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Vulnerability Assessment for Power Transmission Lines under Typhoon Weather Based on a Cascading Failure State Transition Diagram

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Abstract: The analysis of the fault propagation path of transmission lines and the method of identification of vulnerable lines during typhoon weather conditions is of great significance. In this context, this paper introduces the failure probability model of transmission lines under such conditions by considering both wind speed and the load of the lines. The Monte Carlo simulation (MCS) and the DC model based on OPA are applied to simulate the failure of transmission lines. The cascading failure state transition diagram (CFSTD) is proposed based on the failure chains and the criticality ranking of nodes in CFSTD by the average weight coefficient (AWC) for identifying vulnerable lines of the power grid under such conditions. A new weight in CFSTD is proposed to describe the vulnerability of each line and a new resilience index is used to assess the impacts of a typhoon on the system. The proposed method is demonstrated by using the modified IEEE 118-bus test system. Results show that the method proposed in this paper can simulate the fault propagation path, and identify the critical components of power grid under a typhoon.

Keywords: extreme events; power transmission system; vulnerability assessment; cascading failure

1. Introduction

The frequency and perniciousness of extreme weather events around the world have increased dramatically in recent years because of climate change [1]. These high-impact, low-probability (HILP) events may cause massive power outages due to vulnerable components under these events. Take Hurricane Harvey as an example. The strong wind caused great power outages in Texas lasting over two weeks [2]. This clearly highlights the importance to study the mechanism of the impacts on power systems under extreme events, understand failure forms, and identify the vulnerability of power systems in extreme weather to enhance their resilience.

Unlike the well-known concept of reliability for power systems, “resilience” is novel in the field of systems and was first applied to ecological systems in 1973, which is a measure of the persistence of ecological systems and of their ability to absorb change and disturbance [3]. In recent years, the ability of power systems to anticipate, absorb, adapt to, and/or rapidly recover from extreme weather events, namely resilience, has been commonly accepted because of the increasing occurrence of extreme weather events [4]. Compared with the performance of the systems under normal weather conditions, the failure probability of components in the systems under extreme events increased greatly, while the repair speed inversely reduced due to severe weather conditions.

With the increasing of frequency and intensity of HILP events, many researchers have focused on the resilience of the power systems under extreme events, including resilience definitions, methods for evaluating the impacts of extreme weather on the systems, quantitative evaluation metrics, and resilience enhancement strategies. Ref. [5] proposed the concept of a resilience trapezoid for the first time, which divided performance of the power system under extreme weather into three phases: disturbance progress, post-disturbance degraded and restorative state, reflecting the resistance, response, and recovery capability of the system, respectively. The MCS and the DC model based on OPA have been widely used in simulating the operation of components during extreme events [6–9]. Resilience metrics can be categorized into metrics based on resilience features, codes, and reliability [10]. These metrics evaluate resilience of the system in terms of its performance in extreme weather, consequences, efficiency, and economy of recovery. The $\Phi\Lambda E\Pi$ metric was proposed in [5] (Φ denotes how fast resilience drops, Λ represents how low resilience drops, E means how extensive the post-disturbance degraded state is and Π expresses how promptly the network recovers) to assess the resilience trapezoid associated with an event. Based on that, an area metric was added in [11], and the residence index considering disruption (RICD), which considered the characteristics of an extreme event from the view of the disruption that impacts a target system as proposed in [12], along with the loss of energy expectation (LOEE) [8] and loss of load probability (LOLP), Ref. [13] proposed to evaluate the consequences of the systems. Ref. [14] considered the economic factor to propose the total cost ($TCOST$) of the interdependent power and natural gas (NG) systems, and [15] used load importance as a basis to propose the RSE evaluating the ability to quickly and efficiently recover a system with minimal economic costs. Resilience enhancement strategies mainly include improving robustness and reducing response and recovery time [7]. Furthermore, the application of mobile emergency resources and energy storage units has been proven to enhance the resilience of the power grid, namely the optimal operation of mobile energy resources and transportable energy storage [16,17].

In recent studies, the performance of power systems under extreme events also takes into account the impacts of other related systems, such as NG systems. In [14], the highly interdependent model of power and NG systems was developed, and, in general, the interdependent networks are more vulnerable to extreme weather. The impacts of a typhoon on power systems is mainly its strong winds and heavy rain. Therefore, photovoltaic (PV) power generation equipment and wind turbines in the system will be greatly affected. Ref. [2] proposed that, as the capacity of PV and wind turbines increases, the resilience of the power grid decreases, and the recovery costs increase significantly. In addition, a cyber attack is a special kind of resilience event. The performance of cyber power physical systems under cyber attacks may become an important research direction in the future [18].

