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MULTI-SCENARIO OPERATION STRATEGY FOR ESS BASED ON DYNAMIC PROGRAMMING ALGORITHM

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ABSTRACT

The multi-scenario operation of the energy storage system (ESS) improves its economy and makes it more widely used in the power grid. By categorizing the operation scenario into the periodic running and triggering running scenarios, a novel optimal control strategy for the ESS under multi-scenario operation is presented in this paper. In order to evaluate the maximum input/output power of ESS, a new power capability index (PCI) is defined. Base on the PCI, the peak-shaving optimization model is built. Then the dynamic programming algorithm is used to solve this model. Evaluated on a 10kV substation in Shanghai, the proposed control strategy effectively alleviates the peak load pressure of power supply and responds the operation commands by different roles in the power system efficiently.

Keywords: energy storage system, multi-scenario operation, dynamic programming algorithm, peak-shaving, frequency modulation

1. INTRODUCTION

With the development energy storage technology, a large number of energy storage system (ESS) are applied in power system. ESS has many application scenarios in power system [1], such as: peak-shaving, renewable energy consumption, peak-to-valley arbitrage, auxiliary services, etc.

The output characteristics of ESS are constrained by its own power conversion system (PCS) and state of charge (SOC). And the power cost and the capacity cost of ESS are relatively expensive. It is impossible to ensure ESS matches the power requirements of each scene at any time. In the planning stage, [2] uses Monte Carlo algorithm to calculate the influence of ESS capacity on power supply reliability of distribution network, and provide an optimal sizing solution; In [3], peak-shaving, voltage quality adjustment and active power adjustment is selected as operating scenarios, a multi-objective optimization configuration model of ESS is built and solved by the ideal method with weighted minimum modulus. [4, 5] gives an optimal sizing scheme for ESS applied to peak-shaving or peak-to-valley arbitrage. In addition, [6-8] also gives the ESS configuration plan from the perspective of grid auxiliary service and stable operation. For the operation and control of ESS, [9] proposed a battery coordinated fan and traditional unit to participate in the system automatic generation control (AGC) strategy; In [10], an optimal control strategy for ESS to assist traditional unit coordination to participate in AGC is presented. However, the above literatures only deal with the operation control strategy of ESS running in a single scenario. There are few studies on the coordinated control strategy of ESS running in multiple scenarios and switching.

In this paper, a multi-scenario operation optimization control strategy for ESS operating in peak-shaving and frequency modulation (FM) is presented. By defining a new power capability index (PCI), the maximum charge and discharge capacity of the ESS is

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evaluated. Based on the PCI, the optimization model of peak-shaving is constructed, and solved by the dynamic programming algorithm. Finally, the effectiveness of the proposed multi-scenario optimization control strategy is verified by a 10kV substation in Shanghai, China. Simulation results prove that this strategy responds to the triggering operation task efficiently while alleviates the peak load pressure of power supply effectively.

2. MULTI-SCENARIO CONTROL STRATEGY

2.1 Multi-scenario operation mode and strategy

The running tasks in the power system are usually categorized into two types: the periodic running task and the triggering running task. As shown in Fig. 1, for the ESS running in multiple scenarios, a periodic running scenario is generally used as the main scenario, and multiple triggered running scenarios are used as the standby scenario.

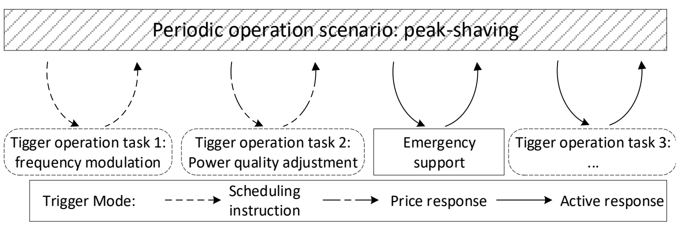


Fig. 1. ESS scenario switching strategy

In this paper, the peak-shaving is taken as the main scenario, and the FM is the standby scenario. The specific control strategy is categorized into three steps:

1) For periodic running scenarios, ESS will control the charge or discharge power in a time period according to the dispatch output curve;

2) When the standby scenario switching condition is satisfied, ESS will determine the output strategy in the triggering running scenario according to the operating state and the running state of the power grid;

3) After the standby operation scenario has been completed, ESS will return to the main scene, update the state information, and re-plan the dispatch output curve.

