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Power transmission risk assessment considering component condition

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Abstract This paper proposes a new method for power transmission risk assessment considering historical failure statistics of transmission systems and operation failure risks of system components. Component failure risks are integrated into the new method based on operational condition assessment of components using the support vector data description (SVDD) approach. The traditional outage probability model of transmission lines has been modified to build a new framework for power transmission system risk assessment. The proposed SVDD approach can provide a suitable mechanism to map component assessment grades to failure risks based on probabilistic behaviors of power system failures. Under the new method, both up-to-date component failure risks and traditional system risk indices can be processed with the proposed outage model. As a result, component failure probabilities are not only related to historical statistic data but also operational data of components, and derived risk indices can reflect current operational conditions of components. In simulation studies, the SVDD approach is employed to evaluate component conditions and link such conditions to failure rates using up-to-date component operational data, including both on-line and off-line data of components. The IEEE 24-bus RTS-1979 system is used to demonstrate that component operational conditions can greatly affect the overall transmission system failure risks.

Keywords Risk assessment, Component failure risk, Outage probability, Condition assessment, Support vector data description

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1 Introduction

With the continuous increase of energy demand, the accurate risk assessment of power systems is of great importance, since risks are increased when a power system is operated close to its stability limits due to distributed generation and market competition. With regard to power system assessment, higher risks lead to lower reliability, and vice versa. The probabilistic behaviors of power system failures are the root origin of risks [1], and an effective risk assessment model can provide quantitative risk indices to represent system reliability. Traditionally, only historical failure statistics are employed in power system risk assessment, however the overall system risk is also related to component operational conditions. When component failure risks change, the overall system risk varies accordingly. Incorporating component risks into the power system risk assessment can improve the accuracy and rationality of risk evaluations.

In the past decade, considerable efforts have been devoted to probabilistic risk assessment of power transmission systems and substation configurations. A widely used framework for power system risk assessment was reported in [1, 2], in which the approach, objective, application and economic cost were discussed in detail [3]. However, in this traditional framework, failure risks of components, such as transformers and circuit breakers, were not considered. Generally, the risk assessment of components in substations was performed separately [4–6]. As a result, there is a lack of a mechanism to convert component operational conditions into failure risks in the traditional framework. In [4], a risk assessment model of a combinative system in a transmission network and substations was proposed. Compared with the traditional framework, in which system risks of transmission networks and substation configurations are assessed separately, the method presented in [4] can evaluate system risks considering both transmission networks and substations by assessing new load curtailments at load points for each failure state. As an improvement, substations are no longer treated as a transmission node and substation configurations, and individual components, such as breakers and transformers, are linked to system risks by analyzing statistical data of substation components. However, component failure data are still based on historical statistics. Consequently, the impact of online component operational conditions cannot be integrated in risk evaluations.

A multi-objective risk assessment framework was presented in [7], and probabilistic indices for assessing real-time power system security levels were derived. However, operation risks of components were still not considered. A failure probability model was developed based on the evidential reasoning (ER) theory for overhead lines in [8], which can accurately reflect the impact of surroundings on failure probabilities. However, component outage rates were set as a fixed value, which was not linked to operational conditions of components. Based on the ER theory and the functional group decomposition principle, a contingency identification method for components was presented in [9].

However, in that research, component conditions, such as operational conditions and monitoring data, were not considered, and components were just treated as part of transmission lines. But actually, each component has its own failure risk, which is influenced by its operational condition. In practice, component condition assessment is usually conducted by experts or trained on-site engineers. As operational conditions could be affected by faults or environment, such as loading conditions and temperatures [5, 6], the failure probability of components is not fixed. Thus, the outage probability of transmission lines changes accordingly. As the component failure probability changes, the results of risk assessment are not fixed values as those of traditional risk assessment models [1], which should be determined by both operational conditions and historical data.

