IMPROVING WIND ENERGY'S ECONOMIC EFFICIENCY IN DIGHA, WEST BENGAL, INDIA: A METAHEURISTIC OPTIMIZATION METHOD EMPLOYING GENETIC ALGORITHMS AND PARTICLE SWARM OPTIMIZATION ALONG THE BAY OF BENGAL COAST

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Abstract

The expanding requirement for sustainable energy has led to enhanced interest in optimizing the economic functioning of wind farms, particularly in coastal regions with plentiful wind resources. This study emphases on the yearly profit optimization of a projected wind farm located in Digha, West Bengal, India—an area along the Bay of Bengal identified for its firm wind flow patterns. Two renowned metaheuristic algorithms—Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)—were engaged to boost the annual profit by optimizing key design and effective parameters of the wind farm, involving turbine placement, hub height, and rotor diameter. Wind data specific to the Digha region were used in the simulation to ensure realistic modelling of energy output and cost considerations. The relative scrutiny discloses that the Genetic Algorithm unswervingly produces higher annual profit values than PSO under identical input conditions. GA's superior performance is attributed to its robust exploration capabilities and adaptability to complex, multi-dimensional search spaces typical of wind farm optimization problems. The study construes that GA is a more competent and reliable tool for profit-driven wind energy optimization in coastal Indian settings. These findings offer valued insights for policymakers, engineers, and renewable energy developers pursuing to capitalize on pecuniary returns from wind energy reserves in the Bay of Bengal region.

Keywords: Bay of Bengal, Genetic Algorithm, Particle Swarm Optimization, Profit Optimization, Wind Energy.

JEL Classification: Q42; Q43; C61;

1. Introduction

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The increasing global emphasis on clean, renewable, and sustainable energy sources has driven an unprecedented focus on wind energy, particularly in developing countries like India, where the dual challenges of energy security and environmental sustainability converge. As fossil fuel reserves deplete and concerns over carbon emissions mount, wind energy has emerged as one of the most viable alternatives due to its abundance, maturity of technology, and decreasing cost of generation. In the Indian context, coastal regions hold significant promise for wind energy deployment because of their favourable wind regimes, proximity to load centres, and availability of vast tracts of land or shallow offshore waters suitable for turbine installations [1].

Digha, a coastal town in the Purba Medinipur district of West Bengal, situated along the northern shoreline of the Bay of Bengal, has attracted growing attention for wind power potential. The region experiences consistent wind speeds due to the interaction of monsoonal and sea breeze systems, making it a promising site for establishing cost-effective wind farms. However, merely identifying a suitable location is not sufficient; optimizing the design and operational parameters of the wind farm to maximize economic return is essential for project feasibility and long-term sustainability. Given the high capital investment required for wind energy projects, economic optimization—particularly the maximization of annual profit—becomes a crucial objective for stakeholders including investors, policymakers, and utility companies [2].

Traditional optimization techniques, while effective in some contexts, often fall short when applied to complex, nonlinear, and multi-objective problems like wind farm planning, where variables such as wind speed variation, turbine spacing, wake losses, installation cost, and operational efficiency interact in non-trivial ways. To overcome these limitations, recent years have witnessed a surge in the application of metaheuristic algorithms, which provide flexible, powerful, and often computationally efficient alternatives for solving real-world optimization problems. Among these, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have emerged as two of the most widely applied techniques in wind energy optimization due to their ability to handle high-dimensional and discontinuous solution spaces [3].

Genetic Algorithm, inspired by the principles of natural selection and genetic evolution, uses operations such as selection, crossover, and mutation to iteratively search for optimal solutions. GA is known for its robust global search capabilities, especially in problems with numerous local optima. On the other hand, Particle Swarm Optimization, inspired by the social behaviour of birds flocking or fish schooling, is a population-based algorithm that updates candidate solutions based on the collective experience of the swarm. PSO generally exhibits faster convergence but may suffer from premature convergence in highly complex landscapes [4].

