Optimizing Wind Farm Layouts with Genetic Algorithms (Enhancing Efficiency in Wind Energy Planning and Utilization in Bosnia and Herzegovina)

Author: Jure Zorić

Bachelor of Electrical Engineering, Faculty of Technical Engineering, University of Bihać, Bosnia and Herzegovina

Email: jure091@gmail.com

Abstract:

This paper proposes a genetic algorithm-based approach to optimize wind farm layouts in Bosnia and Herzegovina, a country with a high potential for wind energy production. The primary objective is to maximize the total power output derived from the wind farm while concurrently minimizing the wake effects resulting from turbine interactions. This balance is pivotal in ensuring the optimal utilization of wind energy resources. In this study, three different wind data scenarios are considered: a single wind direction with overall average velocity, the most prevalent wind direction with overall average velocity, and an all-encompassing wind direction analysis incorporating a weighted objective function. The results of the study suggest that the genetic algorithm is highly effective in identifying optimal solutions across each scenario. This serves as a testament to the algorithm's accuracy, robustness, and applicability in tackling real-world problems, thereby marking a significant step forward in the realm of wind farm optimization. The limitations of this research include the use of a simplified wake model and a fixed turbine type. The implications of this research include the potential for increasing the efficiency and profitability of wind farms in Bosnia and Herzegovina, as well as informing future research on more complex and realistic optimization problems.

Keywords: Wind Farm Layout Optimization, Genetic Algorithm, Wake Effects, Bosnia & Herzegovina, Wind Energy Utilization

1. Introduction

Wind farm layout optimization (WFLO) is a critical aspect of harnessing wind energy more efficiently, as it focuses on maximizing the energy production from wind farms. One of the main challenges in designing wind farms is the turbine interactions, which can cause energy losses between 10-20% and in some instances, as high as 40% (Stanley & Ning, 2019). These interactions are primarily due to the wake effects created by turbines, which disrupt the wind flow and consequently reduce the power generation of downstream turbines.

To address this issue, minimizing wake effects becomes crucial in order to enhance energy production and increase profitability for wind farm operators. This is where genetic algorithms come into play as an effective optimization method. These algorithms, inspired by natural evolution processes, help identify the optimal layout for wind turbines by using independent variables and an objective function, which usually targets maximizing energy output while minimizing wake losses.

Previous research in the field of wind farm layout optimization using a genetic algorithm has shown significant progress and the potential of this method in improving efficiency and harnessing wind energy. Some key studies include the research by Grady et al. (2005), who used a genetic algorithm to study the optimal layout of wind turbines under different wind direction cases.

Chen et al. (2013) focused on optimizing wind farm layouts using a genetic algorithm with different wind turbine heights, revealing that the use of wind turbines of different heights can increase total energy production and reduce costs per unit of power.

Asfour et al. (2022) developed a genetic algorithm-based optimization approach for determining the most suitable locations for wind turbines that maximizes net energy production while minimizing energy costs.

In addition to these key studies, there are many others that have studied various aspects of wind farm layout optimization, including the Monte Carlo model by Marmidis et al. (2008), the ant colony algorithm by Eroğlu and Seçkiner (2012), particle swarm optimization by Chowdhury et al. (2012), and a combination of genetic and Definite Point Selection (DPS) algorithms by Shakoor et al. (2014).

Furthermore, researchers such as Elkinton et al. (2006) have focused on reducing wake effects, Chen et al. (2015) have used more realistic wind models, and Graf et al. (2016) have utilized multiple types of wind turbines. Also, there are standard software for wind farm layout optimization, such as WindPRO and WAsP (Shakoor et al., 2016).

Although previous research has provided valuable insights into various aspects of wind farm layout optimization, it is clear that there are still areas that require further research and improvement.

1.1. Objectives of the Article

The primary objective of this article is to optimize wind farm layouts in Bosnia and Herzegovina using genetic algorithms. To achieve this, I focus on three main aspects: maximizing the power output, minimizing wake effects, and reducing overall costs associated with wind farm layouts.

My research assesses three distinct wind data scenarios: a single wind direction with an overall average velocity, the most prevalent wind direction with an overall average velocity, and an all-inclusive wind direction analysis that incorporates a weighted objective function. The exploration of these scenarios is designed to reveal the unique challenges and opportunities inherent to each, guiding the development of strategies for wind farm layout optimization.

1.2. Significance of the Article

This article has importance within the field of renewable energy, specifically in relation to wind farm layout optimization. It reiterates the application of genetic algorithms to enhance the efficiency of wind farm layouts, an area of untapped wind energy potential. By examining various wind data scenarios, this study aims to summarize current research, offering comprehensive insights into effective wind farm planning and utilization. Furthermore, the research underscores the role of genetic algorithms in optimizing complex energy systems, reiterating their potential beyond current applications. The insights derived can serve to support other renewable energy initiatives globally, contributing to the broader transition towards sustainable energy sources.

2. Methods of Mathematical Modelling and Optimization

This section details the methods for calculating costs and modeling wakes, which are used to construct the wind farm model proposed in this study.

2.1. Jensen's Wake Model…...

The Jensen's wake model, an analytical wake model, is utilized to determine the actual wind velocity experienced by each wind turbine. This model is based on the law of conservation of momentum within the wake. For a single wake scenario, the near field behind the wind turbine is disregarded, allowing the wake to be modeled as turbulent. The wake's radius, when originating from the wind turbine, is equal to the turbine's radius. As a result, the wake's radius, r_1, grows linearly based on the downstream distance, x, as it moves further downstream, as illustrated in Figure 1.

