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Mobile Energy Storage System Scheduling Strategy for Improving the Resilience of Distribution Networks under Ice Disasters

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Abstract: The distribution system is easily affected by extreme weather, leading to an increase in the probability of critical equipment failures and economic losses. Actively scheduling various resources to provide emergency power support can effectively reduce power outage losses caused by extreme weather. This paper proposes a mobile energy storage system (MESS) scheduling strategy for improving the resilience of distribution networks under ice disasters. First, the influence of wind and ice loads on power transmission lines is analyzed, and a detailed fault statistical model of transmission lines under an ice disaster is established. Then, the MESS scheduling problem considering the coupling of transportation-distribution networks is transformed into a two-stage optimization problem. The first stage determines the optimal configuration scheme for MESS, and in the second stage, the optimal path selection for MESS can be obtained. Finally, the effectiveness and feasibility of the algorithm proposed in this paper are verified through an improved IEEE-33 node testing system.

Keywords: ice disasters; distribution networks; mobile energy storage system (MESS); two-stage optimization

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1. Introduction

In recent years, extreme disasters have led to frequent power outages in the power grid. The resilience of the distribution network reflects the ability of the distribution system to withstand disasters and restore power supply, which has received widespread attention [1,2]. In addition, in response to the dual crises of energy depletion and environmental pollution, a large number of distributed generators (DGs) and alternative loads have been connected to the distribution network, providing a solution for load recovery [3]. Therefore, effectively utilizing various distributed resources before and after disasters to reduce power outage losses is of great significance for improving the resilience of distribution networks [4].

Ice disasters occur particularly frequently in natural disasters. In recent years, ice disasters have become increasingly frequent in many southern regions of China, posing a huge threat to the safety and stability of the power system. Especially in 2008, the Southern Power Grid suffered extremely severe freezing disasters, which caused a total of 7541 10 kV and above transmission lines to shut down and other significant losses. The power grid suffered huge economic losses and faced a huge threat to safe operation [5]. Therefore, many scholars have conducted research on optimal repair scheduling and recovery of power systems. Reference [6] proposes an optimization model for emergency repair of transmission networks; Reference [7] establishes an ice melting and repair model for distribution networks with distributed power sources; and reference [8] adopts a taboo search algorithm to optimize the decision-making model of DC ice melting in the power grid. reference [9] proposes a collaborative optimization model for ice melting strategy and unit combination; references [10–12] consider multiple influencing factors to establish an ice disaster risk assessment model and quantify and improve the resilience and recovery ability of the power system; reference [13] quantifies the spatiotemporal impact of ice disasters on components and establishes an active scheduling model; and reference [14] establishes a glaze icing growth model based on heat balance theory. However, in severe disasters, the self-recovery ability of the power system is limited. By scheduling mobile power sources, the safety and stability of the power system can be significantly improved.

Among the resources available for distribution network scheduling, the mobile energy storage system (MESS) is an effective elastic resource suitable for enhancing system resilience in various response stages and is expected to become one of the most promising technologies in the distribution network. Load recovery considering mobile resources has also received attention [15–17]. MESS is a vehicle-mounted container battery energy storage system with standard interfaces that allows for plug-and-play to cope with extreme weather conditions [18]. reference [19] demonstrates the economic feasibility of mobile energy storage by optimizing investment and operation during natural disasters. reference [20] optimizes the access location of MESS with the goal of minimizing load shedding when the distribution network loses power to the main network. reference [21] minimizes the cost of load reduction through multistage scheduling of MESS based on multiple planned microgrids. In response to the issue of post-disaster user satisfaction, reference [22] proposed a dynamic islanding equilibrium recovery strategy for distribution networks that considers emergency power vehicle scheduling. reference [23] proposes a joint recovery scheme that coordinates network reconstruction and MESS scheduling and establishes a MESS scheduling model based on spatiotemporal networks. reference [24] achieved rapid recovery of critical loads through coordinated scheduling of MESS and line maintenance teams. The above research only focuses on the post-disaster recovery stage and does not consider the role of mobile resources in the pre-disaster prevention stage. At present, there are a few studies considering the layout of MESS before disasters. reference [25] considers the impact of typhoon disasters on distribution lines and uses a three-layer robust optimization model to provide a planning plan for MESS. reference [26] proposes a two-stage stochastic programming method before disasters, which utilizes a stepwise hedging algorithm to determine the allocation quantity and location of MESS. reference [27] positions mobile emergency vehicles based on load demand and priority before a disaster and restores the load by dispatching emergency vehicles after a distribution network failure. However, the preconfiguration of the number of emergency vehicles was not considered, and the number of islands was set as a constant in the radiation topology constraint of the distribution network. The above research utilizes mobile power sources independently or in conjunction with fixed resources for load recovery, with less consideration given to power output uncertainty and multisource collaborative operation, and neglects the impact of transportation network status on MESS scheduling in disaster scenarios.

