Research on variable parameter power differential charge–discharge strategy of energy storage system in isolated island operating microgrid

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Abstract

This paper proposed an improved particle swarm optimization (PSO) algorithm for the variable parameter power difference charging and discharging strategy of battery energy storage system (BESS). The charge and discharge power of the BESS under different load intervals and state of charge (SOC) intervals are distributed, and the objective functions of peak shaving and valley filling standard deviation and minimum SOC off-line rate are established. The simulation model of peak shaving and valley filling is built, and the results show that the standard deviation of peak shaving and valley filling reduced by 22.58% compared with PSO. The effectiveness and feasibility of the improved PSO are verified.

Keywords: battery energy storage system; variable parameter power difference; charged state; peak shaving and valley filling; particle swarm optimization

1 INTRODUCTION

Electricity cannot be stored on a large scale; supply and demand must be balanced. As the difference between morning and evening power consumption gradually increases, the peak to valley value of the power load is gradually increasing [1]. Battery energy storage system (BESS) has the characteristics of storing electric energy; it uses BESS to charge when the power load trough discharges at the peak of power load, to achieve peak shaving and valley filling of power load [2]. Therefore, the country vigorously promotes the application of BESS in microgrids. Among them, there are many solving algorithms for BESS models. These methods include decomposition techniques, dynamic programming, Lagrangian relaxation and nonlinear programming. Although these traditional algorithms have different functions, they reduce computing time and memory requirements. In recent years, intelligent algorithm technology, such as genetic algorithm, simulated annealing algorithm and bat algorithm, is also used to solve the problem of BESS operating in microgrid [3].

Currently, there are extensive studies on the problem of peak shaving and valley filling in BESS. In [4, 5], a BESS operating with a constant power (CP) charge and discharge strategy is used and a CP charging and discharging optimization model is proposed based on the sequential second algorithm. In [6, 7], a control strategy of peak cutting and valley filling based on dynamic programming is proposed and, at the same time, the impact of charge and discharge depth on battery life is considered, but it limits the number of charge and discharge per day and the large changes due to load in some scenarios; the energy storage system may need to change the charge and discharge state many times. The authors in [8–10] compare CP and variable parameter power difference (VPPD) control strategies; they show that the control effect of VPPD control strategy is better than the CP control strategy and that using the bat algorithm to solve the objective function, the algorithm process is complicated. In [11, 12], the charging and discharging strategy are optimized based on the improved particle swarm optimization (PSO) and the state interval of SOC is not considered. The authors in [13, 14] use PSO to solve the objective
function but made no improvements to the algorithm, making the solution of the objective function easy to fall into the local optimum and thereby affecting the effect of peak shaving and valley filling. In Reference [15] divide the SOC into five sections by size, determine the current working range of SOC, real-time adjustment of filter constant, established capacity optimization configuration method for energy storage system.

Aiming at the battery energy storage model of microgrid, an improved PSO is proposed to study the VPPD control strategy of BESS. It is based on a constant parameter power difference (CPPD) control strategy, introduces the SOC state interval and takes the SOC evaluation index as one of the objective functions. The improved PSO to solve the objective function, thus, optimizes the VPPD control strategy.

2 VPPD CONTROL STRATEGY

The BESS has a CP control strategy for charging and discharging, a CPPD control strategy and a VPPD control strategy. Among them, the VPPD control strategy [10] fully considers the state of SOC based on the CPPD control strategy, the proposed SOC state adaptive VPPD control strategy, making the BESS avoid the high and low SOC ranges and thereby prolonging the service life of the battery.

2.1 Division of load interval

Through the power difference control strategy, the lower \( P_1 \) limit power \( P_{1\text{ load discharge}} \), the upper limit power \( P_2 \) of BESS charging during charging and discharging of the BESS are determined. Thus, the state of the load is divided into three states, as shown in Figure 1.

The specific steps of the CPPD control strategy are as follows.

1. Through the predicted daily load curve, calculate its average \( P_{av} \), and determine \( P_1, P_2 \) initial value.

2. Initial value \( P_{av} \), the step size is \( \Delta P \) to iterate until it is satisfied that the total amount of charge and the total amount of discharge of the BESS are approximately equal.