This study aims to apply and compare GA and PSO for optimizing the annual profit of a wind farm in Digha, West Bengal, India. The optimization considers critical design and economic parameters, including turbine selection, hub height, rotor diameter, and spacing between turbines, using wind data specific to the Bay of Bengal coastal region. The objective function incorporates not only the projected energy output based on wind speed distribution but also installation costs, operational and maintenance costs, and economic incentives where applicable. By systematically analysing the performance of GA and PSO under identical conditions, this research provides evidence-based insights into which algorithm is more effective for profit maximization in wind farm planning under Indian coastal conditions.

The novelty of this research lies in the combination of site-specific wind resource assessment with advanced metaheuristic optimization techniques in the context of maximizing economic efficiency—a topic of increasing relevance as India seeks to expand its renewable energy capacity to meet national and international climate targets. Furthermore, by focusing on Digha and the surrounding Bay of Bengal region, this study also contributes to regional planning efforts and offers a replicable methodology for similar coastal sites across India and other developing nations.

In the following sections, a detailed methodology is presented, outlining the structure of the optimization problem, the parameters used, and the algorithms implemented. This is followed by a comparative analysis of the results obtained from GA and PSO, a discussion on their relative strengths and limitations, and conclusions that highlight the practical implications of the findings for wind farm developers, energy planners, and policymakers.

2. Objective Formulation

The primary aim of this research is to maximize the annual economic profit from a proposed wind energy system in Digha, a coastal town in West Bengal, India, located along the Bay of Bengal. In the context of India's growing commitment to clean energy and sustainable development, the economic performance of renewable energy installations—especially wind farms—is of significant importance. Profitability is not just a measure of operational success; it also plays a critical role in attracting investment, ensuring long-term sustainability, and contributing to regional economic upliftment. This study formulates a comprehensive optimization problem that captures the key economic, technical, and environmental aspects involved in designing an efficient wind farm for the Digha coastal region [5].

In this work, annual profit is defined as the difference between the total revenue earned from selling the generated electricity and the total costs incurred in setting up, operating, and maintaining the wind farm over its operational lifetime, normalized on an annual basis. The revenue depends on the quantity of electricity generated throughout the year and the prevailing energy tariff or sale price per unit of electricity. The cost component includes a wide spectrum of expenditures such as capital investment (covering turbine procurement, land development, foundation work, electrical connections, and installation), as well as recurring costs like operation, maintenance, and administrative overheads. To simulate realistic operational conditions, the wind resource assessment is based on regional wind speed data extrapolated to various hub heights using power-law or logarithmic profiles. Coastal Digha benefits from a relatively stable wind regime, making it an attractive site for wind energy deployment. The model considers turbine-specific characteristics such as rotor diameter, hub height, efficiency, and rated power to estimate the potential energy output. Moreover, environmental factors like air density, temperature, and seasonal wind variability are included to ensure that the energy estimation reflects the local climatic conditions with accuracy [6].

A set of decision variables is established to be optimized. These variables include:

- The number of turbines to be installed,
- The rotor diameter of the turbines,
- The hub height of the towers,
- The spacing between turbines (to minimize wake losses),
- The selection of specific turbine models suited to the site.

Each of these variables influences both the power output and the cost dynamics of the wind farm. For instance, increasing rotor diameter can significantly boost energy generation but may also lead to higher structural and land costs. Similarly, raising the hub height can allow access to higher wind speeds but entails increased expenses for materials and installation. Thus, the optimization must strike a careful balance between cost and benefit.

The formulation of the problem incorporates practical constraints to reflect real-world limitations. These constraints include:

- Land area availability, limiting the number and spacing of turbines,
- Mechanical and structural bounds on rotor diameters and hub heights based on commercial turbine specifications,
- Budgetary constraints that limit the total allowable capital expenditure,
- Wake effect considerations, ensuring that turbines are not placed too close together, which could reduce efficiency and energy output.

