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Damage Probability Assessment of Transmission Line-Tower System Under Typhoon Disaster, Based on Model-Driven and Data-Driven Views

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Abstract: Under the typhoon disaster, the power grid often has serious accidents caused by falling power towers and breaking lines. It is of great significance to analyze and predict the damage probability of a transmission line-tower system for disaster prevention and reduction. However, some problems existing in current models, such as complicated calculation, few factors, and so on, affect the accuracy of the prediction. Therefore, a damage probability assessment method of a transmission line-tower system under a typhoon disaster is proposed. Firstly, considering the actual wind load and the design wind load, physical models for calculating the damage probability of the transmission line and power tower are established, respectively based on model-driven thought. Then, the damage probability of the transmission line-tower system is obtained, combining the transmission line and power tower damage probability. Secondly, in order to improve prediction accuracy, this paper analyzes the historical sample data containing multiple influencing factors, such as geographic information, meteorological information, and power grid information, and then obtains the correction coefficient based on data-driven thought. Thirdly, the comprehensive damage probability of the transmission line-tower system is calculated considering the results of model-driven and data-driven thought. Ultimately, the proposed method is verified to be effective, taking typhoon 'Mangkhut' in 2018 as a case study.

Keywords: typhoon; damage probability; prediction model; correction coefficient; transmission line-tower system; data analysis

1. Introduction

In recent years, the intensity and frequency of extreme weather events (especially typhoon disasters) have increased [1]. The typhoon disaster is devastating. Under a typhoon disaster, transmission lines, power towers, and poles might be damaged, which may cause large area blackouts [2]. In order to improve the ability of the power grid to withstand typhoons, it is of great significance to predict the damage probability of transmission lines and power towers under typhoon disasters.

In view of the damage prediction of transmission lines and power towers under typhoon disasters, according to the model-driven view, some scholars studied the mechanical characteristics and damage mechanisms and pointed out that the damage of transmission lines and power towers is mainly due to the fact that the typhoon wind speeds exceed the designed wind speeds. Then, different physical models of transmission lines and power towers were proposed to predict the damage probability. In [3], based on the fuzzy mathematics principle, the membership function of a typhoon disaster was obtained by analyzing the relationship between typhoon wind speed and design wind speed and the failure rate of a transmission line was simulated by an exponential function. The mechanical stability of towers and fixings plays an important role in windproofing, but the size of the effect depends on the size of the designed wind speed and the environment situation. In [4,5], in order to analyze the failure probability of the transmission line and power tower under a typhoon disaster, the piecewise function was used to simulate the damage probability, according to the predicted typhoon wind speed and the design wind speed of the transmission line and power tower. In addition to considering the relationship between typhoon wind speed and design wind speed, the importance of non-electrical quantity data to the power system in disaster prevention was pointed out and a space-time early warning framework model for power grid failure rate under typhoons and heavy rainfall was proposed in [6]. In [7,8], considering the micro-topographic features to correct the actual wind speed of the transmission line, a damage early warning model of the typhoon disaster, based on the design wind speed and the actual wind speed, was proposed. In [9], the geographic elevation information was integrated with the geographic information of the transmission channel path and then the failure probability evaluation model of the short-term transmission channel was constructed, however, only the geographic information was considered to correct the failure model.

In summary, the model-driven thought mainly established the damaged physical model by analyzing the damage mechanism of the power grid and the calculation process was relatively simple. Most models only considered the most important influencing factors. When there were many factors to be considered, the model would be more complicated and difficult to solve.

With the development of data analysis and data mining technology, the power grid damage data analysis has been increased. Many scholars have extracted the historical typhoon sample data and have proposed data-driven power grid fault models based on the analysis and mining of sample data.

Based on data-driven thought [10], many statistical models were established to predict power outages caused by natural disasters, such as hurricanes, typhoons, and severe storms [11–16]. In [17], considering the component running time, the pollution level of the transmission line and the lightning density, based on the support vector machine and gray prediction technology, the reliability prediction model of the transmission line was proposed. In [18,19], using the relevant public data affecting the power system, power outage prediction models were established under the hurricane through data mining. In [20], linear regression, exponential regression, linear multiple regression, and neural network association models reflecting the relationship between precipitation, maximum temperature, minimum temperature, and line failure rate were established to predict the line failure rate caused by plant growth. In [21], considering weather factors such as storms, heavy rain, and high temperatures, the original parameter estimation model of a power system, based on fuzzy clustering and similarity, was proposed. The model took into account most of the climatic factors, but did not further assess the damage to the power grid. The data-driven method will be more accurate when the sample size is large and the data quality is high. However, the current collection and collation of power grid sample data is still in the initial stage and there are still problems, such as insufficient sample sizes and low data quality.

In the study of damage assessment of transmission lines and power towers under typhoon disasters, the model-driven methods generally have problems, such as insufficient accuracy or complicated solutions due to consideration of too few or too many variables. Meanwhile, data-driven methods have problems such as insufficient sample sizes or low data quality. This paper mainly aims at the problem of the prediction method of transmission line and power tower damage under typhoon disasters. It overcomes the conflict of previous research and proposes a damage predicting method of transmission lines and power towers under a typhoon disaster, combined with the model-driven and data-driven views. In this method, considering that typhoon wind speed is the main cause affecting the damage of the transmission line and power tower, the model-driven part mainly considers the typhoon wind speed and the designed parameters of the transmission line and power tower and then the damage probability physical model is established. The data-driven part mainly uses the multi-factor sample data from under the previous typhoon disaster. Through data mining analysis, the correction coefficient is obtained to correct the result of the physical model and then the final comprehensive damage probability is obtained. The simulation results based on the typhoon 'Mangkhut' in 2018 have verified its high efficiency and accuracy.

2. Transmission Line-Tower System Damage Prediction Framework

Under the typhoon disaster, the main reason for the damage of the transmission line and power tower is that the actual wind speed exceeds the design wind speed. At the same time, geographic information (such as altitude, slope, underlying surface, etc.), meteorological information (such as wind speed, wind direction, rainfall, etc.) and power grid information (such as the running time) will also have a certain impact on the damage of the transmission line and power tower. This paper intends to use the combination of model-driven and data-driven thought to predict the damage probability of a transmission line-tower system under typhoon disasters.

