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Analysis of Crossover and Mutation Effects on Wind Farm Performance Using Genetic Algorithms at Two Wind Speeds

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***Abstract*— This study addresses the critical challenge of optimizing wind farm layouts, where the performance is highly sensitive to the configuration of evolutionary algorithm parameters. Specifically, the research investigates how varying crossover and mutation rates in Genetic Algorithms (GAs) influences the efficiency of wind farms under two wind speed conditions: 10 m/s and 12 m/s. The aim is to identify parameter settings that maximize energy output. A parametric study is conducted with crossover rates ranging from 0.01 to 0.9 and mutation rates from 0.01 to 0.1. The analysis reveals that at 12 m/s, a crossover rate of 0.9 and a mutation rate of 0.1 yield the best performance, while at 10 m/s, the optimal values are 0.75 and 0.1, respectively. These results underline the importance of adapting GA parameters to specific wind conditions. The study concludes that tailored parameter tuning significantly enhances wind farm efficiency, providing valuable insights for the design of robust and adaptable optimization strategies.**

***Keywords*— genetic algorithms, wind farm, optimization, tuning, GA parameters**

I. Introduction

Wind energy is a key renewable resource, offering cost-effective electricity with minimal environmental impact. By 2050, it may surpass biomass and photovoltaics in affordability [1] [2]. Its rapid growth is driven by climate change, energy security, rising fossil fuel costs, and increasing investor interest [3] [4] [5].

Wind energy availability varies globally, with some regions more suitable due to optimal wind conditions [6] [7]. Proper turbine placement is crucial to maximizing energy output and minimizing costs by reducing wake effects. This phenomenon occurs when a turbine extracts energy from the wind, creating a low-speed zone behind it, which reduces the efficiency of downstream turbines [8] [9]. The wake effect depends on wind speed, direction, and turbine design [10].

Mosetti et al. (1994) first optimized turbine placement using GA [11]. later improved by Grady et al. (2005) with a refined objective function [12]. Marmidis et al. (2008) applied the Monte Carlo method [13]. By 2021, optimization advanced with Wu and Wang’s improved ant colony optimization (ACO) [14]. Ogunjuyigbe’s GA adaptation for multidirectional winds [15]. and Asfour et al.'s (2022) GA-Jensen model integration to enhance energy output and reduce costs [16].

Genetic algorithms, based on Darwin’s evolution theory, generate and evolve solution populations to find optimal ones [17]. Widely used in problem-solving, they are especially effective in wind farm planning [18].

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Starting with a random population, the algorithm applies selection, crossover, and mutation to explore the search space, iterating until a satisfactory solution is found [19].

This study optimizes a wind farm using GAs at 12 m/s and 10 m/s to assess speed variation effects on convergence and identify optimal parameters through trial and error. Results are compared on technical (energy output) and economic (cost) levels to better understand wind speed's impact on GA optimization.

The paper is structured as follows: Section 2 describes the study context. Section 3 outlines the wind farm characteristics and adopted methodology. Section 4 presents and discusses the results, comparing optimal configurations and analyzing wind speed effects. Finally, Section 5 summarizes key findings and future research directions.

II. PROBLEM FORMULATION AND MODELLING APPROACH

In order to estimate the power output, drop that wind turbine wakes cause, several models to describe their impacts have been established since 1980 [20] [21]. In this paper, we have chosen to work with a simple single wake model made by Jensen "Fig. 1", with a linearly expanding diameter [22] [23].

