Operation Strategy Optimization of Energy Storage Power Station Based on multi-Station Integration

Wenbo Xu1*, Qiang Li2, Jing Chen3, Fusheng Yuan1, Zhonghua Bai1, Zongze Yu1, Changhai Miao1, Hongbo Ma1

1Beijing branch -State grid information & telecommunication group, Beijing, China
2State grid information & telecommunication group, Beijing, China
3Beijing Electric Power Economic Research Institute CO., LTD. Beijing, China
*Corresponding author’s e-mail: xuwenbo@sgitg.sgcc.com.cn

Abstract. In the multi-station integration scenario, energy storage power stations need to be used efficiently to improve the economics of the project. In this paper, the life model of the energy storage power station, the load model of the edge data center and charging station, and the energy storage transaction model are constructed. Using the two-layer optimization method and the particle swarm optimization algorithm, it is proposed that the energy storage power station play a role in the integration of multiple stations Optimal operation strategy algorithm in a complex scenario with multiple functions. It is concluded that in a continuous period group with the same electricity price, the energy storage power station is charged and discharged at the same rate as the best operation strategy; the optimal operation strategy is determined by various factors such as time-of-use electricity price, battery life characteristics, and load characteristics of multiple stations in adjacent time groups.

1. Introduction
In 2019, the State Grid Corporation proposed to promote the "multi-station integration" business, dig deep into the potential value of assets, realize asset realization, expand emerging business areas, support the construction of the power Internet of Things. by using land, communications and power distribution resources in substations, build energy storage power stations, edge data centers and electric vehicle charging stations.

Energy storage power station has multiple functions in multi-station integration. For power grid, energy storage power station has the function of peak load regulation [1] frequency regulation [2], and is also a high-quality power grid demand response resource; for data center, energy storage power station has the function of time-sharing electricity price management. For the charging station, the energy storage station has the function of peak shifting and valley filling, which can effectively reduce the power capacity of the charging station.

Scholars have done a lot of research on the optimized operation of energy storage power stations. Wang, D.S, Zhang, W.L., Qi, M., Zhang [3-5] established corresponding mathematical models and studied the operation strategies of energy storage power stations participating in grid peaking and economic dispatch. Zhang, X.S. [6] studied the operation strategy of energy storage power stations in conjunction with photovoltaic power stations to suppress output fluctuations. Li, J.C. [7-8] studied the operation strategy of energy storage power station with wind farm for power regulation and wind abandonment. Lou, Y.C. [9] has studied the strategy of energy storage power station for demand...
response. Xue, Y., Xu, W.B., Fan, H. [10-12] studied the optimized operation strategy of the energy storage power station supporting the electric vehicle charging station. Yao, L. [13] used particle swarm optimization algorithm to study the optimal operation strategy of energy storage power station.

However, the current research on the optimal operation of energy storage power stations still has the following deficiencies:

(1) Lack of research on battery life characteristics. Different charge and discharge depths and rates have a great influence on the life of the battery, which directly affects the economics of the entire life cycle of the energy storage power station.
(2) Lack of research on operating strategies in complex scenarios. The current research is generally aimed at a single scenario, and there is still a gap in how energy storage power stations can play multiple functions in a complex scenario of multi-station integration.

In order to reduce operating costs and improve the economics of multi-station integration projects, this paper first adopts the double-layer optimization method within and between time groups, and proposes an algorithm for optimizing the operation strategy of energy storage power stations in complex scenarios of multi-station integration.

This paper builds mathematical models of energy storage power stations, edge data centers, charging stations, and electricity storage transactions. Considering the battery life constraints of charge and discharge depth and rate, the particle swarm optimization algorithm is used to determine the optimal operation strategy of the energy storage power station. Finally, a case is used to verify the effectiveness of the algorithm.

2. The general form of multi-station integration

At present, the typical model of multi-station integration is based on the construction of substation data center, charging station and energy storage power station. For edge data centers and electric vehicle charging stations, the main function of energy storage power stations is to use peak and valley electricity price policies to reduce operating electricity bills. For the power grid, the current main function of energy storage power stations is to participate in wind curtailment through electricity storage subsidy policies. This paper mainly studies the optimization operation strategy of the energy storage power station when it participates in peak shifting, valley filling and wind abandonment.

