

## Optimization for Variable Height Wind Farm Layout Model

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Received: 03 March 2021; Accepted: 05 April 2021

**Abstract:** The optimization of wind farm layouts is very important for the effective utilization of wind resources. A fixed wind turbine hub height in the layout of wind farms leads to a low wind energy utilization and a higher *LCOE* (levelized cost of electricity). *WOMH* (Wind Farm Layout Optimization Model Considering Multiple Hub Heights) is proposed in this paper to tackle the above problem. This model is different from the traditional fixed hub height model, as it uses a variable height wind turbine. In *WOMH*, the Jensen wake and Weibull distribution are used to describe the wake effect on the wind turbines and wind speed distribution, respectively. An algorithm called *DEGM* (differential evolution and greedy method with multiple strategies) is proposed to solve *WOMH*, which is *NP* hard. In the *DEGM*, seven strategies are designed to adjust the distribution coordinates of wind turbines so that the height of the wind turbines will be arranged from low to high in the wind direction. This layout reduces the Jensen wake effect, thus reducing the value of the *LCOE*. The experimental results show that in the *DEGM*, when the number of wind turbines is 5, 10, 20, 30 and 50, the *WOMH* reduces the *LCOE* by 13.96%, 12.54%, 8.22%, 6.14% and 7.77% compared with the fixed hub height model, respectively. In addition, the quality of the solution of the *DEGM* is more satisfactory than that of the three-dimensional greedy algorithm and the *DEEM* (differential evolution with a new encoding mechanism) algorithm. In the case of five different numbers of wind turbines, the *LCOE* of *DEGM* is at least 3.67% lower than that of *DEEM*, and an average of 6.83% lower than that of three-dimensional greedy. The model and algorithm in this paper provide an effective solution for the field of wind farm layout optimization.

**Keywords:** Optimization of wind farm layout; variable multiple hub heights; differential evolution; Jensen wake model



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## 1 Introduction

Air pollution, climate warming, the energy crisis and other factors are forcing people to find and develop clean energy that can replace fossil fuels. Wind energy is pollution-free and renewable and is currently one of the most competitive and mature green energy sources [1].

The main form of wind energy utilization is to generate electricity through wind farms [2]. Wind turbines are the core equipment used in wind farms to convert wind energy into electricity. The layout of a wind farm has a great impact on the wind turbines. There are three factors that affect the layout of wind farms: the size of the wind farm, the number of wind turbines placed in the wind farm, and the wake effect of upstream wind turbines on downstream wind turbines [3]. The focus of this research is how to eliminate the wake effect between wind turbines. A reasonable layout of wind turbines in wind farms can effectively reduce the wake effect, and a good wind farm layout can improve the power of wind turbines to make better use of wind energy resources.

The layout models of existing wind farms fall into two categories: discrete coordinate models and continuous coordinate models. The discrete coordinate model regards wind turbines as independent and scattered points for layout optimization. In the continuous coordinate model, the wind turbine can be placed anywhere in the wind farm. Because these two models are difficult to solve analytically and have a large amount of computations, many heuristic algorithms have been designed to solve the models. Mosetti et al. [4] proposed a model based on discrete coordinates and used a genetic algorithm to determine the optimal solution. Considering the wake effect of wind farms, a wind farm cost model was designed that takes the *LCOE* (levelized cost of electricity) generated by the wind farm as the objective function. Three kinds of wind scenarios were assigned in the experiment: scenario 1-the wind direction and speed are constant; scenario 2-the wind speed is constant, and the wind direction is uniformly distributed between 0 and 360 degrees; scenario 3-the wind speed is variable, and the wind direction is uneven. Kusiak et al. [5] developed a continuous coordinate model and used the *SPEA* algorithm to solve the problem. They regarded individual wind turbines as a population, so when the number of wind turbines increases, the performance of the algorithm will be seriously degraded, and there may even be dimensional disasters. Subsequently, many researchers [6–10] studied different heuristic algorithms to solve the model based on continuous coordinates. Wang et al. [11] proposed a *DE* (differential evolution) algorithm with a new coding mechanism, which reduced the dimension of the search space to 2 and eliminated a key parameter (population size), thus solving the dimensional disaster problem.

However, only wind turbines with the same height are considered in the above studies. In practice, due to terrain or other reasons, the hub heights of wind turbines will differ. At the same time, different hub heights also help to further reduce the wake effect of the whole wind farm. In previous research, many scholars have discussed the multiple hub height model. Herbert et al. [12] placed wind turbines with two different heights in a line. The results showed that the use of wind turbines of different heights is beneficial for improving the power generation of wind farms. Chowdhury et al. [13] and Long et al. [14] used particle swarm optimization to optimize the multiple hub height model. The experimental results showed that the multiple hub height model can significantly increase the power output of the wind farm. Chen et al. [15] made use of greedy algorithm to solve wind turbines with different hub height models. In an experiment based on three-dimensional coordinates, two kinds of wind turbines with different hub heights were used. Then, two planes in three-dimensional coordinates were used as the candidate positions of the wind turbines. All of their results showed that the existence of wind turbines with different heights in a wind farm is beneficial for improving the power generation of the wind farm.

A wind farm layout optimization model considering multiple hub heights is studied in this paper. The *DEGM* (differential evolution and greedy method with multiple strategies) is proposed in this paper to solve the optimization problem. The complex terrain problem is studied and optimized in an experiment, and the advantages of using multiple hub height wind turbines in wind farms are further studied.

The main contributions of this paper are summarized as follows:

In the process of solving the actual wind farm layout, it is determined that wind turbines with multiple hub heights can effectively reduce the wake effect between wind turbines. In this paper, a novel model named *WOMH* (wind farm layout optimization model considering multiple hub heights) is designed to simulate the optimized layout of wind farms with multiple hub heights.

A series of adjustment strategies are proposed in the *DEGM*. These strategies integrate the position and height information of wind turbines so that the wind turbines are arranged in linear with a high probability to reduce the *LCOE*, and thus to improve the wind farm layout.

The remainder of this article is organized as follows. The second section introduces *WOMH*, and the specific details of the *DEGM* are described. The third part describes the experiment and data analysis. The fourth part summarizes the paper.

