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Increase the Performance of Wind Energy Systems Using Optimal Layout Planning †

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Abstract: As the years progress, the research focal point has been shifted to an alternative way of generating electricity, employing renewable and environmentally friendly approaches, explicitly using wind energy. Today, wind power plant technologies are experiencing a resurgence, as wind turbine promises to be an imperative substitute for fossil fuels. It has been analyzed that, going from 14781MW in 2004 to 51477MW in 2014, the capacity of producing electricity from wind energy has augmented drastically. However, research is underway to optimize the productivity of wind turbines to the point of saturation, so in addition to those already known, this research will be based on an area described as 'Increasing Efficiency by Using Optimal Sizing'. Discussion on the best possible geometrical profile of a turbine, in terms of its size and area, is covered. Along with this, the wake effect theory of wind turbines will be discussed in depth, describing how wind turbines extract energy from wind and reduce wind speed behind the rotor. Furthermore, the major parameter, i.e., cost, will also be scrutinized while discussing different countries and their cost liabilities in making wind turbines effective. Additionally, the research shall cover all the fundamental components used in wind turbine design and how its productivity will proliferate in more economic terms for an average consumer of a power plant.

Keywords: wind turbine; wind energy; efficiency; wind speed; optimal sizing; wake effect

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1. Introduction

Renewable energy, which has emerged as a new technology for heating, transportation, lighting, etc., has long been long to harness the power of nature. According to the reports of RES (Renewable Energy Sources), by 2023, they are expected to account for more than 70% of global growth in electricity and power generation, which will be driven by mostly solar and wind [1]. Wind energy is used to convert mechanical into electrical energy. Wind turbines have mostly advantages, but there are many problems that arise when installing wind turbines because we have to search for best location and ensure the weather conditions of that particular area. Wind turbines are costly as compared to other renewable energies.

Wind power is basically capturing energy from the movement of wind, and it comes from mostly turbines. The main idea of our research is to reduce the wake effect to receive maximum power production, because the wake effect decreases the overall power production of wind turbines [2]. The wake effect is basically that wind turbines extract energy from the wind, and downstream there is a wake from the turbines, where wind speed reduces. Solving the Wind Farm Layout Optimization Problem (WFLOP), which consists of properly placing the turbines inside the wind farm such that wake effects are reduced and therefore predicted power output is maximized, is an essential aspect of wind farm design.

2. Literature Review

We are presenting a general idea about wind farm optimization techniques and its appropriate approaches, which are developed in wind farms for the optimal placement of wind turbines [3]. To increase their power growth and efficiency, optimization of the layout model and procedure of wind farms is critical since large wind farms are established and some are planned due to large amounts that are reserved for wind farms. Looking into all this, our basic objective of the study is to maximize the placement of wind turbines as well as to identify the accountable aspect of minimum velocity deficit for variation in wind farm power output, which had been perceived with reference to the most current studies [4]. Overall efficiency of the wind farm is majorly affected by the layout of the wind farm and the direction of wind.

Optimization of Wind Farms

Mosetti et al. were the first who tended wind farm layout optimization. They used the genetic algorithm (GA) for three different wind scenarios [5]. Grady et al. conducted a study in 2005, based again on genetic algorithms concentrated on the effectiveness of the genetic algorithm optimization method in recognizing optimal arrangements [6]. Rabia et al. used the Definite Point Selection (DPS) to locate the turbines in a safe region to have maximum efficiency as well as power generation [7]. However, they considered an active deficit in the kinetic energy that leads to them taking the wake losses too lightly.

The problem of improving wind farm layout (WFLOP) is based on the outcomes of turbine location (wind farm layout) with the aim of optimizing estimated power output. Developers of wind farms may be likely to earn higher incomes as a result of increased solutions. Researchers and management systems largely ignored the WFLO.

Our research paper contributes to the following main objectives, which are to optimize wind turbine efficiency by implementing appropriate layout design, to propose a model of wind turbine layout based on Particle Swarm Optimization (PSO) and to minimize wake effect by using different models. Our study focuses on wind farm layout optimization.

