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Wind Farm Layout Optimization Using Ant Colony Optimization for Minimizing Cost of Energy

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Abstract

Optimized wind turbine configurations enable sustainable power generation; however, maximizing total power output through wind farm layout optimization (WFLO) remains a critical and complex challenge. WFLO strategically identifies the optimal positioning of the wind turbines within a designated wind farm area to mitigate wake effects and maximize overall power output. Wake effects, where upstream turbines diminish the wind velocity reaching downstream turbines, can substantially lower the overall power output of a wind farm. This study proposes an ant colony optimization (ACO) approach to address WFLO, employing a continuous wind farm model that enables flexible turbine placement to minimize the cost of energy (CoE). Three scenarios were examined: constant wind speed in a single wind direction; constant wind speed in multiple wind directions; and a variable wind speed in multiple directions incorporating direction-specific occurrence probabilities. The proposed framework facilitates continuous spatial optimization, substantially expanding the feasible search space by eliminating grid-based constraints. Its effectiveness was validated through comparative evaluation against methods reported in prior studies. The results demonstrate that the ACO algorithm consistently achieves superior performance, yielding a 2.13–4.03% reduction in CoE and a 2.22–4.06% increase in total power output across diverse wind conditions. This study highlights the potential of continuous spatial optimization as an effective alternative to conventional grid-based approaches in WFLO.

Keywords: wind farm layout optimization; ant colony optimization; wind farm; wind turbine; algorithm; WFLO

Academic Editor: Bo Yang

Received: 3 June 2026

Revised: 29 June 2026

Accepted: 1 July 2026

Published: 3 July 2026

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1. Introduction

Rising socio-economic development and demographic growth are increasing electricity demand [1]. To meet these growing demands and support sustainability, accelerated deployment of renewable energy and electrification are fundamental strategies [2]. Wind energy serves as a cost-competitive renewable technology in climate strategies [3]. Wind turbines (WTs) are the primary technology for converting kinetic energy into electricity [4]. Strategic clustering of wind turbines (WTs) within a wind farm (WF) enhances energy capture; however, wake-induced interactions remain the primary constraint, significantly reducing total power output and efficiency [4]. Upstream turbines generate wake interference, which reduces wind velocity for downstream turbines and consequently diminishes their energy capture due to persistent wake effects. Hence, optimized

turbine layouts are critical for minimizing wake interactions and maximizing energy extraction efficiency in wind farm (WF) projects. This challenge is known as the wind farm layout optimization (WFLO) problem.

Wind farm layout optimization (WFLO) is the process of determining the optimal spatial placement of wind turbines within a designated site to maximize energy generation while minimizing costs [5]. WFLO primarily seeks to maximize total power output or minimize the cost of energy (CoE), where cost models are often simplified empirical functions based solely on turbine count [6]. WFLO is highly non-convex and multimodal, making it computationally challenging to achieve a globally optimal solution [7,8]. To address these challenges, researchers predominantly utilize metaheuristics, offering a robust balance between solution quality and computational tractability. Genetic algorithms (GAs) are widely utilized due to their ability to perform global searches, thereby overcoming local optima in complex and multimodal WFLO problems [9–14]. These six studies establish genetic algorithms (GAs) as a standard approach to the WFLO problem across diverse scenarios and algorithmic variants, using a discrete-grid model. Particle swarm optimization (PSO) is a robust metaheuristic method for solving WFLO problems [15–18], including evolutionary strategies [19–22] and differential evolution (DE) [23–26]. Collectively, these studies demonstrate the effectiveness of evolutionary search methods for WFLO, and in each case, the WFLO problem is formulated using a discrete grid model. These studies propose various DE variants and modeling schemes for WFLO, demonstrating DE's versatility in addressing WFLO problems within a discrete modeling framework. Furthermore, various algorithm frameworks have been developed to optimize the WFLO problem [5,6,27–32]. Mathematical programming methods are also employed for WFLO [33,34].

Previous studies have predominantly adopted discrete WFLO formulations, wherein the wind farm domain is discretized into uniform grid cells with turbine placement restricted to cell centers using binary (0/1) decision variables. Consequently, discretized representations may underexplore intermediate regions, potentially missing globally optimal solutions. Although finer grid resolution partially mitigates this limitation, it escalates computational demands without fully overcoming discrete representation constraints. In contrast, the continuous WFLO model treats turbine locations as continuous spatial variables, permitting placement at any feasible coordinates within the wind farm boundary. This approach enables more flexible turbine placement and solution space exploration. Continuous WFLO models can achieve higher power output and lower energy costs through precise position adjustments that minimize wake interactions. However, this expanded search space introduces greater computational challenges and demands more efficient optimization strategies.

Continuous WFLO models have received less attention in the literature compared with discrete WFLO models. To address this gap, the present study investigates solving continuous WFLO models using the ant colony optimization (ACO) algorithm. Notably, applications of the ACO algorithm to continuous WFLO are particularly scarce. Continuous WFLO models a high-dimensional continuous task, leveraging a 2D Cartesian XY coordinate system to optimize unconstrained turbine placement. The ACO framework represents turbine locations via coordinates, iteratively updating placements within 2D Cartesian XY space to systematically search for optimal, unconstrained arrangements. This approach provides an accurate, practical assessment of turbine placement. The main contributions of this study are summarized as follows:

1. Unlike cell-based discretization, this framework enables continuous spatial optimization, vastly expanding the feasible search space for precise turbine placement.
2. This study proposes the ACO algorithm with a new way to adapt pheromone levels, where the pheromone strength reflects the power losses of each turbine. By giving

more weight to turbines that lose more power due to wake effects, the framework can focus more on reducing these losses during optimization.

3. The results demonstrate that the continuous WFLO model enhances total power output while reducing the cost of energy (CoE), offering novel insights into integrating continuous WFLO modeling with an effective ACO algorithm.

The remainder of this paper is organized as follows: Section 2 reviews the literature in the field. Section 3 outlines the problem formulation for WFLO. Section 4 details the methodology, the fundamental principles of the ACO algorithm, and the procedural workflow for the proposed ACO algorithm for the WFLO problem. Section 5 presents the results, followed by a comprehensive discussion. Finally, Section 6 summarizes the research outcomes and outlines potential directions for future work.

2. Literature Reviews

Metaheuristics are the dominant frameworks for the WFLO problem. Metaheuristic algorithms have the advantage of being simple and straightforward. Mosetti et al. pioneered WFLO research by implementing evolutionary genetic algorithms (GAs) to maximize power across three wind scenarios [9]. Utilizing a 100-cell grid and the Jensen model, they established a fundamental benchmark for simulating wake effects in layout optimization. Subsequently, Grady et al. achieved superior results by increasing the population size and the number of iterations, thereby enhancing the GA's global search efficiency [10]. Distributed genetic algorithms (DGAs) optimize turbine placement to maximize wind farm profits more effectively than traditional genetic algorithms [11]. This is a novel genetic algorithm coding approach and an objective function that enhances wind farm efficiency and total power output compared with Grady's model [12]. The proposed GA framework marginally outperformed the results of Grady et al. across three wind scenarios while significantly reducing the required computational time [35]. The study employed a multi-population genetic algorithm with the 2D Jensen–Gaussian wake model to optimize wind farm layouts, improving power generation and efficiency [14]. They employed a GA, integrating the Jensen wake model, to optimize turbine placement across a 100-cell grid, maximizing power output and efficiency across three distinct wind cases.

