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A Capacity Configuration Control Strategy to Alleviate Power Fluctuation of Hybrid Energy Storage System Based on Improved Particle Swarm Optimization

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Abstract: In view of optimizing the configuration of each unit's capacity for energy storage in the microgrid system, in order to ensure that the planned energy storage capacity can meet the reasonable operation of the microgrid's control strategy, the power fluctuations during the grid-connected operation of the microgrid are considered in the planning and The economic benefit of hybrid energy storage is quantified. A multi-objective function aiming at minimizing the power fluctuation on the DC bus in the microgrid and optimizing the capacity ratio of each energy storage system in the hybrid energy storage system (HESS) is established. The improved particle swarm algorithm (PSO) is used to solve the objective function, and the solution is applied to the microgrid experimental platform. By comparing the power fluctuations of the battery and the supercapacitor in the HESS, the power distribution is directly reflected. Comparing with the traditional mixed energy storage control strategy, it shows that the optimized hybrid energy storage control strategy can save 4.3% of the cost compared with the traditional hybrid energy storage control strategy, and the performance of the power fluctuation of the renewable energy is also improved. It proves that the proposed capacity configuration of the HESS has certain theoretical significance and practical application value.

Keywords: capacity configuration; hybrid energy storage; micropower grid; power fluctuation; particle swarm optimization

1. Introduction

In recent years, with the rapid development of microgrids, it has become a highly efficient and flexible new distribution power grid that can be tightly integrated with existing power systems. The proportion of renewable energy power generation is increasing [1]. However, the output power of renewable energy sources may change due to uncontrollable factors such as weather and seasons, and it is impossible to formulate a precise power generation plan, and the reliability is not high. Especially for stand-alone microgrids containing renewable energy sources, since they will not be able to feed energy from large grids, these problems may cause serious consequences at the load side [2].

The existing energy storage devices are generally divided into two types; one is a power storage unit with a higher power density and lower energy density [3–5], such as supercapacitor [6]. The other is an energy storage unit with higher energy density and lower power density [7,8], such as battery [9].

When the output power of renewable energy is large, the supercapacitor can effectively suppress the short time high-frequency power fluctuation, and the battery can suppress the long-time low-frequency power fluctuation. When the power output of renewable energy is stable and enough, the energy storage system is in charge state and can fully absorb renewable energy. When renewable energy cannot meet the demand of microgrid, the energy storage system can also supply power to all or important loads independently [10,11]. In Reference [12], based on the energy storage characteristics and operating parameters, the virtual state of charge is constructed. The optimal control model for suppressing the power fluctuation of the microgrid tie line is proposed, and the optimal energy storage response quota allocation for accurately tracking the target reference value is realized. In Reference [13], a hierarchical optimization operation strategy of HESS is proposed, which changes the supercapacitor step size control strategy through fuzzy logic rules to smooth the photovoltaic power fluctuation. In Reference [14], by analysing the energy storage characteristics of supercapacitor and accumulators, an energy management strategy based on this HESS is proposed. An annual average of energy storage devices based on the full life-cycle cost (LCC) theory is established. The cost is the objective function, and the energy storage capacity optimization model with the reliability index of independent wind power generation system loss of power supply probability (LPSP) is used as the constraint condition, and the PSO algorithm is used to solve the optimization problem. These studies provide a good reference and facilitate the performance improvements of the control strategy.

In this study, by using the filter as the power allocation control strategy, the multi-objective function is proposed in combination with the control requirements. After fitting, the target function is solved by the PSO algorithm. The specific capacity parameters of the battery and the supercapacitor are obtained. The control signal is produced by the local strategy controller to the optimized storage system, and the final control effect of the microgrid is achieved.

2. Microgrid Structure

2.1. Renewable Energy Generation System and HESS Structure

For the stand-alone operation of microgrids containing renewable energy, it is mainly composed of wind power generation systems, photovoltaic arrays, HESS, DC/AC conversion devices, DC/DC conversion devices, and loads [15]. The structural diagram is shown in Figure 1.

