Wind Farm Layout: Modeling and Optimization Using Genetic Algorithm

Item Type	Article
Authors	Asfour, R.;Brahimi, Tayeb;El-Amin, Mohamed
DOI	10.1088/1755-1315/1008/1/01200
Publisher	IOP Publishing
Download date	2026-04-22 04:39:49
Item License	https://creativecommons.org/licenses/by/3.0/
Link to Item	http://hdl.handle.net/20.500.14131/206

IOP Conference Series: Earth and Environmental Science

Wind Farm Layout: Modeling and Optimization Using Genetic Algorithm

To cite this article: R Asfour *et al* 2022 *IOP Conf. Ser.: Earth Environ. Sci.* **1008** 012004

The 6th International Conference on Energy and Environmental Science IOP Publishing
IOP Conf. Series: Earth and Environmental Science 1008 (2022) 012004 doi:10.1088/1755-1315/1008/1/012004

Wind Farm Layout: Modeling and Optimization Using Genetic Algorithm

R Asfour[1], **T Brahimi**[2] **and MF El-Amin**[2]

1 Master Student, College of Engineering, Effat University, Jeddah, Saudi Arabia.
2 Energy and Technology Research Centre, Natural Science, Mathematics and Technology Unit, College of Engineering, Effat University, Jeddah, Saudi Arabia.
E-mail: tbrahimi@effaatuniversity.edu.sa

Abstract. Wind Farm Layout Optimization (WFLO) is a complex multidisciplinary topic that requires a lot of expertise and is becoming an essential part of today's wind farm planning. Yet, selecting optimum wind farm locations is complex, time-consuming, and influenced by environmental factors and upstream turbines inflow wind. The present study attempts to develop an optimization approach based on the Genetic Approach (GA) to determine the most suitable wind turbine locations that maximize the net energy production while minimizing the Cost of Energy (COE) ($/kWh). The WFLO for the optimized objective function was performed for 500, 1000, and 1500 iterations. The best output was obtained for 1500 iterations with the lowest value for the objective function.

1. Introduction

Wind Farm Layout Optimization (WFLO) is a complex multidisciplinary topic that requires a lot of expertise and is becoming an essential part of today's wind farm evolution. Yet, selecting optimum wind farm locations is time-consuming and influenced by environmental factors and upstream turbines inflow wind. Due to the high electricity demand, there has been a need to install several wind turbines in many countries worldwide. In the last decade, the global wind energy capacity has increased from about 190 gigawatts (GW) in 2010 to 743 GW in 2020 [1], and the market is anticipated to triple in the next decade to avoid the impact of climate change, as reported by the Global Wind Energy Council [1]. As a result, large-scale wind farms need to be installed onshore and offshore to get the maximum energy possible. However, it is important to study and optimize wind turbines placement to reduce deficiencies created by the upfront wind turbines. The power loss can reach up to 40% in a full-wake scenario [2]. WFLO aims to ensure that the different wind turbines (WTs) have optimal locations. The process is anticipated to maximize or minimize the single goal or the multiple objectives while meeting the various constraints. To develop a general approach for potentially positioning wind turbines, the degree of staggering mesh has to be defined first to optimize the wind farm layout. Locating the wind turbines in a given area following the stagger mesh approach is accomplished by shifting every row by half grid width to the right. The purpose of this research is to examine the effects of the genetic algorithm's number of iterations on finding the best distribution for wind turbines that maximizes the produced power, hence minimizing the objective function. The rest of the paper is organized as follows: The literature review is presented in section 2. Then, the mathematical modeling in section 3. Section 4 presents the result and discussion. Finally, the conclusion is provided in section 5.

