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Research on optimal configuration of mobile energy storage in distribution networks considering various energy utilization efficiencies

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The increasing integration of renewable energy sources such as wind and solar into the distribution grid introduces new complexities and instabilities to traditional electrical grids. This study tackles these challenges by optimizing the configurations of Modular Mobile Battery Energy Storage (MMBES) in urban distribution grids, particularly focusing on capacity-limited areas. Our method investigates five core attributes of energy storage configurations and develops a model capable of adapting to the uncertainties presented by extreme scenarios. This approach not only enhances the adaptability of energy storage systems but also equips decision-makers with proactive and flexible tools for decision-making in complex environments. Empirical evidence from the study shows that modular mobile energy storage significantly improves distribution grid performance by effectively managing the challenges posed by renewable integration. Furthermore, the research confirms that optimizing decision-makers' cognitive parameters to align with subjective preferences ensures economic viability and enhances grid resilience. This study offers a new perspective and methodology for configuring energy storage, contributing to more flexible and reliable grid operations amidst widespread renewable integration.

KEYWORDS

mobile energy storage, distribution grid, prospect model, scenario uncertainty, adaptive decision-making, grid resilience

1 Introduction

As urbanization continues to progress, the disparity between peak and off-peak electricity demand in urban core areas has gradually increased. Moreover, electricity consumption in these areas is approaching saturation, and the availability of land for further infrastructure expansion is becoming increasingly limited. The power industry, being a major consumer of energy (Wang et al., 2022a), has drawn extensive attention to the need for energy conservation and loss reduction. In the five segments of the power system, namely, generation, transmission, transformation, distribution, and consumption, distribution networks account for over 60% of the total power losses in the entire grid (Ying et al., 2017). Therefore, achieving energy conservation and loss reduction at the distribution level has become even more critical (Chen et al., 2022).

1.1 Challenges in traditional technical measures

Traditional technical measures for loss reduction in distribution networks primarily involve the replacement of high-energy-consuming distribution transformers, shortening supply radii, balancing three-phase loads, and implementing reactive power compensation. However, these methods are often associated with high investments, construction challenges, and long implementation periods (Zang, 2020).

1.2 Potential of flexible regulation resources

With the widespread adoption of flexible regulation resources in distribution networks, including energy storage systems (Jiang, 2021), there is a growing emphasis on uncovering the loss reduction potential of existing flexible regulation resources. Modular Mobile Battery Energy Storage (MMBES), representing a novel energy storage technology, possesses the flexibility of both time and space. It can be rapidly deployed at specified locations in response to demand, providing services such as emergency response (Zhang et al., 2020), uninterrupted operations (Li et al., 2022a), and peak load management (Li et al., 2022b; Sun et al., 2023) to distribution networks.

1.3 Current energy storage deployment scenarios

Currently, energy storage deployment in the power system can be broadly categorized into three scenarios:

1) Energy storage deployment on the generation side: In this scenario, energy storage is integrated on the generation side. Literature (Ma et al., 2016) has established a comprehensive economic benefit model for Battery Energy Storage Systems (BESS) participating in wind power ancillary services. It assesses the profitability of the BESS by calculating investment return rates, payback periods, and other economic indicators. Literature (Lü et al., 2015) focuses on the relationship between photovoltaic system and energy storage costs, electricity price models, load characteristics, and the economic feasibility of energy storage systems, aiming to find the optimal economic solution.
2) Energy storage deployment on the user side: This scenario involves the installation of energy storage systems at the user's premises. Literature (Nayak and Nayak, 2017) considers only the peak shaving benefits of users after installing energy storage, while literature (Narimani et al., 2017) concentrates on the economic viability of demand-side management. Neither of these studies simultaneously considers both aspects of energy storage benefits in their optimization research.
3) Energy storage deployment on the grid side: In this scenario, energy storage is deployed on the grid side. Literature (Chaspierre et al., 2022) and others have developed dynamic equivalent models that respond to reactive power as much as possible. These models are applied to Battery Energy Storage Systems (BESS) in the main substations of distribution networks. They compensate for the inevitable inaccuracies in fluctuating energy sources, ensuring higher precision operation. Literature (Alasali et al., 2022) and others have designed and developed optimal integration of photovoltaic and Energy Storage Systems (ESS) in Active Distribution Networks (ADN). They use optimization methods like the Golden Ratio Optimization Method (GROM) and Particle Swarm Optimization (PSO) algorithms to find the best configurations, achieving 100% photovoltaic energy consumption. Literature (Mokryani, 2022), in considering the planning, design, and operation of the best stations in the distribution network, highlights the contributions of BESS in providing flexibility, enhancing energy security, and supporting Variable Generation (VG) integration.

1.4 Limitations of fixed energy storage systems

In current energy storage systems, a conventional strategy involves deploying these systems at fixed locations, typically at strategically selected sites such as power generation stations, industrial facilities, or substations near residential areas. This deployment strategy is primarily designed based on the geographical location of facilities and the stability of grid demands, enabling efficient energy transmission from storage sites to demand locations. Fixed energy storage systems are advantageous in providing continuous and stable energy output, particularly suitable for grid environments with high predictability and relatively fixed demands.

However, this fixed deployment approach exhibits several significant limitations. First, the flexibility of fixed systems is limited; they cannot rapidly adjust to real-time changes in grid demands. In situations where there are sudden changes in load or emergencies (such as disruptions caused by natural disasters), fixed systems are unable to quickly reposition or adjust their locations to more effectively support specific areas of the grid. Additionally, the installation and maintenance costs of fixed energy storage systems are high, especially in geographically remote or inaccessible areas. This not only increases the economic burden of initial investments but also may affect the long-term sustainability and efficiency of the system. Lastly, fixed systems often require close integration with existing grid infrastructure, which limits their application potential in emerging or slowly upgrading grids where infrastructure may not support efficient energy distribution and management.

1.5 Advantages of mobile energy storage systems

To further enhance the flexibility of energy storage applications, both domestic and international research has initiated preliminary studies on mobile energy storage. Literature (Lei et al., 2016), for instance, introduced a two-stage scheduling framework for mobile energy storage based on pre-positioning and real-time allocation. This framework enhances resilience by improving the response to unexpected events. Literature (Lei et al., 2019) proposed a mixed-integer programming model to address challenges related to mobile energy storage scheduling and the disparate time scales of distribution system operation, as well as the coupling of road networks and power grids. By optimizing the dynamic scheduling of mobile power sources, this approach enhances the resilience of the distribution network. To encapsulate, the significance of portable energy storage systems stems from their capacity to manage unforeseen circumstances, including traffic congestion and catastrophic events, alongside securing diverse advantages via adaptable deployments. Hence, the unpredictability of such events and the inclination towards decision-making that accounts for multiple benefits are key elements that affect the setup of energy storage solutions.

1.6 The main breakthroughs of this research

This study introduces a refined approach for arranging Modular Mobile Battery Energy Storage (MMBES) within distribution networks, taking into account both overall utility and individual perception. The primary breakthroughs of this research encompass:

1) From the viewpoint of the electric utility company, the research suggests a method for the integrated use of modular energy storage across three situations: standard operation of the distribution network, addressing equipment malfunctions, and managing emergency conditions. In detail, MMBES is utilized for peak shaving in normal operations, providing energy to adaptable loads upon unexpected equipment failures, and allocating power to essential loads in crisis circumstances. This strategy not only improves the comprehensive utility of the energy storage system but also augments the adaptability of the distribution network.
2) To address the varied advantages derived from these three scenarios, alongside the unpredictability linked to extreme events and the individual biases of decision-makers towards these benefits, the paper incorporates prospect theory. This introduces an optimization framework for configuring MMBES, aimed at maximizing the expected value of the wide-ranging benefits (Meng, 2019; Mei et al., 2020).
3) The paper also presents calculation models and solution methods for assessing the prospect values related to reducing distribution losses, improving reliability, delaying upgrade and renovation, reducing outage losses in extreme scenarios, and configuring costs. Notably, the prospect of delaying grid upgrade and renovation is computed from a probabilistic perspective using credible capacity, providing a more accurate measure of the capacity substitution value of energy storage (Qi et al., 2023).

In summary, this research introduces an optimized configuration method for MMBES in distribution networks operated by electric utility companies. It considers comprehensive utility and subjective cognition, addressing various scenarios and benefits. Additionally, it incorporates prospect theory to account for decision-makers' subjective preferences and handles the uncertainty associated with extreme events. Innovative calculation methods for prospect values related to network reliability and upgrade delay are also presented, enhancing our understanding of energy storage deployment in distribution systems.

2 Analysis of configuration strategies and issues for MMBES

The Growing Dependence on Electricity in Modern Society and the Escalating Frequency of Extreme Weather Events. In contemporary society, there is an ever-increasing reliance on electricity, coinciding with a yearly rise in the occurrence of extreme weather events. Presently, the electricity system relies on a combination of redundant network structures, user-owned backup power sources, and emergency repair measures to address extreme disasters. Despite the adaptability of the network and the dependability of user-managed backup energy sources, there is no assurance of a continuous power supply to essential users. Nevertheless, the adaptability of the network and the dependability of consumer-owned backup power solutions cannot ensure a constant power supply to essential users. While deploying a larger number of backup power sources can ensure reliability, it often comes at the expense of cost-effectiveness. To address the challenge of enhancing the resilience of distribution networks, recent scholars from both domestic and international contexts have proposed utilizing distributed resources for on-site dispatch during interruptions in power supply from the larger electrical grid to provide emergency power (Li et al., 2023; Liu et al., 2023). However, due to the scale and distribution characteristics of distributed resources, they are currently unable to serve as a significant resource for ensuring resilience.

