Overview on Risk Assessment of Power System under Typhoon Disaster

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Abstract. With the frequent occurrence of typhoon disaster and the resulting large-scale power outage losses, the risk assessment of power system under typhoon damage has been widely concerned. In this paper, we summarize the research status of risk assessment of power system under typhoon damage. Firstly, we introduce several classical wind field model. Secondly, based on the static classical wind field model, we introduce the research progress of typhoon dynamic wind field model. By summarizing the existing risk assessment theory of typhoon disaster, it is divided into system level and component level. In the systematic risk assessment theory, it is further classified into the traditional risk assessment theory based on reliability principle and the new risk assessment theory based on toughness index. Finally, we make a conclusion and outlook on the research of the topic.

1. Introduction
The prosperity and development of modern society depends on a series of infrastructure which maintains people's regular production and life. With the rapid development of social economy, the power system achieves faster and faster development, and meanwhile, the problem of safe and stable operation of power system also increases. Due to exposure to the natural environment, partial device of the power system is frequently influenced by natural disasters during its operation, e.g., wind damage, ice damage, mountain fire, etc. With the increasing severity of El Nino, the natural disaster occurs more and more frequently.

There are numerous risk resources of power system, such as manual failure, aging system component and extreme climatic disaster. The natural disaster causes huge impact on the power system. According to statistics, since 1980, the United States has suffered a total of 178 natural disasters with power outage costing more than $1 billion, resulting in total losses exceeding $1 trillion. There were 11 power outage costing more than $1 billion in 2012 only[1-3].

By summarizing a large amount of existing literature, we list the existing typhoon wind field models. Based on the theory of power system risk assessment under typhoon environment, we analyze the research status of power system risk assessment under typhoon disaster.

2. Typhoon wind-field model
A typhoon is a powerful cyclonic vortex generated over the tropical ocean. Its central pressure is extremely low, and it has a sharp air pressure gradient and rotating forces, which often cause great wind speed[4]. The circulation wind speed is different at different points in the typhoon wind field. It is related to the location of the point relative to the center of the typhoon, the intensity of the typhoon and the central pressure. The distribution of typhoon pressure and wind field is usually symmetrical. Generally, the power system needs to calculate the fault rate of system components or the overall outage areas.
under typhoon damage according to the speed and direction of typhoon, thus making risk assessment. Therefore, the accuracy of risk assessment is related to the selection of the typhoon wind-field model. Based upon the classical Rankine model[5], the static typhoon wind-field can be described as:

\[ V_p = \begin{cases} 
V_{ov} & R \in [0, R_{sv}] \\
V_{ov} R_{sv} & R \in [R_{sv}, \infty] 
\end{cases} \]  

(1)

where \( V_{ov} \) is speed at the eye of wind, \( R_{sv} \) is radius of the eye of wind, \( R \) is the straight-line distance from a point \( p \) to the center of typhoon.

In addition to the classic Rankine model, several other basic typhoon wind field models are also widely used, including Batts, Shapiro, and CE models. The Batts model superimposes the gradient wind speed and the moving wind speed. The wind speed value at a certain point is determined by the relationship between the typhoon center and the research point. The Shapiro model uses the center of the typhoon as the origin of the coordinate system. When the typhoon moves, the wind speed at the research point is determined by the transformation of the coordinate system. Based on Shapiro model, CE model introduces the concept of double exponential. The CE model has better accuracy in predicting typhoons of higher intensity [6-8].

On the basis of the static model, the dynamic model of typhoon considering the prediction of typhoon motion is established.[9] describes a classic dynamic typhoon model. The model can read the current location information of the typhoon via Geographic Information System (GIS) spatial analysis before typhoon landing, thus generating key points and buffer zones. By selecting the path that is similar to the real-time path from the historical database, the similarity is determined according to the distance between the real-time path record point and the corresponding key points on each similar historical path and the ratio of buffer radius. After the typhoon forecast path is obtained by similarity analysis. Combined with the wind radius of a typhoon, it can obtain the information of predicting the wind speed and direction at a certain position in the path. Similarity analysis method is also used to determine the typhoon path, which together with the typhoon wind circle radius constituted the dynamic model of typhoon[10]. By comparison, the data obtained by the classification and analysis of typhoon before landing 48h and 24h in it is more timely and detailed, and meanwhile, the analysis and prediction on the dynamic typhoon model is more accurate as well. In [11], the similarity prediction method of typhoon was compared with the naive prediction method to specify the problems of the similarity prediction method. The application of the similarity prediction method requires matching the actual path with historical data, but the similarity prediction method of typhoon belongs to a small sample event, resulting in a large prediction error. Moreover, the destructiveness of typhoon to power grid is mainly reflected after landing 6h, but the similarity prediction method requires a longer period of time. Compared with the similarity prediction method, the naive prediction method requires the current path information of typhoon merely, therefore, it is more reliable and practical to the assessment of transmission channel failure. Meanwhile, two ranges of wind circle radius, namely, the 7-level and 10-level were set during the establishment of the dynamic model, which brought a 3-stage piecewise function of the typhoon speed. The establishment of the above dynamic typhoon models provides data sources for the risk assessment of power system under typhoon damage, but there are still certain errors in these dynamic typhoon wind-field models. To solve the errors above, some researchers proposed on-line measurement methods of wind speed, wind direction and other data via situation awareness and distributed optical fiber sensing technologies[12]. These methods may be failure under violent typhoon. Wind speed, wind direction, etc. are mainly provided by the typhoon wind-field model for the risk assessment currently.

