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Optimal Location of Wind Turbines in a Wind Farm using Genetic Algorithm

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Abstract
In the present study, genetic algorithm has been used to resolve the placement of wind turbines in a wind park giving maximum power and efficiency with minimum number of turbines. Unlike past approaches where each plot was subdivided into smaller square grids at the centre of which a turbine can be placed, the present study does not require division of the plot. Thus, a turbine now has more flexibility to be placed anywhere outside a radius of 200m of each other yielding better results. The case of unidirectional uniform wind is considered and 600 individuals evolve 3000 generations. Along with the optimal layout, fitness value, total power output, efficiency and number of turbines have also been reported. Comparison with results of earlier study and possible explanation is also provided.

Keywords: *wind turbine, optimization, wake effect, genetic algorithm*

1. Introduction

One of the major concerns today is increased consumption, increased cost, depleted natural resources, our dependence on foreign sources, and the impact on the environment and the danger of global warming. Alternative energy sources, also called renewable resources, deliver power with minimal impact on the environment. These sources are typically more green/clean than traditional methods such as oil or coal. One such source of energy is wind. This is a great self-renewable source of energy that will never run out. Also it has additional advantages like no pollution or greenhouse gas emissions and is plentiful, clean and widely distributed. Wind turbines also take up less space and can be placed in any terrain or remote locations like offshore, mountains and deserts. Cost of the wind energy technology is reducing rapidly and thus beginning to actually compete with existing fossil-fuel power production methods.

An advantage of a wind farm is that the fixed costs are spread over a bigger investment, thus, making wind energy competitive. Thus, the optimal design of wind farms is of capital interest as it governs the energy obtained from the wind while reducing the cost of installation. One of the most important aspects of wind farm design is the relative distribution of the turbines for obtaining an optimal geometry of the wind farm, because the turbines receive lower wind speeds and less energy captures if they are located behind one another or close together. This effect is called the wake effect and is discussed later. Thus, our primary concern in this project is to develop an efficient algorithm which can generate the optimal layout of the turbines in the farm that can give us maximum power with least expenditure.

Our work is conducted assuming that the concerned farm fulfils all the criteria of site selection and technical aspects. The program code for optimisation is developed in MATLAB, based on genetic algorithm.

2. Past Approaches

According to Bansal *et al*.[1], 10ha/MW can be taken as the land requirement of wind farms including infrastructure. Further studies done by Patel [2] indicate that the optimum spacing is found in rows 8–12-rotor diameters apart in the wind direction, and 1.5–3-rotor

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diameters apart in the crosswind direction. But Ammara *et al.* [3] in 2002 found it inefficient and proposed a dense and staggered scheme giving similar production with less land requirements. The first approach using genetic algorithm in micro-siting was made by Mosetti *et al.* [4]. The aim was to maximise the total power generated and minimise the investment cost. But since the results did not yield even the simplest empirical placement schemes, Grady *et al.* [5] in 2005 made a study based again on genetic algorithm using computerised program in MATLAB. G. Marmidis *et al.* (2008) [6] used a totally different approach known as Monte-Carlo simulation. This was followed by the study based on genetic algorithm done in 2010 by Emami *et al.* [7] using a modified objective function. The present study is done using the same optimisation algorithm but we try to obtain better and more efficient configurations by changing the placement criterion. However, the basic approach remains the same and hence the results of the studies are comparable.

3. Modelling

The wake model used in this analysis is similar to the one developed by N.O.Jensen [8]. This is the same model used by the earlier studies. It is based on global momentum conservation in the wake downstream of the wind turbine. The near field behind the wind turbine is neglected; therefore the resulting wake is modelled as a turbulent wake or negative jet. Since it neglects the contribution of tip vortices, this wake model is applicable only in the far wake region.

