Resilience-oriented Valuation for Energy Storage Amidst Extreme Events*

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Abstract: In power grids, the frequency is increasing of extreme accidents which have a low probability but high risk such as natural disasters and deliberate attacks. This has sparked discussions on the resilience of power grids. Energy-storage systems (ESSs) are critical for enhancing the resilience of power grids. ESSs, with their mechanism of flexible charging and discharging, adjust energy usage as needed during disasters, thereby mitigating the impact on the grid and enhancing security and resilience. This, in turn, ensures the power system's stable operation. Currently, there is limited systematic research quantifying the economic value of energy storage in resilience scenarios. Therefore, a model and methodology were proposed to quantify the value of energy storage systems for enhancing grid resilience during extreme events. A two-stage stochastic optimization mathematical model was developed. The first stage involves pre-deployment based on day-ahead expectations, and the second stage involves simulating potential failure scenarios through real-time scheduling. Considering the temporal dimension, the energy storage systems with flexible regulation capabilities was used as emergency power sources to reduce occurrences of load-shedding. Here, a novel index was proposed that quantifies the resilience value of energy storage as the economic value of energy storage per unit of capacity, as reflected in the emergency dispatch model. This index helps determine the balance between the energy storage investment cost and resilience value. Finally, an IEEE-30 node transmission system was used to verify the feasibility and effectiveness of the proposed method. The findings revealed a significant improvement in the resilience value, with a 23.49% increase observed when energy storage systems were implemented compared to the scenario without energy storage systems. The optimal capacity configurations for the flywheel, lithium-ion batteries, and pumped hydro storage were 10 MW, 11 MW, and 12 MW, respectively, highlight their potential to maximize value in experimental system.

Keywords: Energy storage dispatch model, power system resilience, resilience-oriented valuation, two-stage optimization model

1 Introduction

The urban power grids are crucial infrastructure that supports economic production and human life. However, they face increasing internal and external threats such as extreme natural disasters, malicious attacks, and cascading failures caused by escalating global climate change. These challenges stress the grid's ability to ensure power supply. However, the complexity of the power-grid structure and its operation poses additional challenges.

In 2009, the U.S. Department of Energy released the "Smart Grid Report" [1], which first defined smart grids. The European Joint Research Centre [2] defines resilience as a dynamic concept usually associated with low-probability and high-impact events. The academic community has also introduced concepts

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such as power grid resilience [3] and resilient grids [4] and conducted preliminary research on the theories, methods, and key technologies of power system resilience [5-6]. These studies underscore the importance of building a robust and flexible energy infrastructure that can efficiently withstand and recover from adverse events. By enhancing the resilience of power systems, it can be better prepared for and mitigate the impacts of unexpected challenges and safeguard a reliable and continuous energy supply for communities and industries.

In power grid resilience modeling, researchers have studied different aspects of extreme weather conditions and natural disasters to bolster the resilience and recovery capabilities of power systems. Panteli et al. [7] were the first to propose a probabilistic approach for addressing extreme weather conditions. Subsequently, Yan et al. [8] developed a two-stage resilience model that combined a transmission grid with ice storm disasters and studied the impact of ice storm events on the transmission grid at different stages. Zhang et al. [9-10] proposed a method for coordinating the transmission-distribution grid. Shahinzadeh et al. [11] focused on distribution grids and flood recovery, exploring the potential impact of flood events on distribution grids, and proposing corresponding recovery strategies to improve grid recovery capability and resilience after floods. Ding et al. [12] presented a three-stage natural disaster model that considers the losses and impacts of typhoon events on the transmission grid at different stages. Han et al. [13] investigated the resilience of hydrogen-powered grid resilience. Wang et al. [14] examined the role of distributed energy resources, including electrolytic hydrogen, in resilient low-carbon smart cities. Wu et al. [15] proposed a resilience enhancement model that offered a power-to-hydrogen frequency response.

Researchers have recognized the significant role of energy storage systems (ESSs) as flexible regulation resources in power grid resilience modeling. Based on this characteristic, the ESS plays an important auxiliary role in power systems and can be used to balance the energy supply and demand. Several scholars have integrated energy storage with renewable energy to improve the utilization of intermittent renewable sources [16-18]. To enhance the integration efficiency of energy storage devices and renewable energy, Wu et al. [19] proposed a stochastic day-ahead scheduling method. In the same year, Li et al. [20] also regarded large-scale pumped hydro storage (PHS) as a flexible resource in power systems, modeling large-scale energy storage in both day-ahead and real-time scenarios and highlighted the potential of energy storage systems to enhance flexibility in power systems. As research has progressed, the role of energy storage in power restoration has become increasingly prominent [21-23]. Ding et al. [24] proposed a collaborative power-restoration model based on network reconfiguration and distributed power sources. Prabawa et al. [25] utilized the flexible characteristics of energy storage systems to achieve distribution system service restoration using DG and mobile energy storage systems. Zhang et al. [26] integrated energy storage systems into resilience models, further extending them to the distribution grid and domain of typhoon disasters. Yong et al. [27] simulated the impact of distribution networks and UPS devices on the sufficiency of the consumers' power supply and evaluated the power supply's adequacy to improve reliability.