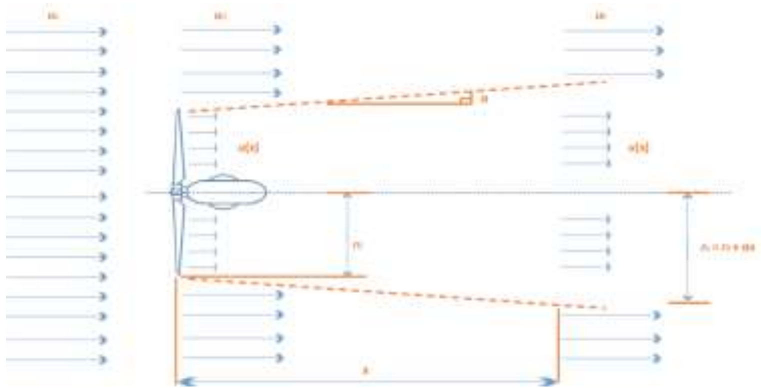

Figure 1. Schematic of Jensen’s Wake Model

The wind speed at downstream, influenced by the wake created by an upstream wind turbine, can be determined using the subsequent formula.

$$u = u_0 \left[1 - \frac{2a}{\left[1 + \frac{\alpha x}{r_1}\right]^2} \right] \qquad (1)$$

where:

- u_0 free stream velocity,
- r_1 radius of wake behind the turbine at distance, x.

$$r_1 = r_d + \alpha x \qquad (2)$$

where:

- r_d radius of wind turbine,
- a axial induction factor.

The axial induction factor, denoted as "a", can be determined using the wind turbine's thrust coefficient, known as c_T.

$$c_T = 4a(1-a) \quad (3)$$

$$\alpha = \frac{0{,}5}{ln\left(\frac{z}{z_0}\right)} \quad (4)$$

where:

- α decay factor,
- z hub height,
- z_0 surface roughness.

The decay factor, α, outlines the breakdown of the wake by defining the expansion of the wake width for every meter traveled downstream. Determining the decay factor depends on factors such as ambient turbulence, turbine-induced turbulence, and atmospheric stability. The parameter, z_0, plays a vital role in calculating the decay coefficient.

In cases where a wind turbine experiences multiple wake effects from upstream turbines, the resulting velocity, u_i, can be determined by equating the combined kinetic energy deficits of each wake to the kinetic energy deficit of the mixed wake at that specific point, as demonstrated in the given formula.

$$u_i = u_0\left[1 - \sqrt{\sum_{i=1}^{N}\left(1-\frac{u}{u_0}\right)^2}\right] \quad (5)$$

The power of the wind turbine is directly proportional to the cube of wind speed. Therefore, to maximize the output power of the wind farm, the wind speed deficit in the previous equation needs to be minimized, as shown in the following expression.

$$Max(P_{total}) \sim Min \sqrt{\sum_{i=1}^{N} \left(1 - \frac{u_i}{u_0}\right)^2} \qquad (6)$$

The cost function, as shown in equation 7 and developed by Mosetti, is based on the number of wind turbines installed. The model is designed to depend solely on the total installed wind turbines in a wind farm (Mosetti et al., 1994).

$$cost = N\left[\frac{2}{3} + \frac{1}{3}e^{-0{,}00174N^2}\right] \qquad (7)$$

where:

- N the number of wind turbines.

The relationship between the cost function and the number of wind turbines can be seen in Figure 2. The visualization shows how the cost function is affected by different numbers of wind turbines within the wind farm, demonstrating the impact on total costs as the size of the installation changes. For smaller wind farms, the cost function is nonlinear, which has a greater impact on the objective function. It is assumed that the cost of individual wind turbines will decrease as more wind turbines are purchased, maintained, or installed.

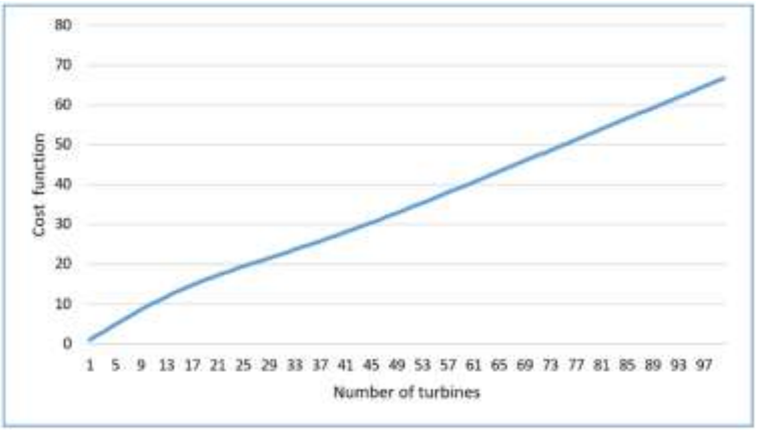

Figure 2. Mosetti's Wind Turbine Cost Model Plot

In general, the objective function for wind farm layout optimization is quite similar across various models. Typically, the objective function involves either maximizing or minimizing a problem, with cost and power or energy as the numerator or denominator.