3. The mathematical model of multi-station integration

3.1. Operation model of energy storage power station

The operation model of energy storage power station is as follows:

\[
\begin{align*}
\text{Soc}_{i+1} &= \text{Soc}_i + \frac{1}{Q_0} \int_{t} V \times I(t) dt \\
\text{Dod}_i &= \text{Soc}_{i+1} - \text{Soc}_i \\
N_{0.2c} &= f(Dod) \\
N &= \beta b \times N_{0.2c} \\
S_{\text{desh}} &= \sum_{i=1}^{m} \frac{1}{N_j} \\
M_{sw} &= \frac{1}{365 \times S_{\text{desh}}} \tag{5}
\end{align*}
\]

Where: I is the charge and discharge current, its positive value means discharge, negative value means charge; Q_0 is the battery's rated energy, kWh; V is the battery's rated voltage, volts; \text{Soc}_i, \text{Soc}_{i+1} are respectively a certain charge and discharge State of Charge (SOC) at the beginning and end of the process, \%; N_{0.2c} is the number of cycles when the battery is discharged at 0.2C rate; \beta b is the actual
battery condition and 0.2C rate operation cycle life ratio during discharge; \( S_{\text{disch}} \) is the life loss rate of the battery in one day; \( M_{\text{act}} \) is the life time of the battery in years.

3.2. Cycle life model of energy storage power station

The cycle life of the battery has a great influence on the economics of the energy storage project, which is mainly affected by the depth of charge and discharge (Depth of discharge, DOD) and the discharge rate.

3.2.1. Effect of depth of charge and discharge.

The battery charge and discharge depth is inversely proportional to the battery cycle life. Taking the current mainstream lithium iron phosphate battery as an example, in the case of 0.5C rate charge or 0.2C rate discharge, the data in Figure 1 is used to fit the mathematical relationship between the battery cycle life and the depth of discharge:

\[
N_{0.2c} = 3946 \times (\text{DOD})^{-1.58}
\]  

![Figure 1. DOD-cycle life curve of lithium iron phosphate battery.](image)

3.2.2. Influence of charge and discharge rate.

Under the same conditions, the higher charge-discharge rate of the energy storage battery, the greater the loss on the battery and the shorter the cycle life of the battery. For lithium iron phosphate batteries, the ratio of battery life under rate discharge conditions to 0.2C discharge conditions has an exponential relationship [14], as follows:

\[
\frac{N_x}{N_{0.2c}} = \exp \left( \frac{0.2721 \times 0.2 - 0.7276}{0.2721 x - 0.7276} \right)
\]  

Where, \( N_x \) is the number of cycles when the battery is discharged at the actual rate.

Therefore, the ratio loss coefficient of the battery is as follow:

\[
\beta_x = \exp (0.0544 - 0.2721 x)
\]  

\[
x = \frac{\text{Soc}_{i+1} - \text{Soc}_i \times Q_0}{\Delta t \times \frac{Q_0}{1h}}
\]  

Where, \( x \) is the battery charge and discharge rate; \( \Delta t \) is the charge and discharge time, h.

3.3. Electricity load model of edge data center

The power load of the edge data center mainly includes two types of IT equipment load and air conditioning equipment load. The electrical energy consumed by IT equipment will also generate some heat energy, while the air conditioning equipment will transfer the heat to the outdoor environment to ensure constant temperature and humidity inside the data center.

IT load is relatively stable. The power consumption of the air-conditioning unit is related to the system's Coefficient of Performance (COP), and the COP is closely related to the outdoor temperature. According to engineering experience: the general outdoor ambient temperature increases by 1°C, and the air-conditioning unit COP decreases by 1.5%. The electricity load can be approximated by the following engineering experience formula:
\[ P_{SI}\text{i} = P_{ITi} + \frac{P_{ITi}}{COP\times[1 + 0.015\times(35-t_i)]} \]  

(11)

Where, \( P_{ITi} \) is the electrical load of the IT equipment in the edge data center at a certain moment, kW; \( P_{SI} \) is the total electrical load of the edge data center at a certain moment, kW; \( t_i \) is the outdoor temperature at a certain moment, °C. Figure 2 provides a typical electrical load curve for the edge data center.

![Power Load curve](image)

**Figure 2.** Typical edge data center daily power load curve.

### 3.4. Electricity load model of automobile charging station

The load of the electric vehicle charging station is related to the time of starting charging, the daily charge of the car and the charging power. The time of starting charging is normally distributed, and the probability density function is [15]:

\[
    f_{sk}(x) = \begin{cases} 
    \frac{1}{\sigma_{sk}\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_{sk})^2}{2\sigma_{sk}^2}\right), & 0 < x \leq \mu_{sk} - 12 \\
    \frac{1}{\sigma_{sk}\sqrt{2\pi}} \exp\left(-\frac{(x+24-\mu_{sk})^2}{2\sigma_{sk}^2}\right), & \mu_{sk} - 12 < x \leq 24 
    \end{cases}
\]  

(12)

Where, \( x \) is the charging start time, \( \mu_{sk} \) is the expected value of the charging start time, \( \sigma_{sk} \) is the variance.

