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Study on variability smoothing benefits of wind farm cluster

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Abstract: Smoothing effect is an important characteristic of large scale wind power. In this paper we analyze the smoothing effect from the prospect of output variability. Specifically, the aggregated output variability of a wind farm cluster may be significantly lower than that of an independent wind farm, and this phenomenon is referred to as the variability smoothing effect. In order to quantitatively analyze the variability smoothing effect, this paper introduces the concept of variability costs and evaluates the variability costs of each wind farm and overall wind farm cluster based on an optimal scheduling model. It is found that the variability cost of a wind farm cluster as a whole is lower than the sum of variability costs of all wind farms. Moreover, the difference between wind farm cluster variability cost and the sum of variability costs of each wind farm is termed the variability smoothing benefit. Meanwhile, the Shapley value method is deployed to equitably allocate the variability smoothing benefits of the wind farm cluster. The results indicate that the combined wind farms have the additional benefits of reducing variability costs as well as encouraging the integration of large scale wind farms.

Key words: Wind farm cluster, variability costs, variability smoothing benefits, Shapley value method

1. Introduction

During recent decades, increasing amounts of wind power have been integrated into power systems. On the one hand, this growth can bring several advantages such as environmental friendliness and cost-effectiveness. On the other hand, it comes with a number of unique challenges due to the natural characteristics of wind, such as output variability and less predictability [1,2]. Specifically, the variability of wind power has to be managed in the short term. As the wind penetration increases, maintaining the energy balance becomes significant because of the increase of variability in the supply of electricity, which can eventually lead to increases in system costs. It is known that large scale wind power has the natural feature of the smoothing effect. Due to the space distribution and time difference between wind farms, the prediction errors and peak-to-valley difference can be considerably decreased [3]. The smoothing effect can reduce the system costs and help increase the wind penetration with minor disturbance to the stability of the electrical grid [4]. More recently, numerous studies have been conducted on the smoothing effect of large scale wind farm clusters. In this paper, the smoothing effect is analyzed from the viewpoint of the wind power variability costs.

In general, the smoothing effect of wind power has been widely investigated from the perspectives of error prediction and output variability.

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(1) Less predictability is one of the main challenges of wind power. To investigate the impact of smoothing effects on the prediction errors, a novel wind power prediction model considering smoothing effects [5] and a multiscale stochastic prediction model [6] have been developed. The results show that the smoothing effects can reduce prediction errors [7], decrease the system costs [8], and help determine the system reserve capacity [9].

(2) Apart from prediction errors, the variability of wind power is another challenge. To better analyze the impact of smoothing effects on the wind output fluctuations, various studies have examined it from different scales: multiple temporal and spatial scales [9,10], temporal scale [11,12], and spatial scale [13–15]. In [9], a variability index is developed to compare the variability in different geographic areas and different time scales. The results indicate that the smoothing effect of distributed wind farms is very strong for short term fluctuation. Ref. [10] shows that combining remote wind farms via electrical transmission is an economically practical way to level wind since the smoothing effect can help to reduce the wind variances and decrease the rate of change.

A number of studies have investigated the smoothing effect from the viewpoint of temporal scale. In [11], a frequency model of wind output variability is proposed and it shows that the smoothing effect of high-frequency wind power components is larger than that of the low-frequency ones. Ref. [12] measures wind power output fluctuations for a period of 1 year with the sampling period of 10 s, and it concludes that a greater degree of smoothing effect can be observed in the region of variations of less than 40 min.

Different studies have examined the smoothing effect from the viewpoint of spatial scale [13–15]. Ref. [14] shows that with the increase in the size of areas including wind farms, the variation in peak-to-valley difference of wind power can be decreased significantly. Ref. [15] asserts that large scale wind power plants can effectively mitigate the variability of wind outputs. Although it has been widely agreed that the smoothing effect can alleviate the variability of wind outputs and bring potential benefits, limited research has been conducted on the calculation of benefits caused by smoothing effects. This paper quantitatively evaluates the benefits caused by the smoothing effects from the perspective of wind variability costs. The wind variability costs are referred to as the additional costs caused by the volatility characteristic of wind electricity, which serve a key role in evaluating the economic value of wind.

Furthermore, how to determine the variability costs of wind power is also a critical problem. Refs. [16,17] calculate the uncertainty costs based on the unit commitment model. The uncertainty costs refer to the extra costs due to the prediction errors of wind power. However, all the above studies focus on the uncertainty costs of wind power. There has been limited research so far on the calculation of the variability costs of wind power. Ref. [18] employs corresponding market prices to determine the variability costs. Ref. [19] measures the variability cost with the ”value factor”. The value factor is defined as the ratio of wind-weighted average electricity price and time-weighted average electricity price. At the same time, it evaluates the value factor for wind to be 0.91–0.95 during the last decade. Ref. [20] applies levelized costs of electricity (LCOE) to estimate the variability cost of wind. LCOE is a metric for comparing total average costs of wind and conventional plants. In the previous research by the authors, the calculation method of the variability costs of wind was introduced [21], and an alternative scenario construction method was proposed to estimate the variability cost of wind power for a single wind power plant. In the present paper, a further study is performed on the variability cost of a wind farm cluster.

