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RESEARCH ARTICLE – RENEWABLE ENERGY

Optimization of the Offshore Wind Turbines Layout Using Cuckoo Search Algorithm

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Abstract

Wind turbines have gained popularity as one of the efficient micro grid energy generation sources over the years. However, wind energy yield has been greatly impacted by the wind farm wake effect, especially when the size of the wind farm becomes very large. One way to address this challenge is through wind turbine arrangements and their scalability. Developing effective means of optimizing wind farm configurations is a major concern for energy communities. This has continuously led to increased power generation and a corresponding cost reduction. As such, this research article developed an optimal large-scale offshore wind turbine placement based on wind farm layout design. The system developed focuses on wind turbine placement in wind farm layouts that have a negative influence on the capital investment due to the increasing wake effect thereby reducing energy production. A multi-objective function consisting of wake effect and component costs within the wind farm is formulated. After-which a cuckoo search algorithm technique is employed in the wind farm model to optimize the optimization problem (minimizing the wake effect while improving power output and cost). Four test case scenarios were considered when implementing the wind model. The results obtained from the developed scheme were compared with those obtained when other optimization techniques were used, using power output and cost as performance metrics. The obtained power output and cost for the test case scenario in the ideal wind turbine position on the wind farm are 18288.3KW, 19680.1KW, 18879.9KW, 21105.8KW and 26.9, 28.7, 26.9, and 29.8KW, respectively. This shows that the result obtained from the developed scheme outperformed that obtained from PSO and that of WOA.

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Keywords: Cuckoo Search Algorithm; Renewable Energy; Wake Effect; Wind Farm; Wind Turbine.

1. Introduction

Energy plays a major role in the development of any nation [1, 2]. Alternative means of generating electricity are now preferred over conventional means due to continuous increases in fuel prices and growing concerns over global climate change [3]. Recently, generating energy from renewable energy sources (RES) is now seen as a better alternative means of generating energy in most nations [4, 5]. Energy from wind and solar are regarded as the most popular resources amongst renewable energy sources due to the numerous advantages inherent in them over the other RES. It was reported in 2015 that 11% of the energy generated was from renewable energy, of which 19% was harvested from wind. Wind power currently has an annual growth rate of 34%, and this makes it the second fastest-growing renewable energy [6, 7]. This has, therefore, led to researchers developing effective techniques/means of maximizing wind energy generation [8]. As such, one of the ways of improving the rate of wind power generation is through the improvement of wind farm planning by optimizing the placement of wind turbines in wind parks [9]. Creation of a wind farm for the installation of a set of wind turbines requires wind data at the location, wind velocities and direction over a year [10]. After this, the challenge of where to place the wind turbines becomes an issue [11]. This is a challenge because, for two overlapping turbines, the front turbine will fully harvest the energy while the rear one will have much less energy. As a result, there is a serious need to find the optimal placement of all turbines to harvest the highest possible wind energy [12].

The wind turbine placement problem, also referred to as the wind farm layout optimization problem, is an optimization problem due to the requirement of minimizing installation costs and maximizing energy production. [11] presented a new turbine layout optimization approach using grid-based problem formulation for improved design performance. A particle swarm optimization algorithm was employed for the wind farm layout optimization. The Larson wake model was used in assessing the wind farm model. However, the results obtained showed that the numerical efficiency and design effectiveness need to be examined. Furthermore, [12] studied a comparative analysis of different optimization techniques to optimally place the wind turbines. The optimization techniques used comprise moth flame optimization, grasshopper optimization, particle swarm optimization, real code ant colony optimization, genetic algorithm, artificial bee colony technique, whale optimization, teaching

Nomenclature & Symbols			
PSO	Particle Swarm Optimization	WOA	Whale Optimization Algorithm
RES	Renewable Energy Sources	MFO	Moth Flame Optimization
CSA	Cuckoo Search Algorithm	StD	Standard Deviation

learning-based optimization and differential evolution algorithm. The results obtained when the different optimization techniques were used for the wind turbine placement were presented using four different scenarios. It was observed that the results obtained from the moth flame optimization (MFO) gave the best result in terms of cost for cases three and four, while real code ant colony optimization gave the best result for cases one and two.

Given the reviewed literature, it is evident that the improper location of wind turbines in wind farm layout will have a negative influence on the capital investment and increase wake effect thereby reducing energy production. As such, there is a need to maximize wind energy production whilst reducing the effect of wake that leads to energy loss to the barest minimum. So, it becomes pertinent to optimally place wind turbines in a large-scale offshore wind farm by formulating a multi-objective function consisting of wake effect and component costs within the wind farm.

2. Problem Formulation

With the increase in electricity demand and the inability of power generation companies to meet this demand, coupled with various forms of losses, there has been a paradigm shift in electricity generation systems [13]. Wind turbines have gained popularity as one of the efficient micro grid energy generation sources over the years. However, wind energy yield has been greatly impacted by the wind farm wake effect, especially when the size of the wind farm becomes very large and the cost models [14]. One way to address this challenge is through wind turbine arrangements and their scalability. Traditional practice by engineers is to design the wind farm layout manually. Nonetheless, the positions of the wind turbines in the traditional practice are not in the optimization procedures. Thus, the improper location of wind turbines will have a negative influence on capital investment and increase the wake effect thereby reducing energy production. Thus, this research proposes the optimal placement of wind turbines in a large-scale offshore wind farm by formulating a multi-objective function consisting of the wake effect and component costs within the wind farm. The proposed work will be modeled using the Levelized Production cost and the cuckoo search algorithm will be used to carry out the optimization.