The support vector data description (SVDD) approach is developed for classification and evaluation with machine learning, which can be employed to aggregate diagnosis information [10, 11]. In particular, regarding the probabilistic and uncertain behaviors of component failures, SVDD is a suitable solution for presenting evaluation of various failure conditions. Based on the outputs of SVDD component evaluation, system operators can obtain overall evaluations of studied components, which can be classified into different condition levels accordingly. The SVDD approach is capable of providing the most recent condition for components in power transmission systems. The objective of this paper is to develop a new risk assessment method for power transmission systems, in which component conditions are considered based on on-line and off-line data. The method comprises of three parts: component evaluation, index transition and system risk evaluation. The proposed method employs SVDD for component risk assessment and the Monte Carlo (MC) simulation [1] for system state selections.

2 SVDD approach to component condition assessment

The SVDD approach is an one-class classification data description method which proposed by Tax [10]. By training with a set of certain samples, the distribution of target class can be obtained by SVDD, so the outliers can be divided. The SVDD approach can provide well distribution area and can be used in condition detection, fault diagnosis and multi-classification, etc. [12–14].

By applying SVDD approach to mechanical condition monitoring and fault diagnosis, machine conditions can be monitored only by using normal condition signals instead of abnormal condition signals. With the method, the machine set conditions (normal or abnormal) can be described by using quantitative indices, and the scientific decision-making basis for equipment management and predictive maintenance can be offered. The method is used to evaluate the condition of the key equipment in power transmission lines, and it correctly evaluates an abnormal condition of the equipment in time and contributes to a successful diagnosis of the incipient fault of a bolt crack.

As a data set containing N data objects: $\{x_i, i = 1, 2, \ldots, N\}$, the basic concept of SVDD is trying to find a sphere with minimum volume, containing all (or most of) the data objects [10]. This is very sensitive to the most outlying object in the target data set. When one or a few very remote objects are in the training set, a very large sphere is obtained which will not represent the data very well. Therefore, [15] considered some data points outside the sphere and introduced slack variable $\xi_i (\xi_i \geq 0,\ i = 1, 2, \ldots, n)$. Of the sphere, described by center a and radius R, the radius is minimized as follows:

$$\min_R F(R,a) = R^2 + C\sum_{i=1}^{n} \xi_i$$
$$\text{s.t.}\begin{cases} [\varphi(x_i)-a][\varphi(x_i)-a]^{\mathrm{T}} \le R^2+\xi_i \\ \xi_i \ge 0, \quad i=1,2,\ldots,n \end{cases}, \tag{1}$$

where the variable C gives the trade-off between the simplicity (or volume of the sphere) and the number of errors (number of target objects rejected); the function φ is a nonlinear mapping function used for mapping objects into the high dimensional.

The dual form of (1) is written as:

$$\max_{\alpha_i} L = \sum_{i=1}^{n} \alpha_i K(x_i \cdot x_j)$$
$$\text{s.t.}\begin{cases} \sum_{i=1}^{n} \alpha_i = 1 \quad i=1,2,\ldots,n \\ 0 \le \alpha_i \le C \quad i=1,2,\ldots,n \end{cases}, \tag{2}$$

where $K(x_i \cdot x_j)$ is the kernel function which satisfies Mercer's theorem:

$$K\left(x_i \cdot x_j\right) = \left[\varphi(x_i)\cdot\varphi(x_j)\right]. \tag{3}$$

The kernel function implicitly maps the objects x_i into some feature space and when a suitable feature space is chosen, a better and more tight description can be obtained. No explicit mapping is required, the problem is expressed completely in terms of $K(x_i \cdot x_j)$.

Finally, parameter α_i can be obtained, and x_i satisfies $\alpha_i > 0$, called the support vector. From the basic concept and definition of SVDD [11], the equation is obtained as follows:

$$R^2 = K(x_k \cdot x_k) - 2\sum_{i=1} \alpha_i K(x_i \cdot x_k) + \sum_{i,j} \alpha_i \alpha_j K\left(x_i \cdot x_j\right) \quad \forall x_k \in \mathrm{SV} \; < C, \tag{4}$$

where R^2 is the distance to the center of the sphere (a); SV means support vector.