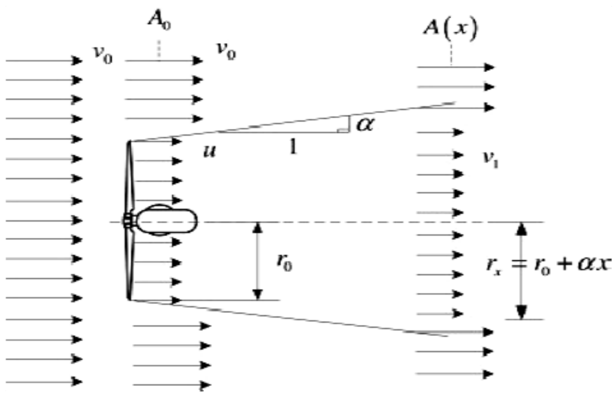


Figure 1. Schematic of Wake Model

Several assumptions have been made in the analysis to simplify the model. At the turbine the wake has a radius r_0. As the wave propagates (as shown in Figure 1) the radius of the wake increases proportionally to the downstream distance, x. with the help of Betz theory and applying the continuity equation we can show that:

Momentum balance gives:

$$\pi r_0^2 v_0 + \pi (r^2 - r_0^2) u = \pi r^2 v \tag{1}$$

Assuming $v_o = \frac{1}{3} u$ and $r = \alpha x + r_0$, we get:

$$v = u[1 - \frac{2}{3}(\frac{r_0}{r_0 + \alpha x})^2] \tag{2}$$

Taking the axial induction factor, $a = \frac{1}{3}$

The velocity of wake at a distance, 'x' simplifies to:

$$v = u[1 - \frac{2a}{(1 + \alpha \frac{x}{r_0})^2}] \ , \tag{3}$$

Where u is the mean wind speed, α is the entrainment constant and r is the downstream rotor radius.
Power produced,

$$P = \frac{1}{2}\eta\rho A u^3 \tag{4}$$

Assuming η = 40%, ρ = 1.2 kg/m³ and A = π x 20^2 sq.m, we get:
Power,

$$P = 0.3u^3 \text{ kW} \tag{5}$$

Here, η stands for efficiency, ρ for density and A for area.
The downstream rotor radius r1 and the turbine coefficient C_T are:

$$r_1 = r_0\sqrt{(1-a)/(1-2a)} \tag{6}$$

$$C_T = 4a\ (1-a) \tag{7}$$

The entrainment constant is given empirically as:

$$\alpha = \frac{0.5}{\ln(z / z_0)} \tag{8}$$

Wwhere z is the hub height of the wind turbine and z_0 is the surface roughness of the site.
Assuming that the kinetic energy deficit of a mixed wake is equal to the sum of the energy deficits, the resulting velocity downstream of N turbines can be calculated using the following expression:

$$(1 - u / u_0)^2 = \sum_{i=1}^{N} (1 - u_i / u_0)^2 \tag{9}$$

In order to calculate the total cost, we used the cost model used by Mosetti et al. in order to optimise the model. They considered that the total cost/year of a wind farm can be formulated as:

$$Cost = N(\tfrac{2}{3} + \tfrac{1}{3}e^{-0.00174N^2}) \tag{10}$$

Efficiency of the wind farm can be calculated as:

$$\text{Efficiency} = P_{total}/(0.3Nu_0^3) \tag{11}$$

The objective function that we considered in our work to find the optimal result (minimum cost per unit of energy produced) is:

$$\text{Objective} = \text{cost}/P_{total} \tag{12}$$

4. Genetic Algorithm and Optimisation

Classical methods would be very complex and difficult to be used to solve a discrete problem like wind farm positioning involving a large number of variables. Unlike calculus-based methods, we require an algorithm that uses only the objective function and do not require its derivatives for search. Genetic algorithms (GAs) are search methods based on principles of natural selection and genetics. GAs encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are referred to as chromosomes, the alphabets are referred to as genes and the values of genes are called alleles. Another important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, we can start to evolve solutions to the search problem [9].

