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Optimized Economic Operation Strategy for Distributed Energy Storage With Multi-Profit Mode

PENG PENG[1], YONGQI LI[1], DINGLIN LI[1], YUDA GUAN[2], PING YANG[2], (Member, IEEE), ZHENKAI HU[1], ZHUOLI ZHAO[3], (Member, IEEE), AND DONG LIU[4], (Senior Member, IEEE)

[1]CSG Power Generation Company Ltd., Guangzhou 510630, China
[2]Guangdong Key Laboratory of Clean Energy Technology, South China University of Technology, Guangzhou 510640, China
[3]School of Automation, Guangdong University of Technology, Guangzhou 510006, China
[4]Department of Energy Technology, Aalborg University, 9220 Alborg, Denmark

Corresponding authors: Ping Yang (eppyang@scut.edu.cn) and Zhuoli Zhao (zhuoli.zhao@gdut.edu.cn)

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ABSTRACT Distributed energy storage (DES) on the user side has two commercial modes including peak load shaving and demand management as main profit modes to gain profits, and the capital recovery generally takes 8-9 years. In order to further improve the return rate on the investment of distributed energy storage, this paper proposes an optimized economic operation strategy of distributed energy storage with multi-profit mode operation. Considering three profit modes of distributed energy storage including demand management, peak-valley spread arbitrage and participating in demand response, a multi-profit model of distributed energy storage is established, and the proposed optimal operation strategy formulates three stages of the energy storage operation, namely month-ahead, day-ahead, and in-day. In the month-ahead optimization stage, the demand charge threshold of the next month is optimized to minimize the electricity cost. In the day-ahead optimization stage, under the constraint of demand charge threshold and with the goal of maximizing returns, the distributed energy storage is controlled to participate in peak-valley spread arbitrage and demand response, and the optimized output curve for the next day is calculated. In the in-day optimization stage, based on the optimized output curve, taking real-time demand response into account, the real-time charge-discharge power of energy storage is adjusted dynamically with the goal of minimizing income loss, thus to realize adaptive adjustment of distributed energy storage and eliminate the risk of income loss. Simulation results of distributed energy storage for typical industrial large users show that the proposed strategy can effectively improve the economic benefits of energy storage.

INDEX TERMS Distributed energy storage, demand management, demand response, peak-valley spread arbitrage, multi-profit model.

I. INTRODUCTION

Due to the characteristics of decentralized layout and flexible charge-discharge, distributed energy storage (DES) can effectively smooth the grid load curve, promote distributed energy consumption, improve power quality and so on, which plays an increasingly prominent role in the construction of smart power grid [1], [2].

Until now, DES on the user side has already had several commercial modes including peak-valley spread arbitrage and demand management as main profit modes to gain profits [3]. Due to factors such as policy support and market environment, the profit modes of DES in countries are different. In California, the electricity cost of the industrial and commercial customer remains high, which result in income of DES comes from the reduction of demand charge and the initial installation subsidy of DES [4]. In Japan, the photovoltaic storage mode of DES and the echelon utilization of batteries

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are the main business modes to gain profits. Based on the concept of aggregation and sharing, Germany became the first country to create a community-based business model of DES [5], [6]. Chinese industrial and commercial enterprises implement the two-part tariff and the peak-valley electricity price, providing two profit modes including demand management and peak-valley spread arbitrage for DES. However, the investment return of DES is relatively low, and the investment recovery period generally takes eight-nine years [7], [8].

In order to improve the investment return of distributed energy storage, academic institutions and industrial sectors have carried out researches on the optimal operation strategy of distributed energy storage under the profit mode of peak-valley arbitrage. In [9], three models are established to analyze the application of energy storage in auxiliary service markets and revenue maximization in the context of feed-in tariffs. Aiming at reducing the operating cost and investment cost of energy storage and obtaining sufficient profits, DES is controlled to participate in spatiotemporal energy arbitrage in [10]. To minimize the whole life cycle operation and maintenance of energy storage system, literature [11] solves the optimization problem of participating in peak load shaving with the second-order cone programming taking into account the factors such as charge and discharge loss, peaking and valley filling efficiency of the energy storage system. Literature [12] determines the charge-discharge power of the battery energy storage system according to the load curve with different peak and valley characteristics and the change of electricity price, and also analyzes the profitability and effect of the scheduling strategy.

To further improve the investment return of distributed energy storage, not only demand management but also peak valley spread arbitrage have been considered in researches. Considering the influence of charge-discharge cycles times per day on the distributed energy storage life, [13] establishes an optimal operation model of distributed energy storage, with the goal of maximum the income of participating in demand management and peak-valley spread arbitrage. Taking the maximization of users' electricity income as optimization objective, [14] sets the upper limit value of users' electricity consumption in advance and dynamically adjusts the energy storage output. Some optimized operation strategies for distributed energy storage in dual-mode operation have been proposed [15], [16]. Aiming at minimizing electricity cost, a mechanism is established in the optimization operation strategy to optimize the demand charge threshold, realizing real-time dynamic optimal operation of distributed energy storage [15]. Literature [16] optimizes the charge-discharge power of distributed energy storage according to the peak and valley characteristics of users' load curves. And the simulation results show that the optimization of optimization operation strategy is not obvious for users with small peak-valley difference. However, the peak-to-valley price difference is relatively low in China. Hence, the investment recovery period of distributed energy storage under dual-mode operation still needs more than seven years.

With the implementation of power demand response mechanisms in multiple regions in China [17], participating in demand response is becoming an important profit mode of distributed energy storage. Taking into account the participation in demand response, [18] proposes an energy management system, which schedules the operation of distributed energy storage based on the day-ahead forecast data to improve the energy storage utilization rate. In [19], the demand charge threshold is considered to increase the benefits of demand response while optimizing the energy storage output in real time to improve the utilization rate of energy storage. The above distributed energy storage optimization problems are generally nonlinear optimization problems with constraints, which can be solved by heuristic algorithms such as genetic algorithm and particle swarm optimization [20]. The multi-period multi-energy scheduling of a multi-carrier energy system is a nonconvex optimization problem, which is reformulated in [21] as a mixed-integer second-order cone programming and solved with a sequential second-order cone programming approach.

So far, no research has been done to establish an optimized operation strategy on the multi-mode operation of distributed energy storage with multiple profit modes: demand management, peak load shaving and participating in demand response. This paper proposes a distributed energy storage optimization operation strategy considering demand management, peak-valley spread arbitrage and participating in demand response to improve the return on investment of distributed energy storage. The contributions of this paper are listed as follows.

(1) A multi-profit model of the distributed energy storage is built based on the analysis towards three profit modes, i.e., the demand management, peak load shaving and participating in demand response, considering the impact of operation plans on the distributed energy storage.

