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Particle swarm optimization for the optimal layout of wind turbines inside a wind farm

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ABSTRACT

The wind turbine's output power is heavily affected by the arrangement of the wind turbine location. Wind farm planning endeavors to firstly maximize the farm's output energy. Secondly, it seeks to minimize the effects of the wake phenomenon. This paper attempts to find the best possible location of a wind turbine inside a square farm using the particle swarm optimization (PSO) method whilst focusing on the three salient cases: the steadiness of wind direction and speed, the variability of the flow direction with a steady speed, and the variability of direction for three discrete wind speeds. The proposed algorithm generated results that will be contrasted to previous studies on the same topic with different metaheuristic methods such as a genetic algorithm. When compared to the optimum findings from prior research, the suggested approach has a reduced cost. It is developed by language C through MATLAB environment considering a square with the dimensions 2×2 kilometers.

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1. INTRODUCTION

Wind energy is a renewable source of energy which does not exude greenhouse gases into the atmosphere [1]. Indeed, it is notorious for its cleanliness and cost-effectiveness [2]. According to the last intergovernmental panel on climate change (IPCC), renewable energy production will be increased to 67% by 2050 to preclude the proliferation of global warming [3]. Low-cost energy production is needed to fulfill this increase [4]. Industrialization, population explosion, and urban growth, among other social processes, have been surrounded by technological development [5], wherein energy usage in its different forms stands out [6]. Today, myriads of instruments and devices that facilitate human life are powered by electricity [7]. As a corollary of the burgeoning electricity demand, wind energy has been capitalized on in several wind farms' installations worldwide [8] thanks to the propitious prospects it carries in the field of energy production [9]. Generally, Wind farms are erected in places where the wind level is prolific to sustain continuous electricity production [10], [11]. To this end, wind farms must be placed in the most appropriate location to ensure lucrative wind energy consumption [12]. The placement of a wind farm is a vital determinant of its power production. On the other side of the coin, one of the colossal hurdles that come into being when laying down a blueprint of a wind park is the wake problem [13], [14]. By the same token, the existence of this effect encumbers the uniformity of the wind speed [15].

In the literature, a study conducted by Mosetti and colleagues [16] sought to determine a solution to the wind turbine's location. Incidentally, a genetic algorithm (GA) was used to locate the turbine in a wind farm of 10×10 cells. By extension, Grady *et al.* [17] expanded on Mosetti *et al.* magnum opus by carrying out the objective function of energy and cost of production to generate ample total power production. This operation was conducted by including more turbines into the design. On the other side of the coin, Gao *et al*. [18] employed a related form of the genetic method to get the optimal layout under average conditions. To corroborate its effectiveness in tackling realistic conditions, this method was used in Hong Kong to a genuine offshore park. In a similar spirit, net present value (NPV) used by Mora *et al*. [19] as the objective function. In the GA, integer codification was applied to explore feasible efficiency-improving measures. Conversely, Emmami *et al*. [20] regarded the total energy produced as the objective function. Whereas Song *et al*. [21] utilized an evolutionary algorithm to optimize the wind farm wherein he employed complex calculations. To tackle the updated bi-criteria optimization model with electricity production and constraint violation as the objective functions, Kusiak *et al*. [21] developed a multiobjective evolutionary strategy method. The procedure converts each constraint into a different goal function, the second of which is lowered to zero. Marmidis *et al*. [22] utilized the Montecarlo method intending to optimize the wind farm location. In doing so, in steady direction, steady speed wind situation, they gathered more accurate findings than GA. Instead, Salcedo Sanz and colleagues [23] proposed the coral reefs optimization (CRO) method to tackle offshore park's construction. In the same line of reasoning, A levelized cost of energy (LCOE) was performed in Chen *et al.* study [24] as like an objective function, and the greedy method was employed to determine where turbines ought to be located on the farm. In Wang *et al.* study [25], and to improve power production, the wind turbine location was addressed using a differential evolution technique and a brand-new encoding technique. Each wind turbine was treated as a unique in the new encoding technique and the population of wind turbines as a whole. In addition, the study by Yang *et al*. [26] who worked on a Boolean code-based modified genetic algorithm. Lastly, Zergane's piece of research [27] is encapsulated in the incorporation of the method of pseudo-random number generation.

The primordial purpose of this study lies in creating a suitable optimization model necessary for the installation of wind turbines inside a square farm. To realize this objective, MATLAB was deployed to create and solve the optimization model, which was in turn developed with C language. Thanks to the particle swarm optimization (PSO) model, the solution was successfully obtained by virtue of its capacity to burgeon the highest power output. In light of the issue this research endeavors to demystify, this piece of research is tremendously significant for several reasons as it takes into consideration the variability of both directions as well as speed using the metaheuristic PSO. Thus, the present study provides avant-garde contributions to the literature wherein two novel cases: variable speed and wind direction were put under the microscope using the PSO method which proved to be highly effective. With that in mind, the results were compared to other metaheuristic methods such as GA [17], Pseudo-number generation method [27], and adapted evolutionary algorithm using the Boolean coding technique [26]. Hence, this study is structured in the following manner. The first section unveils a general explanation of the subject. It also exhibits a comprehensive review of the literature as well as the previously used methods pertaining to this field. The second section provides lucid scrutiny of the wake effect, encompasses a rigorous description of the PSO method in addition to other alternative methods, and presents the field data along with a brief formulation of the problem. Lastly, the results of the MATLAB model were compared and were thereby evaluated.

