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The Sparrow Search Algorithm for Optimum Position of Wind Turbine on a Wind Farm

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Abstract- With more Renewable Energy (RE) integration in recent years, Wind farms (WFs) seem to produce more energy from Wind Turbines (WTs). Most WTs in WFs are designed to face a predetermined wind direction; this means that WTs can generate less electricity than they need due to the intermittent nature of the wind. Due to the non-linear nature of wind energy, optimization techniques are critical for successfully building a wind farm. This process involves performing layout optimization techniques using soft computing. WFs have a construction configuration with multiple turbines situated near together in a restricted terrain, contributing to higher energy losses due to the wake effects. Therefore, WTs on a WF to enhance the generated energy while meeting all constraints are pretty restrictive and complicated. We utilized the newly developed Sparrow Search Algorithm (SSA) to determine the most effective technique for the optimal positioning of WTs in WF. We can obtain the high efficiency of the WTs at the lowest possible level of turbine output. This article examined two case studies: the first one is a Constant Wind Speed (CWS) with Variable Wind Direction (VWD); the second one is a Variable Wind Speed (VWS) with Variable Wind Direction (VWD). It was determined how well the proposed method performed compared to the bulk of prior research that dealt with the same problem. Consequently, SSA is an effective technique for determining the WT position allocation problem to achieve the optimum position.

Keywords Wind Farm Power, Wind Turbine Positioning, Location Optimization, Sparrow Search Algorithm.

1. Introduction

Electricity is an integral part of the earth and forms the basis of all industrial, scientific, transportation, and communication activities, especially present and future. Electricity consumption is increasing enormously, but conventional supplies are becoming scarcer, prompting many academics to look for new energy sources. RE, particularly solar and wind energy, is becoming more prominent and attractive as a technological alternative. Renewable Energy Sources (RES) are being utilized in this area to decrease reliance on conventional energy sources due to the many advantages of RES, including reduced carbon emissions and hazardous gas emissions. Wind energy is among the most efficient forms of electricity generation. WTs are among the most accessible energy supplies available globally due to the stability, environmental friendliness, and affordable character of RES. It will be possible to meet future energy demand by converting wind energy into electrical energy. The efficiency of WTs is relatively poor if WTs are properly not installed in the correct location. So, the construction of WF is meticulous, and thorough work is required.

The best location of WT is important in WF design. An improper WF design contributes to a negative impact of the wake effect of lowering harvested electrical energy. Wake effect caused by upstream WT, which reduces downstream WT speed. As a consequence, downstream WT harvested energy is less in comparison with upstream WT harvested energy. The traditional WTs layout considerably enhances the wake effect; thus, the optimal location of WT inside WF may be an ideal solution for reducing the wake effect and strengthening the WF performance by increasing the collected energy of the WTs. As a result, researchers have taken a significant interest in the best location of WTs to extract maximum electricity from WFs at lower energy prices per kilowatt.

Grady et al. [4] applied a genetic algorithm to establish optimal WF configurations; Castro Mora et al. [5] used an evaluative algorithm to show optimal WF arrangement. Peng Hou et al., [6] and Xiawei Wu et al., [7] used Levelized Production Cost (LPC) with Particle Swarm Optimization (PSO) employed to boost the electrical energy production while minimizing total investment. Feng and Wen [8] used Random Search Algorithm (RSA). Genetic Algorithm (GA) [9]–[11], Multi population genetic algorithm [12], Ant colony optimization [13], Evolutionary algorithm [14], Monte Carlo simulation [15], Particle swarm optimization [16], Pattern search algorithm [17], Differential evolution algorithm [18], Water Cycle Optimization [2], Self-Informed Genetic Algorithm [19], data-driven evolutionary algorithm [20], Adaptive Differential Evolution Algorithm (ADE) [20], and many more meta-heuristic algorithms are employed to optimize WF layout to reduce cost per unit.

