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Optimization of Energy Storage Allocation in Wind Energy Storage Combined System Based on Improved Sand Cat Swarm Optimization Algorithm

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Abstract: In order to improve the operation reliability and new energy consumption rate of the combined wind–solar storage system, an optimal allocation method for the capacity of the energy storage system (ESS) based on the improved sand cat swarm optimization algorithm is proposed. First, based on the structural analysis of the combined system, an optimization model of energy storage configuration is established with the objectives of the lowest total investment cost of the ESS, the lowest load loss rate and the lowest new energy abandonment rate, which not only takes into account the economy of energy storage construction for investors and builders, but also reduces the probability of blackout for users to protect their interests and improves the utilization rate of the natural resources of wind and light, which can achieve a multi-win–win situation. The model can realize the win–win situation in many aspects. Secondly, an improved k-means clustering algorithm is used to cluster the renewable energy power and load data to realize the typical day data extraction. Then, for the proposed multi-objective optimization model, an SCSO is proposed based on the triangular wandering strategy, Lévy flight strategy and lens imaging reverse learning improvement, which can help the algorithm to jump out of the local optimum while improving its global optimization ability, and these improvements can significantly improve the optimization effect of the SCSO. Finally, simulation analysis is carried out in combination with typical daily extraction data, and the results verify the advantages and effectiveness of the proposed model and algorithm.

Keywords: new energy; energy storage system; sand cat swarm algorithm; optimal allocation; multi-objective optimization

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1. Introduction

Climate change is a major issue shared by people around the world, and greenhouse gases are soaring year after year as countries increase their carbon dioxide emissions, threatening ecosystems. Against this backdrop, countries are reducing greenhouse gas emissions by means of a global pact, and China has proposed a low-carbon development goal of carbon peaking and carbon neutrality [1–3]. Therefore, wind power and photovoltaic, as clean energy sources, have been developing rapidly in recent years, and in China, a large number of wind power and PV are integrated into the power grid. However, the instability of wind power generation brings about a decrease in the reliability of the system as well as a higher rate of wind and light abandonment, both of which are problems that need to be solved urgently [4,5]. By configuring energy storage, the wind–power and photovoltaic power output volatility can be effectively suppressed by the wind–power and photovoltaic joint power generation system, which can be flexibly adjusted and can send out excess power when the system output is larger than the load, as well as make up the difference through the grid when the system output cannot meet the load demand. However, the construction, operation and maintenance costs of energy storage devices are high, and an excessive configuration of the storage capacity will greatly increase the investment cost and therefore reduce the economy of the combined generation system [6]. On the other hand, if the capacity is too small, it will lead to a high wind and light abandonment rate and, subsequently, system reliability deterioration, so we need to comprehensively consider the economy, reliability and wind and light dissipation of the storage system capacity's configuration, all of which promote the dissipation of renewable energy and improve the stability of the combined system, which are of great significance [7].

The authors of [8] use particle swarm algorithm to solve the capacity of ESS by considering the construction and maintenance cost of ESS as well as the cost of wind abandonment and carbon treatment. The paper [9] establishes an economic model of wind power-photovoltaic-diesel power-ESS microgrid system with the introduction of outage penalties and the cost of pollution control, and then solves the capacity allocation of the microgrid via genetic algorithm. The study [10] uses system voltage deviation, the daily active network loss and the allocation of ESS capacity as the optimal configuration model of energy storage, while introducing the Tennessee whisker search and Logistic chaotic mapping to improve the multi-objective particle swarm algorithm, which improves its convergence speed and optimization ability. Ref. [11] investigates the optimal configuration of the storage system capacity in the independent photovoltaic system with the objectives of the system load shortage rate and the energy spillover ratio, which can effectively alleviate the energy spillover of the renewable energy sources and increase the renewable energy utilization rate. The authors of [12] studied the impact of the grid-connected location of an ESS on its configuration, and also analyzed and investigated the impact of wind–scenery combinations with different correlations, different sampling time intervals and different numbers of power stations on the configuration of the energy storage as well as on the wind–scenery complementarity. The authors of [13] established a two-layer optimization model for a multi-type energy storage integrated energy system (IES). The first layer optimization model takes the lowest total investment cost of the ESS as the optimization objective, and the second layer optimization model takes the lowest operation and maintenance cost of the ESS as the optimization objective. The study [14] proposes a distributed optimization framework for solving the cost minimization problem in energy storage and power generation planning, which takes into account the initial investment cost and the latter operation and maintenance costs, while at the same time solves the problem posed by large-scale optimization problems. Ref. [15] developed a two-tier optimization model combining PSO and DLOPF, where PSO adjusts and identifies the location of the battery storage system, and DLOPF uses the levelized cost of energy and storage to locate and size the RES in a spatiotemporal framework, which is used to minimize cost while limiting carbon emissions.

It can be seen that most scholars choose some form of a meta-heuristic optimization algorithm (stochastic optimization algorithms) when solving the energy storage allocation problem on the generation side of the power system, and these algorithms have obvious advantages over the traditional linear programming solvers and nonlinear programming solvers in solving the multi-objective optimization problems under multiple constraints, i.e., fast solution speed and good optimization results. The more mature meta-heuristic optimization algorithms include PSO, GA, WOA, BBO and SNO. PSO is an optimization algorithm developed according to the foraging behavior of bird flocks [16], which has the advantages of fast convergence speed, few parameters, simple algorithm and is easy to implement, but there is also the problem of falling into the local optimal solution because of the algorithm's simple structure. The GA algorithm simulates the phenomena of replication, crossover and mutation that occur in natural selection and heredity, and it also simulates the phenomena of natural selection and heredity [17]. In addition, the GA algorithm simulates the behaviors and phenomena, such as replication, crossover and mutation, that occur in the population and chromosome inheritance of species, and relies on the random selection, crossover and mutation operations of the initial population to produce a generation of individuals that are more adaptive and more conducive to survival, i.e., to produce a more optimal set of solutions, which will make the individual particles progressively close to the optimal solution to produce the optimal individual, that is, to generate the optimal solution. The GA algorithm is highly scalable, and it is easy to be combined with other algorithms to create optimization algorithms with a better optimization capacity, and its strong global search ability will not fall into the local optimum. WOA is an optimization algorithm generated by simulating the hunting behavior of humpback whales [18], and the whole process of the algorithm includes three stages: searching for food, contracting the encirclement and updating the position of the spiral. The WOA algorithm has the advantages of fast convergence speed, strong global searching ability and simple algorithm, but it is more sensitive to the parameter settings and needs to be adjusted to achieve a better solution. However, it is more sensitive to parameter setting and needs to be adjusted to achieve better results, and its efficiency will be greatly reduced when dealing with high-latitude problems. BBO is an efficient swarm intelligence optimization algorithm proposed in 2008 [19], which achieves optimization by simulating the migration process of species between multiple habitats in nature and has a better performance in global search, as well as a fast iteration speed in the early stage of the algorithm and a strong ability to process information. However, the algorithm has the disadvantages of precocity and slow convergence in the later stage when dealing with high-complexity high-dimensional multi-objective problems. SNO is a new type of intelligent optimization algorithm proposed in 2018 [20], which mainly simulates the behavior of human beings communicating with each other and sharing their current situation to search for the optimal solution. The algorithm has strong optimal solution searching ability and fast convergence speed, which has the advantages of strong global searching ability, fast convergence speed and effective use of the current population information, but the local optimization ability is weak because it does not incorporate the mechanism of individual guided population.

