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Quantitative Evaluation Methods of Cluster Wind Power Output Volatility and Source-Load Timing Matching in Regional Power Grid

Yongqian Liu [1], Yanhui Qiao [1], Shuang Han [1,*], Yanping Xu [2], Tianxiang Geng [3] and Tiandong Ma [3]

1 State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (NCEPU), School of New Energy, North China Electric Power University, Beijing 102206, China; yqliu@ncepu.edu.cn (Y.L.); ncepuqyh@163.com (Y.Q.)
2 State Key Laboratory of Operation and Control of Renewable Energy & Storage Systems, China Electric Power Research Institute Co., Ltd., Beijing 100192, China; xuyanping@epri.sgcc.com.cn
3 State Grid Ningxia Electric Power Co., Ltd., Yinchuan 750001, China; popback@163.com (T.G.); matiandong@nx.sgcc.com.cn (T.M.)
* Correspondence: hanshuang1008@sina.com

Abstract: The quantitative evaluation of cluster wind power output volatility and source-load timing matching is vital to the planning and operation of the future power system dominated by new energy. However, the existing volatility evaluation methods of cluster wind power output do not fully consider timing volatility, or are not suitable for small sample data scenarios. Meanwhile, the existing source-load timing matching evaluation indicator ignores the impact of wind power permeability on the timing matching degree between wind power output and load. Therefore, the authors propose quantitative evaluation methods of cluster wind power output volatility and source-load timing matching in regional power grid. Firstly, the volatility-based smoothing coefficient is defined to quantitatively evaluate the smoothing effect of wind-farm cluster power output. Then, the source-load timing matching coefficient considering wind power permeability is proposed to quantitatively evaluate the timing matching degree of regional wind power output and load, and the corresponding function model of volatility-based smoothing coefficient and source-load timing matching coefficient is established. Finally, the validity and applicability of the proposed methods are verified by MATLAB software based on the actual power output of 10 wind farms and actual grid load in a certain grid dispatching cross-section of northeast China. The results demonstrated that the proposed volatility-based smoothing coefficient can accurately represent the smoothing effect of wind farm cluster power output while maintaining the volatility continuity of wind power output time series and without affect from the data sample size. The source-load timing matching coefficient can accurately characterize the difference in the timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load.

Keywords: regional power grid; wind power output; grid load; source-load timing matching coefficient; volatility-based smoothing coefficient

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1. Introduction

It is an inevitable trend for future development to implement renewable energy substitution actions, deepen the reform of power systems and build a new power system dominated by new energy. The power system with new energy as the main component means that wind power and photovoltaic power will be the main body of the future power system, and coal power will become an auxiliary energy source. However, wind power output has inherent properties of randomness, intermittence and uncontrollability, and its adverse impact on the power system increases significantly with the continuous increase of permeability [1,2]. Moreover, the load of the power grid is affected by many factors such as economic structure, social factors, climate conditions and electricity price, which also have significant stochastic uncertainty [3]. The double uncertainty characteristics of source and load bring great challenges to the security, stability and economic operation of the new power system with new energy as the main body [4]. It is some relief to consider the spatial smoothing effect of wind farm cluster power output, which can effectively reduce the fluctuation of total output [5,6] and alleviate the negative impact of large-scale wind power integration on the power system. However, the combined power output characteristics of different wind farms and their timing matching with the grid load have obvious differences. Therefore, the quantitative evaluation of the timing matching degree between wind power output and load in the regional power grid is an issue that should be solved in the planning and operation scheduling of the new power system dominated by new energy in the future.

Many scholars have conducted corresponding research on the quantitative evaluation of cluster wind power output volatility and the timing matching of wind power output and load. In the aspect of study on cluster wind power output volatility, Shen et al. [7] established the functional relationship between smoothing effect, output correlation and the number of wind turbines. Liu et al. [8] revealed the mechanism of smoothing effect and analyzed the relationship between the smoothing effect, the number of wind farms, and the regional geographic scope. Li et al. [9] quantified the functional relationship between the smoothing effect and the number of wind turbines, and the correlation coefficient. Yang et al. [10] proposed a quantitative evaluation index of the wind power smoothing effect and investigated the smoothing effect characteristics of a wind farm cluster for different numbers of wind turbines, different wind speeds, different seasons and multiple sampling intervals. Nanahara et al. [11] introduced the average coherence indicator for evaluating the power-system-wide smoothing effects of wind farms. Ye et al. [12] defined an evaluation index for the curve of the absolute value of the offshore wind power output variation ratio to quantify the smoothing effect. Shahriari et al. [13] quantified the scaling of the geographic smoothing effect for large-scale wind energy deployment over various spatial and temporal scales, using a bounding deployment scenario that seeks to incrementally minimize the variance of power output from a portfolio of wind sites.