## 2 System Model

*WOMH* takes *LCOE* as the optimization goal. It contains three submodules: Jensen wake, Weibull distribution and output power. Jensen wake and Weibull distribution are used to describe the wake effect between wind turbines and wind speed distribution respectively. The output power model is made use of quantifying the output power.

### 2.1 The Jensen Wake Model

The Jensen wake model [16] is a one-dimensional wake model suitable for flat terrain. Fig. 1 depicts the Jensen wake model. In the model,  $v_0$  is the natural incoming wind speed,  $v_r$  is the wind speed when the wind passes through the front turbine rotor,  $v$  is the incoming wind speed at the rear exhaust turbine affected by the wake,  $x$  is the distance between the front and rear exhaust turbines,  $R_1$  is the initial radius of the wake area, and  $R_w$  is the wake influence radius.

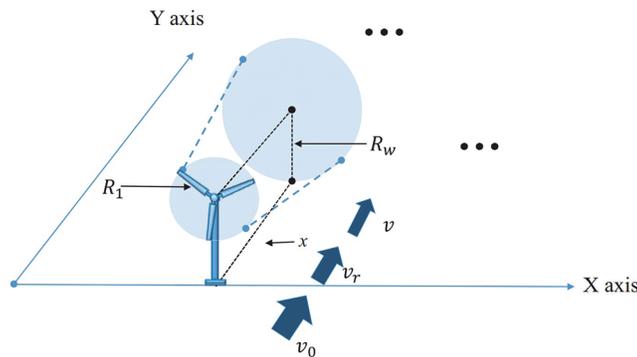


Figure 1: The Jensen wake model

The wind speed  $v$  in the downstream wake region is computed by (1):

$$v = v_0 \left[ 1 - \frac{2t}{\left(1 + k \frac{x}{R_w}\right)^2} \right], \tag{1}$$

where  $k$  is the expansion rate of the wake area radius.  $k$  is related to the height, calculated by (2):

$$k = \frac{0.5}{\ln\left(\frac{H}{n_0}\right)}, \quad (2)$$

where  $H$  is the height of the wind turbine,  $n_0$  is the roughness of the ground.

$R_w$  is calculated by (3):

$$R_w = R_1 + kx \quad (3)$$

$t$  is the axial induction factor, as shown in (4)

$$t = \frac{1 - \sqrt{1 - g_T}}{2}, \quad (4)$$

where  $g_T$  is a fixed thrust coefficient [17,18].

## 2.2 Output Power Model

The wind turbine output power is related to the wind speed at the wind turbine wheel,  $P_i$  [19] is calculated by (5):

$$P_i = f(v) = \begin{cases} 0, & v_o \leq v, v < v_i \\ \frac{e^v}{\alpha + \beta e^v}, & v_i \leq v < v_r \\ P_{rate}, & v_r \leq v \leq v_o, \end{cases} \quad (5)$$

where  $P_i$  represents output power of the wind turbine  $i$ .  $\alpha$  and  $\beta$  are the limiting parameters.  $v_i$ ,  $v_o$  and  $v_r$  represent cut-in speed, cut-off speed and rated speed, respectively. When  $v_i$  is faster than  $v$ , energy cannot be extracted from the natural wind. When  $v_o$  less than the wind speed  $v$ , the wind turbine will cut off and protect itself. If  $v$  is between the rated speed  $v_r$  and  $v_o$ , the wind turbine will sustain the rated output power  $P_{rate}$ .

## 2.3 Weibull Distribution

To use the Jensen wake model, the wind farm is set up on a flat area. The wind turbines can always keep the rotation plane perpendicular to the wind direction by turning their nacelles. The wind direction is  $\gamma$ , and the wind speed is  $v$  which follows Weibull distribution. The probability distribution function [11] is (6):

$$\omega(v, c_i(\gamma), k_i(\gamma)) = \frac{k_i(\gamma)}{c_i(\gamma)} \left( \frac{v}{c_i(\gamma)} \right)^{k_i(\gamma)-1} \times e^{-\left(\frac{v}{c_i(\gamma)}\right)^{k_i(\gamma)}}, \quad 0^\circ \leq \gamma < 360^\circ, \quad (6)$$

where  $k_i(\gamma)$  is the shape parameter and  $c_i(\gamma)$  is the scale parameter respectively.

## 2.4 Wind Farm Layout Model

### 2.4.1 Average Output Power of the Wind Turbines

The average output power  $E(P_i)$  [11] of wind turbine  $i$  can be obtained as (7):

$$E(P_i) = \int_{0^\circ}^{360^\circ} \omega(\gamma) \int_0^\infty f(v) \frac{k_i(\gamma)}{c_i(\gamma)} \left( \frac{v}{c_i(\gamma)} \right)^{k_i(\gamma)-1} \times e^{-\left(\frac{v}{c_i(\gamma)}\right)^{k_i(\gamma)}} dv d\gamma, \quad (7)$$

where  $c_i(\gamma)$  is the scale parameter modified by the wake effect.

### 2.4.2 The Layout Model of the Wind Farm

In optimizing the layout of wind farms, it is hoped that the total power output can be maximized while the cost can be minimized. Therefore, *LCOE* [20] is used as the evaluation function, as computed by (8):

$$LCOE = \frac{\sum_{i=1}^N (Cost_H \times H_i + Cost_b)}{\sum_{i=1}^N E(P_i)}, \quad (8)$$

where  $Cost_b$  is the basic cost of a wind turbine and  $Cost_H$  is the additional cost per unit height of the wind turbine, including the cost of cables and materials. The total number of wind turbines is  $N$ , and  $H_i$  represents the height of the wind turbine  $i$ .

The *LCOE* is the target of optimization in *WOMH*. In three-dimensional coordinates, the position of each wind turbine must ensure that the impeller does not cross the boundary and that the distance between two random wind turbines must be not less than five times the radius of the turbine impeller, that is,  $5R$ . *LCOE* and its constraints are shown in (9):

$$\left\{ \begin{array}{l} \text{minimize: } LCOE = \frac{\sum_{i=1}^N (Cost_H \times H_i + Cost_b)}{\sum_{i=1}^N E(P_i)} \\ \text{subject to: } \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2} \geq 5R, \\ R \leq x_i \leq \bar{x} - R, \\ R \leq y_i \leq \bar{y} - R, \\ i = 1, 2, \dots, N, j = 1, 2, \dots, N \text{ and } j \neq i. \end{array} \right. \quad (9)$$

Suppose the coordinates of wind turbines  $i$  and  $j$  are  $(x_i, y_i, z_i)$ , and  $(x_j, y_j, z_j)$ , respectively, where  $\bar{x}$  and  $\bar{y}$  are the upper bounds of the wind farm. In *WOMH*,  $x, y, z$  are all continuous variables. Where  $z$  represents the height of the wind turbine, and its value range is  $[50, 80]$ .