In addition, from the perspective of scheduling emergency repair resources after disasters, existing mobile energy storage scheduling schemes can be classified into two categories. The first type is to restore the current state after a disaster has occurred and the fault state assessment has been completed. Resource allocation is completed at once without considering the sequential process of system gradual recovery and state changes. reference [28] proposes a two-stage sequential framework for preconfiguration and real-time scheduling of moving generators to segmented locations in the distribution system. reference [29] develops resource allocation for electric vehicles and mobile energy storage to proactively prepare for extreme weather events but does not provide a method for determining the consequences before and after a disaster. In reference [30], a microgrid is formed using mobile power sources and distributed generators to reduce load loss. reference [31] proposes a load recovery method based on microgrids. However, resource allocation involves scheduling MESS in a one-time manner before or in the early stages of a disaster, rather than optimizing temporal and spatial behavior through the recovery process. Therefore, the mobility and flexibility of mobile energy storage fleets are insufficient. The second type is to consider the state changes during the system recovery process and schedule multiple time periods. reference [32] proposes an elastic solution for post-disaster recovery of distribution networks, including scheduling of maintenance personnel, scheduling of mobile generators, and network reconstruction. However, the mobile power sources in these studies are mobile generators and cannot be simply applied to MESS, which requires charging decisions. Considering the charging and discharging process of mobile energy storage, it increases the complexity of the problem.

To sum up, for the dispatching of MESS, the dynamic update of system damage information in the distribution network should be considered, and various repair resources in the system should be coordinated to achieve the best repair effect. In this paper, a MESS scheduling strategy for improving the resilience of distribution networks under ice disasters is proposed. The innovation points of this paper can be summarized as follows:

(1) Currently, there is little research on power system recovery after ice disasters that takes into account the participation of MESS. On the other hand, the assessment of the consequences of natural disasters is often carried out after the occurrence of natural disasters, and the assessment and determination of scheduling strategies may take several hours, which will further expand the range of fault impact and increase economic losses. In this paper, a MESS scheduling strategy before an ice disaster is proposed. By combining meteorological information and fault scenarios using Monte Carlo methods, it can accurately depict the impact of ice disasters on the power system and avoid conservative decision-making.
(2) At present, the transportation network and power energy network are closely coupled, and the damage and congestion of transportation networks caused by ice disasters may affect the timely delivery of MESS, which has often been ignored in previous studies. Therefore, the optimal path selection problem is also a complex but necessary consideration factor in MESS scheduling. The strategy proposed in this paper is a two-stage optimization problem. In the second stage, we fully consider the traffic situation, which can provide a fast-reaching strategy.

The structure of this paper is arranged as follows: first, the modeling method for the fault rate of transmission lines under an ice disaster is introduced, which is used to generate different fault scenarios. Then, the optimal scheduling of MESS is described as a two-stage optimization problem: in the first stage, the configuration scheme of MESS can be determined in the distribution network; in the second stage, the optimal traffic plan can be obtained in the transportation network. Finally, a modified IEEE-33 node test system coupled with a transportation network is used to verify the effectiveness and feasibility of the method proposed in this paper.

2. Modeling of Transmission Line Fault Rate under Ice Disaster

During the ice disaster, the main cause of transmission line failures is the accumulation of ice on the lines and towers caused by rainy and snowy weather and continuous low temperatures, which exceeds the design standards of the transmission line and ultimately leads to the inability of the line to withstand induced disconnection.

Existing icing models are mostly based on fluid mechanics and thermodynamic principles, and different icing models are established by considering different environmental factors. The main models include the Lenhard model, Goodwin model, Makkonen model, and Jones model [33]. The Lenhard model is too simple; does not consider the effects of factors such as wind speed, temperature, and humidity, making it difficult to accurately analyze the growth process of ice cover; and is rarely applied in practice. The Goodwin model is relatively improved compared to the Lenhard model, but in practical applications, the speed of raindrops falling is difficult to measure, so this model also has certain limitations. The Makkonen model is a relatively accurate model, but the values of collision coefficient, adhesion coefficient, and condensation coefficient need to refer to empirical formulas, resulting in high computational complexity. The parameters in the Jones model are the easiest to obtain and can clearly quantify the impact of meteorological parameters on the icing process. Most importantly, the model has high accuracy and is simple and convenient to calculate. Therefore, this paper uses this model to describe ice disasters. During the ice disaster, the transmission line is mainly subjected to two forces: one is the vertical force caused by the line icing, and the other is the horizontal force caused by wind. Therefore, in order to establish a probability model for line faults under ice disasters, it is first necessary to analyze the wind load and ice force load of the line separately.

2.1. Ice Load

Considering the convenience of data collection and the accuracy of the model, this paper adopts the ice calculation model proposed by Jones. First, ice thickness can be calculated according to Equation (1a).

$$R_{eq} = \frac{t}{\rho_I \pi} \sqrt{(r\rho_W)^2 + (3.6 v_g W)^2} \tag{1a}$$

Here, Req represents the ice thickness and ρ_I represents the density of the ice; t represents the duration of freezing rain; ρ_W represents the density of the water; v_g represents wind speed; and W represents moisture content in the air.