(2) An optimized economic operation strategy in three stages (i.e., month-ahead, day-ahead, and in-day stage) is proposed based on the multi-profit model to maximize the economic benefits of the distributed energy storage.

(3) This paper proves that distributed energy storage can obtain economic benefits in multi-profit mode, and the proposed strategy can be applied to any kind of energy storage.

The rest of this paper is as follows. A multi-mode operation based economic benefit model of distributed energy storage is established in Section II. Section III proposes the economic optimization operation strategy of distributed energy storage. The case studies and numerical results are given in Section IV. Finally, Section V concludes this paper.

II. MULTI-MODE OPERATION BASED ECONOMIC BENEFIT MODEL OF DES

Taking into consideration of three profit modes including demand management, peak-valley spread arbitrage and participating in demand response, the multi-mode operation based economic benefit model of DES is established below.

A. ECONOMIC BENEFIT MODEL OF DEMAND MANAGEMENT BASED PROFIT MODE

Chinese industrial and commercial power users adopt a two-part tariff, namely the basic electricity price and energy price [22]. The basic electricity cost is calculated based on the user's the actual maximum demand and the demand charge threshold of the month. Industrial and commercial power users can reduce basic electricity cost by shifting peak load.

The corresponding demand management economic benefit model is as follows:

$$B_I = \begin{cases} p_{dm}(a - a_m) & b \leq 1.05a_m \\ p_{dm}(a - a_m) - 2p_{dm} \cdot (b - 1.05a_m) & b > 1.05a_m \end{cases} \tag{1}$$

where B_I is the income after the power demand control; p_{dm} is the capacity price with the unit of power; a_m is the demand charge threshold; a is the maximum demand value without considering the energy storage output; and b is the actual maximum demand.

B. ECONOMIC BENEFIT MODEL OF SHIFTING PEAK AND FILLING VALLEY BASED PROFIT MODE

The energy price for industrial and commercial users in China is set as peak-valley electricity price according to different time periods. User owned DES gains benefit from the difference of peak-valley electricity price (i.e., discharging in peak hours and charging in valley hours), the corresponding economic benefit model of shifting peak and filling valley is as follows:

$$B_{II} = \sum_{t}^{T_d} P_{dis}(t)\Delta t \cdot p_f - \sum_{t}^{T_c} P_{cha}(t)\Delta t \cdot p_g - C_{loss} \tag{2}$$

where B_{II} is the income of peak shifting and valley filling; $P_{dis}(t)$, $P_{cha}(t)$ is the discharged and charged power of peak shaving and valley filling respectively; p_f, p_g is the peak and valley price of electricity respectively; T_d, T_c is the duration of peak shaving and valley filling respectively; C_{loss} is the single-day charging and discharging cost of the energy storage.

Calculate the charging and discharging cost of the energy storage per day according to the depth of charge-discharge and the charge-discharge cycle times per day [23], the formula is as follows:

$$C_{loss} = N_{eq} \cdot \frac{C_{APV}}{365} \tag{3}$$

$$C_{APV} = C_{op} + C_{PV}\frac{r(1+r)^{T_{Ess}}}{(1+r)^{T_{Ess}} - 1} \tag{4}$$

where C_{APV} is the investment and operation cost of DES with the unit of years; C_{op} is the operation and maintenance cost with the unit of years; C_{PV} is the initial outlay cost; r is the discount rate; T_{Ess} is the energy storage life.

The calculation formula for obtaining the equivalent full-cycle times of energy storage named N_{eq} is as follows:

$$N_{eq} = \sum_{i} (DoD_i)^{k_p} \tag{5}$$

where DoD_i is the actual discharge depth of each cycle of DES, k_p is the curve fitting parameter.

C. ECONOMIC BENEFIT MODEL OF DEMAND RESPONSE BASED PROFIT MODE

The demand response incentive policy in China encourages industrial and commercial power users to participate in the demand response, and users executing response can obtain economic compensation. The corresponding economic benefit model of demand response is as follows:

$$B_{III} = nP_D p_{DR} \tag{6}$$

where B_{III} is the income of participating in the demand response; n is the times of participating in demand response; P_D is the response-able power; p_{DR} is the base price of every 1 kW response-able power provided when participating in demand response.

D. MULTI-MODE OPERATION BASED ECONOMIC BENEFIT MODEL

In order to improve the economic benefits of DES, this paper designs a multi-mode based economic benefit model, which considers three profit modes, namely demand management, peak-valley spread arbitrage and participating in demand response. These three profit models involve the operational control of DES on three different time scales: month-ahead, day-ahead and in-day. The economic benefits of the DES can be maximized by rationally designing the multi-time scale operation control strategy.

In the month-ahead stage, the goal of optimization is to minimize the electricity cost of the user as much as possible. The income calculation model is obtained as follows:

$$B_{total\_m} = B_I + B_{II} \tag{7}$$

where B_{total_m} is profits from DES participating in demand management and peak-valley spread arbitrage.

In the day-ahead stage, the goal of optimization is to maximize the benefits, with consideration of peak-valley spread arbitrage and participating in demand response.

a) **The demand response center does not issue a response invitation.** Under the constraint of demand charge threshold, users owning DES gains profit by peak-valley spread arbitrage.

b) **The demand response center sends out a response invitation.** Considering the constraint of maximum demand, with the goal of maximizing the benefits of DES, suitably allocate energy storage capacity to participate in demand management and demand response to obtain benefits.

Therefore, the day-ahead economic benefit model of multi-mode operation can be obtained as:

$$B_{total\_d} = \begin{cases} B_{II} & DR = 0 \\ B_{II} + B_{III} & DR = 1 \end{cases} \tag{8}$$

where B_{total_d} is profits from the DES participating in demand response and peak-valley spread arbitrage in the day-ahead stage.

In the in-day optimization, the optimal object is ironing out loss of revenue, that is, avoid exceeding demand charge threshold and gain economic benefit by participating in real-time demand response. Taking real-time demand response into account, the calculation model of total benefit can be obtained as:

$$B_{total\_r} = B_I + B_{II} + B_{III} \tag{9}$$

where B_{total_r} is profits from the DES participating in demand response and peak-valley spread arbitrage in the in-day stage.

III. OPTIMIZED ECONOMIC OPERATION STRATEGY IN MULTI-MODE OPERATION

On the premise of satisfying the operational constraints and based on the aforementioned analysis of the three profit modes, an optimized economic operation strategy is designed for the DES through comprehensively considering three profit modes of DES, i.e., the demand management, peak-valley spread arbitrage, and participating in demand response to maximize economic benefits of DES.

A. OPERATIONAL CONSTRAINTS OF DES

In the economic optimization operation of the DES with three different time scales of month-ahead, day-ahead and in-day, the constraints should always be satisfied, namely power balance between the source and load, energy constraints of DES, and equivalent full-cycle times of DES should always be satisfied.