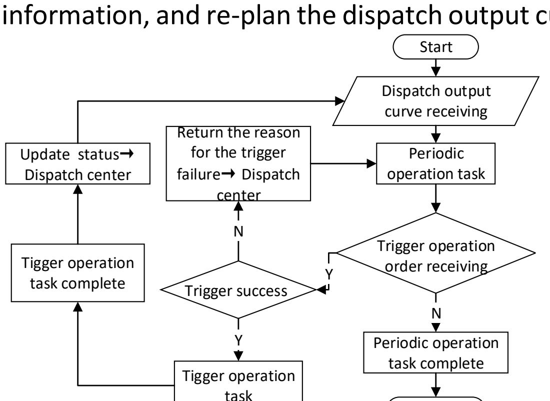


Fig. 2. Multi-scenario control flow of ESS

As shown in Fig. 2, in all the ESS scenario, the peak-shaving output is an optimization problem, and the economy and reliability of the grid operation need to be considered. The difficulties of FM are to reasonably evaluate the energy storage output/input capability and the information exchange between ESS and other roles running in the system.

2.2 *Power capability index*

Generally, energy storage equipment operates under rated power, but in a specific scenario, as shown in (1), ESS can achieve a certain period of overload operation.

$$k_{op}^{pcs} = P_{op}^{pcs} / P^r \tag{1}$$

The maximum overload factor k_{op}^{pcs} is determined by the PCS.

In addition, SOC of ESS should be operated within the specified range. For example, electrochemical energy storage device cannot maintain constant voltage charging or discharging while the SOC is beyond the rated range. That will affect the stability of integration into the power grid. Therefore, the maximum discharge power of ESS considering SOC constraints is:

$$\begin{cases} P_{op,t}^{SOC} = \dfrac{SOC(t) - SOC_{\min}}{\Delta T} E_{ess} \\ k_{op,t}^{SOC} = P_{op,t}^{SOC} / P^r \end{cases} \tag{2}$$

$SOC(t)$ is the remaining capacity of the ESS at time t; $SOC_{\min}$ is the minimum *SOC* specified by the energy storage device, and E_{ess} is the rated capacity of the ESS; The energy constrain factor $k_{op,t}^{SOC}$ is determined by the SOC at the current moment.

The discharge power of ESS also needs to meet the power flow constraints of the grid:

$$k_{op,t}^{Grid} = P_{op,t}^{Grid} / P^r \tag{3}$$

$P_{op,t}^{Grid}$ is the maximum power determined by the line current constraint and node voltage constrain, which means the connection of ESS cannot cause the grid power flow to exceed the limit. $k_{op,t}^{Grid}$ is the power flow constrain factor.

Combining (1)-(3), the discharge capacity index of ESS during $[t, t+\Delta T]$ is defined as:

$$k_{op,t}^{\max} = \min[k_{op}^{pcs}, k_{op,t}^{SOC}, k_{op,t}^{Grid}] \tag{4}$$

The storage capacity characteristics of ESS in the state of charge are similar to those of the discharge capacity. The maximum input/output power that the ESS can provide to the grid during $[t, t+\Delta T]$ is as follow:

$$P_{op,t}^{\max} = k_{op,t}^{\max} \cdot P^r \tag{5}$$

Where P^r is the rated power and $k_{op,t}^{\max}$ is denoted as the PCI of ESS, which describe the multiple of the maximum power that the ESS can input/output to the grid relative to its rated power P^r during ΔT.