For the initialisation of the random individuals of the population certain parameters and procedure need to be followed. Minimum value of objective function is then compared across a range of turbines to find the optimal number. Parameters considered for the initialisation process are:

a) Number of variables: Taken as twice the number of turbines.
b) Population size: is the total number of solutions in a set.
c) Constraints: Size of the wind farm.
d) Optimisation criteria: Maximum number of iterations, stall generations and function tolerance. The flow chart used for this study is shown in Figure 2:

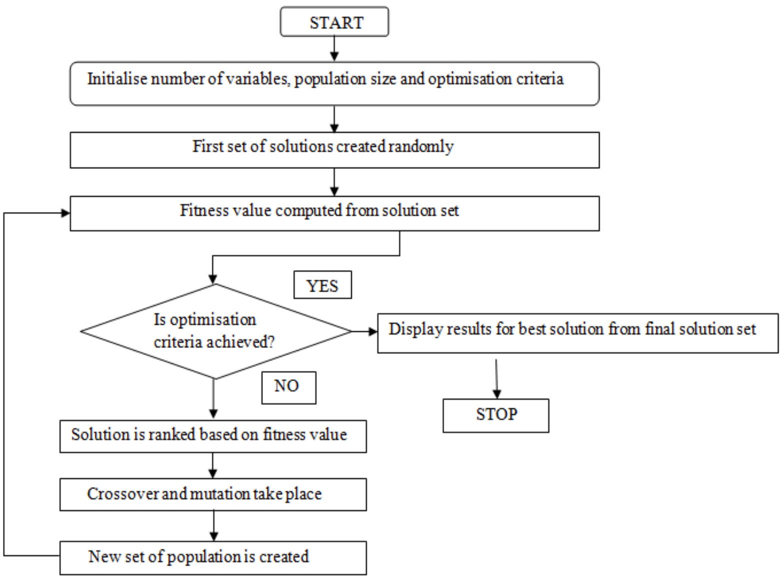


Figure 2. Flow Chart Describing Genetic Algorithm

5. Numerical Procedure

A square plot (2km X 2km) has been chosen. Unlike past approaches which divide the plot into 100 cells for a maximum of 100 turbine locations, the present study just restricts the minimum distance between two adjacent turbines to 200m (as 5D (200m) satisfies the rule of thumb spacing requirements). This minimises the constraints in placing the turbines giving us greater flexibility to increase efficiency and total power. The turbines, now, do not require to be put in columns one after another but can be placed randomly provided they are 200m apart. This further helps in reducing wake effect yielding better results.

The turbine considered for study has properties given in Table 1:

Table 1. Wind Turbine Properties

Hub height	z	60m
Rotor radius	r_0	40m
Thrust coefficient	C_T	0.88
Ground roughness	Z_0	0.3m
Wind velocity	u_0	12m/s
Axial induction factor	a	0.33
Entrainment constant	α	0.094
Downstream rotor radius	r_1	55.75

The thrust coefficient is taken constant throughout the processes and ground roughness of the site is taken as z_0 = 0.3m. The power curve presented in Mosetti *et al.*'s study for the turbine under consideration yields the following expression for power:

$$P = \sum_{1}^{N} 0.3 U_i^{\,3} \,. \tag{13}$$

The case assessed here assumes uniform wind direction with a wind speed of 12m/s.

6. Results and Comparisons

Since this case considers wind speed of 12m/s in a uniform direction, the wake created depends only on the downstream distance. As explained earlier, our program does not restrict the placement of the turbines in specific grids but can be placed anywhere within the area provided they are minimum 200m distance apart and deliver better output. Our study considers 600 individuals to evolve over 3000 generations. Figure 3 illustrates fitness value evolution for a maximum of 1200 generations.

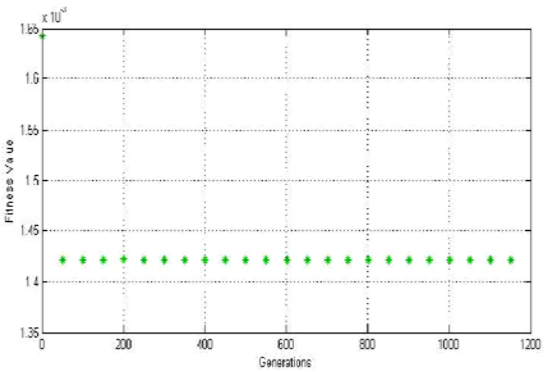


Figure 3. Fitness Curve (No. of turbines is 30)