3. Methodology

3.1. Formulation of the wind farm model

The wind farm layout design was carried out optimally by finding the best placement for several wind turbines in a given area. This was done to achieve the maximum power produced from a wind turbine. As such, the wind farm is modeled as a multi-objective function that considers the effect of wake and cost using the wake diagram presented in Fig. 1. The effect of wake, considering coverage area of the wind turbine and velocity deficit is modeled using The Jansen Wake Model. The intersection of the turbines needs to be computed to predict the velocity deficient that might be experienced by the turbine. The intersection effect was computed using the following equations (1) and (2) [12].

$$A_{ij} = R_i^2 \cos^{-1}\left(\frac{c_{ij}^2 + R_i^2 - R_j^2}{2c_{ij}R_i}\right) + R_j^2 \cos^{-1}\left(\frac{C_{ij}^2 + R_j^2 - R_i^2}{2c_{ij}R_j}\right) - \frac{1}{2}\sqrt{(-c_{ij}+R_i+R_j)(c_{ij}-R_i+R_j)(-c_{ij}+R_i-R_j)(c_{ij}+R_i+R_j)} \tag{1}$$

Where c_{ij} is the distance between the centers of both turbines.

R_i is the wake radius of turbine *i* at the same plane turbine *j*

R_J is the radius of turbine *j*.

The velocity deficit at the *j*-th turbine can then be computed as

$$1 = a\left(\frac{C_0^2}{C(x)^2}\right)\left(\frac{A_{ij}}{A_0}\right) + \frac{V(x)}{V_0} \tag{2}$$

Where A_o is the area of the disk of the turbine?

The most prevalent wake model used today in the field of wind farm optimization is the Jensen wake model [15]. This is due to its practicability and simplicity. As such, in this research work, the Jensen wake model was employed. Three basic wake models are always considered which are the full wake, the no-wake effect, and the partial wake. The schematic representation of the wind speed deficit is presented in Fig. 1.

The upstream wind turbine causes a wind speed deficit, which is calculated by determining the area of effective wake influence. The mathematical expression for wind speed deficit is presented in equations (3 & 4) as follows [12].

$$T_x = T_0 + kx \tag{3}$$

$$U_i = U_0 - U_0(1-\sqrt{1-C_t})\left(\frac{T_0}{T_i}\right)^2\left(\frac{S_{overlap}}{S_0}\right) \tag{4}$$

Where:

U_i is: the speed of the incoming wind,

U_0 is: wind speed in the wake at distance x following the wind flow direction;

Ct is: wind turbine's thrust coefficient,

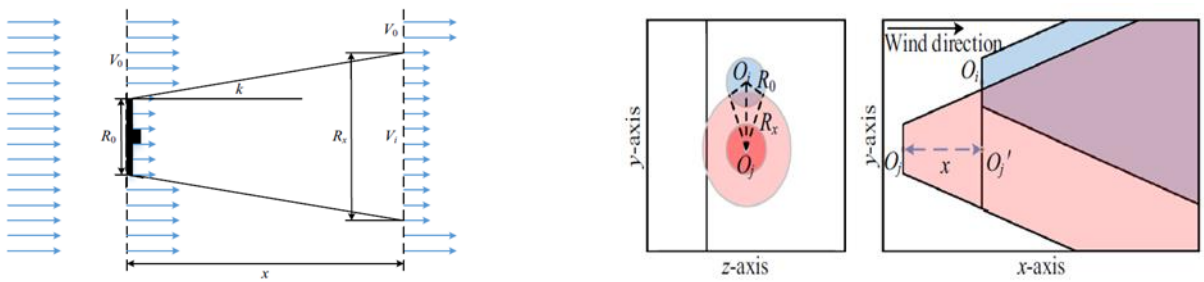
S_0 and $S_{overlap}$ are the rotor-swept area and wake-swept area, respectively;

T_x is: rotor radius

T_i is: radius of the created wake at a distance x from the wind's direction

K is the wake decay constant.

The recommended value of k is 0.04 for the offshore environment [12]. The wind farm layout of a hundred turbines is depicted in Fig. 2.