Based on (4), each support vector can provide the value of R^2. For the test sample z, assuming that:

$$D(a,z) = K(z \cdot z) - 2\sum_{i=1} \alpha_i K(z \cdot x_i) + \sum_{i,j} \alpha_i \alpha_j K\left(x_i \cdot x_j\right) \quad i,j=1,2,\ldots,n. \tag{5}$$

If $D(a, z) \le R^2$, then z is considered as the target, otherwise is considered as the outlier.

For illustration purposes, we define evaluation level as the SVDD result of each component. It corresponds to the relationships between component condition characteristic values and failure probability. For example, based on a transformer dissolved gas analysis (DGA) value, the SVDD evaluation level of this component is graded as 'good', 'normal', 'poor' or 'serious'. Therefore, each level equals an area of failure rate (from 0 to 1), afterwards, the component condition is considered in power transmission risk assessment.

3 Power transmission system risk evaluation considering component risks

In practice, power system risk assessment is concerned with two aspects: i.e., system adequacy and system security [1]. System adequacy mainly relates to the existence of sufficient facilities within a system to satisfy consumer load demands and system operational constraints, while system security relates to the ability of a system to respond to dynamic and transient disturbances arising within the system. Thus, security is associated with the response of a system to perturbations. As most of the risk assessments

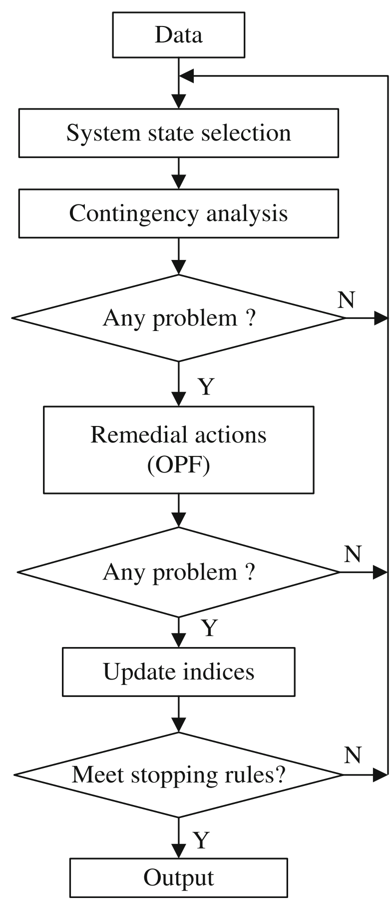

Fig. 1 Procedure of power transmission risk assessment

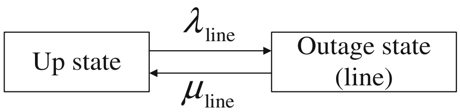

Fig. 2 State space diagram of a two-state repairable forced outage

carried out by utilities are in the domain of adequacy assessment [1], in this paper the system adequacy analysis is set as the risk assessment objective.

The basic procedure of power transmission system risk assessment is shown in Fig. 1 [1]. Firstly, a system sate is selected based on historical failure statistics. Then, the contingency analysis and optimal power flow (OPF) method are performed to identify whether a selected state causes any problems. Finally, risk indices are calculated. In this paper, procedures of outage modeling in system state selections have been modified using the updated outage model considering component failure risks.

3.1 Traditional component failure models

Traditionally, for power transmission system risk evaluation, only failures of transmission components are considered, whereas generating units are assumed to be 100% reliable. Key transmission components include overhead lines, cables, transformers, capacitors, and reactors. Generally, these components are represented by a two-state (up and down) model. Figure 2 shows the diagram of a basic two-state repairable forced outage, which can be used to describe a typical steady up-down-up cycle process.

