Advancements in wind farm layout optimization: a comprehensive review of artificial intelligence approaches

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ABSTRACT

This article provides a detailed evaluation of cutting-edge artificial intelligence (AI) approaches and metaheuristic algorithms for optimizing wind turbine location inside wind farms. The growing need for renewable energy sources has fueled an increase in research towards efficient and sustainable wind farm designs. To address this challenge, various AI techniques, including genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing, artificial neural networks (ANNs), convolutional neural networks (CNNs), and reinforcement learning, have been explored in combination with metaheuristic algorithms. The goal is to discover optimal sites for turbine placement based on a variety of parameters such as energy output, cost-effectiveness, environmental impact, and geographical restrictions. The paper examines the advantages and disadvantages of each strategy and highlights current breakthroughs in the area. This assessment adds to continuing efforts to optimize wind farm design and promote the use of clean and sustainable energy sources by offering significant insights into current advances.

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1. INTRODUCTION

Wind power has emerged as an important actor in the global search for sustainable and eco-friendly energy resources [1], [2]. Wind farms, which are clusters of wind turbines, have proved their ability to capture clean and plentiful wind resources [3], considerably contributing to power generation [4]. The efficacy of a wind farm, on the other hand, is strongly hinging on the appropriate placement of turbines inside the defined region [5], [6]. The optimal configuration of turbines can have a considerable influence on energy output [7], operating efficiency, and economic viability [8]. As a result, academics and practitioners in the renewable energy sector have paid close attention to the placement issue [9]. To solve this issue, the combination of modern artificial intelligence (AI) techniques with metaheuristic algorithms has emerged as a viable path [10], giving creative and efficient ways for optimizing turbine placement.

The topic of wind turbine positioning within farms has been extensively addressed in the literature, which reflects the rising relevance of renewable energy sources [11], [12]. To establish turbine placements, early studies frequently used manual or rule-based methods, but these approaches were restricted in their capacity to account complex and dynamic environmental elements. Researchers resorted to optimization approaches to determine ideal locations as computer power and data availability expanded. To solve this optimization problem, many metaheuristic methods such as genetic methods [13], swarm algorithm [14], and mimicking annealing [15] have been used. Furthermore, the usage of artificial neural networks (ANNs) [11] and convolutional neural networks (CNNs) for analyzing spatial data and optimizing placements based on expected energy outputs has grown in popularity. Reinforcement learning has recently emerged as a viable method for agents to learn from interactions with the environment and make intelligent decisions on turbine placement [16]. Despite tremendous development in the field, a detailed analysis of the strengths and limits of various AI approaches and metaheuristic algorithms in wind turbine site optimization is required [17].

Given the importance pertaining to the efficient turbine’s place in parks of wind and the abundance of AI techniques available, this paper seeks to provide a complete evaluation of current ways to addressing this complicated topic. The next sections will go through several AI approaches in detail, the full range of optimization techniques comprises methods like particle swarm optimization (PSO) [18], simulated annealing (SA) [16], the powerful genetic algorithm (GA) [19], and ANNs. We will cover the underlying ideas, benefits, and limits of each approach as they apply to wind turbine site optimization. Furthermore, we will look at pertinent case studies and research findings that demonstrate the approaches' real-world relevance. The combination of these discoveries will help to improve knowledge regarding the current advancements in wind turbine site optimization, directing future research efforts and encouraging the implementation of more efficient and sustainable wind farm designs.

2. METHOD

This comprehensive review employs a systematic approach, involving extensive research, careful selection of relevant data from various sources, and rigorous analysis. It aims to offer an impartial and comprehensive overview of modern AI and metaheuristic algorithms used in optimizing wind turbine placement within wind farms [20].

