Transactions on Environment, Energy and Earth Sciences
ISSN: 2960-1924, eISSN: 2960-2300 | Volume 5
EMCEME 2025

Research on Capacity Optimization of Wind Solar Complementary Hybrid Energy Storage System

Jiashuo Chen *

School of Electrical Engineering and Automation, Wuhan University, Wuhan, China, 430072

* Corresponding Author Email: 2022312191209@whu.edu.cn

Abstract. With the "dual carbon" aim being widely promoted, there is an urgent need to promote the sustainable development of wind solar complementary power stations (WSCPS). Therefore, this article proposes an optimization model for wind solar complementary hybrid energy storage system. Firstly, establish a mathematical model for the hybrid energy storage system (HESS) and propose a power allocation strategy for the HESS; Then, with the energy storage capacity configuration parameters as optimization variables and the minimum lifecycle cost of HESS in WSCPS as the optimization objective, Cauchy mutation adaptive particle swarm optimization (CMAPSO) is used to solve the actual case study; Finally, the Cauchy mutation adaptive particle swarm optimization (CMAPSO) used in this study is compared with particle swarm optimization (PSO) and adaptive inertia weight particle swarm optimization (AIWPSO). It can be seen from the comparison results that the optimal values of CMAPSO and AIWPSO are 64.3 % and 53.1 % lower than those of PSO, respectively. The optimization ability of CMAPSO is stronger. Comparing the mean and variance, it can also be seen that the optimization accuracy of CMAPSO algorithm is higher and relatively stable, the usefulness and superiority of the suggested scheme and algorithm were demonstrated.

Keywords: Wind Solar Complementary Power Stations, Hybrid Energy Storage System, Cauchy Mutation Adaptive Particle Swarm Optimization, Capacity Configuration.

1. Introduction

With the demand for new energy continues to grow. At the same time, WSCPS are widely used in areas with abundant wind and solar resources and rural microgrids in remote areas [1]. However, considering the intermittent and fluctuating characteristics of new energy, the output power is often difficult to meet the actual needs of the load. At present, energy storage systems (ESS) are the main means to solve the power imbalance between new energy generation and load. However, the current cost of configuring ESS in WSCPS is relatively high. Therefore, it is necessary to develop a reasonable ESS capacity configuration plan based on the actual situation to improve the economic benefits of operators.

Looking back at existing research, it can be found that there are many studies aimed at optimizing WSCPS and energy storage systems, such as Sharma Pradosh Kumar et al. [2] using an improved PSO to optimize the capacity of HESS in WSCPS. Wang C et al. [3] aims to improve power quality by studying HESS in WSCPS. Song Hu et al. [4] improves the battery life by improving the hybrid energy storage scheme. Song Z et al. [5] proposes the optimal ESS capacity configuration through optimization to improve the utilization efficiency of renewable energy. Zhou L. [6] achieves optimization of power system operation configuration by establishing a multi-objective programming model. The above research has to some extent improved the operational economy of WSCPS, but there is still room for further improvement in the accuracy of model establishment and the speed of solution.

In response to the above issues, this article constructs an optimized operation model for WSCPS. To effectively reduce the number of charging and discharging of batteries and achieve the goal of extending their service life, an energy management strategy suitable for HESS is proposed. CMAPSO was used to solve the constructed optimization model and obtain the optimal capacity of HESS. By contrasting the suggested algorithm with other algorithms, its superiority and efficacy were confirmed.

2. Structure of wind solar hybrid energy storage system

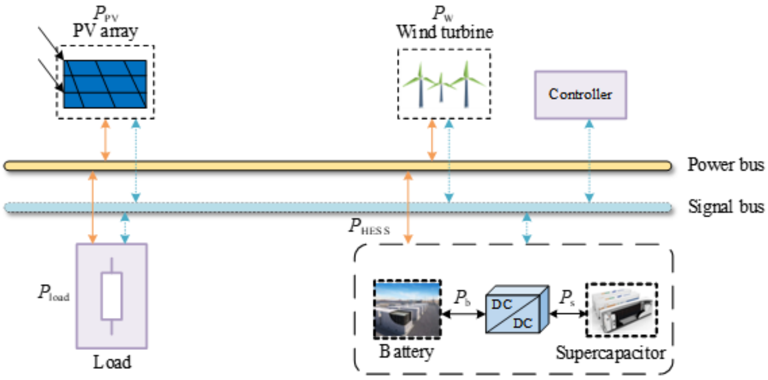

Figure 1. Structure diagram of WSCPS.

