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Research Article

Application of Particle Swarm Optimization for Sustainable Energy Solution in Wind Power Plant

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Abstract: Sustainable Energy demand was observed over the last six decades and reported by many researchers. Few researchers also mentioned the importance of intelligent tools. The authors of this article are of the strong opinion that in a new era, intelligent tools are the only way for automation and the solution for most of the problems like sustainable energy demand. Wind energy is also identified as clean energy and profitable in case operated along with intelligent tools for maximizing its efficiency. The most popular issues in wind energy are related to the wind farm, its shape, turbine selection and maximizing energy output. This study focuses on the creation of a novel Particle Swarm Optimization (PSO) tool that optimizes the objective function of the wind farm. Developing a PSO novel tool is the key importance of this research work. Three basic shapes of the wind farms are proposed viz (i) circular shape (ii) square shape and (iii) rectangular shape for the wind farm. The circular shape is also divided into two methods as a circle method and circle in-line method for Wind Turbine Generator (WTG) placement. Dot net programming-based PSO tool is designed, which is validated by the Rosebrook function and then five case studies with a different constraints with different type of WTG is examined and verified for the sustainable energy solution in the wind farm. Tool developed with defined constrained is novel and tested for validation.

Keywords: PSO, WTG, optimization, AI tools

1. Introduction

For the wind farm Optimal Power Flow (OPF) problem, a hybrid PSO and Gravitational Search Algorithm (GSA) (PSOGSA) are comprehensively presented in [1]. The algorithmic results provide a concluding observation that produces faster convergence and higher quality solutions to the optimal power flow wind energy problem. While there are many other PSO approaches established, hybrid PSO is one of the PSO techniques that is frequently used by researchers. Optimal Capacitor Placement by Particle Swarm Optimization (OCP-PSO) is one of them, evaluating the distribution system's load flow issue while putting constraints on voltage, power factor, and harmonics [2] to increase reliability. Fundamentally, all PSO tools revolve in some way around the velocity and position equations, and simulation is heuristic as if there are numerous solutions to be found. Ordinary force-sharing control may bring about low proficiency of equal converters at low wind speeds if dependability isn't thought of. Neural Network may be the

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tool adoptable as explained in [3]. An adaptive management procedure to induce higher strength and constancy of equal possible power converters bolstered improving voltage distribution. The author of [4] compared numerous approaches and circumstances in the Indian energy market. Even though the present price-taker tactics neglect the consequences of competition, Renewable Power Producers'(RPPs) cleared power may be lower than their bidding power. To fix the aforementioned problem, [5] develops an ideal bidding scheme taking into account the conflict amongst RPPs.

The adjustable power result of RPPs and the competition among RPPs are taken into consideration in the initial proposal of a Bivariate Stochastic Optimization (BSO) model of the offering system. Following that, the Newton technique as well as particle swarm optimization are collected to solve the BSO model (PSO). Since then, interest in self-synchronous wind turbines has grown significantly among both industry and academia. It is difficult to build an adaptive Fault Ride-Through (FRT) control technique. An FRT control method for a self-synchronous wind turbine with dual modes is created as a result. The voltage drop during a minor grid fault is used to directly calculate the amplitude and phase of the internal potential, which is one of the two FRT control procedures. In [6], a fuzzy logic-based wind prediction model is discussed. Samples of predicted wind speed are categorized, and it is determined that the values are accurate. When reactive power is optimized through suitable FACTS device sizing, an evolutionary algorithm based on a fuzzy logic controller is provided [7]. To construct a multilevel Unified Power Quality Conditioner (UPQC) to reduce the power quality concerns, a back-propagation multilayer Artificial Neural Network (ANN) and fuzzy controller system are devised [8]. This controls switching actions in the appropriate order. Every system's availability may suffer if there are too many components in the system. This will prompt efforts to improve such systems reliability. Due to the variable wind generation, such converters' handling power varies noticeably. It is beneficial to utilize a droop control that connects power electronic-based converters to battery storage systems [9, 10].

