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# Electric Power Distribution System Reliability Evaluation Considering the Impact of Weather on Component Failure and Pre-Arranged Maintenance

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**ABSTRACT** The weather has an important impact on the failure probability of components of power systems and on the time interval of pre-arranged maintenance. Therefore, it is essential to evaluate the reliability of distribution networks considering the impact of the weather. In this paper, weather condition models suitable for evaluating the probability of component failure and the pre-arranged maintenance are constructed based on the degree of influence of the main weather elements on them. Further, based on historical reliability data and meteorological data, a component failure model and a pre-arranged maintenance model considering weather conditions and their impact on the health of a component are proposed. The case study on an actual distribution network in Nanjing, China shows the effectiveness and merit of the proposed method.

**INDEX TERMS** Distribution network reliability, weather condition, component failure, pre-arranged maintenance.


## I. INTRODUCTION

The electric distribution system (EDS) is responsible for the supply and distribution of electricity to final users [1], [2]. Its continuous function is essential to the performance of the power system. Therefore, it is important to evaluate the EDS' reliability over a certain period to guarantee the continuous supply to final customers.

Currently, the reliability evaluation methods of the EDS include the analytical method and the simulation-based method. An analytical method refers to the relationship between the various elements in the problem, using the most concise language or formal symbols to express their relationship. The simulation-based method is a method that sets a random process, repeatedly generates a time series, calculates parameter estimates and statistics, and then studies its distribution characteristics. The papers [3]–[5] use analytical methods to evaluate the optimal values of maintenance time and failure rate to improve the reliability of radial power distribution systems. In paper [6], based on the state-sampling

non-sequential Monte Carlo simulation and the direct current load flow-based load shedding model, the expected demand not supplied (EDNS) of the system was evaluated.

One of the major factors that affect the reliability of the EDS is the component failure, which is greatly affected by weather, and the failure rate and recovery time vary widely under different weather conditions [7]. The failure rate of a component under unfavorable weather conditions may be significantly greater than that under normal weather conditions. Similarly, the recovery time in a winter storm is much longer than that on a sunny day [8], [9]. For example, according to Ausgrid's historical data, from May 2014 to May 2016, there were 896 power outages attributed to component failures, of which 598 power outages happened in adverse weathers and 98 power outages were under normal weather conditions [10]. To understand the impact of weather on component failure rates, some studies have been conducted [11]–[14]. Paper [15] uses the failure probability of power overhead line under different weather conditions to predict weather-related failure events on the overhead line every year based on a Bayesian network model. In paper [16], the failure probability of the transmission line is calculated under four extreme

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weather conditions and a novel risk assessment model is proposed. The reliability of the EDS with a ring network is evaluated by using the minimum cut-set method in paper [17]. Paper [18] proposes a “GP-VM” method for power system reliability assessment. Numerical results show that it has better convergence performance and higher estimation accuracy than other methods. To study the reliability of the smart EDS, and paper [19] considers the support from battery storage systems for improving the overall reliability. However, none of the above-mentioned papers considered the impact of weather on the failure of components in the reliability assessment of the distribution network. Paper [20] used multi-layer Monte Carlo method to evaluate the reliability of the distribution network by considering the influence of weather conditions such as strong wind and lightning on component failure and recovery time.

Another factor that affects the reliability of the EDS is the pre-arranged outage. The pre-arranged outage includes the pre-arranged maintenance and the pre-arranged expansion. With the increasing demand of the users on the reliability of power supply, the power supply enterprises need to enhance the depth of reliability management [21], [23].

In this case, to improve the reliability of the distribution network, various factors affecting the pre-arranged outage need to be considered, such as the weather. However, few have been reported on the reliability modelling and forecasting considering the effects of weather on the pre-arranged outages.

The contributions of this paper are as follows: First, this article first analyzes the relationships (through P-value, importance index, correlation) between various weather elements and component failures and maintenance, respectively, selects the main weather elements and divides them into intervals, and then builds two weather condition models based on the combinations of weather elements and intervals specialized for component failure and maintenance respectively. Therefore, the resulting weather condition models can capture the differences of the influence of various weather elements on the failure of different components and maintenance time intervals with a sufficient number of states thanks to a large weather elements database. Secondly, with the defined weather conditions of selected weather elements and the historical data of failures, the failure probability under each weather condition is then derived. By modelling the health of the components, an annual maintenance time interval model considering the impact of weather based on changes in health is derived, which can more accurately describe the impact of maintenance on the reliability of the distribution network, effectively avoiding overhauls and under hauls, reduce waste of human and financial resources. Finally, to embed the proposed methods into the reliability assessment, we proposed a framework which can incorporate the weather condition models and impact from weathers on both component failure and maintenance into the distribution network reliability assessment.

This paper studies the reliability evaluation problem of the EDS considering both component failure and pre-arranged maintenance. In the second section, the degree of influence of the main weather elements on component failure probability and pre-arranged maintenance time interval are analyzed and the weather condition models suitable for component failure analysis and pre-arranged maintenance analysis are built. The third section modelled the component failure model based on historical reliability data and weather and meteorological data and the pre-arranged maintenance interval model by analyzing the influence of weather conditions on the health of components, which is followed the introduction of reliability evaluation method of a distribution network based on Monte Carlo method. Last, the fifth section concludes the paper.

## II. MODELLING THE WEATHER CONDITIONS SUITABLE FOR COMPONENT FAILURE ANALYSIS AND PRE-ARRANGED MAINTENANCE FREQUENCY ANALYSIS

### A. SELECTION OF THE INFLUENTIAL WEATHER ELEMENTS

According to the average number of outages of components of EDS in the suburbs of Nanjing in the four seasons of 2016, the weather has the greatest impact on the overhead lines (OL). As can be seen from Figure 1, summer has a greater impact on the components, and the failure probability of OL is much higher than other components no matter what seasons. Therefore, this paper takes OL as an example to study the influence of weather elements on component failure.

