Renewable Energy 86 (2016) 133–147

Contents lists available at ScienceDirect

Renewable Energy

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

A novel hybrid optimization methodology to optimize the total number and placement of wind turbines

Prateek Mittal [a], Kedar Kulkarni [b], Kishalay Mitra [a, *]

[a] Department of Chemical Engineering, Indian Institute of Technology Hyderabad, Ordnance Factory Estate, Yeddumailaram 502205, India
[b] ABB Corporate Research Center, Mahadevapura, Bangalore 560048, India

ARTICLE INFO

Article history:
Received 23 December 2014
Received in revised form
3 July 2015
Accepted 31 July 2015
Available online xxx

Keywords:
Wind energy
Systems engineering
Micro-siting optimization
Genetic algorithms
Gradient based optimization
Hybrid techniques

ABSTRACT

Due to increasing penetration of wind energy in the recent times, wind farmers tend to generate increasing amount of energy out of wind farms. In order to achieve the target, many wind farms are operated with a layout design of numerous turbines placed close to each other in a limited land area leading to greater energy losses due to 'wake effects'. Moreover, these turbines need to satisfy many other constraints such as topological constraints, minimum allowable capacity factors, inter-turbine distances, noise constraints etc. Thus, the problem of placing wind turbines in a farm to maximize the overall produced energy while satisfying all constraints is highly constrained and complex. Existing methods to solve the turbine placement problem typically assume knowledge about the total number of turbines to be placed in the farm. However, in reality, wind farm developers often have little or no information about the best number of turbines to be placed in a farm. This study proposes a novel hybrid optimization methodology to simultaneously determine the optimum total number of turbines to be placed in a wind farm along with their optimal locations. The proposed hybrid methodology is a combination of probabilistic genetic algorithms and deterministic gradient based optimization methods. Application of the proposed method on representative case studies yields higher Annual Energy Production (AEP) than the results found by using two of the existing methods.

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 [1–3]. According to the Global Wind Energy Council (GWEC) [4], the global cumulative installed wind capacity has increased from 6100 MW to 3,18,105 MW in the last two decades and is expected to reach 1,100 GW over the next five years (~12% of electricity supply of the world). The standard systems engineering approach of capturing the potential wind energy in a farm is to place wind turbines at optimal locations, known as micro-siting, and thereby tapping the maximum energy out of it. The problem of micro-siting optimization is not trivial due to various challenges involved in problem formulation and development of solution methodology. The challenges related to problem formulation appear while handling different kind of constraints such as inter-turbine distance, topology, overall capacity factor, longevity of turbine life, turbine noise, consideration of turbine wakes etc. While dealing with above constraints, micro-siting problems often lead to mixed integer nonlinear programming (MINLP) formulations for which the methodologies which can guarantee the global solution are yet to be developed. Moreover, the fact that the predictions of the commercial softwares [5–7] for designing the layout of turbines in a wind farm till date are still not up to the mark [2] and human intervention is required to reduce the installation and operational costs, shows the scope of improvement in this field both in terms of development of methodologies for efficient problem formulation and solution technique.

A huge amount of work has been done in the area of micro-siting over the past two decades [8–10], where binary-coded Genetic Algorithms (GAs) have been used to maximize the net Annual Energy Production (AEP) with less installation cost over fixed number of turbines in a wind farm. Mosetti's [8] work showed the

* Corresponding author.
E-mail address: kishalay@iith.ac.in (K. Mitra).