(a) Wind speed development in a wake

(b) Partial wake

Fig. 1. Schematic representation of the deficit in wind speed

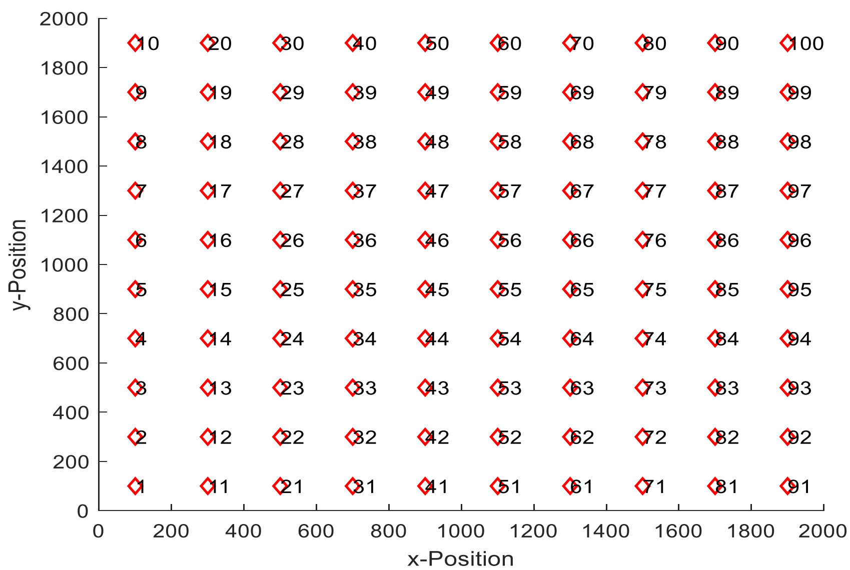


Fig. 2. Wind farm layout of turbines

3.2. Objective function

The purpose of this study is to reduce the impact of the wake effect on the wind turbine system. As a result, utilizing the wake effect and components cost as performance metrics, a multi-objective function was formulated as a minimization problem. The objective function is as follows.

$$F(x) = \min\left(\frac{\mathrm{Cos}\,t}{P_{total}}\right) \tag{5}$$

Where:

P_{total} is the total power produced by wind farm x (x represents a vector of the design variables)

The cost function is computed using equation 6.

$$\text{Cos}\,t = N_T\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N_T^{\,2}}\right) \tag{6}$$

Where N_T is the number of turbines installed. The characteristic of the turbine used with the formulated objective function is presented in Table 1 [12].

Table 1. Characteristic of the turbine used with the formulated objective function [12]

Thrust Coefficient (C_T)	**0.88**
Hub Height (h_0)	60m
Rotor diameter (D_0)	40m
Ground surface roughness (h)	0.3
Air density (ρ_{air})	1.225kg/m^3
Wind speed (V_0)	12m/s
Degree of wind direction	(10,20,30,360 degrees) wind direction angle
Turbine efficiency (η)	40%

The flowchart in Fig. 3 depicts the processes responsible for executing the CSA method for appropriately locating and placing the wind turbines in the wind farm layout. The flow chart used to achieve this method utilizing the CSA to calculate the impact of wake to minimize cost and power losses whilst maximizing the wind farm total output.

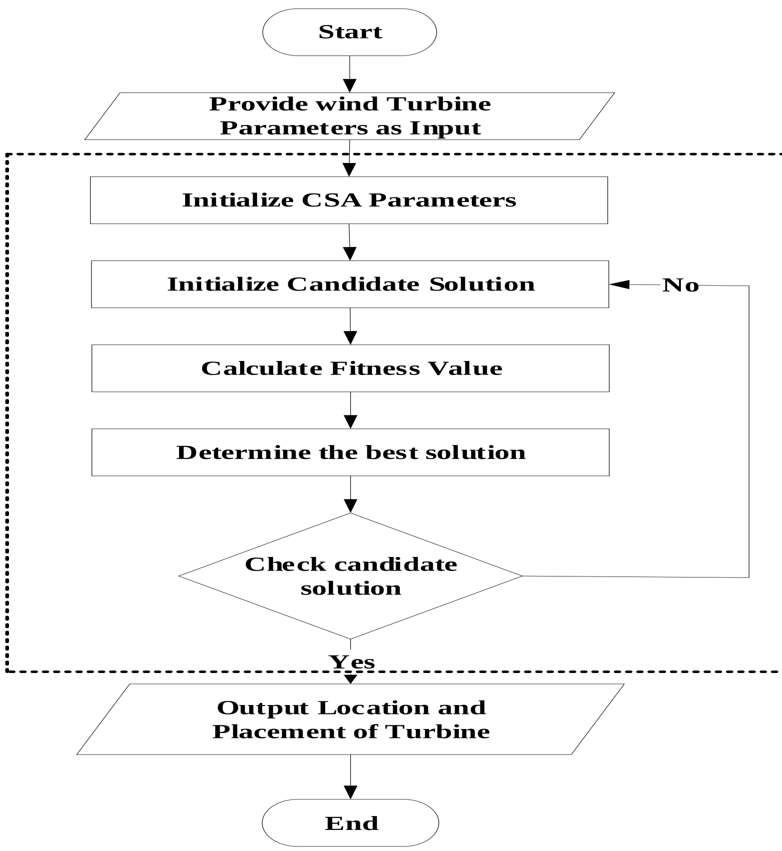


Fig. 3. Optimizing the location and placement of wind turbine using the CSA

Based on the flowchart presented in Fig. 3, four (test solutions) were used to apply the CSA to the formulated wind farm model. These test scenarios are described as follows:

- Scenario I Test Solution: The design in scenario I is to locate the positions of wind turbines on a 10x10 grid. The problem in the scenario involves the wind turbine design variables for the 100 square grids, and the number of wind turbines in the wind farm ranges from one to one hundred (1-100). The amount of energy is computed using the Jansen wake model with a total eclipse and 36 wind directions at a constant wind speed of 12 m/s.
- Scenario II Test Solution: Scenario II is the repetition of scenario I. However, scenario II considers a partial eclipse instead of a total eclipse as used in scenario I.
- Scenario III Test Solution: The design scenario's purpose is to find the placement of 39 turbines. In scenario I, a total of 39 wind turbines must be installed with a placement range of [1, 100] meters utilizing a 10 × 10 square grid. The total energy is calculated using the wake model, which replicates 36 wind directions at a constant speed of 12 meters per second. The scenario I wake model is used to compute total power.