2. Literature Review

The amount of power generated by a wind turbine farm is the only meaningful measure of how successful a wind farm is thus how profitable it is. It is imperative to ensure that a wind turbine farm is designed to consistently generate the maximum power output while minimizing any other factor that would reduce the wind farm efficiency. This is achieved through various optimization techniques used in recent wind turbine farm projects. In 2012, Angelo Teasauro et al. highlighted two common problems in wind farms: arrangement of wind turbine positions and the appropriate type of wind turbines that need to be used. They explored various algorithms, including gradient descent methods, genetic algorithms, viral algorithms, particle swarm algorithms, and greedy heuristic algorithms [3]. Marmidis et al. (2008) optimized the layout of a wind turbine farm in a novel manner by using the Monte Carlo model [4] and for Eroglu et al. using the ant colony algorithm [5].

On the other hand, Chowdhury et al. opted for particle swarm optimization to resolve the non-linear optimization problem that affects the wind turbine layout and employs turbines of varying diameters [6]. Shakoor et al. (2014) studied a combination of generic and definite point selection algorithms to approach the optimal wind turbine layout design problem [7]. Christopher Elkinton et al. [8] focused on minimizing the production costs of the wind turbine farm and maximizing the power output by reducing wake effects. These wake effects are modeled using computational fluid dynamics (CFD) modeling, as achieved by the efficient development of offshore wind farms (ENDOW) project in 2004 [9], to simulate the turbulence effects in the wind flow caused by the wind turbines themselves. In 2015, a study led by Ying Chen et al. created a more accurate simulation of the actual wind conditions instead of more simplified models, leading to real solutions and achieved by a multi-objective genetic algorithm (MOGA) [10]. In 2016, Eirin Fjellanger focused on optimizing the potential relocation of wind turbines, the optimal utilization of the land, and optimizing the wind farm layout, considering the wind speed and wind direction factors [11]. Peter Grat et al. (2016) approach a challenging optimization modeling that includes the optimal placement of wind turbines and that more than one turbine type could be utilized. The study uses the optimization tool CONMIN, which implements a heuristic algorithm [12]. Other standard optimization software for wind turbine farm designs include WindPRO [13] and WAsP [14]. A later study in 2020 by Prateek Mittal and Kishalay Mitra accounts for annual wind speed fluctuations. The solution involves identifying the best and worst possible wind conditions placed in a specified location. These extreme conditions define the design parameters for turbines to withstand the loads imposed on them by wind speed variations while also anticipating the maximum and minimum power generation at a given time [15].

3. Mathematics Modeling and Optimization Method

This section describes cost calculations and wakes to model the wind farm proposed in this research work.

3.1. Wake Model

The Jensens analytical wake model (16) shown in Figure 1 has been used to calculate the actual power extracted from each turbine. The model is based on the conservation of momentum within the wake with a linear expansion in the downstream direction. Applying the law of momentum conservation, we get:

$$\pi r_r^2 u_r + \pi(r_w^2 - r_r^2)u_0 = \pi r_w^2 u_w \tag{1}$$

The radius in the wake expands linearly as $r_w = \alpha x + r_r$ where α is the wake decay constant given by $\alpha = 0.5(ln\ (\frac{z}{z_0}))^{-1}$ with z representing the wind turbine hub height and z_0 the surface roughness height at the site. According to the momentum theory, in the wake, we have $u_r = (1-2a)u_0$ with a the axial induction factor, also related to the thrust coefficient by $C_T = 4a(1-a)$ [16], Substituting in equation (2), we get the normalized downstream wind speed

$$\frac{u_w}{u_0} = 1 - \frac{2a}{\left(1+\alpha\left(\frac{x}{r_r}\right)\right)^2} \tag{2}$$

When a turbine faces different wake impacts from upstream wind turbines, the ensuing speed u_i is calculated by equation the add of the kinetic energy deficits of every wake to the kinetic energy deficit of the mixed wake at that time [16]:

$$u_i = u_{0i} - \left(\sum_{i=1}^{N_T}(u_{0j} - u_{ij})^2\right)^{1/2} \tag{3}$$

u_{0i} and u_{0j} are the velocities at turbine i and turbine j and u_{ij} is the wind speed at turbine i due to the wake of turbine j and N_T is the number of turbines.

