UDC 517

OPTIMAL SITING OF WIND TURBINES IN A WIND FARM

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Abstract

The purpose of micrositing is to find an optimal layout of a group of wind turbines in order to extract maximum power production from a wind farm. In the case of wind farm design, the wake interactions between wind turbines are one of the most critical subjects that should be considered. Because, not only they cause a decrease in wind speed which causes less energy production but also they lead to blade damages on wind turbines and high maintenance costs. Offering high quality layout solutions that needs to be decided before the design of a wind farm will lead to high profits for wind farm investors. Providing options to the investors regarding the quantity and optimal locations of wind turbines is the main concern of this paper, since erecting more turbines in certain locations sometimes may cause energy losses. In this study, a series of latitude-longitude data was generated by scanning the digital map of the wind farm site. The determination of locations where turbines can be placed is presented as a new approach in terms of wind farm area characterization. By doing so, a continuous search space is generated that brings more flexibility to mobilize wind turbines. The solution starts with a heuristic approach, and then a genetic algorithm is followed to find optimal placements of wind turbines considering minimizing the wake loss. At last, the optimum locations of the wind turbines are obtained, and the maximum number of turbines is recommended for the given wind farm.

Keywords: wind Turbines, wind Farm, global warming, optimization, wake model, power model

1. Introduction

2015 is the year that the international community worked to reach a global climate change agreement. In December 2015, 195 countries adopted a universal global climate deal with Paris Agreement. All these governments agreed to limit global warming to well below $2^{\circ}C$, and outlined their national post–2020 mitigation commitments throughout the year. In this context, renewables must take center stage in achieving $2^{\circ}C$ Scenario for climate goals. According to the 2015 report of Global Wind Energy Council (GWEC), the mainstream source of renewable energy supply will be wind power, and it will play a major role in decarbonization [11]. However, becoming mainstream means to function the overall energy system cost–effectively. Thus, the factors that affect energy production adversely have to be considered. One of the most important factors is the placement of wind turbines in a wind farm. Upwind turbines create wind wakes that impact the natural wind flow to adjacent downwind turbines, causing the downwind turbines to produce less energy production, and less overall lifetime of because of increased mechanical loads [7]. So, the wind energy industry has to use technical and financial innovation to drive costs down, and keep sustain the improvement of wind farm reliability. The wind farm layout optimization (WFLO) problem consists of finding the turbine positions that maximizes the expected power production. In the literature, there are several researchers who addressed this problem. In 1994, Mosetti et al. [18] attempted to optimize the placement of wind turbines in a wind farm by utilizing a genetic algorithm. He discretized the terrain in a matrix, used Jensen's wake effect model, and he obtained results for three different wind regime scenarios considering cost and power production. Mosetti's problem was examined by many other researchers. Grady et al. [12] used same approach as Mosetti, and proofed that Mosetti et al.'s results were not showing the optimal placement. Emami et al. [8] proposed a different objective function for a better layout for the same three cases. On the other hand, Marmidis et al. [16] investigated the same problem by using Monte Carlo simulation for the first scenario. Bilbao and Alba [5] used a simulated annealing in their study, while in their second study Bilbao and Alba [4] utilized CHC which is a non-traditional genetic algorithm that combines a conservative selection strategy, and geometric particle swarm optimization in order to maximize the profit per year. Kusiak and Song [15] presented optimizing a multi–objective function that uses evolutionary strategy algorithms. Unlike other studies, a circular plot of wind farm terrain was considered instead of a rectangular shape. Eroglu and Seckiner [9]