MMBES is composed of several independently powered energy storage modules, each consisting of battery units arranged in series and parallel and integrated into containers. These modules provide multiple electrical interfaces and possess the capability for seamless integration with the electrical grid. During normal system operation and in the event of random equipment failures, the energy storage modules are configured in parallel combinations at substations, yielding benefits such as reduced network losses, improved distribution network reliability, and delayed grid upgrade requirements. In scenarios where the power system faces localized disruptions caused by events like typhoons, earthquakes, or intentional sabotage, leading to extended periods of inactivity, MMBES units can be disassembled and relocated to offer temporary power assistance to key regions or users. This enhances distribution network resilience without the need for additional investments.

When configuring MMBES, investors typically exhibit subjective preferences in assessing its various benefits and configuration costs. These preferences include considerations such as the expectation of reducing network losses and generating profit under normal conditions A_1 and ensuring the security of critical loads in extreme scenarios A_2, rather than solely pursuing maximum total revenue. Therefore, taking into account the subjective preferences of investors aligns more closely with the original intent of MMBES planning. Prospect theory is a framework for understanding decision-making that takes into account the cognitive biases of decision-makers. It suggests that individuals demonstrate unequal reactions to comparable positive and negative outcomes, with the perception of an outcome as a gain or a loss being

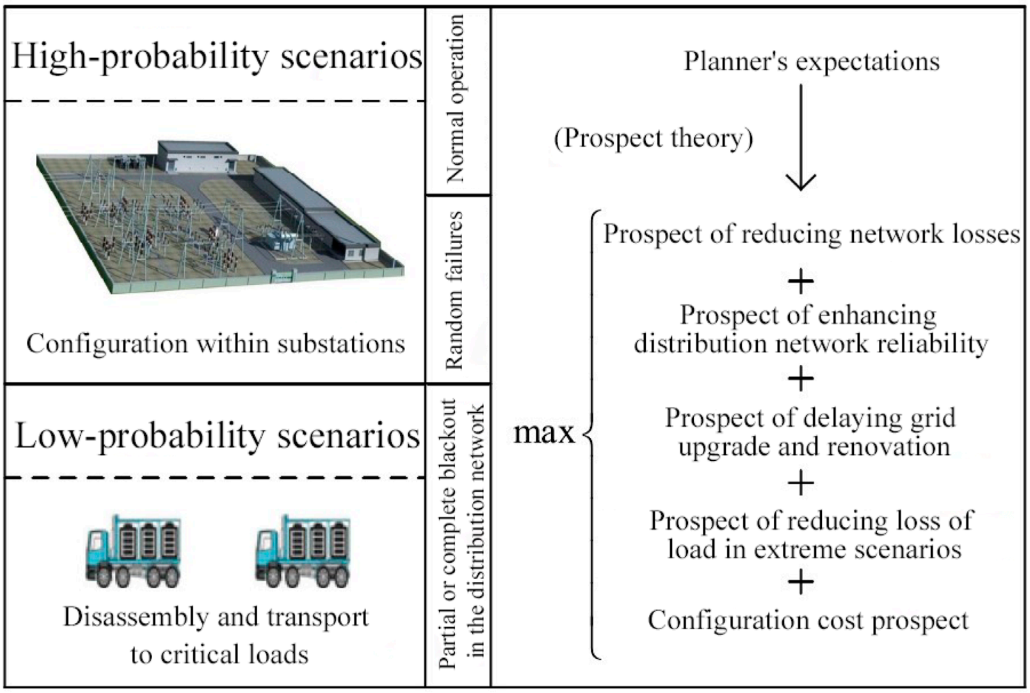

FIGURE 1
The basic approach to MMBES configuration.

determined in relation to the psychological baseline of the decision-maker. In this paper, based on prospect theory, we elaborate on the utility achievable through MMBES configuration, representing it as a set of multiple attributes. These attribute values are framed within a prospect, replacing the scalar gains typically used in traditional optimization, resulting in configuration outcomes that better align with the decision-maker's expectations. Additionally, this approach effectively addresses the impact of extreme events with high uncertainty on planning results. Based on the analysis presented above, the fundamental approach for configuring MMBES in this study is illustrated in Figure 1.

3 An MMBES optimization configuration model incorporating subjective cognition

To comprehensively evaluate the effectiveness of the Modular Mobile Battery Energy Storage (MMBES) configuration, the following evaluation parameters were utilized:

1. Network Loss Reduction (E_{dec})

Definition: Represents the reduction in electrical energy losses within the distribution network achieved by configuring the MMBES. Calculation: The expected reduction in network losses is calculated based on the MMBES's charging and discharging capacities and the state-of-charge (SOC) distribution (see Equations 10–12).

2. Reliability Improvement (E_{rel})

Definition: Evaluates the improvement in system reliability before and after configuring the MMBES. Calculation: The initial reliability level is calculated, followed by the establishment of a reliability model after MMBES configuration and the calculation of the expected improvement in reliability (see Equations 16–21).

3. Deferral Value (E_{del})

Definition: Measures the time period that MMBES can delay upgrades and renovations of the distribution network. Calculation: Based on the reliability model, the dependable capacity of MMBES is calculated, which in turn is used to determine the value of deferring upgrades (see Equations 22–25).

Diverging from the classic anticipated utility model, the framework of prospect theory indicates that decision-makers do not exhibit total rational behavior. The assessment of gains and losses, together with the probabilities linked to the outcomes of decisions, is shaped by the benchmarks established by the decision-makers themselves. The prospect value, V, is defined through the combination of the value function, $v(x)$, and the probability weighting function, $\pi(p)$, illustrating how subjective perspectives influence decision valuation (Sha, 2023) (see Equation 1):

$$V = \pi^{+}(p)\, v^{+}(x) + \pi^{-}(p)\, v^{-}(x) \tag{1}$$

In this context, V denotes the prospect value attributed to the outcome of a decision. The functions $\pi^{+}(p)$ and $\pi^{-}(p)$ refer to the weighting functions, while $v^{+}(x)$ and $v^{-}(x)$ refer to the value functions that the decision-maker associates with gains and losses, respectively. Here, p symbolizes the likelihood of the decision outcome being viewed as a gain or a loss under uncertain conditions; x signifies the quantifiable value of the decision outcome.

The electric utility company's involvement in the electricity market through the deployment of energy storage on the grid side is considered in this study. Five attributes related to energy storage are identified: distribution and transmission losses, power supply reliability, grid expansion investments, blackout losses in extreme scenarios, and the cost of configuring MMBES. This document utilizes prospect theory to address planners' personal inclinations and the unpredictability linked to critical situations. The objective is to maximize the integrated prospect value over the operating cycle of MMBES, as formulated in Equations 2–5 below. In these equations, the dimensional units of each attribute are converted to "currency" to eliminate the influence of different units on the integrated prospect value. The attributes are also discounted to a common present value based on the initial construction period, using the net present value method (Zhang et al., 2023).

$$\max V = \omega_1 V_{dec} + \omega_2 V_{rel} + \omega_3 V_{del} + \omega_4 V_{ext} + \omega_5 V_c \tag{2}$$

$$s.t. \sum_{a \in N_{DG}} p_{DGa.t} + p_{MMBES.t} + p_{input.t} = \sum_{b \in N_{load}} p_{loadb.t} + p_{loss.t} \tag{3}$$

$$U_c^{min} \le U_c \le U_c^{max} \tag{4}$$

$$P_{lde} \le P_{lde}^{max} \tag{5}$$

Where: V represents the integrated prospect value of the electric utility company's MMBES configuration; V_{dec} represents the prospect value associated with minimizing network losses; V_{rel} signifies the potential value associated with improving the reliability of the distribution grid; V_{del} represents the prospect value of delaying grid upgrade and renovation; V_{ext} embodies the potential value derived from minimizing power outage losses under severe conditions; V_c represents the prospect value of the full lifecycle cost of MMBES considering recovery and disposal. ω_1, ω_2, ω_3, ω_4, and ω_5 represent the importance weights assigned to the aforementioned prospects, typically determined by the decision-maker, satisfying $0 \le \omega_1, \omega_2, \omega_3, \omega_4, \omega_5 \le 1$, and $\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1$. The decision variables include the rated capacity (S_n), rated power (P_n), and the minimum state of charge limit ($S_{oc.min}$). These factors are crucial in defining the configuration parameters and operational strategy of the MMBES.

In the constraint conditions, Equation 3 represents the system's active power balance constraint: $p_{DGa.t}$, $p_{MMBES.t}$, and $p_{input.t}$ represent the output of distributed generator a, the output of MMBES (positive for discharging), and the input power to the distribution network at time t respectively. $p_{loadb.t}$ and $p_{loss.t}$ represent the power at load node b and the network losses in the system at time t, respectively. N_{DG} and N_{load} are the numbers of distributed generators and load nodes in the distribution network, respectively. Equation 4 represents the node voltage constraint, where U_c is the voltage magnitude at node c, U_c^{max} and U_c^{min} are the upper and lower voltage limits at that node. Equation 5 represents the line transmission capacity constraint, where P_{lde} and P_{lde}^{max} are the active power flow from node d to node e and the maximum transmission capacity of line $d-e$, respectively.

