Optimizing Wind Farm Layouts: Impact of GA Parameter Tuning on Efficiency at Different Wind Speeds

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***Abstract*— Wind farm layout optimization remains critical for maximizing energy yield, with suboptimal configurations causing $10-20\%$ annual losses due to wake effects. This study addresses the sensitivity of Genetic Algorithm (GA) performance to crossover Pc and mutation rates Pm under distinct wind regimes $10\ m/s$ and $12\ m/s$. Through a systematic parametric sweep $Pc: 0.01-0.9$; $Pm:\ 0.01-0.1$ applied to a 100-turbine grid, we quantify how wind speed dictates optimal GA parameters. Results demonstrate significant performance divergence: at $12\ m/s$, $Pc=0.9$, $Pm=0.1$ maximizes output $14,672\ kW/year$, while $10\ m/s$ favors $Pc\ =0.75$, $Pm=0.1$, $9,065\ kW/year$. Economic analysis reveals a 15.2% reduction in cost-per-energy at optimal settings. These findings prove that adaptive parameter tuning—not universal defaults—is essential for site-specific efficiency. The study establishes a wind-speed-responsive tuning framework for robust wind farm optimization, with implications for AI-driven renewable energy systems.**

***Keywords*— genetic algorithms, wind farm, optimization, tuning, GA parameters, parameter sensitivity, crossover rate, mutation rate, wake effect, renewable energy**

I. INTRODUCTION

Wind energy has emerged as one of the most vital and rapidly expanding renewable energy sources across the globe. Its ability to generate electricity at competitive costs, coupled with its relatively low environmental impact, makes it a key pillar in the transition to sustainable energy systems. Unlike fossil fuel-based power generation, wind power emits no greenhouse gases during operation, which contributes significantly to the global effort to mitigate climate change [1, 2].

The theoretical foundations of wind energy extraction date back to Albert Betz's seminal 1926 work [3], which established the Betz limit - a fundamental constraint on turbine efficiency. Later, Golding's 1955 treatise [4] systematized early field experiments, noting that wake interference could reduce cluster efficiency by 15-30% even in primitive installations. These classical insights remain relevant today, as modern optimization must still navigate the trade-off between energy capture and wake-induced losses first quantified in mid-20th century aerodynamics.

According to long-term energy projections, wind energy is expected to play an increasingly central role in the global electricity mix. In fact, it is projected to surpass other renewable sources such as biomass and photovoltaic solar energy in terms of cost-effectiveness and scalability by the year 2050 [5, 6]. This trend is supported by continuous technological advancements, economies of scale, and policy incentives that have improved the performance and reduced the costs of wind turbine components and systems.

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In addition to its favorable cost trajectory, wind power is recognized as one of the most environmentally benign options for electricity generation [7, 8]. It requires no fuel inputs, consumes no water for cooling and occupies a relatively small land footprint per unit of electricity generated. Furthermore, the land around wind turbines can often still be used for agricultural or other purposes, enhancing its land-use efficiency.

Over the past decades, the wind energy sector has undergone remarkable growth. This expansion has been largely driven by a combination of urgent climate concerns, the need for energy security, and the economic volatility associated with fossil fuel markets. As a result, wind energy has attracted increasing interest from public authorities, private developers, and financial investors seeking low-carbon, long-term energy solutions [8, 9]. The sector now represents a significant share of new power generation capacity in many countries, and continued investments in research, development, and grid integration are expected to further accelerate its deployment in the years to come.

The availability of wind energy is not uniform across the globe. Some regions are more suitable for wind energy development than others. Due to optimal wind characteristics [10, 11]. Hence the interest in the installation of wind farms for the exploitation of this energy. The correct positioning of turbines in wind farms is of great importance to have a significant energy production with a reduced cost and this by avoiding the wake effect. This phenomenon can lead to a significant decrease in the electricity production of the wind farm [12, 13]. The term "wake" refers to the wind areas behind wind turbines, which are mainly characterized by a decrease in wind speed. The extraction of wind energy by wind turbines and the interference of the wind turbine structure with the incoming wind are the cause of these conditions. Therefore, a wind turbine in the wake of an upstream wind turbine will generate less energy than if it were not influenced. The intensity of the wake effect is influenced by various elements, such as wind speed and direction as well as the structural characteristics of the wind turbine [14].