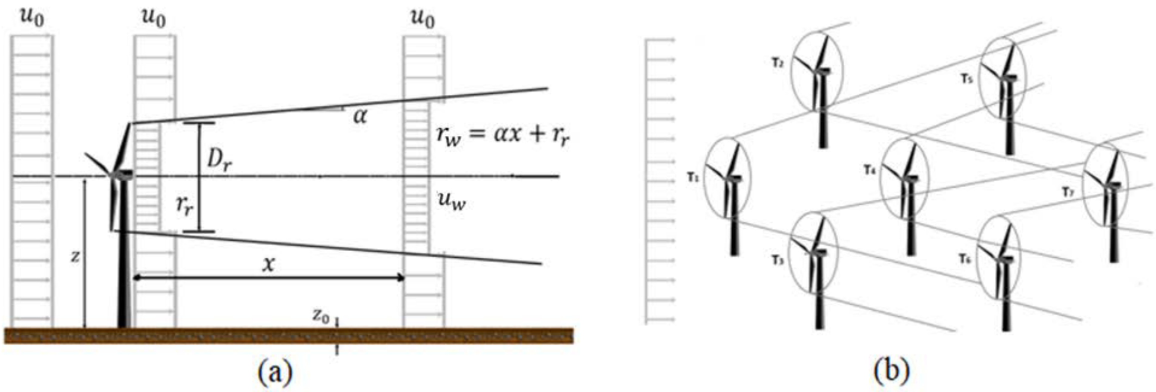

Figure 1. (a) Schematic of Jensen wake model. (b) Multiple wake effects in the wind farm.

The total power extracted by the wind farm is measured by [16]:

$$P_{total} = \sum_i^{N_T} 0.3u_i^3 \ (KW) \tag{4}$$

3.2. Cost Model

The cost model is calculated to estimate the cost of the wind farm. The model is designed to only depend on the number of turbines in the wind farm. This model gives a non-dimensional cost of the wind farm as a function of the number of wind turbines, based on the available discount when many wind turbines are purchased. The total cost of the wind farm per year is calculated using the following equation [16]:

$$Cost = N_T\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N_t^2}\right) \tag{5}$$

Where N_T is the number of wind turbines. To determine the power produced, it should be ensured whether the wind turbine lies in the field of the wake of any other wind turbine or not. If it is in the wake field, which is the case in this study, the wind velocity at the point where the concerning wind turbine is placed is determined using the analytical wake model as discussed earlier. The minimum value of the objective function $Objective = \frac{cost}{power}$ gives the optimal solution.

The essential parameters of the wind turbine farm used in this study are as follows: the hub height is 60 m, and the rotor radius is 20 m. The thrust coefficient of the wind turbine is 0.88, while the axial induction factor is equal to 0.33. Also, the surface roughness length is 0.3m, the entrainment constant is assumed to be 0.0944, and the initial wind velocity is 12 m/s. The number of wind turbines is 60.

3.3. Genetic Model

The optimization process of genetic algorithm applies three different operators: selection, crossover, and mutation. The "selection" process enables the information included in the good chromosomes to survive in the following generation [17]. The "crossover" divides each parent chromosome into two parts that will be exchanged [18]. The "mutation" inverts some genes' values to increase the diversity of the chromosomes in any population [17]. The genetic algorithm finds the minimum objective function given specific parameters mentioned in the previous section for this study. The genetic algorithm is one of the leading optimization random methods that help to determine whether the wind turbine location is optimal or not, thus keeping it or denying it. MATLAB software is mainly used to achieve optimization in this study by using a genetic algorithm to find the best wind turbine distribution with a maximum output power production and minimum cost that yields the minimum objective function. The genetic algorithm is designed to iterate many times. The algorithm inputs are all the parameters written in section 3.2, and the number of iterations is selected thoroughly after examining many numbers and observing the outcomes of the algorithm.