- Scenario IV Test solution: Scenario IV is the repetition of scenario III. However, scenario IV uses the wake model presented in scenario II.

A set of metrics was used to evaluate the proposed research work's performance. The measurements employed are cost minimization concerning the different types of optimizers used. The findings of the devised method are compared to those of the PSO and WOA algorithm, which was also used in the work of [12].

4. Results and Discussion

The cuckoo search algorithm applied to the formulated wind farm model made use of its default parameters in Table 1 to optimize the location and placement of the wind turbine in the wind farm layout. The obtained results for the procedure are presented in Fig. 4. Fig. 4 presents the wake of a turbine in the wind farm layout.

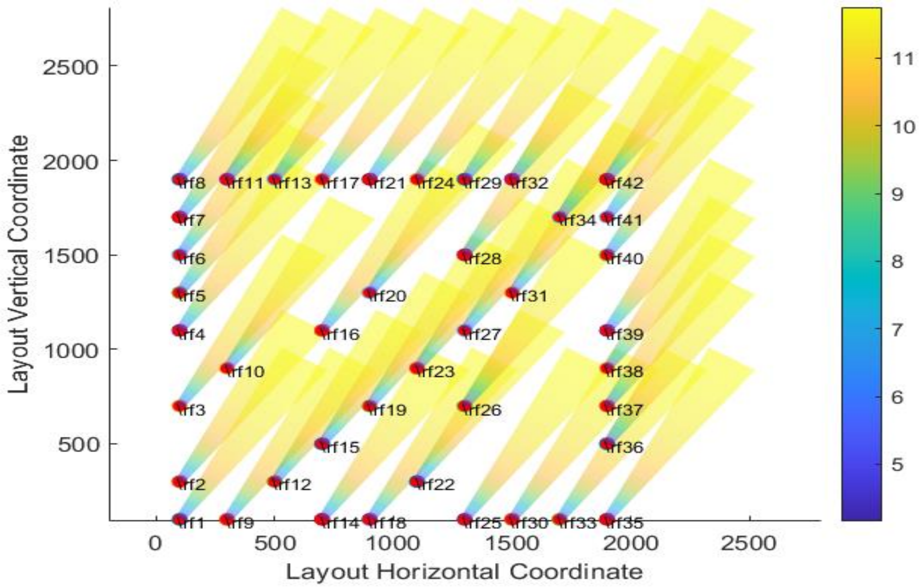


Fig. 4. Demonstration of the wake of a turbine

The wake is formed as the wind passes through the rotating turbine, as shown in Fig. 4, and it is linearly extended as the wake travels away from the turbine. The velocity was believed to be consistent over a wake disk based on the conservation of momentum.

4.1. Scenarios of the wind flow layout optimization for power and cost

The wind turbine placement power output and cost acquired from the best run for the wind flow layout optimization of all test scenarios using the cuckoo search Algorithm (CSA) are discussed and presented in this subsection. These results were obtained after completing ten optimization cycles to solve the wind farm layout optimization problem. Figs. 5 to 8 represent the optimized layout of test scenario I, scenario II, scenario III and scenario IV, respectively.

Based on the test runs for each of the test scenarios, the values of the obtained optimized power and cost are presented in Table 2.

