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Research on hybrid collaborative energy storage configuration in active distribution networks based on improved multi objective optimization

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This article proposes a hybrid collaborative energy storage configuration method for active distribution networks based on improved particle swarm optimization to address the challenges of increased frequency regulation difficulty, increased voltage deviation, and reduced safety and stability when integrating wind and photovoltaic power generation into active distribution networks. The paper analyzes the factors that affect the energy storage configuration caused by the integration of renewable energy generation, analyzes the charging and discharging scheduling strategies of the energy storage system, and establishes corresponding mathematical models. The paper proposes an improved particle swarm optimization algorithm. Simulation and case analysis show that the algorithm can stably achieve optimized configuration, stable frequency regulation, and reduce carbon emissions of the energy storage system.

KEYWORDS

particle swarm, hybrid energy storage, frequency modulation, charging and discharging, configuration

1 Introduction

In the past 50 years, the challenges and uncertainties faced by the global energy system have been at their highest level. Developing a green economy and reducing dependence on traditional energy is an important measure for countries around the world to achieve carbon emissions reduction. It is urgent to encourage the development of the new energy industry, change the traditional economic structure, and develop wind and solar energy to change the current energy institutions (Pathak et al., 2023). According to the 2022 edition of the BP World Energy Statistical Yearbook, energy storage is estimated to be a solution to the energy crisis.

Active distribution network hybrid collaborative energy storage configuration refers to the combination of different types of energy storage technologies (such as battery energy storage, supercapacitors, compressed air energy storage, etc.) with traditional power distribution network systems, achieving flexible scheduling and optimized operation of the power grid through intelligent control and collaborative management (Du et al., 2023). The development of this configuration can be traced back to the demand for the popularization of renewable energy in the power system and the development of energy storage technology. In history, with the increase of renewable energy and the popularization

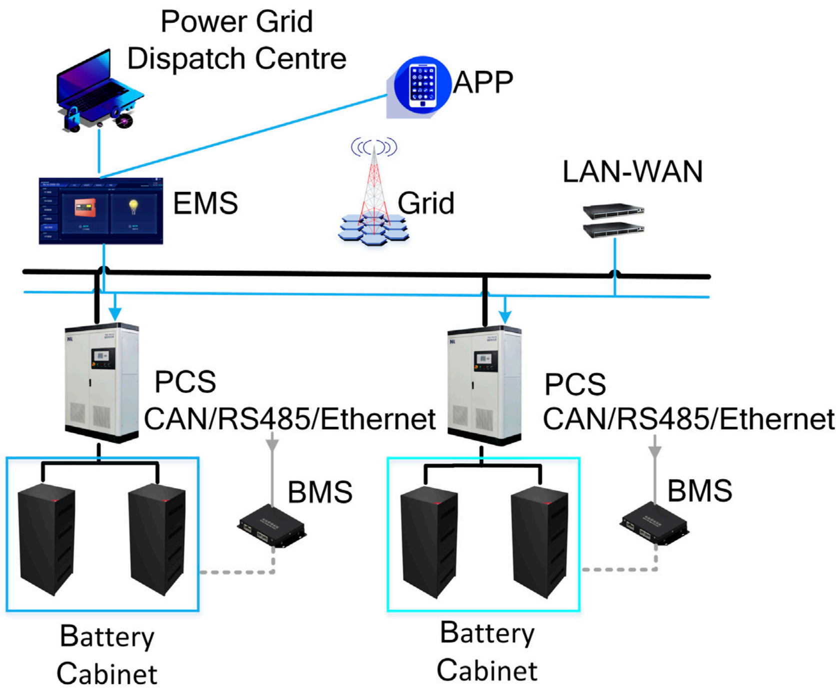

FIGURE 1
Grid structure of energy storage system.

of distributed generation, traditional distribution network systems have faced greater challenges, such as voltage stability, power balance, etc. The introduction of energy storage technology can effectively alleviate these problems (Kroičs and Ģirts, 2022). In terms of development, with the advancement of technology and the increasing demand for clean energy, the hybrid collaborative energy storage configuration of active distribution networks will gradually be more widely applied and developed. A heuristic approach for inserting multiple-complex coefficient filters (DSTATCOM) into the distribution system, as presented by Kumar et al. (2024), has shown significant improvements in power quality (Kumar et al., 2024).

This article proposes a hybrid collaborative energy storage configuration method for active distribution networks based on improved multi-objective optimization. The method considers the optimization control strategy of energy output and energy storage system output participating in grid frequency regulation, and proposes a distributed energy storage capacity optimization configuration method; Establish a two-layer optimization model, improve and enhance the optimization algorithm of the model, achieve close coupling between planning and operation, and make the configuration scheme set more effective.