3. Problem Formulation

In order to accomplish efficiency of the production of electricity from individual wind turbines, optimal modeling of wind farm layout is imperative [8]. By reducing the wake effect, which is by far a key challenge in wind form layout, designing a wind turbine can work more effectively, and together with applying the PSO algorithm, things can become so effective to implement for installation of wind turbines at the best possible position.

3.1. Used Framework

In order to augment the efficiency of a wind turbine, the wake effect should be minimized. There exist various suggested models to reduce the wake effect. However, we have used one of the well-liked models known as "Frandsen's Wake Model" to help diminish the wake effect [9]. Together with this, to locate the best position for each turbine, we used Particle Swarm Optimization (PSO) through MATLAB. This technique will facilitate us to find the finest co-ordinates for each turbine after the calculation of velocity deficit.

3.2. Frandsen's Wake Model

Frandsen's model is a comparatively new wake model, which is a consequence of conservation of momentum. Frandsen further claimed that the model was not for a single wake, but is centered on the wake of the complete wind farm [10]. However, the wind speed within the wake region anticipated by this model is higher than the measured value.

Equation (1) is used to calculate the wake effect/velocity deficit of individual turbine.

$$Ux = \frac{1 - \sqrt{(1 - CT)}}{1 + 2\left(\frac{Kd}{R}\right)} \tag{1}$$

CT is thrust coefficient;
K is wake decay constant;
d is distance between upstream turbine and downstream turbine;
R is radius of upstream turbine;
where *CT* and *K* are the constants.

3.3. Particle Swarm Optimization (PSO)

PSO has been applied to plentiful areas in optimization and in combination with other existing algorithms. The PSO places each particle location by computing the velocity deficit first on each coordinate. It stores the fitness value in arrays during runtime and returns only the best fitness values with least velocity deficit location. A Particle Swarm Optimization (PSO) algorithm is used to identify the optimal location of each turbine in a wind farm overall. In Particle Swarm Optimization (PSO), each particle recalls its own preceding best value [7]. Due to this reason, it has more effectual memory ability than the Genetic Algorithm (GA).

There are a number of optimization techniques that have successfully been used in solving wind farm layout problems, such as Genetic Algorithms, Simulated Annealing, Differential Evolution (DE), Simulated Evolution (SimE), Stochastic Evolution, gradient-based optimization, numerical added simulation and Monte Carlo optimization technique. The PSO algorithm shows numerous preferences over the other algorithms applied to the current optimization issue [7]. This is due to less demanding actualizing parameters and keeping all the particles, not at all like the GA, as an AI strategy that loses half of its populace in each generation and ought to recover. The comparative study between the current work and the past cases clearly shows that PSO can be utilized in optimizing a wind farm close to its different usages in engineering.

Figure 1 shows the randomness of particles when the number of iterations (n) = 1, with inertia coefficient (w) = 0.8 and acceleration coefficients (c1 and c2) = 2 and 2, respectively.

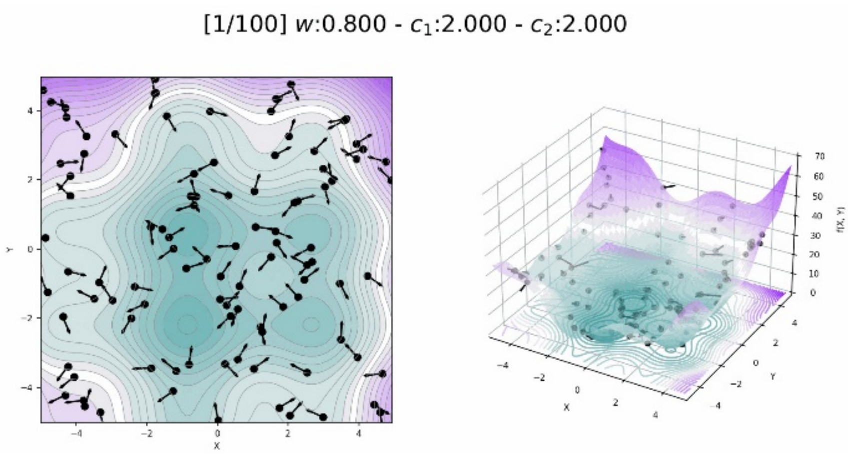

Figure 1. Exploration of Particles ([11], Figure 1).