The WSCPS consists of distributed energy system, load, ESS, power distribution equipment, controller, etc. In Figure 1. The main energy sources are provided by photovoltaic and wind power generation, which supply power to the electricity load and meet its continuous operation requirements. Considering the power demand of users and the supply-demand imbalance in renewable energy generation, HESS has the characteristics of large capacity, low cost, and long service life, greatly meeting the flexibility and economic requirements of HESS and catering to the market demand for large-scale energy storage. The central controller controls the start and stop of the corresponding converters of each energy storage device, smoothing the fluctuation of renewable energy generation to provide stable power supply for user loads and meet their reliability requirements. The reference power signal $P_{\mathrm{HESS}}(t)$ of the HESS:

$$P_{\mathrm{HESS}}(t) = P_{\mathrm{pv}}(t) + P_{\mathrm{wt}}(t) - P_{\mathrm{load}}(t) \tag{1}$$

3. Mathematical Model and Power Allocation Strategy of HESS

3.1. Model of battery

$$E_{\mathrm{bn}} = 1\times10^{-6} mC_{\mathrm{b}}U_{\mathrm{b}} \tag{2}$$

In the formula, E_{bn} is the rated capacity of battery equipped in WSCPS; C_{b}(Ah) is the rated capacity of the battery per unit device; U_{b}(V) is the rated voltage (this article uniformly uses MW·h as the energy unit and MW as the power unit); m is the number of batteries equipped.

The battery pack discharges at a time rate of C10, and its rated power is:

$$P_{\mathrm{bn}} = 1\times10^{-7} mC_{\mathrm{b}}U_{\mathrm{b}} \tag{3}$$

3.2. Model of Supercapacitors

$$E_s = \frac{0.5nC_{\mathrm{s}}U_{\mathrm{s}}^{2}}{3.6\times10^{9}} \tag{4}$$

E_{s} is the capacity of the equipped supercapacitor; C_{s} is the capacitance value of the supercapacitor; U_{s} is the terminal voltage of its; n is the number of supercapacitors equipped.

$$P_{s\max} = 1\times10^{-6} nU_{\max} I_{s\max} \tag{5}$$

$P_{s\max}$ is the rated power of supercapacitor; $I_{s\max}$ is the maximum operating current of single devices, and $U_{\max}$ is rated voltage of single devices.

3.3. Mathematical Model of HESS

The accumulated energy storage $E_b(t)$ and $E_s(t)$ of the battery and supercapacitor from the start time to time t are respectively:

$$\begin{cases} E_b(t) = E_b(0) + \eta_b \sum_{t=1}^{T} P_b(t) X_b(t) \Delta t + \dfrac{\sum_{t=1}^{T} P_b(t) Y_b(t) \Delta t}{\eta_b} \\ E_s(t) = E_s(0) + \eta_s \sum_{t=1}^{T} P_s(t) X_s(t) \Delta t + \dfrac{\sum_{t=1}^{T} P_s(t) Y_s(t) \Delta t}{\eta_s} \end{cases} \tag{6}$$

In above formula, T refers to the system running time; $E_b(0)$ and $E_s(0)$ represent the initial energy storage of the battery and supercapacitor; $X_b(t)$ and $Y_b(t)$ are the charging and discharging states of the battery at time t; $X_s(t)$ and $Y_s(t)$ are the charging and discharging states of the supercapacitor at time t; $P_b(t)$ is the power of the battery at time t. When the battery is in a charging state, $P_b(t)$ is positive, and when the battery is in a discharging state, $P_b(t)$ is negative; Similarly, $P_s(t)$ can be obtained as the power of the supercapacitor at time t; η_b and η_s represent the charging and discharging efficiency of them after passing through the inverter.

3.4. Power allocation strategy for HESS

When the power generated by new energy is greater than the user's load, ESS is used to recover the unabsorbed new energy generation. ESS used enters the charging stage, and with the help of the large capacity of the battery, it starts charging first. When its maximum charging power P_b cannot meet the unbalanced power of the new energy generation system and load, it is recharged by supercapacitors; When the power of new energy is less than the user's load, ESS releases energy to supplement the power. With the help of the fast discharge characteristics of supercapacitors, they start discharging first to ensure sufficient capacity for storage before the next charge. When their maximum discharge power P_s cannot meet the unbalanced power of new energy generation and load, battery discharges to supplement. The flowchart is shown in Figure 2:

