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A probabilistic framework to evaluate seismic resilience of substations based on three-stage uncertainty

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ABSTRACT

Electrical substation systems exhibit vulnerability after an earthquake. It results in significant economic losses because of the uncertainty of the functional state and recovery process. To quantitatively assess the uncertainty of substations, this paper proposes a probability-based seismic resilience assessment framework. This framework considers uncertainty in three stages: functional state, functional recovery, and resource constraints. Based on the functional characteristics of substation systems, a directed acyclic graph was constructed, and the Monte Carlo algorithm was used to obtain the functional state matrix, thereby establishing a probability-based functional state model. Moreover, a dynamic post-earthquake functional recovery analysis framework was built based on recovery efficiency metrics, and functional recovery paths were obtained through iterative simulations. A stepped functional recovery curve was developed based on resource constraints. Three-stage uncertainty parameters were transformed into resilience features for quantitative assessment. By analysing seismic resilience of a typical 220 kV step-down substation, probability distributions of functional recovery curves and confidence intervals for seismic resilience metrics were obtained. Notably, mutual constraint relationships among resource conditions were identified.

1. Introduction

Electrical substations are critical electrical infrastructure within power grid systems. However, the past several earthquakes have shown that substations have been seriously damaged [1]. Therefore, many scholars have conducted research on the seismic response of electrical equipment [2,3], aiming to enhance the seismic resilience of substations by improving the earthquake resistance of equipment [4,5]. However, research at the equipment level cannot meet the seismic assessment requirements of a substation. Therefore, analysing seismic resilience and functional states throughout the entire process is crucial to the ultimate success of substation assessment.

Resilience was initially introduced by Holling in ecosystems [6]. It refers to the ability of a system to resist and recover from the impacts of external forces. In 2003, Bruneau [7] proposed a framework of seismic resilience concepts. They outlined four categories of resilience properties based on physical and social systems. These properties can be utilized to quantify the resilience of various types of engineering systems. Then, Cimellaro [8] built a framework for the analytical quantification of disaster resilience. They emphasized recovery function models, thus laying the foundation for resilience assessment research. Urlainis [9,10] conducted a review of the performance of critical infrastructure to extreme events. They highlight the urgency of studying the vulnerability and resilience of infrastructure to disaster. Because resilience characteristics can comprehensively assess the reliability and recovery capability of a system, resilience has gradually been applied to engineering network systems such as transportation and water distribution [11]. Hosseini [12] conducted a review of resilience research in engineering systems and determined resilience assessment methods into qualitative and quantitative assessments. Qualitative analysis mainly includes the resilience concept and key features, and quantitative analysis refers to indicator definition and structural modeling. Furthermore, many scholars have developed resilience assessment theoretical frameworks [13,14,15]. They outline the features and analysis methods for assessing the resilience of engineering networks. These studies aim to achieve quantitative assessments of resilience by considering the specific functional characteristics of various types of engineering networks. In multi-engineering networks, interdependence exists among various engineering systems. Sharma [16] built a mathematical formulation to model the recovery process, quantify resilience, and optimize resilience

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for interdependent infrastructure. Moreover, Iannacone [17] developed a novel formulation to model the recovery function of infrastructure deterioration after disruption. Zhang [18] proposed hybrid genetic algorithms to optimize the scheduling of functional recovery for both the transportation and power systems. Xiao [19] considered the bidirectional interdependence of lifelines and conducted seismic resilience assessments for urban interdependent lifeline networks. Therefore, many urban lifeline engineering systems have carried out quantitative assessments of seismic resilience [20,21]. Their research on network reliability and functional recovery provides crucial references for the probabilistic assessment of resilience [22].

In recent years, more scholars have conducted simulations on the disaster resilience of power systems. However, because of the unique characteristics and functional requirements of the power infrastructure network, the framework and analysis methods for seismic resilience assessment differ significantly from other engineering systems. Liu [23] and Oboudi [24] proposed resilience assessment methods suitable for electrical grid systems. They identified resilience enhancement measures and recovery strategies through simulation. The aforementioned studies have raised higher demands for the resilience assessment of power systems. It is necessary to fully consider time-varying functionalities and integrate engineering requirements and functional characteristics into research. In substation systems, Yao [25] constructed a network model for substation systems and evaluated its operational status. Li [26,27] used a state tree to build a substation system model. They conducted seismic resilience and post-earthquake recovery path analyses using Monte Carlo methods. The studies mentioned above provide methodological support for constructing the functional model of substation systems. Following that, Liu [28,29] established a seismic resilience assessment framework for substation systems and improved the genetic algorithm to optimize post-earthquake recovery paths. In addition, multi-dimensional seismic resilience improvement strategies were proposed based on resilience key features, thereby reducing the post-earthquake functional losses of substation systems [30].

The functional states and recovery processes of various engineering network systems are uncertain. Based on the aforementioned research, Kameshwar [31] proposed a probabilistic resilience framework for communities. Monte Carlo simulations were used to account for uncertainty in the damage and recovery of infrastructure systems, thereby assessing the resilience levels of these systems. Tabandeh [32] proposed an approach of uncertainty propagation in risk and resilience analysis to reduce the problem dimensionality in hierarchical systems. In addition, both Taghizadeh [33] and Hosseini [34] proposed probabilistic methods for evaluating the seismic resilience of urban road and transportation systems. They addressed the uncertainty in emergency risks and resource scheduling schemes. Therefore, Monte Carlo simulation is an important method for conducting uncertainty analysis, and integrating multidimensional uncertainties is also a crucial means of resilience assessment. However, substations comprise multiple functional zones and equipment, with a high level of redundancy in electrical energy transmission. Consequently, the network structure, functional states, and probabilistic resilience assessment methods for substations exhibit specific characteristics. Evaluation methods developed for other engineering systems are not directly applicable to substation systems. Therefore, research on assessing seismic resilience and uncertainty for substation systems faces significant challenges.

Scholars have developed seismic resilience assessment frameworks for substation systems. Research gaps still exist.

(1) Currently, seismic simulations for substations have not yet adopted specific seismic time history curves to evaluate earthquake intensity. As a result, the functional states of various equipment, network connectivity, and post-earthquake functional recovery processes within substations are uncertain. Existing research lacks a probabilistic assessment of engineering system parameters and seismic resilience [35,36,9]. Therefore, a quantitative assessment method that considers the uncertainty of engineering parameters is yet to be established [19,20,22], and there is a crucial need to build a probability-based seismic resilience framework.

(2) The redundancy of resource conditions directly impacts the efficiency of functional recovery in practical engineering. However, current studies on functional recovery in substations often assume that post-earthquake resource conditions satisfy functional recovery requirements [27,28], without considering the constraining effects of resource conditions [29,18,37]. Therefore, the applicability and realism of substation systems remain limited.

(3) Economic costs associated with equipment replacement and substation system recovery are rarely considered [23,26,28]. There is a lack of determining the conditional probability distribution of post-earthquake economic resource requirements under different seismic intensities [29]. Therefore, considering resource constraints and economic costs, current research challenges lie in the exploration of a probabilistic seismic resilience assessment framework based on the structure and functional characteristics of substations.

According to the knowledge gaps, the research objectives of this study are to (1) determine the uncertainties in the post-earthquake functional states and recovery processes of substation systems, (2) identify the probability distribution characteristics of the substation's seismic resilience, (3) specify the influence of resource constraints on the functional recovery and seismic resilience, and (4) evaluate the post-earthquake functional and economic resource requirements of substation systems.

This paper proposes a probabilistic framework for assessing the seismic resilience of substation systems. The framework is divided into three stages: functional state, functional recovery, and resource constraints. The functional states of substations were obtained by utilizing Monte Carlo simulations. Subsequently, a probabilistic functional recovery model was established. The post-earthquake recovery efficiency of each repair step was determined. Considering the uncertainty of resource constraints on the post-earthquake functional recovery process, this framework achieves a quantitative assessment of substation seismic resilience. Through a seismic resilience assessment of a typical 220 kV step-down substation, the effectiveness and applicability of this framework were verified. The main contributions of this study can be summarized as follows:

1) We construct a probabilistic functional state model for substation systems and proposed the substation functional state matrix to quantitatively solve the probability parameters of the network operating states.
2) We develop a dynamic-based post-earthquake functional recovery framework. Considering the conditional probabilities of recovery time to obtain the functional recovery paths through iterative simulation.
3) We identify the mutual constraint relationships among resource conditions, considering the uncertainty of constraining effects on system functionality.
4) We determine the probability distribution of functional recovery curves and confidence intervals for seismic resilience metrics based on the proposed probabilistic framework.

2. Probabilistic-based seismic resilience framework

This study establishes a probabilistic-based seismic resilience framework for substations based on three stages of uncertainties: functional state, functional recovery, and resource constraints. The specific framework is shown in Fig. 1.