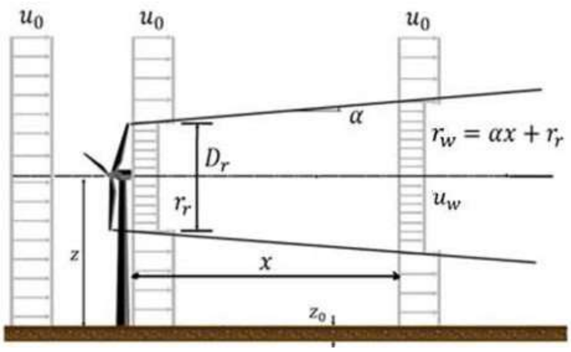

Figure I The Jensen Wake Effect Model

The radius r_1 is proportional to the downwind distance, x and is calculated by the following expression:

$$r_w = \propto x + r_r \qquad (1)$$

The wake's rate of expansion with distance is determined by $\propto$, which is defined as:

$$\propto = \frac{1}{2\,ln\left(\frac{Z}{Z_0}\right)} \qquad (2)$$

Z is the height of the turbine generating the wake and Z_0 is the *surface roughness, depending on the characteristics of the terrain.*

The velocity in the wake at a distance x from the wind turbine can be obtained by solving (3):

$$u_w = u_0\left[1 - \frac{2a}{\left(1+\propto (x/r_1)\right)^2}\right] \qquad (3)$$

This equation defines wake speed based on incoming wind speed. Wind farm costs depend on location, equipment, and wind conditions, but the economic model considers only turbine count in total cost calculation [24]. Thus, annual farm costs are expressed as follows:

$$cost = \left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) \qquad (4)$$

Our main objective is to minimize the cost per unit of energy, namely:

$$fitness = \frac{Cost}{Power} \qquad (5)$$

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In general, the power calculation in a wind farm is based on the starting and stopping wind speed of the wind turbine. Wind power is directly proportional to the cube of wind speed and is generally represented by the following equation:

$$P = \frac{1}{2}\rho A u^3 \eta \qquad (6)$$

In this mathematical statement:

Wind power P in watts (W) depends on the swept area A in m², air density ρ in kg/m³, wind speed u in m/s, and the efficiency coefficient η, which accounts for energy conversion losses.

Having established the modeling approach and objective function, we now describe the implementation of the optimization process using Genetic Algorithms.

III. GENETIC ALGORITHM IMPLEMENTATION FOR WIND FARM OPTIMIZATION

The wind farm consists of 100 cells over a 2 km × 2 km area, each 200 m wide (5 rotor diameters), with a soil roughness of 0.3. GA-based optimization begins with 300 individuals, where grid cells act as chromosomes (1 for a turbine, 0 for absence). The fitness function is the cost/power ratio, and selection assigns reproduction probabilities, maintaining an elitism rate of 0.2.

Crossover and mutation coefficients, set at 0.15 and 0.045, were based on literature values (0.01–0.9 for crossover, 0.01–0.1 for mutation). The method was tested at 12 m/s and 10 m/s to compare performance variations, as shown in Fig. II.

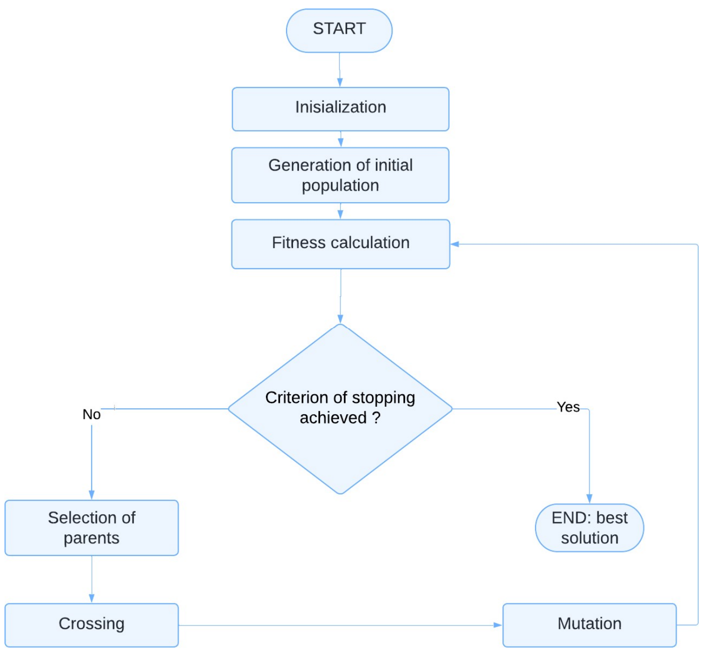

Figure II flowchart of GA method

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With the optimization framework in place, the next section presents and analyzes the results obtained under different crossover and mutation rates at two wind speeds.

