Smart Hybrid Metaheuristic Model for Enhanced Wind Energy Production

Muhammad Rashid, Syed Mohammad Ali Shah, Abdur Raheem, Saeed Uddin Shaikh, Rabia Shakoor, Zeeshan Ahmad Arfeen

Summary — **This study presents a hybrid Particle Swarm Optimization–Genetic Algorithm (PSO-GA) technology integrated into a structured three-phase strategy to address the wind farm layout optimization (WFLO) problem. In order to enhance total energy efficiency through intelligent turbine location, the proposed strategy is applied to a particular wind farm scenario. Three case studies, each representing varying degrees of wake and non-wake settings, are analyzed to assess the robustness of this method. In order to prevent severe wake interference, the system finds the best location for turbines while strictly following to industry-standard spacing standards. The suggested hybrid model consistently improves energy extraction and reduces wake losses by 20–28% in all scenarios when compared to current method like PSO-based design by [21]. The hybrid PSO-GA still has a moderate computational cost, taking about 20 seconds each simulation. This is just 10–15% more than standalone PSO, but it produces far greater convergence stability.**

Keywords — **Hybrid PSO-GA Algorithm; Wind Farm Layout Optimization (WFLO); Wind Turbine Placement**

I. Introduction

The share of renewable energy in global electricity generation has continued to rise, supported by record additions of solar and wind power, as portrayed in Figure 1. According to the Statistical Review of World Energy 2023, solar and wind energy collectively contributed 14% of global electricity generation in 2022. Consequently, the adoption of renewable energy sources continues to gain widespread momentum [1].

The Energy Institute Statistical Review of World Energy 2024 also estimates that in 2023, renewable energy was producing some 30 per cent of the world's electricity, with wind energy generating almost 8 per cent of all electricity in the world [2]. The Global Wind Energy Council (GWEC) Global Wind Report 2024 reveals that total installed wind capacity exceeded 1,020 GW globally in 2023, demonstrating consistent annual growth propelled by offs-

hore and utility-scale installations. These results underscore the growing strategic significance of wind generation in meeting global decarbonization objectives [3, 4].

However, as the number of turbines in a wind farm enhance, the complexity of development grows proportionally with the area required. This has shifted the focus toward minimizing electricity generation costs, optimizing wind farm layouts, and improving the efficient utilization of wind resources.
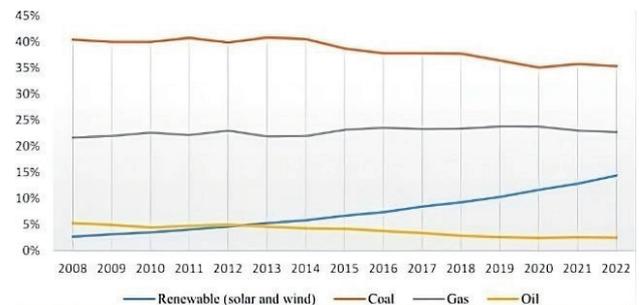

Fig. 1. Share of energy in power by type [1].

The Wind Farm Layout Optimization (WFLO) challenge is inherently nonlinear and constrained, involving multiple interdependent variables. An inefficient arrangement of Wind Turbines (WTs) can adversely affect their operational performance and intensify wake interactions [5]. Accurately simulating wake effects remains one of the most complex and computationally demanding aspects of wind farm optimization. Numerous wind farm layout strategies have been suggested recently to enhance power generation while minimizing wake losses [5].

Frandsen et al. [6] refined the classical Jensen wake framework by considering nonlinear wake boundaries. Subsequent researchers such as Mittal and Mitra [7] adopted the Jensen framework to formulate cost-efficient wind farm layouts, while others [8] have introduced various wake modeling approaches, including Gaussian-based and three-dimensional analytical frameworks. Despite these alternatives, the Jensen framework remains the most widely applied in WFLO due to its simplicity and computational efficiency [9]. In this research, the Jensen wake framework is employed to estimate wake effects, enabling a balance between accuracy and computational cost. Though many metaheuristic optimization strategies have been used for WFLO, the majority of current approaches either just concentrate on maximizing power or are not resistant to changing wind conditions. Furthermore, hybridized evolutionary methods that balance wake interactions, energy production, and computing efficiency have received little attention. Thus, in comparison to

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the state-of-the-art, this study offers a structured hybrid PSO-GA architecture that improves WFLO dependability under three actual wind situations while consistently increasing efficiency and reducing wake loss. The proposed method achieves consistent improvements (0.2% efficiency gain per case) and significantly lowers wake losses compared to the benchmark study in [21].

