Clustering-Based AI Optimization of Radial Cable Infrastructure in Offshore Wind Farms

Keywords: Offshore Wind Farms, Optimization, Clustering-Based Algorithm, Cable Layouts

Abstract: Offshore wind farms play an important role in the global transition to renewable energy, leveraging stronger and more consistent wind conditions compared to onshore sites. However, the high costs associated with installation and maintenance demand efficient design strategies that address both energy yield and infrastructure expenses. While previous studies have focused on optimizing turbine placement to mitigate wake effects and maximize energy production, this work addresses the complementary challenge of optimizing the electrical cable infrastructure. We propose a clustering-based algorithm for the design of cost-effective radial cable layouts, which is integrated into existing AI-driven wind farm design framework. The method groups turbines and determines optimized cable routes to minimize total cable length and reduce transmission losses, while adhering to radial topology constraints. Results demonstrate that the proposed approach effectively supports the design of economically and technically efficient wind farm cable networks, enhancing integrated design frameworks with a practical tool to improve the economic and technical viability of offshore wind projects.

1 INTRODUCTION

The global shift toward sustainable energy has elevated the role of offshore wind farms as a key contributor to clean energy generation. Offshore sites offer some advantages, including stronger and more consistent wind resources, lower turbulence, fewer land-use conflicts, and reduced impact on populated areas (Hou et al., 2016). However, the development of offshore wind farms involves multifaceted challenges, particularly in balancing environmental, economic, and logistical constraints such as water depth, maritime traffic, and long-term wind behavior (Hou et al., 2016). Among these challenges, optimizing turbine placement is critical, as wake effects from suboptimal layouts can reduce wind farm efficiency by 10–15% in Annual Energy Production (AEP) (Barthelmie et al., 2006). Equally important, yet often less emphasized, is the optimization of the electrical infrastructure, especially the submarine cable network, which represents a significant share of both capital expenditures and operational efficiency.

In this paper, we introduce a clustering-based algorithm designed specifically for the optimization of radial cable infrastructure. While prior studies have focused on maximizing energy output through the spatial arrangement of turbines, this contribution addresses the cable routing problem, aiming to reduce infrastructure costs and minimize transmission losses. The proposed method leverages clustering techniques to efficiently group turbines and determine optimized cable paths that connect them to substations, considering the geometric and electrical constraints of radial topologies. This work contributes a specialized module to a broader AI-driven optimization framework, enhancing its capability to support integrated wind farm planning by addressing both energy performance and cost-effective electrical connectivity.

2 OFFSHORE WIND FARM DESIGN CONSIDERATIONS

Offshore wind farms are a key direction for the global transition to renewable energy, taking advantage of stronger and more consistent wind conditions at sea (Pérez et al., 2013). However, the high installation, maintenance, and infrastructure costs associated with these projects require robust optimization strategies to ensure long-term economic viability. Key design aspects include site selection, turbine layout planning, and electrical infrastructure design, particularly subsea cabling configuration, which significantly impacts both capital expenditure and energy transmission efficiency (Espejo et al., 2011; Lakshmanan et al., 2021; CH and Ran, 2016).

A critical factor in offshore wind farm planning is the distribution of wind resources in candidate areas. Long-term wind data is typically used to build probabilistic models of wind direction and intensity, serving as input for wake modeling tools (Barthelmie et al., 2006; Hou et al., 2019). These models estimate

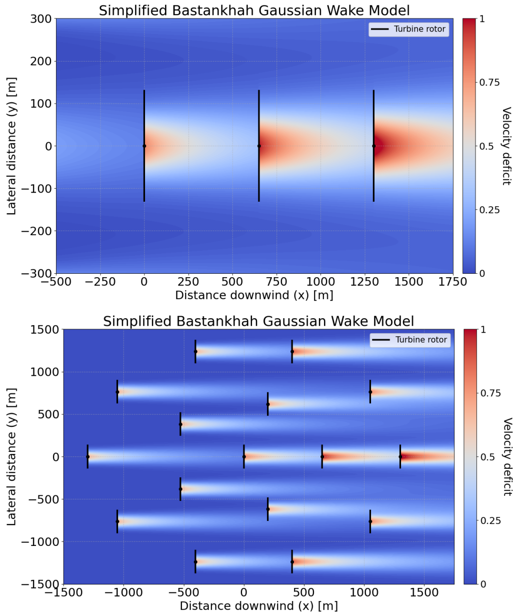


Figure 1: Detailed (upper) and overview (bottom) wake effect.

wake losses, which occur when wind turbines reduce wind speed and increase turbulence for downstream units. Figure 1 shows examples of wake effects. The extent of these losses depends on site-specific wind conditions, turbine characteristics, and the spatial arrangement of turbines.