In the aspect of study on the timing matching quantitative evaluation method between wind power output and load, Ye et al. [14] analyzed the matching relationship between different types of power output and load based on the volatility inconsistency degree of various power sources and load. Wen et al. [15] established an optimal scheduling model for a hybrid wind-solar-hydro power generation system and data center in the load-side based on the load tracking coefficient defined by the source-side power generation change rate and the load-side power consumption change rate. Qu et al. [16] defined the consistency index of wind power and total/static load changes and proposed three optimization control strategies for fluctuation smoothing, load tracking and power balance. Yang et al. [17] proposed a coordinated optimal dispatching scheme to minimize the dynamic source-load tracking coefficient. Yang et al. [18] proposed an optimal scheduling approach on the wind-solar-storage generation system, which considers the correlation among wind power, photovoltaic output and load.

In summary, many scholars proposed smoothing coefficients based on standard deviation or volatility confidence interval to quantitatively evaluate cluster wind power output volatility. Scholars have also proposed the load tracking coefficient based on volatility consistency to quantitatively evaluate source-load timing matching degree;however, there are still some problems, which follow:

(1) The smoothing coefficient based on standard deviation ignores the volatility continuity of the wind power output time series, and the smoothing coefficient based on the volatility confidence interval is not suitable for small sample data scenarios of wind power output, which cannot accurately reflect the smoothing effect of cluster wind power output in some cases.

(2) The load tracking coefficient ignores the influence of wind power permeability on the timing matching degree of wind power output and load, which cannot accurately characterize the difference in timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load.

To solve the aforementioned problems, the quantitative evaluation methods for the smoothing effect of wind farm cluster power output and the timing matching degree between wind power output and load in the regional power grid are proposed in this paper. The main contributions of this study are as follows:

(1) The volatility-based smoothing coefficient of wind farm cluster power output is defined. The proposed volatility-based smoothing coefficient can accurately represent the smoothing effect of wind farm cluster power output, which not only can maintain the volatility continuity of wind power output time series, but is also unaffected by the data sample size.
(2) The timing matching degree evaluation indicator and its formula of regional wind power output and load considering permeability are proposed. The proposed source-load timing matching coefficient can accurately characterize the difference in the timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load.
(3) The exponential function model of volatility-based smoothing coefficient and source-load timing matching coefficient is established. The exponential function model depicts the quantitative relationship between the volatility smoothing effect of wind farm cluster power output and source-load timing matching degree, which makes up for the deficiency of simple qualitative analysis in previous studies.

The rest of this paper is organized as follows: Section 2 describes the basic idea of this paper. Section 3 introduces the smoothing effect of cluster wind power output and its evaluation indicator. Section 4 describes the timing matching degree evaluation indicator of wind power output and grid load. Section 5 elaborates on the case study. Section 6 concludes this paper.

2. The Basic Idea

The basic idea of this paper is mainly divided into two parts: indicators proposal and methods verification, as shown in Figure 1. In the indicators proposal part, the deficiencies of the existing evaluation indicators of cluster wind power output smoothing effect and the timing matching degree between wind power output and grid load are analyzed, and the volatility-based smoothing coefficient and source-load timing matching coefficient are proposed. In the methods verification part, the validity and applicability of the proposed methods are verified based on the actual power output of wind farms and actual grid load by MATLAB software. Firstly, the smoothing effect of cluster wind power output under different numbers and combinations of wind farms is quantitatively analyzed based on the volatility-based smoothing coefficient. Then, the source-load timing matching between cluster wind power output and grid load under different wind farm combinations is quantitatively verified based on the source-load timing matching coefficient. Finally, the corresponding function model of the volatility-based smoothing coefficient and source-load timing matching coefficient is established.