The significance of energy storage lies in its dual role of enhancing power grid resilience and ensuring energy stability, while also necessitating careful evaluation of its economic value for cost-effective integration. Gao et al. [28] proposed a definition of resilience indicators for distribution grids that measures the support and recovery capability of distribution grids for supplying critical loads during natural disasters. This indicator aims to assess whether the distribution grid can take proactive measures to ensure power supply to critical loads during disasters and quickly restore the power to disconnected loads. Based on this definition, the resilience indicators can be further expanded to determine the economic value of energy storage systems during emergency dispatch. However, in previous studies, the economic evaluation of energy storage systems has mainly focused on their integration into the electricity market bidding competition. For example, Li et al. [29] highlighted the competitive advantage of energy storage systems in economic evaluations. He et al. [30] incorporated battery cycle life models into profit maximization models to improve profitability and assess their economic feasibility. Nasrolahpour et al. [31] developed a decision-making tool based on a two-level complementary model that allows the profitability of energy storage systems to be enhanced by participating in different markets and influencing pricing strategies. Wang et al. [32] proposed a method for assessing the reliability value of distributed solar power and storage systems during rare weather events. Yu et al. [33] researched a quality-based data-valuation paradigm for the pricing information of smart grids. Although the aforementioned studies have provided valuable characterizations of energy storage systems and batteries, methods for quantifying their economic value are still lacking.

Drawing on the above research, energy storage systems have the potential to provide economic value by enhancing power grid resilience. Energy storage systems can mitigate economic losses and recovery costs by reducing grid outages and the intermittent starting/stopping of thermal power units. Furthermore, the flexibility of energy storage systems can improve the reliability and stability of the power grid, further increasing economic benefits. However, additional research is required to explore specific methods for quantifying the economic value of energy storage systems in extreme scenarios, integrating energy storage into emergency dispatch strategies, and enhancing power-grid resilience through optimized grid scheduling. The contributions of this study are summarized as follows.

(1) This study presents a two-stage optimization model that accounts for N-K contingency events by integrating energy storage systems with emergency dispatch. This intelligent grid model enhances grid resilience during disasters and ensures a stable power supply in various emergency scenarios, thereby providing valuable inputs for calculating the quantifiable value indicators of energy storage resilience.

(2) This study introduced a set of well-defined resilience indicators for energy storage systems. By analyzing the economic impacts in different resilience scenarios, these indicators facilitate the evaluation of potential economic losses and risks associated with energy storage deployment. The quantified results enable informed decisions to maximize the disaster resilience of the grid.

2 Framework

In practice, many natural disasters and weather events pose risks and challenges for urban power grids and causing numerous faults. Compared to the traditional reliance on thermal power generation, the utilization of other flexible resources as a demand response to enhance resilience has been extensively studied in existing literature. However, factors such as response latency, unreliable communication, and limited resource regulation capabilities often impede efficient resource allocation and coordination during the restoration process, resulting in a slow recovery.

Energy-storage resources, with their faster regulatory capabilities, significantly enhance resilience in disaster scenarios by enabling the system to react and adjust more rapidly to changes. For instance, when faults occur, localized circular shadow zones may appear, depicting scenarios in which there is an insufficient power supply, as shown in Fig. 1. Storage can facilitate smooth system transitions through decentralized control and rapid boosting, thereby reducing fault recovery and downtime. The enhanced grid resilience is illustrated by the line shadow area.