1) POWER BALANCE BETWEEN THE SOURCE AND LOAD

Source-charge power balance refers to that the power input to the grid must be conserved with the plant load and the total load of the DES.

$$P_{\text{in}} = P_{\text{load}} + P_{\text{ESS}} \tag{10}$$

where P_{in} represents the input of active power by the grid; P_{load} represents the sum of the output of active power on the user side; P_{ESS} represents the output of active power by DES.

2) ENERGY CONSTRAINTS OF THE DES

The energy constraint of the DES means that the stored energy in the energy storage is subject to the constraints of charging power and energy consumption, and the State of Charge (SOC) needs to (meet the constraints of upper and lower limits and time sequence continuity. Due to the SOC of energy storage devices is accumulated according to time sequence, the limit of SOC amplitude needs to be satisfied at each time point.

The energy constraints of DES are as follows:

$$SOC(t) - SOC(t + \Delta t) = \frac{P(t)\Delta t}{E_e} \tag{11}$$

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max} \tag{12}$$

where $SOC(t)$ represents the SOC of the energy storage device at time; $P(t)$ represents the active power output of the energy storage device at time; E_e is the rated capacity of the energy storage device; $SOC_{\min}, SOC_{\max}$ is the lower limit and upper limit of SOC of the energy storage device.

3) EQUIVALENT FULL-CYCLE TIMES OF DES

The equivalent full-cycle times of DES are limited within a certain range to extend the life of DES:

$$\sum_{i=1}^{I} (K_D^d DoD_i + B_D^d) \leq N^{\lim} \tag{13}$$

where, on the left side of the inequality, the equivalent full-cycle times of energy storage are calculated, K_D^d and B_D^d are linearized parameters for different discharge depth intervals; $N^{\lim}$ is the maximum equivalent cycle times of DES within the simulation period.

Moreover, in the month-ahead and day-ahead optimized operation of DES, the SOC value at the initial time should be equal to that at the end time within a charging and discharging operation cycle.

$$SOC(0) = SOC(T) \tag{14}$$

where, $SOC(0)$, $SOC(T)$ are the SOC value of the energy storage device at the initial time and the complete cycle time respectively; T is the simulation cycle.

B. MULTI-MODE OPERATION BASED OPTIMIZED ECONOMIC OPERATION STRATEGY

Under the operational constraints of the DES, considering three profit modes including demand management, peak-valley spread arbitrage and participating in demand response, the operation strategy of DES at three stages (i.e., month-ahead, day-ahead and in-day stage) is formulated to maximize the profit of DES.

1) OPTIMIZED OPERATION OF MONTH-AHEAD STAGE

In the month-ahead optimization, with the goal of minimizing the electricity cost, it is necessary to submit the optimal demand charge threshold for demand management according to the profit mode of demand control, sequentially reducing the basic electricity price. Accordingly, the month-ahead optimized operation strategy is designed.

a: CALCULATION OF THE OPTIMAL DEMAND CHARGE THRESHOLD

Since the goal of calculating demand charge threshold is to maximize the economic benefit of the next month, the optimal output control curve of energy storage should be calculated based on the comprehensive load-forecast curve first. To avoid falling into the local optimizations and overcome the difficulty in determining the penalty function, double-fitness particle swarm optimization algorithm is used to obtain the optimal output control curve of energy storage: 1) chaotic map equation is integrated into particle swarm optimization to improve the global optimization ability of the algorithm;

2) the fitness function of standard particle swarm optimization is improved. The typical daily load forecasting curve calculation method and the improved particle swarm optimization algorithm are designed as follows.

1) The typical daily load forecasting curve calculation method. Since the user's maximum demand of the month is mainly determined by the heavy load days of the month and there exists a regularity in the electricity consumption of large industrial users. The heavy-load days with spikes load is taken as typical days in order to facilitate the load analysis of each user. Thus, accumulate the load of the same period and take the arithmetic average to obtain the average load forecasting curve of the month. Additionally, considering the impact of monthly load forecasting inaccuracy [24], to reduce the monthly profit bias, the typical daily load forecasting curve should be appropriately adjusted for different users based on their possible maximum forecast inaccuracy.

$$P_{intgr} = (1 + k_f) \cdot \frac{\sum_{j=1}^{N_{day}} P_j}{N_{day}} \tag{15}$$

where P_{intgr} is the power sequence value of the typical daily load prediction curve; k_f is the inaccuracy of monthly load forecasting; P_j is power sequence values of typical days; N_{day} is the total number of typical days.

2)The double-fitness PSO algorithm calculation process is as follows:

a) Initialization setup of the particle swarm. Initialize particle swarm population size n, particle dimension d, learning factor, inertial parameter and iterations.

b) Initialize particle position and speed. Generate a set of random numbers within the interval of [0,1], denoted as $X_1 = (x_1, x_2, \ldots, x_d)$. By using the logistic equation, X_1 i chaotized to obtain $X_2, X_3, \ldots, X_n$. The chaotic vector $X_1, X_2, \ldots, X_n$ is mapped to the value interval of energy storage charge-discharge power, and the initial position value of each particle can be obtained. Similarly, the above method is used to generate the initial velocity of each particle in the population.

c) Calculate the fitness of particles. Calculate the target fitness and constraint fitness of particles respectively, and compare the fitness of particles according to the double fitness criterion to obtain the individually optimal value namely P_{best} and the globally optimal value namely G_{best}.

The formula of the double fitness function is as follows:

$$fitness(x) = f(x) \tag{16}$$

$$vio(x) = \sum_{j=1}^{P} \left|\min(0, g_j(x))\right| + \sum_{k=1}^{q} |h_k(x)| \tag{17}$$

where, $fitness(x)$ is target fitness; $vio(x)$ is constraint fitness; $f(x)$ is the optimization objective function; $g_j(x)$ is inequality constraint in optimization problem; $h_k(x)$ is the equality constraint.

d) Update particle's speed and position.

$$\begin{cases} v_{id}^{k+1} = wv_{id}^{k} + c_1 \cdot rand() \cdot (P_{id} - x_{id}^{k}) \\ \qquad\quad + c_2 \cdot rand() \cdot (P_{gd} - x_{id}^{k}) \\ x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \end{cases} \tag{18}$$

where v is the speed of the particle; w is the weight of inertia; x is the position of the current particle; P_{id}, P_{gd} are the individual optimal value and the global optimal value of the particle, respectively; $rand()$ is a random number between (0, 1); c_1, c_2 are learning factors.

e) Introduce chaos disturbance. Introduce chaos disturbance to the updated particle positions.

f) Iteration termination judgment. If the iteration termination condition is met, the loop will be jumped out; otherwise, go to step c) and continue the loop until the iteration termination condition is met.

g) The global optimal value of the particle is obtained. After the iteration is terminated, the particle solution with the optimal fitness is taken as the optimal solution.