2 Analysis of energy storage systems and operating factors

2.1 Energy storage system grid structure

The grid structure of energy storage systems usually includes the following main components: energy storage devices, including battery energy storage, supercapacitors, compressed air energy storage, and various types of energy storage devices (Behabtu et al., 2020; Gugulothu et al., 2023). Power conversion device: used to convert the energy stored in energy storage devices into electrical energy, or to convert electrical energy into an acceptable form for energy storage devices. Control and Management System: Responsible for monitoring the operational status of the energy storage system, implementing charge and discharge control of energy storage equipment, and optimizing scheduling of the energy storage system through intelligent algorithms (Guo et al., 2021). As highlighted by Kumar et al. (2024), the use of metaheuristic techniques, such as Particle Swarm Optimization (PSO) and their hybrids, can significantly enhance the stability and efficiency of the energy storage system (Kumar et al., 2022). Connection interfaces with the power system: including power interfaces connected to the distribution or transmission network, as well as interfaces connected to renewable energy generation systems, electric vehicle charging facilities, and other equipment (Ali et al., 2023). Security protection system: used to monitor and protect the energy storage system from potential failures or safety risks during operation, ensuring the safe and stable operation of the system. These components together constitute the grid structure of the energy storage system, realizing the application and operation of energy storage technology in the power system. The grid structure of the energy storage system is shown in Figure 1.

2.2 Analysis of the impact of photovoltaic energy on energy storage configuration

As noted by Kumar et al. (2021a), the integration of renewable energy sources such as photovoltaic (PV) systems into the grid requires careful management to maintain system stability and power

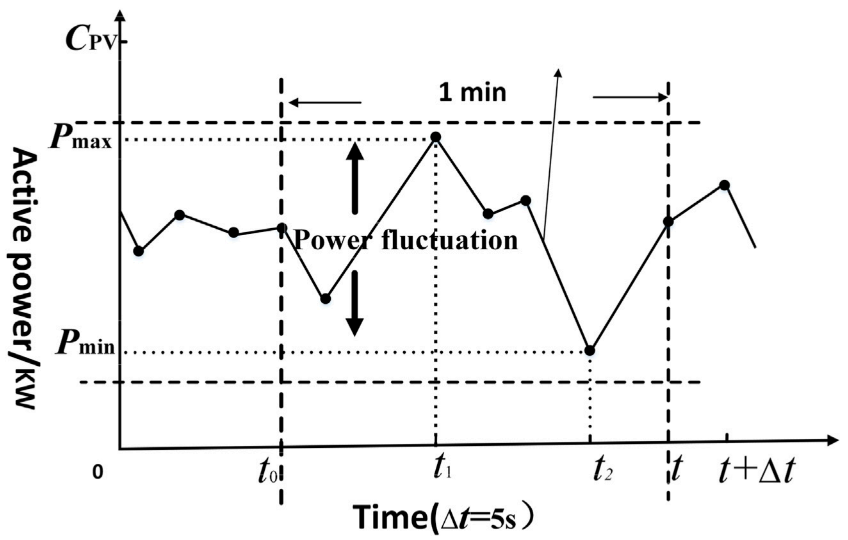

FIGURE 2
Photovoltaic power fluctuation.

quality (Kumar et al., 2021a; Kumar et al., 2021b). Taking the fluctuation of active power in photovoltaic power generation as an example, the fluctuation of wind power and load can be obtained similarly. With the increasing popularity of photovoltaics, if photovoltaic power is directly injected into the public grid without any control, this high-frequency power fluctuation will lead to voltage fluctuations, thereby reducing the reliability and power quality of the power system. Therefore, the power fluctuation of photovoltaic power should be limited within a certain range (Paul et al., 2021). At present, due to the fluctuation of photovoltaic power generation usually occurring less than 1 min apart, the use of energy storage system output is often used to control the smooth fluctuation of photovoltaic power. Usually, when the fluctuation of photovoltaic power does not exceed the maximum allowable power of HESS (Hybrid Energy Storage System), only the power of HESS is used to smooth these power fluctuations while keeping the photovoltaic converter operating in MPPT mode. That is, smooth downward power fluctuations through discharge (positive power, $P_{HESS} > 0$), and on the contrary, smooth upward power fluctuations through charging (negative power, $P_{HESS} < 0$).

