Optimization of Wind Farm Yaw Offset Angle using Online Genetic Algorithm with a Modified Elitism Strategy to Maximize Power Production

Kurniawan, Aris Triwiyatno, Iwan Setiawan
Department of Electrical Engineering, Faculty of Engineering, Diponegoro University, Semarang, Indonesia.

ARTICLE INFO

Article history:

Received January 29, 2023
Revised March 21, 2023
Published March 24, 2023

Keywords:

Wind farm;
Dynamic wake interaction;
Yaw offset angle;
Online genetic algorithm;
Modified elitism strategy

ABSTRACT

The wake interaction in a wind farm occurs when the front turbines block the flow of wind to the turbines behind them, causing a total power loss of approximately 10–25%. Wake interactions can be redirected to reduce bad impacts by optimizing the yaw offset angles. Optimization of the yaw offset angle can increase the total power of the wind farm by approximately 6–9%. However, the fluctuating wind flow angle in the environment causes the behavior of the wake interaction to change, making it difficult to optimize the yaw offset angles. Therefore, this study proposes an online genetic algorithm with a modified elitism strategy to overcome this problem. The contribution of this study is to improve the performance of the genetic algorithm by modifying the elitism strategy in order to optimize the yaw offset angle for each turbine adaptively to a wind farm operating in a dynamic environment. The optimal yaw offset angles are stored in the elite population for various wind flow angles and then reinserted into the search population in each generation according to the actual wind flow angles. A Gaussian-based analytical wake interaction model under a yawed condition developed by Shapiro is employed in this study to evaluate the total power of a wind farm. This study resulted in a convergence speed that was 3.8 times faster than the classical elitism strategy. At several wind flow angles of 270°, 315°, and 360°, an average power increase of 10.52% was obtained. This study shows that the modification of the elitism strategy can increase the convergence speed to adaptively track the optimal yaw offset angle at various wind flow angles, so that the average increase in wind farm power is 1.94% higher than in previous studies.

Corresponding Author:

Iwan Setiawan, Diponegoro University, Semarang, 50275, Indonesia.
Email: iwansetiawan@live.undip.ac.id

1. INTRODUCTION

A large-scale wind power plant is more profitable and more economical if built in the form of a wind farm consisting of several turbines [1], [2]. However, if several turbines are placed in groups, it can cause wake interactions between turbines [3], and the wind farm loses power by 10%–25% of its nominal power [4]. The wake interaction is a decrease in wind flow velocity and an increase in rough air currents in the wind flow after passing through the turbine rotor, which can disturb the turbines behind it [5], [6], [7]. Studying the optimal layout and separation between turbines at the planning stage can anticipate wake interactions [8]. However, economic, logistical, and wind farm area limitations make it impossible to place each turbine with a far enough separation and optimal layout, so that wake interaction between turbines cannot be avoided [1], [9]. The wake interaction strength can be weakened by adjusting the pitch angle, turbine rotation speed [10], and controlling the turbine shaft torque to vary the axial induction effect [11]. In addition, wake interaction can also be minimized by optimizing the yaw offset angle on the front turbine rotor which can deflect the wake interaction so that it stays away from the turbine behind [8], [12], [13], [14].

A wind farm consists of many turbines and has many parameters that must be optimized simultaneously to maximize overall power production. In addition, a wind farm has a dynamic environment such as changes in wind flow velocity, intensity of atmospheric turbulence, wind flow angle, and separation between turbines, all of which greatly affect the behavior of wake interactions [15]. The genetic algorithm is one of the optimization algorithms that performs well on global search to solve parallel multi-parameter optimization problems, such as yaw offset angles on many turbines simultaneously [10]. The genetic algorithm generates a random initial population that provides individuals with diverse solutions and gradually loses its diversity, as indicated by the rapidly increasing fitness value at the beginning of the generation and gradually reaching stagnation when it converges to the optimal solution [16]. The optimal solution obtained only performs well under current environmental conditions, but when environmental conditions change, the optimal solution may no longer be useful, and we must repeat the search process because the genetic algorithm has lost its population diversity [17]. The loss of population diversity makes it difficult for the genetic algorithm to provide potential solutions to explore the search space under new environmental conditions. As a result, the genetic algorithm cannot react instantly to sudden changes that occur in a dynamic environment [18]. Several strategies have been proposed to solve this problem, including increasing diversity when environmental changes occur, maintaining continuous diversity, using multi-populations, implementing memory schemes [17], and adapting crossover and mutation rates [19]. The elitism strategy used in research [10], [20], [21], [22] is the application of a memory scheme that can preserve the best individuals by duplicating and reinserting them into the population for the next generation. However, this strategy is a temporal memory scheme that only protects the best individuals from internal crossover and mutation disturbances and will be lost when external disturbances occur, such as environmental changes, causing slow convergence as shown in the research of Yang e*t al.* [4] and resulting in fluctuating fitness values as shown in the research of Chen et al [23]. Therefore, as a solution to the problem above, this study proposes a modification of the elitism strategy to improve the ability of the genetic algorithm to optimize the yaw offset angle for each turbine so that wind farm power can be maximized even though it operates in a dynamic environment.

Several previous studies related to optimizing wind farms have been carried out by Yang *et al.* with the title "Cooperative Yaw Control of Wind Farm using a Double-layer Machine Learning Framework". In this study, they optimized the yaw offset angle cooperatively on 1×5 aligned turbines with 1 static wind flow angle, the separation between the turbines was 7D, and a power increase of 5.59% was obtained [4]. Sun *et al.* conducted a study entitled "Wind Turbine Power Modeling and Optimization using Artificial Neural Network with Wind Field Experimental Data", they are optimizing the yaw offset angle on 1×5 aligned turbines with an average separation between turbines of 7D using a genetic algorithm. The total power was evaluated at various wind flow angles in the range of 150°–200°, and an average power increase of 8.45% was obtained [12]. Chen *et al.* conducted a study entitled "Modified Beetle Annealing Search (BAS) Optimization Strategy for Maxing Wind Farm Power through an Adaptive Wake Digraph Clustering Approach", they are optimizing the yaw offset angle and axial induction effect on 3×3 aligned turbines with 4D streamwise separation between turbines using the BAS algorithm. The total power was evaluated at various wind flow angles in the range of 270°–360°, and an average power increase of 8.67% was obtained [23]. Gu *et al.* conducted a study entitled "Cooperative Multiagent Optimization Method for Wind Farm Power Delivery Maximization", they are optimizing the axial induction effect on 8×10 turbines with a staggered layout, the separation between the turbines was 7D, analyzed in 2 wind flow angles of 222° and 270°, with an increase in power of 7.51% [24]. Another study was also conducted by Li *et al.* with the title "Study of three wake control strategies for power maximization of offshore wind farms with different layouts", they are optimizing combined the yaw offset angle and axial induction effect on 7×7 aligned turbines with 7D streamwise separation between turbines using the offline classical genetic algorithm. The total power was evaluated at various wind flow angles in the range of 270°–360°, and an average power increase of 8.49% was obtained [10]. According to several previous studies, most of the yaw offset angles are optimized in static wake interaction models. Although the power increase was analyzed at several different wind flow angles, but the optimization of the yaw offset angle was still carried out offline on separate static scenarios. Research investigating online optimization of yaw offset angles in a dynamic environment and in a single scenario frame is still very limited. In addition, Chen *et al.* [23] and Yang *et al.* [4] research has stated that genetic algorithms have low performance, such as unstable fitness values and slow convergence speeds, in optimizing wind farms. The limitations of the optimization method and the weaknesses of the genetic algorithm present opportunities for this study to be carried out. The main goal of this study is to maximize a single objective function, i.e., the total power of a aligned layout wind farm consisting of 3×3 turbines with a 7D streamwise separation and 5D spanwise separation between turbines under the influence of wake interaction in a dynamic environment.