The sand cat swarm optimization (SCSO) algorithm is a meta-heuristic optimization algorithm designed to simulate the behavior of sand cats [21]. It is implemented to find an optimal solution by simulating the two behaviors of a sand cat searching for prey and attacking the prey. Since it was proposed by Amir Seyyedabbasi and Farzad Kiani in April 2022, it has been applied in optimization problems in many fields. The SCSO pair achieves the transition between the two phases by introducing the parameter R. Therefore, it can perform a local search in the global search, and may also jump out of the local optimum to reperform the global search during the local search. It has a better performance in the global search compared to the algorithms presented in the above section. The algorithms presented perform better in high dimensions and multi-objectives. Energy storage capacity optimization is a high-dimensional and multi-objective optimization problem, and SCSO will have an advantage over other algorithms in solving this problem.

In view of this, based on the flexible regulation capability of the ESS, and considering the economy and reliability of the ESS, in this paper, an energy storage capacity optimization method based on an improved SCSO is proposed [22,23]. The method first uses k-means algorithm to cluster wind power, PV and load data to extract typical days [24], and then inputs the extracted typical day data into the ESS optimization model and performs multi-objective optimization search by using the improved SCSO in order to find several energy storage allocation schemes [25].

The main contributions made by this study are listed below:

- Established an optimal allocation model of the ESS that comprehensively considers the economy of the ESS, the reliability of system power supply and the utilization rate of new energy, and we verified its feasibility;
- Improved the k-means algorithm using the clustering effectiveness index BWP to improve its clustering ability;
- Enhanced the SCSO to improve its local optimization and global optimization ability, and added Pareto optimization to make it applicable to multi-objective optimization problems.

The following sections of this paper are as follows. Section II mainly introduces the mathematical formulation and boundary conditions of the energy storage optimization model. Section III details the fundamentals of SCSO and the improvement of the algorithm, which contains the involved formulas. Section IV focuses on the basic principles and improvements of the k-means algorithm, and a flowchart of the typical day extraction performed by the clustering algorithm is displayed. Section V focuses on an example analysis. First, we select the data of a wind farm, a photovoltaic (PV) farm and an area load in China for a whole year in terms of hours, and then use the improved k-means algorithm to cluster these data and extract the typical day data. Subsequently, the typical day data are input into the energy storage allocation optimization model and then solved using the improved SCSO as well as some other optimization algorithms, and their results are compared to verify the advantages of the improved SCSO. Section VI summarizes the entire article, discusses the results achieved and provides an outlook for future work. In addition, a roadmap of the content is shown in Figure 1.

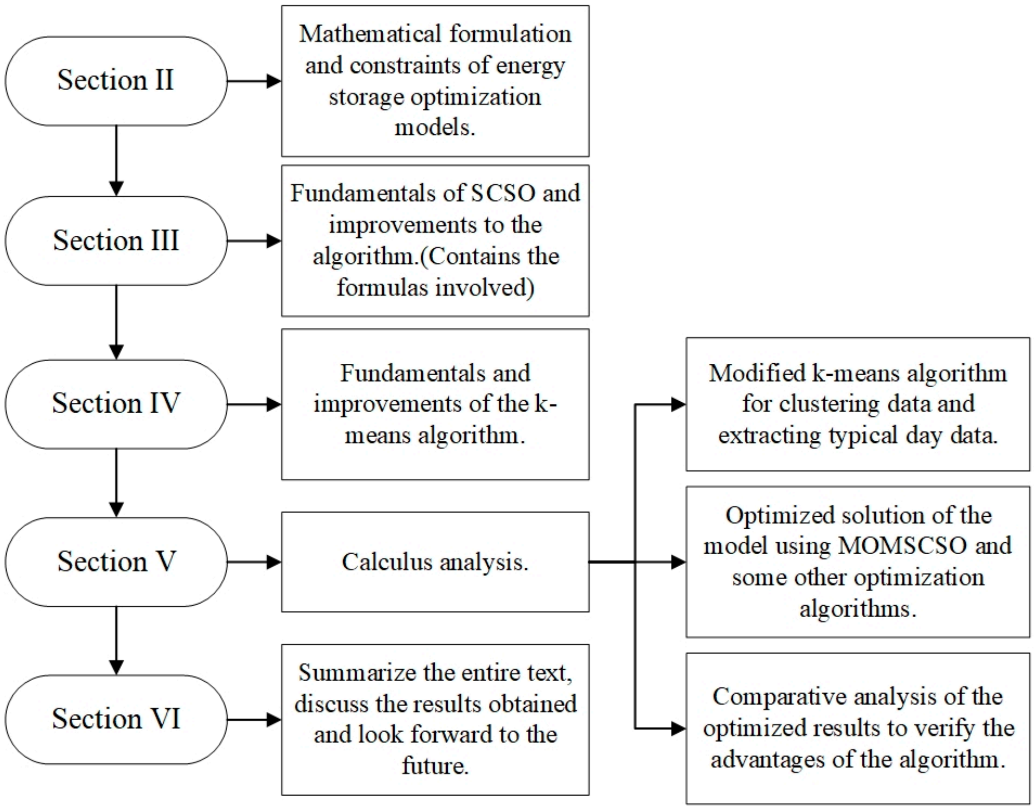

Figure 1. Article Structure Chart.