Under the premise of knowing the cable diameter and calculating the ice thickness, the ice load per unit length of the transmission line can be calculated as follows:

$$L_I = 9.8 \times 10^{-3} \rho_I \pi (D + R_{eq}) R_{eq} \tag{1b}$$

Here, L_I represents the ice load, and D represents the cable diameter.

2.2. Wind Load

On the basis of calculating the ice thickness, the wind load per unit length of the transmission line can be obtained as follows [34]:

$$L_W = CSv_g^2 (D + 2R_{eq}) \tag{2}$$

Here, C represents a constant. In this paper, the value of C is 6.964×10^{-3} and S represents the span factor.

The wind speed v_g can be calculated using Equation (3):

$$v_g = 1.29v + 12.9742 \tag{3}$$

Here, L_W represents wind load; C is a constant coefficient; and S represents the span factor, and generally the value of S is taken as 1. Only when the wind speed is greater than 2.2352 m/s, the span factor needs to be corrected to 1.1–1.2.

2.3. Ice-Wind Load

Without considering the longitudinal component of wind and the galloping of transmission lines, the forces of icing and wind on the transmission lines can be considered perpendicular to each other, as shown in Figure 1. Therefore, based on the synthesis of forces, the ice-wind load transmission line and the angle between the two loads under the combined action of ice and wind can be obtained according to (4) and (5), respectively.

$$L_{WI} = \sqrt{(L_I)^2 + (L_W)^2} \tag{4}$$

$$\theta = \arctan \frac{L_W}{L_I} \tag{5}$$

Here, L_{WI} represents ice-wind load and θ represents the included angle between ice load L_I and wind load L_W.

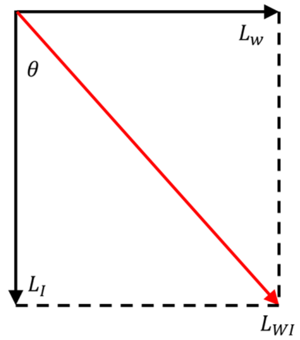

Figure 1. Force analysis of the transmission line under an ice disaster.

During the construction of transmission lines, the corresponding anti-icing design standards are generally adopted according to the region, so that the electric power transmission has a certain resistance to icing. During an ice disaster, if the thickness of the ice cover exceeds this design standard, it may lead to transmission line disconnection. According to the deformation theory of metals, when the force on a transmission line exceeds its limit, its bearing capacity will rapidly decrease exponentially with the increase in force. Therefore, the exponential fault statistical model of the line is established as follows:

$$p = \begin{cases} 0, x \leq a \\ \exp\left[\frac{0.6931(x-a)}{b-a}\right] - 1, a < x < b \\ 1, x \geq b \end{cases} \tag{6}$$

Here, p is the unit failure probability of the transmission line; x is various variables that can affect the icing of the transmission line, such as wind speed, ice thickness, ice-wind load, etc.; and a and b are the first and second threshold values, respectively. When selecting the threshold values, the influence of wind and ice cover should be comprehensively considered.

On this basis, the probability of transmission line failure per unit length based on ice wind load can be calculated as [35]:

$$p_f = \begin{cases} 0, L_{IW} \leq a_{IW} \\ \exp\left[\frac{0.6931(L_{IW}-a_{IW})}{b_{IW}-a_{IW}}\right] - 1, a_{IW} < L_{IW} < b_{IW} \\ 1, L_{IW} \geq b_{IW} \end{cases} \tag{7}$$

Here, a_{IW} and b_{IW} are the first and second threshold values of ice-wind load, respectively.

Finally, it should be noted that due to the random uncertainty of both disaster occurrence and fault generation, the mobile energy storage strategy for improving the resilience of distribution networks can essentially be seen as a stochastic optimization problem. The current meteorological forecasting technology is relatively mature, and the prediction accuracy can be maintained at a high level. Combined with meteorological information, the fault probability of each transmission line can be obtained by using the Monte Carlo method.

3. A Two-Stage MESS Scheduling Strategy Considering Transportation-Electricity Coupling Networks

How to efficiently determine the optimal solution is crucial for the optimal scheduling of MESS. Only by quickly and accurately determining the optimal scheduling strategy of MESS can we reduce economic losses in the power grid and quickly restore power supply. However, the existence of traditional power flow models leads to optimization problems with nonconvex and nonlinear characteristics, greatly increasing the computational burden. In this paper, we establish a two-stage scheduling strategy and use the Distflow model to transform the initial problem into a general mixed integer linear programming problem, which can be quickly solved online using some commercial solvers. To obtain the optimal MESS scheduling scheme, a two-stage optimization framework is designed [36,37]. As shown in Figure 2, in the first stage, the optimal configuration scheme for MESS, including charging and discharging information and node location, can be obtained for system operators, and the optimal path selection for MESS considering road traffic conditions can be obtained in the second stage. Finally, maintenance personnel can quickly reach the responding nodes based on the path selection scheme and configuration strategy, achieving rapid recovery of electrical energy. There are currently two strategies that can be used to determine the installation location of MESS. The first method is the empirical method. The system operators determine the installation location based on the importance of the load. MESS is installed at important load nodes. The advantage of this strategy is that it has a low computational burden and can quickly determine the installation location, but the optimality of the scheduling strategy is hard to guarantee. The second strategy is the optimization method, which introduces integer variables and determines the installation location by solving the optimization problem. The advantage of this method is that it can ensure optimality.