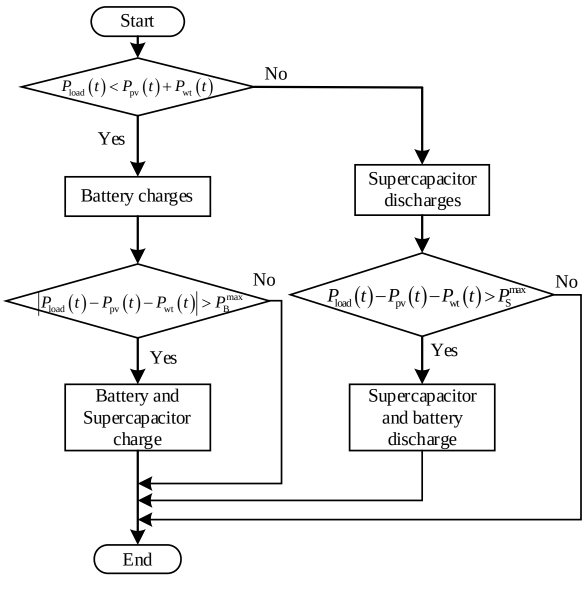

Figure 2. Power allocation strategy for HESS.

4. Optimization model

4.1. Objective Function

This article aims to minimize the Life Cycle Cost (LCC) of HESS [7] as the optimization objective:

$$\begin{aligned}\min f &= f_1 + f_2 + f_3 + f_4 \\ &= (1 + f_{b1} + f_{b2} + f_{b3})mL_b + (1 + f_{s1} + f_{s2} + f_{s3})nL_s\end{aligned} \tag{7}$$

In the formula, f_1 is the initial investment cost of HESS; f_2 is operating cost of HESS; f_3 is maintenance cost of HESS; f_4 is the cost of HESS disposal. L_b and Ls are unit device prices of batteries and supercapacitors, similarly, f_{b1} and f_{s1} are the operating coefficients of them, f_{b2} and f_{s2} are maintenance coefficients of them, and f_{b3} and f_{s3} are the disposal coefficients of them.

4.2. Constraints

(1) Battery restraint

$$\begin{cases}(1-D)E_{bn} \le E_b(t) \le E_{bn} \\ X_b(t)Y_b(t) = 0 \\ X_b(t), Y_b(t) \in \{0,1\} \\ 0 \le |P_b(t)| \le P_{bn}\end{cases} \tag{8}$$

In the formula, D is the maximum discharge depth of the battery.

(2) Supercapacitor constraint

$$\begin{cases}\dfrac{0.5yC_s {U_{s\min}}^2}{3.6\times10^6} \le E_s(t) \le \dfrac{0.5yC_s {U_{s\max}}^2}{3.6\times10^6} \\ X_s(t)Y_s(t) = 0 \\ X_s(t), Y_s(t) \in \{0,1\} \\ 0 \le |P_s(t)| \le P_{s\max}\end{cases} \tag{9}$$

$U_{s\min}$ and $U_{s\max}$ are the upper and lower limits of the terminal voltage of supercapacitor.

5. Algorithm analysis

This article uses CMAPSO to solve the above model. The introduction to PSO has been detailed in reference [8] and will not be repeated in this article.

Assuming the Number of particle population is N and the dimension j is 1,2 ···· d, the initial position and velocity of the *i-th* particle in the *j*-dimension are:

$$\begin{cases}x_i = (x_{i1}, x_{i2}, \cdots x_{id})^T, i = 1, 2, \cdots N \\ v_i = (v_{i1}, v_{i2}, \cdots v_{id})^T, i = 1, 2, \cdots N\end{cases} \tag{10}$$

The formula for updating the velocity and position of the entire particle swarm is:

$$v_{ij}^{k+1} = \omega v_{ij}^k + c_1 r_1 (p_{ij}^k - x_{ij}^k) + c_2 r_2 (p_{gj}^k - x_{ij}^k) \tag{11}$$

$$x_{ij}^{k+1} = x_{ij}^{k} + v_{ij}^{k+1} \tag{12}$$

ω is the inertia weight factor, and its size affects the search ability of particles; c_1 and $c_2$are learning factors, whose sizes respectively affect the particle's self-learning ability and social learning ability; r_1 and r_2 are random numbers obeying U (0,1); p_{ij}^{k} is the optimal value of individual particles in the j-dimension; p_{gj}^{k} is the optimal value of the group in the j-dimension; k is the number of iterations.