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proposed an ant colony optimization algorithm to optimize the same wind farm model as proposed by Kusiak and Song [15]. Also, in 2017 Bansal et al. [3] studied Kusiak and Song's [15] model, and presented a new evolutionary population–based optimization technique called bio–geography based optimization which was inspired by migration of species from one island to another island. Migration and mutation operators are the key parameters since they are responsible to evolve new candidate solutions. Minimizing velocity deficits, and so maximizing the energy production was the objective function in the study. Chowdhury et al. [25] proposed a particle swarm optimization for optimum design of wind farm, and optimum turbine selection in order to maximize the net power production. Identical turbines and different rotor sized turbines were evaluated in two scenarios. They found that installing wind turbines with different rotor diameters improved the efficiency of the wind farm. Frandsen wake model was used for turbine interaction calculations. Chen et al. [28] proposed to install wind turbines that have multiple hub heights. Three–dimensional greedy algorithm was utilized on both linear and particle wake model over flat terrain and complex terrain, respectively. Simulations revealed that in case of using different hub height wind turbines on a complex terrain increases the power production, and decreases the cost per unit power production. Saavedra et al. [24] considered orography and shape of the wind farm, and carried out Monte Carlo simulations of several years of wind speeds. The authors optimized the wind farm model by offering an initial solution obtained by a greedy algorithm, and then proposed a final layout by using an evolutionary algorithm. Rasuo et al. [22] tried a different type of genetic algorithm, called differential evolution for WFLO problem. Instead of placing the turbines at the center of each cell, the locations of turbines were adjusted freely. By this way, they could manage to reduce wake effect, and produce more energy from a given wind farm. Simulation results showed suitability of the proposed algorithm. A bio–inspired algorithm called Coral Reefs Optimization (CRO) was presented for off–shore wind farm design in Salcedo–Sanz et al.'s [20] paper. The proposed algorithm's performance was compared to three different approaches: evolutionary algorithm, differential evolution, and harmony search algorithm. It was proven that CRO approach produces the layout with the highest power production. Kallioras et al. [21] proposed a music–inspired meta–heuristic algorithm called harmony searched for WFLO problem. Two different objective functions were presented: profit maximization for a specific number of wind turbines and the profit maximization for a given energy per year. Jensen wake model was utilized for turbine interactions, while the wind characteristics of the terrain were modeled stochastically. Kwong et al. [27] presented a continuous location model, and included noise minimization with energy maximization as objective functions. They formulated previous test cases of Mosetti's [18]; Jensen's approach for the wake model and multi–objective non–domination sorting genetic algorithm II (NSGA–II) for the optimization were used in this paper. Pareto frontiers were identified regarding the relative importance of the energy production and noise objectives. Mittal et al. [17] also studied energy–noise trade–off problem, proposed a hybrid method of a multi–objective evolutionary algorithm and a single–objective gradient approach. Khan et al. [14] outlined the iterative non–deterministic algorithms in WFLO literature including design issues, different constraints, single and multi–objective aspects of the problem. Serrano Gonzales et al. [1] also presented a review of the optimal placement of wind turbines discussing the main features concerning objective function, application of several algorithms, and wake effect models. The main topic of this paper is to provide the optimum number of wind turbines, and their optimum locations in a given site by applying both heuristic and metaheuristic algorithms. In this case, a 350×1000 m rectangle shaped area is considered for the wind farm. The majority of previous approaches consider square wind farms, and divided into grids where turbines could be placed [24]. Instead of discretizing the wind farm area by meshing, a continuous layout model is used, since using real location variables can avoid choosing optimal grid size [13]. To do so, latitude, longitude (*angles in radians*), and elevation (*in meters*) values of the wind farm are generated by scanning a digital map from Google Earth. Then, these three values are turned into a dataset which introduced to algorithm as candidate locations for wind turbines. By doing so, the algorithm gives the opportunity to explore every potential location on a wind farm to reduce wake losses. Also, this approach provides the opportunity to exploit any irregular shape wind farm micrositing problem. Since the latitude, longitude values are in angles in radians, the distances between each point needed to be calculated by a geodesic approach which is a novelty in a WFLO problem. After turning all the data into metrics, a three–dimensional Cartesian coordinate is generated to create a digital elevation model (DEM) and a contour by Surfer 3D surface mapping software program. Basically, the main novelties of the paper are to introduce a DEM to model the terrain, and assign the locations of wind turbines based on elevation values which are obtained from a digital map. The annual hourly wind data at 10 m is provided from data portal of national meteorological station [19]. According to this data, wind characteristics of the terrain are evaluated. Average wind speed is 6.2 m/s at the height of a 10 m mast. Three prevailing wind directions are considered for the calculations, since the total frequency of them is 92.06 % of all times. A single type, identical wind turbine is considered. Herein, the objective function is to minimize the velocity deficits while maximizing the total output. A combination of a heuristic and a meta–heuristic approach is offered for the optimal placement. Heuristic method is set based on elevation values that ensures the minimum distance between the turbines, and this approach is used for the formation of the initial population. Then, a genetic algorithm is employed for optimal positioning of wind turbines.