The average unavailability of a transmission line in a long-term process is defined as follows [1]:

$$P_{\rm line} = \frac{\lambda_{\rm line}}{\lambda_{\rm line} + \mu_{\rm line}}, \tag{6}$$

$$\begin{cases} \lambda_{\rm line} = \dfrac{8,760}{MTTF_{\rm line}} \\ \mu_{\rm line} = \dfrac{8,760}{MTTR_{\rm line}} \end{cases}, \tag{7}$$

where $P_{\rm line}$ is the outage probability of lines; $\lambda_{\rm line}$ and $\mu_{\rm line}$are the line failure and repair rates (1/year), respectively; $MTTR_{\rm line}$ and $MTTF_{\rm line}$ are the mean time to repair (MTTR) (hours per year) and mean time to failure (MTTF) (hours/year) of lines, respectively.

The historical data are recorded over a one year period and subsequently the failure and repair rates can be derived based on MTTF and MTTR, respectively.

3.2 Outage model integrating component failure risk

A new outage model has been developed based on both historical failure statistics (IEEE RTS-79) [16] and component failure risks. In the traditional outage model, the forced outage probability of transmission lines is denoted by $P_{\rm line}$. Based on (1), the planned outage model and Markov equations [1], the state space diagram considering both the line and component risks is shown in Fig. 3.

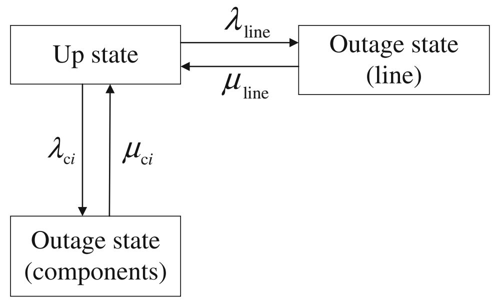

Fig. 3 State space diagram considering both line and component outages

Applying the Markov method based on the state space diagram, the outage probabilities can be obtained as follows:

$$P_{\rm c\it i} = \frac{\lambda_{\rm c\it i}\mu_{\rm line}}{\lambda_{\rm c\it i}\mu_{\rm line} + \lambda_{\rm line}\mu_{\rm c\it i} + \mu_{\rm line}\mu_{\rm c\it i}}, \tag{8}$$

$$P_{\rm up} = \frac{\mu_{\rm line}\mu_{\rm c\it i}}{\lambda_{\rm c\it i}\mu_{\rm line} + \lambda_{\rm line}\mu_{\rm c\it i} + \mu_{\rm line}\mu_{\rm c\it i}}, \tag{9}$$

$$P_{\rm line} = \frac{\lambda_{\rm line}\mu_{\rm c\it i}}{\lambda_{\rm c\it i}\mu_{\rm line} + \lambda_{\rm line}\mu_{\rm c\it i} + \mu_{\rm line}\mu_{\rm c\it i}}, \tag{10}$$

$$\begin{cases} \lambda_{\rm c\it i} = \dfrac{8,760}{MTTF_{\rm c\it i}} \\ \mu_{\rm c\it i} = \dfrac{8,760}{MTTR_{\rm c\it i}} \end{cases}, \tag{11}$$

where $P_{\rm up}$, $P_{\rm line}$ and $P_{\rm c\it i}$ are the probabilities of the up state, the historical line outage state and the failure risk-based outage state of the ith component; $\lambda_{\rm line}$ and $\lambda_{\rm c\it i}$ are the transition rates of historical line outages and component failure risk-based outage states; $\mu_{\rm line}$ and $\mu_{\rm c\it i}$ are the recovery (repair) rates of the historical line outage and the component failure risk-based outage state (repairs/year); $MTTR_{\rm c\it i}$ and $MTTF_{\rm c\it i}$ are the MTTR and MTTF of component, respectively.

In Section 3, the condition assessment of components based on SVDD approach is used as an example to illustrate the procedures for calculating component failure risks. As discussed previously, the overall assessment of a component can be expressed using SVDD approach as a set of evaluation grades, and then component failure rates can be derived in association with the SVDD evaluation levels.

