Wind farm micro-siting optimization using novel cell membrane approach

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Abstract. Micro-siting aims to determine every wind turbine’s position to reduce velocity deficits caused by the wake effect. The Novel CMO (cell membrane optimization) approach is proposed to overcome this weakness. It plays a vital role to utilize more wind resources while the type of wind turbine and the area to build a wind farm have been determined. The work is based on the Jensen wake model, and the hypothetical situations are the same as those used by the former researchers. There are three wind cases: constant speed with one direction, constant speed with variable directions and variable speeds with variable directions. The area of wind farm is assumed to be a plane 2km×2km square. The numbers of the wind turbines is 26, 19 and 15 in three cases respectively. Compared with Gene Algorithm introduced by G. Mosetti, CMO’s results are acceptable and the velocity deficit is smaller, which results from that CMO’s variables is continuous and can make the most of the area the wind turbines can be placed. Moreover, it performs well to avoid the local optimal solutions by dividing the searching particles into different types which move according to different rules.

1. Introduction

The use of renewable energy has been paid attention to due to the energy crisis and environmental pollution in recent years. Power generation with wind energy, solar energy and biomass has been developing rapidly, of which the wind power technology is relatively mature[1]. Because wind resources of middle and western China are plentiful, but far away from load centers which located in the eastern, wind farms in China are often large-scale and the wind power is transported by long-distance transmission network. The layout optimization of wind turbines plays a significant role in reducing the wake deficit in large-scale wind farms. The wind turbines are arranged in accordance with the prevailing wind direction, and are kept a distance from each other to avoid wake deficit nowadays [2]. The wake effect means that the turbine absorbs the wind energy from the wind flows, and converted the energy to mechanical energy, the speed behind the wind turbine decreases, which would obviously affect the downstream wind turbine. But with the distance along the wind direction increasing, the wake effect dies away [3]. Therefore, micro-siting issue, that is to arrange each wind turbine reasonably in the wind farm, is especially important in large-scale wind farm because of the

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large number of wind turbines. Although reasonable arrangement cannot improve the power generation efficiency of every wind turbine, the wake effect of the whole wind farm is reduced by making wind turbine capture more wind energy relatively.

N. O. Jensen proposed a simple wake model which could be used to optimize the wind turbine layout in 1983[4], furthermore the model was developed by Katic in the year of 1987 [5], and the model was accepted by the researchers and even the commercial software. Before G. Mosetti [6] brought the intelligence method (Gene Algorithm, GA) in solving the micro-siting problem, researchers used classic method to solve this complex problem, which would take much time. Many intelligent approaches are introduced to solve the problem after GA, including developed GA [7], particle filtering approach [8], cyber swarm algorithm [9] and so on, and most of them used discrete variables to represent wind turbines’ locations. In parallel, intelligent approaches are easy to trap in local optima. This paper uses a novel approach which uses continuous variables and has less chance to get the local optima, which is compared with other algorithm and the results are acceptable.

2. Micro-siting models

The micro-siting problem is to arrange the layout of the wind turbines to minimize the wake effect of the whole wind farm, and is based on the following assumptions:

- The rated capacity is known because it is determined when the project gets the government approval, and so is the wind turbine type. In this way, the number and the power curve of the wind turbines are determined.
- The wind farm’s scale and the area which the wind turbine can be arranged is known.
- The condition of wind resources is known, including direction, speed and their frequency.

This paper uses the same model as the one in the paper which G. Mosetti wrote. The model is shown as follows, which is divided into three parts, the wake model, objective function and the cases of wind. G. Mosetti divided the wind farm into small squares which wind turbines can be situated, and used Genetic Algorithm to solve the problem. The squares which wind turbines located were represented by ‘1’ and the others were ‘0’. The original numbers were chosen at random, and then new numbers generated by the old ones with crossovers and mutations, the best solution could be found after iterations.

2.1. Jensen wake model

![Jensen wake model](image)

Figure 1. Jensen wake model.