First, a probabilistic functional state model of substations was established. Based on the functional connectivity and the redundancy in

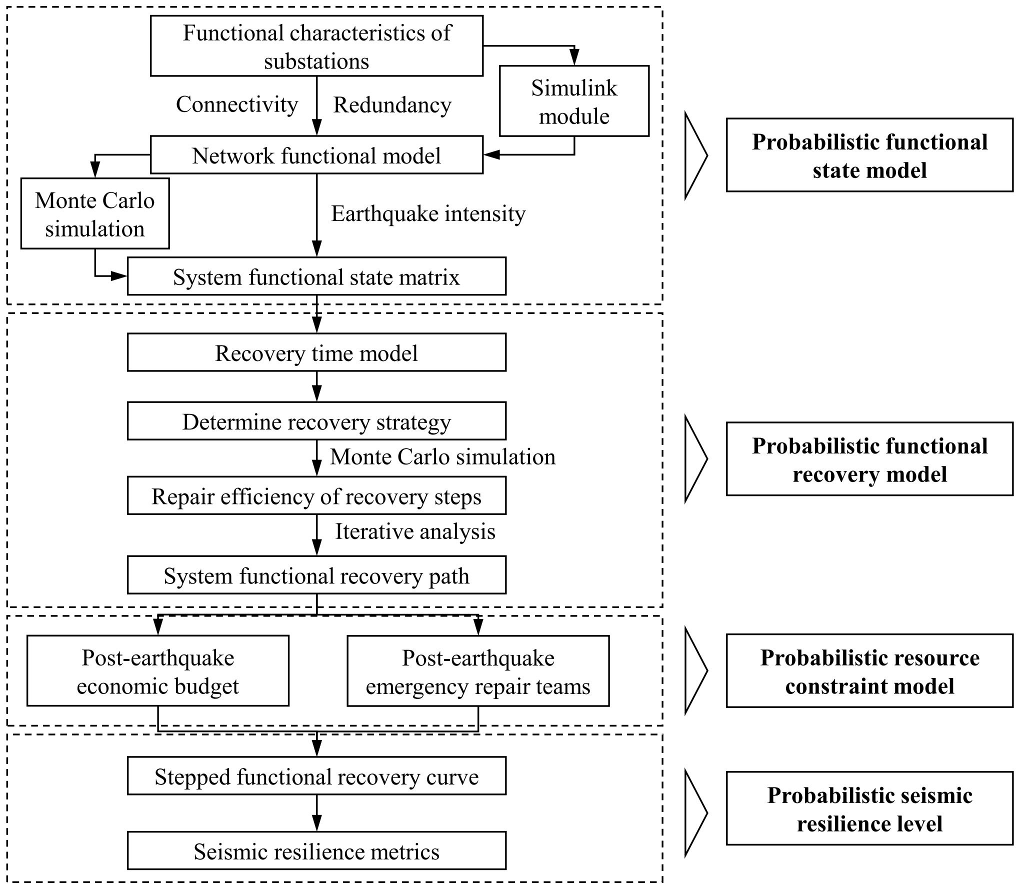

Fig. 1. Probabilistic-based seismic resilience framework for substations.

electrical load, a network functional model was constructed through Simulink modules. It converts the seismic reliability of equipment into node failure probabilities. Under specific earthquake intensities, a Monte Carlo simulation was applied to the network model to obtain the system's functional state matrix. Subsequently, a probabilistic functional recovery model was constructed. Based on post-earthquake recovery strategies, the post-earthquake recovery efficiency for each repair step was proposed, thereby determining the functional recovery path for the system through multiple iterations. Considering the uncertainty related to resource constraints on the post-earthquake functional recovery process, a probabilistic resource constraint model was established. The functional recovery of substations was analysed to achieve a stepped functional recovery curve based on the three stages of uncertainty. Finally, seismic resilience metrics were proposed based on its characteristics to quantitatively assess a substation's seismic resilience.

2.1. Definition of substation systems and functionality

Substation systems are critical infrastructure within the electrical grid. It is a complex network system comprised of numerous electrical devices [38]. The primary function of a substation system is to transform, consolidate, or distribute voltage and current. It serves as a hub for power transmission and distribution in the electrical grid, thereby reducing energy transmission losses and achieving long-distance power delivery requirements. In addition, the equipment in the substation is connected by bus bars. Factors such as the sag, span, and geometric stiffness of the connecting bus bars affect the damping ratio of the interconnected equipment, thereby directly influencing the seismic response of the interconnected equipment [39,40].

Unlike other engineering networks such as transportation and water distribution, substation systems have a defined direction of electrical energy transmission. The system's connectivity and electrical load levels can significantly influence its functional state. Therefore, a substation is a directed network with multidimensional functional constraints.

2.2. Probabilistic functional state model

2.2.1. Network functional model

Based on the functional characteristics of substations, the reliability and connectivity of equipment are determined. References [27,41,42] found that seismic vulnerability curves can reflect the probability of equipment functional failure at different earthquake intensities. Therefore, seismic vulnerability curves are an important method for assessing the seismic capability of equipment. The ground motion intensity measures (IMs) include spectral acceleration (Sa), seismic input energy, peak ground acceleration (PGA), velocity (PGV), et al. Among them, spectral acceleration needs to use equipment's fundamental frequency (T_1) when conducting seismic vulnerability analysis. Owing to the different fundamental frequencies (T_1) of various equipment, spectral acceleration is not applicable to seismic resilience assessment at the substation level.

Therefore, $P(FS \mid \mathrm{IM} = a)$ is used to represent the conditional probability that the functional state of equipment exceeds a predefined failure state at a specific IM. The seismic vulnerability curve of equipment is characterized using the logarithmic normal distribution cumulative function $\Phi()$, where θ represents the median and β represents the logarithmic standard deviation, as shown in Eq. (1). Even for linear architectures with high seismic vulnerability, the specific equipment failure probability under a given IM is determined using the same method. This allows for fitting the seismic vulnerability curve.

$$P(FS|\mathrm{IM}=a)=\Phi\left(\frac{\ln(a/\theta)}{\beta}\right) \tag{1}$$

Simulink modules are a powerful system for constructing network models. They provide an integrated environment for dynamic system modeling, simulation, and comprehensive analysis. Therefore, Simulink modules are used to build network functional models of the substation systems in this study. Equipment's operational states are transferred into the connectivity of nodes in the network modules. The direction of electrical energy is transferred into the analysis direction within the network modules. Bus bars are transferred into network node links. Compared to other methods, Simulink modules offer a visual modeling approach, allowing the construction of complex network directed logical diagrams without extensive programming. Furthermore, Simulink modules support the hierarchical construction of complex systems. Various modules can be organized into multiple subsystems, thereby facilitating the development of large and intricate networks.

The functional failure mechanism of a substation system is assessed based on the functional state of the equipment. Subsequently, the network connectivity of a substation affects its functionality. If both the line-in and line-out units of the network are in a connected state, power transmission can be achieved. This section proposes an example, as shown in Fig. 2(a), where A-J represent 10 sets of equipment. If devices C and E are damaged by an earthquake, the network remains in a connected state, and power transmission is not affected. The connections between the remaining devices are represented by red lines, as shown in Fig. 2(b). Therefore, if only considering the network connectivity of the substation system, the functional state of the substation is considered intact.

However, according to the seismic fortification requirements of substation systems, the equipment in a substation system works at half load under normal operation. When the function of some equipment fails under an earthquake, the power-load capacity of the remaining equipment can be doubled in emergency situations. This method enhances the redundancy of the network in a substation, thereby satisfying the demand for electricity transmission. As a result, the power-load capacity of equipment A, B, and D can be increased to 4/3, and the power-load capacity of equipment F can be increased to 4, ensuring the normal transmission of power at the line-out units, as illustrated in Fig. 2 (c).

In conclusion, the functional failure mechanism of substation systems is analyzed primarily from both the equipment level and the system network level. The seismic reliability of equipment is represented using seismic vulnerability curves. The probabilistic conditions of equipment functionality are transformed into deterministic operational states through Monte Carlo sampling. Subsequently, system functional status assessment is conducted from the perspectives of system network connectivity and redundancy. The network connectivity status is determined based on the operational states of the equipment, and the power-load capacity of the equipment is adjusted according to the seismic fortification requirements of substation systems. This allows for assessing functional states while ensuring system network connectivity and redundancy.

2.2.2. Functional state matrix

The transformed power needs to be delivered to other electrical units through the output ends of the system. Therefore, the number of operational line-out units of substations is set as a parameter for the functional state. Through Monte Carlo simulations of the substation's network functional model, post-earthquake functional states of various types of equipment are obtained. This study proposes a network connectivity matrix **S** to indicate the operational status of the line-out units. In addition, an equipment electrical load matrix **P** is established to represent the power-load capacity of various types of equipment, as shown in Eqs. (2), and (3).

$$\mathbf{S}=\begin{bmatrix} S_1^1 & S_1^2 & \cdots & S_1^N \\ S_2^1 & S_2^2 & \cdots & S_2^N \\ \vdots & \vdots & \ddots & \vdots \\ S_I^1 & S_I^2 & \cdots & S_I^N \end{bmatrix} \tag{2}$$

$$\mathbf{P}=\begin{bmatrix} P_1^1 & P_1^2 & \cdots & P_1^E \\ P_2^1 & P_2^2 & \cdots & P_2^E \\ \vdots & \vdots & \ddots & \vdots \\ P_I^1 & P_I^2 & \cdots & P_I^E \end{bmatrix} \tag{3}$$

Herein, S_i^n represents the operating state of the nth group of line-out units in the ith sampling, N represents the number of line-out units in a substation system, I represents the number of Monte Carlo samples, P_i^e represents the power-load capacity of the eth type of equipment in the ith sampling, and E represents the number of equipment categories in a substation system. The operational status quantities N_{Ci} and N_{Pi} of the line-out units considering network connectivity and equipment load capacity are obtained based on the seismic simulation results, as specified in Eqs. (4), and (5). Consequently, the remaining operational status quantity N_{Ri} of the line-out units in a substation system is obtained, as shown in Eq. (6).

$$N_{Ci}=\sum_{n=1}^{N}S_i^n \tag{4}$$

$$N_{Pi}=\frac{\min\{P_i^1:P_i^E\}}{P_{out}} \tag{5}$$

$$N_{Ri}=\min\{N_{Ci},N_{Pi}\} \tag{6}$$

Herein, $\min\{P_i^1:P_i^E\}$ represents the lower limit of the power-load capacity of equipment in a substation system in the ith sampling, and P_{out} represents the power-load capacity of various groups of line-out units of the substation system. Based on the functional characteristics of a substation system, the functional state matrix **N** is established to represent the post-earthquake functional states of the substation, as

