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An Incremental-Variable-Based State Enumeration Method for Power System Operational Risk Assessment Considering Safety Margin

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ABSTRACT This paper proposes an incremental-variable-based state enumeration method (IVSE) for power system operation risk assessment and develops the risk indices considering the safety margin. Firstly, the traditional risk indices are modified to take into account the safety margin, which is defined as the virtual distance from the operational limits to the current normal operating point. Those indices can provide more potential risk information to operators for reasonable decision-making. Thereafter, an incremental-variable-based state enumeration is developed by utilizing the relationship between high order contingencies and low order contingencies. The proposed method is more efficient and accurate than traditional methods, which makes it more suitable for online application. Finally, case studies are performed on the IEEE-118 bus system. And results verify the accuracy and efficiency of the proposed method in various situations. In addition, it also can diagnose the weak points of the system, which can assist operators in online decision making.

INDEX TERMS Power system, risk assessment, risk indices, state enumeration method, safety margin, variable increments.

I. INTRODUCTION

With the development of the social economy, electric power dependence and power grid scale continue to expand. Meanwhile, the grid structure is increasingly complex and the power load is constantly growing. Besides, the development of new technologies such as electric vehicles, distributed generation, and demand-side response has made the load fluctuations and the interaction between users and the grid increasingly frequent. In short, these all are increasing the potential risk for power system operation. However, the determined criteria used currently cannot judge the uncertain factors, so it tends to get the conservative analysis results,

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which not only cannot adapt to the changes of the grid but also will lead to certain economic waste.

Therefore, the increased uncertainty factors make power system risk assessment more important. So far, there have been many researches in the field. To promote computation efficiency, some optimization methods and mathematical concepts are introduced to power system risk assessment: Reference [1] combines the risk assessment with multiobjective optimization methods to assess the real-time risk. Reference [2], [3] combines the optimal flow with risk assessments. In [4], the random set theory in mathematical concepts is used to assess system risk for obtaining more information which can characterize the risk level. Aiming at various risk in different scenario, researchers also proposed some specific assessment approach: Reference [5] proposed

a probabilistic method for calculating voltage collapse and overvoltage risk. Reference [6] proposed a method for calculating the risk of transient instability at the operating point. In [7], an online branch thermal overload risk assessment method is proposed and the Bayesian time series model is used to simulate the weather conditions of the transmission line. Reference [8] proposed a probabilistic power flow Monte Carlo simulation based on Levenberg-Marquardt with a nonmonotone line search (LMNL) algorithm to calculate risk indices for islanded hybrid AC/DC microgrid. Reference [9] proposed a risk assessment method for large-scale distributed photovoltaic feeding into distribution networks. In addition, the risk-based strategy also is proposed to optimizing actual operation. For example, in [10], the risk-based maintenance optimization model is proposed and the maintenance plan is formulated according to the risks at different times throughout the year.

The above-mentioned papers studies various aspects of power system risk, meanwhile, proposes many quantitative risk indices. In addition, owing to the fact that the safety of the power system is improved continuously by all kinds of protection devices, the probability of violation risk will be decreased accordingly. However, these risk indices did not consider the influence of safety margin, which refers to the virtual distance from the operational limits to the current normal operating point. Therefore, traditional risk indices may lead to conservative decisions. In this regard, this paper proposes the risk indices considering the safety margin.

In addition, in operational risk assessment, high efficiency is necessary to support the online decision but the traditional methods do not meet high-efficiency demand increasingly. Generally, the traditional risk assessment method can be roughly classified into two categories: state enumeration methods (SE) [11]–[13] and Monte Carlo simulations method (MC) [14], [15].

The MC estimates the system risk by randomly sampling the system state. Because it is not limited by the size of the system, it is suitable for large-scale systems. However, its efficiency is very low, especially, in the high-safety system. The reason is that the method requires to spend more sampling times on obtaining acceptable precision demand since the high-safety system usually has lower component failure probability. Therefore, researches proposed some improved MC, such as stratified random sampling [16], [17] variance reduction techniques [18], state space pruning [19], cross-entropy algorithm [20], [21], importance sampling [22] and state-space classification [23] et. al. However, because the above-mentioned methods only focus on the occurrence probability of system states for improving the traditional method, it is still necessary to improve further efficiency by paying more attention to impact factors of system states.

The SE quantifies system risk by enumerating the possible system states. The advantage is that the concept is clear and the assessment results can be theoretically more accurate. However, the complexity of the method is positively correlated with the system scale. And because it is unrealistic to consider all system states in the actual power system, the traditional state enumeration method generally ignores numerous high-order contingency states, which causes the value of risk indices smaller than the true value. Therefore, to solve the problem, many improved SE have emerged as far. References [24], [25] proposed a state expansion method, which can extend to high-order contingency states through loworder contingency states, thereby restraining the accuracy degradation, which caused by ignoring high-order contingency states. Reference [26] proposed a fast sorting algorithm (FSA), which gives the concept of adjacent state sets. The method can rank the probability of the system state by this concept and then considering all high probability states. Further, based on the fast sorting algorithm, [27] introduced the concept of alternative adjacent state and minimum state set and proposed a fast contingency screening technique (FCST).