Figure 2 shows the exploration of particles when the number of iterations (n) = 1, with inertia coefficient (w) = 0.8 and acceleration coefficients (c1 and c2) = 2 and 2, respectively. To analyze the effect of different values of inertia, we can see that, for w $\geq$ 1, velocities increase over time and swarm diverges the particles. However, if we take w = 0.1, the particles stay near that same position, giving no variations in the results. Therefore, the optimal value for the inertia coefficient selected is 0.8.

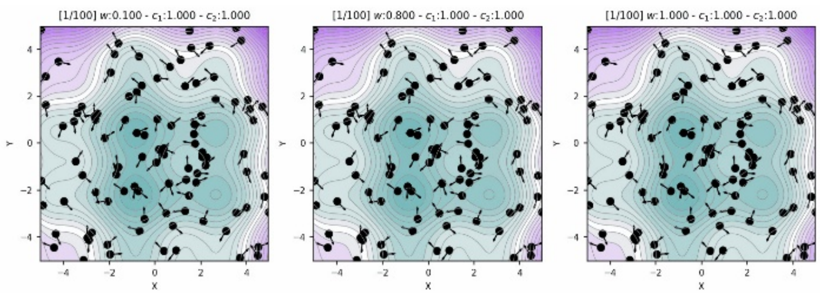

Figure 2. Arrangement of Particles in a Swarm ([11], Figure 2).

From Figure 3, we can analyze what impact different values of C1 and C2 create on the particle movement overall. If the C1 > 0, C2 = 0: particle movement becomes independent as C1 favors Personal Best. However, if C2 > 0, C1 = 0, the movement of particles will be influenced by Global Best, which again will give us biased results. Therefore, in order to remove the bias, we take C1 and C2 as 2, keeping both the values the same.

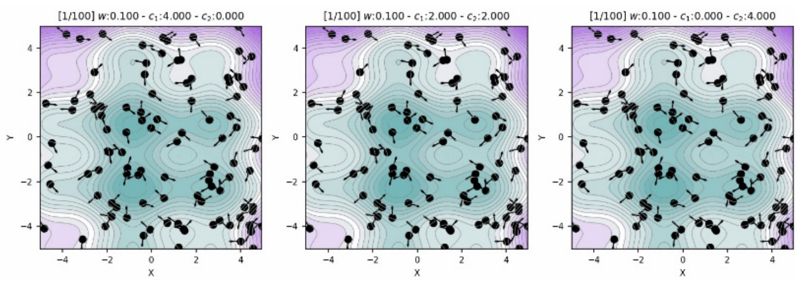

Figure 3. Impact of constants on particles ([11], Figure 3).

PSO helps us to attain the velocity component and position component, which in turn help to give the best possible solution, influenced by Global Best and Personal Best [12]. The values for inertia, acceleration coefficients and random variables are defined, respectively. Conclusively, the Particle Swarm Optimization technique gives the optimal value for placing wind turbines.

3.4. Objective Function

The foremost objective function of the present research is to restrain the wake losses caused by the velocity deficit (U_x) and also to capitalize on the augmented power generation of the farm by Frendsen Wake Model. Below, we can see velocity deviation, which can be measured by Equation (2).

$$U\_x=((1-\sqrt{((1-C\_T))})/(1+2(KS/R)))\ U\_o \tag{2}$$

where U_o is wind velocity of downstream turbine, whereas C_T is thrust coefficient, K is wake decay constant, R is the rotor radius of turbine and S is the distance between the up and down stream turbines.

4. Results

In this chapter, we are focused on determining the best fitness values in a wind farm to place wind turbines, on the basis of research we have performed on the PSO algorithm, together with a fine comparison of wake effect based on two different kinds of wake models, known as Jensen and Frendsen Wake Models. The results show a detailed analysis of how we can place six different wind turbines in a field of 2 km $\times$ 2 km with a distance of approximately 1km between each of the turbines placed accordingly. As PSO favors convergence, we will see values in the graph converging at a point to give the ideal position for all of them. This section gives a closer look of how things proceed step by step while running the PSO algorithm on MATLAB, along with its pseudo code, attached for better understanding in the form of a flowchart.