In this paper, we applied Sparrow Search Algorithm (SSA) [21] to obtain WT optimum positions with the Objective Function (OF) cost/kW. Two case studies, including 1) CWS with VWD and 2) VWS with VWD, are performed. The suggested technique results compared with GA [3], GA [4], BPSO-TVAC [22], and RSA [8]. However, many works of literature [23-27] have used different optimization methods for determining optimal location, thorough and accurate comparisons with the research findings with the same factors and mathematical models that affect the objective function.

The organization of this paper is given below.

- Introduction to problem and literature of work done previously
- Mathematical modelling of the problem, objective function for the wind farm layout optimization mathematical equations and definitions.
- Modelling of Sparrow search algorithm.
- Results and discussions and conclusions.

2. Modelling of the Wind Farm

As a free stream of wind meets turbine blades, the speed drops, and the turbulence level rises, are creating a wake.

Wind velocity in the wake-field calculated with Jensen linear wake decay model [28].

The linear wake paradigm is depicted schematically in Figure 1. The wake impact between WTs is one of the most significant factors influencing WF power production; in the wake area, the momentum is conserved.

In our present analysis, we utilized the wake model of Jensen [28] for the deficit measurement of wind speeds behind a WT with the following eq. (1) [3, 4, 18, 7, 8, and 28].

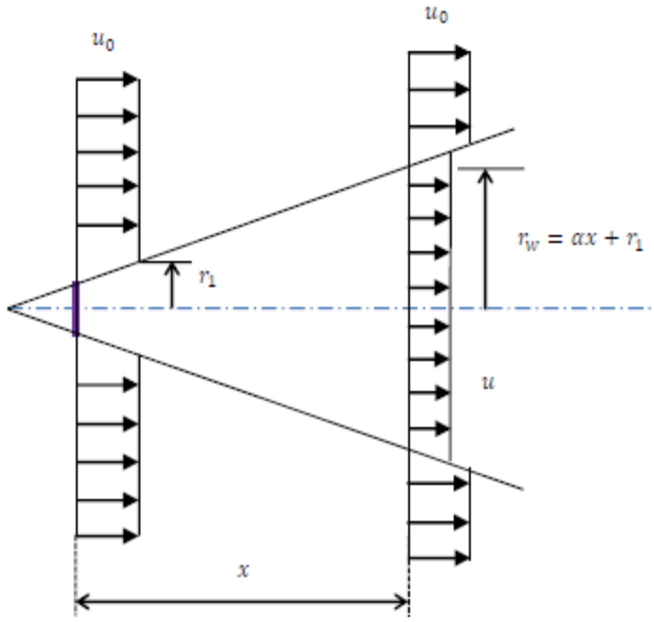

Figure 1 Diagram of a linear wake model

$$u_u = u_{0u}\left[1-\frac{2a_u}{1+\alpha_u\left(x_u/r_{1u}\right)}\right] \quad \dots (1)$$

where u_{0u} is average wind speed, a_u is axial induction factor, α_u is constant entrainment, x_u is the downstream length of the turbine, and r_{1u} is the downstream wind radius. The following eq. determines these parameters. (2) - (4) [18].

$$a_u = \frac{1-\sqrt{1-C_T}}{2} \quad \dots (2)$$

$$r_{1u} = r_{du}\sqrt{\frac{1-a_u}{1-2a_u}} \quad \dots (3)$$

$$\alpha = \frac{0.5}{\ln\left(h/z_0\right)} \quad \dots (4)$$

where C_T is the rotor thrust coefficient, z_0 is the surface roughness of the WFs, r_{du} is the WT rotor radius. Kinetic energy is often equal to the total of the energy deficits from several wakes. The resulting velocity of the i^{th} turbine downstream of the N_T turbines is given by

$$u_i = u_0\left[1-\sqrt{\sum_{j=1}^{N_T}\left(1-\frac{u_{ik}}{u_0}\right)^2}\right] \quad \dots (5)$$

where u_{ik} is the wind velocity of the i^{th} turbine under k^{th} turbine influences. For a linear wake model, the wake area is conical, and the wake region radius is expressed as wake influence radius measured with the following:

$$r_w = ax + r_1 \quad \dots (6)$$

where r_1 is the WT radius. Mosetti et al. [3] developed a Cost Function (CF) model. The same CF is used to calculate the total cost of WTs within WF, which is defined by equation (7).