However, those methods cannot take account into all possible high-order contingency states. In reality, the risk is not only determined by probabilities of contingencies but also affected by their impacts. If we only consider system states with high probability, some low probability and high impact system states will be neglected. In fact, the amount of those system states may be very huge, so the accuracy of those methods above may be limited. In addition, for power system operation risk assessment, calculation efficiency is also important because the results need to guide the dispatching operation department for online decision-making.

Therefore, to solve above-mentioned problems, it is very necessary to design a high-efficient and high-precision power system risk assessment method which considers both probabilistic factors and impact factors, to assist the operator in online making decision. In previous research, we proposed an incremental impact method [28]. This method can improve the calculation efficiency by increasing the weight of the low-order contingency states. Based on this idea, we transform the state variable into an incremental formation and propose an incremental variable based state enumeration method (IVSE) accordingly.

In this paper, the innovation can be described as follows:

1. The concept of safety margin is introduced to the field of risk assessment, and the new risk indices are developed to provide more potential risk information.

2. An incremental variable method is proposed to speed-up the operational risk assessment process.

Section 2 briefly introduces the basic concepts of power system risk assessment. Section 3 proposes the risk indices considering safety margin and develops an incremental-variable -based state enumeration method. Section 4 assesses the IEEE 118-bus system by proposed risk indices and proposed method for verifying the effectiveness and testing the method performance.

II. BASIC CONCEPTS OF POWER SYSTEM RISK ASSESSMENT

Risk assessment is a useful tool to maintain the operational safety of power systems. In order to help planners and

operators comprehensively understand the risk level of the system, quantitative risk indices are necessary. Generally, the risk index of the power system is defined as the product of the uncertainty factors and their impacts, which can be obtained by

$$R = \sum_{s \in \Omega} I_s P_s \tag{1}$$

where *R* is the risk index of the system. Ω is the set of possible system states. *s* is a system state, including both normal and contingency states. *P_s* and *I_s* represent the probability and impact of state *s*, respectively.

Based on the utilized index, risk assessment can be divided into several types, such as the risk-based static security assessment, voltage stability assessment, transient stability assessment, and security domain analysis. In addition, according to the assessment time framework, power system risk assessment can also be divided into planning risk assessment and operational risk assessment. The assessment time framework of planning risk is usually years or decades, and the time framework of operational risk assessment is generally ranged from minutes to hours.

This paper focuses on system-level operation risk assessment, which is generally utilized to support online decisionmaking. Therefore, it requires a high assessment efficiency. The basic process of risk assessment can be performed by the iteration of the following three steps:

Step1: select system state;

Step2: calculate the impact and probability of the state;

Step3: update the risk indices.

In order to enhance the efficiency of the assessment process, this paper proposes an incremental variable method to speed up the impact calculation step. In addition, we modify the traditional definition of state impact by introducing the safety margin, then more information can be provided by the obtained risk indices.

III. INCREMENTAL-VARIABLE-BASED RISK ASSESSMENT CONSIDERING SAFETY MARGIN

This section introduces the risk indices considering the safety margin, which can provide more potential risk information for operators. In addition, we propose an incremental variable based sate enumeration method to efficiently calculate the proposed risk indices. The proposed method can improve efficiency of risk assessment, especially, for high-efficiency demand of operational risk assessment.

A. RISK INDICES CONSIDERING SAFETY MARGIN

At present, since the improvement of various protective devices, power system safety improves continuously, so most contingencies will not cause violation of the state variables (i.e. S or V). However, the traditional risk indices only consider violation operation point, therefore, excessively emphasizing low probability contingencies, which may cause conservative decision-making. To address these issues, this paper develops the risk indices considering the safety margin.



FIGURE 1. Schematic diagram of branches power distribution.

In the proposed indices, the concept of the safety margin considers the safety degree of normal condition. According to the selection of different state variables (i.e. S or V), different risk indices can be defined. This paper takes branch overload and bus low voltage as example.

1) BRANCH OVERLOAD RISK INDEX

When the system is in contingency state, the failure branches are taken out of operation, then the power of the non-failure branches changes. Therefore, the value of the system overload risk is determined by the power of these non-failure branches. Because the occurrence of contingency is assumed as a Poisson distribution in [10], we suppose branches power is bound to obey a certain distribution. This paper assume that it obeys to an arbitrary distribution f_s . That is:

$$S_{\rm i} \sim f_{\rm s}(ES_{\rm i}, \sigma_{S_i}^2)$$
 (2)

where ES_i is the expected power of the *i*th branch; σ_{Si}^2 is the power variance of the *i*th branch. They can all be estimated by sampling.

