An optimal sizing method for energy storage system in wind farms based on the analysis of wind power forecast error

R L Ye, Z Z Guo, R Y Liu, and J N Liu

1Department of Electrical Engineering, Harbin Institute of Technology, Harbin, 150001, China
2State Grid AC Engineering Construction Company, Beijing, 100052, China
1E-mail: 18911267942@163.com

Abstract: Energy storage system (ESS) in a wind farm can effectively compensate the fluctuations of wind power. How to determine the size of ESS in wind farms is an urgent problem to be solved. A novel method is proposed for designing the optimal size of ESS considering wind power uncertainty. This approach uses non-parametric estimation method to analysis the wind power forecast error (WPFE) and the cumulative wind power deviation (CWPD) within the scheduling period. Then a cost-benefit analysis model is established to obtain the optimal size of ESS based on the analysis of WPFE and CWPD. A series of wind farm data in California are used as numerical cases, which presents that the algorithm presented in this paper has good feasibility and performance in optimal ESS sizing in wind farms.

1. Introduction

Given the high environment sensitivity and low predictability, large-scale integration of wind power accompanies great influence on power system and big challenges to grid dispatching operation\cite{1-3}. Therefore, it is of great significance to increase wind power forecast accuracy so as to ensure the safe operation of power system. As of right now, prediction results in large-scale wind farms are not always satisfying, for example, the average value of mean absolute error of wind power prediction around 12 hours varies between 10% (flat terrain) to 22% (complex terrain)\cite{4}, which cannot meet the requirements for generation scheduling. Hence, how to cope with the influence caused by wind power forecast error on generation scheduling and guarantee safe and stable operation of the system deserve further research.

Due to the obvious advantages of energy storage system (ESS) over traditional thermal power generating unit in response speed and regulation accuracy, combined operation of energy storage unit and wind power generation system has already become an effective way of solving the problems of large-scale wind power integration\cite{5-8}. Specifically, to satisfy the requirements of wind power grid-integration, for a same capacity it requires a thermal power generating unit with a capacity that is 1.6-2 times of rated capacity of the wind farm, while a system equipped with energy storage device requires a power capacity that is merely 10-20% of rated capacity of the wind farm\cite{9}.

Recent years have seen lots of scholars and engineers constantly develop large-scale energy storage device and technology. Huge breakthrough has been made in energy storage technology, particularly in compressed-air energy storage\cite{10-13}, which prompts the mass application of energy storage device in wind farms. Equipping ESS in wind farms has become the most direct and efficient way for large-
scale wind power integration areas to restrain the fluctuation of output power and make it satisfy the requirements specified in relevant standards[14-18].

The size of an ESS, i.e. the rated capacity and peak output of an ESS, directly affects the project cost and its application in wind farms. Many papers have proposed methods to optimize the size of ESS for different ESS working conditions[15-28]. HAN et al.[18] pointed out that the application of ESS could help wind farms keep constant and stable output, but require wind farms to equip a bigger energy storage reserve capacity, which will lead to higher project cost of ESS. In [23], the risk theory was harnessed to evaluate the size of ESS in different scenes of electricity market environment and in accordance with the evaluation results, wind power manufacturers needed to buy appropriate energy storage source from the market, which was a dynamic process and of poor maneuverability. LIANG et al.[24] took into account the fluctuations of wind power, and conducted some simulation analysis based on wind farms with different capacities and ESS sizes, and drew the conclusion that the optimal ratio of ESS capacity and wind farm capacity was 1:4. HE et al.[26] focused on an independently operated wind-solar hybrid generation system and set the optimal sizing of ESS in the system as their research target. The maximum load power shortage rate and the maximum instantaneous load power shortage were also considered in determining the capacity of ESS. BREKKEN et al.[27] proposed a power flow control strategy by installing zinc-bromine cell in wind farms and found out the influences of different energy storage control strategies on ESS sizing. The calculation results indicated that the strategy of artificial neural network was slightly better than the simple energy storage response strategy. Drawing lessons from [27] and trying to simplify the process, this paper employs the simple strategy for power control.