2.1. Research and reading

In our investigation, we conducted an exhaustive exploration across reputable academic sources, with a specific emphasis on google scholar, to uncover and collate cutting-edge research in the realm of wind turbine placement optimization. By employing precise and contextually relevant search queries, our pursuit aimed to unearth novel and pertinent studies pertaining to this domain. Assembled papers were judiciously categorized based on their abstracts and introductions, facilitating the identification of salient contributions. With a meticulous approach, we systematically extracted crucial insights from each publication, cultivating a comprehensive grasp of the diverse landscape of AI methodologies and metaheuristic algorithms employed in the optimization of wind turbine siting. Moreover, the Figure 1 provides an illustrative representation, showcasing the evolution of research volume dedicated to wind farm layout challenges from 2011 to 2023. This methodical scrutiny and comparative analysis of scholarly literature endeavor to furnish a holistic panorama encompassing strengths, limitations, and recent strides in this pivotal facet of renewable energy generation. By ensuring the discerning extraction of knowledge from these evaluated works, our approach facilitates an all-encompassing evaluation of contemporary AI techniques for refining wind turbine placements within wind farms.

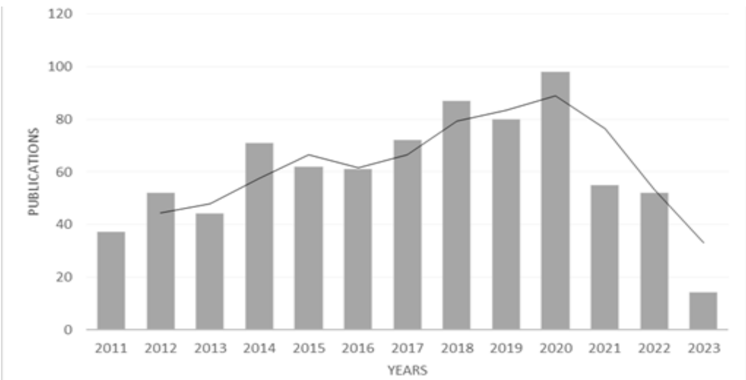

Figure 1. Number of publications in years

2.2. Analysis

In our quest to optimize wind farms and enhance wind energy extraction, our research focuses on the intricate realm of wind turbine placement. Employing a systematic approach, we extensively explore reputable databases like Google Scholar, meticulously curating a comprehensive collection of relevant publications. Our refined search queries ensure the inclusion of cutting-edge research directly aligned with our objectives.

Central to wind farm optimization is the wake effect (WE), a limitation on power production stemming from the slowing of wind due to turbine passage, creating turbulent wake regions. To amplify energy output, wake flow optimization (WFO) techniques, including wake management, are pivotal. Diverse wake models have emerged as shown in Table 1, each aiming to mitigate the WE impact. Notably, the established 1983 jensen wake model, illustrated in Figure 2, often forms the basis for assessing wake turbulence in wind farms.

Table 1. WE model

Wake models	Year
Jensen wake model	1983
Ainslie eddy viscosity model	1985
Katic park model	1986
Dynamic wake meandering	2007

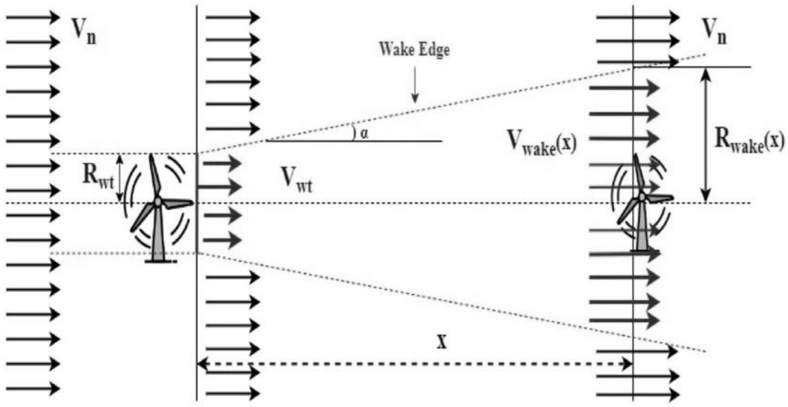

Figure 2. Jensen model [21]

Our methodical process involves meticulous categorization, guided by astute analysis of paper abstracts and introductions. This classification allows us to group papers based on unique strategies for wind turbine placement optimization, showcasing a diverse array of AI methodologies and metaheuristic algorithms. With a structured foundation, we delve into a comprehensive assessment of selected articles, extracting vital insights into methodologies, objectives, and outcomes. This in-depth understanding forms the basis for perceptive comparisons among various approaches, identifying the most promising AI methods and metaheuristic algorithms for achieving optimal wind turbine layouts.

