

Optimization of Wind Farm Self-Discipline Interval and Energy Storage System Configuration

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ABSTRACT The uncertain and stochastic output of the wind farm results in a lot of problems when it is connected to the power grid. In order to improve the wind power's friendship to the grid, the wind farm should have a certain self-discipline level. In this paper, it is studied from the perspective of the wind farm self-discipline interval. First, the concept of wind farm self-discipline interval is proposed, followed by a comprehensive index which is used to evaluate the wind farm self-discipline level by comprehensively considering the interval width and the interval accuracy. Second, an optimization method is discussed to obtain the optimal self-discipline interval. This method has general applicability, not only suitable for normal distribution and other known distributions but also for arbitrary distributions (such as non-symmetric, multi-peak distributions). Finally, the size of the energy storage system (ESS) in the wind farm is optimized to guarantee a suitable wind farm self-discipline level. Simulation results show that the proposed method not only effectively improves the self-discipline level of the wind farm but also has general applicability.

INDEX TERMS Wind power, self-discipline, energy storage system (ESS), optimization.

I. INTRODUCTION

As a clean and widely available resource, wind energy has become one of the most popular renewable sources. However the stochastic and uncertain characteristic of wind power also brings rigorous challenges for the safety and stability of the power grid when large scale wind power is connected to system [1]–[4].

In order to mitigate the uncertain and stochastic nature of wind power, improve the ability of the power grid to accept the wind power, and eventually ensure a healthy and reliable running of the power grid, many previous references have studied it from many different aspects.

In [6], a fuzzy-based discrete Kalman filter approach is proposed for smoothing output power fluctuations of the wind and PV generation systems using a battery energy storage system. The proposed approach incorporates the state of health of the battery as a feedback to not only obtain smooth output power but also improve the battery health by adaptively regulating the battery power. In [7], a coordinated

control system based on two control algorithms is proposed. The first proposed algorithm chooses eligible Smart Parking Lots (SPLs) for charging/discharging activity before receiving a new sample of the wind farm output power. Afterwards, the second proposed algorithm determines qualified vehicles in selected SPLs. In [8], the fluctuation feature of wind power output is analyzed both in time domain and frequency domain. The degree of fluctuation is extracted and illustrated as quantization index (QI). Based on QI clustering, the wind scenario with largest power fluctuation is selected as “worst performance,” according to which, scheduling time horizon, along with the capacity and charging/discharging power of ESS, can be determined. In [9], the authors optimized the capacity of energy storage devices with the objective of minimizing wind power prediction errors. By quantifying the functional relationship between energy storage capacity and unserved energy, the minimum energy storage capacity corresponding to different unserved energy is analyzed. Reference [10] proposes to use discrete Fourier transform (DFT) and discrete wavelet transform (DWT) methods to schedule grid-scale energy storage systems to mitigate wind power forecast error impacts while

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Massaro.

considering energy storage properties. The authors of [11] reduce the impacts of wind power forecast errors while prolonging the lifetime of ESS. In [12], a mathematical model and an optimization method is proposed to compensate the forecast error of wind power and reduce the uncertainty of wind power output. In [13], a direct control strategy is proposed to track the deviation of the wind power plan, the control strategy in this paper can change the charge and discharge power of energy storage in real-time according to the deviation of wind power and the state of charge.

Although massive efforts have been launched to improve the acceptance ability of the grid to the wind power, very little research has performed regarding the detailed analysis from the perspective of the wind farm self-discipline interval. In fact, the power grid itself has a certain ability to accept the uncertainty of the wind power by fully utilizing the spinning reserve to absorb the small uncertainty of the wind farm. On the other hand, for the large scale of uncertainty, the wind farm itself should have some methods of control, which in here means the self-discipline.

Lu *et al.* in [4] has also stated that the coordinated autonomous control strategy is strongly recommend for large scale wind farm, because of its higher reliability and efficiency than the joint operation strategy.

First, in this paper, a concept of wind farm self-discipline interval is proposed. The actual output of the wind farm should be limited within the self-discipline interval. A comprehensive index is also proposed to evaluate the wind farm self-discipline level, not only considering the self-discipline interval width but also the interval accuracy.

Second, in this paper, an optimization method is proposed to solve the optimal self-discipline interval. Since at the same confidence degree, the corresponding self-discipline interval is not unique, how to find the optimal interval becomes a problem need to be solved. The proposed method has general applicability, it is suitable for arbitrary distributions (such as non-symmetric, multi-peak distribution).

Finally, in order to guarantee the self-discipline interval, energy storage system(ESS) is installed in the wind farm. ESS is the device which can store energy at one time and output it at another time. This characteristic enables the ESS to mitigate the stochastic and uncertain output of wind power. How to configure the ESS size is another problem to be discussed in this paper. An optimal ESS size including the optimal ESS rated power (P_{rate}) and the optimal ESS rated capacity (E_{rate}) are configured in this paper.

Simulation results show that the proposed method not only effectively improves the self-discipline level of the wind farm but also has general applicability.

