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Research Article

Harnessing Coastal Winds: Metaheuristic Optimization of Onshore Wind Power Costs in Digha, West Bengal

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Abstract **–** The economic viability of onshore wind energy is critical for sustainable power generation, particularly in coastal regions with abundant wind resources. This study presents a metaheuristic-based optimization framework for minimizing the levelized cost of electricity (LCOE) for onshore wind power generation in Digha, West Bengal, leveraging Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). A comprehensive comparative analysis reveals that GA achieves a lower generation cost of USD 0.0031 per kWh, outperforming PSO, which yields USD 0.0043 per kWh. The enhanced performance of GA is attributed to its superior global search efficiency and adaptability in complex optimization landscapes, leading to more effective wind turbine placement and power dispatch strategies. These findings underscore the efficacy of evolutionary algorithms in optimizing wind energy systems, offering valuable insights for policymakers and energy planners aiming to enhance the cost-effectiveness of renewable energy deployment in coastal regions.

Keywords – Cost Optimization, Genetic Algorithm, Metaheuristics, Onshore Wind Energy, Particle Swarm Optimization.

I. INTRODUCTION

The escalating global demand for sustainable energy solutions has positioned wind power as a pivotal component in the transition towards renewable energy sources. Coastal regions, characterized by consistent and robust wind patterns, present significant opportunities for harnessing wind energy. The town of Digha, situated in the Purba Medinipur district of West Bengal, India, exemplifies such a region with substantial wind energy potential. Despite this potential, West Bengal has historically underutilized its renewable energy resources, harnessing only approximately 8% (around 636 MW) of its capacity, excluding large hydro projects, as of February 2024 [1]. This underutilization underscores the necessity for strategic initiatives to capitalize on the state's renewable energy prospects, particularly in wind-rich coastal zones like Digha. The optimization of wind farm layouts is a complex task that significantly influences the efficiency and economic viability of wind energy projects. Factors such as turbine placement, wake effects, land topography, and economic constraints must be meticulously considered. Wake effects, resulting from aerodynamic interference between turbines, can substantially reduce the overall energy output if not properly managed. Therefore, optimizing turbine placement to mitigate wake losses is paramount for maximizing energy production and ensuring the financial feasibility of wind energy projects [2].

Metaheuristic algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have been extensively applied to address the complexities inherent in wind farm layout optimization. These algorithms offer robust search capabilities to navigate large and intricate solution spaces effectively [3]. Genetic Algorithms, inspired by the principles of natural selection and genetics, operate through mechanisms of selection, crossover, and mutation to evolve solutions over successive generations. In the context of wind farm optimization, GAs have been utilized to determine optimal turbine placements that maximize energy output while minimizing costs. For instance, a study demonstrated that a hybrid approach combining PSO and GA effectively handled problems with multiple local optima, leading to improved wind farm layout optimization [4].

Particle Swarm Optimization, inspired by the social behaviour patterns observed in flocks of birds and schools of fish, utilizes a population of candidate solutions, referred to as particles, which explore the solution space by adjusting their positions based on individual and collective experiences. In wind farm optimization, PSO has been applied to optimize turbine layouts and control strategies. A study developed a PSO-based method for joint optimization of wind farm layout and active yaw control, demonstrating improvements in annual energy production compared to conventional layouts [5]. The efficacy of GA and PSO in optimizing wind farm layouts has been the subject of comparative analyses. While both algorithms aim to enhance energy production and reduce costs, their performance can vary depending on the specific characteristics of the optimization problem. Factors such as the complexity of the solution space, the presence of local optima, and computational resource constraints influence the suitability of each algorithm. Hybrid approaches that integrate the strengths of both GA and PSO have been proposed to leverage their complementary features, resulting in more robust optimization outcomes [6].

This study aims to optimize the onshore wind power generation cost in the coastal area of Digha, West Bengal, by employing GA and PSO. By conducting a comparative analysis of these metaheuristic techniques, the research seeks to identify the more effective algorithm for minimizing generation costs in this specific geographical context. The findings are expected to provide valuable insights into the application of advanced optimization methods for enhancing the economic viability of wind energy projects in underutilized regions.