The hybrid PSO-GA performs well, but it depends on the simplified Jensen model, which might not adequately represent intricate turbulence interactions in offshore or extremely uneven terrain. Performance may change with deeper search parameter customization, and the computational cost rises somewhat with farm size. More advanced wake and cost models can be used in future research to overcome these constraints.

II. Literature review

Several scholars have utilized metaheuristic methods to tackle the problems related to Wind Farm Layout Optimization (WFLO). Application of optimization algorithms for large-scale wind farms was pioneered by Mosetti et al. [10], who sought to maximize energy extraction while lowering installation costs. In a similar vein, Pookpunt and Ongsakul [11] used a genetic algorithm to find the best location for turbines, increasing generation capacity while requiring less land and turbines. Simultaneously, Sood et al. [12] used a random search method similar to Monte Carlo techniques to find the best sites for turbines in small wind farms with different wake characteristics.

Another significant move in the proper improvement process of wind farms and which can enhance the efficiency and effectiveness of wind energy production steps, is Masoudi et al. [13]. An area-rotation layout strategy was created by Shakoor et al. [14] to maximize energy production by optimizing turbine spacing and orientation. A hybrid evolutionary strategy that balances energy production, economic costs, and environmental issues in wind turbine installation was formulate by Bouchekara et al. [15]. Ramli, et al. [16] demonstrated the Multi-Objective Electric Charged Particles improvement process to produce more diverse and robust solutions, which can lead to significant improvements in WF performance. Shin, et al. [17] used the methods of surrogate modeling that enabled to minimize the number of calculations and keep the precision of solutions in large-scale offshore conditions. The authors then concluded that hybrid styles of evolution are especially applicable to offshore WFLO issues because this type of strategy can balance the global exploration and local exploitation in the complex wind conditions. Competitive performance of multi-objective WFLO problems has also been demonstrated by more recent hybrid equilibrium and pattern-search strategies [18].

This research seeks to address the research gap by creating an innovative modified version of Particle Swarm improvement process (PSO) integrated with the Genetic Algorithm (GA), termed PSO-GA, to tackle the WFL-DO challenge.

III. Mathematical Modeling

The optimal operation of a wind farm depends on the strategic placement of turbines to optimize wind resources. Wake interference caused by improper turbine positioning lowers total energy production. In this study, a square area is divided into Nc identical cells (Nc = 100), each measuring 5d × 5d, where "d" stands for the diameter of the turbine rotor. The program finds the best configuration that minimizes cost per energy unit by treating each cell's center as a possible turbine site [18].

PSO-GA hybrid algorithm is evaluated under three distinct wind conditions: (1) constant wind direction and speed, (2) varia-ble wind direction with constant speed, and (3) variable wind direction and speed. In a multi-objective optimization problem, this paradigm aims to maximize energy yield while minimizing cost and wake losses. Extensive simulations demonstrate that PSO-GA outperforms conventional techniques and that the GA component enhances solution refining.

A. Wake Model

Reduced wind velocity downstream of running turbines causes wake losses, which are impacted by intricate nonlinear aerodynamic and environmental phenomena. These consist of blade pitch, yaw angles, airfoil properties, and turbulence intensity. Every turbine creates a wake that grows with distance and interacts with turbines downstream by creating a velocity deficit behind its rotor. Because of its shown dependability in WFLO applications and ease of computing, the Jensen wake model is used here.

As illustrated in Fig. 2, when free-stream wind interacts with the rotor, part of its kinetic energy is extracted for power generation, resulting in a slower airflow downstream. This wake expands due to turbulence, with its radius increasing linearly with distance. Equations (1)–(6) describe the relationship for wake velocity, radius expansion, and partial wake interactions. These expressions enable accurate estimation of wake-induced power losses when multiple turbines operate within proximity.