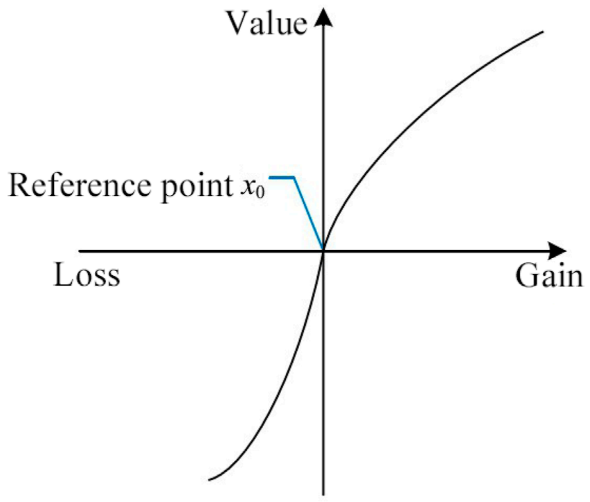

FIGURE 2
The evaluation curve.

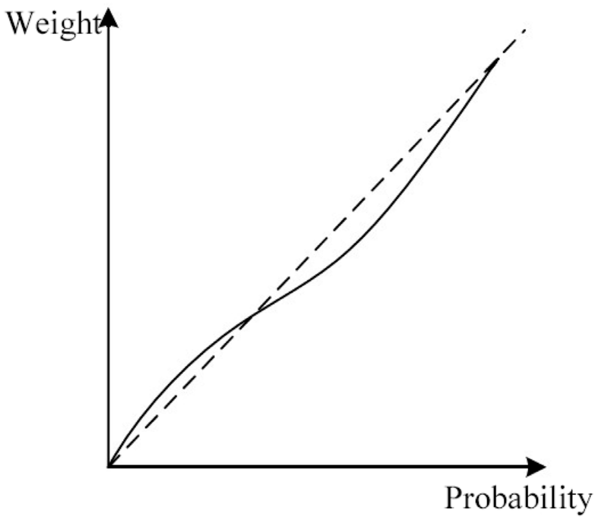

FIGURE 3
The weighting function.

The subjective cognition of decision-makers follows certain patterns. When attributes are considered gains relative to the reference point, decision-makers exhibit risk aversion, and their value function is convex. Conversely, when attributes are perceived as losses relative to the reference point, decision-makers tend to be risk-seeking, and their value function is concave. Furthermore, equal magnitudes of losses and gains result in more significant distress than pleasure for decision-makers, as depicted in Figure 2. Decision weights represent the subjective weighting of uncertain event outcomes with probabilities denoted as "p." For small probabilities, decision-makers often attribute weights that are higher than the actual probability, whereas for large probabilities, the tendency is to assign weights that are lower than the actual probability, as depicted in Figure 3.

1) The exact formulation for the evaluation curve is specified as follows:

① When the attribute indicates a "gain"

$$v^{+}(x) = (x - x_0)^{\alpha}, x \geq x_0 \tag{6}$$

② When the attribute represents 'loss'

$$v^{-}(x) = -\lambda(x_0 - x)^{\beta}, x < x_0 \tag{7}$$

In this context, x_0 is the baseline or reference point for the attribute, encapsulating the subjective perspective of planners. The parameters α and β, both ranging from 0 to 1, represent the coefficients for risk-seeking and risk-averse behaviors, respectively. Additionally, the parameter λ, which is greater than 1, denotes the coefficient for loss aversion.

2) The comprehensive equation for the weighting function is detailed in the following manner:

① Whenever the characteristic represents a "gain"

$$\pi^{+}(p) = p^{\gamma}/[p^{\gamma} + (1-p)^{\gamma}]^{\frac{1}{\gamma}} \tag{8}$$

② Whenever the characteristic indicates a "loss"

$$\pi^{-}(p) = p^{\delta}/\left[p^{\delta} + (1-p)^{\delta}\right]^{\frac{1}{\delta}} \tag{9}$$

Here: Parameters γ and δ represent the coefficients for risk attitudes when decision-makers encounter "gains" and "losses," respectively.

The uncertainty within the scenario presents itself through two distinct dimensions. Firstly, there is uncertainty in the development of distributed power sources and loads. Secondly, there is uncertainty in the occurrence probability of extreme scenarios and outage durations. This paper primarily focuses on the latter aspect. Apart from the losses stemming from outages in extreme scenarios, all other characteristics, when compared to a reference point, are depicted as probabilities of "gain" or "loss" being either 1 or 0. Consequently, the weighting function $\pi(p)$ remains constant as well, set at either 1 or 0. The value function and weight function for reducing outage losses in extreme scenarios should be complemented based on the probability density functions they follow, in addition to the foundation provided by Equations 6–9.

The models for various prospective values are as follows.

3.1 Prospective model for distribution network loss reduction based on power difference control strategy

The presence of MMBES (Modified Multi-Bus Electrical System) within the substation affects the losses of the upstream power grid and the transformers within the substation. When the operating strategy is fixed and errors are not considered, the reduction in distribution network losses is uniquely correlated with the decision variables. Therefore, the value of distribution network loss reduction, denoted as $v(E_{dec})$, is equivalent to the prospective value of distribution network loss reduction, V_{dec}. The specific expression is as follows:

$$\begin{aligned} V_{dec} &= \pi^{+}(p_{dec})\, v^{+}(E_{dec}) + \pi^{-}(p_{dec})\, v^{-}(E_{dec}) \\ &= \begin{cases} v^{+}(E_{dec}) = (E_{dec} - E_{dec.0})^{\alpha}, E_{dec} \geq E_{dec.0} \\ v^{-}(E_{dec}) = -\lambda(E_{dec.0} - E_{dec})^{\beta}, E_{dec} < E_{dec.0} \end{cases} \end{aligned} \tag{10}$$

In the equation: E_{dec} represents the reduction in distribution network losses before and after configuring MMBES; $E_{dec.0}$ represents the anticipated reduction in losses as expected by the planners.

$$E_{dec}(S_n, P_n, S_{oc.min}) = \sum_{k=1}^{N_y} \frac{\sum_{j=1}^{S} \sum_{t=1}^{24/\Delta T} \Delta p_{loss,tj} \cdot \Delta T \cdot n_j \cdot f_{cost}}{(1+i_0)^k} \tag{11}$$

$$N_y = \min\left(N_{life}, N_{war}\right) \tag{12}$$

In the equation provided: N_y represents the operational lifespan of MMBES; S denotes the number of categories into which the daily load profile is divided over the course of a year;n_j denotes the quantity of days within a year that are classified under the jth type of standard daily load profiles; $\Delta p_{loss.tj}$ signifies the difference in distribution network losses before and after configuring MMBES for the jth typical daily load category; ΔT represents the time interval per unit, with this paper using a value of 1 h; f_{cost} denotes the unit cost of purchasing electricity from the grid; i_0 represents the baseline rate of return; N_{life} represents the operational lifespan of the battery system, taking into account the impact of discharge depth and the number of cycles. This lifespan can be determined through the rainflow counting method (Wang et al., 2022b); N_{war} stands for the warranty period provided by the MMBES manufacturer.

The effectiveness of distribution network loss reduction is closely related to the operational strategy of MMBES (Modified Multi-Bus Electrical System). Appropriate management of energy storage systems can equalize the flow of electricity in the primary distribution lines and substation transformers across peak and low-demand periods, thereby diminishing losses in the network. In this paper, a peak shaving and valley filling power difference control strategy is employed during normal grid operation, and its performance is illustrated in Figure 4. MMBES undergoes a complete charge-discharge cycle daily, while adhering to Equations 13–15 as the foundation. The start and stop times t_g $(g \geq 4)$ for charging and discharging, as well as the power levels (P_1 and P_2), are determined based on the configured capacity and state of charge (SOC) constraints. The difference between P_1, P_2, and the actual load represents the charging and discharging power within each time interval.

MMBES Operation Satisfying Equations 13–15:

$$S_{oc.t} = \begin{cases} S_{oc,t-1} + \dfrac{\eta p_{MMBES.t}\Delta T}{S_n}, p_{MMBES.t} \geq 0 \\ S_{oc,t-1} - \dfrac{(1/\eta)\, p_{MMBES.t}\Delta T}{S_n}, p_{MMBES.t} < 0 \end{cases} \tag{13}$$

$$S_{oc.min} \leq S_{oc.t} \leq S_{oc.max} \tag{14}$$

$$|p_{MMBES.t}| \leq P_n \tag{15}$$

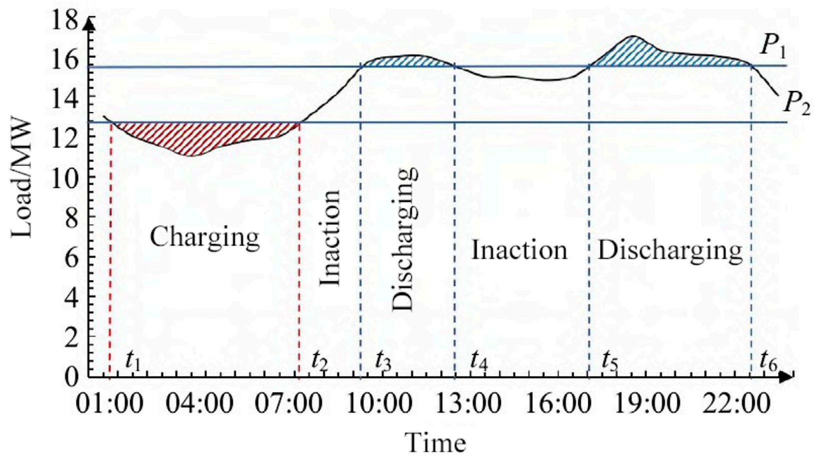

FIGURE 4
Schematic diagram of MMBES operational performance.