In essence, ESS in a wind farm is applied to cope with the random fluctuations of wind power and there is strong correlation between ESS sizing and wind power forecast error (WPFE), while in [15-27], when calculating the optimal size of ESS, the economic benefits was usually taken as the basic consideration and few researches have taken WPFE into consider. Based on the analysis of WPFE, this paper optimizes the size of ESS in a wind farm with cost-benefit analysis method. ESS with larger capacity will have a better performance in smoothing wind power fluctuations, but more cost is required to be paid for energy storage devices. Conversely, ESS with limited capacity or lower peak power can help reduce the cost, but the fluctuation-smoothing effect will be significantly weakened and will in addition lead to more wind curtailment loss or higher reserve capacity compensation.

Given the analyses above, an optimal ESS sizing method based on the analysis of wind power prediction error is presented in this paper. By methods of statistics and probability, the distribution functions of WPFE and the cumulative wind power deviation (CWPD) with respect to dispatching temporal dimension are established, based on which the relation function of the size of ESS and wind energy losses caused by insufficient storage capacity is built. Then the cost-benefit curves of the ESS in a wind farm are finally achieved. Based on the curves, wind farms are able to measure the cost and benefit of an ESS and determine its optimal size.

2. Wind power forecast error analysis

2.1. Calculation of wind power forecast error

Expression (1) gives the calculation of wind power forecast error:

\[ \varepsilon_t = \frac{P_t - \hat{P}_t}{P_{\text{cap}}} \]  

(1)

where \( P_t \) is the actual value of wind farm output power at time t, \( \hat{P}_t \) is the predicted value of wind farm output power at time t, and \( P_{\text{cap}} \) is rated installed capacity of the wind farm.

In order to describe the relation between wind power fluctuations and the capacity of ESS, the cumulative wind power deviation (hereinafter referred to as "CWPD"), namely the wind power
deviation caused by cumulative forecast errors within one dispatching period, is used to measure the capacity of an ESS, as is shown in expression (2).

\[ e_{c,t} = \sum_{r=1}^{t} e_{r} \Delta t, \quad e_{r} = \begin{cases} e_{i}, & e_{i} \leq P_{ESS} \\ P_{ESS}, & e_{i} > P_{ESS} \end{cases} \]  

(2)

where \( e_{c,t} \) is the CWPD caused by cumulative wind power forecast error from period 1 to \( t \); \( \Delta t \) is the time variation and \( P_{ESS} \) is the peak output of ESS.

Normalization is conducted to facilitate the comparison of CWPDs in different forecast periods, as shown in expression (3).

\[ e'_{c,t} = \frac{e_{c,t}}{T} \]  

(3)

where \( T \) is the dispatching period.

2.2. Principles of Non-parametric Estimation

As its estimating functions usually have free forms and few constrains and usually require little for data distribution, non-parametric estimation method has stronger applicability and higher robustness in solving nonlinear and non-homogeneous cases that can’t be described by certainty model, and the whole regression model is totally data driven. Frequently-used non-parametric estimation methods include the kernel density estimation (KDE), the nearest neighbor density estimation (NNDE), etc. KDE method is adopted in this paper.

The fundamental of non-parametric estimation on probability density function is: assuming \( x_1, x_2, \ldots, x_n \) are \( n \) discrete random samples, with the probability density function \( f(x) \) unknown, and the density function estimation is derived from empirical distribution function as shown in expression (4):

\[ f_n(x) = \frac{1}{n} \sum_{i=1}^{n} K_h(x-x_i) \]  

(4)

where \( K(*) \) is the kernel function, \( h \) is the bandwidth coefficient. Common kernel functions include uniform kernel function, Gaussian kernel function, cosine kernel function, triangle kernel function, etc. According to the statistical and experimental findings of Epanechnikov and Scott, different kernel functions have equivalent effects when the bandwidth coefficient is optimal [29]. Therefore the standard Gaussian kernel function and the cross-validation methodology (CV) are employed in this paper to obtain the optimal bandwidth \( h \), and expression (4) is used for density estimation.

The data of a wind farm in Texas, U.S. during the years of 2004-2006 are taken as example for analysis. Wind power forecasts with 1 day in advance are conducted following non-parametric estimation and normal distribution estimation, and the results are shown in figure 1. The kernel function adopted in non-parametric estimation is standard Gaussian kernel function, \( K(x) = \exp(-x^2 / 2) / \sqrt{2\pi} \).