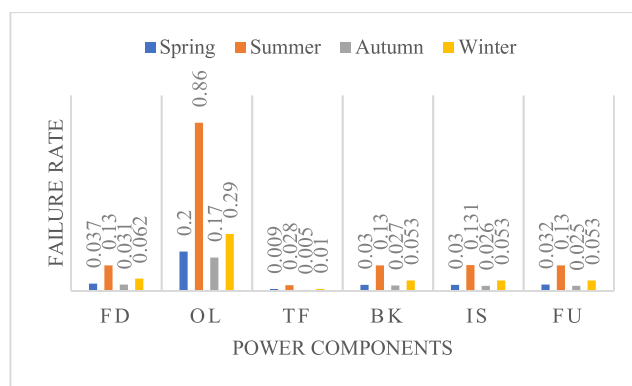


FIGURE 1. The effects of weather condition on the failure rate of components where FD = feeder, OL = overhead lines, TF = transformer, BK = breaker, IS = isolation switch, FU = fuse.

In general, commonly available weather elements include wind data, e.g. directions, gust speed (GS), resultant speed (RS), average speed (AS), rain and snow data, e.g. the largest number of days of rain and snow (LNDRS), total precipitation and snowfall (TPS), and the largest number of days of continuous low temperature (LNDCLT); temperature data, e.g. the highest temperature (HT), the lowest temperature (LT) and the average temperature (AT); the relative humidity (RH); lightning strokes, e.g. latitude, longitude, aggregate lightning stroke current (ALSC) and peak lightning stroke current (PLSC), etc. These weather elements can be directly

measured. By contrast, some collective influential factors cannot be directly measured, thus indicators based on measurable elements are needed. For example, to comprehensively consider the impact of rain and snows, a new index ICE considering LNDRS, TPS, LNDCLT, AT, and LT was created in [24]:

$$ICE = \frac{LNDRS_c}{LNDRS} + \frac{TPS_c}{TPS} + \frac{LNDCLT_c}{LNDCLT} + \frac{AT_c}{AT} + \frac{LT_c}{LT} \quad (1)$$

where, ICE is the composite index, subscripts *c* and *av* are for the current and average value.

However, not all of them are with the same impact on the fault occurrence or component health. In [16], some most relevant weather elements are selected, i.e. the GS, RS, and AS for wind effect, and the ALSC and PLSC for lightning impact.

To achieve the best discretization, data transformation is needed. The discretization method can be used to classify GS, RS, AS, the natural logarithm of total lightning strike current (NLAL), the natural logarithm of peak lightning strike current (NLPL) and ICE as shown in Table 1.

TABLE 1. Weather elements and level classification.

Weather element	Classification
GS	$A_1[0 a_1), A_2[a_1 a_2), \dots, A_m[a_{m-1} Max)$
RS	$B_1[0 b_1), B_2[b_1 b_2), \dots, B_n[b_{n-1} Max)$
AS	$C_1[0 c_1), C_2[c_1 c_2), \dots, C_p[c_{p-1} Max)$
NLAL	$D_1[0 d_1), D_2[d_1 d_2), \dots, D_q[d_{q-1} Max)$
NLPL	$E_1[0 e_1), E_2[e_1 e_2), \dots, E_s[e_{s-1} Max)$
ICE	$F_1[0 f_1), F_2[f_1 f_2), \dots, F_n[f_{n-1} Max)$
HT	$G_1[0 g_1), G_2[g_1 g_2), \dots, G_g[g_{g-1} Max)$
LT	$H_1[0 h_1), H_2[h_1 h_2), \dots, H_h[h_{h-1} Max)$
AT	$I_1[0 i_1), I_2[i_1 i_2), \dots, I_l[i_{l-1} Max)$
RH	$J_1[0 j_1), J_2[j_1 j_2), \dots, J_l[j_{l-1} Max)$

For a specific area, it is enough to represent the key and distinguishing features of its weather by using a part of these weather elements. In this paper, the *p*-value method is used to sort weather elements and then the most important weather elements are selected to describe the weather. The Pearson coefficient  $P_{cc}$  can be calculated by [25]:

$$P_{cc} = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \quad (2)$$

where for component failure: *x* refers to the probability of the occurrence of the weather element, *y* refers to the probability of failure of the component under the weather element; for component pre-arranged maintenance: *x* refers to the probability of the occurrence of the weather element, and *y* refers to the speed of component health decline under the weather element.  $\bar{x}$  and  $\bar{y}$  are the average values of *x* and *y*, respectively.

According to [26], the *p*-value can be calculated by the following formula:

$$p = 2P(z > |z_c|) \quad (3)$$

where *z* is the test statistic and  $z_c$  is the test statistic obtained from sample data.

This paper defines 1-*p* to reflect the importance of weather elements and then selects the most important weather elements to represent the main features of the weather. Take the EDS of Nanjing suburb as an example, the  $P_{cc}$  between weather elements and their importance indexes considering the outage caused by component failure is shown in Figure 2. It can be seen from Figure 2 that the important indexes of GS, RS and NLPL are greater than 0.8, while those of AS, NLAL, ICE, HT, LT, AT and RH are less than 0.5. Therefore, GS, RS, and NLPL are more important for the EDS of Nanjing suburb in studying the outages caused by component failures.