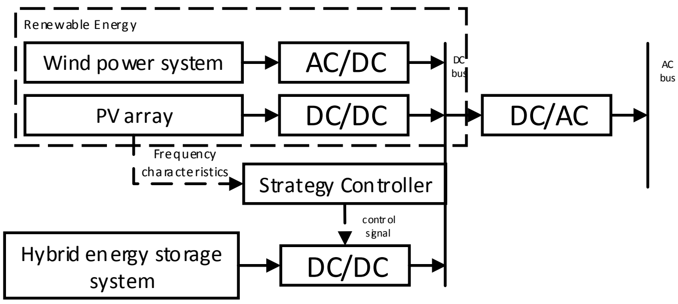

Figure 1. System Structure.

The conversion of renewable energy from different properties to electricity has different properties. For example, wind power is alternating current and photovoltaic power is direct current. Therefore, it is necessary to use AC/DC or DC/DC and DC bus respectively to connect. After the DC bus meets the DC load in the microgrid, the DC/AC module is connected to the AC bus to supply the AC load in the microgrid [16]. However, the instability of renewable energy will cause great fluctuation of power on DC bus and affect the power quality and reliable operation of microgrid [17–19]. Therefore, the power frequency characteristics of renewable energy are detected in real time and controlled by local policy controller [20]. The power fluctuation is divided into two parts of high frequency and low frequency by the improved low pass filter, and then the power stability on the DC bus is maintained by the reduction of the power distribution of different energy storage units in the HESS. As the core of the control strategy, the local strategy controller needs to collect the frequency information of power fluctuation and then completes the calculation steps in the low-pass filter algorithm and other control strategies. Finally, the control signal is generated to control the DC-DC converter.

2.2. The Principle of Smooth Control Strategy of the HESS

Different energy storage units in an energy storage system are responsible for high-frequency or low-frequency power fluctuations generated by renewable energy [21]. Combined with the characteristics of the two types of energy storage units, the smooth control strategy can use supercapacitor to suppress high-frequency part of the fluctuations in P_{ref}, and batteries to stabilize the low-frequency part of P_{ref}. When the output power of the renewable energy fluctuates greatly, the DC bus power of the microgrid will not fluctuate greatly, and the microgrid can operate reliably. The principle of filter smoothing control strategy for hybrid energy storage is shown in Figure 2. The power fluctuations of the battery and supercapacitor in the HESS is established as in Equations (1) and (2):

$$P_{bat} = P_{ref}\frac{Ts}{1+Ts} \tag{1}$$

$$P_{sc} = P_{ref}(1 - \frac{Ts}{1+Ts}) \tag{2}$$

where:
P_{ref} = the power fluctuation of renewable energy (kW)
P_{bat} = the output powers of the battery (kW)
P_{sc} = the output powers of the supercapacitor (kW)
T = filter time constant of low pass filter (s)

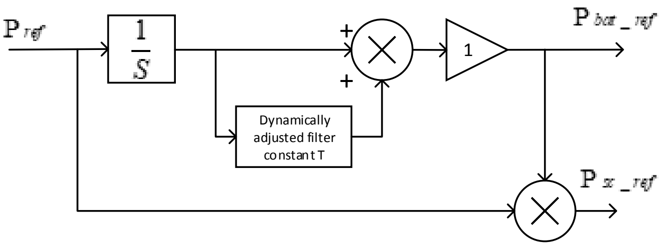

Figure 2. The principle of smoothing control strategy of hybrid energy storage filter.