Note that due to the smoothing effect combining wind farms located in wide areas can reduce the variability of wind power [21]. As the positive and negative output fluctuations from different wind plants can be canceled out, the aggregated variability of a group of dispersed wind plants is expected to be significantly lower than the sum of individual variations [8]. Thus, the variability cost of a wind farm cluster as a whole is lower than the sum of variability costs of each wind farm. This phenomenon is referred to as the variability smoothing effect in this paper, and the difference between variability cost of the wind farm cluster and the sum of variability costs of each wind power plant is termed the variability smoothing benefit.

This paper investigates the variability smoothing benefits from a mathematical point of view and develops a reasonable allocation strategy. The novelties of this paper are as follows:

(1) An alternative scenario construction method is developed to evaluate the variability costs of both the wind farm and the wind farm cluster. The proposed method can construct an appropriate scenario that adds no additional variability to the conventional power plants.

(2) From the perspective of variability costs, a calculation method of variability smoothing benefits is proposed. More specifically, based on the optimal scheduling model, the variability costs of each wind farm and overall wind farm cluster are calculated and the difference between the 2 above costs is the variability smoothing benefit.

(3) An allocation strategy based on the Shapley value method is introduced to distribute the variability smoothing benefits impartially. The results show that, compared with the EANS sharing solution, the Shapley value method can lead to a more equitable allocation.

The remainder of this paper is organized as follows: Section 2 analyzes the variability smoothing benefits and develops a method to estimate them. Section 3 presents the detailed procedures of the variability smoothing benefits allocation strategy. In Section 4, some conclusions are summarized.

2. Variability smoothing benefits of a wind farm cluster

2.1. Quantification of the variability cost of a single wind farm

The relative variability between wind power and load profile plays a key role in evaluating the variability costs of wind power. In this paper, the relative variability index $VIX\left(X,Y\right)$ of wind power is defined as the Euclidean distance between changing rates of X and Y.

$$VIX(X,Y) = \sqrt{\frac{1}{N-1}\sum_{n=2}^{N}(R(x_n) - R(y_n))^2}, \tag{1}$$

where

$$R(x_n) = \frac{x_n - x_{n-1}}{x_{n-1}},\ R(y_n) = \frac{y_n - y_{n-1}}{y_{n-1}}$$

$$X = \{x_1, \cdots, x_n\} Y = \{y_1, \cdots, y_n\},$$

where x_n and y_n respectively denote wind output and load demand value in the period n. N denotes the number of samples. $R(x_n)$ and $R(y_n)$ denote variability ratios. The relative variability index $VIX\left(X,Y\right)$ measures the relative variability of wind outputs with respect to the load demands. For example, if the relative variability index is nearly zero, it means the extent of the relative variability between the wind outputs and the load demands is small.

In the context of the relative variability, Ref. [21] proposes an alternative scenario construction method to calculate the variability cost of a single wind farm. A brief description of this method is presented here; further details can be found in [21].

As indicated in Figure 1, the variability cost of wind power can be calculated by the optimal scheduling model. Note that the detailed formulation of the optimal scheduling model can be found in [21]. The crucial step is to construct a scenario without wind power variability, and then calculate the total system costs under the constructed scenario and the actual one, respectively. The difference between the 2 costs is the wind farm variability cost.

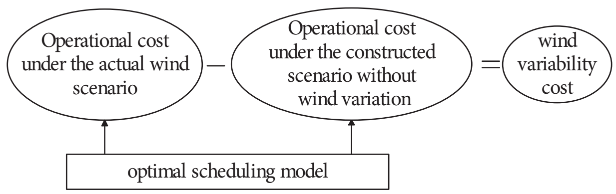

Figure 1. Proposed calculation method of wind power variability costs.

To construct the scenario without wind variation, an energy proxy needs to be established to replace the actual wind power, and an alternative scenario construction method in [21] can be employed for this purpose. Specifically, in our alternative scenario, wind power is changed into the proxy resource according to 2 principles. (1) The energy of proxy resource equals that of actual wind power. (2) The shape of the proxy resource curve and load profile are the same. The specific method is shown in Figure 2.