Taking the power fluctuation of photovoltaics within 1 min as an example, as shown in Figure 2, power fluctuation can be defined as the difference between the maximum and minimum power values measured at the PCC(Point of Common Coupling) within 1 min.

As shown in Figure 2, at time t, $P_{Grid,b}(t)$ represents the power value of PCC before the grid provides the smoothing command, and $P_{Grid,a}(t)$ represents the power value of PCC after the grid provides the smoothing command; The photovoltaic power fluctuations before and after suppression are represented by $\Delta P_{Grid,b}(t)$ and $\Delta P_{Grid,a}(t)$, respectively. Based on the historical data of active power in the power grid, Equation 1 can be used to calculate $\Delta P_{Grid,b}(t)$:

$$\Delta P_{Grid,b}(t) = \begin{cases} P_{\max,b}(t) - P_{\min,b}(t), i \geq j \\ P_{\min,b}(t) - P_{\max,b}(t), i < j \end{cases} \tag{1}$$

Based on the historical data of active power in the power grid, Equation 2 can be used to calculate $\Delta P_{Grid,b}(t)$ by defining the set A of power values measured at PCC.

$$\begin{cases} [P_{\max,b}(t), i] = f_{\max}(A) \\ [P_{\min,b}(t), j] = f_{\min}(A) \\ A = \{P_{Grid}(t_0), P_{Grid}(t_0+\Delta t), \cdots, P_{Grid}(t+\Delta t), P_{Grid}(t)\} \\ t_0 = t - 1\text{ min} \end{cases} \tag{2}$$

Among them, $P_{\max,b}(t)$ and $P_{\max,a}(t)$ respectively represent the maximum and minimum values of set A; i and j indicators representing the maximum and minimum values of set A, A is a set of power values measured in PCC before providing a smoothing command, with a time scale of 1 min for set A; t_0 is the start time; Δt For the sampling interval, $\Delta t = 5s$.

2.3 Charging and discharging scheduling strategy for energy storage systems

ESS (Electric Storage System) is usually charged during load valleys and discharged during peak periods (Chaspierre et al., 2022). Assuming that the charging and discharging strategy of BESS (Battery Energy Storage System) is shown in Figure 3.

Figure 3, based on the equivalent load curve, $T_{c,1}$ and $T_{c,2}$ are divided into two consecutive charging time periods, where $E_{c,1}$ and $E_{c,2}$ respectively represent the charging amount during the corresponding charging time period; $T_{d,1}$, $T_{d,2}$, $T_{d,3}$ are three consecutive discharge time periods; $E_{d,1}$, $E_{d,2}$, $E_{d,3}$ are the discharge levels during their continuous discharge time periods. At present, most studies usually use the charging and discharging power within each time period as the control variable to solve for the charging and discharging strategy (Ivanov et al., 2021). Therefore, there are situations where the charging and discharging states of energy storage systems may occur within the same time period. In this case, only equal charging and discharging amounts can be ensured within the cycle, i.e., $E_{c,1} + E_{c,2} = E_{d,1} + E_{d,2} + E_{d,3}$, without

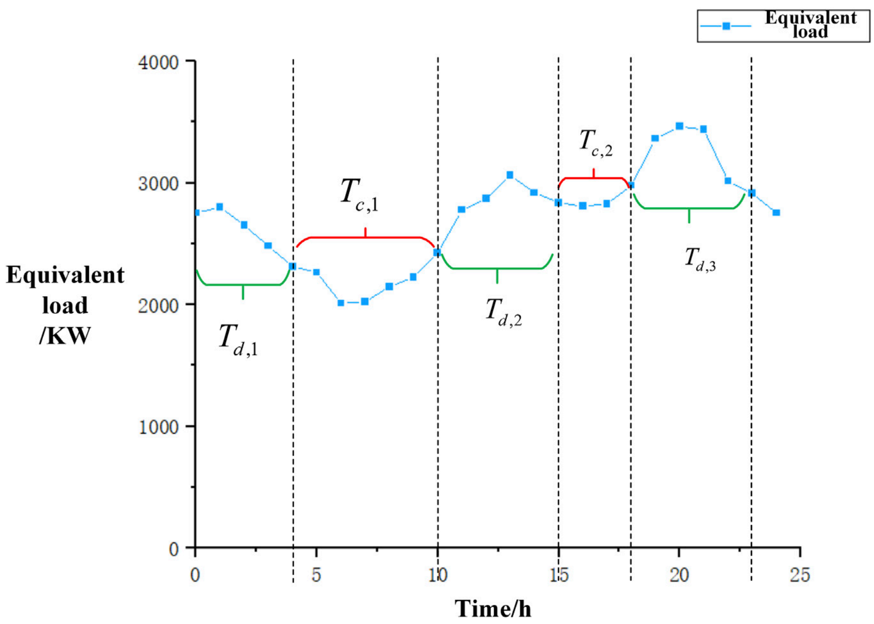

FIGURE 3
Charging and discharging strategies for energy storage systems.