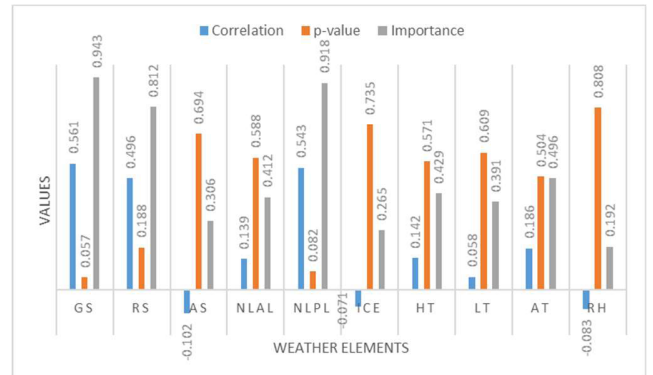


FIGURE 2. The  $P_{cc}$ , *p*-value, and importance of weather elements for component failure.

The  $P_{cc}$  between weather elements and their importance indexes considering the outage caused by pre-arranged maintenance for the EDS of Nanjing suburb is shown in Figure 3. It can be seen from Figure 3 that the important index values of GS, RS, and HT are greater than 0.8, while those of AS, NLAL, NLPL, ICE, LT, AT and RH are less than 0.5. Therefore, GS, RS, and AT are more important for the EDS of Nanjing suburb in studying the outages caused by pre-arranged maintenance.

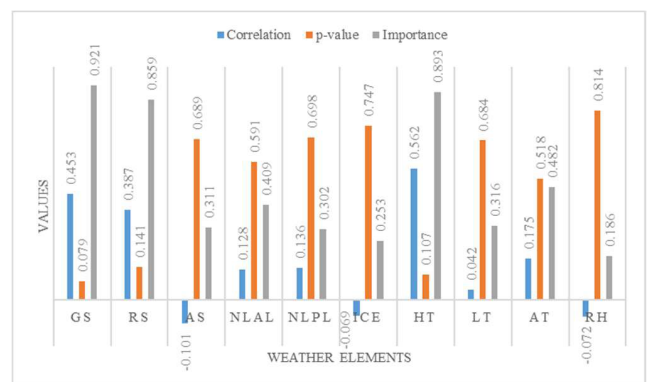


FIGURE 3. The  $P_{cc}$ , *p*-value, and importance of weather elements for component pre-arranged maintenance.

### B. CLASSIFICATION OF WEATHER CONDITIONS

To describe all weather conditions by the selected weather elements, the following definitions are introduced.

**Definition 1:** For the factor  $i$ , if  $\exists F_{ij}$  such that  $\forall f_i^t \in \mathbb{F}_i := \bigcup_{j=1}^{m_i} F_{ij}, \bigcap_{j=1}^{m_i} F_{ij} = \phi$ , then we call  $\mathbb{F}_i$  the interval-set of the factor  $i$ , and  $F_{ij}$  is an interval subset.

**Definition 2:** we define the space of weather conditions as the Cartesian product  $\mathcal{F} := \prod_{i \in I} \mathbb{F}_i$ .

Thus, by Definition 2, we can classify the weather measurements of any time into a specific weather condition in  $\mathcal{F}$ .

Theoretically, a greater number of weather conditions give a more precious description of the weather; however, with the increasing number of weather conditions, the probability of each condition approaches zeros. Therefore, the number of elements and the interval subsets are chosen to obtain a meaningful while accurate classification [27].

Taking the EDS of Nanjing suburb as an example, the weather conditions for component failure by combining the two most important weather elements are given in Table 2.

**TABLE 2. Weather condition classification for the Eds of Nanjing.**

Weather condition	Weather elements	
	GS	NLPL
1	$A_1[0 a_1)$	$E_1[0 e_1)$
2	$A_2[a_1 a_2)$	$E_1[0 e_1)$
...	...	...
$m$	$A_m[a_{m-1} Max)$	$E_1[0 e_1)$
$m+1$	$A_1[0 a_1)$	$E_2[e_1 e_2)$
$m+2$	$A_2[a_1 a_2)$	$E_2[e_1 e_2)$
...	...	...
$m*s$	$A_m[a_{m-1} Max)$	$E_s[e_{s-1} Max)$

### III. THE RELIABILITY ANALYSIS MODELS FOR COMPONENT FAILURE AND PRE-ARRANGED MAINTENANCE

#### A. COMPONENT FAILURE MODEL

Power line fault statistics usually include the weather conditions and fault information, as given in Table 3.

**TABLE 3. Outage database of a power line of the Eds in Nanjing.**

Weather condition	Outage database	Power outage rate
1	$(1, r_{11}), (2, r_{12}), \dots, (N_1, r_{1N1})$	$WCP_1$
2	$(1, r_{21}), (2, r_{22}), \dots, (N_2, r_{2N2})$	$WCP_2$
...	...	...
$m$	$(1, r_{m1}), (2, r_{m2}), \dots, (N_m, r_{mNm})$	$WCP_m$
$m+1$	$(1, r_{(m+1)1}), (2, r_{(m+1)2}), \dots, (N_{(m+1)}, r_{(m+1)N(m+1)})$	$WCP_{(m+1)}$
$m+2$	$(1, r_{(m+2)1}), (2, r_{(m+2)2}), \dots, (N_{(m+2)}, r_{(m+2)N(m+2)})$	$WCP_{(m+2)}$
...	...	...
$m*s$	$(1, r_{(m*s)1}), (2, r_{(m*s)2}), \dots, (N_{(m*s)}, r_{(m*s)N(m*s)})$	$WCP_{(m*s)}$

Theoretically, the relationship between the average failure probability and the weather-related failure probabilities follows equation (4):

$$WCF_{avg} = \sum_{i=1}^N WCF_i * WCP_i \tag{4}$$

where  $WCF_{avg}$  is the average annual failure probability of a component,  $WCF_i$  is the average annual failure probability of

the component under weather condition  $i$ , and  $WCP_i$  is the occurrence probability of weather condition  $i$ . However, the theoretic value of each item in equation (4) is very difficult to obtain; therefore, in practice, estimations from historical data are used to replace them [24][26][28], thus we have:

$$WCF_i^\Delta = WCF_{avg}^\Delta * 1 / (WCP_i^\Delta) * F_i \tag{5}$$

where  $WCF_{avg}^\Delta$  represents the estimated average annual probability of failure of the component,  $WCP_i^\Delta$  represents the estimated probability of occurrence of weather condition  $i$ ,  $F_i$  is the proportion of failures occurring in weather condition  $i$ .