The reactive power as the final product of wind farms was taken into contemplation to regulate the voltage, and the two objective functions were the voltage deviation model. The established optimization model may utilize the reactive power production of wind turbines to achieve the greatest wind power consumption. Nevertheless, this research work does not include any assessment of the reliability parameter. Accordingly, actual power deviation and State of Charge (SOC) operating range, wherein the energy storage system selectively participates in active power control of the integrated system in real time. Centralized Voltage Source Converters (CVSC) are used in modern times to cut costs. A novel power optimization model fundamentally based on the aerodynamic characteristics of the wind in contact with the turbines was developed to address such problems. [11] suggests an intelligent machine learning-based method for simulating and forecasting the output power of Wind Turbines (WTs). The newly developed method uses state-of-the-art machine learning algorithms to build prediction intervals around the WT power samples. In contrast to current methods that generate point-by-point predictions, the suggested method can capture the uncertainty of the forecast inaccuracy by creating lower and upper boundaries around the samples. A Nash equilibrium between the average prediction bandwidth and the prediction confidence level is also attained using the fuzzy min-max method [12].

A reactive power optimization method working with an improved genetic algorithm for wind-farms are proposed in [13]. The status of non-grid-connected wind power throughout the world is explained by [14] whereas [15] thoroughly briefed regarding the validation of global wind for the Indian scenario. By conversion of fossil fuel energy into renewable energy fom a sustainability point of view is given in [16] with appropriate reasons. The number of nodes where reactive power compensating devices and a number of regulated transformers in addition to voltage as a constraint is used to optimize by using a novel genetic-based algorithm. One of the optimizations modeled mathematically represented from equations (1) to (5) for wind farms connected to a grid with constraints such as equality constraints and un-equality constraints.

$$F_{min} = K_v \sum_{j=1}^{N} (U_j - U_{sj}) \tag{1}$$

Active and reactive power flow equations are required to evaluate U_j and U_{sj}. In addition to this following constraints must be monitored. The number of wind units is j, N is the maximum number of WTG and Fmin is the cost function in USD/unit.

$$U_{jmin} < U_j < U_{jmax}$$

$$QG_{jmin} < QG_j < QG_{jmax}$$

$$Qc_{jmin} < Qc_j < Qc_{jmax}$$

The authors contributed to developing a novel mathematical model of objective functions which address the optimal placement of WTG in various constraints as discussed in the methodology section.

2. Methodology

Normalized cost is defined in previous research and is formulated as,

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

Where N is for turbine numbers installed in the wind farm and using the normalized cost (INR/unit), the objective cost is calculated as,

$$objective\ cost = \frac{Normalized\ Cost}{P_{tot}} = \frac{N\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}\right)}{\sum_{i=1}^{i=N} P_i} \tag{3}$$

$$\Pi r_r^2 v + \Pi(r_1^2 - r_r^2)U_0 = \Pi r_1^2 U \tag{4}$$

Where U indicates the wind speed at a distance downstream within the wake. U is an abstract illustration of U_0 that is decremented to be constant over the wake's width. The following is the mathematical representation for U (km/hr), the downstream wind speed inside the wake.

$$U = U_0\left(1-\frac{2}{3}\left(\frac{r_r}{r_r+\propto y}\right)^2\right) \tag{5}$$

Whereas turbine hub-height z (in meters) as well as surface roughness z_0, given in equation (5) is applied to evaluate the effective wind speed for each turbine that is inside one wake.

3. Power modelling

Validating the outcomes of a wind farm layout optimization requires accurately portraying the power output of a fictitious wind farm. In order to account for turbines with different geometries, the current work uses power modeling from the following mathematically represented equation (6):

$$P = \frac{1}{2}\rho A U^3 C_p \tag{6}$$

After the wake passes the rotor of the wind turbine, the wake model assumes a linear wind expansion. Rx is a symbol that denotes the wake radius (in meters) at the axial distance of x (meters), which is modeled as equation (7).

$$r_x = r_0 + \propto x \tag{7}$$

Theory of momentum conservation may help to calculate the wind velocity v_1 (km/hr) within the farm, at an axial distance of x downstream, of the wind turbine generator rotor represented in equation (8).

$$v_1 = v_0\left[1 - 2a\left(\frac{r_0}{r_0 + \propto x}\right)^2\right] \tag{8}$$

Where,

v_0: free stream wind speed.

v_1: wind speed in the wake at the axial distance of x.

r_0: downstream rotor radius.