3. The Objective Function of HESS

3.1. Objective Function

Objective function to reduce the fluctuation of renewable energy power:

Considering that the output power of renewable energy changes rapidly, 1 min is set as a scheduling period. The objective function is established as in Equations (3) and (4):

$$F_1 = \min\sum_{i=2}^{n}|(P_{DG,i} - P_{DG,i-1})| \tag{3}$$

where:
F_1 = the power fluctuation of renewable energy (kW)
n = the number of the scheduling cycle
$P_{DG,i}$ = the output power of the i dispatching cycle after the HESS is stabilized (kW)
$P_{dg,i}$ = the output power of the renewable energy source that has not been stabilized by the HESS (kW)

$$P_{DG,i} = P_{dg,i} + P_{bat,i} + P_{sc,i} \tag{4}$$

where:

$P_{sc,i}$ = the output powers of the supercapacitor in the i-th scheduling period (kW)

$P_{bat,i}$ = the output powers of the battery in the i-th scheduling period (kW)

Objective function to meet the minimum cost of construction operation:

At the present stage, the construction and operation of Microgrid need higher cost. If more HESS are configured, they can meet the normal operation of the Microgrid, but they will have high construction, operation and maintenance costs. If fewer HESS are configured, the normal operation of the Microgrid cannot be met. Therefore, the objective function is introduced in order to meet the operation of the Microgrid and the minimum construction operation cost, defined as Equation (5):

$$F_2 = \min(m_1 \frac{E_{bat}}{\eta_{bat}} + m_2 \frac{E_{sc}}{\eta_{sc}} + m_3 P'_{bat} + m_4 P'_{sc}) \tag{5}$$

where:

F_2 = construction and operation costs

m_1 = the cost of each degree of the storage unit of battery, including the cost of its supporting equipment

m_2 = the cost of each degree of the storage unit of a supercapacitor, including the cost of its supporting equipment

m_3 = the scheduling costs when the battery participated in the long-term scheduling of the microgrid

m_4 = the scheduling costs when the supercapacitor participates in the long-term scheduling of the microgrid

E_{bat} = the installed capacity of the battery (AH)

E_{sc} = the installed capacity of a supercapacitor (F)

η_{bat} = the energy conversion efficiency of the battery

η_{sc} = the energy conversion efficiency of the supercapacitor

P'_{bat} = the average power when the battery participates in the long-term scheduling of the power grid (kW)

P'_{sc} = the average power when the supercapacitor participates in the long-term scheduling of the power grid (kW)

3.2. Constraint Condition

(1) In order to prevent the overcharge and over-discharge of the energy storage unit, the remaining capacity of the energy storage system is limited, defined as Equation (6):

$$\begin{gathered} 20\% < SOC_{sc} < 90\% \\ 30\% < SOC_{bat} < 80\% \end{gathered} \tag{6}$$

where:

SOC_{sc} = the state of charge (SOC) of a supercapacitor in the HESS

SOC_{bat} = the SOC of the battery in the HESS.

(2) Considering the broken state of the renewable energy in the microgrid, the HESS needs to be able to output relatively large power in a certain time to meet the normal operation of the microgrid. At the same time, it is also necessary to consider that the maximum allowable output power of each energy storage unit and each power converter cannot be exceeded, described as Equation (7):

$$\begin{cases} P_{uc,i} + P_{bat,i} \geq P_{\max} \\ P_{uc,\min} \leq P_{uc,i} \leq P_{uc,\max} \\ P_{bat,\min} \leq P_{bat,i} \leq P_{bat,\max} \end{cases} \tag{7}$$

where:

$P_{uc,\min}$ = the minimum power that the supercapacitor and power converter can withstand (kW)
$P_{uc,\max}$ = the maximum power that the supercapacitor and power converter can withstand (kW)
$P_{bat,\min}$ = the minimum power that the battery and power converter can withstand (kW)
$P_{bat,\max}$ = the maximum power that the battery and power converter can withstand (kW)
$P_{\max}$ = the output relatively large power in a certain time to meet the normal operation of the microgrid (kW)

(3) Energy constraint conditions.

