage sag risk prediction model based on Elman neural network. The model contains two hidden layers, the first layer contains 20 neurons and the second layer contains one neuron. The mean square error (MSE) is used as the loss function. The input is voltage sag multi-source data and the output is residual voltage amplitude.
After setting the basic parameters of the model, 65 pieces of training data are input to train the model. The comparison between the training data results and the actual data is shown in Fig.4(a).
Comparing the training data results with the actual results in Fig.4(a), it can be seen that the trend of the two is approximately similar. And the mean square error (MSE) between the training data and the test data is 0.0174 within the allowable range of error. The training basically meets the requirements.
After the training process, the model has the ability to predict voltage sag risk. 10 pieces of test data are used to test the model. The comparison between the test data and the actual data is shown in Fig.4(b).
Comparing the test data results with the actual results in Fig.4(b), it can be seen that the trend of the test data results and the actual results is basically consistent. And the mean square error of the two is 0.0074, and the error is small.

![Fig. 4. Data test results](image)
(a) Comparison between train data and actual results  
(b) Comparison between test data and actual results

According to the above results, it can be concluded that the mean square error (MSE) of 65 pieces of training data has reached 0.0174, and the neural network loss has met the requirements. In the 10 pieces of test data, the mean square error (MSE) is 0.0074, and the error is within the allowable range. The model has good adaptability to both training data and test data, taking into account the fitting degree and generalization ability of the model. These verifies the feasibility and effectiveness of the voltage sag risk prediction model.

5. Conclusion
As a serious power quality problem, voltage sag causes huge economic losses to users every year. Accurate and efficient voltage sag risk prediction is an important means to reduce voltage sag loss.
This article explores the factors affecting voltage sag risk from multiple levels and constructs multi-source data as the data support of the model. It evaluates the voltage sag risk from multiple aspects and multiple dimensions, and the results are closer to reality and more accurate. Secondly, Elman neural network with excellent stability and high efficiency is used as the data mining method to train multi-
source data, and a voltage sag risk prediction model based on multi-source data is established to realize the function of voltage sag risk prediction, which avoids the complex calculation of traditional fault simulation method, improves the efficiency, and is suitable for today's complex power grid. Finally, it is verified by examples that it is a feasible and effective voltage sag risk prediction method.

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