Considering the problems existing in the conventional particle swarm optimization algorithm, including slow convergence speed, low solution accuracy, limited search range, and susceptibility to getting stuck in local optima, improvements are made from two aspects to enhance its superiority. Firstly, the ω and c_1, c_2 values of this algorithm are generally fixed, which limits its traversal and makes it prone to getting stuck in local optima. Therefore, the following improvements can be made to enable it to adaptively adjust the search range and improve its solution accuracy.

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min})\exp(-(\tau \frac{k}{k_{\max}})^2) \tag{13}$$

$$\begin{cases} c_1 = c_{1\max} + (c_{1\min} - c_{1\max})\dfrac{k^2}{k_{\max}^2} \\ c_2 = c_{2\min} + (c_{2\max} - c_{2\min})\dfrac{k^2}{k_{\max}^2} \end{cases} \tag{14}$$

$\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of ω; τ is determined by experience, generally ranging from 20 to 55; $c_{1\max}$ and $c_{1\min}$ are the maximum and minimum values of c_1; $c_{2\max}$ and $c_{2\min}$ are the maximum and minimum values of c_2; $k_{\max}$ is the total number of iterations of the algorithm. In the early stage of iteration, when ω is larger and c_1 is larger, c_2 is smaller, which makes the particle have stronger self-learning ability and weaker social learning ability. This is beneficial for enhancing the global search ability of the particle in the early stage and preventing premature convergence problems. As the number of iterations increases, c_1 gradually decreases, c_2 gradually increases, and the particle's local search ability gradually enhances, making it easier for the algorithm to converge.

In addition, considering the introduction of mutation strategy, in equation (12), Cauchy mutation is considered as a parameter to control the mutation step size to increase the diversity of population [9] and improve the search accuracy of algorithm. The Cauchy distribution function is:

$$f(x) = \frac{1}{\pi\gamma[1 + (\frac{x - x_0}{\gamma})^2]} \tag{15}$$

In the formula, γ is the scale parameter; x_0 is the position parameter; When x_0=0 and γ=1, the above equation becomes the standard Cauchy distribution, denoted as C (0,1).

During the motion of particles, they need to refer to the empirical information of other particles for decision-making, and the particle swarm converges towards the optimal point of the group, which can easily fall into the trap of local optima. Due to the smaller distribution at the peak and longer distribution on both sides of the Cauchy distribution compared to the normal distribution, particle swarm optimization can quickly jump out of the local optimal position and search for other neighboring intervals after mutation. Therefore, equation (12) can be updated to:

$$x_{ij}^{k+1} = x_{ij}^{k} + v_{ij}^{k+1}[1 + \varphi C(0,1)] \tag{16}$$

In the formula, φ is the Cauchy variation intensity, which is taken as 0.8 in this article.

6. Example analysis

6.1. Simulation analysis

Select one day's historical data from a wind solar complementary power station in the northwest region for case analysis, as shown in Figure 3. Set ω_{max} and ω_{min} to 0.9 and 0.4, c_{1max} and c_{1min} to 2.5 and 0.5, c_{2max} and c_{2min} to 2.5 and 0.5, respectively. The maximum iteration count k_{max} of the algorithm is set to 1500. Based on the parameters of the energy storage devices [10,11] used in Table 1, CMAPSO was used to solve the optimization model. The capacity configuration results of HESS are shown in Table 2.

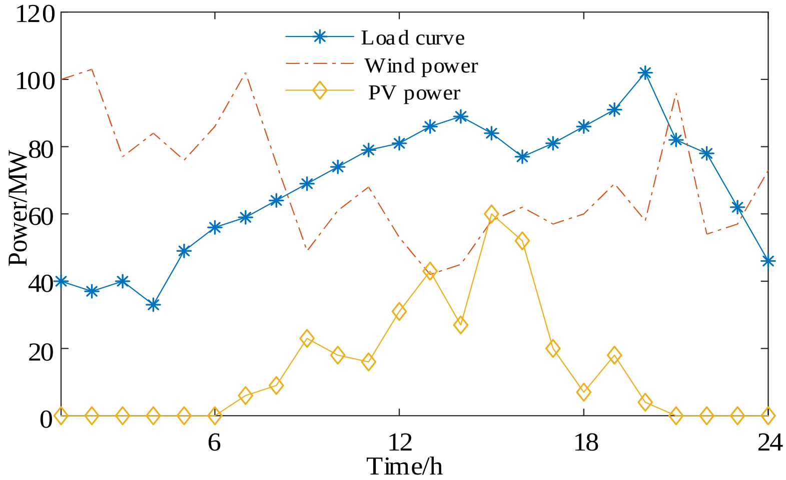

Figure 3. Power Curve of Wind Solar Complementary Power Station.

