Real-time Optimization of Distributed Energy Storage System Operation Strategy Based on Peak Load Shifting

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Abstract. To take advantage of the energy storage system (ESS) sufficiently, the factors that the service life of the distributed energy storage system (DESS) and the load should be considered when establishing optimization model. To reduce the complexity of the load shifting of DESS in the solution procedure, the loss coefficient and the equal capacity ratio distribution principle were adopted in this paper. Firstly, the model was established considering the constraint conditions of the cycles, depth, power of the charge-discharge of the ESS, the typical daily load curves, as well. Then, dynamic programming method was used to real-time solve the model in which the difference of power $\Delta s$, the real-time revised energy storage capacity $S_k$ and the permission error of depth of charge-discharge were introduced to optimize the solution process. The simulation results show that the optimized results was achieved when the load shifting in the load variance was not considered which means the charge-discharge of the energy storage system was not executed. In the meantime, the service life of the ESS would increase.

Keywords. Distributed energy storage; Peak load shifting; Real-time optimization; Dynamic programming.

1. Introduction

With the economic development of the increase in demand for electricity, distribution peak pressure increase. The traditional expansion and expansion program has caused the equipment utilization rate to be low and the investment risk is large. The use of the battery energy storage system (BESS) peak load shifting is an effective solution. The centralized energy storage system installed on the low side of the transformer cannot effectively alleviate the phenomenon that the line is overloaded and the terminal voltage of the distribution network is low, therefore, the distributed energy storage system installed on the load side can effectively relieve the peak regulation of the distribution network, and alleviate the phenomenon that the voltage of the distribution line is overloaded and the terminal voltage of the distribution network is low. There are many researches on the operation strategy of distributed and large-scale energy storage in power grid peak load shifting and micro-grid distributed power supply at home.
and abroad, and the literature on distributed energy storage in mitigating pressure of distribution network is relatively few [1-5].

Based on the theory of centralized, large-scale energy storage and micro-network distributed power supply, this paper studies the operation strategy of distributed energy storage system based on distribution peak load shifting. In the literature [6-7], by analyzing the predicted load, the problem of tracking load is high and the load is peaked from the highest to the low, and the problem of the load peak weakening is not obvious. In the literature [8], considering the battery energy storage life constraint and the power fluctuation constraint of the wind storage system, three kinds of operation modes of the energy storage system, namely, the peak load filling mode, the power smoothing mode and the power tracking mode are proposed, which reduces the dependence on the predicted load; In the literature [9], a real-time optimization model based on dynamic programming is proposed. By short-term load forecasting, the impact of short-term load forecasting accuracy is reduced. The algorithm for solving the optimization strategy is divided into two categories, namely, intelligent algorithm and classical algorithm. In the literature [10-13], intelligent algorithm is adopted, including genetic algorithm, particle swarm optimization and simulated annealing algorithm. The advantage of this is that it can deal with nonlinear problems well, but the disadvantage is that there are more local optimal solutions, It is difficult to guarantee convergence for the global optimal solution; In the literature [14-15], the classical optimization algorithm is adopted, including the gradient algorithm, the dynamic programming algorithm, the gradient algorithm is very dependent on the initial value, and cannot deal with the intermittent problem, while the dynamic programming algorithm is in the global optimal solution and processing intermittent, non-linear problems can achieve very good results, and easy to computer programming.

Based on the above theory, this paper presents a real-time optimization strategy of distributed energy storage system based on peak load shifting. The optimization model of the charge and discharge strategy is established by taking into account the network conversion coefficient and the energy storage life. The influence of the dynamic life of the battery is analyzed by using the dynamic algorithm and the actual load and the forecast load. The state variables improve the accuracy of the optimization results.

2. Real-time optimization modeling of peak load shifting

Energy storage system on the power system peak load shifting, according to the owner of the different, mainly divided into two ways to achieve. Energy storage system for the user, focusing on the energy efficiency of energy storage system, usually consider the market price difference, the biggest economic interests for the purpose of modeling; energy storage system for the power grid side of the general to delay the expansion of the grid for the purpose of smoothing the load Curve for the goal of establishing an optimization model. In this study, the mathematical variance is introduced from the grid side, and the optimization model is established.