considering the changes in SOC of energy storage. Due to the simultaneous determination of charging and discharging power at different time periods within the cycle, it is difficult to ensure the difference between the discharge amount of the energy storage system during the discharge time period and the remaining electricity before discharge, which may lead to the occurrence of situation $E_{d,1} > E_{c,2}$. This situation is not realistic.

While considering the charging and discharging power, the constraints on the discharge capacity during the continuous discharge time period are considered, given the known charging and discharging time periods. Divide the continuous charging and discharging periods using time of use electricity prices: the low electricity price period corresponds to the low load period, and charge the energy storage system during this stage; During periods of high electricity prices corresponding to peak load periods, the energy storage system discharges. However, under the high penetration rate of volatile energy, the load will be locally supplied by volatile energy, so the demand for peak valley difference of the load will be affected, and the advantage of peak shaving and valley filling in energy storage systems cannot be fully utilized. Therefore, considering the impact of volatile energy on peak and valley load demand, a mathematical model is established to obtain the division of HESS charging and discharging time periods based on the solution situation.

3 Collaborative configuration of hybrid energy storage

3.1 Frequency modulation control process

The system frequency fluctuation mainly involves two situations: an increase in frequency and a decrease in frequency. When the frequency increases, it is only necessary to reduce the output of the wind turbine. That is, adjusting the pitch angle reduces the amount of wind energy captured by the wind turbine. Therefore, this article mainly studies the situation of frequency reduction in the power grid. When the frequency of the power grid suddenly drops, the frequency regulation control strategy of the wind storage joint system is as follows: (1) When the system frequency deviation Δf is higher than the upper limit of frequency deviation, the frequency deviation is set to 0.2 Hz in this article, reducing the output of the wind farm until the frequency deviation is below 0.2 Hz. (2) When the system frequency deviation Δf is lower than the lower limit of frequency deviation (−0.2 Hz), the system needs to increase active power. When the wind turbine is in MPPT mode, the frequency regulation task of the system mainly relies on HESS to provide active power output to compensate for the power shortage of the system. Therefore, at high wind speeds, wind turbines use the adjustment of blade pitch angle a to achieve load reduction operation. When β occurs, the wind turbines use the reserved 20% active power output to complete frequency regulation tasks while meeting the requirements of $\Delta P \leq P_{m\arg in}$. (3) When $P_{WG}(t) \leq P_{WG,\max}$ occurs, that is, when the reserved output power of the wind turbine cannot compensate for the power shortage of the system, the wind storage joint system issues control instructions to allow the HESS to discharge and output active power to participate in frequency regulation until the grid frequency returns to the standard fluctuation range. (4) When frequency drops occur in low wind speed areas or during start-up wind speed areas, wind turbines can only operate in MPPT mode, and the system can only use HESS to complete frequency regulation tasks, which needs to meet the requirements of $SOC_{HESS}(t) \geq SOC_{HESS,\min}$. (5) After completing the frequency regulation task, the rotor speed needs to be restored to the value of the conventional generator. At this time, when a frequency restoration is required, the wind turbine needs to absorb energy from the power grid for the rotor speed