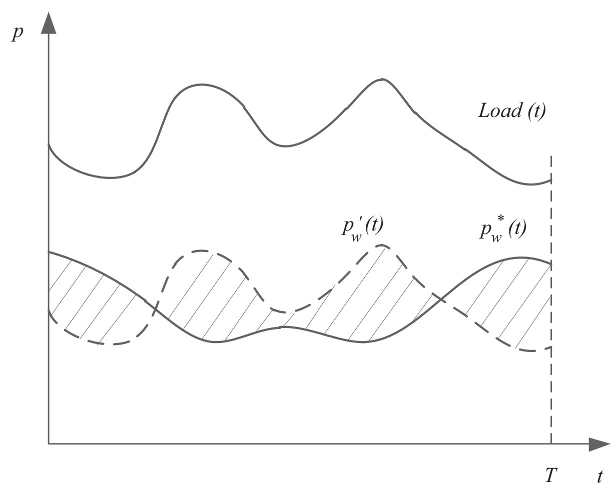

Figure 2. Schematic diagram of the proposed alternative scenario construction method.

Mathematically, the equivalent energy proxy in the constructed scenario is obtained as follows:

$$\begin{cases} \sum_{t=1}^{T} p_w'(t) = \sum_{t=1}^{T} p_w^*(t) & \quad (2a) \\ & t = 2, 3, \cdots, T \\ \dfrac{p_w'(t) - p_w'(t-1)}{p_w'(t-1)} = \dfrac{Load(t) - Load(t-1)}{Load(t-1)} & \quad (2b) \end{cases}$$

where $p_w^*(t)$ is the actual wind power output, $p'_w(t)$ is the equivalent proxy resource, and $Load\,(t)$ is the load demand.

Equation (2a) assures that the power generation of the energy proxy equals that of the actual wind plants in a scheduling period; (2b) means that the energy proxy curve should be the same shape as the load curve. These 2 principles assure that the proxy resources and conventional plants take fair responsibility of following the load fluctuations. This implies that the conventional power plants do not need to ramp more frequently or operate in a less efficient way to balance the fluctuations of the proxy resources. Therefore, the energy proxy does not induce additional variability cost for the power system.

2.2. Quantification of variability smoothing benefits of a wind farm cluster

This paper extends the alternative scenario construction method to calculate the variability costs of a wind farm cluster and each wind in the cluster.

2.2.1. The variability cost of each wind farm in the cluster

It is assumed that there are two wind farms in the cluster, namely "Wind Farm 1" and "Wind Farm 2". For example, to calculate the variability cost of Wind Farm 1, there are 3 steps, which are also displayed in Figure 3:

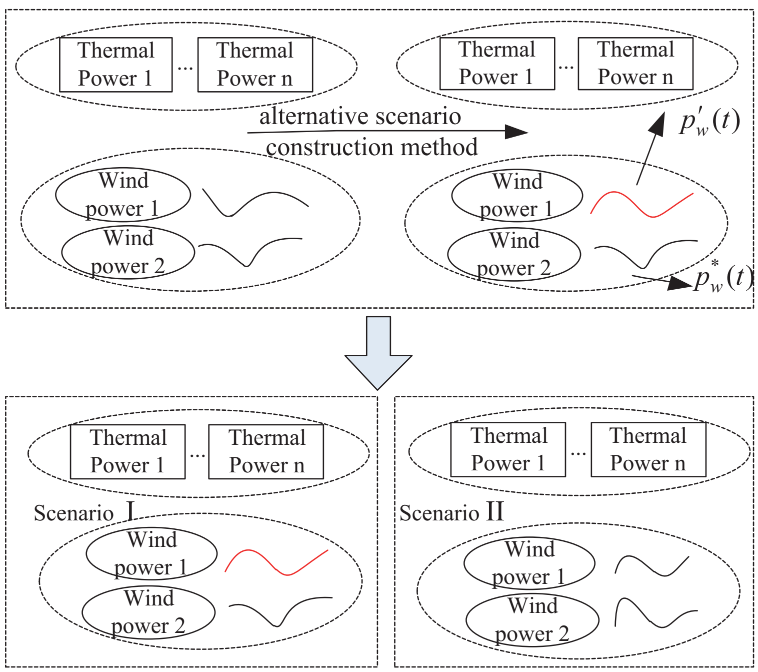

Figure 3. Proposed calculation method of the variability cost of single wind farm.

Step 1: Following the principles of the alternative scenario construction method, we construct 2 scenarios:

Scenario I: Based on Eq. (2), the output profile of Wind Farm 1 is converted into the equivalent energy proxy, and then Wind Farm 1 and Wind Farm 2 are integrated into the power system with the equivalent energy proxy and actual output, respectively. Note that the black curves denote the actual wind outputs and the red curves denote the equivalent energy proxies.

Scenario II: Wind Farm 1 and Wind Farm 2 are integrated into the power system with actual outputs.

Step 2: Calculate the total system costs of Scenario I and Scenario II based on the optimal scheduling model.