When the goal is to maximize, the function considers the power over cost ratio, whereas in minimization problems, the focus is on the cost over power ratio. Two widely used maximization objective functions can be found in wind farm layout optimization, referred to as equation 8 and 9.

$$objective = \max\left(\frac{P_{total}}{cost}\right) \tag{8}$$

$$objective = \max\sum_{i=1}^{n}\left(\frac{P_{i_{total}}}{cost}\cdot f_i\right) \tag{9}$$

where:

- f_i value of the wind speed distribution function i,
- n number of directions of wind speeds

The actual total power generated in a wind farm, taking into account the wake effect, can be determined using the following equation.

$$P_{total} = \sum_{i=0}^{N}(0{,}3 \cdot u_i^3) \tag{10}$$

3. Optimization via Genetic Algorithm

In this paper, the author uses genetic algorithm in MATLAB to search the optimal layout of a given wind farm. Drawing inspiration from the principles of natural selection, genetic algorithms employ a population-based approach where a diverse set of candidate solutions is allowed to evolve over multiple iterations or generations. Each candidate solution, represented as a chromosome, is composed of genes that encode the problem-specific variables. The fitness of each chromosome is evaluated using a fitness function, which quantifies how well the candidate solution satisfies the problem's objectives and constraints.

Central to the functioning of genetic algorithms are the genetic operators, which mimic the processes of selection, crossover, and mutation. Selection simulates the survival of the fittest, where fitter chromosomes are more likely to be chosen as parents for the next generation.

Crossover, inspired by genetic recombination, combines the genetic material of two parent chromosomes to create offspring, thereby promoting the exchange of beneficial traits among the solutions. Mutation, analogous to random genetic mutations in nature, introduces small perturbations in the chromosomes, ensuring diversity and exploration of the solution space.

In addition to the aforementioned genetic algorithm processes, other crucial steps such as initialization and termination play significant roles. The initialization phase is a fundamental step in the genetic algorithm process, laying the foundation for the subsequent evolution of candidate solutions. This critical stage is responsible for generating an initial population, which serves as the starting point for the exploration and exploitation of the solution space. A well-defined termination strategy is essential for the success of a genetic algorithm, as it determines when the algorithm should cease its search for optimal solutions. The flowchart of a simple genetic algorithm is given in Figure 3.

Further application-specific details of the genetic algorithm, including the definition of genes and chromosomes within the context of this wind farm layout problem, the specification of the fitness function, and the particular parameters or settings used, will be discussed in detail in the following chapter, where the results of this optimization approach are presented.

Figure 3. Flowchart of a Simple Genetic Algorithm

4. Results and Discussion

In this study, as previously mentioned, the author explores three distinct wind data scenarios to optimize the wind farm layout using the genetic algorithm. The scenarios are as follows:

- Case 1: The layout is optimized for a single wind direction. In this case, the wind is assumed to approach perpendicular to the turbine face, and we consider the overall average wind velocity.

- Case 2: The layout is optimized considering only the most prevalent wind direction, along with the overall average wind velocity.
- Case 3: The layout is optimized for all wind directions, calculated using the average wind velocity in each direction. This scenario incorporates a weighted objective function to provide a balanced solution.

Each of these cases is visually represented in Figure 4, which demonstrates the wind directions used in the genetic algorithm for each scenario.

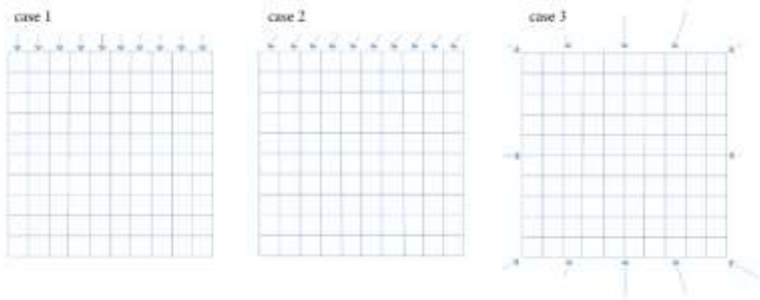

Figure 4. Visualization of Wind Directions Used in the Genetic Algorithm for Each Case

Various recommendations have been made for wind turbine spacing, with a minimum of 3 and up to 5 times the rotor diameter perpendicular to the wind direction, and 6 to 10 diameters along the wind direction (Porté-Agel et al., 2020). In this particular study, the grid optimization method will be executed using square grid sizes equal to 5 times the rotor diameter.

In setting up the genetic algorithm several tuning parameters must be carefully considered. These include the number of individuals, the maximum number of generations, the generation gap, sub-population size, migration, and migration generation. These parameters play a critical role in the effective operation of the genetic algorithm. In particular, the number of individuals and the maximum generations are crucial for achieving convergence in the solution. Increasing either or both of these parameters may enhance the efficiency of convergence. Specifically, increasing the number of individuals may reduce the number of generations required for convergence, thus speeding up the attainment of optimized solutions.

Table 1 presents the tuning parameters of genetic algorithm used for the first two cases. Table 2 outlines the wind turbine properties selected for the first two cases.