However, few studies exist addressing the vulnerability assessment of the power systems under extreme weather. In [19,20], a traversing method is adopted, which assumes that a transmission line is reliable enough to never fail, and the critical lines of the system are ranked according to the sequence of consequences. The traversing method, however, is limited because it takes much time and computing resources to identify the vulnerable lines in large-scale networks.

These studies mainly focus on the consequences of extreme events on the systems and ignore the failure development process. Moreover, few effective methods are presented to assess the vulnerability of systems to extreme weather. On the above premises, this paper presents a vulnerability assessment to identify the critical components of the power system under a typhoon. The main contributions of this research include: (1) A new vulnerability assessment index is proposed, which considers the importance of the lines in the developed cascading failure state transition diagram (CFSTD); (2) the construction of CFSTD is based on the cascading failure chains, which considers both the sequence of failed lines and the consequence of failure chains; and (3) the development of a cascading failure model of transmission lines under a typhoon using the derived failure probability. To illustrate applicability of the proposed framework, a test system located in the coastal areas of South China under a typhoon that hit China in 2013 is studied.

The rest of the paper is organized as follows: Section 2 describes the framework of the resilience assessment. Section 3 introduces the failure probability model of transmission lines under typhoon weather. The cascading failure model is proposed in Section 4. Section 5 develops a vulnerability assessment based on the CFSTD. In Section 6, the proposed method is implemented in a numerical case study. Finally, conclusions are given.

2. Framework Design Resilience Assessment

The proposed method for modeling the performance and identifying vulnerable components of a power system under a typhoon is shown Figure 1. This framework includes the typhoon impacts model, which calculates the failure probability of lines based on wind speed and power flow, a cascading failure model, which applies the MCS and the DC model based on OPA to simulate the operation of the grid, and the vulnerability assessment model, which builds the CFSTD for identifying the critical lines. Finally, resilience enhancement measures were proposed based on the vulnerability of the lines.

	Input	Models	Output
Typhoon impacts model	1) The IEEE 118-bus test system's lat./long. data shown in TABLE A1. 2) Typhoon data including time, location and wind speed from [30].	Typhoon Impacts Model According to the typhoon information (location and intensity) and the power flow, calculating the failure probability of lines based on (5)	1) Failure probability of lines considering wind speed and power flow.
Cascading failure model	1) Power grid parameters including grid parameters: bus, branch, generator and load power from [29]. 2) Failure probability of lines.	Cascading Failure Model MCS and DC model based on OPA were used to simulate the operation of power system under typhoon weather	1) Failure chains of lines. 2) loss of load expectation (LOLE) of the power system.
Vulnerability assessment model	1) Failure chains of lines. 2) LOLE of power system.	Vulnerability Assessment Mode The CFSTD is generated based on failure chains and AWC is used to sort the critical rank of lines	1) Critical rank of lines. 2) Resilience enhancement measures based on Critical rank.

Figure 1. The resilience assessment framework during a typhoon.

(1) The first part is the typhoon impacts model, which evaluates the effect of a typhoon on transmission lines, since the indoor substations and generators are considered 100% reliable during a typhoon. The failure probability considers both the disconnection and overload caused by strong wind and the change of the power flow, respectively.

(2) The second part is the cascading failure model, which uses the MCS to simulate the failure of transmission lines under a typhoon, and the DC model based on OPA to calculate the power flow and optimal load reduction. The output of this model are failure chains of lines and loss of load expectation (LOLE).

(3) The last part is the vulnerability assessment model. The CFSTD derived from the failure chains describes the transfer of the lines' failure, and applies the AWC index to evaluate the importance of nodes in the CFSTD. Finally, the resilience enhancement measures based on the vulnerability of the lines are proposed.

3. Evaluation of Typhoon Impacts on Transmission Lines

The impacts of a typhoon on the power system are mainly due to its strong wind speed, which may lead to direct or indirect grounding of transmission lines, causing a short circuit or disconnection of such lines, and rendering them out of service. When portion of lines are out of service, the power flow of the system changes, and the remaining lines have the risk of exceeding the limit, which triggers a large-scale power outage. Therefore, this paper mainly focuses on the influence of wind speed and load of transmission lines in a typhoon, and does not consider derivative disasters.