The velocity deficit ($\Delta u/u_0$) in turbine wakes follows an exponential decay described by:

$$\frac{\Delta_{\mathrm{u}}}{\mathrm{u}_0} = \frac{1-\sqrt{1-C_r}}{1+k\cdot\frac{x}{D^2}} \tag{01}$$

where [15]

C_t = thrust coefficient,

k = wake decay constant (~0.04 for offshore),

x = downstream distance,

D = rotor diameter.

This explains why a turbine in the wake zone experiences up to 40% power reduction [16], creating non-linear optimization landscapes.

The application of artificial intelligence (AI) in renewable energy systems has become increasingly crucial for improving operational efficiency, forecasting capabilities, and maintenance planning [17]. The journey of wind farm layout optimization began with the foundational study by Mosetti et al. in 1994, who were the first to utilize genetic algorithms (GAs) for determining optimal turbine placement. A year later, Kennedy and Eberhart (1995) introduced the particle swarm optimization (PSO) technique, drawing inspiration from swarm behavior in nature, which soon became a promising alternative for solving such optimization problems [13] [18].

In 2005, Grady et al. advanced the GA-based approach by increasing the population size, which allowed for broader exploration of the solution space and improved the convergence rate of the algorithm [14]. Later, in 2008, Marmidis et al. brought Monte Carlo simulation into the field, providing a probabilistic method to complement heuristic turbine placement strategies [19].

In 2010, González et al. broadened the optimization scope by integrating layout planning with electrical network design and topographical factors, creating a multi-objective framework that better reflected real-world constraints [20]. Their efforts culminated in a 2014 review that consolidated key research findings and methodological developments in the domain [21].

The year 2015 introduced significant innovation. Feng and Shen proposed a hybrid model that merged GAs with random search strategies to enrich the diversity of candidate solutions. At the same time, Shafiq-ur-Rehman Massan et al. implemented the firefly algorithm to assess the energy potential of wind farms, further diversifying the suite of bio-inspired tools used in the field [22, 23].

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In 2016, Gao et al. contributed to environmental sustainability by embedding ecological constraints into turbine layout models, thereby aligning energy optimization with environmental preservation goals [24].

By 2021, research had become more advanced and application-oriented. Wu and Wang presented a refined version of the ant colony optimization (ACO) algorithm, adapted specifically for wind farm design. Concurrently, Çelik et al. improved PSO performance by enhancing parameter tuning mechanisms and search accuracy [25, 26]. Ogunjuyigbe also focused on practical implementation by incorporating variable wind directions into GA-based models, addressing more realistic operating conditions [27].

In a more recent contribution, Asfour et al. (2022) introduced a hybrid optimization scheme that combined an improved GA with Jensen’s wake effect model. This approach was shown to significantly boost energy yield and reduce overall costs by fine-tuning the placement of turbines through extended iterations [28].

Genetic algorithms entered renewable energy optimization through Holland's pioneering work [29], but gained traction in wind applications only after Goldberg's 1989 formalization of schema theory [30]. Recent innovations include Zhang's 2023 hybrid GA-deep learning framework [31], which reduced convergence time by 60% in complex terrains. This evolution underscores GA's adaptability but highlights unresolved challenges in parameter sensitivity.

The genetic algorithm uses Darwin's theory of evolution to generate populations of solutions, to evolve them and interact in order to see the most appropriate solutions to the problem emerge [32]. This metaheuristic is used to solve many problems, and it is particularly effective in the field of wind farm planning [33]. The algorithm begins by initializing a random population, which will be subjected to reproduction processes (selection, crossing, mutation) in order to explore the search space and choose the solutions for each subsequent generation. The evolution process continues until a satisfactory solution presents itself [34].