The contribution of this study is to improve the performance of the genetic algorithm by modifying the elitism strategy in order to optimize the yaw offset angle for each turbine adaptively to a wind farm operating in a dynamic environment, i.e., the wind flow angle, which fluctuates randomly every 200 seconds in the range of 270°–360°. In addition, to applying the online search method, the genetic algorithm can find and track the optimal yaw offset angle directly, adaptively, and continuously while a wind farm is operating.

2. METHODS

In this section, the method used in the study is described, starting from identifying the problem and dynamics of a wind farm, carrying out wind farm modeling to calculate the total power generated, designing an online genetic algorithm, modifying the elitism strategy, and testing the optimization of yaw offset angles for all turbines in a wind farm. as shown in Fig. 1.

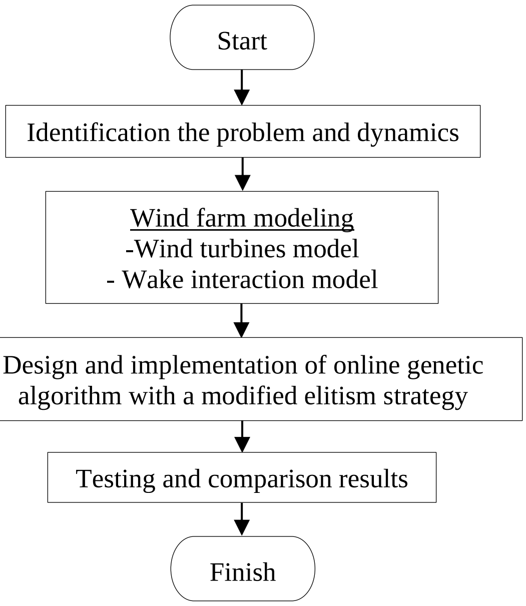
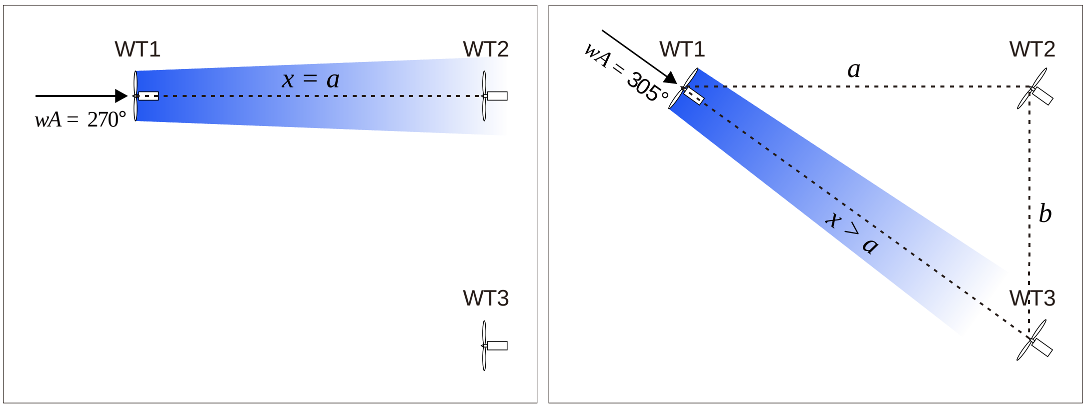


Fig. 1. Research Method Flowchart

2.1. Wind Farm Problem and Dynamics

The main problem in a wind farm is the occurrence of wake interaction between turbines along a row of turbines aligned to the wind flow angle. When the wind flow angle varies, the relative locations and separations between the turbines, as well as the wake interaction behavior, also change [24]. Fig. 2 shows the wake interaction dynamics caused by wind flow angle changes.



(a) (b)

Fig. 2. Wake Interaction Dynamics

The wake interaction occurs in full when the wind flow angle lines up with the row of turbines, whereas when the wind flow angle is slightly deviated from the turbine row, the wake interaction is also slightly reduced, and in certain wind flow angles, there are conditions where no wake interaction occurs for all turbines. Based on Fig. 2(a), when the wind flow angle is 270°, WT1 blocks WT2, but in Fig. 2(b), when the wind flow angle is 305°, WT1 blocks WT3. The relative location and separation between interacting turbines have different values at different wind flow angles. The relative separation can be calculated using the Pythagorean theorem by the following equation:

$$x = \sqrt{a^2 + b^2} = \frac{a}{cos(wA - 270°)} \tag{1}$$

where a and b are the streamwise and spanwise absolute separations, and x is the relative separation between the rear turbines that are impacted by the wake interaction of the front turbines. The separation x is a variable that affects the strength of the wake interaction and the wind flow velocity captured by the rear turbine.

The relative separations between WT1-WT2 and WT1-WT3 have different values, the strength of the wake interaction and turbines power reduction is also different, so it requires a different optimal yaw offset angle to adjust the optimal wake bending. In other words, the yaw offset angle must be able to instantly track the optimal value in varying wind flow angles [25], [26], [27].

2.2. Wind Farm Modeling

The wind farm under investigation consisted of 3×3 turbines aligned vertically and horizontally, with a separation between turbines of 5 times the turbine rotor diameter for the spanwise separation and 7 times the turbine rotor diameter for the streamwise separation, as shown in Fig. 3.

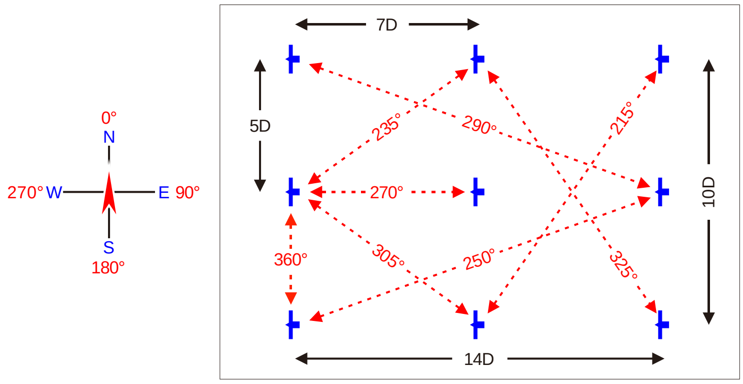


Fig. 3. Wind Farm Layout

The dashed arrows in Fig. 3 shows several wind flow angles that have the potential to cause wake interactions. A wind farm with a regular and symmetrical layout has 16 probability wind flow angles that have the potential to cause wake interactions. Aligned or regular layout is not optimal when compared to an irregular layout [28]. The wind farm model consists of 2 model blocks, i.e., the wind turbine model and the wake interaction model. Fig. 4 represents 1×3 aligned turbines.

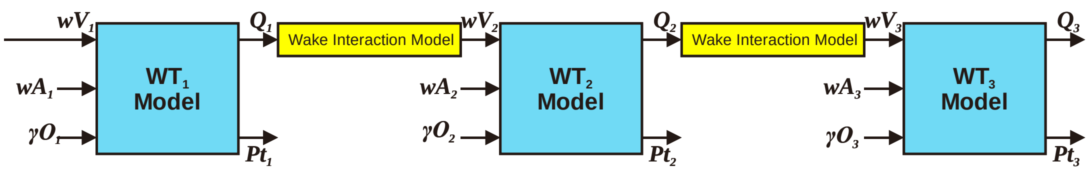


Fig. 4. Wind Farm Model

The wV_i variable in Fig. 4 is the wind flow velocity for each WT_i. Each WT_i model produces Pt_i output, which is the turbine power, while the variable $Q_i = [a_i\ \gamma O_i\ wA\ wV_i]$ consists of the axial induction effect, the yaw offset angle, the wind flow angle, and the wind flow velocity passing through WT_i, respectively. The Q_i variable is passed into the wake interaction model to calculate the wake bending and wind flow velocity captured by the rear turbines after passing through the front turbine rotor. Wind flow data in a wind farm environment consists of wind flow velocity, wind flow angle fluctuation, turbulence intensity, and air mass, described in Table 1.