In multi-station integration, the charging station is generally located in the urban commercial area, and the load characteristics of the charging station in the community are quite different. The charging peak is generally within a period of time after work. According to statistical data, the charging peak is concentrated around 10:15, so \( \mu_{sk} \) takes a value of 11.25 and \( \sigma_{sk} \) takes a value of 3.5.

The logarithm of the charging time of electric vehicles is normally distributed, and its probability density function [16] is:

\[
    f_{sc}(x) = \frac{1}{16.67x\sigma_{sc}\sqrt{2\pi}} \exp\left(-\frac{(\ln 16.67x-\mu_{sc})^2}{2\sigma_{sc}^2}\right)
\]  

(13)

Where, \( x \) is the charging time, min; \( \mu_{sc} \) is the expected value of charging time, min; \( \sigma_{sc} \) is the variance. According to statistical data, \( \mu_{sc} \) takes a value of 3.20 and \( \sigma_{sc} \) takes a value of 0.88.

During a day, the charging load curve of the charging station conforms to the joint distribution of the above two distribution functions. According to statistical data, Figure 3 provides a typical load curve of the charging station.
3.5. Electricity trading model of energy storage power station

In order to promote the consumption of wind curtailment, some provinces have implemented electricity storage trading systems to provide subsidies to users who use energy storage power stations to absorb electricity during wind curtailment periods. Electricity trading is generally carried out in a bidding mode on the grid auxiliary service platform. The operators of energy storage power stations declare the amount of electricity and prices absorbed during the wind curtailment period on the previous day. Called in order within the day. If the energy storage operator deviates from the declared plan during actual implementation, the power company will fine the operator according to the penalty factor. The mathematical model is as follows:

\[
B_{bi} = \sum_{i=1}^{96} R_{bi} \times Q_{sb_i} - K_{cf} \times R_{bi} \times |Q_{sb_i} - Q_{sji}|
\]  

(14)

Where, \(B_{bi}\) is the subsidy for the abandoned wind energy storage transaction within the day, rmb; \(R_{bi}\) is the subsidy unit price for the abandoned wind energy storage transaction at the \(i\)-th 15min point in a day, rmb /kWh; \(Q_{sb_i}\), \(Q_{sji}\) is the \(i\)-th 15min within a day The declared consumption and actual consumption of the abandoned wind power energy storage transaction at the point in time, kWh; \(K_{cf}\) is the penalty coefficient for the deviation of the amount of electricity consumed.

4. Solving Process Analysis

Assuming that the initial SOC of each hour is set to \(S_{oci}\), an operation strategy of the energy storage power station can be represented by a vector of 24 \(S_{oci}\): \(X=[S_{oc0}, S_{oc1}, \ldots, S_{oc23}]\)

The essence of the solution is to find the vector \(X\) under the specific boundary conditions that makes the energy storage power station obtain the maximum net profit in the whole cycle life.

By summarizing, \(S_{oci}\) with the same characteristics can be grouped to reduce the dimension of the vector. For example, consecutive hours with the same electricity price are grouped together to form a time period group. In this way, this complex optimization problem is decomposed into two levels for analysis. The first layer studies the optimal combination of initial SOC and end SOC for each hour within a time group; the second layer considers each time group as a whole and studies the optimal combination of initial value and end value in different time groups.

4.1. Style and spacing First level optimization

4.1.1. Optimization model. In the same time period group, the charge and discharge power and the electricity price are the same, so the charge of the charge or the benefit of the discharge is the same. For different strategies, the charge and discharge volume and rate per hour are different, which causes
different losses to battery life. Therefore, the strategy that minimizes battery life loss is the optimal strategy.

For the time period group containing n hours, the initial and final state of charge are $S_{ocbg}$ and $S_{oced}$ respectively, and multiple discharge strategies are designed (see Figure 4). The discharge amount and discharge rate of each strategy are different per hour. The mathematical model is established as follows:

$$
S_{smsh} = \frac{1}{1.58} \exp \left( 0.2721 \times \left( S_{oc_i} - S_{oc_{i+1}} \right) - 0.0544 \right) \min \left( \frac{2 \times 3946 \times \left( S_{oc_i} - S_{oc_{i+1}} \right)}{1.58} \right)
$$

(15)