4. Results and Discussion

4.1. Wind Turbine Optimization Layout

The optimal layouts of the turbine distributions are found by applying the genetic algorithm that simulates Darwinian natural evolution. The genetic algorithm is run three times with 500, 1000, and1500 iterations while fixing the values of the parameters listed in Table 1 unchanged for all iterations. The goal of running various iterations is to find the optimal output power and cost with as few iterations as possible. Figure 2 to Figure 4 depict the best wind farm layout optimization (WFLO) for the optimal power Popt with three different iterations, 500, 1000, and 1500 constituting three cases studied in this research. The blue circles represent the possible locations of the turbines according to the staggered mesh approach. In contrast, the asterisks represent the optimal locations among the possible staggered mesh locations for the turbines yielding optimal output power. The layout and number of the turbines (asterisks) and the objective function differ with iterations.

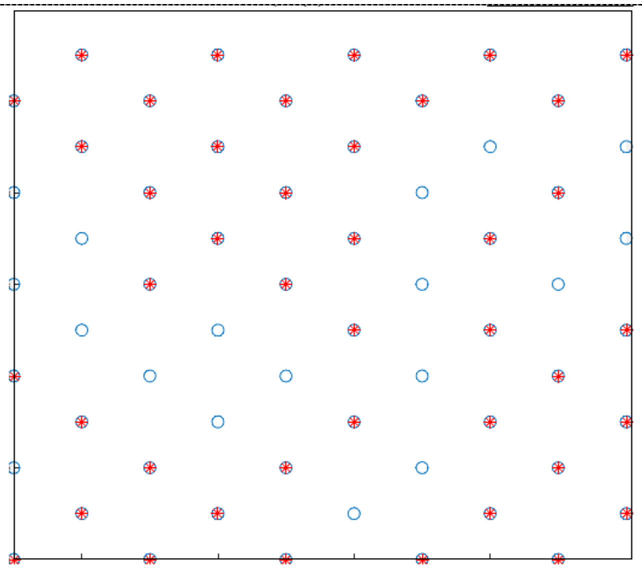

Figure 2. Best wind farm layout optimization for P_{opt} when iteration = 500. Blue circle: possible position, red circle: optimal position.

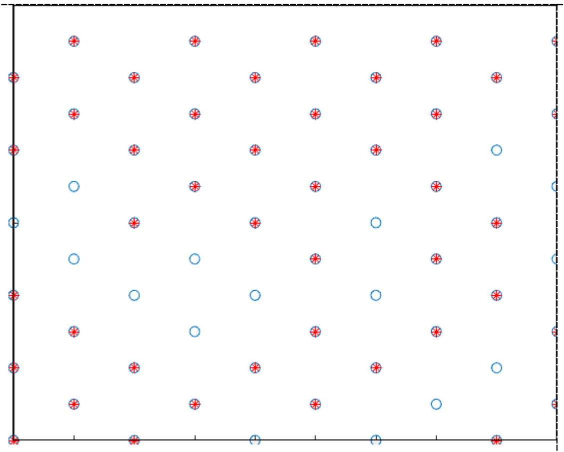

Figure 3. Best wind farm layout optimization for P_{opt} when iteration = 1000. Blue circle: possible position, red circle: optimal position.

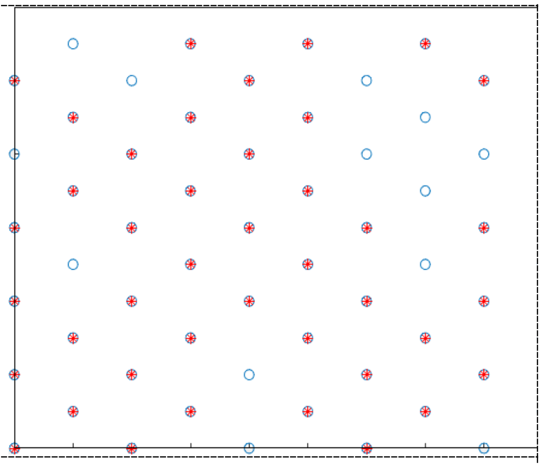

Figure 4. Best wind farm layout optimization for P_{opt} when iteration = 1500. Blue circle: possible position, red circle: optimal position.

