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Differential evolutionary algorithm based PCS equipment optimization scheme and grid voltage and frequency support strategy for energy storage power plants

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Abstract The progress of technology promotes the energy storage power station to play an increasingly important role in the energy system. In this paper, a multi-objective cooperative control strategy based on improved differential evolutionary algorithm is proposed for the optimization of power conversion system (PCS) equipment of lithium iron phosphate battery energy storage power station. An operation model considering the dynamic energy efficiency characteristics of the battery is constructed, and the optimal operation strategy is converted into an objective function solving problem. The differential evolutionary algorithm is introduced and combined with adaptive parameter adjustment and hybrid mutation strategy to optimize the power allocation and charging/discharging scheduling of the PCS equipment. It is shown that the improved differential evolutionary algorithm can effectively regulate the PCS equipment under the influence of two power steps: 0.9 MW output and 15 MW of discharge and 15 MW of charge, and the algorithm can still stably output effective optimization strategies under the two extreme conditions of SOC close to the extremes of 0.75 and 0.85. Comparison of the four objective evaluation indexes shows that the improved differential evolutionary algorithm has better performance than the other algorithms.

Index Terms differential evolutionary algorithm, PCS equipment scheduling, adaptive parameter tuning, mixed-variance strategy

I. Introduction

As a result of the global energy crisis and the growing concern about fuel depletion, power shortage and global warming, the substitution of fossil energy sources has received more and more attention [1], [2]. New energy with renewable energy as the core has the characteristics of non-pollution, wide distribution and abundant resources, which provides a new direction for power supply, and in recent years, governments have paid attention to and increased investment in the development of new energy [3], [4]. With the development of the economy, the user's demand for electricity is also gradually increased, so the scale of the power grid for this problem is also gradually increased. The power grid is a complex and variable system, and its operation state is affected by many factors, such as load fluctuation, uncertainty of renewable energy generation, fault events, etc. These factors lead to fluctuations in parameters such as grid voltage, frequency and power, which affects the stable operation of the power system [5]-[7].

The function conversion system (PCS), as an interface device between the energy storage system and the grid, needs to have a good grid-adaptive control strategy to cope with these complex and variable grid conditions, and its control strategy directly determines the responsiveness and stability of the energy storage system to the grid [8], [9]. It is the core component in the energy storage system, which is used to convert the electrical energy in the energy storage system into usable power and regulate the parameters such as AC and DC voltage and frequency to stabilize the power supply network [10], [11].

With the changes in global energy policies and the rapid development of green energy, the demand for PCS devices is gradually increasing in the context of the popularization of green energy and the gradual maturation of the energy storage market [12]. In grid practice measurements, the response delay of PCS devices increases the FM capacity waste. Moreover, there is a risk of harmonic resonance in the power grid, and the design life of IGBT modules is affected by factors such as frequency and temperature, which leads to limited use of the devices [13]-[15]. In addition, since the voltage frequency is the basic requirement for the normal operation of the power system, but the use of new energy in the power system makes the grid frequency fluctuation grow [16]. Therefore, optimization of PCS equipment and improvement of voltage frequency support provide a guarantee for precise control of power grid operation stability and safety.

Based on the dynamic energy efficiency characteristics of lithium iron phosphate battery, this paper constructs the operation model of energy storage power station and specifies the optimization objective function and constraints. The applicability and specific process of differential evolution algorithm in solving nonlinear optimization problems are introduced and analyzed. Aiming at the limitations of the traditional differential evolution algorithm with fixed parameters, an improvement method based on adaptive adjustment and hybrid variation strategy is proposed to enhance the performance of the algorithm in power allocation and battery state-of-charge (SOC) balancing, so as to realize synergistic optimization of maximizing the energy efficiency of the power plant and minimizing the loss of the equipment. The robustness of the algorithm under complex working conditions is verified through experiments to check its application effect.

II. PCS equipment optimization and grid voltage and frequency support related technology implementation

II. A. Energy storage plant operation model considering battery energy efficiency

II. A. 1) Dynamic energy efficiency characteristics of lithium iron phosphate batteries

The energy efficiency characteristics of electrochemical energy storage are different compared to other energy storage, and the energy efficiency characteristics of electrochemical energy storage of different materials are also different. This paper takes the mainstream electrochemical energy storage medium lithium iron phosphate, which is currently used in grid-side energy storage power stations, as an example.

