Energy 80 (2015) 567–574

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

The lazy greedy algorithm for power optimization of wind turbine positioning on complex terrain

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ARTICLE INFO

Article history:
Received 27 June 2014
Received in revised form
30 October 2014
Accepted 4 December 2014
Available online 30 December 2014

Keywords:
Wind farm micro-siting
Wind turbine wake model
Submodular

ABSTRACT

Wind farm micro-siting is to determine the optimal positions of wind turbines within the wind farm, with the target of maximizing total power output or profit. This paper studies the performance of the lazy greedy algorithm on optimization of wind turbine positions above complex terrain. Instead of the traditional linear models, computational fluid dynamics and virtual particle wake flow model are employed in the present study for a more accurate evaluation of wind energy distribution and wind power output of wind farm on complex terrain. The validity of the submodular property used by the lazy greedy algorithm is discussed for the wind farm micro-siting optimization problem. By conducting the numerical tests, results demonstrate that the combination of the lazy greedy algorithm and the virtual particle wake model is effective in optimizing wind turbine positioning on complex terrain, for it produces better solution in less time comparing to the previous bionic method.

1. Introduction

Wind power generation is one of the clean and renewable energy sources with the most matured technologies of utilization. China is facing extreme energy and environment problem, which makes it urgent to develop highly efficient wind power generation technologies. To increase the power production efficiency of a wind farm, optimal designs of the wind turbines and the wind farm micro-siting are both important. This paper studies the wind farm micro-siting problem on complex terrain. Wind power generation efficiency is affected by the wind turbine layout in two ways. One is due to the non-uniform distribution of wind resources caused by the topography. Another is due to the velocity reduction caused by turbine wake flow. Therefore, the wind turbine layout must be carefully designed to reduce wake flow interaction and to increase total power output. In the past, much research has been carried out on the optimization of wind turbine layouts.

Among those approaches, the GA (genetic algorithm) is the most popular method. Mosetti, et al. [1] introduced GA to the wind farm micro-siting problem for the first time. In their paper, the wind farm area is discretized into Cartesian grids, and binary-coding is used to represent which grids have turbines installed. The installation cost is considered as a function only related to the total number of turbines. Their results demonstrate the effectiveness of GA in solving the wind farm micro-siting optimization problem. After that, many other models and optimization approaches have been studied for this problem. Albadi, et al. [2] studies the optimum tower height problem of wind turbines. An installation cost function which is linearly correlated with the tower height is used. Chen, et al. [3] did research on the optimization of wind turbine positioning with different hub heights using genetic algorithm, employing the similar linear cost function for wind turbine installation. González, et al. [4,5] used the NPV (Net Present Value) as a more realistic cost function, which includes the initial investment, the decommissioning, the present residual value, the financial benefit, and the ordinary operation and maintenance costs. Wan, et al. [6] used real-coding in GA, where turbines can be sited freely in the designated region, instead of being restricted to the grid nodes. These previous studies all indicate that GA is an effective approach for this problem. However, one of the disadvantages of GA is that it requires a large population and a huge number of generations of evolution. During its optimization process, millions of different wind turbine layouts emerges. Their power outputs and turbine wake flow effects all need to be evaluated, so that GA can eliminate worse solutions and retain better solutions. Therefore, in

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http://dx.doi.org/10.1016/j.energy.2014.12.012
0360-5442/

most of the studies using GA and similar algorithms, the linear model [7] is used to simulate wind turbine wake flow, which limits the approaches to be valid only for flat terrain. For complex terrain scenarios, non-uniform flow field distorts the turbine wake flow. Applying linear model to non-uniform flow field will bring additional error.

The virtual particle model has been developed in previous study [8] for simulating wind turbine wake flow effect in non-uniform flow field. This model reflects the characteristics of wake flow interactions much more realistic than the traditional linear model, and costs much less time than detailed numerical calculation on flow field around the turbine blades. It has already been validated in assessing wind power production [9]. Since the virtual particle model requires much longer time than the linear model, integrating it with GA would result in unacceptable time for engineering applications. Previous study has also introduced the bionic method to optimize the wind turbine layout [10]. The bionic method implements the concept of greedy algorithm. This method deals with only one turbine layout. In each step, it adds or moves one turbine to a better location that bring higher power output for the turbine. After several cycles of adding and moving turbines, the optimized solution is obtained. The bionic method requires much less times of conducting wake flow calculation, and can be integrated with the virtual particle model.

The lazy greedy algorithm, as a variation of the original greedy algorithm, has been introduced to the wind farm micro-siting optimization problem by Zhang et al. [11]. Their paper reveals that the problem has a so-called submodular property. With this property, the optimization process of greedy can be significantly simplified, saving much computation time. Terrain complexity has been considered in their study. However, the wake flow is simulated by a modified linear model, which takes the velocity direction at the turbine hub under consideration, but ignores the flow field non-uniformity in the downstream regions.