Table 1. Wind flow Data

Parameters	Values
Wind flow velocity (m/s)	10
Wind flow angle (°)	Random [270, 290, 306, 325, 360]
Turbulence intensity (%)	1
Air mass (kg/m^3)	1.225

Table 1 shows the wind farm environmental parameter data used in this study. The wind flow velocity is set at a fixed value of 10 m/s because it does not analyze its changes, while the wind flow angle fluctuates within a certain range to determine the dynamics of wake interaction behavior. A regular and symmetrical wind farm layout also allows for symmetrical wind flow angles. As a result, the 16 probabilities of wake interactions in the 0°-360° wind flow angle range can be represented in the 270°-360° wind flow angle range with only 5 probabilities.

2.3. Wind Turbine Model

In order to rotate an electric generator, wind turbines transform the potential energy of wind flow into mechanical power, which can be written in the following equation based on [29].

$$P_m = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta) wV_0{}^3 \tag{2}$$

where P_m is the turbine mechanical power, ρ is the air mass, R is the turbine rotor radius, λ is the tip speed and wind flow velocity ratio, β is the blade pitch angle, and wV_0 is the wind flow velocity.

The value of the power coefficient C_p, which is a function of λ and β, can be calculated using a mathematical model in the following equation [30]:

$$\begin{gathered} C_p(\lambda,\beta) = c1\left(\frac{c2}{\lambda i} - c3\beta - c4\right)e^{-\frac{c5}{\lambda i}} + c6\lambda, \\ \frac{1}{\lambda i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3} \end{gathered} \tag{3}$$

where $c1$, $c2$, $c3$, $c4$, $c5$ and $c6$ are turbine blade geometry constants, and β is the turbine blade pitch angle. In order to achieve maximum power coefficient values at various wind flow velocities, wind turbines must operate at optimal λ values (λ_{opt} = 8.1) which can be adjusted by varying the rotational speed of the turbine [31]. In order for the λ value to be at an optimal value at various wind flow velocities, the turbine rotation speed reference value can be determined using the following equation:

$$\omega_m^* = \frac{\lambda_{opt}\, wV_0}{R} \tag{4}$$

where ω_m^* is the turbine rotational speed reference value. Then the mechanical torque on the turbine rotor shaft can be obtained by the following equation [29]:

$$T_m = \frac{P_m}{\omega_m} \tag{5}$$

where ω_m is the actual turbin rotational speed. The turbine rotor shaft which is directly connected to the electric generator shaft using the single-mass drive train model, is shown by the following equation [30]:

$$\frac{d\omega_m}{dt} = \frac{1}{J}(T_m - T_e - f_v\omega_m) \tag{6}$$

where T_e is the electromagnetic torque on the generator, f_v is the friction force on the turbine rotor shaft bearings, and J is the generator's and turbine rotor's moment of inertia. The 10 kW Alizé wind turbine in Table 2 provided the specifications for the model of wind turbine.

Wind turbines equipped with tail fins automatically adjust the turbine rotor to always track the wind flow angle. The yaw offset angle is the misalignment angle between the turbine rotor shaft angle to the wind flow angle, as depicted in Fig. 5.

Table 2. Wind turbine specification data

Parameters	Values
Nominal output power (kW)	10
Blades	3
Hub height (m)	30
Turbine rotor diameter (m)	7
Min - Nom wind flow velocity (m/s)	3 - 10

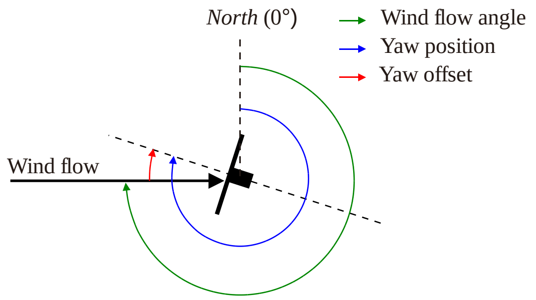


Fig. 5. Wind Turbine Yaw Angle Variables

Acording Fig. 5, the yaw offset angle can bend the direction of the wake interaction caused by the front turbine, but it can also affect the potential energy of the wind captured by the front turbine. As a result, the equation used to calculate wind turbine power can be changed [32].

$$P_m = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta)\cos^3(\gamma O)\, wV_0{}^3$$
$$\gamma O = \gamma P - wA \tag{7}$$

where γO is the yaw offset angle, γP is the yaw posision of the turbine rotor shaft angle, and wA is the wind flow angle.

2.4. Wake Interaction Model

Wake interaction modeling is used to compute the wake bending and wind flow velocity loss for each turbine, with or without a yaw offset angle. In this study, wake interactions were constructed using the model proposed by Shapiro [33]. Fig. 6 illustrates the adjustment of the wake bending by controlling the yaw offset angle in a front turbine.

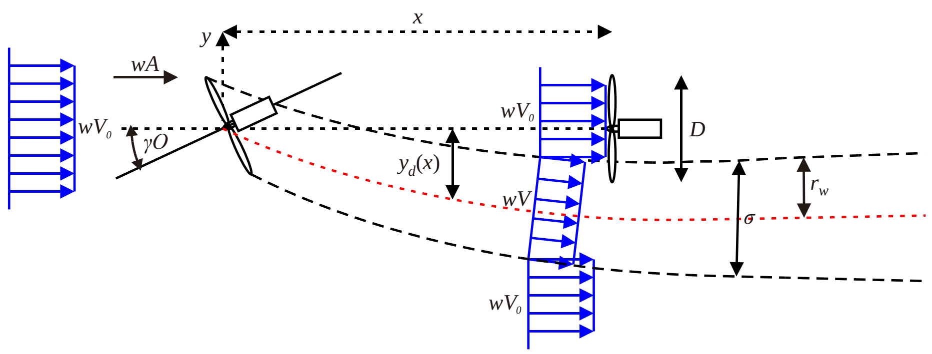


Fig. 6. Adjustment of Wake Bending by Controlling the Yaw Offset Angle

According to Fig. 6, the bending of the wake interaction between the two turbines is a function of the yaw offset angle of the front turbine. Research conducted by Ma et al [21], showed that the Shapiro wake-bending model has higher accuracy than the model proposed by Qian [34]. The wake bending which is affected by the yaw offset angle in the front turbine is modeled by the following equation [33]:

$$y_d(x) = \int_{-\infty}^{x} \frac{-\delta v(x')}{wV_0}\, dx' \tag{8}$$

$$\delta v(x) = \frac{\delta v_0}{d_w^2(x)} \frac{1}{2}\left[1 + \text{erf}\left(\frac{x}{r_0\sqrt{2}}\right)\right] \tag{9}$$

$$\delta v_0 = \frac{1}{4} wV_0 C_T cos^2(\gamma O) sin(\gamma O) \tag{10}$$

where $y_d(x)$ is the wake bending at separation x, $\delta v(x)$ is the mean wind flow velocity deficit in the spanwise direction at the hub height, δv_0 is the initial wind flow velocity deficit in the spanwise direction, C_T is the turbine thrust coefficient, wV_0 is the upstream wind flow velocity, and d_w is the width of turbine wake obtained by the following equation [33]:

$$d_w(x) = 1 + k^* \ln\left(1 + exp\left[\frac{x - 2r_0}{r_0}\right]\right) \tag{11}$$

where r_0 is the turbine rotor radius, k^* is the wake decay coefficient, expressed by:

$$k^* = 0.11 C_T^{1.07} I_a^{0.2} \tag{12}$$

where I_a is the turbulence intensity. The wind flow velocity captured by the rear turbine due to the wake interaction from the front turbine is expressed by the following equation [33]:

$$wV = wV_0 - \Delta wV(x, y) \tag{13}$$

$$\Delta wV(x, y) = \delta u(x) \frac{D^2}{8\sigma_0^2} \exp\left(-\frac{\left(y - y_d(x)\right)^2}{2\sigma^2(x)}\right) \tag{14}$$

$$\delta u(x) = \frac{\delta u_0}{d_w^2(x)} \frac{1}{2}\left[1 + \text{erf}\left(\frac{x}{r_0\sqrt{2}}\right)\right] \tag{15}$$

$$\delta u_0 = wV_0\left(1 - \sqrt{1 - C_T \cos^2(\gamma O)}\right) \tag{16}$$

where wV is the downstream wind flow velocity, $\Delta wV(x, y)$ is the wind flow velocity deficit at streamwise x and spanwise y, $\delta u(x)$ is the mean wind flow velocity deficit in the streamwise direction at the hub height, δu_0 is the initial wind flow velocity deficit in the streamwise direction, $\sigma_0 = 0.235D$, and $\sigma(x)$ is the Gaussian width or standard deviation of the wake. Fig. 7 depicts the front view of the area affected by wake interactions.