As shown in Figure 1, \(u_0\) represents the free wind speed without wake effect, \(u\) represents the wind speed affected by wind turbine \(i\) at the distance of \(x\) along the wind direction, \(r_d\) is the rotor radius
\[ u = u_0 \left[ 1 - 2a \times \left( 1 + a \frac{x}{r_d} \right)^{-2} \right] \]  

where \( a \) represents entrainment constant, \( a \) is axial induction factor. Entrainment constant \( a \) can also be expressed as Equation (2):

\[ a = 0.5 \times (1 - (1 - c_t)^{1/2}) \]  

where \( c_t \) is rotor thrust coefficient. Axial induction factor \( a \) can be expressed as Equation (3):

\[ a = 0.5 \times \left( \frac{z}{z_0} \right)^{-1} \]  

where \( z \) represents the hub height of the wind turbine and \( z_0 \) represents the surface roughness, in this paper it is 0.3m.

2.2. Objective function

The parameters of the wind turbine are shown by Table 1 below.

| parameter          | value |
|--------------------|-------|
| Hub height (m)     | 60    |
| Roter diameter (m) | 40    |
| \( c_t \)          | 0.88  |

The power curve can be expressed as Equation (4):

\[ P = 0.5 \times C_p \times \rho \times \pi \times R^2 \times u^3 \]  

Assuming the value of \( \rho \) is 1.2kg/m\(^3\), the power coefficient \( C_p \) is 40%, and \( R \) is 20m, and the unit of \( P \) is changed from watt to kilowatt. Equation (4) can be simplified as follows:

\[ P = 0.001 \times 0.5 \times 0.4 \times 1.2 \times 3.14 \times 20^2 \times u^3 \approx 0.3 \times u^3 \]  

And the power the whole wind farm generates is

\[ P_{tot} = \sum_{i=1}^{N} 0.3 \times u_i^3 \]  

where \( N \) is the number of the wind turbines in the wind farm.

G. Mosetti supposed that if the number of the wind turbine is large enough the cost of the wind farm can be reduced by one third.

\[ Cost = N \times \left( \frac{2}{3} + \frac{1}{3} e^{-0.00174N^2} \right) \]  

where \( N \) is the number of the wind turbines in the wind farm.

And the objective function is:

\[ Obj = \omega_1 \times P_{tot}^{-1} + \omega_2 \times Cost \times P_{tot}^{-1} \]  

where \( \omega_1 \) and \( \omega_2 \) are weights and \( \omega_1 \) is kept small relatively, the \( \omega_2/\omega_1 \) value is 9 in this paper.
2.3. Cases of wind

- Case A: The wind speed is 12m/s and the direction is constant.
- Case B: The wind speed is 12m/s, the direction is divided into 36 parts and every direction is of equal frequency.
- Case C: There are three speeds, which are 8m/s, 12m/s and 17m/s, and still 36 directions. But their frequency is different, which can be seen from Figure 2.

![Wind Frequency Distribution](image)

Figure 2. Frequency distribution of wind angles and speeds.

3. CMO algorithm based micro-siting

Micro-siting is a multi-dimensional nonlinear optimization problem and is difficult to solve with traditional optimization methods. Since genetic algorithm was used to solve this problem by in 1993, heuristic algorithms have been paid more attention to. But heuristic algorithm is easy to fall into local optima, so this paper introduces a new optimization algorithm - membrane optimization algorithm to avoid this problem. Based on the researches of DNA molecule computing, Cell Membrane Computing was proposed Gheorghe Paun in the year of 1998 [10]. Then a number of scholars established different membrane computing models according to different rules. In the year of 2007, membrane computing and optimization methods are combined for the first time by Huang Liang, and was called Cell Membrane Optimization [11]. And then Tanshi Heng proposed a simple CMO according to the material transport inside and outside the cell membrane [12], which is used in this paper.

3.1. Basic steps of the CMO algorithm

3.1.1. Step 1: Substance initialization
Randomly generate \( m \) n-dimensional materials in the solution space, with each material randomly distributed in the space. Calculate their function values, and place the substance whose function value is the smallest in \( X_{\text{best}} \).

3.1.2. Step 2: Classify the substances
Calculate the concentration of each position where the substance stays based on Equation (9). Sort the substances based on the order of their concentration, from small to large, and sort the top 50% of the substances into the low-density material (LS). Consider the others of higher concentration as the high-
density material (HS). Divide HS into FS and NS. The substance in HS whose number is odd is classified as fat-soluble, and the even number is classified as non-fat-soluble.

\[ con = \frac{s}{m} \]  

where \( s \) represents the number of the substances whose distance from the set substance is smaller than a set length; \( m \) is the number of all the substances.