4. Stepwise problem description

The type of turbine selected is the major decisive to find the power generated which depends on the velocity. If the selected turbine is "Enercon E82/2300" then the power equation P (in KW) is modeled through the curve fitting equation (9).

$$P = -0.001v^6 + 0.0791v^5 - 2.1711v^4 + 25.158v^3 - 101.69v^2 + 140.71v - 29.255 \tag{9}$$

Similarly for "Gamesa G128/4500" then the power equation P (in KW) is modeled through curve fitting equation (10).

$$P = -0.0015v^6 + 0.1108v^5 - 2.8074v^4 + 27.005v^3 - 46.135v^2 + 42.071v - 70.897 \tag{10}$$

Similarly for "Nordex N90/2500" then the power equation P (in KW) is modeled through curve fitting equation (11).

$$P = -0.0012v^6 + 0.0925v^5 - 2.5112v^4 + 28.686v^3 - 112.8^2 + 142.18v - 23.882 \tag{11}$$

Similarly for "Repower MM82" then the power equation P (in KW) is modeled through curve fitting equation (12).

$$P = -0.0004v^6 + 0.0234v^5 - 0.5516v^4 + 4.3387v^3 + 13.727^2 - 94.538v + 59.401 \tag{12}$$

Similarly for "Vestas V112/3000" then the power equation P (in KW) is modeled through curve fitting equation (13).

$$P = -0.0014v^6 + 0.107v^5 - 3.0307v^4 + 37.156v^3 - 171.68^2 + 286.84v - 88.467 \tag{13}$$

As per the turbine selection, the power output is computed for every instant of time from the above equations. However, the selected turbine is rated for the power in kW and for simplicity investment cost is calculated with a standard rate assumed as 30,000 INR per kW for simplicity and the overall investment cost per turbine is calculated through equation (14)

$$C_i = 0.3P_{rated} * T_n \tag{14}$$

Where P rated is the rated power of a turbine (in KW) and T_n is the number of turbines installed. Energy is the product of generated power and time. Considering the 60% of efficiency per turbine and 2 INR as the selling cost, then the cost of energy is expressed as C (INR/KW)

$$C_e = P \times 8760 \times 0.6 \times 0.00002 \tag{15}$$

The generalized objective is to place the WTG in the appropriate place and to find the number of possible turbines placed. Then the investment cost, maintenance cost and profit are to be calculated so that the objective function is evaluated. Total investment (in INR) is expressed in equation (16, 17)

$$C_{oi} = C_i + C_m + C_o + \frac{C_f + C_c + C_r}{10} \tag{16}$$

And

$$f_{obj} = C_e - C_{oi} \tag{17}$$

Where C_{oi} is the overall investment cost; C_i is the total investment cost in the turbine; C_m is the maintenance cost C_o is the operating cost; C_f is the field cost; C_c is the cable cost; C_r is the road construction cost and f_{obj} is the objective function cost. All cost functions are in INR.

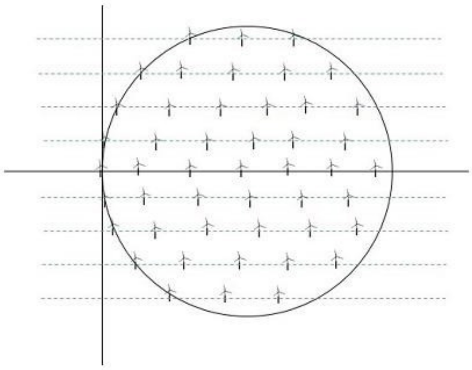


Figure 1. Circle in line method

4.1 *Computations in circular shape*

Following equations are represented for the computation of a number of turbines along with their x and y coordinates. In circular case, specifically in line in circle case, a number of WTG lines are calculated by equation (18) which is developed through simple mathematical law.

$$TLL = \frac{(r - 0.1)}{0.5} \times 2 + 1 \tag{18}$$

TLL is then further acknowledged as TLL_1, TLL_2, …, TLL_n etc. Number of WTG place on TLL_n line is evaluated by equation (19) developed through circle equations within Figure 1.

$$TLL_n = \sqrt{\frac{(r^2 - (n \times dttn^2)) - 0.2}{dttn}} \tag{19}$$

TLL_n is then rounded as a number of turbines must be in integer form.