3.1. Wind Speed Model of Typhoons

The modified Rankine vortex model has been proved to have its capability to reproduce the wind field data measured by buoy and aircraft for Hurricane Iniki [21]. It has been widely employed to simulate the wind field of typhoons [22,23]. The modified Rankine vortex model assumes that the wind flow in an idealized stationary tropical cyclone is represented by concentric circles. Its wind speed in the center is zero and increases steeply to its maximum at the radius of the maximum wind speed, and then decreases to zero as the radius continues to increase. The wind speed distribution of the modified Rankine vortex model is defined as follows:

$$V = \begin{cases} V_{\max} \left(\frac{r}{R_{\text{mw}}} \right)^X & r < R_{\text{mw}} \\ V_{\max} \left(\frac{R_{\text{mw}}}{r} \right)^X & R_{\text{mw}} \leq r \end{cases} \quad (1)$$

where r is the radial distance from the center of a typhoon, R_{mw} is the radius of the maximum winds, and $V_{\max}$ is the max wind speed at that moment. This model requires user specified parameters as R_{mw} and $V_{\max}$ instead of calculating wind fields based on the central pressure. The shape parameter X is to adjust the wind speed distribution, which in a range of $0.4 < X < 0.6$ [24].

3.2. Outage Model for Transmission Lines

During a typhoon, the strong winds may cause faults such as a short circuit and disconnection in transmission lines. When some lines fail due to a typhoon, the power flow of some lines may be cut off and out of service due to the dramatic change of power flow. Therefore, this paper takes the impacts of wind speed and power flow on the lines into account. The fragility curves of a transmission line are shown (Figure 2 [6]).

Figure 2. Fragility curves of transmission line.

3.2.1. Impacts of Weather Condition on Transmission Lines

During a typhoon, the fierce wind may cause the line to break, trees to collapse, and other damages that affect the operation of lines, and render them out of service. It can be seen from (1) that the wind speed on the transmission line is determined by its radial distance from the typhoon

center. This is due to the long distance between two buses in a system, while the wind speed varies on the same transmission line. In order to improve the computational efficiency and without loss of generality, the transmission line is divided into an appropriate number of equal segments based on its location, with the wind speed of each segment being equal to its central wind speed. Then, the failure probability of segment i in line m caused by the weather conditions (wind speed) is as follows:

$$p_{m1}^i = \begin{cases} 0 & 0 < v_m^i \leq V_{des} \\ \exp \left[\frac{0.6931(v_m^i - V_{des})}{V_{des}} \right] - 1 & V_{des} < v_m^i < 2V_{des} \\ 1 & 2V_{des} \leq v_m^i \end{cases} \quad (2)$$

where v_m^i is the wind speed of the center of segment i in line m , and V_{des} is the design wind speed of the transmission line [25].

The failure probability of transmission line m is composed of k segments in a series that have the following form:

$$p_{m1} = 1 - \prod_{i=1}^k (1 - p_{m1}^i). \quad (3)$$

3.2.2. Impacts of Power Flow on Transmission Lines

When some transmission lines out of service due to strong wind, the topology of system changes and the power flow is redistributed. Ref. [26] shows that, when the power flow of a line exceeds its rated transmission capacity, the failure probability caused by hidden faults increases with the rising of the line's power flow. The failure probability caused by power flow changes p_{m2} is as follows:

$$p_{m2} = \begin{cases} p_{m20} & 0 < P_m \leq P_N \\ \frac{(1-p_{m20})(P_m - P_N)}{P_{lim} - P_N} & P_N < P_m \leq P_{lim} \\ 1 & P_{lim} < P_m \end{cases} \quad (4)$$

where p_{m20} is the failure probability of line m under normal weather conditions, which highlights the impacts of a typhoon when assuming that $p_{m20} = 0$ in this paper. Additionally, P_m is the power of line m , and P_N and P_{lim} are the rated and ultimate power of line m , respectively.

Assuming that the failure probability of the lines caused by weather conditions and changes of power flow are independent, the failure probability of line m is:

$$p_m = 1 - \prod_{i=1}^2 (1 - p_{mi}). \quad (5)$$

4. Cascading Failure Model of Transmission Lines

The Monte Carlo-based cascading failure model evaluates the failure chains for transmission lines during a typhoon based on the location of the typhoon and the fragility curves of a transmission line. The MCS is a calculation method based on probability and statistics theory that can be used to provide approximate solutions to complex problems by massive simulations [27]. In this paper, the MCS is used to simulate the failure of transmission lines. To find more cascading failure chains for transmission lines in a typhoon, in each simulation step, all lines with failure probability greater than a random number are added to the candidate fault set, and, unlike [28], one of the lines is randomly selected as the failed line in the next step, in order to select the line with the highest fragility value as the failed line at the next step.