## 2.5 DEGM Algorithm

In view of the variable hub height of wind turbine in *WOMH*, *DEGM* is proposed to solve this model. Before the advent of *DEGM*, many algorithms updated the coordinates of wind turbines in a way that was passive. Most of these algorithms use crossover, mutation or traversal when updating wind turbine coordinates. None of these methods is very purposeful. But *DEGM* is a purposeful algorithm. The *DEGM* not only integrates heuristic algorithms, such as *DE* and greedy algorithm, to balance the global search and local search capabilities but also adds six adjustment strategies to further improve the *LCOE*. In addition, a parameter adaptive mechanism [21,22] is introduced to give the *DEGM* a good robustness and ensure the quality of the solution. *DEGM* flowchart is shown in Fig. 2.

### 2.5.1 Seven Strategies

Seven adjustment strategies are the core of the *DEGM*, which can adjust the positions of wind turbines to optimize *LCOE*. The following are the details of the seven adjustment strategies:

Strategy 1: Update the positions of wind turbines based on *DE* and greedy algorithm.

Strategy 2: Randomly select  $n$  wind turbines in the wind farm and set  $Y$  to the value of the  $y$  coordinates of one of the wind turbines. Then, the  $y$  coordinates of the  $n$  wind turbines are all set to  $Y$ . Strategy 2 is shown in Fig. 3.

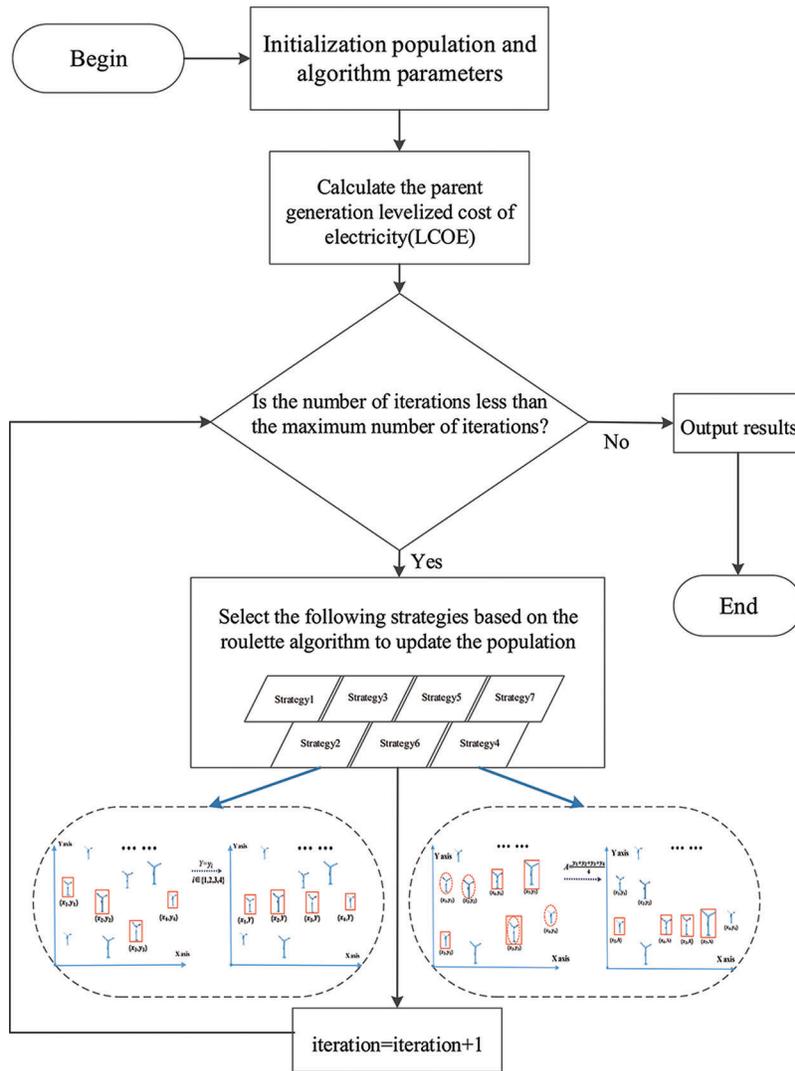


Figure 2: DEGM flowchart

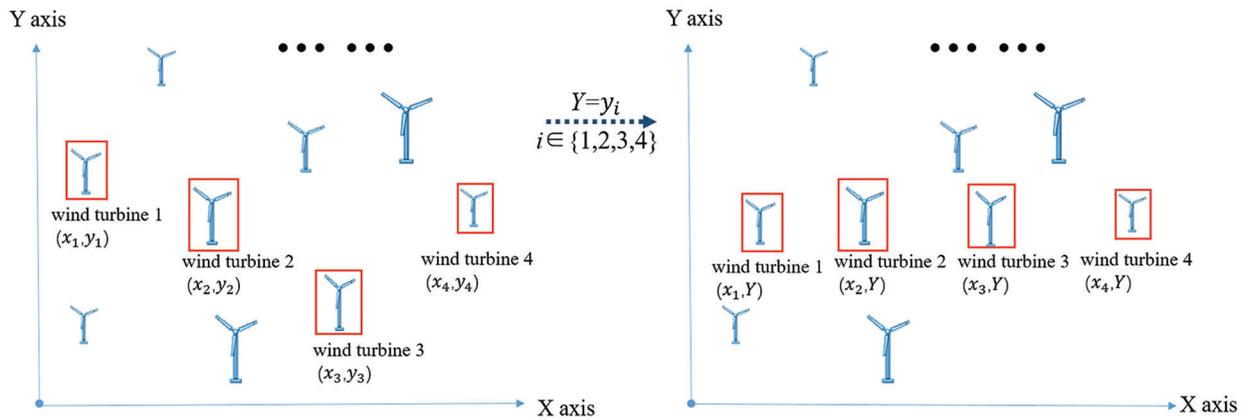


Figure 3: Strategy 2

Strategy 3: Randomly select  $n$  wind turbines in the wind farm and set  $X$  to the value of the  $x$  coordinates of one of the wind turbines. Then, the  $x$  coordinates of the  $n$  wind turbines are all set to  $X$ .