In each period group, either fully charged or fully discharged, $S_{oc}$ monotonically increases or decreases monotonically, namely:

$$
\begin{align*}
S_{oc_i} &< S_{oc_{i+1}} \\
S_{oc_i} &> S_{oc_{i+1}} \\
S_{ocbg} &\geq S_{oc} \geq S_{oced} \\
S_{ocbg} &\leq S_{oc} \leq S_{oced}
\end{align*}
$$

(16)

(17)

4.1.2. Optimization result. To analyse the best strategy, take the 9-hour time period group as an example, from 10% to 95% charge, using particle swarm optimization algorithm to calculate, the best strategy is the SOC at the end of each hour: [10%, 19.4%, 28.9%, 38.3%..., 85.6%, 95.0%]. The objective function is $2.86 \times 10^{-5}$, and the calculation process is shown in Figure 5. It can be concluded that: within the same electricity price period group, it is optimal for the energy storage power station to charge and discharge at the same rate.
In order to verify this rule, 16 typical charging strategies are set (see Figure 6). Among them, strategies 1-4 first use low rate and then high rate; strategy 5 uses the same rate throughout; strategy 6-16 use high rate first, and then use low rate.

The analytical method is used for calculation. The objective function of each strategy is shown in Figure 7, which can be seen from the figure:

1. When the charge/discharge rate is the same every hour, the loss rate of the battery is the smallest;
2. The closer to strategy 5, the smaller the loss rate, and the farther away, the greater the loss rate.
Figure 7. Curve of loss rate under different strategies.

It can be inferred from this: within the same electricity price period group, the best operation strategy of the energy storage power station is: charge and discharge at the same rate every hour.

4.2. Second level optimization

4.2.1. Optimization analyse. The second level of optimization needs to solve the best operation strategy between groups of different electricity price periods. The section mainly solve the following problems:

(1) How to determine whether each period group is charged or discharged. In order to obtain the maximum peak-valley spread, it should be charged in the period of the lowest electricity price and discharged in the period of the highest electricity price, but the duration of such a period group is shorter, resulting in an increase in charge and discharge rate and shortened battery life. Appropriate charging and discharging cycles during the next lowest electricity price period and the next highest electricity price period may result in better overall revenue.

(2) How to determine the charge and discharge depth of each period group. The greater the depth of charge and discharge, the greater the profit per cycle, but the greater the loss of battery life. Properly reducing the depth of charge and discharge will greatly extend the battery life, so there is an optimal depth of charge and discharge.

4.2.2. Optimization model. First, the time-sharing electricity price curve and the wind curtailment subsidy curve are superimposed, and divided into m time group groups according to the actual electricity price segmentation (see Figure 8). Then each strategy is an m-dimensional vector group.

Take the total net income of the project in the entire life cycle as the objective function, that is, the energy saving income of the energy storage power station minus the increase in electricity cost caused by the system loss, and then minus the life loss value of the energy storage power station. Consider the time value of funds and use their present value as the objective function.

\[
\text{Max} B = \text{Max} \left( \sum_{i=1}^{m} \frac{B_{sy} - B_{shk} - B_{zshk}}{(1 + r)^i} \right)
\]

\[B_{sy} = 365 \times Q_i \times \sum_{i=1}^{m} (\text{Soc}_i - \text{Soc}_{i+1}) \times R_i\]

When \( \text{Soc}_i - \text{Soc}_{i+1} \geq 0 \),

\[B_{shk} = 365 \times (1 - \eta) \times Q_i \times \sum_{i=1}^{m} (\text{Soc}_i - \text{Soc}_{i+1}) \times R_i\]
\[ B_{zjsh} = 365 \times Q_0 \times C_0 \times \sum_{i=1}^{m} \frac{1}{N_i} \]  

(21)

Where: \( B \) is the objective function, rmb; \( B_{sy} \) is the annual electricity cost savings of the energy storage power station, rmb; \( B_{xlsh} \) is the annual electricity cost loss caused by the charge and discharge efficiency of the energy storage power station, yuan; \( B_{zjsh} \) is the discount caused by the life loss of the energy storage power station Loss value, rmb; \( R_i \) is the actual electricity price in a certain period, rmb/kWh; \( r \) is the social discount rate, taken 6%; \( \eta \) is the energy storage system efficiency, taken 90%; \( C_0 \) is the unit capacity investment of the energy storage power station, Take 1800 rmb/kWh.

(2) Constraints

The constraints of charge and discharge depth and rate and battery life are formulas (4) and (7).

The discharge amount of the energy storage power station in a certain period of time cannot be higher than the total power consumption of the data center and the charging station:

\[ Q_i \times (Soc_i - Soc_{i+1}) \leq P_{dci} + P_{cdzi} \]  

(22)

Where, \( P_{cdzi} \) is the electricity load of the charging station, kW.