When the typhoon arrives, a portion of the transmission lines out of service and the power flow of the system is redistributed. Under both the line's load and wind speed, more lines will drop out of service which may lead to power outages. As the typhoon wind field changes constantly with time, the failure probability of transmission lines also changes constantly. After obtaining the initial failure

set, the line most likely to fail is selected as the subordinate fault line according to (5). The cascading failure model in this research is established by following three principles: (a) In each simulation step, only one of the lines in the candidate fault set is broken randomly, and the DC model based on OPA is used to adjust the generator output and load to ensure that the load of the remaining lines does not exceed the limit. (b) If there is no power plant in a sub-grid, all load in nodes cut down in that sub-grid; otherwise, the island reaches equilibrium based on DC-OPA. (c) When there are no more new failed lines, all sub-grids split or the impacts of the typhoon on the power system has ended, an MCS process will end and a chain of failure will be obtained.

The cascading failure chains is obtained according to the proposed procedures for a cascading failure model (Figure 3). The MCS is applied to generate failure chains, while the appropriate dispatch tool is DC-OPA. In each step Δt , the location and strength of the typhoon are updated. The failure probability of line m (p_m) depends on its load and wind speed. To find more failure chains, p_m compares with a random number r from a uniform distribution, if $p_m \geq r$, line m is added to the candidate fault set, and one of them is randomly selected as the subordinate disconnected line. Then, update the parameters of the grid, running DC-OPA and recording LOLE (P_{loss}). If t is less than T_{tyend} (the time that no more component failures because of the typhoon), the simulation increases one step (Δt) and continues to run the loop until reaching the termination criterion. If t equals to T_{tyend} , this simulation terminates and begins the next MCS. It is worth noting that the size of the simulation step (Δt) is particularly important. If Δt is too large, it may ignore some failed lines, and a small Δt may reduce the calculation efficiency greatly. After many attempts, it is determined that $\Delta t = 5$ min would balance the above two points well.

Figure 3. The proposed procedures for cascading failure model.

5. Vulnerability Assessment Model

Based on research regarding cascading failure, it is found that the development of large-scale failures is always connected to vulnerable transmission lines, and the vulnerability of power grids is an important reason for cascading failure developing into outages. In this study, a novel vulnerability assessment method based on CFSTD is proposed.

5.1. Cascading Failure State Transition Diagram

A cascading fault graph (CFG), which describes the relationship between failed lines is constructed by taking failed lines as virtual nodes, the correlation index as an edge weight, and an accident chain as a link [28]. The process of converting the accident chains into CFSTD is shown where L_i is the transmission line number (Figure 4). There are several differences between failure chains in the typhoon scene and failure chains obtained by the traversal calculation method in [28]: (a) When a typhoon path is certain, the failure chain is relatively fixed, and the fault lines only account for a small part of the whole grid. (b) The ending condition is different while the ending condition in [28] is when LOLE of the system reaches a certain threshold. (c) The method described in [28] considers the possibility of all lines as initial faults, which is too redundant.

Figure 4. Turn failure chains into CFSTD.

In this paper, the ending condition is when there are no more new failed lines or system splitting; therefore, the failure chain is not long enough to reflect the harm of the cascading failure. Additionally, if the typhoon's influence area is larger, then the fault chain is long, leading to massive power outages. Thus, the weight between the node pair (L_i, L_j) of different failure chains in the CFSTD is defined as below:

$$\omega_{ij} = \sum_{c=1}^h \Delta P_{ij} \times p_{ij} \times \frac{P_{\text{loss},F}}{n_F} \quad (6)$$

where h is the number of failure chains contained in (L_i, L_j) , n_F is the number of lines in chain F , which is the length of the failure chain. p_{ij} and ΔP_{ij} are the failure probability and the loss of load of line j from being out of service while line i faulted, respectively. The product of them represents the risk of fault transfer from line i to j , and it shows the importance of (L_i, L_j) in a failure chain. $P_{\text{loss},F}$ is the loss of load of chain F (LOLF). The ratio between $P_{\text{loss},F}$ and n_F represents the damage of chain F to the power system. When n_F is certain, the greater $P_{\text{loss},F}$ is, the more serious the harm is, and vice versa. In addition, (6) fully considers the relationship between the length of the failure chain and its risk. w_{ij} describes the consequences and probabilities of node pair (L_i, L_j) from both a single failure chain and all of them, and when (L_i, L_j) has a great w_{ij} , the more likely it is that line i causes subsequent failures and line j is affected by other failed lines.