In the present study, the lazy greedy algorithm is integrated with CFD (computational fluid dynamics) and virtual particle wake flow model. In order to focus on discussing the validity and effectiveness of the submodular property and the lazy greedy algorithm, the present study only considers the optimization of power output of the wind farm. The combination produces a more accurate approach to optimize wind turbine layout on complex terrain. Numerical cases have been used for testing. Results show that the present method is effective in solving the wind farm micro-siting problem on complex terrain, for it not only obtains better solutions, but also takes much less time than the previous methods.

2. Wind power evaluation models

To develop an optimization method that produces wind turbine layout with high power output, it is essential to employ models that can accurately evaluates the power output of a wind farm according to given turbine layout. In present study, the evaluation is done in the following three steps: (1) The flow field of the empty layout (with no turbines, only the terrain topography) is numerically calculated using CFD. This calculation is carried out for only once. During the later optimization process, this flow field for empty layout maintains unchanged, providing the background flow field for wake flow simulation. (2) Simulate the turbine wake flow by using virtual particle model. The simulated effect is then superimposed to the background flow field, obtaining the wake influenced flow field. (3) Power output and turbine efficiencies can be calculated by introducing the turbine power curve model. The details of the models are stated in the following subsections.

2.1. Computational fluid dynamics

The optimization problem studied in this paper is for wind farm design before its construction. The instantaneous status of flow field is not interested. Therefore, the RANS (Reynolds Averaged Numerical Simulation) with standard k-ε model [12] is used to solve the steady Navier–Stokes equations. The governing equations are

$$\frac{\partial u_i}{\partial x_i} = 0 \tag{1}$$

$$\rho u_j \frac{\partial u_i}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left(\mu_t \frac{\partial u_i}{\partial x_j}\right) \tag{2}$$

$$\rho u_j \frac{\partial k}{\partial x_j} = \frac{\partial}{\partial x_j}\left(\frac{\mu_t}{\mathrm{Pr}_k}\frac{\partial k}{\partial x_j}\right) + \frac{\mu_t}{2}\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right)^2 - \rho\varepsilon \tag{3}$$

$$\rho u_j \frac{\partial \varepsilon}{\partial x_j} = \frac{\partial}{\partial x_j}\left(\frac{\mu_t}{\mathrm{Pr}_\varepsilon}\frac{\partial \varepsilon}{\partial x_j}\right) + C_1\frac{\mu_t}{2}\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right)^2 \frac{\varepsilon}{k} - C_2\rho\frac{\varepsilon^2}{k} \tag{4}$$

where the turbulent viscosity is

$$\mu_t = \rho C_\mu \frac{k^2}{\varepsilon} \tag{5}$$

For the wind farm with large open space, the constants in the equations are chosen as: $C_1 = 1.44$, $C_2 = 1.92$, $\mathrm{Pr}_k = 1.0$, $\mathrm{Pr}_\varepsilon = 1.85$, $C_\mu = 0.033$ [13].

In applications, wind velocities on the surrounding borders are difficult to measure. One of the usual way is to couple the CFD calculation with meso-scale simulation, such as KAMM [14] or WRF [15] models. The present study concentrates on discussing the performance of optimization algorithms, the terrain is randomly generated by the diamond-square algorithm [16]. Generally, the typical exponential profile is used for boundary conditions, as listed below.

$$\begin{aligned} u(z) &= u_{\mathrm{ref}}\left(\frac{z}{z_{\mathrm{ref}}}\right)^\alpha \cos\theta \\ v(z) &= u_{\mathrm{ref}}\left(\frac{z}{z_{\mathrm{ref}}}\right)^\alpha \sin\theta \\ w(z) &= 0 \end{aligned} \tag{6}$$

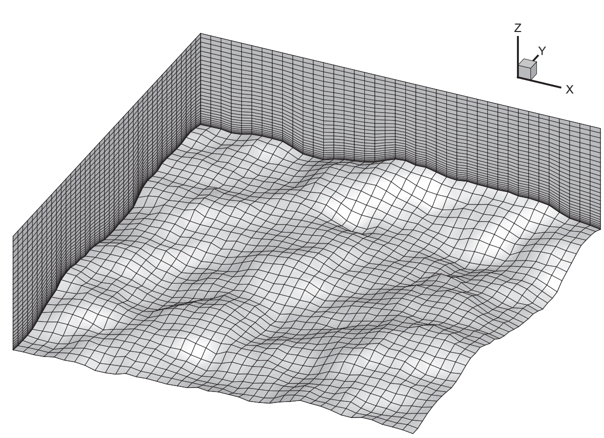

Fig. 1. The terrain following mesh and elevation.