Discharge link, lithium iron phosphate battery in a reasonable depth of discharge range of voltage is basically unchanged, the efficiency with the increase in charge and discharge current will have a different degree of decline. According to the relationship between lithium iron phosphate battery voltage and battery state of charge (SOC), the relationship between energy efficiency and charge/discharge current and SOC, the discharge efficiency curve of lithium iron phosphate battery can be derived. The discharge efficiency of lithium iron phosphate batteries decreases approximately linearly. In this paper, it is processed by approximate linearization. The charging stage and the discharging stage have the same principle and can be treated uniformly.

II. A. 2) Operational objectives of electrochemical energy storage plants

The objective of the optimal operation of grid-side electrochemical energy storage plant is to maximize the energy efficiency and economy of the whole station, which is the optimization objective that can be equated to the minimization of the energy storage charging and discharging losses at the station end, i.e., the minimization of P_{loss}.

Assuming that there are i power conversion systems (PCSs) in the energy storage station, the charging and discharging power of each PCS is P_i, and the corresponding energy efficiency of the PCS at this charging and discharging power is η_i, the charging and discharging power loss of the PCS is $\left(\frac{1-\eta_i}{\eta_i}\right)P_i$.

In summary, the objective function F for the operation of the grid-side electrochemical energy storage plant is constructed.

$$P_{loss} = \sum_{i=1}^{n}\left(\frac{1-\eta_i}{\eta_i}\right)P_i \tag{1}$$

$$F = \min P_{loss} \tag{2}$$

Approximate linearization of the energy efficiency curve of Li-FePO4 battery in section 2.1.1, construct the relationship between energy efficiency and charging/discharging power as

$$\eta_i = \alpha P_i + \beta \tag{3}$$

where, α, β is the self-characterization of lithium iron phosphate battery, which is independent of the operation mode of the energy storage plant and can be considered as a constant, where the energy efficiency range $\eta_i \in (0,1)$. Substituting Eq. (3) into Eq. (1), it can be obtained:

$$P_{loss} = \sum_{i=1}^{n}\left(\frac{1-\alpha P_i - \beta}{\alpha P_i + \beta}\right)P_i \tag{4}$$

II. A. 3) Storage plant operational requirements and constraints

1) Satisfy the scheduling power command requirements, including real-time AGC commands or planning curves issued by the scheduling system, which is the main optimization objective. The power objectives are

$$P_{target} = \sum_{i=1}^{n} P_i \tag{5}$$

2) Satisfy the operating conditions and maximum chargeable and dischargable power constraints of each PCS.

$$P_{i\min} \le P_i \le P_{i\max} \tag{6}$$

where, $P_{i\min}$ and $P_{i\max}$ are derived from the combined assessment of the PCS operating status as well as the BMS operating status, which is generally uploaded by the PCS to the station EMS.

Combining Eq. (4) and Eq. (5), it can be concluded that

$$P_{loss} = \sum_{i=1}^{n} \left(\frac{1-\alpha P_i - \beta}{\alpha P_i + \beta} \right) P_i = \sum_{i=1}^{n} \frac{P_i}{\alpha P_i + \beta} - P_{target} \tag{7}$$

Since P_{target} is a constant, the objective function can be transformed into

$$F = \min P_{loss} = \min \sum_{i=1}^{n} \frac{P_i}{\alpha P_i + \beta} \tag{8}$$

The above model constraints have been linearized, the objective function is a convex function on the definition domain of the power variables, and the variables are of continuous type, so for the nonlinear optimization problem, it can be solved by convex programming. For the normal operation condition, the energy storage unit is not limited to power operation, and Jensen's inequality can be used to simplify the calculation.

If $f(x)$ is a convex function on the interval (a,b), then for any $x_1, x_2, x_3, \cdots, x_n \in (a,b)$, there is the inequality

$$f\left(\frac{x_1 + x_2 \cdots + x_n}{n} \right) \le \frac{f(x_1) + f(x_2) + \cdots + f(x_n)}{n} \tag{9}$$

The equal sign holds if and only if $x_1 = x_2 = x_3 = \cdots = x_n$.