In the equation: $S_{oc.t}$ represents the state of charge (SOC) of MMBES at time t; η denotes the charging and discharging efficiency of MMBES.

3.2 Prospective model for enhancing distribution network reliability in the presence of random equipment failures

In the event of a malfunction on the high-voltage side of the substation or within the substation transformer itself, MMBES can supply energy to the loads within the same island throughout the fault rectification period. This capability significantly boosts the dependability of the distribution system. The dependability traits of the distribution grid are constant, and the advantage of enhancing supply dependability, denoted by $v(E_{rel})$, corresponds to the anticipated benefit of bolstering the distribution grid's reliability, V_{rel}. The specific formulation is presented below:

$$V_{rel} = \pi^+(p_{rel})\,v^+(E_{rel}) + \pi^-(p_{rel})\,v^-(E_{rel}) = \begin{cases} v^+(E_{rel}) = (E_{rel} - E_{rel.0})^{\alpha}, E_{rel} \ge E_{rel.0} \\ v^-(E_{rel}) = -\lambda(E_{rel.0} - E_{rel})^{\beta}, E_{rel} < E_{rel.0} \end{cases} \tag{16}$$

In the equation: E_{rel} represents the economic benefits resulting from the enhancement of distribution network reliability; $E_{rel.0}$ represents the anticipated economic benefits as expected by the planners.

This research utilizes the metric known as Expected Energy Not Supplied (EENS) to assess the dependability of the distribution grid.

$$E_{rel}(S_n, P_n, S_{oc.min}) = \sum_{k=1}^{N_y} \frac{\Delta E_{ENS} \cdot (f_{sell} + f_{comp} \cdot R_{IEA})}{(1+i_0)^k} \tag{17}$$

In the equation: ΔE_{ENS} represents the difference in Expected Energy Not Supplied (EENS) before and after configuring MMBES; f_{sell} denotes the average unit selling price of electricity from the grid; f_{comp} represents the production-to-electricity ratio per unit of energy not supplied; R_{IEA} stands for the User Evaluation Coefficient.

Reliability assessment methods can primarily be classified into two major categories: analytical methods and simulation methods. Battery energy storage exhibits temporal characteristics, but Monte Carlo sampling simulations are time-consuming for optimization problems. Therefore, in this paper, we employ the analytical approach known as Fault Consequence Analysis to perform the calculations. The residual energy capacity of MMBES is contingent upon real-world operating conditions and has a direct impact on the outcomes of system failures. Therefore, conducting a statistical analysis of the State of Charge (SOC) in line with the operational strategy is crucial. This analysis enables the determination of the probabilities linked to various SOC levels, which, in turn, facilitates the calculation of the distribution network's reliability at each SOC level. The comprehensive reliability assessment is achieved by compiling these findings using suitable weighting methods.

The specific formula for calculating EENS is as follows:

$$E_{ENS} = \sum_{h=1}^{J} \left\{ \frac{a_h}{A} \sum_{b=1}^{B} \left[E_{ENSb} - \min(E_{ENSb}, S_{oc.h})\, p_{rec.b} \right] \right\} \tag{18}$$

$$E_{ENSb} = \sum_{m=1}^{N_b} (\lambda_m \mu_m)\, P_b \tag{19}$$

$$S_{oc.h} = S_n \sum_{n=1}^{a_h} \frac{b_{hn}}{a_h} \tag{20}$$

$$p_{rec.b} = \sum_{m=1}^{I_s} (\lambda_m \mu_m) \Big/ \sum_{m=1}^{N_b} (\lambda_m \mu_m) \tag{21}$$

In the equation, J denotes the total number of scenarios corresponding to different SOC levels; A signifies the aggregate count of SOC samples; a_h represents the quantity of samples for the hth SOC scenario; and B indicates the complete number of loads within the distribution network; E_{ENSb} is the annual expected energy not supplied for the bth load;$S_{oc.h}$ represents the anticipated residual energy of the MMBES for the hth State of Charge (SOC) scenario; $p_{rec.b}$ is the expected ability of MMBES to supply power to the bth load during a fault; N_b represents the elements that can cause a power outage for the bth load due to a fault; λ_m and μ_m are respectively the failure rate and repair time for the mth element;

P_b is the required power to ensure normal power supply for load b during an outage; b_{hn} represents the nth sample value for the hth SOC scenario; I_S represents the elements for which MMBES and the load are in the same island after a fault.

3.3 Prospective model for delaying power grid upgrades based on credible capacity

The traditional assessment method for delaying power grid upgrades is based on measuring the number of years the expansion can be postponed by evaluating the maximum load reduction before and after energy storage configuration. Despite the potential benefits, the intrinsic likelihood of failures within energy storage systems means they cannot ensure uninterrupted adherence to the $N-1$ criterion for grid reliability. This limitation leads to an overestimation of the systems' advantages. The phrase "credible capacity" for energy storage refers to the volume of supply capacity that can be dependably replaced with a given degree of dependability. It offers a finer assessment of MMBES's addition to the grid and its replacement worth. The specific expression for the prospective value V_{del} of delaying power grid upgrades is given by (Zhao et al., 2023):

$$\begin{aligned} V_{del} &= \pi^+(p_{del})v^+(E_{del}) + \pi^-(p_{del})v^-(E_{del}) \\ &= \begin{cases} v^+(E_{del}) = (E_{del} - E_{del.0})^{\alpha}, E_{del} \ge E_{del.0} \\ v^-(E_{del}) = -\lambda(E_{del.0} - E_{del})^{\beta}, E_{del} < E_{del.0} \end{cases} \end{aligned} \tag{22}$$

$$E_{del}(S_n, P_n, S_{oc.min}) = \sum_{k=1}^{\Delta T_y} \frac{c_{inv} \cdot \left(1 - e^{-i_0 \cdot \Delta T_y}\right) / \Delta T_y}{(1 + i_0)^k} \tag{23}$$

$$\Delta T_y = \lg\left(1 + \frac{P_{rel}}{P_{max}}\right) / \lg(1 + \tau) \tag{24}$$

In the equation: E_{del} represents the benefits of postponing distribution network expansion; $E_{del.0}$ represents the anticipated benefits as expected by the planners; c_{inv} is the required investment for substation and line expansion; ΔT_y is the number of years by which MMBES delays power grid upgrades;τ represents the annual rate of load growth; P_{max} signifies the peak load of the system prior to the integration of MMBES; P_{rel} denotes the credible capacity of MMBES.

In this research, following the concept of matching reliability, the credible capacity of MMBES is evaluated using the Effective Load Carrying Capability (ELCC) indicator. The exact correlation is outlined below:

$$R(L_0) = R'(L_0 + \Delta L) \tag{25}$$

Within the formula, R and R' represent the dependability of the distribution grid prior to and subsequent to the deployment of MMBES, respectively. These reliability levels are assessed using the reference Equations 18–21, specifically for the evaluation metric EENS; L_0 and ΔL represent the original total load at various load points within the distribution network and the additional load, respectively. When Equation 25 holds true, the corresponding ΔL represents the credible capacity P_{rel} of MMBES. The step-by-step calculation process is depicted in Figure 5 for reference.

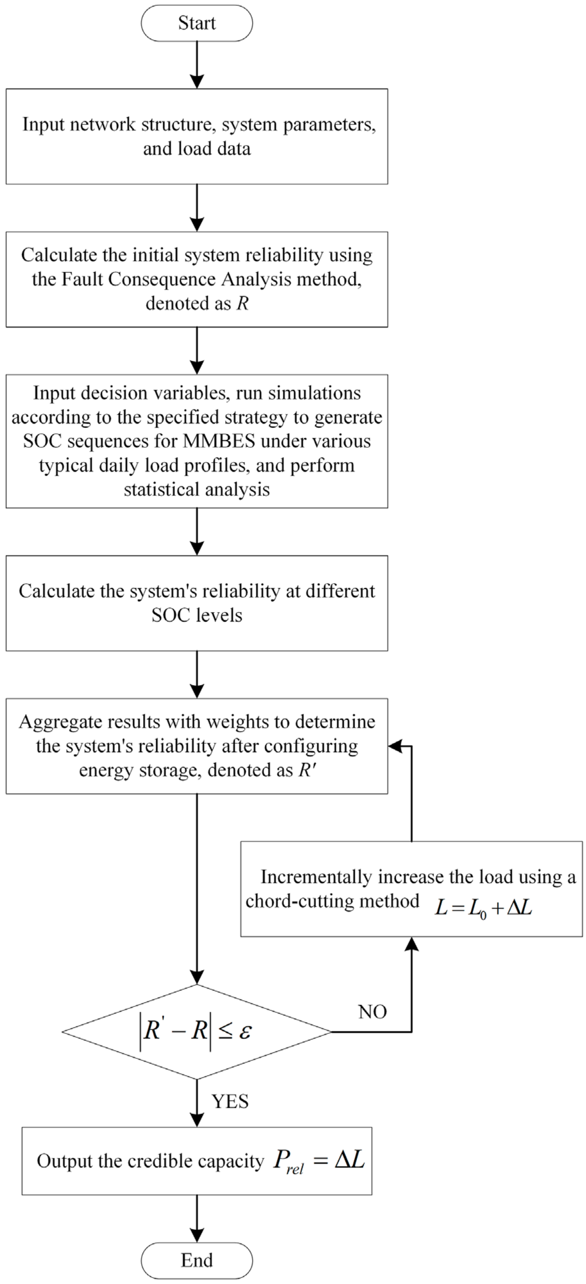

FIGURE 5
The calculation process for MMBES credible capacity.