Step 3: Obtain the difference between costs in Scenario I and Scenario II, which is the wind power variability cost C_i.

2.2.2. The variability cost of the wind farm cluster

For convenience of description, we assume that there are n wind farms distributed in different nodes, namely "Wind Farm 1", "Wind Farm 2" ... and "Wind Farm n". The rest of generations are thermal power units, which are shown in Figure 4. To calculate the variability cost of the wind farm cluster, the crucial step is to construct 2 scenarios:

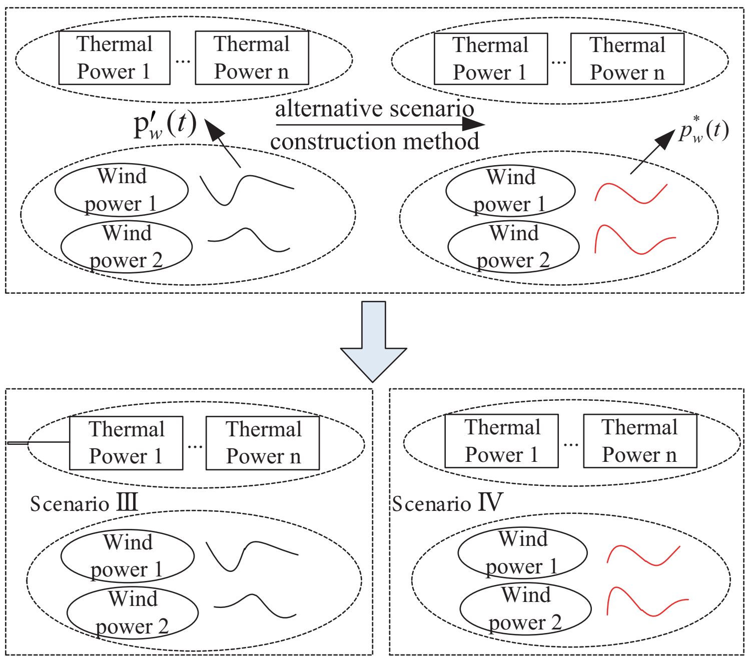

Figure 4. Proposed calculation method of the variability cost of wind farm cluster.

Scenario III: All the wind farms are integrated into the power system with the actual outputs.

Scenario IV: All the output profiles of wind farms are changed into the equivalent energy proxies and then integrated into the power system with equivalent energy proxies.

Then calculate the total system costs of Scenario III and Scenario IV based on the optimal scheduling model, and the difference between 2 system costs is the variability cost of wind farm cluster $C_{cluster}^{smooth}$.

2.2.3. Variability smoothing benefits

The variability smoothing benefits are determined by subtracting the aggregated variability cost from the sum of the variability costs of each wind farm, which are displayed in Figure 5. Note that the vertical scale is in $.

Mathematically, it can be expressed as

$$C_{cluster}^{\Sigma} = \sum_{i=1}^{n} C_i \tag{3}$$

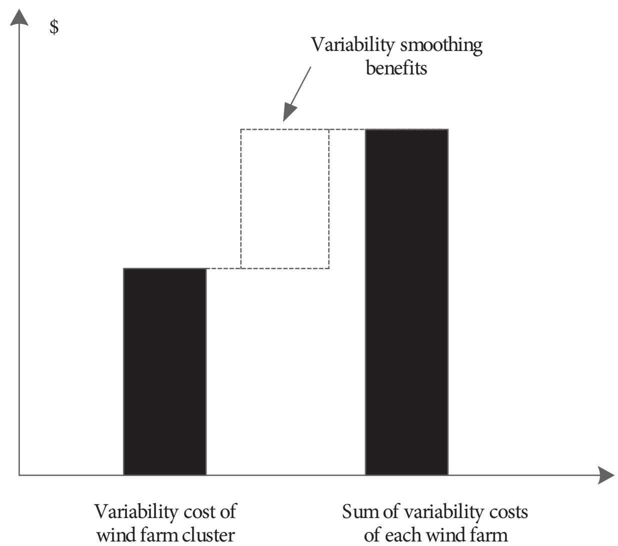

Figure 5. The diagram of variability smoothing benefits of wind farm cluster.

$$\phi = C^{\Sigma}_{cluster} - C^{smooth}_{cluster}, \tag{4}$$

where n is the number of wind farms in the cluster. $C^{\Sigma}_{cluster}$ denotes the sum of variability costs of wind farms and ϕ denotes the variability smoothing benefit.

2.2.4. Solution algorithm

To solve the optimal scheduling model of the wind power, various optimization algorithms have been proposed, including genetic algorithm [22], particle swarm optimization algorithm [23], Lagrangian relaxation methods [24], dynamic programming [25], and the mixed integral linear programming (MILP) optimization method [26]. The MILP algorithm is the most common method to solve the optimization problems, and many studies have examined the power system problems with the MILP method [27–29]. In this paper, we transform the optimal scheduling model into the MILP optimization problems, which can be solved using MILP solver under CPLEX software on Intel Core i5 CPU at 2.60 GHz and 8 GB of memory.