Wake models can be categorized into two broad categories: computational fluid dynamics (CFD) models, which are highly accurate but computationally intensive (Andersen et al., 2014), and analytical models, which offer simplified and scalable solutions for layout optimization (Hou et al., 2015; Bastankhah and Porté-Agel, 2016; Baker et al., 2019; Thomas and Ning, 2018). Among the latter, the Bastankhah Gaussian wake model (Bastankhah and Porté-Agel, 2016) is widely adopted due to its balance of accuracy and efficiency, and is often used in large-scale optimization studies. Simplified versions of this model, as in (Baker et al., 2019), incorporate key parameters such as turbulence intensity, thrust coefficients, and rotor diameter to simulate energy losses in a computationally tractable manner.

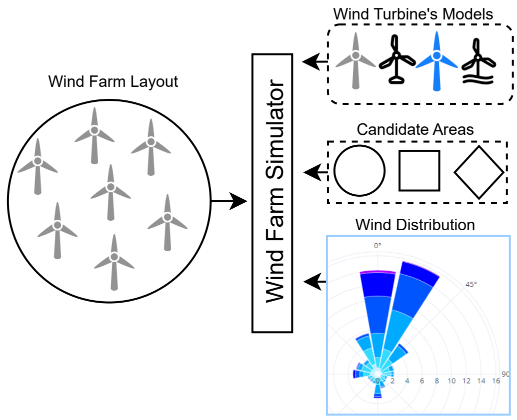


Figure 2: Overview of wind farm simulation and layout evaluation framework (Silva et al., 2025).

The wind turbine placement problem involves selecting coordinates that maximize energy production while minimizing wake effects and infrastructure costs. This task is commonly addressed using simulation-based optimization tools, which evaluate different layouts by estimating the expected AEP under realistic wind conditions. The simulator proposed in (Baker et al., 2019) provides a standardized framework for such evaluations, incorporating wind direction distributions, turbine models, and wake interactions, as illustrated in Figure 2. It supports performance comparisons across algorithms and enables the design of high-performance layouts under fixed evaluation constraints.

In addition to aerodynamic efficiency, the electrical layout, particularly the cabling topology, also influences the overall wind farm performance. Radial configurations are widely used due to their simplicity and cost-effectiveness, but must be optimized to reduce total cable length, transmission losses, and connection costs while satisfying engineering and operational constraints (Lakshmanan et al., 2021; CH and Ran, 2016). The integration of cable optimization into the wind farm design phase enables more accurate trade-offs between energy production and infrastructure costs, especially when jointly considered with turbine layout.

In this work, we adopt the evaluation framework from (Baker et al., 2019), the layout optimization approach proposed by (Silva et al., 2025; Da Silva et al., 2025), and extend them by incorporating a dedicated cable optimization component based on a clustering heuristic. Our approach allows the independent modeling of turbine locations and radial cable layout, offering a modular and flexible tool for exploring cost-effective offshore wind farm configurations.

3 AI-DRIVEN FRAMEWORK FOR WIND FARM LAYOUT OPTIMIZATION

Designing offshore wind farms involves a complex interplay of environmental, technical, and economic factors. To address these challenges, we have developed an AI-driven framework that supports wind farm planning through the optimization of turbine layouts. This modular framework enables the integration of advanced optimization techniques with domain-specific simulation tools to support the design of efficient and cost-effective offshore wind energy systems.