3.1.3. Step 3: Free diffusion of fat-soluble HS

Each fat-soluble HS diffuses toward the direction of the LS group \( l \) times. Choose the best location as the final result of diffusion. The diffusion method is as follows: choose any substance from the LS group to determine the direction vector of the movement, and unitize the vector.

\[ F^* = (LS^{rand} - FS^*) \times \left( \left( \frac{1}{l} \sum_{i=1}^{l} (LS_i^{rand} - FS_i^*) \right) \right)^{\frac{1}{2}} \]

The fat-soluble HS then moves to the LS group based on this vector to obtain a new material.

\[ newFS_k = \begin{cases} 
FS_i^* + rand() \times F_i \times (u_k - LS_i^{rand}) & F_i \geq 0 \\
FS_i^* + rand() \times F_i \times (LS_i^{rand} - 1) & F_i < 0 
\end{cases} \]

\[ k = 1, L, n \]

3.1.4. Step 4: Movement of non-fat-soluble HS

Non-fat-soluble HS cannot freely diffuse the same as the fat-soluble FS because it requires a carrier when it moves to the LS group. This process is known as facilitated diffusion. Non-fat-soluble HS moves toward the global optimum material when no carrier is required.

The movement of non-fat-soluble HS can be described into three steps:

- Distinguish whether a carrier exists.
- The non-fat-soluble FS that has a carrier moves in support of the carrier, just as free diffusion.

\[ F^* = (LS^{rand} - NS^*) \times \left( \left( \frac{1}{l} \sum_{i=1}^{l} (LS_i^{rand} - NS_i^*) \right) \right)^{\frac{1}{2}} \]

\[ newNS_k = \begin{cases} 
NS_i^* + rand() \times F_i \times (u_k - LS_i^{rand}) & F_i \geq 0 \\
NS_i^* + rand() \times F_i \times (LS_i^{rand} - 1) & F_i < 0 
\end{cases} \]

\[ k = 1, L, n \]

- The non-fat-soluble FS without a carrier moves toward the global optimum material.

\[ newNS_k = NS_i^* + rand() \times (X_i^{best} - NS_i^*) \]

\[ k = 1, L, n \]

3.1.5. Step 5: Movement of LS

The movement of LS requires a carrier and energy so that the two judgments should be conducted.

The LS that cannot meet the conditions of energy moves in the searching area at random \( l \) times, and the best position is chosen as the final result.

\[ newLS_k = l_k + rand() \times (u_k - l_k) \]

\[ k = 1, L, n \]

The LS that meets the energy condition but not the carrier condition moves toward the current optimum material.

\[ newLS_k = LS_k + rand() \times (X_k^{best} - LS_k) \]

\[ k = 1, L, n \]

The LS that has both energy and carrier can move toward the HS group.
\[ F = (HS^{\text{rand}} - LS') \times (|HS^{\text{rand}} - LS'|)^{1/2} = (HS^{\text{rand}} - LS') \times \left( \sum_{k=1}^{n} (HS^{\text{rand}} - LS') \right)^{1/2} \]  

\[ \text{new}LS'_i = \begin{cases} 
LS'_i + \text{rand}() \times F_i \times (u_i - LS^{'\text{rand}}_i) & F_i \geq 0 \\
LS'_i + \text{rand}() \times F_i \times (L_i - LS^{'\text{rand}}_i) & F_i < 0 
\end{cases} \]

3.1.6. Step 6: Movements of the current optimal material

A better-quality material always exists in the vicinity of a good-quality material. Thus, searching around the current optimum substance to improve the accuracy of the material is necessary. This study sets the current optimum material as the centre and in a radius that gradually shrinks to search for a better substance and then uses it to replace the current best material.

3.1.7. Step 7: Update substance

Use new \( X^{\text{best}} \), new fat-soluble FS, new non-fat-soluble HS, and new LS to replace the old ones relatively after all the movements, and retain the old \( X^{\text{best}} \) to replace any one of the new substances.