2.3. Simulation of variability smoothing benefits of the wind farm cluster

In this section, a discussion is given on the variability smoothing benefit of the wind farm cluster, which is shown on a modified system of IEEE118-bus. The system contains 54 sets of thermal power units, 186 branches, and 91 load terminals. We use realistic hourly ERCOT market load and wind generation data from 25 July 2017 until 31 July 2017. Note that the wind production data are from 3 geographically dispersed installations. The load profile and wind generation of each scheduling period are respectively shown in Figures 6 and 7.

To quantify the correlation between the wind output and the load demand, Pearson's correlation coefficient is applied. Pearson's correlation coefficient can be used to measure the linear correlation between 2 sets of data and its value varies between –1 and 1. The positive coefficient indicates the positive correlation of the compared variables while the negative coefficient indicates the negative correlation of the compared variables.

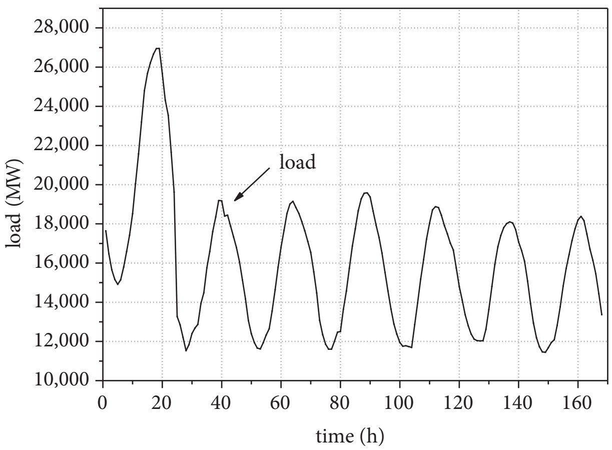

Figure 6. One week of load profile.

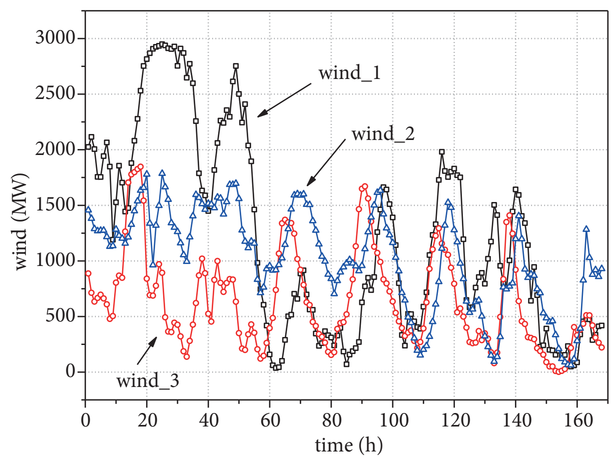

Figure 7. One week of wind generation data.

More precisely, the Pearson's correlation coefficient can be computed as defined in Eq. (5):

$$\left\{ \begin{array}{l} \rho\left(X,Y\right) = \dfrac{\sum\limits_{n=1}^{N}\left(x_n - \overline{X}\right)\left(y_n - \overline{Y}\right)}{\sqrt{\sum\limits_{n=1}^{N}\left(x_n - \overline{X}\right)^2}\sqrt{\sum\limits_{n=1}^{N}\left(y_n - \overline{Y}\right)^2}} \\ X = \left\{x_1, \ldots x_n\right\} \qquad Y = \left\{y_1, \ldots y_n\right\} \end{array} \right. , \tag{5}$$

where x_n and y_n respectively denote wind output and load demand value in the period n. N denotes the number of samples. $\overline{X}$ and $\overline{Y}$ respectively denote the average value of samples X and Y.

First of all, the optimal scheduling model is employed to calculate the total system costs of Scenario I and Scenario II. Then the difference C_i between the total cost of Scenario I and Scenario II is obtained and shown in Table 1. Based on Eq. (1), the relative variability indexes of different wind farms can be obtained and are shown in Figure 8. Note that Figure 8 shows the absolute value of the average variability cost of wind_2. It can be observed that the average variability cost increases from \$1.805 to \$11.743 when the relative variability index grows from 0.094 to 0.417. This means that the average variability cost of wind is positively associated with relative variability index. Furthermore, from the results of Pearson's correlation coefficients, it can be seen that the positive correlation between the output of wind_2 and the load demand is strong while the correlation between the output of wind_1 or wind_3 and the load demand is extremely weak. The negative variability cost of wind_2 is due to its strong positive correlation with the load demand. This indicates that positive correlation can lead to negative variability costs.