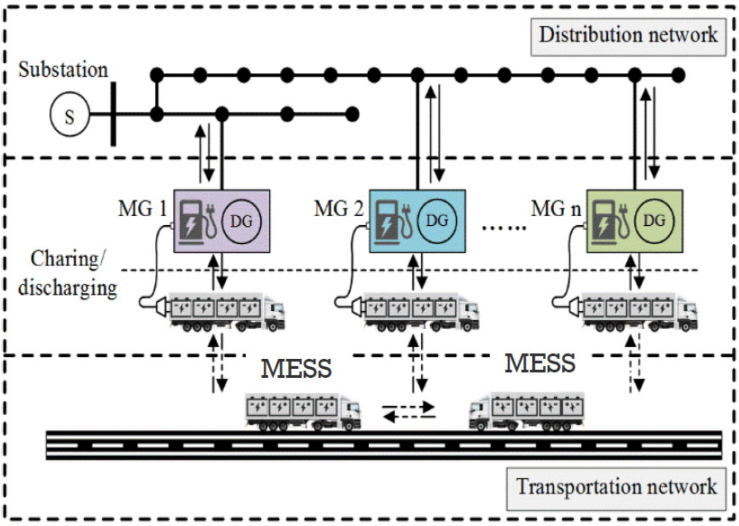

Figure 2. Schematic diagram of a two-stage optimization framework for MESS.

3.1. Stage-1: Distribution Network Level

The purpose of MESS access is to reduce system losses caused by disasters. Therefore, the objective function of this section of the model is to minimize the total operating cost of the system (including the operating cost of MESS and the loss cost of the load):

$$\min \sum_{s \in S} \sum_{m \in M, i \in B, t \in T} C^{mes} \cdot \left| p^{mes}_{m,i,t,s} \right| + \sum_{i \in B, t \in T} C^{VoLL}_i \cdot p^{ld}_{i,t,s} \tag{8}$$

Here, S represents fault scenarios set, C^{mes} represents equipment cost of MESS, $p^{mes}_{m,i,t,s}$ represents charge and discharge power at the node i for the m-th MESS in the scenario s, C^{VoLL}_i represents loss cost of load shedding at node i, and $p^{ld}_{i,t,s}$ represents the amount of load shedding at node i in the scenario s.

Meanwhile, power flow constraints (9)–(13) and MESS operation constraints (14)–(21) should be satisfied.

$$\sum_{h|(j,h) \in \mathbf{L}} f^p_{jh,t,s} = f^p_{ij,t,s} - r_{ij} \frac{\left(f^p_{ij,t,s}\right)^2 + \left(f^q_{ij,t,s}\right)^2}{v^2_{j,t,s}} - P^d_{j,t} + g^p_{j,t,s} + p^{mes}_{m,j,t,s} \tag{9}$$

$$\sum_{h|(j,h)\in\mathbf{L}} f^{q}_{jh,t,s} = f^{q}_{ij,t,s} - x_{ij}\frac{\left(f^{p}_{ij,t,s}\right)^2 + \left(f^{q}_{ij,t,s}\right)^2}{v_j^2} - Q^{d}_{j,t} + g^{q}_{j,t,s} + q^{mes}_{m,j,t,s} \tag{10}$$

$$v^2_{j,t,s} = v^2_{i,t,s} - 2\cdot\left(r_{ij}f^{p}_{ij,t,s} + x_{ij}f^{q}_{ij,t,s}\right) + \left({r_{ij}}^2 + {x_{ij}}^2\right)\left(\frac{f^{p}_{ij,t,s} + f^{q}_{ij,t,s}}{v^2_{i,t,s}}\right) \tag{11}$$

$$\begin{bmatrix} f^{p}_{ij,t,s} \\ f^{q}_{ij,t,s} \end{bmatrix} \le \begin{bmatrix} f^{p}_{ij\max} \\ f^{q}_{ij\max} \end{bmatrix} \tag{12}$$

$$\begin{bmatrix} V_{\min} \\ 0 \\ 0 \end{bmatrix} \le \begin{bmatrix} v_{i,t,s} \\ g^{p}_{j,t,s} \\ g^{q}_{j,t,s} \end{bmatrix} \le \begin{bmatrix} V_{\max} \\ G^{P}_{\max} \\ G^{q}_{\max} \end{bmatrix} \tag{13}$$

$$e_{m,t,s} = e_{m,t-1,s} + \sum_{i\in B} p^{mes}_{m,i,t-1,s}\cdot K^{mes} \tag{14}$$

