International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 0843

OPTIMAL OPERATION STRATEGY FOR A WIND-STORAGE INTEGRATED SYSTEM CONSIDERING THE TEMPORAL CORRELATION OF WIND POWER

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ABSTRACT

Based on the uncertainty surrounding the temporal correlation of wind power forecast error, an energy storage system (ESS) is applied to both a peak shaving mode and a plan following mode, and a multimode optimization model for a wind-storage integrated system is proposed. Considering the large-scale mixed integer programming (MIP) problem, a peak shaving coefficient of ESS capacity and a two-layer optimization algorithm is proposed. Thus, the problem can be solved iteratively, and capacity allocation can be evaluated in different modes. The simulation results show that pool purchase price, penalty price and the stochastic characteristics of wind power influence the optimal operation of a wind-storage integrated system. The proposed model can realize reasonable allocation and efficient utilization of limited ESS capacity.

Keywords: wind-power integrated system, temporal correlation of wind power, multimode coordination, peak shaving coefficient, sensitivity analysis

1. INTRODUCTION

Recently, the rapid development of renewable energy sources (RESs) has attracted extensive attention all over the world. By the end of 2017, the installed capacity of wind had reached 165 GW in China, ranking first in the world [1]. However, the power output of wind is stochastic, and the security and stability of the power system are greatly challenged by the integration of large-scale variable wind power.

With advantages such as rapid adjustability ability, high energy density and flexible configuration, energy storage systems (ESS) have been commercially implemented in many fields [2]. ESS can compensate for the fluctuation of wind generation to improve power quality and enhance the economy and safety of whole grids. Thus, a wind-storage hybrid system can play an important role in the utilization of volatile wind energy sources.

The optimal operation strategy for wind-storage integrated systems has become a research focus due to their stable power supply and increased operational efficiency. In [3], a detailed model of a battery ESS was established to maximize selling revenue. In [4], an ESS was used for peak shaving in the day-ahead market and for plan following in real-time scheduling. In [5], multiple scenarios were used to describe uncertain wind power generation. In consideration of various constraints, such as the frequent charge and discharge of the battery, the optimization model was built to maximize the expectation of the selling revenue and minimize the penalty cost of wind curtailment. In [6], the factors used to determine ESS parameters were discussed on the planning level, which could inform the future planning and construction of ESS.

The existing research has three main shortcomings: (1) The lack of consideration of the temporal correlations of wind power. (2) The lack of fast and effective solutions for the optimal operation of wind-storage integrated systems with high-dimensional and stochastic features. (3) The lack of guidelines to determine the optimal operation mode of wind-storage integrated systems.

Given the current state of the research, a multidimensional Gaussian distribution is first used to model the wind power forecast error by considering its temporal correlation. Then, a multimode optimization model for a wind-power integrated system is proposed, which comprehensively considers the coordination between the two ESS application modes of peak shaving and plan following. The peak shaving coefficient of ESS capacity is proposed to evaluate the ESS capacity allocation in different modes, and a two-layer optimization algorithm based on the coefficient is further proposed to solve the model quickly. Finally, the performance of the proposed model is demonstrated based on the actual data, and the influence of price factor and wind power stochastic characteristics on the optimal operational mode of the ESS are analyzed, which provides an important point of reference for the optimal operation of a wind-storage system.

2. A MULTIMODE OPTIMIZATION MODEL FOR A WIND-STORAGE INTEGRATED SYSTEM

2.1 Wind power uncertainty model considering temporal correlation

Due to the stochastic nature of wind power, the integrated operation of wind-storage is a stochastic programming problem. This problem mainly involves short-term uncertainty, which is generally described by the probability distribution of the wind power forecast error. However, the optimal operation for an ESS is a multistage decision problem, so the state of charge (SOC) of an ESS is closely related to the magnitude and sequence of wind power fluctuations. Therefore, the uncertainty model of wind power needs to consider not only the edge distribution of the error but also its temporal correlation. In this paper, a probability measure transformation [7] method is used to transform the wind power forecast errors at each time point into a Gaussian distribution sequence. Then, a multidimensional Gaussian distribution is used to model the temporal correlation of the errors at each time point. Based on the uncertainty model, wind power fluctuation scenarios can be generated by sampling.