Fig.1 shows a schematic diagram of probability distribution of the *i*th and the *j*th branches power. Vertical axis and horizontal axis respectively represent probability and branches power; S_e is rated branch power; $1.1S_e$ represents critical limited value; ES_i and ES_j respectively refer to expected power value of the *i*th and the *j*th branches; the shadow part refers to power violation part of branches.

As shown in Fig.1, for the *i*th branch, due to the fact that the area of shadow part *a* account for only a small part, the cumulative probability of the power violation part is very low. In fact, with increasing power system security, this situation will heavily increase in occurrence probability. And because traditional risk indices consider a large number of this situation, assessment results may tend to conservative and cause poor economy. Aiming at the problem, we find this situation can be reflected through which the expected value of the branch power is less than critical limited value. Therefore, the paper defines the concept of safety margin which refers to



FIGURE 2. Schematic diagram of bus voltage distribution.

the virtual distance from the operational limits to the current normal operating point.

It is can be found in Fig1 that the normal operating point of the *i*th branch is more than its power violation point because ES_i is less than $1.1S_e$. Therefore, the safety margin of the *i*th branch is considered so large enough that the branch can be thought safe. On the contrary, for the *j*th branch, the shadow part *b* and *a* constitute its power violation part, then ES_j is greater than $1.1S_e$, hence the *j*th branch is considered unsafe. Further, as long as most of the branches are known as safe, the whole system is considered safe enough. Conversely, when most of the branches are easy to violate, the safety margin of the system is considered to be less than the violation risk.

Based on the above analysis, we define $R_{i|S}$ as the overload risk function of the *i*th branch:

$$R_{i|S}(ES_i) = \max(0, ES_i - 1.1S_e)$$
(3)

2) BUS LOW VOLTAGE RISK INDEX

The risk of voltage violation in the power system can be divided into overvoltage risk and low voltage risk. In general, the use of lightning protection devices and relay protection measures can minimize the overvoltage risk. However, in terms of the low voltage risk, its impact more serious on the power system. The low voltage risk is mainly caused by the lack of reactive power, which not only causes a series of serious problems such as increased branch loss, reduced generator output and motor burnout but also even may damage the stable operation of the power system. Based on the above description, only the low voltage risk is introduced in this paper.

Similarly, as shown in (4), we also assume the bus voltage is subject to an arbitrary distribution f_v . σ_{Vi}^2 is the voltage variance of the *i*th bus; EV_i refers to the expected voltage value of the *i*th bus; Fig.2 shows a schematic diagram of the *i*th and *j*th bus voltage probability distribution. The horizontal axis represents bus voltage; U_{lim} represents critical limited voltage; The shadow part refers to a voltage violation part.

$$V_i \sim f_V(EV_i, \sigma_{V_i}^2) \tag{4}$$

As shown in Fig.2, shadow part *c* represents violation part of the *j*th bus and shadow part *d* and *c* denotes violation part of the *i*th bus. Therefore, the EV_i is less than the U_{lim} and the EV_j is greater than the U_{lim} . The low voltage risk function of the *i*th bus can be described as (5).

$$R_{i|V}(EV_i) = \max(0, 1 - EV_i) \tag{5}$$

It should be noted that the voltages in this paper all are standard values. As shown in (5), when the expected voltage value is less than 1, the bus is considered unsafe and risk value a linear function of the expected voltage value. In contrast, as long as the EV_i is greater than 1, the bus is known as safe enough.

B. INCREMENTAL VARIABLE APPROACH

In this section, we develop an efficient risk assessment method based on the idea of impact increment [28]. It is notable that the original impact increment method can be used only when the impact of the high-order contingency can be expressed as the function of the impacts of the corresponding low-order contingencies. However, the above assumption is not suitable for risk assessment. In this paper, we denote the incremental variable as the difference of the state variables (e.g. *S* and *V*) between the contingency state and the normal state. Then the IVSE is developed accordingly. Therefore, the major difference between the two methods is the research object.

According to (3) and (5), we find that the risk indices of the *i*th component can be obtained through the expectation of the corresponding state variable X_i (e.g. bus voltage V_i & branch power flow S_i). Therefore, the incremental variable based SE method is used in this section to calculate EX_i , where EX_i is generalization for ES_i and EV_i .