2. Numerical Methods of the Present Study

2.1. Wake Model

The term «wake effect» originates from the wake behind a ship. Like ships, wind turbines also create wakes. For wind turbines, wake effect relates to the velocity deficit of the wind and decreased energy content after leaving a wind turbine. By extracting energy from the wind, a wind turbine formed an imaginary cone (*wake*) that creates slower and more turbulent air behind it [7]. When a uniform incoming wind encounters a wind turbine, a linearly expanding wake behind the turbine occurs. A portion of the free stream wind's speed will be reduced from its original speed u_0 to u. According to this model the wake is turbulent, it expands linearly with downstream distance as shown in Fig. ??. The velocity deficit is defined as the fractional reduction of freestream wind speed in the wake of the turbine. Based on the momentum conservation assumption in the wake, the velocity deficit at turbine $i(vel\_def_{ij})$ which has the distance of $x_{i,j}$ from turbine j can be calculated by Eq. (1).

$$vel\_def_{ij} = 1 - \frac{u}{u_0} = \frac{2a}{\left(1 + \propto \frac{x_{i,j}}{r_r}\right)^2} \tag{1}$$

where u_0 (m/s) is the wind speed perpendicular to the rotor plane, $x_{i,j}$ (m) is the downstream distance of the wind turbine, u is the downstream wind speed after $x_{i,j}$ distance, r_r (m) is the rotor radius, a is the axial induction factor which is calculated from the thrust coefficient (C_T) of the wind turbine. According to IEC $61400-1$ standard [6], (C_T) is the characteristic wind turbine thrust coefficient for the corresponding hub height wind velocity which is shown as u_{hub} in Eq. (6.2). (C_T) and a calculations are given in Eq. (2) [10] and Eq. (3):

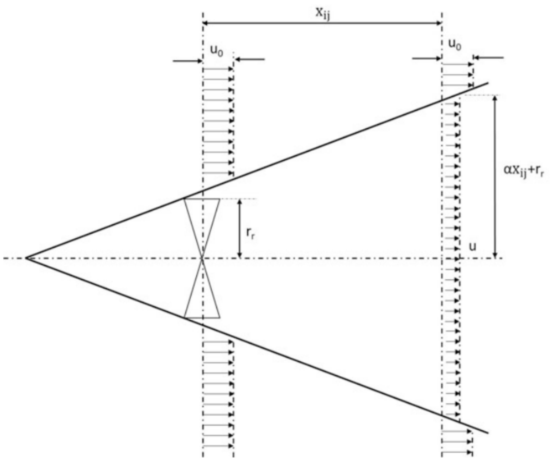

Figure 1. Wake model [2]

$$C_T = 3.5 \cdot \left(\frac{2u_{hub} - 3.5}{u_{hub}^2}\right) \tag{2}$$

$$a = 0.5\left(1 - \sqrt{1 - C_T}\right) \tag{3}$$

and a is the wake spreading or entrainment constant, and shows how fast the wake expands. It can be calculated from Eq. (4).

$$\propto = \frac{0.5}{\ln}\left(\frac{\mathcal{Z}_H}{\mathcal{Z}_0}\right) \tag{4}$$