There are normally a number of components in the same transmission line or bus, and the line or bus fails when one of the main components fails. As a result, the maximum component failure risk value is selected to represent the overall failure probability of components in the same line. Considering failure risks of components, the transmission line outage probability integrating both historical failure statistics and component failure risks can be expressed in the following (13):

$$P_{\mathrm{c}} = \max(P_{\mathrm{c}1}, P_{\mathrm{c}2}, \ldots, P_{\mathrm{c}n}), \tag{12}$$

$$P_{\mathrm{L}} = P_{\mathrm{line}} + P_{\mathrm{c}} = \frac{\lambda_{\mathrm{line}}\mu_{\mathrm{c}i} + \lambda_{\mathrm{c}i}\mu_{\mathrm{line}}}{\lambda_{\mathrm{c}i}\mu_{\mathrm{line}} + \lambda_{\mathrm{line}}\mu_{\mathrm{c}i} + \mu_{\mathrm{line}}\mu_{\mathrm{c}i}}, \tag{13}$$

where P_{L} is the overall outage probability of transmission lines; P_{c} is the maximum component failure risk among n components in the same transmission line; $P_{\mathrm{c}n}$ is the outage probability of the nth component in the same line.

As shown in (13), it is assumed that the ith component has the maximum failure risk.

3.3 Load curve models and contingency analysis

In this paper, for the state enumeration or state sampling method (nonsequential MC simulation), a nonchronological load duration curve is utilized. A single load curve is considered and loads at all buses are scaled proportionally to follow the shape of the given load curve. A multiple-step model is established to represent the load duration curve [1]. Regarding the contingency analysis on adequacy risk assessment, the capacity balance between the generation and the load demand is important. As a result, the DC power-flow-based contingency analysis is employed in this study, because it provides fast and sufficiently accurate real power flows following line outages for risk assessment, in which a large number of outage events are considered.

3.4 Optimization models for load curtailment

When an outage causes system problems, a special OPF model is used to reschedule generations and alleviate constraint violations. At the same time, load curtailment needs to be avoided if possible or the total load curtailment is required to be minimized if unavoidable. The objective function of an OPF model is to minimize the total load curtailment, whereas load curtailment at buses is the solution of the OPF model. The risk indices are then calculated based on load curtailments in selected system outage states and their probabilities of occurrence. To reduce the computational burden, the DC power-flow-based OPF model is usually employed in the adequacy risk assessment [1]. It can be expressed in the following equations:

$$\min \sum_{i \in ND} C_i, \tag{14}$$

$$\text{s.t.} \begin{cases} \boldsymbol{T}(S) = \boldsymbol{A}(S)(\boldsymbol{PG} - \boldsymbol{PD} + \boldsymbol{C}) \\ \sum\limits_{i \in NG} PG_i + \sum\limits_{i \in ND} C_i = \sum\limits_{i \in ND} PD_i \\ PG_i^{\min} \le PG_i \le PG_i^{\max} \quad i \in NG \\ 0 \le C_i \le PD_i \quad i \in ND \\ |T_k(S)| \le T_k^{\max} \quad k \in L \end{cases}, \tag{15}$$

where i is the bus number; C_i is the load curtailment at the ith bus; $\boldsymbol{T}(S)$ is the real power flow vector in the outage state; $\boldsymbol{A}(S)$ is the relation matrix between real power flows and power injections in the outage state S; $\boldsymbol{PG}$ and $\boldsymbol{PD}$ are the generation output and load power vectors, respectively; $\boldsymbol{C}$ is the load curtailment vector; PG_i, PD_i, C_i and $T_k(S)$ are the elements of $\boldsymbol{PG}$, $\boldsymbol{PD}$, $\boldsymbol{C}$ and $\boldsymbol{T}(S)$, respectively; the subscript "min", "max" are the limits, respectively; NG, ND and L are the sets of generation buses, load buses and branch circuits in a system.

The objective of the model is to minimize the total load curtailment while satisfying the power balance, DC power flow relationships and limits on line flows and generation outputs.

