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

Qian Wang [1], Guangqi Lu[2], Xiaoyu Li[2], Yichi Zhang[2], Zejian Yun[2] and Di Bian[2]

[1]Electric Power research Institute of Guangdong Power Grid Co, Ltd., Guangzhou, Guangdong 510080, and China;
[2]College of Electrical Engineering, Northeast Electric Power University, Jilin, Jilin 132012, China.

Corresponding author e-mail: 27626223@qq.com

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 Δs, the real-time revised energy storage capacity Sk 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

IOP Conf. Series: Earth and Environmental Science **108** (2018) 052014 doi:10.1088/1755-1315/108/5/052014

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

$$P_{BESS\Sigma} = [\mathrm{a}_1, \mathrm{a}_2, \cdots \mathrm{a}_{\mathrm{i}} \cdots, \mathrm{a}_m] \times \begin{bmatrix} P_{BESS1,1}, & P_{BESS1,2}, \cdots, & P_{BESS1,j}, \cdots, & P_{BESS1,N} \\ P_{BESS2,1}, & P_{BESS2,2}, \cdots, & P_{BESS2,j}, \cdots, & P_{BESS2,N} \\ \cdots \\ P_{BESSi,1}, & P_{BESSi,2}, \cdots, & P_{BESSi,j}, \cdots, & P_{BESSi,N} \\ \cdots \\ P_{BESSm,1}, & P_{BESSm,2}, \cdots, & P_{BESSm,j}, \cdots, & P_{BESSm,N} \end{bmatrix} \tag{1}$$

Where: $P_{BESS\Sigma}$ 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; $P_{BESSi,j}$ 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.

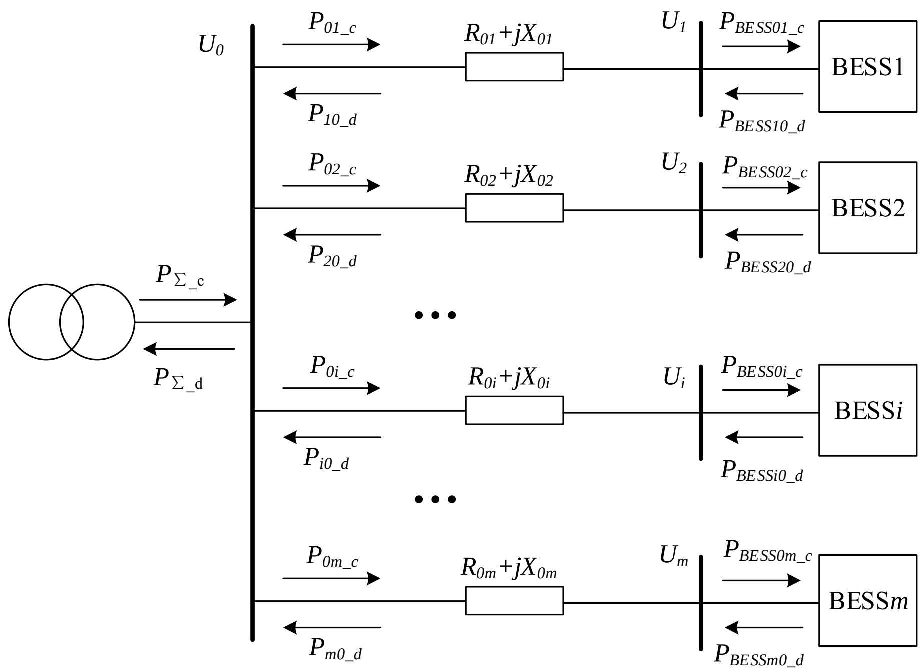


Fig. 1 Schematic diagram of charging and discharging in distributed energy storage system

As shown in Figure 1, for the distributed energy storage system charge and discharge diagram.
(1) i time storage system charge, U0 for the rated voltage, there are:

$$P_{0i\_c} = P_{BESS0i\_c} + \Delta P_{0i} \tag{2}$$

Where, ΔP_{0i} is the active loss of the branch from node 0 to node i when the battery is charged.