In this method, the model-driven part only needs to consider the most important influencing factors (gust wind speed and design wind speed) to establish a model, without considering all the influencing factors, controlling the complexity of the model. As a consequence of the different structure of the transmission line and power tower, the damage analysis method is different. Therefore, this paper first establishes the damage probability model of the transmission line and the power tower, respectively. Then, the transmission line and power tower are considered as an overall system, called the 'transmission line-tower system'. Then the damage probability of the transmission line-tower system is calculated based on the damage probability of the transmission line and power tower.

In the data-driven part, this paper considers the possible influencing factors (altitude, slope, underlying surface, etc.), and collects and sorts out the historical typhoon information that has affected the power grid in China's coastal area and obtains the correction coefficient, through the data analysis method, to correct the model-driven results. Finally, the probability of comprehensive damage is obtained. The advantage of this approach, compared with existing methods, is that it not only analyzes the physical mechanism of the typhoon disaster on the transmission line and power tower, but also controls the complexity of the model. The historical data analysis transforms the factors affecting the damage of the transmission line and power tower into a correction coefficient. The prediction framework of the transmission line and power tower damage probability is shown in Figure 1.

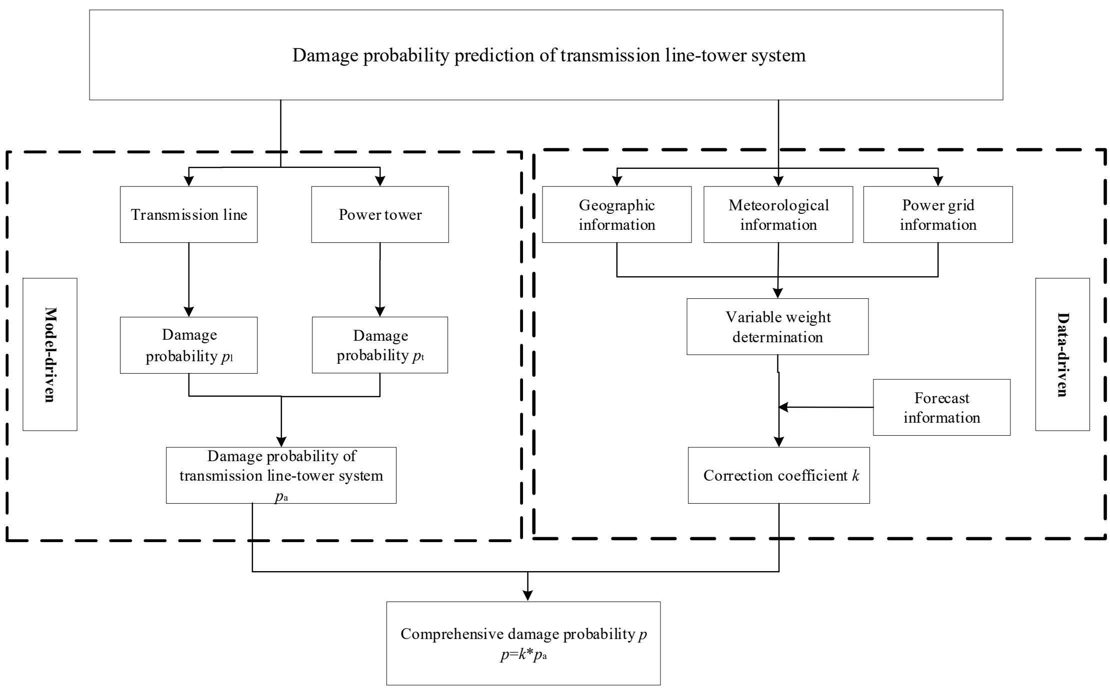


Figure 1. Damage probability prediction framework of the transmission line-tower system.

3. Data-Driven Correction Coefficient Calculation

In [22], when the damage prediction of the transmission line and power tower under typhoon disaster is carried out, only the relationship between the actual wind speed and the design wind speed is considered to establish the model. Under actual circumstances, the transmission line and power tower damage should also consider other factors, such as the elevation, the slope, and the underlying surface of the geographic information, all of which will affect the damage to the transmission line and power tower.

To this end, based on the data-driven approach, this paper comprehensively considers the influencing factors, such as geographic information, meteorological information, and power grid information, to correct the damage probability of the transmission line-tower system.

3.1. Influence Factor Weight Calculation

In the calculation of variable weights, the typhoon data that caused damage to the Guangdong power grid in China over the years are selected as samples and the weights of the variables are obtained by analyzing and processing the sample data.

The feature information contained in the sample is as follows:

Geographic information: Elevation, slope direction, slope, slope position, underlying surface, roughness, etc.;

Meteorological information: Gust wind speed;

Power grid information: Design wind speed, running time.

The correction coefficient calculation framework is shown in Figure 2.

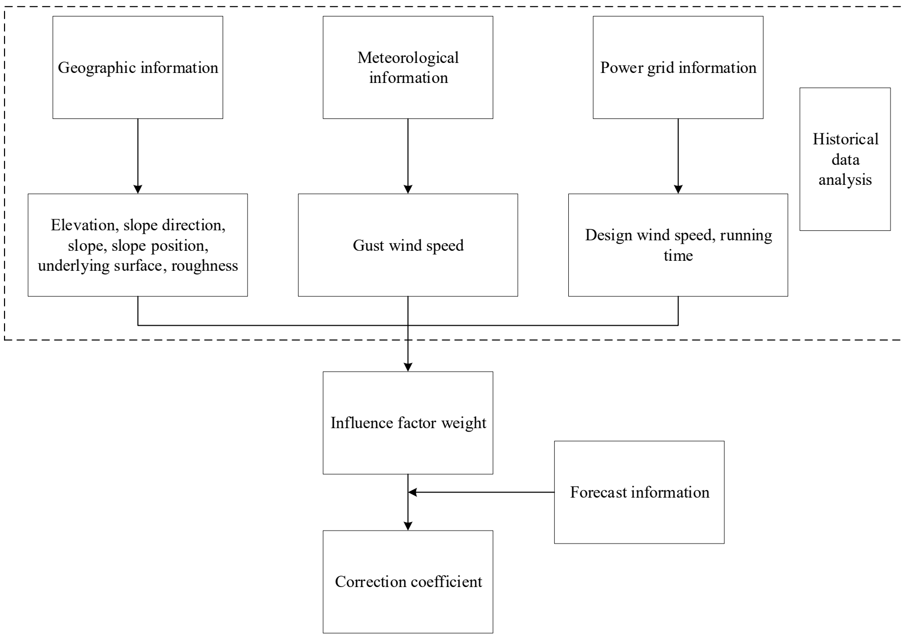


Figure 2. Correction coefficient calculation framework.