2.1. Conversion of distributed energy storage system

In order to avoid the introduction of complex power flow calculation time and optimization time, reduce the optimization accuracy of the case, the introduction of network loss conversion coefficient, there are
\[ P_{\text{BESS}} = [a_1, a_2, \ldots, a_i, \ldots, a_m] \times \]
\[
\begin{bmatrix}
P_{\text{BESS}_1} & P_{\text{BESS}_1,2} & \ldots & P_{\text{BESS}_1,j} & \ldots & P_{\text{BESS}_1,N} \\
P_{\text{BESS}_2} & P_{\text{BESS}_2,2} & \ldots & P_{\text{BESS}_2,j} & \ldots & P_{\text{BESS}_2,N} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
P_{\text{BESS}_i} & P_{\text{BESS}_i,2} & \ldots & P_{\text{BESS}_i,j} & \ldots & P_{\text{BESS}_i,N} \\
P_{\text{BESS}_m} & P_{\text{BESS}_m,2} & \ldots & P_{\text{BESS}_m,j} & \ldots & P_{\text{BESS}_m,N}
\end{bmatrix}
\] (1)

Where: \( P_{\text{BESS}} \) is the total charge-discharge active power converted to the transformer side of the distributed energy storage system; \( a_i \) is the loss factor of the \( i \)-th distributed energy storage to the transformer side energy storage; \( P_{\text{BESS}_i,j} \) is \( j \) moment, the discharge power of the \( i \)-th energy storage unit; \( N \) is the number of load data points in a day divided into \( N \) times; \( m \) is the number of distributed energy storage units.

As shown in Figure 1, for the distributed energy storage system charge and discharge diagram. (1) \( \text{i time storage system charge, U}_0 \) for the rated voltage, there are:

\[ P_{0i,c} = P_{\text{BESS}_0,i} + \Delta P_{0i} \] (2)

Where, \( \Delta P_{0i} \) is the active loss of the branch from node 0 to node \( \text{i} \) when the battery is charged.
\[ \Delta P_{0} = \frac{P_{0}^2 R}{U_0^2} \]  

(3)

Take the form (3) into (2)

\[ \frac{P_{0}^2 R}{P_{BESS01,c}^2 U_0^2} - \frac{P_{0, c}}{P_{BESS01,c}} + \frac{1}{P_{BESS01,c}} = 0 \]  

(4)

Let \( \frac{P_{0, c}}{P_{BESS01,c}} = a_i \), then

\[ \frac{R}{U_0^2} \alpha_i^2 - \frac{1}{P_{BESS01,c}} a_i + \frac{1}{P_{BESS01,c}} = 0 \]  

(5)

There are:

\[ a_i = \frac{U_0^2 \pm \sqrt{U_0^4 - 4U_0^2 RP_{BESS01,c}}}{2RP_{BESS01,c}} \]  

(6)

And \( \frac{U_0^2}{2RP_{BESS01,c}} \approx \frac{U_0^2}{2\Delta U_{0i}} \gg 1 \), and by the actual situation available in the charge \( a_i \) should be slightly greater than 1, so when charging \( a_i = \frac{U_0^2 - \sqrt{U_0^4 - 4U_0^2 RP_{BESS01,c}}}{2RP_{BESS01,c}} \).

(2) i time storage system discharge, \( U_i \) for the rated voltage, there are:

\[ P_{0, i,d} + \Delta P_{0} = P_{BESS0i,d} \]  

(7)

Similarly, available

\[ a_i = 1, \frac{RP_{BESS01,d}}{U_i} \]  

(8)

The rated voltage of the system is \( U_N \), and the energy storage system \( P_{BESS} \) is defined as negative when charging, and the discharge is positive

\[ a_i = \begin{cases} \frac{\sqrt{U_N^4 + 4U_N^2 RP_{BESS}} - U_N^2}{2RP_{BESS}} & \text{(Charge)} \\ 0 & \text{(Constant-compare charge)} \\ 1 - \frac{RP_{BESS}}{U_N^2} & \text{(Discharge)} \end{cases} \]  

(9)
2.2. Real-time optimization modelling of peak load filling

(1) Objective function

The variance indicates that the random variable deviates from the mean, so the load variance is generally able to reflect the smoothness of the load curve. In the study, the load curve is also smoother. Therefore, based on the peak load shifting of the distributed energy storage system operation strategy optimization model, this paper establishes the following objective function.

$$\min f(X) = \frac{1}{N} \sum_{i=1}^{N} (P_{\text{load},i} - P_{\text{BESS},i}) - \frac{1}{N} \sum_{i=1}^{N} (P_{\text{load},i} - P_{\text{BESS},i})^2$$

(10)

Where, $P_{\text{load},i}$ is the active load of the system at time $t$; $P_{\text{BESS},i}$ is the time $t$, the distributed energy storage system is converted to the transformer side, the total charge and discharge active power.