Previous work by (Silva et al., 2025; Da Silva et al., 2025) focused on optimizing wind turbine placement to maximize AEP, using a genetic algorithm integrated with a full-field wake simulation model. The optimization problem was formulated to maximize AEP based on historical wind data, turbine power curves, and wake interactions. The genetic algorithm represented wind farm layouts as vectors of turbine coordinates, evolving them through selection, crossover, and mutation operations to explore the design space efficiently. Each candidate layout was evaluated by a simulator adapted from (Baker et al., 2019), which estimated AEP by accounting for wind direction frequencies and wake-induced power losses. The fitness function used in the optimization corresponds to the total AEP:

$$AEP = \left(\sum_{i=1}^{N} f_i P_i^{farm} \right) \cdot 8760 \frac{\text{hrs}}{\text{yr}} \tag{1}$$

where f_i is the frequency of wind from direction i, and P_i^{farm} is the total power produced by all turbines under that condition. The turbine power output follows a piecewise function based on wind velocity, constrained by cut-in, rated, and cut-out thresholds. Optimization is further subject to spatial constraints, including minimum spacing between turbines (at least $2D_r$) and boundary limits defining the installation area.

To improve computational efficiency, extensive code profiling was performed, revealing that wake calculations were a major bottleneck. These improvements enabled the framework to handle larger and more complex optimization problems within practical time constraints. Using this approach, the framework is capable of producing high-quality wind farm layouts that maximize energy production while respecting spatial and physical constraints. The framework proposed by (Silva et al., 2025; Da Silva et al., 2025) demonstrated strong and consistent performance when evaluated against the benchmark problems presented in (Baker et al., 2019). Across the three turbine scenarios: 16, 36, and 64 turbines, the optimized genetic algorithm achieved AEP values that ranked among the top solutions, securing second place in the 16- and 36-turbine cases and fourth place in the 64-turbine case. Notably, the approach outperformed all other gradient-free methods in every scenario. These results confirm the effectiveness of their optimization strategy, which reached up to 89.34% of the theoretical maximum AEP while remaining competitive with leading gradient-based approaches. This highlights the robustness and applicability of that framework for tackling complex wind farm design problems under realistic constraints.

Building on this foundation, the present work extends the framework by introducing a new component focused on the *optimization of the electrical cable infrastructure*. While turbine layout optimization addresses aerodynamic efficiency, the cost and performance of submarine cable networks are critical to the overall viability of offshore wind farms. In this paper, we propose a clustering-based algorithm to design optimized *radial cable layouts* over turbine configurations already optimized with respect to wake effects and energy yield. This new component enhances the framework's ability to support holistic wind farm design, by minimizing cable length and electrical losses while adhering to radial topology constraints, ultimately contributing to both performance and cost-effectiveness in offshore wind energy systems.

4 CLUSTERING-BASED CABLE ROUTING

Efficient selection of cable routing and conductor sizing in wind-farm networks significantly impacts both energy losses and infrastructure cost (Zhao and Mutale, 2019). In this section, we present a cable optimization component that determines the radial topology, conductor cross-sectional areas, and estimates total resistive (Joule) losses of the electrical collection system. Cable optimization is performed after the turbine layout has been defined by the layout-focused (wake effect) optimizer.

4.1 Turbine Clustering Methodology

To automate the design of radial cable topologies in wind farms, we developed a clustering-based approach that groups turbines into electrical strings according to their spatial orientation relative to the substation. This approach enhances the organization of radial collection systems by minimizing cable complexity and promoting efficient routing.

The method begins by calculating a direction vector from each turbine to the substation, effectively capturing the turbine's relative orientation. We then extract the angular component of these vectors to represent the directional relationship between turbines and the substation. To group turbines with similar directional characteristics, we employ a modified K-Means clustering algorithm, adapted to operate on direction angles instead of traditional Euclidean distances.

Cosine similarity (Singhal, 2001) is used as the distance metric to account for directional alignment between turbines, independent of their absolute positions. This formulation ensures that turbines grouped within the same cluster share a consistent angular orientation, which aligns naturally with radial cable paths and simplifies the resulting network structure. While standard K-Means minimizes intra-cluster variance using Cartesian coordinates, our adaptation allows clustering based on angular proximity, as required for radial string design (Hartigan and Wong, 1979).