1) CALCULATION FORMULA

Firstly, as shown in (6), the risk value of the system is calculated by summing the risk values of all components. And the risk value of the single component is obtained by substituting the expected state variable of the component into the above risk function.

$$R_{A|X} = \sum_{i=1}^{N} R_{i|X} (EX_i)$$
(6)

Secondly, we just focus on how to calculate the EX_i . According to the (1), the EX_i can be determined by the (7):

$$EX_i = \sum_{j \in \Omega_s^k} P_j X_{i,j} \tag{7}$$

$$\Omega_s^k = \{j | j \subset s, Card(j) = k\}$$
(8)

where Card(j) represents the cardinality of the *j*th contingency state; Ω_s^k is the *k*-order contingency state sets and



FIGURE 3. Schematic diagram of outage branches with long distances.

if k = 0, $\Omega_s^k = \phi$; P_j is the occurrence probability of the *j*th contingency state; $X_{i,j}$ is the state variable of the *i*th component for the *j*th contingency state, which is calculated according to the following formula:

$$X_{i,j} = X_{i,0} + X_{i,j}^{add}$$
(9)

where $X_{i,0}$ is the state variable of the *i*th component in the normal state; $X_{i,i}^{\text{add}}$ is the amount of change in the state variable of the *i*th component for the *j*th contingency state.

Next, substituting (9) into (7) to obtain (10):

$$EX_{i} = \sum_{j \in \Omega_{s}^{k}} P_{j} \left(X_{i,0} + X_{i,j}^{add} \right)$$
$$= X_{i,0} + \sum_{j \in \Omega_{s}^{k}} P_{j} X_{i,j}^{add}$$
$$= X_{i,0} + EX_{i,j}^{add}$$
(10)

where $EX_{i,j}^{add}$ refers to the expected value of the $X_{i,j}^{add}$. Finally, as shown in (11), the $EX_{i,j}^{add}$ can be calculated by the IVSE method for an N-order system. $P^{u}(j)$ is used to indicate the unavailability rate of the failure component for the *j*th contingency state; $\Delta X_{i,j}^{add}$ represents variable increment. As shown in (11), the variable increment is the difference value between variable and low-order variable increment. In addition, the specific derivation and the proof process have been described in [28].

$$EX_{i,j}^{add} = \sum_{k=0}^{N} \sum_{j \in \Omega_s^k} P_j^u \Delta X_{i,j}^{add}$$
(11)

$$\Delta X_{i,j}^{add} = X_{i,j}^{add} - \sum_{k=1}^{n_j - 1} \sum_{u \in \Omega_s^k} \Delta X_{i,u}^{add}$$
(12)

Two facts can be observed from the above formulas. On the one hand, the weight of the low-order contingency state is increased due to the fact that the availability rate also is eliminated; on the other hand, because variable increment is positive value, the state variable of high-order contingency state is less than its original state variable, which further makes the weight of the high-order contingencies be reduced.

2) REDUCTION OF HIGH ORDER CONTINGENCY

In an actual power system, when the failed component is far apart in space, the failure component has a relatively independent impact on the entire system, as shown in Fig.3. Therefore, as shown in (13), the high-order contingency state s which has independent component can be split into two unrelated sub-states s_1 and s_2 :

$$X_{i,s=s_1\cup s_2}^{add} = X_{i,s_1}^{add} + X_{i,s_2}^{add}$$
(13)

where s denotes a failed component set and $s_1 \in s$, $s_2 \in s$. Based on the above assumptions, as shown in (14), the state variable increment of the states s can be derived by (13).

$$\Delta X_{i,s}^{add} = X_{i,s}^{add} - X_{i,s_1}^{add} - X_{i,s_2}^{add} = 0$$
(14)

For the *N*-order system, the specific proof process is shown in [25]. Therefore, owing to the fact that most of the highorder contingency states may be independent, elimination of independent high-order contingencies will significantly reduce the computational burden.

In order to quantify the independence, this paper uses sensitivity analysis methods to determine whether each branch is relatively independent. Since the failure branch has an impact on the power flow of the system, it is reasonable to check the correlation between the branches by sensitivity of the power flow of the branch I to the impedance of the branch H (represented by $S_{PZ}(H, I)$). S_{PZ} can be calculated by the perturbation method, then we need to set threshold δ_s to determine the correlation. Finally, according to the values of S_{PZ} and δ_s , the correlation flag d_{ij} between the *i*th branch and *i*th branch can be determined, thereby obtaining the independence matrix Ds of the system state s. The specific calculation steps are introduced in [28]. When all components in the matrix D_s are reachable, it corresponds to $\Delta X_{i,s}^{add} \neq 0$; Otherwise, $\Delta X_{i,s}^{add} = 0$, so there is no need to analyze the

C. PROCESS OF THE PROPOSED METHOD

The calculation process of the proposed method is as follows:

Step 1: Enter system data and preset parameters, including the maximum order of contingency state order N_{ctg} , the branch sensitivity threshold δ_s , and the initial state order k = 1.

Step 2: Calculate the sensitivity matrix $[S_{pz}]$ of each branch.

Step 3: Determine the correlation flag of each branch based on the sensitivity matrix $[S_{pz}]$ and the threshold δ_s .

Step 4: Select the *i*th system component to analyze, i.e. the *i*th branch or the *i*th bus.

Step 5: In the system normal state, calculate the power flow of the branch or the bus voltage as the reference value of the state variable.