Given the nonlinear, multi-dimensional nature of the objective and constraints, traditional optimization methods are not adequate for handling such complexity. Therefore, this study employs two nature-inspired metaheuristic optimization algorithms—GA and PSO—to navigate the solution space and identify the optimal configuration of variables that leads to the highest possible annual profit. Both algorithms are known for their global search capabilities, robustness, and adaptability to problems with multiple local optima, which are characteristics commonly observed in wind farm design scenarios [7].

In the Genetic Algorithm, a population of possible solutions evolves over generations using operators such as selection, crossover, and mutation. These operators mimic biological evolution and promote diversity in the solution space, helping the algorithm to explore broadly and avoid premature convergence. On the other hand, Particle Swarm Optimization simulates the collective intelligence of swarms, where each solution (called a particle) moves through the search space by updating its position based on its own experience and the experience of neighbouring particles.

Both algorithms are applied to the same optimization model with identical boundary conditions, wind resource profiles, cost functions, and technical constraints. The objective formulation aims not only to yield economically optimal wind farm designs for Digha but also to provide a generalized methodology that can be adapted for similar coastal regions across India and other parts of the world. This approach aligns with India's national renewable energy goals and supports the global transition toward a low-carbon future. By systematically defining the problem space, identifying the most influential variables, accounting for real-world constraints, and applying intelligent optimization techniques, this research sets out to develop a technically sound and economically viable wind energy solution for Digha, West Bengal.

3. Optimization Algorithm

In order to solve the complex optimization problem of maximizing the annual profit from a wind energy system in Digha, this study harnesses the potential of two well-established metaheuristic algorithms: GA and PSO technique. Both algorithms are capable of efficiently navigating high-dimensional, nonlinear, and multimodal search spaces. However, their inspiration, mechanics, and search dynamics differ fundamentally, providing complementary strengths for problem-solving in renewable energy system design.

3.1 Genetic Algorithm (GA):

The Genetic Algorithm is a bio-inspired technique modelled on the principles of natural selection and Darwinian evolution. It conceptualizes each potential solution to the optimization problem as a "chromosome," composed of a series of "genes," which correspond to the decision variables—such as turbine number, rotor diameter, and hub height—in the context of this wind farm optimization.

- A population of such chromosomes evolves over generations through biologically inspired operations:

- Selection determines which individuals get to pass their genetic material to the next generation based on their fitness—here, the fitness is measured in terms of the annual profit they yield.

- Crossover (recombination) combines segments of two parent solutions to form new offspring, enabling exploration of novel configurations by inheriting traits from both parents.

- Mutation introduces random alterations in individual genes to maintain diversity within the population and to prevent premature convergence to suboptimal solutions.

What makes GA particularly effective in this domain is its robust global search capability and adaptability to diverse constraints. It does not require the gradient of the objective function, which is advantageous for problems involving discrete decisions and discontinuities, as is often the case in wind farm design.

Moreover, GA's parallelism allows it to explore multiple regions of the solution space simultaneously, increasing the likelihood of identifying globally optimal or near-optimal designs. Its evolutionary approach also makes it well-suited for handling the multi-variable interdependencies inherent in turbine placement, wake loss mitigation, and terrain-specific design choices [8].

3.2 Particle Swarm Optimization (PSO):

In contrast to the biological foundation of GA, Particle Swarm Optimization draws its inspiration from social behaviour patterns found in nature—such as bird flocking, fish schooling, or insect swarming. Each solution in PSO is termed a "particle," which represents a point in the multidimensional design space. Unlike chromosomes in GA, these particles do not undergo crossover or mutation. Instead, they iteratively adjust their positions based on both their individual experience and the collective intelligence of the swarm.