IOP Conf. Series: Earth and Environmental Science **108** (2018) 052014 doi:10.1088/1755-1315/108/5/052014

$$\Delta P_{0i} = \frac{P_{0i\_c}^2 R}{U_0^2} \tag{3}$$

Take the form (3) into (2)

$$\frac{P_{0i\_c}^2 R}{P_{BESS0i\_c}^2 U_0^2} - \frac{P_{0i\_c}}{P_{BESS0i\_c}^2} + \frac{1}{P_{BESS0i\_c}} = 0 \tag{4}$$

Let $\frac{P_{0i\_c}}{P_{BESS0i\_c}^2} = a_i$, then

$$\frac{R}{U_0^2} a_i^2 - \frac{1}{P_{BESS0i\_c}} a_i + \frac{1}{P_{BESS0i\_c}} = 0 \tag{5}$$

There are:

$$a_i = \frac{U_0^2 \pm \sqrt{U_0^4 - 4U_0^2 RP_{BESS0i\_c}}}{2RP_{BESS0i\_c}} \tag{6}$$

And $\frac{U_0^2}{2RP_{BESS0i\_c}} = \frac{U_0^2 / U_i}{2\Delta U_{0i}} \approx \frac{U_0^2}{2\Delta U_{0i}} >> 1$, and by the actual situation available in the charge ai should be slightly greater than 1, so when charging $a_i = \frac{U_0^2 - \sqrt{U_0^4 - 4U_0^2 RP_{BESS0i\_c}}}{2RP_{BESS0i\_c}}$.

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

$$P_{0i\_d} + \Delta P_{i0} = P_{BESS0i\_d} \tag{7}$$

Similarly, available

$$a_i = 1 - \frac{RP_{BESS0i\_d}}{U_i^2} \tag{8}$$

The rated voltage of the system is UN, and the energy storage system P_{BESSi} is defined as negative when charging, and the discharge is positive

$$a_i = \begin{cases} \frac{\sqrt{U_N^4 + 4U_N^2 RP_{BESSi}} - U_N^2}{2RP_{BESSi}} & \text{(Charge)} \\ 0 & \text{(Constant-compare charge)} \\ 1 - \frac{RP_{BESSi}}{U_N^2} & \text{(Discharge)} \end{cases} \tag{9}$$

IOP Conf. Series: Earth and Environmental Science **108** (2018) 052014 doi:10.1088/1755-1315/108/5/052014

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.

$$\min f(X) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(P_{load,t} - P_{BESS\Sigma,t} - \frac{1}{N}\sum_{t=1}^{N}(P_{load,t} - P_{BESS\Sigma,t}))^2} \tag{10}$$

Where, $P_{load,t}$ is the active load of the system at time t; $P_{BESS\Sigma,t}$ 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 The 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.

$$\begin{cases} SOC_{i\min} \le SOC_{i,t} \le SOC_{i\max} \\ SOC_{i,t} = SOC_{i,t-1} - \dfrac{P_{BESSi,t} \cdot \Delta t}{C_{i0}} \\ DOD_{i,t} = 1 - SOC_{i,t} \end{cases} \tag{11}$$

Where, $SOC_{i\min}$ and $SOC_{i\max}$ are the minimum and maximum values of the battery charge state of the *i*-node, $DOD_{i,t}$ 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.

$$\begin{cases} P_{ic,\max} \le P_{BESSi,t} \le 0 & \text{(Charge)} \\ 0 \le P_{BESSi,t} \le P_{id,\max} & \text{(Discharge)} \end{cases} \tag{12}$$

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

IOP Conf. Series: Earth and Environmental Science **108** (2018) 052014 doi:10.1088/1755-1315/108/5/052014

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..

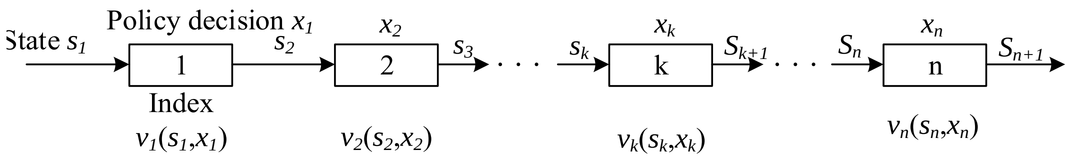


Fig. 2 Basic flow of dynamic programming

Where the state variable is s_1, $s_2 \cdots s_{n+1}$, the decision variable is x_1, $x_2 \cdots x_{n+1}$. 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

$$s_{k+1} = T_k\left(s_k, x_k\right) \tag{13}$$

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

$$f_{k+1}(s_{k+1}) = \underset{\{x_1,\cdots,x_{k+1}\}}{opt} [v_{k+1}(s_{k+1}, u_{k+1}), f_k(s_k)] \tag{14}$$