3.2. Optimization steps

Assuming that the land is 2km\( \times \)2km, Figures 4-10 describe the 2km\( \times \)2km square land, the little squares and circles in the land are wind turbines respectively. And the target is to optimize the layout of the wind farm in the three cases which was mentioned previously.

- Setting the values of X-axis to be the first half of the materials, and the other are the value of Y-axis. For example, the wind turbines’ number is 30, the dimension \( n \) should be 60, and 1~30 are X-axis values of the 30 wind turbines and 31~60 are Y-axis values.
- Finding the wind turbines whose wake affect its speed for each wind turbine, and calculate the actual speed.
- Calculating the power generated by each wind turbine and whole wind farm.
Calculating the objective function value. Move the materials towards the best one. For the one which cannot meet the distance need, set its function value to be a large enough number to delete it.

4. Results and Discussion

In case A, the wind blows from one direction, which is from the upper part to the lower half of figure 3 and figure 4. In this case, the wind turbines’ number is set to be 26, so the dimension of the variable is 52, and the optimal layout obtained by CMO is shown in figure 4 and the one obtained by GA method in G. Mosetti’s paper is shown in figure 3. The efficiency of the CMO is 92.4%, which increases in this paper compared with 91.645% in G. Mosetti’s paper and 92.015% [6] in Grady’s paper [7]. The reason why the CMO gets better results may be that the wind turbines cannot be placed arbitrarily but can only at the centre of the divided squares with GA method. The wind turbines can be placed closer to the boundary and the land can be made better use of in this way.

As the wind turbine’s wake will affect the downstream wind turbine, the distance along the wind direction is longer relatively, that is the vertical distance is longer than the horizontal distance of the wind turbines in the picture. And the two pictures are similar in this way, and this is easy to understand because the only direction of the wind is blowing top to bottom in the picture.
In case B, the number of wind turbines is 19, the wind of 12m/s blows from 36 directions, therefore, the wind turbines distribute along the edge of the land as closer as possible to make the distance longer from each other, which can be seen from figure 5 and figure 6. Furthermore, the frequency of every direction is equal so the wind turbines distribute around evenly. And the efficiency of the layout shown in figure 5 and figure 6 is 93.859\% [6] and 95.15\%, which is improved obviously on the condition that the numbers of wind turbines are equal in both of the two layouts.

As this paper tries to justify the effectiveness of the CMO method, so the number of the wind turbines isn’t set to be a variable to be optimized. The objective function values are different when the weights $\omega_1$ and $\omega_2$ changes, so this paper doesn’t compare the objective function values in the paper. The generations of the CMO is different as we can see in the explanation of it, in every generation each kind of materials moves many times, so the generations may less than ten times, but the number of the iterations may be a hundred or even thousand. That’s because the materials are divided into different kinds and moves according to different rules, which is the reason why the CMO has little chance to trap in the local optima.
In case C, the wind condition is more complicated and the number of wind turbines is only 15. There are 36 directions as in case B, the wind speeds are 8m/s, 12m/s and 17m/s and the frequency of different directions and speed may vary in a large range. As in case B, the wind turbines scatter in the area. But as the frequency of the wind around 300° is larger than the others, so the distance along this direction is longer. And the efficiency of GA conducted by G. Mosetti is 94.62% [6] and CMO’s is 97.12%. But the improvement of the efficiency may be owe to the number’s decrease of the wind turbines compared to case B. Set the number to be 20 and the optimal layout is shown in Figure 9 and the efficiency is reduced to 94.48%. So the number of the wind farm is still needed to be optimized in the future, the wake effect increases as the number increases, but the rated power of the wind farm also increases.
5. Conclusions

- The novel optimization method, which is called CMO method, can be used to solve the micro-siting problem. This paper carries out the progress to optimize a wind farm of 2km×2km in three cases, and compare the results with other methods. The reason why the efficiency of the wind farm is improved can be that the discrete values of the positions are converted into continuous ones, which makes better use of the land.
- The CMO method has little chance to get the local minima by dividing the searching area into two parts and the material can move from one area to another.
- It turns out that this method can be applied into micro-siting problem, but it needs to be applied in more complex situations in which the number of wind turbine is larger and the model may be more complicated.

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