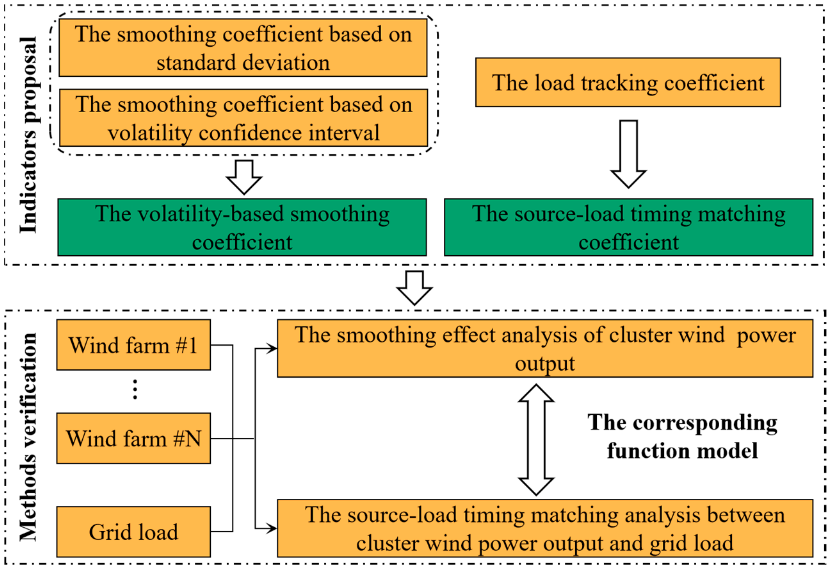

Figure 1. The basic idea of this paper.

3. The Smoothing Effect of Cluster Wind Power Output and Its Evaluation Indicator

3.1. The Smoothing Effect of Cluster Wind Power Output

The smoothing effect of cluster wind power output refers to the phenomenon that the volatility of wind farm cluster power output decreases with the expansion of the regional scale due to the delay effect and filtering effect on the time scale [19,20], and the distribution effect on the spatial scale [8]. Among them, the spatial distribution effect is an important factor and necessary condition for the smoothing effect, which is the inconsistent change of power output caused by the difference of spatial distribution of wind resources; in essence, the resulting power output fluctuations offset each other in the superposition process, and the overall power output fluctuation is significantly lower than the individual [7].

3.2. The Existing Smoothing Effect Evaluation Indicators and Their Deficiencies

In order to quantitatively evaluate the smoothing effect of cluster wind power output, the smoothing coefficients based on standard deviation and the volatility confidence interval are usually used as the basic indicators.

(1) The smoothing coefficient based on standard deviation

The smoothing coefficient based on standard deviation characterizes the relative change of the normalized power output standard deviation of a single wind farm and wind farm cluster [9], as shown in Formula (1).

$$S_1 = \frac{\sigma_{single} - \sigma_{cluster}}{\sigma_{single}} \tag{1}$$

where S_1 is the smoothing coefficient based on standard deviation, σ_{single} is the normalized power output standard deviation of a single wind farm, and $\sigma_{cluster}$ is the normalized power output standard deviation of wind farm cluster. The larger the value of S_1, the stronger the smoothing effect of wind farm cluster power output.

The smoothing coefficient based on standard deviation is used to quantitatively evaluate the smoothing effect of cluster wind power output from the perspective of overall volatility. However, the standard deviation reflects the dispersion degree of data deviation from the average value in the statistical theory, ignoring the volatility continuity of wind power output time series. Therefore, the smoothing coefficient based on standard deviation may ignore the problem of local smoothing effect in some periods within the statistical time interval, making it inaccurate to reflect the smoothing effect of cluster wind power output in some cases.

(2) The smoothing coefficient based on volatility confidence interval

The smoothing coefficient based on the volatility confidence interval characterizes the relative change of the normalized power output volatility confidence interval of a single wind farm and wind farm cluster under the same cumulative probability [9], as shown in Formula (2).

$$\begin{cases} S_2 = \frac{R_{single} - R_{cluster}}{R_{single}} \\ P(X \leq R) = q \end{cases} \tag{2}$$

where S_2 is the smoothing coefficient based on volatility confidence interval, R_{single} is the normalized power output volatility confidence interval of a single wind farm under the given cumulative probability, and $R_{cluster}$ is the normalized power output volatility confidence interval of wind farm cluster under the given cumulative probability. P is the probability density function, X is the standard unit value of wind farm power output fluctuation, and q is the given cumulative probability, which is 0.95 in this paper. The larger the value of S_2, the stronger the smoothing effect of wind farm cluster power output.

The smoothing coefficient based on the volatility confidence interval is used to quantitatively evaluate the smoothing effect of cluster wind power output from the perspective of probability distribution characteristics. However, the fitting quality of the probability distribution function is closely related to the sample size in the probability theory. As a result, the smoothing coefficient based on volatility confidence interval is not applicable to wind farm power output in small sample data scenarios and cannot evaluate the smoothing effect at shorter time scales.

3.3. The Volatility-Based Smoothing Coefficient

In order to overcome the shortcomings of the existing smoothing evaluation indicators, a volatility-based smoothing coefficient is proposed. The volatility-based smoothing coefficient mainly characterizes the decrease-rate of power output fluctuation of wind farm cluster compared to that of an individual wind farm, which is from the perspective of wind power output time series volatility. Not only can it maintain the volatility continuity of wind power output time series, but it also is unaffected by the data sample size.