The flowchart of the double-fitness PSO algorithm is shown in Fig. 1.

After solving the optimized output curve of energy storage, the demand range that DES can reduce and the reduced load curve will be calculated to obtain the appropriate maximum demand value, which will be submitted as the demand charge threshold of that month.

b: OPTIMIZATION OPERATION STRATEGY BASED ON NEXT MONTH'S DEMAND CHARGE THRESHOLD

Based on solving the demand charge threshold of the next month, the flowchart of optimized operation strategy on the month-ahead stage is shown in Fig. 2.

2) OPTIMIZED OPERATION OF DAY-AHEAD STAGE

In the day-ahead optimization, with the goal of maximizing the next-day economic benefit, it is necessary to obtain optimized output curves of DESs based on the day-ahead load forecasting curve. Accordingly, the day-ahead optimized operation strategy is designed.

(1) If the demand response center does not send a response invitation, with the constraint of the demand charge threshold, the optimization goal is set as maximizing the return of peak-valley spread, our objective can be written as to maximize the economic income calculation model involved in peak-valley spread arbitrage. The optimized output curve for the next day is obtained by using the solution software of mixed-integer programming based on the day-ahead load-forecasting curve.

(2) If the demand response center sends a response invitation, with the constraint of the maximum demand and the goal of maximizing the total revenue, the optimal response power is obtained by the binary iteration method based on the day-ahead load forecasting curve and the multi-mode operation economic benefit model. Based on the calculated optimal response power, the mixed-integer programming solution software is used to obtain the energy storage output.

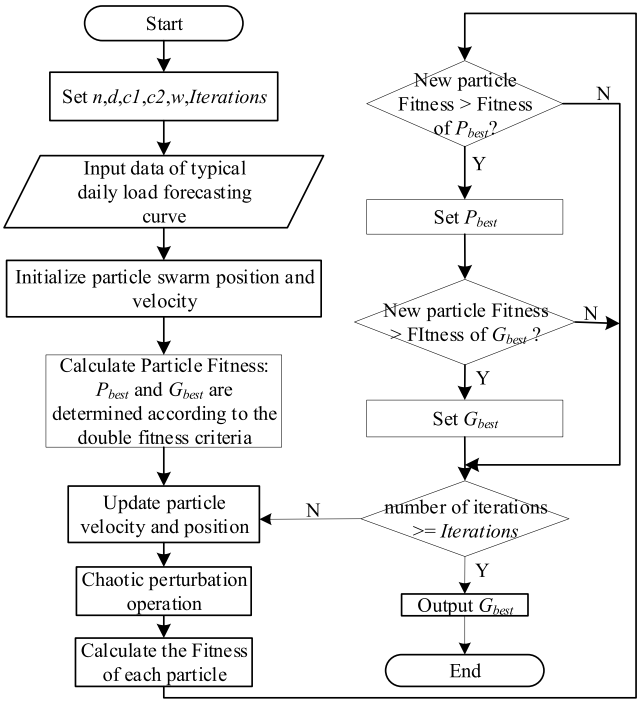

FIGURE 1. **Flowchart of double fitness chaotic particle swarm optimization algorithm for solving output curve of energy storage optimization.**

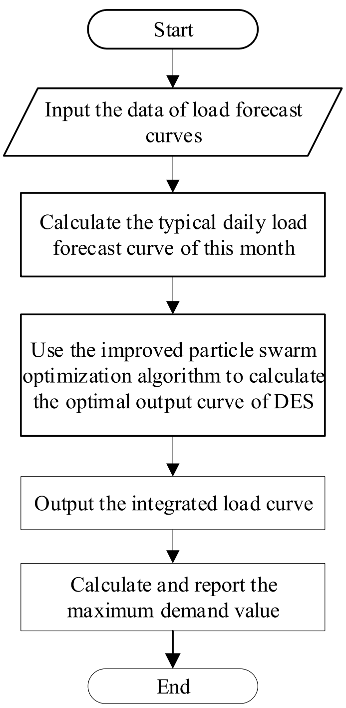

FIGURE 2. **Flowchart of optimized operation strategy before the month.**

The flowchart of the binary iteration method is shown in Fig. 3.

Based on solving the optimized output curve of the next day, the flowchart of the optimized operation strategy on day-ahead stage is shown in Fig. 4.

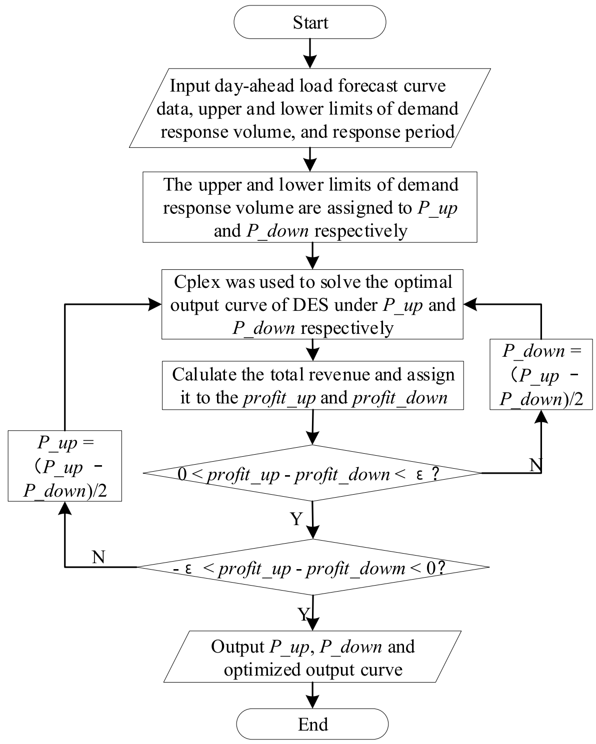

FIGURE 3. **Flowchart of binary iteration method for solving optimal response power.**

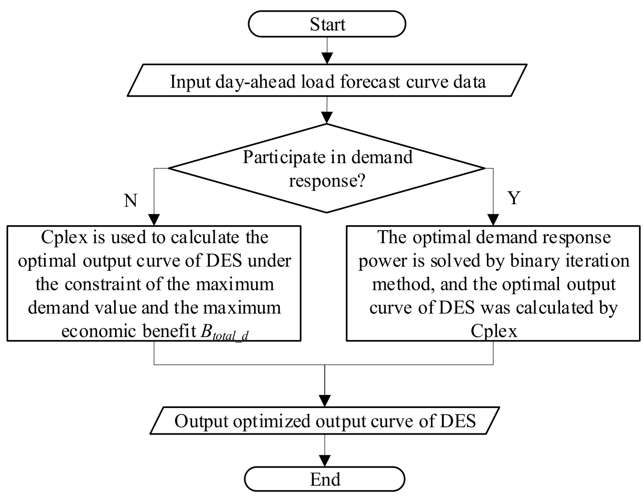

FIGURE 4. **Flowchart of day-ahead optimized operation strategy.**

Since the accuracy rate of the day-ahead load forecasting curve can reach more than 95% [25], [26], the maximum load demand is still within the demand charge threshold range even in the most extreme case (i.e., the peak load forecast value is 5% smaller), and DES reserves a certain amount of extra charging and discharging space, the inaccuracy of day-ahead load forecast curve may not be considered.