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

$$\begin{cases} \sum_{i=1}^{m} a_{i,t} P_{ice,\max} \le P_{BESS\,\Sigma,t} \le 0 & \text{（Charge）} \\ 0 \le P_{BESS\,\Sigma,t} \le \sum_{i=1}^{m} a_{i,t} P_{ide,\max} & \text{（Discharge）} \end{cases} \tag{15}$$

Where, $P_{ice,\max}$ is the rated power of the i-node energy storage system at charge time, and $P_{ide,\max}$ 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:

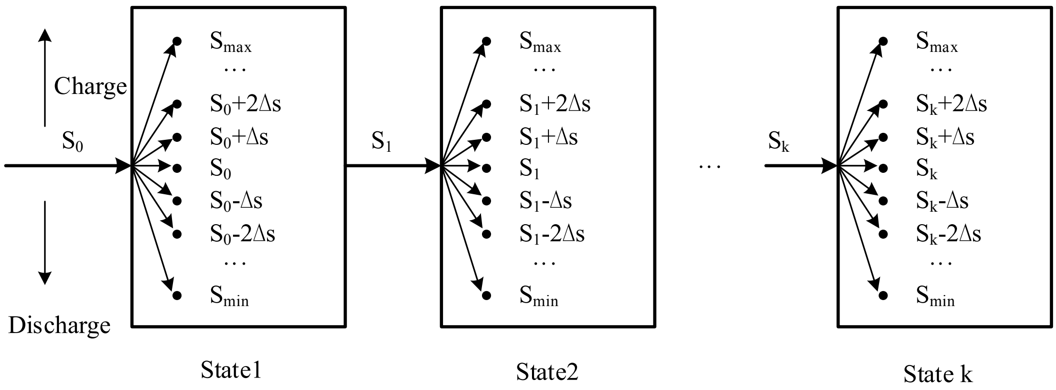


Fig. 3 the basic flow of optimization strategy based on dynamic programming

(1) 1 day to Δt 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

$$K = \frac{T \cdot P_{eBESS\Sigma}}{\Delta s} \tag{16}$$

Where, T is the time of 1 day; $P_{eBESS\Sigma}$ 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; Δs is the power difference in the adjacent state. When the Δs value is small, the optimization path is relatively large and is suitable for accurate calculation. When there is a time requirement, Δs 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

$$DOD_k = \frac{S_k}{T \cdot P_{eBESS\Sigma}} \tag{17}$$

Due to the existence of Δs, the model is discrete, in order to ensure that the optimization process can be a good termination, allowing *DOD* ± 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

$$\begin{aligned} v_{k+1}(P_{BESS\Sigma,k}, x_k) = \Big| & P_{load,k} - P_{BESS\Sigma,k} \\ & - \frac{1}{k+1}\sum_{t=1}^{k+1}(P_{load,t} - P_{BESS\Sigma,t}) \Big| \end{aligned} \tag{18}$$

Where, xk 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. Smax and Smin correspond to arrows for decision making boundaries.

(4) The initial state to the k-state index function

$$V_{1,k}=\sqrt{\frac{1}{k}\sum_{i=1}^{k}v_k^2(P_{BESS,k},x_k)} \tag{19}$$

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

$$V_{1,k}^2=\frac{1}{k}\left[(k-1)V_{1,k-1}^2+v_k^2(P_{BESS,k},x_k)\right] \tag{20}$$

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

$$f(P_{BESS\,k})=\min V_{1,k} \tag{21}$$

(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 The 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_k, so

$$S_k = S_k \pm \frac{n}{2}\Delta s \quad n=1,2,3\cdots \tag{22}$$

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, Δs 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.