Firstly, the output of a single wind farm is normalized [21], as shown in Formula (3).

$$P_i'(t) = \frac{P_i(t) - P_{i,\min}}{P_{i,\max} - P_{i,\min}} \tag{3}$$

where $P_i'(t)$ is the normalized power output of the i-th wind farm at time t, $P_i(t)$ is the power output of the i-th wind farm at time t, and $P_{i,\max}$ and $P_{i,\min}$ are the maximum and minimum power output of the i-th wind farm in the time scale of investigation, respectively.

Then, the normalized power output of wind farm cluster is calculated, as shown in Formula (4).

$$\begin{cases} P'_{cluster}(t) = \sum_{i=1}^{N} \alpha_i P_i'(t) \\ \alpha_i = \frac{P_i^R}{\sum_{i=1}^{N} P_i^R} \end{cases} \tag{4}$$

where $P'_{cluster}(t)$ is the normalized power output of wind farm cluster at time t, P_i^R is the rated installed capacity of the i-th wind farm, α_i is the proportion of the rated installed capacity of the i-th wind farm in the total installed capacity of the wind farm cluster, and N is the number of wind farms.

Finally, the volatility-based smoothing coefficient of wind farm cluster is calculated, as shown in Formula (5).

$$\begin{cases} S_3 = 1 - \dfrac{\sum\limits_{t=1}^{n-1} \left| \Delta P'_{cluster}(t) \right|}{\sum\limits_{t=1}^{n-1} \sum\limits_{i=1}^{N} \left| \alpha_i \Delta P'_i(t) \right|} \\ \Delta P'_i(t) = P'_i(t+1) - P'_i(t) \\ \Delta P'_{cluster}(t) = P'_{cluster}(t+1) - P'_{cluster}(t) \end{cases} \tag{5}$$

where S_3 is the volatility-based smoothing coefficient, $\Delta P'_i(t)$ is the normalized power output fluctuation of the i-th wind farm at time t, $\Delta P'_{cluster}(t)$ is the normalized power output fluctuation of wind farm cluster at time t, and n is the number of wind power output data in the time scale of investigation. The larger the value of S_3, the stronger the smoothing effect of wind farm cluster power output.

4. The Timing Matching Degree Evaluation Indicator of Wind Power Output and Grid Load

4.1. The Existing Source-Load Timing Matching Degree Evaluation Indicator and Its Deficiencies

At present, the load tracking coefficient based on volatility consistency is usually used to quantitatively evaluate the timing matching of wind power output and grid load [14–18], as shown in Formula (6).

$$\begin{cases} I_T = \frac{1}{n-1} \sum\limits_{t=1}^{n-1} \left| \Delta W'(t) - \Delta P'(t) \right| \\ \Delta W'(t) = W'(t+1) - W'(t) \\ \Delta P'(t) = P'(t+1) - P'(t) \end{cases} \tag{6}$$

where I_T is the load tracking coefficient, $\Delta W'(t)$ and $\Delta P'(t)$ is the normalized load fluctuation and wind farm power output fluctuation at time t, $W'(t)$ and $P'(t)$ are the normalized load and wind farm power output at time t, and the normalization method is the same as Formula (3). The closer I_T is to 0, the more consistent the change characteristics of wind farm power output and grid load in the time scale of investigation, and the better the tracking performance of power output on the grid load.

The load tracking coefficient is the normalized output and load data, which does not change with the wind farm installed capacity; that is, the wind power permeability. Therefore, the load tracking coefficient ignores the influence of wind power permeability on the timing matching degree of wind power output and load, which cannot accurately characterize the difference in the timing matching degree between wind power output and grid load under different wind power permeability, and the influence degree on grid load.

4.2. The Source-Load Timing Matching Coefficient

In order to overcome the deficiencies of the existing source-load timing matching evaluation indicator, a source-load timing matching coefficient considering permeability is proposed, which can accurately characterize the difference in the timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load from the perspective of wind power output and load volatility by introducing the theoretical permeability coefficient of wind power, as shown in Formula (7).

$$\begin{cases} I_M = \dfrac{\sum\limits_{t=1}^{n-1} \left| \Delta W'(t) - \eta * \sum\limits_{i=1}^{N} \alpha_i \Delta P'_i(t) \right|}{\sum\limits_{t=1}^{n-1} \left| \Delta W'(t) \right|} \\ \eta = \dfrac{\sum\limits_{i=1}^{N} P_i^R}{W_{\max}} \end{cases} \tag{7}$$

where I_M is the source-load timing matching coefficient, η is the wind farm cluster permeability coefficient, and $W_{\max}$ is the maximum grid load in the time scale of investigation or longer time scale. The smaller the value of I_M, the better the timing matching degree between wind farm cluster power output and grid load.

