

Failure probability estimation of overhead transmission lines considering the spatial and temporal variation in severe weather

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Abstract Estimation for weather-related failure probability of overhead transmission lines is essential in the reliability assessment of a power system. This paper analyzes the outage and weather data of 110 kV overhead transmission lines in the Guangxi Zhuang Autonomous Region of China during 2011–2014. The result reveals obvious uneven distributions of outage events for time and space due to the spatial and temporal variation of severe weather. Based on the results, an estimation method is proposed in this paper. Split and aggregation is used to smooth the

outage and weather data. The poisson model is adopted in our method to investigate the statistic characteristics of transmission line outage events. Regression analysis is applied to obtain the correlation between the weather intensity and history failure rate. Furthermore the method proposed is validated against the empirical outage data.

Keywords Severe weather, Transmission line, Poisson model, Failure probability, Regression analysis

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1 Introduction

Overhead transmission lines are exposed to nature and are vulnerable to severe weather, such as lightning, storms and hurricanes and so on [1–4]. Operational security of overhead transmission lines has a close relationship with the external meteorological conditions. Weather factors need to be taken into consideration for a reliability assessment of overhead transmission lines, which is important for economic- security decision making [5–7]. Failure probability of overhead transmission lines is essential in applying an appropriate reliability assessment method.

The Markov model [8] is widely used to estimate the failure rate of overhead transmission lines. Considering the intensity of the weather factors, the Markov model is being developed as a two-state, three-state, and multi-state weather model and so on [9–11]. Chong Wang presents a Markov-based deterioration model for transmission components [12]. Ali Arab et al. use partially observable Markov decision processes to develop a generic model for integrated condition-based maintenance of the electric power systems infrastructure [13]. Yong Liu and Chanan Singh introduced a DC-OPF based Markov cut-set method



to evaluate composite power system reliability considering weather effects [14]. These models are primarily suitable for relatively long-term applications. There are both temporal and spatial variations of weather factors [15, 16]. Estimation of the weather influence on transmission lines is required to capture the stochastic behavior of the weather [17].

The Monte Carlo method is applied to simulate the stochastic behavior after the modeling of complex system operational conditions [18]. Billinton and Wenyuan [19] used the two-state weather model and the Monte Carlo sampling technique to incorporate the variable weather conditions in a composite analysis. Mathaios Panteli and Pierluigi Mancarella introduced a novel sequential Monte-Carlo-based time-series simulation model to assess power system resilience [20]. The Monte Carlo simulation depends on random experiments and its convergence may require acceleration by using other techniques [15].

In order to establish a simple relationship between failure probability and weather factors, statistical analysis and the artificial intelligence method are also adopted [21]. For example, the noisy OR-gate model, regression model and fuzzy model are proposed in many literatures [22–25]. In these methods, the average failure rate model is still used after data splitting and aggregation. Weather can affect all the transmission lines in a certain area. The outage event in this area has a random nature and statistical characteristic, which is ignored in the average failure rate model. The poisson model is proposed in [26] to consider the statistical characteristics of transmission line outage events. But the model is not fully described and not validated against empirical outage data.

In order to determine the distribution of outage events on time and space, outage and weather data of an 110 kV overhead transmission line from the Guangxi Zhuang Autonomous Region of China during 2011–2014 are analyzed in this paper. A failure probability estimation method for overhead transmission lines is proposed in this paper considering lightning and wind. Statistical characteristics of an outage event are investigated based on the poisson model. The relationship between the poisson model parameter and history failure rate is presented. Furthermore the model is validated against the empirical outage data.

2 Outage events of transmission lines in Guangxi Zhuang Autonomous Region

Outage events of 110 kV transmission lines in Guangxi Zhuang Autonomous Region of China during 2012–2014 are classified as shown in Fig. 1. Weather-related outage events account for 78.09% in total. Lightning and wind are

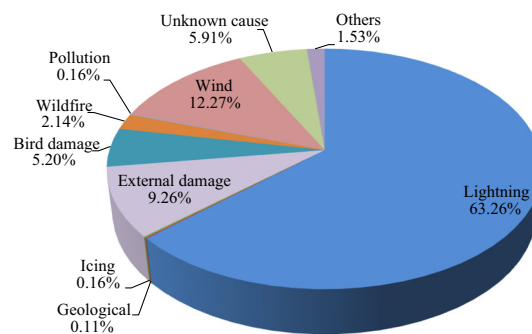


Fig. 1 Proportion of transmission line outage causes

the two main severe weather factors, which are taken into consideration in the following analysis.