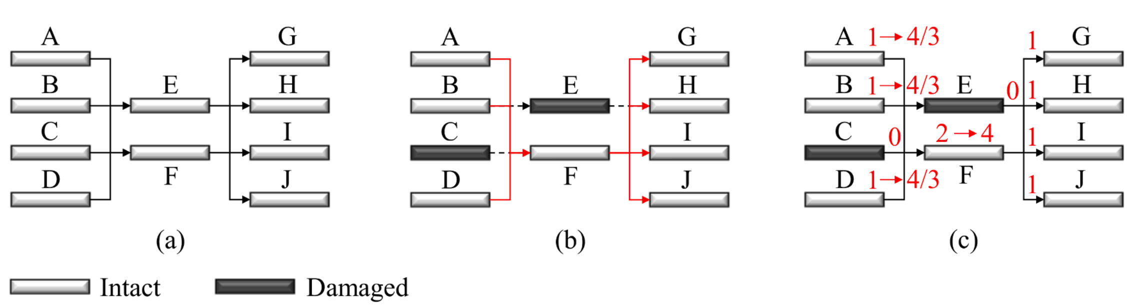

Fig. 2. (a) A network case, (b) The impact of network connectivity on system functionality, (c) The impact of power-load capacity on system functionality.

specified in Eq. (7).

$$\mathbf{N} = \begin{bmatrix} N_{C1} & N_{P1} & N_{R1} \\ N_{C2} & N_{P2} & N_{R2} \\ \vdots & \vdots & \vdots \\ N_{CI} & N_{PI} & N_{RI} \end{bmatrix} \tag{7}$$

The voltage levels and structural networks of substation systems vary across different regions. Therefore, the quantity of line-out units at the output terminal varies. To improve the applicability of functional assessment parameters in the probability-based seismic resilience framework, normalization is applied to the functional states of the substation output terminal. The functional state K_i is established to characterize the functional level of substation systems, as shown in Eq. (8).

$$K_i = \frac{N_{Ri}}{N} \tag{8}$$

2.2.3. Probability-based functional state model

Seismic vulnerability curves of equipment determine that the system's functional state is a conditional probability issue, thereby leading to uncertainty in the function of substations. Combining equipment seismic vulnerability, network node connectivity, and probability distribution functions, a probability-based functional state model for substations is proposed, as shown in Fig. 3.

First, it is essential to determine the uncertainty of equipment operating states. The seismic vulnerability curve is used to represent the reliability of equipment. When IM $= a$, the functional failure probability of equipment is P_a. The operating state of the equipment is determined by comparing P_a with a random number x, thereby assessing the operating states of E types of equipment in the substation. This approach quantitatively analyzes the seismic reliability of equipment and converts functional conditional probabilities into deterministic operating states.

Subsequently, the substation system is mapped into a directed logic graph using Simulink modules, and a network functional model is constructed. The power-load capacity of equipment and system connectivity are determined based on the equipment's operating states. The network connectivity matrix **S** and equipment electrical load matrix **P** are obtained through multiple Monte Carlo simulations, thereby determining multiple sets of post-earthquake functional state parameters for the substation.

Finally, the probabilistic functional states of the substation are determined. The operational status quantities of line-out units in the substation are classified using the functional state matrix **N**. The distribution of system functional states is identified to fit probability distribution functions. The probabilistic seismic performance is upscaled from the local to the global scale based on the network model and the Monte Carlo algorithms. This approach quantifies the uncertainty of the functional states of a substation.

2.3. Probabilistic functional recovery model

2.3.1. Recovery time model

Equipment in a substation is damaged and requires replacement to restore system functionality after an earthquake. However, the replacement of damaged equipment is influenced by factors such as equipment transportation in practical engineering, equipment hoisting, and the experience of repair teams. Therefore, the functional recovery time of individual pieces of equipment is uncertain. Because this study focuses on the functional recovery process of substations, we do not consider traffic congestion or impassable conditions during the equipment transportation process.

Currently, there is no specific reference data for the functional recovery time of electrical equipment in substation systems. Through discussions with maintenance and emergency repair personnel from power utilities, we observed that the replacement time for equipment is influenced by the experience of the repair team and the type and volume of equipment. But it generally follows a normal distribution function. Therefore, we assumed that the functional recovery time of individual equipment follows a normal distribution in subsequent resilience assessments. The probability density function $f(t_e)$ for the recovery time of the e type of equipment is given by Eq. (9), where μ represents the mean, and σ represents the standard deviation.

$$f(t_e) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t_e-\mu}{\sigma}\right)^2} \tag{9}$$

The total recovery time is influenced by the number of damaged devices. Therefore, the post-earthquake functional recovery time T_{ei} for the eth type of equipment is established based on Monte Carlo simulations, as shown in Eq. (10).

$$T_{ei} = N_{ei} t_{ei} \tag{10}$$

Herein, N_{ei} represents the number of damaged devices for the eth type of equipment in the ith sampling, and t_{ei} represents the recovery time for an individual device in the ith sampling. It is difficult to ensure that only one type of equipment is damaged in a substation. Therefore, the post-earthquake functional recovery time T_i for E types of equipment is established, and its probability density function is obtained, as shown in Eq. (11).

$$\sum_{e=1}^{E} N_{ei} t_{ei} = T_i \sim N\left(\sum_{e=1}^{E} N_{ei}\mu_e, \sum_{e=1}^{E} N_{ei}^2 \sigma_e^2\right) \tag{11}$$

Herein, μ_e represents the mean value of recovery time for the eth type of equipment, and σ_e represents the standard deviation of the recovery time for the eth type of equipment.

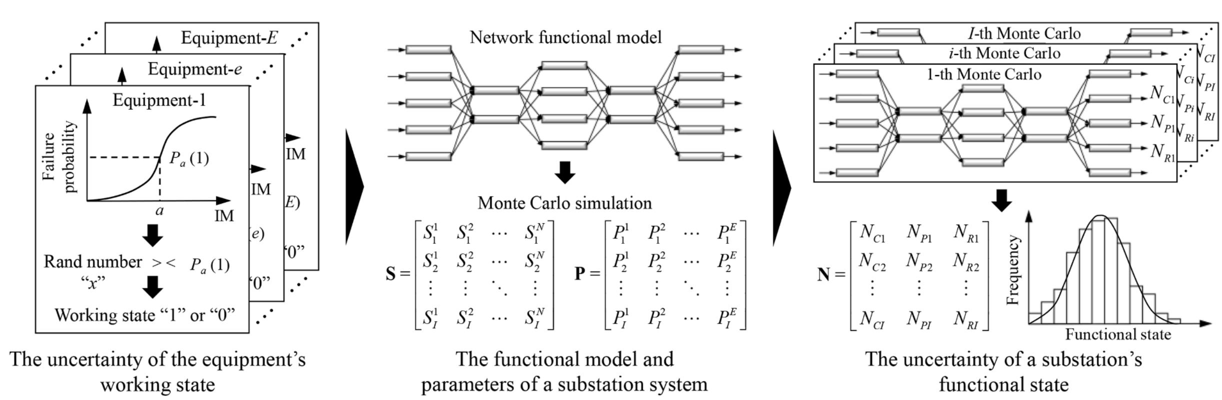

Fig. 3. Probability-based functional state model for substations.

2.3.2. Functional recovery path

It is essential to determine post-earthquake functional recovery strategies and repair equipment for each recovery step after an earthquake. Therefore, the recovery efficiency metric Ef is proposed to quantify the functional recovery efficiency of each recovery step. Because probabilistic parameters based on Monte Carlo sampling are not suitable for deterministic evaluation, the expected value $E(Ef)$ is used to specify the differences in repair efficiency for different recovery steps, as shown in Eq. (12).

$$E(Ef) = \sum_{i=1}^{I} Ef_i P(Ef = Ef_i) = \sum_{i=1}^{I} \frac{\Delta K_i}{T_i} \frac{1}{I} \tag{12}$$

Herein, ΔK_i represents the improvement in the functional state before and after the repair step in the ith sampling, T_i represents the functional recovery time of the recovery step in the ith sampling, and $P(Ef{=}Ef_i)$ represents the probability of the recovery efficiency $Ef = Ef_i$ in the ith sampling. Here, $1/I$ is used to indicate the occurrence probability.

The nodes of the network functional model will change according to the functional recovery process. The functional recovery efficiency for each recovery step is a dynamic parameter. Therefore, a dynamic-based post-earthquake functional recovery analysis framework is proposed to identify the functional recovery paths of substations, as shown in Fig. 4.

Based on the functional characteristics and engineering requirements of a substation, the system's functional recovery strategy is determined, thereby defining the types and quantities of equipment involved in each recovery step. The network functional model of the substation is simulated I iterations using the Monte Carlo algorithm, seeking the expected value $E(Ef_j)$ of recovery efficiency for the jth recovery steps. The recovery step with the highest recovery efficiency is set as the priority recovery path (kth recovery step). Subsequently, restore the functional status of all equipment in the first recovery step and update the network functional model. Repeat this process in a loop ($k = k + 1$), the recovery efficiency of the remaining equipment is simulated through Monte Carlo sampling ($q = q{-}1$). The priority recovery step for each iteration is determined by a step-wise analysis. When the number of iterations equals the number of recovery steps ($k = Q$), the dynamic-based functional recovery analysis is completed, and the functional recovery path of the substation can be obtained.