Real-time optimization method is mainly through the call of different data to achieve, in a certain time state optimization, the state before the data call real-time load data, after the data call forecast load data.

(2) Constraints

To ensure the life of the energy storage system, optimize the model to establish the following constraints.

Battery charge and discharge number of constraints. After the battery is connected to the power system, it is divided into three kinds of operating states, namely, charging, discharging and floating state. When the battery charge and discharge loss is not taken into account, the system can be regarded as zero power charging or discharging. Therefore, only the intermittent charge or discharge, that the battery only a charge or discharge. Based on this, the model establishes the $i$-energy storage system charge and discharge times the constraint is $k_i$ times.

Battery charge and discharge depth constraints.

$$\begin{align*}
\text{SOC}_{i\min} & \leq \text{SOC}_{i,t} \leq \text{SOC}_{i\max} \\
\text{SOC}_{i,t} &= \text{SOC}_{i,t-1} - \frac{P_{\text{BESS},i} \Delta t}{C_{i0}} \\
\text{DOD}_{i,t} &= 1 - \text{SOC}_{i,t}
\end{align*}$$

(11)

Where, $\text{SOC}_{i\min}$ and $\text{SOC}_{i\max}$ are the minimum and maximum values of the battery charge state of the $i$-node, $\text{DOD}_{i,t}$ is the battery charge and discharge depth of the $i$-node, and $C_{i0}$ is the rated capacity of the $i$-th energy storage system.

Battery charge and discharge power constraints.

$$\begin{align*}
P_{\text{c,\max}} & \leq P_{\text{BESS},i,t} \leq 0 \quad \text{(Charge)} \\
0 & \leq P_{\text{BESS},i,t} \leq P_{i\max} \quad \text{(Discharge)}
\end{align*}$$

(12)

Where $P_{\text{BESS},i,t}$ is the charge / discharge power at time $t$ of the $i$-th node, $P_{\text{c,\max}}$ is the maximum charging power of the $i$-th node energy storage system, and $P_{i\max}$ is the maximum discharge power of the $i$-th node energy storage system.

By analyzing the optimization model, it can be seen that the objective function is a nonlinear model, and after the charge and discharge depth constraint is introduced, the model is no longer continuous and can not be solved by the continuous model optimization algorithm. This paper proposes a dynamic programming method to solve this model.
3. Optimization of Optimization Model Based on Dynamic Programming

3.1. Classic dynamic planning
The basis of the dynamic programming algorithm is the optimal theory: the optimal strategy contains
the sub-strategy must be the optimal sub-strategy. And with no effect, that is, the stages in a certain order
after a good, for a given stage of the state, its previous stages of the state can not directly affect its future
decision-making, but only through the current state. The above is the theoretical basis for solving the
optimization model in real time.

Dynamic programming method is divided into reverse order solution and sequential solution, the key
is to correctly write the dynamic programming of the recursive relationship. In general, when the initial
state given, with the inverse method is more convenient, when the termination of the state given, with
the push method is more convenient. But also according to the actual situation of the problem, select the
appropriate recursive method. As shown in Figure 2, for the stage of the decision process, for the
dynamic planning of the basic process..

![Fig. 2 Basic flow of dynamic programming](image)

Where the state variable is \( s_1, s_2, \ldots, s_{n+1} \), the decision variable is \( x_1, x_2, \ldots, x_n \). In the \( k \)-th stage, the
decision \( x_k \) causes the state \( s_k \) to be shifted to \( s_{k+1} \), and the state transition function is

\[
s_{k+1} = T_k(s_k, x_k)
\]

(13)

The process indicator function is related to the function of each stage

\[
f_{k+1}(s_{k+1}) = \text{opt} \left\{ v_k(s_k, x_k) \right\}
\]

(14)

Analysis available, classical dynamic programming also has the following advantages: for more
complex models of constraints, dynamic programming can turn complex problems into a series of simple
subproblems, making it easier to obtain global optimal solutions; for some difficult to express the
nonlinear problem, discrete problem, dynamic programming method can be easily processed; dynamic
programming to solve the characteristics of the process, so that it can get a set of solutions, is conducive
to the analysis of the problem.