Table 1. Genetic Algorithm Tuning Parameters

Genetic algorithm tuning parameters	Value
Number of individuals	30
Maximum generation wanted	10000
Random starts	50
Generation gap	2
Probability of mutation	0.2

Table 2. Wind Turbine Properties

Wind turbine dependent variables	Value
Power coefficient	0.4
Free stream velocity	12 m/s
Rotor diameter	108 m
Rotor radius	54 m
Swept area	9 160 m^2
Hub height	80 m
Surface roughness	0.03 m
Decay factor	0.146
Axial induction factor	0.324
Wind angle	0° (case 1); -30° (case 2)

Utilizing the grid optimization method, the wind farm's accessible area for optimization, in conjunction with the aforementioned tuning parameters and turbine properties, must be supplied to produce turbine coordinates. The genetic algorithm, however, employs binary strings rather than "real values" to manipulate data. Consequently, these binary strings need to be transformed into real values or coordinates assigned to the wind turbines in the objective function segment.

In case 1, an area of 5.4 km x 5.4 km is considered for the wind farm. This total area is further divided into 100 cells of equal size (540 m x 540 m) which correspond to square cells equal to 5 times the rotor diameter in both directions, ensuring the recommended safety distance that will help avoid interference between wind turbines.

This means that there are 100 potential positions for wind turbines, hence, 100 independent variables. For the first case, a fixed number of wind turbines (30) are chosen to be placed at the most optimal locations relative to each other, and the following chromosome is obtained as shown in Figure 5.

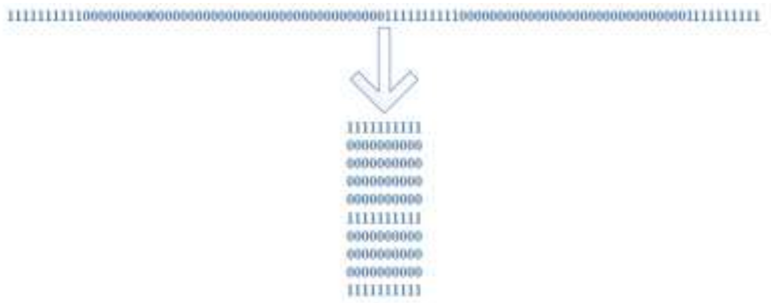

Figure 5. Binary Wind Farm Layout Representation for Case 1

The resulting chromosome, as illustrated in Figure 6, has full rows of ones in the first, sixth, and tenth row, representing the optimized layout of wind turbines achieved through the genetic algorithm. This layout is considered the optimal solution primarily because it minimizes losses due to the effects of wake. Interference occurs when wind turbines are placed too close to each other, causing downstream wind turbines to experience reduced wind speed and, consequently, lower output power. Directly behind the first row of wind turbines, the speed deficit is the greatest, so fewer wind turbines are placed there.

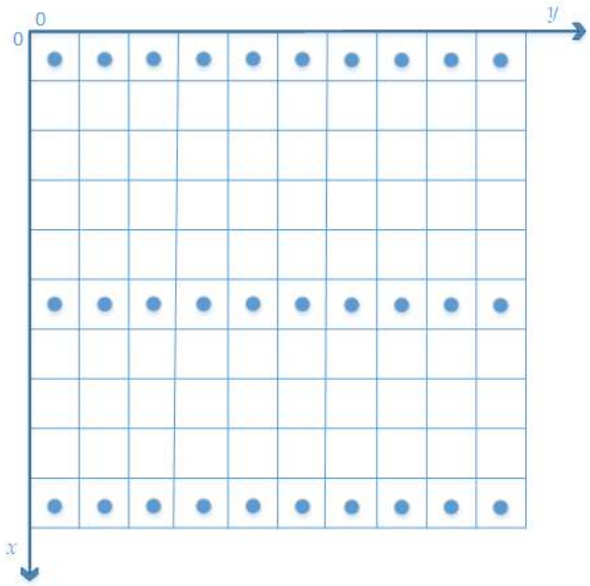

Figure 6. Example of Wind Turbine Layout Optimization for Case 1

In this configuration, the layout allows sufficient spacing between wind turbines and ensures that the wind flow remains relatively unhindered when reaching downstream wind turbines, allowing them to more efficiently harness wind energy. Additionally, this configuration takes into account the recommended safety distance for spacing wind turbines, further contributing to the reduction of interference losses. The algorithm converges at about 6000 generations and a fitness of 1305.7153, as can be seen in Figure 7.

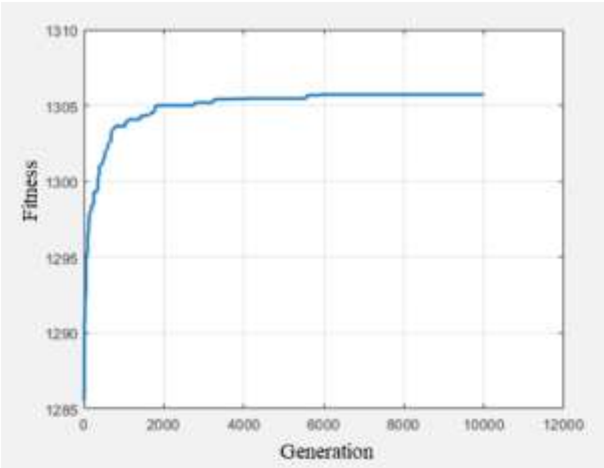

Figure 7. Convergence of the Genetic Algorithm for Case 1

The genetic algorithm aims to find the best possible situation where wind turbines produce as much energy as possible while considering the cost function. The total power produced stated in Table 3 makes sense because at an average speed of 12 m/s at wind turbine level, one wind turbine produces about 3.85 MW of power. Such an optimized layout through the grid optimization method does not offer much variation in the layout, forcing wind turbines to be placed in areas where they are exposed to the effects of wake. This wouldn't be a problem with a larger area that would prevent downstream wind turbines from experiencing reduced wind speed and consequently, lower output power or for the wind turbines in the last rows to experience fully recovered wind speed.