$$Cost = N\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}\right) \quad \dots (7)$$

where N wind turbines are included in the wind park. The proposed model assumes that the number of turbines in a WF is the only variable that can be used to determine the cost of electricity. Non-dimensional cost per year is assumed as 1 and the maximum cost reduction is 1/3.

Table 1 describes some of the turbines parameters that were considered for this analysis, and the power output can be determined using the equation [18]:

$$P_i = 0.5 \times \rho \times \pi r^2 \times u_i^2 \left(C_P \div 100\right) \quad \text{... (8)}$$

In this paper re-writes the formula (8) and uses it with little numerical approximation [3] and [4]. It also compares the previous results of the same formula with the previous results.

$$P_i = 0.3 \times u_i^3 \quad \text{... (9)}$$

where ρ is the air density, r is the rotor diameter, u is the wind speed and C_P is the rotor efficiency, The total output power of the WF with N number of turbines is calculated [18],

The total output power of the WF having N no. of turbines,

$$P_T = \sum_{k=0}^{360} \sum_{i=1}^{N} f_k P_i(u_i) \quad \text{... (10)}$$

where f_k is the wind probability for a wind speed from a particular direction

and $\sum_{k=0}^{360} f_k = 1$; P_i is the i^{th} turbine actual power output as a function of wind speed u_i.

Table 1 describes the Nomenclature and acronyms and table 2 describes the turbines and other related information for the problem and corresponds to the data in [3] and [4].

Table 1: Nomenclature and acronyms

u_0	local wind speed/ constant wind speed
x	distance downstream of the turbine
r	radius of turbine rotor
r_1	downstream rotor radius
h	hub height of turbine
α	the entrainment constant
a	axial induction factor
C_T	thrust coefficient of the wind turbine rotor
z_0	surface roughness of the wind farm
N_T	Number of turbines
u_{ij}	wind velocity at i^{th} turbine under the influence of j^{th} turbine

Table 2: Numerical Data

S. No.	Parameter	Value
1	Rotor diameter (2r)	40 m
2	Thrust coefficient (C_T)	0.88
3	Hub height (h)	60 m
4	Rotor efficiency (C_P)	0.4
5	Air density (ρ)	1.2254 kg/m^3
6	Atmospheric Pressure	101.3 kPa
7	Temperature	25^{oC}
8	Wind farm surface roughness (z_0)	0.3m
9	Axial induction factor (a)	0.2 - 0.4
10	Local wind speed, (u_0)	12 m/s

The main objective is to determine the best WF configuration for the lowest unit cost of energy generated and maximize the generated power P_i, thus lowering WF installation costs.

The objective function 'cost/kW' utilized in this article as a criterion for deciding the WFs optimal configuration Grady et al., [4] have shown. The equation that describes this OF is as follows (11).

$$\text{The OF is } \frac{\cos t}{P_T} \quad \text{... (11)}$$

where cost is the combined power generated by all N turbines in the wind farm, and P_T is the total power output of the WF cost. This goal would reduce the cost per unit of energy generated to the lowest possible amount.

To measure the performance of a WF with the following equation:

$$\text{Efficiency } (\eta) \text{ is } \eta = \frac{\sum_{k=0}^{360} \sum_{i=1}^{N} f_i P_i(u_i)}{\sum_{k=0}^{360} \sum_{i=1}^{N} f_i P_{i,\max}(u_{i,\max})} \quad \text{... (12)}$$

where, $P_{i,max}$ is the i^{th} turbine maximum power output as a function of most feasible wind speed $u_{i,max}$ had there been no wake effect and f_k is the wind probability for a wind speed from a particular direction.