3. Risk assessment theory under typhoon damage

The risk assessment under typhoon damage is mainly divided into two levels, namely, system level and component level. In the system level, the risk assessment includes traditional risk assessment and toughness theory-based risk assessment. The traditional one is to establish an estimated fault set of the
power grid and to predict the outage area for risk assessment according to the reliability principle. While the toughness theory-based one is to carry out risk assessment of the power grid according to toughness index. In the component level, a fault early-warning model is established by calculating the fault rate of components.

3.1. Risk assessment in the system level

3.1.1. Traditional risk assessment in the system level. In [13], an expected fault set on risk assessment of power grid is established for the calculation of outage areas under typhoon damage, thus evaluating the transient stability risk of the power grid and forming a complete risk assessment flow. In [14], Sequential Monte Carlo Simulation is taken to calculate the reliability level of the power distribution system at the maximum wind speed during typhoon landing according to the fault rate of different components of power distribution network in typhoon and combined with the existing feeder load partitioning idea. But the method fails to take full into consideration to the economic losses of outage caused by typhoon from the angle of fault rate only, and overlooks the relation of the fault rate to operating life and running status of the components. Based on this, [15-16] propose a novel assessment method under typhoon damage combined with fault rate and pole running status, and a long-term assessment method for the risk of power system in combination with climate change. The method emphasizes on the influences of economic benefit to supplement the shortcomings of the previous literatures, which has certain significance to the investment decision-making for a long time. Typhoon can cause power outage, and the assessment and prediction on the order of severity of outage is important to the risk assessment of the power system under typhoon damage. In [17-18], Random Forest Method is applied to study a outage prediction model under typhoon damage, and it is a relatively mature prediction model. But there are some problems and limitations in the methods of the outage prediction models for the power system under typhoon damage used in the above literatures, such as inadaptability to the dynamic changes of typhoons and low accuracy. On this basis, in [19], the prediction inaccuracy of typhoon was taken into consideration and brought into decision support and application of power-failure modeling, which studied the influence of the typhoon track prediction error on typhoon shutdown prediction model, thus improving the accuracy of the outage prediction model. In [20], an additive model in broad sense was proposed to bring certain guiding significance to the improvement of prediction accuracy. However, there is a common problem in the above literatures, namely, redundant input variables of the prediction model and ambiguous correlations among variables, it is easy to cause data loss and prediction errors. To solve the problem, [21] proposed a more concise typhoon outage prediction model by reducing input variables, so as to solve complex data processing.

3.1.2. Toughness assessment in the system level. The reliability of power system is mainly concerned with the long time load loss expectation of the whole system. Power system resilience focuses on the impact of an accident. A power system with high reliability does not necessarily have high toughness. Therefore, the quantification index of power system toughness is difficult to be reflected from the reliability index. It is proposed in [22] that the toughness assessment under typhoon damage in system level need to quantitate the toughness index firstly. Majority of the existing quantitative indexes are determined by a curve of a performance function $Q(t)$ selected on the basis of power system over time in extreme events. $Q(t)$ of the power system shows the performance of the power system in any time, for example, power supply, node voltage, branch power flow and other situations with time. $Q(t)$ of the power system keeps normal level and is represented by $Q_0(t)$ in normal condition. When the power system suffers an extreme event at $t_0$, resulting in the decline of performance function, a variation curve on the performance index function of the power system may be represented by $Q_1(t)$. The system returns to the normal level after a period of time. As shown in Figure.1
In [23], toughness index is defined as the performance loss area of the system, namely, a toughness triangle, indicating an integral of the performance loss portion of the system with time. This is a common quantitative index of toughness at present and is a basis to quantitate the toughness index. The value of performance function ranges from 0 to 1, of which, 0 indicates that the system is not in service, 1 indicates that the system is in normal condition, and in case of an extreme event, the operating range of the performance function is within 0 to 1. The performance function can be described as:

\[ R = \int_{t_0}^{t_1} \left[ 100 - Q_i(t) \right] dt \]  

(2)

(2) is the most widely used quantitative index of toughness.