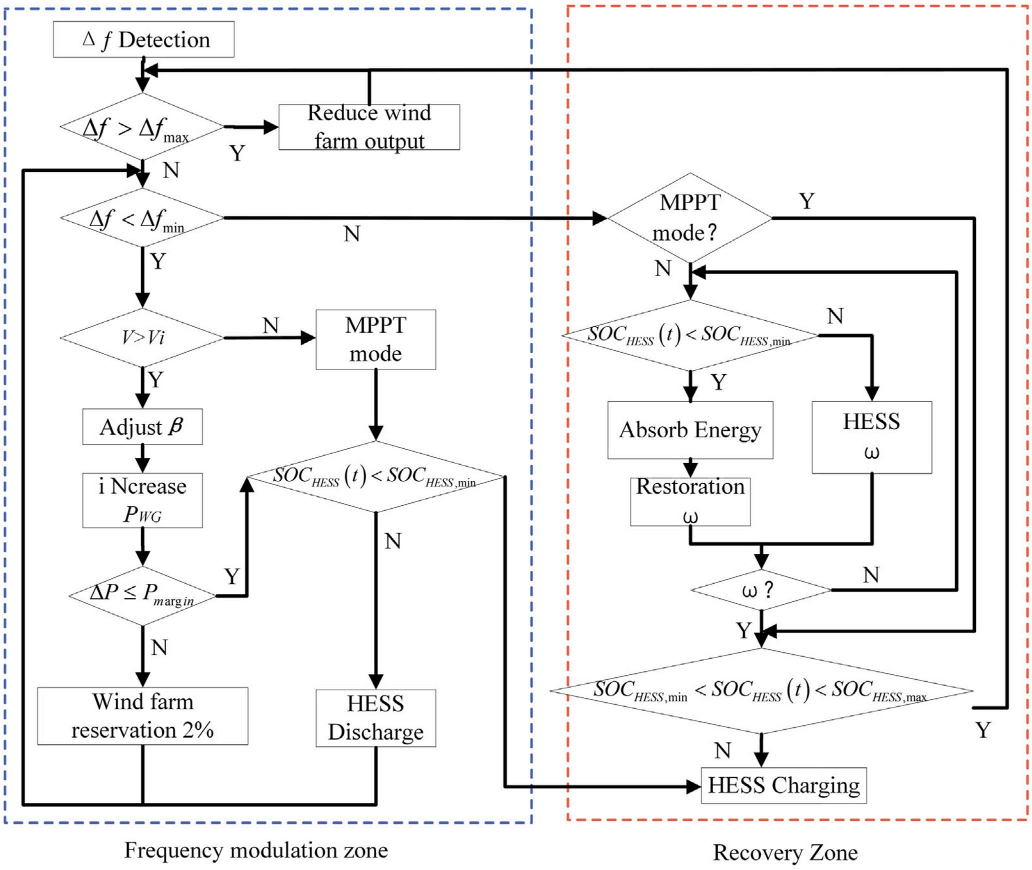

FIGURE 4
Frequency modulation control flowchart.

recovery process. To avoid another frequency drop in the power grid during this period, the wind turbine uses the output of the energy storage system to complete the rotor speed recovery. (6) When HESS (Hybrid Energy Storage System) participates in frequency regulation, HESS conducts the charging phase according to the operating strategy (Verma et al., 2023). After completing the frequency recovery of the power grid, it is necessary to check again whether the SOC (State of Charge) at this time is within the normal operating range of the energy storage system. Only when the SOC of the energy storage system returns to the normal range, can the frequency regulation process of the wind-storage joint system be considered complete (Alasali et al., 2022).The specific frequency regulation control process diagram of the wind storage joint system is shown in Figure 4:

3.2 Particle swarm optimization

The initial population of the particle swarm algorithm is randomly generated. Assuming that the problem to be solved has an m-dimension, the position and velocity of the i-th particle are defined in Equations 3, 4, respectively.

$$P_i = (p_{i1}, p_{i2}, \cdots, p_{in}), i = 1, 2, \cdots, n \tag{3}$$

$$V_i = (v_{i1}, v_{i2}, \cdots, v_{in}), i = 1, 2, \cdots, n \tag{4}$$

The current experience fitness is defined by Equation 5.

$$P_{b,i} = (p_{b,i1}, p_{b,i2}, \cdots, p_{b,i2}), i = 1, 2, \cdots, n \tag{5}$$

The global optimal solution for the entire population after updating the velocity and position of the current particle is Equation 6:

$$g_b = \left(p_{g1}, p_{g2}, \cdots, p_{gm}\right) \tag{6}$$

The velocity and position of particles are updated using Equations 7, 8:

$$V_i = \omega V_i + \alpha r_1 \left(g_b - P_i\right) + \beta r_2 \left(P_{b,i} - P_i\right) \tag{7}$$

In the formula: ω represents the inertia weight of the particle, represents the degree to which the particle's velocity is affected by the previous velocity, and the value of ω can balance the relationship between global and local search capabilities (Yong et al., 2023). The smaller the value, the smaller the former's capability is. Therefore, in order to avoid searching only locally during the solving process, the value of inertia weight is worth exploring, making it suitable for various optimization problems (Lei et al., 2022). The traditional method for updating inertia weights is Equation 9; α And β represents the learning factor, the former represents the influence of the experiences of other particles, and the latter represents the influence of the