Each particle maintains a record of its personal best position (i.e., the solution it has found with the highest profit so far) and is also influenced by the global best position identified by any member of the swarm. With every iteration, particles update their velocity and position based on these two guiding forces. This dual feedback mechanism ensures that particles converge towards promising regions of the search space without requiring any hard-coded rules for selection or reproduction.

PSO is especially known for its fast convergence and computational simplicity. It requires fewer tuning parameters compared to GA and often reaches near-optimal solutions in a relatively short number of iterations. This makes it suitable for real-time or large-scale simulations where quick decision-making is essential.

In the context of wind farm optimization, PSO's strength lies in its fluid exploration and exploitation balance—it can swiftly hone in on profitable design zones by leveraging collective learning while avoiding the randomness introduced by GA's mutation operator. While both algorithms are applied to the same wind farm profit maximization problem, they offer distinct advantages:

- GA is ideal for exploring highly rugged landscapes of the profit function, where multiple local optima exist and discrete decisions play a major role.

- PSO, on the other hand, excels in smooth and continuous search spaces, delivering high-quality solutions with less computational overhead.

Their unique strengths make them not just alternative techniques, but also candidates for hybridization in future research. By employing both, this study leverages the diverse problem-solving paradigms of evolutionary biology and swarm intelligence, offering a well-rounded perspective on wind farm economic optimization [9].

4. Results and Discussion

To evaluate the performance of the GA and PSO in optimizing the annual profit of a wind energy system in Digha, West Bengal, a comprehensive simulation study was conducted. The simulation was configured based on real-world constraints, techno-economic parameters, and wind resource data relevant to the coastal region along the Bay of Bengal. For the economic analysis, the selling price of electricity was assumed to be 0.033

USD/kWh, which is within the typical range of renewable energy tariffs in the Indian market, particularly under government-subsidized or incentivized schemes. This value serves as a realistic benchmark for estimating the potential revenue generated from the annual energy output of the optimized wind farm design.

To ensure a robust and statistically significant evaluation, both optimization algorithms were executed with a population size of 500 candidate solutions and allowed to evolve or update over 500 iterations. This relatively large population and iteration count were chosen to ensure adequate exploration of the multidimensional design space, minimize the risk of premature convergence, and allow each algorithm to demonstrate its full optimization capability. The same parameters were applied consistently to both GA and PSO in order to maintain fairness in performance comparison.

The objective function—maximization of annual profit—was computed using detailed cost and energy models, incorporating turbine specifications, wake losses, investment costs, and maintenance expenditures. Both algorithms were tasked with identifying optimal configurations for key decision variables such as turbine number, rotor diameter, hub height, and inter-turbine spacing within the defined constraints.