At any time, the power balance must be guaranteed in the microgrid. The power relation can be described as Equation (8):

$$P_{sc,i} + P_{bat,i} + P_{pv,i} + P_{w,i} = P_{L,i} + P_{loss,i} \tag{8}$$

where:

$P_{sc,i}$ = the power of the supercapacitor at the current sampling time (kW)
$P_{bat,i}$ = the power of the battery at the current sampling time (kW)
$P_{pv,i}$ = the output power of Photovoltaic (PV) at the current sampling time (kW)
$P_{w,i}$ = the output power of wind power at the current sampling time (kW)
$P_{L,i}$ = the power at the DC bus at the current sampling time (kW)
$P_{loss,i}$ = the power consumption of surplus power through the load unloading device (kW)

4. Using PSO to Solve Multi-Objective Functions

4.1. Adaptive Weighted PSO

PSO is an intelligent algorithm that simulates the process of flock search for food. Its advantage is that the algorithm process is simple, the parameters are less than other algorithms, and it is easy to implement. Its position and speed are updated according to the formula of Equation (9):

$$\begin{cases} v_{ij}^{t+1} = wv_{ij}^{t} + c_1 r_1 (p_{best,ij}^{t} - x_{ij}^{t}) + c_2 r_2 (g_{best,ij}^{t} - x_{ij}^{t}) \\ x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \end{cases} \tag{9}$$

where:

t = the number of iterations of the algorithm
w = the inertia weight of each particle during flight
v_{ij}^{t} = the velocity of the particle at the i-th row and the j-th column at t
c_1,c_2 = the learning factors of the algorithm
r_1,r_2 = random numbers
p^{best} = the optimal fitness of each particle respectively Optimal fitness
x_{ij}^{t} = the position of the particles in row i and column j at t
g^{best} = the global of each particle respectively Optimal fitness

w is the inertia weight, which plays a role in maintaining the original motion state of the particle—the bigger the w, the stronger the global optimization ability.

The inertial constant w is a very important constant in the PSO. The larger the value of w, the faster the particle's search speed, but the lower the search accuracy. The smaller the value of w, the slower the particle's search speed, but the higher the search accuracy. Therefore, compared to the PSO algorithm with fixed inertia weights, the adaptive optimization method of decrementing the inertia weight can guarantee the search accuracy without losing the algorithm speed, so that the value of w can be changed according to Equation (10):

$$w = \begin{cases} w' + k' \frac{d_{vid}}{d_t} & \mathrm{g'}_{\mathrm{best}} > \Delta\mathrm{error} \cdot 10 \\ w' - k'' \frac{d_{vid}}{d_t} & \mathrm{g'}_{\mathrm{best}} < \Delta\mathrm{error} \end{cases} \tag{10}$$

where:

w' = the reference value of w
k', k'' = compensation coefficients
v_{id} = the current particle velocity
Δerror = the allowable error of the system

4.2. Worst Particle Elimination Strategy

In order to exert the advantages that all the particles in the particle should have, and increase the efficiency of the algorithm, in the algorithm, a knock-out judgment strategy is also introduced. That is, in each iteration of the system, the particles with the least fitness are replaced by the particles with the best fitness, new speeds and positions are set, and a research step is performed, the optimal particle fitness does not change. After adding the worst particle elimination strategy, the algorithm's convergence and local search capabilities will be significantly improved. The specific steps are as follows:

Step 1: algorithm initialization operation, calculate the initial fitness of each particle, etc.;

Step 2: Prepare for iterative operations, find out the individual extreme p^{best} and the individual worst fitness p^{worst}, use p^{best} instead of p^{worst};

Step 3: Calculate and find the global extreme g^{best} and global worst fitness g^{worst}, replace g^{best} with g^{worst};

Step 4: Update the position and velocity of the particle based on the particle velocity update formula and the position update formula;

Step 5: Determine whether the loop limit condition is reached (reach the allowable error or the number of iterations reaches the upper limit) and exit the algorithm if it is reached. If it does not, go back to the second step, continue execution.

