ISSN: 2414-1895 DOI: 10.6919/ICJE.202105_7(5).0063

A Vertical-axis Wind-solar Complementary Power Generation System Optimized based on Adaptive Particle Swarm Algorithm

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Abstract

Wind energy and solar energy are inexhaustible green, clean and renewable energy sources on the earth. Comprehensive utilization of wind and solar resources and the development of wind-solar complementary power generation technology has become a research and development trend in the field of new energy. The wind and solar hybrid power generation system is a power generation system that combines wind power and solar photovoltaic power generation, which is mainly composed of wind turbines, solar photovoltaic battery packs, controllers, batteries, inverters, AC and DC loads and other parts. This paper systematically expounds the composition of the wind-solar hybrid power generation system and the characteristics of each part, proposes a new type of vertical axis wind turbine, and uses a newly proposed improved particle swarm algorithm (YAPSO) to optimize the multi-objective battery in wind-solar hybrid power generation. The simulation experiment proves the feasibility and practicability of the proposed algorithm.

Keywords

Vertical-axis Wind and Solar Hybrid Power Generation; Microgrid; Optimization Algorithm; Self-adaptation; Multi-objective Optimization.

1. Introduction

Energy is an important material basis for global economic development and people's lives. However, as energy and climate issues have become increasingly prominent, new energy technologies represented by wind and solar energy have developed rapidly in recent years. As a kind of natural resources, wind and solar energy are inexhaustible to a certain extent. Globally, wind and solar energy resources are abundant, and many countries have vigorously developed wind and solar power generation in recent years. It has excellent complementarity with solar energy in time and space, but the original wind-solar hybrid power generation system simply combines the wind power generation system and the solar photovoltaic power generation system. Due to technical reasons, it has not been further developed. In recent years, with the improvement of wind power generation technology and solar photovoltaic power generation technology, the integrated wind and solar hybrid power generation [1, 2] has higher power generation efficiency and lower power generation cost, which is of outstanding significance to alleviate the global energy crisis.

The wind and solar hybrid power generation system is a power generation system that combines wind power and solar photovoltaic power generation, which is mainly composed of wind turbines, solar photovoltaic battery packs, controllers, batteries, inverters, AC and DC loads and other parts. For wind turbines and solar photovoltaic generators that have been designed, the room for improvement is not obvious. Therefore, we can optimize from the storage battery energy, microgrid power dispatch and other aspects. Optimization is a technology that studies how to determine the optimal value of

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the unknown parameters of the target system under certain constraints. Through optimization, we can get the best value of the system goal and find the best solution among a series of available solutions. Obviously, optimization problems are common in all fields. Due to the needs of practical applications and advances in computing technology, the research on optimization methods has developed rapidly. From the 1960s and 1970s, people introduced artificial intelligence technology and biological evolution mechanism into optimization methods, and gradually formed a group of refreshing modern optimization methods completely different from traditional optimization methods, such as genetic algorithm (GA) [4], Particle Swarm Optimization (PSO) [5], Differential Evolution (DE) [6], Bat Algorithm (BA) [7], Ant Colony Optimization (ACO), etc. Therefore, for wind-solar hybrid power generation, microgrid dispatch can be solved by using an optimized algorithm to obtain an optimal solution. Below, we will explain in detail the technology and implementation methods used in this article. The second part is the introduction and proposal of particle swarm optimization (PSO). An improvement of a new adaptive particle swarm algorithm (YAPSO), the fourth part is the experiment and experimental conclusions, the fifth part is to solve the actual engineering, and finally is the summary of this article.

2. Particle swarm algorithm and improvement of particle swarm

2.1 Particle Swarm Optimization (PSO) algorithm

PSO is a classic population-based intelligent optimization algorithm. First, initialize a set of particles in the search space. Each particle represents the potential optimal solution of the extreme value optimization problem, with three indicators of position, speed and fitness value. The particles move in the solution space, and the pre-defined fitness function is used to evaluate the pros and cons of their positions. In each iteration, the particle updates its velocity and position by tracking a single historical extremum and the overall extremum. v_{ij} is the velocity of the i-th particle x_i in the j-th dimension.The update formula is as follows:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r\left[p_{ij}(t) - x_{ij}(t)\right] + c_2 r[g_{ij}(t) - x_{ij}(t)] \quad (1)$$

Among them, t is the current iteration number. ω_t is the weight of inertia; c_1 and c_2 are learning factors, also called acceleration constants; r is a random number between 0 and 1, which will increase the randomness of particle motion. $x_{ij}(t)$ represents the current position of the particle, $p_{ij}(t)$ represents its historical best position, and $g_{ij}(t)$ represents the current overall global best position, $\omega = 0.9$.