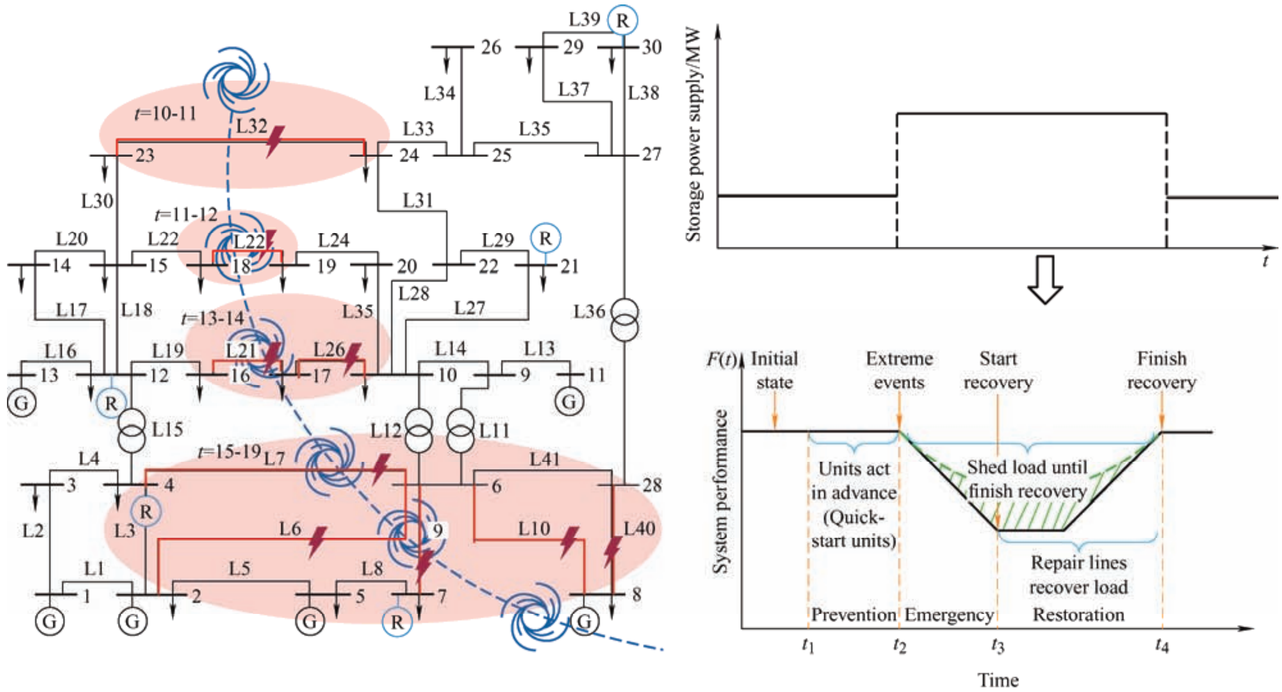

Fig. 1 Grid load zones under disaster scenarios

3 System model

3.1 Disaster modeling and failure scenario setting

Typhoon prediction serves as a significant meteorological task in natural disaster modeling because of its substantial impact on society and the economy. A typhoon's trajectory and wind field are crucial factors to be considered. These models typically rely on meteorological data, historical typhoon paths, and other environmental factors to forecast trajectories and wind fields through numerical simulations and data analyses. The intensity and duration of a typhoon primarily determine its impact, which can be described using typhoon wind-field models. In addition, the severity of different weather conditions can cause varying rates of line failure. To address this, this study developed an improved Yan-Meng model [34]. In the Yan-Meng model, the wind field of a moving typhoon boundary layer is calculated by considering the layer's physical characteristics and the ground terrain conditions. The typhoon disaster model is computed following Eqs. (1)-(2).

$$E\left(\varphi_{s,t}^{\mathrm{SL}}\right)=\underline{\varphi_{s}^{\mathrm{TC}}}+\Delta\varphi_{s,t}^{\mathrm{P/C}}\exp\left(-\left(\frac{\overline{R_{s,t}^{\mathrm{TP}}}}{R_{s}^{\mathrm{P/C}}}\right)^{\alpha^{\mathrm{PP}}}\right) \tag{1}$$

$$\frac{\partial V_{s,t}^{\mathrm{TP}}}{\partial t}+V_{s,t}^{\mathrm{TP}}\cdot\nabla V_{s,t}^{\mathrm{TP}}=-\frac{1}{\alpha^{\mathrm{AO}}}\nabla\chi_{s}^{\mathrm{D}}-\alpha^{\mathrm{CF}}\times V_{s,t}^{\mathrm{TP}}+F_{s,t}^{\mathrm{AB}} \tag{2}$$

In the above expressions, $\varphi_{s,t}^{\mathrm{SL}}$ represents sea-level pressure, $\underline{\varphi_{s}^{\mathrm{TC}}}$ represents central (minimum) pressure, $\Delta\varphi_{s,t}^{\mathrm{P/C}}$ represents the air pressure difference between the periphery and the center, $\overline{R_{s,t}^{\mathrm{TP}}}$ represents the radius of maximum wind speed, $R_{s}^{\mathrm{P/C}}$ represents the radial distance from the typhoon's center, α^{PP} represents the pressure profile constant, $V_{s,t}^{\mathrm{TP}}$ represents the typhoon-induced wind velocity, α^{AO} represents the air density, χ_{s}^{D} represents the failure probability, α^{CF} represents the Coriolis force coefficient, $F_{s,t}^{\mathrm{AB}}$ represents the friction force of the atmospheric boundary layer.