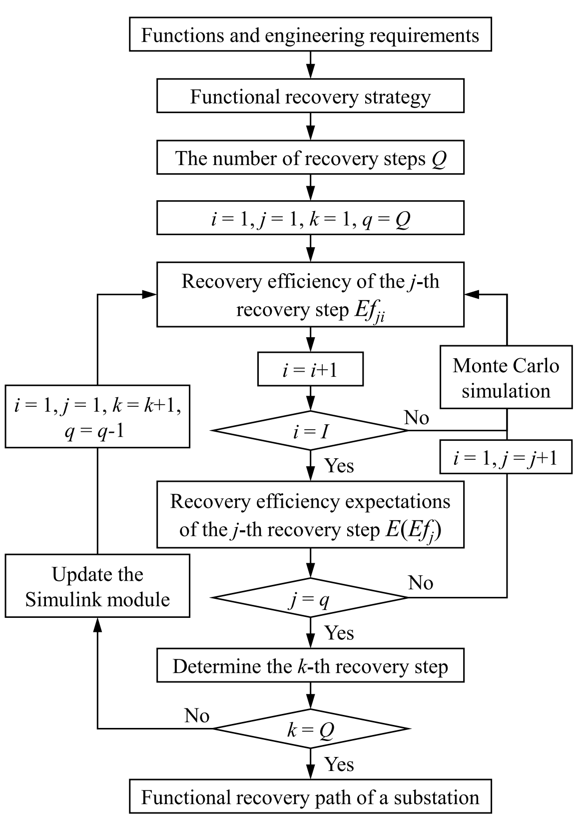

Fig. 4. A dynamic-based functional recovery framework for substations.

2.4. Probabilistic resource constraint model

The recovery time and restoration path of substations are crucial parameters in post-earthquake recovery analysis. However, the functional recovery process is constrained by resource conditions in practical engineering. These resources mainly include economic budgets and the number of emergency repair teams. A sufficient number of repair resources can facilitate a rapid recovery of the substation's functionality. Because of the influence of numerous subjective and objective factors, post-earthquake resource conditions exhibit strong uncertainty.

2.4.1. Post-earthquake economic budget

The economic resource budget refers to whether the substation has sufficient economic resources to replace damaged equipment after an earthquake. One common type of damage is cracking and tilting. If the economic conditions of the substation are insufficient to meet the economic requirements of replacing all damaged equipment, the substation cannot be restored to its original functional state. Therefore, the post-earthquake economic demand E_D is established to assess the economic requirements of the recovery process of substations, as shown in Eq. (13).

$$E_{Di} = \sum_{e=1}^{E} N_{ei} C_e \tag{13}$$

where N_{ei} represents the number of damaged devices of the eth category in the ith sampling, C_e represents the economic cost of replacing a single device of the eth category, including dismantling, transportation, installation, and labor costs. Considering the functional status of equipment, the economic demand for a substation system is uncertain. In addition, to analyze the impact of economic resource budgets on the functional recovery of substations, it is assumed that the time during the equipment transportation process is not considered. Also, we have not yet delved into a comprehensive evaluation and comparison of the cost, benefits, risks, and market competition of seismic performance and post-earthquake recovery techniques.

2.4.2. Post-earthquake emergency repair teams

Emergency repair teams refer to teams that can quickly arrive at the substation for repair work after an earthquake. It mainly includes repair workers and repair facilities. Although increasing the number of repair teams can reduce the recovery time of a substation, the concept of repair teams is relatively vague, making it difficult to be quantitatively assessed. Therefore, to determine the impact of repair teams on the process of restoring the functionality of substations, we assume that one repair team cannot simultaneously replace multiple sets of equipment, and multiple repair teams cannot simultaneously repair a set of equipment. In addition, when different-sized repair teams are involved in post-earthquake recovery, the repair experience and efficiency within each group of repair teams have no difference.

2.5. Seismic resilience metrics

The function of a substation is restored as the repair time increases. However, the functional recovery of a substation differs from the linear recovery characteristics observed in other engineering networks. Functional partitions in a substation operate independently. If the connectivity of some line-out units and the electrical load of a substation meet functional demands, partial functionality of the system can be restored, thereby transmitting part of the electrical energy. Therefore, the functional recovery process of substations exhibits a stepped curve. Compared to the functional recovery time, the duration of earthquakes is extremely brief; hence, the duration of an earthquake is not considered temporarily.

The stepped functional recovery curve $K(t)$ for substations is represented by a simplified network example. The functional recovery process can be divided into four stages: normal operation, functional loss, functional recovery, and total recovery, as illustrated in Fig. 5. Where, t_0 represents the moment of the earthquake occurrence, t_r represents the time when the functional state is fully restored, K_L represents the lost functionality, and K_R represents the remaining functionality after the earthquake. Before the earthquake, the network was in the normal operation stage with a functionality state of 100 % (Fig. 5(a)). However, some equipment was damaged after the earthquake, resulting in a significant reduction in system functionality (Fig. 5(b)). Subsequently, Monte Carlo simulations were conducted based on the dynamic-based functional recovery framework. The different colors on the stepped recovery curve represent the simulation process of various recovery steps (Fig. 5(c)). Finally, the connectivity and functionality of the network system were fully restored, thereby meeting the electrical energy supply and engineering requirements again (Fig. 5(d)).

The key features of seismic resilience include seismic robustness, recovery rapidity, and resource redundancy. Based on the stepped functional recovery curve $K(t)$, the uncertainties in the functional states, functional recovery, and resource constraints of the substation system are quantitatively assessed. This is reflected in the functional recovery curve and seismic resilience assessment of the substation system, as shown in Fig. 6(a). The post-earthquake functional state parameters ($K_{R\text{-}d}$) of the substation are obtained using multiple Monte Carlo simulations. Based on the conditional probability parameters ($P_{R\text{-}d}$) for different functional states, the functional probability distribution function is carried out. This allows for a quantitative assessment of the seismic robustness of substation systems. During the functional recovery process, deterministic analysis of M sets of post-earthquake functional recovery paths is conducted using iterative simulations. The functional recovery rapidity is quantitatively evaluated based on the mean and standard deviation of the functional recovery time. To quantify the resource condition redundancy, including the economic budget (EB) and the number of emergency repair teams (TN), various states of resource condition ($S_{RC\text{-}n}$) are simulated to determine the conditional probability parameters of the functional recovery process of substation systems. This allows for the quantitative assessment of the functional recovery curve and seismic resilience level (R_n) of substation systems.

The three stages of uncertainty are combined with the functional recovery curve and seismic resilience assessment of substation systems, as illustrated in Fig. 6(b). Where Q represents the number of recovery steps of the substation system, K_q represents the functional state of the substation system after the qth recovery step, T_q represents the restoration time for the qth recovery step, $S_{RC(EB,TN)}$ represents the resource constraint state of the substation system, and $T_{RC(EB,TN)}$ represents the variation in the restoration time under different resource constraint states.

Based on the three-stage uncertainty of substation systems, the shaded area in Fig. 6(b) is defined as the seismic resilience metric R, thereby representing the system's ability to resist functional loss and recover, as shown in Eq. (14).

$$R\left(K_R, K_{(1:Q)}, T_{(1:Q)}, S_{RC(EB,TN)}\right) = \int_{t_0}^{t_r} (1 - K(t))dt \tag{14}$$

ehere K_R, $K_{(1:Q)}$, $T_{(1:Q)}$, and $S_{RC(EB,TN)}$ represent the uncertainty parameters in the three stages influencing the seismic resilience of the substation. A smaller seismic resilience metric indicates a stronger seismic resistance and functional recovery capability of a substation.

3. Case study

3.1. A typical 220 kV step-down substation

The applicability of the seismic resilience framework was demonstrated using a typical 220 kV step-down substation. The function of this typical substation is to step down the electrical energy from 220 kV to 110 kV and transmit it to the community through the line-out units. The general plan of the substation is illustrated in Fig. 7(a). It contains five functional zones. Six groups of 220 kV line-in units are responsible for transferring electrical energy into the substation system. Two groups of 220 kV bus bar units connect line-in units with transformer units. Three transformer units step down the electrical energy. Then two groups of 110 kV bus bar units transmit the low-voltage energy to line-out units. Finally, twelve groups of 110 kV line-out units transfer the electrical energy out of the substation. The section diagrams of the line-in units and line-out units are shown in Fig. 7(b) and (c), respectively. In addition, the substation system comprises six types of equipment: horizontal disconnect switches (DSH), vertical disconnect switches (DSV), circuit breakers (CB), current transformers (CT), post insulators (PI), and transformers (TF). These equipment types are distributed across the various functional zones of the substation and are connected through flexible bus bars. Because of the different functions of various devices and their considerable spacing, their operational states do not mutually affect each other. In addition, structures like portal frames and electrical wires typically do not damage under an earthquake. Therefore, they do not affect the functional state of the substation system. Moreover, the impact of bus bars between equipment on the dynamic characteristics of the equipment is a complex study, and little clear data or comprehensive

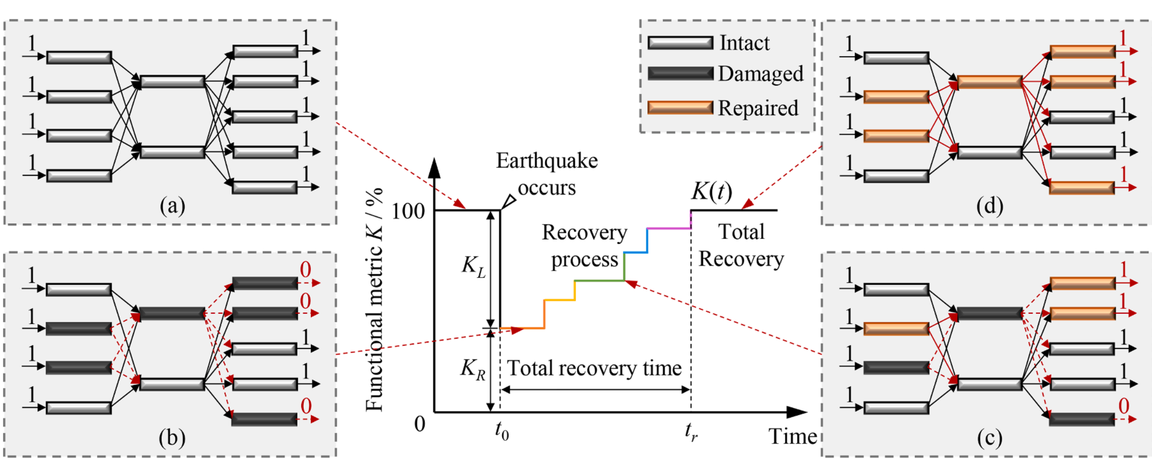

Fig. 5. The stepped functional recovery curve for substations.