Due to the temporal and spatial variation of weather factors, the distribution of weather-related outage events is uneven for time and space. As shown in Figs. 2 and 3, lightning-related outages in Fangchenggang city, Wuzhou city and Guilin city are the top three, accounting for 14.55%, 12.29% and 11.43% respectively. Strong wind primarily affects the coastal areas, such as Beihai city, Qinzhou city and Fangchenggang city and the outages account for 35.71%, 22.77% and 21.88% respectively. The

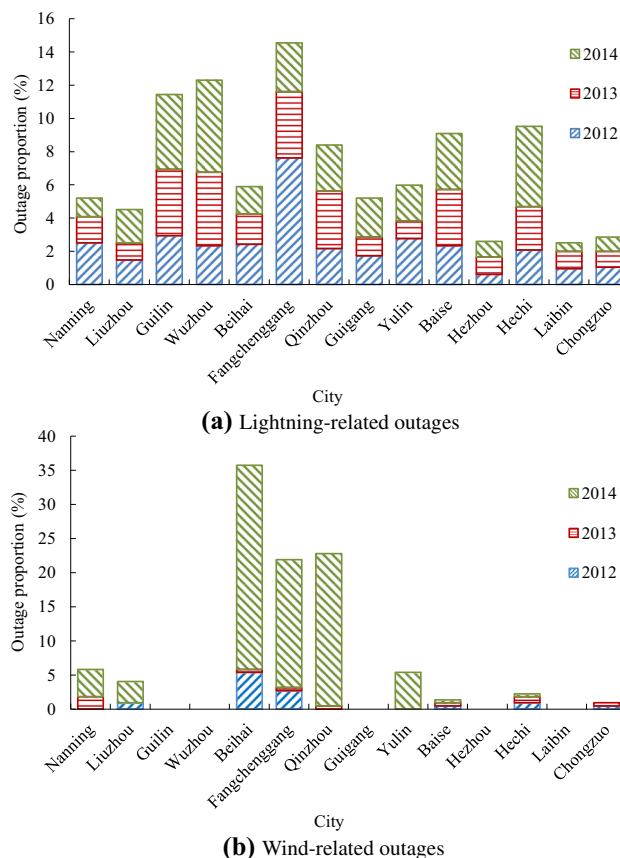


Fig. 2 Spatial variation of weather-related transmission line outages

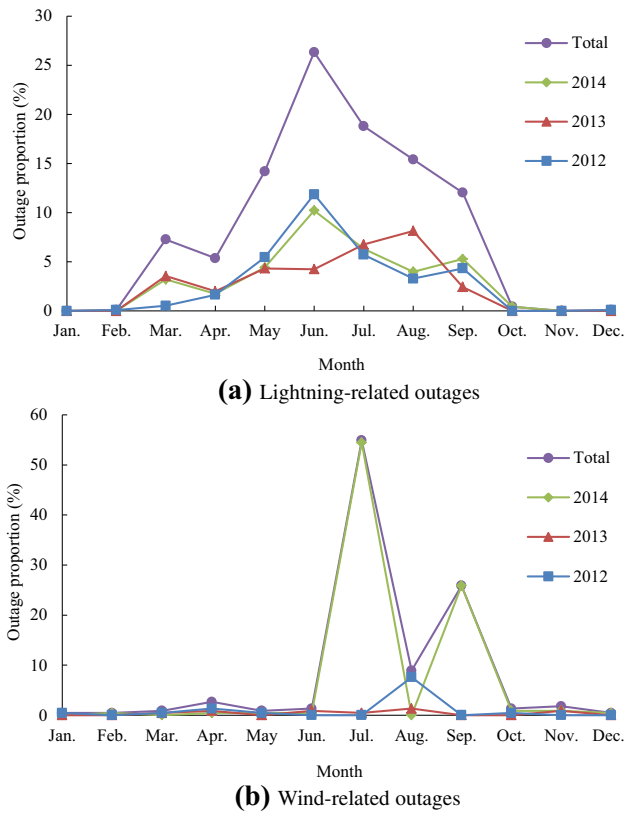


Fig. 3 Temporal variation of weather-related transmission line outages

monthly variation of outage events is closely related to the activities of lightning and wind. It is primarily concentrated from May to September, which accounts for 78.59% of the whole year. Outages induced by wind are primarily concentrated from June to October and are related to typhoon activity. Because of the uneven distribution of weather factors for time and space, there are obvious differences for transmission line outages between various regions in each month. It is necessary to deal with the temporal and spatial variations of weather factors and outage events to make short-term predictions.