2.2 A multimode optimization model for a wind-storage system

The main applications of an ESS are peak shaving and plan following. The peak shaving mode aims to maximizing selling revenue. According to the price difference between the peak period and the valley period, the wind power at the valley period is shifted to the peak period by the ESS to provide peak shaving service for the power grid. The plan following mode aims to minimize the penalty price. By controlling an ESS, the deviation between the combined outputs of a wind-storage system and the day-ahead generation plan is reduced, which improves the controllability and reliability of wind power and reduces the reserve demand of the power grid. Due to stochastic factors such as wind power, the power and capacity of an ESS in a single application mode may be surplus and not fully utilized. Therefore, this paper applies the ESS to both modes at the same time.

The objective function is the expectation of selling revenue, penalty price and storage cycle cost of a wind-storage system in different wind power scenarios, as shown in equation (1):

$$\min \sum_{\omega=1}^{N}\sum_{t=1}^{T}(-\pi_t(P_{Wt}^{\omega}+P_{dt}^{\omega}-P_{ct}^{\omega})+Pun_t^{\omega}+\lambda_{cd,t}^{\omega}+\lambda_{dc,t}^{\omega}) \tag{1}$$

where ω represents the wind power scenario and N is the number of scenarios. t is the time period. T is the length of the optimal period. π_t is the pool purchase price of the wind-storage system. P_{Wt}^{ω} is the wind power. P_{ct}^{ω} and P_{dt}^{ω} are the charge /discharge power of the storage system. Pun_t^{ω} is the penalty price for the wind-storage system's deviation from the day-ahead plan. $\lambda_{cd,t}^{\omega}$ and $\lambda_{dc,t}^{\omega}$ are the transformation costs when the storage system is converted from charge to discharge or from discharge to charge.

2.2.1 Penalty price constraints

In the paper, the penalty price is expressed in terms of linear constraints:

$$\begin{cases} Pun_t^{\omega} \ge \alpha_{up,t}(P_{Wt}^{\omega}+P_{dt}^{\omega}-P_{ct}^{\omega}-(P_t+\Delta P_{wide})) \\ Pun_t^{\omega} \ge \alpha_{down,t}((P_t-\Delta P_{wide})-(P_{Wt}^{\omega}+P_{dt}^{\omega}-P_{ct}^{\omega})) \\ Pun_t^{\omega} \ge 0 \end{cases} \tag{2}$$

where P_t is the day-ahead generation plan submitted by the wind-storage system. ΔP_{wide} is the deviation of wind power from the plan value allowed by the power grid; $\alpha_{up,t}$ and $\alpha_{down,t}$ are the penalty prices for going over the upper/lower limit of power output. The relationship between the penalty price for going over the upper limit and the pool purchase price shows the different dispatch principles for wind power.

2.2.2 Cycle price constraints

The cycle cost is divided into two parts, charge to discharge and discharge to charge. It also utilizes linear constraints as in equation (2) to avoid absolute value terms in the model, as shown in equation (3):

$$\begin{cases} \lambda_{cd,t}^{\omega} \ge \tau_{cd}(u_{d,t}^{\omega}-u_{d,t-1}^{\omega}) \\ \lambda_{dc,t}^{\omega} \ge \tau_{dc}(u_{c,t}^{\omega}-u_{c,t-1}^{\omega}) \\ \lambda_{cd,t}^{\omega} \ge 0, \lambda_{dc,t}^{\omega} \ge 0 \end{cases} \tag{2}$$

where τ_{cd} and τ_{dc} are the state transition prices for converting charge to discharge and converting discharge to charge. $u_{c,t}^{\omega}$ and $u_{d,t}^{\omega}$ are the charge/discharge states of the ESS, which are 0-1 variables.