$$0 \le e_{m,t,s} \le E^{\max}_{m} \tag{15}$$

$$-P^{mes\max}_{m}\cdot u_{m,i,t,s} \le p^{mes}_{m,i,t,s} \le P^{mes\max}_{m}\cdot u_{m,i,t,s} \tag{16}$$

$$-\frac{\sqrt{1-K^2}}{K}P^{mes\max}_{m}\cdot u_{m,i,t,s} \le q^{mes}_{m,i,t,s} \le \frac{\sqrt{1-K^2}}{K}P^{mes\max}_{m}\cdot u_{m,i,t,s} \tag{17}$$

$$\sum_{m\in M,t\in T} u_{m,i,t,s} \le N^{MES}_{i} \tag{18}$$

$$\sum_{i\in B,t\in T} u_{m,i,t,s} \le N^{MES} \tag{19}$$

$$u_{m,i,t,s} - u_{m,i,t+1,s} \le 1 - u_{m,j,t+\Delta,s} \tag{20}$$

$$u_{m,i,1,s} = loc_{m,i} \tag{21}$$

Here, $f^{p}_{ij,t,s}$ and $f^{q}_{ij,t,s}$ represent active power flow of line ij at time t under scenario s; $p^{ld}_{j,t,t}$ represents the load power of node j at time t; $v_{i,t,s}$ represents the voltage of node i at time t under scenario s; r_{ij} and x_{ij} represent the resistance and reactance of line ij, respectively; and $g^{p}_{j,t,s}$ and $g^{q}_{j,t,s}$ represent the active/reactive power output of the generator of node i at time t under scenario s. For MESS, (14) represents the power constraint before and after charging and discharging of MESS; (15) represents the upper and lower bound capacity constraints of MESS; (16) represents the upper and lower bounds on the active output of MESS; (17) represents the upper and lower bounds on the reactive power output of MESS; (18) represents the constraint on the number of nodes that allow MESS to access; (19) represents the constraint on the number of MESS accessed in the distribution network at the same time; and (20) represents the constraint of changing the location of MESS. When mobile energy storage arrives at another location from one location, it is not connected to any node in the distribution network; (21) represents the position constraint at the initial time. Among them, the specific meanings of each variable are as follows: $e_{m,t,s}$ represents the electricity level at time t of the m-th MESS under scenario s; $E^{\max}_{m}$ represents the maximum electricity level of MESS; $u_{m,i,t,s}$ represents the location variable for MESS; when its value is 1, it means that MESS has access to the distribution networks. K represents the power factor of MESS, K^{mes} represents the charge/discharge efficiency of MESS, N^{MES}_{i} represents the maximum number of MESS that a node can access, and N^{MES} represents the total number of MESS in the system. $loc_{m,i}$ represents the variable for the initial position of MESS.

Meanwhile, for faulty lines, the power flow should meet constraints (22) and (23):

$$f^{p}_{ij,t,s} = 0 \tag{22}$$

$$f^{q}_{ij,t,s} = 0 \tag{23}$$

Due to the nonlinearity of power flow constraints and the commonly used DC power flow that requires line resistance to be significantly less than reactance, it is not suitable for medium- and low-voltage distribution networks. For the convenience of calculation, this paper uses the Distflow linearized power flow model (24)–(26) to reduce computational complexity:

$$\sum_{h|(j,h)\in \mathbf{L}} f^{p}_{jh,t,s} = f^{p}_{ij,t,s} - P^{d}_{j,t} + p^{ld}_{j,t,s} + p^{mes}_{m,j,t,s} \tag{24}$$

$$\sum_{h|(j,h)\in \mathbf{L}} f^{q}_{jh,t,s} = f^{q}_{ij,t,s} - Q^{d}_{j,t} + q^{ld}_{j,t,s} + q^{mes}_{m,j,t,s} \tag{25}$$

$$v_{j,t,s} = v_{i,t,s} - \frac{r_{ij} f^{p}_{ij,t,s} + x_{ij} f^{q}_{ij,t,s}}{V_0} \tag{26}$$

3.2. Stage-2: Transportation Network Level

By solving the optimal configuration strategy for MESS in stage 1, the installation location of MESS at each time period can be determined, with the goal of passing through the transportation network as quickly as possible and reaching the destination. At this point, the route between two points needs to be determined by listing all paths between the two points and calculating the time sum of all road sections on each path. To select the shortest path in time, the shortest path can be determined by Equations (27) and (28):

$$\min \sum_{\zeta \in k} \tau^{\zeta} \cdot \delta^{od}_{\zeta,k} \tag{27}$$

$$s.t.\ k \in \Theta_{od} \tag{28}$$

Here, Θ_{od} represents the set of all paths between o and d; the path k and corresponding set of paths and Θ_{od} can be determined using breadth search algorithms or depth search algorithms.