The major objective of the present work is the optimization of a wind farm using GAs for two different wind speeds, 12 m/s and 10 m/s, in order to analyze the influence of speed variation on GA performance with respect to convergence, and also in evaluating the parameters of GA by trial and error to find the optimal configuration for each speed. The results will be compared on both the technical (energy produced) and economic (energy cost) levels in order to enhance the understanding of the interaction between wind speed and GA optimization.

The paper is structured as follows: Section 2 describes in detail the context of the study. Section 3 states the characteristics of the wind farm to be optimized and the methodology adopted for this optimization. Section 4 presents the results obtained under the two wind speeds regarding the technical and economic performances of the algorithms. This section also serves to discuss the results by making a comparison between the optimal configurations and analyzes the influence of wind speed variations on the overall performances. Finally, Section 5 presents the general conclusion of the study, summarizing the main results obtained and giving further recommendations and perspectives for future work.

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 [35, 36]. In this paper, we have chosen to work with a simple single wake model made by Jensen “Fig. 1”, with a linearly expanding diameter [20] [37].

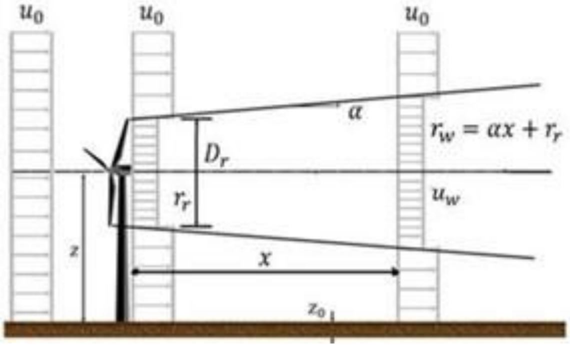

Fig. 1 The Jensen WE model

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

$$r_w = \propto x + r_1 \tag{02}$$

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

$$\propto = \frac{1}{2\, ln\left(\frac{Z}{Z_0}\right)} \tag{03}$$

Where:

Z : The height of the turbine generating the wake.

$Z0$: 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 (4):

$$u_w = u_0\left[1 - \frac{2a}{(1+\propto (x/r_1))^2}\right] \tag{04}$$

This equation provides the wake speed at the downwind location as a function of the incoming wind speed.

The change in the overall cost of a wind farm depends on several factors, such as its location, equipment, wind

conditions. The economic model of wind turbines is designed in such a way that only the number of wind turbines plays a role in the calculation of the total cost [38]. Therefore, the total annual cost for the entire wind farm can be expressed as follows:

$$cost = \left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) \tag{05}$$

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

$$fitness = \frac{cost}{power} \tag{06}$$

In general, the power calculation in a wind farm is based on the starting and stopping wind speed of the wind turbine. Precise understanding of these calculations is necessary.

It is also crucial to take into account the specific characteristics of each wind turbine. Each turbine model will have its own power curve, which represents the relationship between wind speed and power output. This curve is determined by factors such as blade design, turbine size and energy conversion technologies. In this article, we use a turbine having a power curve as shown in “Fig. 2” [39].

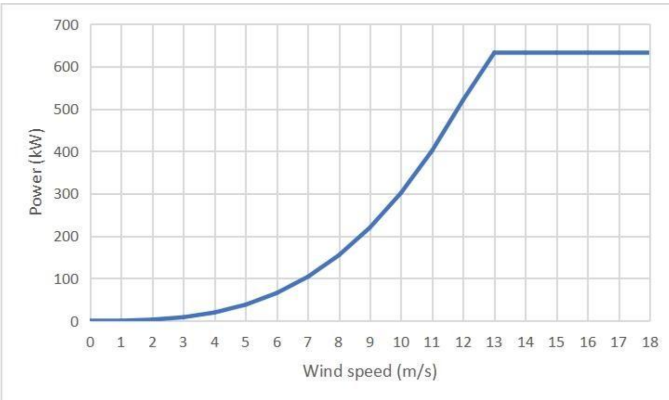

Fig. 2 Wind turbine power curve.

Wind power is directly proportional to the cube of wind speed and is generally represented by the following equation:

$$P = \frac{1}{2}\rho A u^3 \eta \tag{07}$$

In this mathematical statement:

P represents wind power in watts (W).