II. METHODOLOGY

The optimization of wind power generation cost involves multiple interdependent factors, including wind resource characteristics, turbine placement, wake losses, and economic constraints. In this study, we employ GA and PSO to minimize the Levelized Cost of Energy (LCOE) for an onshore wind farm in Digha, West Bengal. Both algorithms are implemented using MATLAB, leveraging real wind speed data and turbine specifications. The workflow consists of data preprocessing, initialization, fitness evaluation, constraint handling, and algorithm execution until convergence criteria are met.

Digha, a coastal town in West Bengal, experiences moderate to high wind speeds due to its proximity to the Bay of Bengal. The wind regime in this region exhibits seasonal variations, with peak wind speeds observed during the monsoon months. To ensure accuracy in modelling, wind speed data were collected using an anemometer purchased through the departmental research fund of Jadavpur University. The researchers deployed the anemometer in Digha, ensuring precise measurement of wind speeds. The collected data were further analysed and validated using historical records from the India Meteorological Department (IMD) and the Global Wind Atlas. The wind speed distribution was characterized using the Weibull probability density function, where the shape parameter (k) and scale parameter (c) were estimated through the maximum likelihood estimation (MLE) method. Additionally, terrain roughness and elevation variations were incorporated into the analysis using NASA's Shuttle Radar Topography Mission (SRTM) digital elevation models (DEMs). The presence of sand dunes and vegetation was considered by adjusting the surface roughness coefficient, ensuring realistic simulation of wind flow characteristics over the Digha coastal landscape.

To accurately estimate the energy generation potential of onshore wind power in Digha, a standard 3.45 MW wind turbine was selected for simulation. The turbine features a hub height of 100 meters and a rotor diameter of 126 meters, making it well-suited for harnessing coastal wind resources. The selection was based on turbine models commonly deployed in similar coastal regions, ensuring practical feasibility. The power curve of the wind turbine was modelled using cubic polynomial interpolation, a technique that ensures smooth and precise approximation based on manufacturer-provided specifications. The power output at a given wind speed was determined using the following relationship in Eq. (1):

$$P(v) = \begin{cases} 0, & v < v_{cut-in} \; or \; v > v_{cut-off} \\ P, & v_{rated} \leq v \leq v_{cut-off} \\ \frac{1}{2}\rho A C_p v^3, & v_{cut-in} \leq v < v_{rated} \end{cases} \tag{1}$$

Where, ρ symbolizes the density of air, A is the swept-area, C_p represents the co-efficient of generated power. V_{rated}, V_{cut-in}, $V_{cut-off}$ signify rated, cut-in and cut-off wind speeds respectively. For this study, the cut-in, rated, and cut-out wind speeds were set at 3.5 m/s, 14 m/s, and 20 m/s, respectively, based on standard operational parameters of similar 3.45 MW turbines. The power coefficient, representing the efficiency of energy extraction, was modelled as a function of wind speed and rotor characteristics, with an upper limit of 0.45, consistent with Betz's law constraints. By integrating these specifications into the wind energy model, a realistic and practical estimation of power generation was achieved, ensuring that the economic optimization analysis was based on precise and site-specific turbine performance data. The aim of this study is to minimize the Cost of Energy (CoE), a formulation initially presented at the 22nd Genetic and Evolutionary Computation Conference in 2015 [7].