3.5 Risk indices

There are various risk indices, which are used for quantifying system risks. In practice, loss-of-load probability (LOLP) and expected demand not supplied (EDNS) are two most popular indices, which are employed in this research. LOLP indicates the probability of load loss caused by element capacity shortage (1/year). It can be expressed in the following equation:

$$L_{\mathrm{LOLP}} = \sum_{x \in X} I_{\mathrm{f}}(x) P(x), \tag{16}$$

where $P(x)$ is the probability of system state x; $I_{\mathrm{f}}(x)$ is a two valued function of system state x. If x

Table 1 Evaluation level corresponding to failure rate

Evaluation level	Failure rate (1/year)
Good	0–0.2
Normal	0.2–0.8
Poor	0.8–1.0
Serious	Outage

Table 2 Results of SVDD classification

Actual/evaluation	Good	Normal	Poor	Serious	Total
Good	39	7	4	0	50
Normal	5	42	2	1	50
Poor	0	1	26	3	30
Serious	0	2	1	27	30
Total	44	51	35		130

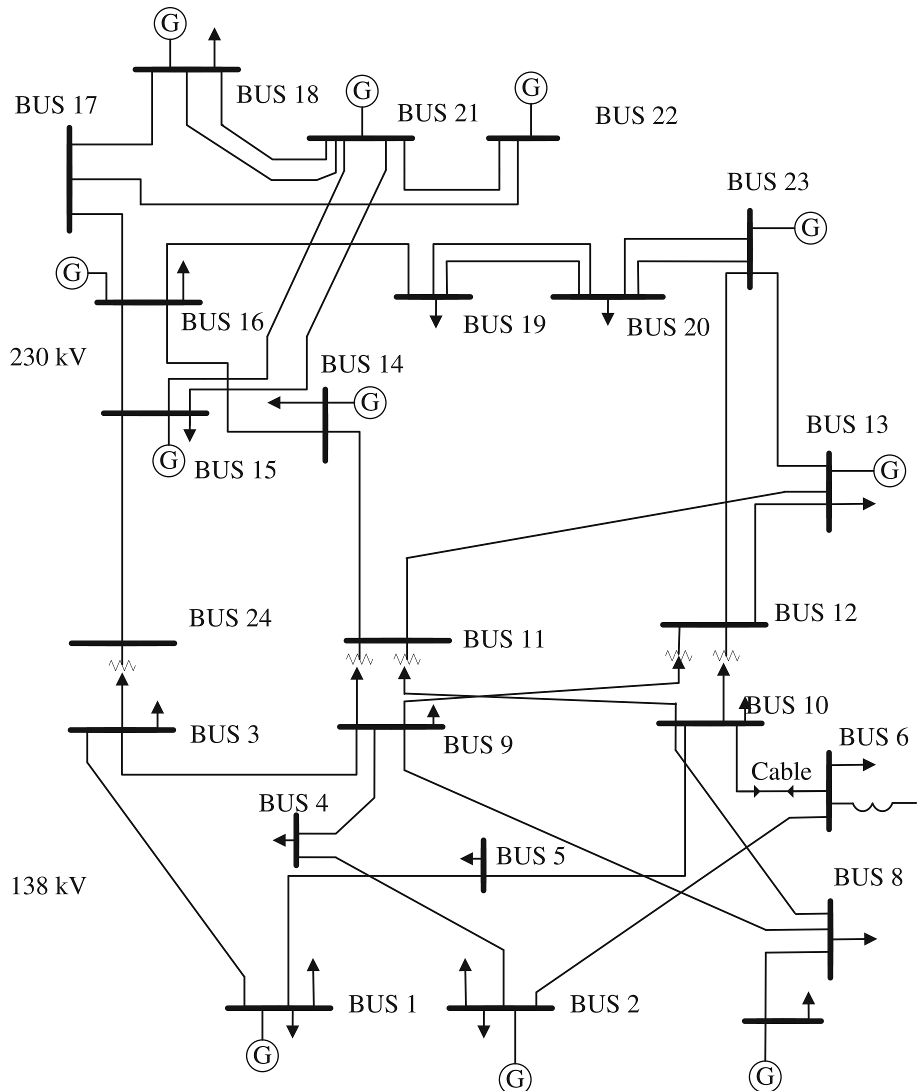

Fig. 4 IEEE RTS-79 test system

indicates the failure state, then I_f is equal to 1, otherwise 0.