3 Estimation for transmission line failure probability

3.1 Temporal and spatial split of weather and outage data

According to the weather and outage data of transmission lines, appropriate weather factors are determined in the method and denoted as w_1, w_2, \dots, w_p respectively. Due to the temporal and spatial variations of weather factors, temporal and spatial splits are needed. Distribution of

weather factors is uneven over a vast area, such as a province. A transmission line might be in multiple areas with a different meteorological environment. A spatial split is the division of weather areas. Assuming that the meteorological environment in each weather area is consistent, the divided weather areas are denoted as WA_1, WA_2, \dots, WA_q respectively. According to the data from the meteorological department, the weather area is divided the same as the administrative area. There are several lines in one weather area, which are in the same meteorological environment. All transmission lines with the same voltage level are taken as the basic samples for the estimation of one weather area. Temporal treatment of weather data contains both split and aggregation. First weather and outage data are split by a step of one day and the weather data is classified into several intensities. Based on the intensity classification, the weather and outage data with the same intensity are aggregated. Both temporal and spatial aggregation result in data smoothing and provides more meaningful patterns and it converts the time distribution of the weather factors to the intensity distribution. There are several weather factors in one area and the combination of different weather factors is defined as a weather block. As the weather factor w_1 and w_2 in a weather area is at level k and m respectively, the weather block is defined as WB_{km} . The outage data is divided according to the classification of the weather block.

3.2 Probability distribution of a transmission line failure based on poisson model

In each weather area, the outage events per day resulting from the condition of each weather block can be considered as discrete rare events. The failure probability satisfies the poisson model and its expression is:

$$P(X = k) = e^{-\theta} \theta^k / k! \quad k = 0, 1, \dots \tag{1}$$

where X is the occurrence number of the random event.

It is assumed that there are n lines in the weather area WA_i , and the line lengths are l_1, l_2, \dots, l_n respectively. X is the line outage event per unit time resulting from the condition of the weather block WB_{km} . Outage event per unit time of each transmission line is X_1, X_2, \dots, X_n respectively, and they are independent events. The observation value of each event is x_1, x_2, \dots, x_n respectively. X follows the poisson model, and the failure probability of the transmission line per unit time is:

$$P(X \geq 1) = 1 - e^{-\theta} \tag{2}$$

According to the maximum likelihood estimation method, the likelihood function is:



$$L(\theta) = \prod_{i=1}^n p(x_i, \theta) = \prod_{i=1}^n e^{-\theta} \frac{\theta^{x_i}}{x_i!} = e^{-n\theta} \theta^{\sum_{i=1}^n x_i} \left(\prod_{i=1}^n x_i! \right)^{-1} \tag{3}$$

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n x_i \tag{4}$$

T_{WB} is defined to denote the days of the weather block and z_1, z_2, \dots, z_n denote the outage times of each transmission line occurring in the duration of the historical data respectively. Because the repairing time is too small it can be neglected and the failure rate is approximately represented as the failure frequency in unit length and unit time as follows:

$$\begin{aligned} \lambda^* &= \left(T_{WB} \sum_{i=1}^n l_i \right)^{-1} \sum_{i=1}^n z_i = \left(\frac{1}{n} \sum_{i=1}^n x_i \right) \left(\frac{1}{n} \sum_{i=1}^n l_i \right)^{-1} \\ &= \frac{1}{n \times \bar{L}} \sum_{i=1}^n x_i = \frac{\hat{\theta}}{\bar{L}} \end{aligned} \tag{5}$$

$$\bar{L} = \frac{1}{n} \sum_{i=1}^n l_i \tag{6}$$

where L is the average length of the transmission lines in the weather area.

Historical outage data of transmission lines can be used to calculate the parameter of the poisson model. According to historical weather and outage data, the relationship between the historical failure rate and weather factors can be established. Based on the poisson model, the failure probability of the transmission line can be predicted using the weather forecast data.