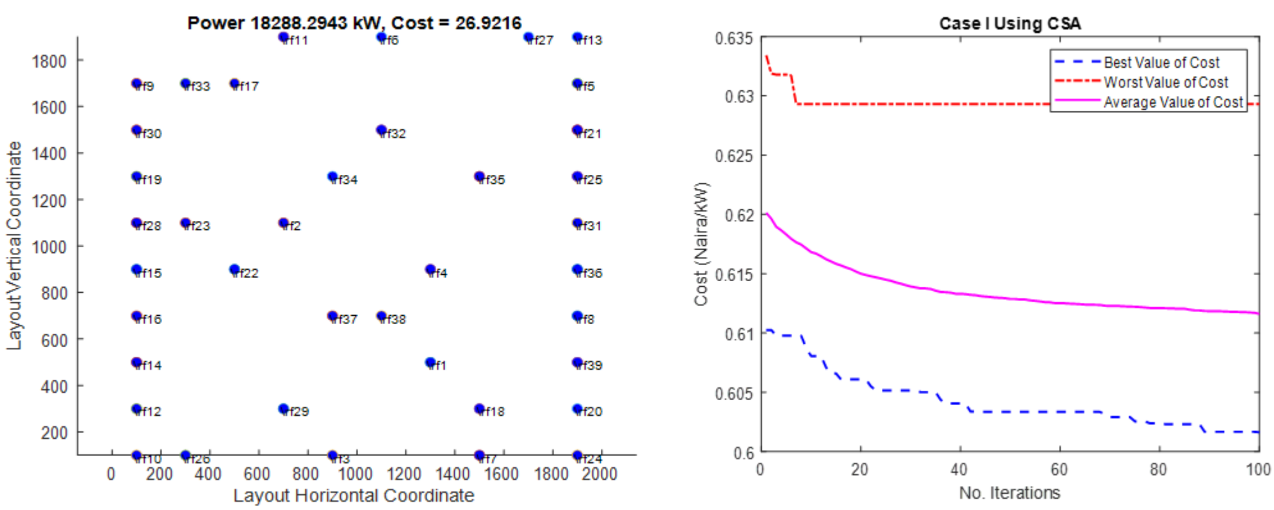


Fig. 5. Power output and cost of test scenario I

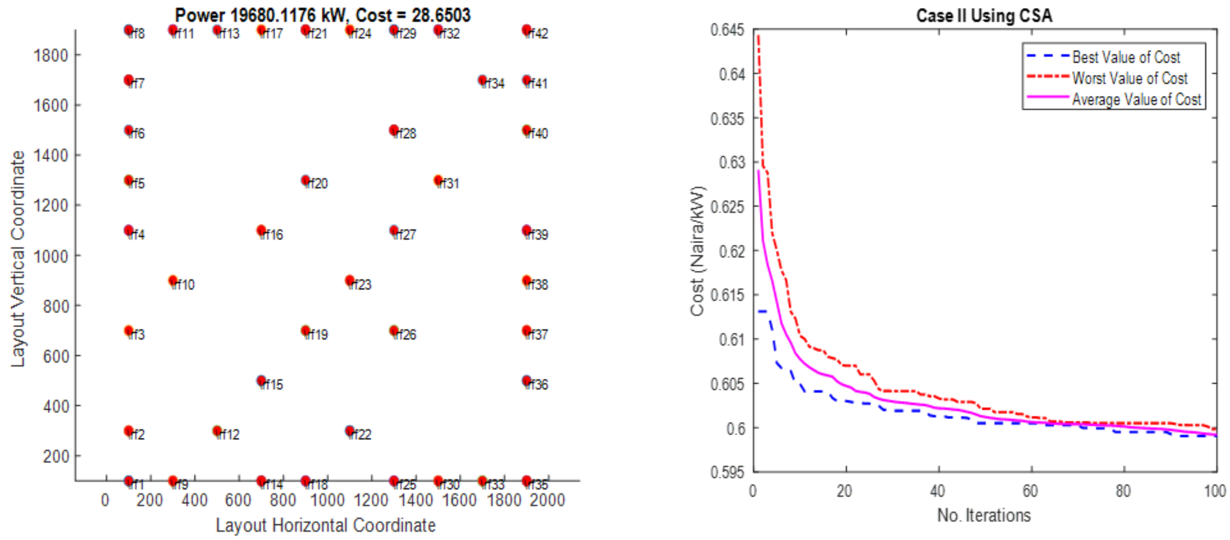


Fig. 6. Power output and cost of test scenario II

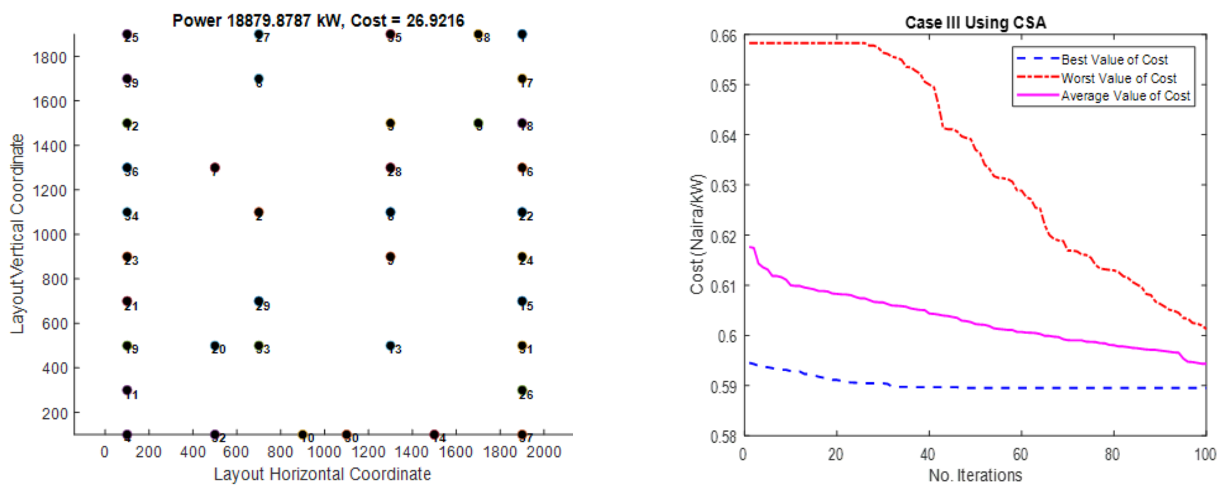


Fig. 7. Power output and cost of test scenario III

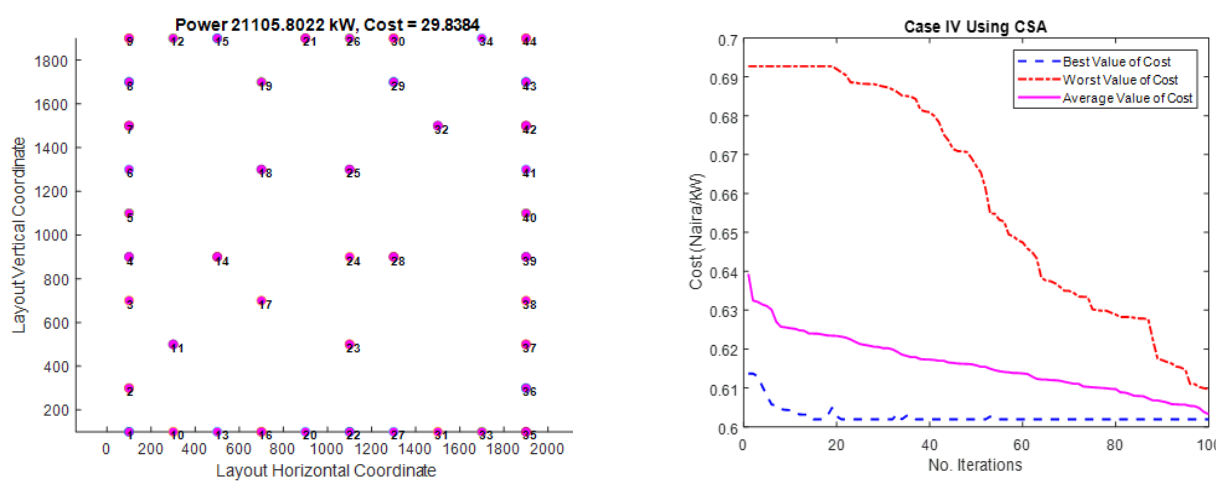


Fig. 8. Power output and cost of test scenario IV

Table 2. Power output and cost

Scenarios	Output power (KW)	Cost
Scenario 1	18288.3	26.9
Scenario 2	19680.1	28.7
Scenario 3	18879.9	26.9
Scenario 4	21105.8	29.8

Based on the data presented in Table 2, scenario IV has the highest output power. However, this is also at a relatively high cost. The scenario with a relatively good output power and fair cost is scenario III.

4.2. Simulation result for applying CSA to the formatted wind farm

The comparative results of using the cuckoo search Algorithm (CSA) based on the objective function values for all the test scenarios are presented in this subsection. The parameters used for the comparison are the best case, worst case, average, and standard deviation, as presented in Table 3.