Here, z_0 (m) represents the surface roughness height of the site, and z_H (m) represents the hub height of the wind turbine. $x_{i,j}$ is the distance between the turbine i and j , and it is calculated based on the given wind direction θ (*degree*). Details of Eq. (5) can be found in Kusiak and Song's [15] paper.

$$x_{i,j} = |(x_i - x_j)\cos\theta + (y_i - y_j)\sin\theta| \tag{5}$$

In order to calculate the produced power from a wind turbine, it should be ensured whether the wind turbine is located in the wake of other wind turbine(s) or not. To illustrate the wake area behind a wind turbine, an imaginary cone can be drawn, see in Fig. 2 [2]. Wind

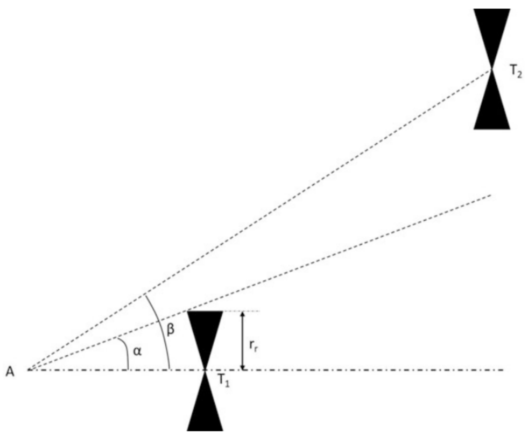

Figure 2. Imaginary cone of a wind turbine [2]

blows from left with a given wind direction θ . Any two turbines i and j positioned perpendicular to the wind direction and locate at (x_i, y_i) and (x_j, y_j), respectively. The point A is the imaginary vertex, the angle $\alpha\left(0 \leqslant \alpha \leqslant \frac{\pi}{2}\right)$ is calculated as $\arctan(\alpha)$, and the distance between A and the hub is $\frac{r_r}{\alpha}$. $\beta(0 \leqslant \beta \leqslant \pi)$ is the angle used to determine if turbine i is in the cone of turbine j given the wind direction θ . For example, in Fig. 2, if the angle between the vectors AT_2 and AT_1 which is β is greater than the angle α, then T_2 will not be inside the cone, which means T_2 will not be under the wake of T_1 . On the contrary, if β is smaller than the angle α, then T_2 will face velocity deficit due to wake effect of T_1. The calculation of the angle β is shown in Eq. (6). $a_1 = (x_i - x_j)$ $b_1 = (y_i - y_j)$

$$\beta_{ij} = \cos^{-1}\left(\frac{a_1\cos\theta + b_1\sin\theta + \frac{r_r}{\propto}}{\sqrt{(a_1 + \frac{r_r}{\propto}\cos\theta)^2 + (b_1 + \frac{r_r}{\propto}\sin\theta)^2}}\right) \tag{6}$$

Large wind farms experience a cumulative effect of multiple wakes. When many turbines are located in a wind farm, the direction of the wind changes regularly, that causes certain turbines to be in the wake of other turbines. In this case, multiple wakes have to be considered. u_i (m/s) which is the downstream wind speed of the turbine i can be calculated by Eq. (7).

$$u_i = u_0(1 - vel\_def_{ij}) \tag{7}$$

And the calculation of multiple wake deficits on turbine i can be seen in Eq. (8).

$$vel\_def_i = \sqrt{\sum_{j=1, j\neq i, \beta_{ij}<\alpha}^{N} vel\_def_{ij}^2} \tag{8}$$

2.2. Power Model

The power production, P (Watt), from a single wind turbine is given in Eq. (9).

$$P = 0.5\rho\pi r_r^2 u^3 C_p \tag{9}$$

where ρ (kg/m^3) is the air density, and power coefficient C_p (*unitless*) is the fraction of available power in the wind that captured by the turbine. This stands for turbine power conversion efficiency which is 42 % in this problem. Total power generated in a wind farm is the sum of individual turbine powers. As wind flows through a turbine, the volume of air downwind of the turbine has a lower wind speed and higher turbulence than wind in the freestream. So each of the turbines may be subjected to different wind speeds caused by wakes, otherwise power is calculated using the freestream speed, u, as Eq. (10).