EDNS denotes the average shortage of power supply per year (MW/year).

$$L_{\mathrm{EDNS}} = \sum_{x \in X} I_f(x) L_C(x) P(x), \tag{17}$$

where $L_C(x)$ represents the minimum load loss for recovery in the outage state x.

4 Case study

4.1 Component failure risk mapping

The condition assessment of transformers is used as an example to illustrate the procedures for calculating component failure risks. For other components, the procedures can be performed in a similar manner. As discussed previously, the overall assessment of a component can be expressed as a set of evaluation grades, then component failure rates can be derived in association with the SVDD evaluation levels. For illustration purposes, Table 1 lists the corresponding relationships between evaluation levels and failure rates. For example, based on historical statistics or operation experience, the failure rate of a component is 0.14 per year, and then the SVDD evaluation level of this component is graded as 'good'.

Table 1 only gives reference values for illustration purposes, and in practice, this table may be modified based on operation situations and historical statistics analysis. It is defined that the SVDD evaluation grade, that is 'serious', 'poor', 'normal' or 'good', with the maximum value is treated as the final evaluation grade of a component. Using this mapping table, the failure rate λ_c can be derived by the proposed SVDD approach. Likewise, the repair rates μ_c can

Table 3 Case I: LOLP and ENDS results at different sampling frequencies

Sampling times	LOLP (%)	LOLP considering component	EDNS (MW/year)	EDNS considering component
10,000	8.72	9.38	14.29	14.42
20,000	8.69	9.25	14.62	14.39

be defined similarly. In the meantime, λ_{line} and μ_{line} can be derived from historical statistic data, and finally the outage probability of components can be calculated by using (8).

4.2 SVDD-based component failure risk evaluation

In this paper, 260 sets of transformer monitoring data sample are adopted. These samples are acquired from the DGA monitoring of transformers. Thereinto, 130 sets are used for training (50 sets are in good condition, 50 sets are normal, 30 set are poor and 30 sets are serious) and others are used for testing. By adopting the SVDD approach, the evaluation results are listed in Table 2.

In the evaluation results, the total accuracy is about 84%. The accuracy of 'good', 'normal', 'poor' and 'serious' are 78%, 84%, 87% and 90%, respectively.

Based on the mapping relations listed in Table 1, the failure rate of a component can be generated randomly between the areas. However, the mapping relation is only for illustrating reference values, those values can be defined based on the practice or experience.

4.3 System risk assessment: Case I

In this case study, the IEEE RTS-79 system is employed as the test system [15] as shown in Fig. 4. In the IEEE RTS-79 test system, the load model gives hourly loads for one year on a per unit basis, expressed in chronological fashion so that daily, weekly and seasonal patterns can be modeled. The generating system contains 32 units, ranging from 12 to 400 MW. The transmission system contains 24 load/generation buses connected by 38 lines or autotransformers at two voltage levels, i.e. 138 kV and 230 kV. The transmission system includes cables, lines on a common right of way, and lines on a common tower. The transmission system data include the line length, impedance, ratings, and reliability data.

In MC simulations different sampling frequencies lead to different convergences, therefore the sampling frequencies of the MC simulation are set with different values. As a result, the derived risk index values at different sampling frequencies are presented in Table 3.

It is assumed that all the transformers in the system are operated under a 'normal' condition, and the component failure rates are set as a random value between 0.2 and 0.8 randomly according to Table 1.

Compared with the results without considering component risks the LOLP and EDNS have rarely increased.

Table 4 Case II: LOLP and ENDS results at different sampling frequencies

Sampling times	LOLP considering component	EDNS considering component
10,000	12.01	16.68
20,000	10.65	15.28

4.4 System risk assessment: Case II

In Case II, the component failure rates are set higher than that of Case I and all system components are assumed to be operated under a 'poor' condition. The component failure risks are generated between 0.8 and 1.0 mapping to the 'poor' level for each line. Different sampling frequencies are also compared, as shown in Table 4.