3.4 Prospective model for reducing power outage losses in extreme scenarios

In situations where the electrical power system encounters severe weather phenomena or widespread power interruptions due to military operations, the continuous provision of power to vital loads is essential. MMBES can be divided into various autonomous supply entities depending on the specific nature of the fault, with a focus on guaranteeing power delivery to essential loads should backup power sources fail. If there is surplus capacity, it can then be used to safeguard some of the secondary loads that lack backup support. The prioritization for protection ought to be thoroughly evaluated across three critical dimensions: the safety of human life, the security of the nation, and the potential for economic losses.

Diminishing losses from power outages in critical situations correlates with the likelihood and length of these scenario events. Since both of these factors are uncertain, this attribute follows a certain probability distribution rather than a deterministic value. Its value function should be improved based on Equations 6, 7, as shown specifically in Equation 26. In the weight functions, Equations 8, 9, the probability, denoted as p, for attributes being either gains or losses is no longer 1 or 0. Instead, it is calculated based on the probability density functions as indicated in Equations 27, 28, respectively:

$$v(x) = \begin{cases} \int_{x_0}^{+\infty} (x - x_0)^{\alpha} f(x)\, dx, x \geq x_0 \\ \int_{-\infty}^{x_0} -\lambda (x_0 - x)^{\beta} f(x)\, dx, x < x_0 \end{cases} \tag{26}$$

$$p = F(+\infty) - F(x_0) \tag{27}$$

$$p = F(x_0) - F(-\infty) \tag{28}$$

Within the formulas: $f(x)$ denotes the probability density function associated with the attribute, while $F(x)$ symbolizes the attribute's cumulative distribution function.

Integrating Equations 8, 9 together with Equations 26 through 28, the prospective model for reducing power outage losses in extreme scenarios, denoted as V_{ext}, can be formulated as follows:

$$\begin{aligned} V_{ext} &= \pi^{+}(p_{ext})\, v^{+}(E_{ext}) + \pi^{-}(p_{ext})\, v^{-}(E_{ext}) \\ &= \frac{(G_{+})^{\gamma}}{\{(G_{+})^{\gamma} + [1 - F_{ext}(+\infty) + F_{ext}(E_{ext.o})]^{\gamma}\}^{1/\gamma}} \\ &\quad \cdot \left[\int_{E_{ext.0}}^{+\infty} (E_{ext} - E_{ext.0})^{\alpha} f_{ext}(E_{ext})\, dE_{ext} \right] \\ &\quad + \frac{(G_{-})^{\delta}}{\{(G_{-})^{\delta} + [1 - F_{ext}(E_{ext.0}) + F_{ext}(-\infty)]^{\delta}\}^{1/\delta}} \\ &\quad \cdot \left[\int_{-\infty}^{E_{ext.0}} -\lambda (E_{ext.0} - E_{ext})^{\beta} f_{ext}(E_{ext})\, dE_{ext} \right] \end{aligned} \tag{29}$$

In the equation:$G_{+} = F_{ext}(+\infty) - F_{ext}(E_{ext.0})$;$G_{-} = F_{ext}(E_{ext.0}) - F_{ext}(+\infty)$; E_{ext} represents the benefits of reducing power outage losses in extreme scenarios; $E_{ext.0}$ represents the anticipated benefits as expected by the planners; p_{ext} represents the probability that E_{ext} is expressed as either gains or losses relative to $E_{ext.0}$.

$$E_{ext}(S_n, P_n, S_{oc.min}) \sim f_{ext}(E_{ext}) = \sum_{k=1}^{N_y} \frac{\sum_{b=1}^{N_{imp}} (H - f_{tra.b}) \cdot \zeta_{ext} \cdot f_{\zeta_{ext}}(\zeta_{ext})}{(1 + i_0)^k} \tag{30}$$

$$W_{sup.b} = \min\left[W_{rem.b}, \max\left[\left(t_{fai} \cdot f_{t_{fai}}(t_{fai}) - t_{tra.b} \right), 0 \right] \cdot P_b \right] \tag{31}$$

In the equation:$H = W_{sup.b} \cdot (f_{sell} + f_{comp} \cdot R_{IEA})$; N_{imp} represents the number of critical loads to be protected; $W_{sup.b}$ represents the amount of electricity supplied by the energy storage unit to load b during a power outage; $f_{tra.b}$ represents the cost of transporting the energy storage unit to load b; ζ_{ext} is the probability of extreme scenarios occurring; $W_{rem.b}$ represents the remaining energy of the energy storage unit supplying load b; t_{fai} is the outage duration, not exceeding 7 days (Zhao et al., 2023); $t_{tra.b}$ represents the duration needed for the energy storage unit to establish a connection with load b.

3.5 Model for assessing entire lifecycle costs including recycling and treatment processes

The full lifecycle cost of configuring MMBES falls under expenditures. When the cost exceeds a reference value, decision-makers perceive it as a loss, and when it is less than the reference value, they perceive it as a gain. The specific expression for the prospective value V_c is as follows:

$$\begin{aligned} V_c &= \pi^{+}(p_c)\, v^{+}(C_{cyc}) + \pi^{-}(p_c)\, v^{-}(C_{cyc}) \\ &= \begin{cases} v^{+}(C_{cyc}) = (C_{cyc.0} - C_{cyc})^{\alpha}, C_{cyc} \leq C_{cyc.0} \\ v^{-}(C_{cyc}) = -\lambda (C_{cyc} - C_{cyc.0})^{\beta}, C_{cyc} > C_{cyc.0} \end{cases} \end{aligned} \tag{32}$$

In the equation:C_{cyc} represents the full lifecycle cost of configuring MMBES; $C_{cyc.0}$ represents the anticipated cost as expected by the planners.

The full lifecycle cost consists of three parts: the initial investment and construction cost C_{con}, the operational and maintenance cost C_{ope}, and the post-disposal recycling and treatment cost C_{rec}.

$$C_{cyc}(S_n, P_n) = C_{con} + C_{ope} + C_{rec} \tag{33}$$

The upfront investment and construction expenses encompass the energy costs for a specified battery capacity and the costs related to energy conversion, monitoring, and management.

$$C_{con} = c_s S_n + c_p P_n \tag{34}$$

In the equation: c_s represents the unit capacity investment cost of MMBES; c_p represents the unit power investment cost.

Operational and maintenance costs include fixed charges based on rated power and variable costs related to energy losses, stemming from the energy storage system's processes of charging and releasing energy.

$$C_{ope} = \sum_{k=1}^{N_y} \frac{c_{ope} P_n + [(1 - \eta) W_{ch} + (1/\eta - 1) W_{dch}] \cdot f_{cost}}{(1 + i_0)^k} \tag{35}$$

In the equation: c_{ope} represents the unit power annual operational and maintenance cost; W_{ch} and W_{dch} denote the yearly energy quantities for charging and discharging in MMBES.

The post-disposal recycling and treatment cost is the difference between the production cost for decomposing and handling the discarded batteries and the revenue obtained from recovering extracted metal materials.

$$C_{rec} = -\frac{c_r S_n}{10^3 \cdot \rho_e (1 + i_0)^{N_y}} = \frac{\left[c_{han} - \sum_{u=1}^{v} (c_{uv} \rho_{uv}) \right] S_n}{10^3 \cdot \rho_e (1 + i_0)^{N_y}} \tag{36}$$

In the equation: c_r represents the unit weight battery recycling price; ρ_e represents the particular energy capacity characteristic of the battery; c_{han} represents the cost associated with processing a unit weight of discarded batteries; v indicates the variety of metals contained within the battery; c_{uv} is the recycling value of metal u; and ρ_{uv} quantifies the proportion of metal u per unit weight present in MMBES.