5.2. The Criticality Ranking of Nodes in CFSTD

CFSTD is a directed graph with power, the nodes, connection edges, and edge weights are represented as failed lines, fail-overs, and correlation indicators. The critical nodes in CFSTD reflect the vulnerability of lines in the system under a typhoon. In this paper, the average weight coefficient (AWC) is proposed to identify the critical nodes in CFSTD and considers both the weight and degree of the nodes. The AWC of node i in CFSTD is defined by the following:

$$\text{AWC}_i = \frac{\sum_{j=1}^{D_i} \omega_{ij}}{D_i} \quad (7)$$

where D_i is the degree of node i . The AWC of node 1 is the average weight of edges connected with it (Figure 4) that is $AWC_2 = (\omega_{12} + \omega_{23} + \omega_{25})/3$. The higher the AWC for a node, the more important that node in CFSTD is and the transmission line it represents has more vulnerability under the typhoon.

To avoid the excessive difference of the AWC for each line, a unified method of AWC is applied:

$$AWC'_i = \frac{AWC_i - AWC_{\min}}{AWC_{\max} - AWC_{\min}}. \quad (8)$$

5.3. Average Load Loss of Failure Chains

To evaluate the impacts of a typhoon on the power system and identify the vulnerable lines of the grid, a new resilience index (average load loss of failure chains, ALFC) describes the severity of the disaster is proposed, which is defined by the following:

$$W_F = \frac{P_{\text{loss},F}}{n_F} \quad (9)$$

where $P_{\text{loss},F}$ represented the severity of the outage due to a typhoon, and the denominator means that the failure chains that have smaller n_F are more disruptive while causing the same LOLF. Therefore, (9) can be used to evaluate the damage of different failure chains to the power system and to identify the critical components in a power grid under a typhoon.

6. Case Studies

To validate the effectiveness of the proposed method, the performance of IEEE 118-bus test system under Typhoon Usagi (which was the 19th super typhoon developed in the Western North Pacific Ocean and the South China Sea in 2013) is tested.

6.1. Test System and Data

The proposed method is illustrated using the IEEE 118-bus test system [29]. Each node is assumed to be in the longitude and the latitude (Table A1 and Figure 5) to study the performance of power system under extreme weather. The red dashed line represents the path of the typhoon (Figure 5).

Figure 5. Geographic diagram of the test system and the path of Usagi.

The data regarding Typhoon Usagi, including wind speed and location in times, are provided by the Joint Typhoon Warning Center (JTWC) [30]. The linear interpolation is applied to obtain the typhoon data between two analysis time intervals, while the typhoon data are updated every

six hours in the event of a tropical cyclone. First, assume that all the transmission lines have the same $V_{des} = 30$ m/s and $P_{lim} = 1.3 P_N$ [25,31]. For modeling the failure probability of transmission lines, every 10 km is divided into a segment. To verify the importance of the failure probability of transmission lines by considering wind speed and its load, as well as the effectiveness of the cascading failure model proposed in this paper, two cases are studied.

(1) Case 1: Failure probability of lines only based on wind speed of Typhoon Usagi, and the overload of lines is eliminated by removing the capacity of generators and load curtailment;

(2) Case 2: Failure probability of lines considering both wind speed and its load, the overload lines may be considered out of service according to Section 3.

6.2. Simulation Results

The number of MCSs is set to 1000. Due to space limitations, only the 20 failure chains with the most LOLF are listed (Table 1). C1 and C2 are Case 1 and Case 2, respectively. It can be seen from the table that, when the influence of the line's load on line faults is not considered, the number of failed lines, the amount of load loss, and the ALFC of the system under typhoon weather are much lower than Case 2 while the maximum of n_F and W in Case 1 are 22 and 23.35, respectively. Conversely, these two indicators are 66 and 30.77 in Case 2. This is because a portion of lines out of service due to the flow exceeding the limit in Case 2 while the factor of failure in Case 1 is only based on wind speed. Furthermore, the total load of the IEEE 118-bus test system is 4242 MW, and the maximum of LOLF in Case 1 is 397 MW, which has not yet accounted for 10%. Therefore, the impacts of the typhoon on the system in Case 1 have been underestimated seriously. In addition, by comparing the 3rd and 4th failure chains in Case 2, the former appears to have fewer fault lines; however, it can cause greater load loss, which shows that the system is more vulnerable when these lines fail. This shows the necessity of the resilience index proposed in this paper to consider the length of a failure chain. The color bar in Figure 6 represents the failure rate of lines in 1000 simulations, while the black lines never fail.