Equation 1 depicts that if there is no wake loss then downstream velocity of ith turbine is same as free stream wind velocity.

$$v_i = v_o \tag{1}$$

Betz limit is used to measure wind speed for downstream wind turbine as mentioned in equation 2.

$$v = v_o \left[1 - \frac{2a}{1 + \left(\frac{\alpha d}{r}\right)^2} \right] \tag{2}$$

where, r represents the wake radius at distance of d behind the turbine

$$C_T = 4a(1 - a) \tag{3}$$

The wake radius r can be calculated from equation 4.

$$r = \alpha d + r_1 \tag{4}$$

r_1 called the downstream radius of wind turbine and can be measured by equation 5, and α is the wake decay constant and was calculated by equation 6.

$$r_1 = r_r \sqrt{\frac{1 - a}{1 - 2a}} \tag{5}$$

The wind speed that a turbine experiences when its wake is not completely formed is known as the partial wake wind speed. The wind speed in this area, which is nearer the upstream turbine, may

change. It takes into account the wake model and how the wake only partially covers the rotor area of the downstream turbine, which slows down the wind relative to undisturbed flow.

$$v = v_o \left[1 - \frac{2a}{1 + \left(\frac{\alpha d}{r_1}\right)^2} \right] \frac{A_{T,wake,i}}{A_{T,total,i}} \qquad (6)$$

$A_{T,wake,i}$ is the wake-affected area of the ith turbine.

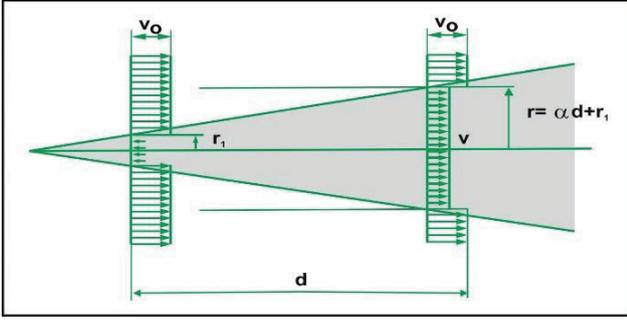$A_{T,total,i}$ is total area covered by rotor of the ith turbine.

Fig. 2. Single wake effect model.

B. Power Model

The power output of a wind turbine (Pwt) is governed by air density, wind velocity, and rotor radius [19].

Total electrical power (available) by the turbine is measured from equation 7.

$$\text{Electrical Power} = \frac{1}{2}\rho * \pi * r^2 * v^3 * C_p \qquad (7)$$

where, ρ is air density, v is the wind velocity, r is the rotor radius & is Power coefficient.

Downstream power taken out from the turbine is measured by the following equation [20].

$$P_{wt} = 0.3V^3 \qquad (8)$$

where, v is the downstream wind velocity.

C. Cost Model

The total cost of a wind farm is determined by summing the costs of all installed turbines as expressed in equation (9), where N represents the number of turbines. This cost function is integrated into the optimization objective to ensure a balance between financial feasibility and energy efficiency.

The cost of whole WF is measured by:

$$\text{Cost} = N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) \qquad (9)$$

where N is the total number of WTs -

D. Objective Function

The primary objective functions of the model is to: (1) Minimize the wake loss (2) Maximize total annual energy production, and (3) Minimize the cost per produced electrical power , as given in equations (10), (11), and (12).

Objective functions of the study are as under.

$$\text{Objective} = \text{Minimize} \left[1 - \frac{2a}{1 + \left(\frac{\alpha d}{r}\right)^2} \right] \qquad (10)$$

$$\text{Objective} = \text{Maximize} \frac{1}{2}\rho * \pi * r^2 * v^3 * C_p \qquad (11)$$

$$\text{Objective} = \text{Minimize} \frac{\text{Cost}}{\text{Electrical Power}} \qquad (12)$$

E. Constraints Modeling

First, all turbines must be located within the predefined wind farm boundary.

$$x_{min} \leq x_i \leq x_{max}$$
$$y_{min} \leq y_i \leq y_{max} \text{ where, } i = 1:n$$

In this study, the minimum distance is set to eight times the rotor radius (8R), consistent with standard industry guidelines.

IV. Hybrid Optimization Algorithm

This section gives the two metaheuristic algorithms principles—Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)—that form the foundation of the proposed hybrid framework.