3. Mathematical Model and Algorithm

Jiankai Xue and Bo Shena [21] have formulated a new swarm optimization method: the Sparrow Search Algorithm (SSA). SSA developed with sparrow's group wisdom, hunting, and anti-predatory behavior. Jiankai Xue and Bo Shena built the mathematical model to construct SSA. We simplified the sparrow behavior and developed the appropriate rules to represent this simplification.

Generally, producers have almost unlimited energy resources, and they encourage scavenging for all scroungers. It plays a crucial role in finding rich sources of food. Personal levels of fitness affect energy resources.

When the sparrow senses the predator, the individuals start chirping as disturbing signs. If the warning value exceeds the protection level, the production companies must get all screeners to a safe place.

- All sparrows can be producers, yet the number of scroungers and producers remains constant in the overall population.
- High energy sparrows become productive. Many hungry scroungers often fly to different locations to find food to obtain sufficient energy.
- The scroungers go from place to place to find sufficient food. In the meantime, certain scroungers will watch the farmers continuously and fight for food to raise their food predation rate.
- The sparrow at the outside of a group walks instantly to a secure position to have a better place when it detects a threat; if the sparrow is at the group's center, try to move randomly nearer to the other.

We were required to use sparrows in the numerical simulation to locate food. The following matrix can determine the location of sparrows [21].

$$X = \begin{vmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,dim} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,dim} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,dim} \end{vmatrix} \quad \dots (13)$$

where *dim* indicates dimension size, n represents total sparrows, and the next vector will then represent the fitness value of all sparrows [21]:

$$F_X = \begin{vmatrix} f([x_{1,1} & x_{1,2} & \cdots & x_{1,dim}]) \\ f([x_{2,1} & x_{2,2} & \cdots & x_{2,dim}]) \\ \vdots & \vdots & \vdots & \vdots \\ f([x_{n,1} & x_{n,2} & \cdots & x_{n,dim}]) \end{vmatrix} \quad \dots (14)$$

Each row value of F_X reflects the fitness value. In SSA, producer priority with a better fitness value is acquiring food in the quest process. Furthermore, the producers have the responsibility to look for food and direct the whole population movement. The producers will then hunt for food in a wide variety of ways, compared with scroungers. According to rules (1) and (2), the producer's position changes as follows for each iteration [21]:

$$X_{i,k}^{t+1} = \begin{cases} X_{i,k}^{t} \times \exp\left(\dfrac{-i}{\alpha \times it_{max}}\right) & \text{if } RN_2 < ST \\ X_{i,k}^{t} \times Q \times L & \text{if } RN_2 \geq ST \end{cases} \quad \dots (15)$$

where t denotes the current iteration, k = 1, 2, ..., dim, $X_{i,k}^{t}$ i^{th} sparrow k^{th} dimension at t^{th} iteration, α [0, 1] is a random integer, it*max* is total iterations, RN_2 [0, 1] is a caution value, and ST ϵ [0.5, 1.0] is a threshold value. Q is a normal-distributed random number, and *L* reveals a matrix of 1 × dim for which every component within is 1. If RN_2<ST shows no predators discovered around the search space, the producer will fly around the search space. If RN_2≥ST offers predators around the search space, the producer quickly moves to safe areas.

The scroungers require executing rules (4) and (5); certain scroungers monitor the producers more regularly. When they discover that the producers have found a good food source, they quickly leave their present location to compete for food. The updated food location by the follows (16) [21].

$$X_{i,k}^{t+1} = \begin{cases} Q \times \exp\left(\dfrac{X_{worst}^{t} - X_{i,k}^{t}}{i^2}\right) & \text{if } i > n/2 \\ X_{i,k}^{t+1} + \left|X_{i,k}^{t} - X_{P}^{t+1}\right| \times A^{+} \times L & \text{otherwise} \end{cases} \quad \dots (16)$$

where X_P reflects the producer's optimum position, the new global worst location is X_{worst}. *A* is a matrix size of 1 × dim, for which every component range is a random value (-1,1), and $A^+ = A^T(AA^T)^{-1}$. If *i > n/2* reflects the worst fitness value of i^{th} scrounger.