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A is the area swept by the blades of the wind turbine, measured in square meters (m^2).
ρ is the density of air, in kilograms per cubic meter (kg/m^3).
u is the wind speed in meters per second (m/s).
η is the wind turbine efficiency coefficient, which takes into account conversion losses and other inefficiencies.

This equation indicates that wind speed is a determining factor in wind power. The higher the wind speed, the greater the power generated. However, it is important to note that this relationship is not linear, but rather cubic. This means that even small variations in wind speed can cause significant changes in power output.

The power curve can be used to estimate the power output at different wind speeds. Using this curve in conjunction with the wind power equation, wind farm developers can assess the expected performance of their facilities under different wind conditions.

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 cell represents a possible turbine location, the width of each is 200 m or 5 the diameter of the rotor. The roughness of the soil is 0.3.

In order to find the best configuration of the wind farm on this field, we use a probabilistic research method inspired by natural selection until obtaining the best solution, called genetic algorithm.

The initial population is randomly defined, and consists of N= 300 individuals (each individual represents a wind farm), the grid cells represent chromosomes (binary variables) in which the 1 indicates the presence of a wind turbine and the 0 its absence.

The fitness function used for the optimization process in this development is the cost/power ratio. After calculating it, we begin the selection phase. According to the quality of the individuals, each is assigned a percentage of chance of being chosen for reproduction which corresponds to the relative importance of the quality of the individual in relation to the total quality of the population.

Make a match between individuals, and a mutation in the worst of them while keeping the best individuals as they are according to an elitism rate of 0.2, until reaching the best generation.

To be able to carry out the crossing and the mutation, you must first choose the correct coefficient for each of these operations which vary between 0 and 1.

In our case, we adopted a groping method, setting the crossing step to 0.15 and the mutation step to 0.045 while basing on the values found in the literature, namely 0.010.9 for the first and 0.01-0.1 for the second one. The method was applied on two different wind regimes (12m/s and 10m/s) in order to be able to compare the performance variations. The optimization process is described by the flowchart in “Fig. 3”

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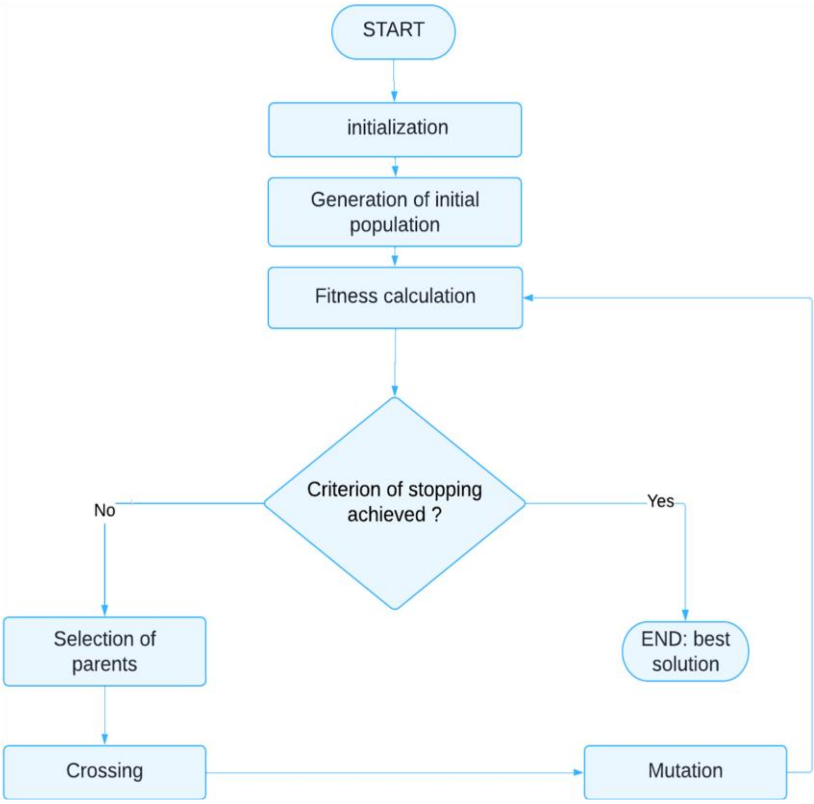