2. Optimization Model for Energy Storage Capacity Allocation

When designing an ESS, the construction cost of the storage system, the reliability and the consumption of wind and solar resources must be considered at the same time [26]. Therefore, this paper establishes an optimization model of the ESS with the objectives of minimizing the overall cost of the system, the load shortage rate and the new energy abandonment rate, the expression of which is shown in Equation (1):

$$\mathrm{minF} = \min \sum_{t=1}^{T} (C_A, \eta_{LPSP}, \eta_{EWR}) \quad (1)$$

In the formula: C_A is the total system investment cost; η_{LPSP} is the load shortage rate; η_{EWR} is the wind and light rejection rate.

2.1. Total System Investment Cost

The total expense of the ESS mainly includes the initial investment of the ESS built at one time, and the cost during operation and maintenance of the ESS after it is built [27]. In addition to this, the system will purchase shortfall power from the distribution grid when the output cannot meet the load, so the power purchase cost of the system should also be considered. In order to establishing the total investment cost of the system, the formula is:

$$C_A = C_0 + C_m + C_{np} \tag{2}$$

In the formula: C_0 is the initial investment of ESS; C_m is the cost of operation and maintenance of ESS; C_{np} is the joint system power purchase cost.

The initial investment of the ESS is proportional to the capacity size of the ESS, which is discounted to the average annual cost of the completed project, Eq:

$$C_0 = \frac{r(1+r)^n}{(1+r)^n - 1} \lambda_{BESS} S_{BESS} \tag{3}$$

In the formula: λ_{BESS} is the initial investment of the energy storage battery and the built-in inherent cost coefficient; S_{BESS} is the capacity of the ESS; n is the service life of the ESS; r is the discount rate, which is taken as 5%.

The ESS will cause damage to the equipment when running for a long time, so it requires regular maintenance and management, the cost of which is related to the initial investment in the ESS. The formula is:

$$C_m = aC_0 \tag{4}$$

In the formula: a is the parameter of the ratio of the operation and maintenance cost of the ESS to its initial investment cost; C_m is the annual maintenance cost of the ESS.

When both wind and solar output and storage output cannot fulfill the load requirement, the system would then have to purchase a portion of the power to fill the shortfall, thus incurring a power purchase cost, for which, the formula is:

$$C_{np} = p_{buy} \left[\sum_{t=1}^{T} P_{load}(t) - P_{PV}(t) - P_{WT}(t) + P_{BESS}(t) \right] \Delta t \tag{5}$$

In the formula: P_{BESS} is the power of storage batteries (positive value when charging, negative value when discharging); P_{PV} and P_{WT} are the output power of photovoltaic and wind power, respectively; P_{load} is the power of system power demand; p_{buy} is the purchase price of electricity.

2.2. System Power Supply Reliability

The load deficit rate characterizes the reliability of the system's power supply, and the load deficit rate is related to the combined output of the load and the system [28,29]. The formula is:

$$\eta_{LPSP} = \frac{\sum_{t=1}^{T} [P_{load}(t) - P_{out}(t)] \Delta t}{P_{load}(t)} \tag{6}$$

In the formula: $P_{out}(t) = P_{PV}(t) + P_{WT}(t) - P_{BESS}(t)$; the smaller η_{LPSP} is, the higher the reliability of the system power supply.

2.3. Total System Investment Cost

When supply exceeds demand, neither the load nor the energy storage system can fully consume the power generation, which will result in a waste of resources, so the new energy abandonment rate is also introduced as one of the optimization objectives [30,31]. Its formula is:

$$\eta_{EWR} = \frac{\sum_{t=1}^{T}[P_{out}(t) - P_{load}(t)]\Delta t}{\sum_{t=1}^{T}[P_{PV}(t) + P_{WT}(t)]\Delta t} \tag{7}$$

In the formula: η_{EWR} is the rate of wind and light abandonment, the smaller η_{EWR} is, the higher the energy utilization rate.

2.4. Constraint

The state of charge (SOC) of a battery represents the ratio of the battery's current remaining charge to its charge when fully charged [32,33]. The formula is:

$$S_{OC}(t) = S_{OC}(t-1) + \frac{\eta P_{BESS}}{C_{BESS}}\Delta t \tag{8}$$

In the formula: $S_{OC}(t)$ is the SOC value of Li-ion battery at time t; P_{BESS} is the charging and discharging power of the Li-ion battery (positive value when charging, negative value when discharging); C_{BESS} is the rated capacity of Li-ion battery; η is the charging and discharging efficiency (0.65~0.85 when charging, 1.00 when discharging [34,35]); Δt is the sampling time period.

In order to prolong the life of the battery and prevent it from being overcharged and discharged to cause harm to the battery, the SOC of the lithium battery is set with upper and lower limits:

$$S_{OC,min} \leq S_{OC}(t) \leq S_{OC,max} \tag{9}$$

In the formula: $S_{OC,min}$ and $S_{OC,max}$ are the upper and lower limits of the SOC of the lithium battery, respectively, $S_{OC,min} = 0.1, S_{OC,max} = 0.9$ [36,37].

The capacity of the ESS will be limited by preset upper and lower limits during optimization.

$$S_{BESS,min} \leq S_{BESS} \leq S_{BESS,max} \tag{10}$$

In the formula: $S_{BESS,min}$ and $S_{BESS,max}$ are the min and max capacities of the ESS, respectively.

Constraining the charging and discharging power of the ESS and controlling it within a specified range can effectively extend the service life of the battery:

$$P_{ch,min} \leq P_{BESS}(t) \leq P_{ch,max} \tag{11}$$

$$P_{disch,min} \leq p_{BESS}(t) \leq P_{disch,max} \tag{12}$$

In the formula: $P_{ch,min}$ and $P_{ch,max}$ are the min and max values of the charging power of the ESS, respectively; $P_{disch,min}$ and $P_{disch,max}$ are the min and max values of the discharging power of the ESS, respectively.

3. Improvement of SCSO

The algorithm (SCSO) used in this paper then focuses on the merit-seeking process by simulating the sand cat's searching-for-prey and attacking-prey behaviors, and also proposes a mechanism to achieve a balance between the searching and exploiting phases.

3.1. Search Stage

Sand cats in the search for prey mainly rely on emitting a low-frequency noise, where the low-frequency noise will be reflected when it touches the object and then the sand cats that receive these low-frequency noises will determine the location of the prey. Therefore, the sensitivity of the cat to low-frequency sound determines the scope of the cat's search for prey: the higher the sensitivity, the larger the search range. According to this characteristic principle of the sand cat, the mathematical formula to define the range of the general auditory sensitivity of a sand cat is as follows:

$$r_G = S_M - \left(\frac{2 \times S_M \times iter_c}{iter_{Max}}\right) \tag{13}$$

In the formula: S_M is the hearing ability of sand cats; $iter_c$ is the number of current iterations; $iter_{Max}$ is the max number of iterations; and r_G is the general auditory sensitivity range of the sand cat.