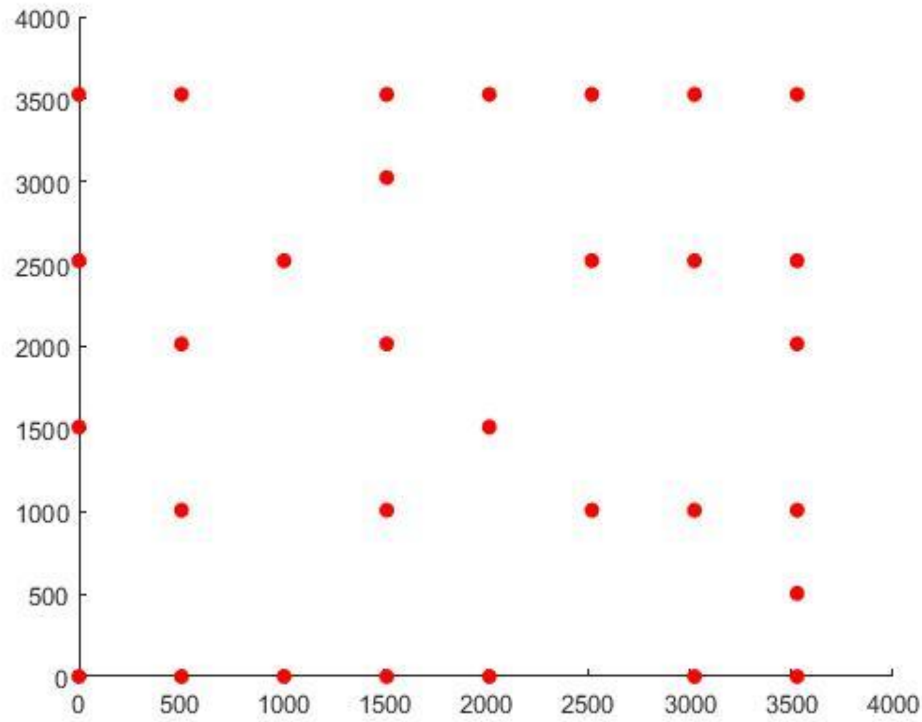

Fig. 1: Optimal Positioning of Wind Turbines in 4000 m x 4000 m Layout of Wind Farm at Digha, West Bengal Obtained by Genetic Algorithm

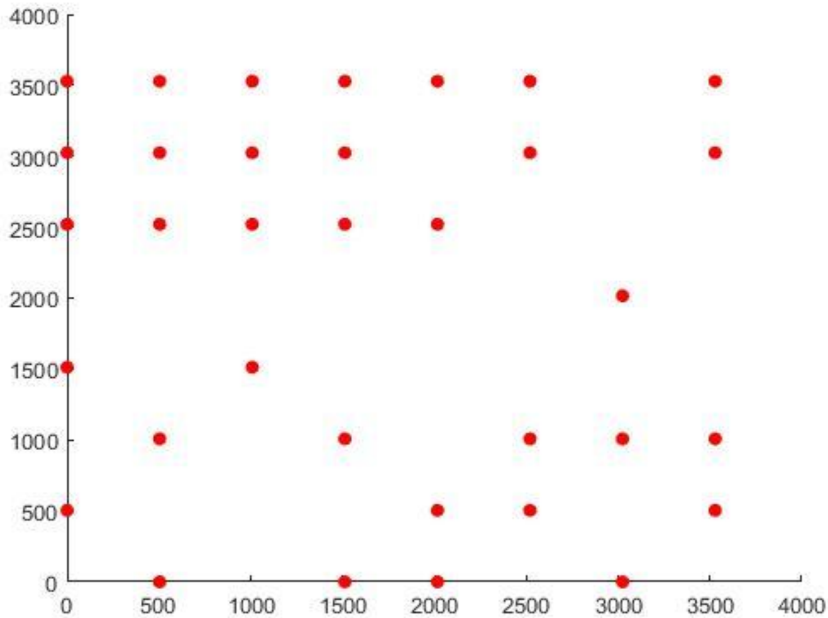

Fig. 2: Optimal Positioning of Wind Turbines in 4000 m x 4000 m Layout of Wind Farm at Digha, West Bengal Obtained by Particle Swarm Optimization Algorithm