Based on the typhoon disaster model, Yang et al. [35] proposed an outage model for transmission lines and towers and provide a fragility curve that illustrates the relationship between the failure probability and wind speed, as shown in Fig. 2. This curve is based on empirical statistical data from utility companies and can be used to adjust the fragility curve to reflect the actual behavior of transmission lines and towers.

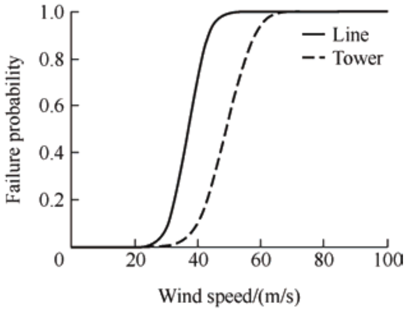

Fig. 2 Fragility curves of transmission lines and towers

3.2 The resilience-oriented dispatch model

In the resilience-oriented dispatch model, before a disaster, the operation of thermal power generation units is planned based on the predicted probabilities of different disaster occurrences. This is done to prevent failures to meet the power demand or load shedding, even if the thermal power units are temporarily started or stopped during a disaster. During a disaster, the model considers the temporary starting/stopping of thermal power units and the integration of energy storage as flexible regulatory resources in the grid and imposes penalties for load shedding. Please refer to Eqs. (3)-(24) for the overall model.

$$f(x)=\min_{x\in R}\sum_{t=1}^{T}\left[C_t^{\mathrm{DA}}+\sum_{s=1}^{S}\chi_s^{\mathrm{D}}C_{s,t}^{\mathrm{RT}}\right] \tag{3}$$

$$C_t^{\mathrm{DA}}=\sum_{t=1}^{T}[(C_i^{\mathrm{UP}}S_{i,t}^{\mathrm{UP}}+C_i^{\mathrm{DN}}S_{i,t}^{\mathrm{DN}})] \tag{4}$$

$$C_{s,t}^{\mathrm{RT}}=\sum_{t=1}^{T}\left\{\sum_{i=1}^{N_{\mathrm{TG}}}\left(C_{i,t}^{\mathrm{TG}}S_{i,t}^{\mathrm{CR}}+\rho_i^{\mathrm{TG}}S_{s,i,t}^{\mathrm{U/D}}\right)+\sum_{j=1}^{N_{\mathrm{SG}}}\left(C_j^{\mathrm{SG}}S_{s,j,t}^{\mathrm{SG}}\right)+C^{\mathrm{LD}}P_{s,t}^{\mathrm{DR}}\right\} \tag{5}$$

$$\sum_i\left(P_{s,i,t}^{\mathrm{TG}}\right)=\sum_i\left(P_{s,j,t}^{\mathrm{cha}}-P_{s,j,t}^{\mathrm{dis}}\right)+P_{s,t}^{\mathrm{DR}} \tag{6}$$

$$-\overline{P_{s,t}^{\mathrm{TG}}}\leqslant P_{s,i,t}^{\mathrm{TG}}\leqslant\overline{P_{s,i}^{\mathrm{TG}}} \tag{7}$$

$$C_{i,t}^{\mathrm{TG}}=\sum_{i=1}^{N_{\mathrm{TG}}}\sum_{t=1}^{T}\left(a_i\left(P_{s,i,t}^{\mathrm{TG}}\right)^2+b_iP_{i,t}^{\mathrm{TG}}+c_i\right) \tag{8}$$

$$\sum_{\gamma=t-T_i^{\mathrm{UP}}}^{t}S_{i,k}^{\mathrm{UP}}\leqslant S_{i,\gamma}^{\mathrm{CR}} \tag{9}$$

$$\sum_{\gamma=t-T_i^{\mathrm{DN}}}^{t}S_{i,k}^{\mathrm{DN}}\leqslant 1-S_{i,\gamma}^{\mathrm{CR}} \tag{10}$$

$$S_{i,t}^{\mathrm{CR}}-S_{i,t-1}^{\mathrm{CR}}=S_{i,t}^{\mathrm{UP}}-S_{i,t}^{\mathrm{DN}} \tag{11}$$

$$S_{i,t}^{\mathrm{UP}}+S_{i,t}^{\mathrm{DN}}\leqslant 1 \tag{12}$$

$$P_{i,s,t+1}^{\mathrm{TG}}-P_{i,s,t}^{\mathrm{TG}}\leqslant R_{i,t}^{\mathrm{UP}}S_{i,t}^{\mathrm{CR}}+\underline{P_i^{\mathrm{TG}}}S_{i,t+1}^{\mathrm{UP}} \tag{13}$$

$$P_{i,s,t}^{\mathrm{TG}}-P_{i,s,t+1}^{\mathrm{TG}}\leqslant R_{i,t}^{\mathrm{DN}}S_{i,t}^{\mathrm{CR}}+\underline{P_i^{\mathrm{TG}}}S_{i,t+1}^{\mathrm{DN}} \tag{14}$$