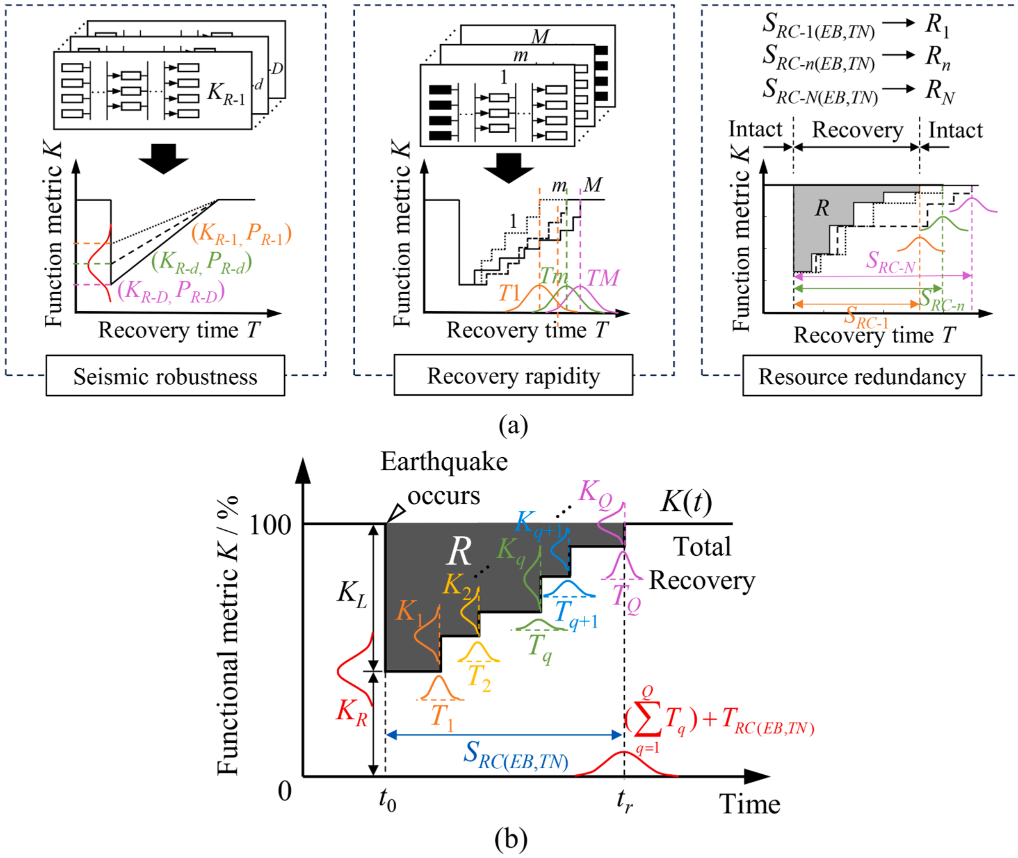

Fig. 6. (a) The quantitative evaluation of three-stage uncertainty, (b) The functional recovery curve and seismic resilience metric based on three-stage uncertainty.

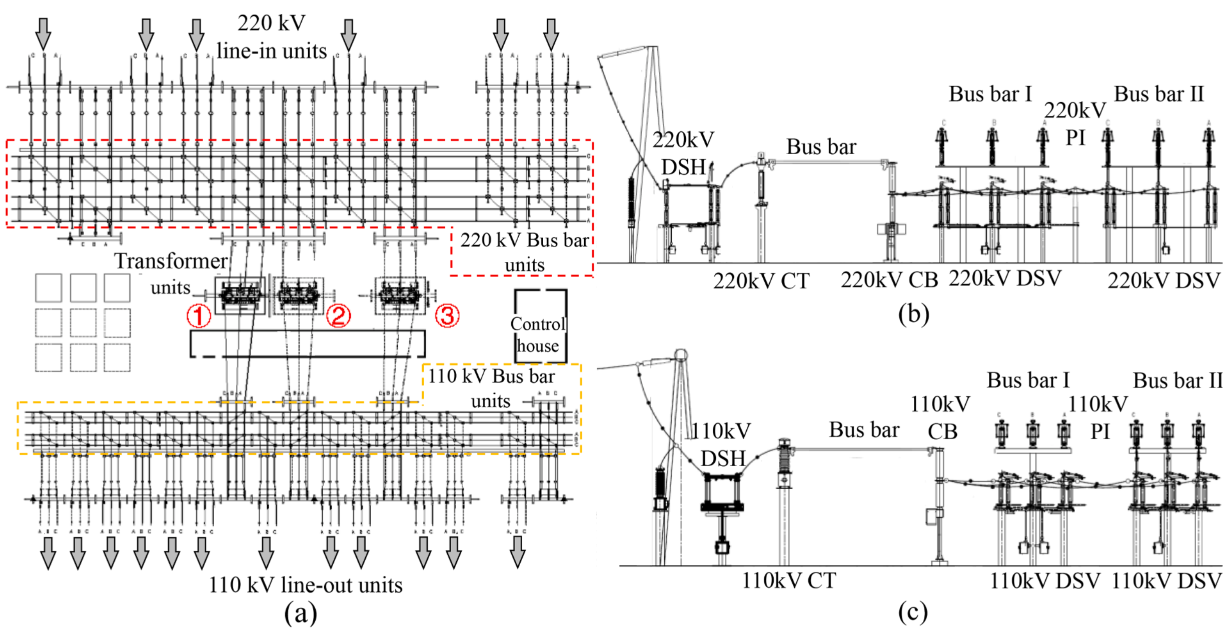

Fig. 7. (a) The general plan of a typical 220 kV step-down substation, (b) Section diagram of 220 kV line-in units, (c) Section diagram of 110 kV line-out units.

information is available as a reference. Therefore, it is insufficient to study the seismic resilience of substations considering the impact of connecting bus bars based on existing research.

The study mainly studies the direct influence of primary earthquake disasters on the seismic capability of substation systems. Therefore, the influence of geological conditions and other secondary disasters is not considered.

3.2. Probabilistic functional model

The electrical equipment is expensive and bulky, making it challenging to conduct vibration table tests. To establish seismic vulnerability curves for various electrical equipment in the substation, seismic vulnerability parameters for 220 kV and 110 kV equipment were obtained based on references [43,44,45], as shown in Table 1. We did not consider the installation of seismic isolation units for equipment. Therefore, the seismic resistance of the equipment will not change. In addition, PGA is widely used and highly reliable. Furthermore, PGA can effectively measure seismic intensity and assess the seismic resilience of substations. Therefore, this study adopts PGA as the IM for the analysis of this typical 220 kV step-down substation.

Based on the network connectivity and redundancy characteristics of the substation system, a Simulink module was employed to construct the connection network of each unit within the typical 220 kV step-down substation. The interconnections of equipment within each functional unit are illustrated in Fig. 8.

Section 2.3.1 emphasizes the distribution characteristics of the replacement time. Therefore, we assumed the replacement time parameters for various types of equipment as shown in Table 2. These parameters were obtained through communication with maintenance and repair personnel. Therefore, they have a high level of reliability. Furthermore, Table 2 serves as a prerequisite for seismic resilience assessment, but it does not affect the applicability of the seismic resilience assessment framework.

3.3. Resource constraint model

The volume and functionality of equipment directly impact the construction costs of the substation system. To obtain the economic cost of various backup equipment, the economic cost budgets for different types of equipment in a typical 220 kV step-down substation system were obtained through communication with the operational personnel and referencing references [46,47,48], as shown in Table 3. The economic cost includes dismantling, transportation, installation, and labor expenses.

4. Results and discussion

4.1. Post-earthquake functional state

The seismic simulation was conducted on the functional model of the typical 220 kV step-down substation. We found that 1000 Monte Carlo samples effectively reflect the probability of the substation system's post-earthquake functional states and recovery time. The three sets of parameters in the functional state matrix were classified, and the probability distribution of the substation system's functional states was obtained through probability analysis. This approach can reflect the conditional probability of system functional states under different earthquake intensities and considerations, as shown in Fig. 9. There are twelve line-out units in this typical 220 kV step-down substation. Bar charts are used to represent the occurrence frequency of various functional states in the Monte Carlo samples, with the left axis labeled in black. Line charts depict the cumulative conditional probabilities of functional states, with the right axis labeled in red.

Fig. 9 shows that the functional state of the substation system remains essentially intact when PGA $\leq$ 0.1 g. However, the number of equipment failures in the substation system increases as the earthquake intensity increases. Because the uncertainty in equipment functional states affects the substation's functional states, the bar charts become flatter, indicating a gradual increase in the discreteness of the system's functional states. When PGA $>$ 0.5 g, the substation loses its functionality completely, so we do not go further research in this study.

Fig. 9(b) and (c) exhibit a higher level of similarity, indicating that the power-load capacity of equipment significantly impacts the post-earthquake functional state of the substation system more than network connectivity. Furthermore, when 0.3 $g \leq$ PGA $\leq$ 0.4 g, the substation system rarely experiences a situation where a few line-out units continue to operate normally. The reason is that the seismic resistance of the low-voltage side equipment is higher than that of the high-voltage side equipment. Therefore, the function of high-voltage side equipment directly affects the system's functional state. If the high-voltage side equipment is completely damaged, the substation system loses functionality. While some high-voltage side equipment's functions remain intact, the substation system operates based on the power-load capacity of the high-voltage side equipment. Consequently, power-load capacity and functional states of high-voltage side equipment are the primary factors influencing the post-earthquake functional state of the substation system.