4 Model solving

Due to the absence of uniform specifications for energy storage batteries, this study approaches decision variables as continuous entities. It utilizes a differential evolution algorithm to address the nonlinear optimization model presented. The methodology is depicted in Figure 6, with the detailed procedures outlined below:

1) Enter the fundamental parameters and initiate the decision variables S_n, P_n, and $S_{oc.min}$.
2) Establish reference points for each attribute: $E_{dec.0}$, $E_{rel.0}$, $E_{del.0}$, $E_{ext.0}$, and $C_{cyc.0}$, along with their respective importance weights ω_1, ω_2, ω_3, ω_4, and ω_5.
3) Initialize the iteration counter, n, to 1.
4) Initialize the population count, m, to 1.
5) Execute the approach depicted in Figure 4 by determining the charging and discharging capacity of MMBES for different standard daily load patterns and constructing the likelihood distribution of the State-of-Charge (SOC) for the energy storage system over multiple periods.
6) Compute the prospective network loss reduction according to Equations 10–12.
7) Assess the system's reliability before configuring MMBES using Equations 16–21, then establish a model for network reliability after MMBES configuration and calculate the prospective improvement in network reliability.
8) Based on the reliability model from step 7, calculate the dependable capacity of MMBES using Equation 25, and subsequently, compute the prospective value of deferring grid upgrade and retrofitting based on Equations 22–24.
9) Compute the anticipated residual energy of MMBES using the outcomes from step 5, and assess the prospective value of diminishing outage losses in severe conditions through Equations 29–31.
10) Compute the cost prospect value based on Equations 32–36.
11) Calculate and output the comprehensive prospect value based on Equations 2–5, considering the results obtained in steps 6, 7, 8, 9, and 10.
12) If $m \le M_{NP}$, proceed to step 5; otherwise, perform mutation, crossover, and selection operations across the populace.
13) If $n \le N_{ite}$, return to step 4; otherwise, present the best configuration outcomes for MMBES.

Here is the pseudocode for the algorithm: Optimize MMBES Configuration Using Differential Evolution.

Input: Fundamental parameters, population size M_{NP}, maximum iterations. N_{ite}

Initialize: Decision variables S_n, P_n, $S_{oc.min}$. Reference points $E_{dec.0}$, $E_{rel.0}$, $E_{del.0}$, $E_{ext.0}$, $C_{cyc.0}$ Importance weights ω_1, ω_2, ω_3, ω_4, ω_5 Set iteration counter $n = 1$ Set population count $m = 1$.

Procedure: 1. While $n \le N_{ite}$ do: 2. While $m \le M_{NP}$ do: 3. Execute SOC and load pattern analysis - Determine charging/discharging capacities for standard daily load patterns - Construct SOC distribution over multiple periods 4. Compute network loss reduction using Equations 10–12 5. Assess initial system reliability using Equations 16–21 6. Model network reliability post-MMBES configuration—Calculate improvement using derived reliability model 7. Determine dependable capacity of MMBES using Equation 25 8. Compute value of deferring grid upgrades using Equations 22–24 9. Estimate residual energy of MMBES and value of reduced outage losses using Equations 29–31 10. Calculate cost prospect using Equations 32–36 11. Compute comprehensive prospect value considering all results from steps 4 to 10 12. If $m \le$

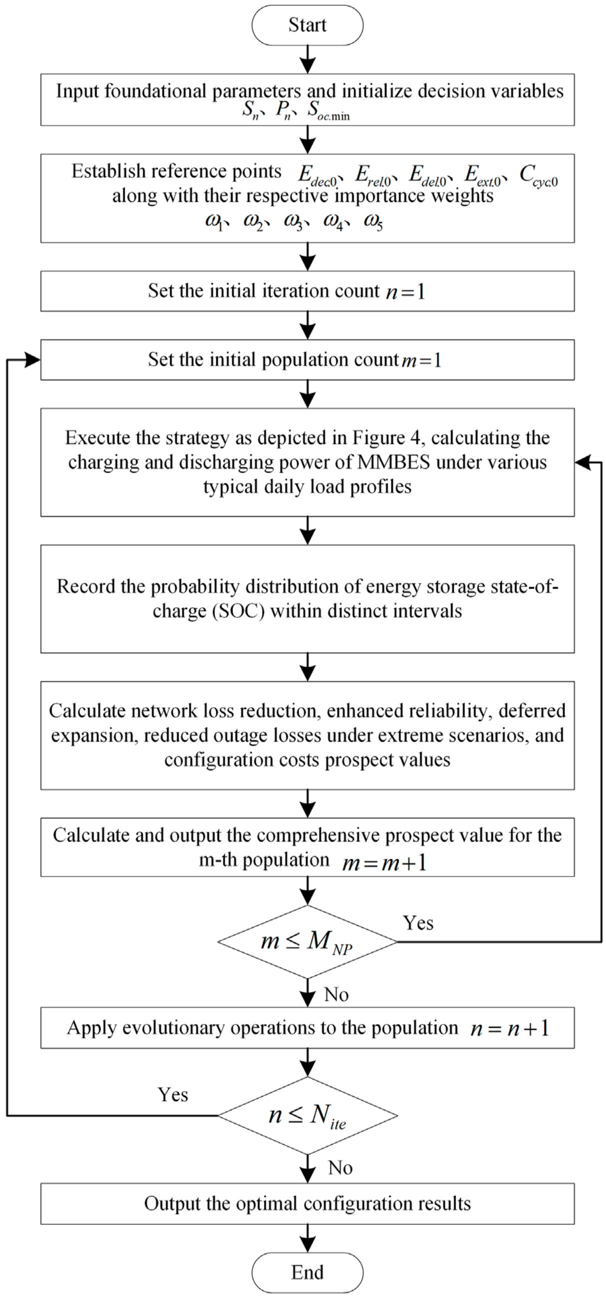

FIGURE 6
Solving process flowchart.

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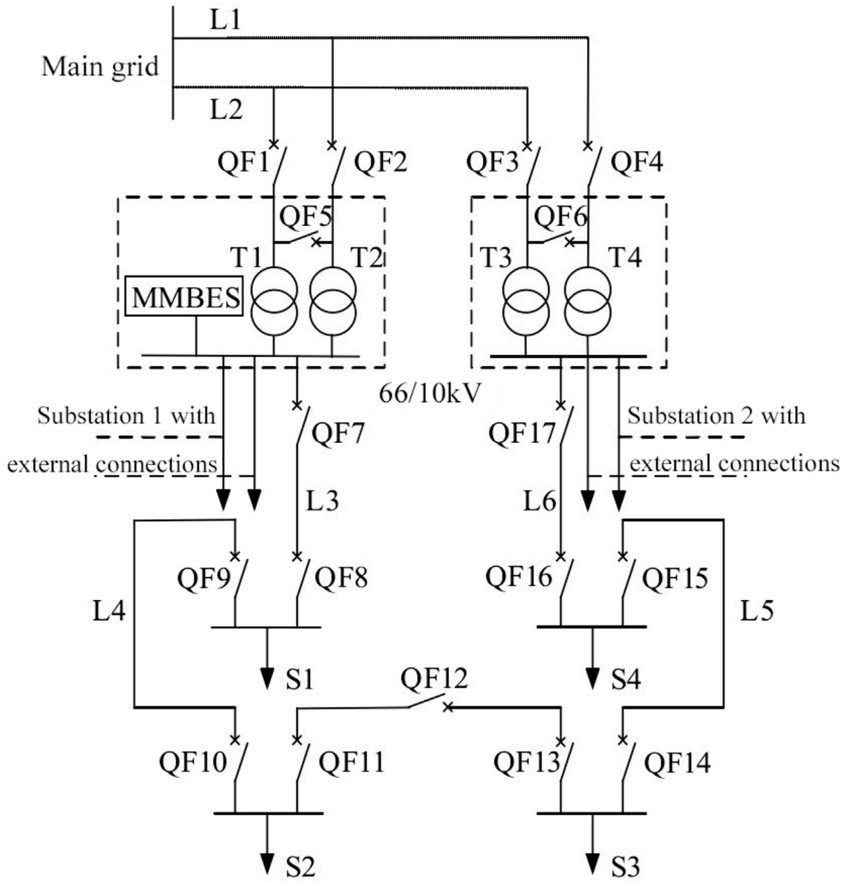

FIGURE 7
Regional distribution network system structure.

M_{NP} then: Perform mutation, crossover, and selection operations - Increment population count m by 1 Else: Reset population count m to 1—Increment iteration counter n by 1 13. Output the best MMBES configuration results.

End Procedure.

5 Scenario analysis

5.1 Scenario specifications

The paper examines a Class A distribution network in City A, which receives its power from a 220 kV substation connected in a T-shaped configuration to a 66 kV transformer station. The 10 kV output from the 66 kV transformer station is set up in a looped arrangement, as illustrated in Figure 7.

The distribution ratio between substations 1 and 2 stands at 0.55. The schematic displays three outgoing lines, with the main trunk lines designed similarly to the depicted structure. All circuit breakers, with the exceptions of QF5, QF6, and QF12, remain in a normally closed position. MMBES is deployed within substation 1, influencing the electricity flow in the 66 kV and higher voltage networks. Nevertheless, given the urban power grid's complexity, this study limits its focus to the sectors most impacted, specifically, the alterations in losses for L1, L2, T1, and T2. In the event of a regional network failure, MMBES is activated to segment and reroute power, aiming to reestablish service to vital loads, with S1 and S3 identified as critical loads requiring protection.