IV. RESULTS AND DISCUSSIONS

This section presents the impact of varying crossover (P_c) and mutation (P_m) rates on wind farm performance at two wind speeds: 12 m/s and 10 m/s. The Genetic Algorithm was executed under multiple parameter settings, and the total annual power output and the corresponding fitness values were recorded. The detailed results are summarized in Table 1.

Table 1 Total power and fitness value results for 12m/s and 10m/s

Pc	Pm	Total Power (kW/yr) (12 m/s)	Fitness Value (12 m/s)	Total Power (kW/yr) (10 m/s)	Fitness Value (10 m/s)

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Pc	Pm	Total Power (kW/yr) (12 m/s)	Fitness Value (12 m/s)	Total Power (kW/yr) (10 m/s)	Fitness Value (10 m/s)
0.01	0.01	14451	0.00156444	8115	0,00278591
0.01	0.055	14530	0.00155593	8195	0.00275872
0.01	0.1	14621	0.00154625	8278	0.00273106
0.15	0.01	14658	0.00154234	8300	0.00277382
0.15	0.055	14651	0.00154308	8362	0.00270338
0.15	0.1	14628	0.00154551	8260	0.00273696
0.3	0.01	14642	0.00154403	8597	0,00262972
0.3	0.055	14637	0.00154456	8595	0.00262970
0.3	0.1	14613	0.00154709	8778	0.00257489
0.45	0.01	14662	0.00154192	8830	0.00255993
0.45	0.055	14620	0.00154635	8025	0.00281686
0.45	0.1	14597	0.00154879	8128	0.00278130
0.6	0.01	14557	0.00155304	8483	0.00266499
0.6	0.055	14663	0.00154182	8077	0.00279897
0.6	0.1	14460	0.00156346	8362	0.00270338
0.75	0.01	14602	0.00154826	8780	0.00257489
0.75	0.055	14641	0.00154413	8545	0.00264548
0.75	0.1	14615	0.00154688	9065	0.00249376
0.9	0.01	14514	0.00155764	8831	0.00255993
0.9	0.055	14465	0.00156292	8597	0.00262970
0.9	0.1	14672	0.00154087	8311	0.00277006

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The Figure III presents the variation of total power output as a function of (P_c, P_m) at both wind speeds.