Step 6: Create all k-order contingency state set Ω_4^k .

Step 7: Select the *j*th *k*-order contingency state.

Step 8: Calculate its reachable matrix *D_s*.

Step 9: Use the breadth-first search algorithm to check the reachability of the elements in the D_s . If so, go to the next step. Otherwise, select the next k-order contingency state and return to Step 8.

Step 10: Calculate the variation of state variable $X_{i,i}^{add}$ by the PF calculation program.



FIGURE 4. The overall process of the proposed approach.

Step 11: Calculate the incremental variable $\Delta X_{i,j}^{add}$ by (12).

Step 12: Calculate the expected variation of state variable EX_{i}^{add} by (11).

Step 13: Check if all k-order contingency states have been analyzed. If so, go to the next step. Otherwise, select the next k-order contingency state and return to Step 8.

Step 14: Check if $k = N_{ctg}$. If so, go to the next step. Otherwise, k = k + 1 and return to Step 7.

Step 15: Calculate the expected state variable EX_i for the *i*th component by (7)

Step 16: Check if all components have been analyzed. If so, go to the next step. Otherwise, i = i + 1 and return to Step 4.

Step 17: Calculate the risk value of the component by (3) and (5).

Step 18: Calculate the risk value of the whole system by (6).

TABLE 1. Comparison of the three results (IEEE-118).

Methods	N _{ctg}	MC Num	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	<i>R</i> _{A V} (*10 ⁻²)	<i>R</i> _{A V} Error
Benchmark	-	10^{6}	1437.16	53.675	-	24.952	-
MC	-	10^{5}	172.45	53.682	0.013%	24.923	0.120%
SE	2	-	44.61	48.979	8.749%	24.039	3.657%
IVSE	2	-	46.59	53.660	0.028%	24.944	0.032%

IV. NUMERICAL RESULTS AND ANALYSIS

In the case study, the effectiveness, applicability and practicability of the proposed method are tested on the IEEE 118-bus test system which involves 118 buses, 54 generation units, 186 branches, 54 generations (PV) buses, and 64 loads (PQ) buses. The total generation capacity and load demands are 9966 MW and 4242 MW. Reference [29] introduces the data of this system in detail.

Firstly, the IEEE 118-bus system was used to verify the accuracy and efficiency of the proposed method and the traditional state enumeration method (SE) was utilized to be comparison. Secondly, we analyzed the influence of the preset parameters on the proposed method. Next, we tested the applicability of the proposed method after changing the load level and component unavailability rate. Finally, the weak links of the system are found out and modified to reduce system risk through the proposed method.

A. ACCURACY AND EFFICIENCY

In this part, the system risk is assessed by below three methods: the SE method in which preset parameters N_{ctg} are set as 2, the IVSE method whose preset parameters are set as follows: $N_{ctg} = 2$, $\delta_s = 0$ and the MC method which convergence criterion is set to the total sampling number $MCNum=10^6$. And the assessment result of the MC method is used as the benchmark for accuracy. The results are shown in Table. 1.

As shown in Table. 1, since the SE method only considers the impacts of the first two order contingencies, the assessment results are smaller than the benchmark value. However, because the proposed method shifts the weight of high-order contingencies into corresponding low-order contingencies, the risk value is very close to the benchmark value. Because the computation process of the proposed method is more complex than the SE, the CPU time of the proposed method is slightly greater than that of the SE but within the acceptable range.

B. EFFECTS OF PRESET PARAMETERS

The proposed method has two preset parameters: maximum enumeration orders *Nctg* and high-order contingency elimination threshold δ_S . By adjusting their values, the accuracy and the calculation time can be controlled to responding to the requirements in different situations. The part analyzed the influence of preset parameters on the computational efficiency and accuracy by changing the above two preset parameters.

 TABLE 2. Impacts of N_{ctg} on accuracy and efficiency (IEEE-118).

Methods	N _{ctg}	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	$R_{A V}$ (*10 ⁻²)	<i>R_{A V}</i> Error	Ctg Num
SE(1)	1	1.64	45.637	14.975%	23.482	5.891%	240
SE(2)	2	44.61	48.979	8.749%	24.039	3.657%	28920
SE(3)	3	3303.72	51.599	3.868%	24.521	1.727%	2304200
IVSE(1)	1	2.12	54.019	0.641%	24.781	0.681%	240
IVSE(2)	2	22.11	53.854	0.333%	24.872	0.321%	14539
IVSE(3)	3	2950.70	53.777	0.190%	24.892	0.240%	1299528

TABLE 3. Impacts of δ_S on accuracy and efficiency (IEEE-118).