2.3. Summary

In summarizing the collective findings of literature, it becomes evident that the pivotal challenge in wind turbine placement revolves around mitigating the WE. This phenomenon significantly impedes energy production within wind farms, prompting a comprehensive examination of its intricacies. The WE emerge as a consequence of wind turbulence created when a free stream of wind traverses a wind turbine's rotor. Mathematically, the velocity deficit in the wake (V_deficit) and the total power extracted according to the jensen model (P_wake) can be expressed as (1) and (2):

$$V_{deficit} = \frac{2.a.U}{1+\frac{2.a.x}{D}} \quad (1)$$

$$P_{wake} = \frac{1}{2}.\rho.A.(1-a).U^3 \quad (2)$$

where:
a represents the axial induction factor, U denotes the wind speed upstream of the turbine, x signifies the downstream distance from the turbine, D is the rotor diameter, ρ represents air density, and A denotes the

rotor area. The majority of literature adopts an objective function that combines cost considerations with total power output. Specifically, the cost metric introduced by mosetti serves as a cornerstone, defined by:

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

where N is the number of turbines. The overarching objective function, derived from this synthesis, encapsulates the endeavor to minimize the mosetti-defined cost while maximizing the total power extracted:

$$\text{F(x)} = \frac{\text{Cost}}{\text{P}_{\text{total}}} \tag{4}$$

in general, the problem-solving process, depicted in Figure 3, encompasses a sequential optimization approach. This orchestrated methodology typically commences with inputting wind data and the number of turbines. The subsequent steps involve applying the jensen wake model to estimate wake-induced effects, followed by metaheuristic methods to iteratively optimize wind turbine positions. This dynamic optimization process ensures a holistic and systematic resolution to the intricate wind turbine placement challenge. Numerous methodologies have been extensively explored in the existing literature, each aiming to enhance the precise turbines position into the park and ultimately maximize electricity extraction. These diverse strategies should be categorized into the subsequent classes as shown in Figure 4:

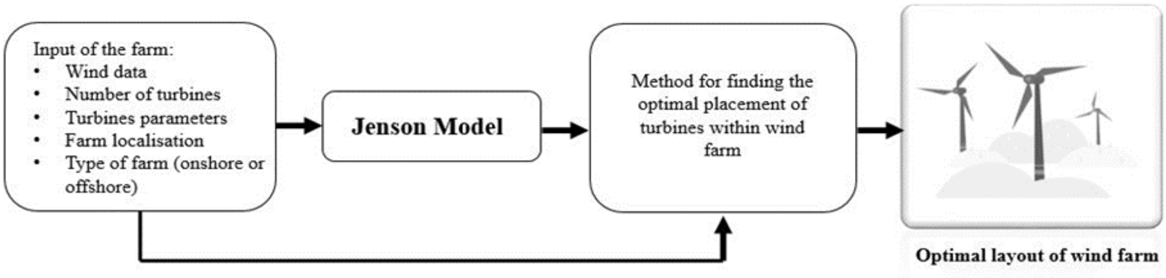

Figure 3. Representation of wind farm optimization layout using optimizarion approaches