The position of the particle is updated according to the speed change, as shown in the following formula:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

As a typical stochastic optimization technology, PSO has been widely recognized in the field of intelligent computing. Since its proposal in 1995, people's enthusiasm for its research has not diminished. A large number of scholars are engaged in more in-depth research, and strive to improve the algorithm's global search ability and execution efficiency.

2.2 Improved particle swarm optimization (YAPSO)

Similar to other meta-heuristic algorithms, PSO has the problems of local optimal stagnation and low convergence accuracy. Scholars have made many improvement attempts, such as adjusting its parameters and mixing them with other algorithms, and proposed a binary version [9], which has achieved good results. However, in real life, there are usually problems that are more complicated or the problem target is not only the only problem. Therefore, the use of adaptive strategies to improve the PSO algorithm is more in line with the problems we want to solve in the future. For this reason, this article proposes A new adaptive particle swarm algorithm (YAPSO).

In this article, we have designed three adaptive adjustment methods to optimize the exploration, development, and convergence of the PSO algorithm and run through the entire algorithm iteration,

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effectively improving the optimization ability and convergence speed of the PSO algorithm. These three adaptive methods respectively automatically control the inertia weight, acceleration coefficient and other parameters. The following article will describe the implementation principles of the three adaptive methods in detail:

2.2.1 Control of acceleration coefficient

In the PSO update rate, the parameter c_1 represents "self-recognition", which pulls the particle to the best position in its own history, which helps to explore the local niche and maintain the diversity of the population. The parameter c_2 represents "social influence", which promotes the group to converge to the current global optimum, thereby helping the algorithm to converge quickly. Since these two parameter learning mechanisms are different, they will play different roles in the process of algorithm iteration. In this article, the acceleration coefficient is consistent with the original PSO algorithm. $c_1 = c_2 = 2.0$.

(1) Strategy 1: Increase c_1 and decrease c_2 when the algorithm is in the exploratory state: It is important to explore the optimal value as much as possible in the exploratory state. And use Gaussian mutation [8] to increase the probability of the algorithm jumping out of the local optimum.

(2) Strategy 2: Use the form of Cauchy mutation in the development state to slightly increase c_1, and slightly decrease in c_1: In this state, the particles use local information according to the possibility indicated by the best position in the history of each particle The local optimal niches are grouped. In addition, Cauchy's mutation walk has a small step length, which can enable the population to search and utilize the best of individuals.

(3) Strategy 3: In the state of convergence, increase c_1 slightly, and increase c_2 slightly. In the state of convergence, the cluster seems to have found the global optimal area, but c_2 is an important indicator to guide the particle optimization, we fly Lévy flight [9] The method of mutation c_2 will further affect other particles to enter the possible global optimal region.

Table 1. Benchmark functions

$Function$	Dim	f_{min}
$F_1 = Sphere\ Function$	50	−1400
$F_2 = Rotated\ Bent\ Cigar\ Function$	50	−1200
$F_3 = Rotated\ Discus\ Function$	50	−1100
$F_4 = Rotated\ Rosenbrock's\ Function$	50	−900
$F_5 = Rotated\ Griewank'sFunction$	50	−500
$F_6 = Rotated\ Schwefel'sFunction$	50	100
$F_7 = Composition\ Function\ 1\ (\mathrm{n} = 5, \mathrm{Rotated})$	50	700
$F_8 = Composition\ Function\ 2\ (\mathrm{n} = 3, \mathrm{Unrotated})$	50	800

3. Experimental analysis and conclusion

In order to verify the performance of our proposed YAPSO, this article will test some CEC2013 benchmark functions, including 3 single-mode functions ($f_1 \sim f_3$), 3 multi-mode functions ($f_4 \sim f_8$) and 2 complex functions ($f_9 \sim f_{11}$). It is compared with PSO and PPSO [10] to calculate the optimal value, average value and standard deviation respectively to ensure that the performance of the algorithm can be comprehensively evaluated. The convergence curve of the test function is shown in Figure 1.