From figure 1, it can be found that the probability density estimating function obtained by non-parametric estimation greatly fits the distribution of wind power forecast error, and the best bandwidth is 0.02434. The maximum value of wind power forecast error is 0.8959, the minimum value is -0.7592, and the distribution curve is not symmetrical about 0. The probability of negative error is higher than that of positive. When adopting the normal distribution method to fit the wind power forecast error, the variance is 0.03854 and the fitting effect is not ideal.

Setting the dispatching period \( T=24h \) and normalizing the CWPD by expression (3), the maximum value of cumulative wind power forecast deviation -11.2348 and the minimum value of 8.7886 are obtained. Non-parametric estimation and normal distribution estimation methods are respectively...
conducted to estimate CWPD, as is shown in figure 2. In non-parametric estimation, the optimal bandwidth is 0.1718; while in normal distribution estimation, the variance is 2.928.

3. Determination of Energy Storage System Scale

Energy storage devices installed in wind farms can not only compensate the deviation between forecast and actual value of wind power, but also effectively restrain the wind power fluctuations. In this paper, the scale of ESS is determined from the perspective of compensating the wind power forecast error. The probability method is harnessed to describe WPFE and CWPD; based on the distribution function of forecast error, a method of determining the scale of ESS in wind farms is proposed; the model of peak output and rated capacity of energy storage device is established; furthermore, in accordance with the cost and benefit curves, the optimal scale of ESS is worked out.

In order to measure the benefit of ESS, variable $W_{\text{loss}}$ is introduced to denote the wind energy loss caused by shortage of ESS capacity and the relations of peak output $P_{\text{ESS}}$ and rated capacity $C_{\text{ESS}}$ with $W_{\text{loss}}$ are established respectively. When analyzing the relationship between $P_{\text{ESS}}$ and $W_{\text{loss}}$, $C_{\text{ESS}}$ is presumed as infinite; while when analyzing that between $C_{\text{ESS}}$ and $W_{\text{loss}}$, $P_{\text{ESS}}$ is presumed as infinite. Eventually, a mathematical model, in which the wind power loss is the objective function and the peak output and rated capacity of ESS are variables, is established and the relationships among the three are shown in a three-dimensional graph.

3.1. Determination of ESS Rated Power
When ESS is short in maximum charge-discharge power, wind energy loss or reserve compensation would occur even if ESS capacity is enough. The loss of wind energy caused by the lack of power of ESS can be calculated by expression (5)

$$W_{loss,P} = W_{loss1,P} + W_{loss2,P}$$  \hspace{1cm} (5)

where $W_{loss1,P}$ is the loss of wind energy caused by the lack of charging power, $W_{loss2,P}$ is the loss of wind energy caused by the lack of discharging power. $W_{loss1,P}$ and $W_{loss2,P}$ can be calculated as follows:

$$W_{loss1,P} = \int_{f_{loss1}}^{f_{max}} f(e_i)(e_i - P_{ESS}) \, de_i$$  \hspace{1cm} (6)

$$W_{loss2,P} = \int_{-1}^{P_{ESS}} f(e_i)(e_i - P_{ESS}) \, de_i$$  \hspace{1cm} (7)

3.2. Model of ESS Rated Capacity

Generally speaking, determining the rated capacity of ESS is much more complex than determining the peak output of it. The usage of stored energy is normally processed in certain intervals to ensure the continuous operation of ESS. In order to ensure ESS capacity meet the requirement of compensating the cumulative energy errors, the most conservative method is to set forecast error $\varepsilon$ as 100%, and in the meantime set ESS capacity as 2 times of the capacity of the wind farm in one dispatching period, i.e. $C_{ESS} = 2 \times T \times P$. We can find from the distribution of forecast errors that the probability of forecast error being extremity ($\varepsilon = 100\%$) is relatively low, hence the conservative method of determining the capacity of ESS will waste many resources. For this reason, this paper proposes a new method of determining the relation between ESS capacity and wind energy loss through analyzing the CWPD $e^*_c$ caused by wind power forecast error $e_i$ in one dispatching period.

The method harnesses the basic energy storage response strategy to evaluate the capacity of ESS. In other words, presuming that the grid dispatches wind farms in accordance with the forecast wind power values, and putting the forecast errors as input of ESS, and using the cumulative forecast energy deviation in one dispatching period as the the capacity of ESS. Firstly, according to the requirements of a specific energy storage dispatching period, calculate CWPD in each period, and find out the maximum CWPD $e^*_{c,max}$. Secondly, analyze the cumulative wind power forecast errors based on non-parametric estimation and empirical distribution model so as to obtain the probability density function $g(e^*_{c})$ and cumulative distribution function $G(e^*_{c})$ with respect to the cumulative forecast errors in the dispatching period.