3) OPTIMIZED OPERATION OF IN-DAY STAGE

In the in-day optimization, with the goal of minimizing the loss of revenue, it is necessary to optimize the energy storage

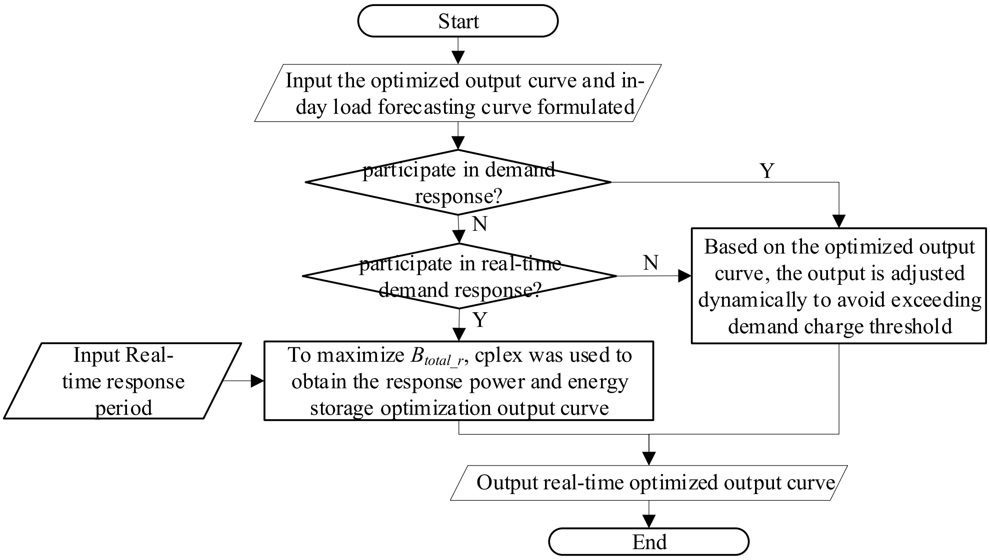

FIGURE 5. Flowchart of in-day optimized operation strategy.

output in real-time stage. Accordingly, the in-day optimized operation strategy is designed.

(1) If the demand response center does not issue an invitation for the real-time demand response, DES will be operated according to the optimized output curve formulated before the day. Meanwhile, since the control frequency of the charging and discharging power is at the second level [27], the output of energy storage can be adjusted in real time to ensure that the actual maximum demand does not exceed the demand charge threshold of 1.05 times. The calculation formula of the adjusted real-time output of energy storage is as follows

$$P_{Ess\_real}(t) = P_{Ess\_d}(t) + (P_{load\_real}(t) - 1.05 \cdot a_m) \tag{19}$$

where $P_{Ess\_real}(t)$ is the adjusted real-time output of energy storage; $P_{Ess\_d}(t)$ is the energy storage optimization output curve formulated recently; $P_{Ess\_d}(t)$ is the user real-time load size.

(2) If the demand response center sends an invitation for real-time demand response, and there is no day-ahead demand response task at this time, then DES will be controlled to participate in real-time demand response, and the in-day optimized output curve is obtained by using the solution software of mixed-integer programming based on the in-day load forecasting curve and the multi-mode operation economic benefit model.

Based on solving the in-day optimized output curve, the flowchart of the in-day optimized operation strategy is shown in Fig. 5.

IV. CASE STUDIES

A. SIMULATION DESIGN

To verify the effectiveness of the proposed multi-mode operation optimization strategy and solution algorithm in this paper, a double-fitness particle swarm algorithm combined with a mixed-integer programming software (CPLEX) method is developed in the environment of Python 3.6. Additionally, for verifying the universality of the proposed strategy and evaluate the economic operation performances of DES with the proposed strategy, several typical large industrial power consumers A, B, and C in a certain area are selected as research examples to simulate the proposed optimized operation strategy. In the simulation, 1) the tested area adopts a two-part electricity rate; 2) the actual maximum demand is calculated and collected at a basic electricity fee of ¥39 /(kW·month); 3) the DES participates in the day-ahead agreed response(1st of June) and real-time demand response(16th of June) within one month; 4) the economic compensation for 1 kW·h of the day-ahead agreed response and real-time response is ¥5; 5) the response period of day-ahead agreed response and real-time response is 16:00-18:00. In addition, the electricity price of peak-valley is shown in Tab. 1.

TABLE 1. Peak-valley time-of-use price.

Peak-valley price	Period	Price/(¥/kW·h)
Valley	0:00—8:00	0.3507
Flat	12:00—17:00, 21:00—24:00	0.7014
Peak	8:00—12:00, 17:00—21:00	1.1373

The typical daily load forecasting curve of industrial power consumers A, B, and C are shown in Fig. 6. The day-ahead load forecasting curve of industrial power consumers A, B, and C in June are shown in Figs. 7-9. The sample interval is 15 min, thus we have 96 samples per day. From the figures, the following points can be observed.

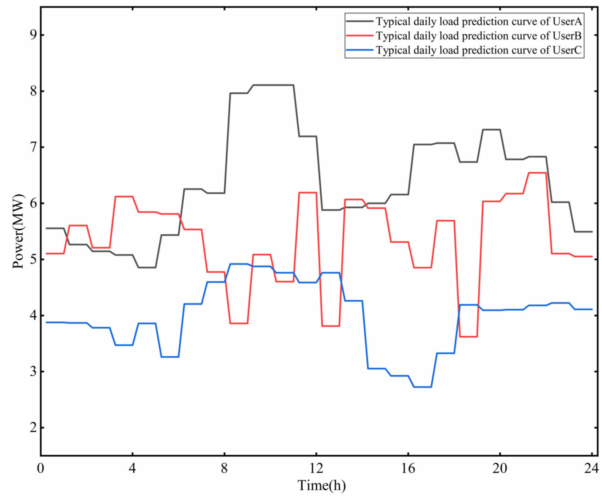

FIGURE 6. The typical daily load forecasting curve of industrial power consumer A, B, and C.