Various metaheuristic approaches, including particle swarm optimization (PSO) [15–18], evolutionary strategies [19–22], differential evolution (DE) [23–26], and other advanced algorithms [5,6,27–32], have been effectively utilized to address the WFLO problem, alongside mathematical programming approaches [33,34]. However, optimizing wind farm layout to maximize total power output while minimizing costs of energy (CoEs) remains a major research challenge; thus, advancing metaheuristic algorithms remains a promising approach to address these complex layout challenges effectively.

The literature indicates that grid-based approaches to WFLO problems are common due to their simpler implementation and lower computational cost. In contrast, discrete grid-based methods limit turbine positions to specific points, which may lead to sub-optimal configurations due to stricter spatial limitations [36]. Continuous approaches enable turbine placement within an unrestricted spatial domain, potentially yielding more efficient layouts by exploring a larger solution space. However, continuous formulations increase problem complexity and computational demands.

3. Problem Formulation for WFLO

3.1. Wake Model

A primary objective in the wind farm layout optimization (WFLO) problem is to mitigate energy losses arising from wake interactions between turbines. To accurately evaluate these wake-induced losses, an appropriate wake model must be employed. The Jensen

wake model [37] has been widely employed in wind farm layout studies and continues to serve as a benchmark engineering wake model. In this study, the original Jensen wake model is adopted as a reference to evaluate the proposed ACO algorithm under conditions consistent with prior studies. The Jensen wake model is widely used in WFLO frameworks due to its mathematical tractability and low computational cost. These characteristics are particularly advantageous for iterative metaheuristic algorithms that require a vast number of objective function evaluations [14].

This study focuses exclusively on horizontal-axis wind turbine (HAWT) configurations in the analysis. In the Jensen wake model, the wake shown in Figure 1a is assumed to originate with the turbine rotor diameter and to expand linearly in the downstream direction. As illustrated in Figure 1a, the Jensen wake model characterizes wake formation under uniform wind conditions. Upon interaction with the rotating turbine, a wake is generated and subsequently undergoes linear expansion as it propagates downstream from the rotor. Applying the principle of momentum conservation, the velocity is assumed to remain uniform across the wake cross-section and is derived as follows [9,37,38]:

$$\frac{\Delta v}{v_0} = \frac{2a}{\left(1 + \alpha \frac{x}{r_0}\right)^2} \quad (1)$$

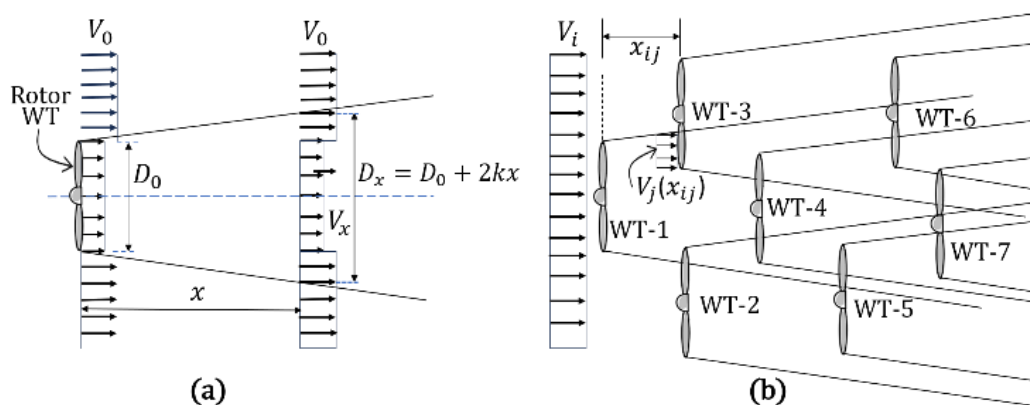


Figure 1. (a) Jensen wake model and (b) multiple wake effect in the wind farm.

The full wind velocity is denoted as v_0 , Δv is the velocity deficit, and the wind velocity within the wake at a downstream distance x from the turbine is represented as $v(x)$. The turbine rotor radius is r_0 . The parameter a is determined as follows [9,39]:

$$C_T = 4a(1 - a) \quad (2)$$

$$a = 0.5(1 - \sqrt{1 - C_T}) \quad (3)$$

In this formulation, C_T represents the turbine thrust coefficient. The downstream wake radius at distance x is subsequently calculated as [9,39]

$$r_1 = r_0 + \alpha x \quad (4)$$

where the entrainment constant α depends on hub height and terrain roughness of the wind farm [9,39]:

$$\alpha = \frac{0.5}{\ln\left(\frac{z}{z_0}\right)} \quad (5)$$

Wake interactions in wind farms (WFs) become stronger as the number of installed wind turbines (WTs) increases, intensifying the overall wake impact. A downstream tur-

bine can be strongly influenced by the combined wakes of multiple upstream turbines, a phenomenon known as the multiple wake effect, as illustrated in Figure 1b.

The wake velocity is given by the following expression [39]:

$$\frac{V_x}{V_0} = 1 - \frac{2a}{\left(1 + \alpha \frac{x}{r_0}\right)^2} \quad (6)$$

$$V_x = V_0 - V_0 \left(\frac{2a}{\left(1 + \alpha \frac{x}{r_0}\right)^2} \right) \quad (7)$$

For wind turbines operating under multiple wake interactions, the kinetic energy of the combined wake flow is determined by the linear superposition of the individual kinetic energy deficits. The total velocity deficit is calculated as follows [9,10,28,38–40]:

$$\left(\frac{v_x}{v_o}\right)^2 = \left(1 - \frac{2a}{\left(1 + \alpha \frac{x}{r_0}\right)^2}\right)^2 \quad (8)$$

or

$$v_i = v_o \left[1 - \sqrt{\sum_{j=1}^{N_{OV}} \frac{2a}{\left(1 + \alpha \frac{x_i}{r_0}\right)^2}} \right] \quad (9)$$

where N_{OV} represents the number of upstream turbines whose wakes overlap with the target turbine.

3.2. Wind Farm Layout Optimization (WFLO) Problem

The primary aim of the optimization algorithm is to minimize or maximize a specified objective function. The objective function in the WFLO problem incorporates investment costs and total turbine power output to determine the optimal placement of turbines within the wind farm area. The investment cost is modeled as a function of the total number of installed turbines N within the wind farm (WF) with the unit annual cost of the first turbine and a cost reduction factor of $1 - \frac{1}{3} (N - 1)$ applied to additional turbines. The function *Cost* of the wind farm is defined as follows [9]:

$$Cost = N \left(\frac{2}{3} + \frac{1}{3} e^{-0.00174N^2} \right) \quad (10)$$

The main objective of this study is to minimize the cost of energy (CoE). Accordingly, the optimization objective is formulated as given in Equation (11).

$$\text{Minimize } CoE = \frac{Cost}{P_{total}} \quad (11)$$

P_{total} denotes the total power output of the wind farm, accounting for wake effects, and is computed as follows [9,10,28,40]:

$$P_{total} = \sum_{i=1}^N P_i \quad (12)$$

$$P_i = \sum_{i=1}^N 0.3 v_i^3 \quad (13)$$

Here, v_i denotes the effective wind speed of turbine i . In addition, the park efficiency E_p , which evaluates the effectiveness of the wind turbine layout, is computed as follows [28,38,40]:

$$E_p = \frac{P_{total}}{P_{total,max}} \quad (14)$$

where $P_{total,max}$ denotes the maximum power output in the absence of wake effects.