Strategy 4:  $n_1$  wind turbines are randomly selected from wind farms, and the average  $y$  coordinates of these wind turbines are recorded as  $A$ . Then, select  $n_2$  wind turbines from the wind farm and set the  $y$  coordinates of these wind turbines to  $A$ . Strategy 4 is shown in Fig. 4.

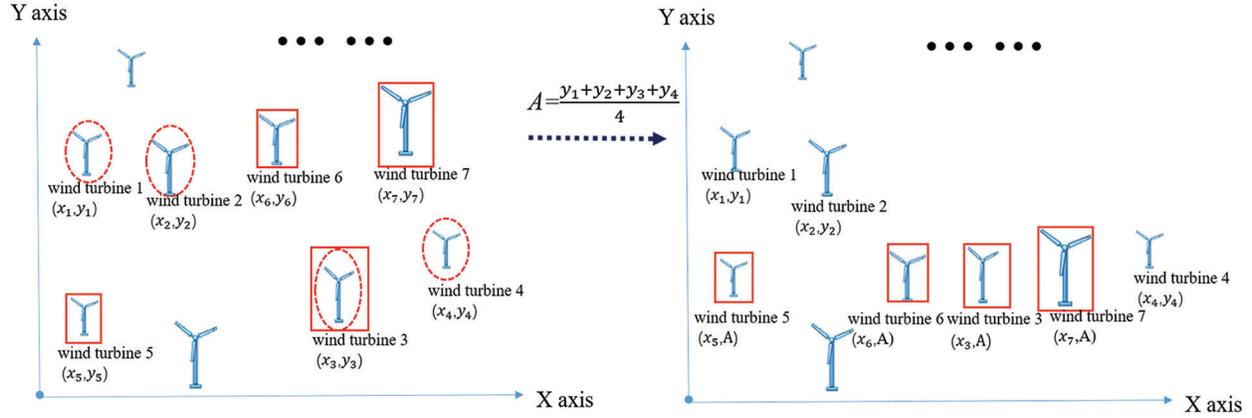


Figure 4: Strategy 4

Strategy 5:  $n_3$  wind turbines are randomly selected from wind farms, and the average  $x$  coordinates of these wind turbines are recorded as  $B$ . Then, select  $n_4$  wind turbines from the wind farm and set the  $x$  coordinates of these wind turbines to  $B$ .

Strategy 6: Randomly select  $n$  wind turbines and set them to random values.

Strategy 7: Randomly select Strategy 1 to Strategy 6 as Strategy 7.

These seven adjustment strategies can guide the algorithm to seek breakthroughs in different goals. To a certain extent, the algorithm not only has the global search ability, but also has a good local search ability.

### 2.5.2 Strategy Selection

In this paper, the roulette wheel algorithm is adopted to select the above seven strategies. The advantage of using this mechanism is that each strategy has the opportunity to be selected in each iteration, which increases the diversity of the position and the height of the wind turbine, so the algorithm has a good global search ability.

When the fitness value of population which selects  $s_i$  is less than the previous one, the corresponding selected probability  $\lambda(s_i)$  will be updated. The probability of being selected is calculated by (10)-(11):

$$\Phi(s_i) = \frac{g(s_i)}{\sum_{i=1}^N g(s_i)}, \quad (10)$$

$$\lambda(s_i) = \frac{1 - \Phi(s_i)}{\sum_{i=1}^N (1 - \Phi(s_i))}, \quad (11)$$

where  $s_i$  refers to population  $i$ ,  $g(s_i)$  is the fitness value of strategy  $i$ ,  $\Phi(s_i)$  is the weight of the fitness value, and  $\lambda(s_i)$  is the selected probability for this strategy.

### 3 Experimental Design and Results

#### 3.1 Experimental Scheme Design

*DEGM*, *DEEM* and three-dimensional greedy algorithm are used to conduct experiments on fixed-hub height and multiple hub height in *WOMH* to verify that multiple hub heights can further improve the utilization of wind resources. In addition, the experiments also compare the performance of *DEGM*, *DEEM* and three-dimensional greedy algorithm in the above two models. *DEEM* refers to differential evolution with a new encoding mechanism. *GREEDY* is used instead of “three-dimensional greedy algorithm”. *GREEDY* is a classical mathematical probability algorithm, and *DEEM* is the latest and effective algorithm. So we chose these two algorithms to compare with *DEGM*. Finally, the probability of the emergence of seven adjustment strategies and the impact of these probabilities on the algorithm are analyzed.

In order to ensure the rationality of the results, the experiments are conducted on different numbers of wind turbines in a wind scenario [4,15,23], and the scale of the wind farm is changed for each number of wind turbines. The specific parameters are shown in Tab. 1.

**Table 1:** Wind turbine parameters

Parameter	Explanation	Value Range
$H$	the height of the wind turbine (m)	[50,80]
$R$	wind turbine radius (m)	40
$g_T$	coupling	0.88
$n_0$	ground roughness	0.3
$\alpha$	power curve parameter	6.0268
$\beta$	power curve parameter	0.0007
$Prate$	rated power	1500
$Cost_b$	basic cost of wind turbine	593.87
$Cost_H$	high cost per unit tower	1.5

In order to simulate the real wind scenario, the following definition is adopted in this paper. The wind direction is defined as  $0^\circ$  from west to east,  $90^\circ$  from south to north,  $180^\circ$  from east to west and  $270^\circ$  from north to south.  $\varepsilon_n$  is the weight of each wind direction.  $k_i(\gamma)$  is the shape parameter and  $c_i(\gamma)$  is the scale parameter respectively. For details of  $\varepsilon_n$ , please see [11]. The specific parameters of the wind scenario are shown in Tab. 2.