As can be seen from the figure 1, the YAPSO proposed in this article has achieved the first results in 9 benchmark functions, which strongly shows that YAPSO is an improved version of successful PSO, which has better convergence and robustness. It provides strong support for us to solve complex engineering problems in the follow-up. In order to make it easier to understand the algorithm of this article, we will give the flow chart of the algorithm below, see figure 2.

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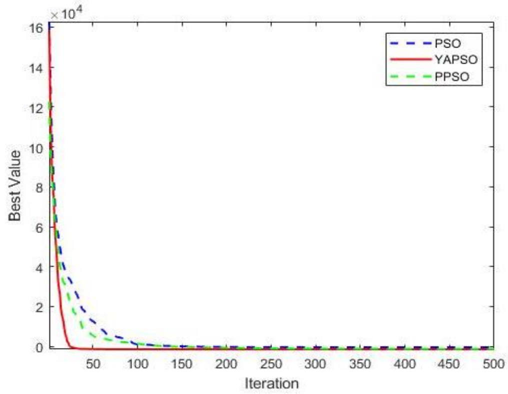
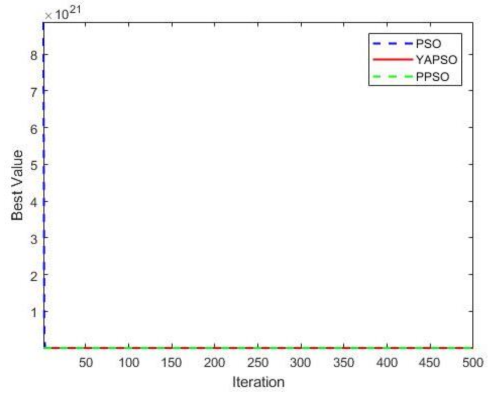


F_1



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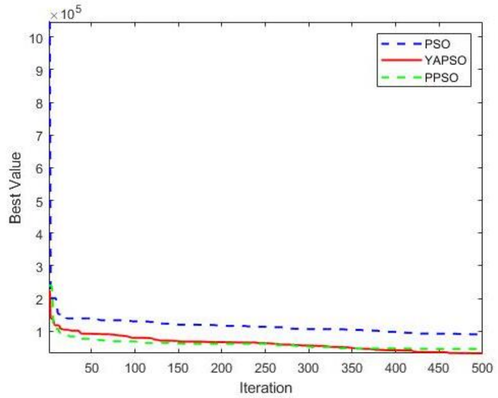

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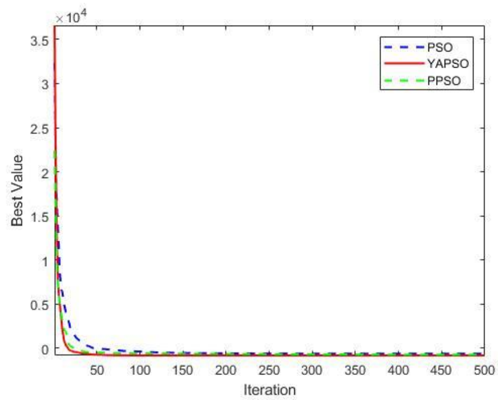
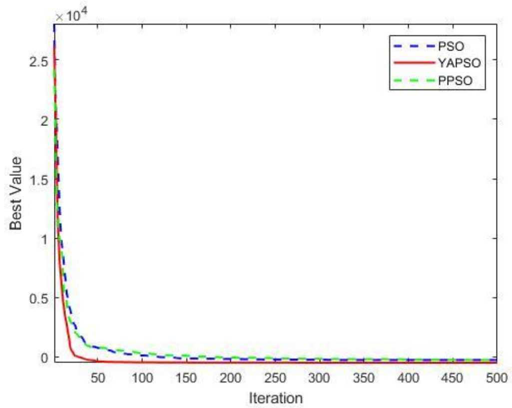
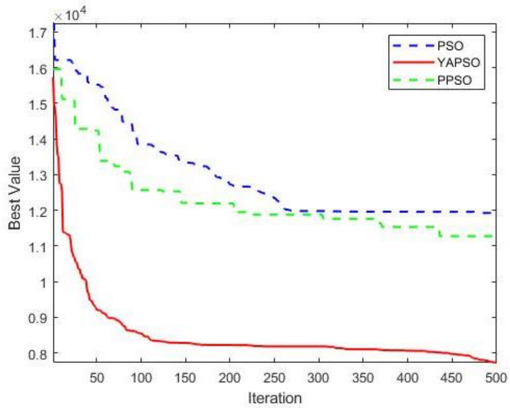