The distribution network outage database (e.g. Table 3) records the time of each failure of components and the corresponding weather conditions. Through the accumulation of long-term power outage data (e.g. 10 years), the portion of failures of a component in each weather condition can be counted, thus,  $F_i$  can be estimated; by ignoring weather conditions, we can count the number of component failure and estimate  $WCF_{avg}^\Delta$ . Similarly, we can also estimate the probability of occurrence of weather condition  $i$ ,  $WCP_i^\Delta$ , by the same power outage database.

The outage data records the restoration times for each power outage. In a weather condition, the restoration time of power lines can be estimated using the average restoration time of all outages. For the  $i$ th weather, the restoration time of power lines is:

$$RT_i = \frac{1}{WCB_i} \sum_{j=1}^{WCB_i} RT_{ij} \tag{6}$$

where  $RT_{ij}$  is the power line recovery time for the  $j$ th blackout in the  $i$ th weather and  $WCB_i$  is the total number of outages in the  $i$ th weather condition.

#### B. COMPONENT PRE-ARRANGED MAINTENANCE MODEL

To achieve a safe operation of the EDS, it is necessary to carry out regular maintenances and expansions. As the expansion is closely related to the increase of the load and not even remotely related to weather. Therefore, this paper does not consider the relationship between EDS' expansion and weather.

The health of a normal state component is generally between  $h$  and 1, and when the component is damaged, its health is close to 0. Therefore,  $h$  can be regarded as the critical value of health. When the health drops to  $h$  and then the component failure increases rapidly, so the component needs maintenance. The health-time chart of a component is shown in Figure 4, it can be found that it is a regular curve when the weather is not considered and the curve becomes irregular when considering the weather. The different failure rates in different weather conditions in Figure 4 also indicate the effect of weather on the probability of failure. According to the regular maintenance and theoretical health curve, there may be failures that have not been repaired or repaired in advance, both of which have an impact on reliability.

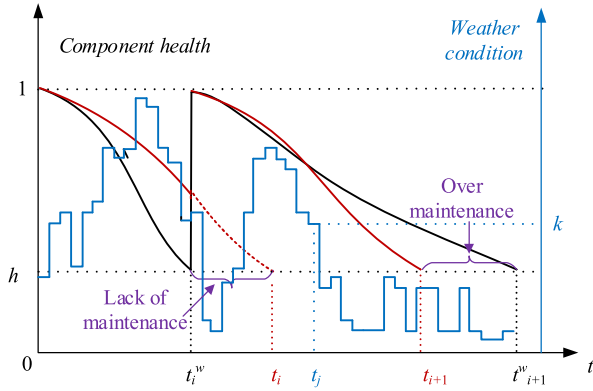


FIGURE 4. Component maintenance interval and weather elements.

The health of a component within the interval of maintenance can be described by its average probability of failure.

$$\overline{WCF}_i = \sum_{j=1}^{m \times n \times p \times q \times r} CBF_j \frac{\Delta RT_{ij}}{\Delta RT_i} \quad (7)$$

where  $\overline{WCF}_i$  represents the average failure rate of the interval of maintenance  $\Delta RT_i$  of component,  $\Delta RT_i$  is the total time of the  $i$ th weather condition in the interval of maintenance, the  $CBF_j$  is the probability of failure rate of the component in the  $j$ th blackout and  $\Delta RT_{ij}$  is the total time of the  $i$ th weather condition in the interval of maintenance in the  $j$ th blackout.

#### IV. RELIABILITY EVALUATION AND PREDICTION OF THE EDS CONSIDERING WEATHER IMPACT

##### A. THE RELIABILITY INDICES OF THE EDS

TCOH is defined as the sum of products of the number of customers at each load point and its annual outage time. TCO is defined as the sum of products of the number of customers at each load point and its annual outages.

$$TCOH = \sum_{i \in R} U_q N_q \quad (8)$$

$$TCO = \sum_{q \in R} O_q N_q \quad (9)$$

where  $U_q$ ,  $O_q$  and  $N_q$  are the annual outage time, outages and the number of customers at load point  $q$  respectively;  $R$  is the number of load points of the EDS.

There are many EDS reliability indices [25] widely used in practical EDSs, including SAIDI (System Average Interruption Duration Index), SAIFI (System Average Interruption Frequency Index), ASAI (Average Service Availability Index) and ASUI (Average Service Unavailability Index).

$$SAIDI = \frac{TCOH}{\sum_{q \in R} N_q} \quad (10)$$

$$SAIFI = \frac{TCO}{\sum_{q \in R} N_q} \quad (11)$$

$$ASAI = 1 - \frac{TCOH}{8760 \sum_{q \in R} N_q} \quad (12)$$

$$ASUI = 1 - ASAI \quad (13)$$

From equations (10)-(13), it is obvious that the key steps in the reliability evaluation of the EDS are to calculate TCOH and TCO.