Table 3. Power Output for Case 1

Wind direction	Case 1
Power output	115,367 MW

The plot shown in Figure 8 illustrates the achieved power output of solution (expressed in megawatts) for different random initial conditions, giving us a realistic picture of oscillations between local maxima that the algorithm uncovers and the global maximum. It is significant to note that the difference between the worst and best-found solution is very small, indicating the efficiency of the genetic algorithm in this optimization problem. The worst solution that the algorithm generated is 115.32 MW, while the best solution achieved 115.367 MW. This data confirms the high degree of precision and convergence of the algorithm in finding optimal solutions, which is a result of the simplicity of the problem configuration.

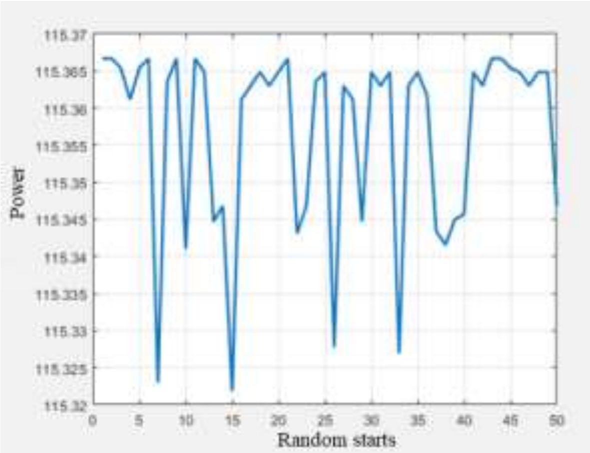

Figure 8: Achieved Power Output for Various Random Starts for Case 1

The plot in Figure 9 shows the movement of average quality through generations of the genetic algorithm for a random start for which the best solution was obtained. From the plot, it is evident that the average quality in the population significantly improves after a few initial generations, after which it oscillates. The analysis indicates that the genetic algorithm quickly converges to optimal solutions for this problem.

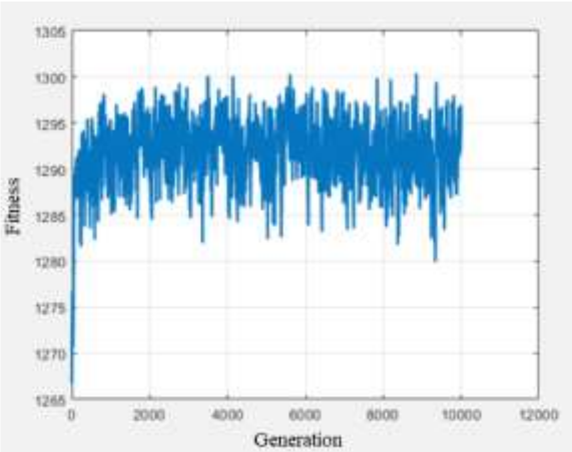

Figure 9. Graph of Average Fitness Quality for Case 1

Now the analysis of the obtained results will be carried out for the second case where only the most prevalent wind direction from the real wind data in case 3 is taken into account. Variable values that depend on a specific wind turbine and parameters for setting the genetic algorithm are identical as for case 1 (Tables 1 and 2) except for the value of the wind angle, which has the value of -30° in this case because this angle represents the most dominant wind direction for case 3.

The area, analogous to the first case, is divided into a hundred equal cells of dimensions 540 m x 540 m. This further suggests that there are a hundred possible positions for placing wind turbines, and therefore a hundred independent variables, as in the first case. For the second case, a fixed number of wind turbines (30) is also chosen to be placed in the most optimal locations in relation to each other and the following chromosome shown in Figure 10 is obtained.

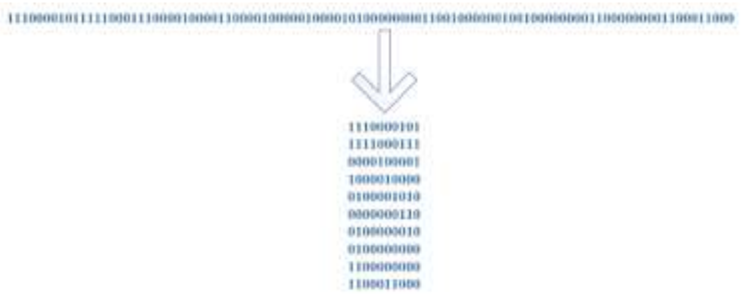

Figure 10. Binary Wind Farm Layout Representation for Case 2

The obtained chromosome shows a more complex, but optimized layout of wind turbines achieved through the genetic algorithm. Unlike the first case, where the wind turbines are concentrated in a few rows, in this scenario the wind turbines are spread over several locations, suggesting that this layout form provides better performance for the specific problem. Zeros and ones are transformed into the desired formation of wind turbines as can be seen in Figure 11.