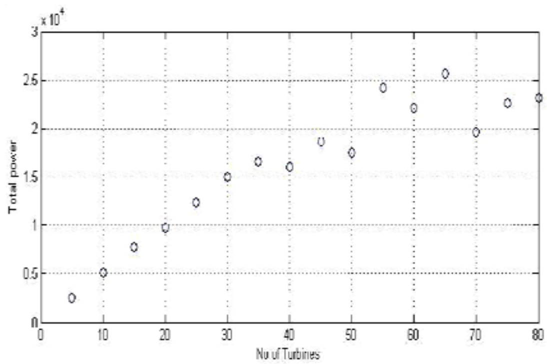


Figure 4. Total power vs. no. of Turbines

The values suggest that initially the fitness value is very high but then drops drastically to settle down to a constant value of .001421. The graph is similar to the results in earlier papers.

When the program was run for different number of turbines, the total power increased linearly (till around 1.7 x 10^4kW) for a maximum of approximately 35 turbines. As the number of turbines was further increased, there were only slight increase seen in the total power output and it settled to a value of around 2.4x10^4 kW (Figure 4).

With the new approach of placing the turbines, we found that our results are better than that of the previous studies. Results computed for different number of turbines are tabulated and shown. Table 2 is a comparison of the results of the present study and earlier results.

Table 2. Comparison of Solution Characteristics

	Mosetti et al.	Grady et al.	Marmidis et al.	Emami et al.			Present study				
No. of turbines	26	30	32	20	30	10	26	30	32	20	10
Total Power (kW/year)	12352.00	14310.00	16395.00	10164.00	14310.00	5184.00	13471.00	15019.00	16552.18	10365.86038	5184.00
Fitness value	0.00162	0.001544	0.0014107	Discrepancies present			0.001500	0.00140	0.0013973	0.001607	0.0018263
Efficiency	91.645	92.015	Not reported	98	92	100	99.8	96.5700	99.77	99.97	100
weight of cost (w1)	Taken to be small. Value not mentioned	weights not considered	weights not considered	0.35	0.2	0.6	weights not considered				
w2				0.65	0.8	0.4					

The tabulated data indicates that in each of the cases our turbine configuration produces larger power output giving better efficiency. The fitness values obtained are also lesser than values earlier reported. This work has tried to improve upon some drawbacks present in the earlier studies. A detailed comparison of earlier studies is given in Table 3.

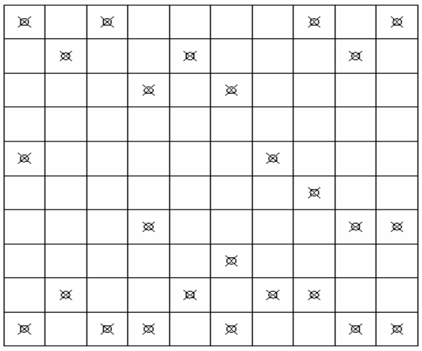
Table 3. Detailed Descriptions of Past Approaches

	Mosetti et al. (1994)	Grady et al. (2005)	Marmidis et al. (2008)	Emami et al. (2010)
Objective function (minimise)	Single objective	Single objective	Single objective	Multi-objective
Cost/year	Same	same	same	same
Technique used	Genetic algorithm	Genetic algorithm	Monte Carlo simulation	Genetic algorithm
Power	reported	reported	reported	reported
Efficiency	Not considered a parameter	Not considered a parameter	Neither calculated nor considered	Considered and calculated in some cases

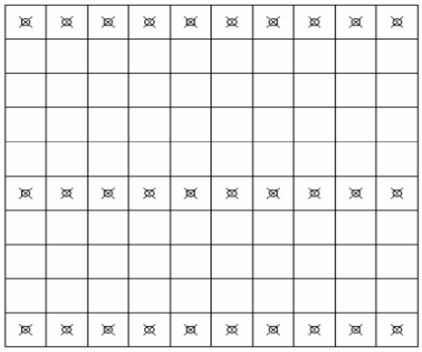
The layout of the earlier works and the present study is given below (Figure 5) for comparison.