From equations (8) and (9) it can be deduced that

$$\begin{aligned} P_{loss} &= \sum_{i=1}^{n} \frac{P_i}{\alpha P_i + \beta} \ge n \frac{\left(\frac{\sum_{i=1}^{n} P_i}{n} \right)}{\left(\alpha \sum_{i=1}^{n} P_i \right) / n + \beta} \\ &= \frac{P_{target}}{\frac{\alpha}{n} P_{target} + \beta} = \frac{n P_{target}}{\alpha P_{target} + n\beta} \end{aligned} \tag{10}$$

At this point, $P_1 = P_2 = \cdots = P_n$, i.e., the whole station power is equally distributed.

For power-constrained conditions, such as partial PCS alarms or BMS alarms, where the average allocation crosses the power allowance, convex programming is required to solve the problem.

II. B. Differential Evolutionary Algorithm

II. B. 1) Differential Evolutionary Algorithm Description

Differential evolutionary algorithm (DE) is a swarm intelligence algorithm designed to solve continuous type optimization problems. It simulates the evolutionary process in nature and searches for optimal solutions by means of continuous iteration. Compared with traditional algorithms, the differential evolution algorithm has many advantages. The differential evolution algorithm searches the solution space through difference operations and crossover operations, has a strong global search capability, can find the global optimal solution or a solution close to the optimal solution, and is suitable for solving various types of optimization problems, including continuous optimization problems, discrete optimization problems, and multi-objective optimization problems, etc., which is suitable for the energy storage power plant in this paper. PCS equipment optimization scheduling problem in this paper. In addition, the differential evolutionary algorithm is relatively insensitive to the selection of the initial population and the adjustment of the parameters, has good robustness, is not easy to fall into the local optimal solution, and also has good parallelism, the algorithm's computation process between the individuals is independent of each other, and it can effectively utilize the computational resources and accelerate the optimization process, which has a broad application prospect. However, to successfully solve the optimization problem, it is also necessary to carefully select the parameters and design a suitable fitness function to ensure that better optimization results can be achieved.

II. B. 2) Algorithm basic flow analysis

1) Initialize the population

In an optimization problem, each individual in the population represents a potential solution, and their position information is used to determine the candidate solutions, before the optimization starts, the positions of all the populations must be initialized to ensure that the populations are uniformly distributed throughout the D -dimensional optimization space, here a random method is usually used to generate the initial populations, and the size of the populations is denoted as NP, and Eqn. (11) is used to calculate the initial population position distribution of the initial population:

$$x_{i,j}(0) = x_{i,j}^{L} + rand(0,1)\left(x_{i,j}^{M} - x_{i,j}^{L}\right) \quad i = 1,2,3,\ldots,NP, j = 1,2,\ldots,n \tag{11}$$

where NP is the number of individuals in the population, n is the dimension, $x_{i,j}^{L}$ denotes the lower bound of individual optimization, $x_{i,j}^{M}$ denotes the upper bound of individual optimization, and the function $rand(0,1)$ denotes the generation of $[0,1]$ random numbers with a uniform distribution in the range.

2) Variation operation

The variation operation in differential evolutionary algorithm refers to randomly selecting one individual in the population as the base vector, and randomly selecting two or more other individuals as the difference vector, for each dimension j, calculate the difference between the difference vector and the base vector and multiply it by a scaling factor F, and then add the scaled difference to the base vector to get a new solution vector. The formula for the variation operation is:

$$V_i^{t+1} = x_{r_1}^t + F(x_{r_2}^t - x_{r_3}^t) \tag{12}$$

In Eq. (12), $x_{r_1}^t$, $x_{r_2}^t$, and $x_{r_3}^t$ are three individuals randomly selected from the t -generation population, and the parameter F is the scaling factor, which is an important parameter used to control the degree of the variation operation, and which usually takes a value in the range of $[0,1.5]$, and is used to scale the difference vector's size to control the generation of new solution vectors.

