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Review on Risk Assessment of Power System under Rainstorm-Flood and Disaster Control Improvement Strategies

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Abstract: The global warming and El Nino effects are becoming more and more obvious now. These result in frequent rainstorms, especially in coastal areas. It is necessary to deeply study evolution mechanism of rainstorm-flood disasters, assess disaster risk of power grid, and formulate efficient power grid flood control strategies. Firstly, the research progress of disaster modeling is summarized according to the disaster evolution mechanism. The differences between hydrological models and machine learning models are compared, and the possibility of combining them is discussed. Secondly, current disaster risk assessment methods of power grid and their application in rainstorm-flood disasters to quantify flood prevention capacity are reviewed. Thirdly, the power grid flood control measures are studied from the perspective of pre-disaster grid reinforcement and post-disaster repair to improve resilience. Finally, in view of the above content, the shortcomings of current researches and feasible research directions in the future are proposed.

1. Introduction

Global warming and El Nino result frequent rainstorms in globally. Especially in coastal areas and some inland along river areas, the frequency of rainstorm-flood disasters is as high as more than 50%. Heavy precipitation has a serious impact on life safety, ecological safety, economy and society through floods and waterlogging. From 2000 to 2019, global flood losses were estimated at 651 billion dollars. Most flooding disaster were caused by heavy rainfall, and majority of them took place in Asia [1]. In 2022, 33.853 million Chinese people were affected by floods and 128.9 billion yuan in direct economic losses [2].

In order to study the impact of rainstorm-flood disaster on power grid, it is firstly necessary to have a systematic understanding of disaster evolution mechanism. Especially when rainstorm and flood disasters are interrelated and act on power grid, the disaster factors and evolution process will be more complex. Current flood disaster modeling methods are mainly divided into two categories: hydrological model method and machine learning model method [3-4]. The hydrological models contain complex flood evolution mechanism, which are close to the reality but has poor universality [5]. As a black-box model, the machine learning model has high accuracy for a specific disaster, but its practicability still needs test [6]. The advantages of the two methods can also be combined to establish a hybrid model. The flood simulation results will be helpful for pre-disaster risk analysis of power grid [7].

To quantitatively assess the vulnerability of electric power facilities to rainstorm-flood disasters, it is necessary to study a targeted risk assessment method. The risk of flood disaster mainly comes from corrosion and physical damage caused by large area of water accumulation and flow impact. For transmission pole, the foundation is easy to be washed away by floods, making it lose its stability and toppling [8]. In addition, landslide and drift can impact electric power facilities and damage transmission pole or substation external wall. Prolonged submergence will also reduce insulation performance of underground cables and distribution terminals, causing short circuit accidents [9]. Therefore, a set of power grid risk quantitative assessment indexes under flood disaster should be established to provide basis for pre-disaster reinforcement and post-disaster repair.

There have been many achievements in resiliency improvement and emergency repair optimization during pre- and post-disaster stages. They can be applied into rainstorm-flood situation and make improvements [10]. Many scholars often identify high-risk power equipment before flood disaster. Then solve power grid reinforcement and resource pre-allocation strategy as robust optimization problems [11]. After the disaster, the post-disaster emergency repair and power restoration strategies under limited resources are formulated based on flood situation. Through the above methods to repair the security risks, operator can improve the resilience of power grid under rainstorm-flood disaster and avoid outage expands further [12].

This research reviews current study progress on the problem of power grid rainstorm-flood control. The content covers rainstorm-flood modeling, risk assessment and power grid resilience improvement. The rest of this research is organized as follows: Section II summarizes the current common rainstorm-flood models. Section Ⅲ explains the risk assessment technology and application in power grid for rainstorm-flood disaster. Section Ⅳ outlines the flood control capacity improving method of power grid from the pre-disaster and post-disaster perspective. Section Ⅴ summarizes the whole research and introduces future research directions.

2. Review on Rainstorm-Flood Disaster Models

The current rainstorm-flood models are mainly divided into two categories: hydrological models and machine learning models. Hydrological models belong to traditional model, both open-source model and commercial software have been developed relatively mature. Most of them cover one-dimensional (1D), two-dimensional (2D) and three-dimensional (3D) hydrological modeling, and can establish high-precision precipitation meteorological models and urban drainage models. [13] uses urban flooding model RUFIDAM to establish a 1D drainage network model, which is used to quickly simulate urban overflow points and reduce simulation time. [14] uses the PROMETHEE II model to analyze urban drainage system and reverse estimate surface runoff of catchment area, so as to obtain flood-prone area. [15] uses FLO-2D model to analyze surface flooding after river flooding and identify high risk houses. The above references focus on building a single 1D model or 2D model, which can obtain results with acceptable accuracy in a short time. However, single-dimensional modeling is bound to lose drainage network or surface information and difficult to establish an accurate model. Its performance may be insufficient in face of complex scenarios. Therefore, the establishment of 1D-2D coupling model is more in line with real flood scene. It can simulate the flow exchange between drainage network and surface better. [16] establishes a set of large 1D-2D coupled flood model based on high precision geographic information system, which can better show the characteristics of flood spread. [17] builds an urban waterlogging model based on 1D SWMM model and 2D MOHID Land model to calculate the waterlogging depth and duration of traffic roads. Eq. (1) shows 1D-2D stagnant water overflow and converge [18].