4.2. Functional recovery time and path

The functional recovery process of a substation is influenced by resource conditions. To assess the uncertainty in the functional recovery time and seismic resilience of the substation system, it is assumed that only one emergency repair team is responsible for functional recovery, and economic resource constraints are temporarily not considered. Section 4.4 will provide a further assessment and analysis of resource constraint uncertainty.

Based on the post-earthquake functional states of equipment under different earthquake intensities, the functional recovery time parameters for the substation system were determined. The probability distribution for functional recovery time was obtained based on Monte Carlo sampling results, as shown in Fig. 10. Bar charts are used to represent the occurrence frequency of recovery time in the Monte Carlo samples. A normal distribution function was fitted to obtain the mean μ and standard deviation σ.

Fig. 10 shows that the post-earthquake recovery time for the substation system is mostly less than three days when PGA $\leq$ 0.2 g. When PGA $=$ 0.3 g, it takes approximately two weeks to complete the post-earthquake functional recovery. When PGA $\geq$ 0.4 g, the increased number of damaged pieces of equipment significantly prolongs the post-earthquake recovery time, requiring at least one month for post-earthquake recovery. In addition, the variability in post-earthquake recovery time increases with an increase in earthquake intensity. Therefore, the differences in post-earthquake functional recovery efficiency are highlighted under a strong earthquake. Because equipment is rarely damaged when PGA $=$ 0.1 g, the functional recovery time is short, and no detailed recovery strategy is needed. Several pieces of damaged equipment can be replaced to restore system functionality. Therefore, further research is not required for this scenario.

Because the equipment in different functional zones within the substation has a significant impact on the system's functional state, functional zones were used as recovery steps. The repair efficiency of each functional zone was evaluated through Monte Carlo simulations. Subsequently, the post-earthquake recovery path of the substation system and the probability density of recovery time for each recovery step were determined following iterative analysis, as shown in Fig. 11. The horizontal axis represents the functional zones corresponding to each

Table 1
Seismic vulnerability curve parameters of 220 kV and 110 kV equipment.

Equipment	220 kV DSH	220 kV DSV	220 kV CT	220 kV CB	220 kV PI	110 kV DSH	110 kV DSV	110 kV CT	110 kV CB	110 kV PI	TF
θ /g	0.57	0.54	0.42	0.53	0.7	0.82	0.75	0.75	0.7	0.8	0.59
β	0.22	0.34	0.27	0.33	0.42	0.59	0.7	0.7	0.7	0.42	0.56

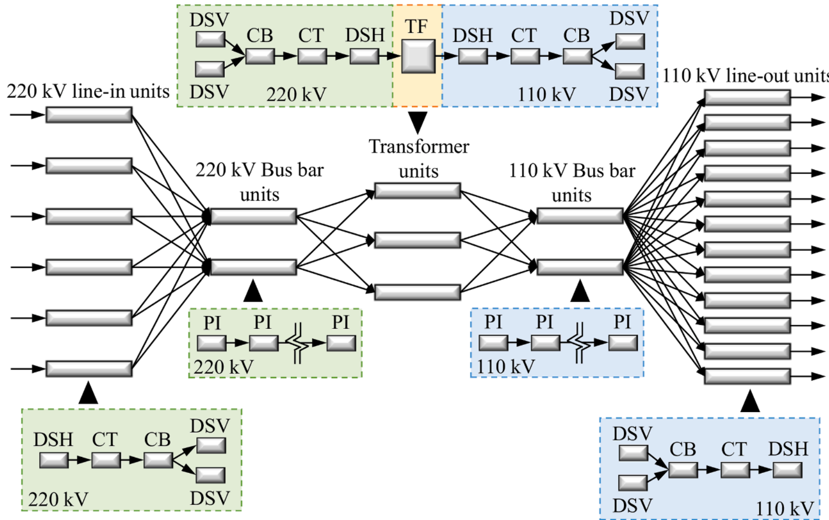

Fig. 8. Network functional model of a typical 220 kV step-down substation.

Table 2
Replacement time parameters of equipment (unit: day/team).

Equipment	220 kV DSH	220 kV DSV	220 kV CT	220 kV CB	220 kV PI	110 kV DSH	110 kV DSV	110 kV CT	110 kV CB	110 kV PI	TF
μ /g	3	3	3	3	1	2	2	2	2	0.6	5
σ	0.8	0.8	0.8	0.8	0.2	0.6	0.6	0.6	0.6	0.1	1

Table 3
Economic cost budget of equipment (unit: yuan/set).

Equipment	Total cost
220 kV DSH	80,000
220 kV DSV	99,000
220 kV CT	16,4000
220 kV CB	131,000
220 kV PI	40,000
TF	1,665,000
110 kV DSH	62,000
110 kV DSV	80,000
110 kV CT	13,5000
110 kV CB	94,000
110 kV PI	33,000

recovery step, while the vertical axis represents the recovery time after each recovery step.

Fig. 11 determines the post-earthquake recovery paths and quantifies the recovery time for each repair step using normal distribution parameters. It shows that the bus bar units have the highest priority in post-earthquake functional recovery, and their recovery time is quite short. Following that, it is essential to restore the functionality of the transformer units as quickly as possible to ensure the substation system's electrical energy conversion capability. Because of the numerous equipment components at the line-in and line-out units, their recovery times are relatively longer. In addition, the functional recovery of 220 kV equipment takes precedence over 110 kV equipment. Therefore, it confirms that the functional state of high-voltage side equipment is a primary factor influencing the functionality of the substation system.

4.3. Functional recovery curves and seismic resilience metrics

Based on the functional recovery path of the substation system, the improvement in functional status and recovery time for each recovery step was obtained using Monte Carlo simulations. Probability assessments were conducted for the functional status and recovery time of each recovery step. Finally, the probability distributions of the substation system's functional recovery curves were determined, as shown in Fig. 12.

Fig. 12 assesses the conditional probability of the functional recovery extent of the substation system. When PGA = 0.2 g, the substation has an 80 % probability of ensuring that the functionality is greater than 83.3 %. At PGA = 0.3 g, as long as the recovery time reaches 5 days, the substation has a probability of over 95 % to guarantee 50 % of the function. When PGA = 0.4 g, the substation has a 95 % probability of ensuring complete functional recovery in less than 42.5 days. However, when PGA = 0.5 g, a significant amount of equipment is damaged. Therefore, the uncertainty in the functional recovery process is mainly concentrated in mid-term recovery.

Because the system's functional recovery curve directly influences the seismic resilience metrics, the confidence interval for the seismic resilience metrics of the typical 220 kV step-down substation was obtained based on the probability distribution of the functional recovery curve, as detailed in Table 4. It represents the confidence intervals of the seismic resilience under different earthquake intensities, thereby revealing the development of the seismic resilience metrics. The seismic resilience metrics of the substation increase rapidly when PGA > 0.3 g, indicating that the sensitivity range of the seismic capability for this typical 220 kV step-down substation is located between 0.3 g and 0.4 g.

Based on the probabilistic-based seismic resilience assessment framework for substation systems, the probability distribution of functional recovery curves and the confidence interval for the seismic resilience metrics of a typical 220 kV step-down substation were obtained. This quantitatively evaluates the impact of uncertainty on the functional recovery and seismic resilience of the substation system. In addition, the results from this section can be used for reliability and risk analysis of functionality and resilience. This fulfills the seismic analysis requirements for various substation systems and other engineering networks.

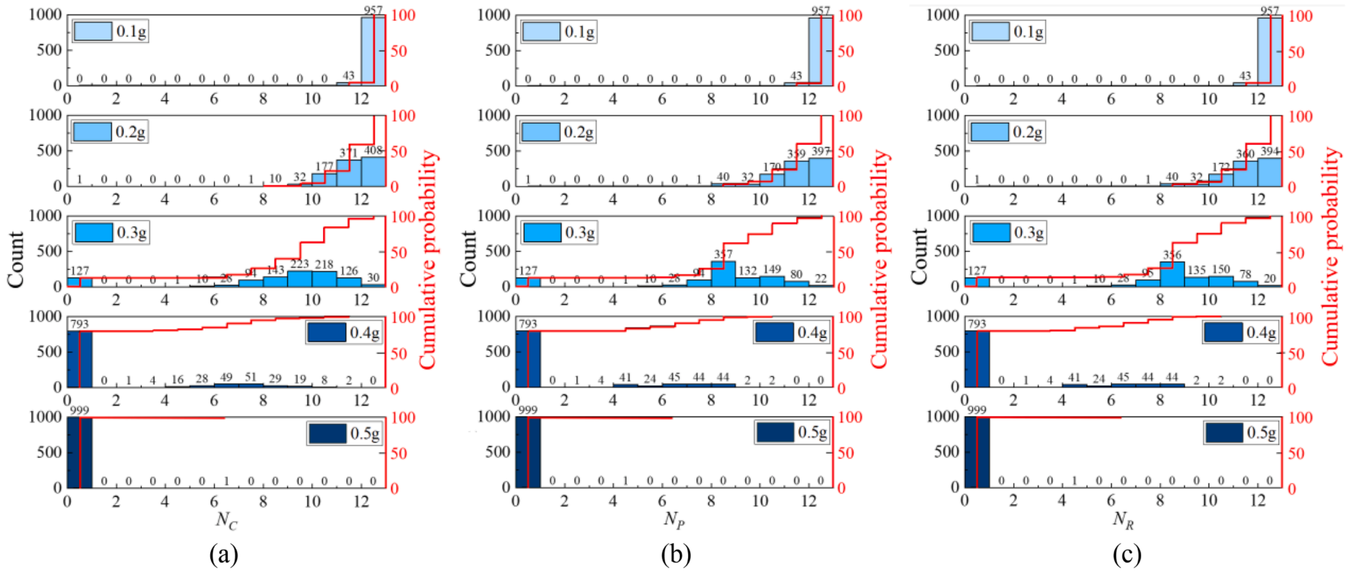

Fig. 9. Post-earthquake functional states of the substation system, (a) N_C, (b) N_P, (c) N_R.