The simulation experiment believes that 10 to 20 percent of the overall population account for these danger-conscious sparrows. The initial locations of these sparrows are created spontaneously by the community. The mathematical equation is formed by the following rule (6) [21]:

$$X_{i,k}^{t+1} = \begin{cases} X_{best}^{t} + \beta \times \left|X_{i,k}^{t} - X_{best}^{t}\right| & \text{if } f_i > f_g \\ X_{i,k}^{t} + H \times \left(\dfrac{X_{i,k}^{t} - X_{worst}^{t}}{(f_i - f_w) + \varepsilon}\right) & \text{if } f_i = f_g \end{cases} \quad \dots (17)$$

There, the current optimum global position is X_{best}, β is a normal-distributed random number between 0 and 1; H ∈ [−1, 1] is arbitrary. Here f_i, f_g, and f_w are the sparrow's current, highest, and least fitness values, respectively; ε is a constant value is used to prevent zero-division error.

For simplicity, when $f_i > f_g$ indicates that the producer is at the edge of the group, $f_i = f_g$ shows that the producers are in the middle of the population, are aware of the threat. Then producers quickly move to safe areas. H indicates the path in which the movement of sparrow and is also the step size control coefficient. The SSA fundamental step-by-step procedure is designed as pseudo-code shown in the below Table 3 and the flow chart of the SSA as shown in figure 2.

4. Results and Discussions

To analyze performance of the suggested technique, we tested over 50 times, selected the better value for 'OF' of both case studies, and performed estimates power for 36 various wind directions. The suggested technique implemented on MATLAB 2021a and developed on a computer with 8GB RAM and Intel Core i3 CPU@2.0GHz.

This research is performed on a square WF with 100 feasible positions for WTs (10×10). All WT was placed in the middle of the cell. The size of every cell is 200m, shown in Figure 2. In one column with another in neighboring columns, the cell selection, equivalent to the rotor diameter, prevented the wake impact between turbines.