If ESS is required to compensate all wind power deviations, the rated capacity of it should be set as the difference of maximum and minimum value of CWPD, as shown in expression (8):

$$C_{ESS,0} = e^*_{c,max} - e^*_{c,min}$$  \hspace{1cm} (8)

As a matter of fact, the distribution of CWPD mostly concentrates around value 0, and the probability of big deviation is tiny. Hence installing an ESS with big capacity to compensate the small probability of wind power deviation would inevitably lead to huge waste of resources.

As the value of wind power forecast error could be either positive or negative, and the charging process or discharging process of ESS goes reversely with the polarity of the forecast error, the cases that CWPD is positive or negative need be considered separately.

a) When the CWPD is positive, the actual wind power is higher than forecast. If the charging capacity of ESS is insufficient, wind curtailment or system reserve compensation would occur; since the loss of wind curtailment equals to unit cost of reserve compensation, the loss caused by insufficient chargeable capacity of ESS can be described by expression (9):
\( W_{\text{loss1,C}} = \int_{\bar{C}_{\text{ESS}}} \left[ g\left( e_{c,t}^*\right)\left( e_{c,t}^* - \bar{C}_{\text{ESS}}\right) \right] de_{c,t}^* \)  

(9)

b) On the contrary, when CWPD is negative, the actual wind power is lower than forecast. If the discharging capacity of ESS is insufficient, the output power deviation needs to be balanced by system reserve. Although no direct wind energy loss occurs in the case, yet the safe and stable operation of grid would be severely harmed, as shown in expression (10):

\[ W_{\text{loss2,C}} = \int_{-1}^{\frac{\bar{C}_{\text{ESS}}}{1}} \alpha \cdot g\left( e_{c,t}^*\right)\left( \bar{C}_{\text{ESS}} - e_{c,t}^*\right) de_{c,t}^* \]  

(10)

Wind energy loss caused by insufficient capacity of ESS can be calculated by expression (11):

\[
W_{\text{loss,C}} = W_{\text{loss1,C}} + W_{\text{loss2,C}} = \int_{(1-\beta)\bar{C}_{\text{ESS}}}^{\frac{\bar{C}_{\text{ESS}}}{1}} g\left( e_{c,t}^*\right)\left( e_{c,t}^* - (1-\beta)\bar{C}_{\text{ESS}}\right) de_{c,t}^* + \int_{-1}^{\frac{\bar{C}_{\text{ESS}}}{1}} \alpha \cdot g\left( e_{c,t}^*\right)\left( \beta\bar{C}_{\text{ESS}} - e_{c,t}^*\right) de_{c,t}^* \]

(11)

\[
\bar{C}_{\text{ESS}} = \bar{C}_{\text{ESS}} + \bar{C}_{\text{ESS}} = (1 - \beta)\bar{C}_{\text{ESS}} + \beta\bar{C}_{\text{ESS}} \]

(12)

where \( \alpha \) is the compensation coefficient, denoting the compensation for the loss generated by insufficient power output of the wind farm; \( \bar{C}_{\text{ESS}} \) is the charging capacity of ESS; \( \bar{C}_{\text{ESS}} \) is the discharging capacity of ESS; \( \beta(0 \leq \beta \leq 1) \) is the sliding coefficient, denoting the charging or discharging status of ESS.

For each dispatching period, the initial status of ESS (charging/discharging) is determined by the distribution of cumulative forecast error. For a same ESS capacity, different initial statuses correspond to different effective operation times of stored energy. Presuming that an ESS is at its extreme charging status, if at this moment a negative forecast error occurs, the ESS can’t release the power, which means that the ESS can’t work effectively.