II. WIND FARM SELF-DISCIPLINE

Because the power grid has some spinning reserve, so it has a certain absorption ability for the uncertainty of the wind power. We should fully utilize the spinning reserve of the grid to absorb some small uncertainty of the wind farm. As for the large uncertainty of the wind power, the wind farm should

have a certain self-discipline to compensate. That is to say, the wind farm output should be limited within a appropriate interval, so that the wind output will be more friendly to the power grid and can be more accepted by the grid.

If the wind farm output can be limited within a certain appropriate interval, we call the wind farm has a certain self-discipline.

A. THE SELF-DISCIPLINE INTERVAL

1) SELF-DISCIPLINE INTERVAL

The concept of self-discipline interval of the wind farm is first defined in this paper.

Firstly, we will analyze the wind power actual output(P_{act}) and the predict output(P_{pre}). Figure1 shows the actual wind power and the predict wind power, Figure2 shows the wind power predict error(e).

$$e = P_{act} - P_{pre} \tag{1}$$

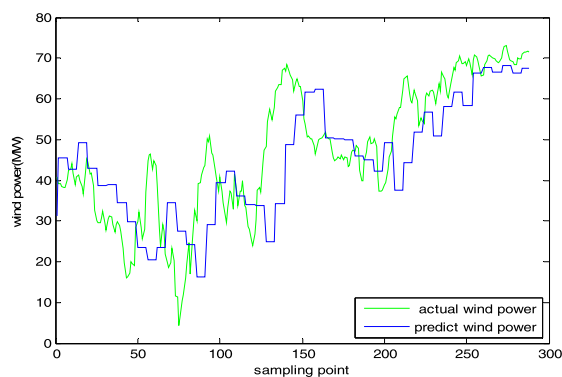


FIGURE 1. Wind power predict output and actual output.

where,

- e is the wind power predict error;
- P_{act} is the wind power actual output;
- P_{pre} is the wind power predict output.

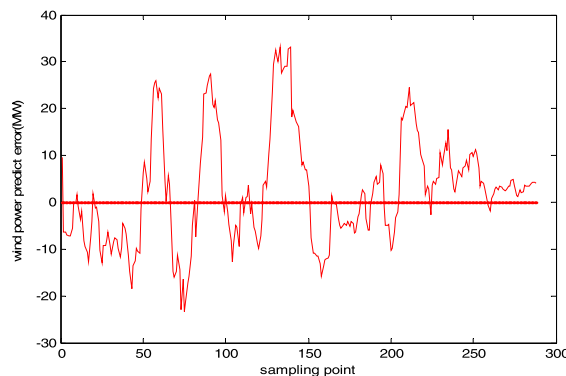


FIGURE 2. Wind power predict error.

From the historical data of the wind farm, we can obtain the error distribution law. After the error distribution law is determined, then the confidence interval under a certain confidence degree($\alpha\%$) can be obtained, as shown in Figure(3).

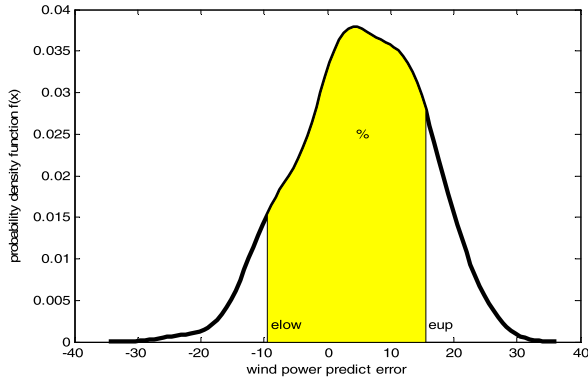


FIGURE 3. Wind power predict error probability density function.

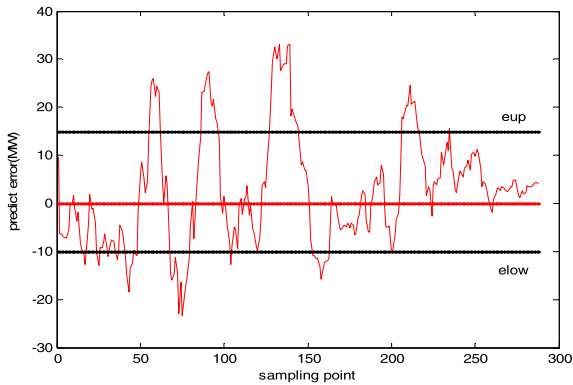


FIGURE 4. Wind power predict error and the confidence interval under $\alpha\%$ confidence degree.

e_{up} and e_{low} are upper limit and lower limit of the confidence interval $\alpha\%$.

By analyzing the wind power predict error and the error confidence interval, we can obtain the wind power predict interval, the upper limit(P_{up}) of the interval is the predict power add e_{up} , the lower limit(P_{low}) is the predict power add e_{low} , as shown in Figure(5).

$$P_{up} = P_{pre} + e_{up} \quad P_{low} = P_{pre} + e_{low} \quad (2)$$

The wind farm self-discipline interval is defined as the interval between the P_{up} and P_{low} .