We employ Cartesian coordinates (x, y) to specify the two-dimensional positions of the N turbines within the wind farm. The decision variables are the turbine coordinates, where x_i and y_i denote the x - and y -coordinates of turbine i , respectively (where $i = 1 \dots N$), and N is the number of turbines in the WF. The objective function can be written as

$$\text{Maximize } P_{\text{total}} = \sum_{i=1}^N P_i(x_i, y_i) \quad (15)$$

Here, $P_i(x_i, y_i)$ denotes the power generated by turbine i at position (x_i, y_i) , accounting for wake losses. A minimum safe distance must be maintained between adjacent wind turbines. The inter-turbine spacing is constrained to a minimum of five rotor diameters (5D), in accordance with the standard practice in the WFLO literature [9,10,28,38,40]. Industry practice commonly recommends a spacing of at least 5D between turbines to minimize turbulence generated by upstream wakes. The spacing requirement between any two turbines, i and j , is mathematically expressed by the following constraint:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} > 5D \quad \forall i, j = 1 \dots N \quad i \neq j \quad (16)$$

The spatial arrangement of wind turbines within the wind farm is subject to a set of constraints, which can be expressed mathematically as follows:

$$0 \leq x_i \leq L_x, \quad 0 \leq y_i \leq L_y, \quad \forall i \quad (17)$$

Here, L_x and L_y denote the horizontal and vertical dimensions of the wind farm, respectively.

The coordinates of turbine i in the northwest coordinate system centered at turbine j are (x_i, y_i) . The relative position of turbine i with respect to turbine j is transformed into wind-aligned coordinates via a rotation matrix defined by wind direction θ . Thus, the coordinates of turbine i , (x'_i, y'_i) relative to the wind direction θ are derived by rotating the original positions using the rotation equation [41]:

$$(x'_i, y'_i) = (x_i, y_i) \cdot \begin{bmatrix} \cos \theta_d & -\sin \theta_d \\ \sin \theta_d & \cos \theta_d \end{bmatrix} \quad (18)$$

Once inter-turbine distances are determined, the velocity deficit for each turbine is calculated.

4. Methodology

4.1. Ant Colony Optimization (ACO) Algorithm

The ant colony optimization (ACO) algorithm is a metaheuristic algorithm inspired by ant foraging, in which pheromone trails guide the search for the shortest paths between the nest and food sources [42]. ACO has demonstrated strong effectiveness and has been widely employed to solve a variety of power system optimization problems, including many that are NP-hard in nature. The algorithm mimics the collective foraging behavior of ant colonies, and its search procedure can be decomposed into the following:

- Ants randomly explore the search space to generate candidate solutions.
- Ants deposit pheromones on the paths corresponding to constructed solutions.
- Pheromone levels are updated in proportion to solution quality.
- Subsequent ants probabilistically favor paths with higher pheromone intensity.

Ants traversing from source point A to destination point B deposit pheromones τ_{ij} along path edges (i, j) . Subsequent ants detect these trails and select the next edge probabilistically, favoring higher concentrations [43]:

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l=1}^{N_i} [\tau_{il}(t)]^\alpha [\eta_{il}(t)]^\beta} \quad (19)$$

where p_{ij}^k is the probability for ant k choosing edge (i, j) , α and β are heuristic parameters, $\eta_{ij} = 1/d_{ij}$ is the visibility (inverse distance), and N_i denotes feasible neighbors from node i .

A fundamental characteristic of this metaheuristic is the global pheromone update mechanism executed at the conclusion of each iteration. In this process, the pheromone intensity on the edge connecting nodes is systematically adjusted based on the aggregate contributions of the entire population of agents that successfully constructed a solution during that iterative cycle. The pheromone level τ_{ij} on edge (i, j) updates according to the following rule [43]:

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij} + \sum_{k=1}^m \Delta\tau_{ij}^k \quad (20)$$

where $\rho \in (0, 1)$ represents the pheromone evaporation rate, m denotes the total number of ants, and $\Delta\tau_{ij}^k$ quantifies the pheromone deposited by ant k on edge (i, j) , proportional to its solution quality:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k} & \text{if ant } k \text{ edge } (i, j) \text{ in its tour,} \\ 0 & \text{otherwise,} \end{cases} \quad (21)$$

where $Q > 0$ is a fixed deposit constant, and L_k represents the total cost of the solution constructed by ant k . Figure 3 illustrates the procedural framework of the ACO algorithm. The flowchart of the basic ACO framework is shown in Figure 2.

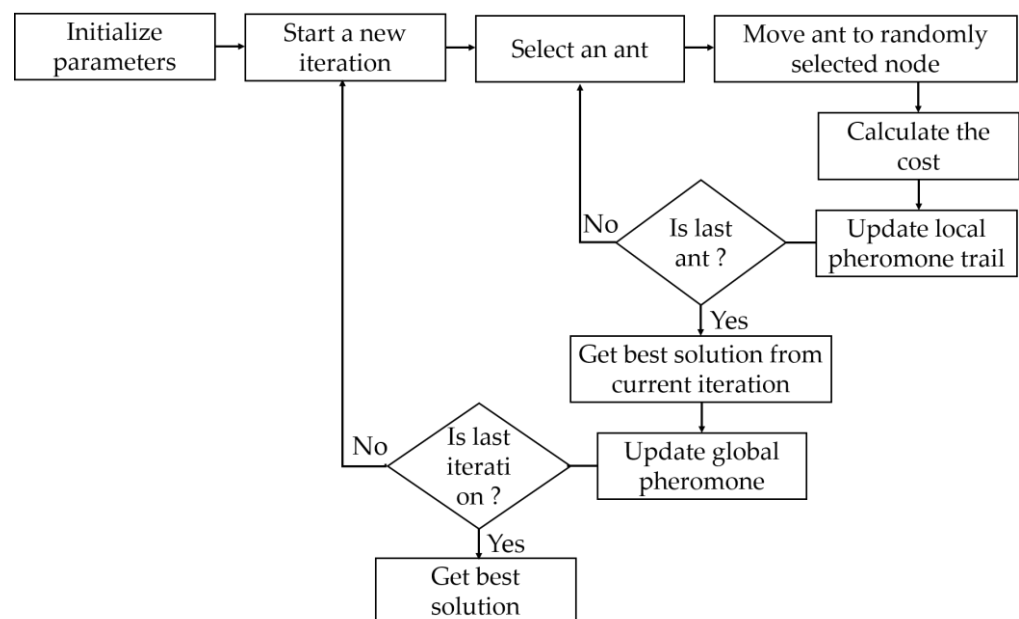


Figure 2. Basic ACO framework.