Table 1. Energy Storage Equipment Parameters.

Storage battery		Supercapacitor	
System parameter	Parameter values	System parameter	Parameter values
Rated capacity/Ah	100	Capacitor/F	3500
Rated voltage/V	12	Rated voltage/V	2.7
Depth Of Discharge	0.4	Minimum operating voltage/V	0.8
Charge efficiency	0.75	Maximum operating current/A	1500
Discharge efficiency	0.85	Charge-discharge efficiency	0.98
Cycle life/time	1500	Cycle life/time	500000
Maintenance factor	0.02	Maintenance factor	0.003
Operating factor	0.1	Operating factor	0.01
Unit price/CNY	400	Unit price/CNY	350
Processing coefficient	0.08	Processing coefficient	0.04

Table 2. Energy Storage Capacity Configuration Results.

Battery/piece	Supercapacitor/piece	LCC/CNY
11731	7972	6.79×10^{13}

Figure 4 shows the output power variation curves of HESS within a day. Compared with batteries, supercapacitors' output power changes faster, and the unbalanced power in the system is mainly borne by supercapacitors. This is because supercapacitors have fast charging and discharging characteristics and high cycle times, which is conducive to reducing the cycle times of batteries, extending their service life, and thus reducing the life cycle cost of energy storage devices in WSCPS.

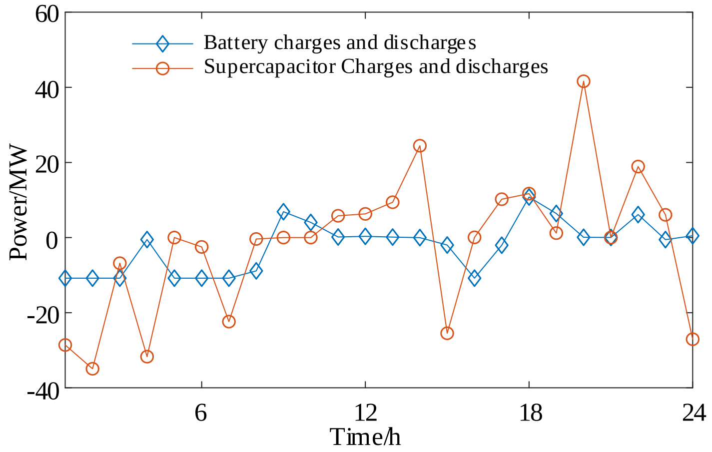

Figure 4. Output power curve of energy storage device.

6.2. Algorithm Comparison

Compare the CMAPSO used in this article with the PSO, and the AIWPSO proposed in reference [12]. Each algorithm aims to minimize HESS' lifecycle cost. In the PSO, the inertia weight ω=1 and the learning factor c_1=c_2=2. The curve is shown in Figure 5. From the graph, the convergence speed of traditional PSO is faster, but it tends to stabilize around the 500th generation, which means that traditional PSO is prone to falling into local optima. Compared to the AIWPSO, the CMAPSO tends to be stable around the 1300th generation and produces the lowest lifecycle cost for HESS. This indicates that compared to the other two algorithms, CMAPSO has a wider search range and is more likely to jump out of local optima, demonstrating better global search ability and faster convergence speed.

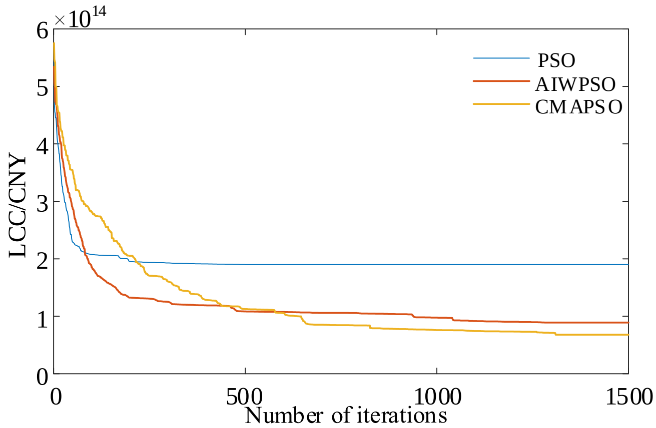

Figure 5. Algorithm convergence curve.