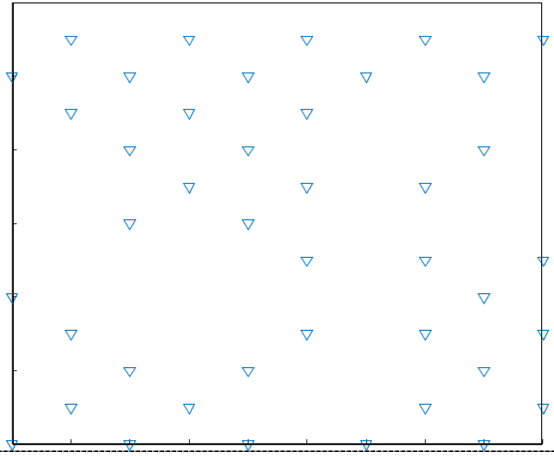

Figure 5. Best WFLO for objective function when iterations = 500. Triangle: optimal position.

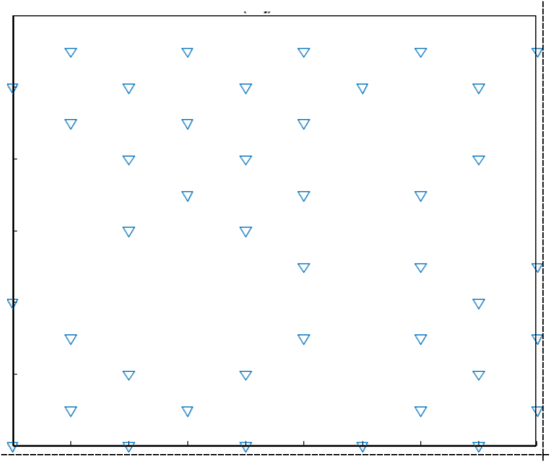

Figure 6. Best WFLO for objective function when iterations = 1000. Triangle: optimal position.

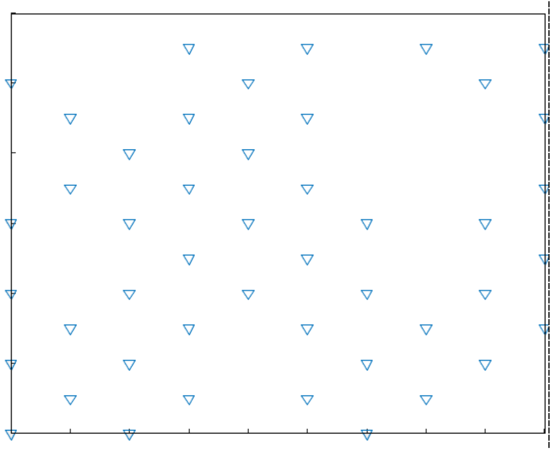

Figure 7. Best WFLO for objective function when iterations = 1500.Triangle: optimal position.

The WFLO for the optimized objective function in the three cases can be seen in Figure 5 to Figure 7. The blue triangles are the best spots for placing the wind turbines that minimize the objective functions within the specific area. The increase in the number of iterations results in decreasing the cost. From Table 1, the lowest cost is found when the number of iterations equals 1500. The objective function is cost overpower (see equation (13), so increasing the denominator, the power, and decreasing the numerator, the cost, reduces the objective function. Hence, the minimal cost and the optimum power there are 1500 iterations leads to having the optimal objective function value of $7.8x10^{-8}$ in comparison with the others.

In short, the objective function is a function of the cost and power output generated. The study examines the effects of increasing the number of iterations on the output power and objective function separately. A cost is a non-dimensionalized unit that is considered to be equal to 1. Therefore, it does not have a natural effect on the objective function. For that reason, minimizing the objective function is dependent only on maximizing the output power. So, the distribution of the wind turbines over a wind farm is the same for output power and objective function, from Figure 2. to Figure 7. Those figures show the best distributions for the power and objective functions that were studied separately.