2.2.3 Operation constraints for an ESS

The operation of an ESS also needs to meet the power and capacity limits and the charge and discharge state mutual exclusion constraints, as shown in equation (4):

$$\begin{cases} 0 \le P_{dt}^{\omega} \le u_{d,t}^{\omega} P_{d\max} \\ 0 \le P_{ct}^{\omega} \le u_{c,t}^{\omega} P_{c\max} \\ u_{d,t}^{\omega} + u_{c,t}^{\omega} = 1 \\ SOC_{\min} \le SOC_0 - \sum_{k=1}^{t} (\frac{P_{dk}^{\omega}}{\eta_d} - P_{ck}^{\omega}\eta_c) \frac{\Delta t}{S_{rate}} \le SOC_{\max} \end{cases} \tag{4}$$

where P_{cmax} and P_{dmax} are the maximum charge/discharge power values. SOC_0 is the initial state of SOC. η_c and η_d are the charge/discharge efficiencies. S_{rate} is the rated capacity of the ESS. Δt is the time interval. SOC_{max} and SOC_{min} are the maximum allowable charge/discharge depths.

The multimode optimization model for the wind-storage integrated system is obtained by combining equations (1)-(4). When the objective function only contains the first and third terms of equation (1), the ESS is in peak shaving mode, and its charge/discharge power is determined only by the price of electricity. When the objective function only contains the second and third terms of equation (1), the ESS is in plan following mode.

2.3 Two-layer optimal solution

The multimode optimization model proposed in 2.2 is a high-dimensional mixed integer linear programming (MILP) problem. Its scale is related to the number of wind power fluctuation scenarios, and the computational complexity increases exponentially with scale. Therefore, most references adopt the scenario reduction method to obtain a set of scenarios for wind power fluctuation by aggregating similar scenarios and eliminating low-probability scenarios.

In the multimode optimization model, the day-ahead generation plan for the wind-storage integrated system is a pivotal variable that links various wind power scenarios, and it is the main reason for the significant increase in computational complexity. Therefore, the paper decomposes the solution into two layers. The outer layer is optimized for the day-ahead generation plan separately, and the inner layer decouples and optimizes each wind power scenario on this basis. Through the iteration between the outer layer and the inner layer, the difficulty of the model can be greatly reduced. The outer layer model takes peak shaving revenue as the objective to guide the ESS to allocate part of its capacity to the peak shaving mode, as shown in equation (5):

$$\min \sum_{t=1}^{T} -\pi_t (P_{dt} - P_{ct}) + \beta_1 P_{dt}^2 + \beta_2 P_{ct}^2$$
$$s.t. \begin{cases} 0 \le P_{dt} \le rP_{dt0} \\ SOC_{\min} \le SOC_0 - \sum_{k=1}^{t} (\frac{P_{dk}}{\eta_d} - P_{ck}\eta_c) \frac{\Delta t}{S_{rate}} \le SOC_{\max} \\ SOC_T = SOC_0 \end{cases} \tag{5}$$

where P_{dt} and P_{ct} are the day-ahead peak shaving power values for the wind-storage system. β_1 and β_2 are the squared coefficients of the charge/discharge power, which can rationally allocate power during the same electricity price period while maximizing peak shaving revenue. The constraints include the limit of peak shaving depth, SOC state constraints and the final value of SOC—SOC_T.

The limit of peak shaving depth in equation (5) is proportionally corrected based on the maximum peaking depth P_{dt0} in peak shaving mode. r is the peak shaving coefficient of ESS capacity proposed in the paper, and $0 \le r \le 1$. From a physical point of view, r represents the allocation ratio of the limited capacity of the ESS in peak shaving and plan following modes. When r equals 1, the ESS capacity is all used for peak shaving, and when r equals 0, the ESS capacity is all used for plan following. The peak shaving coefficient of the ESS is used to construct a family of proportionally varying power generation planning curves. In fact, this approach limits the boundary conditions of the original problem, and optimization is searched for only on the constructed surface. As a result, the high-dimensional MIP problem is decomposed into a one-dimensional single-peak optimization problem at the outer layer and a multi-scenario decoupling low–dimensional MIP problem at the inner layer.