3.3 Regression analysis

Regression analysis is used in this paper to establish the relationship between the historical failure rate λ^* and weather factors w_1, w_2, \dots, w_p . Because λ^* is too small to be calculated, λ' is defined to denote the logarithm of λ^* , which is shown as follows:

$$\lambda' = \ln(\lambda^*) = \ln \left(\left(T_{WB} \sum_{i=1}^n l_i \right)^{-1} \sum_{i=1}^n z_i \right) \tag{7}$$

The regression model of λ' and weather factors can be expressed in matrix form as follows:

$$\lambda' = \mathbf{B}\mathbf{W} \tag{8}$$

where $\mathbf{B} = [b_0, b_1, b_2, \dots, b_p]$ and it is the regression coefficient matrix; \mathbf{W} is the weather factor matrix.

The least square method is used to obtain the regression coefficient matrix. Furthermore, the significance test and applicability test are adopted to test the regression equation. Then the regression equation can be used to estimate.

3.4 Failure probability of transmission lines

If the average line length in a weather area is known, the outage time per line in unit time can be obtained:

$$\bar{\lambda} = \bar{L}e^{BW} = \frac{1}{n} \sum_{i=1}^n x_i = \hat{\theta} \tag{9}$$

Failure probability of transmission line in unit time can be calculated as follows:

$$P = 1 - e^{-\bar{\lambda}} \tag{10}$$

If a line passes through several weather areas, the non-failure probability “ $1 - P$ ” is the product of “ $1 - P_{WA_q}$ ” which means the non-failure probability of the line in each weather area. The total failure probability is calculated as follows:

$$1 - P = (1 - P_{WA_1})(1 - P_{WA_2}) \cdots (1 - P_{WA_q}) \tag{11}$$

Based on the above principles, the following steps are used to make a concrete calculation as shown in Fig. 4.

- 1) Determine main weather factors by analyzing the historical outage and weather data. Weather and outage data is classified according to the division of the weather area.

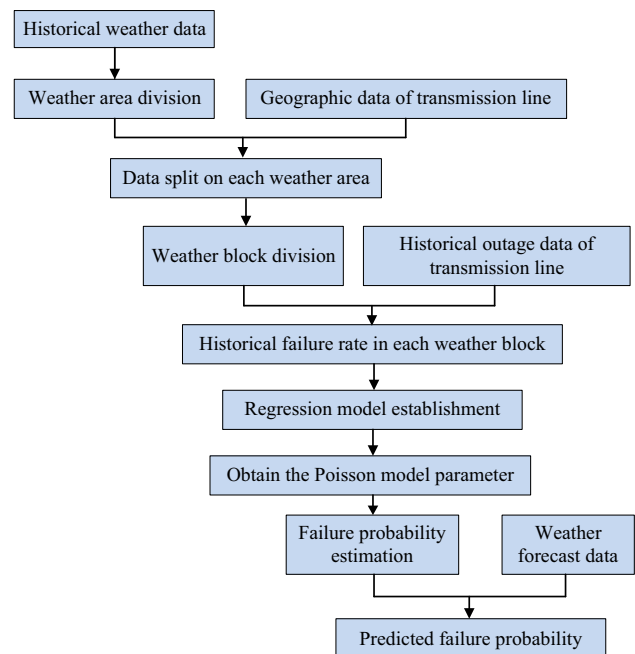


Fig. 4 Flow chart of estimation method proposed

- 2) Classify the weather intensity and establish the weather block.
- 3) Count the outage number in different weather blocks and calculate the historical failure rate of the transmission line.
- 4) Establish the regression model of the historical failure rate and weather intensity and select the suitable regression model via the hypothesis test.
- 5) Obtain the poisson model parameter based on the historical outage and weather data.
- 6) Calculate the failure probability of the transmission line with the weather forecast data.

4 Example

4.1 Temporal and spatial split of historical data

According to the weather and outage data of the 110 kV transmission line in the Guangxi Zhuang Autonomous Region of China during 2012–2014, two parameters denoted as w_1 and w_2 are chosen as the lightning density and maximum wind speed per day. The lightning density data is obtained from LLS [27] and the wind speed data is the instantaneous value obtained on the ground from the meteorological service of Guangxi. Taking Fangchenggang city with the most outages for example, the weather area of the whole city is named as WA_0 . Four counties in its jurisdiction, Gangkou, Fangcheng, Shangsi and Dongxin, are named as WA_1 , WA_2 , WA_3 and WA_4 respectively. Gangkou and Dongxin are next to the sea, and Shangsi is farthest from the seaside.