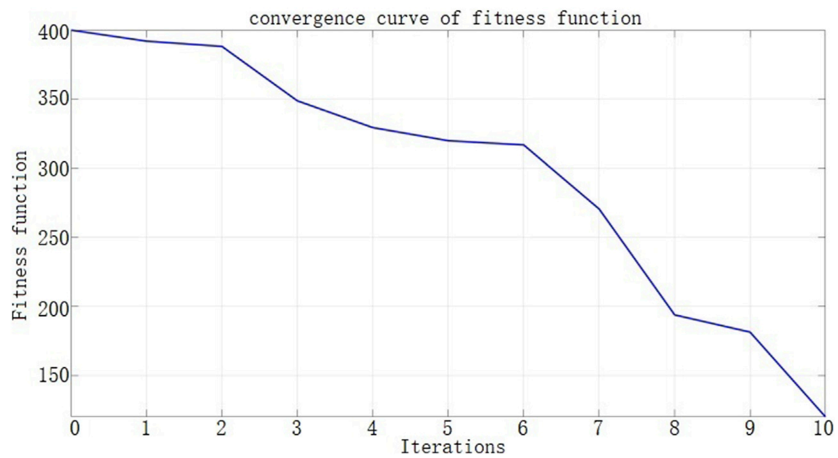

FIGURE 5
Convergence curve of fitness function.

experiences of the particles themselves; r_1 And r_2 represents the number randomly produced between [1,0].

$$\omega = \begin{cases} \omega_{\min} - \dfrac{(\omega_{\max} - \omega_{\min})(f - f_{\min})}{(\bar{f} - f_{\min})} & , f \le \bar{f} \\ \omega_{\max} & , f > \bar{f} \end{cases} \tag{8}$$

Equation 9 that needs to be supplemented in the paper is as follows:

$$v_i(t+1) = \alpha v_i(t) + \beta r_1 (P_{best} - x_i(t)) + \beta r_2 (g_{best}(t) - x_i(t)) \tag{9}$$

The solution steps are: initialize the population information, which includes the number of populations, the positions and velocities of each particle; Each particle is fed into the fitness function for solving P_{best}; Update the local optimal solution, P_{best} compare the fitness function value of the particle with the current local optimal solution g_{best}, and replace it if it is better than it. Update the global optimal solution, by comparing the fitness function value of particles with the current global optimal solution, and replacing it if it is better than it. Update speed and location; If the end condition is met, exit.

4 Analysis of examples

4.1 Calculation examples and results

Select historical data from a city in western China for analysis in 2022, with a 600 kW wind turbine and a 30 MW load. Selecting 1 year as the data collection unit, the sampling interval for photovoltaic power and load power is 10 min. Verify the typical day data taken in the previous section in a 33 node power system. Install wind power with a rated power of 600 KW at nodes 6 and 32 respectively, and plan to install one energy storage system. The installation location can be selected from any node from node 1 to node 33. In the process of configuring energy storage, calculate the average value of the energy storage configuration capacity in the objective function, and finally converge to 612,931 yuan with the comprehensive cost as the goal. Record the iterative trend of Pareto solution set, and the convergence process curve is shown in Figure 5.

TABLE 1 Economic costs and carbon emission indicators.

Parameters	Before	After	Contrast
Investment/yuan	1120	900	−19.64%
Cost/yuan	374	317	−15.24%
Network loss/yuan	17.12	12.00	−29.84%
Electricity cost/yuan	172.30	142.10	−17.53%
Carbon emissions/ton	840	420	−50%

4.2 Economic and carbon emission analysis

The one-time investment cost of this system for energy storage is RMB 9 million, and the maintenance cost is RMB 3.17 million. After configuring the energy storage system, there are still some photovoltaic power stations whose actual output power is too small to meet the load demand, and the energy storage capacity has also been discharged to the lowest point. Therefore, the network loss cost is RMB 120100, the electricity purchase cost is RMB 1.421 million, and the total cost after adding the weight coefficient is RMB 1.2672 million. The economic costs and corresponding carbon emission data of each part are shown in Table 1.