$$Q_n = \begin{cases} c_0 S\sqrt{2g\left(h_{1D} - h_{2D}\right)}, h_{2D} < h_{1D} \\ c_w w h_{2D}\sqrt{2g h_{2D}}, h_{1D} \le H < h_{2D} \\ c_0 S\sqrt{2g\left(h_{2D} - h_{1D}\right)}, H \le h_{1D} < h_{2D} \end{cases} \tag{1}$$

where Q_n is the exchange flow between 1D drainage network and 2D surface. c_0 is the discharge coefficient of shaft mouth. c_w is the weir coefficient. S is the area of 1D drainage network and 2D surface exchange nodes. w is the crest width. h_{1D}, h_{2D}, H represent 1D drainage network node water level, 2D surface water level and surface elevation respectively. g is the gravitational constant.

The above hydrological models have a high customization ability and can reproduce most disaster scenarios. However, they have poor universality and rely on high-precision pipeline network and geographic data. And the missing data may be filled in excessively subjective and idealized during modeling. It will lead to simulation results deviation and is difficult to detect. Machine learning models can learn the complex relationship between flood disasters and impact factors from a large amount of data. As black-box models, they do not need to pay attention to various intermediate variables. With the rapid development and wide application of remote sensing technology and artificial intelligence, high-precision data sets can be obtained quickly and easily [19]. [20] defines the flood area recognition as a binary classification problem, and uses Convolutional Neural Network to identify flood diffusion area based on high-resolution remote sensing satellite data. [21-22] further extend it to identify flood areas occluded by buildings and vegetation. But the above methods rely on satellite images to train models, and it may be difficult for some scholars to obtain high-quality data. What's more, machine learning models can also take data such as population density, GDP per capita and building type as input to directly formulate a risk assessment model [23]. [24] also builds a temporal column prediction model based on Recurrent Neural Networks. Floods can be warned in near real time. However, the generalization performance of machine learning models remains to be verified. [25] pre-trains a flooding model in one urban and then applied it to a similar area, showing that pre-training can improve the generalization of the model. But for models that cannot generalize to new situations, they must be trained for a new study case each time. Due to the detection equipment lack and data collection lag, it is difficult for machine learning to apply an effective rainstorm-flood model in practice.

At present, machine learning models have little advantage over hydrological models, and they are difficult to predict water depth. In the future, researchers can consider combining them both to establish a mixed model. Machine learning models can be used to predict rainstorm precipitation, identify surface buildings, and other data as hydrological model input.

3. Review on Rainstorm-Flood Disaster Risk Assessment for Power Grid

Different from natural disasters such as typhoon and earthquake, it is difficult to ensure the timeliness and accuracy of rainstorm-flood disaster data. It is not rigorous to judge the power grid working state only by using methods such as flood depth or risk coefficient threshold. Usually, the power grid failure probability interval is constructed based on historical failure data. Then the failure consequences should be analyzed and quantified. Finally, the two should be combined to obtain risk assessment result [26-27]. [28] quantifies the vulnerability of transmission and distribution networks by predicting high-risk meteorological disasters and power generation. [29] uses the 2D hydrological model to estimate water depth, and combined flood hazard curve with vulnerability curve for nuclear power plant risk analysis. [30] uses linear function to estimate the damage caused by prolonged flooding to underground cables. All these above references use probability functions to approximately fit the failure risk situation in the power grid, which may not accurately describe the flood control ability. Therefore, the design and installation standards of facilities in power grid should be considered and develop more realistic risk quantification methods.

Some studies focus on building physical models from real-world data to analyze disaster details. [31] establishes a finite element model to study the flood control ability of different substation wall structures. When the water depth exceeds 1.0 m or the flow rate exceeds 3 m per second, the wall may be displaced and deformed. [32] finds that after raising the substation flood control threshold from 20cm to 30cm, the flood impact could be significantly delayed. For distribution network, the installation height data of some equipment in Table 1 can be obtained according to the design code of China's distribution network [33]. In order to quantify the equipment flooding risk, it can be set that the flooding depth below 0.2m has less impact, and the distribution facility is at low risk. The flooding depth from 0.2m to 0.5m is medium risk, and flooding depth above 0.5 m is high risk. The flooding depth of less than 0.1 meters generally has no impact on distribution facility and is set as risk-free.