3) Crossover Operation

The crossover operation refers to comparing the new solution vector obtained after mutation with the original solution vector and selectively retaining part of the dimensions of the new solution vector with a certain probability, while retaining other part of the dimensions of the original solution vector, so as to generate a crossover solution vector.The main purpose of the crossover operation is to introduce a certain degree of variation based on the preservation of the original solution vector in order to promote the diversity of the population and the search space for the Exploration. The crossover probability is another important parameter of the algorithm, which determines how often the crossover operation occurs. The formula for the crossover operation is:

$$u_{i,j}^{t+1} = \begin{cases} V_i^{t+1}, & if\ rand(0,1) < CR\ or\ j = jrand \\ x_{i,j}^t, & else \end{cases} \tag{13}$$

In equation (13): CR is the crossover probability, $rand(0,1)$ is a random number between 0 and 1, and $jrand$ is a random integer between $[1, D]$.

4) Selection operation

The selection operation of the differential evolutionary algorithm adopts greedy selection, when determining the new generation of population, the individuals generated by the previous crossover operation are compared with the original individuals, and according to the fitness value of the individuals to choose whether to replace the individuals in the corresponding position in the original population, the purpose of this selection operation is to ensure that the new generation of population contains the individuals with higher fitness, so as to evolve in the direction of more optimal solutions. The selection operation is shown in equation (14):

$$x_{i,j}^{t+1} = \begin{cases} u_i^{t+1} & f(u_i^{t+1}) \le f(x_i^t) \\ x_i^t & f(u_i^{t+1}) > f(x_i^t) \end{cases} \tag{14}$$

5) The basic steps of the algorithm

Step 1: Set the parameters of the algorithm, the maximum number of iterations of the algorithm $Maxiter$, the variation operator F, the crossover operator CR, the upper limit of the variable ub and the lower limit of the variable lb, and the number of populations NP.

Step 2: Initialize the population and calculate the initial position distribution of each individual using equation (11).

Step 3: Enter the main loop of optimization search and use formula (12) to mutate the population.

Step 4: Crossover the population using formula (13).

Step 5: Check the boundary and perform selection operation using formula (14).

Step 6: Determine whether the maximum number of iterations $Maxiter$ is reached, if so, output the value of the objective function; otherwise, return to Step 3.

II. C.Improved differential evolutionary algorithms and their application to energy storage system configuration

In the process of solving the energy storage system configuration problem, although the traditional differential evolutionary algorithm shows some effectiveness, it is often limited by fixed parameter settings and a single search strategy when facing highly complex and multi-constraint optimization scenarios, which leads to inefficient searching and difficulty in achieving ideal optimization results. In order to cope with these challenges, this study adopts an improved differential evolutionary algorithm to solve the proposed model, which significantly improves the adaptability, robustness and optimization efficiency of the algorithm through the introduction of adaptive parameter tuning mechanism and hybrid mutation strategy.

Firstly, the improved differential evolution algorithm introduces an adaptive parameter adjustment mechanism for two key parameters in the traditional differential evolution algorithm, the scaling factor F and the crossover probability CR. The scaling factor F is responsible for controlling the amplification ratio of the difference vector, which directly affects the diversity and exploration range of the population; the crossover probability CR determines the degree of acceptance of the genetic information of the individuals in the crossover operation, which is related to the convergence speed and the precision of the algorithm. In traditional differential evolutionary algorithms, these two parameters are usually set to fixed values, and this static setting limits the ability of the algorithm to adapt to different optimization stages. In the improved algorithm, on the other hand, these two parameters will be dynamically adjusted according to the diversity of the population and the quality of the solution in the current iteration process, so that the algorithm can more flexibly balance the global exploration and the local utilization during the search process, improve the convergence speed, and reduce the risk of falling into the local optimum. For the adaptive adjustment of the scaling factor F, see equation (15).

$$F_i = F_{\min} + \left(F_{\max} - F_{\min}\right) \times rand_i\left(0,1\right) \tag{15}$$

where, F_i - scaling factor for the i th individual, $F_{\max}$ - the maximum value of the scaling factor, $F_{\min}$ - the minimum value of the scaling factor, $rand_i(0,1)$ - random numbers generated by the i th individual in the range $[0,1]$.

For adaptive adjustment of the crossover probability CR, see equation (16).

$$CR_i = CR_{\min} + \left(CR_{\max} - CR_{\min}\right) \times rand_i\left(0,1\right) \tag{16}$$

where, CR_i - crossover probability for the i th individual, $CR_{\min}$ - the minimum value of the crossover probability, $CR_{\max}$ - the maximum value of crossover probability.

