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A Novel and Efficient Hybrid Optimization Approach for Wind Farm Micro-siting

Prateek Mittal*, Kedar Kulkarni, Kishalay Mitra*****

**Indian Institute of Technology, Hyderabad, Ordnance Factory Estate, Yeddumailaram, 502205, INDIA (email:ch12m1010@iith.ac.in)*
***ABB Corporate Research centre, Mahadevapura, Bangalore, 560048, INDIA (e-mail: kedar.kulkarni@in.abb.com)*
**** Indian Institute of Technology, Hyderabad, Ordnance Factory Estate, Yeddumailaram, 502205, INDIA (email:kishalay@iith.ac.in)*

Abstract: Due to increasing penetration of wind energy in the recent times, wind farm owners tend to generate increasing amount of energy out of wind farms. In order to meet targets, many wind farms are operated with a layout of numerous turbines placed close to each other in a limited area leading to greater energy losses due to 'wake effects' instead of generating more power. To solve the problem in the most optimal way, these turbines need to satisfy many other constraints such as topological constraints, minimum allowable capacity factors, inter-turbine distances etc. Existing methods to solve this complex turbine placement problem typically assume knowledge about the total number of turbines to be placed in the farm, which might be unrealistic. This study proposes a novel hybrid optimization methodology, a combination of evolutionary and classical optimization approaches, to simultaneously determine the optimum number of turbines to be placed in a wind farm along with their optimal locations. Application of the proposed method on a representative case study yields 43% higher Annual Energy Production (AEP) than the results found by one of the existing methods.

Keywords: Wind energy systems engineering; micro-siting optimization; genetic algorithms; gradient based optimization.

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1. INTRODUCTION

Wind energy has turned out to be a promising alternative energy source in order to compete with the depleting conventional sources. Due to its wide-scale availability, low cost and environment friendly operation, the idea of utilizing wind power at a massive scale has become a primary focus in the power industry, government policies and academic research (Chowdhary et al. 2012, Khan and Rehman 2013, Duan et al. 2014). According to the Global Wind Energy Council (GWEC, 2014), the global cumulative installed wind capacity is expected to nearly double from today's capacity (~300GW) by the end of 2018. Wind farm micro-siting is the process of determining optimal layout of turbines in a wind farm to extract maximum energy out of it. However, the predictions of the commercial software's for designing the layout of turbines in a wind farm are still not up to the mark and need human intervention to reduce the installation and operational costs for yielding the maximum energy and efficiency of wind farm after tackling the wake effects (Khan and Rehman, 2013). These facts set the importance of solving the complex micro-siting problem considering various practical aspects of it.

Many research articles are available, where binary–coded Genetic Algorithms (GAs) have been used to maximize the net Annual Energy Production (AEP) while minimizing the installation cost over fixed number of turbines in a wind farm (Gonzalez, 2014). Apart from GAs, evolutionary strategy based multi-objective algorithm (maximization of expected energy and minimization of constraint violation) has been proposed and the effect of wake loss with increasing number of turbines in a wind farm has been studied (Gonzalez, 2014). Ant Colony Optimization and Particle Filtering Approach have also been tested to deal with the optimal placement of turbines in a wind farm layout (Gonzalez, 2014). Recently, Chowdhary et al. (2012) attempted to maximize the power and efficiency of a wind farm with identical and non-identical turbines using Particle Swarm Optimization (PSO). Zhang et al. (2014) presented Constrained Programming and Mixed Integer Programming models to maximize the total farm-level energy produced for simple to complex wind scenarios. Most of these existing models deal with the micro-siting problem with a fixed number of turbines. However, wind farm developers are not sure of the maximum number of turbines that can actually be fitted in a farm to attain the maximum net AEP. Recently, Kulkarni and Mittal (2014) developed a novel heuristic approach where the optimal number of turbines and their optimal locations can be found out simultaneously in order to maximize the net AEP and minimize the wake losses in a wind farm. It suffers from the drawback of grid-based methods i.e. since all candidate turbine-locations lie on the grid, possibly better locations lying between grid-points can never be chosen. Moreover, refining the grid resolution to better represent the wind farm area may make the problem computationally very

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demanding. Another limitation of this approach is that the performance of the algorithm is driven by the selection of the starting solution. To overcome these limitations, a novel hybrid methodology has been proposed in this work which makes use of a bi-level optimization formulation. GA has been used in the first level to determine the number of turbines out of certain number of possible candidate locations (a discrete formulation) whereas a classical optimization technique improves those locations in the second level assuming the number of turbines in the layout as obtained from the first level are fixed (a continuous formulation). The paper is organized as follows. Section II describes the problem formulation, AEP and wake calculations in the model. The proposed methodology is explained in section III, whereas section IV presents the results of a representative case study. Conclusions along with the scope of future work is given in section V.