In Case II, it is clear that when evaluation levels of all transformers are changed from 'normal' to a worse level like 'poor', LOLP increases significantly. Compared with these of Case I, LOLP considering component risks increases nearly by 15%, while ENDS considering components is raised by 6%.

4.5 System risk assessment: Case III

In this case, only the component between BUS 3 and BUS 24 is set as outage, while other components in the system are considered as 'normal'. According to Table 1, the probability of the outage component is 100%, and failure rates of other components are between 0 and 0.2. Different sampling frequencies are applied and its results concerning LOLP and ENDS are listed in Table 5. Compared with Case II, LOLP and EDNS are 8 and 3% more than those of Case I, which indicates that when a transformer is working under a 'serious' condition, the overall system risk increases. However, the risks are less than those in Case II, which indicates that when failure risks of several components change from 'normal' to a 'poor' or 'serious' grade, the risk values

Table 5 Case III: LOLP and ENDS results at different sampling frequencies

Sampling times	LOLP considering component	EDNS considering component
10,000	9.81	14.70
20,000	9.92	14.82

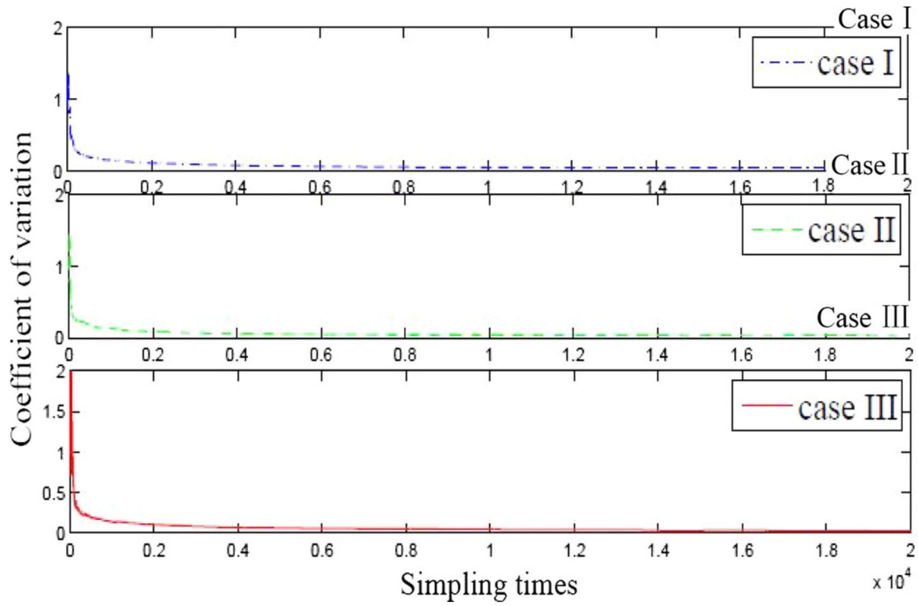

Fig. 5 Convergence variation of EDNS

increase much more than the situation that only one component is in the 'serious' grade.

The variation convergence curves of EDNS in three cases are illustrated in Fig. 5, which shows that when the sampling frequency is over 20,000 times, the variation convergence is relatively small under 0.2. It means that, for three cases the derived coefficients are reliable when the sampling frequency is over 20,000 times.

5 Conclusion

A new method for transmission system risk assessment considering component monitoring data is proposed. The proposed SVDD-based approach can provide a suitable mechanism to map component evaluation grades to failure risks based on the probabilistic behaviors of power system failures. Using the new method, both up-to-date component condition status and traditional system risk indices can be processed with the developed outage model. In this study, transformer DGA data have been used to calculate component failure risks. The simulation results indicate that transmission system risks are affected not only by component operational conditions, but also by historical statistics data. In case studies, the implementation procedures of component risk evaluation using SVDD and system risk assessment are demonstrated.

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