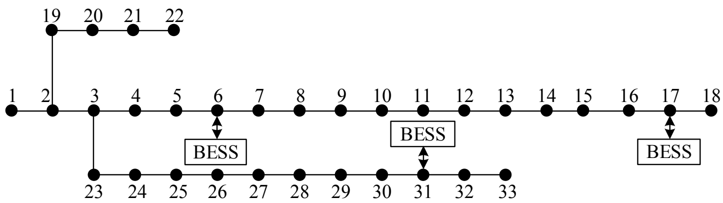


Fig. 4 Network structure and location diagram of distributed energy storage system

Table 1. Installed capacity of distributed energy storage syste

Location	Energy storage system capacity (kW • h)	Rated power of converter kW
6	400	100
17	600	150
31	600	150

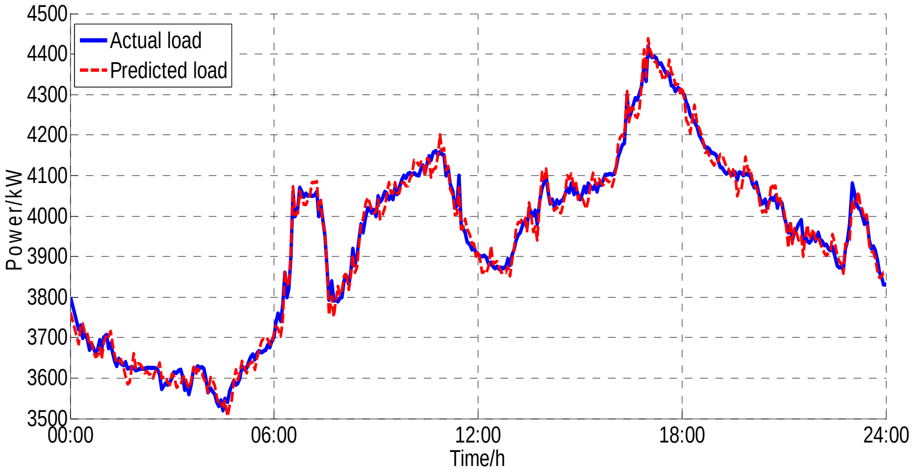


Fig. 5 Typical daily load curve

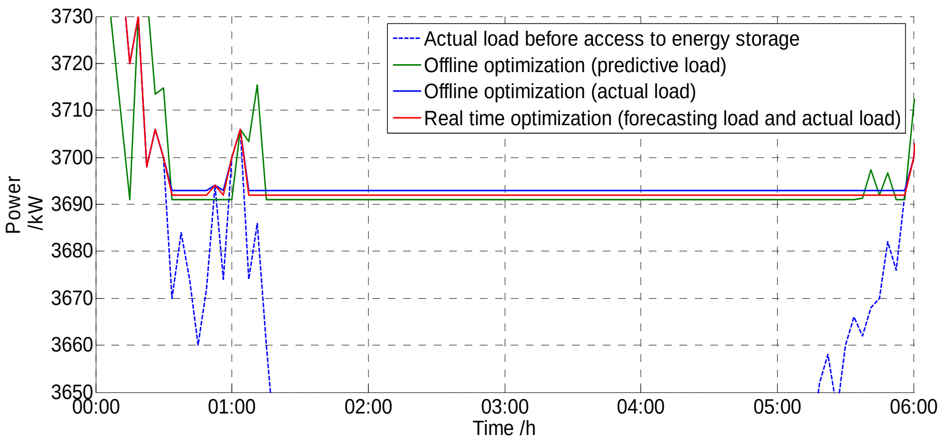
4.1. Comparison of real-time optimization and off-line optimization results

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

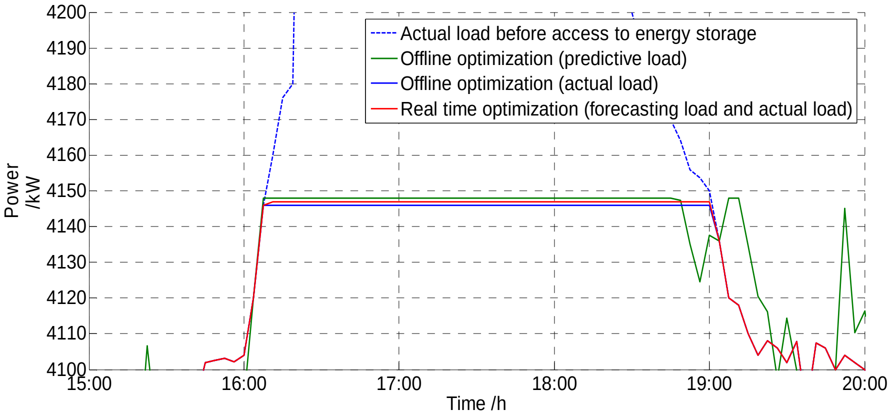
It can be seen from the results that the variance of the real-time optimization result is closer to the optimization result using the actual load, and the error is less than the off-line optimization error of the forecast load.