Table 1. Optimized Parameters

	Iterations = 500	Iterations = 1000	Iterations = 1500
Objective Function	9.8×10^{-8}	8.4×10^{-8}	7.3×10^{-8}
Optimal Output Power ($P_{opt} in\ Watts$)	2.9×10^{8}	3.5×10^{8}	4.2×10^{8}
Minimum Cost	14	16.6	14.7
Number of Turbines	42	44	46

5. Conclusion

This study investigated the impacts of the number of iterations for the genetic algorithm on minimizing the objective function. The study found that optimizing the objective function is only affected by maximizing the power generated by the wind turbines. Moreover, increasing the number of iterations leads to having a better wind turbine distribution, thus increasing the output power and reducing the objective function.

6. References

[1] Global Wind Report 2021 - Global Wind Energy Council, https://gwec.net/global-wind-report-2021/#Download (accessed 30 October 2021).
[2] Wind farm power optimization through wake steering | PNAS, https://www.pnas.org/content/116/29/14495 (accessed 30 October 2021).
[3] Tesauro A. State of the Art of Wind Farm Optimization. 12.
[4] Marmidis G, Lazarou S, Pyrgioti E. Optimal placement of wind turbines in a wind park using Monte Carlo simulation. *Renewable Energy* 2008; 33: 1455–1460.
[5] Eroğlu Y, Seçkiner SU. Design of wind farm layout using ant colony algorithm. *Renewable Energy* 2012; 44: 53–62.
[6] Chowdhury S, Zhang J, Messac A, et al. Unrestricted wind farm layout optimization (UWFLO): Investigating key factors influencing the maximum power generation. *Renewable Energy* 2012; 38: 16–30.
[7] Shakoor R, Hassan MY, Raheem A, et al. Wind farm layout optimization by using Definite Point selection and genetic algorithm. In: *2014 IEEE International Conference on Power and Energy (PECon)*. 2014, pp. 191–195.
[8] Elkinton C, Manwell J, Mcgowan J. Offshore Wind Farm Layout Optimization (OWFLO) Project: Preliminary Results. Epub ahead of print 9 January 2006. DOI: 10.2514/6.2006-998.
[9] Barthelmie R, Larsen G, Pryor S, et al. ENDOW (efficient development of offshore wind farms): modelling wake and boundary layer interactions. *Wind Energy* 2004; 7: 225–245.
[10] Chen Y, Li H, He B, et al. Multi-objective genetic algorithm based innovative wind farm layout optimization method. *Energy Conversion and Management* 2015; 105: 1318–1327.
[11] Fjellanger EM. Wind Farm Layout Optimization - A case study on maximizing the annual energy production in Creyke Beck B., https://bora.uib.no/bora-xmlui/handle/1956/12637 (2016, accessed 29 October 2021).
[12] (PDF) Wind Farm Turbine Type and Placement Optimization, https://www.researchgate.net/publication/308852503_Wind_Farm_Turbine_Type_and_Placement_Optimization (accessed 29 October 2021).
[13] Virtual reality modelling of wind farms including the countryside https://wenku.baidu.com/view/5a7ee559ae1ffc4ffe4733687e21af45b307fe28.html (accessed 29 October 2021).
[14] Mortensen NG, Heathfield DN, Myllerup L, et al. Getting Started with WAsP 9. 69.
[15] Mittal P, Mitra K. In search of flexible and robust wind farm layouts considering wind state uncertainty. *Journal of Cleaner Production* 2020; 248: 119195.
[16] Mosetti G, Poloni C, Diviacco B. Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm. *Journal of Wind Engineering and Industrial Aerodynamics* 1994; 51: 105–116.
[17] Optimization of Wind Farm Layout Using Genetic Algorithm. *www.esteco.com*, https://www.esteco.com/modefrontier/optimization-wind-farm-layout-using-genetic-algorithm (2013, accessed 29 October 2021).
[18] Amaral R de M. *Métodos computacionais em engenharia mecânica*. masterThesis, FCT - UNL, https://run.unl.pt/handle/10362/1800 (2008, accessed 29 October 2021).

Acknowledgments

The authors gratefully acknowledge the support of Effat College of Engineering at Effat University, Jeddah, Saudi Arabia.