1) Distribution system structure parameters: Line L1 and L2 have a length of 5 km, while L3, L4, L5, and L6 are each 3.5 km long. The unit length resistance and reactance are both 0.17 Ω/km and 0.395 Ω/km, respectively. There are 4 transformers with short-circuit losses ΔP_k = 88.35 kW, short-circuit voltage percentage U_k% = 10.5, no-load losses ΔP_0 = 19.20 kW, and no-load current percentage I_0% = 0.69.
2) MMBES related parameters: MMBES, using lithium-ion batteries as an example, possesses advantages such as high energy density, low self-discharge rate, long cycle life, and fast charge-discharge capability. This battery type is among the most prevalent in energy storage applications. Key parameters are detailed in Table 1.
3) Load details: Figure 4 illustrates the typical daily load pattern for transformer station 1, including data for various load points as shown in Table 2. An annual load increase of 1.5% is assumed, and the power factor is kept constant at 0.9.

TABLE 1 Parameters for lithium-ion batteries.

Performance metrics	Values and units
Cost of electricity c_p	500 yuan/kW
Capacity cost c_s	2,000 yuan/(kW·h)
Maintenance cost c_{ope}	85 yuan/(kW·year)
Efficiency of charging and discharging η	95%
State of charge (SOC) range	0.2~0.8
Warranty period N_{war}	9 years
Recycling price c_r	8,000 yuan/t
Specific energy ρ_e	0.18 kW·h/kg

TABLE 2 Load node data.

S1/(kVA)	S2/(kVA)	S3/(kVA)	S4/(kVA)
2,580	2,200	1,560	3,220

TABLE 3 Parameters for component dependability.

Components/ Comparable parts	Rate of malfunction	Time to repair a Failure/h
Line	0.05 times/(km·year)	5
Transformer	0.015 times/year	48
Circuit Breaker	0.006 times/year	4
With external connection nodes	0.2 times/year	5

4) Reliability metrics for components: See Table 3.
5) Financial parameters: Consult Table 4.

5.2 MMBES optimal configuration simulation analysis

The population size for the Differential Evolution Algorithm, MNP, is set to 100, and other parameters are referenced from (Liu et al., 2021). The parameters related to prospect theory in the model: α is 0.88, β is 0.88, λ is 2.25, γ is 0.61, δ is 0.69. Through the analysis of significant historical incidents in the area, the probability of extreme scenario occurrence, ζ ext (times/year), follows a uniform distribution U (0.005, 0.1), which corresponds to an occurrence frequency of once every 10–200 years. Setting the outage duration according to guidelines (National Energy Administration, 2018): $t_{fai}(h) \sim U(12, 168)$, equivalent to a restoration time of half a day to 7 days.

TABLE 4 Economic-related parameters.

Economic parameters	Values and units
Average selling price of electricity f_{sell}	0.55 yuan/(kW· h)
Purchase cost of electricity f_{cost}	0.37 yuan/(kW· h)
Generation efficiency f_{comp}	13.6 yuan/(kW· h)
Benchmark interest rate i_0	8%
Expansion investment c_{inv}	5,000 million yuan
Transportation cost f_{tra}	20 yuan/km

Given that all attributes are deemed equally significant, we set $\omega_1, \omega_2, \omega_3, \omega_4$, and ω_5 each at 0.2. After configuring MMBES, the expected benefits for delaying grid upgrade, enhancing reliability, reducing outage losses in extreme scenarios, and reducing network losses are 100, 90, 50, and 50 thousand yuan, respectively. The expected cost expenditure is half of the net benefits, which is 145 thousand yuan, as shown in Table 5.

Based on the parameters mentioned above, conducting simulation calculations using the Differential Evolution Algorithm converges in 200 iterations, with a maximum iteration limit set at 300 iterations. The optimization configuration results for MMBES, along with the benefits/costs and prospects for each attribute, total benefits, and comprehensive prospects, can be found in Table 6.

The data extracted from the table suggests that the optimal configuration for MMBES features a storage capacity of 4986.83 kW-hours (kW· h), a rated power of 1,600.5 kW (kW), and maintains the operational State of Charge (SOC) at a maximum limit of 0.8. The net profit is 2,793.85 million yuan. The attribute benefits/costs, in descending order, are as follows: Delayed expansion benefit E_{del}, enhanced reliability benefit E_{rel}, configuration cost C_{cyc}, reduced outage loss benefit under disasters E_{ext}, and loss reduction benefit E_{dec}. As the reference point values are relatively small, E_{del}, E_{rel}, E_{ext}, and C_{cyc} are all greater than the reference points, resulting in positive prospects for benefit attributes and negative prospects for cost attributes. E_{dec} is 0, which is less than the reference point, resulting in a negative prospect.

The potential benefits of postponing grid upgrades and renovations are the most significant, particularly when considering MMBES with a substantial capacity of 3,330 kW. In line with the current rate of load growth, this delay can extend the need for expansion by a remarkable 12 years, aligning with the original configuration intent. Following closely is the potential value associated with enhancing the reliability of the distribution network. By doing so, it is possible to reduce the annual electricity deficit by a substantial 2,162.29 kW· h. The probability of extreme scenarios occurring is relatively low, which explains the smaller prospective value of mitigating outage losses in such circumstances. However, in the unfortunate event of a disaster, MMBES can still contribute to reducing outage losses by a significant 3,989.46 kW· h. It is essential to note that the chosen study area exhibits minimal load fluctuations, and the cost of reducing losses is tied to the grid's electricity purchase cost. Consequently, the optimized outcome suggests a relatively high lower limit for state of charge (SOC), which may not

TABLE 5 Baseline benchmarks for each benefit/cost characteristic.

$E_{dec.0}/(10^6 \cdot \text{yuan})$	$E_{rel.0}/(10^6 \cdot \text{yuan})$	$E_{del.0}/(10^6 \cdot \text{yuan})$	$E_{ext.0}/(10^6 \cdot \text{yuan})$	$E_{cyc.0}/(10^6 \cdot \text{yuan})$
0.5	0.9	1	0.5	1.45

TABLE 6 Optimal configuration results and attribute benefits/costs and prospects.

Optimal configuration results	S_n (kW· h)	P_n/kW	$S_{oc.min}$
	4,986.83	1,600.5	0.8
Attribute benefits/costs/total benefits	E_{dec}/yuan	$E_{rel}/(10^7\text{yuan})$	$E_{del}/(10^7\text{yuan})$
	0	1.83	1.94
	$E_{ext}/(10^6\text{yuan})$	$C_{cyc}/(10^7\text{yuan})$	$E/(10^7\text{yuan})$
	1.77	1.15	2.79
Attribute prospects/comprehensive prospects	$V_{dec}/10^5$	$V_{rel}/10^6$	$V_{del}/10^6$
	−2.33	2.35	2.47
	$V_{ext}/10^5$	$V_c/10^6$	$V/10^5$
	1.61	−3.27	2.96

be advantageous for minimizing network losses. The outcomes of the optimization distinctly show that, considering the established benchmarks and their relative significance, energy storage systems remain fully charged under normal operational conditions and activate to provide power only during disruptions, leading to the maximum aggregate prospective value (V).

When optimizing with the objective of maximizing net profit, the MMBES configuration results are as follows: S_n = 9,043.75 kW· h, P_n = 1712.1 kW, $S_{oc.min}$ = 0.8. Both capacity and power are greater than the optimization results when aiming to maximize comprehensive prospects. This is because the positive attribute benefits are weakened while the negative ones are strengthened when aiming to maximize net profit, as decision-makers tend to be more risk-averse, resulting in smaller configuration results. Additionally, when not considering extreme scenarios, the configuration results do not significantly increase, but the net profit decreases by 321.64 million yuan. This suggests that portable energy storage units can improve the overall effectiveness of the configured energy storage system.

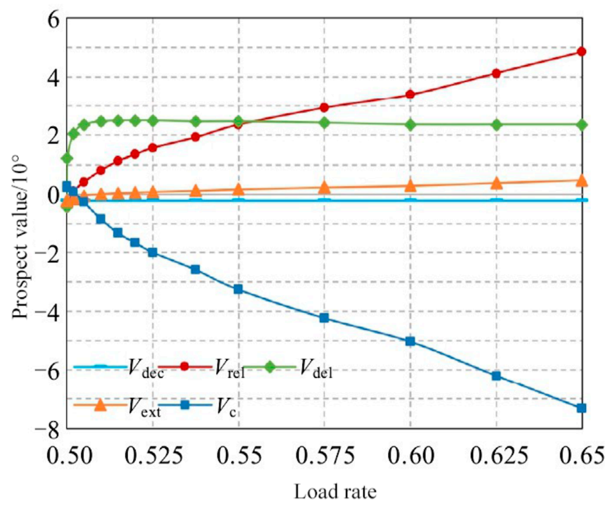

FIGURE 8
The prospects of various attributes at different levels of adequacy.

5.3 The impact analysis of system adequacy on the optimization configuration results of energy storage

Exploring the substantial advantages of postponing grid upgrades while improving reliability, this research delves deeper into the consequences of system sufficiency on the outcomes of the configuration analysis. The substation load rate is increased from 0.50 in a geometric progression to 0.65, and the changes in the prospects of various attributes are shown in Figure 8.

As network adequacy decreases, the system's demand for MMBES capacity S_n and power P_n increases continuously, and the optimization configuration results increase monotonically from 0 to 11,019.44 kW· h and 4,711.5 kW, respectively. The holistic outlook, denoted as value V, demonstrates a pattern characterized by a sharp ascent followed by a gradual decline, reaching its zenith at approximately a load rate of 0.505. This is because at this point, S_n and P_n are relatively small, leading to lower cost prospect value

V_c, and the delayed expansion prospect value V_{del} is already ideal. However, as adequacy decreases further, although the reliability prospect value V_{rel} increases significantly, the increase in V_c is even greater, resulting in a decrease in the overall prospect value V.