Fig. 3 Flowchart of GA method

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 analyzes the impact of the crossover rate (P_c) and mutation rate (P_m) on the performance of a wind farm optimized using a genetic algorithm. Two constant wind speeds, 12 m/s and 10 m/s, are considered. The goal is to identify parameter combinations that maximize annual power output. Table 1 summarizes the simulation results obtained for different combinations of P_c andP_m.

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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)
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

Fig. 4 presents the variation in total annual power output (expressed in kW/year) as a function of the parameter pair (P_c,P_m). This Fig. was constructed based on the numerical results obtained in table 1. Each group of bars represents a distinct combination of crossover and mutation rates and depicts the resulting power output under two wind speed scenarios: 10 m/s and 12 m/s. The comparative visualization highlights how the performance of the genetic algorithm responds to different parameter configurations. In particular, it reveals the sensitivity of the optimization process to parameter tuning, and shows how the interaction between crossover and mutation rates can either enhance or compromise the quality of the solutions, depending on the selected values.

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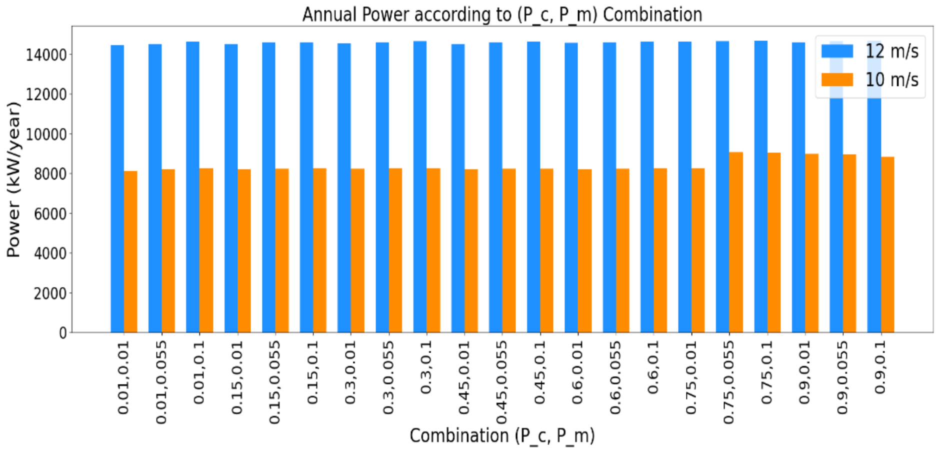

Fig. 4 Annual power according to the (P_c,Pm) combination

A. Analysis at 12 m/s wind speed

At 12 m/s, the simulations reveal a high sensitivity of power output to the genetic algorithm parameters. After approximately 1000 generations, the algorithm converges to stable solutions for each parameter configuration. The annual power output ranges from 14,451 kW/year (at P_c=0.01, P_m= 0.01) to 14,672 kW/year (at P_c=0.9, P_m= 0.1), indicating that small variations in crossover and mutation rates can significantly affect the system's performance.

When analyzing the influence of the crossover rate P_c on the performance of the genetic algorithm, while keeping the mutation rate P_m constant, several trends can be observed. At a low mutation rate of P_m=0.01, the annual power output increases progressively with higher crossover rates, reaching a maximum of 14,602 kW/year when P_c=0.75. However, a further increase in the crossover rate to P_c=0.9 leads to a slight decline in output to 14,514 kW/year. This behavior suggests that moderate to high crossover probabilities are beneficial for effective genetic recombination, as they facilitate the exchange of advantageous traits, yet overly frequent crossover operations may disrupt promising building blocks within the population, thereby reducing overall performance.