3. According to Step (2), determine the upper and lower charging limits of the BESS, and determine the charge and discharge power according to the actual situation.

As can be seen from Figure 1, according to \( P_1 \) and \( P_2 \), divide the load into three parts; they are load 1 interval, load 2 interval and load 3 interval.

2.2 Division of SOC interval

By introducing two parameters \( S_{up} \) and \( S_{down} \), divide the SOC state interval into five parts to avoid the problem of overcharge and overdischarge of the BESS and to prolong the service life of the battery, as shown in Figure 2 [11].

1. Lower limit interval of SOC:

\[
0 < S(t) < S_{\text{min}} \quad (1)
\]

2. Low range of SOC:

\[
S_{\text{min}} \leq S(t) < S_{\text{down}} \quad (2)
\]

3. Normal range of SOC:

\[
S_{\text{down}} \leq S(t) < S_{\text{up}} \quad (3)
\]

4. High value range of SOC:

\[
S_{\text{up}} \leq S(t) < S_{\text{max}} \quad (4)
\]
(5) Upper limit range of SOC:

\[ S_{\text{max}} \leq S(t) < 1, \quad (5) \]

where \( S(t) \) is the SOC value of the BESS at time.

### 2.3 Research and implementation of adaptive power difference control

1. The lower limit interval of SOC: the BESS only performs charging operations.
   - Load intervals 1 and 2: the BESS is charged with the discharge upper limit \( P_1 \) as the target.
   
   \[ P_c = K_1 (P_2 - P_1) + (1 - K_1) \min(P_c P_1 - P_1), \quad (6) \]
   
   where \( P_c \) is the charging power of the BESS, \( P_e \) is the rated power of the BESS and \( P_1 \) is the load power at the moment.
   
   The BESS stands still in the load 3 interval.

2. The low range of SOC: according to different load intervals, charge and discharge the BESS.
   - In load 1 interval, the BESS is charging. At this time, the SOC value is relatively low and it is easy to enter the lower limit of SOC, so increase the charging power.
   
   \[ P_c = K_1 (P_2 - P_1) + (1 - K_1) \min(P_c P_1 - P_1), \quad (7) \]
   
   where \( 0 < K_1 < 1 \).
   
   In load 2 interval, the BESS stands still.
   
   In load 3 interval, the BESS is charging, the SOC value is relatively low at this time and the excessive discharge power makes it easy to enter the lower limit of SOC.

   \[ P_d = K_2 (P_2 - P_1), \quad (8) \]
   
   where \( 0 < K_2 < 1 \).

3. The normal range of SOC.
   - In load 1 interval, the BESS is charging.
   
   \[ P_c = P_2 - P_1 \quad (9) \]
   
   In load 2 interval, the BESS stands still.
   
   In load 3 interval, the BESS discharges.

   \[ P_d = P_1 - P_1 \quad (10) \]

4. The high value range of SOC: contrary to the low SOC range.
   - In load 1 interval, the BESS is charging.
   
   \[ P_c = K_3 (P_2 - P_1), \quad (11) \]

   where \( 0 < K_3 < 1 \).

   In load 2 interval, the BESS stands still.
   
   In load 3 interval, the BESS discharges.

\[ P_d = K_4 (P_1 - P_1) + (1 - K_1) \min(P_c P_1 - P_2), \quad (12) \]

where \( 0 < K_4 < 1 \).

5. The upper limit range of SOC: contrary to the SOC lower limit interval.
   - In load 1 interval, the BESS stands still.
   
   In load 2 and 3 intervals, the BESS discharges.

\[ P_d = \min(P_c P_1 - P_2) \quad (13) \]

The above is the charging and discharging situation of the BESS in different load intervals and SOC intervals.

Through \( S_{\text{up}}, S_{\text{down}}, K_1, K_2, K_3, K_4 \), the six parameters for rolling optimization, realize the adaptive power difference control in different load intervals and SOC intervals; the flowchart is shown in Figure 3.

### 3 RESEARCH ON OBJECTIVE FUNCTION AND IMPROVED PSO

The main contents of this paper are the BESS charging and discharging optimization strategy and the establishment of load shaving and valley filling, SOC cross-line rate objective function and grid power balance and BESS constraint conditions, using improved PSO to model the model optimization. Therefore, the BESS achieves a good effect of peak shaving and valley filling.