The peak shaving coefficient of ESS capacity links the optimization models between two layers. A one-dimensional function optimization method can be used. The golden section method is used in this paper.

3. SIMULATION VERIFICATION AND SENSITIVITY ANALYSIS

3.1 Wind power fluctuation scenario modeling

The simulation chooses a forecast and measured data for a wind farm with an installed capacity of 124

MW from the wind power integrated database of the National Renewable Energy Laboratory (NERL) [8]. First, a nonparametric estimation method [9] is used to model the edge distribution of the errors for 24 forecast periods. After measurement transformation, the temporal correlation of the error is modeled by a multidimensional Gaussian distribution, and the covariance matrix for the Gaussian distribution is fitted, as shown in Figure 1. It can be seen that the closer the temporal interval is, the higher the correlation of errors, which is determined by the temporal persistence characteristics of wind resources.

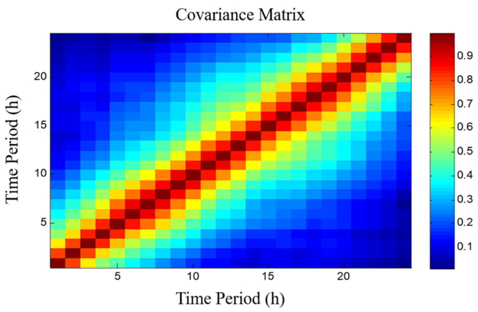

Fig 1 The covariance matrix for forecast error

Due to the temporal correlation of the forecast error, there will be situations in which the consecutive errors will be positive or negative for a period of time, which will increase the demand for ESS capacity. Figure 2 is the frequency distribution diagram for consecutive positive/negative forecast error quantity. Obviously, a model that considers temporal correlation better reflects the long-tail effect of the distribution and fits the actual data better.

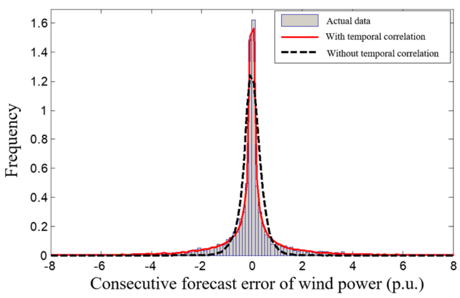

Fig 2 Frequency distribution of consecutive error quantity

3.2 *Algorithm validation*

The wind-storage simulation system consisted of a 124 MW wind farm in 3.1 and an all-vanadium redox flow battery of 24.8 MW/99.2 MWh (20% of the rated power of the wind farm and 4 h of the complete discharge time), and the uncertain set of wind power data consisted of 100 aggregated wind power fluctuation scenarios. We assume that the pool purchase price is the peak-level-valley time-of-use electricity price and that the price is 0.2 RMB/kWh during valley time (0:00-7:00), 0.8 RMB/kWh during peak time (11:00-15:00, 19:00-21:00) and 0.5 RMB/kWh during level time (8:00-10:00, 16:00-18:00, 22:00-23:00) . The amount of output deviation from the plan value allowed by the grid is ±5%. The penalty price is set at 1.1 times the electricity price.

Five simulation scenarios are set: 1) Without an ESS, the day-ahead generation plan adopts the expectation of fluctuation scenarios of wind power. 2) The ESS is in peak shaving mode. 3) The ESS is in plan following mode. 4) The ESS is in multimode optimization. Then, 100 aggregated wind power scenarios are adopted, and the solution is based on the two-layer optimal method. 5) The ESS is in multimode optimization. Then, 5 aggregated wind power scenarios are adopted, and the solution is based on the global optimization. The expectation values for various economic indicators are calculated according to 100 aggregated wind power scenarios. The results are shown in table 1.