4. Case Study

4.1. The Introduction of Test System

In this section, we use an improved IEEE-33 node testing system for case validation. On the basis of traditional distribution network topology, the coupling transportation network is also considered, consisting of three Nguyen Dupuis transportation network testing systems connected in series. The detailed network topology and node coupling relationship are shown in Figure 3. The program is written using YALMIP and solved by Cplex solver using MATLAB 2016b. All calculations were analyzed on an Intel (R) Core (TM) i5-7500 CPU at 3.40 GHz desktop computer with 8 GB of memory. For the failure probability of an ice disaster, combined with Monte Carlo simulation, ice disaster scenarios are generated. The line fault model established in this article under ice disaster is shown in Table 1. In Figure 3b, some stars with number mean intersections of transportation and distribution networks at a geographical location, and some stars without number mean nodes only exist in the transportation network.

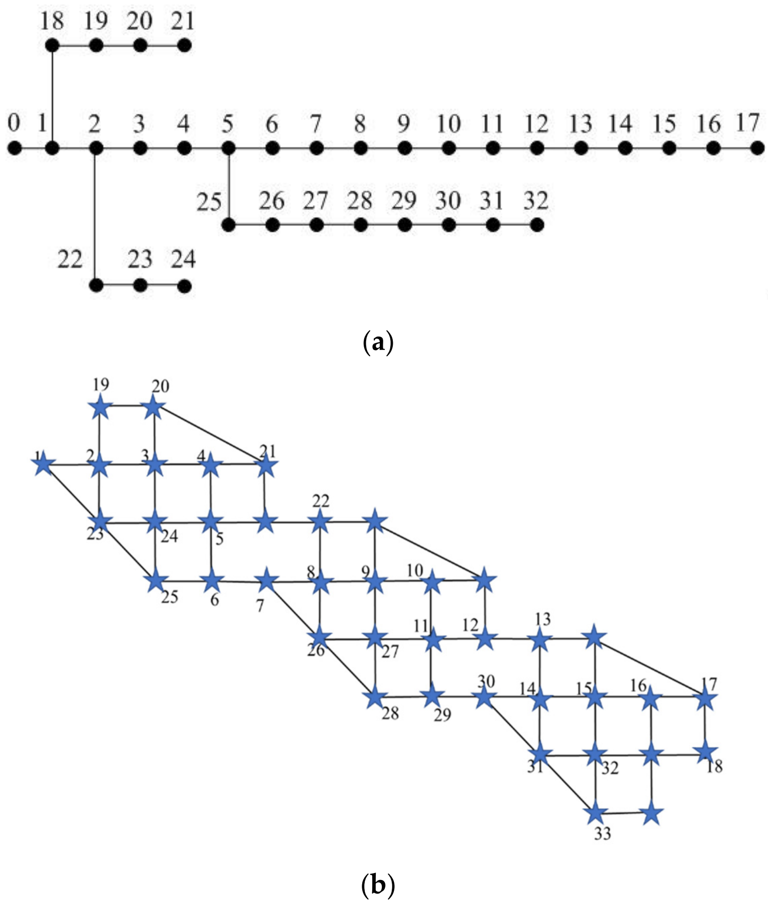

Figure 3. Schematic diagram of a coupling distribution-transportation networks. (**a**) The topology of the IEEE-33 distribution network. (**b**) The topology of the transportation network.

Table 1. Fault probability of the line after ice disaster.

Line Number	Fault Probability	Line Number	Fault Probability	Line Number	Fault Probability
1	0.0200	12	0.2968	23	0.0496
2	0.0224	13	0.0419	24	0.0464
3	0.0455	14	0.0416	25	0.1903
4	0.0252	15	0.2487	26	0.0172
5	0.1286	16	0.2529	27	0.1186
6	0.0216	17	0.0749	28	0.0287
7	0.0446	18	0.0898	29	0.0186
8	0.0543	19	0.3072	30	0.0830
9	0.1695	20	0.1651	31	0.1461
10	0.0429	21	0.3333	32	0.1463
11	0.1315	22	0.0204		

The case study in this paper includes a MESS with a capacity of 1.5 MW and a maximum power of 130 kW. The total load in the distribution network is 3.6713 MW. Through Monte Carlo sampling, when the system load loss variance coefficient is less than 0.05, the sampling process should be stopped. After 1000 samples, the frequency of the optimal access point for MESS in 1000 samples is shown in Figure 4, and the convergence trend of the outage loss variance coefficient is shown in Figure 5. By observing Figure 4, it can be seen that the optimal access location for MESS is node 13.

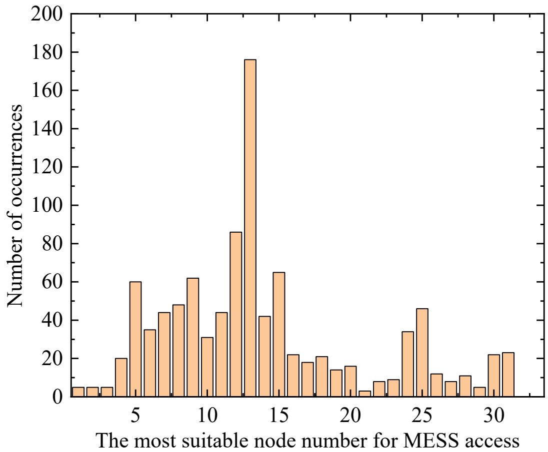

Figure 4. The frequency of the optimal access point for MESS in 1000 samples.