Table 2. Comparison of the results of real-time optimization and offline optimization

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



(b) Optimization results of peak shaving period

Fig. 6 Comparison of the results of real-time optimization and offline optimization

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 $-407\text{kW} \le P_{BESS\Sigma} \le 396\text{kW}$, $\Delta s = 10kw□5min$, 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

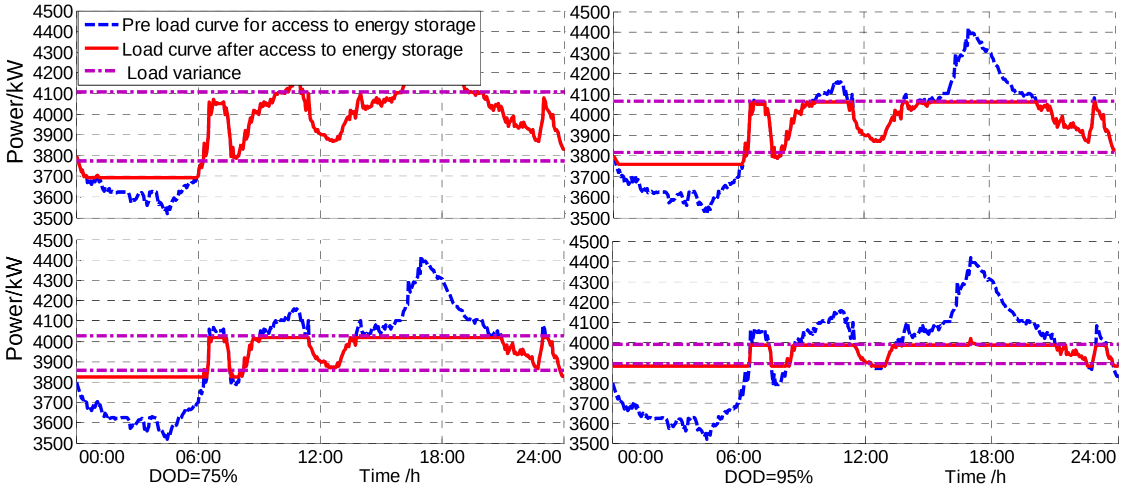


Fig. 7 Comparison of different DOD optimization results

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 Δs 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_k.

(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.

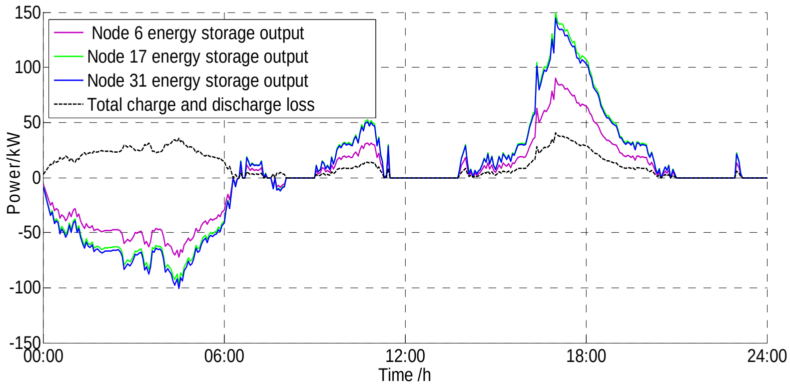


Fig. 8 Output of each node energy storage system and total charge and discharge losses

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 Δs 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.

About the Author:

Wang Qian (1978), male, engineer, master of engineering, research direction for the power system analysis and new energy grid;

Xu Jing (1989), male, in the master's degree graduate student, research direction for the power system storage, the mailbox is 775295732@qq.com.