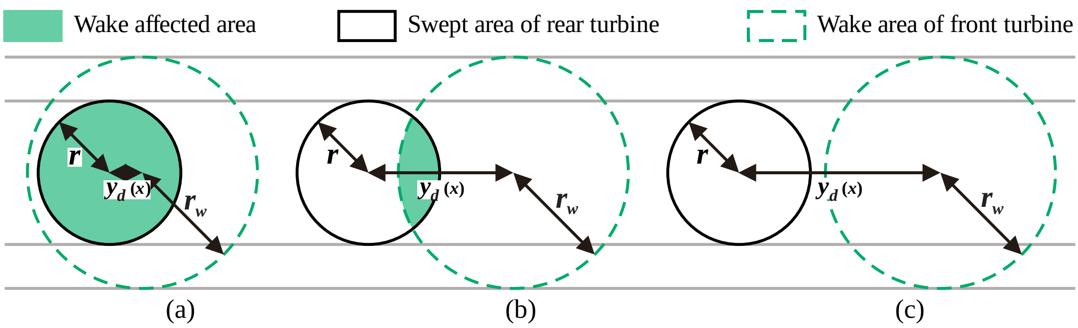


Fig. 7. Front View Wake Interaction

In Fig. 7(a), when $y_d(x) < r_w - r$, the wind flow to the rear turbine is completely blocked by the front turbine wake interaction. In Fig. 7(b), when $r_w - r \le y_d(x) \le r_w + r$, the wind flow to the rear turbine is only slightly blocked by the front turbine wake interaction. In Fig. 7(c), when $y_d(x) > r_w + r$, the wind flow to the rear turbine is not blocked at all by the front turbine wake interaction.

2.5. Design and Implementation of Online Genetic Algorithm with a Modified Elitism Strategy

Genetic algorithm is a metaheuristic search method that mimics the evolutionary process of living things at the chromosome level [12], [35], [36]. The basic principle is to search for optimal solutions in the form of parameters encoded with structured recombination and randomization techniques such as crossover, mutation, and elitism strategies [10], [37]. In this study, a genetic algorithm with an online search method was used, which allows the parameter search to be carried out continuously while the system is operating [36] and the resulting parameters can be executed directly by the controller on the system [38]. The genetic algorithm architecture proposed in this study is shown in Fig. 8.

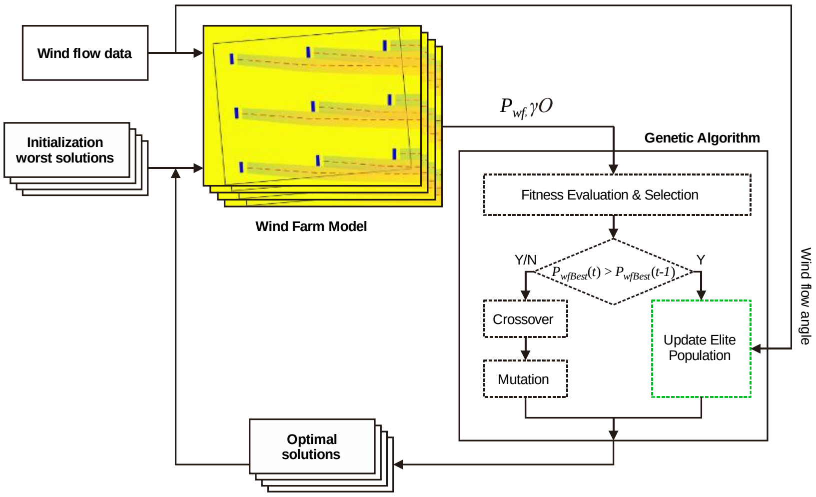


Fig. 8. Architecture of Online Genetic Algorithm with Modified Elitism Strategy

In Fig. 8, the fundamental distinction between the proposed and the classical genetic algorithm lies in the elitism strategy used. The classical elitism strategy duplicates the best individuals and inserts them into the search population in each generation [10], [20], [21], [39], whereas the proposed elitism strategy duplicates and retains the best individuals in the elite population at various wind flow angles and then reintroduces them into the search population in each generation according to the actual wind flow angle conditions. Table 3 displays the parameters used in the proposed genetic algorithm.

Table 3. Parameters of the genetic algorithm

Parameters	Values
Search pop. size	4
Elite pop. size	90
Crossover prob.	1
Mutation prob.	0.1
Optimized parameters range	-40° ~ 40°

In Table 3, the search population size is the number of individual wind farms consisting of 9 turbines for each, and the elite population size is the number of combinations of yaw offset angles in various wind flow angles in the range of 270°–360° with an interval of 1°. Crossover operations are carried out in each generation with a probability of 100%, while the operation is performed with a probability of 10%. The optimized parameter ranges are the upper and lower limits of the effective yaw offset angle for influencing the bending of the wake interaction. The procedure for optimization is as follows:

Step 1: Defining a population consisting of 4 wind farms, each wind farm contains 9 wind turbines, along with the yaw offset angle parameters for all turbines as shown in Fig. 9.

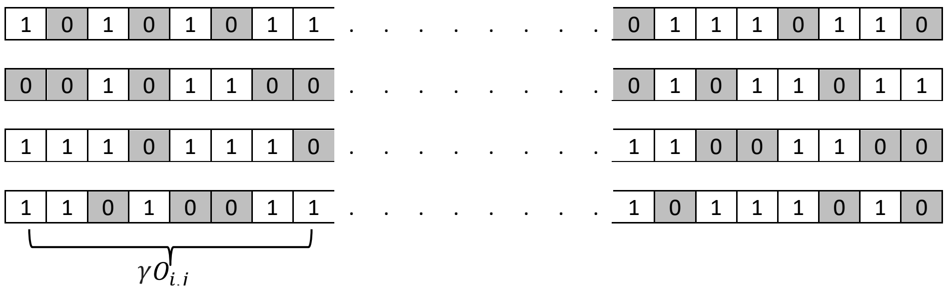


Fig. 9. Population Representation

where $\gamma O_{i,j}$ is the yaw offset angle on the i-th wind farm, and the j-th turbine, which has been encoded in 8-bit binary number, so that in 1 individual wind farm there is 1 binary number series consisting of 8×9 bits. Parameter encoding into binary numbers is shown in the following equation.

$$b_{i,j} = 255\frac{\gamma O_{i,j} - LB\gamma O_{i,j}}{UB\gamma O_{i,j} - LB\gamma O_{i,j}} \tag{17}$$

where $b_{i,j}$ is the yaw offset angle in binary, $LB\gamma O_{i,j}$ and $UB\gamma O_{i,j}$ are the lower and upper bounds of the yaw offset angle. At the beginning of the generation, the yaw offset angle for all turbines is initialized at ±0° to ensure that all turbines are in a non-optimal condition.

Step 2 : Evaluating the fitness value to calculate the power produced by each wind farm. The fitness value that must be maximized.

$$P_{wf} = \sum_{i=1}^{n_t} P_i \tag{18}$$

where n_t is the quantity of turbines, and P_i is the power generated by the i-th wind turbine based on (7).

Step 3 : Performing individual selection of wind farm by selecting 2 wind farms that produce the highest P_{wf} power to be used as parents using the ranking method.