Table 1. Installation Height Data of Distribution Facilities

Facility type	Installation height
10kV column transformer	≥3m
Floor type distribution box	≥0.2m
Wall-mounted distribution box	≥1.5m
Fixed switch box	1.3m~1.5m
Other distribution facilities	0.3m~0.5m

4. Review on Improving Power Grid Flood Control Capacity

In order to improve overall power grid flood control ability, the reinforcement strategies can be formulated based on rainstorm-flood risk assessment before disaster. The emergency repair strategies under influence of waterlogging can be formulated after disaster. [30] adopts robust optimization ideas to find the worst flood disaster scenarios and formulated a three-stage pre-disaster line hardening strategy to effectively reduce disaster losses. [34] combines traditional hydrology with rock and soil mechanics to evaluate the pole collapse probability in flood disaster. The mixed integer linear programming is used to optimize flood flow direction to avoid water directly hitting the vulnerable power poles. [35] uses probability distribution function to generate substation rainstorm-flood scenes, and established a risk precognition model to identify high-risk substations. It balances cost and resilience by using flood sandbags to improve substation flood resistance. The above references improve the power grid resilience against flooding with limited resources. But this idea believes that once facilities are reinforced, they will no longer fail. Some optimization measures also have high-cost problem and difficulty in implementation, which is too idealistic. So, the pre-disaster strategies should be divided into long-term and short-term with considering the cost. Long term planning is needed for strategies that require much time and money, such as substation lifting, drainage pipe diversion and additional storage tanks [36]. Although this kind of strategies have higher cost, they have the most significant effect on improving flood control capacity [37]. Strategies like line hardening, stacking sandbags and replacing waterproof components can be quickly deployed at low cost to fill the flood control gap [38].

In terms of the emergency repair strategies optimization after rainstorms-flood, most scholars adopt previous emergency repair ideas of power grid after disasters. They consider reconstructing the power grid to build a microgrid after disaster, and regard the repair scheduling optimization strategy as traveling salesman problem [39]. [40] proposes an active microgrid scheduling method to enhance resilience for flood disaster. After identifying vulnerable facilities, it configures the active microgrid by using resilience resources such as network reconfiguration and energy storage devices to minimize power loss of critical loads. Some scholars will also introduce mobile emergency generation vehicles or couple the power grid and traffic network to establish a multi-stage scheduling optimization model. [41] uses distributed power to form dynamic islands through network reconfiguration, and proposes an optimal scheduling model for repair team and mobile emergency generators to make full use of power grid resilience. [42] proposes a post-disaster power grid restoration scheme based on coordination of repair teams and mobile power vehicles. It comprehensively considers the coupling of traffic network and power network under different time scales. However, the above researches do not mention that floods will also affect traffic conditions, and severe rainstorm-floods will even block roads and make repair vehicles impassable [43]. As a natural disaster lasting long time and affecting widely, rainstorm-flood disaster situation will change with time. In the future, the study should also focus on dynamic change of disaster situation during repair process. For example, the use of unmanned aerial vehicle, vehicle networking and 5G network to transmit real-time traffic information helps to flexibly formulate repair paths [44].

5. Conclusion and Prospect

This research reviews from three parts: rainstorm-flood model, power grid risk assessment and power grid flood control capacity improvement. The current research progress and shortcomings are explained respectively, and the relationship among the three is also expounded. First of all, the rainstorm and flood model studies are the basis for understanding the causes of flood disasters and constructing research scenarios. Then assessing power grid risk under rainstorm-flood disaster can quantify the power grid disaster control capability. Finally, improving power grid flood control capacity is the ultimate goal of formulating flood control strategy before and after the disaster. In view of the above three aspects, this research also carries out the following prospects as future study direction.

5.1. Rainstorm-flood disaster model

Both hydrological models and machine learning models have the disadvantages of high data accuracy requirements and poor generalization ability. In the future, the advantages of these two type models can be combined to establish a more efficient hybrid model. For example, the machine learning model can modify the hydrological model to reduce dependence on drainage network data. In addition, relying on the air-ground monitoring system to analyze flood disasters can also improve data quality. Such as using deep learning methods to analyze high-resolution satellite images, and obtain flood area or water depth

5.2. Rainstorm-flood disaster risk assessment for power grid

At present, there are few studies on the risk assessment of power facility under flood disaster. In the future, machine learning models can be used to mine facilities fault information under flood disasters and cluster analyze fault types. Supervised learning can be carried out to construct a more scientific facilities fault curve. Because the whole flood disaster usually lasts a long time, the state of power facilities can be predicted online in real time with short-term forecast system. Moreover, intelligent devices can monitor key indicators to correct prediction model and provide reference for dispatchers.

5.3. Power grid flood control strategy and capacity improvement

In face of rainstorm-flood disaster, previous pre-disaster prevention measures and post-disaster repair strategies have certain applicability. In future study, the Internet of things and 5G communication technology can be introduced to update traffic information in real time. In addition, some severely flood areas have to wait for water drain out before repair work. The time delay risk caused by it should also be included in future study.

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