Generally the range of auditory sensitivity affects the search range of the entire sand cat population, but to avoid falling into a local optimum, each sand dune cat has a different range of sensitivity, so the equation for individual sensitivity is:

$$r = r_G \times rand(0,1) \tag{14}$$

In the search phase, the sand cat updates its next position based on the global optimal solution and the current position of the individual, thus moving to other positions that may be easier to find prey, and then obtains the latest local optimum from the new search area. The above search process is mathematically modeled by the following equation:

$$P(t+1) = r \times (P_{bc}(t) - rand(0,1) \times P_c(t)) \tag{15}$$

In the formula: P_{bc} is the optimal position; P_c is the present position.; r is the personal sensitivity range.

3.2. Attack Phase

The attack behavior of the sand cat also relies on its sense of hearing, and the second phase of the SCSO algorithm is mathematically modeled based on the attack behavior of the sand cat. The formula is:

$$P(t+1) = P_{bc}(t) - r \times P_{rand}(t) \times \cos\theta \tag{16}$$

$$P_{rand}(t) = |rand(0,1) \times P_{bc}(t+1) - P_c(t)| \tag{17}$$

In the formula: P_{bc} is the optimal position; P_c is the present position; P_{rand} is the random position.

The flow of the attack phase is as follows. P_b and P_c are used to generate a random position P_{rand}. In addition, a roulette wheel is introduced to provide each sand cat with a randomly selected angle, increasing the randomness in turn to ensure population diversity; and finally, the attack on the prey is realized by using the equation. Among them, the random position can ensure that the sand cat is close to the prey, and the random angle can avoid the algorithm from falling into local optimization.

3.3. Transition between Search Phase and Attack Phase

Setting the parameter R determines whether the sand cat is in the search or hunt phase. The formula is:

$$R = 2 \times r_G \times rand(0,1) - r_G \tag{18}$$

When $|R| > 1$, the sand cat will be in the search phase, at which point the position is updated according to the search phase formula. When $|R| < 1$, the sand cat will be in the attack phase, at which point the position is updated according to the attack phase formula. It is easy to see that R is a random value in the interval $[-r_G, r_G]$, where r_G gradually decreases from 2 to 0 during the iteration process, while in $r_G > 1$, $|R|$ may be greater than 1 or less than 1, so the sand cat may be in any stage of the search or the attack. This transformation method facilitates the ability of individuals to extricate themselves from a local optimum when they are trapped in it, in order to expand the global search capability.

3.4. Algorithmic Improvements

The inclusion of the triangular wandering strategy in the search phase makes it possible to improve the search range by not approaching the prey directly and quickly while the sand cat searches for the prey, but rather by randomly wandering around the prey [38]. The formula is:

$$L_1 = P_{bc}(t) - P_c(t) \tag{19}$$

$$L_2 = rand(0,1) \times L_1 \tag{20}$$

$$\beta = 2 \times \pi \times rand(0,1) \tag{21}$$

$$P_t(t) = {L_1}^2 + {L_2}^2 - 2 \times L_1 \times L_2 \times \cos\beta \tag{22}$$

$$P_{new}(t+1) = P_{bc}(t) + r \times P_t(t) \tag{23}$$

In the formula, P_{new} is the position obtained through the triangular random wandering strategy.

Lévy flight is an improved method that can add randomness to the algorithm. Lévy flight can provide a random wandering method with a step length conforming to the Lévy distribution. However, the Lévy flight sometimes has too long a step length. In order to be more consistent with the sand cat's behavior of attacking its prey, the Lévy flight is multiplied by a constant, thus reducing the step length and allowing the sand cat to wander as close as possible to its prey; the formula is as follows:

$$P_{new}(t+1) = P_{bc}(t) + (P_{bc}(t) - P_c(t)) \times \mathrm{C} \times Levy \tag{24}$$

In addition, the lens imaging direction learning strategy is introduced, which extends the search by using an individual's current position to generate another position opposite to it, so that arithmetic can jump out of the current position and expand the search range, improving the diversity of the population. Its main formula is as follows:

$$k = \frac{\frac{a+b}{2} - x}{x^* - \frac{a+b}{2}} \tag{25}$$

$$x_j^* = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} - \frac{x_j}{k} \tag{26}$$

In the formula, a and b are the upper and lower bounds of x; x^* is the point where x is image-reversed through the convex lens; x_j is the position of the individual in the j th dimension and x_j^* is the inverse solution of x_j. a_j and b_j are the maximal and minimal bounds, respectively, in the j th dimension of the search space.

Finally, Pareto is introduced to make it applicable to the multi-objective optimization problem.

3.5. Application of Improved Algorithms and Processes

The optimization model of the energy storage capacity allocation of the combined wind ESS developed in the paper takes the capacity of the ESS as the decision variable, which is the position information of an individual sand cat in the improved multi-objective SCSO. The optimization algorithm to solve the energy storage capacity allocation problem requires coding the model:

$$\begin{cases} X = [x \;\; P] \\ x = S_{BESS} \\ P = [P_{BESS} \;\; P_{PV} \;\; P_{WT} \;\; P_{load}] \\ F = [f_1 \;\; f_2 \;\; f_3] \\ f_1 = \mathrm{C_A} \\ f_2 = \eta_{\mathrm{LPSP}} \\ f_3 = \eta_{\mathrm{EWR}} \end{cases} \tag{27}$$

When using the algorithm to solve the model, the charging and discharging power, capacity constraints and SOC constraints of the storage system as described above are used to limit the wandering range of the sand cat, and then the capacity of the storage system can be calculated based on the wind and PV power and load demand of the combined system at each time node.

Based on the improved multi-objective SCSO to solve the ESS capacity problem, the flow chart is shown in Figure 2.