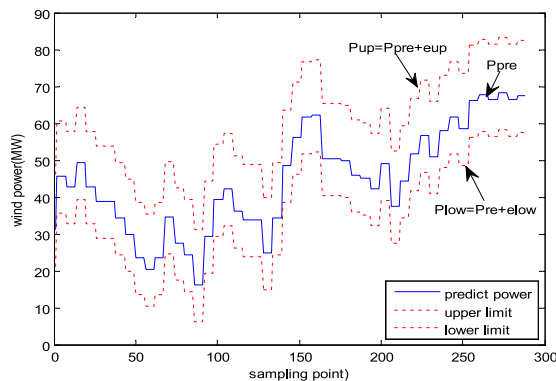


FIGURE 5. Wind power self-discipline interval.

We expect the actual output of the wind farm can be limited within the self-discipline interval, the actual wind output outside the self-discipline interval can be compensated by the energy storage system(ESS).

2) SELF-DISCIPLINE INTERVAL WIDTH

The width of the self-discipline interval is defined in formula (3).

$$\begin{aligned} WIDTH &= P_{up} - P_{low} \\ &= (P_{pre} + e_{up}) - (P_{pre} + e_{low}) = e_{up} - e_{low} \quad (3) \end{aligned}$$

where,

$WIDTH$ is the self-discipline interval width;

e_{up} is the upper limit of the error;

e_{low} is the lower limit of the error;

P_{up} is the upper limit of the wind power;

P_{low} is the lower limit of the wind power.

The width of the self-discipline interval is an important index. The narrower the wind power self-discipline interval is, the less spinning reserve the grid needs. If the width is too large, the self-discipline interval will be meaningless. Under the same confidence degree, the corresponding self-discipline interval is not unique, how to find the minimum width interval among these intervals is very important for the wind farm self-discipline and for the power grid.

B. MINIMIZE THE SELF-DISCIPLINE INTERVAL WIDTH

1) WIND POWER PREDICT ERROR DISTRIBUTION

In order to obtain the minimum self-discipline interval width, we should first analyze the wind power predict error distribution.

Some previous references assumed that the error distribution obeys a certain known distribution, such as normal distribution, gamma distribution, beta distribution and so on [17]–[20]. But the wind power predict error is uncertain and stochastic, by far, there are still no specific known distribution that can accurately describe it. If a specified known distribution being used, inaccuracy will occur.

A non-parametric kernel density estimation method is introduced to estimate the error distribution in this paper [12]. The non-parametric kernel density estimation method is suitable for arbitrary shape error distribution. It can be applied more generally and fits the distribution of the real data well. It doesn't use any prior knowledge of data distribution, nor any assumptions of data distribution. Instead, it is a method to study data distribution characteristic by data sample itself. Thus it can describe the data distribution more accurately.

The general expression of non-parametric kernel density estimation method is:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{x - x_i}{h}\right) \quad (4)$$

where,

$f(x)$ is the probability density function;

N is the total number of the sample;

h is the bandwidth or smooth parameter;
 x_i is a given sample;
 $K(\cdot)$ is the window function.

The common window functions are Uniform function, Gaussian function, trigonometric function, Gamma function, etc. When Gaussian window function is used, its probability density function is:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-x_i}{h}\right)^2\right) \quad (5)$$

The advantage of this estimation is its general applicability. It fits arbitrary shape distribution and is more consistent with the true data distribution which leads to a better estimation accuracy.

2) SOLVE THE MINIMUM SELF-DISCIPLINE INTERVAL

When the confidence degree($\alpha\%$) is the same, the corresponding self-discipline interval is not unique, as shown in Figure(6). Figure(6) shows some of the intervals (not all intervals) which satisfied the $\alpha\%$ confidence degree. The goal is to find the minimum interval.

For the symmetric distribution, we can use the traditional method (symmetrical quantile method) to solve the minimum self-discipline interval. For the arbitrary shape distribution(e.g. non-symmetric, or multi-peak), if we use the traditional method (symmetrical quantile method) to solve the self-discipline interval, the result is not necessarily the minimum. How to find the minimum interval width of the arbitrary shape distribution is a problem to be discussed in this section.

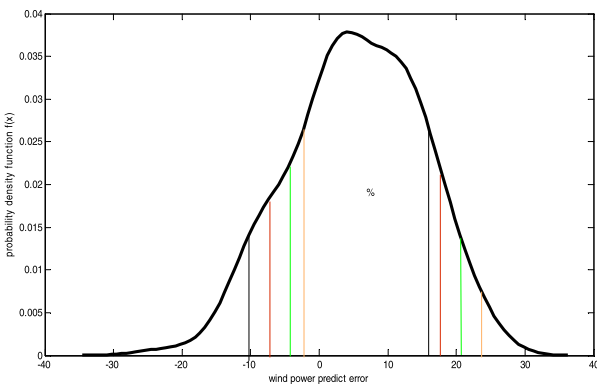


FIGURE 6. Different self-discipline intervals under $\alpha\%$ confidence degree.