Methods	δ_s	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	$R_{A V}$ (*10 ⁻²)	<i>R_{A V}</i> Error	Ctg Num
IVSE (0)	0	46.59	53.660	0.028%	24.944	0.032%	28920
IVSE (0.0005)	0.0005	29.96	53.618	0.106%	24.910	0.129%	20185
IVSE (0.005)	0.005	22.11	53.854	0.333%	24.874	0.313%	14539
IVSE (0.01)	0.01	20.10	54.059	0.715%	24.872	0.321%	13520
IVSE (0.05)	0.05	17.79	54.086	0.766%	24.837	0.462%	11943



FIGURE 5. Impacts of δ_s on accuracy and efficiency (IEEE-118).

On the one hand, we fix δ_S to 0.005 and change N_{ctg} to test the influence of N_{ctg} on the proposed method. The assessment results are shown in Table. 2. As shown in Table. 2, although the calculation complexity of the proposed method is slightly larger than that of the SE, the introduction of the high-order contingencies elimination can effectively improve efficiency under ensuring a certain accuracy. However, when Nctg = 1, high-order contingencies elimination does not work, so the calculation time of the IVSE is still slightly higher than that of the SE.

On the other hand, we fix N_{ctg} to 2 and change δ_S to test the influence of δ_S on the proposed method. The assessment results are shown in Table. 3 and Fig.5. It can be observed from the table that when $\delta_S = 0$, the number of contingencies is 28920, which means that all first-order and second-order contingencies are not ignored. As the increasing δ_S , the selected high-order contingencies reduced in amount and the accuracy also decreased accordingly. But the

Methods <i>i</i>	N _{ctg}	MC Num	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	$R_{A V}$ (*10 ⁻²)	<i>R_{A V}</i> Error
Benchmark	-	10^{6}	1524.40	74.218	-	29.540	-
MC	-	10^{5}	182.75	74.270	0.070%	29.638	0.332%
SE	2	-	41.57	44.880	39.517%	23.381	20.849%
IVSE	2	-	42.77	79.844	7.580%	29.509	0.105%

 TABLE 5. Impacts of low unavailability component on accuracy and efficiency (IEEE-118).

Methods	N _{ctg}	MC Num	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	$R_{A V}$ (*10 ⁻²)	<i>R_{A V}</i> Error
Benchmark	-	10^{7}	15543.9	46.999	-	23.718	-
MC	-	10^{6}	1366.90	47.012	0.027%	23.720	0.008%
SE	2	-	40.06	46.661	0.719%	23.661	0.240%
IVSE	2	-	42.68	46.990	0.019%	23.717	0.004%

calculation speed is gradually improved. Therefore, in the case where the accuracy requirement is not very high but the fast calculation is required, we can achieve the corresponding requirement by increasing δ_S .

C. EFFECTS OF LOAD LEVEL AND UNAVAILABILITY

In order to test the impact of the unavailability rate on the performance of the proposed method, the proposed method was applied to the IEEE-118-bus system where the unavailability rate of branches has been modified.

This part shows the two scenarios where the unavailability rate is increased and reduced by 3 times respectively. The preset parameters and the benchmark method have been set the same as in Section A. The scenario of the high unavailability rate is shown in Table. 4. It can be seen from the table that the error of the indices assessed by the proposed method is superior to the SE method. However, the calculation error becomes larger compared with the scenario of the original unavailability rate. The reason may be the increasing unavailability rate makes the weight of high-order contingencies increase, which is not conducive to reducing error for the IVSE method.

The scenario of the low unavailability rate is shown in Table. 5. We found that owing to the fact that decreasing the unavailability rate may make the accuracy of the MC method decline, the accuracy assessment results are somewhat up and down compared with the original system. However, the error evaluated by the proposed method is about 0.1% and it still is superior to the SE method. So, the proposed method can be applied to the IEEE-118-bus system with low unavailability rate.

In addition, in order to test the impact of load level on the performance of the proposed method, the proposed method was applied to the IEEE-118-bus system in which load level has been changed. The preset parameters and the benchmark method have been set the same as in Section A.

TABLE 6. Impacts of high load level on accuracy and efficiency (IEEE-118).

Methods	N _{ctg}	MC Num	CPU Time (s)	$R_{A S}$	<i>R_{A S}</i> Error	<i>R</i> _{A V} (*10 ⁻²)	<i>R_{A V}</i> Error
Benchmark	-	10^{6}	1392.94	61.289	-	47.054	-
MC	-	10^{5}	169.95	61.336	0.076%	47.111	0.121%
SE	2	-	41.67	54.739	10.687%	43.673	7.185%
IVSE	2	-	43.70	61.208	0.133%	47.105	0.108%

TABLE 7. Impacts of low load level on accuracy and efficiency (IEEE-118).



FIGURE 6. Risk of overload of each branch.

Table. 6 shows the performance of the proposed method after the load level is increased by 1.2 times. With increasing load levels, the occurrence probability of high-order contingencies increased. Therefore, the calculation accuracy of the SE method and the proposed method all decreased. However, the risk indices assessed by the proposed method is still very close to the benchmark value and the error is within 0.2%. Besides, not only its accuracy is much higher than that of the SE method but the CPU time is obviously less than the MC method. Therefore, the proposed method can be applied to the scenario with 1.2 times load level.