Step 4 : Implementing a modified elitism strategy to protect the best individual from internal disturbances (crossover and mutation) and external disturbances (wind flow angle fluctuation) by keeping it in an elite population. In each generation, the elite population is constantly updated with the best individual parameters to guarantee evolution in a better direction. The conditions that must be fulfilled to update the elite population are that if the individual produces a current P_{wfBest}(t) value greater than the P_{wfBest}(t-1) stored in the elite population, then the old individual parameters stored in the elite population will be replaced with the newest individual parameters, but if these conditions are not fulfilled, then the old individual parameters will still be maintained in the elite population. The elite population stores 2 pieces of information, i.e., a set of optimal yaw offset angle parameters and wind flow angle information, described in Table 4.

Table 4. Elite population

Wind flow angle	$\gamma O_{i,1}$	$\gamma O_{i,2}$	$\gamma O_{i,3}$	$\gamma O_{i,4}$	$\gamma O_{i,5}$	$\gamma O_{i,6}$	$\gamma O_{i,7}$	$\gamma O_{i,8}$	$\gamma O_{i,9}$
270°	20°	18°	18°	17°	18°	15°	-3°	1°	0°
271°	-15°	-20°	16°	15°	-18°	0°	-10°	2°	-1°
272°	10°	-15°	12°	6°	-8°	1°	-16°	0°	-3°
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
360°	18°	17°	0°	-10°	-19°	5°	12°	-2°	1°

Table 4 represents the elite population that stores the 9 optimal yaw offset angles ($\gamma O_{i,1}$, $\gamma O_{i,2}$, ..., $\gamma O_{i,9}$) for each turbine at various wind flow angles. There are 90 slots allocated to store 9 yaw offset angles for various possible wind flow angles in the range of 270°–360° with 1° interval. Each optimal combination of yaw offset angles in the elite population is reintroduced to the search population according to the actual wind flow angle in each generation.

Step 5 : Crossover reproduction, the data contained in the 2 individual parent parameters generated in the selection step will be exchanged with multi-point crosses to produce 2 new individuals, which are called individual offspring. Individual offspring have some of the genetic material from the two individual parents, so the best genetic traits possessed by the individual parents will always be preserved from generation to generation.

Step 6 : Mutation reproduction, the individual offspring generated in the crossover step will be given small random changes with probability *Pm*. Mutation aims to maintain the diversity of individual parameters in the population so that the search is explorative and avoids getting stuck in the local optimum [40]. The randomly selected genes will be reversed or bit-flipped.

Step 7 : The formation of a new population consisting of 1 parent individual parameter, 2 offspring individual parameters, and 1 elite individual parameter will be reinserted into the population in the next generation. This new population contains parameters that constantly evolve from generation to generation, which are then used as a reference for the optimal yaw offset angles for all turbines in the wind farm. The above steps will be repeated continuously as long as the wind farm is operating.

2.6. Testing and Comparison Results

The proposed genetic algorithm will be compared with the classical genetic algorithm used in a previous study [10] to determine the convergence speed of each. Both algorithms were tested in the same scenario, i.e., by optimizing the yaw offset angle of all the turbines in the wind farm according to Fig. 3 and operating in a dynamic environment according to Table 1. Optimization of the yaw offset angle is carried out online while the wind farm operates in fluctuating wind flow angles within a single scenario frame. The next comparison is to compare the results of increasing wind farm power from this study with those from previous studies [10] and [23] to validate the novelty of this study.

3. RESULTS AND DISCUSSION

The results of comparison and analysis are given in this section. The performance of the online genetic algorithm with the modified elitism strategy was compared to the genetic algorithm with the classical elitism strategy used in previous studies. Then the results of increasing the total power of the wind farm were also compared with the results of previous similar studies.

3.1. Elitism Strategies Performance Results

A performance test, specifically the convergence speed, must be carried out prior to optimizing the yaw offset angle in a wind farm by employing an online genetic algorithm with a modified elitism strategy. Fig. 10 shows a performance comparison between the modified and classical elitism strategies.

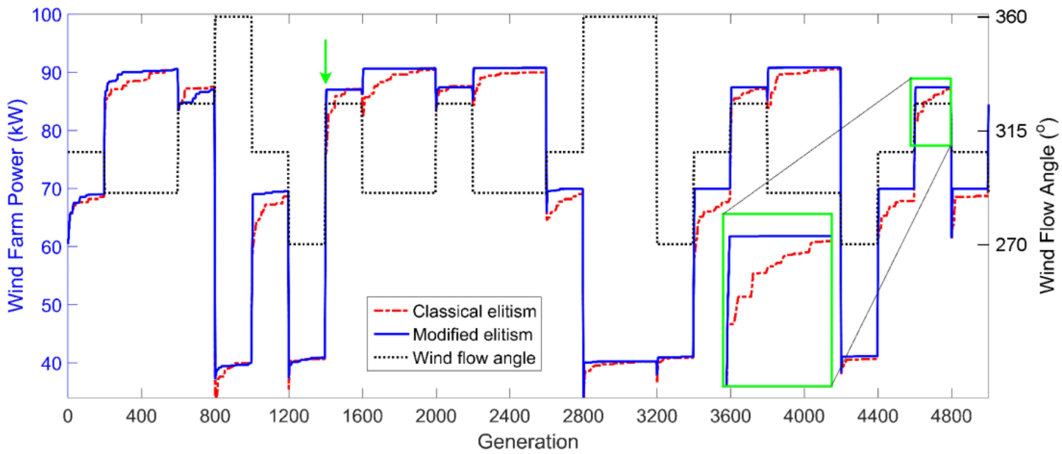


Fig. 10. Performance Comparison of Elitism Strategies on Genetic Algorithms

The number of generations or iterations required to attain the highest fitness value is used to calculate the convergence speed [41]. The modified elitism strategy in this study and the classical elitism strategy in a previous study [10] were compared to determine the performance of the genetic algorithms. Both genetic algorithms with each elitism strategy were evaluated in the same scenario to obtain valid and fair results, i.e., to optimize the yaw offset angle of the wind farm according to Fig. 3 in the environment with wind flow data according to Table 1.

In Fig. 10, changes in wind flow angle cause the behavior of the wake interaction to change, so that the search direction for the optimal yaw offset angle and the fitness value also change. The genetic algorithm with the classical elitism strategy always repeats the search from the beginning continuously, with a low convergence speed in every change in wind flow angle. Unlike the case with the modified elitism strategy, although the early generations had almost the same performance as the classical elitism strategy, after reaching 1400 generations, the convergence speed increased significantly.

As shown in the green box, during testing both genetic algorithms have encountered the same wind flow angles, i.e., 325°, as many as 5 times; however, the classical elitism strategy cannot maintain the fitness value that has been achieved in previous generations. At the same condition, the modified elitism strategy achieved a high fitness value in the 1400th generation and maintained it up to the 4600th generation. The average number of generations required to achieve the highest fitness between the two elitism strategies, measured from the 1400th to the 4800th generations. The average number of generations in the classical elitism strategy is 140 generations, with the highest fitness of 73.86 kW, while the average number of generations in the modified elitism strategy is 37 generations, with the highest fitness of 74.46 kW.

3.2. Yaw Offset Angle Optimization Results

This test was conducted to determine the distribution of each turbine's power output, wind flow velocities, and optimal combination of yaw offset angles. The wind flow data is where the operation of the wind farm starts, as shown in Table 1. During the wind farm operation, the genetic algorithm with the modified elitism strategy performs an online search until all the yaw offset angles reach optimal values in all wind flow angles, i.e., random [270, 290, 306, 325, 360]. The optimal yaw offset angle combination and wind flow velocity distribution for each turbine are shown in the wind farm layout in Fig. 11.