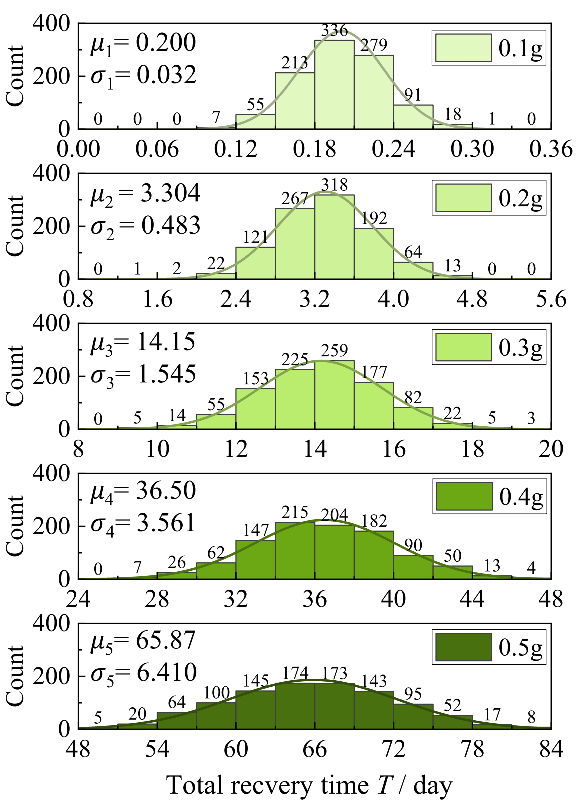

Fig. 10. Post-earthquake recovery time of the substation system.

4.4. Variation of seismic resilience with resource constraint

The functional states and economic costs of various equipment were obtained using Monte Carlo simulations. A probability density curve for the economic requirements of the substation system was fitted, as shown in Fig. 13.

Fig. 13 shows that the post-earthquake economic demand probability density curve exhibits a tri-peak state. The reason is that the functional state of transformer equipment directly influences economic demand. Because the substation's function is basically intact under small seismic effects, it primarily shows a single-peak state when PGA = 0.2 g. As the seismic intensity increases, the probability of functional loss in transformers gradually rises, resulting in an increase in the number of peaks and a more obvious trend in the economic demand probability density curve. Therefore, enhancing the seismic resilience of transformers is a crucial method to reduce post-earthquake economic demand.

The post-earthquake economic budget and the number of emergency repair teams directly impact functional recovery efficiency and seismic resilience levels. However, these resource conditions are constrained by the importance of substations and regional economic conditions, leading to considerable uncertainty. Because the impact patterns of resource conditions on the substation system are similar under different seismic intensities, PGA = 0.4 g was taken as an example. The seismic resilience mean value is considered a quantifiable standard for resource condition analysis. The limitations of resource conditions on the seismic resilience metrics of the substation system were obtained, as shown in Fig. 14.

Fig. 14 shows that increasing the number of repair teams and the economic resource budget significantly reduces seismic resilience metrics. However, increasing the repair team quantity does not significantly reduce the seismic resilience metrics when the economic resource budget is limited. This illustrates that because the economic budget is insufficient to meet the economic demands for functional restoration, it is not possible to effectively reduce the seismic resilience metrics. In addition, when the economic resource budget exceeds 2.4 million yuan and fully meets the economic demands for functional restoration, additional economic resources exceeding 2.4 million yuan do not decrease the seismic resilience metrics of the substation system if the number of repair teams remains unchanged. Only increasing the number of repair teams can significantly reduce the seismic resilience metrics. This indicates that resource constraints not only limit the seismic resilience of the substation system but also have mutual constraint relationships among resource conditions. Appropriate resource conditions can maximize post-earthquake functional recovery efficiency, thereby reducing seismic resilience metrics.

4.5. Seismic resilience improvement discussion

Through seismic resilience probability assessment of the typical 220 kV step-down substation system, we identified important equipment and seismic-sensitive zones within the substation system. Based on the seismic capacity and the post-earthquake functional recovery process of

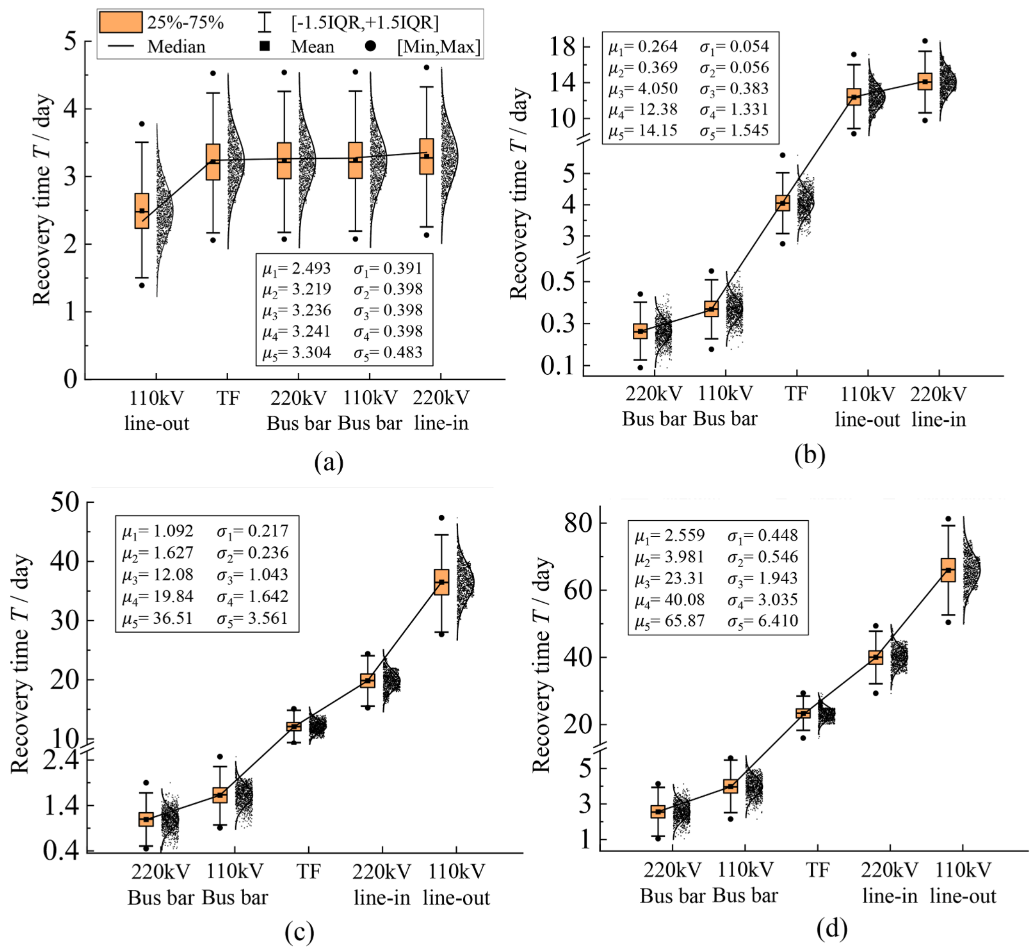

Fig. 11. Functional recovery time and path of substation system, (a)0.2 g, (b)0.3 g, (c)0.4 g, (d)0.5 g.

the substation system, this section proposes several measures to improve the seismic resilience of substation systems.

1) During the analysis of post-earthquake functional recovery paths in the substation, the bus bar units had the highest priority for post-earthquake functional recovery. This indicates that bus bar units play a crucial role in connecting various functional zones within the substation system. Therefore, bus bar units are considered critical equipment in substation systems and should be prioritized for repair. This aligns with the principle in power systems that bus bar units should be fortified to the highest standards. Ensuring the normal operation of bus bar units can reduce post-earthquake functional losses and improve post-earthquake functional recovery efficiency, thereby significantly enhancing the seismic resilience of substation systems.
2) The functional failure of transformers leads to a tri-peak state in the post-earthquake economic demand probability density curve. This indicates that the functional status of transformers directly affects the post-earthquake direct economic losses of the substation. In addition, considering the cost of various electrical equipment, maintenance expenses, as well as the importance of electrical functionality, many power companies designate transformers as critical components within substation systems. Therefore, it is essential to install base isolation and friction dampers for transformers to reduce its seismic response. The approach reduces post-earthquake recovery time and improves the seismic reliability of the substation system, thereby improving the seismic resilience level.
3) According to the seismic resilience assessment results, we found that the seismic intensity-sensitive range of the substation system lies between 0.3 g and 0.4 g. Therefore, the economic budget and resource allocation should be adjusted based on the active seismic intensity range of the substation's location. Insufficient resource conditions may result in severe functional losses and a decrease in seismic resilience. Conversely, excessive resource conditions may lead to resource surplus and redundancy. By adjusting resource conditions, the seismic intensity-sensitive range of the substation system can be shifted away from the active seismic intensity range of the area. This approach enhances the seismic resilience level of the substation system. Furthermore, there exists a mutual constraint relationship among resource conditions. Appropriate resource conditions can maximize the seismic capacity and post-earthquake functional recovery efficiency of substation systems.