A. Particle Swarm Optimization (PSO)

PSO is inspired by the social behavior of birds flocking or fish schooling. Each potential solution is modeled as a 'particle' moving within the search space, influenced by its own best-known position and that of its neighbors [21]. Figure 3 illustrate the PSO process, showing how particles iteratively update positions toward optimal solutions.

B. Genetic Algorithm (GA)

Genetic Algorithm (GA) is a population-based optimization method that draws inspiration from natural selection. To develop superior solutions over successive generations, it uses genetic operators like selection, crossover, and mutation [22]. Figure 4 presents the flowchart of the GA optimization process.

C. Hybrid PSO-GA Model

The hybridization strategy has two optimization mechanisms. PSO first does global exploration with 100 iterations. They were the inertia weight (w = 0.7), cognitive coefficient (c1 = 2.5) and social coefficient (c2 = 2.5).

Once the convergence has stopped or the PSO iterations are complete, the best 20 percent of the particles in terms of their fitness values are elites. These elite structures are passed on as the first population to the GA module. GA proceeds to use 500 refinement generations with crossover (0.7 rate) and mutation (0.02 rate). Elitism will guarantee that the best solution of PSO prevails. Hybrid transition criterion is activated when the improvement of PSO is less than 10^{-5} on 20 consecutive iterations. Such a design makes PSO do global search and GA improve the local exploitation.
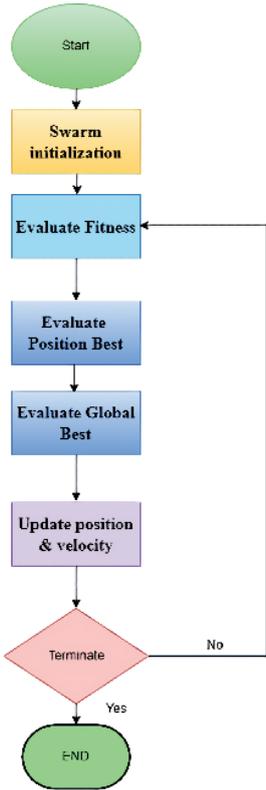

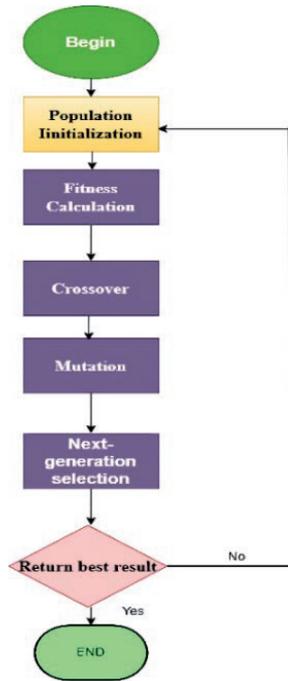Fig. 3. Flow chart of particle swarm improvement process algorithm.

Fig. 4. Flow chart of Genetic algorithm.

V. Results and Discussion

The PSO-GA technique showed a notable increase in the WF's energy yield and cost efficiency through rigorous simulation utilizing the suggested framework.

Three distinct WF designs, each containing a 2 km × 2 km area divided into 100 cells of 200 m × 200 m, were examined in the case studies. With a constant focus on minimizing wake interference while retaining high turbine efficiency and power generation output, the framework was evaluated under various wind speed and wind turbine direction situations.

PSO algorithm explored a broad search space, effectively navigating through multiple local optima to identify promising candidate solutions. The PSO's ability to adjust the particle positions in the search space using its velocity and acceleration coefficients allowed it to investigate various regions of the WF layout space

without getting stuck in suboptimal solutions.

GA was used to fine-tune the turbine locations after the PSO had identified a nearly optimal architecture, increasing the energy yield and further minimizing wake disturbance. The genetic operators (crossover and mutation) enabled the algorithm to explore variations in turbine positioning, balancing power yield improvement process with the minimization of wake effects. Through the iterative refinement process, the PSO-GA algorithm outperformed standalone PSO and GA algorithms in terms of the total electrical energy yield.