As shown in Figure 2, the geographic information, meteorological information, and power grid information from previous typhoon disasters are selected as sample data. The weights of each variable are first obtained by analyzing and calculating the sample data and then the correction coefficient is obtained according to the predicted variable data. In this paper, three kinds of analysis methods are used to evaluate the importance of each variable. Finally, the reasonable weights of the three kinds of analysis results are used to calculate the correction coefficient.

1. Variable importance evaluation based on the Gini index.

The random forest (RF) was proposed by Breiman et al. in 2001 and has now become one of the most commonly used tools in data mining and bioinformatics [23]. RF can effectively analyze nonlinear, collinear, and interactive data and give variable importance scores while analyzing the data.

In the process of generating a decision tree, the RF algorithm divides each node based on the Gini index (one of the strategies). The Gini index can characterize the importance of a node and thus the importance of the variable [24]. Therefore, the importance of the variables can be evaluated accordingly, based on the Gini index.

Assuming that there are m variables, this paper intends to calculate the weight of the variable X_j ($j = 1, 2, \ldots, m$) according to the Gini index, based on the random forest algorithm.

In this paper, the damage of the transmission line-tower system is regarded as the two-category variable, that is, damaged and not damaged, then the Gini index is calculated as follows:

$$GI_m = 2p_m(1 - p_m), \tag{1}$$

where p_m is a probability estimate of the sample belonging to any class at node m.

The importance of the variable X_j at the node m is VIM_{jm}, that is, the Gini index change before and after the node m branch is as follows:

$$VIM_{jm} = GI_m - GI_l - GI_r, \tag{2}$$

where GI_l and GI_r represent the Gini indices of the two new nodes split by node m, respectively.

If the variable X_j appears M times in the ith tree, the importance of the variable X_j in the ith tree is as follows:

$$VIM_{ij} = \sum_{m=1}^{M} VIM_{jm}. \tag{3}$$

The Gini importance of the variable X_j in RF is defined as follows:

$$VIM_j = \frac{1}{n}\sum_{i=1}^{n} VIM_{ij}, \tag{4}$$

where, n is the number of classification numbers in the RF.

2. Variable importance assessment based on mean decrease accuracy.

Mean decrease accuracy is a commonly used feature selection method that directly measures the impact of each feature on the accuracy of the model [25]. The main idea is to disrupt the order of the eigenvalues of each feature and measure the impact of sequence changes on the accuracy of the model. For variables that are not important, the scrambling order does not affect the accuracy of the model too much. For important variables, the disordered order will reduce the accuracy of the model.

Assuming that there are m variables, this paper intends to calculate the weight of the variable X_j ($j = 1, 2, \ldots, m$) according to the mean decrease accuracy based on the random forest algorithm.

The specific steps are as follows:

Step 1: The sample data is divided into a training set and a test set, of which 80% are training samples and 20% are test samples.

Step 2: Train and adjust the RF model to obtain the accuracy rate acc.

Step 3: Calculate the effect of the variable X_j on the test accuracy. The impact score is represented by score$_j$. The feature data corresponding to the variable X_j is randomly shuffled n times and, at the same time, the corresponding test accuracy rate, shuff_acc$_{ij}$ ($i = 1, 2, \ldots, n$), will be obtained when the feature data is be shuffled at ith time.

$$\text{score}_{ij} = (\text{acc} - \text{shuff\_acc}_{ij})/\text{acc}_{ij}. \tag{5}$$

The effect of variable X on the test accuracy is represented by score$_j$.

$$\text{score}_j = \frac{1}{n}\sum_{i=1}^{n} score_{ij}. \tag{6}$$

Step 4: Calculate the importance weight w_j of each variable.

$$w_j = \text{score}_j / \sum_{j=1}^{m} score_j. \tag{7}$$

3. Variable importance assessment based on the entropy weight method.

The entropy weight method is commonly used for multi-factor weight analysis [26], because its conclusion is more objective and the calculation process is simple. In the entropy weight method, the information entropy of each index is negatively correlated with the degree of numerical difference. The larger the numerical difference degree, the smaller the information entropy, and the larger the information amount, the final weight will be larger [27].

The specific steps of the entropy weight method are as follows:

Step 1: Assuming there are n damaged samples, each sample has m variables. The evaluation matrix X was obtained according to Reference [28].

$$X = (X_{ij})_{nm}. \tag{8}$$

Step 2: Calculate the specific gravity size P_{ij} of the ith sample in the variable X_j. Calculate the entropy, e_j, of the variable X_j.

$$P_{ij} = X_{ij} / \sum_{i=1}^{n} X_{ij} \ , \quad i = 1, 2, \cdots, n \ , \quad j = 1, 2, \cdots, m \quad , \tag{9}$$

$$e_j = -k \sum_{i=1}^{n} P_{ij} \ln P_{ij} \ , \quad k = 1/\ln n \ , \quad j = 1, 2, \cdots, m \quad . \tag{10}$$

Step 3: Calculate the entropy weight a_j.

$$a_j = (1 - e_j)/(m - \sum_{j=1}^{m} e_j) \ , \quad j = 1, 2, \cdots, m \ . \tag{11}$$

3.2. Optimal Weight Determination Method

Since the above three variables importance weight determination methods have advantages and disadvantages, considering the actual situation and human subjective judgment, this paper intends to use the fuzzy multi-criteria decision-making method [29] to evaluate the variable importance determination method and select the relatively superior determination method.