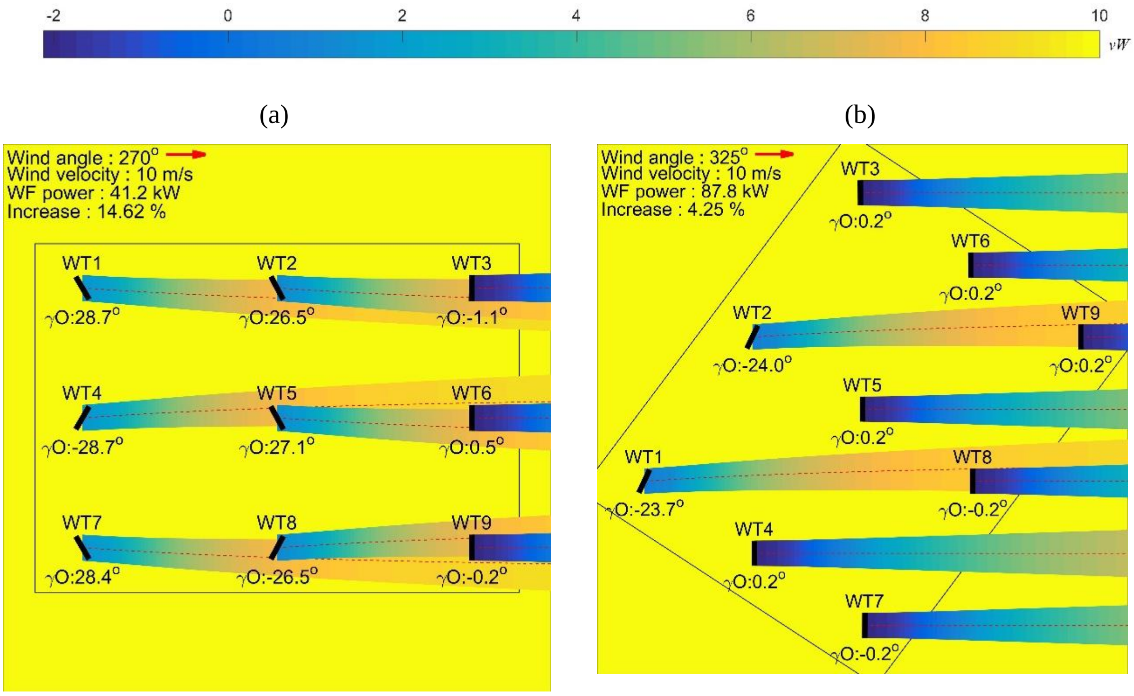


Fig. 11. Optimal Combination of Yaw offset and Wind Flow Velocity Distribution, (a) $wA = 270°$, (b) $wA = 325°$

In Fig. 11, the optimal yaw offset angles between the front, middle, and rear turbines has a different combination with every change in wind flow angle. Basically, the genetic algorithm provides the optimal yaw offset angle distribution with a downward trend along the turbine row aligned to the wind flow angle. In Fig. 11(a), the front turbines, WT1, WT4, and WT7, have an optimal average yaw offset angle of 28.6°, while the middle turbines, WT2, WT5, and WT8, have an optimal average yaw offset angle of 26.7°, to bending the wake interaction to stay away from the rear turbines. The optimal average yaw offset angle for the rear turbines WT3, WT6, and WT9 is 0.6° because there is no turbine behind them. Therefore, they must capture as much kinetic energy as possible from the wind. The power distribution generated by the optimal wind farm and the baseline wind farm was compared. A baseline wind farm is a wind farm without any yaw offset angles.

In Fig. 12(a), due to the front turbines obstructing the wind flow to the turbines behind them, the power distribution in the baseline wind farm exhibits a declining tendency in each row of turbines. At the optimal wind farm, the wake interaction can be deflected by the optimal yaw offset angle. Although there is a slight decrease in the power of the front and middle turbines due to the given yaw offset angle, the power of the rear turbines increases significantly. Therefore, it can increase the overall power output of the wind farm.

At wind flow angle 325°, as shown in Fig. 12(b), the increase in wind farm power is lower than at wind flow angle 270°. This is due to the fact that the wake interaction only affects 2 turbines and has a relatively large separation between them. In other words, the wake interaction has no real effect on the wind flow in the wind farm. As a result, the wind farm's total power is almost at its maximum and cannot be increased further.

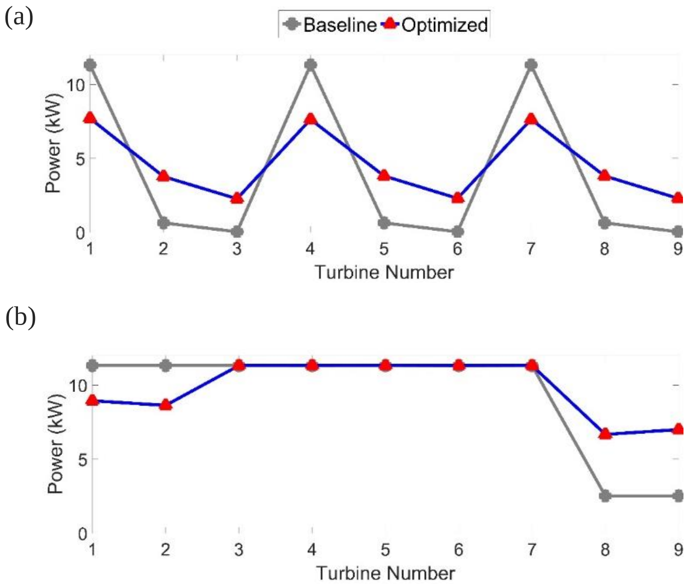


Fig. 12. Baseline and Optimized Wind Farm Power Distribution,
(a) $wA = 270°$, (b) $wA = 325°$

3.3. Study Comparison with Previous Works

This section compares the findings from several studies on optimizing wind farms in an effort to increase the power generated. This comparison was carried out to determine the performance of the optimization algorithm used and the achievement of increased wind farm power at various wind flow angles. Table 5 shows a comparison between the findings in this study and the findings from several previous studies.

Table 5. Comparison of our study with previous studies

Author	Optimization parameters	Optimization algorithm	Number of iterations to achieve the highest fitness	Power Increase at various wind flow angles (kW)	Average power increase (kW)
Li *et al.* (2022) [10]	Combined yaw offset and axial induction	Offline GA with classical elitism strategy	140	W (270°) : 7.77% NW (315°) : 0.01% N (360°) : 17.68%	8.49%
Chen *et al.* (2021) [23]	Combined yaw offset and axial induction	Modified Beetle Annealing Search	120	W (270°) : 9.00% NW (315°) : 1.00% N (360°) : 16.00%	8.67%
Our study	Yaw offset	Online GA with modified elitism strategy	37	W (270°) : 14.62% NW (315°) : 0.00% N (360°) : 16.95%	10.52%

In Table 5, Li et al. [10] optimized the combined yaw offset angles and axial inductions on a regular layout wind farm consisting of 7×7 turbines with 7D streamwise separation and 5D spanwise separation using a genetic algorithm with a classical elitism strategy. The optimal wind farm was evaluated at various wind flow angles, and it was found that optimizing the combination resulted in a higher power increase of 8.49% than optimizing only one of them. But the optimization is done offline in a separate wind flow angle scenario; in other words, the wind flow angle that varies with time is not considered during optimization, which can reduce optimization efficiency.

Chen et al. [23] used a modified beetle annealing search algorithm to optimize the combined yaw offset angles and axial inductions in a regular layout wind farm consisting of 3×3 turbines with 4D streamwise separation and 2D spanwise separation. They found that dividing the wind farm into separate subsets reduced the computation time, allowing the proposed algorithm to only require 120 iterations to quickly reach the highest fitness. As a result, online optimization of a wind farm operating at varying wind flow angles is possible. The average increase in power achieved while the wind farm operates in the 270°–360° wind flow angle range is 8.67%.

In this study, a regular layout wind farm consisting of 3×3 turbines with 7D streamwise separation and 5D spanwise separation is optimized. Significant differences with previous studies, this study optimizes the yaw offset angle while evaluating the overall wind farm power during operation in a dynamic environment, i.e., a wind flow angle that fluctuates over time. The findings of this study indicate that the performance of the genetic algorithm can be improved by modifying the elitism strategy and applying it as an experiential memory scheme. The modified elitism strategy allows the genetic algorithm to only require fewer iterations than previous studies to achieve the highest fitness. In addition, the online optimization method allows the genetic algorithm to always update the experience memory based on new environmental conditions. As a result, the genetic algorithm can track the optimal yaw offset angle quickly and adaptively in a dynamic environment that fluctuates over time.