An optimization method is proposed to obtain the minimum self-discipline interval. Let $f(x)$ be the probability density function of the predict error, it is given by formula (5), let $F(x)$ be the error probability distribution function, so $F(x)$ equals the integral of the $f(x)$, as shown in formula(6).

$$F(x) = \int f(x)dx = \int \frac{1}{Nh\sqrt{2\pi}} \sum_{i=1}^N \exp\left(-\frac{1}{2}\left(\frac{x-x_i}{h}\right)^2\right)dx \quad (6)$$

Let x_1 be the lower limit of the confidence interval; x_2 be the upper limit of the confidence interval. Let $P(x_1 \leq x \leq x_2)$

be the confidence degree($\alpha\%$), which means the probability occurred in the interval ($x_1 \sim x_2$), then:

$$P(x_1 \leq x \leq x_2) = F(x_2) - F(x_1) \quad (7)$$

The optimization problem can be expressed as follows:

Objective function:

$$\min(x_2 - x_1) \quad (8)$$

Constraint condition:

$$F(x_2) - F(x_1) = \alpha\% \quad (9)$$

where,

$$\begin{aligned} & F(x_2) - F(x_1) \\ &= \int_{x_1}^{x_2} f(x)dx \\ &= \frac{1}{Nh\sqrt{2\pi}} \sum_{i=1}^N \int_{x_1}^{x_2} \exp\left[-\frac{1}{2} \times \left(\frac{x-x_i}{h}\right)^2\right]dx \\ &= \frac{1}{Nh\sqrt{2\pi}} \sum_{i=1}^N h\sqrt{\frac{\pi}{2}} \left[\operatorname{erf}\left(\frac{x_2-x_i}{\sqrt{2}h}\right) - \operatorname{erf}\left(\frac{x_1-x_i}{\sqrt{2}h}\right) \right] \\ &= \frac{1}{2N} \sum_{i=1}^N \left[\operatorname{erf}\left(\frac{x_2-x_i}{\sqrt{2}h}\right) - \operatorname{erf}\left(\frac{x_1-x_i}{\sqrt{2}h}\right) \right] \end{aligned} \quad (10)$$

where:

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \times \int_0^x e^{-\frac{1}{2}t^2} dt \quad (11)$$

We use the interior-point method to solve this optimization problem, and the minimum self-discipline interval can be obtained.

C. EVALUATION OF THE SELF-DISCIPLINE LEVEL

The width of the self-discipline interval is an important index of the wind power self-discipline level. The narrower the self-discipline interval width, the less the spinning reserve needed of the grid.

The minimum self-discipline interval of the wind farm is always expected for the grid. However, is the self-discipline interval width enough to evaluate the wind farm self-discipline level? Besides the interval width, we should also consider the accuracy of the self-discipline interval. The interval accuracy is the percentage of actual values falling into the interval [21], [22].

The index *PICP* (the prediction interval coverage probability) can be used to evaluate the self-discipline interval accuracy. *PICP* is the percentage of actual values falling into the confidence interval, as shown in formula (12).

$$PICP = \frac{1}{N} \sum_{i=1}^N c_i \quad (12)$$

where,

N is the number of test samples;

If the test sample is located in the confidence interval, $c_i = 1$, otherwise $c_i = 0$.

We always hope the wind farm self-discipline interval has narrower width and larger *PICP*. But in fact, these two indexes are conflict and restrict each other mutually. Under the same confidence degree, the narrower the width, the smaller the *PICP*, while the wider the width, the larger the *PICP*. How to comprehensively evaluate these two contradictory indexes is an urgent problem.

In this paper, a comprehensive evaluation index F-measure from the field of information retrieval is introduced to the field of the wind power. F-measure can comprehensively evaluate the two indexes which restrict and contradict mutually [12].

F-measure equals the weighted harmonic average of the two contradictory indexes. In this paper, the wind farm self-discipline level (*SDL*) can be evaluated by F-measure. *SDL* is defined as the weighted harmonic average of *PICP* and *WIDTH*, as shown in formula(13).

$$SDL = \frac{2 \times PICP \times \frac{1}{WIDTH}}{PICP + \frac{1}{WIDTH}} \quad (13)$$

SDL comprehensively considers the two contradictory indexes. It gives us an easy method to evaluate the level of the wind farm self-discipline.

III. THE ENERGY STORAGE SYSTEM CONFIGURATION

In order to provide an optimal self-discipline interval of the wind farm, ESS should be installed in the wind farm to compensate the actual wind power outside the self-discipline interval.

When the actual wind power is greater than the upper limit of the self-discipline interval, the ESS charges; when the actual wind power is less than the lower limit of the self-discipline interval, the ESS discharges; when the actual wind power is between the lower limit and the upper limit, the ESS does not work. Through the appropriate ESS configuration, the wind farm output can be limited in the interval between the lower limit and the upper limit, which means the wind farm can provide a self-discipline interval to the grid.

In this section, we will discuss how to configure the ESS to provide the optimal wind farm self-discipline interval to the grid [27].

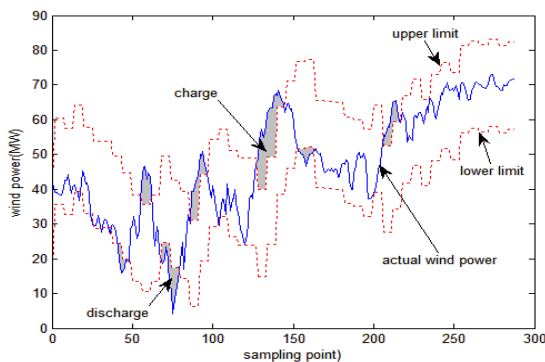


FIGURE 7. Self-discipline intervals and the actual wind power.