5. Case Study

5.1. Data

The validity and applicability of the proposed methods are verified based on the actual power output of 10 wind farms and actual grid load in a certain grid dispatching cross-section of Northeast China. The geographical distribution and rated installed capacity of some wind farms in northeast China are shown in Figure 2; the cluster wind farms are located northeast, in the Inner Mongolia Autonomous Region of China. With flat terrain and wide distribution, the maximum and minimum rated installed capacities are 400.5 MW and 45 MW, respectively. The maximum grid load in this grid dispatching cross-section is 1736.33 MW. The data selected in this paper mainly include the actual power output of wind farms and actual grid load, the data time length is 1 year, and the time resolution is 15 min.

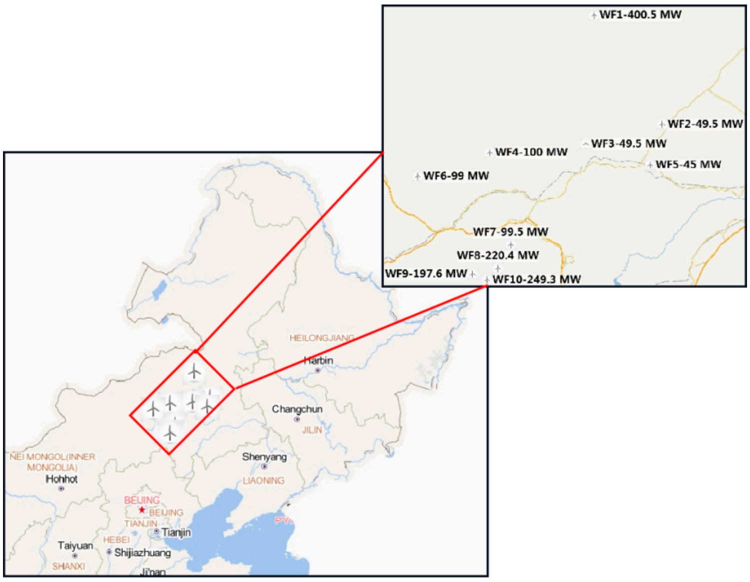

Figure 2. The geographical distribution and rated installed capacity of some wind farms in northeast China.

5.2. Results

5.2.1. The Smoothing Effect Analysis of Wind Farm Cluster Power Output

The essence of the smoothing effect of wind farm cluster power output is ascribable to differences in wind farm power output in the region. Generally, the stronger the output correlation, the weaker the smoothing effect. Based on the actual power output of the wind farm cluster, the Spearman nonlinear correlation coefficient [21] and three smoothing coefficients are used to quantitatively analyze the wind farm cluster power output smoothing effect under different combinations, as shown in Figure 3.