3. OPTIMIZATION MODEL FOR PEAK-SHAVING

3.1 Objective function

In order to reduce the capacity of the rotating standby, ESS applied to the peak-shaving of the power grid needs to fully exert its decoupling capability to make the grid load curve as flat as possible. The variance of a series of columns is typically applied to describe the degree of dispersion of a set of data. The ESS-added load curve variance in one day reflects the peak-shaving effect of ESS.

N is the number of collecting load point in daily load forecasting curve. The charging and discharging states of ESS are discretized into individual points. Aiming at the minimum dispersion of daily load curve after peak-shaving, the objective function can be obtained as shown in (6):

$$\begin{aligned}\min f(P_{ess}) = \ & \frac{1}{N}\sum_{i=1}^{N}[(P_l(i)+P_{ess}(i)) - \\ & \frac{1}{N}\sum_{j=1}^{N}(P_l(j)+P_{ess}(j))]^2\end{aligned} \tag{6}$$

$P_l(i)$ is the load during time i and $P_{ess}(i)$ is the ESS output of time i (while charging is positive). When i is less than the current time n, the above variables are state variables and the actual operation value is adopted; when i is greater than or equal to the current time n, the energy storage output is the control variable and the load power is predicted.

To ensure that ESS can run continuously, while ignoring the loss, the average charge and discharge power of ESS in one operation cycle should be zero, so $\frac{1}{N}\sum_{j=1}^{N}(P_l(j)+P_{ess}(j))$ can be recorded as the average value of the daily load prediction curve $\overline{P_l}$ and (6) can be simplified as:

$$\min f(P_{ess}) = \frac{1}{N}\sum_{i=1}^{N}[(P_l(i)+P_{ess}(i)) - \overline{P_l}]^2 \tag{7}$$

Generally, compared with the small capacity of the system load ESS, the process of optimizing the system load variance to zero will face the problem of insufficient capacity of ESS. Therefore, an improved objective function of peak-shaving optimization considering phase objectives is shown in (8):

$$\begin{cases}\min f(P_{ess}) = \dfrac{1}{N}\sum\limits_{i=1}^{2\eta}\sum\limits_{j\in N_i} P_{vj}^2 \\ P_{vj} = P_l(j) + P_{ess}(j) - P_i^{obj}\end{cases} \tag{8}$$

η is the daily charge/discharge cycle times, P_{vj} is the difference between the ESS-add load curve and the expectation peak-shaving target during time j and P_i^{obj} is the expectation peak-shaving target in the stage i. The charge/discharge cycle times divide the peak-shaving period into 2η parts. According to the capacity of the ESS and the actual load situation of the locality, the peak-shaving target of each part is reasonably selected to ensure that the local load peak-to-valley difference is effective relieve, while not excessively wasting ESS resources.

3.2 Model Constraints

For most electrochemical energy storage devices, η determines the loss of the energy storage battery. In order to reduce the operating loss, η in one operating cycle should be minimized. Generally, the number of daily charging/discharging cycles applied to ESS for peak-shaving is not more than three. In addition, the operation of ESS must also meet the PCI constraints. Therefore, the constraints of ESS optimization model are shown as follows:

$$\begin{cases}P_{op,t} = k_{op,t}\cdot P^r \\ k_{op,t} \le k_{op,t}^{\max} \\ \eta \le \eta_{\max}, \eta = 1,2,...\end{cases} \tag{9}$$

3.3 Solution Approach

The dynamic programming algorithm is used to solve the above optimization problem. The optimization process is divided into multiple ordered states to find the recursive formula between states. By continuously obtaining the local optimal solution in each state, the optimal solution of the whole process is finally obtained. The recursive equation of the dynamic programming algorithm can be expressed by (10):

$$\begin{cases}f(r_0) = 0 \\ f(r_n) = \min\limits_{u_n\in d(r_n)}\{f(r_{n-1}) + v_n(r_n,u_n)\}\end{cases} \tag{10}$$

r_n is the ESS state during time n; u_n is the decision variable of phase n; $d(r_n)$ is the set of allowed decisions determined by r_n; $v_n(r_n,u_n)$ is the stage indicator of phase n.