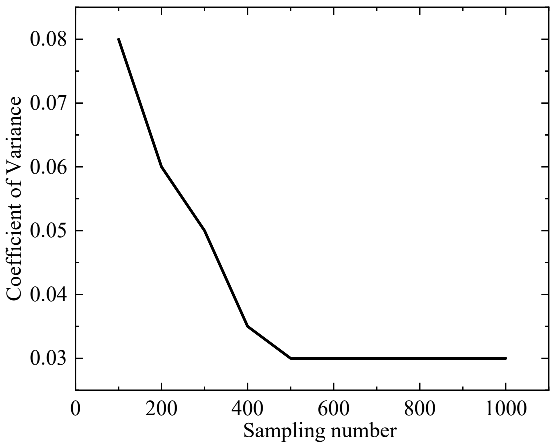

Figure 5. Convergence trend of the outage loss variance coefficient.

4.2. The Feasibility of the Proposed Method

In order to provide a more intuitive explanation of the advantages of the method proposed in this paper, two different scenarios are set, and the details are listed as follows:

Scenario 1: MESS is fixedly installed on node 13 and can only control whether it is connected and cannot be moved to other nodes, that is, the flexibility of the transportation network cannot be utilized.

Scenario 2: The initial location of MESS is node 13, and the access location of MESS can be changed through the transportation network, that is, the flexibility of the transportation network cannot be utilized.

Figure 6 shows the changes in the installation location of MESS during different time periods in two different scenarios.

It should be noted that when the access node of MESS is 0, it means that MESS is not connected to the distribution network. Compared with fixed-battery energy storage systems, MESSs have strong adaptability to the constantly changing operating status of the distribution network by changing the time and location of access. This is fundamentally different from traditional energy storage operation methods, making it more convenient, easier to achieve accident isolation, and flexible according to actual situations. The charging and discharging power and state of charge curves of MESS under two different scenarios are shown in Figures 7 and 8, respectively. Through comparison, it was found that the MESS optimal scheduling strategy, considering the transportation network, has stronger flexibility. Due to the time-varying nature of disaster fault information, the proposed method can flexibly adjust the installation location of MESS through the transportation network, improving the resilience of the power system and reducing load shedding. On the other hand, by observing Figures 7 and 8, it can be seen that after considering the transportation network, the charging and discharging behavior of MESS has a certain lag compared to the charging and discharging behavior in scenario 1. This is because MESS requires a certain amount of time to reach the optimal access point through the road, thus reducing the conservatism of traditional methods.

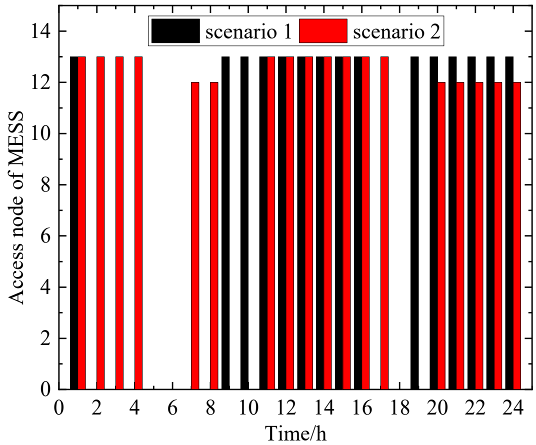

Figure 6. Installation location of MESS during different time periods in two different scenarios.

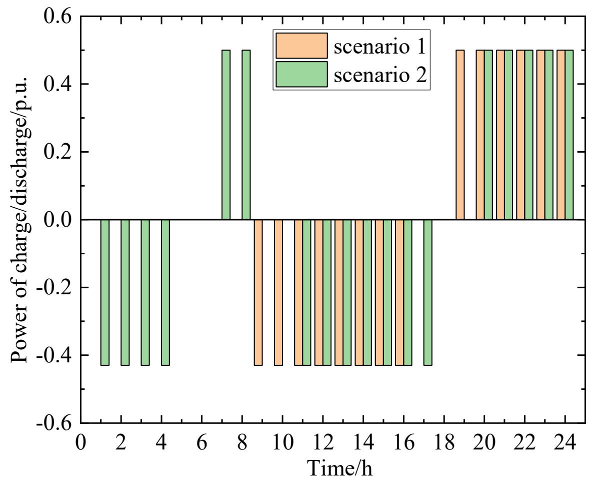

Figure 7. The charging and discharging power of MESS under two different scenarios.