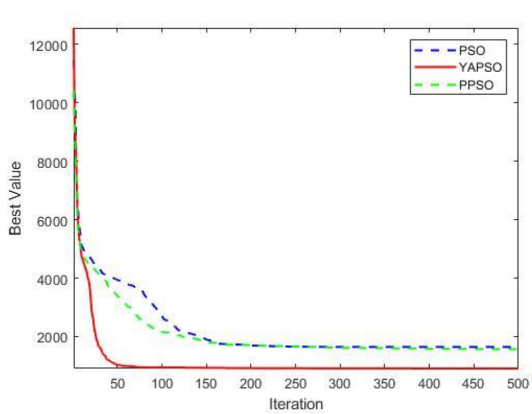
F_4



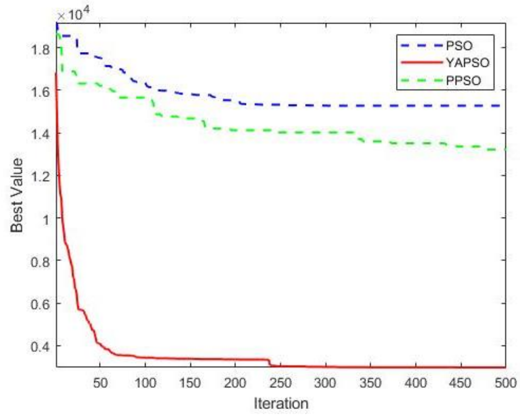
F_5



F_6



F_7



F_8

Figure 1. Convergence curves of the three algorithms

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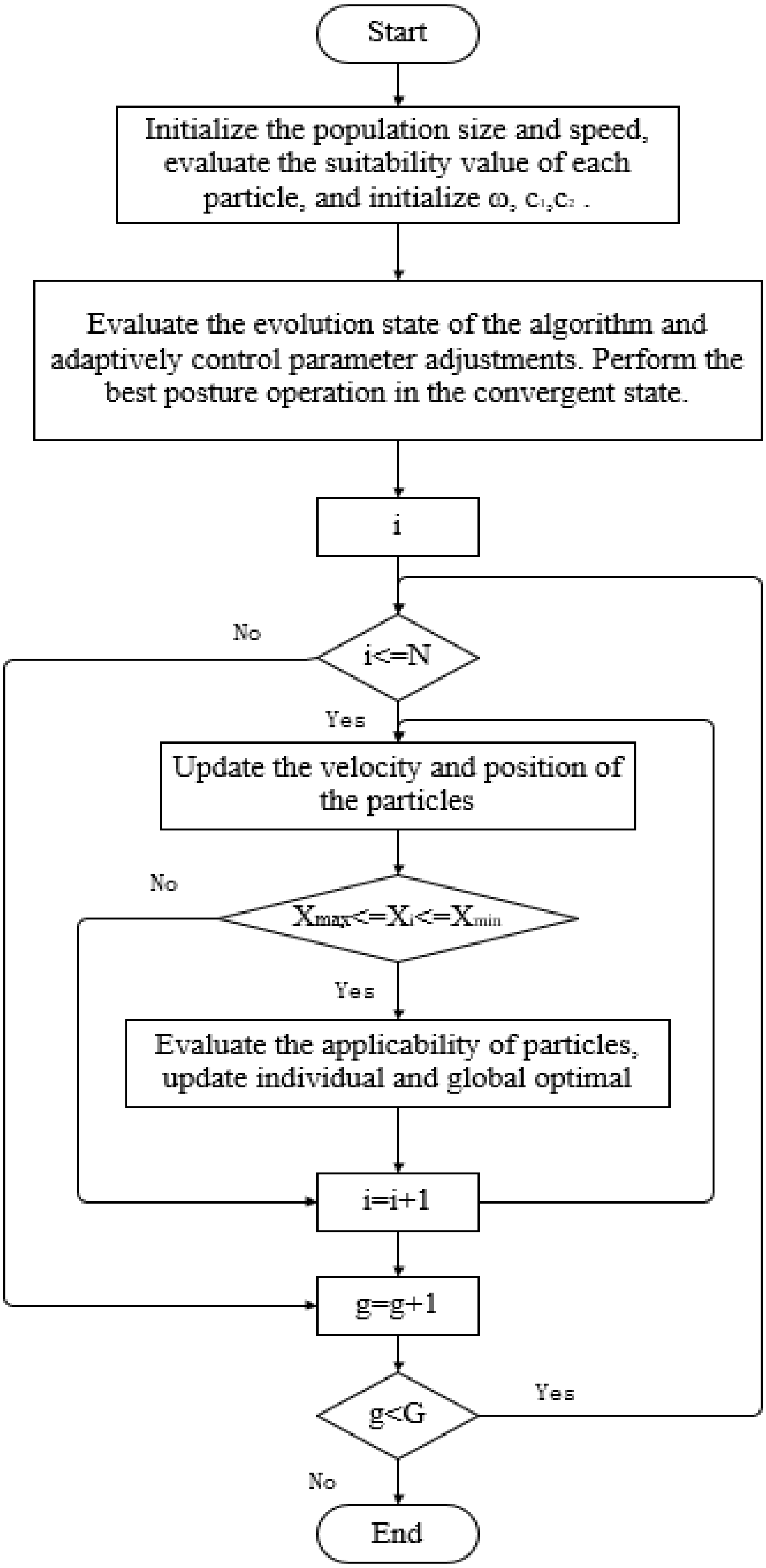