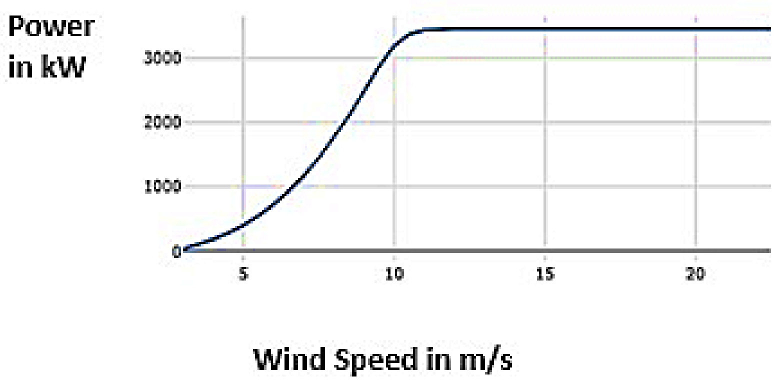

Fig. 1 Wind Turbine Power Curve

III. OPTIMIZATION ALGORITHM

Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are employed to optimize wind farm costs by efficiently configuring turbine layouts. GA, a bio-inspired search heuristic, evolves solutions iteratively through selection, crossover, and mutation. The process begins with the random initialization of wind farm layouts, followed by fitness evaluation based on the Levelized Cost of Energy (LCOE). The best-performing layouts with lower LCOE are selected for crossover, where turbine positions are exchanged to create new layouts. A mutation step introduces diversity by randomly relocating some turbines. The algorithm terminates when no significant improvement in LCOE is observed over 50 consecutive generations. The GA parameters used in this study include a population size of 100, a crossover rate of 0.8, a mutation rate of 0.1, and a maximum of 500 generations.

On the other hand, PSO simulates the social behaviour of particle swarms to explore optimal solutions. Each particle, representing a wind farm layout, adjusts its position iteratively to minimize costs using velocity and position update equations. The velocity of each particle is influenced by its best-known position and the global best position of the swarm, weighted by inertia and acceleration coefficients. The position is updated accordingly. The PSO parameters used in this study include a swarm size of 500, an inertia weight of 0.7, acceleration coefficients of 1.5 and 1.7, and a maximum of 500 iterations. These two optimization techniques provide effective solutions for minimizing wind farm costs by intelligently configuring turbine placements.

IV. RESULTS AND DISCUSSION

The optimization of the wind farm layout was conducted for a 3000 m × 3000 m area using GA and PSO. The primary objective was to minimize the LCOE while ensuring an efficient spatial distribution of wind turbines. The optimal placements determined by GA and PSO are illustrated in Figures 2 and 3, respectively.