Supposing there are n ($x_1, x_2, \ldots, x_n$) schemes for determining weights, considering m variable factors, specific steps are as follows:

Step 1: Establishing the decision matrix $\boldsymbol{Y}$ based on the results of n kinds of weight determination.

$$\boldsymbol{Y} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}, \tag{12}$$

where X_{mn} represents the weight of the mth variable under the nth weight calculation method.

Step 2: Normalizing the decision matrix $\boldsymbol{Y}$ base on the minimum value, and the relative membership degree matrix $\boldsymbol{R}$ is obtained.

$$\boldsymbol{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix}, \tag{13}$$

where $r_{ij} = \min_j(x_{ij})/x_{ij}$.

Step 3: Calculating the weight vector of $\boldsymbol{R}$.

$$W = \begin{pmatrix} w_1 & w_2 & \cdots & w_m \end{pmatrix}, \tag{14}$$

$$w_i = \frac{\alpha \sum\limits_{j=1}^{n} r_{ij}}{\sum\limits_{i=1}^{p} \sum\limits_{j=1}^{n} r_{ij}}. \tag{15}$$

In this paper, $p = m$ is taken and all the weights are to be determined, and $\alpha = 1$.

Step 4: Calculating the decision vector D.

$$D = W\boldsymbol{R} = \begin{pmatrix} d_1 & d_2 & \cdots & d_n \end{pmatrix}. \tag{16}$$

To this end, the scheme corresponding to the maximum value in the decision vector D is selected as a relatively optimal scheme. According to the actual situation, the range of values for each variable is shown in Table 1.

Table 1. Value range of each variable.

Variable	Gust Wind Speed	Design Wind Speed	Elevation	Slope Direction	Slope	Slope Position	Underlying Surface	Roughness	Running Time
Symbol	NMG	NDW	NAL	NAS	NSL	NSP	NUS	NR	NT
Range	0–60	20–50	−102–2483	0–360	0–90	0, 1, 2, 3	0–9	0–30	0–40
Unit	m/s	m/s	m	0	0	-	-	m	year

3.3. Correction Coefficient Calculation

It is assumed that the weight of each variable (m variables) is $w = \begin{pmatrix} w_1 & w_2 & \cdots & w_m \end{pmatrix}$ and the predicted value corresponding to each variable is $x = \begin{pmatrix} x_1 & x_2 & \cdots & x_m \end{pmatrix}$.

In this paper, the correction coefficient is calculated based on the value range of the variables and the prediction data. The specific steps are as follows:

Step 1: Comprehensive scoring benchmark.

Considering that the numerical growth of each variable has different effects on the damage situation, the gust wind speed, running time, slope and roughness are positively correlated with the damage of the transmission line-tower system and the design wind speed, altitude, underlying surface, slope direction, and slope position are negatively correlated with the damage of the transmission line-tower system [30]. To this end, in the calculation of the score, the positive correlation variable front symbol is 'positive' and the negative correlation variable front symbol is 'negative'.

$$W_{B_{\max}} = \max\left(\sum_{i=1}^{m} w_i x_{B_{i,\max}}, \sum_{i=1}^{m} w_i x_{B_{i,\min}}\right), \tag{17}$$

$$W_{B_{\min}} = \max\left(\sum_{i=1}^{m} w_i x_{B_{i,\max}}, \sum_{i=1}^{m} w_i x_{B_{i,\min}}\right), \tag{18}$$

where $W_{B_{\max}}$ and $W_{B_{\min}}$ are the maximum and minimum values of the comprehensive scoring benchmark, respectively. The value w_i is the weight of each variable and $x_{B_{i,\max}}$, $x_{B_{i,\min}}$ are the upper and lower bounds of the variable range, respectively.

Step 2: Comprehensive forecast score.

$$W = wx^T = \sum_{i=1}^{m} w_i x_i, \tag{19}$$

where W is the comprehensive forecast score and x_i is the forecast value of the ith variable.

Step3: Correction coefficient.

Based on reference [7,31], this paper maps the comprehensive prediction score to the interval (0.9, 1.3) and obtains the correction coefficient k as follows:

$$k = 0.4\frac{W - W_{B_{\min}}}{W_{B_{\max}} - W_{B_{\min}}} + 0.9. \tag{20}$$

In this paper, the correction coefficient k is used to correct the damage probability of the transmission line-tower system under a typhoon disaster and the final comprehensive damage probability prediction result is obtained. At the same time, since some of the variables that can be collected are based on a 1 km × 1 km mesh, in order to match the data of each variable and ensure the accuracy of the data, this paper performs a 1 km × 1 km mesh division on the prediction area and calculates the correction coefficients of each grid separately.

4. Model-Driven Damage Probability Calculation

This paper mainly analyzes the transmission line and power tower and proposes a damage prediction model of the transmission line-tower system. The flow chart for the damage prediction of the transmission line-tower system is shown in Figure 3.

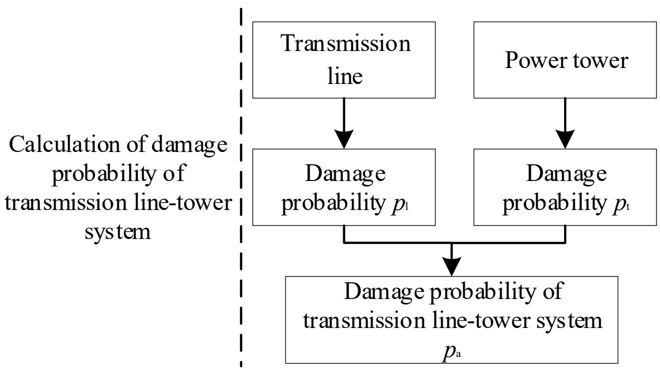


Figure 3. Damage prediction flow chart of the transmission line-tower system.

4.1. Calculation of Damage Probability of the Transmission Line

According to the reliability theory of the engineering structure [32], the damage probability of an overhead transmission line can be calculated based on the theory of stress strength interference.