$$P(u) = \begin{cases} 0 \text{ kW}, \ u < 3.5 \\ 0.73u^3 \text{ kW}, \ 3.5 \leqslant u < 13 \\ 850 \text{ kW}, \ 13 \leqslant 0 < 20 \\ 0, \ u \geqslant 20 \end{cases} \tag{10}$$

$$P_{tot} = \sum_{i}^{N} P_i \tag{11}$$

where N is the total number of wind turbines. And the objective function is

$$\max \sum_{i}^{N} P_i$$

3. Methodology

3.1. Problem Formulation

In this paper, a 350×1000 m of a wind farm site is considered. Terrain data is digitized from a map in Google Earth. First, desired terrain is scanned by Path command, and a set of 1568 scanned data is collected. This data consists of latitude, longitude, and elevations. However, latitude and longitude values are both angles in radians, while corresponding elevations are in meters. Due to the different dimensions of the data, it is necessary to convert the coordinate data into metric system. In order to do this, geodesic distances between latitude and longitude points on the earth's surface should be calculated. Several approaches can be found in literature for the calculation of distance on earth surface. Since the earth is not a perfect sphere, and the radius of the earth varies at the poles and the equator, the Vincenty formula given in Eq. (12) and Eq. (13) is used in this paper. Because this approach models the earth as ellipsoidal, and takes into account the earth's ellipticity [26]. $a_1 = \cos\phi_2 \times \sin(\Delta\lambda)^2$, $b_1 = \cos\phi_2 \times \cos(\Delta\lambda)^2$

$$\Delta\sigma = \\ = \arctan \frac{\sqrt{a_1 + (\cos\phi_1 \times \sin\phi_2 - \sin\phi_1 \times b_1)}}{\sin\phi_1 \times \sin\phi_2 + \cos\phi_1 \times \cos\phi_2 \times \cos(\Delta\lambda)^2} \tag{12}$$

$\Delta\sigma$ is the central angle, λ_1 and λ_2 are longitude of the points, ϕ_1 and ϕ_2 are latitude of the points, and all of them are angles in radian. The arc length or the distance, d, is the multiplication of earth mean radius, r, by the central angle between two points, given in Eq. (13).

$$d = r \times \Delta\sigma \tag{13}$$

After calculating the distances between the points, the dataset turns into a digital elevation model (DEM) by Surfer which is a 3D mapping software program. The DEM is a representation of the terrain with elevations at regularly spaced intervals. Wireframe model in Fig. 3 and surface model in Fig. 4 are given to illustrate the geographical formation of the terrain. Based on this formation the wind characteristics, disturbed and undisturbed wind flow are modeled. The difference between the maximum and the minimum altitude within the area is 70 m. The hourly average wind speeds and directions for a whole year have been supplied from a 10 m met mast from the portal of national meteorological station [19], and the annual average wind speed is found 6.2 m/s. In wind direction analysis, the wind rose split sixteen equal sectors. Winds are frequently oriented in the North (N) with 29.45 %, North North West (NNW) with 29.53 %, and North West (NW) with 33.08 %, while the remaining 7.94 % is blown from the other 13 sectors. The aim of the problem is to find how many turbines can be installed at most in a given terrain, and give an opinion to the wind farm investor that how many installation of them would be feasible. In the literature, most of the studies take into account subdividing the available terrain into cells. The size of a cell is accordingly chosen to keep the minimum distance between two adjacent turbines, and every turbine can be installed only at the center of a cell. So the available positions are finite in a given wind farm site. However, in this study every single point of the terrain is considered as a possible turbine location. Extraction of the wind farm contour provides the opportunity to make the search space continuous. Thus, it is clear that due to more flexibility in placing wind turbines, more wind turbines can be placed in