When optimizing the initial operation status of ESS, presuming the total energy storage capacity is fixed and we hope that the effectively-operating time of ESS lasts as long as possible, the model can be described by expression (13):

\[
\max t_{\text{ESS}} = G\left( (1 - \beta)\bar{C}_{\text{ESS}}\right) - G\left( \beta\bar{C}_{\text{ESS}}\right) \]

(13)

Wind energy losses in wind farms correlate simultaneously with the peak output and rated capacity of ESS, based on which, the relations between \( W_{\text{loss}} \) and \( P_{\text{ESS}} \), \( W_{\text{loss}} \) and \( C_{\text{ESS}} \) are established and can be described as shown in expression (14):

\[
W_{\text{loss}}\left( C_{\text{ESS}}, P_{\text{ESS}}\right) = \int_{\beta\bar{C}_{\text{ESS}}}^{1} \Phi\left( e_{c,t}^*, P_{\text{ESS}}\right) de_{c,t}^* + \int_{(1-\beta)\bar{C}_{\text{ESS}}}^{\beta\bar{C}_{\text{ESS}}} \Phi\left( e_{c,t}^*, P_{\text{ESS}}\right) de_{c,t}^* \]

(14)

where \( \Phi\left( e_{c,t}^*, P_{\text{ESS}}\right) \) is the probability density function of \( e_{c,t}^* \) when \( P_{\text{ESS}} \) is given. In application, the peak output and capacity of ESS are normally integral multiples of unit power and unit capacity of it; hence they could be derived through interpolation method. Calculation processes are as follows:

1) Determine the peak output value of the ESS and calculate the loss of wind energy caused by insufficient peak output in accordance with expression (5);

2) Calculate the CWPD \( e_{c,t}^* \) based on the peak output determined in 1);

3) Calculate the loss of wind energy caused by insufficient capacity of ESS in accordance with expression (12);

4) The total wind energy loss under the specific capacity of ESS is the sum of the two losses calculated in 1st and 3rd step.

3.3. Cost-Benefit Analysis of Energy Storage System
The benefit of installing an ESS in a wind farm is that the safe and stable operation of the grid would be influenced without the ESS. When the wind power forecast deviation is negative, reserve usage fee must be paid to the grid; when the wind power forecast deviation is positive, wind energy loss occurs. The benefit $B_{ESS}$ that an ESS brings to a wind farm is equivalent to the wind energy loss saved by installing the ESS minus the wind energy loss caused by not installing the ESS minus the installation cost of ESS, as is shown in expression (15):\

$$B_{ESS} = (W_{loss,inst} - W_{loss,uninst}) \times LC \times P_{wind} - C_{inst}$$ (15)\

Where $W_{loss,inst}$ and $W_{loss,uninst}$ are respectively the wind energy losses before and after the installation, and both can be derived by expression (14); $LC$ is the lifespan of the ESS; $P_{wind}$ is the rated capacity of the wind farm; $C_{inst}$ is the cost of ESS installation, which is normally a linear function of peak output and rated capacity of ESS.

4. Analysis of Examples
To verify the effectiveness and feasibility of the optimal ESS sizing method proposed in this paper, a wind farm in Texas, U.S. as well as the data it released during 2004-2006 is taken as example for analysis. When the CWPD is positive, ESS should be charged; while when it is negative, ESS should change into the discharge status. In order to ensure the ESS can operate effectively in a long time, the initial status of ESS in each dispatching period are presumed to be fixed. The CWPDs in each dispatching period within the three years are collected and analyzed and the distribution function is obtained, as shown in figure 3, where the x-axis is CWPD and the y-axis is the distribution function of it.

It can be seen from figure 3 that different sliding coefficients $\beta$ lead to different probabilities of effective operation of ESS. For a same ESS capacity $C_{ESS}$, when $\beta$ is B1 and B2 respectively, the effective action times of ESS are correspondingly $t_{ESS,1}$ and $t_{ESS,2}$, $t_{ESS,1}$ is obviously bigger than $t_{ESS,2}$. Hence it can be derived from above that the determination of the initial status of ESS does influence the adjustment of CWPD, and the initial status of ESS needs to be optimized.

![Figure 3. Distribution function of cumulative wind power forecast deviation](image)

According to expression (13), when the capacity of ESS is given, we can establish the model targeting at the effective working time of ESS to be the longest, and work out optimal sliding coefficients and the corresponding possibilities $\lambda_{ESS}$ of ESS acting effectively under different
conditions by interpolation, as shown in figure 4, and finally gain the optimum charging/discharging sliding coefficient values of ESS at the beginning of each dispatching period.