Table 1 Profit comparison of five application cases

10 thousand RMB

Scenarios	Selling revenue	Penalty expectation	Operation cost	Total revenue
Scenario 1	79.02	20.18	0	58.85
Scenario 2	82.69	20.18	1.27	61.48
Scenario 3	77.73	12.41	1.03	64.06
Scenario 4	79.86	13.31	1.26	65.29
Scenario 5	78.93	13.44	1.26	64.23

In scenario 2, the ESS is only applied in peak shaving mode: it has maximum selling revenue, but it has the same penalty price as scenario 1. In scenario 3, the ESS is only applied in plan following mode: it has the minimum penalty price, but it also has minimum selling revenue. In addition, the storage operation cost in scenario 3 is the lowest, which means that the plan following mode has fewer cycles. In scenario 4, the ESS is in multimode optimization, so the value of a single indicator is between the values for scenario 2 and 3, while the total revenue is highest. The total revenue in scenario 5 is smaller than that in scenario 4 because the plan was optimized for the scenarios after a large reduction. The accuracy of the optimal solution for the reduction model is lower than the suboptimal solution obtained by the proposed two-layer solution method.

3.3 *Sensitivity analysis for operation mode*

Previous literature has usually analyzed sensitivity from a planning perspective. However, in regard to operational dispatch, stochastic factors, such as pool purchase price, penalty price and wind power characteristics, vary seasonally or daily. The optimal operation mode of the wind- storage system will change accordingly. The proposed peak shaving coefficient of ESS capacity can quantitatively analyze the variation law for the operational strategy of a wind-storage system with external factors, which gives an important point of reference for the optimal operation of a wind-storage system.

3.3.1 The influence of price factors

The optimal operation mode of an ESS is closely related to price factors. Penalty price reflects the severity of the gird's requirement for grid-connected wind power, while the peak and valley prices reflect seasonal changes in grid peak shaving demand.

Figure 3 shows the variation in economic indicators and peak shaving coefficients for different application modes with penalty factor. With increasing penalty factor, the selling revenue in a single application mode is almost unchanged, but penalty price increases continuously. When the penalty factor is greater than 0.7, the total revenue for plan following mode is greater than that for peak shaving mode. The peak shaving coefficient in the multimode optimization is gradually reduced, indicating that the ESS capacity is gradually shifted from peak shaving mode to plan following mode, so its selling revenue is continuously reduced.

Figure 4 shows the variation in the indicators of different application modes with changes in electricity price difference between the peak and the valley. With increasing price difference, selling revenue in a single application mode also increases, and the penalty price is almost unchanged. When the difference in electricity price between the peak and the valley is greater than 700 RMB/MWh, the total revenue of peak shaving mode is greater than that of plan following mode. In addition, at that time, the cycle number of peak shaving mode increases, which means that the total peak shaving capacity increases. Variation in the total peak shaving capacity of the ESS and the peak shaving coefficient is also shown in the figure. When ESS capacity gradually shifts from plan following mode to peak shaving mode, the penalty price increases accordingly.

3.3.2 The influence of wind power characteristics on ESS operation mode

The peaking and uncertain characteristics of wind

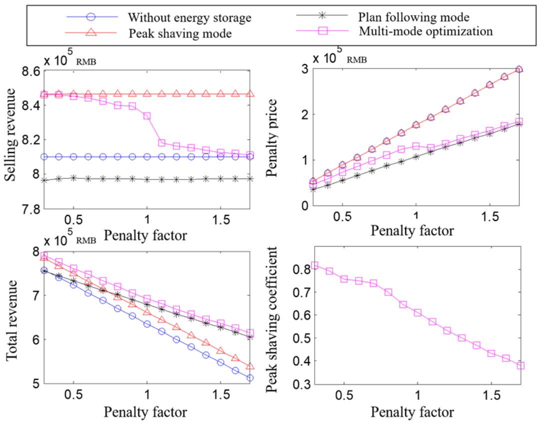

Fig 3 The variation of economic indicators and peak shaving coefficients with the penalty factor