4.2. Proposed Ant Colony Optimization (ACO) Algorithm for WFLO

Continuous adaptations of ACO for optimization have shown effectiveness in multiple studies [44–46]. The proposed ant colony optimization (ACO) algorithm for continuous wind farm layout optimization (WFLO) proceeds through the following steps:

Step 1: Initialization Phase

Random positions (x_i^0, y_i^0) are initialized for all N turbines within the wind farm boundaries $[0, L_x] \times [0, L_y]$, while enforcing a minimum safe distance of $5D$ between every turbine pair $(i \neq j)$. For each candidate position, the coordinates (x_i, y_i) are drawn uniformly at random from $[0, L_x]$ and $[0, L_y]$, and the Euclidean distances to all previously placed turbines are then computed. A candidate is accepted only if all pairwise distances satisfy $d_{ij} \geq 5D$ in Equation (16). Otherwise, a new candidate position is gener-

ated until a feasible location is found. In this way, the boundary and minimum spacing constraints are explicitly enforced during the coordinate generation stage. Wake-induced velocity deficits are computed using the Jensen model, accounting for multiple wakes (Equation (9)), which yields turbine-specific wind speeds. The power of turbine i and total power output Equations (12) and (13) identify this initial wind farm layout as the best wind farm layout. The pheromone intensity τ_i associated with turbine i is calculated using the equations below:

$$P_{losses,i} = P_{max,i} - P_i \quad (22)$$

$$\tau_i = \frac{P_{losses,i}}{\sum_{i=1}^N P_{losses,i}} \quad (23)$$

$P_{max,i}$ denotes the power output of turbine i in the absence of wake effects. The initial pheromone intensity is calculated using Equations (22) and (23).

Step 2: Main Optimization Loop (for $t = 1$ to $\max_iter$)

This step is carried out for each iteration and for each of the N_{ant} operating in parallel, where N_{ant} denotes the total number of ant agents employed in the ACO algorithm.

Step 2.1: pheromone-guided ant allocation

In the proposed ACO algorithm, the pheromone intensity is calculated through direct power loss evaluation using Equations (22) and (23), which significantly enhances the computational efficiency of the algorithm. This approach eliminates the need for iterative wake simulations, enabling rapid pheromone updates while preserving solution quality.

The number of ants allocated to turbine i , denoted by $\mathbf{Tant}_i$, is directly proportional to its pheromone level. The equations are presented below:

$$\mathbf{Tant}_i = \tau_i \times N_{ant} \quad (24)$$

Step 2.2: turbine coordinate relocation

Each ant randomly perturbs the coordinates (x, y) of its assigned turbine. The new positions are then projected onto the feasible space, enforcing the wind farm boundaries and a minimum spacing constraint of 5D between turbines. For each ant's updated layout, wake-induced velocity deficits are computed using the Jensen model, including multiple-wake interactions (Equation (9)), which yields turbine-specific wind speeds. The new power output of each turbine and the total wind farm power are subsequently computed using Equations (12) and (13).

Step 2.3: elite selection

If $P_{i,t} > P_{i,t-1}$, then the new coordinates (x_i, y_i) and the power output of turbine i are updated; furthermore, if $P_{total,t} > P_{total,t-1}$, the updated turbine layout is accepted and stored as the best layout, indicating an improvement in the objective function.

Step 3: Pheromone Update Phase

The pheromone intensity associated with each turbine is updated according to the best layout identified so far, as defined in Equation (23).

Step 4: Termination and Output

Once the maximum-iteration criterion ($\max_iter$) is satisfied, the algorithm returns the optimal turbine layout (x_i^*, y_i^*) , along with the maximized total power output, minimized cost of energy (CoE), and maximized wind farm efficiency, respectively.

The proposed ACO algorithm optimizes continuous WFLO through initialization, pheromone-guided ant perturbations, elite selection, and termination, converging on optimal turbine layouts that maximize power while respecting wake effects and spacing constraints. The flowchart of the proposed ACO for WFLO is shown in Figure 3.

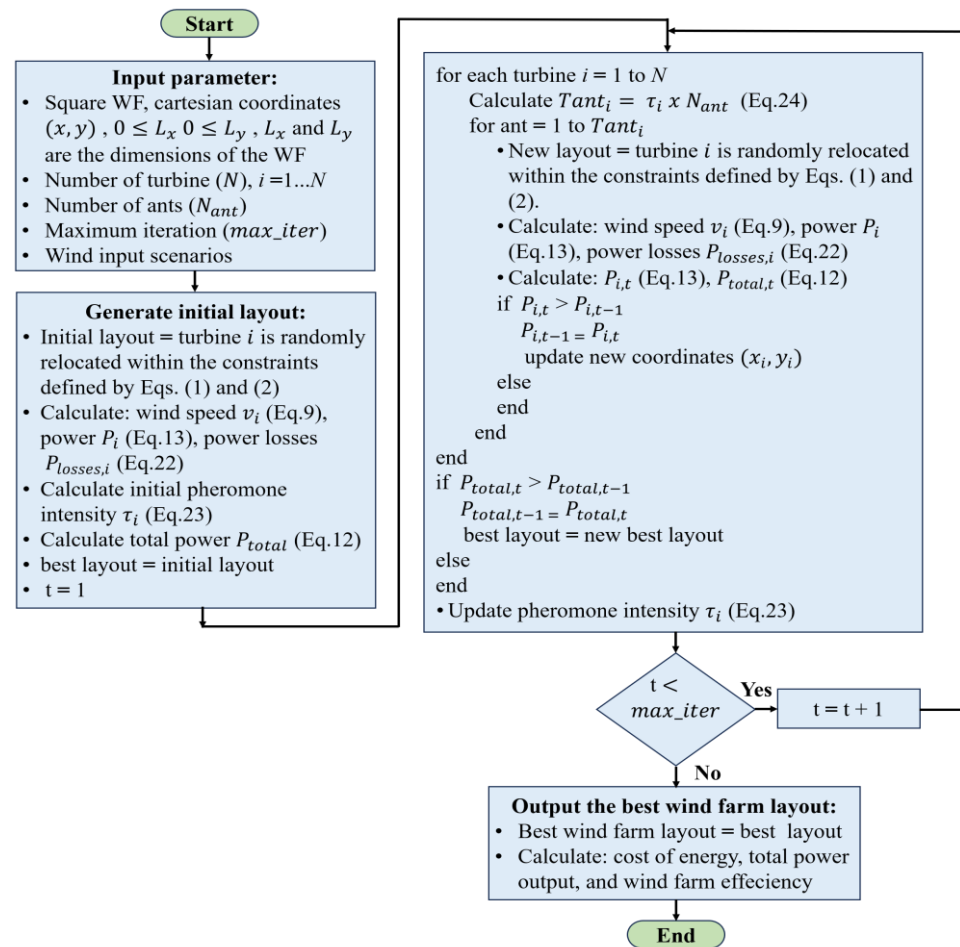


Figure 3. Flowchart of proposed ACO for WFLO.