Table. 7 shows the performance of the proposed method after the load level is decreased by 0.8 times. Due to the decreasing load level, the system becomes safer. And the accuracy of the MC may incline, which resulted in the accuracy of other methods also is reduced. However, the proposed method still is more suitable for the system with a 0.8 times load level compared with the SE method.

D. WEAK LINK ANALYSIS AND IMPROVEMENT

In order to verify the feasibility of the proposed method in risk improving, we first get the value of branch overload risk and bus low voltage risk of each component through the proposed risk indices and the proposed method. Then the high-risk components can be found, as shown in Fig.6 and Fig.7.



FIGURE 7. Low voltage risk of each bus.

TABLE 8. Risk reduction on three load level (IEEE-118).

	Overl	oad Risk	Low vol (*	ltage Risk 10 ⁻²)
Load level	Original	Improved	Original	Improved
1.0	53.660	8.846	24.944	13.632
1.1	56.900	9.499	33.932	13.914
1.2	61.208	11.263	47.105	16.240

In the IEEE-118-bus system, since branches 65-66, 68-81 and 81-80 all are power transmission channels from the generation intensive area to the load center, they are prone to cause overload risks. Bus 53, 76, 118 are all connected to a generator bus of low voltage, so they are easy to result in low voltage risk.

Based on the above analysis, it is possible to effectively reduce system risk by focusing on the high-risk component. Specifically, in this paper, the system risk value is reduced by expanding the capacity of the high-risk branches and increasing the voltage of the corresponding low voltage generator node. As shown in Table. 8, after the system is improved, we tested the system overload risk and low voltage risk at three load levels. As load demand increases, the risk value of the component and system all is gradually increasing. However, by improving the high-risk component, system risk can be dramatically reduced. Therefore, the proposed method can effectively reduce the system risk value and can adapt to different load demands.

V. CONCLUSION

This paper proposes an incremental variable based state enumeration (IVSE) for operation risk assessment and the risk indices considering the safety margin. First, the new risk indices are developed incorporating the concept of safety margin, which can help operators avoid a conservative decision. Second, an incremental variable method is proposed to speed the risk assessment process to adapt to the online application. The proposed method has been tested on the IEEE-118-bus system. The results show that the proposed method can efficiently and accurately evaluate the operational risk of power systems. The accuracy of the proposed method is similar to the Monte Carlo method yielded to a large sampling number, but its calculation speed is 4-300 times faster. Comparing to the SE method, the proposed approach is 10-1000 times more accurate with similar time consumption. In addition, the accuracy and efficiency of the proposed method can be controlled by the preset parameters to adapt to various scenarios.