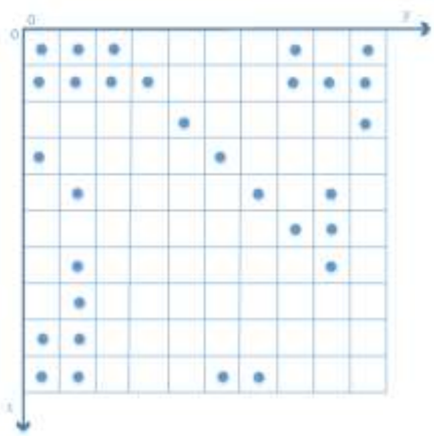

Figure 11. Example of Wind Turbine Layout Optimization for Case 2

In this layout, the algorithm converges at about 4000 generations and a fitness of 1316.2625 as can be seen in Figure 12.

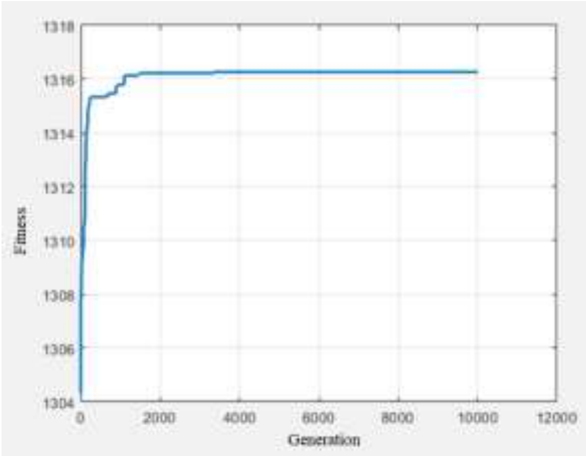

Figure 12. Convergence of the Genetic Algorithm for Case 2

The total power produced is stated in Table 4 and according to it, one wind turbine produces around 3.88 MW of power for this case.

Table 4. Power Output for Case 2

Wind direction	Case 2
Power output	116.299 MW

The chart in Figure 13, illustrating the frequency with which the algorithm successfully finds optimal solutions, allows us to observe the achieved power output of solution (expressed in megawatts) for different random initial conditions, giving us a realistic picture of oscillations between local maxima that the algorithm uncovers and the global maximum, for case 2. We again have a small difference between the worst and best-found solution, indicating the efficiency of the genetic algorithm in this optimization problem. The worst solution that the algorithm generated is 116.245 MW, while the best solution achieved 116.299 MW. This data confirms a high degree of precision and convergence of the algorithm in finding optimal solutions, which is again due to the simplicity of the problem configuration.

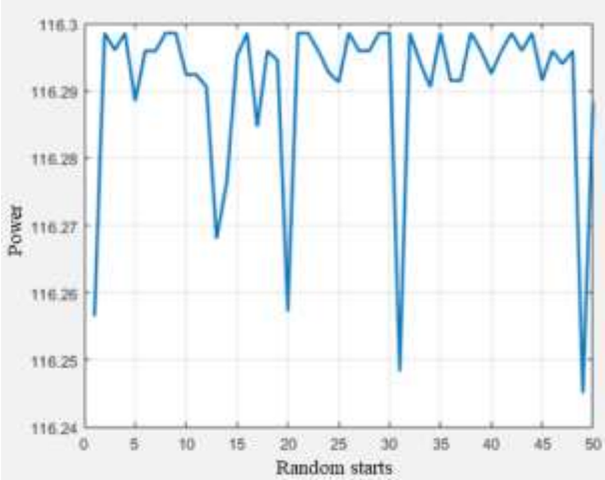

Figure 13: Achieved Power Output for Various Random Starts for Case 2

The graph in Figure 14 shows the movement of average quality through generations of the genetic algorithm for a random start for which the best solution was obtained for case 2. As in the first case, it can be seen that the average quality in the population significantly improves after a few initial generations, after which it oscillates. The analysis indicates that the genetic algorithm quickly converges to optimal solutions for this problem.

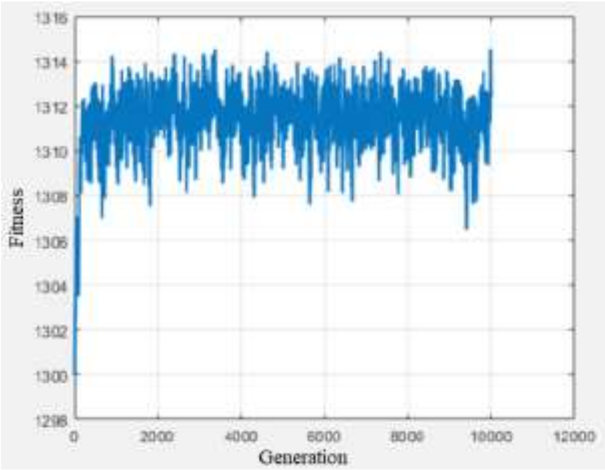

Figure 14. Graph of Average Fitness Quality for Case 2

For the third case, wind data will be used that was experimentally obtained for the purposes of setting up the Mesihovina Wind Farm, further processed to correspond to the wind speed at a rotor hub height of 130 m and is given in Table 5. It is expected that the use of real wind data for this research will yield more realistic results.