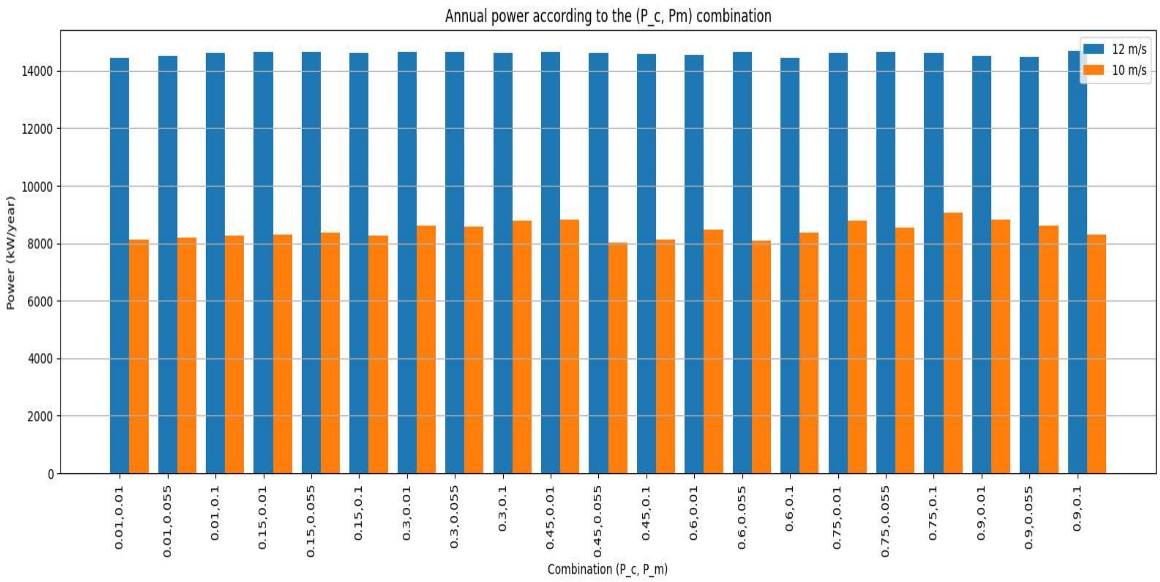

Figure IV Annual power according to the (Pc,Pm) combination

A. Analysis of Crossover Rate Impact (P_m=0.1)

To isolate the effect of crossover rate, we analyzed results with a fixed mutation rate of P_m = 0.1. At 12 m/s, the power output exhibits an overall increasing trend with P_c, peaking at 14,672 kW/year when P_c= 0.9. This indicates that higher crossover rates effectively promote exploration and diversity within the population, facilitating the discovery of high-quality solutions. However, the gain is not strictly linear, suggesting that too frequent recombination may disrupt building blocks in some cases.

Conversely, at 10 m/s, the power output reaches a maximum of 9,065 kW/year at P_c= 0.75, then drops when P_c increases to 0.9. This decline suggests that under lower wind energy availability, excessive crossover may lead to premature convergence or destruction of promising individuals before they can fully evolve.

B. Analysis of Mutation Rate Impact (P_c= 0.01)

By fixing P_c= 0.01, we examined the sensitivity of power output to changes in the mutation rate. Results show that increasing P_m from 0.01 to 0.1 enhances performance at both wind speeds. At 12 m/s, power rises from 14,451 kW/year to 14,621 kW/year, and at 10 m/s from 8,115 kW/year to 8,278 kW/year.

This trend can be attributed to the fact that mutation helps maintain genetic diversity and avoids local optima. However, additional tests with higher P_c values reveal that excessive mutation may reduce performance, as seen when P_m= 0.1 leads to lower power than P_m= 0.055 in some cases. Thus, there is an optimal mutation threshold beyond which disruptive mutations outweigh their benefits.

Both parameters (P_c, P_m) show strong interaction effects and should not be optimized independently. These results underscore the non-universality of optimal parameters and reinforce the idea that algorithm tuning should consider environmental conditions—in this case, wind speed. The key conclusions and implications of this study are summarized in the next section.

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V. Conclusion

This study represents the important influence of wind speed and genetic algorithm (GA) parameters on optimization performance of a wind farm. The results show that the optimal combination of crossover (P_c) and mutation (P_m) rates is different for each case due to different characteristics of the wind farm. At a wind speed of 12 m/s, values of P_c = 0.9 and P_m = 0.1 give the highest power of 14672 kW/yr, while the optimum parameters for 10 m/s are P_c = 0.75 and P_m = 0.1 with a power of 9065 kW/yr. These variations point out the non-universality of optimal parameters and the necessity of a new approach to adapt the parameters in dependence on a wind farm's characteristics—most typically, wind speed—to better increase performance and efficiency without trial-and-error recalibration so that the robustness and efficiency of AGs in any context or particular condition of the wind farm are improved. Future studies could also explore advanced metaheuristic approaches such as the Grey Wolf Optimizer (GWO) and the African Vulture Optimization Algorithm (AVOA) to further enhance optimization performance.

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