#### 3.2 Experimental Results and Analysis

Tab. 3 records the *LCOE* obtained by *GREEDY*, *DEEM* and the *DEGM*. -F means the algorithm is applied to the wind farm with the fixed hub height, and -M means the algorithm is applied to a situation with multiple hub heights. In the experiment, both *DEEM* and the *DEGM* will be run 30 times. *GREEDY* is deterministic, so it only runs once.

In this kind of wind scenario, the distribution of the wind direction is very irregular. The probability distribution of the wind speed in each wind direction is also different, which puts higher requirements on the performance of the algorithm. In every case, the results of *DEGM-M* are smaller than those of *DEEM-M* and *GREEDY-M*.

**Table 2:** The specific parameters of the wind scenario

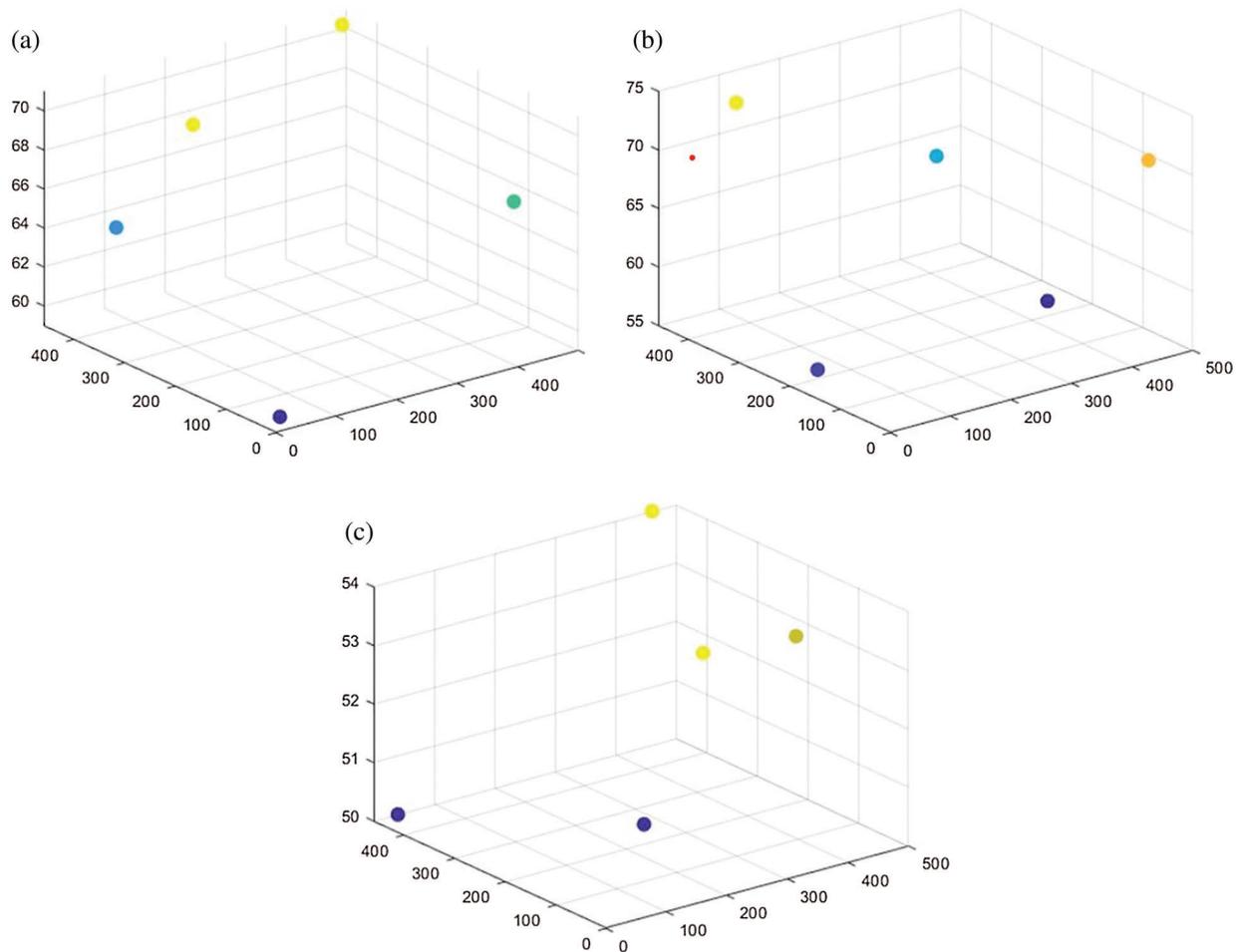
$n$	$\gamma$	$k_i(\gamma)$	$c_i(\gamma)$	$\varepsilon_n$	$n$	$\gamma$	$k_i(\gamma)$	$c_i(\gamma)$	$\varepsilon_n$
1	7.5°	2	7	0.0003	13	187.5°	2	10	0.1909
2	22.5°	2	5	0.0072	14	222.5°	2	8.5	0.1162
3	37.5°	2	5	0.0237	15	217.5°	2	8.5	0.0793
4	52.5°	2	5	0.0242	16	232.5°	2	6.5	0.0082
5	67.5°	2	5	0.0222	17	247.5°	2	4.6	0.0041
6	82.5°	2	4	0.0301	18	262.5°	2	2.6	0.0008
7	97.5°	2	5	0.0397	19	277.5°	2	8	0.001
8	112.5°	2	6	0.0268	20	292.5°	2	5	0.0005
9	127.5°	2	7	0.0626	21	307.5°	2	6.4	0.0013
10	142.5°	2	7	0.0801	22	322.5°	2	5.2	0.0031
11	157.5°	2	8	0.1025	23	337.5°	2	4.5	0.0085
12	172.5°	2	9.5	0.1445	24	352.5°	2	3.9	0.0222

**Table 3:** Comparison of the LCOE of the three algorithms when N is 5, 10, 20, 30 and 50, respectively

N	Algorithm					
	GREEDY-F	GREEDY-M	DEEM-F	DEEM-M	DEGM-F	DEGM-M
5	1.854	1.783	1.826	1.726	1.848	<b>1.590</b>
10	1.927	1.856	1.893	1.825	1.922	<b>1.681</b>
20	1.890	1.811	1.824	1.790	1.850	<b>1.698</b>
30	1.875	1.804	1.826	1.810	1.857	<b>1.743</b>
50	1.959	1.873	1.894	1.889	1.957	<b>1.805</b>