For the first line, the Y coordinate is 0 and for the next line onwards Y coordinate is increased by 0.5 for the above first line and decreased by 0.5 below the first line as the distance between the turbines should be 0.5 as selected in this case. X coordinate of each turbine is calculated as per the following equation and then added by 0.5 till the end of the line as graphically indicated in Figure 1 for the circular shape of the wind farm.

$$Xcord = r - \sqrt{r^2 - dttn^2} + 0.1 \tag{20}$$

4.2 *Computations in square shape*

In the case of square shape farm, the length and breadth are the same and calculated as

$$Length = Breadth = \sqrt{area} \tag{21}$$

The number of lines on which WTGs are placed is calculated as

$$TTL = \frac{length - 0.2}{dttn} \tag{22}$$

The total number of maximum WTGs placed in a line is given by

$$TLN = \frac{length - 0.1}{dttn} \tag{23}$$

The total number of WTGs placed in the square farm is then given by

$$TNT = TTL \times TLN \tag{24}$$

Total Turbine Lines (TTL) and Turbines on Line Number (TLN) must be rounded for getting the integer number. X coordinate and Y coordinate of the first turbine are 0.1, 0.1 and consecutive coordinates are calculated as the first line keeping the y coordinate at 0.1 and adding the 0.5 for next all possible turbines in a line. Similarly for the next line onwards, adding 0.5 in y coordinate and repeating x coordinates for all possible lines as given in Figure 2. For further computations of C_e, C_i, C_{oi} and f_{obj}, the equations above are referred to.

4.3 *Computations in rectangular shape*

In the case of rectangular shape farm, length and breadth is different. If length is given then breadth is calculated as

$$Breadth = \frac{area}{length} \tag{25}$$

The number of lines on which WTGs are placed on breadth is calculated as

$$TTL = \frac{breadth - 0.2}{dttn} \tag{26}$$

The total number of maximum WTGs placed in a length line is given by

$$TLN = \frac{length - 0.1}{dttn} \tag{27}$$

The total number of WTGs placed in the square farm is then given by

$$TNT = TTL \times TLN \tag{28}$$

Again, TTL, TLN and Total Number of Turbines (TNT) must be rounded for getting the integer number and these do not have the unit. X coordinate and Y coordinate of the first turbine are 0.1, 0.1 and consecutive coordinates are calculated as the first line keeping the y coordinate at 0.1 and adding the 0.5 for next all possible turbines in a line. Similarly for the next line onwards, adding 0.5 in y coordinate and repeating x coordinates for all possible lines as shown in Figure 3. For further computations of C_e, C_i, C_{oi} and f_{obj}, the equations above are referred to.

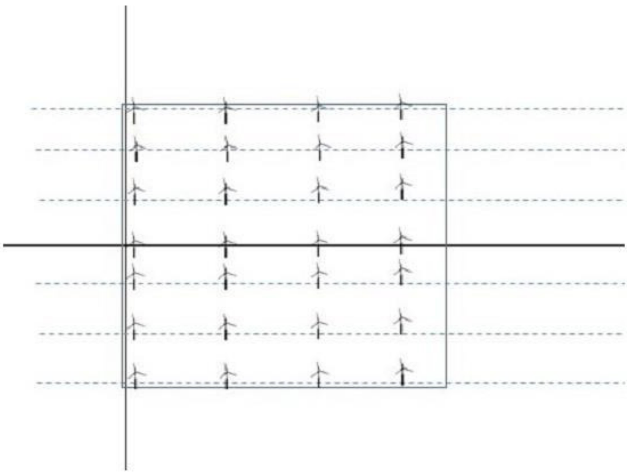


Figure 2. Square farming method

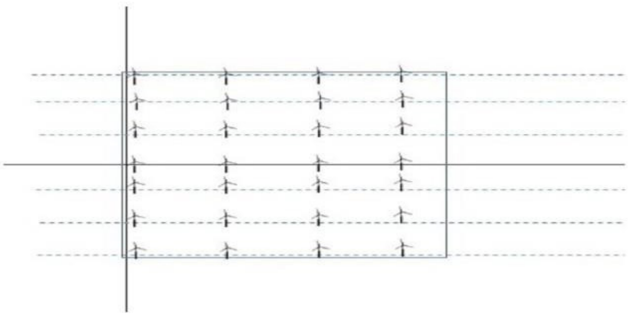


Figure 3. Rectangular farming method

4.4 *Computations in PSO*

Particle Swarm Optimization is a tool to find the best-optimized solution along with constraints. PSO follows two equations based on particle velocity and position as given by

$$v_n = \left(0.5 + \frac{r}{2}\right) \times v_n + 2r(P_{best} - x_n) + 2r(g_{best} - x_n) \tag{29}$$

$$x_n = x_n + v_n \tag{30}$$

The evaluated objective function is converted in the PSOFEED table and that is provided to find the minimum error by using the above PSO equations 29 and 30 which are cited from ref. [1] so that an appropriate number of WTGs placed at selected locations to get the maximum profit for all stakeholders.