Table 3 shows the comparison of the results of three algorithms. The results show that the optimal value of CMAPSO and AIWPSO compared with PSO, the life cycle cost of HESS is reduced by 64.3% and 53.1% respectively, which shows that its optimization ability is stronger. By comparing the average value, CMAPSO has higher optimization accuracy. From the perspective of variance, although PSO is more stable than CMAPSO, it is easy to fall into local optimum. By comparing the variance of CMAPSO and AIWPSO, CMAPSO is relatively stable.

Table 3. Comparison of algorithm results.

	PSO	AIWPSO	CMAPSO
Iteration times	1500	1500	1500
Optimal value /CNY	1.90×10^{14}	8.91×10^{13}	6.79×10^{13}
Average value /CNY	1.97×10^{14}	1.20×10^{14}	1.23×10^{14}
Variance	9.61×10^{26}	6.71×10^{27}	3.23×10^{27}

7. Conclusion

1) The mathematical model of HESS including battery and supercapacitor is established, and a power distribution strategy based on equipment characteristics is proposed. This strategy effectively reduces the number of cycles of the battery and prolongs its service life.

2) The optimal operation model of wind-solar complementary energy storage system is established. CMAPSO is used to solve it, and the optimal configuration results of HESS are as follows: 11731 batteries and 7972 supercapacitors.

3) Compared with PSO and AIWPSO, it can be seen from the comparison results that the optimal value of CMAPSO is better than the other two, which shows that its optimization ability is stronger. By comparing the mean and variance, it can also show that the optimization accuracy of CMAPSO is higher and more stable.

4) With the development of ESS, future research can explore the integration of various types of ESS such as pumped storage, compressed air energy storage, and new flow batteries into HESS, and study multi-type energy storage under more complex architectures. Collaborative optimization configuration and control strategies to tap greater technical and economic potential.

References

[1] Weijun Xu, Qian Lu, Jing Wang. Research on capacity optimization configuration of distributed photovoltaic energy storage system[J]. Journal of Physics: Conference Series, 2025, 2963 (1):012027-012036

[2] Sharma P K, Kumar D A, William P, et al. Energy storage system based on hybrid wind and photovoltaic technologies[J]. Measurement: sensors, 2023, 30(5): 100915-100923.

[3] Wang C, Jiao S, Li Y, et al. Capacity optimization of a hybrid energy storage system considering Wind-Solar reliability evaluation based on a novel Multi-strategy snake optimization algorithm[J]. Expert Systems with Applications, 2023, 23(1): 120602-120627.

[4] Hu S, Yang H, Ding S, et al. Model simulation and multi-objective capacity optimization of wind power coupled hybrid energy storage system[J]. Energy, 2025, 319(3): 134887-134902.

[5] Song Z, Zhang M, Chi Y, et al. Research on the coordinated optimization of energy storage and renewable energy in off-grid microgrids under new electric power systems[J]. Global Energy Interconnection,2025,8(2):213-224.

[6] Zhou L, Ma T. Analysis of Energy Storage Operation Configuration of Power System Based on Multi-Objective Optimization[J]. Journal of Electronic Research and Application,2022,6(4):13-38.

[7] Paul D, Pechancová V, Saha N, et al. Life cycle assessment of lithium-based batteries: Review of sustainability dimensions[J]. Renewable and Sustainable Energy Reviews, 2024, 206: 114860-114877.

[8] Kennedy J, Eberhart R. Particle swarm optimization [C] //Proceedings of ICNN'95-international conference on neural networks. ieee, 1995, 4: 1942-1948.

[9] Chunhui R E N, Sheng L I U, Weikang Z, et al. Optimization and Application of Cauchy Mutation Camel Algorithm[J]. Journal of Computer Engineering & Applications, 2021, 57(21): 87-94.

[10] Yang Jun, Zhang Jiancheng, Whuang Leilei, et al. Energy Storage Capacity Optimization for Independent PV Power System Based on Improved PSO Algorithm [J]. East China Electric Power, 2012, 40(08): 1370-1374.

[11] Jia Honggang, Yue Yuanyuan, Yan Huan, et al. Study on capacity optimization of hybrid energy storage system based on particle swarm algorithm [J]. Automation & Instrumentation, 2023, (10):282-287.

[12] Zhang Y, Hu H, Geng A, et al. Capacity optimization configuration of hybrid energy storage system for electrified railway considering peak load shifting[J]. Electric Power Automation Equipment, 2023, 43(2): 44-50.