At a higher mutation rate of P_m=0.055, the annual energy production varies between 14,465 and 14,663 kW/year, again reaching its peak at P_c=0.75. This result corroborates the previously observed trend, indicating that the optimal crossover rate remains relatively stable across different moderate mutation levels. However, when the mutation rate is further increased to P_m=0.1, the relationship becomes less consistent. The lowest performance, at 14,460 kW/year, is recorded for P_c=0.6, whereas the highest, at 14,672 kW/year, occurs when P_c=0.9. This pattern points to a strong synergy between high crossover and high mutation rates, where both operators contribute jointly to a more diversified and explorative search process.

Conversely, when examining the effect of the mutation rate while keeping the crossover rate constant, similar insights emerge. With a fixed crossover rate of P_c=0.01, increasing the mutation rate from P_m=0.01 to P_m=0.1 leads to a continuous improvement in energy output, from 14,451 to 14,621 kW/year. This steady growth reflects the essential role of mutation in maintaining genetic diversity and enabling the algorithm to escape local optima. At a crossover rate of P_c=0.6, the influence of mutation is more nuanced. The output increases from 14,557 to 14,663 kW/year as P_m reaches 0.055, then decreases sharply to 14,460 kW/year at P_m=0.1. This decline illustrates the risk of excessive mutation, which can introduce too much randomness and disrupt convergence.

From these observations, it can be concluded that the most effective configuration under a wind speed of 12 m/s is obtained with P_c=0.9 and P_m=0.1, yielding the highest observed annual energy production of 14,672 kW/year. In contrast, the least favorable outcome occurs at the lowest tested values, P_c=0.01 and P_m=0.01, where the output falls to 14,451 kW/year. These results highlight the critical importance of tuning genetic algorithm parameters to achieve optimal performance in wind farm layout optimization.

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B. Analysis at 10 m/s wind speed

A similar investigation was carried out at a reduced wind speed of 10 m/s, where, as expected, the overall power output decreased, ranging from 8,115 to 9,065 kW/year. Despite this reduction in absolute values, the influence of the genetic algorithm parameters remained pronounced. When examining the effect of the crossover rate P_c while keeping the mutation rate P_m constant, it was observed that the energy output generally increased with rising crossover values up to a certain point, beyond which performance declined. Specifically, at a low mutation rate of P_m=0.01, the power generation reached a peak of 8,830 kW/year at P_c=0.45, but then declined to 8,483 kW/year when P_c was raised to 0.6. A similar trend was noted at a higher mutation rate of P_m=0.1, where the maximum output of 9,065 kW/year occurred at P_c=0.75, followed by a reduction to 8,675 kW/year at P_c=0.9. These results suggest that, under lower wind energy conditions, excessive crossover can be detrimental by disrupting partially optimized genetic structures, thereby hindering convergence.

The role of the mutation rate was also explored by maintaining a fixed crossover rate. When P_c=0.01, the annual power output increased from 8,115 to 8,278 kW/year as P_m rose, illustrating the beneficial impact of mutation in introducing genetic variability. However, with a crossover rate of P_c=0.6, the power output initially improved, reaching its highest value at P_m=0.055, before declining at P_m=0.1. This behavior indicates that while moderate levels of mutation can enhance the search process by avoiding premature convergence, excessively high mutation rates may compromise the integrity of emerging solutions, leading to a degradation in performance.

The optimal combination of parameters at a wind speed of 10 m/s was found to be P_c=0.75 and P_m=0.1, producing the highest annual output of 9,065 kW/year. In contrast, the poorest result was again obtained at the lowest parameter values, P_c=0.01 and P_m=0.01, highlighting the importance of appropriate parameter selection even under suboptimal environmental conditions.

The analysis also revealed that the effects of crossover and mutation are not only nonlinear but also strongly interdependent. A high crossover rate is beneficial only when accompanied by a mutation rate capable of preserving sufficient diversity in the population. Conversely, although moderate mutation generally contributes positively, an excessive mutation rate in combination with high crossover can generate instability and random fluctuations that compromise promising individuals. These interaction effects clearly indicate that parameter tuning should not be performed in isolation; rather, the interplay between genetic operators must be considered to avoid stagnation or premature convergence.