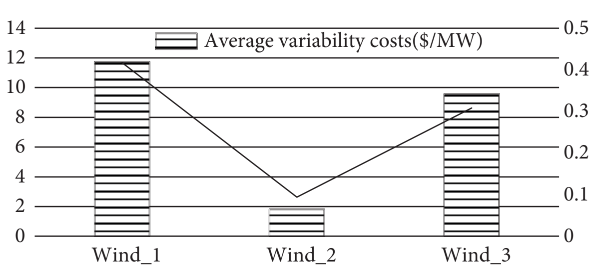

Figure 8. The average variability costs and relative variability indexes of different wind farms.

Table 1. The variability cost of each wind farm.

Wind power serial number	Total wind power (MW)	Relative variability index	Average variability costs ($/MW)	Pearson correlation coefficient
Wind_1	204602.1	0.417	11.743	0.0711
Wind_2	107735.7	0.094	–1.805	0.7963
Wind_3	171877.7	0.308	9.580	0.0959

Secondly, the optimal scheduling model is employed to calculate the total system costs of Scenario III and Scenario IV. Table 2 presents the comparison of the difference between the total costs of Scenario III and Scenario IV, which is the variability cost $C_{cluster}^{smooth}$ of three wind farms. It can be seen that the relative variability index of the wind farm cluster is less than the average relative variability index of the 3 wind farms. This implies that the total output variability in the wind farm cluster is smaller than that of the aggregated value produced by the independent wind farm.

Table 2. The variability cost of wind farm cluster.

Total wind power (MW)	Relative variability index	Total variability costs ($)	Average costs variability ($/MW)
484,215.5	0.293	7,677,168	7.961

Based on Eqs. (3) and (4), the variability smoothing benefits can be obtained and are shown in Table 3. It can be seen that the variability cost of the wind farm cluster is decreased by 23.78% compared with the sum of variability costs of the single wind farm. The results indicate that the combined wind farms obtain additional benefits by reducing the variability costs.

Table 3. The variability smoothing benefits of wind farm cluster.

The variability cost of wind farm cluster ($)	The sum of variability costs of wind farms ($)	The variability smoothing benefits ($)
7,677,168	10,072,974	2,395,806

As a result, 3 conclusions can be drawn from this case study. First, the average wind variability cost increases with increasing relative variability index. Second, a positive correlation can lead to negative variability costs. Third, due to the variability smoothing effect, the sum of variability costs of the single wind farm is greater than the variability cost of the wind farm cluster.

3. Allocation strategies of variability smoothing benefits of the wind farm cluster

The last sections discuss how variability smoothing benefits are determined. A related question is how to allocate variability smoothing benefits amongst the wind farms equitably. If the benefits are allocated by electricity or capacity, it will be detrimental to the small capacity wind farm. When the volatility of the large capacity wind farm is relatively high, it may distribute more variability smoothing benefits to the large capacity wind farm than its own contribution.

In the field of benefits distribution, the equal allocation of nonseparable costs (EANS) sharing solution [30] and Shapley value method [31] are widely used. The principle of EANS sharing solution is to average nonseparable benefits amongst all the members; Shapley value is indicative of the extent of each member's marginal contribution to the coalition. It can lead to an equitable allocation. In this paper, the performances of the 2 above methods used for allocating the variability benefits of wind farm cluster are analyzed and compared.

3.1. The allocation strategy based on EANS sharing solution

EANS is a nonseparable benefit sharing solution, and its principles of allocation are shown in (6)–(8).

$$\phi_i = SC_i + \frac{1}{n} NSC \tag{6}$$

$$SC_i = v(N) - v(N \backslash \{i\}) \tag{7}$$

$$NSC = v(N) - \sum_{i=1}^{N} SC_i, \tag{8}$$

where n denotes the number of participants in the static cooperative game (corresponding to the number of wind farms), SC_i denotes the separable benefits of participant i, $v(N)$ denotes the total benefits of all participants (the variability benefits of multiple wind farms), $v(N\backslash \{i\})$ denotes total benefits of $n-1$ participants not containing participant i (the sum of the variability benefits of the $n-1$ wind farms not containing wind i), NSC denotes inseparable benefits for all participants, and ϕ_i denotes the sharing solution of participant i (that is the allocated variability benefit of wind farm i).