Table 3. Optimization Results of the Objective Function Values

Metrics	Scenario I	Scenario II	Scenario III	Scenario IV
Best	0.001416	0.001457	0.001421	0.001461
Average	0.001422	0.001457	0.001423	0.001461
Worst	0.001426	0.00147	0.001426	0.001471
StD	2.97207E-06	4.01194E-06	1.32E-06	2.9731E-06

Based on the presented result, scenario II performed better with the CSA as compared to other scenarios. Concerning the standard deviation, scenario II has the smallest value, which implies that scenario II has a better search consistency in determining the values of the optimal result.

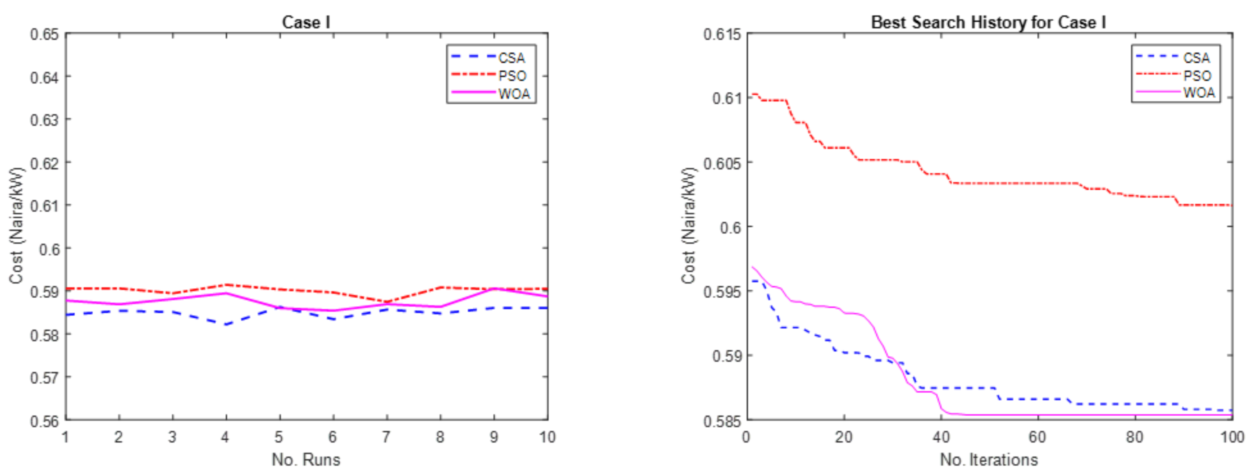
4.3. Validation via comparison

This subsection presents the comparative analysis of the algorithm using the mean search convergence and the best search convergence concerning the CSA, PSO, and WOA. The convergence rate and consistency of optimization algorithms are measured using the mean values and standard deviation of objective function values (Mean) as presented in Tables 6 to 9 in this subsection. The performance comparison of the algorithms for test scenario I is presented in Table 4.