Figure 2. Algorithm flow chart

4. Solve practical problems

In the wind and solar hybrid power generation system, the battery-supercapacitor hybrid is used as the energy storage device. The system composition is shown in Figure 3. It consists of wind turbines, photovoltaic arrays, batteries, supercapacitors, converters, loads, etc.

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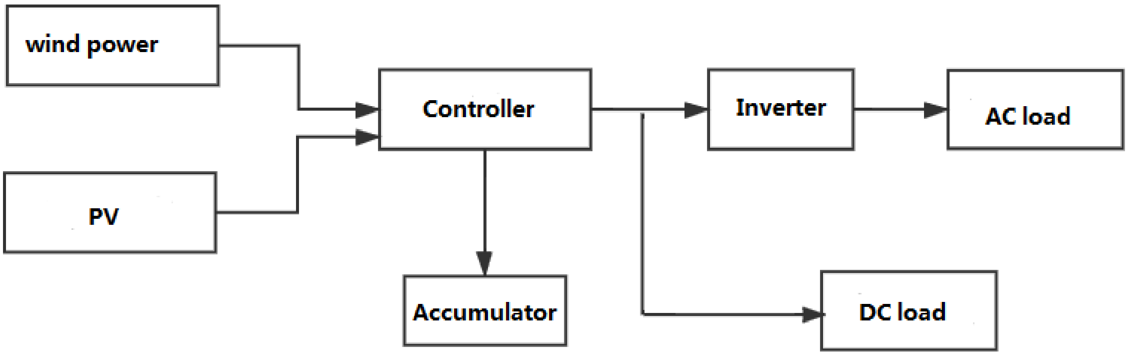

Figure 3. Schematic diagram of wind and solar hybrid power generation system

4.1 Multi-objective optimization of wind-solar complementary microgrid dispatch

Since microgrid dispatching is usually not only for one objective function, when solving this problem, this article will use multi-objective optimization to solve the problem. Without loss of generality, the multi-objective problem can generally be described as:

$$\begin{cases} \min f(x) = \left(f_1(X), f_2(X), \dots, f_m(X)\right)^T \\ \quad s.t.\ \ X = (x_1, x_2, \dots, x_n)^T \epsilon \mathrm{D} \end{cases} \tag{3}$$

Where x is the vector of n decision variables, and $D \subset R^n$ is the decision space. m is the number of targets. $F(x) \in \Lambda \subset \mathbb{R}^n$ is a target vector with a target.

The proposed YAPSO is combined with multi-objective optimization to complete the optimization of this problem. The following article will introduce the multi-objective problems solved in the wind-solar hybrid microgrid.

4.1.1 Solar photovoltaic cells

Light intensity is a key factor affecting photovoltaic power generation. In general, photovoltaic cells should work in maximum power point tracking (MPPT) mode. Its output power can be expressed by the following formula:

$$P_{pv} = \zeta \eta_m S_p \eta_p cos\theta \tag{4}$$

Among them, P_{pv} is the actual power of photovoltaic power generation; ζ is the intensity of sunlight; η_m is the efficiency in the maximum power point tracking mode; S_p is the area of the panel; η_p is the efficiency of the photovoltaic cell; θ is the incident angle of light.