After dividing the weather area, lightning density and maximum wind speed of each weather area are collected and the weather intensity is classified into a weather block

as shown in Fig. 5. The number of days in which lightning density is more than 0.9 times/($\text{km}^2 \cdot \text{a}$) accounts for 0.4% in total days. Therefore, this paper focuses on the analysis of the outages with a lightning density between 0–0.9 times/($\text{km}^2 \cdot \text{a}$). Lightning density is divided into 10 levels with an interval of 0.09 times/($\text{km}^2 \cdot \text{a}$), named as 1–10. The number of days in which the maximum wind speed is more than 14 m/s represents 0.16%, so the outages with the maximum wind speed between 0–14 m/s are analyzed in this paper. Maximum wind speed is divided into 10 levels with an interval of 1.4 m/s, named as 1–10. Combined with the outage data, statistics of the outage numbers at different weather blocks are obtained for subsequent calculation.

4.2 Historical failure rate of the transmission line

According to the third step of the calculation process, the outage numbers at different weather blocks are counted. The historical failure rate of the transmission line is calculated. The data during January 2012 to July 2014 is taken to establish the estimation model and the data during August 2014 to December 2014 is taken to verify the model.

Taking WA_2 as an example, the total outage numbers and day numbers of each weather block are shown in Fig. 6a and b respectively. According to (7), historic failure rate in each weather block is shown in Fig. 6c. The day number with the lowest weather intensity is generally more than that with the highest weather intensity. Because the occurrence probability of severe weather is low, the outage number under strong weather intensity could be small. But the stronger the weather intensity is, the higher the failure rate will be. The historical failure rate in other weather areas is roughly the same as that of WA_2 .

4.3 Estimation and verification of model

According to the historical failure rate and weather intensity in each weather block, the regression model of λ' and also the weather factors is established. Comparing the hypothesis test result of multiple regression models, the polynomial regression model in (12) to (16) has the highest goodness of fit. The value of p in the f -test is less than 0.01 and the value of p in the t -test is less than 0.05. In the applicability test, the residuals are all subject to the normal distribution and there is no difference and self-correlation. The regression results are significant.

$$\lambda'_{WA_0} = -13.2719 + 2.8091w_1 - 0.2515w_1w_2 - 0.1438w_1^2 + 0.0963w_2^2 \tag{12}$$