#### 3.1 Objective function

The purpose of the BESS participating in load shaving and valley filling is to increase the load of the wave valley, reduce the load of the wave peak and ensure the stability of the load.

1. The effect of load peak shaving and valley filling is evaluated and the evaluation index is \( F_1 \).

\[ F_1 = \sqrt{\frac{\sum_{t=0}^{T+\Delta T} (P_{\text{out}(t)} - P_{\text{out-a}})}{\bar{\Delta}t}}, \quad (14) \]

where \( P_{\text{out}(t)} \) is the power on the load side at time and \( P_{\text{out-a}} \) is the time period \( [T, T + \Delta T] \) average power on the load side.

2. SOC evaluation index.

To consider the SOC state of the BESS, lead into \( [T, T + \Delta T] \) the SOC over-line rate during time period \( F_2 \).

\[ F_2 = \frac{\sum_{t_{s=0}}^{t_{s<s_{\text{max}}} + t_{s<s_{\text{min}}}} \Delta t} \times 100\% \quad (15) \]
where: \( t_{s > \text{smax}} \) is the time for SOC value to enter the upper limit interval in this period and 
\( t_{s < \text{smin}} \) is the time when SOC values enter the lower range in this period.

### 3.2 Determine the weight of the objective function

As can be seen from Section 2.1, the objective function in this paper is composed of sub-objective functions \( F_1, F_2 \), sicilicet,

\[
F = \min \{ F_1, F_2 \}.
\]  

Since \( F_1, F_2 \) represents different sub-objective functions, therefore, the weight coefficient of the sub-objective function \( \lambda_i \) analysis, as shown in Equations (17) and (18).

\[
F = \lambda_1 F_1 + \lambda_2 F_2 \quad (17)
\]

\[
\lambda_1 + \lambda_2 = 1 \quad (18)
\]

In this paper, the variation coefficient sorting method is adopted to determine the weight coefficient of the sub-objective function \( \lambda_i \); the specific steps are as follows [12].
(1) Assuming there are n sub-objective functions, calculate the optimal solution of the sub-objective function separately \( \min F(x) \), marked as \( X_i \) (\( i = 1, 2, \ldots, n \));
(2) Iterate on the optimal solution of the sub-objective function, and calculate the corresponding sub-objective function value \( F_j(\tilde{X}_i) \);
(3) Calculate the coefficient of variation of the sub-objective function under different solutions \( l_i \).

\[
l_i = \frac{1}{F_i(\tilde{X}_i)} \sqrt{\frac{\sum_{j \neq i}^{n} (F_i(\tilde{X}_j) - F_i(\tilde{X}_i))^2}{n - 1}} \tag{19}\]

Coefficient of variation: the deviation of the objective function value from the optimal solution of the sub-objective function.
(4) Calculate the weight coefficient of the sub-objective function \( c(\lambda_i) \).

\[
c(\lambda_i) = \frac{l_i}{\sum_{j=1}^{n} l_j}, (i = 1, 2, \ldots, n) \tag{20}\]
(5) Sort the aforementioned coefficient of variation from small to large, and sort the weight coefficient from large to small. The sub-objective function with the smaller coefficient of variation is multiplied by the larger weight coefficient and vice versa, and it is multiplied by the smaller weight coefficient. Better determine the weight coefficient of the objective function.

### 3.3 Constraints

In this model, only the physical model related to the BESS and the constraint conditions generated by the grid power balance are considered [14].

(1) Grid power balance constraints:

\[
P_{\text{out}} = P_{\text{load}} - P_{\text{ess}}, \tag{21}\]

where \( P_{\text{out}} \) is the output power of the grid; \( P_{\text{load}} \) is the load power of the user; \( P_{\text{ess}} \) is the output of energy storage batteries, when the energy storage battery is discharged; and \( P_{\text{ess}} > 0 \) and vice versa \( P_{\text{ess}} \leq 0 \).

(2) Constraints of BESS

- Constraints of SOC:

\[
SOC_{\text{min}} \leq SOC(t) \leq SOC_{\text{max}}, \tag{22}\]

where \( SOC_{\text{min}} = 20\% \) and \( SOC_{\text{max}} = 80\% \).