4.1.2 Wind power

The output power of a wind turbine is related to the wind speed, and its power output is:

$$P_{WT} = \begin{cases} 0 \quad v_r \le v \le v_{co} \\ \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} v_{ci} \le v \le v_r \\ P_r \quad v_r \le v \le v_{co} \end{cases} \tag{5}$$

Among them, P_{WT}, P_r are the actual power and rated power of the wind turbine respectively; v_{ci}, v_{co}, v_r are the cut-in wind speed, cut-out wind speed, and rated wind speed of the wind turbine, respectively.

4.1.3 Battery storage

In the wind and solar hybrid power generation system, the battery can detect the change of wind and solar power for charging and discharging, and it plays a role in buffering wind and solar unbalanced power generation in the power grid, effectively improving the power supply reliability and continuity of the power grid.

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$$E_s(t)=\begin{cases}E_S(t-1)+\left(P_{all}(t)-\frac{P_{load}(t)}{\eta_{inv}}\right)\eta_{sb}\Delta t & DG\geq 0\\ E_S(t-1)-\left(P_{all}(t)-\frac{P_{load}(t)}{\eta_{inv}}\right)\eta_{sb}\Delta t & DG\leq 0\end{cases} \tag{6}$$

Among them, $E_s(t)$ and $E_s(t-1)$ are the capacity of the battery from t to $t-1$ respectively; $P_{all}(t)$ is the total power output of the microgrid at time t; $P_{load}(t)$ is the total load of the system at time t; η_{inv} is the inverter efficiency; η_{sb} is the battery charge and discharge efficiency.

4.1.4 Optimize the life cycle cost of energy storage batteries

Life Cost Cycle (LCC) is also called life cycle cost. Here, we give the established applicability equation:

$$fitness_{LCC}=C_I+C_O+C_M+C_D \tag{7}$$

Among them, C_I is the purchase cost of the equipment; C_O is the operating cost of the equipment; C_M is the maintenance cost of the equipment; C_D is the processing cost of the equipment.

In order to further explain the applicability equation we proposed, the equation can also be expressed by the following formula:

$$fitness_{LCC}=(1+f_{sa}+f_{ma}+f_{da})N_aP_a+(1+f_{sb}+f_{mb}+f_{db})N_bP_b \tag{8}$$

Among them, f_{sa} and f_{sb} are operating coefficients of batteries and capacitors; f_{ma} and f_{mb} are maintenance coefficients of batteries and capacitors; f_{da} and f_{db} are processing coefficients of batteries and capacitors; N_a and N_b batteries and capacitors, P_a and P_b are batteries And the unit price of the capacitor.

4.1.5 Constraints

(1) Electricity output restriction of microgrid

$$P_{i,min}\leq P_i\leq P_{max} \tag{9}$$

Among them, $P_{i,min}$ and $P_{i,max}$ are the upper and lower limits of power output from the microgrid.

Balance constraints of microgrid power supply

$$\sum_{i=1}^{N}P_i+P_{IL}=P_L-P_{BS} \tag{10}$$

Among them, P_i and P_L are micro power source and micro grid load respectively; P_{BS} is battery charging and discharging power.

(3) Battery operation constraints

$$P_{BS,min}\leq PBS\leq P_{BS,max} \tag{11}$$

$$E_{BS,min}\leq E_{BS}\leq E_{BS,max} \tag{12}$$

Among them, $P_{BS,min}P_{BS,max}$ are the minimum and maximum charge and discharge power of the battery, respectively; $E_{BS,min}, E_{BS,max}$ are the minimum and maximum capacity of the battery, respectively.

4.1.6 Experimental results and simulation analysis

According to the objective function, constraint conditions and fan parameter examples designed above, we solved the problem of multi-objective YAPSO (MOYAPSO) and MOPSO, and the results are shown in figure 4:

Through the three curves obtained from the simulation experiment, we can intuitively see that the wind-solar hybrid power generation optimized by the YAPSO algorithm has a significant increase compared with the original PSO algorithm to optimize the wind-solar hybrid power generation. It can be seen from Figure 5 that the battery energy storage balance optimized by the YAPSO algorithm The load capacity is more prominent, and the cost of YAPSO is lower in the maintenance of the entire system. The minimum life cycle cost at this time is 159,500 yuan, which is much lower than the 164,900 yuan obtained by the native PSO.