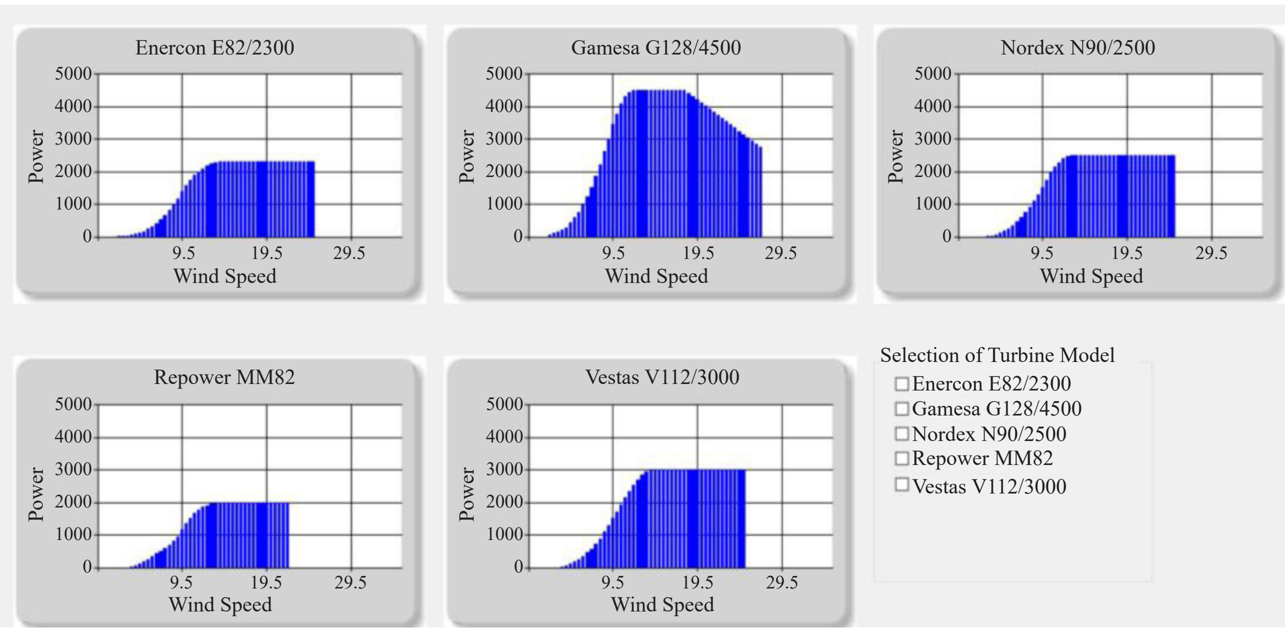


Figure 4. Wind velocity vs turbine power

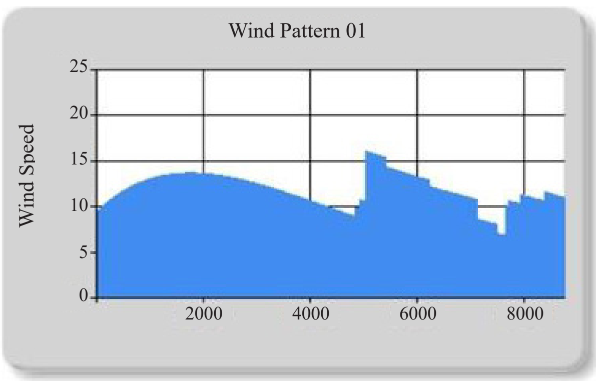


Figure 5. Annual wind trends in Jaipur, Rajasthan

Particle swarm optimization method is implemented through dot net programming based novel tool developed herein this research work. PSO comes under the intelligent tool category and is selected due to its capability to address the multi-objective functions. Figure 4 represents the snap of wind velocity vs WTG power. Whereas, Figure 5 represents annual wind trends in Rajasthan.