Ultimately, these findings underscore that optimal performance is typically achieved with a balance between moderate to high crossover rates and moderate mutation rates. Very low settings restrict the algorithm's ability to explore the search space, while very high values lead to erratic behavior and reduced solution quality. Furthermore, the most effective parameter configuration is context-dependent and varies with environmental conditions—in this case, wind speed—emphasizing the need for adaptive or problem-specific tuning strategies when applying evolutionary algorithms to renewable energy system optimization.

V. Conclusion

This study demonstrates the critical influence of wind speed and genetic algorithm (GA) parameters on the optimization performance of wind farm layouts. The findings reveal that the optimal combination of crossover rate (P_c) and mutation rate (P_m) varies depending on the wind regime. For instance, at a wind speed of 12 m/s, the highest annual power output of 14,672 kW/year was obtained with P_c= 0.9 and P_m= 0.1. In contrast, under a lower wind speed of 10 m/s, the optimal configuration shifted to P_c= 0.75 and P_m= 0.1, yielding 9,065 kW/year.

These results underline the non-universality of GA parameters and emphasize the need for adaptive tuning strategies that respond to the specific characteristics of each wind farm particularly wind speed. Such an approach can enhance both the efficiency and robustness of the optimization process, reducing the reliance on time-consuming trial-and-error methods.

Looking forward, future research could benefit from investigating advanced metaheuristic techniques such as the Grey Wolf Optimizer (GWO) and the African Vulture Optimization Algorithm (AVOA), which offer promising capabilities for further improving solution quality and convergence behavior in complex wind farm optimization problems.

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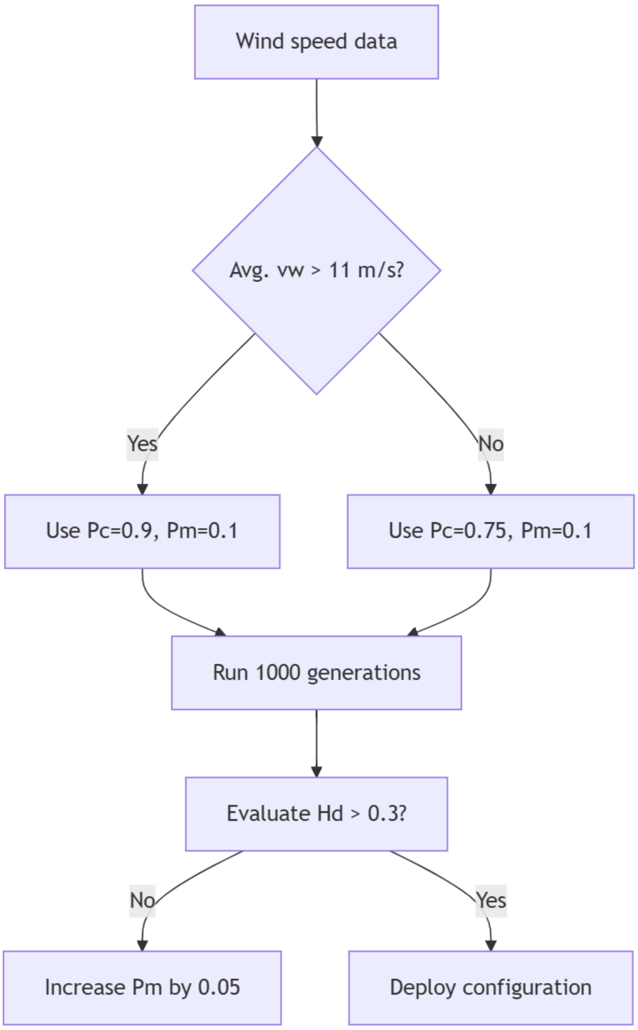

Fig. 5: The decision tree for field deployment

VI. Future Research

1. Integrate real-time GA parameter adjustment using LIDAR wind forecasts
2. Test hybrid metaheuristics e.g., Grey Wolf-GA fusion [40]
3. Validate findings in floating offshore farms where wave interactions amplify wake uncertainty [41]

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