5. Results and Discussion

This study examines wind farm layout design in a standard $2000 \times 2000 \text{ m}^2$ flat terrain area, consistent with prior WFLO studies. The proposed ACO algorithm models the WFLO problem on a continuous grid, with turbines located at continuous (x, y) coordinates, as shown in Figure 4. Table 1 presents the wind turbine and wind farm specifications used in layout optimization, consistent with prior studies.

Table 1. Wind turbine and wind farm characteristics.

Property	Value	Property	Value
Rotor diameter (D_0)	40 m	Cut-in wind speed (v_{cut-in})	4 m/s
Hub height (h)	60 m	Cut-out wind speed ($v_{cut-out}$)	26 m/s
Thrust coefficient (C_T)	0.88	Wind farm size	2 km $\times$ 2 km
Power coefficient (C_p)	0.39	Minimum spacing	200 m (5D)
Surface roughness length (z_0)	0.3	Wind directional degree	$\{10^\circ, 20^\circ, 30^\circ, \dots, 360^\circ\}$
Air density (ρ)	1.225 kg/m ³		

The performance of the proposed ACO algorithm for the WFLO problem was evaluated by optimizing wind turbine layouts across three wind scenarios and by comparing the results with prior literature findings. Three wind speed scenarios were examined to assess the optimization performance: (a) constant speed in a single direction, (b) constant speed in multiple directions, and (c) variable speed in multiple directions. Case study (a) assumes a constant 12 m/s wind from the north, validating the wake model and layout (Figure 5a). Case study (b) divides the azimuth into 36 equal-angle sections, with uniform

12 m/s wind generated from all directions (Figure 5b). Case study (c) adopts 36 wind directions, as in (b), incorporating three wind speeds (8, 12, and 17 m/s) with varying occurrence probabilities (Figure 5c). Figure 6 shows the probability distribution of wind direction for case study (c). The 12 m/s and 17 m/s wind speeds occur more frequently in wind directions between 270° and 350° , indicating northwest as the prevailing wind direction for the wind farm.

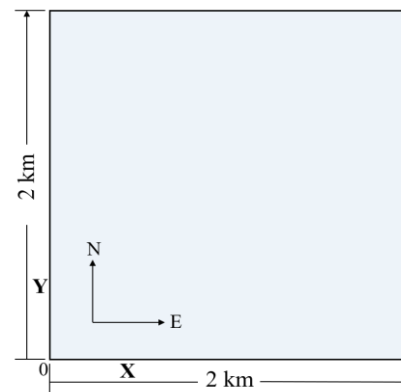


Figure 4. Continuous spatial model for flat terrain wind farm.

The proposed ACO algorithm for WFLO was coded and implemented in MATLAB R2013a on a PC with an Intel Core i7 processor and 16 GB of RAM. This study evaluated the proposed ACO algorithm across wind farm layouts with 30, 39, 40, and 41 turbines. Configurations employed 80 and 200 ant colonies, respectively, with maximum iterations of 300 and 1000. The proposed ACO algorithm for WFLO was executed independently ten times. The mean values from the ten independent runs represented the WFLO solutions.

The computational results were benchmarked against prior WFLO studies using results reported in the referenced literature, including Grady et al.'s [10] and recent studies. Grady et al. [10] are widely recognized in the prior literature for benchmarking enhanced metaheuristic algorithms in wind farm layout optimization.

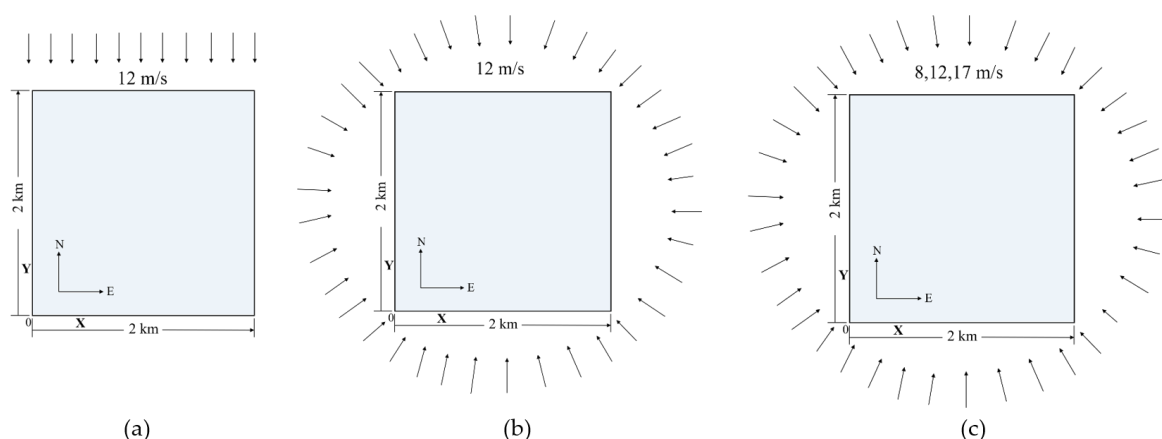


Figure 5. Wind cases: (a) constant speed, single direction; (b) constant speed, multiple directions; and (c) variable speed, multiple directions.

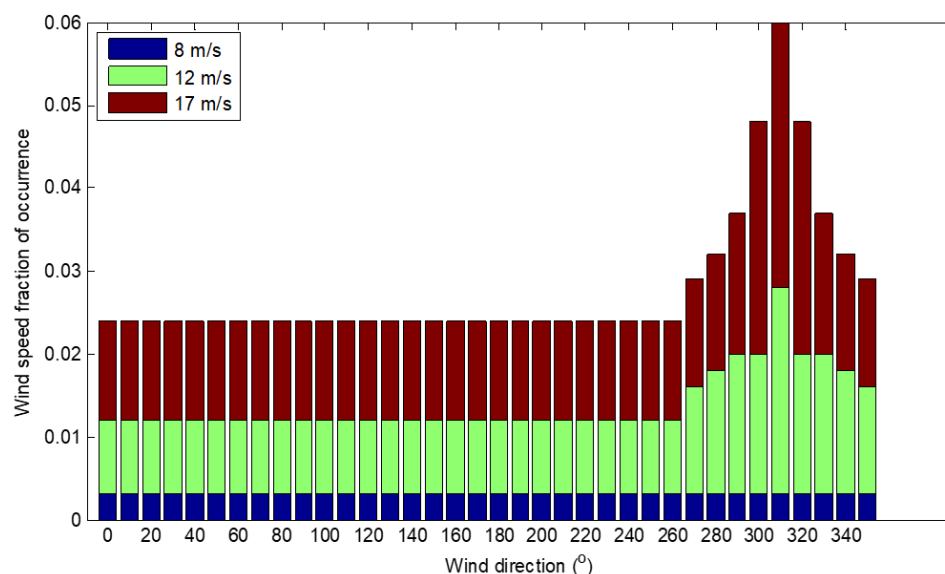


Figure 6. Wind direction probability distribution for case study (c).