References

[1] Sun Xiaofeng, Hao Yancong, Wang Baocheng, Shen Hong, Guo Xiaoqiang. State balance and

voltage recovery of micro grid distributed energy storage unit [J/OL]. proceedings of the Chinese society of electrical engineering, 2016,36 (15): 4047-4055.

[2] Mao Meiqin, Zhang Yongning, Wang Yang Yang, Zhang Liu Chen. Peak strategy for microgrid [J]. southern power grid energy optimization technology of multiple time scales, 2016,10 (08): 23-31.

[3] Pei Wei, Sheng Kun, hole force, Qi Zhiping. Effect of distributed generation on distribution network voltage quality and improve the [J]. Chinese of the CSEE, 2008, (13): 152-157.

[4] Jin Shang, Tai nengling, Liu Qi, Chen Bin, Chen Jinxiang, Huidong. The battery range control can load operation control strategy [J]. Journal of electric technology of power station, 2015,30 (16): 221-229.

[5] Zhu Jizhong, Yu Pengfei, and Xie Pingping. PZ, comprehensive economic dispatching method considering [J/OL]. wind power and energy storage of the China Southern Power Grid technology, 2017,11 (02): 2-7.

[6] Purvins A, Papaioannou I T, Debarberis L. Application of battery-based storage systems in household-demand smoothening in electricity-distribution grids[J]. Energy Conversion and Management, 2013, 65: 272-284.

[7] Purvins A, Sumner M. Optimal management of stationary lithium-ion battery system in electricity distribution grids[J]. Journal of Power Sources, 2013, 242: 742-755.

[8] Xu Hanchen, Yuan Zhichang, Lu Chao, et al. Multimodal optimization of wind storage system based on modern interior point method [J]. automation of electric power systems, 2013, 37 (16):1-6.

[9] Bao Guannan, Lu Chao, Yuan Zhichang, et al. Real-time optimization of peak shaving and valley filling in battery energy storage system based on dynamic programming [J]. automation of electric power systems, 2012, 36 (12):11-16.

[10] CAU T D H, KAYE RJ. Evolutionary optimization method for multi-storage hydrothermal scheduling[J]. IEE Proceedings of Generation, Transmission and Distribution, 2002, 149(2):152-156.

[11] CHACRA F A, BASTARD P, FLEURY G, etal. Impact of energy storage costs on economic performance in a distribution substation[J]. IEEE Transon Power Systems,2005,20(2):684-691.

[12] LEE T Y.Operating schedule of battery energy storage system in a time-of-use rate industrial user with wind turbine generators: a multipass iteration particle swarm optimization approach[J].IEEE Trans on Energy Conversion,2007,22(3): 774-782.

[13] FUNG C C,HO S C Y C,NAYAR V. Optimisation of a hybrid energy system using simulated annealing technique [C] //Proceedings of IEEE International Conference on Computer, Communication,Control and Power Engineering: Vol 5,October 19-21, 1993, Beijing, China:235-238.

[14] HU Weihao,CHEN Zhe,BAK-JENSEN B.Optimal operationstrategy of battery energy storage system to real-time electricity price in Den-mark[C]//Proceedings of IEEE Power and Energy Society General Meeting,July 25-29,2010,Minneapolis,MN,USA:1-7.

[15] OUDALOV A,CHERKAOUI R,BEGUIN A.Sizing and optimal operation of battery energy storage system for peak shaving application[C]//IEEE Pro-ceedings of Power Tech,July 1-5,2007,Lausanne,Switzerland.

[16] Luo min, Cheng Nan, Wang Yi, Zhu Wenjun, Lin state, que Huakun. Prediction of large customer load personalized wavelet denoising and decision tree [J]. Southern Power Grid Technology Based on 2016,10 (10): 37-42.

[17] Xie min, Deng Jialiang, lucky, Liu Mingbo. Prediction method of cooling load based on information entropy and variable precision rough set optimization support vector machine [J]. power system technology, 2017,41 (01): 210-214.

[18] Chen Haoyong, Fu Xue Qian, Niu Ming, Jin Xiaoming. The short-term regional power load forecasting system design of [J]. electric power construction, 2014,35 (02): 13-17.