As both component failure and pre-arranged maintenance contribute to the unreliability of an EDS, we divide the TCOH into two parts, i.e. TCOH-F (Total Customer Outage Hours due to component failures) and TCOH-P (Total Customer Outage Hours due to planned outages). Similarly, other indicators, such as TCO-F, TCO-P, SAIDI-F, and SAIDI-P can be defined. For the sake of simplicity and space, TCOH is used as an example to illustrate its process of calculation and prediction.

##### B. RELIABILITY PREDICTION PROCESS

After obtaining the weather condition models, and the component failure and maintenance reliability model introduced in the previous sections, we can use them to predict the reliability of an EDS. The steps of the reliability prediction can be briefly described as follows:

- 1) Collect the historical weather data and reliability data related to the EDS in the study;
- 2) Based on the historical weather data, component failure data and component pre-arranged maintenance data, by equations (2) and (3), the P values, important values, and correlations are calculated and sorted. Select certain numbers of weather elements that have greater impacts on component failure and pre-arranged maintenance to form weather conditions suitable for the analysis of them;
- 3) Based on the weather conditions, the reliability analysis models, including the component failure model (equations (4)-(6)) and the component pre-arranged maintenance model (equation (7)) can be built;
- 4) Obtain the weather forecast for the period during which reliability assessment is to be performed;
- 5) Input the predicted weather into the reliability analysis models constructed in step (3), and calculate the failure rates, restoration times, and maintenance intervals of components;
- 6) Calculate the reliability indices of the EDS using the Monte Carlo method.

#### V. FRAMEWORK OF THE RELIABILITY ASSESSMENT CONSIDERING WEATHER CONDITIONS

The reliability assessment considering weather impacts on the component failure and maintenance schedule is more complicated than the traditional reliability assessment procedure. The major differences include the formation of the weather condition and calculate their impact on the component failure probability as well as their health deterioration. In this section, we describe the procedures of the reliability assessment proposed in this paper, which can be summarized as follows:

- 1) Reliability modelling of power components considering the influence of weather conditions:

Based on the input historical weather (GS, RS, AS, NLAL, NLPL, ICE, HT, LT, AT, RH) data, historical fault data and maintenance data; through P-value analysis, importance

values, correlation methods, the main weather elements that affect the failure probability and maintenance time interval of power components are selected, and the selected weather elements are further divided into different intervals, as shown in Table 1.

By combining different weather element intervals into weather conditions, the failure probability and the repair time of a component in each weather condition can be established as the power component failure model. Similarly, we can calculate the maintenance time interval and the repair time of a component under each weather condition to establish the power component maintenance model.

2) Identifying the state of power components considering the impact of weather conditions:

For each simulation time step, i.e. 12 hours in this paper, according to the weather condition model, a weather condition is assigned to the network; then the failure probability  $WCF_i$  of component  $i$ ,  $\forall i$  can be calculated. By comparing  $WCF_i$  with a random number  $\delta_i$  ( $\delta_i = 1 - e^{-WCF_i t}$ ,  $\delta_i \in (0, 1)$ ,  $\forall i$ ) to select a set of potential components to fail. As in the reliability assessment, we only consider N-1 criterion; therefore, we select the component with the minimum TTF from the potential components set and compare it with the simulation time step. If the TTF is less than the time step, this component is regarded as a failed component, otherwise, no component fails in this time step. Further, if the failed component can be replaced by a spare component, then the repair time is defined as the time to energize the spare component, otherwise, the repair time is set to its mean repair time. Similarly, for each simulation time step, a weather condition is assigned, and the health of the component (represented by the failure probability) is calculated considering the current weather condition (i.e. to calculate the failure probability in the next 12 hours). If the failure probability of a component is greater than a certain threshold, then maintenance operation is performed on this component (i.e. failure probability decreases to a predefined value, e.g. 0).

3) Load transfer and reliability index calculation:

For any appearance of out-of-service component, be they due to failure or maintenance, the improved fault traverse

algorithm is employed to determine the type of load in the distribution network. In this algorithm, all load buses are classified into A (not-affected load bus), B (no need to be transferred), C (need to be transferred), and D (impossible to be transferred) categories. Based on the categorization of the load buses and other relevant parameters, the nodal reliability indices, such as outage times  $f_{ij} = f_{ij} + 1$ , outage duration  $t_{ij} = t_{ij} + t_R$ , out-of-service-energy etc., can be calculated. Further, the reliability indices of the entire system can be obtained.

## VI. CASE STUDY

### A. WEATHER MODEL AND RELIABILITY MODEL PARAMETERS ANALYSIS

To verify the validity of the proposed method, we take a partial EDS in a suburb of Nanjing as an example. The studied EDS is a 12.66kV medium voltage network with a peak load of 1546 MW, 2748 load points, 6753 lines. Within the geographic scope of the EDS, the corresponding weather elements are given in Table 4. We can employ the approach described in section II to classify different weather conditions. For example, we can define ( $A_1[0\ 5)\ E_1[0\ 3)\ G_1[0\ 12)$ ) as ‘condition 1’, ( $A_1[0\ 5)\ E_1[0\ 3)\ G_2[12\ 24)$ ) as ‘condition 2’, ..., ( $A_5[20\ 25)\ E_5[12\ \text{max})\ G_4[36\ \text{max})$ ) as ‘condition 100’.

Based on the historical weather data and outage data of the relevant EDS, by setting the thresholds of the indices as reported in Table 5, 6 different weather condition models with different numbers of weather elements (3 for component fault and 3 for maintenance) can be created.

The weather condition occurrence frequency, component failure rate, and restoration time for different weather condition models are given in Figure 6.