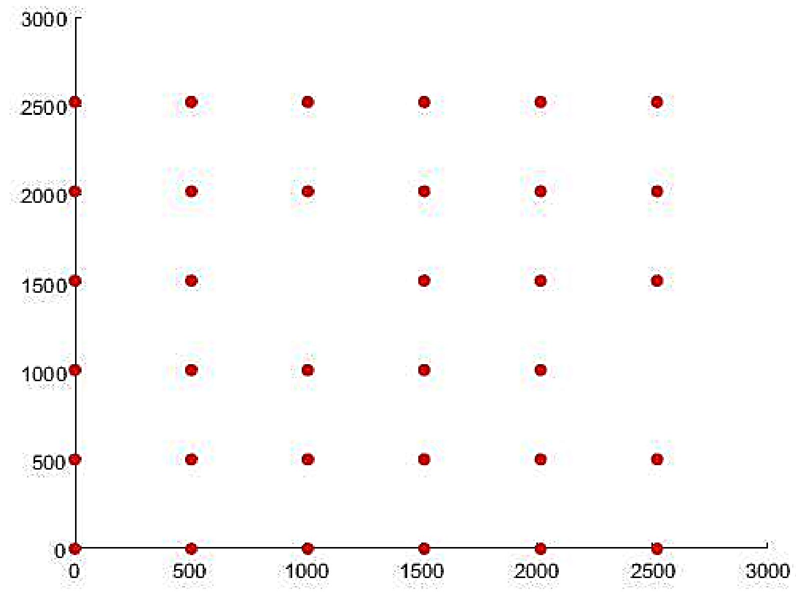

Fig. 2 GA Optimized Layout

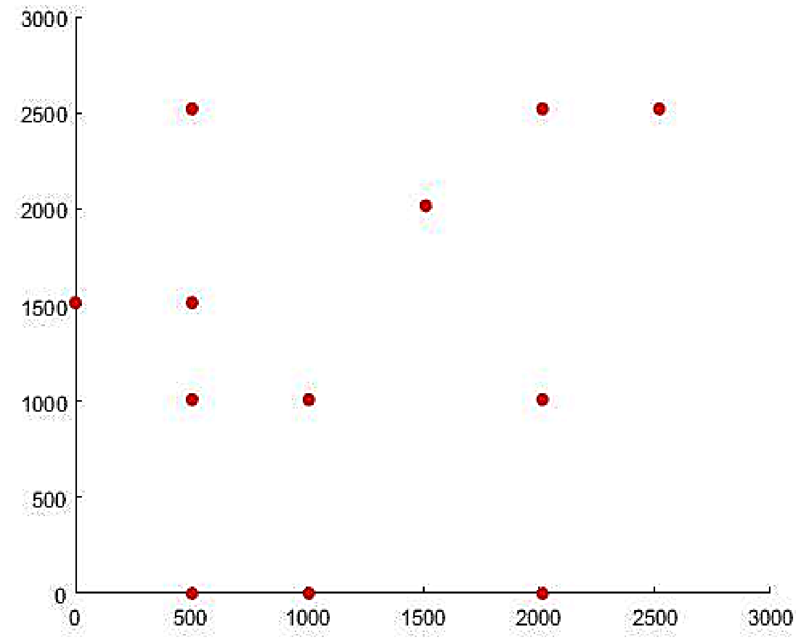

Fig. 3 PSO Optimized Layout

The results indicate that GA outperforms PSO in minimizing the LCOE. The optimal cost value obtained using GA is USD 0.0031, whereas PSO yielded an LCOE of USD 0.0043. This significant difference highlights GA's superior ability to explore the search space and refine solutions through iterative selection, crossover, and mutation operations. The mutation mechanism in GA introduces additional diversity in the search process, preventing premature convergence and leading to a more globally optimized turbine arrangement.

In contrast, PSO, while efficient in navigating the solution space, exhibits a higher tendency to converge prematurely to local optima, which limits further cost reductions. The velocity and position update equations of PSO heavily depend on the swarm's best-known solutions, which sometimes restrict exploration beyond certain regions. Consequently, the turbine layout obtained from PSO, though effective, does not achieve the same level of cost minimization as GA. The spatial distribution of turbines in GA's optimized layout demonstrates better wake loss mitigation, resulting in higher energy output and reduced operational inefficiencies. The strategic spacing between turbines ensures minimal aerodynamic interference, maximizing the farm's overall efficiency. Conversely, the PSO-optimized layout features a clustering effect in some regions, potentially leading to increased wake interactions, thereby affecting the overall energy production and cost-effectiveness.

Table 1. Comparison of Results

Optimization Algorithm	**Optimum LCoE (in USD/kWh)**	**Number of Wind Turbines**
GA	0.0031	34
PSO	0.0043	12

The convergence trends of both algorithms further reinforce GA's superiority. Over 500 generations, GA continuously refines solutions, leading to a gradual and steady reduction in LCOE. On the other hand, PSO exhibits faster initial convergence but stagnates after a certain number of iterations, indicating a suboptimal solution. The long-term adaptability of GA allows it to explore a wider range of potential layouts, ultimately leading to a more cost-effective wind farm configuration. This study demonstrates that GA is a more robust and effective optimization tool for wind farm layout design when minimizing LCOE is the primary objective. While PSO provides a competitive solution, its tendency to settle into local optima results in a higher energy cost compared to GA. Future improvements could involve hybridizing GA and PSO to leverage the exploratory strengths of GA and the rapid convergence of PSO, potentially leading to even better optimization outcomes.

V. CONCLUSION

This study demonstrates the effectiveness of metaheuristic-based optimization in minimizing the levelized cost of electricity (LCOE) for onshore wind power generation in Digha, West Bengal. Through a comparative analysis of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), GA emerges as the superior approach, achieving a lower generation cost of USD 0.0031 per kWh compared to PSO's USD 0.0043 per kWh. The superior performance of GA is attributed to its enhanced global search capability and adaptability in complex optimization landscapes, enabling more efficient wind turbine placement and power dispatch strategies. These results highlight the potential of evolutionary algorithms in optimizing renewable energy systems, offering critical insights for policymakers and energy planners. By leveraging such optimization frameworks, coastal regions with abundant wind resources can achieve greater economic viability in wind energy deployment, contributing to a more sustainable and cost-effective power generation infrastructure.

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