Figure 6. Failed lines under Usagi.

In Case 1, the total number of possible failed lines is 30, and all of them are distributed near the typhoon path. As the wind speed reduces after landfall, the failure number of lines far away from the coastline decreases. It can be seen from Case 2 that some lines far away from the typhoon center are also at risk of failure. This is because cascading failures caused by fragile lines can be transmitted far away in terms of geographical distance [32]. By comparing the two cases, Case 2 appears to be more objective and better assesses the failure of the power system in typhoon weather conditions. The above conclusion supports that the effect of a typhoon is a continuous process, and the strong wind causes the line to be disconnected. Furthermore, there is a great risk of failure due to the power flow exceeding the limit, which leads to cascading failures.

Table 1. Top 20 failure chains with most LOLF in Case 1 and Case 2.

C1	n_F	$P_{loss,F}$ (MW)	W_F	C2	n_F	$P_{loss,F}$ (MW)	W_F
1	18	397	22.05	1	58	1740	30.00
2	18	397	22.05	2	53	1631	30.77
3	17	397	23.35	3	53	1531	28.88
4	17	374	22.00	4	59	1495	25.33
5	17	335	19.70	5	55	1424	25.89
6	18	335	18.61	6	64	1420	22.18
7	17	315	18.52	7	66	1357	20.56
8	18	315	17.50	8	52	1330	25.57
9	20	315	15.75	9	50	1316	26.32
10	19	315	16.57	10	55	1234	22.43
11	16	315	19.68	11	53	1226	23.13
12	20	315	15.75	12	57	1177	20.64
13	18	315	17.50	13	47	1174	24.97
14	22	315	14.31	14	55	1143	20.78
15	18	315	17.50	15	58	1142	19.69
16	18	315	17.50	16	51	1061	20.80
17	18	315	17.50	17	44	1059	24.06
18	17	315	18.52	18	51	1057	20.72
19	15	315	21.00	19	47	1033	21.97
20	19	315	16.57	20	44	1017	23.11

6.3. Resilience Enhancement to a Typhoon

To identify the critical transmission lines of the power system under the typhoon, the method proposed in Section 5 is applied. Without loss of generality, converting all 1000 failure chains are converted to the CFSTD and the AWC of each node is calculated, which is the vulnerability ranking of the transmission line.

The vertical axis represents the AWC and failure probability, while the horizontal axis shows the circuits ranking (i.e., 1 to 30, the lines ranked with the top 30 AWC from left to right), their maximum failure probability only based on wind speed (PFW), and the mean of failure probability (MPF) during the typhoon (Figure 7). It can be seen from the figure that the lines closer to the coastline have a larger MPF and AWC, especially lines 138, 134, and 142, which indicates that these lines are more vulnerable. Some of them, however, are far from the typhoon center with little wind speed and have a great failure probability and AWC, especially lines 119, 89, 102, and 64. This means that the effect of the line's load on the failure probability of a line is great. Combined with (6) and (7), the AWC value of line 119 is largest because it has a higher probability of failure and that causes a larger LOLF when experiencing failure.

To verify the vulnerability assessment method proposed in this paper and enhance the resilience of the system, a robustness measure is applied, that is, some transmission lines are assumed to be invulnerable under the typhoon. Considering the cost, it is impractical to improve the wind resistance level of all lines in the typhoon. In addition, instead of applying these hardening strategies to a single, individual line, the transmission lines are divided in resilience enhancement groups according to their AWC ranking; each group contains five lines (Figure 7). For example, the first group is composed of the first five lines with the highest AWC, the second group contains lines 6 to 10, and so on. Each case is simulated 100 times by the MCS. The results are shown (Table 2) where Group 0 is the case that no lines are invulnerable, and W_{av} is the average of W_F in each case.

Figure 7. AWC, MPF, and PFW of transmission lines.

Table 2. The change of the index after adopting resilience enhancement measures.