Secondly, the improved differential evolutionary algorithm chooses to adopt a hybrid mutation strategy, which enables the algorithm to explore the solution space more comprehensively and enhances the diversity of solutions by choosing the most appropriate mutation strategy during iteration according to the characteristics of the optimization problem and the current search state. For DE/rand/1, DE/best/1, and DE/current-to-best/1 variation strategies, see Eqs. (17)-(19).

$$v_i = x_{rand_1} + F \times \left(x_{rand_2} - x_{rand_3}\right) \tag{17}$$

$$v_i = x_{best} + F \times \left(x_{rand_1} - x_{rand_2} \right) \tag{18}$$

$$v_i = x_i + F \times \left(x_{best} - x_i \right) + F \times \left(x_{rand_1} - x_{rand_2} \right) \tag{19}$$

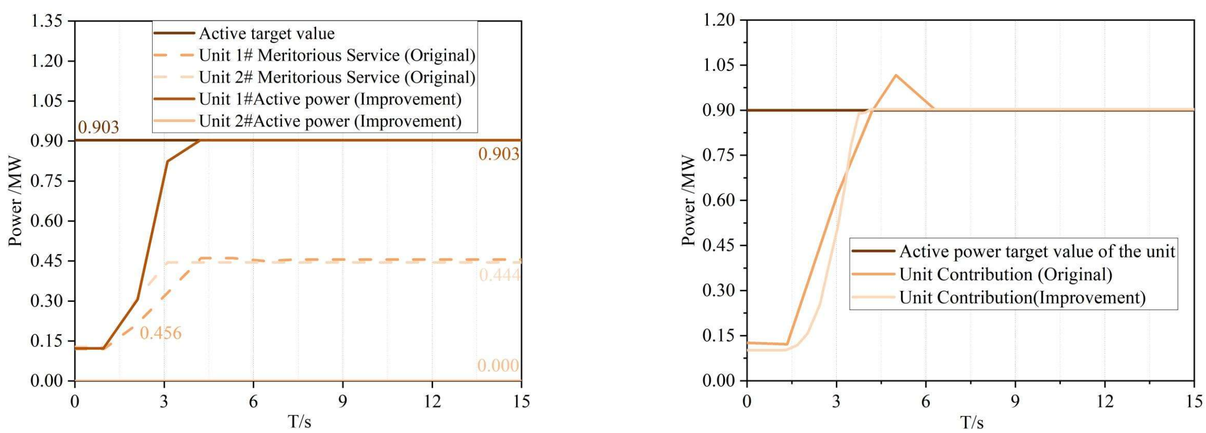
where, v_i - the variation vector; x_{rand_1}, x_{rand_2} and x_{rand_3} are 3 different individuals chosen at random, x_{best} - the best individual in the current population, x_i - the current target vector.

III. Optimization practice based on improved differential evolutionary algorithm

III. A. Effect of Output Power Steps

III. A. 1) Effect of small power steps

In order to determine whether the improvement of the differential evolution algorithm is effective or not, the step response tests of the differential evolution algorithm and the improved differential evolution algorithm at the time of parameter adjustment are set up. Figure 1 demonstrates the output power response of the algorithm for 2 units when increasing the output by 0.9 MW. From Fig. 1(a), it can be seen that under different allocation strategies, the units all start to act 2s after the command is given and are adjusted within 5s. Since the active step is 0.900 MW, the two units under the average allocation strategy of the traditional differential evolutionary algorithm regulate the active power of 0.444 MW and 0.456 MW, respectively, and their regulation curves basically conform to the linear relationship. The unit using the optimization strategy of the improved differential evolutionary algorithm allocates all the active power to unit 1#, and achieves stability after regulating to 0.903MW, and its regulation curve shows a trend of first fast and then slow. Figure 1(b) demonstrates the unit active at the whole station under the two algorithmic allocation strategies. The active regulation curves under different allocation strategies are similar to that of a single unit, and the average allocation strategy under the unimproved one has a linear relationship, and its overshooting phenomenon occurs for a short period of time after reaching the target value of active, which is maintained at 0.903-1.02 MW for 2.11s. The improved regulation curve becomes fast and then slow, and no overshooting occurs. The improved allocation strategy is able to ensure a consistent regulation response speed in response to step regulation, and it is also less prone to overshooting or unstable regulation speed due to its dynamic adjustment of the parameters of the control unit.