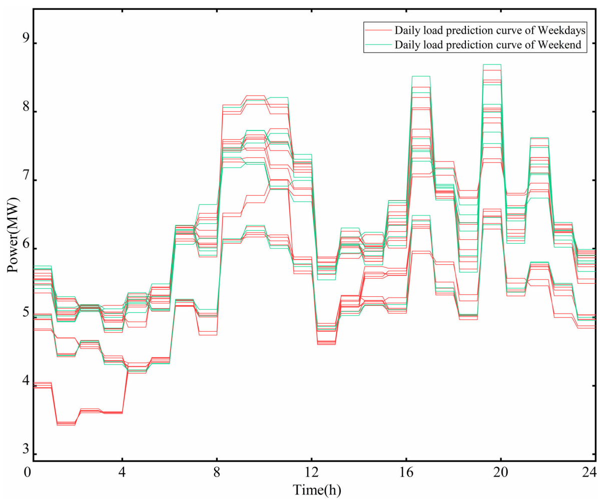

FIGURE 7. The day-ahead load forecasting curve of industrial power consumer A in June.

For the industrial power consumer A, the maximum demand is close to 9 MW, whereas the load curve shows obvious bimodal characteristics, i.e., distributed from 8:00 to 12:00 in the morning and from 13:00 to 20:00, and the electric power consumption at night is lower than that during the day. For the industrial power consumer B, the electricity consumption constantly keeps in the peak state throughout the day, and there will occur a low load during the shift, resulting in a significant peak-to-valley difference. For the industrial power consumer C, the peak electricity consumption is mainly concentrated at working hours in the daytime, and there has power consumption at night and before working hours in the morning, but the consumption is lesser.

According to the load levels of these three industrial power consumers, the parameters of the DES are shown in Table 2[28]. The storage charge and discharge depth is set to 0.85. $SOC(0)$ is set as 0.15, and $SOC_{\min}$ and $SOC_{\max}$ are 0.1 and 1.0, respectively.

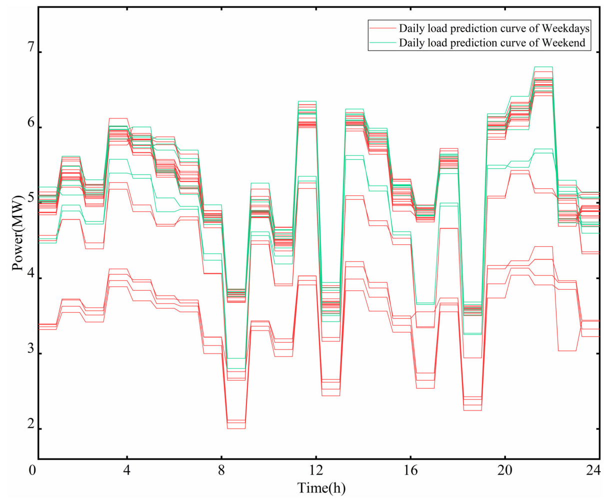

FIGURE 8. The day-ahead load forecasting curve of industrial power consumer B in June.

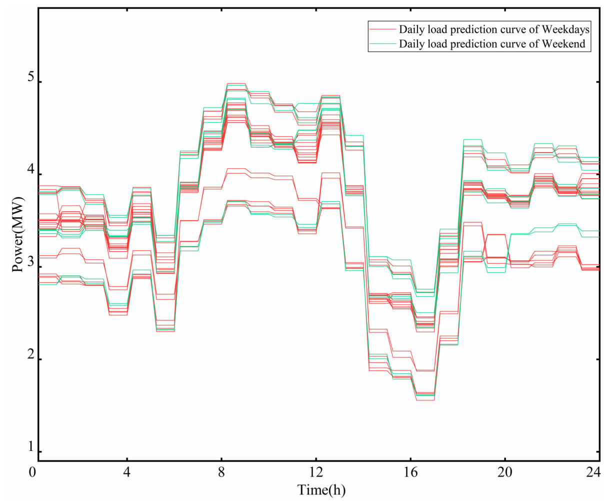

FIGURE 9. The day-ahead load forecasting curve of industrial power consumer C in June.

TABLE 2. Parameters of distributed energy storage.

Consumer	P_{max}/MW	E_{max}/MW·h	Coulombic efficiency/%
A	2.5	7	95
B	2.6	7	95
C	1.5	4	95

B. ANALYSIS OF DES OPTIMIZING OPERATION

1) ECONOMIC BENEFITS OF DISTRIBUTED ENERGY STORAGE IN MULTI-MODE OPERATION

Every industrial power consumer's load curve is simulated and analyzed to verify the universality of the proposed strategy, and the simulation results are shown in Tab. 3 and Fig. 10.

It can be seen from Tab. 3 that the monthly electricity bill of each industrial power consumer has been greatly reduced because DES reduces the industrial power consumer's load.

TABLE 3. Optimization results of each industrial power consumer.

Consumer	Maximum demand submitted/ MW	Peak load shaving based arbitrage/ (¥10^4 per Month)	Demand cuts based arbitrage/ (¥10^4 per·Month)	DR compensation/ (¥10^4 per Month)	Total revenue/ (¥10^4 per Month)
A	7.81	13.78	3.52	6.4	23.7
B	5.95	13.08	5.97	6.07	25.12
C	4.77	7.97	1.02	3.97	12.96