Table 5: Wind Speed, Direction and Frequency Used in Case 3

Wind Speed	Direction	Frequency	Wind Speed	Direction	Frequency
9.10	0	18	8.90	180	11
8.57	30	29	5.15	210	4
4.14	60	6	5.73	240	8
2.82	90	3	4.89	270	3
4.84	120	5	2.86	300	1
8.39	150	12	2.89	330	1

Table 6 presents the tuning parameters of genetic algorithm used for the last case. Table 7 outlines the wind turbine properties selected for the third case.

Table 6. Genetic Algorithm Tuning Parameters

Genetic algorithm tuning parameters	Value
Number of individuals	30
Maximum generation wanted	10000
Random starts	20
Generation gap	2
Probability of mutation	0.2

Table 7. Wind Turbine Properties

Wind turbine dependent variables	Value
Rotor diameter	130 m
Rotor radius	65 m
Swept area	13 273 m^2
Hub height	110 m
Surface roughness	0.03 m
Decay factor	0.146

Axial induction factor	0.258
Cut-in wind speed	4 m/s
Rated wind speed	9.8 m/s
Cut-out wind speed	25 m/s

In terms of parameter values for setting the genetic algorithm for this case compared to previous ones, the only difference is now the number of random starts has been reduced to 20 to decrease the necessary computation time. It takes approximately 30 minutes per random start on the computer that was used for executing the algorithm. This ensures the algorithm ends within an acceptable 10 hours timeframe.

Now an area of 6.5 km x 6.5 km is considered for the wind farm. The area is further divided into 100 equal size cells (650 m x 650 m) that correspond to square cells equal to 5 times the rotor diameter in both directions ensuring the recommended safe distance that will assist in avoiding interference between wind turbines. As in previous cases, there are 100 potential positions, therefore, 100 independent variables. Again, a fixed number of wind turbines (30) to be placed in the most optimal locations relative to each other have been selected, and a chromosome is obtained as shown in Figure 15.

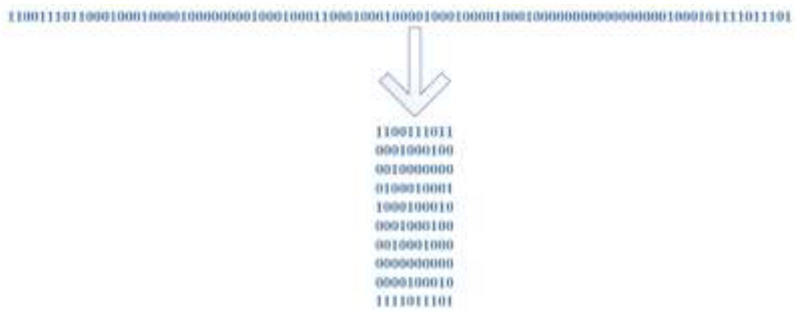

Figure 15. Binary Wind Farm Layout Representation for Case 3

The obtained chromosome shows a more complex but optimized layout of wind turbines achieved through a genetic algorithm. Unlike the first case, where the wind turbines are concentrated in several rows, in this scenario, the wind turbines are distributed in multiple locations, suggesting that this form of arrangement provides better performance for the specific problem. Furthermore, it is worth noting that some rows are relatively dense, such as the first and last row, while others are sparse,

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which could be a consequence of the objective to minimize wake between wind turbines. Considering that the wind speed deficit can be most pronounced in the rows immediately behind the row with wind turbines, such seemingly irregular arrangement might actually provide optimal output power with regard to wind direction. Zeros and ones are transformed into a desired wind turbine formation as can be seen in Figure 16.

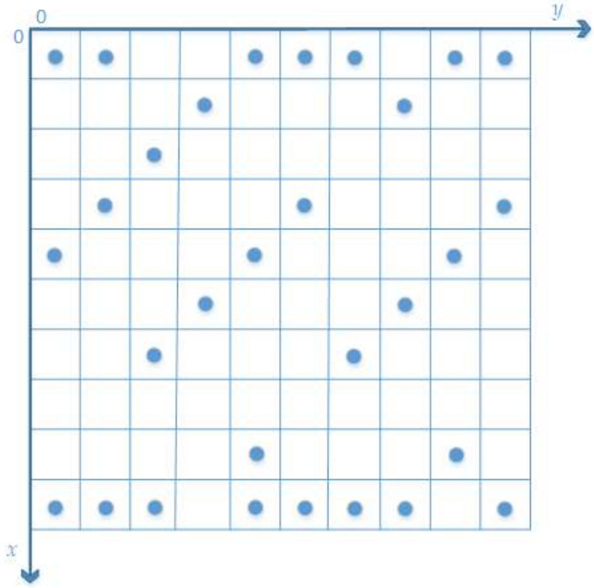

Figure 16. Example of Wind Turbine Layout Optimization for Case 3

In this layout configuration, the algorithm converges after about 6000 generations and with a fitness of 604.0969 as can be seen in Figure 17.