A. Case I

Figure 5(a) represents the improved layout obtained through the proposed hybrid PSO-GA approach. While, 5(b) reflects the reference layout used for comparison.
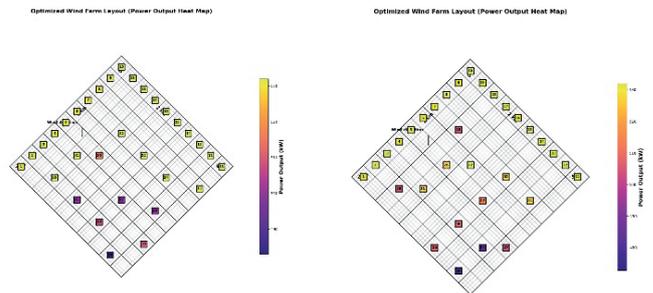

Fig. 5 (a). Layout of wind farm by proposed work.

Fig. 5 (b). Layout of wind farm [23].

The optimum configuration produces a maximum power output with 32 turbines working under a uniform inflow wind speed of 12 m/s, as shown in Figures 6(a) and 6(b). An average turbine efficiency of roughly 98.8% and individual turbine efficiencies ranging from 98.8% to 100% show that the algorithm converges on a highly efficient configuration. There is little variance in the effective wind speed distribution between 11.62 and 12.00 m/s throughout the farm.
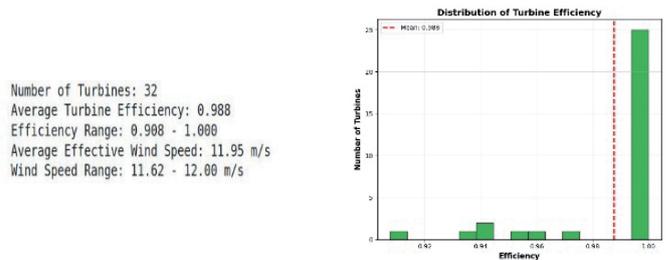

Number of Turbines: 32
Average Turbine Efficiency: 0.988
Efficiency Range: 0.908 - 1.000
Average Effective Wind Speed: 11.95 m/s
Wind Speed Range: 11.62 - 12.00 m/s

Fig. 6. (a) Optimization outcomes.

Fig. 6 (b) Spectra of frequency.

TABLE I
PERFORMANCE ANALYSIS OF CASE – I

Strategy	Nt	Power Extracted	Wake Loss	AEP (MWh)	Efficiency %
Proposed	32	16389.73	199.06	143574.04	98.8
[23]	32	16326.59	262.2	143020.98	98.42

Table I demonstrates the performance of the proposed layout with previous research. The proposed strategy extracts 16389.73 kW, which is higher than the earlier reported 16326.55 kW. A major difference appears in wake losses: the proposed configuration records 199.06 kW units, in place of 262.21 kW units, indicating that the proposed layout better minimizes wake interactions. Overall, the proposed layout demonstrates superior optimization by

enhancing power capture and reducing wake-induced losses, out-performing the approach presented in [23].

B. CASE 2

Figure 7 (a) represents the improved layout obtained through the proposed hybrid PSO-GA approach. While, 7 (b) reflects the reference layout used for comparison.
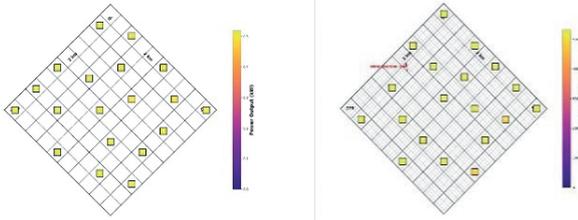

Fig. 7 (a). Layout of wind farm by proposed work.

Fig. 7 (b). Layout of wind farm [23].

The optimum configuration produces a maximum power output with 19 turbines working under a uniform inflow wind speed of 12 m/s, as shown in Figures 8(a) and 8(b). With an average turbine efficiency of roughly 99.2% and individual turbine efficiencies ranging from 94.98% to 100%, the algorithm converges on a highly efficient arrangement. There is little fluctuation in the effective wind speed distribution between 11.76 and 12.00 m/s throughout the farm.


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Best Wind Direction: 310°
Constant Wind Speed: 12.0 m/s
Number of Turbines: 19
Average Turbine Efficiency: 0.99216073
Efficiency Range: 0.94073569 - 1.00000000
Average Effective Wind Speed: 11.97 m/s
Wind Speed Range: 11.76 - 12.00 m/s
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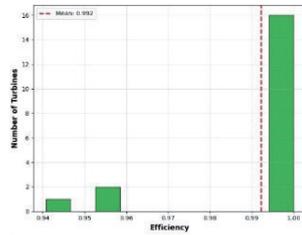
Fig. 8. (a) Optimization results.