http://dx.doi.org/10.1016/j.renene.2015.07.100
0960-1481/

effectiveness of GA for solving such problems. The results for different wind conditions shown in this work were improved later by Grady [9] by considering a higher population size and number of generations thus allowing candidate solutions to have sufficient time to converge. In the study of Emami and Noghreh [10], the conflict of AEP and the cost involved in the project was expressed in the form of weighted sum of these two objectives and better results were found for certain set of weight values in the objective function. These studies consider a farm of regular shape (rectangle) that can be sub-divided into several cells of the size of five times the rotor diameter of the turbines. Assuming only one turbine can be accommodated in each of these cells, these formulations ensure the turbines are placed sufficiently away from one another to avoid wake effects. Mittal [11] considered cells 40 times finer in a grid and showed the effectiveness of the approach by improving the earlier results [8,9] substantially. Wan et al. [12] used real coded GA to solve the positioning problem of fixed number of turbines and obtained better results as compared to the work of Grady [9]. Mora et al. [13] proposed variable length chromosomes in GA to handle different types of turbines in micro-siting and developed novel crossover and mutation operators to handle these chromosomes of different lengths. Gonzalez et al. [14] proposed another variable length codification in an efficient GA setup to optimize the layout of turbines by calculating net yearly income obtained by selling net energy produced by each turbine considering various kinds of energy losses. The step of codification represents each of the chromosomes as different layouts, where the length of chromosome is driven by the total number of turbines in a farm and information related to turbine attributes is also coded. Apart from GA, other evolutionary techniques such as Imperialist Competitive Algorithm [15], Strength Pareto Evolutionary Algorithm (SPEA) [16], Ant Colony Optimization [17], Particle Filtering Approach [18], Particle Swarm Optimization [3] etc. were used to deal with the optimal placement of turbines in a wind farm layout and solve different single or multi-objective optimization formulations. In another multi-objective formulation, Kwong et al. [19] considered the maximization of AEP and minimization of the noise level for a fixed number of turbines in a wind farm. Zhang et al. [20] presented Constrained Programming and Mixed Integer Programming models to maximize the total farm-level energy produced for simple to complex wind scenarios. Currently, several commercial software programs are available addressing the problem of wind farm layout and design. The most widely used is WAsP [5], which offers modules that allow assessing wind behavior in complex terrain using computational fluid dynamics (CFD). It helps to develop wind farm design by considering previously obtained wind climate observations and wake effect is calculated using Katic model [21]. Windfarmer [6] optimizes the layout using Reynolds Average Navier–Stokes (RANS) based CFD model. It considers uncertainty, noise, and electrical infrastructure as additional aspects. WindPro [7] designs the layout by sequentially adding the wind turbines at positions with maximum available energy while optimizing the net AEP of a farm.

Most of the existing models and software packages solve the micro-siting problem assuming the total number of turbines in a wind farm is fixed i.e. the rated power capacity of a wind farm is known and the goal here is to find out the turbine locations. In this case, the problem is a nonlinear programming problem, where turbine locations are the only decision variables. Under different circumstances, either the rated power capacity has been driven by certain business decisions or it has been arrived at based on past experiences of the experts. There are issues with either of these approaches. If the rated capacity is higher than the optimal rated capacity (which is unknown and needs to be found out), the rated capacity will be misleading and will never be realizable. On the other hand, if the rated capacity is lower than the optimal value, the purpose of tapping the full potential of wind energy can be jeopardized. However, the optimal rated capacity can be found by formulating an optimization problem which can calculate the total number of turbines that can be placed in a farm layout as well as their locations. A common practice observed in many practical installations is to erect as many turbines as possible in a wind farm ignoring the wake effect and thereby generating an inefficient as well as sub-optimal micro-siting plan. Therefore, it is more realistic to find out the optimal total number of turbines as well as their locations simultaneously while performing micro-siting in presence of several other constraints.

Though some of earlier studies address this issue of simultaneous determination of optimal total number and locations of turbines in a wind farm, a severe compromise has been made in terms of assuming the locations of the turbines only at fixed locations. For example, a wind farm is divided into certain number of cells and the center of the cell is assumed to be the only location of a turbine in that cell. No additional constraint for tackling the inter turbine distance has been considered; instead the size of each of these cells is assumed to be some integer times (e.g. five times) the rotor diameter of the turbine. Simultaneous determination of optimal total number and locations of turbines in a wind farm for an objective, say maximization of AEP, involves both binary (“yes/no” decisions for turbines at several locations) and continuous variables (turbine coordinates) and leads to mixed integer (non) linear programming (MINLP) formulations. Assuming the total number of turbines to be installed is N_t and the whole farm area under study is divided into N_{cell} units, the possible number of distinct solutions that has to be considered during optimization can be given by (1) [22].

$$N_{sol} = \binom{N_{cell}}{N_t} = \frac{N_{cell}!}{N_t!(N_{cell} - N_t)!} \tag{1}$$

The size of the problem and thereby the complexity increase with the increase in number of cells in the search space (the case of division of the wind farm into finer grids) and the problem size could be unmanageable after a certain extent of granularity in the grid/cell size. Recently, Chen et al. [23] adopted a mix of real and binary coded GA to solve this problem where each layout is represented by a triplet of a fictitious number (N_f number for each of them) of x, y coordinates and binary variables. Depending on the number of ‘1's present in the N_f binaries, the total number of turbines in a layout is calculated whereas their corresponding x and y coordinates are their respective locations in the layout. Since the total number of turbines is not known here, several optimization runs with different values of N_f are recommended. The amount of complexity involved in this formulation can be guessed from the estimates of number of solutions to be considered from (1) since the real values of the coordinates can assume any value within the given bounds. In another study, Kulkarni and Mittal [24] 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 other grid-based methods: 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 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