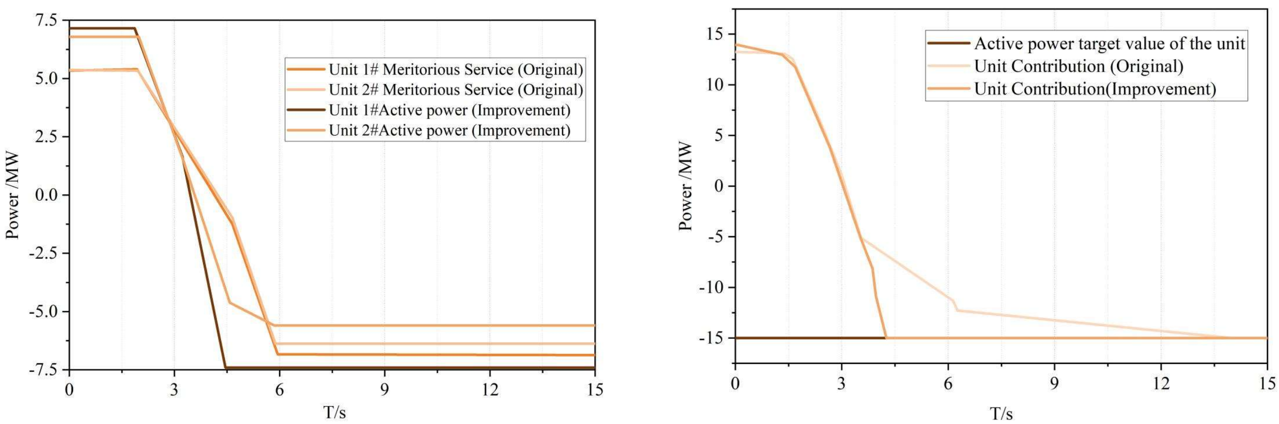
(a) Single unit response (b) Whole-Station Response

Figure 1: Corresponding outpbut power of the two units

III. A. 2) Effects of high power steps

The step response test of the two algorithms in regulating from discharging 15 MW output to charging 15 MW output was carried out and Fig. 2 shows the experimental results. Figure 2(a) shows the output power response of the 2 units. It can be seen that the units all start to act within 3s after the command is given and finish regulation within 6s, and the improved unit can shorten the regulation time to 4.5s compared with the pre-improved one. The active step is 30MW, and the two units regulate the active power from 15MW to -6.836MW and -6.378MW respectively under the allocation strategy of the traditional differential evolution algorithm, and the regulation curves basically conform to the linear relationship. The unit using the improved differential evolutionary algorithm allocation strategy allocates the active power to 2 units, of which, the power of 1# unit is larger, 7.154MW, and the allocated power of

2# unit is smaller, 6.789MW, and its regulation curve shows a trend of first fast and then slow. Comparing the regulation errors as a whole, the regulation accuracy of the allocation strategy of the improved differential evolutionary algorithm is better than that of the traditional differential improvement algorithm, and the introduction of the adaptive parameter adjustment mechanism in the differential evolutionary algorithm is effective to find a better global solution.



(a) Single unit response (b) Whole-Station Response

Figure 2: Step response experimental results

III. B. Algorithm optimization strategy effect and stability verification

III. B. 1) Changes in SOC of each cell under the optimization strategy

After verifying the effectiveness of the improved differential evolutionary algorithm for strategy optimization, it is applied in the optimization solution of the operation model of the actual large-scale energy storage power plant to obtain the final optimization strategy. Figure 3 shows the change of SOC of each unit in the optimization strategy. The strategy gives priority to the unit with better economy in the unit group Units1 optimization model. According to the output demand in different time periods, the energy consumption is reduced by dynamic adjustment of parameters to obtain the integrated highest economic efficiency.