The smaller the number of iterations required to achieve the highest fitness, the higher the convergence speed of the algorithm in finding optimal parameters. The results of the comparison show that the online genetic algorithm with a modified elitism strategy has advantages, i.e., the convergence speed is 3.8 times faster and the average increase in wind farm power is 1.94% higher than in previous studies. The advantage of this study can be obtained due to the ability of the elite population to protect the best yaw offset angles from internal disturbances such as crossover failure and mutation randomness and also protect them from external disturbances, i.e., loss of individual diversity caused by fluctuations in wind flow angle. The limitation of the optimization algorithm method in this study is the poor performance at the beginning of the iterations because the elite population has not been filled with useful knowledge. These knowledges are optimal combinations of yaw offset angle that are updated over time.

4. CONCLUSION

In this study, the yaw offset angle of each turbine in a regular layout wind farm consisting of 3×3 turbines was optimized. Optimization is done online while the wind farm operates at a wind flow angle that fluctuates randomly every 200 seconds with a range of 270°–360° using an online genetic algorithm. The findings of this study are that the performance of the genetic algorithm can be improved by modifying the elitism strategy as an experiential memory scheme. Comparison results with previous studies validate these findings, i.e., an online genetic algorithm with a modified elitism strategy has a convergence speed 3.8 times faster and the average increase in wind farm power is 1.94% higher than previous studies. As a result, the online genetic algorithm with a modified elitism strategy has excellent performance in tracking the reference value of the optimal yaw offset angle of each turbine in a wind farm operating in wind flow angles that fluctuate over time. The online optimization method makes possible the search for optimal parameters and updates of the elite population continuously while the wind farm operates. The findings from this study shed new light on genetic algorithm performance improvement strategies for optimizing yaw offset angles to sustainably maximize wind farm power under dynamic environmental conditions.

In future work, in addition to wind flow angle fluctuations, wind farm optimization evaluation will also consider wind flow velocity fluctuations, turbulence intensity fluctuations, and the dynamics of the wind turbine yaw angle drive control system because environmental dynamics are influenced by many variables that can reduce the efficiency of the optimization algorithm. The online genetic algorithm with a modified elitism strategy will also be enhanced with adaptive crossover and mutation to maximize wind farm power in that environment.

Acknowledgments

The authors are grateful to Ministry of Research and Technology / National Research and Innovation Agency of Republic Indonesia for giving the financial support for this works with PTUPT scheme (contract number 187-71/UN7.6.1/PP/2021).

REFERENCES

[1] R. K. Balakrishnan and S. Hur, "Maximization of the Power Production of an Offshore Wind Farm," *Appl. Sci.*, vol. 12, no. 8, p. 4013, 2022, https://doi.org/10.3390/app12084013.

[2] D. Hendrawati, A. Soeprijanto, and M. Ashari, "Turbine wind placement with staggered layout as a strategy to maximize annual energy production in onshore wind farms," *Int. J. Energy Econ. Policy*, vol. 9, no. 2, pp. 334–340, 2019, https://doi.org/10.32479/ijeep.7437.

[3] B. P. Rak and R. B. Santos Pereira, "Impact of the wake deficit model on wind farm yield: A study of yaw-based control optimization," *J. Wind Eng. Ind. Aerodyn.*, vol. 220, p. 104827, 2022, https://doi.org/10.1016/j.jweia.2021.104827.

[4] S. Yang, X. Deng, Z. Ti, B. Yan, and Q. Yang, "Cooperative yaw control of wind farm using a double-layer machine learning framework," *Renew. Energy*, vol. 193, pp. 519–537, 2022, https://doi.org/10.1016/j.renene.2022.04.104.

[5] C. L. Archer *et al.*, “Review and evaluation of wake loss models for wind energy applications,” *Appl. Energy*, vol. 226, pp. 1187–1207, 2018, https://doi.org/10.1016/j.apenergy.2018.05.085.
[6] V. R. Padullaparthi, S. Nagarathinam, A. Vasan, V. Menon, and D. Sudarsanam, “FALCON- FArm Level CONtrol for wind turbines using multi-agent deep reinforcement learning,” *Renew. Energy*, vol. 181, pp. 445–456, 2022, https://doi.org/10.1016/j.renene.2021.09.023.
[7] J. W. Lin, W. J. Zhu, and W. Z. Shen, “New engineering wake model for wind farm applications,” *Renew. Energy*, vol. 198, pp. 1354–1363, 2022, https://doi.org/10.1016/j.renene.2022.08.116.
[8] J. Kuo, K. Pan, N. Li, and H. Shen, “Wind Farm Yaw Optimization via Random Search Algorithm,” *Energies*, vol. 13, no. 4, p. 865, 2020, https://doi.org/10.3390/en13040865.
[9] J. Sun *et al.*, “Quantitative evaluation of yaw-misalignment and aerodynamic wake induced fatigue loads of offshore Wind turbines,” *Renew. Energy*, vol. 199, pp. 71–86, 2022, https://doi.org/10.1016/j.renene.2022.08.137.
[10] B. Li *et al.*, “Study of three wake control strategies for power maximization of offshore wind farms with different layouts,” *Energy Convers. Manag.*, vol. 268, p. 116059, 2022, https://doi.org/10.1016/j.enconman.2022.116059.
[11] R. Nash, R. Nouri, and A. Vasel-Be-Hagh, “Wind turbine wake control strategies: A review and concept proposal,” *Energy Convers. Manag.*, vol. 245, p. 114581, 2021, https://doi.org/10.1016/j.enconman.2021.114581.
[12] H. Sun, C. Qiu, L. Lu, X. Gao, J. Chen, and H. Yang, “Wind turbine power modelling and optimization using artificial neural network with wind field experimental data,” *Appl. Energy*, vol. 280, no. July, p. 115880, 2020, https://doi.org/10.1016/j.apenergy.2020.115880.
[13] M. E. Nakhchi, S. Win Naung, and M. Rahmati, “A novel hybrid control strategy of wind turbine wakes in tandem configuration to improve power production,” *Energy Convers. Manag.*, vol. 260, p. 115575, 2022, https://doi.org/10.1016/j.enconman.2022.115575.
[14] P. A. Fleming *et al.*, “Serial-Refine Method for Fast Wake-Steering Yaw Optimization,” *J. Phys. Conf. Ser.*, vol. 2265, no. 3, p. 032109, 2022, https://doi.org/10.1088/1742-6596/2265/3/032109.
[15] L. Zhao, L. Xue, Z. Li, J. Wang, Z. Yang, and Y. Xue, “Progress on Offshore Wind Farm Dynamic Wake Management for Energy,” *J. Mar. Sci. Eng.*, vol. 10, no. 10, p. 1395, 2022, https://doi.org/10.3390/jmse10101395.
[16] M. Ayaz, M. Danish, M. S. Ali, A. Bilal, and A. F. Hashmi, “Derivation of unit hydrograph using genetic algorithm-based optimization model,” *Model. Earth Syst. Environ.*, vol. 8, no. 4, pp. 5269–5278, 2022, https://doi.org/10.1007/s40808-022-01464-w.
[17] E. Gazioğlu and A. S. Etaner-Uyar, “Experimental analysis of a statistical multiploid genetic algorithm for dynamic environments,” *Eng. Sci. Technol. an Int. J.*, vol. 35, p. 101173, 2022, https://doi.org/10.1016/j.jestch.2022.101173.
[18] H. Yu, Z. Yao, X. Sui, G. Gu, and Q. Chen, “Focusing through disturbed multimode optical fiber based on self-adaptive genetic algorithm,” *Optik (Stuttg).*, vol. 261, p. 169129, 2022, https://doi.org/10.1016/j.ijleo.2022.169129.
[19] F. Zhang, S. Xu, B. Han, L. Zhang, and J. Ye, “Neutrosophic Adaptive Clustering Optimization in Genetic Algorithm and Its Application in Cubic Assignment Problem,” *Comput. Model. Eng. Sci.*, vol. 134, no. 3, pp. 2211–2226, 2023, https://doi.org/10.32604/cmes.2022.022418.
[20] Z. Huang, Z. Guo, P. Ma, M. Wang, Y. Long, and M. Zhang, “Economic-environmental scheduling of microgrid considering V2G-enabled electric vehicles integration,” *Sustain. Energy, Grids Networks*, vol. 32, p. 100872, 2022, https://doi.org/10.1016/j.segan.2022.100872.
[21] H. Ma, M. Ge, G. Wu, B. Du, and Y. Liu, “Formulas of the optimized yaw angles for cooperative control of wind farms with aligned turbines to maximize the power production,” *Appl. Energy*, vol. 303, p. 117691, 2021, https://doi.org/10.1016/j.apenergy.2021.117691.
[22] L. Cao *et al.*, “Wind farm layout optimization to minimize the wake induced turbulence effect on wind turbines,” *Appl. Energy*, vol. 323, p. 119599, 2022, https://doi.org/10.1016/j.apenergy.2022.119599.
[23] Y. Chen, Y.-H. Joo, and D. Song, “Modified Beetle Annealing Search (BAS) Optimization Strategy for Maxing Wind Farm Power through an Adaptive Wake Digraph Clustering Approach,” *Energies*, vol. 14, no. 21, p. 7326, 2021, https://doi.org/10.3390/en14217326.
[24] B. Gu, H. Meng, M. Ge, H. Zhang, and X. Liu, “Cooperative multiagent optimization method for wind farm power delivery maximization,” *Energy*, vol. 233, p. 121076, 2021, https://doi.org/10.1016/j.energy.2021.121076.
[25] S. Kanev, “Dynamic wake steering and its impact on wind farm power production and yaw actuator duty,” *Renew. Energy*, vol. 146, pp. 9–15, 2020, https://doi.org/10.1016/j.renene.2019.06.122.
[26] E. Simley, P. Fleming, J. King, and M. Sinner, “Wake Steering Wind Farm Control With Preview Wind Direction Information,” in *2021 American Control Conference (ACC)*, pp. 1783–1789, 2021, https://doi.org/10.23919/ACC50511.2021.9483008.
[27] M. F. Howland *et al.*, “Optimal closed-loop wake steering – Part 2: Diurnal cycle atmospheric boundary layer conditions,” *Wind Energy Sci.*, vol. 7, no. 1, pp. 345–365, 2022, https://doi.org/10.5194/wes-7-345-2022.
[28] J. Serrano González, M. Burgos Payán, J. M. Riquelme Santos, and Á. G. González Rodríguez, “Optimal Micro-Siting of Weathervaning Floating Wind Turbines,” *Energies*, vol. 14, no. 4, p. 886, 2021, https://doi.org/10.3390/en14040886.
[29] S. E. Chehaidia *et al.*, “Robust Nonlinear Terminal Integral Sliding Mode Torque Control for Wind Turbines Considering Uncertainties,” *IFAC-PapersOnLine*, vol. 55, no. 12, pp. 228–233, 2022, https://doi.org/10.1016/j.ifacol.2022.07.316.
[30] K. Palanimuthu, G. Mayilsamy, S. R. Lee, S. Y. Jung, and Y. H. Joo, “Comparative analysis of maximum power extraction and control methods between PMSG and PMVG-based wind turbine systems,” *Int. J. Electr. Power Energy*