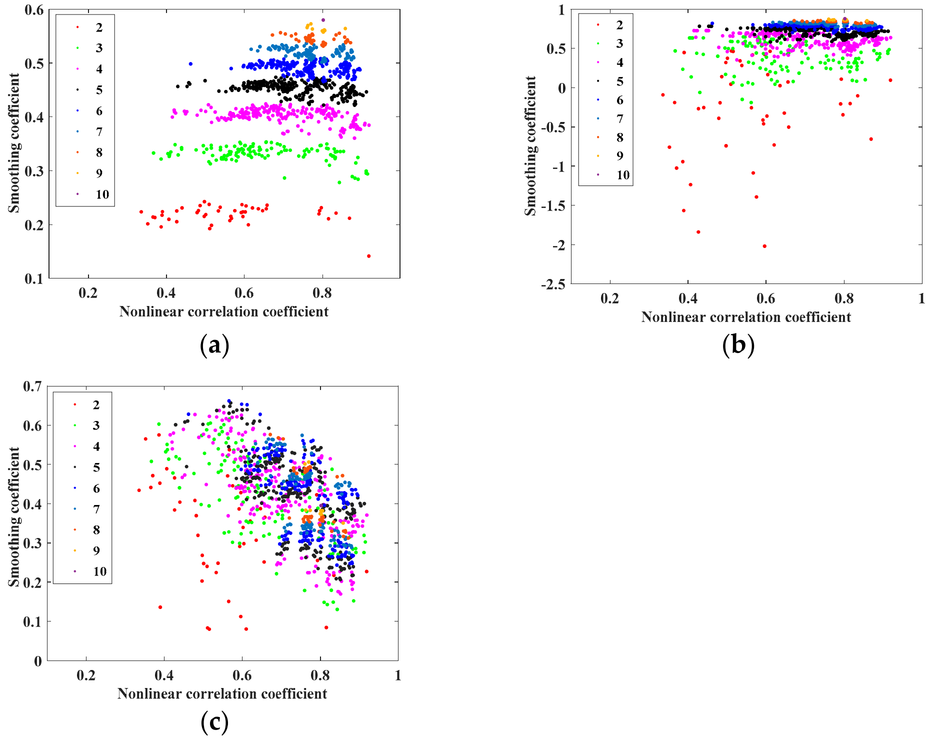

Figure 3. The smoothing coefficients under different wind farm combinations. (**a**) The volatility-based smoothing coefficient; (**b**)The smoothing coefficient based on standard deviation; (**c**) The smoothing coefficient based on volatility confidence interval.

As shown in Figure 3a, the volatility-based smoothing coefficient increases with the increase of the number of wind farm combinations, indicating that the smoothing effect of wind farm cluster power output is enhanced, but the increasing speed is gradually slowed down. The main reason is that the nonlinear correlation between the power output of the wind farm cluster and the power output of the new single wind farm is enhanced, the smoothing effect is gradually weakened, and there is a certain smoothing saturation effect, which accords with the general law. Under the same number of wind farm combinations, there is a significant negative linear relationship between the volatility-based smoothing coefficient and the nonlinear correlation coefficient, and the slope gradually increases with an increase in the number of wind farm combinations. This indicates that the smoothing coefficient decreases faster with the increase of the nonlinear correlation coefficient, which corresponds to the slower growth rate of the volatility-based smoothing coefficient as the number of wind farm combinations increases. As shown in Figure 3b, the smoothing coefficient based on standard deviation varies with the number of wind farm combinations, and the nonlinear correlation coefficient is similar to the volatility-based smoothing coefficient; however, the smoothing coefficient is negative under the two wind farm combinations. The main reason is that the smoothing coefficient based on standard deviation is used to quantitatively evaluate the smoothing effect of wind farm cluster power output from the perspective of overall volatility, which ignores the volatility continuity of wind power output time series. Therefore, the smoothing coefficient based on standard deviation may ignore the problem of local smoothing effect in some periods within the statistical time interval. As shown in Figure 3c, the smoothing coefficient based on volatility confidence interval decreases with the increase of the nonlinear correlation coefficient, and the smoothing effect of wind farm cluster power output is enhanced, but there is no obvious rule between the smoothing coefficient and the number of wind farm combinations. At the same time, it should be noted that the volatility confidence interval is greatly affected by the data sample size. In summary, the volatility-based smoothing coefficient can accurately represent the smoothing effect of cluster power output under different combinations of wind farms, which can maintain the volatility continuity of wind power output time series and be unaffected by the data sample size.

Based on the volatility-based smoothing coefficient, the smoothing effect under different numbers of wind farms is quantitatively evaluated, as shown in Figure 4. It can be seen from Figure 4 that the volatility-based smoothing coefficient increases with an increase in the number of wind farms, but the increase amplitude gradually decreases. This indicates that the smoothing effect of wind farm cluster power output is enhanced, and the wind farm cluster can effectively reduce the overall power output fluctuation, but there is a certain smoothing saturation effect. The fitting function of the volatility-based smoothing coefficient varying with the number of wind farms is shown in Formula (8).

$$S_3 = 0.42 \times e^{0.02726N} - 0.3729 \times e^{-0.4694\ N} \tag{8}$$

Analyzing Formula (8), it can be seen that with the increase of the number of wind farms, the volatility-based smoothing coefficient shows a double exponential function. For wind farm cluster with different locations and wind conditions, the coefficients of double exponential function are different, but the double exponential function relationship remains unchanged.

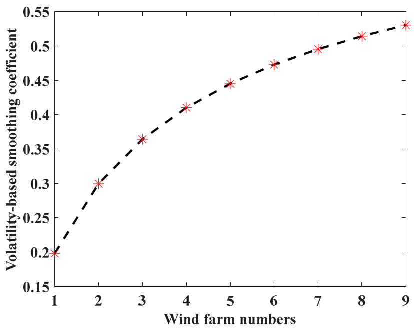

Figure 4. The volatility-based smoothing coefficient under different number of wind farms.

5.2.2. The Source-Load Timing Matching Degree Analysis

The timing matching degree of cluster power output and grid load under different wind farm combinations are quantitatively analyzed based on the load tracking coefficient and source-load timing matching coefficient, as shown in Figure 5.