Fig. 8 (b) Distribution of frequency.

The performance of the proposed layout with the previous research is shown in Table II. The suggested method extracts 9770.8 kW, which is marginally more than the 9741.3 kW. Wake loss indicates a significant difference: the suggested configuration records 78.7968 kW units, instead of 108.3 kW units. This suggests that the proposed structure more effectively reduces wake interactions. Overall, by improving power capture and lowering wake-induced losses, the proposed configuration exhibits improved optimization than the technique existing in [23].

TABLE II

PERFORMANCE ANALYSIS OF CASE - 2

Strategy	Nt	Power Extracted	Wake Loss	AEP	Efficiency %
Proposed	19	9770.8032	78.7968	85592236	99.2
[23]	19	9741.3	108.3	85333788	98.9

In comparison to Asaah et al. (2021), the proposed PSO-GA diminished wake loss by 26.5% in Case 1 and 24.3% in Case 2, concurrently enhancing AEP by roughly 0.2% for each case. In contrast to [23], which depends exclusively on PSO exploration, the hybrid method improves local refinement and convergence dependability.

C. CASE 3

Figure 9 illustrates that the chance of wind speed is higher when the wind direction is between 270 and 350. The performance of the suggested layout with the earlier study is shown in Table III. The suggested method extracts 7713.79 kW, which is somewhat more than the 7,690.46 kW. Wake losses indicate a significant difference: the proposed configuration records 62.21 kW units, instead of 85.54 kW units, suggesting that the proposed layout more effectively reduces wake interactions. Overall, by improving power capture and lowering wake-induced losses, the proposed layout do better than the method implemented in [23].

TABLE III

PERFORMANCE ANALYSIS OF CASE - 3

Strategy	Nt	Power Extracted	Wake Loss	AEP	Efficiency %
Proposed	15	7713.79	62.21	67572800.4	99.2
[23]	15	7,690.46	85.54	67368429.6	98.9

Fig. 9. Wind condition of Case 3.

VI. CONCLUSION
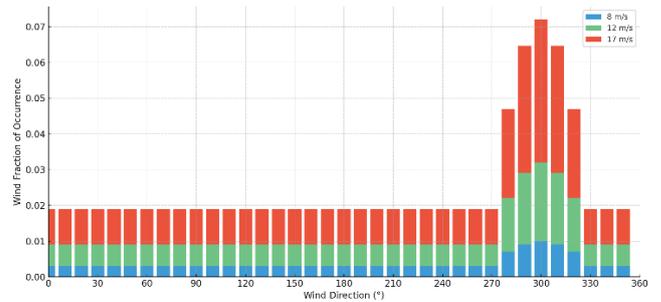
To address the WFLO problem in actual wind conditions, the current study presents a novel hybrid optimization technique that successfully combines Hybrid PSO-GA integrated with the Jensen wake model. Unlike previous research that just used traditional evolutionary algorithms, this approach incorporates a dynamic goal function that takes cost, energy yield, and efficiency by minimizing the wake loss. The paper delineated the optimum WFLOs under the three case studies of wind speed and direction. In order to obtain the maximum possible output power, each WT's position was appropriately selected. In short, the hybrid PSO-GA algorithm provided a very effective method for optimizing wind farm layouts, leading to significant increases in power output and cost effectiveness while preventing severe wake disruption. The algorithm's practical relevance in real-world wind farm design is demonstrated by its robustness across many case studies and its capacity to manage the trade-off between electricity generation and turbine cost. The suggested PSO-GA significantly reduced wake-loss and improved efficiency by up to 0.2% as compared to previous WFLO techniques. The cited 0.2% enhancement pertains to overall agricultural efficiency, whilst the 20–28% decrease specifically relates to wake loss percentage in comparison to the benchmark study. The hybrid framework may be successfully used in actual wind farm planning, as evidenced by the computational cost remaining reasonable. To further increase accuracy, future research might use sophisticated wake models like Gaussian or CFD-based wake formulations.

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