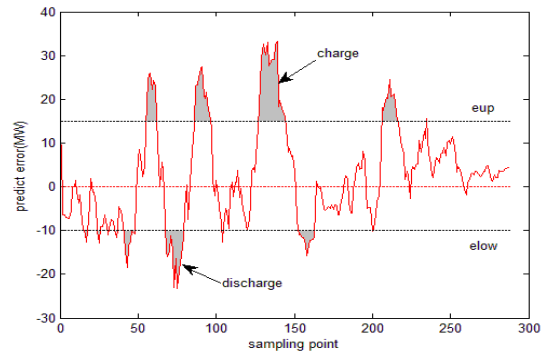


FIGURE 8. Self-discipline interval and the actual wind power.

A. THE ESS RATED POWER

Let $P_{ESS}[i]$ be the actual charging and discharging power of the ESS, as shown in the following formulas:

When $P_{act} > P_{up}$ or when $e > e_{up}$:

$$P_{ESS}[i] = P_{act} - P_{up} = P_{act} - (P_{pre} + e_{up}) = e - e_{up}$$

When $P_{act} < P_{low}$ or when $e < e_{low}$:

$$P_{ESS}[i] = P_{act} - P_{low} = P_{act} - (P_{pre} + e_{low}) = e - e_{low}$$

$$P_{low} < P_{act} < P_{up}$$

When:

$$P_{ESS}[i] = 0$$

where,

$P_{ESS}[i]$ is the actual charging and discharging power of the ESS;

e_{up}, e_{low} are the upper limit and lower limit of the wind power predict error;

P_{up}, P_{low} are the upper limit and lower limit of the wind power self-discipline interval;

P_{act} are actual wind power.

To sum up:

$$P_{ESS}[i] = \begin{cases} 0 & P_{low} < P_{act} < P_{up} \\ P_{act} - P_{up} & P_{act} > P_{up} \\ P_{act} - P_{low} & P_{act} < P_{low} \end{cases} \quad (14)$$

Or

$$P_{ESS}[i] = \begin{cases} 0 & e_{low} < e < e_{up} \\ e - e_{up} & e > e_{up} \\ e - e_{low} & e < e_{low} \end{cases} \quad (15)$$

The ESS rated power is the maximum absolute value of $P_{ESS}[i]$, as shown in formula (16).

$$P_{rate} = \max |P_{ESS}[i]| \quad (16)$$

B. THE ESS RATED CAPACITY

In this paper, the time window is taken as one day to configure the ESS rated capacity [26]. The output data of several typical days are extracted from the whole year's data

of the wind farm, and then the mathematical expectation value of all typical daily energy storage configuration results is calculated, which is the optimal configuration result of the ESS.

By accumulating the charge and discharge of the ESS at each sampling time, the energy fluctuation of ESS relative to the initial state at different sampling time can be obtained as formula (17).

$$E[n] = \sum_{i=1}^n (P_{ESS}[i] \times \Delta t) \quad (17)$$

where,

$E[n]$ is the energy fluctuation of ESS at the n th sampling point relative to the initial state, i.e., the sum of accumulative charge and discharge of the ESS in the first n sampling periods. The unit is MWh;

$P_{ESS}[i]$ is the actual charging and discharging power of the ESS, as shown in formula (14) and (15);

Δt is the sampling period. The sampling period in this paper is 10 min, i.e., 1/6 hour, the unit is hours;

i is the n th sampling point;

n is the number of sampling point, If the time window is one day, then $n = 144$.

According to the energy fluctuation in the whole sampling period, the difference between the maximum and minimum energy fluctuation can be calculated [5]. Considering the limitation of the state of charge (SOC), the rated capacity of the ESS can be obtained, as shown in formula(18).

$$E_{rate} = \frac{\max(E[n]) - \min(E[n])}{S_{up} - S_{low}} \quad (18)$$

where,

E_{rate} is the rated capacity of the ESS.

$\max(E[n]), \min(E[n])$ are the maximum and minimum energy changes relative to the initial state in the whole sampling period respectively.

S_{up} and S_{low} are upper and lower limit constraints of the state of charge (SOC) respectively. In practice, in order to avoid over-charging and over-discharging in actual operation of the ESS, the values should be appropriately taken in (0, 1). In this paper, the values are 0.9 and 0.1 [24], [25].

From the method in this section, we can obtain the optimal ESS configuration to guarantee the optimal wind farm self-discipline interval.

IV. CASE STUDIES

Field data of a wind farm in Ohio from 1 January to 31 December 2012 are studied in this paper. The sampling interval is 10 min, and the maximum output of the wind farm is 100 MW. Lithium batteries are selected for the ESS.