Usually, the design wind load of overhead transmission lines obeys normal distribution [22] and the probability density function of design wind load is as follows:

$$f_R(w_d, u_d, \sigma_d) = \frac{1}{\sigma_d\sqrt{2\pi}} \cdot e^{\frac{-(w_d-u_d)}{2\sigma_d{}^2}}, \tag{21}$$

where w_d is the design wind load of the overhead transmission line and u_d and σ_d are the mean and standard deviation of design wind load, respectively.

In addition, the probability distribution function of the actual wind load can be fitted with an extreme I distribution function [33] as follows:

$$F_1(w_x; a, u) = \exp(-\exp(-a(w_x - u))), \quad (a > 0, -\infty < u < +\infty)\ , \tag{22}$$

where w_x is the actual wind load of the overhead transmission line, a is the scale parameter of distribution, and u is the location parameter of distribution.

Based on the stress intensity interference model, the reliable probability of an overhead transmission line is as follows:

$$\begin{aligned} p_r = p(w_x < w_d) &= \int_0^{+\infty} f_R(w_d) \cdot (\int_0^{w_d} f_1(w_x) dw_x) dw_d \\ &= \int_0^{+\infty} f_R(w_d) \cdot F_1(w_d) dw_d \end{aligned}, \tag{23}$$

where $f_1(w_x)$ is the probability density function of the actual wind load.

Then, the damage probability of overhead transmission line is as follows:

$$p_1 = 1 - p_r = 1 - \int_0^{\infty} \frac{1}{\sigma_d\sqrt{2\pi}} \cdot e^{\frac{-(w_d-u_d)^2}{2\sigma_d{}^2}} \cdot \exp(-\exp(-a(w_d - u))) dw_d, \tag{24}$$

where a and u are the scale parameters and positional parameters of the extreme value I distribution, respectively.

In Equation (24), the relationship between the mean, u_d, and the standard deviation, σ_d, is defined according to reference [34].

$$\sigma_d = Z \cdot u_d, \tag{25}$$

where Z is called the coefficient of variation of the transmission line and its general selection range is 0.05–0.2 [34]. In this paper, the coefficient of variation Z was chosen to be 0.18 when calculating the damage probability of the transmission line.

In Equation (24), the wind load w_d can be calculated as follows [31]:

$$w_d = \frac{\alpha v^2 \mu_z \mu_{sc} d L_p \sin^2\theta}{1600}, \tag{26}$$

where a is the wind pressure asymmetrical coefficient, μ_z is the wind pressure height coefficient, μ_{sc} is the shape coefficient of the transmission line, d is the outer diameter of the transmission line, L_p is the span of the transmission line, and θ is the angle between the wind and the transmission line.

4.2. Calculation of the Damage Probability of the Power Tower

Considering the exponential growth characteristics of the power tower when deformed by external force, based on the relationship between the design wind load and the actual wind load of the transmission tower, the prediction model of the damage probability of the power tower under a typhoon disaster is established. The damage probability p_t is calculated as follows [35]:

$$p_t(w_x) = \begin{cases} 0, \quad w_x \leq w_d \\ \exp\left[\frac{\ln 2(w_x - w_d)}{w_d}\right] - 1 \quad , \quad w_d < w_x < 2w_d \\ 1, \quad w_x \geq 2w_d \end{cases} \tag{27}$$

where w_d and w_x are the design wind load and the actual wind load of the power tower, respectively.

4.3. Calculation of the Damage Probability of the Transmission Line-Tower System

In the power grid, each transmission line is formed by a series of transmission lines and multi-base transmission towers. Therefore, the entire transmission line can be regarded as a series structure when calculating the damage probability of the transmission line. Under the typhoon disaster, the entire line will not be broken. Therefore, this paper selects a base transmission tower and transmission line on both sides, as analysis and calculation units, and calculates the damage probability p_a in the unit. The result has not been corrected by multiple factors, called the pre-correction damage probability in this paper.

$$p_a = 1 - (1 - p_l)(1 - p_t)^2. \tag{28}$$

4.4. Calculation of the Comprehensive Damage Probability of the Transmission Line-Tower System

Based on the pre-correction damage probability and the data-driven correction coefficient calculation stated above, the calculation equation of the transmission line-tower system's comprehensive damage probability is as follows:

$$p = k \cdot p_a, \tag{29}$$

where k is the correction coefficient calculated by data-driven thought. As it is the damage probability corrected by coefficient factors, it is called the post-correction damage probability in this paper.

4.5. Influence of the Line Span on the Damage Probability

Under the typhoon disaster, the line span will affect the wind load of the transmission line, as well as the damage probability. Therefore, analyzing the relationship between the line span and the damage probability can provide some guidance for the transmission line windproof work.

According to Equations (24)–(26), the relationship between the line span and the damage probability is shown in Figure 4.

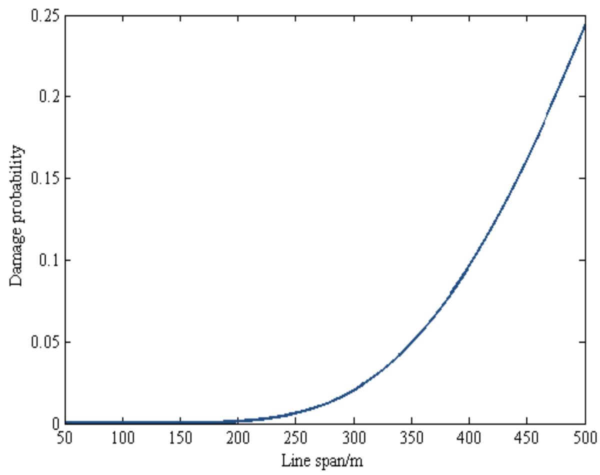


Figure 4. Relationship curve between line span and damage probability.

As shown in Figure 4, as the transmission line span increases, the probability of damage increases. Therefore, in order to reduce the risk of damage to the transmission line under a typhoon disaster, when designing the transmission line the line span can be appropriately reduced or, before the typhoon disaster, there should be a focus on the reinforcement of long-span lines to improve their ability to withstand typhoons.

4.6. Influence of the Coefficient of Variation on the Damage Probability

In the damage prediction model of the transmission line under typhoon disaster, there is a coefficient of variation Z reflecting the relationship between the mean and the variance of the transmission line's designed wind load. According to Equations (24)–(26), the relationship between the coefficient of variation and the damage probability of the transmission line is shown in Figure 5.