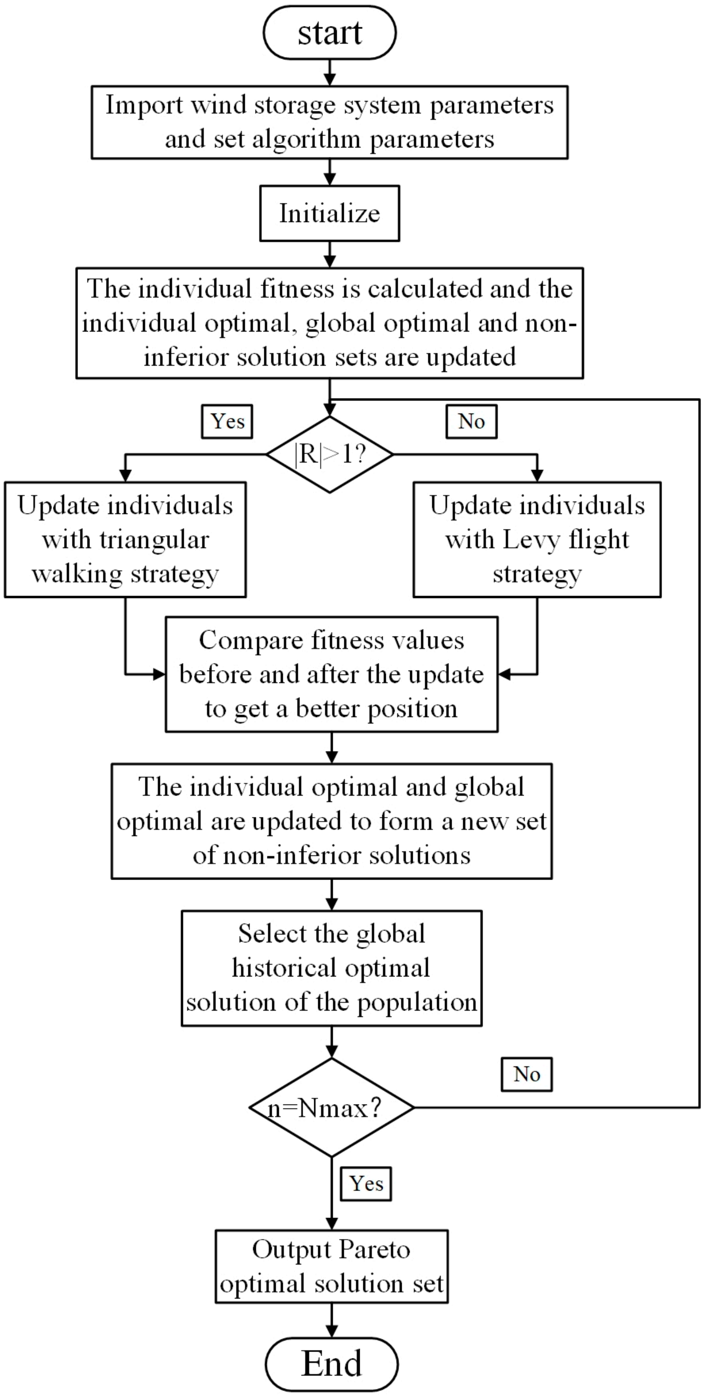

Figure 2. Flowchart of the improved algorithm.

4. Improved k-Means Clustering Algorithm

The k-means algorithm is one of several most widely used and frequently used clustering algorithms [39,40]. Its main principle and working method is: When given a value of K and K initial class cluster centroids, classify each point (data) into the class cluster represented by the nearest class cluster center point. After all the points have been assigned, take the average of all the points in a cluster as the centroid of that cluster, and then iteratively assign the points and update the center of the clusters until either the centroid of the class clusters, which is calculated multiple times, changes slightly, or to achieve a specified number of iterations [41].

4.1. Algorithmic Improvements

The process of using the conventional k-means algorithm to analyze the dataset clustering is relatively simple [42]. When the amount of data in the dataset is large, the data clustering effect is also better. However, the algorithm must determine an initial number of clusters before use, because if the set number of clusters is unreasonable, this will affect the clustering effect of this algorithm. To address this problem, we chose to modify the algorithm by using BWP, a clustering effectiveness metric proposed in the literature [21], and the modified clustering algorithm can determine the optimal number of clusters.

After improvement, the specific steps of k-means clustering algorithm are:

(1) Set the search range of the clustering algorithm;
(2) Select initial clustering centroids based on the maximum and minimum distances between data in the dataset;
(3) The centroids of the clusters are iteratively updated using the clustering algorithm until the centroids of the clusters converge or a preset maximum number of iterations is reached;
(4) Calculate the average value of the BWP index for all samples in the clustering result;
(5) Compare the size of the average BWP metrics and finalize the optimal number of clustering scenarios;
(6) Output the clustering results.

4.2. Typical Daily Extraction Process for Wind, PV and Load Power

Since the original scenes of wind, PV and load power are excessive in amount and not representative, in order to obtain the corresponding typical scenes, the improved k-means clustering algorithm is adopted to process all the data, reduce and merge the data of the whole year into several typical scenes, and then select the data with the highest frequency of occurrence from these typical scenes as the typical day [43]. The generation process of typical scenes is shown in Figure 3.