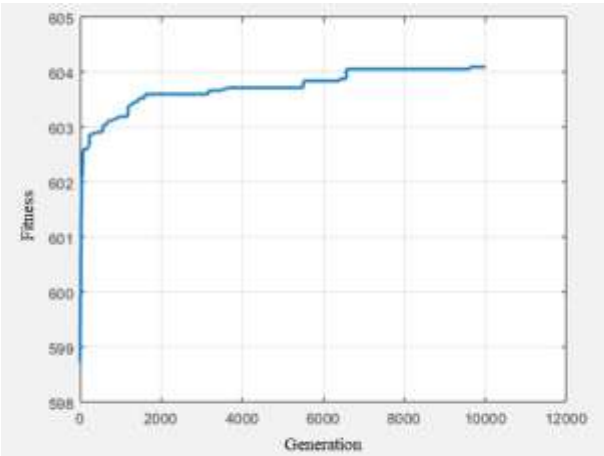

Figure 17. Convergence of the Genetic Algorithm for Case 3

As in previous cases, the genetic algorithm aims to find the best possible situation in which the wind turbines produce as much energy as possible taking into account the cost function. The total power output presented in Table 8 is in line with expectations given that a moderate wind speed was utilized for this case. As such, it wasn't anticipated that the power production of a single wind turbine would reach the theoretical maximum of 3.4 MW per unit.

Table 8. Power Output for Case 3

Wind direction	Case 1
Power output	53.375 MW

In Figure 18, a plot is shown illustrating the frequency with which the algorithm successfully finds optimal solutions. By observing achieved power output of solution (expressed in megawatts) for different random initial conditions, we get a realistic picture of the oscillations between local maxima that the algorithm discovers and the global maximum. Again, as in previous cases, the difference between the worst and best-found solution is small, indicating the efficiency of the genetic algorithm in this optimization problem. The worst solution generated by the algorithm amounts to 53.348 MW, while the best solution reached 53.3751 MW. Again, we have data that confirms the high degree of precision and convergence of the algorithm in finding optimal solutions.

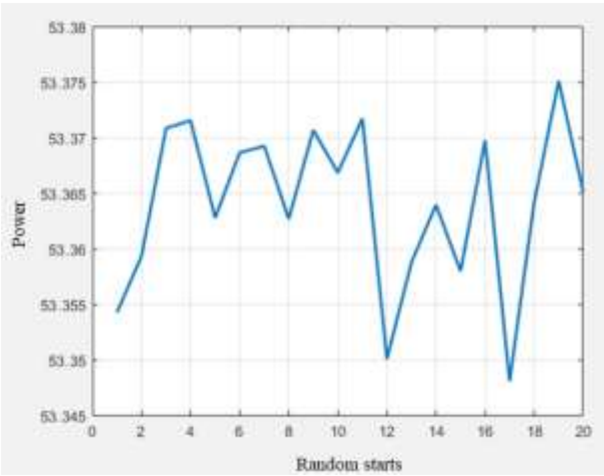

Figure 18: Achieved Power Output for Various Random Starts for Case 3

Finally, the plot in Figure 19 shows the movement of the average quality through generations of the genetic algorithm for the random start for which the best solution was obtained for case 3.

From the plot, it is clear how the average quality in the population significantly improves after a few initial generations, after which it oscillates more than it did in previous cases. However, the oscillations are not as pronounced and, as with previous cases, it can be said that the genetic algorithm quickly converges towards optimal solutions for this problem.

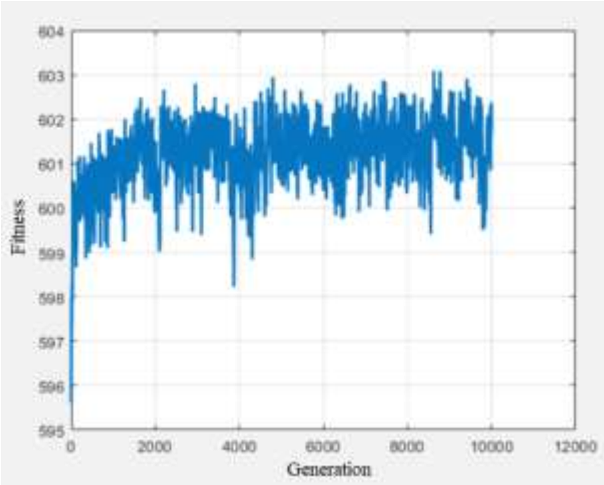

Figure 19. Graph of Average Fitness Quality for Case 3

5. Conclusion

This research aimed to enhance the efficiency of wind farm layout optimization in Bosnia and Herzegovina using genetic algorithms. By considering three distinct wind data scenarios - representing a single wind direction, the most prevalent wind direction, and a weighted encompassing of all wind directions - insights into effective wind farm planning and utilization were gleaned.

The study confirmed the efficacy of the genetic algorithm in achieving a highly efficient wind farm layout, evident in all three cases. The genetic algorithm was able to converge to optimal solutions effectively, demonstrating precision and resilience to local optima. Even though the complexity of the optimization problem increased in the third case - with the introduction of more realistic, experimentally-obtained wind data - the genetic algorithm consistently performed well, highlighting its robustness and applicability to real-world settings.

Obtained results provide additional evidence to the application of genetic algorithms in optimizing wind farm layouts, contributing to the wider body of knowledge in the field of wind energy.

The research shows that the application of genetic algorithms can successfully address the complex problem of maximizing power output while minimizing wake effects and overall costs associated with the wind farm layout.

Furthermore, the versatility of the genetic algorithm demonstrated in this study underlines its potential in other areas of renewable energy systems optimization. Given the growing importance of renewable energy sources, the findings can inform more efficient utilization and planning of these resources globally. Future work could extend this research to other renewable energy sources or incorporate more complex wake models and varying topographies, further expanding the potential of genetic algorithm-based optimization in the renewable energy sector.

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