4.1. Best Fitness Value through Matlab Code

According to the previous analysis made on the PSO algorithm, exploration and exploitation play a significant role in determining the best possible solution for a particle in a swarm. Therefore, by exploration, we can have range of random values, and each value differs from the previous one and also covers the field overall [13]. However, exploitation aims to find definite results based on the best solution.

Therefore, by looking at the values, we analyze that PSO supports convergence; each new value is lesser than the preceding value. For example, Bestfitnessvaluet (i) = Globalbest.cost; hence, for n = 50 iteration and randomly generated position and velocity arrays, we obtain the Global Best value as 5.5356×10^{-9}, which is near to zero but will never touch the zero line. Therefore, after 50 iterations, we achieved our best fitness value according to the coordinate defined for the position, as indicated in the graph below.

As the PSO algorithm is more inclined towards convergence as shown in Figure 4. The fitness values will always be exponentially decreasing but will never touch the zero line, with a best fitness value < 0 [14]. Table 1 shows the best fitness values of wind turbines at different coordinates.

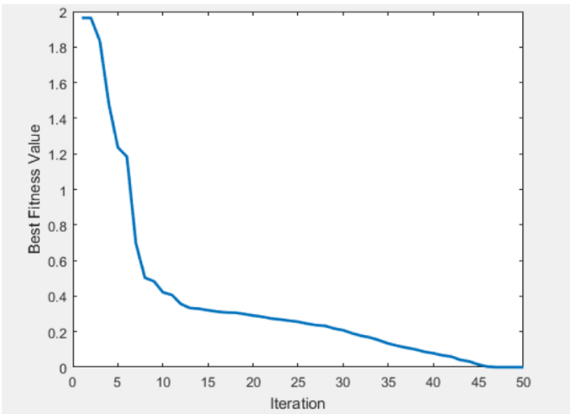

Figure 4. Convergence Curve.

Table 1. Fitness values of wind turbine.

No of Turbines	Co-Ordinates (x, y)	Best Fitness Value
1	(0, 0)–(0, 1)	1.5618×10^{-18}
2	(1, 0)–(0, 0)	2.7336×10^{-17}
3	(1, 0)–(1, 1)	1.0000
4	(1, 0)–(2, 1)	9.6006×10^{-12}
5	(0, 1)–(1, 2)	1.2178×10^{-4}
6	(1, 1)–(1, 2)	1.2312×10^{-5}
7	(1, 1)–(2, 2)	9.9792×10^{-11}
8	(1, 2)–(2, 2)	4.0000 s

In Figure 5, with a field of area 2 km × 2 km, we can place our six (6) turbines in such a way so that we can achieve our optimal distance between two turbines as 903 m, or approximately 1 km. So, we placed our six (6) turbines at the positions (0, 1), (0, 2), (1, 0), (1, 1), (1, 2) and (2, 1). We carried out 50 iterations for obtaining the best fitness value for each turbine through running the PSO algorithm on MATLAB. According to our methodology, we considered a symmetrical area of 2 km × 2 km for an ideal situation. However, it can be adjusted to the field area for installing wind farms.

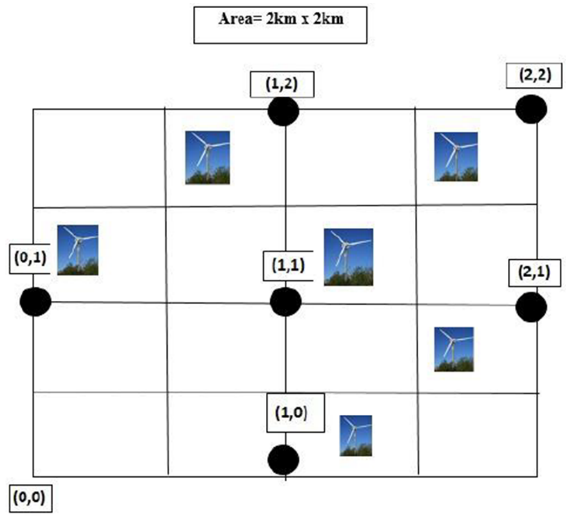

Figure 5. Wind Turbine Model.