$$-\underline{P_i^{\mathrm{TG}}}S_{i,t+1}^{\mathrm{DN}}\leqslant P_{i,s,t+1}^{\mathrm{TG}}-P_{i,s,t}^{\mathrm{TG}}\leqslant\underline{P_i^{\mathrm{TG}}}S_{i,t+1}^{\mathrm{UP}} \tag{15}$$

$$S_{i,t}^{\mathrm{CR}}\underline{P_i^{\mathrm{TG}}}\leqslant P_{i,s,t}^{\mathrm{TG}}\leqslant S_{i,t}^{\mathrm{CR}} \tag{16}$$

$$0\leqslant P_{s,j,t}^{\mathrm{cha}}P_{s,j,t}^{\mathrm{dis}}\leqslant\overline{P_{s,j,t}^{\mathrm{SG}}} \tag{17}$$

$$E_{s,j,t+1}^{\mathrm{SG}}=E_{s,j,t}^{\mathrm{SG}}+P_{s,j,t}^{\mathrm{cha}}\eta_i^{\mathrm{cha}}-P_{s,j,t}^{\mathrm{dis}}/\eta_i^{\mathrm{dis}} \tag{18}$$

$$\underline{E_{s,j}^{\mathrm{SG}}}\leqslant E_{s,j,t}^{\mathrm{SG}}\leqslant\overline{E_{s,j}^{\mathrm{SG}}} \tag{19}$$

$$C_j^{\mathrm{SG}}=C_j^{\mathrm{life}}+C_j^{\mathrm{main}} \tag{20}$$

$$C_j^{\mathrm{life}}=\mu_j^{\mathrm{PW}}P_j^{\mathrm{SG}}+\mu_j^{\mathrm{Cap}}P_j^{\mathrm{SG}}\frac{r\left(1+r\right)^{Y_j^{\mathrm{SG}}}}{\left(1+r\right)^{Y_j^{\mathrm{SG}}}-1} \tag{21}$$

$$m_j^{\mathrm{DOD}}=\frac{\overline{N_j^{\mathrm{Cir}}}}{N_{s,j,t}^{\mathrm{Cir}}}=\left(\frac{D_{s,j,t}^{\mathrm{dis}}}{\overline{D_j^{\mathrm{dis}}}}\right)^{0.19}\exp\left[-1.69\left(1-\frac{D_{s,j,t}^{\mathrm{dis}}}{\overline{D_j^{\mathrm{dis}}}}\right)\right] \tag{22}$$

$$Y_j^{\mathrm{SG}}=\frac{N_j^{\mathrm{Cir}}D_j^{\mathrm{dis}}\overline{E_j^{\mathrm{SG}}}}{\sum_{stor}\sum_{Dday}\sum_{pro}m_{stor,day,pro}^{\mathrm{DOD}}E_{j,stor,day,pro}^{\mathrm{SG}}} \tag{23}$$

$$C_j^{\mathrm{main}}=\mu_j^{\mathrm{main}}S_{s,j,t}^{\mathrm{SG}}P_{s,j,t}^{\mathrm{SG}} \tag{24}$$

In Eq. (3), χ_s^{D} represents the probability of a disaster scenario, while C_t^{DA} and $C_{s,t}^{\mathrm{RT}}$ represent the costs before and after a disaster, respectively. Eq. (4) describes the factors influencing the day-ahead costs, $S_{i,t}^{\mathrm{UP}}$ and $S_{i,t}^{\mathrm{DN}}$ are binary variables representing the start and stop states of thermal power units, C_i^{UP} and C_i^{DN} represent the startup and shutdown costs, respectively. Eq. (5) represents the costs during a disaster, $C_{i,t}^{\mathrm{TG}}$ represent the operational cost of thermal power units , and $S_{i,t}^{\mathrm{CR}}$ represents the present status with binary variables. ρ_i^{TG} represent the penalty cost of the temporary start-stop of thermal power units, $S_{s,i,t}^{\mathrm{U/D}}$ indicating the state of thermal power unit start-stop, C_j^{SG} represent the costs of energy storage, $S_{s,j,t}^{\mathrm{SG}}$ represent the usage states of energy storage. C^{LD} and $P_{s,t}^{\mathrm{DR}}$ represents the cost and power consumption of load shedding when affected by a disaster.

In Eq. (6), $P_{s,i,t}^{\mathrm{TG}}$ represents the power generated by thermal power plants, $P_{s,j,t}^{\mathrm{cha}}$ represents the power charge for energy storage, $P_{s,j,t}^{\mathrm{dis}}$ represents the power discharge for energy storage, and $P_{s,t}^{\mathrm{DR}}$ represents the power demand response.