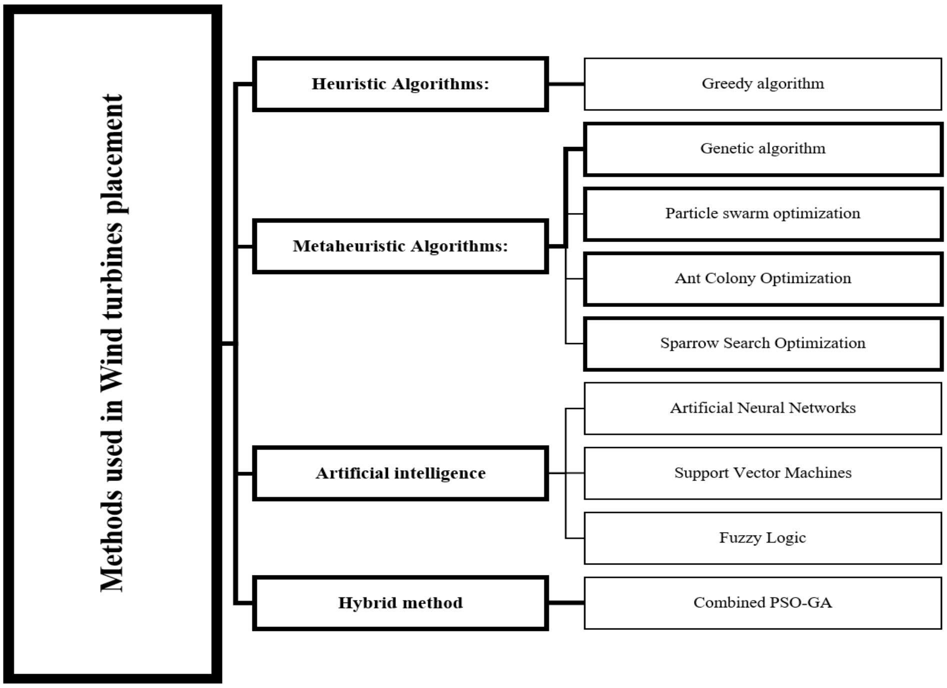

Figure 4. Different existing methods for wind farm optimization layout

3. RESULTS AND DISCUSSION

Our endeavor to optimize wind farm layouts and enhance wind energy extraction has revealed a wide array of methodologies and algorithms. Our results provide a thorough glimpse into these approaches, showcasing their effectiveness in addressing the complex task of wind turbine placement optimization. From heuristic and metaheuristic methods to the incorporation of AI techniques, our findings contribute valuable insights to the advancement of renewable energy generation by strategically positioning turbines.

3.1. Heuristic algorithms

The use of heuristic algorithms offers practical solutions to complex challenges, making them integral in wind farm optimization. Among these, the greedy algorithm stands out as a noteworthy heuristic method designed specifically for wind turbine placement. It excels in its localized approach, efficiently prioritizing turbine locations to maximize electricity generation. Its simplicity and efficacy make it particularly suitable for initial design considerations and quick assessments. This algorithm serves as a beacon within heuristic methods, effectively addressing turbine placement in wind farms. Its combination with advanced techniques underscores the ongoing commitment to optimize wind farm layouts and enhance energy extraction for a sustainable future [22]. Table 2 provides an extensive survey of outcomes achieved via the greedy algorithm approach, illustrating diverse enhancements in energy output across a spectrum of scenarios.

Table 2. The main results obtained from greedy algorithm

Name of method	Ref.	Application	Input variables	Benefits	Limitations
Greedy algorithm	[22]–[25]	Turbine placement in small wind farms	- Wind data - Farm size	Simplicity Suitable for quick assessments and preliminary layout designs	Susceptible to local optima, may not explore the entire solution space

3.2. Metaheuristic algorithms

3.2.1. GA

The GA is a computational method inspired by natural selection and evolution. In wind turbine placement optimization, GA mimics genetic processes to iteratively refine turbine positions, aiming to maximize energy output while considering constraints. Through mechanisms like crossover and mutation, GA gradually converges towards optimal layouts. Table 3 summarizes the results of GA application for wind turbine placement, encapsulating references, applications, inputs, benefits, and limitations. This comprehensive information enhances our understanding of GA's efficacy in improving energy extraction and contributes to the advancement of wind farm design [26].

Table 3. The main results obtained from GA

Name of method	Ref.	Application	Input variables	Benefits	Limitations
GA	[13], [19], [26]–[30]	Wind farm layout optimization	- Wind data (speed, direction) - Number of turbines	Global optimization, ability to handle large solution spaces, efficient and robust,	Computationally expensive for large-scale wind farms,

3.2.2. PSO algorithms

PSO is a widely utilized heuristic algorithm inspired by collective behaviors observed in nature. In wind turbine placement optimization, PSO simulates the dynamic movement of particles within a multidimensional solution space. Each particle's position is influenced by its historical best and the collective best position of the swarm. Across successive iterations, PSO navigates the optimization landscape, aiming to pinpoint turbine locations that maximize energy output while adhering to constraints [29].