In Figure 6(a) and Figure 6(b), the curves of the frequency of the occurrence of the weather conditions are low on both sides and high in the middle, similar to the normal distribution. The failure rate curve and restoration time curve of components are monotonically increasing, indicating that as the weather becomes worse, the higher the component failure rate, the more the restoration time. The curves in

TABLE 4. Weather elements and level classification in Nanjing Suburb.

Weather condition	GS	RS	AS	NLAL	NLPL	ICE	HT	LT	AT	RH
unit	(m/s)	(m/s)	(m/s)	(/KA)	(/KA)	/	(°C)	(°C)	(°C)	(%)
max	25	16	12	80	max	20	max	max	max	100
min	0	0	0	0	0	0	0	-10	-4	0
$\Delta$	5	4	3	20	3	5	10	8	8	20

TABLE 5. Thresholds of weather elements selection.

Thr/Ele	2E		3E		4E	
	FT	MT	FT	MT	FT	MT
Importance	>0.9	>0.89	>0.8	>0.85	>0.49	>0.48
p-value	<0.1	<0.11	<0.19	<0.15	<0.51	<0.52
Correlation	>0.5	>0.45	>0.49	>0.38	>0.18	>0.17
Selected Ele	GS,NLPL	GS,HT	GS,NLPL,RS	GS,HT,RS	GS,NLPL,RS,AT	GS,HT,RS,AT

Note: Thr = Threshold; Ele = Element; FT = fault; MT = Maintenance.

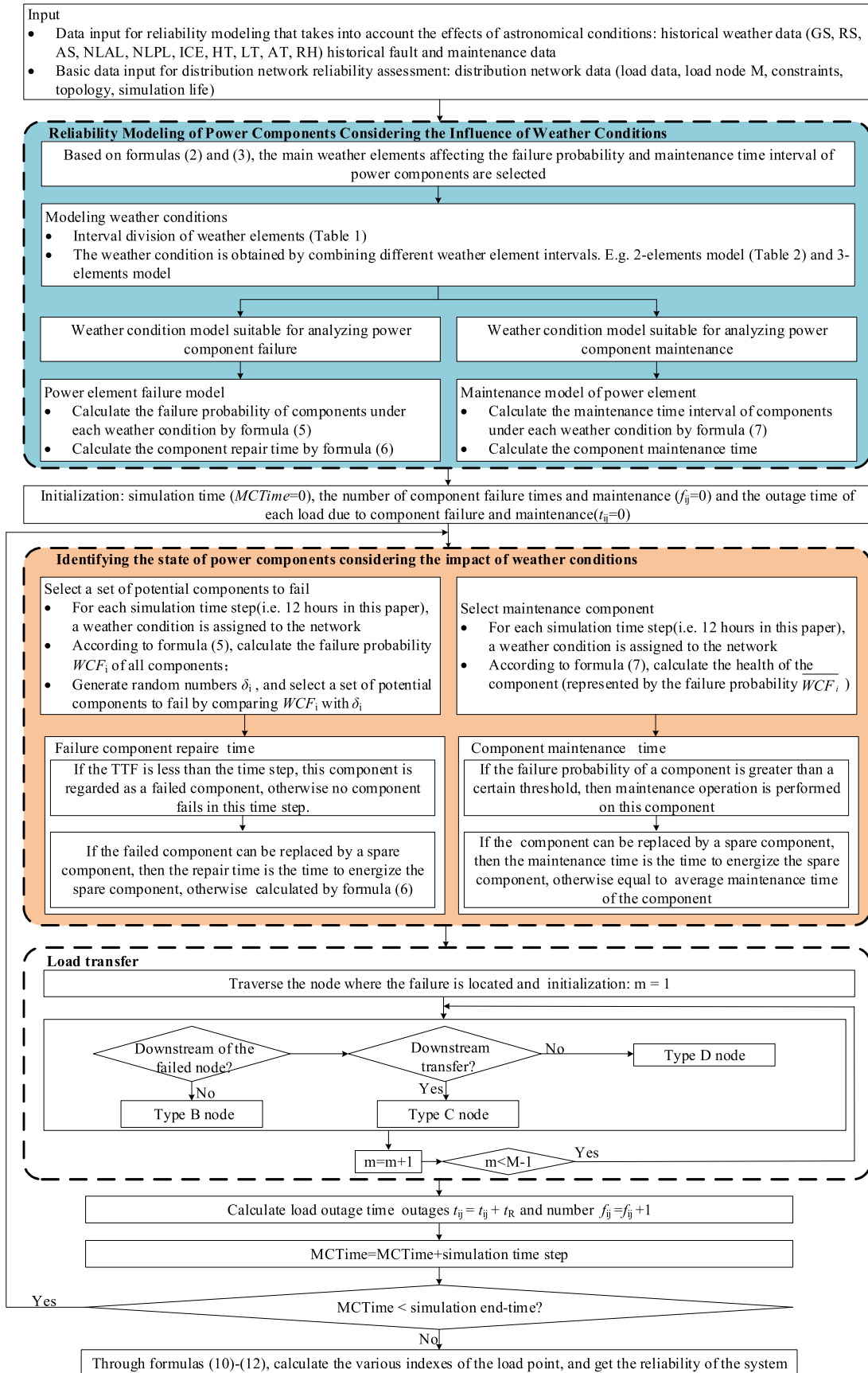
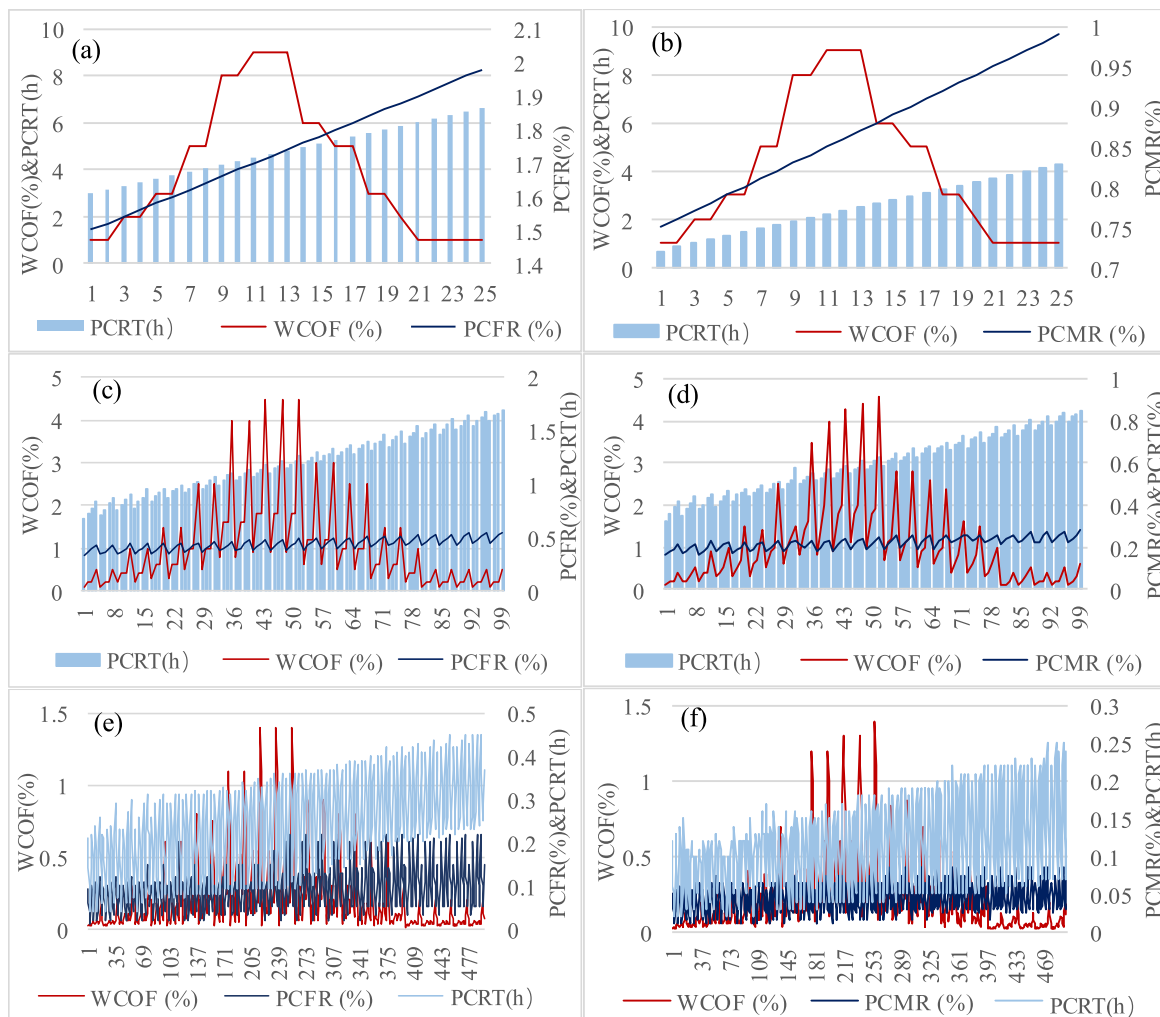