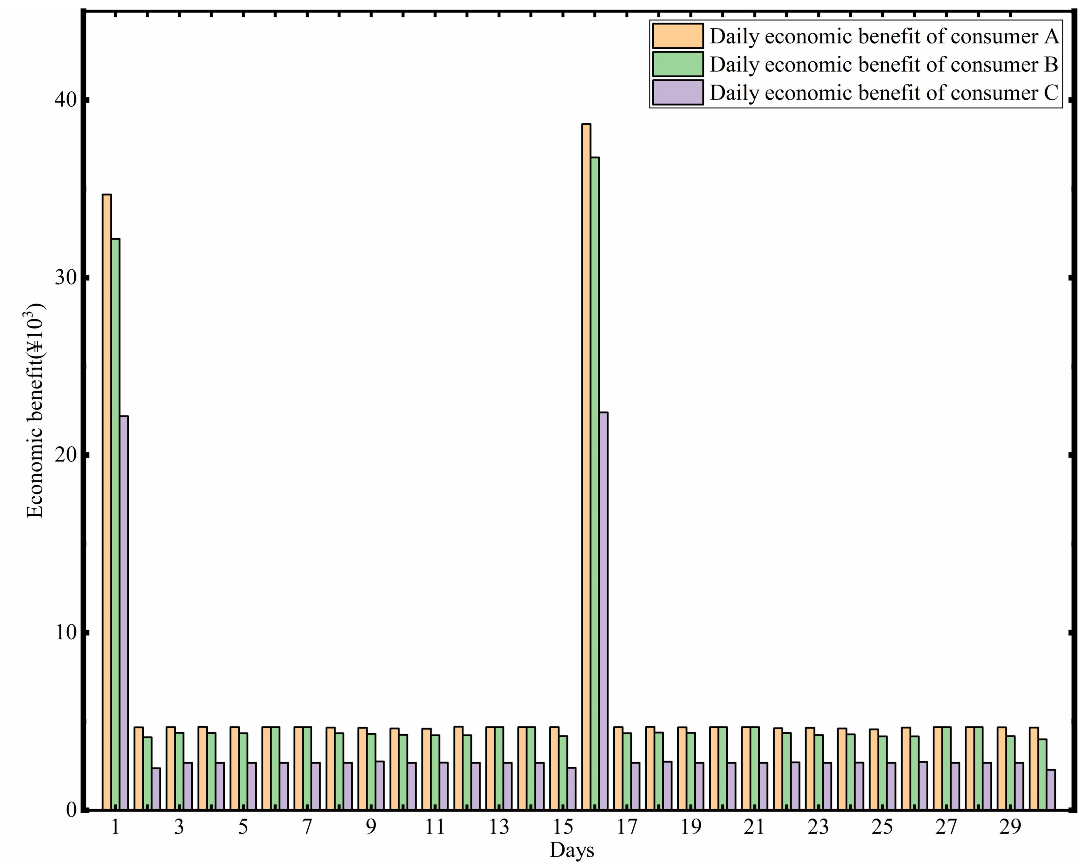

FIGURE 10. Economic benefit of consumer A, B, C in June.

Owing to the load peak and valley and the peak-valley time-of-use electricity price appear in the same period, the peak-valley price difference of industrial power consumer A is larger. In the case of participating in demand response twice a month, it can be concluded from Tab. 3 that the demand arbitrage of each industrial power consumer is less than the compensation of demand response. It can be seen that participating in demand response can effectively improve energy storage revenue when demand response becomes a regular peak-regulating method in the future. Additionally, it is found that the energy storage system charge and discharge once a day due to the constraint of equivalent full-cycle times.

Furthermore, the industrial power consumer A is selected as an example for detailed analysis. Four operating situations of the DES are simulated under multi-mode operation:

1) Operating condition #1: the demand response center does not issue a response invitation, and there is no peak in the load curve the next day.

2) Operating condition #2: the demand response center does not issue a response invitation, but the load curve appeared peak the next day.

3) Operating condition #3: the demand response center issues a response invitation, and the load curve appeared peak the next day.

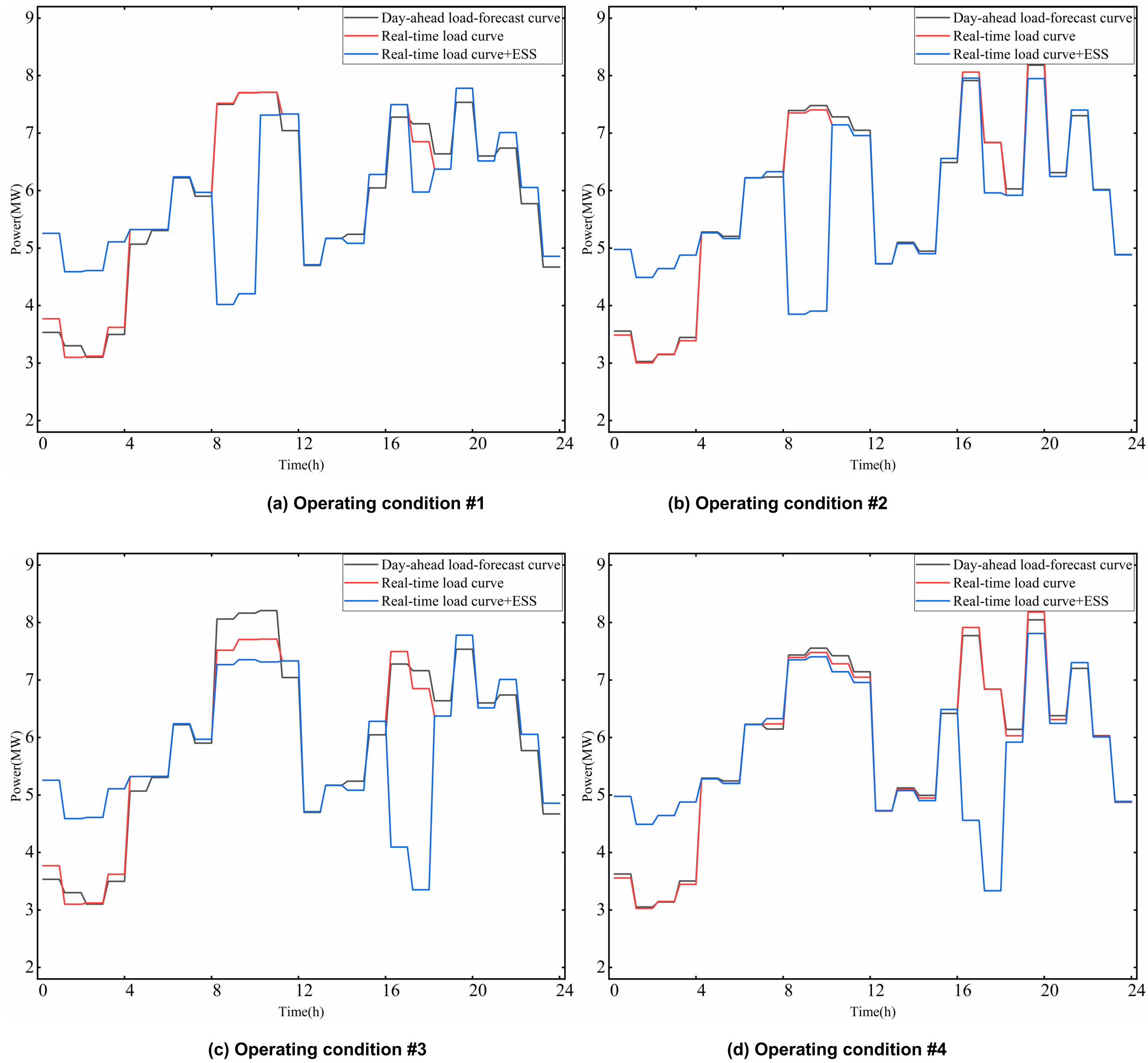

FIGURE 11. Load curve of industrial power consumer A with and without the energy storage.

4) Operating condition #4: the demand response center issues a response invitation, but there is no peak in the load curve the next day.

Fig. 11 (a) and Fig. 11(b) present the load curves before and after the peak load shaving under the operating condition #1. The figures show that the DES eliminate peak load of the customer to avoid the maximum demand exceeding the demand charge threshold, and obtain stable benefits through peak load shaving, cutting down the sum of energy cost and demand charge.