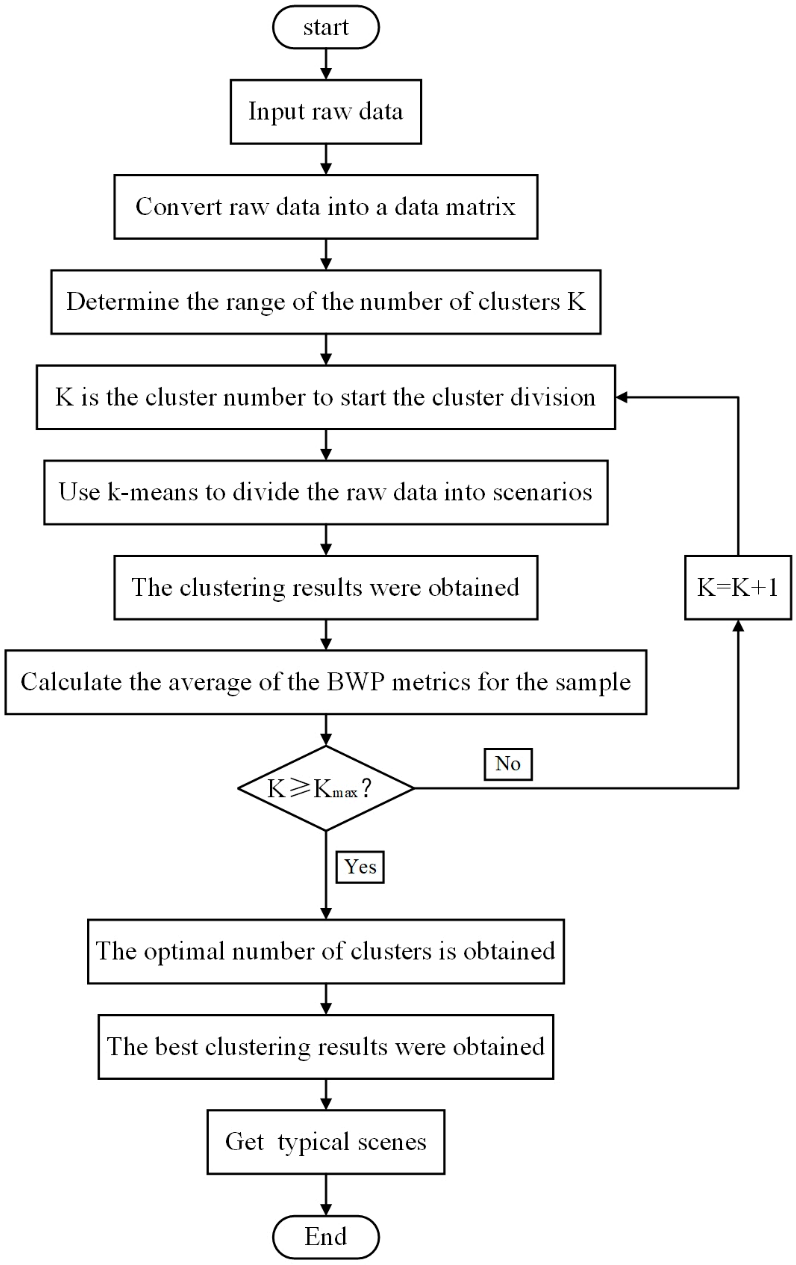

Figure 3. Typical day withdrawal process.

5. Calculus Analysis

5.1. Typical Day Extraction Results

Based on the measured wind turbine, photovoltaic (PV) and load data for the whole year in a certain place in China, the improved k-means clustering algorithm is used to cluster the scenarios, in which the wind turbine and the PV have a total installed capacity of 800 kW and 820 kW, respectively. All the scenarios for the whole year for wind power are shown in Figure 4, and all the typical scenarios obtained from the clustering are shown in Figure 5.

Among them, Scenario 3 in Figure 5 has the highest percentage of 53% among the four typical scenarios, so the data of Scenario 3 are selected as the typical day of wind power.

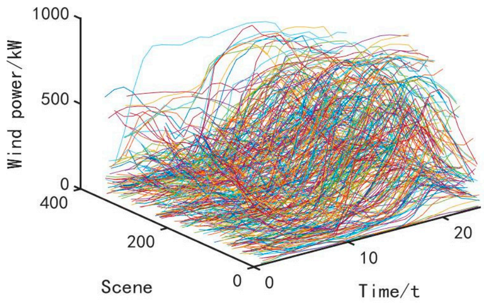

Figure 4. Wind power year-round scenarios.

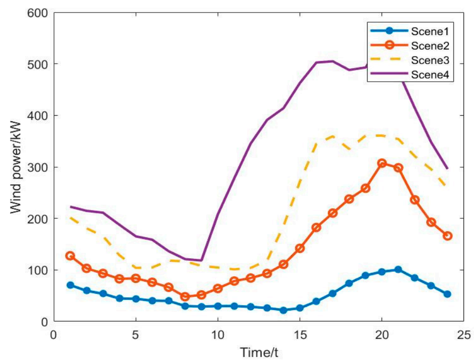

Figure 5. Typical scenarios for wind power.

The same algorithm is used to obtain the year-round scenarios of PV power in Figure 6 and all the typical scenarios obtained from clustering in Figure 7.

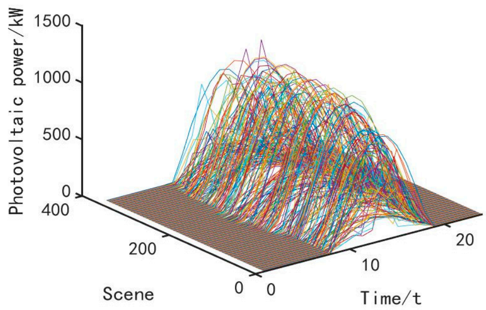

Figure 6. PV power year-round scenarios.

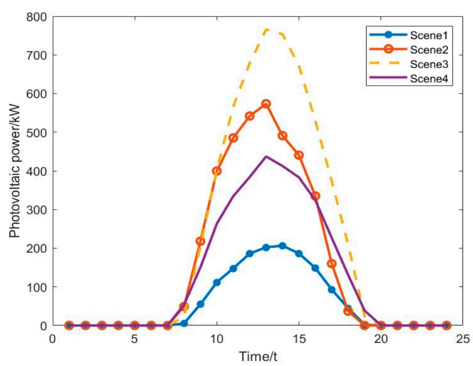

Figure 7. Typical scenarios for photovoltaic power.

Among them, Scenario 2 in Figure 7 has the highest percentage of 47% among the four typical scenarios, so the data of Scenario 2 are selected as the typical day of PV power [44].

Finally, the year-round load data were clustered, and the year-round scenarios of the resulting load power are shown in Figure 8, and all the typical scenarios from the clustering are shown in Figure 9.

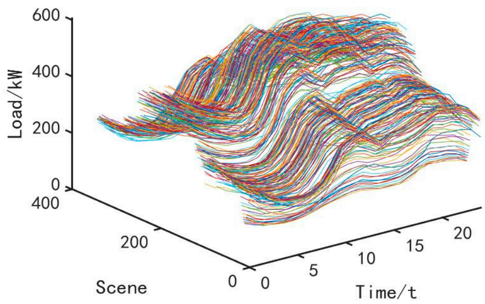

Figure 8. Load demand year-round scenarios.

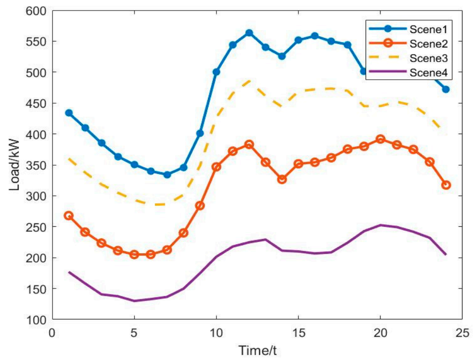

Figure 9. Typical scenarios for load demand.

Scenario 2 in Figure 9 has the highest percentage of 51% among the four typical scenarios, so the data from Scenario 2 are selected as the load power typical day. The final resulting typical days for wind, PV and load power can be seen in Figure 10.