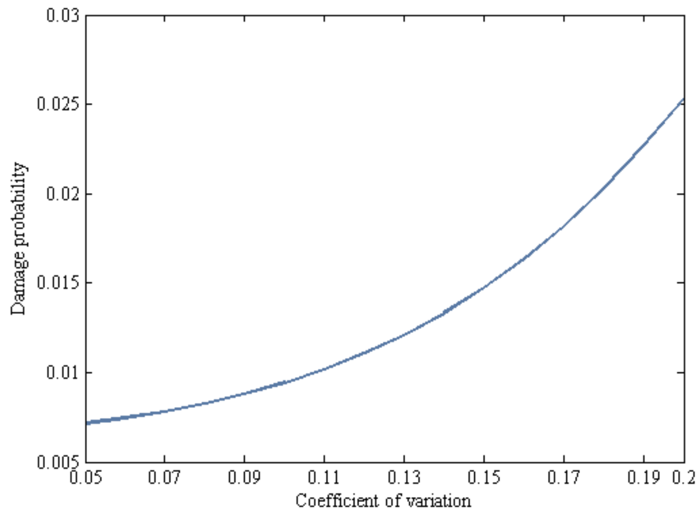


Figure 5. Relationship curve between the coefficient of variation and the damage probability.

As shown in Figure 5, as the coefficient of variation increases, the damage probability increases. Therefore, when planning and designing transmission lines, the appropriate coefficient of variation can be selected according to the wind speed division of the line location to reduce its damage probability under windstorms and to enhance its disaster prevention capability.

5. Results

Taking the typhoon 'Mangkhut', No. 22 of 2018, as an example, it was formed in the northwestern Pacific on the afternoon of 7 September. After moving into the northeastern part of the South China Sea on the morning of 15September, it quickly moved westward, attacking the China Pearl River Delta and causing serious impact on the Guangdong Province in China. 'Mangkhut' is the typhoon that has the widest range of land surface winds, the longest duration of strong winds, and the highest gust wind speed. It caused damage to a line of 35 kV and above, with 10 base towers and 13 broken (dropped) lines, which had a certain impact on Guangdong Province in China [36].

In this paper, the actual meteorological and power data of the typhoon 'Mangkhut' is taken as an example to predict the transmission line-tower system damage situation of a city in Guangdong Province, China. The simulation results verify the effectiveness and acurracy of the proposed method.

5.1. Correction Coefficient Calculation Based on Data-Driven Thought

This paper collects and records 630 samples from the typhoon ('Rammasun', 'Mujigae', and 'Hato') affected Guangdong Power Grid in China over the years. The nine characteristics of the sample data mainly include geographic information, meteorological information, and power grid information.

Among them, geographic information includes elevation, slope, slope direction, slope position, roughness, underlying surface; meteorological information includes gust wind speed; and power grid information includes design wind speed and running time.

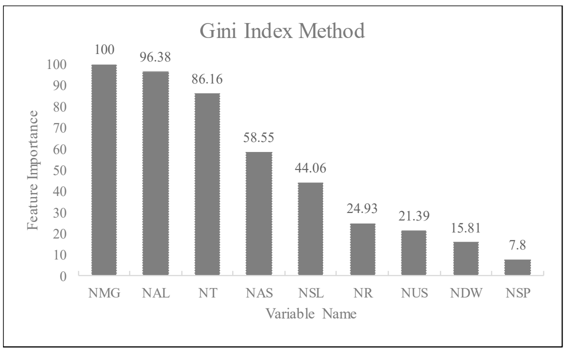
Step 1: Influence factor weight calculation.

The importance weights of each variable based on the Gini index (represented by the scheme A in the table), the mean decrease accuracy (represented by the scheme B in the table), and the entropy weight method (represented by the scheme C in the table) are calculated. The results are shown in Table 2.

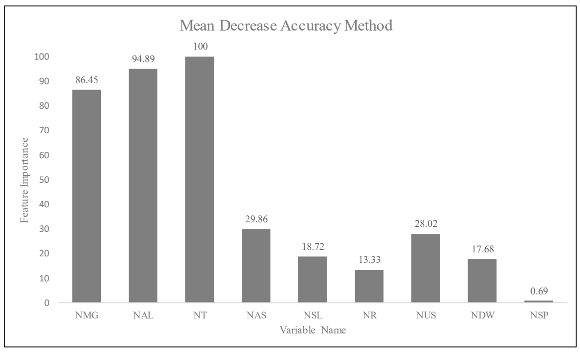
Table 2. Each variable importance weight evaluation result.

Variable		Gust Wind Speed	Design Wind Speed	Elevation	Slope Direction	Slope	Slope Position	Underlying Surface	Roughness	Running Time
Symbol		NMG	NDW	NAL	NAS	NSL	NSP	NUS	NR	NT
Scheme	A	0.2196	0.0349	0.2115	0.1285	0.0972	0.0173	0.0471	0.0549	0.1890
	B	0.2254	0.0466	0.2455	0.0712	0.0436	0.0020	0.0869	0.0264	0.2523
	C	0.0223	0.2736	0.0898	0.0166	0.0545	0.1743	0.2717	0.0578	0.0395

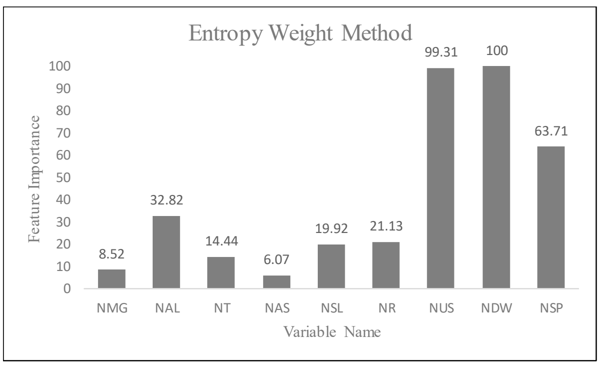
In order to visualize the importance relationship of each variable, the weight relationship diagram is shown in Figure 6.