Group (M1)	Invulnerable Lines (M1)	W_{av}	Group (M2)	Invulnerable Lines (M2)	W_{av}
Group 0	None	17.47	Group 0	None	17.47
Group 1	119,138,139,134,107	8.66	Group 1	141,135,137,162,161	15.27
Group 2	131,89,102,64,33	13.98	Group 2	140,136,143,138,139	7.41
Group 3	36,142,137,136,143	13.65	Group 3	133,134,131,142,132	16.82
Group 4	105,140,65,108,15	15.12	Group 4	130,120,119,107,104	15.40
Group 5	67,106,88,52,55	15.27	Group 5	185,108,129,186,105	15.02
Group 6	111,129,133,135,141	17.41	Group 6	106,116,102,65,97	15.04

To verify the effectiveness of the method in this paper, a control method proposed in [28] is applied (that is, only the ratio between the associated factor and length of the cascading failure is considered in (6)). Clearly, Table 2 shows that W_{av} is reduced by applying the hardening strategies in M1 (the method proposed in this paper), but W_{av} of Group 1 is not the minimum of all the groups in M2, thus proving the validity of the proposed method. In addition, in M1, W_{av} is 8.66 when the first five critical lines are invulnerable, which is much less than the value of 17.47 in Group 0. In M2, after measures are taken for the lines in each group, the minimum value of W_{av} appears in Group 2 instead of Group 1, which means that the vulnerable lines identified in M2 cannot truly reflect the vulnerability of the power system. Combined with the previous values (Figure 7), these five lines have the highest AWC, indicating that the failure probability and LOLF are both great during the impacts of the typhoon, assuming these five lines are invulnerable can greatly improve the system's resistance and reduce the vulnerability. Therefore, the 119th, 138th, 139th, 134th, and 107th transmission lines are the critical lines in the system under Typhoon Usagi, and the result verifies the effectiveness of the proposed method in this paper. In addition, by comparing Group 0 and Group 6, the W_{av} values of the two groups are close. This is because, when the lines in Group 6 are reinforced, the accident chain that caused the large-scale power outage event is not blocked, so its role is limited. This means that strengthening some lines without vulnerability may not enhance the resilience of the power system under the typhoon; it merely increases costs and waste. Different from the conventional method of reducing the area of resilience trapezoid to improve of the system resilience [5,33], this paper proposes a method to identify vulnerable lines and applies the enhancement measures of improving the wind resistance level of the vulnerable lines to reduce the impact of extreme events on power systems. This is the significance of assessing the vulnerability of the grid in extreme weather. Before a typhoon comes, it predicts the typhoon path, simulates the operation of the power system, identifies vulnerable lines, and takes reinforcement measures according to the AWC indicators, which can greatly improve reliability and enhance resilience of the power system under extreme weather.

6.4. Sensitivity Analysis

In this section, a parameter sensitivity analysis is undertaken for both the time step (Δt) and the number of MCSs, which is used to evaluate how different Δt and different values of the number of MCSs affect simulation results. As shown in Table 3, $\bar{n}_F$ is the average number of failure chains. When $\Delta t = 20$ min, the average line is 9.90, and ignores many possible failed lines, leading to over-optimistic results. In comparison, while Δt is set to 2 min and $\bar{n}_F$ is 30.44, reducing the computational efficiency and leading to pessimistic results. Therefore, to balance the accuracy and computational efficiency, Δt is set as 5 min.

Table 3. Sensitivity analysis of Δt .

Δt	2 min	5 min	10 min	20 min
$\bar{n}_F$	30.44	23.50	17.10	9.90

In addition, different values of the number of MCSs (n_{MCSs}) are employed to analyze the sensitivity. Figure 8 shows how the value of n_{MCSs} affects the performance. In each case, the five most vulnerable lines are found based on the method proposed in this research, and applying the proposed enhancement measure to improve the wind resistance level of these lines, and $W_{av,min}$ is the average of W_F in each case. As the value of n_{MCSs} increases, $W_{av,min}$ decreases and approaches to be a constant. It indicates that, when the number of MCSs is small, the CFSTD constructed by a small number of failure chains is insufficient to identify the most vulnerable lines. Therefore, the number of MCSs is set to 1000 in this particular research.

Figure 8. Sensitivity analysis of the number of MCSs.

7. Conclusions

This paper presents an evaluation of resilience and vulnerability assessment of power systems under a typhoon. The failure probability of transmission lines are obtained by considering the wind speed and power flow, and then applying the MCS and DC model based on OPA to simulate the operation of the power system affected by Typhoon Usagi. According to the simulation results, the CFSTD is built based on failure chains and LOLF. By combining the CFSTD with the AWC, the vulnerability ranking of lines are obtained while the resilience enhancement strategy assumed that some lines were invulnerable. Finally, the proposed method is validated by using the IEEE 118-bus test system and the real data of Typhoon Usagi. The results show that lines with high wind speeds may not be the most vulnerable components, which are related to many factors, namely LOLF and the length of the failure chain. The transmission lines are divided in different groups based on their AWC ranking; the simulation results indicate that the system performs best ($W_{av} = 8.66$) when the lines in

Group 1 are assumed to be invulnerable, verifying that the proposed method is useful to identify the vulnerable transmission lines of in the power system under a typhoon.