For the energy storage peak-shaving scheduling optimization model given in this paper, the objective function is shown in equation (8), and the recursive phase index is expressed by equation (11):

$$v_n(P_{ess}, u_n) = \frac{1}{N}[(P_{l,n} - P_{ess,n}) - \overline{P_l}]^2 \tag{11}$$

By recursive the optimal solution of the ESS at each moment, the optimal output curve in all operating cycles can be obtained, and the dynamic programming algorithm calculation result is updated in real time according to the actual operating state.

4. CASE STUDY

4.1 Peak-shaving results

A 10kV substation in Shanghai is used to test the performance of the proposed method. Fig. 3 show the daily load curve of this substation. The accuracy of measurement time is 5 minutes. It is assumed that the daily load forecasting curve is the same as the real-time load. The load curve has two peaks in one day, the maximum load peak-valley difference is 14.68 MW, the daily average load is 11.26 MW, and the daily load variance is 18.03. The peak shaving target of energy storage charging is shown in Table 1. The rated power of ESS is 6MW, the rated capacity is 24MWh, the SOC range is [0.10, 0.90], and the maximum discharge multiple constrained by PCS $k_{op}^{pcs}=1.2$. Assuming that the SOC of ESS reaches the minimum value of 0.15 at the initial time, the scheduling output curve is calculated by using the dynamic programming control strategy presented in this paper.

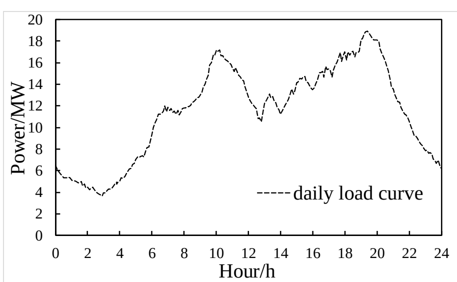


Fig. 3. Daily load curve of the 10kV substation

Table 1 Peak shaving targets

η =1	Stage 1	8.76MW	Stage 2	13.76MW
η =2	Stage 1	8.76MW	Stage 2	13.76MW
	Stage 3	13.76MW	Stage 4	13.76MW

Simulation results of the scheduling optimization are shown in Fig. 4. When η is 1, the calculated output curve of ESS is shown in Fig. 4(a) and the ESS-added daily load curve is shown in Fig. 4(b). It can be seen that the peak-valley difference of system load curve decreases obviously after peak-shaving with ESS. At the end of the cycle, the SOC limitation of ESS leads to insufficient power capability, which cannot continue to participate in system peak-shaving. While η is 2, the calculated output curve and the ESS-added daily load curve is shown in Fig.4 (c), (d). By comparison, it can be seen that the ESS with two charging/discharging cycles (η =2) is charged with the daytime load valley at 12 o'clock. Therefore, it has more remaining energy to cope with the upcoming second load peak. For the ESS applied to peak-shaving, larger the load peak-to-valley difference of the system during the day is, more obvious the effect of charging/discharging time is.