A. THE OPTIMIZATION OF THE WIND FARM SELF-DISCIPLINE INTERVAL

1) WIND POWER PREDICT ERROR DISTRIBUTION

The non-parameter kernel density method is used to estimate the predict error distribution. It is suitable for arbitrary shape

distribution, and is only determined by data itself, so it can fit the data distribution more accurately. The result is shown in figure (9). For comparison, the normal distribution and the frequency histogram are also shown. It is obvious that the non-parameter kernel density estimation method can better fit the real data.

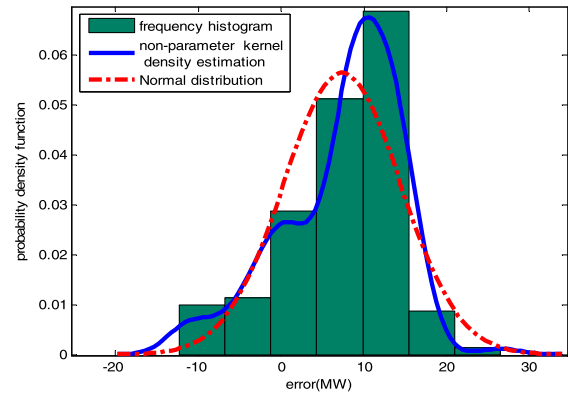


FIGURE 9. Wind power predict error distribution.

2) MINIMIZE THE WIDTH OF THE SELF-DISCIPLINE INTERVAL

For the arbitrary shape probability density function, we use the optimization method in section II B to solve the minimum self-discipline interval. The objective function is shown in equation (8), and the constraints are shown in equations (9). The optimization result is calculated and shown in table (1).

For comparison, we also use the traditional method (symmetric point method) to calculate the self-discipline interval, the result is shown in Table (1).

TABLE 1. The self-discipline interval width under different confidence degree.

| method | Self-discipline interval | 95% | 90% | 85% | 80% | 75% | 70% |
|--------------------|--------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| proposed method | upper and lower limit | (-9.39, 19.18) | (-4.98, 18.26) | (-2.81, 17.40) | (-1.04, 16.96) | (0.69, 16.77) | (2.59, 16.77) |
| | width | 28.57 | 23.23 | 20.21 | 18.00 | 16.08 | 14.18 |
| traditional method | width | 28.70 | 23.49 | 20.53 | 18.40 | 16.66 | 15.11 |
| | upper and lower limit | (-8.73, 19.97) | (-5.84, 17.65) | (-3.93, 16.60) | (-2.57, 18.41) | (-1.45, 15.21) | (-0.45, 14.66) |

From table (1), we can find that when the confidence degree is the same, the corresponding self-discipline interval is not unique. Under every confidence degree, the self-discipline interval width obtained by the proposed method in this paper is smaller comparing to the traditional method.

Taken 90% and 70% confidence degree as example, Figure(10)~ Figure(13) show the different interval obtained by the two methods respectively.

From above analysis, by using the proposed optimization method in this paper, we can obtain the minimum self-discipline interval under every confidence degree.

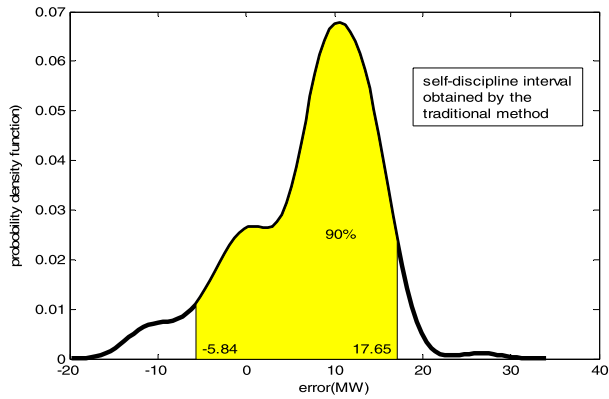


FIGURE 10. Self-discipline interval obtained by the traditional method under 90% confidence degree.

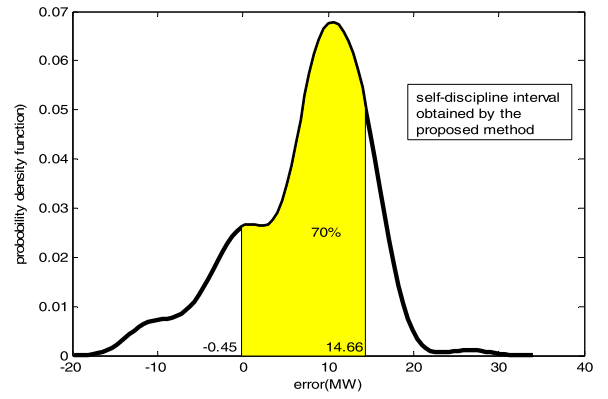


FIGURE 13. Self-discipline interval obtained by the proposed method under 70% confidence degree.

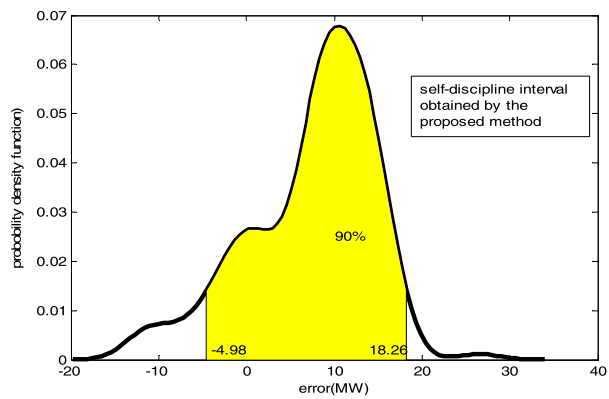


FIGURE 11. Self-discipline interval obtained by the proposed method under 90% confidence degree.