(**a**)



(**b**)



(**c**)

Figure 6. Variable weight relation graph. (**a**) Gini index method; (**b**) Mean decrease accuracy method; and (**c**) Entropy weight method.

It can be seen from Figure 6a to Figure 6c that gust wind speed, the running time, and the altitude are more important based on the Gini index method and the mean decrease accuracy method. In the importance evaluation of variables based on the entropy weight method, the design of wind speed, the underlying surface, and the slope position is of great importance. The evaluation mechanism of the three methods is inconsistent, resulting in different final evaluation results. In order to choose a relatively reasonable evaluation mechanism, this paper intends to use fuzzy multi-criteria decision-making to select the optimal evaluation scheme.

Step 2: Evaluation scheme selection.

According to the evaluation results of the three schemes in Step 1, the decision weights of each scheme are calculated based on fuzzy multi-criteria decision making. The results are shown in Table 3.

Table 3. Decision weights for each scheme.

Scheme	Gini Index Method	Mean Decrease Accuracy Method	Entropy Weight Method
Weight	0.4422	0.3155	0.3739

It can be seen from Table 3 that the weighting scheme based on the Gini index method has the largest decision weight and its evaluation results are more consistent with the subjective experience. Therefore, the Gini index method is used to evaluate the importance of variables in this paper.

Step 3: Comprehensive scoring benchmark.

This paper analyzes the probability of damage to the transmission line-tower system under the typhoon "Mangkhut" in a city in Guangdong Province. Since the data of each variable provided is in a 1 km × 1 km grid, in order to facilitate the collection and sorting of each variable data, this example performs 1 km × 1 km mesh division for the city and obtains the correction coefficient of each grid. Part of the calculation results are shown in Table 4 below.

Table 4. Partial results of correction coefficient.

No.	Lon	Lat	k	No.	Lon	Lat	k
1	113.83	22.487	1.2725	8840	114.42	22.967	1.2646
2	113.83	22.497	1.2721	8841	114.42	22.977	1.2636
3	113.83	22.507	1.2686	8842	114.42	22.987	1.2769
4	113.83	22.517	1.2714	8843	114.42	22.997	1.2600
5	113.83	22.527	1.2709	8844	114.42	23.007	1.2661
6	113.83	22.537	1.26895	8845	114.42	23.017	1.2690
7	113.83	22.547	1.2696	8846	114.42	23.027	1.2683
8	113.83	22.557	1.2705	8847	114.42	23.037	1.2718
9	113.83	22.567	1.2731	8848	114.42	23.047	1.2900

In Table 4, No. indicates the serial number of the mesh, Lon indicates the longitude of the mesh center, lat indicates the latitude of the mesh center, and k indicates the correction coefficient of the corresponding mesh. Due to the limited space, Table 4 only lists partial results (1st to 9th and 8840th to 8846th grid data).

It can be seen from Table 4 that, due to the influence of various variables, the correction coefficient of each grid in the city is greater than 1, the final comprehensive damage probability will be greater than the damage probability based on model-driven thought, and the damage risk is higher than the risk before the correction.

5.2. Damage Probability Calculation Based on Model-Driven Thought

The damage probability model of the transmission line-tower system in each mesh is established, and their damage probability is calculated. Part of the results are shown in Table 5.

In Table 5, p_a represents the basic damage probability based on model-driven thought. In order to visually reflect the prediction results of the damage probability of Table 5 and make the emergency command of the relevant departments of the power grid more intuitive and convenient, we visualize the results based on ArcGIS software.

Table 5. Partial damage probability results of pre-correction.

No.	Lon	Lat	p_a	No.	Lon	Lat	p_a
1	113.83	22.487	0.5802	8840	114.42	22.967	0.5428
2	113.83	22.497	0.5638	8841	114.42	22.977	0.5332
3	113.83	22.507	0.5446	8842	114.42	22.987	0.5151
4	113.83	22.517	0.5348	8843	114.42	22.997	0.4826
5	113.83	22.527	0.5273	8844	114.42	23.007	0.4737
6	113.83	22.537	0.5268	8845	114.42	23.017	0.4734
7	113.83	22.547	0.5265	8846	114.42	23.027	0.4731
8	113.83	22.557	0.5250	8847	114.42	23.037	0.4729
9	113.83	22.567	0.5195	8848	114.42	23.047	0.4728

5.3. Comprehensive Damage Probability Calculation

According to Equation (28), the comprehensive damage probability of post-correction of each grid in the city is calculated. Part of the results are shown in Table 6.

Table 6. Partial damage probability results of post-correction.

No.	Lon	Lat	p	No.	Lon	Lat	p
1	113.83	22.487	0.7383	8840	114.42	22.967	0.6744
2	113.83	22.497	0.7173	8841	114.42	22.977	0.6509
3	113.83	22.507	0.6909	8842	114.42	22.987	0.6163
4	113.83	22.517	0.6800	8843	114.42	22.997	0.5969
5	113.83	22.527	0.6702	8844	114.42	23.007	0.5994
6	113.83	22.537	0.6684	8845	114.42	23.017	0.6004
7	113.83	22.547	0.6685	8846	114.42	23.027	0.5999
8	113.83	22.557	0.6670	8847	114.42	23.037	0.6013
9	113.83	22.567	0.6615	8848	114.42	23.047	0.6096

In Table 6, p represents the comprehensive damage probability of post-correction in order to visually reflect the damage probability results of Table 6 and better guide the relevant departments of the grid for emergency command.

6. Discussions

In order to visually represent the results of the analysis, this paper visualizes the results based on ArcGIS software [37]. Under typhoon 'Mangkhut', the actual breaking line and tower failure in the city was mainly distributed in the southeast coastal areas. The actual damage distribution is shown in Figure 7c. According to the damage probability results of pre-correction in Table 5, the result is divided into four levels and plotted on the map in different colors, as shown in Figure 7a.

It can be seen from Figure 7a that the larger damage probability is mainly concentrated in the southeast direction of the city and the distribution area is small. Under the typhoon "Mangkhut", damaged transmission line-tower systems based on the model-driven view are distributed in different areas of damage probability.