Table 4. Comparison of CSA with PSO and WOA on Scenario I

Metrics	CSA	PSO	WOA
Best	0.001416	0.001438	0.001413
Average	0.001422	0.001443	0.001429
Worst	0.001426	0.001446	0.001436
StD	2.97207E-06	2.8679E-06	3.77309E-06

Based on the stated result, the WOA iterates the objective function the fewest number of times to achieve the best result, whereas the CSA iterates the average amount of times, and the PSO iterates the most times to achieve the best result. The CSA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean and best search convergences for scenario I are presented in Fig. 9.



(a) Mean search convergence (b) Best search convergence

Fig. 9. Mean and Best Search Convergence Comparison for Scenario I

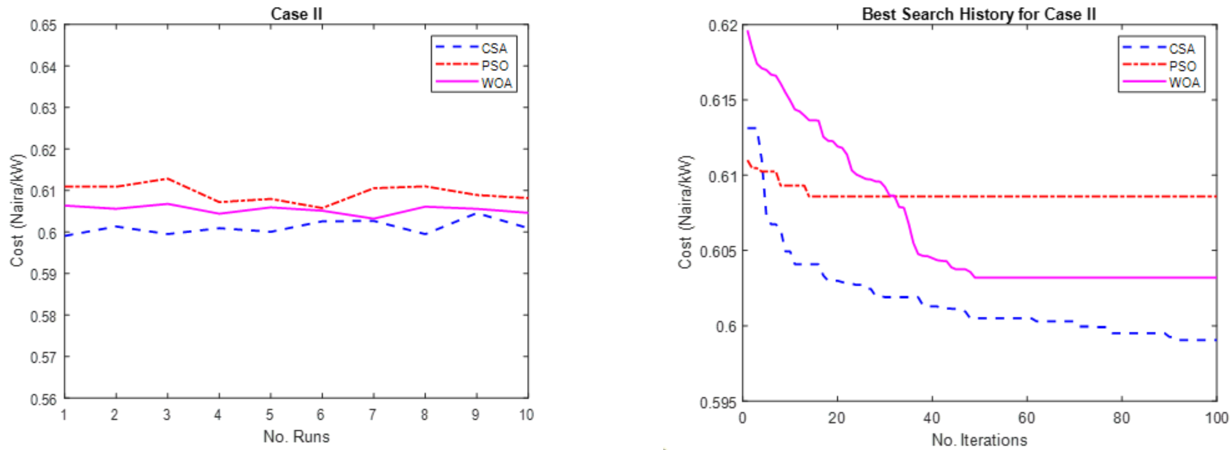
From Fig. 9(a), it can be seen that the CSA has the lower mean value which implies that the CSA has the better convergence speed as compared to the WOA and PSO. Fig. 9(b) presents the best search convergence history for scenario I. From Fig. 9(b), it can be seen that the best optimization run for scenario I is the CSA in comparison to the PSO and WOA.

The performance comparison of the algorithms for test scenario II is presented in Table 5.

Based on the stated result in Table 5, the WOA iterates the objective function the fewest number of times to achieve the best result, whereas the CSA iterates the average amount of times, and the PSO iterates the most times to achieve the best result. The WOA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean and best search convergences for scenario II are presented in Fig. 10.

Table 5. Comparison of CSA with PSO and WOA on Scenario II

Metrics	CSA	PSO	WOA
Best	0.001454	0.00148	0.001467
Average	0.001457	0.00148	0.001475
Worst	0.00147	0.0015	0.001475
StD	4.01194E-06	5.84824E-06	2.44068E-06



(a) Mean search convergence (b) Best search convergence

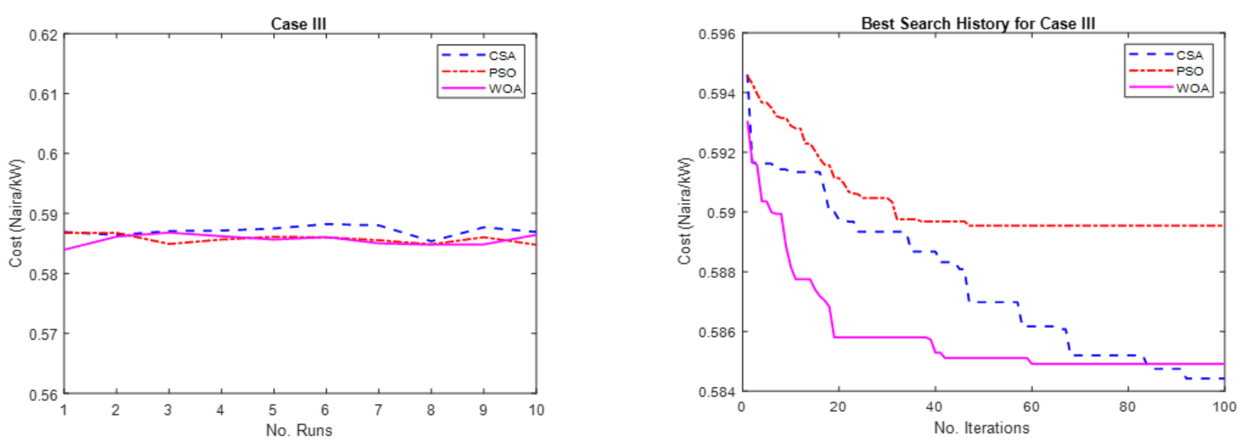
Fig. 10. Mean and best search convergence comparison for scenario II

The performance comparison of the algorithms for test scenario III is presented in Table 6.