Table 3: The pseudo-code of SSA.

```
Input:
G: the maximum iterations
PD: the number of producers
SD: the number of sparrows who perceive the danger
R2: the alarm value
n: the number of sparrows
Initialize a population of n sparrows and define its relevant parameters.
Output: Xbest, fg.
1: while (t < G)
2: Rank the fitness values and find the current best individual and the current worst individual.
3: R2 = rand(1)
4: for i = 1 : PD
5: Using equation (3), update the sparrow's location;
6: end for
7: for i = (PD + 1) : n
8: Using equation (4), update the sparrow's location;
9: end for
10: for l = 1 : SD
11: Using equation (5), update the sparrow's location;
12: end for
13: Get the current new location;
14: If the new location is better than before, update it;
15: t = t + 1
16: end while
17: return Xbest, fg.
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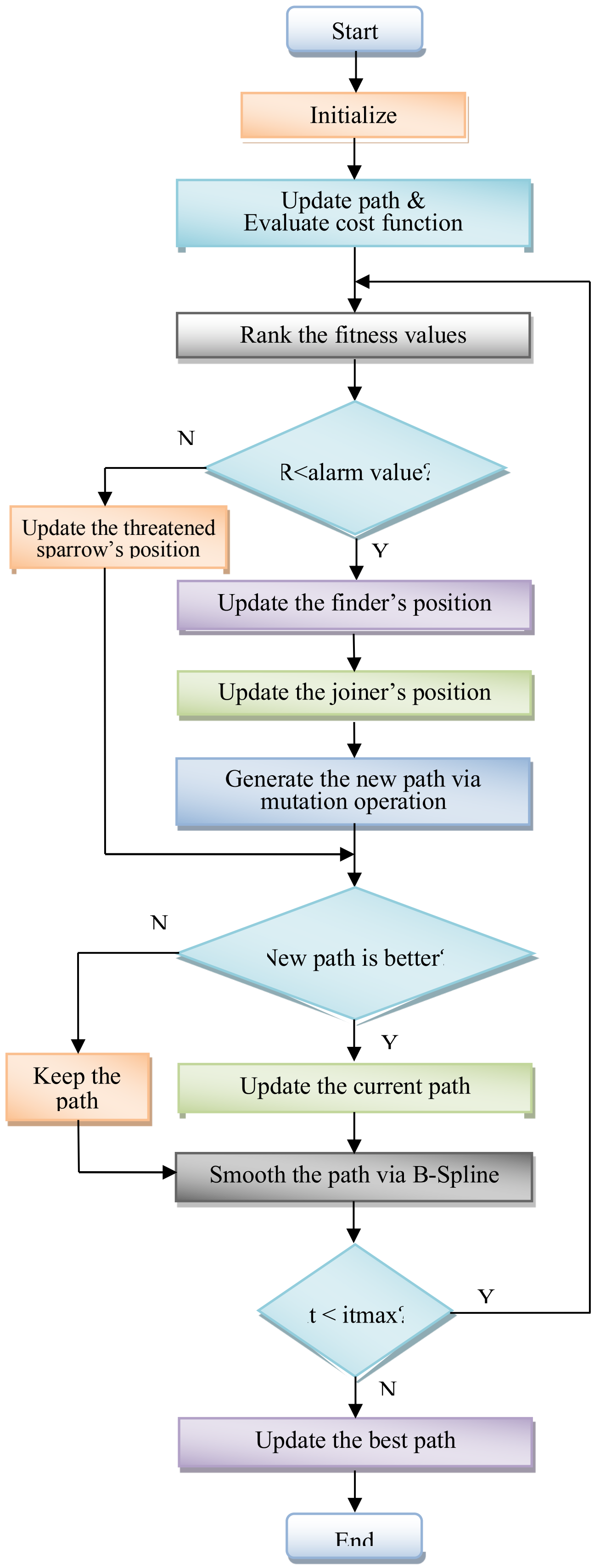

Figure 2: Flow chart for the proposed SSA

The main objective is to enhance the optimal positioning of the WTs within WF to reduce the overall cost of power generation. For case 1, we assume CWS with VWD.

The WF utilized in this analysis included Table 1 specifications. We considered the roughness of site field Z_0 to be 0.3 m. Here we considered 12 m/s CWS and wind flows in every direction with the same probability by examining 36 angles from 0^0 to 360^0 in steps of 10^0.

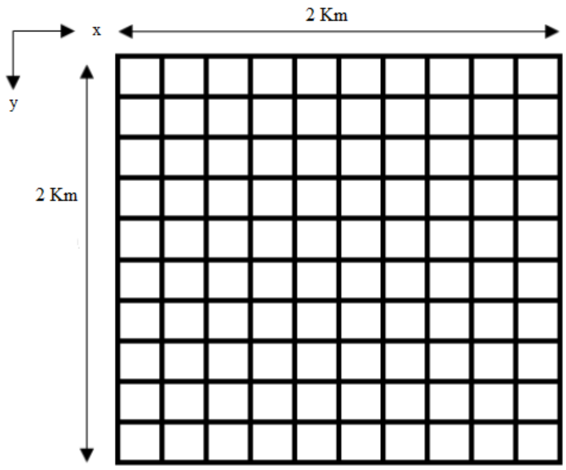

Figure 3 Wind Farm Topology

Table 4 SSA user defined parameters

Parameter	Value
Population size (nPop)	30
Percent of the total population size	0.2
Maximum iterations (itmax)	500
Lower bounds (lb)	0
Upper bounds (ub)	1
Dimension size (dim)	100

Table 5 of SSA Results Comparison with GA, BPSO-TVAC, and RSA for case 1

Reference Method for Optimization	No. of turbines	Power (MW)	Wind Farm Efficiency (η %)	Objective Function (Cost/MW)
GA [3]	19	9.245	93.86%	0.0000017371
GA [4]	39	17.22	85.17%	0.0000015666
BPSO-TVAC [22]	35	15.796	87.06%	0.0000015648
RSA [8]	40	17.406	NA	0.0000015479