5.1. Case Study (a): Constant Wind Speed, Single Direction

Case study (a) assumes a constant 12 m/s wind from the north, with turbines positioned accordingly. Table 2 summarizes the computed layout optimization results. Table 2 compares the proposed ACO algorithm's results with those reported in prior references for benchmarking.

Table 2. Case study (a) layout optimization results.

Authors	Method		Number of Turbines	Total Power (kW)	Efficiency (%)	Objective (Cost/kW) 10 ⁻³
Turner et al. [33]	MILP	Reported	30	14,800	95.160	NA
		Calculated	30	14,752	94.860	1.497
Present study	ACO		30	15,343	98.657	1.440

Bold values indicate the best results.

The proposed ACO algorithm demonstrates an energy cost (CoE) that outperforms both previously reported figures and our recalculated benchmarks, yielding a 3.80% reduction. The proposed ACO algorithm also achieves 3.66% higher total power output than Turner et al. [33]. The proposed ACO algorithm produces the near-optimal layout, resulting in the highest total power output of 15,343 kW and the most favorable economic performance, with a cost of energy (CoE) of 1.440×10^{-3} . Although efficiency was not the primary optimization objective in this study, the proposed ACO algorithm achieves competitive efficiency compared with previous studies reported in the literature. The optimal wind farm configuration identified by the ACO algorithm is illustrated in Figure 7, alongside the benchmark results reported by Turner et al. [33].

5.2. Case Study (b): Constant Wind Speed, Multiple Directions

In case study (b), the wind speed was set to 12 m/s, and the wind direction was measured at 36 discrete points from 0° to 360° in 10° increments; the results are presented in Table 3.

Table 3. Case study (b) layout optimization results.

Authors	Method		Number of Turbines	Total Power (kW)	Efficiency (%)	Objective (Cost/kW) 10 ⁻³
Biswas et al. [28]	L-SHADE	Reported	40	17,920	86.420	1534
		Calculated	40	17,904	86.341	1.536
Rezk et al. [40]	WCA	Reported	40	17,878.32	86.220	1.538
		Calculated	40	17,890	86.276	1.537
Daqaq et al. [38]	MRFO	Reported	40	17,880	86.260	1.538
		Calculated	40	17,897	86.308	1.536
Daqaq et al. [38]	CMRFO5	Reported	41	18,337	86.280	1.530
		Calculated	41	18,309	86.142	1.533
Present study	ACO		40	18,624	89.814	1.476
			41	18,965	89,232	1.480

Bold values indicate the best results.

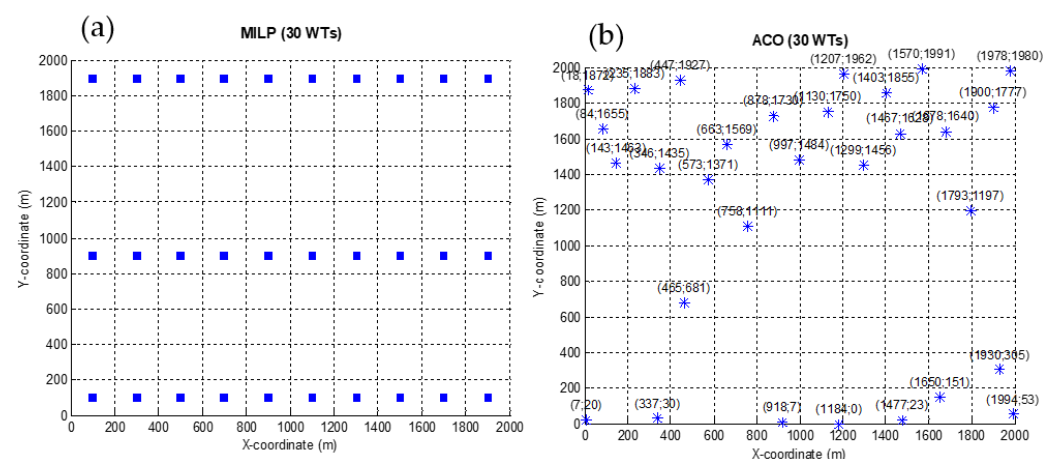


Figure 7. Optimal layout configurations of case a (constant wind speed, single direction): (a) MILP (Turner et al.'s [33] study); (b) ACO (present study).

The proposed ACO algorithm achieves a cost of energy (CoE) that significantly outperforms established literature values and our recalculated benchmarks. By optimizing the 40-turbine layout, the resulting layout yields CoE reductions of 3.78%, 4.03%, and 3.52% relative to the results of Biswas et al. [28], Rezk et al. [40], and Daqaq et al. [38], respectively. Also, optimizing the 41-turbine layout, the resulting layout yields CoE reductions of 3.26% compared with Daqaq et al.'s layout [38]. The proposed ACO algorithm identifies the optimal layout, yielding higher power outputs of 18,624 kW and 18,965 kW for the 40- and 41-turbine configurations, respectively. The proposed ACO algorithm demonstrates competitive efficiency, achieving performance exceeding that reported in prior studies, despite efficiency not being the primary focus of the optimization. The optimal wind farm configuration identified by the ACO algorithm is illustrated in Figure 8, alongside the benchmark results reported by Daqaq et al. [38].

5.3. Case Study (c): Variable Wind Speed, Multiple Directions

This case study was investigated to more accurately represent the variability in wind speed and direction observed in real conditions. This case utilizes modeling frameworks to replicate the complex, non-linear dynamics of wind speed and directionality inherent in large-scale empirical environments. Case study (c) incorporates 36 wind directions and three wind speeds of 8, 12, and 17 m/s with direction-specific occurrence probabilities.

Figure 6 presents the probability data. The total wind farm power output is derived by integrating the full range of wind directionality with three distinct wind speed probability scenarios. These wind conditions incorporate higher levels of complexity, presenting significant computational challenges for optimization algorithms tasked with addressing the WFLO problem.