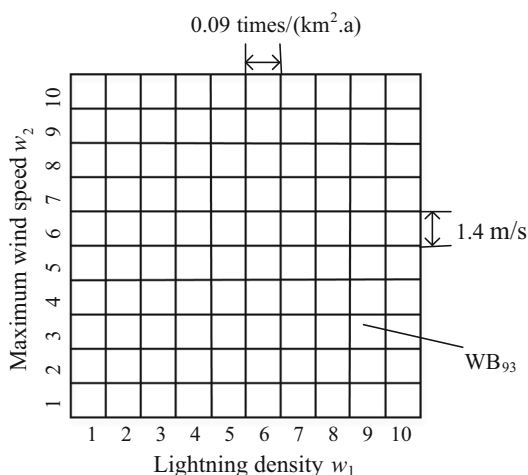


Fig. 5 Division of weather block



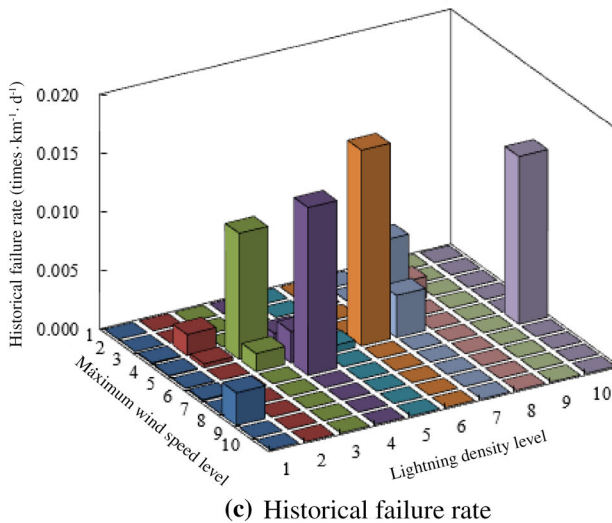
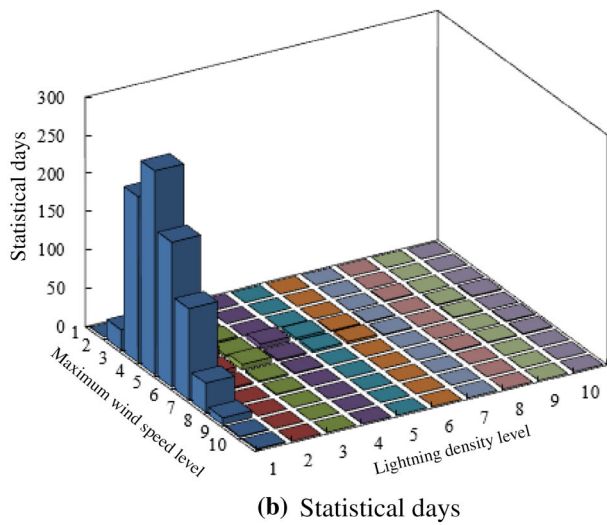
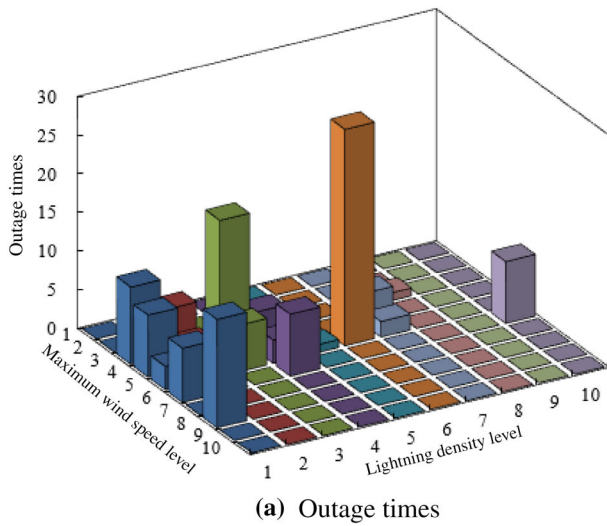


Fig. 6 Historical statistics of transmission line outages in different weather blocks of WA₂

$$\lambda'_{WA_1} = -13.9225 + 3.1331w_1 - 0.0791w_1w_2 - 0.2645w_1^2 + 0.0727w_2^2 \tag{13}$$

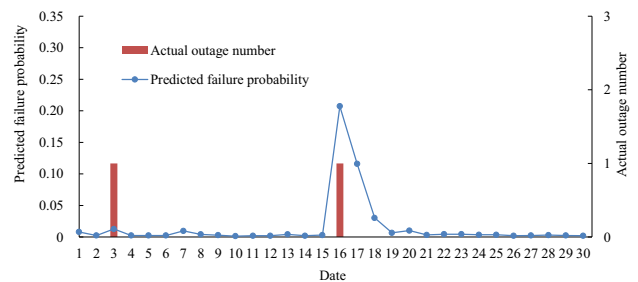
$$\lambda'_{WA_2} = -11.9084 + 1.6476w_1 - 0.0387w_1w_2 - 0.1069w_1^2 + 0.0595w_2^2 \tag{14}$$

$$\lambda'_{WA_3} = -11.8423 + 1.0980w_1 + 0.2043w_1w_2 - 0.2692w_1^2 + 0.0515w_2^2 \tag{15}$$

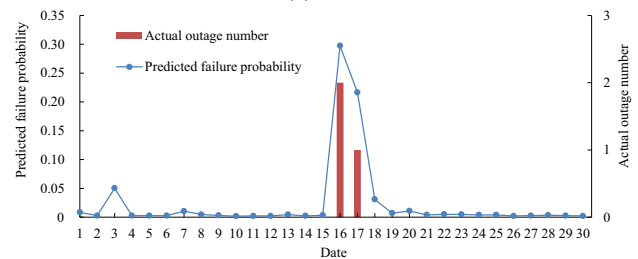
$$\lambda'_{WA_4} = -13.5802 + 3.2945w_1 - 0.2511w_1w_2 - 0.2008w_1^2 + 0.1078w_2^2 \tag{16}$$

According to the above formulas and (5), the poisson model parameter is calculated. Using (10), the estimation model for failure probability of each weather area is finally obtained. Putting the forecast weather data into the estimation model, the failure probability of the transmission line can be predicted.