In Eq. (7), thermal power generation has power generation limits, minimum startup and shutdown time requirements, and the upward and downward ramp rates, as shown in Eqs. (8)-(12). To describe the binary start-stop states, Eqs. (13)-(16) describe the current start-stop states of thermal power generation and the relationship between the start and stop states.

In Eqs. (17)-(19), $P_{s,j,t}^{\text{cha}}$ and $P_{s,j,t}^{\text{dis}}$ represent the charging and discharging power of the energy storage system, $\overline{P_{s,j,t}^{\text{SG}}}$ represents the upper limit of the charging and discharging power of $E_{s,j,t}^{\text{SG}}$ represents the stored energy, η_i^{cha} and η_i^{dis} represents the charging and discharging efficiency of the energy storage, and $\underline{E_{s,j}^{\text{SG}}}$ and $\overline{E_{s,j}^{\text{SG}}}$ represents the lower and upper energy storage limits. Storage aging and maintenance are shown in Eq. (20), C_j^{SG} represents the maintenance cost of the energy storage, which can be divided into aging costs C_j^{life} and regular maintenance costs C_j^{main}.

In Eq. (21), μ_j^{PW} and μ_j^{Cap} represent the unit power and unit energy capacity prices of the energy storage, respectively, P_j^{SG} represents the power capacity of the energy storage, r is the discount rate, and Y_j^{SG} represents the economic service life of the storage. In Eq. (22), m_j^{DOD} represents the actual depth of the discharge conversion factor, and $\overline{N_j^{\text{Cir}}}$ and $N_{s,j,t}^{\text{Cir}}$ represent the rated and actual cycle counts, $D_{s,j,t}^{\text{dis}}$ and $\overline{D_j^{\text{dis}}}$ represent the actual and rated depth of discharge. In Eq. (23), $\overline{E_j^{\text{SG}}}$ represents the rated energy capacity of the energy storage system, and $E_{j,stor,day,pro}^{\text{SG}}$ represents the energy value during the discharge process. In Eq. (24), C_j^{main} calculates the daily maintenance cost, μ_j^{main} represents the unit operating cost of energy storage, and $S_{s,j,t}^{\text{SG}}$ represents the start-stop state.

3.3 Storage resilience valuation index

Following the need for a resilience-oriented dispatch approach, this study proposes an energy storage resilience quantification index to quantify the impact and value of energy storage on the system. This index is a robust and practical metric for evaluating the contribution of energy storage resources to enhancing the system’s resilience. The index measures the effectiveness and cost-effectiveness of incorporating energy storage technologies into a power system by considering the ratio of the economic value to the lifecycle cost of energy storage per unit. The mathematical expression for the energy storage resilience quantification index is given by Eq. (25)

$$\omega = \frac{\Delta f(x)}{\overline{E^{\text{SG}}}\mu^{\text{SG}}} \tag{25}$$

In Eq. (25), ω represents the economic value per unit of energy storage capacity, and $\Delta f(x)$ represents the difference between the objective function and baseline point, which represents the economic value. $\overline{E^{\text{SG}}}$ represents the energy storage capacity and μ^{SG} represents the cost of energy storage per unit of electricity.

This index offers several advantages for assessing the impact of energy storage on system resilience. It allows decision-makers to evaluate the economic benefits of energy storage relative to its costs, providing a clearer understanding of its overall value. In addition, by considering the lifecycle costs, including installation, operation, maintenance, and replacement expenses, the index provides a comprehensive evaluation of the long-term viability of energy storage.

Another benefit of the Energy Storage Resilience Quantification Index is its focus on per-unit capacity, enabling meaningful comparisons across different systems. This standardized metric allows the effectiveness of energy storage for enhancing system resilience to be evaluated, which facilitates benchmarking against industry standards and best practices.

The energy storage resilience quantification index provides decision-makers with a practical and concise tool for assessing the benefits of integrating energy storage resources and ensuring the deployment of cost-effective and resilient energy storage solutions in diverse power systems.

4 Solution algorithm & resilience evaluation

4.1 Solution method

In this study, the Matlab and CPLEX optimization engines were used to solve this problem. The solution was implemented according to the basic flowchart in Tab. 1.

Tab. 1 Algorithm for two-stage resilient unit commitment

Steps	Generator type
Step 1	for s=1:S
Step 2	for t=1:T Set the initial thermal unit, energy storage, network and load data
Step 3	Determine the disaster scenario
Step 4	Day-ahead dispatch units $S_{i,t}^{\mathrm{UP}}$ and $S_{i,t}^{\mathrm{DN}}$ in advance according to the forecasted scenario
Step 5	Real-time update unit status $S_{i,t}^{\mathrm{CR}}$, $S_{s,i,t}^{\mathrm{U/D}}$ and $S_{s,j,t}^{\mathrm{SG}}$ based on extreme conditions
Step 6	Day-ahead dispatch units in advance according to the forecasted scenario
Step 7	Case: add constraints Eqs. (6)-(24) Break
Step 8	End
Step 9	End
Step 10	Solve the resilience-oriented dispatch model
Step 11	Calculate resilience value per unit of energy storage

To ensure a stable power supply during various disasters, a two-stage scheduling model was designed. Currently, the occurrence of extreme natural disasters were anticipated on the following day, which could lead to N-K level failures in the power grid. To address these disasters, a real-time scenario model that focused on N-K level random scenarios was developed. Through advanced scheduling and planning, the goal is to minimize the expected loss of real-time loads.