REFERENCES

- F. Xiao and J. Mccalley, "Power system risk assessment and control in a multiobjective framework," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 78–85, Feb. 2009.
- [2] W. Fu and J. Mccalley, "Risk based optimal power flow," in *Proc. IEEE Porto Power Tech Proc.*, Porto, Portugal, Sep. 2001, p. 6.
- [3] F. Xiao and J. D. Mccalley, "Risk-based security and economy tradeoff analysis for real-time operation," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2287–2288, Nov. 2007.
- [4] Z. Hou, B. Liu, and S. Zhang, "Power system operational risk assessment based on random set theory," *Power Syst. Technol.*, vol. 41, no. 12, pp. 3757–3763, 2017.
- [5] H. Wan, J. Mccalley, and V. Vittal, "Risk based voltage security assessment," *IEEE Trans. Power Syst.*, vol. 15, no. 4, pp. 1247–1254, Nov. 2000.
- [6] V. Van Acker, J. Mccalley, V. Vittal, and J. Pecas Lopes, "Risk-based transient stability assessment," in *Proc. Power Tech Budapest*, Aug./Sep. 2003, p. 235.
- [7] J. Zhang, J. Pu, J. Mccalley, H. Stern, and W. Gallus, "A Bayesian approach for short-term transmission line thermal overload risk assessment," *IEEE Trans. Power Del.*, vol. 17, no. 3, pp. 770–778, Jul. 2002.
- [8] H. Peng, M. Su, S. Li, and C. Li, "Static security risk assessment for islanded hybrid AC/DC microgrid," *IEEE Access*, vol. 7, pp. 37545–37554, 2019.
- [9] L. Wang, M. Yuan, F. Zhang, X. Wang, L. Dai, and F. Zhao, "Risk assessment of distribution networks integrating large-scale distributed photovoltaics," *IEEE Access*, vol. 7, pp. 59653–59664, 2019.
- [10] Y. Jiang, M. Ni, and J. D. Mccalley, "Risk-based maintenance allocation and scheduling for bulk electric power transmission system equipment," in *Proc. 15th Int. Conf. Syst. Eng.*, Las Vegas, NV, USA, Aug. 2002, pp. 1–7.
- [11] R. Billinton and K. Bollinger, "Transmission system reliability evaluation using Markov processes," *IEEE Trans. Power App. Syst.*, vols. PAS–87, no. 2, pp. 538–547, Feb. 1968.
- [12] R. Billinton and G. Singh, "Application of adverse and extreme adverse weather: Modelling in transmission and distribution system reliability evaluation," *IEE Proc., Gener. Transm. Distrib.*, vol. 153, no. 1, pp. 115–120, 2006.
- [13] C. Dichirico and C. Singh, "Reliability analysis of transmission lines with common mode failures when repair times are arbitrarily distributed," *IEEE Trans. Power Syst.*, vol. 3, no. 3, pp. 1012–1019, Aug. 1988.
- [14] R. Billinton and L. Wenyuan, "A novel method for incorporating weather effects in composite system adequacy evaluation," *IEEE Trans. Power Syst.*, vol. 6, no. 3, pp. 1154–1160, Aug. 1991.
- [15] M. Bhuiyan, "Inclusion of weather effects in composite system reliability evaluation using sequential simulation," *IEE Proc., Gener. Transm. Distrib.*, vol. 141, no. 6, pp. 575–584, 1994.
- [16] A. Breipohl, F. N. Lee, J. Huang, and Q. Feng, "Sample size reduction in stochastic production simulation," *IEEE Trans. Power Syst.*, vol. 5, no. 3, pp. 984–992, Aug. 1990.
- [17] A. C. G. Melo, G. C. Oliveira, M. Morozowski Fo, and M. V. F. Pereira, "A hybrid algorithm for Monte Carlo/enumeration based composite reliability evaluation (power systems)," in *Proc. 3rd Int. Conf. Probabilistic Methods Appl. Electr. Power Syst.*, London, U.K., Jul. 1991, pp. 70–74.
- [18] G. Oliveira, M. Pereira, and S. Cunha, "A technique for reducing computational effort in Monte-Carlo based composite reliability evaluation," *IEEE Trans. Power Syst.*, vol. 4, no. 4, pp. 1309–1315, Nov. 1989.
- [19] C. Singh and J. Mitra, "Composite system reliability evaluation using state space pruning," *IEEE Trans. Power Syst.*, vol. 12, no. 1, pp. 471–479, Feb. 1997.
- [20] R. A. Gonzalez-Fernandez, A. M. Leite Da Silva, L. C. Resende, and M. T. Schilling, "Composite systems reliability evaluation based on Monte Carlo simulation and cross-entropy methods," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4598–4606, Nov. 2013.
- [21] Y. Wang, C. Guo, and Q. H. Wu, "A cross-entropy-based three-stage sequential importance sampling for composite power system shortterm reliability evaluation," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4254–4263, Nov. 2013.

- [22] M. Pereira, M. Maceira, G. Oliveira, and L. Pinto, "Combining analytical models and Monte-Carlo techniques in probabilistic power system analysis," *IEEE Trans. Power Syst.*, vol. 7, no. 1, pp. 265–272, Feb. 1992.
- [23] M. Benidris, J. Mitra, and S. Elsaiah, "Power system reliability evaluation using a state space classification technique and particle swarm optimisation search method," *IET Gener., Transmiss. Distrib.*, vol. 9, no. 14, pp. 1865–1873, Nov. 2015.
- [24] R. Billinton and W. Zhang, "State extension in adequacy evaluation of composite power systems-concept and algorithm," *Electr. Power Syst. Res.*, vol. 47, no. 3, pp. 189–195, Nov. 1998.
- [25] R. Billinton and W. Zhang, "State extension for adequacy evaluation of composite power systems-applications," *IEEE Trans. Power Syst.*, vol. 15, no. 1, pp. 427–432, Feb. 2000.
- [26] H. Liu, Y. Sun, P. Wang, L. Cheng, and L. Goel, "A novel state selection technique for power system reliability evaluation," *Electr. Power Syst. Res.*, vol. 78, no. 6, pp. 1019–1027, Jun. 2008.
- [27] Y. Jia, P. Wang, and X. Han, "A fast contingency screening technique for generation system reliability evaluation," *IEEE Trans. Power Syst*, vol. 28, no. 4, pp. 4127–4133, Jun. 2013.
- [28] K. Hou, H. Jia, X. Yu, L. Zhu, X. Xu, and X. Li, "An impact incrementsbased state enumeration reliability assessment approach and its application in transmission systems," in *Proc. IEEE Power Energy Soc. General Meeting (PESGM)*, Jul. 2016, pp. 1–5.
- [29] IEEE 118-Bus System, Illinois Center for A Smarter Electric Grid. Accessed: Mar. 20, 2019. [Online]. Available: http://publish.illinois. edu/smartergrid/ieee-118-bus-system



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