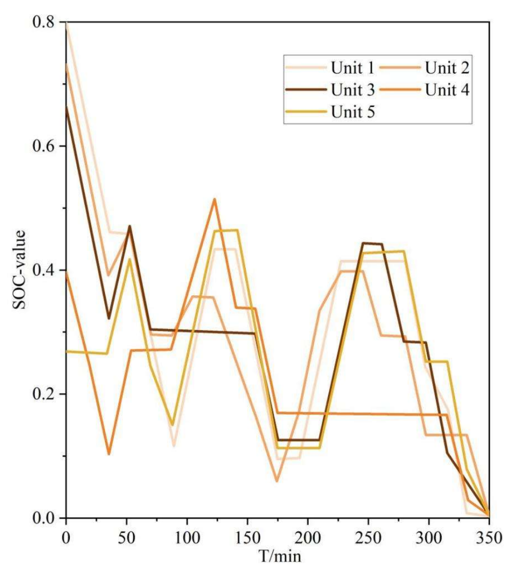
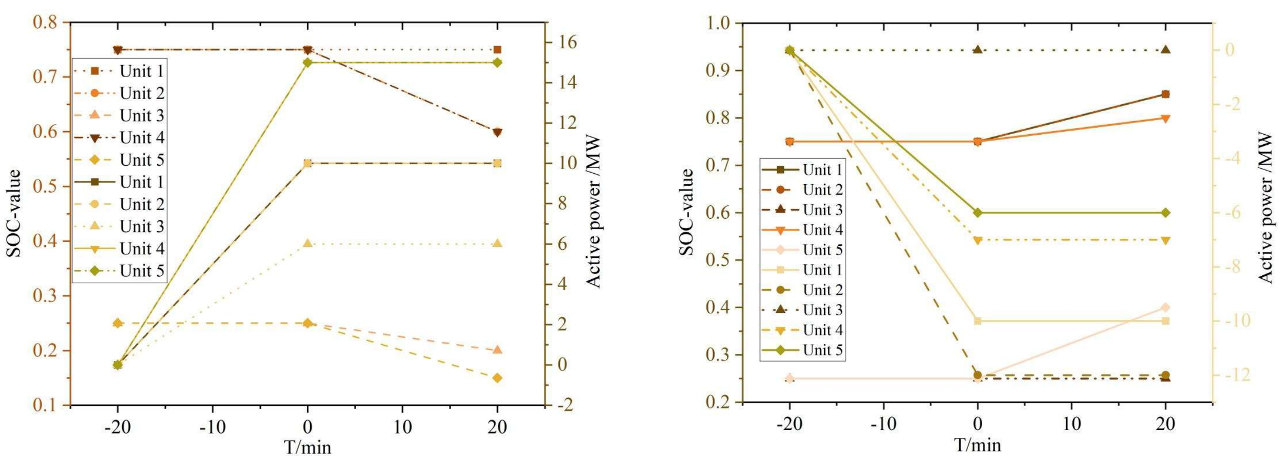


Figure 3: Changes in SOC of each unit in the optimization strategy

The equipment optimization strategy with improved differential evolutionary algorithm can reduce the number of charging and discharging transformations of 5 units, divide the unit group into charging group and discharging group, and when there is a demand for discharging in the power station, the output priority of the discharging group is greater than that of the charging group. For example, when the power demand is 20MW in 75~100min, also due to the opposite power status in the next moment, only the cost of FM is taken into consideration, at this time, the strategy in this paper calculates the maximum number of power required num through AGC instruction, and then dynamically adjusts it when the current power demand can not be satisfied. By the method of charging/discharging grouping and dynamic adjustment of the number of power outputs, the strategy in this paper allows unit 2 and unit 4 to make power outputs, and the state of charge (SOC) of the battery of unit 2 rises from 0.29 to 0.36, and the SOC of unit 4 rises from 0.27 to 0.51, while unit 3 stays unchanged, and unit 5 and unit 1 do not make power outputs. In this scenario not only reduces the life cycle cost, but also greatly reduces the number of charge/discharge conversion times, which correspondingly reduces the charge/discharge conversion cost. At the same time, in order to ensure the durability of the energy storage plant in response to the FM command, the strategy introduces the resistance coefficient related to the current SOC of each unit when constructing the objective function of minimizing the life cycle cost, so as to avoid overcharging and discharging of the units with better economy. It can be seen that the charging and discharging of each unit is always dynamic, and there is no case of overcharging and discharging of a certain unit.