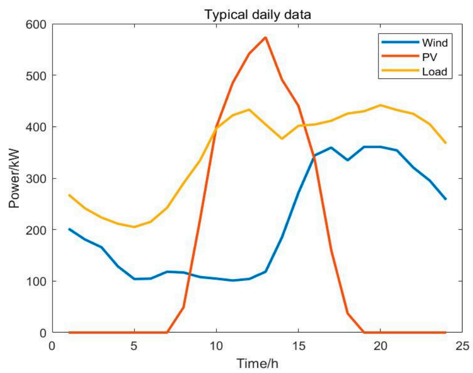

Figure 10. Typical day of wind–photovoltaic–load power.

5.2. Energy Storage Allocation Optimization Results

The proposed model and method are validated by taking the combined wind turbine and storage system as an experimental object, based on the typical daily data extracted using the improved k-means clustering algorithm.

(1) Energy storage uses battery storage, and the cost of battery unit capacity is 1300 yuan/kWh.
(2) The price of electricity purchased from the local grid is taken from the average price of electricity purchased from the local grid, which is 0.43 yuan/kWh [45,46].

The parameters of the SCSO are shown in Table 1.

Table 1. Algorithm parameter setting.

Parameter Name	Parameter Data
Population size	100
Maximum number of iterations	100
Auditory characterization parameter	2
Lévy flight initial angle	3

MSCSO, SCSO, WOA and PSO are used to solve the capacity optimization allocation model of the ESS, respectively, and the resulting iterative plots of each algorithm optimized for each objective value are shown in Figures 11–13.

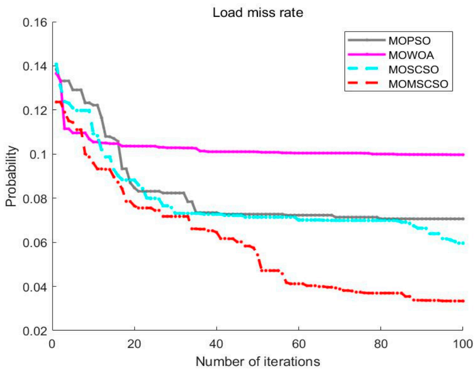

Figure 11. Comparison chart for optimization of load miss rate.

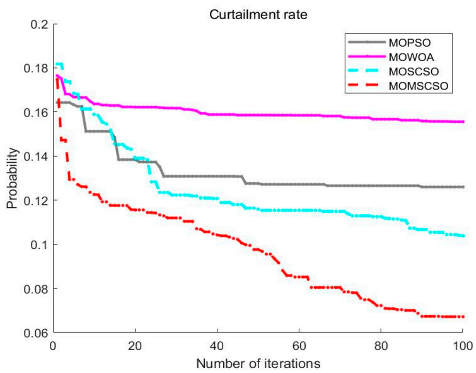

Figure 12. Optimized comparison chart of new energy power abandonment rates.

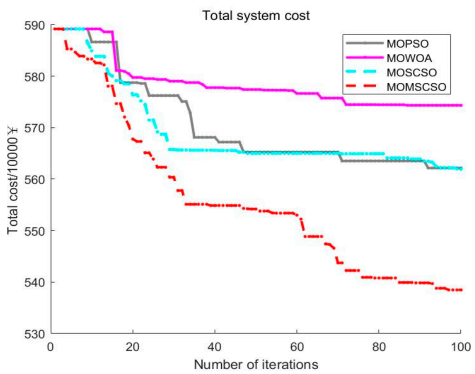

Figure 13. Total cost of ownership optimization comparison chart.

From Figures 11–13, it can be seen that for the problem of optimizing the allocation of energy storage capacity, compared with SCSO, WOA and PSO, MSCSO solves the problem faster, with better quality and a higher solving accuracy, which further reduces the unnecessary operation cost and load shortage rate of the combined wind, light and storage system, and at the same time, enhances the rate of consumption of renewable energy.

In addition, from the Pareto optimal solution distribution graphs in Figures 14 and 15, it can be seen that under the condition of the same number of populations and the number of iterations, the feasible solutions obtained via MSCSO are larger than the other algorithms in terms of both range and number.

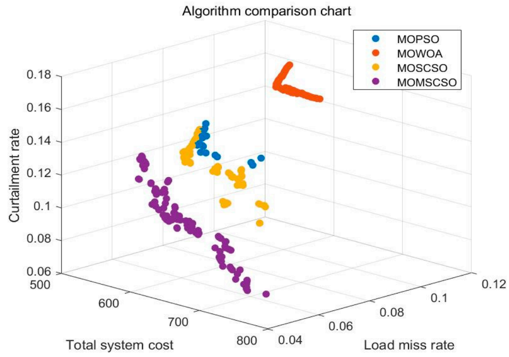

Figure 14. Comparison of Pareto optimal solution sets for each algorithm.

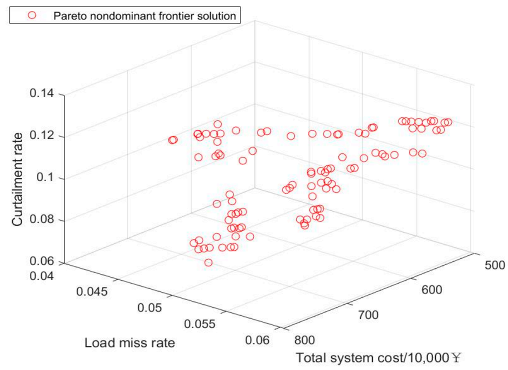

Figure 15. Improved Pareto optimal solution set for sand cat swarm algorithm.

In order to fully demonstrate the superiority of MOMSCSO in solving this problem, the results of several scenarios with roughly the same overall cost of the system in Figure 14 are selected and compared and shown in the following Table 2.

Table 2. Comparison of the same total cost scenarios with different algorithms.

Algorithm Name	Rated Capacity /kWh	Total Cost /Yuan	Load Miss Rate /%	New Energy Power Abandonment Rate/%
MOPSO	943	7.04×10^6	7.9	9.2
MOWOA	929	7.02×10^6	9.1	12.6
MOSCSO	930	7.0×10^6	5.4	9.5
MOMSCSO	986	7.0×10^6	4.9	8.3

From the table, it can be seen that under the same cost, the optimized load miss rate and the new energy power abandonment rate of MOSCSO are lower than that of MOWOA, and the load failure rate of MOMSCSO is lower than that of the other three schemes, although the new energy power abandonment rate of MOSCSO is slightly higher than that of MOPSO. Therefore, MOSCSO has more obvious advantages in a multi-objective solution, especially when it is applied to complex problems such as wind and solar energy storage, and the improvements made also enhance its optimization effect.