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Appendix A

The longitude and latitude of buses in the power system are shown in Table A1.

Table A1. The location of buses in the test system.

Bus	Longitude (°)	Latitude (°)	Bus	Longitude (°)	Latitude (°)	Bus	Longitude (°)	Latitude (°)
1	110.6478	24.9763	41	113.3561	24.9051	81	115.0647	24.3207
2	111.2342	24.8342	42	113.5914	25.1054	82	114.8282	23.7180
3	110.8434	24.6454	43	113.3210	24.5342	83	114.6202	23.3568
4	111.0434	24.3234	44	113.5210	24.7342	84	114.4001	22.9322
5	111.1423	23.8723	45	113.6717	24.5051	85	114.7031	22.7322
6	111.4345	23.9342	46	113.3612	24.3104	86	114.9012	22.8035
7	111.9312	23.9452	47	113.6717	24.1641	87	115.2012	22.7531
8	111.2452	22.9992	48	114.0000	24.0314	88	114.9000	23.2000
9	111.2332	22.2786	49	114.0637	24.3120	89	115.2001	23.4003
10	111.4324	21.8274	50	113.9214	24.5481	90	115.3034	22.9703
11	111.4546	24.3567	51	114.2016	24.6102	91	115.6074	23.0003
12	111.8562	24.7567	52	114.0000	24.7021	92	115.5944	23.3713
13	112.0324	24.2654	53	114.2214	25.2041	93	115.8674	23.4023
14	112.3354	24.5344	54	114.7012	25.3102	94	115.9141	23.9098
15	112.5154	24.0265	55	114.5621	24.6501	95	115.9172	23.7023
16	112.0354	23.6345	56	114.0214	25.4015	96	115.3175	23.9314
17	112.4135	23.5134	57	113.9213	24.8914	97	115.4223	24.2387
18	112.7935	23.6014	58	114.2015	24.8954	98	115.9654	24.3611
19	113.0956	23.6244	59	114.6012	25.7411	99	116.2749	24.5917
20	112.8134	23.0124	60	115.6012	25.3102	100	116.4121	24.0265
21	112.7354	22.6554	61	115.7012	25.0000	101	116.2134	23.4342
22	112.6354	22.3565	62	115.0137	24.9910	102	115.9564	22.9613
23	112.7124	22.0651	63	115.1021	25.3100	103	116.5021	23.6791
24	113.0154	22.6554	64	115.3012	24.8102	104	116.5276	24.3564
25	112.4139	21.9021	65	114.3541	24.3549	105	117.1201	24.6478
26	112.4643	22.0801	66	114.5617	24.8154	106	116.6317	24.9474
27	111.7257	21.8635	67	114.9999	24.6914	107	117.5347	24.3514
28	111.6554	22.2358	68	113.8556	23.8989	108	117.2418	24.3248
29	111.4334	22.7653	69	113.5647	23.5617	109	117.1111	23.9999
30	112.5434	23.1235	70	113.5934	23.1261	110	116.7923	23.7212
31	111.7422	22.7765	71	113.5238	22.6287	111	116.6523	23.3061
32	112.3565	22.5562	72	113.2031	22.4987	112	117.3225	23.6978
33	112.8014	24.5142	73	113.4458	22.3257	113	112.1455	23.0342
34	112.7617	24.0012	74	113.9342	22.6981	114	111.8255	22.3645
35	113.2032	24.3514	75	114.3341	22.6586	115	112.1255	22.3245

Table A1. Cont.

Bus	Longitude (°)	Latitude (°)	Bus	Longitude (°)	Latitude (°)	Bus	Longitude (°)	Latitude (°)
36	112.9917	23.9012	76	114.0987	23.6987	116	114.2649	24.1026
37	113.2641	24.0124	77	114.4081	23.7081	117	112.3556	24.9677
38	113.2214	23.2000	78	114.8500	24.0000	118	114.1013	23.2584
39	112.8411	24.8614	79	114.7564	24.5017			
40	113.0134	24.9654	80	115.4974	24.5356			

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