To solve the complexity of calculation, (2) was simplified in [24]. The loss portion of the system function performance is directly equivalent to a simplified toughness triangle. In this case, the toughness index is equal to half of the product between the reduced value of the system performance function and the system recovery time, and the calculation formula can be described as:

\[ R = \left[ Q_i(t_0) - Q_i(t_1) \right] \times (t_1 - t_0) \]  

(3)

On the basis of the quantitative toughness index, the [25] proposed a quantitative toughness assessment frame of the power system under typhoon to evaluate the strength of influence of typhoon damage in consideration of the toughness index of the extreme event duration. In [26], wire frame reconstruction and power recovery process in disaster areas were taken into consideration to quantitatively evaluate the toughness absorptivity, adaptation rate and repairing rate of power distribution network under typhoon damage. In [27], by converting the disturbance caused by typhoon disaster to the power system into quantifying the impact of failure rate of different lines, the toughness index of the whole system can be calculated, and the toughness index of each line can be calculated to determine the lines with low toughness index under typhoon disaster.

3.2. Risk assessment in the component level

Due to large geographic span of the power system, different components are located in different environment in real life. In the risk assessment of components, it is not possible to treat all components in one environment when the geographical factor gap is too large. In view of this problem, some scholars take microtopography and micrometeorology into consideration in risk assessment, which improves the accuracy of assessment and prediction. The wind speed is corrected by putting forward the wind speed correction coefficient under microtopography. The correction factor can be calculated as [28]:

\[ \eta = \left[ 1 + K \cdot \tan \alpha \left( 1 - \frac{z}{2.5H} \right) \right]^2 \]  

(4)

where \( \tan \alpha \) is a slope of a peak or hillside on the windward side, if \( \tan \alpha \) is greater than 0.3, 0.3 is taken. K is the \( a \) coefficient, peak takes 2.2, hillside takes 2.2. H is full height (m) of the hillside or peak. Z is height of the building between its calculated position and the ground, being pole's line length (m), and
when \( z > 2.5H, z = 2.5H \). Early warning and assessment are performed after correcting wind speed to effectively improve the accuracy rate. Weather monitoring cannot be installed on some transmission lines because of environmental factors. For these transmission lines, it is impossible to obtain real-time environmental information, thus it is impossible to carry out effective disaster warning for transmission lines. To solve the problem, [29] proposed a set of wind-deviation flashover warning methods for power transmission lines based on numerical weather reports according to an idea of inverse distance mapping. According to the different environmental factors in different geographical regions, the transmission line area is divided into grids. Then, according to the real-time typhoon prediction data provided by the meteorological department, the longitude and latitude coordinates of the center of the typhoon at the time of warning are determined, and the distance between the center of the typhoon and the center of the grid at the time of warning is calculated[30]. The damage probability of power transmission lines was obtained in combination with the fitting of an extremum I-type function and the design of a wind load probability density function. In high winds, there is a risk of foreign bodies hanging on the power transmission line, and the risk is related to wind speed and wind direction. Therefore, a risk assessment method for the floater on power transmission lines is proposed, which combined with extreme wind speed and direction, probability density function as well as characteristic parameters of power transmission lines and geographical conditions. The most important point lies in the division of geographic areas to obtain parameters of floating objects in different areas[31]. Besides power transmission line, power poles and towers are prone to failure under typhoon damage. The line broken accident of power transmission and distribution lines is always caused by the collapse of tower. The bearing capacity of the pole and tower varies from its service life. Thus, service life of the pole and tower should be taken into consideration. [32] proposes an early warning method for the collapse risk of power transmission poles and towers in combination with fatigue damage. By combining the mathematical model of low cycle fatigue damage with the improved Poisson formula. By using the improved model and typhoon nowcasting information, the inverted tower probability is constantly revised. In the method, it is taken into consideration that the service life of poles and towers is closer to the real service condition thereof. On this basis, an accumulative damage model of power transmission poles and towers under typhoon is established as the damage of typhoon on poles and towers has an accumulative effect within certain range in [33], thus calculating the probability of poles and towers collapse. Usually, people always consider the action of wind speed and wind load only, but overlook wind direction in the collapse prediction model of poles and towers, resulting in a large error in the predication of collapse probability. Therefore, [34] proposes a prediction model for the probability of tower collapse and broken line in combination with wind speed and wind direction. The product of a wind speed probability density function and wind direction frequentness indicates a joint probability density function to obtain the bearing capacity of the tower at maximum wind speed in each direction, thus achieving the accuracy prediction of tower collapse probability.

4. Conclusion and outlook

Currently, the risk assessment study mainly focuses on: The risk assessment in the system level under typhoon damage includes the traditional risk assessment theory, the toughness assessment theory in the system level, and the risk assessment in the component level. But there are some problems in the existing risk assessment theories: (1) frequent overlook of influences of the heavy rainfall accompanied with typhoon on the risk assessment of power system. (2) less studies on the application of toughness index in the risk assessment of power system under typhoon damage. (3) failure of acquiring accurate typhoon data in time.

Correspondingly, the following points may be taken into consideration in the future: (1) the variable function of the heavy rainfall accompanied with typhoon on the risk assessment of power system. (2) improvement for the application of the toughness index in risk assessment of the power system under typhoon damage. (3) the combination of the dynamic typhoon wind-field models with on-line measurement techniques to provide timely and accurate data sources for the risk assessment of power system.
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