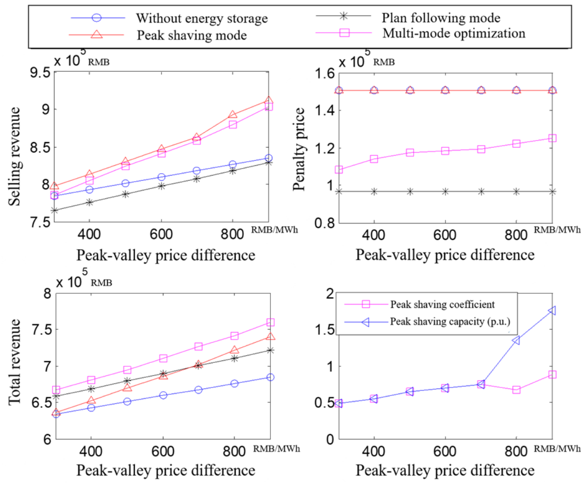

Fig. 4 The variation of economic indicators and peak shaving coefficient with peak-valley price difference

power are the two main stochastic factors affecting the economic operation of power grids and are related to the optimal operational mode of an ESS. Wind power uncertainty is closely related to the forecast output level, so the wind power uncertainty is measured by the expectation of the wind power output forecast. In addition, the correlation coefficient between the wind power forecast and pool purchase price is used to measure the peaking characteristic of wind power. Figure 8 shows the calculation of the distribution of the peak shaving coefficient of ESS capacity for a multimode optimization operation with different wind power characteristics within a year.

As shown in Figure 5, the peak shaving coefficient of ESS capacity first decreases and then increases with an increase in the wind power forecast, which is related to the change of wind power uncertainty. The greater the uncertainty of wind power is, the greater the capacity of the ESS for plan following; thus, the peak shaving coefficient is smaller. In addition, the peak shaving coefficient increases with decrease in the correlation coefficient of wind power peaking because more capacity of the ESS is utilized for peak shaving when wind power has a strong reverse peaking characteristic.

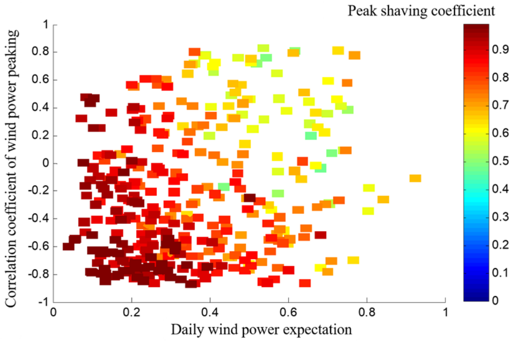

Fig 5 The relationship between the peak shaving coefficient of ESS capacity and the characteristics of wind power

Based on the above analysis, the optimal operational mode for an ESS is not fixed, and the optimal mode is related to stochastic factors, such as price and wind power characteristics. The coordinated optimization model proposed in this paper can better adapt to the changes in relevant factors and can realize the rational allocation of the limited capacity of an ESS in different application modes, thus effectively improving the utilization efficiency of an ESS.

4. CONCLUSION

Based on an uncertainty model considering the temporal correlation of the forecast error of wind power, this paper proposes a multimode optimization model and a two-layer optimal method for a wind-storage integrated system. The main conclusions are as follows: 1) The optimal ESS operation is a multiperiod optimization problem. A short-term uncertainty model of wind power should consider the temporal correlation of the forecast error; otherwise the required ESS capacity will be underestimated. 2) The two-layer optimization algorithm proposed decomposes the high-dimensional MIP problem, which has strong practical value. 3) The concept of a peak shaving coefficient for ESS capacity can quantitatively evaluate capacity allocation of an ESS in peak shaving and plan following modes, which will help analyze the factors influencing ESS application mode and provide information to dispatchers about the plan operation status and the schedulable capacity of the ESS. 4) The optimal operation mode of an ESS is related to stochastic factors, such as price and wind power fluctuation. In general, a small penalty price, a large peak-valley electricity price difference, an obvious reverse peaking characteristic, and relatively large and small power output forecast will cause a large peak shaving coefficient.

ACKNOWLEDGEMENT

The authors thank the National Key R&D Program of China 2017YFB0902200 and Science and Technology Project of State Grid Corporation of China 5228001700CW.

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