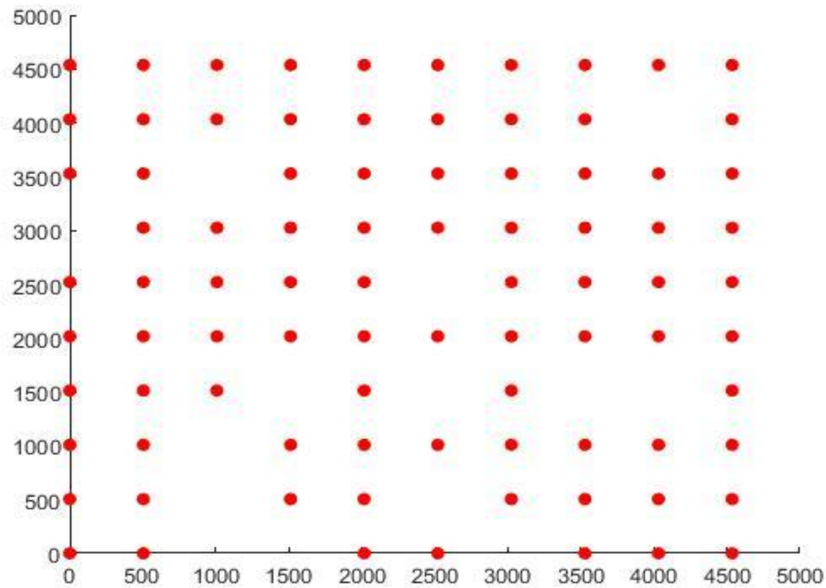

Fig. 3: Optimal Positioning of Wind Turbines in 5000 m x 5000 m Layout of Wind Farm at Digha, West Bengal Obtained by Genetic Algorithm

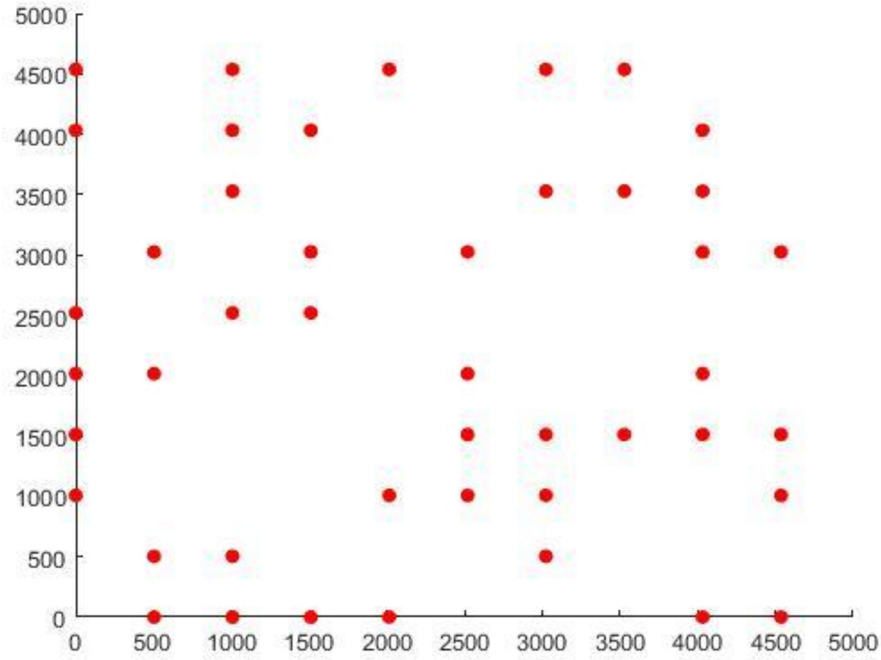

Fig. 4: Optimal Positioning of Wind Turbines in 5000 m x 5000 m Layout of Wind Farm at Digha, West Bengal Obtained by Particle Swarm Optimization Algorithm