In the case of  $N = 5, 10, 20, 30,$  and  $50$ , *DEGM-M* reduces the *LCOE* by 7.91%, 7.91%, 5.13%, 3.67%, and 4.45% compared with *DEEM-M*, respectively. Compared with *GREEDY-M*, *DEGM-M* was reduced by 10.81%, 9.43%, 6.88%, 3.38%, and 3.64%, respectively. This shows that the *DEGM* has a strong adaptability when facing complex wind scenes. In addition, no matter how the number of wind turbines varies, the performance of different algorithms in *WOMH* is always better than that of fixed hub height model. For example, when the number of wind turbines is 5, the *LCOE* of *DEGM-M*, *DEEM-M* and *GREEDY-M* are 13.96%, 5.48% and 3.83% lower than those of *DEGM-F*, *DEEM-F* and *GREEDY-F*, respectively. This shows that multiple hub heights are beneficial for reducing the influence of the wake effect.

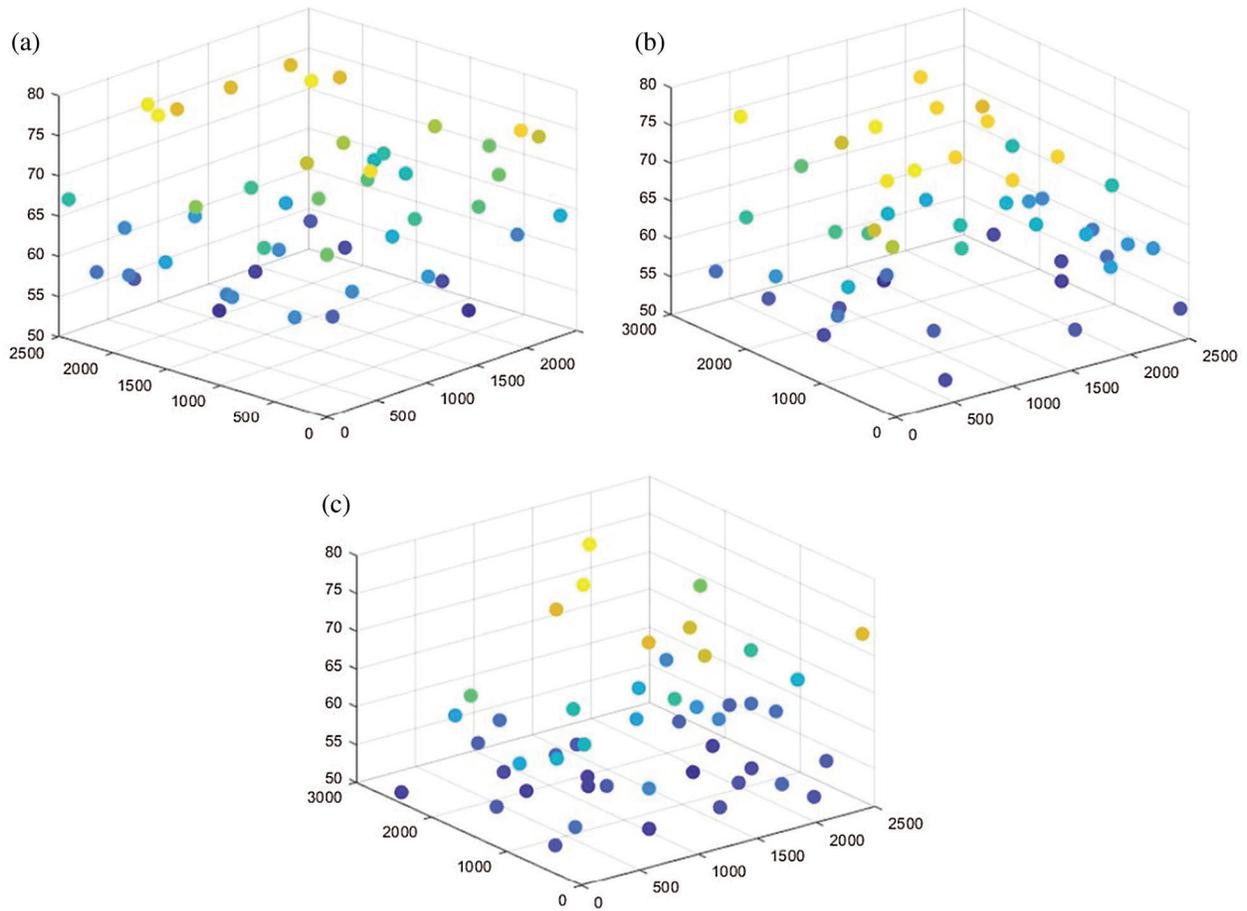
**Figs. 5** and **6** reflect the layout of wind turbines under different algorithms. Here we take the number of wind turbines as 5 and 50 as examples. The trend of *DEGM* arranging from low to high along a certain wind direction is obvious. The main reason the *DEGM* achieves an excellent performance in the complex wind scenario is that its seven adjustment strategies. These seven adjustment strategies constantly update the coordinates of wind turbines so that they are roughly arranged in lines. This layout further reduces the wake effect.