Fig. 11(c) and Fig. 11(d) show the load curves of the industrial power consumer A with and without the energy storage under the operating condition #3 and #4. From the peak load curve in Fig. 11(c), it can be seen that under the proposed optimized operation strategy, energy storage participates in the demand response, and the discharge response occurs from 16:00 to 18:00. By reducing the peak load, the maximum demand is limited, which means not only the income of peak-valley spread arbitrage but also the compensation income of the demand response is obtained. Fig. 11(d) shows the load curve of the industrial power consumer without load spikes. The response power of participating in the demand response increases, thus more compensation benefits will gain.

2) COMPARISON OF DISTRIBUTED ENERGY STORAGE ECONOMIC BENEFITS UNDER DIFFERENT OPERATING MODES

For further verifying the effectiveness of the proposed optimized operation strategy, different operating modes of the industrial power consumer A in a single month is simulated. Simulation results about three operation schemes are presented in Tab. 4 to show the superiority of the proposed operation strategy.

1) Single-mode operation #1: DES only participates in peak load shaving.

TABLE 4. Analysis of economic benefits of industrial power consumer A in different operation modes.

Operating scheme	Maximum demand submitted/MW	Peak load shaving based arbitrage/ (¥10^4 per Month)	Demand cuts based arbitrage/ (¥10^4 per·Month)	DR compensation/ (¥10^4 per Month)	Total revenue/ (¥10^4 per Month)
#1	/	14.04	/	/	14.04
#2	7.81	13.82	3.52	/	17.34
#3	7.81	13.78	3.52	6.4	23.7

2) Multi-mode operation #2: DES participates in both demand management and peak load shaving.

3) Multi-mode operation #3: DES participates in demand management, peak shifting and valley filling, and demand response.

Under operation scheme #1, the DES only participates in peak-valley spread arbitrage. Although its income is stable, the static recovery period will reach 8.8 years while the initial cost of energy storage is calculated at ¥2k per kWh. Under operation scheme #2, the economic benefit of DES is effectively improved by participating in demand management and peak-valley spread arbitrage. However, the static recovery period is still over seven years. Under operation scheme #3 (i.e., the proposed optimized economic operation strategy), the number of demand responses in the year is stable at more than 20 times. In addition, the monthly income from participating in demand response is very high, and the static recovery period only took about 4.5 years.

V. CONCLUSION

This paper proposes an optimized economic operation strategy with a multi-stage for the DES. The simulation results demonstrate the universality of the strategy and the economy of multi-mode operation. The following points can be obtained based on the results.

1) The DES under the proposed multi-mode operation can obtain considerable income from the demand response while saving electricity cost by peak-valley spread arbitrage, and the income from the response compensation depends on the compensation price and response times.

2) When DES has a certain capacity and rated power, the correlation between the peak/valley of the industrial power consumer's load curve and the peak/valley of peak-valley electricity price is the main influencing factor of the income level.

3) The income from participating in demand response is closely related to the average monthly response times. With the increase of average demand response times in the coming months, the participation in the demand response will obtain more economic benefits, which provides a new idea for the profit source in the commercial application of the energy storage.

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PENG PENG received the M.S. degree from the Huazhong University of Science and Technology, Wuhan, China, in 2012.

He is currently an Engineer with CSG Power Generation Company Ltd. His research interests include electrical equipment maintenance and battery energy storage technology of pumped storage power plant.

YONGQI LI received the M.S. degree from Northeast Electric Power University, Jilin, China, in 2020.

He is currently a Professor level Senior Engineer with CSG Power Generation Company Ltd. His research interests include electrical equipment maintenance and battery energy storage technology of pumped storage power plant.

DINGLIN LI received the B.E. degree from Guizhou University, Guizhou, China, in 1991.

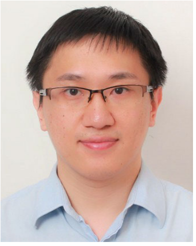
He is currently a Senior Engineer with CSG Power Generation Company Ltd. His research interest includes construction and transportation of pumped storage power stations.

YUDA GUAN received the B.E. degree from the South China University of Technology, Guangzhou, China, in 2020, where he is currently pursuing the M.S. degree.

His research interest includes application of energy storage in power market and auxiliary service market.

PING YANG (Member, IEEE) received the M.S. and Ph.D. degrees in control theory and engineering from the South China University of Technology, Guangzhou, China, in 1994 and 1998, respectively.

She is currently a Professor with the School of Electric Power, South China University of Technology. She is also the Director of the National-Local Joint Engineering Laboratory, Wind Power Control and Integration Technology, and the Key Laboratory of Clean Energy Technology, Guangdong Province. Her research interests include integration of renewable energy into power systems, microgrid control and management, and prediction modeling for wind and solar power.



ZHENKAI HU received the M.S. degree from the Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2008.

He is currently an Engineer with CSG Power Generation Company Ltd. His research interests include electrical equipment maintenance and battery energy storage technology of pumped storage power plant.

ZHUOLI ZHAO (Member, IEEE) received the B.S. and Ph.D. degrees from the South China University of Technology, Guangzhou, China, in 2010 and 2017, respectively.

From October 2014 to December 2015, he was a Joint Ph.D. Student (Sponsored Researcher) with the Control and Power Research Group, Department of Electrical and Electronic Engineering, Imperial College London, London, U.K. He was a Research Associate with the Smart Grid Research Laboratory, Electric Power Research Institute, China Southern Power Grid, Guangzhou, from 2017 to 2018. He is currently an Associate Professor with the School of Automation, Guangdong University of Technology, Guangzhou. His research interests include microgrid control and energy management, power electronic converters, smart grids, and distributed generation systems. He is an Active Reviewer for the IEEE TRANSACTIONS ON POWER ELECTRONICS, the IEEE TRANSACTIONS ON SMART GRID, the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, IEEE ACCESS, and the *Applied Energy*.

DONG LIU (Senior Member, IEEE) received the B.Eng. and M.Sc. degrees in electrical engineering from the South China University of Technology, Guangzhou, China, in 2008 and 2011, respectively, and the Ph.D. degree in energy technology from the Department of Energy Technology, Aalborg University, Aalborg, Denmark, in 2018.

From 2011 to 2014, he was a Research and Development Engineer with Emerson Network Power Company Ltd., Shenzhen, China. From May 2017 to November 2017, he was a Visiting Scholar with the Center for Power Electronics Systems (CPES), Virginia Tech, Blacksburg, VA, USA. Since 2018, he has been a Postdoctoral Researcher with the Department of Energy Technology, Aalborg University. His main research interests include modeling and control of power electronics converters, high-efficiency power conversion systems, and power electronics applications in renewable energy power generations.