Table 6. Comparison of CSA with PSO and WOA in Case III

Metrics	CSA	PSO	WOA
Best	0.001421	0.001428	0.001423
Average	0.001423	0.001428	0.001423
Worst	0.001426	0.001436	0.00143
StD	1.32E-06	2.05E-06	1.91E-06

Based on the stated result in Table 6, the CSA iterates the objective function the fewest number of times to achieve the best result, whereas the WOA iterates the average amount of times, and the PSO iterates the most times to achieve the best result. The CSA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean and best search convergences for scenario III are presented in Fig. 11.



(a) Mean search convergence (b) Best search convergence

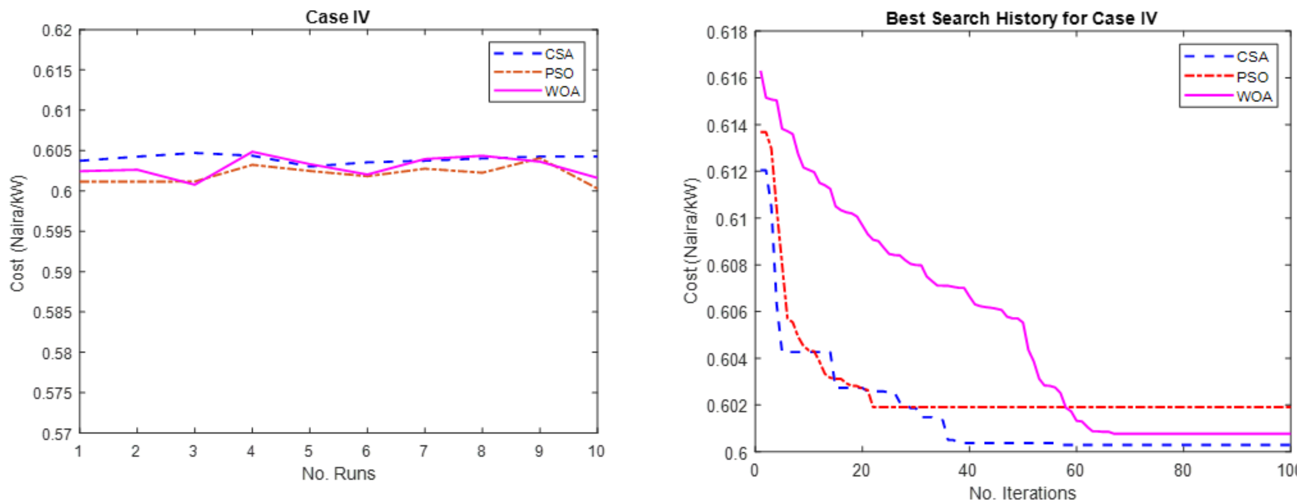
Fig. 11. Mean and best search convergence comparison for scenario III

The performance comparison of the algorithms for test scenario IV is presented in Table 7.

Table 7. Comparison of CSA with PSO and WOA in Case IV

Metrics	CSA	PSO	WOA
Best	0.001461	0.001466	0.001462
Average	0.001461	0.001466	0.001465
Worst	0.001471	0.00147	0.001462
StD	2.9731E-06	1.1211E-06	1.0363E-06

Based on the stated result in Table 7, the CSA iterates the objective function the fewest number of times to achieve the best result, whereas the WOA iterates the average amount of times, and the PSO iterates the most times to achieve the best result. The WOA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean and best search convergences for scenario IV are presented in Fig. 12.



(a) Mean search convergence (b) Best search convergence

Fig. 12. Mean and best search convergence comparison for scenario IV

In conclusion, with the presented scenarios, it can be stated that the CSA outperforms the WOA and PSO. This can be seen in scenario I, where the CSA iterates an average of time and has a higher search consistency in obtaining the values of the best results. This is also observable in scenarios II and IV. Nonetheless, in Scenario III, the WOA outperforms the CSA and PSO in terms of search consistency in obtaining the values of the best results and has the fewest number of times to iterate for the optimum result.

In general, it is evident that using CSA for wind turbine placement will aid in achieving the best possible location within the fastest time as compared to using PSO and WOA. This is due to the nature of the system model and the CSA optimization algorithm used.

5. Conclusion

This work developed a new scheme for evaluating the ideal location and arrangement of wind turbines in an offshore wind farm plan. the technique developed involves integrating the cuckoo search algorithm with the wind farm model taking into account the impact of wake on location and placement. four wind farm layout optimization test problems taking into consideration the wake effect was considered. this research is important in power systems since it identifies weaknesses in the system's wind turbine placement. the defect of poor wind turbine placement will have a negative impact on capital investment and will enhance the wake effect, limiting energy production. The purpose of this research is to reduce power losses while simultaneously lowering costs in wind farm layout. The presented technique improves the wind farm layout optimization. The obtained power output and cost for the test case scenario in the ideal wind turbine position on the wind farm are 18288.3kw, 19680.1kw, 18879.9kw, 21105.8kw, and 26.9, 28.7, 26.9, and 29.8kw, respectively. this shows that the result obtained from the developed scheme outperformed that obtained from PSO and WOA.

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