

ADAPTATION OF ANT COLONY OPTIMIZATION FOR WIND FARM LAYOUT OPTIMIZATION: METHODOLOGY AND THEORETICAL ANALYSIS

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ABSTRACT

Wind Farm Layout Optimization (WFLO) is a complex renewable energy problem involving nonlinear, nonconvex objectives, where gradient-based methods often fail to find the global optimum due to numerous local optima. This study introduces a continuous Ant Colony Optimization (ACO) approach to address the WFLO problem by determining turbine layouts that maximize power output while considering wake effects, boundary constraints, and minimum spacing requirements. In contrast to conventional ACO methods that operate in discrete spaces, the proposed approach combines pheromone-guided region selection with the continuous generation of turbine coordinates. This continuous ACO approach enables direct optimization in continuous space, rather than at discrete locations, thereby enhancing flexibility and effectiveness in wind turbine layout design. The continuous ACO framework enables direct optimization of turbine locations in a continuous search space, offering near-infinite placement resolution and a stronger potential to mitigate wake interactions than discrete formulations. This study focuses on establishing the theoretical foundation for applying continuous ACO to the WFLO problem and identifies a promising direction for the future development of advanced optimization techniques in renewable energy systems.

Keywords: ACO, renewable energy, wind farm, wind turbine, WFLO

1. INTRODUCTION

Wind Farm Layout Optimization (WFLO) is a critical problem in the field of renewable energy. Its primary objective is to determine the optimal placement of wind turbines to minimize power losses due to wake effects, thereby maximizing total energy output and reducing the overall cost of energy (Chen et al., 2026). WFLO is formulated as a mathematical optimization problem in which turbine positions are treated as continuous variables within the

wind farm area. The optimal configuration is identified using complex mathematical and engineering models. Continuous optimization is a core branch of mathematical modeling where decision variables are treated as real numbers within an n -dimensional space R^n (Andréasson et al., 2020). Unlike discrete or combinatorial problems, which admit a finite set of feasible solutions, continuous optimization problems are characterized by an inherently infinite search space (Zhan et al., 2022). WFLO is a representative example of a modern complex optimization problem, characterized by nonlinearity, in which the objective function's output is not proportional to variations in the input variables (Sawant et al., 2024). This often leads to non-convexity, where the optimization landscape contains multiple local optima (Bower et al., 2018).

The complexity of the WFLO problem arises from the highly nonlinear and nonconvex nature of its objective function (Malisani et al., 2025). This complexity is further compounded by aerodynamic interactions among turbines, as upstream units generate velocity deficits and turbulence that diminish the performance of downstream turbines (Malisani et al., 2025; Cheikh et al., 2026). Evaluating annual energy production (AEP) is numerically demanding and computationally time-consuming, as it requires integrating analytical wake models with stochastic wind-field variability (Cheikh et al., 2026; Malisani et al., 2025). Furthermore, the optimization process must strictly adhere to spatial constraints, most notably the minimum distance requirements between turbines to prevent excessive turbulence and mechanical fatigue (Cheikh et al., 2026; Xu et al., 2022).

Traditional optimization methods, especially gradient-based approaches, often encounter difficulties with WFLO. These methods frequently fail to identify the global optimum due to the non-convex and nonlinear nature of wind energy objective functions, which contain many local optima (Cheikh et al., 2026). Additionally, discontinuities that arise from discrete turbine placement decisions and complex wake interference patterns can render gradient calculations numerically unstable or infeasible (Cheikh et al., 2026). In response to these challenges, metaheuristic algorithms have become the predominant solution strategy in this domain (Zhan et al., 2021). Unlike traditional methods, metaheuristic algorithms such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) do not rely on derivative information and are designed to perform global searches over extensive, potentially unbounded continuous domains (Cheikh et al., 2026; Sheta et al., 2023).

Ant Colony Optimization (ACO) is a particularly promising research direction for WFLO, due to its distinctive search mechanisms inspired by the collective foraging behavior of ants (Jia et al., 2022). Despite challenges such as the computational overhead associated with pheromone updating, integrating ACO into WFLO remains a promising research direction for maximizing Annual Energy Production (AEP) and mitigating complex wake interference in sustainable energy systems. Moreover, despite substantial advances in metaheuristic applications, a significant research gap persists in the use of ACO for continuous search spaces, as the algorithm was originally developed for discrete problems such as the Traveling Salesman Problem (Jia et al., 2022). Because WFLO requires determining the precise coordinates of

turbines within a continuous spatial domain, traditional grid-based methods often suffer from limited spatial resolution and may result in suboptimal energy capture (Wu et al., 2020). As a continuous optimization problem, WFLO is therefore well suited to being addressed using a suitably adapted ACO algorithm. The application of ACO to the WFLO problem hinges on its ability to be adapted to continuous search spaces (Jaadi et al., 2024). By leveraging such adaptive pheromone update rules, ACO offers a sophisticated approach for enhancing annual energy production in modern wind farm developments. This work makes three main contributions:

1. It develops a conceptual framework for adapting ACO to continuous optimization in the WFLO problem.
2. It presents theoretical arguments and qualitative analyses regarding the potential effectiveness and efficiency of ACO in the WFLO problem.
3. It provides a clear direction for future empirical studies on the application of ACO to the WFLO problem.

2. LITERATURE REVIEW

Continuous optimization presents substantial computational challenges due to the inherent complexity of the search space, which, unlike discrete domains, contains an infinite number of candidate solutions defined over continuous decision variables (Hu et al., 2010; Zhan et al., 2021). The primary difficulty lies in the non-linear and non-convex nature of the objective functions, which typically gives rise to a rugged landscape characterized by a high density of local optima (Fu et al., 2024; Shaikh et al., 2025). The search space expands exponentially, resulting in the so-called “curse of dimensionality,” where the computational cost and resource demand for function evaluations become prohibitively high (Houssein et al., 2024; Shaikh et al., 2025). Additionally, solving large-scale global optimization problems remains computationally intensive, particularly for metaheuristic algorithms. Although robust in multimodal and nonlinear landscapes, these algorithms require substantial computational resources to achieve convergence (Fu et al., 2024; Houssein et al., 2024). To address these challenges, metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GAs), Differential Evolution (DE), and Covariance Matrix Adaptation Evolution Strategy (CMAES) have become essential tools for global optimization due to their ability to navigate complex, multimodal, and non-convex environments (Fu et al., 2024; Houssein et al., 2024). However, recent evaluations of more than 160 metaheuristic algorithms indicate that many still suffer from premature convergence, primarily due to an imbalance between the exploration and exploitation phases (Shaikh et al., 2025). Current research emphasizes the need for greater methodological rigor and the development of parameter-free or low-parameter algorithms to more effectively manage the conceptual and practical complexity of real-world optimization scenarios (Houssein et al., 2024; Shaikh et al., 2025).

ACO is a prominent population-based metaheuristic inspired by the collective foraging behavior of natural ant colonies and is designed to solve complex optimization tasks through a distributed and adaptive search mechanism (Abdulghani & Abdulghani, 2024; Pathak et al., 2025). In this framework, artificial ants construct solutions sequentially and probabilistically, traversing the search space according to a stochastic transition rule (Abdulghani & Abdulghani, 2024; Cai et al., 2024). This selection probability is fundamentally governed by two factors: the intensity of the artificial pheromone trail, which encodes accumulated search experience, and heuristic information, which typically provides problem-specific guidance, such as the inverse of path distance (Cai et al., 2024). To guide the colony toward promising regions of the search space, pheromone levels are updated based on solution quality, with higher-quality paths receiving larger pheromone deposits that reinforce successful search patterns (Cai et al., 2024; Othman & Ibrahim, 2025). Simultaneously, a pheromone evaporation process is applied to gradually reduce pheromone concentrations over time. This mechanism is critical for preventing premature convergence and maintaining diversity by encouraging the exploration of new regions of the search space.

While ACO was originally developed to address discrete combinatorial optimization problems, most notably the Traveling Salesman Problem (TSP), job-shop scheduling, and network routing, it has increasingly been adapted to address the complexities of continuous search spaces (Abdulghani & Abdulghani, 2024; Pathak et al., 2025). In these traditional settings, artificial ants construct solutions by traversing discrete edges in a graph and depositing pheromones to reinforce high-quality paths (Pathak et al., 2025). However, recent advances have extended the algorithm to the continuous domain through variants of Continuous ACO (Danesh & Danesh, 2023; Taranto et al., 2025). In these continuous extensions, the core innovation lies in the representation of pheromones: rather than being stored on discrete edges, pheromone information is encoded as probability distributions or maintained within a solution archive, often implemented using Gaussian kernels or grid-based sampling schemes (Danesh & Danesh, 2023; Taranto et al., 2025).