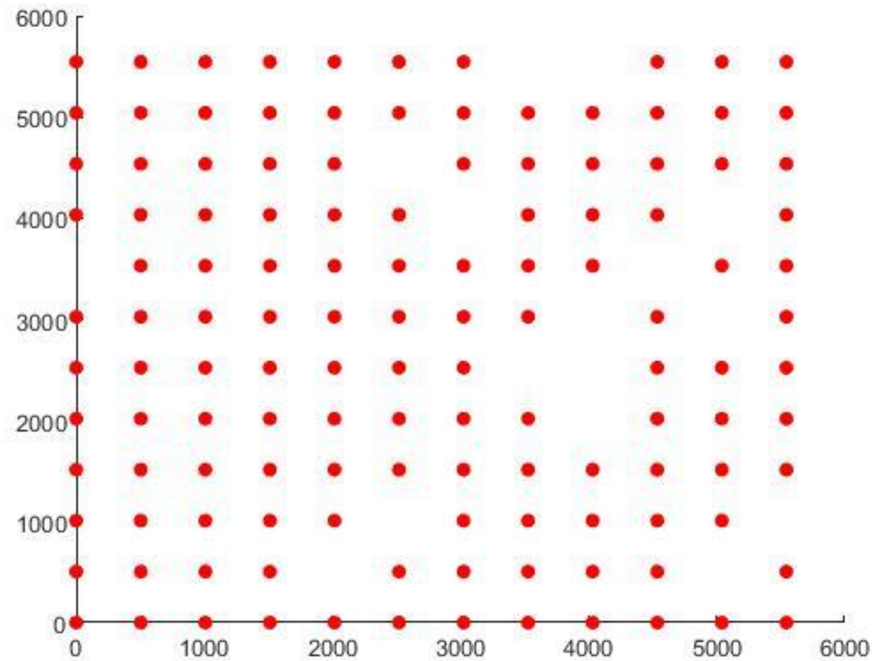

Fig. 5: Optimal Positioning of Wind Turbines in 6000 m x 6000 m Layout of Wind Farm at Digha, West Bengal Obtained by Genetic Algorithm

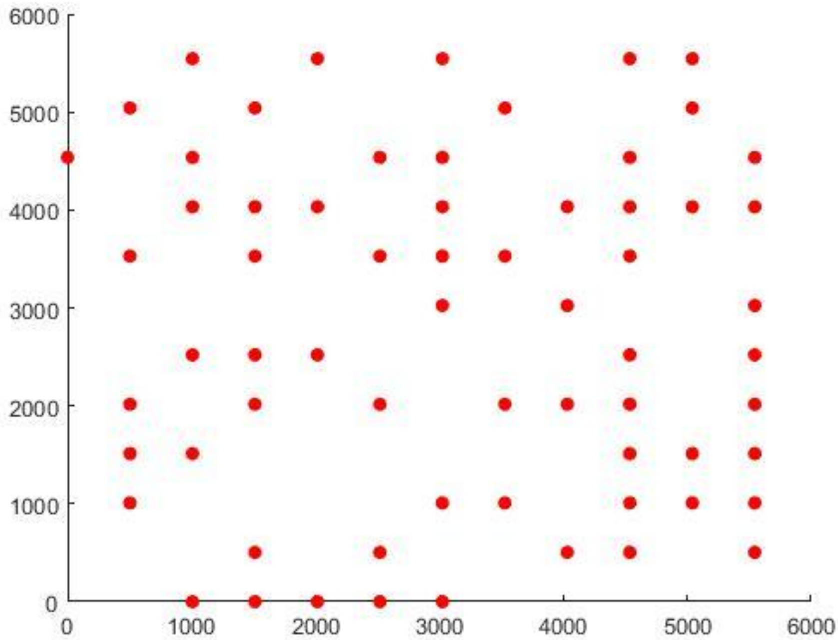

Fig. 6: Optimal Positioning of Wind Turbines in 6000 m x 6000 m Layout of Wind Farm at Digha, West Bengal Obtained by Genetic Algorithm

Optimization Algorithm	Optimal Annual Profit for 4000 m x 4000 m Layout	Optimal Annual Profit for 5000 m x 5000 m Layout	Optimal Annual Profit for 6000 m x 6000 m Layout
Genetic Algorithm	USD 2070.2	USD 2228.5	USD 2426.8
Particle Swarm Optimization Algorithm	USD 2042.6	USD 2124.5	USD 2206.1

Table 1: Comparison of Optimal Annual Profit Obtained for All Considered Layouts Calculated by Genetic Algorithm and Particle Swarm Optimization Algorithm

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Optimization Algorithm	Optimal Count of Wind Turbines for	Optimal Count of Wind Turbines for	Optimal Count of Wind Turbines for