4.3. Multi-Objective Function Fitting

Since the PSO can only calculate a single objective function, but we propose multiple objective functions here, so it is necessary to fit multiple objective functions. The conventional practice is to propose a set of parameters $\lambda_i(i = 1, 2, 3 \cdots)$, the sum of the parameters is 1, according to the important length of each objective function, artificially relying on the experience of the method to set, doing so in many cases will produce a larger error.

The fitted multi-objective function should be described as in Equation (11):

$$\begin{cases} F = \lambda_1 F_1 + \lambda_2 F_2 + \cdots + \lambda_m F_m \\ \lambda_1 + \lambda_2 + \cdots + \lambda_m = 1 \end{cases} \tag{11}$$

where:

Sen,i = the actual state of charge at the end of the charging of the *i*-th electric car.
F = the fitted objective function
λ_m = the weighting coefficient of m
F_m = the objective function of m

Based on the traditional multi-objective function fitting, this paper proposes a method based on the difference between the current value and the average value as the discriminant principle and uses the entropy weight method to determine the weighting coefficient. The coefficients are determined by weighing all the indices using the entropy weight of each index. The method is as shown in Equation (12):

$$\Delta_i^j = f_i^j - f_{average} \tag{12}$$

where:

Δ_i^j = the difference between the current particle and the average fitness
f_i^j = the fitness of the current particle of each objective function
$f_{average}$ = the average of the fitness of all particles of each objective function

The difference reflects the difference between the current particle's flight according to the current flight trajectory and speed and the optimal value. If the difference is large, it will increase the gap between the current configuration and the optimal solution. According to the difference, the method for determining each utility coefficient before each objective function using the entropy weight method is as follows:

Step 1: Determine the loop control variable m according to the number of objective functions, and find the optimal solution for a single objective function as f_i;

Step 2: Bringing the optimal solution of every single goal into a different objective function to obtain the corresponding objective function fitness f_i^j;

Step 3: Calculate the difference Δ_i^j of the optimal solution for each objective function;

Step 4: Calculate the average difference of each objective function: $u_i = \frac{\sum\limits_{j=1}^{m} \Delta_i^j}{m}$ $i = 1, 2, \cdots, m$;

Step 5: Calculate the weighting factor for each objective function: $\lambda_i = \frac{u_i}{\sum\limits_{j=1}^{m} u_j}$ $i = 1, 2, \cdots, m$.

4.4. Solving Multi-Objective Functions

Using the improved PSO to solve the objective function after fitting. The calculation process is as follows:

Step 1: Initialize the algorithm, calculate the fitness of the multi-objective function of each particle based on the objective function after fitting, and input constraint condition;

Step 2: Determine the fitness of each particle's multi-objective function is within the range of feasible solutions, and search for g^{best} and p^{best} according to the initial value;

Step 3: Calculate the position and velocity of each particle at the next iteration based on the particle velocity and position update formula, and recalculate the fitness of each particle;

Step 4: Judge whether the conditions for stopping the iteration has reached, such as reaching the accuracy requirement or reaching the number of iterations. If it is not reached, choose a new p^{best}, and g^{best} is selected from it, and re-execute step 3 n. If the stop iteration condition is reached, the loop is stopped;

Step 5: Output algorithm results.

The calculation flowchart of the algorithm is shown in Figure 3.