In summary, particle swarm optimization can optimize the operating strategy of energy storage systems, reducing the cost of purchasing electricity and charging and discharging energy storage equipment. By dynamically adjusting the operating parameters of the energy storage system, energy storage equipment can be more effectively utilized, reducing the cost of system operation. Particle swarm optimization algorithm can help energy storage systems achieve maximum revenue in market operations. By optimizing the charging and discharging strategies of the energy storage system,

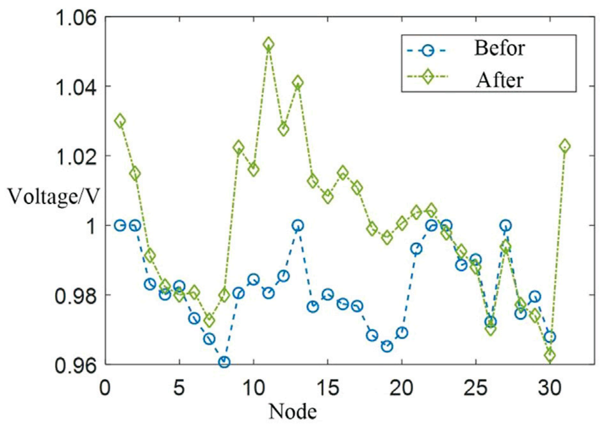

FIGURE 6
Node voltage amplitude before and after energy storage system participation.

the system can charge during high electricity price periods and discharge during low electricity price periods, thereby maximizing the system's revenue (Wei et al., 2023). The particle swarm optimization algorithm can optimize the energy conversion efficiency and storage efficiency of energy storage systems, reducing losses during energy storage and release, thereby improving the overall energy utilization efficiency of the system.

4.3 Power system performance analysis

The node voltage deviation and node voltage amplitude before and after the participation of the energy storage system are shown in Figure 6. While the overall voltage profile has shown improvement after integrating the hybrid collaborative energy storage system, it is important to note that there has been an increase in voltage deviation (Figure 6). This phenomenon can be attributed to the dynamic nature of renewable energy sources, such as wind and solar power, which introduce variability into the grid. The integration of energy storage systems can sometimes amplify these fluctuations if not properly managed.

When not connected to the energy storage system, the voltage deviation meets the requirements. After connecting to the energy storage system, the voltage deviation meets the requirements and is reduced compared to the voltage deviation before connection. The voltage quality is improved, and the voltage fluctuation is also improved to a certain extent. Before the integration of the energy storage system, the voltage levels were subject to natural fluctuations due to varying load demands and generation patterns from renewable sources. Post-integration, the energy storage system attempts to stabilize these voltages by absorbing excess power during peak generation periods and releasing stored energy during high demand or low generation times. However, this process can lead to transient overshoots or undershoots in voltage levels, contributing to increased deviation.

The voltage amplitude before and after connecting to the energy storage system meets the requirements, and the voltage amplitude increases and the fluctuation decreases at each moment after connecting to the energy storage system.

5 Conclusion

This article considers the power grid losses caused by the integration of energy storage systems into active distribution networks and their impact on improving the voltage of distribution networks. It provides a theoretical basis for the capacity optimization configuration of two-stage hybrid energy storage systems in the future. An IEEE33 node system is used, for example, analysis, and the improved chaotic particle swarm optimization algorithm and PSO algorithm are used as model solving methods. Establish a double-layer optimization configuration model based on the impact of volatile energy on energy storage systems. On the basis of a multi-objective optimization model, the upper layer uses wind, light, and load daily prediction values to plan the distribution network and the hybrid energy storage system of lead-acid batteries and supercapacitors. The goal is to optimize the comprehensive cost, network loss, and node voltage deviation, and an improved multi-objective optimization particle swarm optimization is used to solve the initial capacity configuration value; The optimal model for adjusting the system frequency deviation index of energy storage system output based on wind power output in the lower layer, solving the correction value of the configuration capacity of supercapacitors, and introducing a quantum particle swarm with chaotic mechanism to further optimize the output of various units in the power grid.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

MX: Conceptualization, Writing–original draft, Writing–review and editing. GL Guo ping: Methodology, Writing–review and editing. YH: Data curation, Software, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Alasali, F., Salameh, M., Semrin, A., Nusair, K., El-Naily, N., and Holderbaum, W. (2022). Optimal controllers and configurations of 100% PV and energy storage systems for a microgrid: the case study of a small town in Jordan. *Sustainability* 14 (13), 8124. doi:10.3390/su14138124

Ali, Z. M., Calasan, M., Aleem, S. H. E. A., Jurado, F., and Gandoman, F. H. (2023). Applications of energy storage systems in enhancing energy management and access in microgrids: a review. *Energies* 16 (16), 5930. doi:10.3390/en16165930

Behabtu, H. A., Messagie, M., Coosemans, T., Berecibar, M., Anlay Fante, K., Kebede, A. A., et al. (2020). A review of energy storage technologies'application potentials in renewable energy sources grid integration. *Sustainability* 12 (24), 10511. doi:10.3390/su122410511