Syst., vol. 143, p. 108475, 2022, https://doi.org/10.1016/j.ijepes.2022.108475.

[31] H. Kelele, L. Frøyd, M. Kahsay, and T. Nielsen, "Characterization of Aerodynamics of Small Wind Turbine Blade for Enhanced Performance and Low Cost of Energy," *Energies*, vol. 15, no. 21, p. 8111, 2022, https://doi.org/10.3390/en15218111.

[32] L. Zhao, F. Gong, S. Chen, J. Wang, L. Xue, and Y. Xue, "Optimization study of control strategy for combined multi-wind turbines energy production and loads during wake effects," *Energy Reports*, vol. 8, pp. 1098–1107, 2022, https://doi.org/10.1016/j.egyr.2022.05.146.

[33] C. R. Shapiro, D. F. Gayme, and C. Meneveau, "Modelling yawed wind turbine wakes: a lifting line approach," *J. Fluid Mech.*, vol. 841, p. 12, 2018, https://doi.org/10.1017/jfm.2018.75.

[34] G.-W. Qian and T. Ishihara, "A New Analytical Wake Model for Yawed Wind Turbines," *Energies*, vol. 11, no. 3, p. 665, 2018, https://doi.org/10.3390/en11030665.

[35] I. A. Ja'e, M. Osman Ahmed Ali, A. Yenduri, Z. Nizamani, and A. Nakayama, "Optimisation of mooring line parameters for offshore floating structures: A review paper," *Ocean Eng.*, vol. 247, p. 110644, 2022, https://doi.org/10.1016/j.oceaneng.2022.110644.

[36] A. Rodríguez-Molina, A. Herroz-Herrera, M. Aldape-Pérez, G. Flores-Caballero, and J. A. Antón-Vargas, "Dynamic Path Planning for the Differential Drive Mobile Robot Based on Online Metaheuristic Optimization," *Mathematics*, vol. 10, no. 21, p. 3990, 2022, https://doi.org/10.3390/math10213990.

[37] F. P. García Márquez and A. Peinado Gonzalo, "A Comprehensive Review of Artificial Intelligence and Wind Energy," *Arch. Comput. Methods Eng.*, vol. 29, no. 5, pp. 2935–2958, 2022, https://doi.org/10.1007/s11831-021-09678-4.

[38] A. M. Zanchettin, C. Messeri, D. Cristantielli, and P. Rocco, "Trajectory optimisation in collaborative robotics based on simulations and genetic algorithms," *Int. J. Intell. Robot. Appl.*, vol. 6, no. 4, pp. 707–723, 2022, https://doi.org/10.1007/s41315-022-00240-4.

[39] Z. Avdagic, A. Smajevic, S. Omanovic, and I. Besic, "Path route layout design optimization using genetic algorithm: based on control mechanisms for on-line crossover intersection positions and bit targeted mutation," *J. Ambient Intell. Humaniz. Comput.*, vol. 13, no. 2, pp. 835–847, 2022, https://doi.org/10.1007/s12652-021-02937-z.

[40] X. Xia, H. Qiu, X. Xu, and Y. Zhang, "Multi-objective workflow scheduling based on genetic algorithm in cloud environment," *Inf. Sci. (Ny).*, vol. 606, pp. 38–59, 2022, https://doi.org/10.1016/j.ins.2022.05.053.

[41] P. Han, Y. Guo, C. Li, H. Zhi, and Y. Lv, "Multiple GEO satellites on-orbit repairing mission planning using large neighborhood search-adaptive genetic algorithm," *Adv. Sp. Res.*, vol. 70, no. 2, pp. 286–302, 2022, https://doi.org/10.1016/j.asr.2022.04.034.

BIOGRAPHY OF AUTHORS

Kurniawan received his bachelor's degree in Electrical Engineering from the Faculty of Industrial Technology, Institut Teknologi Nasional Yogyakarta, Yogyakarta, in 2016. He is studying for a master's degree at Department of Electrical Engineering, Faculty of Engineering, Diponegoro University, Semarang. His research interest includes control system, artificial intelligence, wind turbine, and renewable energy. Email: mafikurniawan@gmail.com

Aris Triwiyatno is Lecturer at Department of Electrical Engineering, Faculty of Engineering, Diponegoro University, Semarang. He received his Ph.D. degree in Sepuluh Nopember Institute of Technology, Surabaya, in 2012. His research interest includes artificial intelligence, automatic and industrial control. Email: aristriwiyatno@gmail.com

Iwan Setiawan is Lecturer at Department of Electrical Engineering, Faculty of Engineering, Diponegoro University, Semarang. He received his Ph.D. degree in Sepuluh Nopember Institute of Technology, Surabaya, in 2016. His research interest includes instrumentation system, and control system. Email : iwansetiawan@live.undip.ac.id