Following the K-Means assignment, a rule-based heuristic refines the clusters to improve balance. The process first identifies any cluster exceeding a predefined target size, T. A turbine is then reassigned from this 'donor' cluster to the 'recipient' cluster that would yield the highest possible average intra-cluster cosine similarity after the move. This iterative process continues until all clusters meet the target size constraint, resulting in more uniform and directionally cohesive strings.

The complete clustering procedure is summarized in Algorithm 1. Once the clusters (i.e., strings) are formed, turbines within each string are ordered by their distance to the substation to facilitate the construction of radial paths that comply with single-path connectivity and current flow assumptions used in Joule loss estimation.

Algorithm 1 Directional Clustering for Radial Cable Layout

Require: Turbine positions, substation position, nº of strings K, target T
Ensure: Turbine groups assigned to radial strings
1: Compute direction vector from each turbine to the substation
2: Extract angular position of each turbine relative to the substation
3: Apply K-Means clustering on direction angles
4: Apply greedy iterative refinement to balance cluster size and cohesion
5: Sort turbines in each cluster by distance to the substation
6: Assign sorted groups as radial strings

This clustering-based methodology produces radial cable configurations that are both topologically feasible and electrically efficient. By aligning turbine groupings with natural orientation patterns and maintaining balanced group sizes, the approach ensures compatibility with practical layout constraints and improves downstream energy loss modeling.

4.2 Radial Topology Design

A radial layout was chosen due to its simplicity, fault isolation properties, and lower installation cost compared to meshed configurations. In radial systems, each turbine connects to the substation via a single unique path, simplifying current flow modeling and eliminating the need for complex protection schemes (Glover et al., 2012; IEE, 1997). This design is consistent with industry practice for medium-voltage collection systems (30–66 kV), offering proven reliability and cost-effectiveness (IEE, 1997).

4.3 Joule Loss and Cost Estimation

The total power loss in the collection system is computed as the sum of three-phase resistive losses across all cable segments. For each segment with length L, copper resistivity ρ, and conductor cross-sectional area CSA, the resistance R is given by:

$$R = \frac{\rho \cdot L}{CSA} \tag{2}$$

Given a current I flowing through the cable, the power loss on a three-phase segment is:

$$P_{\text{loss}} = 3 \cdot I^2 \cdot R \tag{3}$$

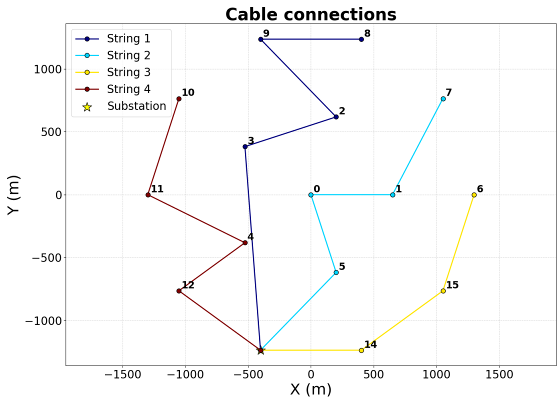
To guarantee thermal safety and operational feasibility, the conductor cross-sectional area must satisfy a current density threshold d_I, resulting in:

$$CSA = \max\left(\frac{I}{d_I}, CSA_{\min}\right) \tag{4}$$

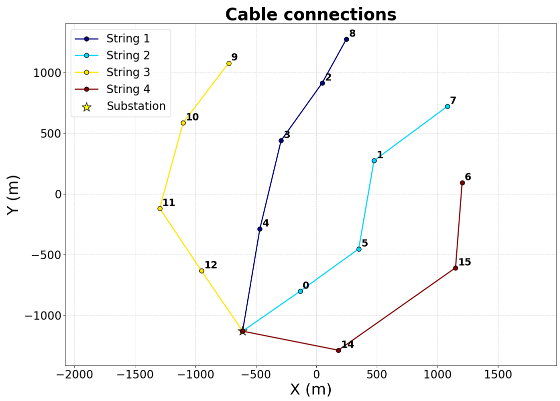
where $CSA_{\min}$ is the minimum allowable cross-sectional area.