To underscore its significance, we introduce a dedicated Table 4 that illustrates outcomes achieved through PSO. This case study offers a practical demonstration of the algorithm's power output results, encompassing both constant and variable wind speeds. This application sheds light on PSO's efficacy in optimizing turbine placement across varying wind conditions, adding to our broader understanding of its role in wind farm design [31]. The Table 5 encapsulates key aspects, including references, inputs, benefits, limitations, and the observed power output variations under different wind scenarios, further underscoring PSO's prominence and utility in the field.

Table 4. The main results obtained from GA

Parameter	PSO results	
	Constant wind direction	Variable wind direction
Number of turbines	32	19
Total power	16326.59 kW	9741.30 kW
Efficiency	98.42%	93.90%

Table 5. The main results obtained from PSO

Name of method	Ref.	Application	Input variables	Benefits	Limitations
PSO	[14], [18], [31]–[36]	Optimizing turbine positions	- Wind data - Number of turbines	Synergy between optimization and prediction, better exploration of solution space	May require careful tuning of parameters for optimal performance, can be sensitive to initial particle distribution

3.2.3. Ant colony optimization algorithms

Ant colony optimization (ACO) is a metaheuristic algorithm inspired by the collaborative behavior of ants in nature. Applied to wind turbine placement optimization, ACO emulates how ants establish pheromone trails to navigate and discover efficient paths. This algorithm iteratively adjusts virtual “ants” representing turbine locations, enabling exploration and exploitation to converge towards optimal solutions that maximize energy output while accommodating constraints [37], [38]. Notably recognized as a prevalent technique in this context, we provide a dedicated Table 6 presenting the results obtained through ACO.

Table 6. The main results obtained from ACO

Name of method	Ref.	Application	Input variables	Benefits	Limitations
ACO	[15], [37]–[40]	Wind turbine siting for power extraction	- Wind data - Pheromone parameters	Effective exploration of solution space through colony-based search,	Computational overhead due to pheromone update and decision-making processes

3.2.4. Sparrow search optimization

Sparrow search optimization (SSO) is a contemporary metaheuristic algorithm inspired by the foraging behavior of sparrows. Within the domain of wind turbine placement optimization, SSO emulates the search patterns of sparrows as they seek optimal foraging locations. The algorithm iteratively adjusts potential turbine positions, employing a balance of exploration and exploitation to converge towards arrangements that maximize energy output while considering constraints [16]. Due to its relevance in wind turbine placement optimization, we offer a dedicated Table 7 that illustrates the outcomes stemming from SSO.

Table 7. The main results obtained from SSO

Name of method	Ref.	Application	Input variables	Benefits	Limitations
SSO	[16]	Wind farm layout optimization	- Wind data - Sparrow parameters	Fast convergence and effective exploration	Limited studies and applications in wind farm layouts

3.3. AI methods

AI techniques, notably ANNs, support vector machines (SVM), and fuzzy logic, play a pivotal role in advancing the domain of wind turbine placement optimization:

ANNs: ANNs are computational models inspired by the human brain's neural structure. These networks consist of interconnected nodes, or “neurons”, that process information through layers. In the context of wind turbine placement, ANNs analyze various parameters, such as wind speed, direction, and topography, to predict optimal turbine locations. The network learns from historical data and adapts its parameters to enhance accuracy over time [41], [42].

SVM: SVM is a machine learning algorithm that identifies decision boundaries in multidimensional data. Applied to wind turbine placement, SVM aims to classify potential turbine locations as optimal or suboptimal based on input features. By creating a hyperplane that maximizes the margin between classified points, SVM enhances turbine placement precision [43].

Fuzzy logic: fuzzy logic is a mathematical approach that deals with uncertainty and imprecision. In wind turbine placement optimization, fuzzy logic systems accommodate vague or ambiguous data, enabling the incorporation of qualitative assessments. By assigning degrees of membership to different categories, fuzzy logic aids in determining suitable turbine positions that balance multiple factors [44]. Table 8 provides a concise encapsulation of the outcomes achieved through the application of AI techniques, specifically ANNs, SVM, and fuzzy logic, in wind turbine placement optimization.