7. Conclusion

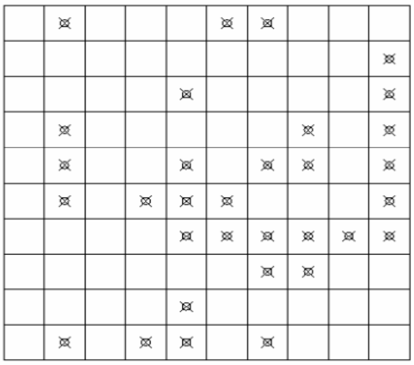
The present study shows that genetic algorithm is very effective in predicting the optimal turbine configurations. Our new approach of placing the turbines anywhere in the area at a minimum distance of 200m from each other clearly reduces the overall wake effect in the farm and generates more power. In fact, in real world it is not difficult to place turbines with co-ordinates measured in units of metres. Also our study has involved a working out layouts for different number of turbines ranging from 10 to 32 and all have shown better results.



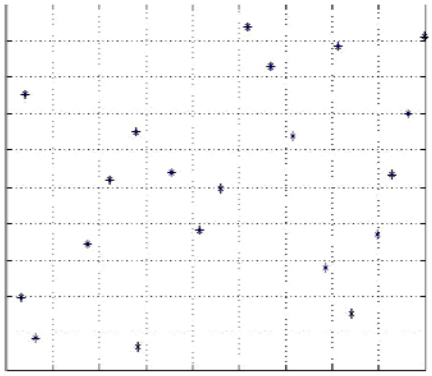
Mosetti et al.'s optimal layout



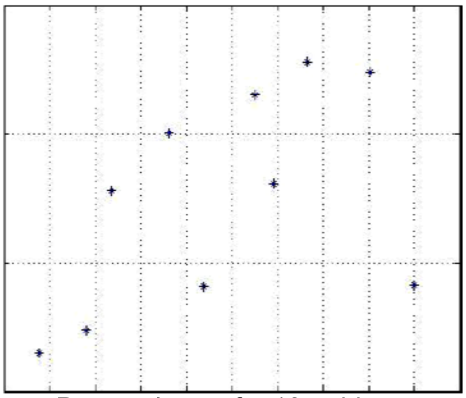
Grady et al.'s and Emami et al.'s optimal layout



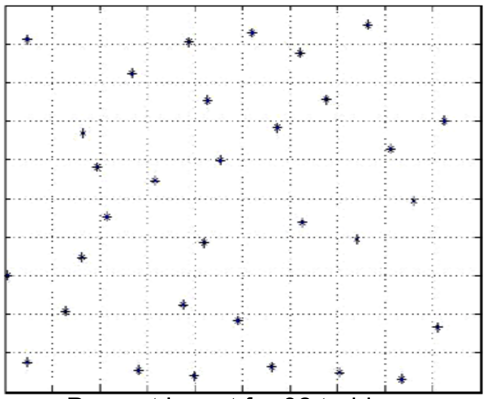
Marmidis et al.'s optimal layout



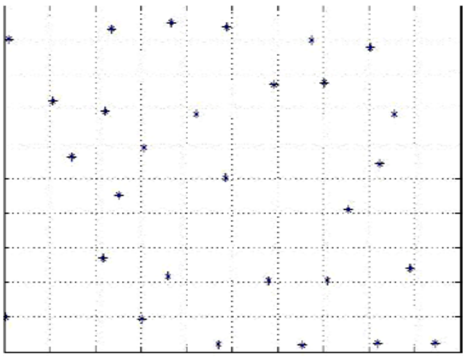
Present layout for 20 turbines



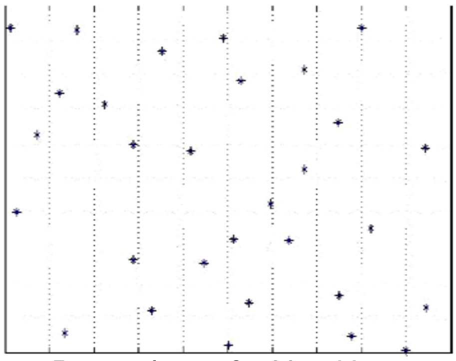
Present layout for 10 turbines



Present layout for 32 turbines



Present layout for 29 turbines



Present layout for 30 turbines

Figure 5. Layouts of the Wind Farm from Different Studies

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