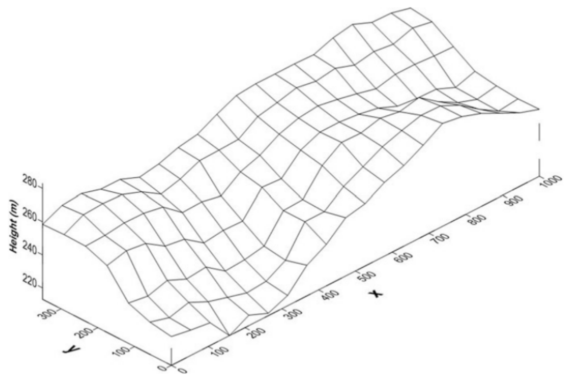

Figure 3. 3D wireframe model of wind farm site

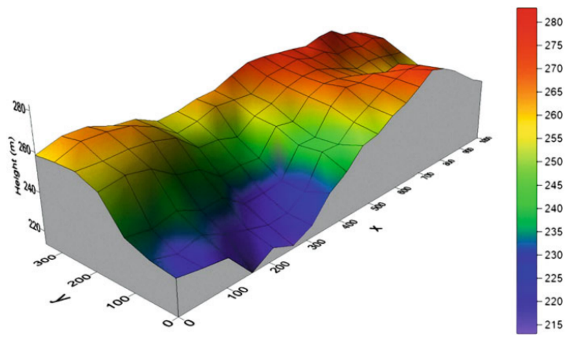

Figure 4. 3D surface model of the wind farm

a given wind farm. The wind speeds of each point of dataset are calculated based on power law wind profile. One single type of wind turbine is considered for the wind farm, and its features are displayed in Table 1. The minimum turbine installation distance is considered four rotor diameter (4D), which is 240 m. The aim is to create the best layout for the turbines to generate maximum energy with minimum wake loss. Since wind speed changes with height, as known as vertical wind shear phenomena, elevation values are utilized. Thereof, a new approach based on the elevation values of the terrain is proposed to obtain an initial population to be optimized by genetic algorithm. Finally, in the lights of above formulas the velocity deficits and power production of the proposed wind farm are calculated, and compared.

Table 1. Features of turbine used in this study

Rated power	850 kW
Cut-in wind speed	3.5 m/s
Rated wind speed	13 m/s
Cut-out wind speed	20 m/s
Hub height ($\mathcal{Z}_H$)	50 m
Rotor radius (r_r)	30 m
Power coefficient (C_P)	0.42

4. Conclusion

In this paper, the WFLO problem which is an important issue that needs to be solved during the design of a wind farm is described. In large wind farms, wake effects lead to considerable power loss, for this reason it is desirable to minimize them in order to maximize the power production [23]. Therefore, wake loss consideration is getting serious among the wind farm investors, since power production is mainly based on placing the turbines on the right location. In this paper, a wind turbine placement model which mainly depends on the number of wind turbines, wind speed and direction, characteristics of terrain and wind turbine features is addressed. First, wind farm's geographic position data which are latitude, longitude, and elevation are generated by scanning a digital map in Google Earth. The latitude and longitude angles of the terrain are transformed into geodesic distances in meters, so that the dataset turned into a three-dimensional Cartesian coordinates defined by (x, y, z) in metrics. This dataset is introduced to algorithm as possible installation locations for WTs. By doing this, a continuous search space is generated which gives the opportunity to locate the wind turbines more liberate. With the help of Surfer software, DEM is generated to model the terrain. Since wind speed changes with height, as known as vertical wind shear phenomena, elevation values are utilized in heuristic approach. The solution starts based on this heuristic approach which aims to create initial layouts. Then, the genetic algorithm is proposed to optimize these initial layouts considering to minimize the wake loss, and maximize the power production while keeping the minimum distance between two turbines. The power production of the wind farm is calculated using technical information of WTs, the wake effects, and wind resource taking into account the multiple wind directions and roughness of the terrain. For the validation of the offered algorithm, the same problem solved by only GA. The results showed a hybrid approach including a heuristic mindset offered better layouts in terms of total wake loss and power production.

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