- Constraints on the charging and discharging power of energy storage batteries:

\[
0 \leq P_c \leq P_e \tag{23}\]
\[
0 \leq P_d \leq P_e \tag{24}\]

### 3.4 Improved PSO

PSO is a swarm intelligence optimization algorithm, which has the characteristics of fast running speed and simple algorithm. However, PSO still has the problem of easily falling into local optimization and the ergodicity of chaos theory is used to solve the local optimization problem of PSO. Update the velocity and position of the particles according to the following formula, as shown in Equations (25) and (26) [15–17].

\[
V_{ij(t+1)} = \omega V_{ij(t)} + c_1 r_1 (p\text{best}_{ij(t)} - x_{ij(t)}) + c_2 r_2 (g\text{best}_{ij(t)} - x_{ij(t)}) \tag{25}\]
where \( i \) is the number of particles; \( j \) is the first dimension of the particle; \( w \) is the inertia factor; \( c_1 \ c_2 \) is the learning factor; \( V_{ij(t+1)} \) is the velocity component of the particle \( i \) in the \( j \) dimension when it evolves to generation \( t + 1 \); \( X_{ij(t+1)} \) is the position component of the entire particle swarm; \( p_{bess\ ij(t)} \) is the particle evolves to the optimal position component of the \( j \) dimension when it evolves to generation \( T \); \( g_{bess\ ij(t)} \) is the particle evolves to the \( j \) dimension of the \( T \) generation, the optimal position component of the entire particle swarm; \( X_{ij(t+1)} \) is the component of the particle \( i \) in the \( j \) dimension when it evolves to the \( T + 1 \) generation; and \( x_{ij(t)} \) is the component of particle \( i \) in the \( j \) dimension when it evolves to generation \( T \).

Because chaos theory is ergodic and can effectively change the distribution of particles, it improves the global search capability of the algorithm. The classic chaotic system is Logistic, as Equation (2) shows:

\[
Z_{n+1} = \mu Z_n (1 - Z_n), 0 < Z_n < 1, \mu = 4,
\]

where \( Z_{n+1} \) is the next state of the chaotic system, \( Z_n \) is the current state of the chaotic system and \( \mu = 4 \) is a state of complete chaos.

The specific steps of the algorithm are as follows and the algorithm flowchart is shown in Figure 4.

1. Initialization: set the number of particles \( \text{num} = 60 \), the dimension of the particle \( D = 3 \), the learning factor \( c_1 = c_2 = 2 \) and the inertia factor \( \omega = 0.9 \). The speed of the particle, the maximum number of iterations, the accuracy of the particle and initialization of chaotic variables, excluding the five fixed points in the chaotic iterative equation \((0, 0.25, 0.5, 0.75)\).

2. Order \( t = 0 \) and generate \( D \) chaotic variable factors \( chaosi(i), 1 \leq i \leq D; t \) is the number of iterations.

3. Calculate the fitness value of the particle, according to Equations (25) and (26), and update the speed and position of the particles.

4. Determine whether the particle falls into a local optimum (according to the position of multiple particles are close or coincide): if it is not locally optimal, perform Step (6); otherwise, perform the next step.

5. Use chaotic variables to assign values to particle positions chaotically, and substitute Logistic, among Equation (26) iterative attention; to distinguish chaotic variable intervals \([0,1]\), map the value range of the corresponding variable.

6. Determine the solution of particle multi-object fitness \( g_{best} \) and \( p_{best} \).

7. Determine whether the particle meets the termination condition: if not satisfied, perform Step (3); otherwise, perform the next step.

8. The result is output and the program ends.

### 4 SIMULATION

In this paper, a typical daily load data in a commercial area is used as an example to analyze the effectiveness of the improved PSO.

#### 4.1 Improved PSO control strategy simulation

The energy storage batteries in this commercial area are lithium batteries; the typical daily load forecast curve is shown in Figure 5. Low electricity consumption in the commercial area is about 4:00, and there are two peaks in electricity consumption, which are around 11:30 and 20:00; it is basically in line with the actual situation.