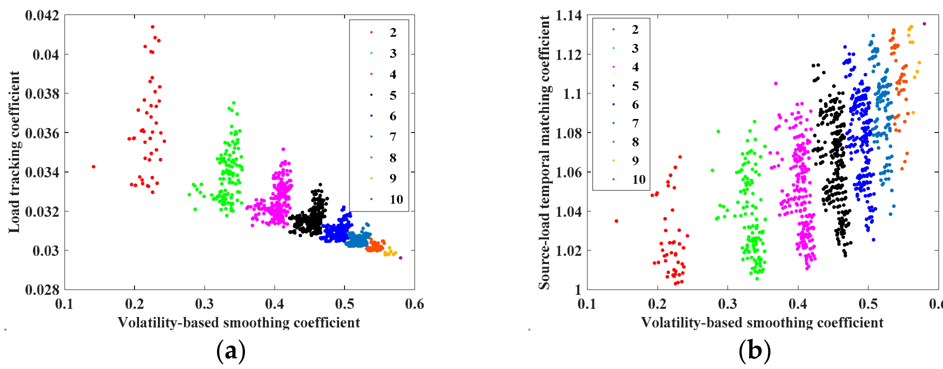

Figure 5. The source-load timing matching degree under different wind farm combinations. (**a**) The load tracking coefficient; (**b**) The source-load timing matching coefficient.

As shown in Figure 5a, the volatility-based smoothing coefficient of wind farm cluster power output gradually increases, and the load tracking coefficient linearly decreases with the increase of the number of wind farm combinations, which indicates that the fluctuation consistency of wind farm cluster power output and grid load in the time scale of investigation gradually increases, and the better the tracking performance. However, the adverse impact on the grid load is more obvious with the increase of wind power permeability for the same grid load in general. Nevertheless, the load tracking coefficient cannot reflect the difference in the timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load. As shown in Figure 5b, The source-load timing matching coefficients decrease with the increase of the volatility-based smoothing coefficient for the same number of wind farm combinations (wind power permeability), indicating that the timing matching degree of wind farm cluster power output and grid load are gradually enhanced. The source-load timing matching degree can be enhanced by improving the smoothing effect of wind farm cluster power output. The volatility-based smoothing coefficient gradually increases, and the source-load timing matching coefficient shows a linear increase with the increase of the number of wind farm combinations, indicating that the timing matching between wind power output and grid load becomes worse with the increase of wind power permeability.

However, due to the obvious differences in the rated installed capacity of different wind farms, it cannot accurately quantify the influence of wind power permeability on source-load timing matching. The rated installed capacity of different wind farms are converted into the hypothetical rated installed capacity (100 MW) in an equal proportion to quantitatively analyze the timing matching degree of wind farm cluster power output and grid load, and the corresponding functions of the volatility-based smoothing effect coefficient, load tracking coefficient and source-load timing matching coefficient are respectively fitted, as shown in Figure 6.

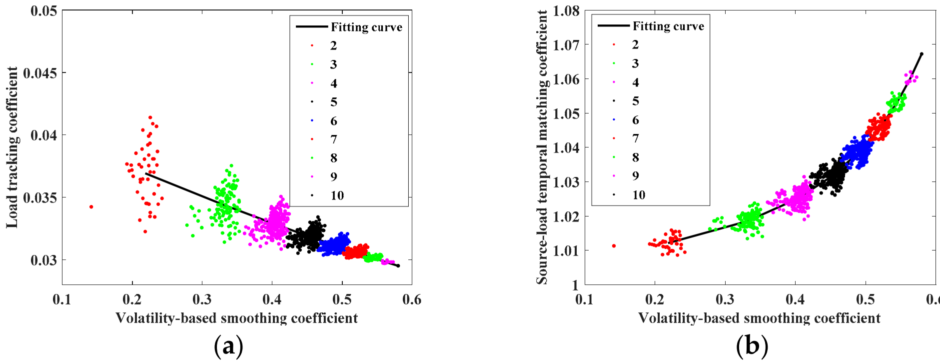

Figure 6. The source-load timing matching degree under different wind farm combinations (assumption). (**a**) The load tracking coefficient; (**b**) The source-load timing matching coefficient.

As shown in Figure 6a, the corresponding relationship between the volatility-based smoothing coefficient and load tracking coefficient under the assumed rated installed capacity is not significantly different from the actual rated installed capacity. This further proves that the load tracing coefficient cannot reflect the matching difference between wind power output and grid load under different permeability and the influence degree on grid load. The load tracking coefficient and volatility-based smoothing coefficient present the significant negative linear correlation under different wind power permeability. The fitting function is as follows:

$$I_T = -0.02039S_3 + 0.04121 \quad (9)$$

An analysis of Formula (9) shows the load tracking coefficient and volatility-based smoothing coefficient present a significant negative linear correspondence. With the increase of wind power permeability, the volatility-based smoothing coefficient gradually increases, and the load tracking coefficient presents the linear attenuation characteristic; that is, the timing matching of wind farm cluster power output and grid load is enhanced, which does not conform to the basic law that the adverse impact of wind power on the safe and stable operation of the grid increases significantly with the increase of wind power permeability. For different wind farm cluster and grid load, the negative linear function coefficients of the load tracking coefficient and volatility-based smoothing coefficient are slightly different, but the negative linear function relationship remains unchanged.