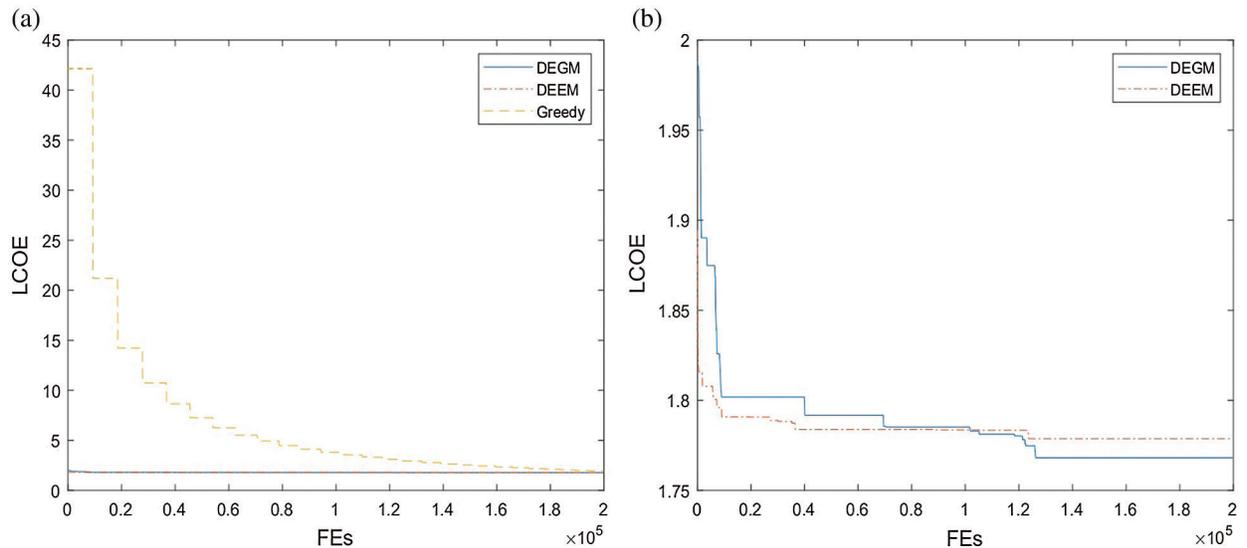
**Figure 5:** The layout of wind turbines under three algorithms when the number of wind turbines is 5 (a) The layout obtained by GREEDY-M (b) The layout obtained by DEEM-M (c) The layout obtained by DEGM-M

Fig. 7 records  $LCOE$  of three algorithms when  $FES$  changes from 0 to 200000. From Fig. 7a, we can see that *GREEDY* is the most unsatisfactory in terms of the convergence speed and solution quality. Fig. 7b magnifies the results of *DEEM* and *DEGM*, and it shows that *DEEM* quickly converges to the a local optimal solution. In addition, it can also be observed in Fig. 7b that the curve of *DEGM* decreases significantly several times, which is not available in *DEEM*. Because the adjustment strategy of *DEGM* plays an important role, so that it will not converge to the local optimal solution prematurely.

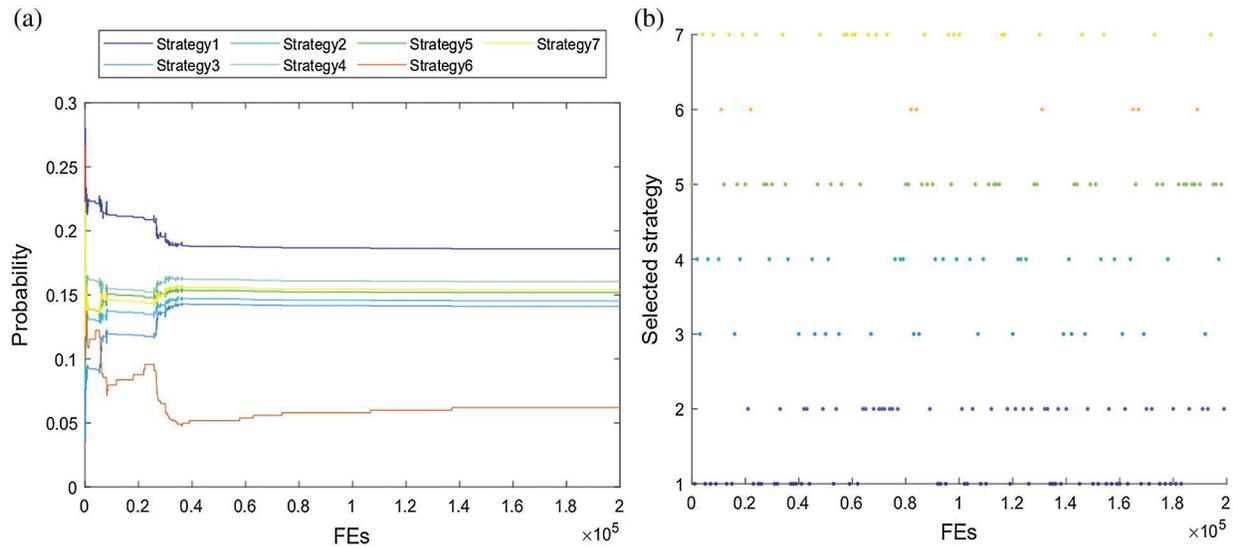
Fig. 8 records the relationship between strategy selected probability, selected strategy and  $FES$ . From Fig. 8a, we can see that the probabilities of all strategies fluctuate obviously when  $FES$  is less than 20000. When  $FES$  is greater than 20000 and less than 40000, the probability of Strategy 1 and Strategy 6 decreases gradually, while the probability of other strategies increases. When  $FES$  is greater than 40000, the probability of all strategies tends to be stable. In the end, the probability of Strategy 1 is the highest, and the probability of Strategy 6 is the lowest. It fully reflects that various strategies can show different performance in different periods of the algorithm, which reflects that the algorithm has a good adaptive ability. It is observed from Fig. 8b that although the probability of selecting different strategies varies, all kinds of strategies have the chance of being selected. Through Fig. 8a, we can find that the probability of strategy 6 being selected in the later stage is low, but from Fig. 8b we can see that it is still possible to be selected, which shows that the algorithm retains a certain diversity. To sum up, *DEGM* has good adaptive ability and maintains the diversity.



**Figure 6:** The layout of wind turbines under three algorithms when the number of wind turbines is 50 (a) The layout obtained by GREEDY-M (b) The layout obtained by DEEM-M (c) The layout obtained by DEGM-M



**Figure 7:** The LCOE convergence comparison among the three algorithms (a) The LCOE provided by DEEM, DEGM, GREEDY (b) The LCOE provided by the DEEM and DEGM



**Figure 8:** The relationship between strategies selected probability, selected strategy and FES (a) The relationship between selected probability of seven strategies and FES (b) The selected strategy corresponding to FES

#### 4 Conclusions

A novel model called *WOMH* is proposed in this paper. Different from the traditional fixed hub height model, *WOMH* can effectively reduce the wake effect and achieve lower *LCOE*. In order to solve the *WOMH*, *DEGM* was proposed. In *DEGM*, the seven adjustment strategies are designed to update the coordinates of wind turbines and further reduce the Jensen wake effect between wind turbines. *WOMH* with *DEGM* provides a reference solution for the field of wind farm layout optimization. The wind farm layout optimization under the flexible multi-stage long-term planning optimization model of distributed multi-energy system will be further researched, which will comprehensively consider multiple dynamic factors, including energy demand, price.