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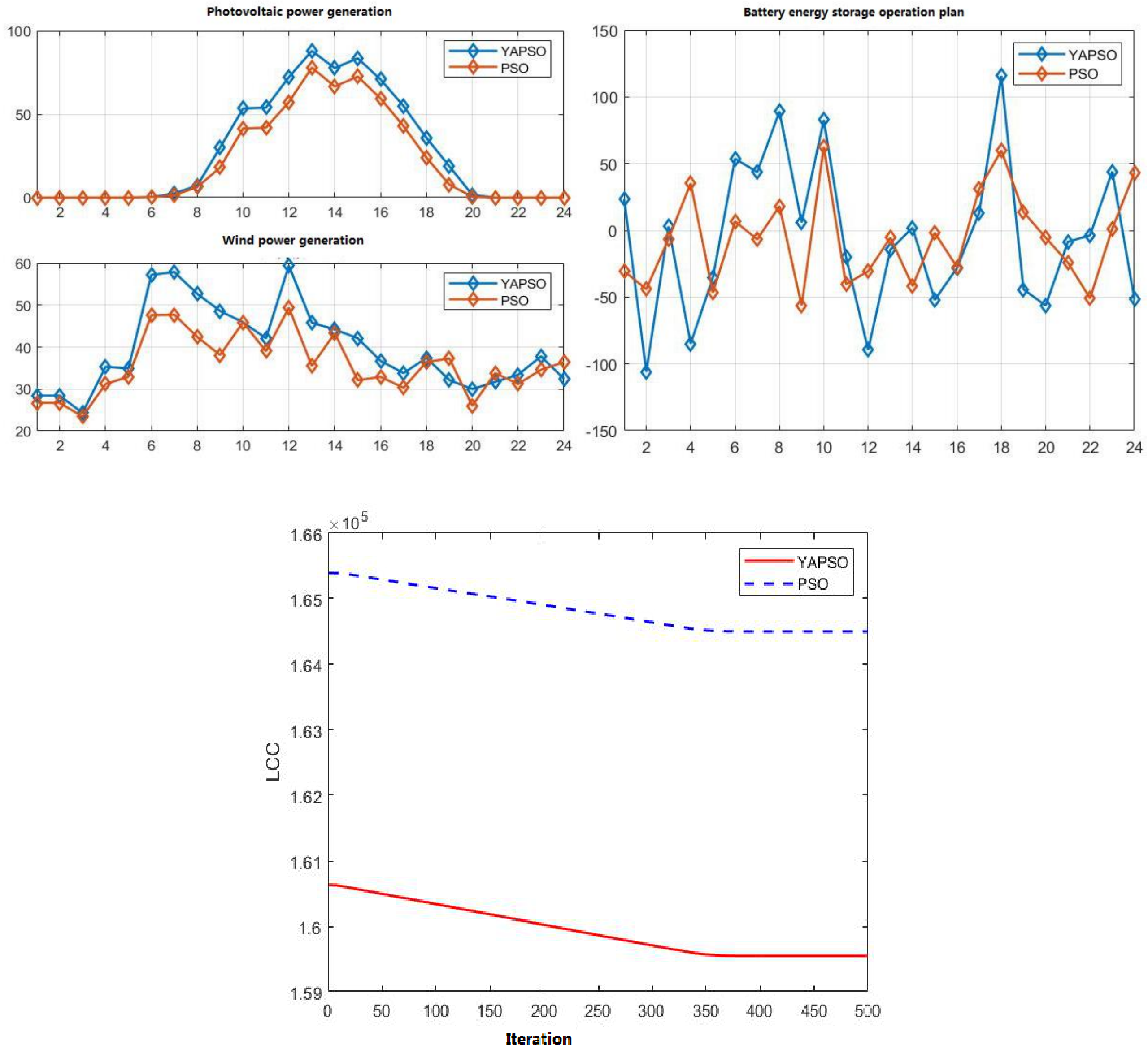

Figure 4. Multi-objective optimization results

5. Conclusions

Energy is an important support for global energy development. This article focuses on wind-solar hybrid power generation. For overall performance, this paper innovatively proposes a new adaptive PSO algorithm (YAPSO), which has passed the test of related benchmark functions and proved to be an improved version of a feasible optimization algorithm. In solving actual power grid engineering problems, this paper uses the proposed YAPSO algorithm to solve multi-objective engineering applications. Simulations prove that the proposed YAPSO algorithm has good performance and extremely high engineering application value.

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