WFLO is a critical research area that seeks to determine the optimal placement of wind turbines within a fixed geographical area to maximize total power output while minimizing wake-induced losses (Dhoot et al., 2021). Wake effects generated by upstream turbines significantly reduce wind speeds and increase turbulence intensity for downstream turbines, leading to decreased power generation. Recent studies have reported that average power losses can reach 10–20% in large offshore wind farms as a result of these wake interactions (Wang et al., 2024). Consequently, WFLO has become an essential approach for mitigating wake interactions during the initial design phase, with the primary objectives of maximizing annual energy production (AEP) and minimizing infrastructure costs under stochastic wind conditions (Dhoot et al., 2021; Wang et al., 2024). The Jensen wake model, originally proposed on the basis of mass conservation principles, remains one of the most widely used models in WFLO studies due to its robustness, relative simplicity, and computational efficiency (Cazzaro, 2022; Quaeghebeur et al., 2021; Wang et al., 2024; Wu et al., 2020). Improved analytical wake models have subsequently been developed, including the Larsen, Frandsen, and Bastankhah and Porté-

Agel Gaussian models (Cazzaro, 2022; Dhoot et al., 2021; Wang et al., 2024). The Gaussian wake model assumes that the velocity deficit follows a Gaussian distribution, thereby providing a more realistic representation of the wake shape than the linear wake expansion used in Jensen's model (Wang et al., 2024).

Recent studies have investigated discrete optimization approaches for WFLO, in which potential turbine locations are typically defined on a cartesian grid. In this context, optimization algorithms can be broadly categorized into gradient-based methods (e.g., sparse nonlinear optimizer, sequential convex programming, sequential least-squares quadratic programming) and gradient-free heuristic techniques (e.g., GA, PSO, ACO, greedy algorithms) (LoCascio et al., 2022; Pérez-Rúa et al., 2023; Wang et al., 2024). Researchers have also examined the multimodal characteristics of WFLO problems, showing that the number of local minima increases with both turbine count and wind farm size (Poole, 2025). In such cases, optimal layouts are typically characterized by either turbines distributed around the perimeter of the farm or strategically placed within the central region (Poole, 2025).

In the context of WFLO, a continuous optimization approach opens up extensive and promising opportunities for spatial exploration. Rather than restricting turbine placement to predefined candidate locations, as in discrete formulations, this approach defines the decision variables directly as the spatial coordinates (x, y) of each turbine within the wind farm boundary. In other words, turbines can, in principle, be placed at any real-valued position within the farm area. This continuous formulation offers substantial flexibility by removing artificial grid constraints, enabling fine-grained adjustment of turbine locations to more effectively mitigate wake effects and, in theory, approach the true global optimum in terms of annual energy production (AEP).

The hypothesis of this study is that an adapted ACO algorithm, specifically tailored for continuous search spaces, can provide competitive or even superior performance in maximizing annual energy production compared to established metaheuristics. Given that WFLO objective functions are characterized by extreme multimodality (Poole, 2025), the pheromone-based exploration mechanism of ACO is hypothesized to be particularly effective at avoiding local optima in the continuous (x, y) domain. By integrating robust wake models, such as the Jensen model, which has demonstrated high precision in predicting observed wake losses (Cazzaro, 2022), this research aims to show that an adapted ACO approach can effectively balance exploration and exploitation. In doing so, it seeks to identify more efficient turbine layouts under complex wind regimes.

3. METHODS

3.1 Formulation of the WFLO Problem

The Wind Farm Layout Optimization (WFLO) problem is mathematically formulated to determine the optimal spatial configuration of N turbines within a predefined geographical boundary. The project area is modeled as a continuous two-dimensional domain bounded by the coordinate intervals $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$. For a farm consisting of N turbines, the

decision variable for each turbine i is represented by its position vector $p_i = (x_i, y_i)$ for $i = 1, \dots, N$. The geometric properties of the turbines, most notably the rotor diameter D , serve as a critical parameter in modeling the wake interactions that determine energy capture efficiency. The primary objective of the WFLO task is to maximize the total power output P_{total} of the wind farm. This is defined as the summation of the individual power generated by each turbine, expressed as:

$$\max P_{total} = \sum_{i=1}^N P_i(p_i, \dots, p_N) \quad (1)$$

In this formulation, the power P_i generated by turbine i is not only a function of its own position but is also highly dependent on the positions of all other turbines $(p_1, \dots, p_N)$ due to the wake effect. When wind passes through a turbine, it creates a downstream region of reduced wind speed and increased turbulence, which can significantly degrade the performance of turbines located within its wake (LoCascio et al., 2022; Wang et al., 2024). To ensure the physical and operational feasibility of the generated layout, the optimization process is subject to two primary sets of constraints. The first set consists of boundary constraints, which require that every turbine remains strictly within the designated site limits:

$$x_{min} \leq x_i \leq x_{max}, y_{min} \leq y_i \leq y_{max} \quad (2)$$

Second, a minimum spacing constraint d_{min} is imposed to prevent mechanical interference and to reduce structural fatigue caused by excessive turbulence from neighboring turbines. This proximity requirement is formally enforced through a minimum separation distance between every pair of turbines:

$$\|p_i - p_j\| \geq d_{min}, i \neq j \quad (3)$$

where d_{min} is typically specified as a multiple of the rotor diameter D . By enforcing these conditions, the optimization process seeks to identify a set of turbine coordinates that balances high energy production with reduced wake-induced losses.

To accurately predict the energy production of a given layout, a wake model is employed to characterize the velocity deficit downstream of each turbine. In this study, the Jensen wake model (also known as the Katic model) is selected as the primary analytical tool due to its computational efficiency and robustness in large-scale optimization processes (Shakoor et al., 2016). Research suggests that the Jensen model, based on mass conservation within a linearly expanding wake, remains one of the most widely adopted approaches for wind farm layout optimisation and has demonstrated satisfactory accuracy in predicting wake losses compared with more complex analytical models (Cazzaro, 2022; Quaeghebeur et al., 2021). Although high-fidelity approaches such as Computational Fluid Dynamics (CFD) can provide more detailed physical representations, the Jensen model offers a practical balance between computational efficiency and predictive capability, which is particularly important for handling the highly multimodal search spaces typical of coordinate-based optimisation (Poole, 2025; Wang et al., 2024).

The reduction in wind speed downstream of a turbine is typically modeled as a function of the distance between upstream and downstream turbines. According to the Jensen model, the wake expands linearly with a wake decay constant (α), which quantifies the entrainment of wind flow into the wake region (Wang et al., 2024). The effective wind speed at a downstream turbine is determined by first calculating the velocity deficit, which is greatest immediately behind the rotor and decreases as the wake expands and recovers (LoCascio et al., 2022; Wang et al., 2024). In cases involving multiple wake interactions, the superposition of velocity deficits is typically addressed using the sum-of-squares method (LoCascio et al., 2022). This method accounts for the cumulative influence of multiple upstream turbines on a single downstream unit in the final wind-speed estimate (LoCascio et al., 2022).

The power output of each individual turbine P_i is estimated from the effective wind speed reaching its rotor plane. Since wind power output scales with the cube of wind speed, even modest reductions in velocity due to wake interactions, which can average 10–20% in large wind farms, may result in substantial decreases in total energy yield (Dhoot et al., 2021; Wang et al., 2024). The total power production is computed as the sum of the power outputs of all N turbines. This aggregated power serves as the scalar objective function used to quantify overall wind farm efficiency. The optimization algorithm then iteratively updates the turbine position vector (x_i, y_i) so as to minimize wake-induced losses and thereby maximize the estimated annual energy production (Dhoot et al., 2021; Wang et al., 2024).

3.2 Adaptation of ACO for Continuous WFLO

The adaptation of ACO to continuous search spaces is a critical advancement for addressing high-precision WFLO problems. Although classical ACO was originally formulated for discrete path-finding tasks, the WFLO problem is inherently continuous because turbine positions are modeled as real-valued (x, y) coordinates to maximize spatial flexibility and energy capture. In this continuous formulation, each “ant” encodes a candidate solution as a set of coordinate vectors $p = (x, y)$ for all N turbines located within the wind farm boundaries. In this continuous formulation, each “ant” explores the search space by constructing a new candidate layout, that is, by assigning (x, y) coordinates to every turbine within the wind farm boundaries. In other words, each ant actively searches for a complete set of turbine locations. The resulting configuration of coordinates is then treated as a distinct candidate solution, which is subsequently evaluated in terms of its expected energy production performance.

Transitioning from a discrete to a continuous representation is essential for effectively navigating the highly multimodal objective function of WFLO, where the number of local optima increases significantly with both the number of turbines and the wind farm area. In a continuous search domain, purely combinatorial structures are insufficient to guide the search process. To address this challenge, the methodology introduces a continuous pheromone representation that encodes and exploits information across the real-valued decision space. The algorithm replaces a discrete pheromone matrix with probability distribution functions defined over the (x, y) plane. This continuous representation enables ants to sample new turbine positions according to probability densities derived from previously high-performing layouts.