Chaspierre, G., Panciatici, P., and Cutsem, T. V. (2022). Control of a battery energy storage system to compensate for ADN equivalents inaccuracies. *Electr. Power Syst. Res.* 213, 108455. doi:10.1016/j.epsr.2022.108455

Du, J., Shen, Z., Song, M., and Zhang, L. (2023). Nexus between digital transformation and energy technology innovation: an empirical test of A-share listed enterprises. *Energy Econ.* 120, 106572. doi:10.1016/j.eneco.2023.106572

Gugulothu, R., Nagu, B., and Pullaguram, D. (2023). Energy management strategy for standalone DC microgrid system with photovoltaic/fuel cell/battery storage. *J. Energy Storage* 57, 106274. doi:10.1016/j.est.2022.106274

Guo, X., Chen, Q., Liang, W., Wang, S., Wang, Y., and Qin, Y. (2021). Intelligent optimization algorithm of active distribution network based on load storage cooperative optimization of source network. *Proc. 2021 IEEE 4th Int. Conf. Automation, Electron. Electr. Eng. (AUTEEE)*, 355–360. doi:10.1109/auteee52864.2021.9668647

Ivanov, O., Neagu, B. C., Grigoraş, G., Scarlatache, F., and Gavrilaş, M. (2021). A metaheuristic algorithm for flexible energy storage management in residential electricity distribution grids. *Mathematics* 9 (19)–2375. doi:10.20944/preprints202109.0090.v1

Kroičs, K., and Ģirts, S. (2022). Bidirectional interleaved DC–DC converter for supercapacitor energy storage integration with reduced capacitance. *Electronics* 12 (1), 126. doi:10.3390/electronics12010126

Kumar, R., Ashfaq, H., Singh, R., and Kumar, R. (2024). A heuristic approach for insertion of multiple-complex coefficient-filter based DSTATCOM to enhancement of power quality in distribution system. *Multimed. Tools Appl.* doi:10.1007/s11042-024-19778-5

Kumar, R., Diwania, S., Khetrapal, P., and Singh, S. (2022). Performance assessment of the two metaheuristic techniques and their Hybrid for power system stability enhancement with PV-STATCOM. *Neural Comput. and Applic* 34, 3723–3744. doi:10.1007/s00521-021-06637-9

Kumar, R., Diwania, Khetrapal, P., Singh, S., and Badoni, M. (2021a). Multimachine stability enhancement with hybrid PSO-BFOA based PV-STATCOM. *Sustain. Comput. Inf. Syst.* 32, 100615. doi:10.1016/j.suscom.2021.100615

Kumar, R., Singh, Ashfaq, H., Singh, S. K., and Badoni, M. (2021b). Power system stability enhancement by damping and control of Sub-synchronous torsional oscillations using Whale optimization algorithm based Type-2 wind turbines. *Isa Trans.* 108, 240–256. doi:10.1016/j.isatra.2020.08.037

Lei, G., Huang, Y., Dai, N., Cai, L., Deng, L., Li, S., et al. (2022). Optimization strategy of hybrid configuration for volatility energy storage system in ADN. *Processes* 10 (9), 1844. doi:10.3390/pr10091844

Pathak, P. K., Yadav, A. K., and Padmanaban, S. (2023). Transition toward emission-free energy systems by 2050: potential role of hydrogen. *Int. J. Hydrogen Energy* 48 (26), 9921–9927. doi:10.1016/j.ijhydene.2022.12.058

Paul, S., Dey, T., Saha, P., and Sen, R. (2021). Review on the development scenario of renewable energy in different country. *Innovations Energy Manag. Renew. Resour.* 52042, 1–2. doi:10.1109/iemre52042.2021.9386748

Verma, N., Kumar, N., and Kumar, R. (2023). Battery energy storage-based system damping controller for alleviating sub-synchronous oscillations in a DFIG-based wind power plant. *Prot. Control Mod. Power Syst.* 8, 32. doi:10.1186/s41601-023-00309-7

Wei, P., Abid, M., Adun, H., Kemena Awoh, D., Cai, D., Zaini, J. H., et al. (2023). Progress in energy storage technologies and methods for renewable energy systems application. *Appl. Sci.* 13 (9), 5626. doi:10.3390/app13095626

Yong, X., Wu, Y., Zhou, J., Tao, Y., and Chen, W. (2023). Prospects and barriers analysis framework for the development of energy storage sharing. *Sustain. Cities Soc.* 89, 104368. doi:10.1016/j.scs.2022.104368