The objective function is found and graphically represented in Figure 6 and also mathematically expressed by equation (1). This term is achieved by solving the objective function and such objectives are fed to PSO intelligent tool through PSOFEED equations as tabulated in Table 1.

Table 1. PSO FEED equations for farm optimization for the rectangular shape with L = 1.7

Sr. No.	WTG Type	Coefficients					
		A	B	C	D	E	F
1	Enercon	0.000000009	-0.000002	0.000056	-0.0009	0.0032	1.0564
2	Gamesa	0.00000001	-0.0000008	0.00005	-0.0006	0.0021	1.0588
3	Nordex	0.000000011	-0.000002	0.000054	-0.0008	0.0029	1.0571
4	Repower	0.00000001	-0.0000012	0.000072	-0.0008	0.0029	1.0564
5	Vestas	0.000000024	-0.000002	0.00007	-0.001	0.0035	1.0546

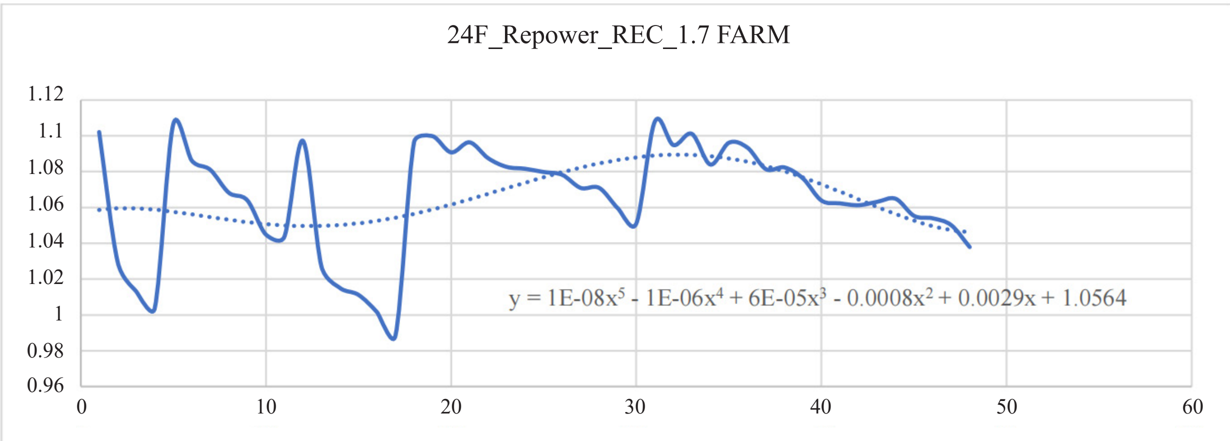


Figure 6. Curve fitting for objective function in rectangular with L = 1.7 shape for farm optimization

Figure 4 indicates the wind velocity in km/hr on the x-axis and WTG power in kw on y axis. Whereas in Figure 5 represents the annual wind trend in Jaipur Rajasthan where x-axis represents the total hours in a year and y-axis represents wind speed in km/hr. Figure 6 is a typical case study of objective functions on y-axis (which is rounded to unity by average value) Vs the number of WTGs on x-axis.

5. Observations

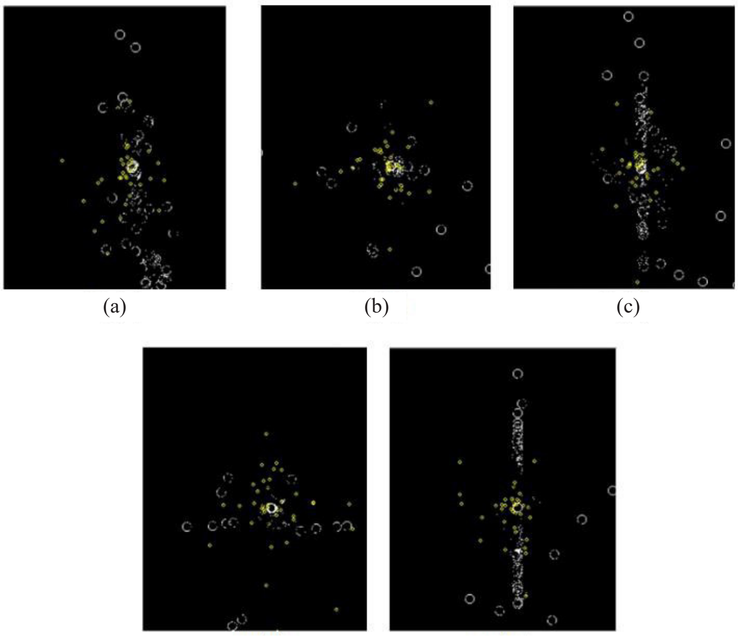
Sustainable energy solutions in the wind farm through PSO as an intelligent tool may be seen in various case studies of this research. Even though 150 cases are studied, tested and validated, only a few of them are discussed here.