FIGURE 5. Solution flowchart based on time series Monte Carlo simulation.



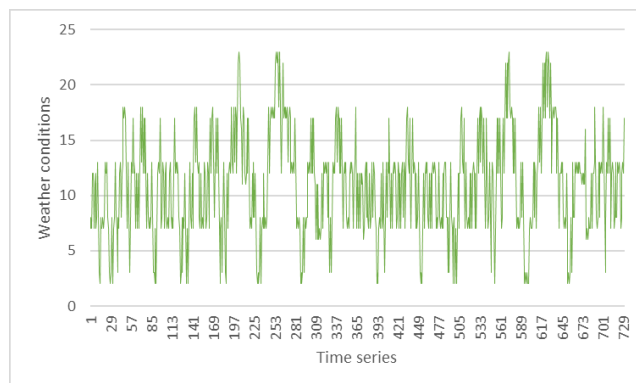
**FIGURE 6.** Weather condition occurrence frequency curves, component failure rate curve, and restoration time curve; (a) 2E for component fault; (b) 2E for maintenance; (c) 3E for component fault; (d) 3E for maintenance; (e) 4E for component fault; (f) 4E for maintenance.

Figure 6(a) and Figure 6(c) are overall similar, but compared with Figure 6(a), Figure 6(c) considers the weather element RS as well, so that the number of weather conditions increases from 25 to 100, and all the curves of the frequency of occurrence of weather conditions, the failure rate and restoration time of the component have zigzag characteristics. The zigzag characteristics indicate that the failure rate and restoration time of the component under the three-factor model is more accurate. The general trend of the curves in Fig. 6(e) and Fig. 6(c) are well aligned, but Fig. 6(e) has a finer resolution for the curves due to a higher number of weather conditions.

**B. ACCURACY ANALYSIS OF THE PROPOSED METHOD**

To test the validity of the proposed method, we evaluate the reliability of the studied EDS in 2017 by the proposed algorithm and compared it with the actual statistics.

As the input, Figure 7 gives an example of the weather conditions of a feeder in 2017, with a resolution of two points per day.



**FIGURE 7.** Weather condition for a distribution line of the EDS of Nanjing suburb in 2017.

The reliability evaluation results are shown in Figure 7. It is clear that the values of SAIDI, SAIFI, and ASAI calculated by the 3E model based reliability analysis model are closer to the actual statistical results than the ones calculated by



the 2E model based reliability model. The more the weather elements are considered, the more accurate the reliability evaluation or prediction results are.