4.2 Data description

Two-stage optimization dispatch in emergencies using an improved IEEE 30-node system was analyzed as a case study.

To capture the daily patterns of workload and electricity cost profiles, the problem over one day (T=24 h) with a granularity of one hour was studied. The optimization window H was set to 12 h. The system had a maximum load of 2 702 MW and included six thermal power units, one energy storage unit, two wind power units, and two solar power units, with a total installed capacity of 565 MW. The detailed parameters of the power units can be found in and Tab. 2 [36].

Tab. 2 Systems power unit parameters

Bus No. for units	Generator type	$P_{\max}$/MW
1	Thermal	80
2	Thermal	80
4	Storage	60
7	Wind	80
12	Solar	10
13	Thermal	40
21	Wind	70
22	Thermal	50
23	Thermal	30
27	Thermal	55
30	Solar	10

Considering the variation in electricity demand on the load side throughout the day, different combinations of units were designed to meet the demand peaks and optimize costs. The load-demand curve is shown in Fig. 3.

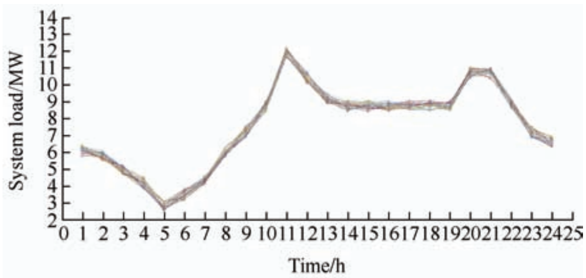

Fig. 3 System load demand curve over 24 h

Assuming a disaster scenario, as depicted in Fig. 2, where a typhoon passed through the entire power grid, resulting in partial line outages, shutting down of thermal power plants, and intermittent starting/stopping states in generating thermal power to meet the load demand. To compare the impact of energy storage on the resilience of the power grid in a disaster scenario, this study considers seven cases. The first case represents a system that does not have energy storage. Cases 2-4 involve systems equipped with energy storage capacities of 100 MW, 200 MW, and 300 MW. Cases 5-7 involve systems equipped with different 100 MW energy-storage-type lithium-ion batteries, flywheels, and pumped hydro. Please refer to Tab. 3 for details.

Tab. 3 Case settings

Case No.	System equipment	Efficiency(%)
Case 1	System without storage	—
Case 2-4	Different capacity: 100 MW, 200 MW, 300 MW	90
Case 5-7	Different storage type: Lithium-ion batteries, flywheels, pumped hydro	85, 90, 95

4.3 Impact of storage capacity and type

In the absence of energy storage, disasters lead to severe load shedding owing to line failures, as shown in Fig. 4. The disruption of the power grid caused by natural disasters underscores the need for energy-storage solutions to enhance disaster resilience and ensure a stable electricity supply during crises.

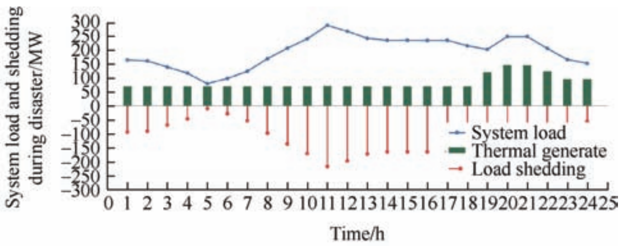

Fig. 4 System load shedding under the disaster scenario

The model assumes a disaster impact period from 10:00 to 19:00. Based on the resilience-oriented dispatch model, pre-reserved renewable energy and stored energy are utilized to meet daily demand peaks. The experimental results demonstrated the importance of energy storage in mitigating the impact of disasters, as shown in Fig. 5. When a disaster was anticipated at 12:00 during a peak electricity demand period, renewable energy and energy storage effectively supplemented the power supply. However, as the disaster duration increased while electricity demand remained constant, the availability of renewable energy gradually diminished. Under such circumstances, the critical role of energy storage becomes evident, enabling continuous electricity supply during extended disaster periods. Relying on

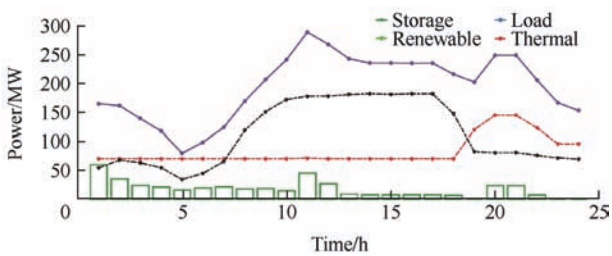

Fig. 5 System optimization result under the disaster scenario

stored energy bridges the gap between renewable energy fluctuations and an uninterrupted power supply, ensuring grid resilience and reliability when faced with prolonged disasters.