Figure 6 represents objectives for the rectangular shape of the length 1.7 km for the farm constraint while local mode particle swarm is applied. Here are the particle positions for the search for the optimal objective function for placement of the appropriate number of the wind turbine.

Table 2 tabulates the PSO solutions for the five case studies in this research on optimization. It may be seen that without an intelligent tool (PSO), 48 wind turbines are suggested and seems to be a good solution. However, PSO application to find the best solution is somehow different. One can see the number of iterations and best fitness value are also mentioned in Table 2. If the best fitness value is under the minimum set error value, the outcome of PSO is acceptable.

Table 2. Farm optimization results of rectangular shape with local/global PSO & L = 1.7

Case	Opti method		without	Farm					
	WTG	Shape		Local PSO	itr	best fitness	Global PSO	itr	best fitness
21	Enercon	REC_1.7	48	9	193	5.44E-06	22	200	12.7127
22	Gamesa	REC_1.7	48	48	200	0.0001	18	200	0.9753
23	Nordex	REC_1.7	48	43	200	0.000244	10	200	0.2352
24	Repower	REC_1.7	48	35	124	2.54E-06	4	200	0.0258
25	Vestas	REC_1.7	48	9	200	4.66E-05	11	200	0.0325



(a) (b) (c)

(d) (e)

Figure 7. Particle positions in five turbines while PSO in local mode operation for rectangular shape wind farm

The application of the rectangular farm shape is being researched, with a length of 1.7 km. All of the recommended wind turbines are going to witness PSO optimization (Enercon, Gamesa, Nordex, Repower, and Vestas). PSOFEED equations are retrieved for the assessment and compiled in Table 1. Figure 6 for case 24 shows the detailed graphical representation of a repower turbine for farm optimization.

The 1.7 km as length, rectangular wind farm accomplishes its desired purpose. 48 turbines can fit in the chosen shape without the use of an optimization program. Instances 21 through 25 were subjected to the test. The global PSO also undergoes a similar exercise.

Subfigures (a) to (e) in Figure 7 depict a typical particle movement or position for each of the five turbines that were utilized for monitoring purposes. Table 2 presents every single one of the wind turbines with the farm as a constraint that both the local and global PSO recommend for rectangular forms with 1.7 km as length. The values of the optimal fitness function produced during the investigation, along with the number of iterations, are reported. This sub-research investigates ten case studies, five of them consist of local PSO cases and five of the above are global PSO cases.

6. Conclusion

After the above observations, concluding remarks for the given cases are: the setting for PSO iteration number is allowed at 200 as the most of researcher reports with 100 as the best iteration number. Forty-eight Gamesa turbines are investigated as maximum placed turbines, while PSO running in local mode. Similarly, nine Enercon turbines are reported as minimum investigated or selected turbines for the local PSO. In the case of global PSO, 22 Enercon turbines are the maximum selection, whereas repower was reported as the minimum turbine selected for PSO in this rectangular shape of 1.7 km as a length in farm optimization. The best fitness in PSO local for 35 repower turbines in 124 iterations is recorded as 2.54E-06 and also the best fitness in PSO global with 4 repower turbines in 200 iterations is recorded as 0.0258. The best fitness function is always mentioned as being important when adopting the offered solution. This way the best sustainable solution by application of intelligent tool (PSO) is applied in wind power plants. The possible future scope may be by adapting artificial intelligence for a placed turbine for the hub angle and height as an added constraints. Few researchers may take the challenge of forecasting based on wind farm locations and wind energy generation for the different shapes in the wind farm through NPV analysis.

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Conflict of interest

The authors of this article have no conflict to publish the paper in AECM.

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