![Figure 4. Probability distribution of storage system's effectiveness times](image)

From figure 4 it can be seen that there isn’t a linear relation between ESS’s initial sliding coefficient and its effective action time. Table 1 gives the optimal sliding coefficients when $P_{ESS}$ is 0.9p.u., 0.6p.u., 0.3p.u., and $C_{ESS}$ is 0.6p.u., 0.3p.u., and 0.1p.u.

**Table 1. Optimal sliding coefficients and $\lambda_{ESS}$**

| $P_{ESS}$ | $C_{ESS}$ | Sliding coefficient $\beta$ | $\lambda_{ESS}$ |
|-----------|-----------|-----------------------------|-----------------|
| 0.3       | 0.1       | 0.486023                    | 0.656715        |
| 0.3       | 0.3       | 0.502373                    | 0.977021        |
| 0.6       | 0.1       | 0.459388                    | 0.625912        |
| 0.6       | 0.3       | 0.502769                    | 0.951459        |
| 0.6       | 0.6       | 0.494132                    | 0.998177        |
| 0.9       | 0.1       | 0.459388                    | 0.52577         |
| 0.9       | 0.3       | 0.47965                     | 0.950471        |
| 0.9       | 0.6       | 0.484902                    | 0.997797        |

It can be observed from Table 1 that the optimal sliding coefficients vary corresponding to the values of $P_{ESS}$ and $C_{ESS}$. When $P_{ESS}$ and $C_{ESS}$ are respectively in different values, the corresponding optimal sliding coefficients are not identical.

![Figure 5. Relation between peak output of energy storage system and wind energy loss](image)
Based on the expression (5), presuming the capacity of energy storage system is infinite, the relation between the peak output of ESS and wind energy loss is calculated, as shown in figure 5. It can be derived from the figure 5 that the shorter the forecast period, the more precise the forecast, and the lower the wind energy loss. Analyzing each of the forecast curves, it can be seen that wind energy loss saved by the increase of peak output of unit storage energy goes down with increase of the output.

Likewise, presuming the peak output of ESS is infinite, and the relation between rated capacity of storage system and wind energy loss could be calculated out by the expression (11), as is shown in figure 6.

![Figure 6. Relation between rated capacity of energy storage system and wind energy loss](image)

It can be observed in figure 6 a relation similar to that in figure 5: when the rated capacity of ESS rises, wind energy loss correspondingly reduces, and the wind energy loss saved by the increase of unit storage system capacity decreases gradually.

Based on the forecast (with 1 day in advance) data and the expression (14), the relation between ESS scale and wind energy loss is worked out as shown in figure 7.

![Figure 7. 3D diagram of relation between scale of energy storage system and wind energy loss](image)

We can find in figure 7 that when the peak output of ESS is 0.8959p.u. and the rated capacity is 0.8343p.u., the wind energy loss is 0, which can ensure a full integration of wind power into grid, but the cost is extremely high.

Compressed-air energy storage device can constantly generate electricity for over 24 hours with low energy consumption, long energy-storing time and working hours. Specifically, a compressed-air
energy storage station could work for 30-40 years after installation. Therefore, a compressed-air ESS is adopted in this paper to calculate the cost of ESS.

Based on the cost-benefit optimization principle, the capacity of ESS is optimized according to expression (15). Presuming the electricity price is 0.15$/kWh, and the reserve cost and wind curtailment cost are 1.5 times of normal electricity price, namely 0.225$/kWh. According to the studies worked out by the Institute of Engineering Thermal Physics, Chinese Academy of Sciences, the cost of compressed-air energy storage is 400$/kW, 50$/kWh, with 30 years of lifetime, and the results of this example are shown in figure 8. When the rated power of ESS is 0.5p.u. and the capacity is 0.4p.u., ESS’s installation cost is $214,880,000 and the wind energy loss saved is $476,101,187, which means a maximum net benefit (income) of $261,221,187 for wind farm. The results indicate that the existence of ESS in a wind farm can greatly reduce wind energy loss and the installation cost of ESS can easily be recovered.

5. Conclusions

With combination of non-parametric estimation and empirical distribution estimation, the forecast error of wind farms in different forecast periods is analyzed; based on which models of peak output, rated capacity and wind energy loss of installing an ESS are established; furthermore, in accordance with cost-benefit optimization principle, the scale of ESS is optimized, and the optimum ESS matching scheme is worked out. In the end, through the analysis on an example of a wind farm in Texas, the optimal ESS sizing method proposed in this paper is verified to be of feasibility and effectiveness.

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