3.2. The allocation strategy based on Shapley value method

A disadvantage of the EANS approach is that it ignores alliances other than the major leagues and alliances including $n-1$ participants, and this may affect the results of assignment. The Shapley value method treats each participant in the alliance as an analytic object that considers the effects of all possible alliances on the allocation results. The crux of the Shapley value is to allocate benefits according to the marginal contribution of each alliance member to the reduction of the variability costs. The principle for the Shapley value allocation method is

$$\phi_i(v) = \sum_{S \subseteq N \backslash i} \frac{s!\,(n-s-1)!}{n!} \left[v(S \cup \{i\}) - v(S) \right], \tag{9}$$

where n is all participating members of the arrangements (corresponding to the number of wind farms in the cluster), s denotes the number of participants in the coalition (corresponding to the number of wind farms that take part in the coalition), $v(S \cup \{i\})$ denotes the total benefits of alliance S not containing participant i, $v(S)$ denotes the benefit of the alliance S, and $\phi_i(v)$ denotes the allocated variability benefit of wind farm i.

3.3. Simulation of variability smoothing benefits allocation strategy

In this section, a comparison is performed between the EANS sharing solution and the Shapley value method. We use a realistic hourly ERCOT market load and wind generation data for 3 geographically dispersed wind farms on 10 August, which are shown in Figure 9. Using the method in Section 2.2, the variability costs of wind_4, wind_5, wind _6, and the wind farm cluster are obtained and shown in Table 4.

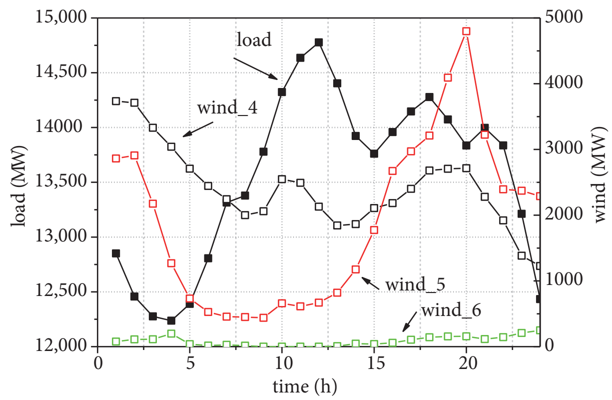

Figure 9. 24 h load profile and wind generation data.

Table 4. Variability costs of multiple wind farms.

	Wind_4	Wind_5	Wind_6
Variability costs ($)	122,800.7	304,321.3	197,733.9
Average variability costs ($)	2.127	6.682	9.83
Relative variability index	0.115	0.287	0.314
Pearson correlation coefficient	–0.3345	0.0116	–0.396

The sum of variability costs of the 3 wind farms is $C_{cluster}^{\Sigma} = \$624855.86$, and the total combined variability cost is $C_{cluster}^{smooth} = \$389744.843$; therefore the variability smoothing benefit is $\phi = C_{cluster}^{\Sigma} - C_{cluster}^{smooth} = \$235111.017$. The combined variability costs among multiple wind farms are shown in Table 5. Note that wind_4, 5 represents combined wind farm of wind_4 and wind_5.

Table 5. Combined variability costs of multiple wind farms.

	Wind_4,5	Wind_4,6	Wind_5,6
Relative variability index	0.162	0.298	0.173
The sum of variability costs ($)	427,122	3,205,334.56	502,055.17
Combined variability costs ($)	348,135.3	297,389.7	380,600.1
Variability smoothing benefits ($)	78,986.72	23,144.86	121,455.1

According to the results of Table 5, the relative variability index of wind_5, 6 is smaller than that of wind_5 and wind_6. The relative variability indexes of wind_4, 5 and wind_4, 6 are between their minimum and maximum values.

Then the calculation procedures of the Shapley value method are as follows. Firstly, the marginal contribution of each wind in all possible alliances is calculated and shown in Table 6.

Table 6. The marginal contribution of multiple wind farms.

Order of arrival	Marginal contribution of wind_4 ($)	Marginal contribution of wind_4 ($)	Marginal contribution of wind_4 ($)
4,5,6	$v(4) = 0$	$v(4,5) - v(4) = 78,986.72$	$v(4,5,6) - v(4,5) = 156,124.3$
4,6,5	$v(4) = 0$	$v(4,5,6) - v(4,6) = 211,966.2$	$v(4,6) - v(4) = 23,144.86$
5,4,6	$v(4,5) - v(5) = 78,986.72$	$v(5) = 0$	$v(4,5,6) - v(4,5) = 156,124.3$
5,6,4	$v(4,5,6) - v(5,6) = 113,655.9$	$v(5) = 0$	$v(5,6) - v(5) = 121,455.1$
6,4,5	$v(4,6) - v(6) = 23,144.86$	$v(4,5,6) - v(4,6) = 211,966.2$	$v(6) = 0$
6,5,4	$v(4,5,6) - v(5,6) = 113,655.9$	$v(5,6) - v(6) = 121,455.1$	$v(6) = 0$