III. B. 2) SOC and active output of each unit under different operating conditions

In order to verify the effectiveness of the improved differential evolutionary algorithm under extreme operating conditions, the following two extreme operating conditions are conducted using the system parameters under stable operating conditions. Extreme condition 1: the SOC parameters of unit 1-5 are 0.3, 0.3, 0.3, 0.7, 0.7; the charging and discharging states are discharging, discharging, discharging, charging, charging, and the AGC command is 50 MW; condition 2: the SOC parameters of unit 1-5 are 0.3, 0.3, 0.3, 0.7, 0.7; the charging and discharging states are discharging, discharging, discharging, charging, charging, and the AGC command is -50 MW; Fig. 4 is a diagram of the extreme conditions. ; AGC command is -50 MW.Fig. 4 shows the SOC and active output of each unit under different working conditions. Although the SOC is close to the extreme condition of 0.75 under extreme operating condition 1, the active power of the five units can still be efficiently dispatched between -2 and 16 MW. Under extreme operating condition 2, the SOC is close to the extreme condition of 0.85, and the active power of the five units can still be effectively dispatched between -12 and 0 MW. From this, it can be judged that even under extreme operating conditions, the improved differential evolution algorithm used in this paper can still work properly, and under the guaranteed grid-connection criteria and response constraints, the charging and discharging behaviors of the PCS devices of the five units can be correctly scheduled, so as to optimize the decision-making for the power output of the energy storage plant and to improve the economic returns.



(a) Condition 1 (b) Condition 2

Figure 4: SOC and active power output of each unit under working conditions

III. C. Comparative Experiments and Analysis of Results

In order to further judge the advantages of this paper's method, four objective evaluation metrics are selected as algorithm evaluation criteria. The evaluation indexes include root mean square error (RMSE) of power shortage, energy storage utilization, system operation cost and calculation time. Among them, the energy storage utilization rate is defined as the ratio of the actual charge and discharge to the rated capacity; the system operating cost includes the peaking cost of conventional units and the storage loss cost in Yuan/MW·h. The experiments comprehensively evaluate the performance of the proposed methods by comparing the traditional rule-based method, the single MPC method, and the optimization method based on the improved differential evolution algorithm proposed in this paper.

Table 1 shows the performance comparison results of the three methods. Compared with the traditional rule-based method, the coordinated optimization method proposed in this paper shows significant advantages in all indicators. The power shortage RMSE is only 20.16 MW, which is much less than the 80.27 MW and 56.48 MW of the other 2 compared methods. The energy storage utilization rate reaches 90.13%, which is higher than the 58.49% and 69.24% of the compared methods. Meanwhile, the system operation cost is only 237.91 Yuan/MW·h, which is less than the 500.35 Yuan/MW·h of the traditional rule-based method and the 402.74 Yuan/MW·h of the single MPC method, and the computation time is 13.84s, which is slightly lower than the comparison methods of 14.56s and 16.73s.The significant effect of the proposed method in this paper in improving the power balance accuracy, increasing the energy storage utilization efficiency and reducing the system operation cost.

Table 1: Performance comparison of different methods

Method	Power shortage RMSE/MW	Energy storage utilization rate /%	System operating cost/yuan /(MW·h)	Calculate time /s
Traditional rule-based method	80.27	58.49	500.35	14.56
Single MPC method	56.48	69.24	402.74	16.73
Article optimization method	20.16	90.13	237.91	13.84

IV. Conclusion

In this paper, an improved differential evolutionary algorithm is used to realize the dynamic solution of the PCS equipment optimization and grid support strategy of the energy storage plant. The improved differential evolution algorithm has faster regulation time and smaller regulation error in the small power step of increasing 0.9 MW output and the high power step of regulating from discharging 15 MW output to charging 15 MW output. The number of charging and discharging transitions of the five scheduling units under the optimization strategy is reduced, which improves the economic return.The algorithm in this paper can still output the scheduling optimization strategy stably under the extreme working conditions with SOC values of 0.75 and 0.85. The root mean square error (RMSE) of power shortage is 20.16MW, the utilization rate of energy storage reaches 90.13%, the system operation cost is only 237.91 Yuan/MW·h, and the computation time is 13.84s, which makes this paper's method better than the 2 compared methods. Future research can further integrate deep learning techniques to enhance the generalization ability of the improved differential evolution algorithm for complex working conditions.

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