4.2. Comparative Study of Applied Algorithm

The research paper presents the comparative ideas of previous studies that have been carried out on the following topic. The idea presented by M. Rashid named "Design of wind farm layout Optimization for the decline of Wake Effect" discussed that the core idea of this research is to design wind farm layout optimization for the decline of wake effect. Therefore, proposed studies have developed a 3D simulator that can simulate the wind farm layout in a continuous space of 3 km × 3 km by applying a Particle Swarm Optimization (PSO) algorithm based on Frandsen's wake model. On the contrary, Rabia Shakoor in 2016 used Jensen's wake model and explains the important distinction between far and near wake models, but due to the use of genetic algorithm, the results were not obtained to an accurate level. The main idea behind this research paper is to use Frandsen's wake model along with the Particle Swarm Optimization algorithm. This research paper is limited by the fact that it can only find the best values for where to locate wind turbines, but the power will not be maximized, although it can target the best position to locate wind turbines.

5. Conclusions

After a deep analysis of each section, we were able to define a future direction for our research. In the first section, the PSO algorithm was run, with iterations = 50, and we were able to find the best fitness values for a defined position, with velocity array initialized randomly. Moreover, for further comparison, we took a field of area 2 km by 2 km, where we placed our six turbines, with a distance of 1km between each one of them, as the optimal distance between two wind turbines is defined as 7D, where D is diameter of a rotor. For each turbine, the best fitness value is calculated.

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References

1. Mirza, U.K.; Ahmad, N.; Majeed, T. An overview of biomass energy utilization in Pakistan. *Sci. Direct* **2008**, *12*, 1988–1996. [CrossRef]
2. Fridleifsson, I.B. Geothermal energy for the benefit of the people. *Renew. Sustain. Energy Rev.* **2001**, *5*, 299–312. [CrossRef]
3. Kralova, I.; Sjöblom, J. Biofuels-renewable energy sources: A review. *J. Dispers. Sci. Technol.* **2010**, *32*, 409–425. [CrossRef]
4. Ohansson, T.B.W.R.; Kelly, H.; Reddy, A.K.N. Wind energy systems renewable fuels electric a growing world econonic definition achievement potential. *Energy Stud. Rev.* **1993**, *4*, 199–212.
5. Devibala, P. *Optimal Micro-Siting of Wind Turbines in a Wind Park Using Particle Swarm Optimization Algorithm Department of Mechanical Engineering*; Anna University of Technology Coimbatore K: Chennai, India, 2012; pp. 1–6.
6. Hwang, C.; Jeon, J.-H.; Kim, G.-H.; Kim, E.; Park, M.; Yu, I.-K. Modelling and simulation of the wake effect in a wind farm. *J. Int. Counc. Electr. Eng.* **2015**, *5*, 74–77. [CrossRef]
7. Dafrose, B.; Bajaro, C.M. *Horizontal and Vertical Axis Wind Turbines: Wind Energy*; Springer: Berlin, Germany, 2012; pp. 1–9.
8. M'echali, M.R.P.; Barthelemie, R.; Frandsen, S.; Jensen, L. Wake effects at Horns Rev and their influence on energy production. In Proceedings of the European Wind Energy Conference and Exhibition, Athens, Greece, 27 February–2 March 2006.
9. Samorani, M. *Handbook of Wind Power Systems*; Springer: Berlin, Germany, 2013; Volume 12, pp. 3–4.
10. Herbert, G.M.J.; Iniyan, S.; Sreevalsan, E.; Rajapandian, S. A review of wind energy technologies. *Renew. Sustain. Energy Rev.* **2007**, *11*, 1117–1145. [CrossRef]
11. Thevenot, A. Particle Swarm Optimization (PSO) Visually Explained. Available online: https://towardsdatascience.com/particle-swarm-optimization-visually-explained-46289eeb2e14 (accessed on 21 December 2020).
12. Mann, J.; Teilmann, J. Environmental impact of wind energy. *Environ. Res. Lett.* **2013**, *8*, 90–98. [CrossRef]
13. Qiao, L.; Lauha, F.; Sawyer, S. *Global Wind Report Annual Market Update*; Global Wind Energy Council GWEC: Brussels, Belgium, 2010.
14. Bayar, T. German Onshore Wind Growth Slows. Available online: https://www.powerengineeringint.com/renewables/german-onshore-wind-growth-slows/ (accessed on 21 December 2020).