The total Joule loss in the wind farm is the sum of losses from all cable segments. The current in each segment is the cumulative output of its upstream turbines, calculated under a worst-case, full-load scenario derived from a 3.35MW turbine model. This model is chosen for consistency with the layouts under analysis (Baker et al., 2019; Silva et al., 2025; Da Silva et al., 2025). While this simplified full-load approach does not model variable power output, it provides a robust basis for comparing the relative electrical performance of different network topologies under maximum thermal stress.

Cabling costs are determined by the NREL marine-energy cost model(Nakhai, 2023), which incorporates conductor cross-sectional area and conductor count. This linear model provides a standardized cost estimate, though practical installation costs

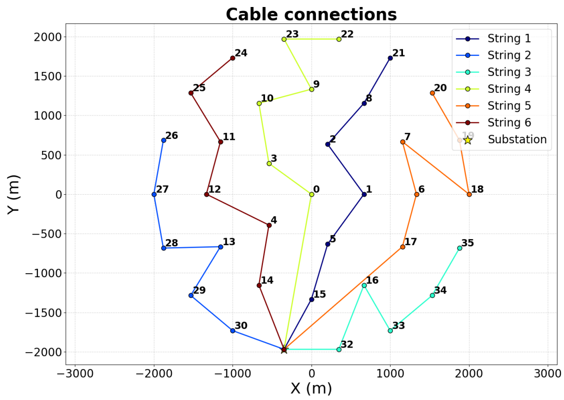


(a) Baseline layout, 12.61km, 120mm².

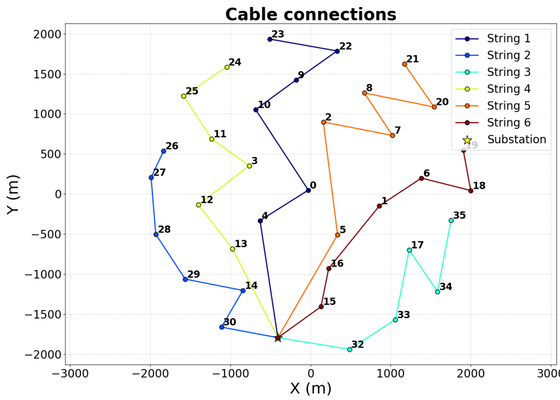


(b) GA-optimized layout, 10.53km, 120mm².

Figure 3: Baseline vs. optimized layouts for a 16-turbine farm with cabling topology.

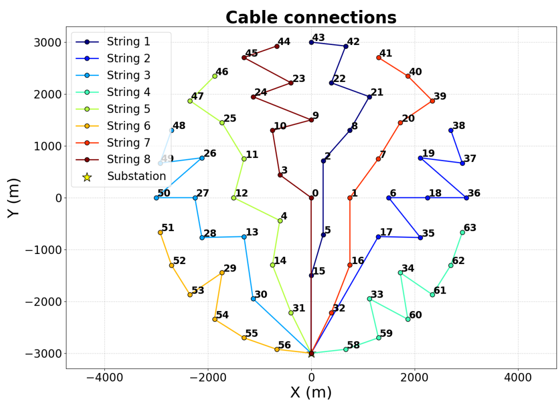


(a) Baseline layout, total length: 28.26km, cross-sectional area: 185mm².

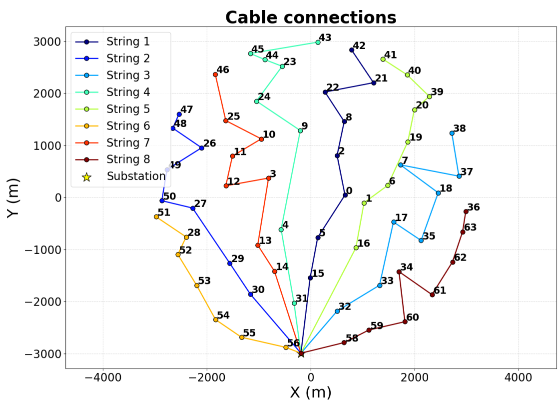


(b) GA-optimized layout, 27.73km, 185mm².

Figure 4: Baseline vs. optimized layouts for a 36-turbine farm with cabling topology.