2. PROBLEM FORMULATION

The development of mathematical model for wind farm micro-siting is limited to certain assumptions (A1 – A5). A1: N number of wind turbine locations are described as (x_i, y_i) where i = 1,…, N; A2: In order to maintain consistency in a problem, homogenous wind turbines are considered; A3: For simplicity, a widely used and well-known Jensen (1983) wake model is used to calculate the velocity deficit due to wake effects; A4: For a specific direction, height and location, wind speed follows a two parameter Weibull distribution $C_v(u,A,k)=1-\exp(-(u/A)^k)$, where A is the scale parameter and k is the shape parameter and Cv (.) is the cumulative distribution function, which is a well-accepted concept worldwide (Kulkarni and Mittal, 2014); A5: Power and thrust coefficient curve is used to evaluate the power and coefficient of thrust (CT) for the corresponding wind speed. (Fig. 1).

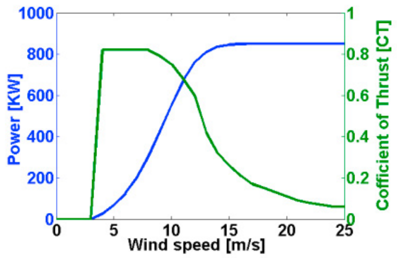

Fig. 1. Power and CT curve for Vestas-V52 850 kW (Kulkarni and Mittal, 2014)

Mathematically, the problem can be represented as:

$$\text{Objective Function:}\quad \underset{N_t}{Max}\ \underset{x_i,y_i}{Max} \sum_{1}^{N_t} AEP(x_i,y_i) \tag{1}$$

Subject to two inequality Constraints:

$$g_1(x_i,y_i) = n_{space} * D - \sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \le 0, \quad j\neq i, i,j=1,\dots,N_t \tag{2}$$

$$g_2(x_i,y_i) = OCF^{\lim} - \sum_{1}^{N_t} AEP(x_i,y_i)/(8766)*N_t*\Pr \le 0 \tag{3}$$

Here $g_1(x_i,y_i)$ is the inter turbine distance (ITD), which is considered to keep enough spacing between turbines (3 times the rotor diameter of the turbines) in order to minimize the wake loss and fatigue loads. Another constraint $g_2(x_i,y_i)$ is overall capacity factor (OCF), which is a measure of wind farm performance and defined as a ratio of overall power generated in wind farm to the power generated if all turbines were at their rated capacity. Here, the limit for OCF is decided by a wind farm owner (Eq. 3). In this case study, n_{space} is 3, D is the diameter of turbine in consideration, $OCF^{\lim}$ is assumed to be 20% and $\Pr$ is rated power of turbine's (850 kW). Also the overall number of turbines (N_t) is taken as upper level decision variables and the location co-ordinates of these turbines (x_i, y_i) are considered as lower level decision variables whereas the geographical boundary limits are described by lb and ub. For a regular shaped rectangular 500×500m^2 grid farm considered here, lb and ub for (x_i, y_i) can be 0 and 500, respectively.

This problem is mixed integer nonlinear programming problem (MINLP) in nature which are generally very hard (NP-hard) to solve due to the combinatorial complexity involved. Due to discontinuous nature of the energy calculation step in the above formulation, it is difficult to solve this problem using efficient MINLP solvers such as DICOPT and others available in the GAMS environment.

3. AEP CALCULATION AND WAKE MODELLING

3.1 AEP Calculation

To calculate the energy produced accurately, the spatial and the temporal distribution of wind resource must be known which is generally expressed in terms of Wind Resource Grid (WRG) that stores information about Weibull parameters at a given location. The net AEP (kWh) at a given location of wind farm can be expressed as (Kulkarni and Mittal, 2014):

$$AEP=(8766)\sum_{i=1}^{360^\circ}\sum_{j=1}^{u_{\max}} Pwr(\theta_i,u_j)\ p(\theta_i)\ p(u_o)\,\Delta\theta_i\,\Delta u_j \tag{4}$$

Where, $p(\theta_i)$ and $p(u_o)$ determine the probability that the wind blows in direction θ_i at free-stream wind speed u_o and are obtained from Wind Resource Grid (WRG) data (Kulkarni and Mittal, 2014). Depending on whether a turbine is affected by wake and the number of upstream turbines generating the wake, the reduced velocity u_j at the turbine affected by wake is calculated. The corresponding power $Pwr(\theta_i,u_j)$ for that particular speed can be calculated using the turbine power curve (Fig. 1). Here the WRG data is adapted from WindRose and contains the spatial distribution of speed and direction at regularly spaced points in the form of A, k and f parameters. The two-parameter Weibull distribution is used to calculate the probability of wind speed at given locations $p(u_o)$ by using (5) and (6)