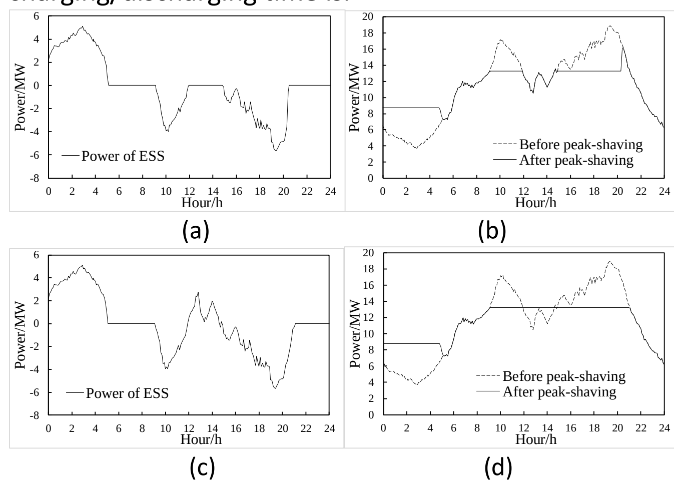


Fig. 4. Results of dynamic programming calculation

The variance of the system load curve after peaking-shaving is shown in Fig. 5 while $\eta=0$ means no ESS installed. It is obviously that configuring the energy storage device in the system greatly reduces the dispersion of the system load. In the meantime, increasing the number of charging/discharging cycles can further improve the peak-shaving effect. In this case, since the peak-to-valley difference of the grid during the day is small, the effect of increasing the number of charging/discharging times is not obvious.

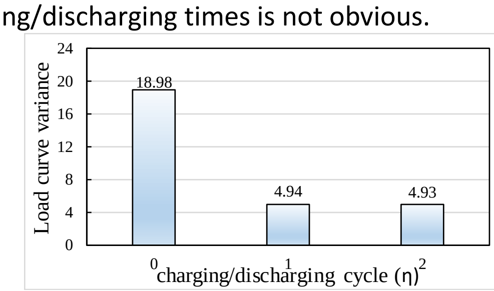


Fig. 5. Variance of system load curve

4.2 Multi-scene switching results

For the ESS running in peak-shaving scenario in this case, the charging/discharging cycle time constraint is 2. Assuming that the dispatching center sends FM trigger instructions at 10:00 a.m., the message content is as shown in Table 2.

Table 2 FM trigger instruction message

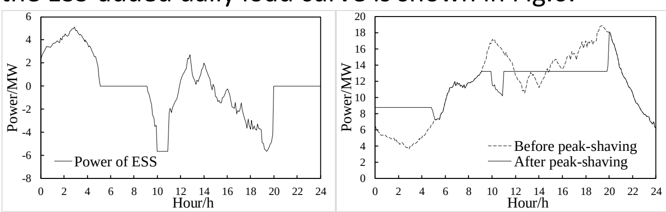
Number	Send reason	Command duration (min)	Demand power (MW)
1	FM	60	5.65

According to the multi-scene operation control flow of ESS shown in Fig. 2, the operation status can be calculated as Table 3:

Table 3 ESS operation status table

ID	Status	Scenario	SOC (%)	Storage capacity (MW)
001	Discharging	Peak-shaving	73.78	7.20

The peak-shaving scenario is switched to FM and participates in the cooperative completion by AGC units. After completing the FM, ESS sends message to the dispatching center, updates the equipment status, and returns to peak-shaving. The calculated output curve and the ESS-added daily load curve is shown in Fig.6.



(a) (b)

Fig. 6. Peak-shaving results of ESS running in multiple scenarios

As the simulation results shows, based on the multi-scenario operation optimization control strategy, the ESS responds to the FM order at 10:00 a.m. and returns to the peak-shaving scenario at 11:00 a.m. The output curve is redesigned according to the state of the ESS after FM is done.

Additionally, it can be seen that the multi-scenario operation control strategy of ESS given in this paper not only satisfies the optimization operation of the periodic task, but also responds to the trigger task order efficiently.

5. CONCLUSION

Through the optimization control strategy proposed in this paper, the multi-scenario optimization operation of ESS is realized. A new PCI of ESS is defined in order to evaluate the charge and discharge capacity of ESS. Based on the PCI, the peak-shaving optimization model is built and solved by dynamic programming algorithm. The effectiveness of the algorithm is verified by a simulation of a 10kV substation in Shanghai, China.

The reduction of the variance of the load curve reflects that the ESS can effectively suppress the peak-to-valley difference of the grid load. And through comparison, it has been shown that increasing of charging/discharging cycle times improves the peaking effect. In addition, the simulation results also prove that the control strategy proposed in this paper responds to the triggering operation task in time, adjusts the operation mode of the ESS and updates the output curve effectively.

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