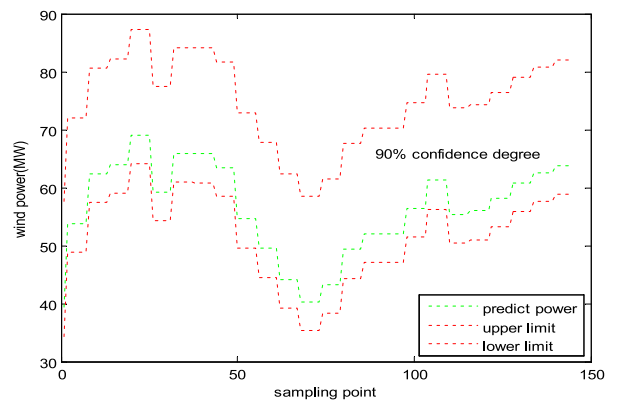


FIGURE 14. The minimum self-discipline interval at 90% confidence degree.

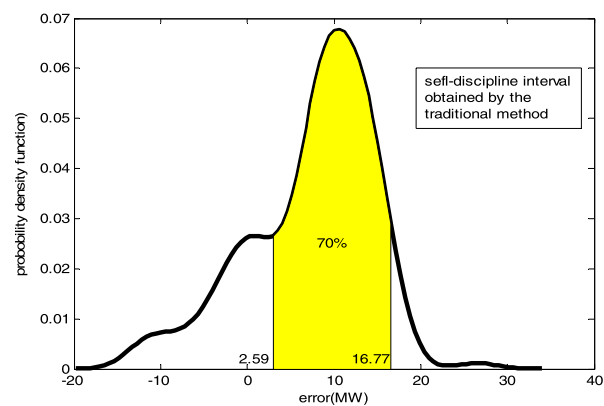


FIGURE 12. Self-discipline interval obtained by the traditional method under 70% confidence degree.

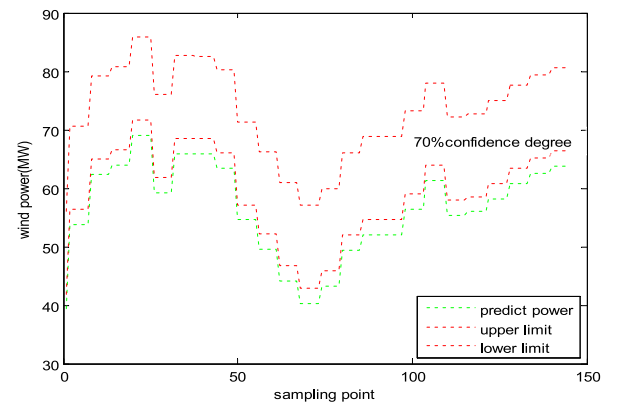


FIGURE 15. The minimum self-discipline interval at 70% confidence degree.

Figure (14) and Figure (15) show the minimum self-discipline intervals under 90% and 70% confidence degree respectively.

3) THE EVALUATION OF THE SELF-DISCIPLINE LEVEL

In order to evaluate the wind power self-discipline level comprehensively, we calculate the PICP and SDL, the result is shown in Table(2).

From Table(2), we find that under every confidence degree, the self-discipline interval width obtained by the proposed method is always the smaller. At 95%, 75% and 70% confidence degree, the PICP obtained by the proposed method are larger than that from the traditional method. At 90%, 85% and 80% confidence degree, although the PICPs are smaller, the SDLs obtained by the optimal method are larger. This larger SDL trend is also found in other confidence degree levels.

TABLE 2. The self-discipline interval comparison under different confidence degrees.

| Confidence degree | Method | Interval width | PICP | SDL |
|-------------------|--------------------|----------------|---------------|---------------|
| 95% | traditional method | 28.70 | 95.14% | 0.0672 |
| | proposed method | 28.57 | 95.83% | 0.0675 |
| 90% | traditional method | 23.49 | 93.75% | 0.0814 |
| | proposed method | 23.24 | 93.06% | 0.0823 |
| 85% | traditional method | 20.53 | 90.28% | 0.0924 |
| | proposed method | 20.21 | 89.58% | 0.0938 |
| 80% | traditional method | 18.40 | 88.89% | 0.1024 |
| | proposed method | 18.00 | 86.11% | 0.1044 |
| 75% | traditional method | 16.66 | 81.94% | 0.1200 |
| | proposed method | 16.08 | 85.42% | 0.1243 |
| 70% | traditional method | 15.11 | 72.92% | 0.1322 |
| | proposed method | 14.18 | 74.31% | 0.1409 |

Since SDL can comprehensively reflect the wind farm self-discipline level, the larger the SDL, the better the self-discipline level, we can conclude that the self-discipline interval obtained by the proposed method in this paper is optimal.