3.2. Solving the optimization model based on dynamic programming
The upper layer control module of the distributed energy storage system can calculate the output of the
PCS according to the principle of distributed energy storage capacity ratio distribution to the energy
storage nodes by dynamic programming algorithm. As a result of the principle of distribution by capacity
ratio, so the energy storage and discharge depth of each node is synchronized, the overall charge and
discharge depth can be expressed with a node energy storage. Charge and discharge power constraints

\[
\begin{align*}
\sum_{i=1}^{m} a_{i,j} P_{\text{acc},\max} & \leq P_{\text{BESS},\Sigma,j} \leq 0 \quad \text{(Charge)} \\
0 & \leq P_{\text{BESS},\Sigma,j} \leq \sum_{i=1}^{m} a_{i,j} P_{\text{dis},\max} \quad \text{(Discharge)}
\end{align*}
\]

(15)
Where, $P_{\text{ic,max}}$ is the rated power of the i-node energy storage system at charge time, and $P_{\text{id,max}}$ is the rated power of the i-node energy storage system during discharge.

To simplify the computational complexity, the model is solved by dynamic programming as follows:

![Diagram showing the basic flow of optimization strategy based on dynamic programming](image)

**Fig. 3** the basic flow of optimization strategy based on dynamic programming

1. 1 day to $\Delta t$ interval is divided into N stages, corresponding to the $N$ states of the dynamic programming. The total capacity of the energy storage system is divided into $K$ states

$$K = \frac{T \cdot P_{\text{DESS}}}{\Delta t}$$  

(16)

Where, $T$ is the time of 1 day; $P_{\text{DESS}}$ is the total rated power of the total installed power of the distributed energy storage system to the total rated power of the low side of the transformer; $\Delta t$ is the power difference in the adjacent state. When the $\Delta t$ value is small, the optimization path is relatively large and is suitable for accurate calculation. When there is a time requirement, $\Delta t$ is appropriate to take a larger value to shorten the optimization time.

2. The actual total capacity at time $k$ is $S_k$, the charge and discharge depth at this time is

$$DOD_k = \frac{S_k}{T \cdot P_{\text{DESS}}}$$  

(17)

Due to the existence of $\Delta t$, the model is discrete, in order to ensure that the optimization process can be a good termination, allowing $DOD \pm 1\%$ error. 1% of the value of energy storage system, including charge and discharge efficiency factors, as well as the loss factor of the network loss factor.

3. The $k$-th state to the $k + 1$ stage decision indicators

$$v_{k+1}(P_{\text{BESS},k} + x_k) = \left| P_{\text{load},k} - P_{\text{BESS},k} \right| - \frac{1}{k+1} \sum_{t=1}^{k+1} \left| P_{\text{load},t} - P_{\text{BESS},t} \right|$$  

(18)

Where, $x_k$ is the decision variable for the state $sk$ to $sk+1$, as shown in Figure 3, and each arrow represents the decision from the previous state to the next. $S_{\text{max}}$ and $S_{\text{min}}$ correspond to arrows for decision making boundaries.

4. The initial state to the $k$-state index function
\[ V_{i,k} = \left[ \frac{1}{k} \sum_{j=1}^{k} v_j^2(P_{BESS,k}, x_k) \right] \]  

(19)

In order to facilitate programming, expressed in the form of recursive relationships

\[ V_{i,j} = \frac{1}{k} \left[ (k-1)V_{i,j-1}^2 + v_k^2(P_{BESS,k}, x_k) \right] \]  

(20)

The optimal index function of the initial state to the k-th state is

\[ f(P_{BESS,k}) = \min V_{i,k} \]  

(21)

(5) When performing off-line optimization, only the predicted load as the original data, a full state of the overall optimization, can be the best path. Therefore, considering the error of load forecasting may affect the optimization results, this paper introduces the real-time optimization method. It can be seen from the optimal theory that the path from the initial state to the k-th state is optimal when proceeding to the k-th state in the dynamic planning process, but the optimal path must not be the whole path of the optimal path of the process. Therefore, it is necessary to perform the overall optimization of the whole state in each state, so as to ensure that the optimal path when optimizing to a certain state is closer to the real optimal sub-path.

(6) Optimization results \( DOD \) still cannot reach the error allowable value, by changing the minimum error corresponding to the optimal strategy to achieve the state of \( S_i \), so

\[ S_i = S_i \pm \frac{n}{2} \Delta s \quad n = 1, 2, 3 \ldots \]  

(22)

Return to step (2) and continue to optimize the solution until the desired optimization results are met.

4. Case study

Using the network structure for the IEEE33 node system, distributed storage system installation location shown in Figure 4, the installation capacity shown in Table 1. The system of a typical daily load data and its predicted load data MATLAB is plotted as shown in Figure 5, with a predicted load error within ±5% [16-18]. Take the value of \( N = 288 \), \( \Delta s \) directly affect the speed of the calculation [9], so according to the different needs of the value, assuming that the initial battery capacity and termination time equal.