(a) Baseline layout, 57.64km, 240mm².



(b) GA-optimized layout, 53.48km, 240mm².

Figure 5: Baseline vs. optimized layouts for a 64-turbine farm with cabling topology.

can be influenced by non-linear factors like seabed conditions:

$$\text{Cost} = 0.3476 \times \text{CSA} \times N_{\text{cond}}\ [\text{USD/m}] \quad (5)$$

4.3.1 Ohmic Resistance Correction Due to Skin Effect and Temperature According to IEC 60287-1-1 and IEC 60228

The cores of power cable conductors are stranded, meaning that the cross-sectional area is composed of several smaller wires rather than being completely solid. This construction creates small gaps between the wires, which makes Eq. (2), valid for solid conductors, only an approximation for stranded conductors.

According to (Paula, 2023), the ohmic resistance of the conductor core is calculated using Eq. (6), where R_c is the direct current resistance, Y_s is the alternating current ohmic resistance correction factor, and Y_t is the temperature correction factor. The proximity effect was not considered in this work.

$$R = R_c \cdot (1 + Y_s + Y_t) \quad (6)$$

The maximum direct current ohmic resistance per kilometer of a stranded copper or aluminum conductor at $20,^\circ$C for an insulated cable is presented in table form in IEC 60228 for each conductor cross-sectional area, according to (Paula, 2023).

The alternating current ohmic resistance is higher than the direct current resistance due to the skin effect. This phenomenon occurs because the magnetic field generated by the alternating current induces internal currents that cause the current density to concentrate near the conductor surface. Therefore, increases in frequency reduce the effective conduction area, according to (Paul et al., 2022).

As stated in (Paula, 2023), the calculation of Y_s is standardized by IEC 60287-1-1 in Eq. (7), where f is the network frequency, and X_s is a factor that, when less than or equal to 2.8, uses Eq. (8). This is valid for cables up to $1200,\text{mm}^2$ at $60,\text{Hz}$, where X_s does not exceed 2.8.

$$X_s = \sqrt{\frac{8\pi f \times 10^{-7}}{R_c}} \quad (7)$$

$$Y_s = \frac{X_s^4}{192 + 0.8X_s^4} \quad (8)$$

The skin effect is significant at $60,\text{Hz}$ for cables with a cross-section of $95,\text{mm}^2$ for copper and $150,\text{mm}^2$ for aluminum.

The conductor material resistance varies with temperature according to the resistance temperature coefficient defined by α. IEC 60287-1-1 standardizes the temperature correction using Eq. (9), where $T_1 = 20,^\circ$C and T_2 is the conductor temperature. The coefficients are $\alpha_{Cu} = 1/254{,}5,^\circ\text{C}^{-1}$ and $\alpha_{Al} = 1/248,^\circ\text{C}^{-1}$, according to (Paul et al., 2022).

$$Y_t = \alpha(T_2 - T_1) \quad (9)$$

4.4 Comparative Analysis and Discussion

Table 1 presents a comparative analysis of the estimated annual energy losses due to Joule dissipation and the associated cabling costs for three wind farm configurations with 16, 36, and 64 turbines. The baseline layouts reproduce the uniform grid structures proposed by Baker et al.(Baker et al., 2019), while the optimized layouts are derived from the layout optimization framework reported in (Silva et al., 2025; Da Silva et al., 2025). Notably, while energy production was the primary optimization target in (Silva et al., 2025; Da Silva et al., 2025), this study applies our proposed automatic cable routing method to both layout variants, baseline and optimized, to evaluate the electrical implications of layout decisions.

The analysis of the results, presented in Table I and visualized in Figures 3-5, offers a nuanced validation of our two-stage optimization strategy. The GA-optimized layouts consistently yield lower cabling costs and electrical losses. This stems from an indirect aerodynamic benefit: in minimizing wake effects, the GA tends to produce more compact spatial arrangements than a rigid grid, thus establishing a superior geometric foundation for our subsequent clustering-based routing algorithm.