Further, a comparison between the proposed method and the method in [29] is also performed. It is manifested from Figure 8 that the 2E model, the 3E model and the 4E model have better evaluation results than that of [29]. Obviously, more accurate results can be obtained by considering more weather elements, yet the increase of the accuracy is not in proportion to the number of considered weather elements. It is clear that the reliability assessment accuracy is significantly improved from 2E model to 3E model; while that does not crease much from 3E model to 4E model. Therefore, 3E model would be the most practical one for the distribution network reliability assessment of the city in study.

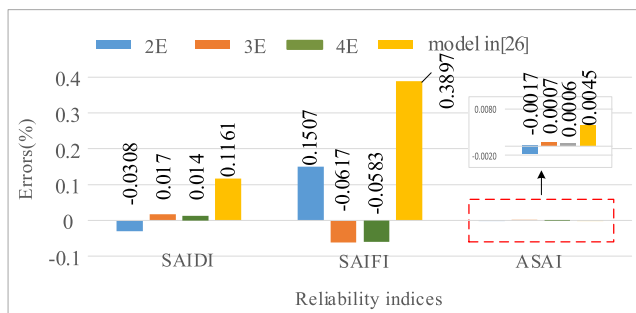


FIGURE 8. Reliability evaluation error comparison of the different models.

### C. IMPACT OF VARIOUS WEATHER ELEMENTS ON THE RELIABILITY OF THE EDS

In this section, we analyze the relationship between the weather elements on EDS reliability.

The elements of the weather conditions corresponding to each distribution network outage of the studied EDS from the year 2008 to the year 2017 have been counted, as given in Figure 9. The statistical results show that the component failure frequency curve and the restoration time curve corresponding to weather elements are similar, indicating that the weather elements have similar effects on the component failure and the restoration time.

Furthermore, with the change of weather element A and weather element B, the component failure frequency curve and restoration time curve change dramatically, but when the weather element E and factor G change, the component failure frequency curve and the repair time curve do not change much.

In addition, the contribution of weather elements' intervals to the loss of reliability is investigated, as given in Figure 10. For the loss of the SAIDI caused by component failure, the weather element intervals that have a greater contribution are A3 [10,15) and B3 [8,12); and for the loss of the SAIDI caused by the maintenance of the component, the largest contributions come from A4 [15,20), B3 [8,12), and G3 [24,36). Regarding the contribution of weather element intervals to

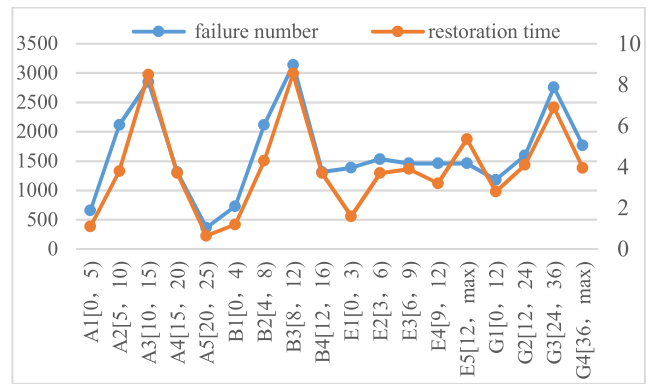


FIGURE 9. The number of failures and the restoration time of outages under each weather element in the studied EDS from 2008 to 2017.

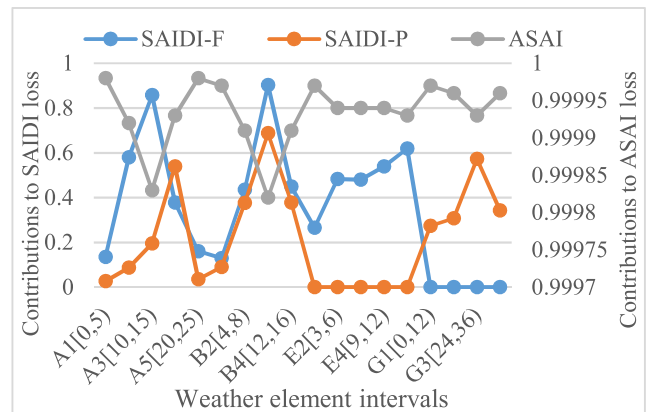


FIGURE 10. The contributions of weather elements to reliability loss of Nanjing suburb from the year 2008 to the year 2017.

the loss of ASAI, except for A3 [10,15) and B3 [8,12), other weather element intervals have similar contributions.

This analysis gives a direct indication that for the studied EDS, the system operator should pay more attention to the system reliability when some weather elements reach certain levels.

### VII. CONCLUSION

The calculation of the reliability of an electric power distribution network must consider the weather, which has a great impact on both the component failure and the predefined maintenance.

In this paper, we proposed a framework for evaluating and predicting the EDS reliability considering the impact of weather via the interaction of the weather condition models and the models for component failure and pre-arranged maintenance. A reliability evaluation approach based on Monte Carlo method was used to integrate the proposed models. By comparing and analyzing the reliability evaluation results of the proposed method and another method from the literature on a part of EDS of Nanjing, it can be seen that the evaluation result of the proposed method that considers the weather impact is much accurate than the one without in other literature. In addition, we can further improve the evaluation results by considering more numbers of weather elements in

the reliability analysis. Further, the contribution of different weather elements to the reliability loss of the EDS of Nanjing was investigated, the results can help power supply companies to formulate the operation scheduling strategies and planning solutions for certain weather elements that affect the reliability of the EDS.

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