Then, according to (8), the allocation results of the Shapley value method are

$$\begin{aligned}\phi_4 &= \tfrac{1}{6}v(4) + \tfrac{1}{6}v(4) + \tfrac{1}{6}[v(4,5) - v(5)] + \tfrac{1}{6}[v(4,5,6) - v(5,6)] \\ &\quad + \tfrac{1}{6}[v(4,6) - v(6)] + \tfrac{1}{6}[v(4,5,6) - v(4,6)] = \$54907.24\end{aligned}$$

$$\begin{aligned}\phi_5 &= \tfrac{1}{6}[v(4,5) - v(4)] + \tfrac{1}{6}[v(4,5,6) - v(4,6)] + \tfrac{1}{6}v(5) + \tfrac{1}{6}v(5) \\ &\quad + \tfrac{1}{6}[v(4,5,6) - v(4,6)] + \tfrac{1}{6}[v(5,6) - v(6)] = \$104062.4\end{aligned}$$

$$\begin{aligned}\phi_6 &= \tfrac{1}{6}[v(4,5,6) - v(4,5)] + \tfrac{1}{6}[v(4,6) - v(4)] + \tfrac{1}{6}v(6) + \tfrac{1}{6}v(6) \\ &\quad + \tfrac{1}{6}[v(5,6) - v(5)] + \tfrac{1}{6}[v(4,5,6) - v(4,5)] = \$76141.43\end{aligned}$$

The results obtained from the EANS sharing solution and the Shapley value method are shown in Table 7. The allocation results of variability smoothing benefits are also displayed in Figure 10. As indicated in Table 6, wind_5 pays the greatest amount of variability cost, and wind_4 pays the smallest amount of variability cost. However, they get equal variability smoothing benefits based on the EANS sharing solution, and thus it is detrimental for the wind farms to contribute more to the alliance. For the Shapley value method, wind_5 is rewarded through the largest variability smoothing benefits. Table 4 indicates that wind_5 is positively correlated with load, while wind_4 and wind_6 are negatively correlated with load. That means wind_5 counteracts the relative variability of wind_4 and wind_6. Therefore, wind_5 gets larger variability benefits and wind_4 gets less variability smoothing benefits based on the Shapley value method. The Shapley value method shows each wind's contribution to the reduction of wind variability costs, which is more equitable than the EANS sharing solution.

Table 7. Allocation results.

	Wind_4	Wind_5	Wind_6
EANS($)	78,370.3	78,370.3	78,370.3
Shapley value($)	54,907.2	104,062.4	76,141.43

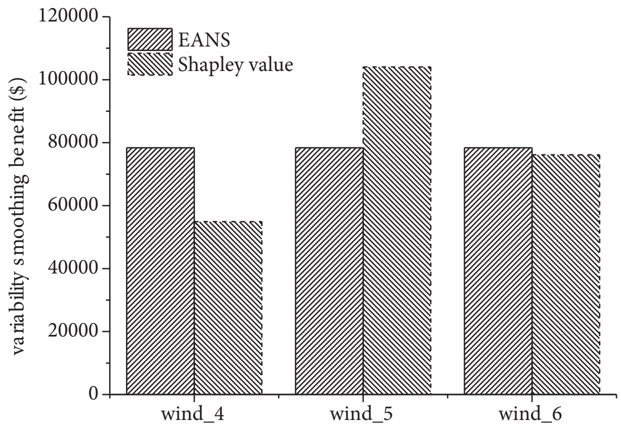

Figure 10. The allocation results of variability smoothing benefits.

The results indicate that: (1) The EANS sharing solution is simple, but it ignores the fact that each wind farm's contribution to the reduction of variability costs is not equal. (**??**) The Shapley value method reflects the marginal contribution of each wind farm to the wind farm cluster. It can lead to a more equitable allocation.

4. Conclusion

In this paper, variability smoothing benefits of a wind farm cluster are studied from a mathematical point of view, and a reasonable strategy for allocating variability smoothing benefits is introduced. The main conclusions are as follows:

(1) The previous wind variability cost calculation method is expanded from a single wind farm to a wind farm cluster. The calculation results demonstrate that the variability cost of wind power increases with increasing relative variability index. Moreover, the variability cost of the wind farm cluster as a whole is lower than the sum of variability costs of each wind farm.

(2) To investigate the impact of the variability smoothing effects on the wind power fluctuations, a calculation method based on the variability costs is proposed. The results show that the variability smoothing effect of a large scale wind farm cluster can contribute largely to its output fluctuations and variability costs.

(3) The Shapley value method is developed to allocate the variability smoothing benefits of the wind farm cluster based on the marginal contribution of each wind farm. The results indicate that compared with the EANS sharing solution, the Shapley value method can lead to a more equitable allocation.

In future work, we plan to consider the integration of wind power capacity into generation planning, the unit commitment, and economic dispatch. Moreover, we may further consider other strategies to mitigate the impacts on the power system operation by the variability of wind power, such as demand response and battery energy storage.

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