5. Example

5.1. Basic conditions of the example

For a multi-station integration project, the energy storage power station adopts lithium iron phosphate battery with rated capacity of 220kW·h and PCS power of 330kW. The edge data center consists of 20 cabinets with a rated power consumption of 190kW. The total installed capacity of the charging station is 140kW.

Table 1 is the local time-sharing tariff policy.

Table 1. Time-of-use price.

| Classification | Electricity price / rmb / kWh | Time slot       |
|----------------|-------------------------------|-----------------|
| Peak           | 1.12                          | 10:00-15:00     |
|                |                               | 18:00-21:00     |
|                |                               | 7:00-10:00      |
| Flat section   | 0.67                          | 15:00-18:00     |
|                |                               | 21:00-23:00     |
| Low point      | 0.37                          | 23:00-7:00      |

The energy storage transaction of local abandoned wind power adopts unified subsidy and no deviation penalty. See Table 2 for details.

Table 2. Transaction subsidy for wind energy storage.

| Classification | Transaction subsidy for wind energy storage / rmb / kWh | Time slot       |
|----------------|--------------------------------------------------------|-----------------|
| Stage one      | 0.20                                                   | 23:00-2:00      |
| Stages two     | 0.10                                                   | 5:00-7:00       |
|                |                                                        | 2:00-5:00       |

According to the time-sharing electricity price and wind abandonment subsidy, the actual electricity price distribution map is drawn and divided into 8 time periods. See Figure 8 for details.
5.2. **Calculation results**

Particle swarm optimization algorithm is adopted to solve the problem. The best operation strategy of the case is shown in Table 3. The objective function is 484835 rmb.

| Time  | SOC  | Time  | SOC  |
|-------|------|-------|------|
| 23:00 | 0.1157 | 11:00 | 0.8781 |
| 0:00  | 0.2259 | 12:00 | 0.7933 |
| 1:00  | 0.3362 | 13:00 | 0.7084 |
| 2:00  | 0.4465 | 14:00 | 0.6236 |
| 3:00  | 0.5149 | 15:00 | 0.5388 |
| 4:00  | 0.5833 | 16:00 | 0.5363 |
| 5:00  | 0.6518 | 17:00 | 0.5337 |
| 6:00  | 0.8111 | 18:00 | 0.5312 |
| 7:00  | 0.9705 | 19:00 | 0.3952 |
| 8:00  | 0.9680 | 20:00 | 0.2593 |
| 9:00  | 0.9654 | 21:00 | 0.1233 |
| 10:00 | 0.9629 | 22:00 | 0.1195 |

Figure 10 provides the process of MATLAB solving the best strategy.
5.3. Result analysis

Figures 11 and 12 provide typical operation strategies, optimal strategies and their objective functions for the above cases.

C0 is the best operation strategy. C2 strategy only charges in the lowest price period and discharges only in the highest price period. C1 strategy charges at a lower price and discharges at a higher price. C3 is almost the same as C0, but its depth of charge and discharge is slightly higher than C0. C4-C9 is a random operation strategy. From the comparison of its objective function, we can see that:

1) C2 strategy can get the most profit in one cycle, but it can't use the second lowest (second highest) price period to work, which leads to high charge discharge ratio and large battery life loss, which is not the best strategy.

2) C1 strategy has the largest daily cycle times and the largest daily income, but its average life consumption income is small, which is not the best strategy.

3) Compared with C0 strategy, C3 strategy has a greater depth of charge and discharge, and the daily gain is more than C0 strategy. However, too high depth of charge and discharge leads to a greater loss of battery life, which is not the best strategy.
6. Conclusion
When the energy storage power station plays multiple functions in multi station integration, its optimal operation strategy has the following rules:

(1) In the period group of same real price, the best operation strategy is to charge and discharge at the same rate per hour.

(2) Between time groups with different electricity prices, the optimal operation strategy is determined by the time-sharing electricity price, battery life characteristics, and load characteristics of multiple stations.

(3) If the gain obtained by a certain charge and discharge cycle is less than the loss of power station life loss, it is not economical to use the electricity price difference $\Delta R$ to shift the peak and fill the valley, so the requirement $\Delta R$ should be greater than the critical value.

(4) If the electricity price difference $\Delta R$ between two adjacent periods is less than the critical value, the group should be charged (or discharged) in both periods. When the two time periods are of equal duration, there is an optimal distribution ratio of their charge (discharge) power. This ratio is related to the ratio of electricity prices, unit investment of energy storage power stations, and battery life characteristics.

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