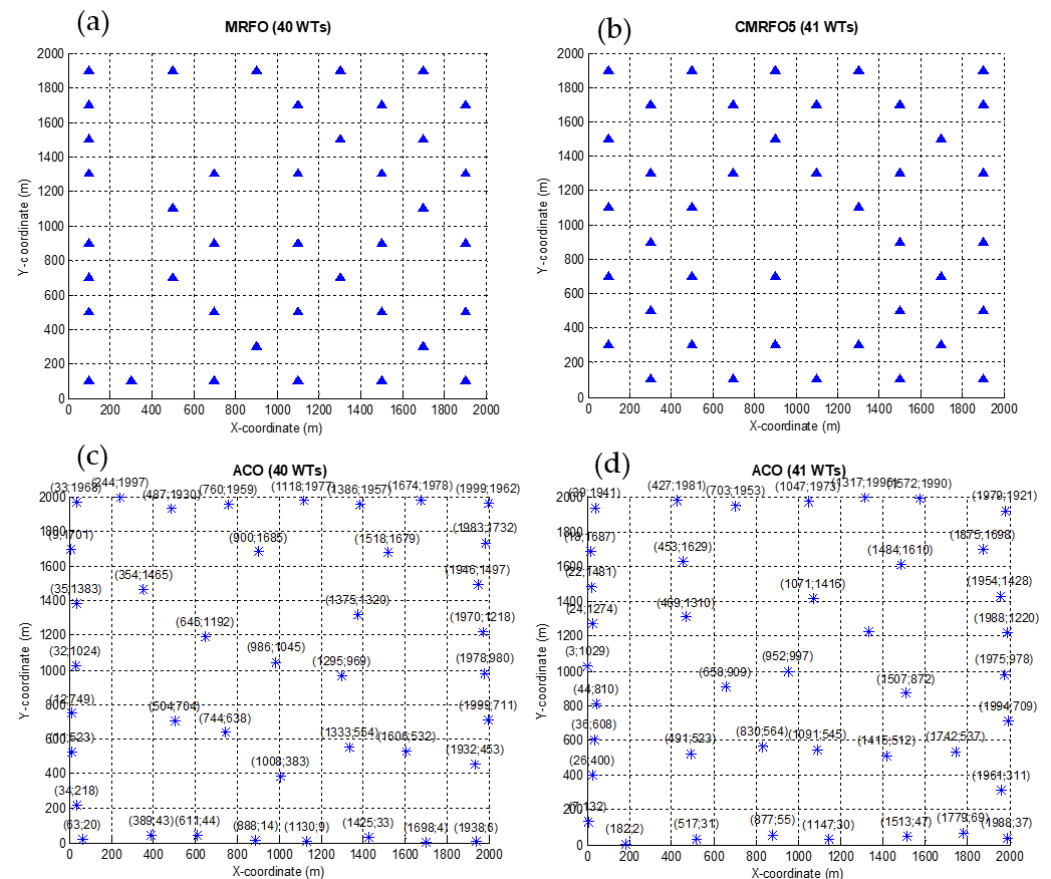


Figure 8. Optimal layout configurations of case b (constant wind speed, multiple directions): (a) MRFO (Daqaq et al.'s [38] study); (b) CMRFO5 (Daqaq et al.'s [38] study); (c) 40-WTs (present study); and (d) 41-WTs (present study).

As shown in Table 4, the ACO algorithm achieves a lower cost of energy than the reference methods, yielding a 2.13% reduction compared with Biswas et al.'s results [28] for a 39-wind-turbine layout. For a 40-turbine configuration, the ACO algorithm yields CoE reductions of 2.31%, 2.66%, and 2.16% compared with the method of Rezk et al. [40] and the MRFO and CMRFO5 variants developed by Daqaq et al. [38], respectively. The ACO algorithm also achieves 2.39% higher total power output than Biswas et al.'s results [28] for a 39-turbine configuration. In a 40-turbine layout, the ACO algorithm demonstrates superior performance, yielding power output increases of 2.36%, 2.74%, and 2.22% over the benchmarks established by Rezk et al. [40] and the MRFO/CMRFO5 variants of Daqaq et al. [38], respectively.

Table 4. Case study (c) layout optimization results.

Reference	Method		Number of Turbines	Total Power (kW)	Efficiency (%)	Objective (Cost/kW) 10 ⁻³
Biswas et al. [28]	L-SHADE	Reported	39	32,351	86.680	0.8322
		Calculated	39	32,275	86.497	0.8339

Rezk et al. [40]	WCA	Reported	40	33,005	87.000	0.8330
		Calculated	40	32,793	85.688	0.8383
Daqaq et al. [38]	MRFO	Reported	40	32,884	85.900	0.8360
		Calculated	40	32,652	85.320	0.8420
Daqaq et al. [38]	CMRFO5	Reported	40	33,052	86.340	0.8317
		Calculated	40	33,052	86.366	0.8318
Present study	ACO		39	33,127	88.780	0.8144
			40	33,786	88.283	0.8137

Bold values indicate the best results.

The ACO algorithm effectively optimizes the turbine layout, resulting in maximum power outputs of 33,127 kW and 33,786 kW for the 39- and 40-turbine scenarios, with superior CoE values of 0.8144×10^{-3} and 0.8137×10^{-3} , respectively. The ACO algorithm achieves superior wind farm efficiency compared with benchmarks in the existing literature, despite efficiency not being the primary objective of this optimization study. The optimal wind farm configuration identified by the ACO algorithm is illustrated in Figure 9, alongside the benchmark results reported by Biswas et al. [28], Rezk et al. [40], and Daqaq et al. [38]. The proposed ACO algorithm demonstrates superior optimization efficiency, yielding performance metrics that surpass benchmarks established in the recent literature. The wind farm efficiency demonstrates superior performance using the ACO algorithm than in the other literature, despite efficiency not being the primary focus of this optimization study.

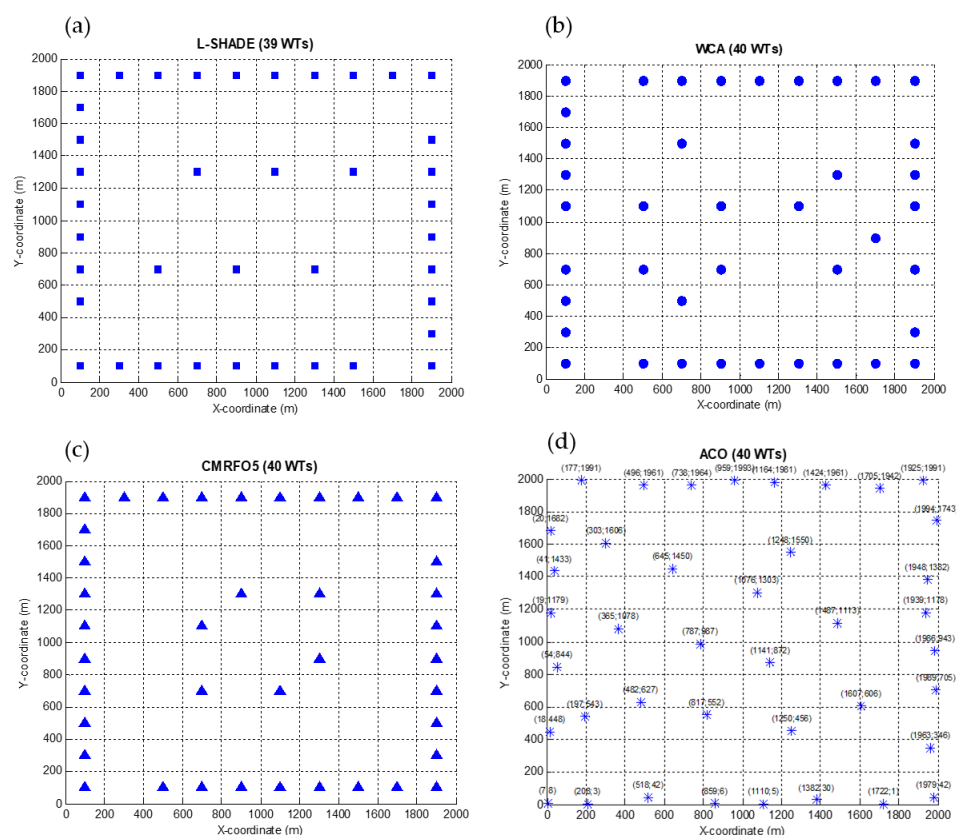


Figure 9. Optimal layout configurations of case c (variable wind speed, multiple directions): (a) Biswas et al.'s [28] study; (b) Rezk et al.'s [40] study; (c) Daqaq et al.'s [38] study; and (d) present study.