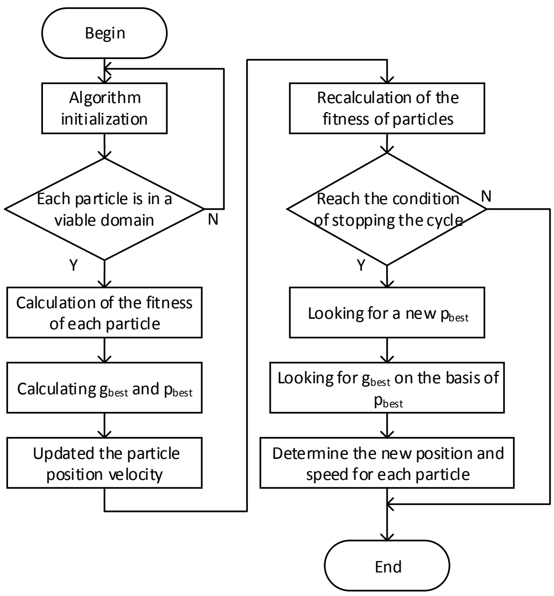

Figure 3. algorithm calculation flow chart.

5. Experimental Results and Analysis

The main parameters of the selected Microgrid model in the experiment are shown in Table 1.

Table 1. Main parameters of the Microgrid model.

Parameter Name	Parameter Symbol	Parameter Values
Battery voltage	V_{bat}	70–85 V
Supercapacitor voltage	V_{sc}	60–75 V
DC Bus Voltage	U_{dc}	120 V
The maximum output power of a battery	P_{bat_max}	800 W
The maximum output power of supercapacitor	P_{sc_max}	2000 W
Transmission efficiency	η	0.95
Sampling frequency	f_{bat}	40 kHz
Switching frequency	T	10 kHz
Rated load of DC bus	P_{load}	3000 W

5.1. Analysis of Experimental Results of Economic Benefit

Table 2 shows the economic analysis of the traditional Hybrid energy storage capacity of the configuration and the economic benefits analysis of the traditional Hybrid energy storage capacity of the configuration after optimization. The traditional energy storage equipment control strategy [22] is based on the energy storage capacity already equipped. The traditional method is to meet the control strategy requirements within the set range, and this paper considers the operation cost of the HESS based on the basics.

Table 2. Economic benefit analysis of traditional hybrid energy storage capacity of the configuration.

Parameter Name	Traditional	Optimized
Equivalent discharge cycles of accumulators in 1 load cycles	3.2	1.8
Equivalent discharge cycles of ultracapacitor in 1 load cycles	5.4	7.4
Replacement times of battery in the whole lifecycle	3.6	1.5
Replacement of super capacitor during the whole lifecycle	0.2	0.3
Charge per batch of battery per batch/yuan	1592	1592
Cost per unit of supercapacitor per batch/yuan	28,497	28,497
The cost/element of the battery for the whole lifecycle	5731	2388
The cost/element of the super capacitor during the whole life cycle	5699	8549
Cost/yuan of a HESS in the whole life cycle	11,430	10,937

The analysis of the calculated results shows that the optimized hybrid energy storage capacity of the configuration can save 4.3% of the operating cost in a single operating cycle. Moreover, the number of times the battery needs to be replaced is also significantly reduced.

5.2. Analysis of Experimental Results of Fluctuating Power Fluctuations in Renewable Energy Sources

The experiment in this area use one day as the scheduling period to observe the suppression effect of the HESS. The contrastive object of the experiment is the traditional hybrid energy storage capacity of the configuration. In a Microgrid operation cycle, the correctness and effectiveness of the improved control strategy can be verified by comparing the control effects of the improved hybrid energy storage capacity of the configuration and hybrid energy storage capacity of the configuration. The comparison results are shown in Figures 4 and 5.

From the comparison chart, we can see that, when the control strategy is not used, although the supercapacitor bears most of the high-frequency fluctuations, the grid-connected power generated by the power generation unit cannot be controlled, causing the battery to be cut off by the safety module because of the excessive discharge power between 6 o'clock and 15 o'clock. From the P_{LINE} curves, the use of this control strategy is more excellent in suppressing bus power fluctuations. The working status of the battery has also been significantly improved. Overcharging and over-discharging are basically avoided, which can effectively extend the service life of the battery. The improved hybrid energy storage control strategy has improved the working conditions of the battery, and basically, no overcharge and discharge has occurred.