According to the damage probability results of post-correction in Table 6, the distribution of damage probability of post-correction is shown in Figure 7b.

It can be seen from Figures 7a and 7b that the damage probability of the transmission line-tower system in each mesh has an increasing tendency, after considering the correction coefficient. All the accidents are distributed in the maximum damage probability area after considering the correction coefficient.

At the same time, as shown in Figure 7b, the maximum damage probability distribution area of post-correction is consistent with the actual damage distribution area (as shown in Figure 7c) and the prediction result of post-correction is better than the result of pre-correction (as shown in Figure 7a).

This illustrates the necessity of calculating the correction coefficient considering multiple influencing factors and it shows the rationality of the method proposed in this paper.

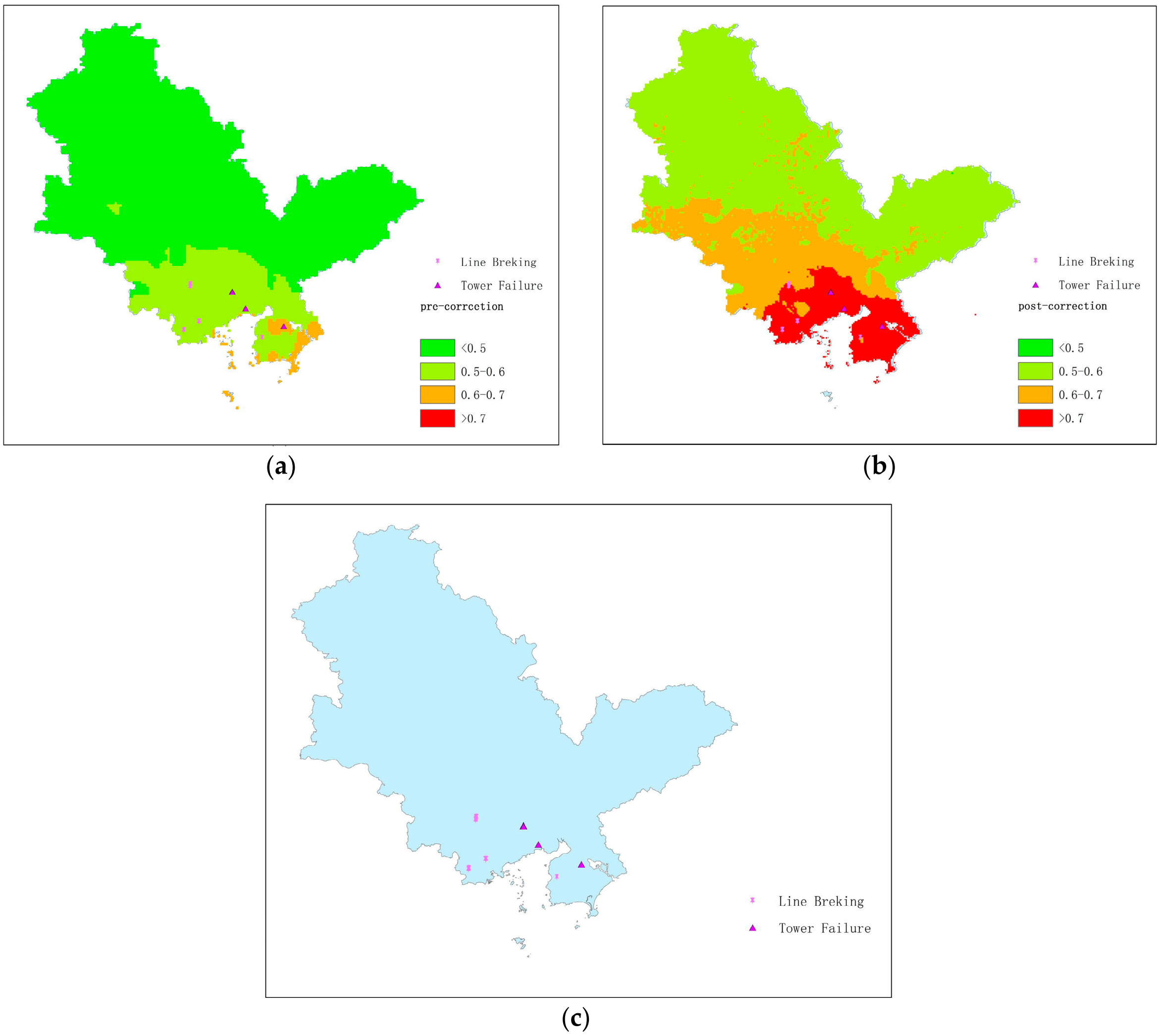


Figure 7. Predicted and actual damage distribution map. (**a**) Damage probability distribution map of pre-correction; (**b**) Damage probability distribution map of post-correction; (**c**) Actual damage distribution map.

7. Conclusions

In this paper, a method for predicting the damage probability of a transmission line-tower system under typhoon disasters, combined with model-driven and data-driven views, is proposed.

(1) This paper established a physical model based on the model-driven view. It not only considers the most important factors affecting the damage of the transmission line-tower system, but also increases the comprehensiveness of the model and the solution is easier.

(2) This paper obtained the correction coefficient reflecting the relationship between multi-factor and damage through the analysis and mining of historical sample data.

(3) This paper proposed a comprehensive damage probability assessment method of a transmission line-tower system, based on both model-driven and data-driven views. The comparison between the pre-correction and post-correction prediction results illustrated the necessity of the comprehensive damage probability calculation considering multiple factors in the damage probability assessment and the assessment result of post-correction is more in line with the actual situation.

(4) Through the prediction and analysis of the damage situation of the transmission line-tower system in a city under the typhoon 'Mangkhut', the scientific and rationality of the proposed method is verified.
(5) This paper can provide more convenient services for emergency response under typhoon disasters by visualizing the results with ArcGIS software.
(6) This study only considered the transmission lines and power towers, which cause the most serious damage to the power grid, under a typhoon disaster, for modeling. At the same time, only the existing data is applied when we calculate the correction coefficient based on the data-driven view. In subsequent research, it is a major task to collect and sort out more relevant data for analysis to improve the prediction accuracy.

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