As a result, the search process (x, y) systematically guided toward regions characterized by higher wind speed recovery and reduced wake interference. Through iterative updates of these continuous distributions, the algorithm systematically enhances turbine placement to increase energy capture. This mechanism enables the effective mitigation of complex wake-induced velocity deficits inherent in large-scale wind farm configurations. Consequently, it facilitates a more robust balance between exploration and exploitation, thereby improving convergence toward

The proposed ACO algorithm for the WFLO problem is organized as a sequence of well-defined computational phases. Each phase comprises solution construction, pheromone model updating, and search-space refinement, all tailored to the continuous wind farm layout representation. The complete procedure is detailed in the following algorithmic description.

1. Initialization: Initialize the ant population, pheromone matrix, algorithm parameters, and wind farm boundaries. The objective function is defined as the maximization of the total wind farm power output while explicitly accounting for wake effects.
2. Grid region selection: Each ant selects promising search coordinates (x, y) according to a probabilistic transition rule governed by pheromone intensity and heuristic information.
4. Continuous turbine position generation: Generate continuous turbine coordinates (x, y) within the selected grid region. The turbine locations are not restricted to predefined discrete points, thereby enabling a fully continuous search space.
5. Wind farm power evaluation: Compute the total power output of the wind farm using the generated turbine coordinates while taking into account wake interactions among turbines.
6. Solution improvement assessment: Compare the current layout with the layout previously generated by the same ant. If the current layout yields a higher total power output, the turbine coordinates are updated accordingly.
7. Global best layout update: Compare all layouts generated by the ant population. If a layout achieves a higher total power output than the current global best solution, it is stored as the new global best layout.
8. Pheromone reinforcement: Deposit pheromone on search regions associated with high-quality layouts, thereby increasing the probability that these regions will be selected in subsequent iterations.
9. Pheromone evaporation: Decrease pheromone intensity through evaporation to prevent premature convergence and maintain sufficient exploration capability.
10. Iteration update: Repeat the above phases until the maximum number of iterations is reached or a predefined convergence criterion is satisfied.
11. Optimal continuous layout output: Return the global best turbine coordinates and the corresponding maximum total wind farm power output as the optimal continuous WFLO solution.

Figure 1 presents the flowchart of the proposed Continuous Ant Colony Optimization (ACO) algorithm for solving the Wind Farm Layout Optimization (WFLO) problem.