SSA	40	17.781	85.74%	**0.0000015461**

We applied the suggested approach for case 1, and better solutions were obtained and compared with the previously reported in Table 5. The optimal arrangement of WFs obtained by SSA compared with GA [3], GA [4], BPSO-TVAC [22], and RSA [8]. The SSA obtained better solutions for the same objective function. The convergence curve of the objective function is shown in Figure 4. SSA has discovered the optimum configuration of wind form in figure 5. The suggested approach produced 17,780.96 kW annual power generations from 40 turbines with less cost/kW 0.0015461 and an efficiency of 85.74%. We can observe that the SSA performed very well compared with other approaches.

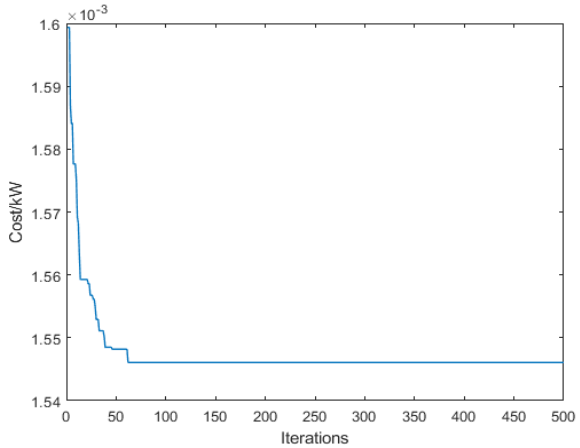

Figure 4 Convergence of SSA algorithm for case 1

To confirm the validity of the proposed approach for optimum positioning of WF for case 2, we assume VWS with VWD. Here we considered 8 m/s, 12 m/s, and 17 m/s with 36 angles from 0º to 360º in steps of 10º.

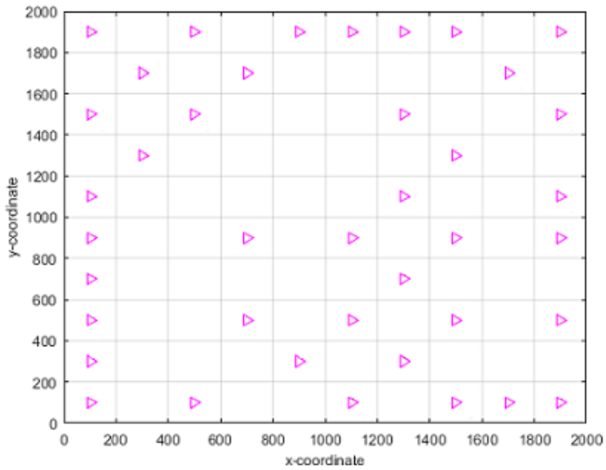

Figure 5 Optimum configuration of wind form by SSA for case 1

Table 6 of SSA Results Comparison with GA, BPSO-TVAC, and RSA for case 2

Reference Method for Optimization	No. of Turbines	Power (MW)	Wind Farm Efficiency (η %)	Cost/MW
GA [3]	15	13.46	94.92%	9.941e-7
GA [4]	39	32.038	86.62%	8.403e-7
BPSO-TVAC [22]	46	36.433	82.76%	8.523e-7
RSA [8]	39	32.096	NA	8.492e-7
SSA	39	32.498	86.11%	**8.377e-7**

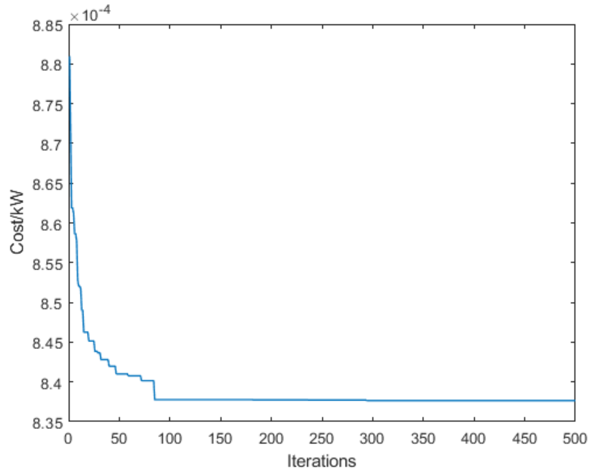

Figure 6 Convergence of SSA algorithm for case 2

We applied the suggested approach SSA for case 2, and better solutions were obtained and compared with the previously reported techniques in Table 4. The optimal arrangement of WFs obtained by SSA compared with GA [3], GA [4], BPSO-TVAC [22], and RSA [8]. The SSA obtained better solutions for the same objective function. The convergence curve of the objective function is shown in figure 6. SSA has discovered the optimum configuration of wind form in figure 7. The suggested approach produced 32139.36 kW annual power generations from 39 turbines with less cost/kW 0.0008377 and an efficiency of 86.11%. We can observe that the SSA performed very well compared with other approaches.