Based on the outage and weather data of the transmission line during August 2014 to December 2014, the estimation model is verified. Taking two transmission lines in weather area WA₀ as an example, the lightning density and maximum wind speed in September 2014 are converted into weather intensity and substituted into the model. Comparison between the predicted failure probability and actual outage number is shown in Fig. 7. Line X₁ is the Zhuhuang No. 2 line in weather area WA₂ and WA₄, which



(a) Line X₁



(b) Line X₂

Fig. 7 Comparison between the predicted failure probability and the actual outage number

is 30.73 km long. Line X_2 is the Xinjiangshen line in WA_1 , WA_2 and WA_4 , which is 60 km long. Weather area WA_1 and WA_4 are nearer to the seaside than weather area WA_2 . The minimum distances between these two lines and the seaside are all about 2 km. Because line X_2 is longer and passes through weather area WA_1 , there is a longer line near the seaside. Most insulators used in these two lines are FXBW4-110/100.

Predicted failure probability from the estimation model is consistent with the actual outage events. When the predicted failure probability is high, the actual outage event happened. The predicted failure probability is largest on September 16, 2014 and it was the day when the typhoon “seagull” was striking the coast. In order to evaluate the accuracy of the prediction, predicted failure probability curves of two lines during August 2014 to December 2014 are presented in Fig. 8.

There is only one peak value more than 0.2 on the two curves of the predicted failure probability, which is during the typhoon “seagull.” In the curve of line X_1 , most of the predicted failure probability is less than 0.05 and the proportion is about 97.4%. There was just one outage on September 3, 2014 with the predicted failure probability less than 0.1. The outage reason recorded is lightning. But the weather data shows very low lightning activity density on this day. There are two days during typhoon “seagull” with one outage and the predicted failure probability is more than 0.2. In the curve of line X_2 , 96.1% of the predicted failure probability is less than 0.05. There is no outage with the predicted failure probability less than 0.1. There are two days during typhoon “seagull” with two

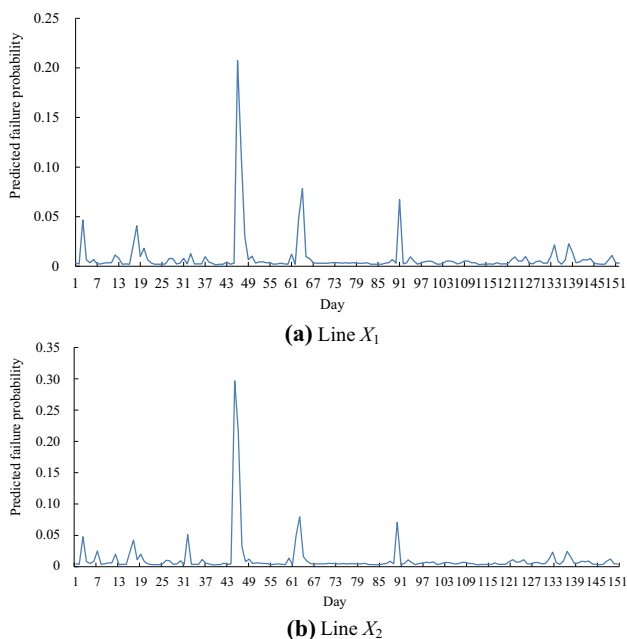


Fig. 8 Predicted failure probability of two lines during August 2014 to December 2014

outages and the predicted failure probability is more than 0.3. In general, the calculation model can reliably predict the outage probability of transmission lines. 0.2 can be set as a pre-warning value of outage probability for the power grid company.

5 Conclusion

- 1) Weather-related outage accounts for 78.09% according to the outage data analysis of the 110 kV transmission line in the Guangxi Zhuang Autonomous Region of China during 2012–2014. The distribution of weather-related outages for time and space is consistent with the temporal and spatial variation of weather factors.
- 2) An estimation method for failure probability of transmission lines is proposed in this paper. It splits and aggregates the historical weather and outage data with an interval of one day for each weather area. The weather data is converted to weather intensity and aggregated as a weather block. The statistical characteristics of the outage event in each weather block are investigated based on the poisson model. The relationship between the poisson model parameter and weather data is analyzed via regression analysis.
- 3) The example shows that the model can reliably predict the failure probability of transmission lines. It can effectively reflect the influence of a typhoon. According to the weather forecast data, the power grid company could predict the failure probability for each weather area using this method. 0.2 can be set as a pre-warning value of the outage probability. Then the power grid company can send operational staff to the area with the highest probability, especially more than 0.2. When there is an outage of transmission lines caused by severe weather, the repair time could be reduced.

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