The magnitude of this improvement, however, is contingent on the baseline configuration. The sparse 16-turbine grid provides significant scope for optimization, resulting in a remarkable 16.49% cost reduction. In contrast, the baseline for the 36-turbine case, already being relatively compact, offers less room for improvement, leading to a more modest 1.87% gain. These findings validate the efficacy of our modular, decoupled approach. While theoretically suboptimal compared to a simultaneous joint optimization, this pragmatic strategy demonstrates that applying a dedicated cabling heuristic as a post-processing step leads to final designs that are robustly improved in both cost-effectiveness and electrical efficiency.

5 RELATED WORK

Several gradient-free (GF) methods were employed in the Wind Farm Layout Optimization (WFLO)

Table 1: Comparison of Annual Energy Loss and Cabling Costs for Baseline and Optimized Layouts.

Farm Size	Metric	Baseline	Optimized
16 Turbines	Annual Energy Loss (GWh)	1.70	1.32(-22.35%)
	Cabling Cost (M USD)	2.104	1.757(-16.49%)
36 Turbines	Annual Energy Loss (GWh)	5.53	5.41(-2.16%)
	Cabling Cost (M USD)	7.269	7.133(-1.87%)
64 Turbines	Annual Energy Loss (GWh)	15.26	14.24(-6.68%)
	Cabling Cost (M USD)	19.234	17.846(-7.21%)

study (Baker et al., 2019). The main approaches include: (i) *Pseudo-Gradient Method*: Approximates turbine interactions using vectors proportional to wind speed deficits from wake effects, substituting traditional gradients to guide layout adjustments (Quaeghebeur et al., 2021). (ii) *Particle Swarm Optimization (PSO)*: Uses randomly initialized particles to explore the non-convex solution space, enhancing AEP by avoiding local optima (Asaah et al., 2021). (iii) *Genetic Algorithm with Matrix Representation*: Encodes layouts as binary 10x10 matrices, where each cell denotes the presence or absence of a turbine, reducing computational time and improving optimization efficiency (Emami and Noghreh, 2010). (iv) *Multi-Population Genetic Algorithm (MPGA)*: Extends traditional genetic algorithms with immigration and coevolution mechanisms, promoting diversity and preserving elite individuals across evolving subpopulations (Gao et al., 2015).

To address the Wind Farm Cable Routing Problem (WFCRP), several metaheuristics, *Simulated Annealing*, *Tabu Search*, *Variable Neighborhood Search*, *Ant Colony Optimization* and *Genetic Algorithm*, are implemented with in-depth parameter tuning and seeded by a multistart Sweep constructor (Cazzaro et al., 2020). For WFCRP at scale, a *MILP* model is embedded in a matheuristic framework that iteratively fixes variables via random, distance-based and sector-based strategies to reduce problem size (Fischetti and Pisinger, 2016). Furthermore, an *Adaptive Particle Swarm Optimization* algorithm integrates cable investment and a detailed power-loss cost model to jointly optimize substation location, cable layout and sectional area under uncrossing constraints (Jin et al., 2019).

6 CONCLUSION

This work extends a modular optimization framework for offshore wind farm design by introducing a new component focused on the optimization of the electrical cable infrastructure. Building on the work proposed by (Silva et al., 2025; Da Silva et al., 2025), which focused on maximizing AEP through turbine layout optimization using a genetic algorithm, this paper addresses the subsequent challenge of designing cost-efficient and low-loss radial cable topologies.

To this end, we proposed a clustering-based algorithm adapted from K-Means to generate radial cable layouts over turbine configurations optimized for wake effects and wind conditions. The algorithm produces cable routing solutions that minimize total cable length while satisfying radial topology constraints, offering a practical and computationally straightforward solution for the early design phase. Results show that the proposed method yields competitive performance in terms of transmission efficiency and infrastructure cost, enhancing the overall viability of wind farm projects.

The modular nature of the framework supports flexibility and extensibility, making it suitable for integrating additional optimization criteria or accommodating multiple design scenarios. Future work will focus on incorporating cable layout optimization into the turbine placement process, enabling joint and multi-objective optimization of both aerodynamic and electrical infrastructure aspects (Rodrigues et al., 2016). This integration aims to further improve system-wide efficiency and provide comprehensive decision support for offshore wind farm development.

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