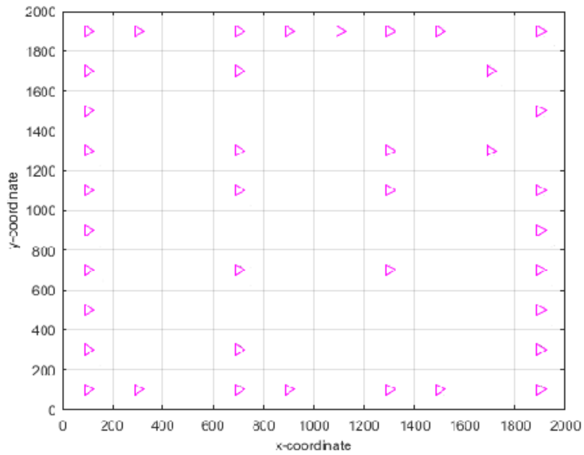

Figure 7 Optimum configuration of wind form by SSA for case 2

Finally, the achieved results validated the validity and reliability of the suggested SSA in optimally configuring turbines in a WF for both cases. The suggested approach gave the most reliable solution compared to other approaches.

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Finally, the achieved results validated the validity and reliability of the suggested SSA in optimally configuring turbines in a WF for both cases. The suggested approach gave the most reliable solution compared to other approaches.

5. Conclusions

The optimal position of wind turbines was determined employing the newly developed Sparrow Search Algorithm. We selected the objective function to minimize overall cost/kW to enhance the optimum position of the wind turbine on a wind farm. We considered two cases: the first one is a Constant Wind Speed (CWS) with Variable Wind Direction (VWD); the second one is a Variable Wind Speed (VWS) with Variable Wind Direction (VWD). The optimized configurations of wind turbines can be obtained through the use of the sparrow search algorithm, this configuration of wind turbines can produce high output power, despite their efficiency. This study shows that it is the most effective algorithm for WF layout optimization and the SSA algorithm performs better than most other algorithms WF layout optimization. This algorithm significantly improves the efficiency of wind turbines. The obtained results by SSA compared with those obtained by GA, GA, BPSO-TVAC, and RSA. The comparison of the various techniques validated that the SSA-based optimum position of WTs on WF was the best amongst other techniques like GA, GA, BPSO-TVAC, and RSA.

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