5. Conclusions

This study built a probabilistic framework to assess seismic resilience for substation systems. This framework divides the uncertainty of seismic resilience into three stages: functional state, functional recovery, and resource constraints. A probabilistic functional state model was proposed for substations, considering the structural and electrical functional characteristics. Based on network connectivity and equipment power load capacity, a network functional model was established, and a functional state matrix based on probabilistic parameters was constructed. The probabilistic seismic performance is upscaled from the local to the global scale based on the network model and Monte Carlo algorithms, quantifying the uncertainty of the functional state of substation systems. Subsequently, based on the uncertainty of functional recovery time for substations, the probability density functions for the

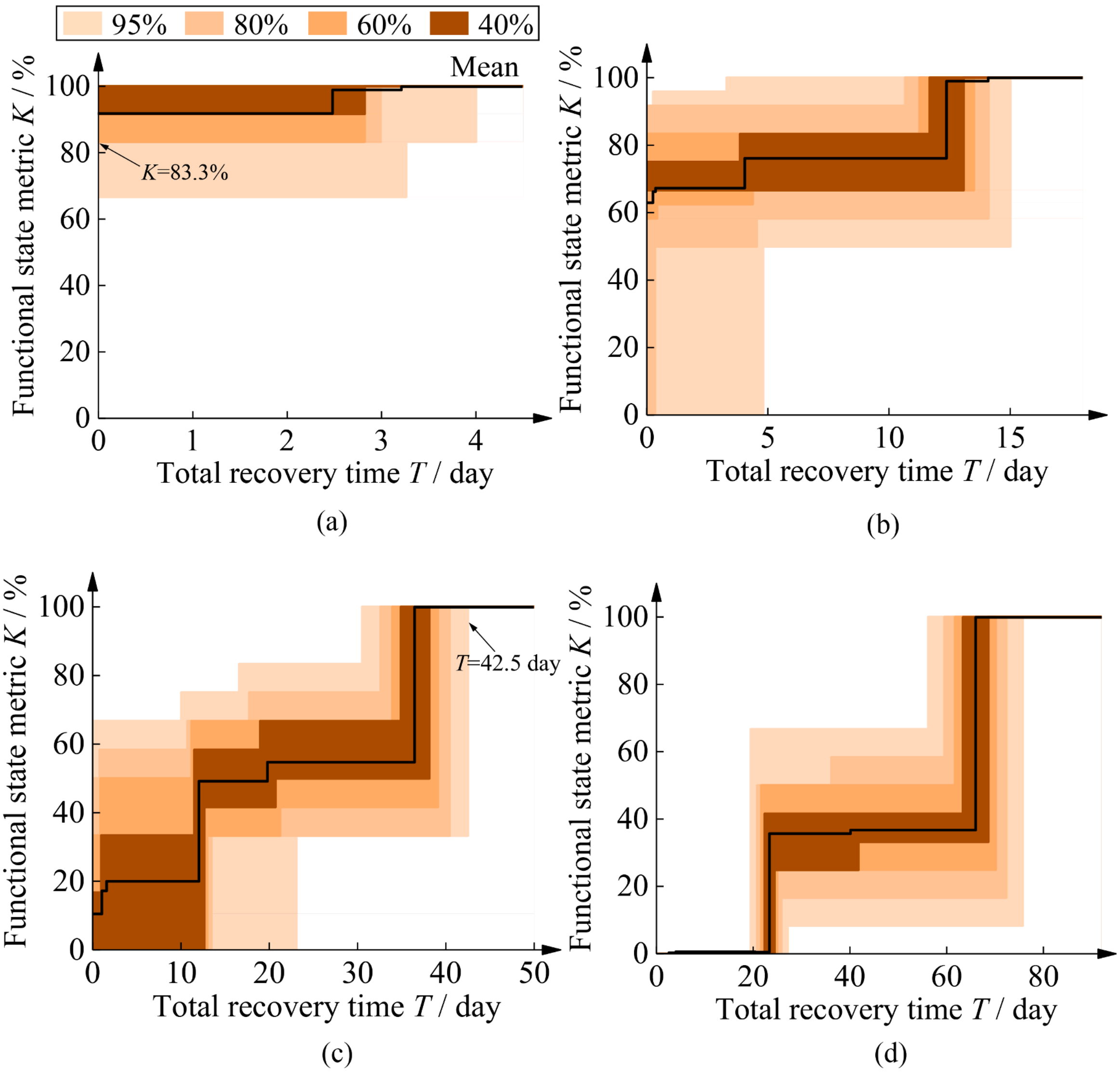

Fig. 12. Probability distribution of the substation's functional recovery curve, (a)0.2 g, (b)0.3 g, (c)0.4 g, (d)0.5 g.

Table 4
Confidence interval of seismic resilience metrics.

PGA	Confidence value								Mean value
	40 %		60 %		80 %		95 %		
	Min	Max	Min	Max	Min	Max	Min	Max	
0.2 g	0	0.23	0	0.47	0	0.50	0	1.21	0.21
0.3 g	2.27	4.36	1.88	4.70	0.89	6.42	0.15	9.90	3.34
0.4 g	16.27	26.04	13.33	28.88	10.59	31.42	7.31	36.01	21.25
0.5 g	46.23	55.24	41.71	58.82	38.25	64.55	31.74	71.63	50.30

recovery time of various types of equipment were established. A dynamic-based functional recovery framework was constructed for substations, determining the functional recovery path of the substation system through iterative simulation. Finally, considering economic resource requirements and repair teams, the impact of uncertain resource conditions on functional recovery was identified. Based on the functional recovery characteristics of substation systems, a stepped functional recovery curve and seismic resilience metrics were established. This transformed the three-stage uncertainty parameters into key resilience features, thereby achieving a quantitative assessment of the seismic resilience of substations.

The seismic resilience assessment of a typical 220 kV step-down substation was conducted. The probability parameters for post-earthquake functional states and recovery times were determined. The probability distribution of functional recovery curves and the confidence interval for the seismic resilience metrics were obtained based on the functional recovery path. Considering the constraining effect of resource conditions on system functionality, the post-earthquake economic demand probability density curve was derived. We revealed mutual constraint relationships among resource conditions. The effectiveness and applicability of the proposed resilience framework were demonstrated through this case study. In addition, the framework can be

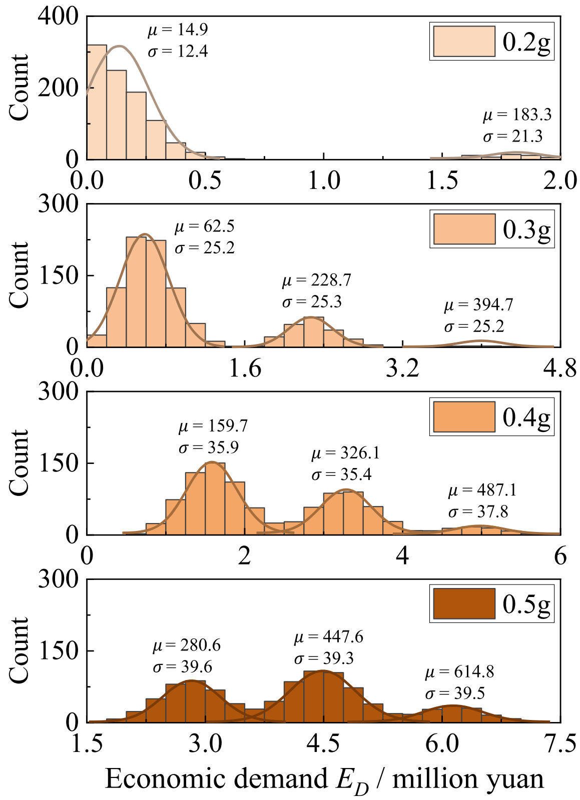

Fig. 13. Post-earthquake economic demand of the substation system.

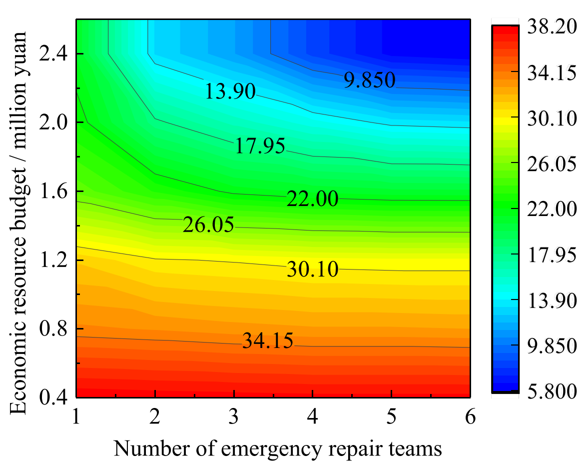

Fig. 14. Variation of seismic resilience metrics with resource constraint.

developed and improved based on the functional characteristics of other engineering networks. The functional recovery curves are adjusted according to engineering requirements to achieve reliable assessments of functional state and uncertain analyses of seismic resilience.

However, Monte Carlo simulation involves a certain degree of randomness, and certain assumptions were made in the functional recovery process of this study. In seismic resilience frameworks, the impact of connecting bus bars on the seismic performance of interconnected equipment has not been adequately considered, and the regional economic losses caused by power outages have not been studied. Therefore, these aspects need further research. In future studies, owing to resource conditions directly affect the seismic resilience of substation systems, a comprehensive evaluation of the economic benefits, risks, and market competition associated with seismic reinforcement and post-earthquake recovery techniques should be conducted. It is essential to rationally allocate resources within limited economic budgets and find the optimal resilience improvement strategies. Furthermore, we are currently considering the impact of multidimensional seismic intensity measures on resilience assessment. Therefore, the differentiated resilience assessments for substations based on various intensity measures are a primary issue for future research.

CRediT authorship contribution statement

Xiao Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Qiang Xie:** Supervision, Resources, Investigation, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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