The prospect value V_{rel} for enhancing distribution network reliability and the prospect value V_{ext} for reducing losses in extreme scenarios both exhibit a monotonically increasing trend. The annual deficit in electricity supply and outage losses after disasters that can be reduced increase from 0 to 4778.03 kW· h and 8,815.55 kW· h, respectively. The cost prospect V_c monotonically decreases, with configuration costs increasing from 0 to 2,665.14 million yuan. The prospect V_{del} for delaying grid upgrade and renovation first increases rapidly and then slightly decreases, with the peak occurring near a load rate of 0.52. This is because when the load rate is greater than 0.5 but less than 0.52, as S_n and P_n increase, the number of years ΔT_y that expansion can be delayed increases rapidly, leading to a rapid increase in V_{del}. However, when the load rate is greater than 0.52, although ΔT_y and the total amount of future-year expansion investment still increase with S_n and P_n, when ΔT_y is large, the present value of the profits for the later years is relatively small, resulting in an overall decline in prospects. Furthermore, despite fluctuations in the load rate, the prospect value V_{dec}, aimed at decreasing network losses, invariably holds a steady negative figure, while the optimization results for State of Charge (SOC) consistently stay at the maximum threshold of 0.8 for every load rate scenario.

5.4 Analyzing the influence of attribute importance and cognitive parameters on the configuration outcomes

Recognizing the persistent high level of network loss rate at 6.28% within the distribution system, efforts to enhance this metric entail elevating the significance of the loss reduction attribute ω_1. This research investigates how cognitive factors related to decision-making, as informed by prospect theory, affect the outcomes of optimization. When $\omega_1 = 0.95$ and $\omega_2 = \omega_3 = \omega_4 = \omega_5 = 0.0125$, and the reference points are as shown in Table 5, the optimization configuration re-sults differ from Table 6. The configured capacity and power experience a rise from 4986.83 kW· h and 1,600.5 kW–11,051.02 kW· h and 1,663.2 kW, correspondingly. Simultaneously, the lower limit of State of Charge (SOC) decreases to 0.20. This adjustment is necessitated by the need for MMBES to achieve reductions in network losses, which entails implementing a strategy of discharging during peak load periods and charging during off-peak periods. This strategy requires a larger capacity and a smaller State of Charge (SOC). Prior to configuring the energy storage system, the network loss stands at 788.17 million kW· h, and post-configuration, it diminishes to 780.49 million kW· h, resulting in a network loss rate decrease to 6.22%.Therefore, it becomes clear that by elevating ω_1, the attribute related to reducing losses is no longer eclipsed by the remaining three attributes, leading to a significant decrease in losses.

If the emphasis is on enhancing the resilience of the distribution network and the importance of reducing losses in extreme scenarios ω_4 is increased, when ω_4 is set to 0.6, and the values of $\omega_1, \omega_2, \omega_3$ and ω_5 are each adjusted to 0.1, the configured capacity and power increase to 9,043.75 kW· h and 1,712.1 kW, respectively, with an SOC lower limit of 0.8. This is due to the necessity of maintaining the uninterrupted provision of critical loads during extreme scenarios. To achieve this, MMBES requires a larger anticipated surplus energy, which, in turn, demands a larger capacity and State of Charge (SOC). At this level of importance, the reduction in outage losses in extreme scenarios increases from 3,989.46 kW· h to 7,234.00 kW· h, significantly enhancing the resilience of the power distribution network.

The decision-maker's subjective expectations are not constant. When cognitive parameters change, to study their impact on the optimization results, the expected cost expenditure $C_{cyc,0}$, which has a significant impact on the comprehensive prospect value V in Figure 8, is increased to 1,500 million yuan. The MMBES configuration capacity and power increase to 6,626.80 kW· h and 1,646.7 kW, respectively, which is a 32.89% increase for capacity and a 2.89% increase for power compared to Table 6. This phenomenon arises from the fact that when there is an increase in the psychological anticipation of investment, it can shift the prospect value of investment costs from negative to positive. Given the decision-maker's inclination to be risk-averse when it comes to losses as opposed to gains, a reduction in cost, while keeping other attribute expectations constant, results in an increase in configured capacity and power.

We have conducted a comparative analysis between our proposed scheme for optimizing the configuration of Modular Mobile Battery Energy Storage (MMBES) and existing systems, focusing on several key factors. Our analysis evaluates the performance and effectiveness of our approach in the context of renewable energy integration and grid stability.

5.4.1 Economic benefits

Our proposed scheme significantly boosts the economic benefits of integrating MMBES into distribution grids. By fine-tuning the configuration of MMBES, we demonstrate a notable improvement in the net profit compared to existing systems. For instance, when aiming to maximize net profit, the configuration results for capacity and power are 9,043.75 kW· h and 1,712.1 kW, respectively, which are higher than the results aimed at maximizing comprehensive prospects.

5.4.2 Reliability Improvement

The reliability prospect value for enhancing distribution network reliability increases monotonically as the adequacy of the system decreases. This indicates that our proposed scheme enhances the reliability of the distribution grid, especially in scenarios where the system adequacy is low.

5.4.3 Cost-effectiveness

We analyze the cost prospect value, which demonstrates a monotonic decrease as the adequacy of the system decreases. This suggests that our proposed scheme is more cost-effective compared to existing systems, especially when the system adequacy is lower.

5.4.4 System adequacy impact

As the substation load rate increases, the system's demand for MMBES capacity and power also increases. The optimization configuration results for Sn and Pn increase monotonically from 0 to 11,019.44 kW· h and 4,711.5 kW, respectively, indicating that our proposed scheme adapts well to changes in system adequacy.

5.4.5 Extreme scenario consideration

Our scheme takes into account the reduction of outage losses in extreme scenarios, which is reflected in the increasing trend of the prospect value. This shows that our approach enhances the resilience of the distribution grid in the face of severe weather events or other extreme conditions.

5.4.6 Comprehensive prospect value

The comprehensive prospect value initially increases sharply and then gradually declines as the system adequacy decreases. This pattern indicates that our scheme optimally balances the trade-offs between cost, reliability, and system adequacy.

6 Conclusion

This phenomenon arises from the fact that when there is an increase in the psychological anticipation of investment, it can shift the prospect value of investment costs from negative to positive. Considering the decision-maker's tendency to favor risk-averse strategies regarding losses rather than gains, decreasing costs, with the expectation of other attributes remaining unchanged, leads to enhanced capacity and power. The effectiveness of the model and methodology is confirmed via a case study focusing on a city's distribution grid. The results of the case study indicate the following: 1) Considering the benefits of extreme scenarios, mobile energy storage can achieve additional benefits in terms of resilience without significantly increasing costs; 2) When greater emphasis is placed on a specific profit/cost attribute, increasing the ω value can effectively bias the growth towards that attribute, directly affecting the planning results; 3) When the psychological expectation of a certain attribute is increased, the configuration results will move in a direction favorable to that prospect; 4) As the network adequacy decreases, the optimization configuration results for energy storage capacity and power monotonically increase. However, influenced by the cognitive preferences of prospect theory, the comprehensive prospect value shows a trend of initially increasing and then decreasing.

This study conducted a case study on a specific city's distributed grid, validating the effectiveness of the model and methodology employed, and explored the potential of mobile energy storage in enhancing grid resilience and reducing network losses. Although our case study provided some positive insights, its limitations also indicate necessary directions for future research.

Firstly, our research was primarily based on a specific city's grid, and its applicability may be affected by differences in grid scale or technical conditions. Additionally, the setting of key parameters such as ω had a significant impact in this study, but these settings were based on specific assumptions, which may limit their general applicability. Furthermore, decision-makers' psychological expectations were analyzed qualitatively in this study, necessitating the development of quantitative tools and methods to specifically quantify these changes in future research.

For future studies, we suggest expanding the geographical scope and network types of case studies to validate the model's broad applicability. Further research should consider how to optimize the setting of key parameters to improve the model's adaptability and flexibility across different grid environments. Additionally, we plan to introduce opportunity-constrained planning to address the uncertainties in grid demand and energy storage system performance in extreme scenarios. By optimizing the configuration of energy storage, we aim to further enhance the system's resilience and reliability.

We will also consider user needs and comfort, incorporating user behavior and demand patterns into future research to adjust the scheduling strategy of energy storage equipment to meet users' electricity demands and comfort requirements. Through in-depth analysis and simulation of different user groups' electricity usage behaviors, we anticipate that technological innovations will achieve more refined energy management.

Through these improvements, we hope to further demonstrate the potential of mobile energy storage technology and its contributions to grid systems, while promoting further research and optimization in the field.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

DF: Writing–original draft, Software, Methodology, Conceptualization. BL: Writing–review and editing, Project administration, Formal Analysis, Conceptualization. LY: Writing–review and editing, Validation, Data curation. XS: Writing–review and editing, Validation, Formal Analysis. HC: Writing–review and editing, Formal Analysis.

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Conflict of interest

Authors DF, BL, LY, XS, and HC were employed by State Grid Anshan Electric Power Supply Company.

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Publisher's note

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