According to the Pareto solution set obtained by solving the improved sand cat swarm algorithm, a large number of solutions can be provided for the current problem of the optimal allocation of storage capacity in the combined wind and storage power generation system. Since there is often no absolute superiority or inferiority among the solutions of the multi-objective problem, five optimal allocation solutions are selected from Figure 15 for comprehensive comparison, and each solution is shown in Table 3.

Table 3. Comparison of different energy storage capacity configuration options.

Configuration Options	Rated Capacity /kWh	Total Cost /Yuan	Load Miss Rate /%	New Energy Power Abandonment Rate/%
Option 1	586	5.42×10^6	6.0	12.8
Option 2	792	6.01×10^6	4.9	11.1
Option 3	936	6.62×10^6	4.2	10.5
Option 4	986	7.0×10^6	4.9	8.3
Option 5	1087	7.57×10^6	5.1	7.2

As can be seen from Table 2, if priority is given to the economy, Option 1 can be selected as the ESS configuration scheme; if the load miss rate of the system is minimized from the perspective of power supply reliability, Option 3 is selected to configure the ESS; if the utilization rate of new energy is mainly considered, Option 5 can be selected to configure the ESS; if the economy of the system, the utilization rate of new energy and the reliability of the power supply are taken into account, options 2 and 4 are selected to complete the optimization of the configuration of the ESS.

The wind and solar storage power distribution diagram of Option 3 is selected (see Figures 16 and 17). From Figure 16, it can be seen that at 1–8, the overall wind and solar power generation is less than the power required by the load, so the system meets the load demand by purchasing power from the grid and discharging from the storage. From Figure 16, it can be seen that at 10–17, the wind and solar power generation is more than the load of the system, so a part of the remaining power is charged to the storage, and the remaining will be discarded, while at 18–24, wind power generation decreases and cannot meet the system load demand, and the energy storage battery discharges again to provide power to the system.

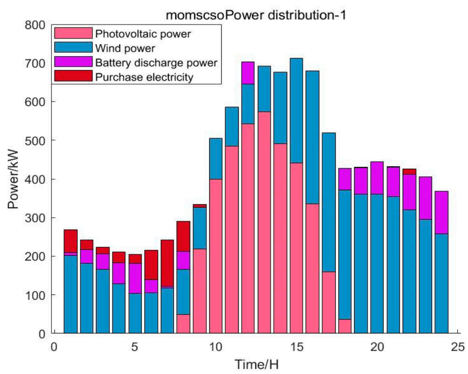

Figure 16. System load power composition.

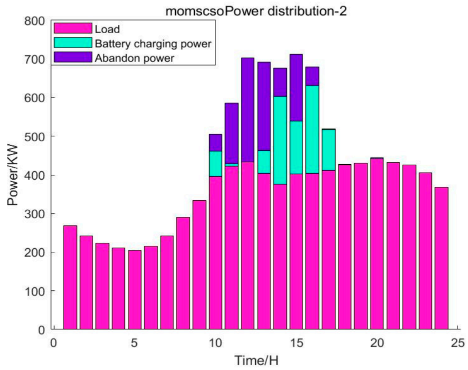

Figure 17. Wind excess power distribution.

In addition, the state of the battery charge for energy storage can be seen in Figure 18, where its SOC is 0.5 at the initial moment, and the state of charge decreases continuously from 1 to 9 o'clock with the continuous discharge of the battery. The battery continues to be charged between 10 o'clock and 17 o'clock because of an increase in PV power generation, which is greater than the load demand; therefore, the battery continues to be charged. The PV power generation is gradually reduced to zero from 18 o'clock to 24 o'clock, and once again, the load demand is greater than power generation; therefore, the batteries are discharged again and the state of charge of the batteries for energy storage gradually decreases. At 24 o'clock, it again decreases to about 0.5.

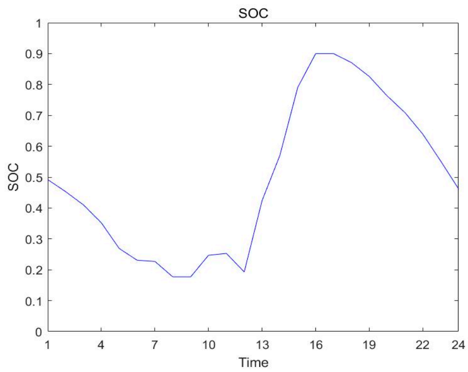

Figure 18. State of charge of energy storage batteries.

From the above results, it is easy to see that the reasonable configuration of the capacity of the storage battery for the wind independent power generation system is an extremely critical issue, which is not only a matter of economy, but also involves the utilization of resources and the reliability of power supply, which are particularly critical in the context of the new energy in the overall power system in the proportion of the increasing.

6. Conclusions

In order to ensure the safe and reliable operation of a microgrid, this paper proposes an ESS capacity allocation method based on the improved SCSO. K-means clustering algorithm is used to extract the typical daily data. For the proposed optimization model, the improvement of triangular wandering strategy, Lévy flight strategy and lens imaging inverse learning strategy are used for solving. The above results and analysis lead to the following conclusions:

1. MSCSO can effectively deal with the problem of the optimal allocation of energy storage capacity with high-dimensional nonlinear characteristics. Compared with the unimproved SCSO, WOA and PSO, the solution accuracy and breadth of the improved algorithm are effectively improved, and the search speed of the algorithm is also greatly improved.

2. The energy storage capacity allocation scheme obtained by using the proposed model and the improved method effectively reduces the load shortage rate and improves the rate of renewable energy consumption under the premise of ensuring economy.

However, the improved algorithm in this study still has some shortcomings, and will occasionally fall into local optimality when performing multi-objective optimization, leading to less satisfactory final results. Therefore, we will make more reasonable improvements to it in the future to address this problem, so that it can show better results when performing multi-objective and high-dimensional optimization.

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Data Availability Statement: Data are available within the article. The wind power, photovoltaic power and load data used in this paper were collected from actual operations in one part of China.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
BBO	Biogeography-based Optimization
SNO	Social Network Optimization
SCSO	Sand Cat Swarm Optimization
SOC	State Of Charge
ESS	Energy Storage System

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