As shown in Figure 6b, the corresponding relationship between the volatility-based smoothing coefficient and source-load timing matching coefficient under the assumed rated installed capacity is more compact than that of the actual rated installed capacity. Under different wind power permeability, the relationship between the source-load timing matching coefficient and volatility-based smoothing coefficient presents an approximately exponential function, and the fitting function is as follows:

$$I_M = 1.004 * e^{(0.02601 * S_3)} \tag{10}$$

An analysis of Formula (10) shows the source-load timing matching coefficient and volatility-based smoothing coefficient present an approximate exponential function relationship. With the increase of wind power permeability, the volatility-based smoothing coefficient increases gradually, and the source-load timing matching coefficient presents a linear increasing variation law; that is, the smoothing effect of wind farm cluster power output becomes stronger, while the timing matching degree between wind power output and grid load becomes worse with the increase of wind power permeability. This is in line with the basic law that the adverse impact of wind power on the safe and stable operation of power grid increases significantly with the increase of wind power permeability. For different wind farm cluster and grid load, the exponential function coefficients of the source-load timing matching coefficient and volatility-based smoothing coefficient are different, but the exponential function relationship remains unchanged.

In summary, the source-load timing matching coefficient can accurately characterize the difference in timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load, and the influence of wind power permeability is greater than the smoothing effect of wind farm cluster power output.

6. Conclusions

This paper proposed the quantitative evaluation methods of cluster wind power output volatility and source-load timing matching in regional power grid. Firstly, the volatility-based smoothing coefficient is defined to quantitatively evaluate the smoothing effect of wind farm cluster power output. Then, the source-load timing matching coefficient considering wind power permeability is proposed to quantitatively evaluate the timing matching degree of regional wind power output and load, and the corresponding function model of the volatility-based smoothing coefficient and the source-load timing matching coefficient is established. Finally, the validity and applicability of the proposed methods are verified based on the actual power output of 10 wind farms and actual grid load in a certain grid dispatching cross-section of Northeast China. The conclusions are as follows:

(1) The volatility-based smoothing coefficient can accurately represent the smoothing effect of wind farm cluster power output, which not only can maintain the volatility continuity of wind power output time series, but also is not affected by the data sample size. The volatility-based smoothing coefficient presents a double exponential growth feature with the increase of wind farm numbers, and the specific coefficients are determined by locations and wind conditions of wind farms.

(2) The ssource-load timing matching coefficient can accurately characterize the difference in timing matching degree between wind power output and grid load under different wind power permeability and the influence degree on grid load. The source-load timing matching coefficient decreases linearly with the increase of the volatility-based smoothing coefficient under the same wind power permeability, indicating that the source-load timing matching degree can be improved by the smoothing effect of wind farm cluster power output. The source-load timing matching coefficient and the volatility-based smoothing coefficient show an approximate exponential function

relationship under different wind power permeability, indicating that the source-load timing matching degree becomes worse with the increase of wind power permeability, and the influence of wind power permeability is greater than the smoothing effect of wind farm cluster power output.

(3) The exponential function model depicts the quantitative relationship between the volatility smoothing effect of wind farm cluster power output and the source-load timing matching degree, which makes up for the deficiency of simple qualitative analysis in previous studies.

(4) The proposed indicators can be applied to cluster wind farms' capacity planning and operation scheduling. In the capacity planning stage, the volatility-based smoothing coefficient can help to determine the installed capacity proportion in wind farm cluster joint planning to reduce the volatility of wind power combined output. In the operation scheduling stage, the proposed source-load timing matching coefficient can improve the timing matching degree between wind power output and grid load to reduce the adverse impact of wind power grid connection on the power system.

There are several possible directions to further the present work. The quantitative evaluation method of source-load timing matching degree based on the similarity measurement of wind power output and grid load time series can be further studied. Moreover, the proposed source-load timing matching coefficient can be further applied to cluster wind farms capacity planning and operation scheduling, and it should be noted that other parameters, such as the wind farm capacity coefficient, wind power penetration limitation and energy storage capacity, need to be considered in the practical applications.

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