Table 8. The main results obtained from AI methods

Name of method	Ref.	Application	Input variables	Benefits	Limitations
ANNs	[11], [41]–[52]	Power forecasting and turbine placement	- Wind data - Historical data	Non-linear modeling, ability to handle complex relationships, accurate predictions, adaptable to different wind farm configurations.	Requires substantial computational resources, reliance on quality and representativeness of training data.
SVM		Wind turbine placement and power prediction	- Wind data - Historical data	Effective in handling non-linear relationships, robust against overfitting, accurate predictions for turbine performance.	Performance may depend on kernel and hyper parameter selection, sensitivity to the choice of training data.
Fuzzy logic		Wind farm optimization under uncertainty	- Wind data	Handling uncertainty and imprecision in wind data, incorporating expert knowledge for decision-making in turbine placement optimization.	Quality of fuzzy membership functions and rules significantly impact results, can be computationally intensive for large-scale wind farms.

3.4. Hybrid methods

While the field predominantly explores individual methods, the concept of hybridization remains relatively unexplored. Existing literature primarily highlights a combined PSO-GA hybrid approach, indicating a gap in harnessing the full potential of hybrid methodologies. We provide a dedicated Table 9 presenting the results obtained from the hybrid method.

Table 9. Show the results obtained from the hybrid method

Name of method	Ref.	Application	Input variables	Benefits	Limitations
Combined GA-PSO	[53], [54]	Wind farm layout optimization	- Wind data - Number of turbines	Synergy between optimization and prediction, enhanced robustness and efficiency, better exploration of solution space	May require careful tuning of parameters for optimal performance

3.5. Discussion

In the context of wind energy optimization, a diverse array of techniques showcases specific strengths and limitations, each tailored to different aspects of the optimization challenge. The greedy algorithm stands out for its efficient early assessments and rapid prototype generation. Conversely, the GA excels in complex solutions and global optimization, albeit with potentially heightened computational demands. PSO, when finely tuned, swiftly searches for optimal solutions, while ACO offers adaptability, requiring iterative refinement for optimal outcomes. Notably, the SSO method holds significant promise, despite its limited presence in current literature. ANNs and SVM prove adept at precise predictions while accommodating data complexities. Fuzzy logic's robust handling of uncertainty stands out, although its implementation complexity may introduce design considerations. Importantly, the GA and PSO have been extensively studied across various turbine counts, wind speeds, and directions. Rigorous comparisons between these methodologies, alongside other approaches, and provide a robust foundation for insightful findings and a comprehensive evaluation.

Undoubtedly, the amalgamation of AI methods and metaheuristic algorithms holds more advantages than AI methods alone, as metaheuristic algorithms aim to optimize the inputs of AI methods. When comparing the frequency of utilization, particularly in AI methods, it becomes evident that PSO and GA are recurrently employed. Remarkably, this combination approach remains relatively underexplored, with few instances in existing literature. This study proposes a novel integration of the ANN algorithm with PSO, aiming to synergize their strengths for enhanced wind farm layout optimization. By initially pinpointing the optimal turbine positions using PSO and subsequently validating or suggesting adjustments using ANN based on historical wind data, a comprehensive and effective optimization strategy can be achieved. This hybrid methodology holds potential for unlocking superior outcomes and advancing the quest for greener and more sustainable energy solutions.

4. CONCLUSION

In summary, this study has extensively explored strategies for optimizing wind turbine siting in wind farms, encompassing heuristic and metaheuristic algorithms along with AI techniques. Each approach offers distinct advantages and limitations in predicting optimal turbine positions for enhanced power extraction. The fusion of AI methods with metaheuristic algorithms emerges as a promising avenue, capitalizing on their complementary strengths. Notably, PSO stands out as a prevalent metaheuristic algorithm paired with AI techniques. Looking ahead, our perspective includes combining AI and metaheuristic methods to leverage their respective advantages and tackle complex cases of variable wind speed, direction, and turbine hub height. This holistic approach aims to provide innovative solutions to intricate wind energy optimization scenarios. Our ongoing research endeavors are dedicated to advancing a sustainable and energy-efficient future, where wind energy contributes significantly to a greener and resilient world.

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