To compare the different energy storage systems, the model parameters were set according to a compilation of references [37-38], as shown in Tab. 4. Considering the variation in electricity demand on the load side throughout the day, different combinations of units were designed to meet the demand peaks and optimize costs.

Tab. 4 Energy storage systems parameters

Energy storage technology	Cost/($/kW)	Response time	Discharging time	Efficiency (%)
Lithium-ion batteries	1 408-1 947	Sub-second to seconds	Minutes to a few hours	85
Flywheels	1 080-2 880	Sub-second	Seconds to a few minutes	95
Pumped hydro	1 504-2 422	Several seconds to minutes	Several hours to days	80

Based on the numerical simulations, the experimental results shown in Fig. 6 indicate that the influence of different energy-storage efficiencies on the grid's resilience is insignificant.

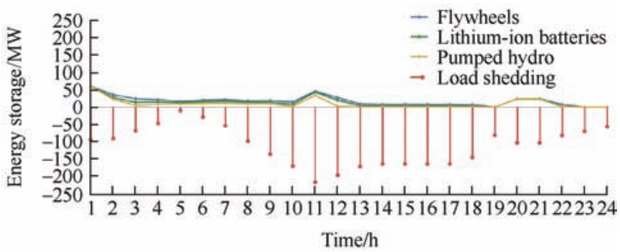

Fig. 6 Impact of storage types on load reduction

To enhance grid resilience, it is more practical to prioritize cost as a primary factor in planning energy storage systems. By optimizing the cost-effective deployment of energy storage technologies, power system operators can achieve a balanced approach that effectively improves grid resilience without being overly reliant on a specific energy storage type.

4.4 Resilience valuation index

Furthermore, the resilience value per unit of capacity of different energy storage systems was analyzed. The value of the energy storage varies with its capacity. Fig. 7 illustrates the costs of various energy storage systems as their capacities vary. Regardless of the type of energy storage, the cost plateaued after reaching a certain capacity level.

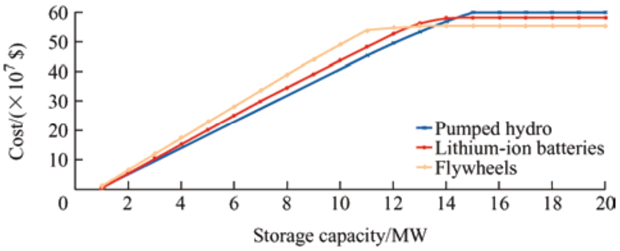

Fig. 7 Variation in energy storage value for different energy storage systems

Based on Eq. (23), further resilience values were calculated. The results showed that different energy-storage capacities could be configured based on different unit resilience values. The optimal capacity configurations for the flywheel, lithium-ion batteries, and pumped hydro-storage were 10 MW, 11 MW, and 12 MW, respectively. The benefit gap for the flywheel was particularly significant, whereas the unit resilience value for pumped hydro-storage showed a more gradual change, as seen in Fig. 8.

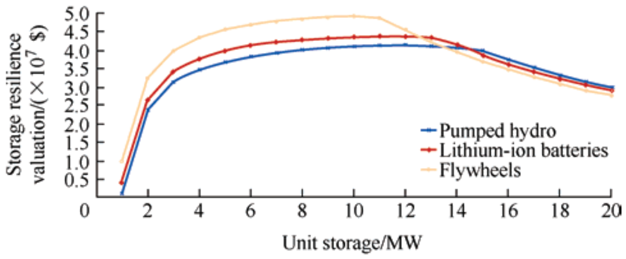

Fig. 8 Unit capacity energy storage price

5 Conclusions

This study demonstrated a two-stage emergency dispatch model for optimizing power system operations under extreme conditions. Through extensive case analysis using real-world data, the proposed model incorporates thermal power generation, renewable energy, and energy storage into its strategy. The results of the model effectively addressed load-shedding issues caused by extreme conditions, enhanced the resilience of the power system through coordinating different unit commitments, contributed to balancing the power system, and optimized the combination of generation units. By defining the resilience value of energy storage per unit, this study provides valuable strategies for configuring different energy storage systems and capacities.

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