B. THE ESS CONFIGURATION

In order to guarantee the optimal wind power self-discipline interval to the grid, the ESS should be installed in the

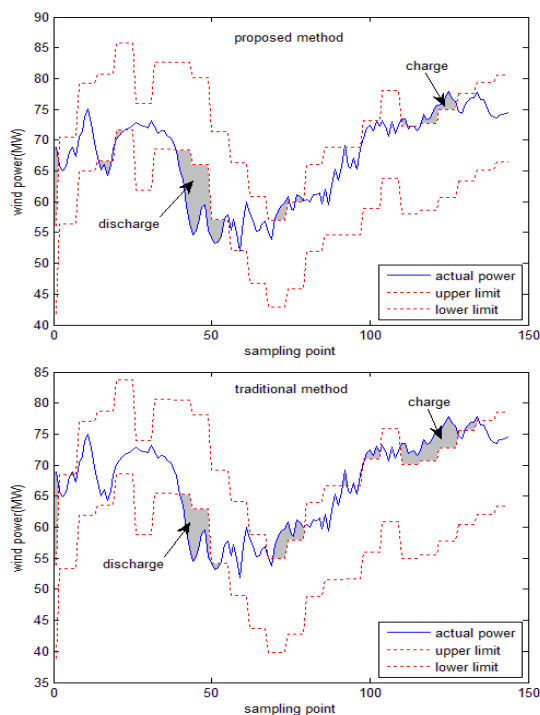


FIGURE 16. Self-discipline interval and ESS configuration by different methods under 70% confidence degree.

wind farm to compensate the actual wind power outside the self-discipline interval.

When the wind farm actual output is larger than the upper limit of the self-discipline interval, the ESS charges; when the the wind farm actual output is smaller than the lower limit of the self-discipline interval, the ESS discharges. when the wind power actual output is between the lower limit and the upper limit, the ESS does not work.

The ESS installed in the wind farm should be optimally sized to be able to provide the necessary compensation and guarantee the optimal wind self-discipline interval. Through the proposed method in section III, formula(16) and formula(18), we can calculate the ESS rated power P_{rate} and ESS rated capacity E_{rate} . Different self-discipline interval will need different ESS configuration. For comparison, we also calculate the P_{rate} and E_{rate} obtained by the traditional method.

Taken 70% as example, the self-discipline interval obtained by the proposed method is different from the interval obtained by the traditional method, so that the needed ESS configuration is also different, as shown in Figure(16).

For other confidence degrees, the results are shown in Table(3). From Table(3), we find that the ESS configuration is different between the two methods.

By the proposed ESS configuration, the wind farm output can be limited within the optimal self-discipline interval, and thus the wind farm can provide an optimal self-discipline interval to the grid.

TABLE 3. The ESS configuration under different confidence degrees.

| confidence degree | | 95% | 90% | 85% | 80% | 75% | 70% |
|-------------------|--------------------|------|------|------|-------|-------|-------|
| P_{rate} (MW) | proposed method | 0.6 | 4.35 | 6.52 | 8.29 | 10.03 | 11.92 |
| | traditional method | 0.53 | 3.49 | 5.40 | 6.76 | 7.88 | 8.88 |
| E_{rate} (MWh) | proposed method | 0.28 | 3.61 | 6.87 | 10.17 | 22.46 | 78.41 |
| | traditional method | 0.16 | 2.78 | 7.18 | 11.68 | 16.25 | 20.88 |

V. CONCLUSION

In this paper, we discussed the problem of how to mitigate the uncertainty of the wind power from the aspect of the wind farm self-discipline interval. A novel optimization method to obtain the optimal wind farm self-discipline interval is proposed. The ESS configuration issue is also addressed in this paper based on the historical wind data.

1) The concept of wind farm self-discipline interval is first proposed in this paper. In order to evaluate the wind farm self-discipline level, the indexes of the wind farm self-discipline interval are also introduced, not only considering the interval width but also the interval accuracy.

2) An optimization method is proposed to obtain the optimal self-discipline interval. In order to guarantee the optimal self-discipline interval of the wind farm, the ESS size is

optimally configured to be able to provide the necessary compensation.

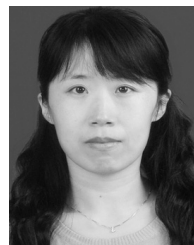
3) Compared with the traditional method, the proposed method has general applicability, not only suitable for normal distribution and other known distributions but also for arbitrary distributions, such as non-symmetric, multi-peak distribution.

Case studies with historical wind power data are fulfilled to demonstrate that the proposed method can effectively improve the wind power self-discipline level and the acceptance ability of the grid to the wind power, which can provide a powerful decision-making base for the grid planning and running.

In the future research, the wind farm, the solar energy and the electric vehicle will be considered. The wind energy and the solar energy can compensate each other, while the electric vehicle can act as a kind of ESS to deal with the uncertainty of the new energies.

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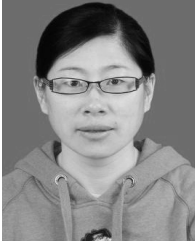
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