**Table 1.** Installed capacity of distributed energy storage system

| Location | Energy storage system capacity (kW • h) | Rated power of converter kW |
|----------|----------------------------------------|----------------------------|
| 6        | 400                                    | 100                        |
| 17       | 600                                    | 150                        |
| 31       | 600                                    | 150                        |
4.1. Comparison of real-time optimization and off-line optimization results

In order to reduce the impact of energy storage battery life constraints on the results, the energy storage DOD = 25%, k = 1, calculated by $-407\text{kHz} \leq P_{\text{BESS}} \leq 396\text{kHz}$. In order to improve the accuracy of the results of comparison, take $\Delta s=1\text{kHz} \cdot 5\text{min}$, the optimization results shown in Table 2 and Figure 6 shows.

It can be seen from the results that the variance of the real-time optimization result is closer to the optimization result using the actual load, and the error is less than the off-line optimization error of the forecast load.

| Project                                    | Load variance |
|--------------------------------------------|---------------|
| Offline optimization (forecast load)       | 168.4         |
| Offline optimization (actual load)         | 167.0         |
| Real-time optimization                     | 167.5         |

(a) Optimization results of grain filling time
4.2. Real-time optimization results analysis
It can be seen from the literature [9] in the case of a certain charge and discharge depth, the number of battery charge and discharge to reach the peak number, if continue to increase the optimization results remain basically unchanged. Based on this, combined with the original data to study the energy storage system charge and discharge depth on the optimization results. Let , in order to extend the life of the energy storage system, set the optimization process within the load variance within the load peak valley is not processed, that is not charge and discharge. It is of little significance to peak load shifting in the rated capacity of the equipment in actual situation. Take $-407\text{kW} \leq P_{\text{BESS}} \leq 396\text{kW}$, $\Delta t = 10\text{kw} \cdot 5\text{min}$, the optimization results shown in Table 3 and Figure 7.

Table 3. Comparison of different DOD optimization results

| DOD(%) | Load variance | Peak power (kW) | charge-discharge cycles |
|--------|---------------|-----------------|-------------------------|
| 25     | 167.5         | 4145            | 1 charge 1 discharge    |
| 50     | 124.4         | 4060            | 1 charge 1 discharge    |
| 75     | 85.34         | 4020            | 2 charge 2 discharge    |
| 95     | 47.97         | 3995            | 3 charge 3 discharge    |

Fig. 7 Comparison of different DOD optimization results
The results show:

(1) When the DOD = 25% and DOD = 95% under the state of the clipping power of the odds of 5 times the case, This is because when $\Delta s$ is large, the optimization result can not be guaranteed within the allowable error range of the DOD. At this time, a more accurate result is obtained by changing the corresponding $S_i$.

(2) Load variance decreases with increasing charge and discharge depth, and the number of charge and discharge cycles increases. In this case, when the DOD is increased from 75% to 95%, the optimization result is halved, and the "glitch" phenomenon occurs due to the constraint of the discharge power. Therefore, the above four states select DOD = 75% best.

(3) Because the peak load with a large battery capacity, configuration converter rated power is also large, this paper select the converter rated power values are only the energy storage battery capacity value of 1/4, only in the DOD = 95% when the short term "glitch" phenomenon, so for the smaller charge and discharge power constraints under the optimization strategy research is of little significance.

In Figure 7, DOD = 75% optimization results refer to the corresponding charge and discharge power of each node as shown in Figure 8. Energy storage system charge is negative, the discharge is positive.

![Fig. 8 Output of each node energy storage system and total charge and discharge losses](image)

5. Conclusion

The method of introducing the loss coefficient and the principle of equal capacity ratio distribution are used to simplify the problem. In addition to the method of reducing $\Delta s$ to improve the accuracy of the optimization result, in the dynamic planning process, adjusting the size of $S_i$ can also improve the accuracy of the results, the introduction of DOD allows errors to prevent the calculation process from falling into an infinite loop.

It is proposed to use the method of not dealing with the peak and valley values within the load variance, which can effectively prolong the service life of the energy storage system while achieving the better optimization effect.

The results show that when the main function of the distributed energy storage system is used to peak load shifting, the energy storage and discharge power constraint in the optimization strategy has little effect on the optimization result, only need to be limited to the rated charge and discharge power.

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