According to the typical daily load forecast curve and power difference control strategy, calculate the typical daily load forecast curve discharge lower limit power \( P_1 = 3255.08kW \), the maximum charging power \( P_2 = 2129.17kW \) and the daily average load power \( P_{av} = 2469.08kW \). Assuming that the upper limit of the SOC of the BESS is 0.8, the lower limit of SOC is 0.2 and the charge and discharge efficiency is 100%. The relevant parameters of the BESS are shown in Table 1. Among them, an improved PSO is used to optimize the adaptive power difference control strategy. The simulation results are shown in Figures 6–8.
Table 2. Comparison parameters of peak shaving and valley filling.

|                  | Traditional | Improved | Absolute value | Improved rate (%) |
|------------------|-------------|----------|----------------|-------------------|
| Peak valley (kW) | 3850        | 3400     | 450            | 11.68             |
| Valley (kW)      | 1495        | 1895     | 400            | 26.75             |
| Standard deviation of load | 802.31     | 621.14   | 181.17         | 22.58             |
| Mean value of load | 2485.18  | 2520.20  | 35.02          | 1.40              |
| Load rate (%)    | 60.96       | 74.12    | 13.16          | 21.60             |

As shown in Figure 6, the SOC range of the BESS floats in [0.2, 0.8], under the action of the VPPD control strategy, realizes the self-adaptive adjustment of SOC, which is conducive to load peak shaving and valley filling and prolonging the service life of BESS. Among them, the SOC curve fluctuation range of the improved VPPD control strategy is larger, which effectively expands the SOC variation range, thereby optimizing the VPPD control strategy.

As shown in Figure 7, the output state of the energy storage battery changes with the change of the load power. The output of the BESS under the power difference control strategy and the traditional VPPD control strategy is relatively flat, the BESS under the improved VPPD control strategy and the output fluctuates greatly, so the effect of load peak shaving and valley filling is ensured, the output of the generator set is reduced and economy of the power grid is improved.

As shown in Figure 8, the load peak-shaving and valley-filling effect under the traditional VPPD control strategy is poor and the improved VPPD control strategy significantly improves the load curve and is smoother, thereby reducing the load peak-valley difference and improving the smoothness of the load curve to achieve the purpose of cutting peaks and filling valleys. The specific parameters before and after the VPPD optimization are shown in Table 2. Compared with the traditional VPPD control strategy, the load peak value under the improved VPPD control strategy is reduced from 3850 kW before optimization to 3400 kW after optimization, the trough value was increased from 1495 kW before optimization to 1895 kW after optimization and the standard deviation of the objective function is reduced by 181.17; in addition, the increase in load rate improves equipment utilization, reduces network loss and improves the power quality. The calculation formula of load factor is shown in (2).

\[ g = \frac{P_{av}}{P_{max}}, \]  

where \( P_{max} \) is the maximum power of the load.

4.2 Comparative analysis of the effects of different control strategies

As shown in Figure 6, the SOC range of the BESS floats in [0.2, 0.8], under the action of the VPPD control strategy, realizes the self-adaptive adjustment of SOC, which is conducive to load peak shaving and valley filling and prolonging the service life of BESS. Among them, the SOC curve fluctuation range of the improved VPPD control strategy is larger, which effectively expands the SOC variation range, thereby optimizing the VPPD control strategy.

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\[ g = \frac{P_{av}}{P_{max}}, \]  

where \( P_{max} \) is the maximum power of the load.
5 CONCLUSION

In this paper, the VPPD control strategy is studied theoretically and the influence of SOC interval on the VPPD control strategy is analyzed. On this basis, the VPPD charging and discharging strategy of the energy storage system in isolated island operating microgrid is designed. According to the ergodicity of chaotic variables, the local optimal problem of PSO is solved; thus, the VPPD control strategy is optimized. The main results are as follows.

(1) By analyzing the VPPD control strategy, determine the charging and discharging power of the BESS in different load intervals and SOC intervals.

Improved PSO optimizes SOC interval, thus, the VPPD control strategy is optimized, to achieve a good peak load clipping effect.

(2) By comparing the optimization ability of PSO and the improved PSO with MATLAB, the results show that the PSO improved by chaotic perturbation improves the particle search ability, the VPPD control strategy is optimized and the standard deviation of the load was reduced by 22.58%.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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