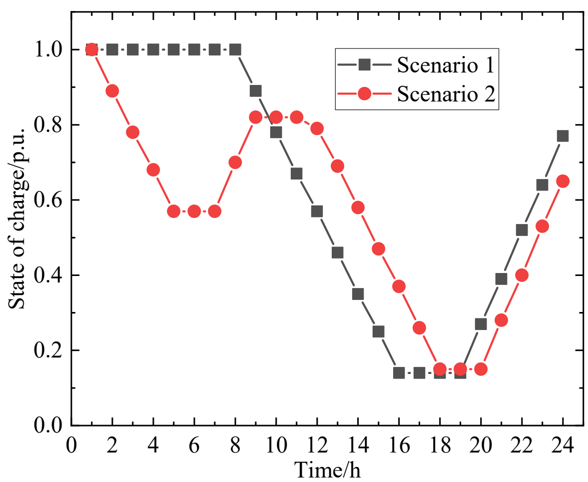

Figure 8. State of charge curves of MESS under two different scenarios.

Finally, we analyzed and compared the system load loss in two scenarios, as shown in Table 2. By scheduling MESS, system load loss was reduced from 3.756 MWh to 3.248 MWh, effectively improving the safe operation level of the system. In summary, the scheduling of MESS in the coupled electrical-transportation network is crucial for ensuring power supply and improving the reliability of the distribution network. By analyzing Table 2, it can be found that the method proposed in this paper can determine the optimal access node of MESS for each time period and quickly transfer using the transportation network. Although time is consumed in road traffic, the scheduling flexibility and power supply capacity of MESS can be further explored. However, due to the limited capacity and quantity of emergency power vehicles, as well as the small and scattered load of some nodes, there is still a small amount of load shedding in the system. It should be noted that the method used in this paper is essentially a stochastic optimization model based on multiple scenarios, and the computational efficiency depends on the number of selected scenarios. When the number of scenarios is 5, 10, 15, and 20, the calculation time is 74.6 s, 168.2 s, 248.6 s, and 345.5 s, respectively. Overall, the calculation time is approximately linear with the number of scenarios selected. The more scenarios selected, the longer the calculation time.

Table 2. Comparison of load loss between two different scenarios.

Different Scenarios	Scenario 1	Scenario 2
System load loss/MWh	3.756	3.248
Moving time in transportation networks	/	1.163

Table 2 compares the results of system load loss. In order to further intuitively quantify the economic benefits brought by MESS, three different strategies are given here, and the strategy proposed in this paper is strategy 3. The specific costs are as follows: the operating cost of the distribution network (electricity purchasing and selling costs from the distribution network to the upper power grid), the cost of load shedding, the cost of road traffic, and the operating cost of MESS. The economic costs of different strategies are given in Table 3.

Table 3. Economic cost of different strategies.

Different Strategies	Strategy 1	Strategy 2	Strategy 3
Operating cost of the distribution network/$	34,927.6	32,468.2	31,488.7
Cost of load shedding/$	7246.4	3765.0	3248.0
Cost of road traffic	/	/	581.5
Operating cost of MESS	/	1924.6	1685.8
Total cost	42,174.0	38,157.8	37,004.0

Strategy 1: MESS does not participate in the post-disaster recovery of the power system.

Strategy 2: MESS participates in the post-disaster recovery of the power system, and the installation location can be changed through the transportation network.

Strategy 3: MESS participates in post-disaster recovery of the power system and is installed at a fixed node.

From Table 3, it can be seen that the operation cost of the distribution network in strategy 1 is higher than that of strategies 2 and 3, and the total cost of strategy 3 is the lowest. This is because when MESS does not participate in scheduling, the electricity demand of the distribution network can only be met by purchasing electricity from the upper-level grid. When MESS participates in scheduling, due to its own power supply function, it reduces the power demand of the distribution network from the upper-level power grid. And strategy 1 has the highest loss cost of load shedding, which also leads to its highest total cost. This also indirectly reflects the importance of MESS. Compared with strategy 3, the operating costs of the distribution network and MESS in strategy 2 are slightly higher because when the installation location of MESS is fixed, MESS needs to provide more electricity to reach long-distance load nodes. Although strategy 2 does not require payment of road traffic costs, the scheduling flexibility of MESS cannot be fully explored, which also leads to an increase in total operating costs.

5. Conclusions

Actively scheduling MESS based on weather forecast information can increase the utilization efficiency of MESS and shorten the time of load outages. Therefore, first, the fault probability of distribution network lines under ice disaster is established in this paper, and Monte Carlo sampling is used to obtain the fault scenarios; then, considering the impact of road traffic flow, a two-stage optimization model is given: the first stage determines the optimal configuration scheme for MESS; in the second stage, the optimal path selection for MESS can be obtained. Finally, the modified IEEE-33 node distribution system was used as a testing system to verify the effectiveness of pre-disaster location scheduling. The case shows that by scheduling MESS, it can effectively reduce system load loss and improve power supply reliability.

The scheduling strategy proposed in this paper mainly focuses on the steady-state scheduling of the power system, which is essentially a classic SCOPF problem (i.e., security-constrained optimal power flow) and does not involve the transient characteristics of the power system. The stability impact of MESS on the power system is not considered in this paper. The analysis of the transient support capability of power systems by MESS and corresponding transient stability control methods such as soc-based droop coefficients stability region analysis and disturbance observer-based sliding mode control algorithm are also our future research directions.

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