	4000 m x 4000 m Layout	5000 m x 5000 m Layout	6000 m x 6000 m Layout
Genetic Algorithm	31	86	128
Particle Swarm Optimization Algorithm	34	45	65

Table 2: Comparison of Optimal Count of Wind Turbines Obtained for All Considered Layouts Calculated by Genetic Algorithm and Particle Swarm Optimization Algorithm

The comparative analysis of wind farm layout optimization using GA and PSO reveals critical insights into both economic returns and turbine deployment strategies across varying land dimensions (4000 m × 4000 m, 5000 m × 5000 m, and 6000 m × 6000 m).

Across all layout sizes, the GA outperformed PSO in terms of optimal annual profit:

- For the 4000 m × 4000 m layout, GA achieved a 1.35% higher profit than PSO.
- For the 5000 m × 5000 m layout, the profit improvement rose to 4.90%.
- The 6000 m × 6000 m layout showed the most significant gain, with GA yielding a 10.01% higher annual profit than PSO.

This trend of increasing percentage gains with layout size suggests that GA scales more effectively in larger and more complex design spaces. Its superior global search capabilities allow it to navigate the increasing number of possible turbine configurations to locate more economically favourable layouts.

The number of wind turbines also differed significantly between the two algorithms:

- In the 4000 m × 4000 m layout, PSO placed 9.68% more turbines than GA, yet achieved a lower profit, indicating possible inefficiencies or suboptimal placement.
- In the 5000 m × 5000 m layout, GA deployed 91.11% more turbines than PSO.
- In the 6000 m × 6000 m layout, GA used 96.92% more turbines than PSO.

These findings reveal a strategic contrast: GA aggressively utilizes available space, opting for higher turbine counts to maximize power generation and, consequently, revenue. PSO, in contrast, adopts a more conservative placement strategy, which may lead to underutilization of available area and lower profitability. The growing disparity in performance with increasing layout size implies that GA is more capable of optimizing larger wind farms, where the solution space is vast and highly nonlinear. GA's crossover and mutation operations likely promote diverse solution exploration, enabling the discovery of higher-profit configurations even at the cost of increased turbine count.

From a practical standpoint, the results suggest that while PSO may be computationally faster or simpler, it may not always capture the full economic potential of large-scale wind farm layouts. In contrast, GA provides a better trade-off between computational complexity and long-term financial gains, making it a more suitable choice for high-return, utility-scale projects. In conclusion, selecting the appropriate optimization technique is crucial not only for maximizing profit but also for making efficient use of land and infrastructure. The GA's demonstrated advantage in both profit and adaptability to larger layouts underscores its value in real-world wind farm design scenarios.

4. Conclusion

This study has demonstrated the comparative effectiveness of the GA and PSO Algorithm in optimizing wind farm layouts across three different land sizes. The results clearly indicate that GA consistently yields higher annual profits than PSO, with percentage improvements in profitability growing from 1.35% to 10.01% as the layout size increases.

The GA also deployed significantly more wind turbines in the medium and large-scale layouts—up to 96.92% more than PSO—suggesting its superior capacity to exploit available land area for maximizing energy generation. Although this strategy may incur higher capital costs, it translates into notably greater annual revenues, especially in larger farms where spatial configuration becomes more complex.

In contrast, PSO demonstrated a more conservative approach, resulting in lower turbine counts and, consequently, lower profits. While this may be suitable for scenarios with stricter budget or infrastructure constraints, it may not fully capitalize on the economic potential of available land.

Overall, the findings underscore the importance of algorithm selection in wind farm layout optimization. The Genetic Algorithm proves to be a robust and scalable method, particularly well-suited for large-scale wind energy projects where maximizing long-term financial return is a priority. Future work may consider hybridizing these techniques or incorporating multi-objective frameworks that also factor in wake effects, installation costs, and environmental impact for a more comprehensive optimization approach.

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