**Funding Statement:** This paper was supported in part by Project funded by China Postdoctoral Science Foundation under Grant 2020M671552, in part by Jiangsu Planned Projects for Postdoctoral Research Funds under Grant 2019K223, in part by NUPTSF(NY220060), in part by the Opening Project of Jiangsu Key Laboratory of Data Science and Smart Software (No.2020DS301), in part by Natural Science Foundation of Jiangsu Province of China under Grant BK20191381, in part by the National Natural Science Foundation of China under Grant 61772286, Grant 61771258 and Grant 61876089.

**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

#### References

- [1] M. Tan and Z. J. Zhang, "Wind turbine modeling with data-driven methods and radially uniform designs," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 3, pp. 1261–1269, 2016.
- [2] Y. S. Hamed, A. A. Aly, B. Saleh, A. F. Alogla, A. M. Aljuaid *et al.*, "Vibration performance stability and energy transfer of wind turbine tower via pd controller," *Computers, Materials & Continua*, vol. 64, no. 2, pp. 871–886, 2020.
- [3] R. Maheswari and R. Umamaheswari, "Wind turbine drivetrain expert fault detection system: Multivariate empirical mode decomposition based multi-sensor fusion with Bayesian learning classification," *Intelligent Automation & Soft Computing*, vol. 26, no. 3, pp. 479–488, 2020.

- [4] G. Mosetti, C. Poloni and B. Diviacco, "Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 51, no. 1, pp. 105–116, 1994.
- [5] A. Kusiak and Z. Song, "Design of wind farm layout for maximum wind energy capture," *Renewable Energy*, vol. 35, no. 3, pp. 685–694, 2010.
- [6] F. Wang, D. Y. Liu and L. H. Zeng, "Study on computational grids in placement of wind turbines using genetic algorithm," in *2009 World Non- Grid-Connected Wind Power and Energy Conference*, IEEE, pp. 1–4, 2009.
- [7] R. Q. Sun, Z. H. He, L. Gao and J. L. Bai, "Station layout optimization genetic algorithm for four stations today location," *Journal of Physics: Conference Series*, vol. 1176, pp. 062008, 2019.
- [8] J. W. Park, B. S. An, Y. S. Lee, H. Jung and I. Lee, "Wind farm layout optimization using genetic algorithm and its application to daegwallyeong wind farm," *JMST Advances*, vol. 1, no. 4, pp. 249–257, 2019.
- [9] J. F. Cao, W. J. Zhu, W. Z. Shen and Z. Y. Sun, "Wind farm layout optimization with special attention on noise radiation," *Journal of Physics: Conference Series*, vol. 1618, pp. 042022, 2020.
- [10] Y. Wu, S. Zhang, R. Q. Wang, Y. F. Wang and X. Feng, "A design methodology for wind farm layout considering cable routing and economic benefit based on genetic algorithm and GeoSteiner," *Renewable Energy*, vol. 146, no. 3, pp. 687–698, 2020.
- [11] Y. Wang, H. Liu, H. Long, Z. Zhang and S. X. Yang, "Differential evolution with a new encoding mechanism for optimizing wind farm layout," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 3, pp. 1040–1054, 2018.
- [12] J. Herbert-Acero, J. Franco-Acevedo, M. Valenzuela-Rendón and O. Probst-Oleszewski, "Linear wind farm lay-out optimization through computational intelligence," in *Mexican Int. Conf. on Artificial Intelligence*, Springer, pp. 692–703, 2009.
- [13] S. Chowdhury, J. Zhang, A. Messac and L. Castillo, "Optimizing the arrangement and the selection of turbines for wind farms subject to varying wind conditions," *Renewable Energy*, vol. 52, no. 1–2, pp. 273–282, 2013.
- [14] H. Long, Z. J. Zhang, Z. Song and A. Kusiak, "Formulation and analysis of grid and coordinate models for planning wind farm layouts," *IEEE Access*, vol. 5, pp. 1810–1819, 2017.
- [15] K. Chen, M. X. Song, X. G. Zhang and S. F. Wang, "Wind turbine layout optimization with multiple hub height wind turbines using greedy algorithm," *Renewable Energy*, vol. 96, no. 1, pp. 676–686, 2016.
- [16] I. Katic, J. Hojstrup and N. O. Jensen, "A simple model for cluster efficiency," *European Wind Energy Association Conference and Exhibition*, vol. 1, pp. 407–410, 1986.
- [17] Y. Chen, H. Li, K. Jin and Q. Song, "Wind farm layout optimization using genetic algorithm with different hub height wind turbines," *Energy Conversion and Management*, vol. 70, no. 11–12, pp. 56–65, 2013.
- [18] N. Mohanapriya and B. Kalaavathi, "Adaptive image enhancement using hybrid particle swarm optimization and watershed segmentation," *Intelligent Automation and Soft Computing*, vol. 25, no. 4, pp. 663–672, 2019.
- [19] H. Long and Z. J. Zhang, "A two-echelon wind farm layout planning model," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 3, pp. 863–871, 2015.
- [20] M. A. Lackner and C. N. Elkinton, "An analytical framework for offshore wind farm layout optimization," *Wind Engineering*, vol. 31, no. 1, pp. 17–31, 2016.
- [21] J. S. González, M. B. Payán, J. M. R. Santos and F. G. Longatt, "A review and recent developments in the optimal wind-turbine micro-siting problem," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 133–144, 2014.
- [22] Y. Xue, T. Tang, W. Pang and A. X. Liu, "Self-adaptive parameter and strategy based particle swarm optimization for large-scale feature selection problems with multiple classifiers," *Applied Soft Computing*, vol. 88, no. 4, pp. 106031, 2020.
- [23] L. H. Zhu, Z. Q. Wu, L. Wang and Y. Wang, "The identification of the wind parameters based on the interactive multi-models," *Computers, Materials & Continua*, vol. 65, no. 1, pp. 405–418, 2020.