To further characterize the stochastic nature of the results, each WFLO instance was executed in 30 independent runs, and the best, worst, mean, and standard deviation of the efficiency values are reported in Table 5. The 95% confidence interval for the mean efficiency was also estimated to indicate the statistical precision of the reported averages. Let $x_1, x_2, \dots, x_{30}$ denote the efficiency values obtained from the 30 independent runs of a given test case, where $\bar{x}$ and s denote the sample mean and sample standard deviation, respectively. The 95% confidence interval for the mean efficiency was calculated as $\bar{x} \pm t_{0.975,29} \frac{s}{\sqrt{30}}$ where $t_{0.975,29}$ is the critical value of Student's t-distribution with 29 degrees of freedom. As shown in Table 5, the small standard deviations and narrow 95% confidence intervals indicate that the proposed ACO framework yielded statistically stable efficiency estimates across runs. These results provide further evidence that the proposed algorithm performs consistently across repeated runs and that the performance gains reported in Tables 2–4 are unlikely to be due to a single favorable execution.

Table 5. Performance variation of ACO algorithm in 30 runs for the ideal test problem.

Number of Turbines	Case Study (a) Efficiency (%)				Case Study (b) Efficiency (%)				Case Study (c) Efficiency (%)			
	Best	Worst	Mean	Std.	Best	Worst	Mean	Std.	Best	Worst	Mean	Std.
30	99.12	98.12	98.65	0.28	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
39	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	89.25	88.20	88.78	0.28
40	N/A	N/A	N/A	N/A	90.30	89.30	89.81	0.30	88.81	87.80	88.28	0.31
41	N/A	N/A	N/A	N/A	89.72	88.70	89.23	0.29	N/A	N/A	N/A	N/A

As shown in Figure 10, the CoE values for all 10 runs decrease rapidly during the initial iterations and then stabilize with only minor fluctuations. This pattern demonstrates that the ACO search converges effectively in each run, so the 30-run statistics in Table 5 represent the algorithm's performance at convergence.

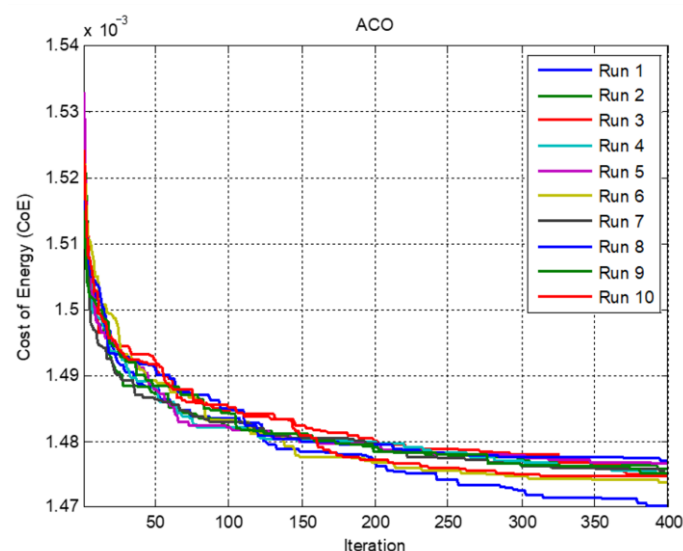


Figure 10. Cost of energy (CoE) for 10 independent ACO runs in case (b) with 40 wind turbines.

6. Conclusions

The ACO algorithm was applied to address the WFLO problem by minimizing the ratio of cost to total power output. This objective function guides the determination of the optimal turbine arrangement within the wind farm to enhance overall efficiency. The ACO algorithm was employed to solve the WFLO problem across three distinct wind sce-

narios. The experimental results were benchmarked against several established optimization methods reported in the literature to evaluate performance. This comparative analysis highlights the relative effectiveness of the proposed approach in terms of key metrics such as total power output and cost of energy.

The ACO algorithm yields a lower cost of energy (CoE) in wind condition case (a) compared with values reported in previous studies. Correspondingly, the total power output achieved by the ACO algorithm surpasses previously published results. This indicates that the proposed ACO algorithm effectively reduces energy costs while simultaneously increasing power generation under this wind scenario. Under wind condition case (b), the ACO algorithm demonstrates superior performance by achieving a significantly lower cost of energy (CoE) compared with previously reported benchmarks. Concurrently, it generates a total power output that surpasses earlier published results under similar wind conditions. Case (c) reflects realistic wind conditions, offering critical insights for optimizing turbine placement within wind farms. The ACO algorithm achieves a significantly lower cost of energy (CoE), surpassing previously established benchmarks. Additionally, it generates a total power output that exceeds earlier reported results under comparable conditions. These findings demonstrate the ACO algorithm's capability to enhance both economic performance and energy generation in practical wind farm scenarios.

This framework enables continuous spatial optimization, significantly expanding the feasible search space for precise turbine placement by removing grid-based constraints. The present study confirms this through results showing that the ACO algorithm consistently achieves superior cost of energy (CoE) and total power output across all wind condition cases. These results demonstrate that the proposed continuous spatial framework allows the algorithm to bypass the resolution constraints of traditional fixed-grid systems, leading to a 2.13% to 4.03% improvement in cost of energy and a 2.22% to 4.06% increase in total power output across diverse wind scenarios.

Future research should focus on incorporating load constraints and turbine fatigue analysis into the optimization process to ensure turbine longevity while maximizing power output. Exploring multi-objective optimization frameworks that balance the cost of energy, power generation, and turbulence reduction can yield more comprehensive solutions for real-world applications. Additionally, optimizing cable layout concurrently with turbine placement can reduce overall infrastructure costs in large-scale onshore wind farms. A simplified cubic power model in Equation (13), consistent with several benchmark WFLO studies based on the Jensen wake model, is employed in this work. Although this model does not explicitly capture the cut-in, rated-power, and cut-out regions of the turbine power curve, the selected turbine specifications remain appropriate for the wind speed range considered. Incorporating a more realistic turbine power curve is, therefore, identified as an important direction for future work.

Author Contributions: Conceptualization, O.A.W.R., B.S., and N.S.; methodology, O.A.W.R.; software, O.A.W.R.; coding, O.A.W.R.; validation, O.A.W.R., B.S., and N.S.; formal analysis, O.A.W.R.; investigation, O.A.W.R., and B.S.; resources, O.A.W.R.; data, O.A.W.R.; writing—original draft preparation, O.A.W.R.; writing—review and editing, O.A.W.R.; visualization, O.A.W.R.; supervision, B.S. and N.S.; project administration, B.S. and N.S.; funding acquisition, O.A.W.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the doctoral program at Institut Teknologi Sepuluh Nopember (ITS). Number: 0000000091278083.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors gratefully acknowledge the academic support and guidance provided throughout this investigation.

Conflicts of Interest: The authors declare no conflicts of interest.

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