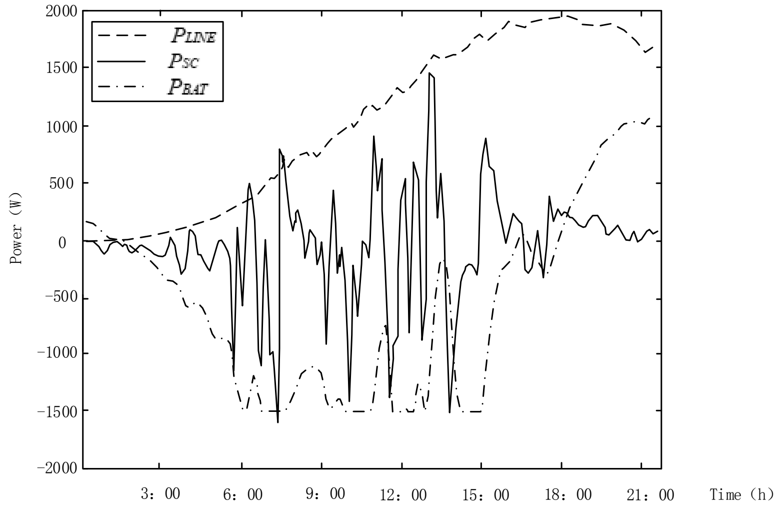

Figure 4. Microgrid operation during the traditional hybrid energy storage capacity of the configuration.

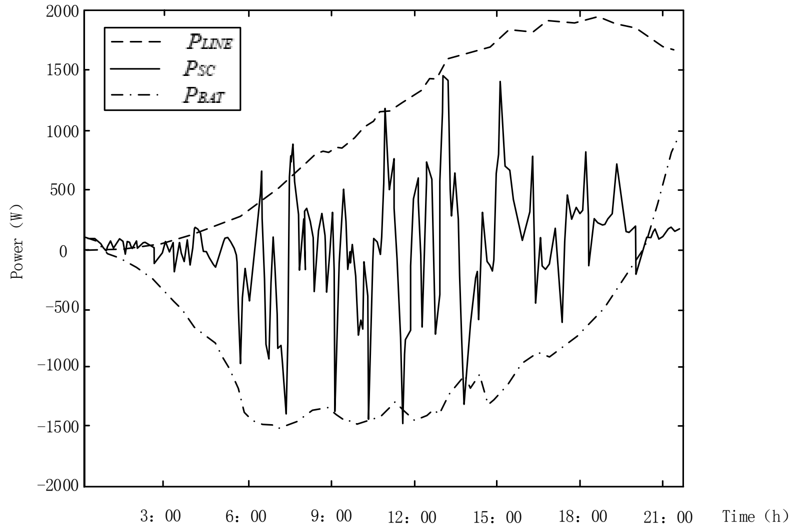

Figure 5. Microgrid operation during the optimized hybrid energy storage capacity of the configuration.

6. Conclusions

This paper uses a HESS consisting of a battery and a supercapacitor to suppress the power fluctuation of the Microgrid caused by renewable energy. Based on the multi-objective function of the minimum power fluctuation on the DC bus and the optimal capacity ratio of each energy storage system in the HESS, the improved PSO is used to solve the objective function. Experiments show that hybrid energy storage capacity of the configuration can attenuate power fluctuations on the DC bus, and the fluctuation of the high-frequency components of the battery is reduced, the cycle life of the battery is extended, and the cost of the system is also reduced. Compared with the traditional hybrid energy storage capacity of the configuration, the strategy can save 4.3% of the cost, and the performance of modulating power fluctuations in renewable energy has also been significantly improved. It proves that the proposed energy management strategy has certain theoretical significance and practical application value.

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