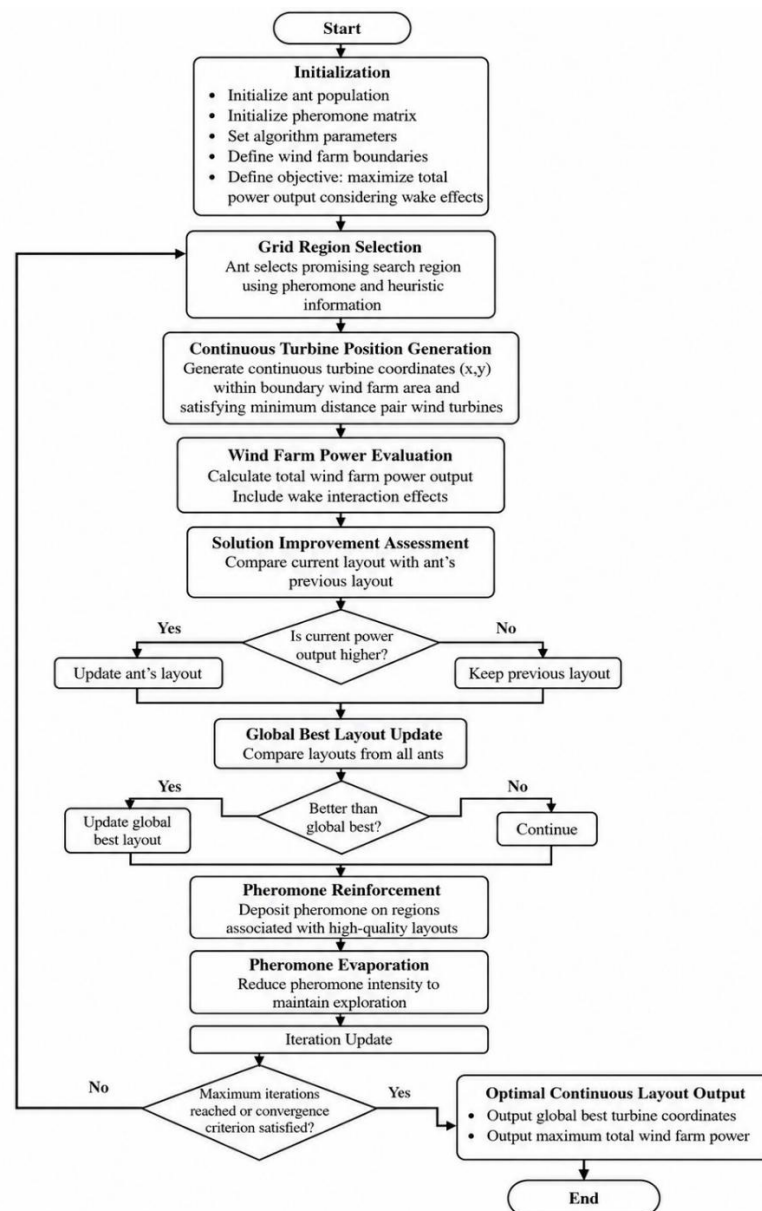


Figure 1. Flowchart of the ACO Algorithm for Solving the WFLO Problem.

The adaptation of ACO to continuous search spaces overcomes limitations of traditional heuristic benchmarks by providing improved computational scalability and greater precision. The algorithm uses continuous pheromone update and evaporation processes, governed by a persistence parameter, to balance exploration of new spatial configurations with exploitation of known high-yield regions. Studies show that this continuous coordinate-based approach can increase total power output in complex wind regimes.

4. RESULTS AND DISCUSSION

Recent optimization research demonstrates a strong conceptual and functional alignment between Ant Colony Optimization (ACO) and the challenges associated with Wind Farm Layout Optimization (WFLO). WFLO is characterized by a highly multimodal objective

landscape with numerous local minima that increase rapidly with turbine count and project area. This complexity renders WFLO a non-convex, nonlinear problem in which gradient-based methods frequently become trapped in local optima (Pérez-Rúa et al., 2023; Wang et al., 2024). As a gradient-free metaheuristic, ACO provides significant advantages by employing directed exploration and collective learning through pheromone deposition to identify promising regions of the search space. This approach distinguishes ACO from other methods, including Genetic Algorithms and Particle Swarm Optimization (Dorigo & Stützle, 2018; Cai et al., 2024). In contrast, PSO updates velocity vectors based on individual and global best positions, while GA relies on stochastic crossover and mutation without a persistent search history. ACO, however, establishes a collective learning framework through accumulated pheromone trails. In continuous WFLO applications, this memory is encoded by probability density functions, such as Gaussian distributions, which represent pheromone intensity across the wind farm's (x, y) coordinates (Parada et al., 2017).

Despite the conceptual alignment of adapted ACO with the multimodal demands of WFLO, several limitations of the current study. The present work is primarily theoretical and qualitative, lacking direct empirical validation or large-scale experimental comparisons with established metaheuristics such as GA, PSO, or Teaching–Learning-Based Optimization. Given that metaheuristics are inherently non-deterministic and sensitive to parameter settings and initial population diversity, the practical viability of this framework as a superior alternative requires comprehensive numerical experiments across diverse wind regimes.

Empirical validation is essential to demonstrate the practical utility of the Ant Colony Optimization (ACO) framework in industrial wind farm design. Future research should implement continuous ACO for WFLO problem and compare it experimentally with established metaheuristics, such as Genetic Algorithms, and Particle Swarm Optimization. Further studies should explore hybridizing ACO with local-search refinements and evaluate the algorithm across varied environmental conditions, including complex terrains with strongly non-linear wake interactions.

5. CONCLUSION AND LIMITATION

This work proposes that Ant Colony Optimization (ACO), originally developed for discrete problems, can be adapted to continuous domains by using probability density functions to represent pheromone intensity. The continuous framework enables near-infinite resolution in turbine placement, permitting precise positioning that minimizes wake-induced velocity deficits. Nonetheless, the methodology is limited by its reliance on theoretical and qualitative analysis and lacks the extensive experimental benchmarking necessary for definitive comparisons with established metaheuristics such as Genetic Algorithms and Particle Swarm Optimization.

The conceptual framework outlined here establishes directions for future research in several areas. First, studies should implement continuous ACO at full scale to transition from theoretical modeling to practical validation across diverse wind regimes. Second, researchers

should develop hybrid strategies that combine pheromone-driven global exploration with localized neighborhood search or gradient-based refinement, and should also investigate ACO's applicability to other complex engineering problems with non-linear constraints and high-dimensional search spaces.

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