2. METHOD

2.1. Mathematical modelling of the wake effect

To produce electricity, each turbine pulls out from the wind kinetic energy. When the wake effect occurs [28], the wind speed decreases each time the wind passes through a turbine. It affects the environment in two ways: It results in a reduction in wind speed [14], which ultimately dwindles the turbine's output power and leads to a decrease in life span due to the increase in turbulence intensity. There exists a scalar that identifies the wake and indicates how the expansion of the wake occurs at a specific distance. The scalar is denoted k. In (1) expresses the relationship between this scalar and the parameters of the wind turbine, the height of the hub is denoted Z, and the coefficient of roughness is indicated by Z_0,

$$\mathrm{k} = \frac{0.5}{\ln\left(\frac{z}{z_0}\right)} \tag{1}$$

To make the theory of the wake phenomena easier to understand, the example of two turbines is used in Figure 1, one turbine producing the effect and the other one being the victim of the effect. In reality, one wind turbine can be the victim of several wake effects, which are generated by several downstream turbines.

The total velocity deficit according to the Jensen model at the position i is,

$$u_{itotal} = \left(\sum_{j\in S(i)} {u_{ij}}^2\right)^{\frac{1}{2}} \tag{2}$$

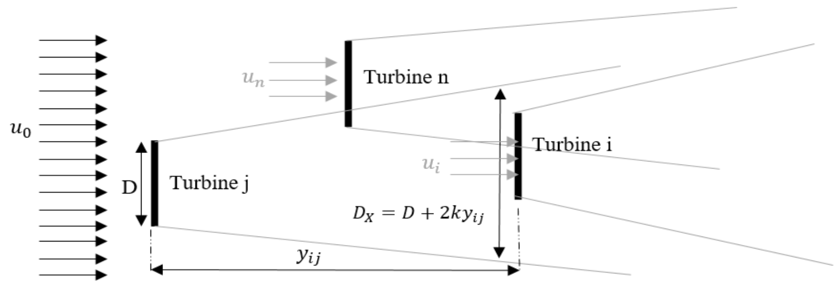


Figure 1. Multiple wake effect

We include all turbines that cause the wake effect and that affect a wind turbine at a position denote i, in a set S (i). This set is defined,

$$S(i) = \left\{ (x_j, y_j) \, , \begin{matrix} y_i \geq y_j \\ |x_i - x_j| \leq x_j \end{matrix} \right\} \tag{3}$$

The following is the new radius taken into account when calculating the speed of a turbine influenced by the wake effect (where turbine j∈S (i)),

$$r_j = ky_{ij} + r_r \tag{4}$$

The expression of wind speed at turbine in position i will be expressed like,

$$u_i = u_0(1 - u_{itotal}) \tag{5}$$

u_0: factor of axial induction.
To compute the velocity loss when there are several wake effects, two other factors will be taken into consideration:
- A_i : rotor area of turbine i
- A_{ij}: Intersection between the area created by the rotor of turbine i and the area of wake created by turbine j.

$$u_{ij} = \frac{2a}{\left(1+2k\frac{y_{ij}}{D}\right)^2} * \frac{A_{ij}}{A_I} \tag{6}$$

a: axial induction factor.
Betz relations show the link between C_T (The thrust coefficient) and the axial induction factor a,

$$C_T = 4a(1 - a) \tag{7}$$

The Figure 2 illustrates the intersection between the area created by the rotor of turbine i and the area of wake created by turbine j that generates the phenomenon.
The expressions of the angles shown in Figure 2 are,

$$\begin{cases} \alpha_1 = 2\cos^{-1}\left(\frac{{r_r}^2+{x_{ij}}^2-{r_j}^2}{2r_r x_{ij}}\right) \\ \alpha_2 = 2\cos^{-1}\left(\frac{{r_j}^2+{x_{ij}}^2-{r_r}^2}{2r_j x_{ij}}\right) \end{cases} \tag{8}$$

The Figure 2 shows that we can distinguish between three possible cases concerning the value of A_{ij},

$$A_{ij} = \begin{cases} 0, for\ x_{ij} > r_j + r_r \\ \pi {r_r}^2, for\ x_{ij} < r_j - r_r \\ \frac{1}{2}\left[{r_j}^2(\alpha_1 - \sin\alpha_1) + {r_r}^2(\alpha_2 - \sin\alpha_2)\right], for\ r_j - r_r < x_{ij} < r_j + r_r \end{cases} \tag{9}$$

From a wind turbine the power that can be pulled out must be expressed [3],

$$P = \frac{1}{2} C_P \rho A U^3 \quad (10)$$

Where: C_P the power coefficient, ρ: the density of air (1.225 kg/m3), U: the wind speed and A: the rotor swept area.

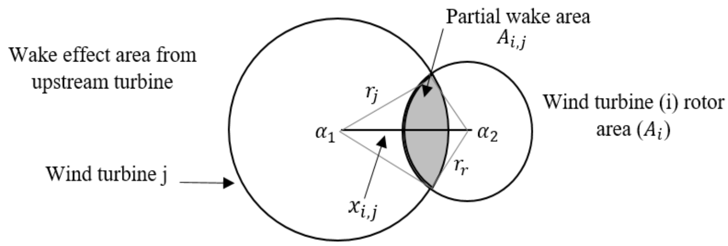


Figure 2. Intersection area [17]

As it is proved by (10), a wind turbine i generates a power at its output which is proportional to the wind speed's the cube. This output power is equal to,

$$P(u_i) = \begin{cases} 0, u_i \leq 2.3\, m/s \\ 0.3{u_i}^3, 2.3\, m/s \leq u_i \leq 12.8\, m/s \\ 630, 12.8\, m/s \leq u_i \leq 18\, m/s \\ 0, 18\, m/s \leq u_i \end{cases} \quad (11)$$

2.2. Metaheuristic methods

2.2.1. The metaheuristic of genetic algorithm GA

Genetic algorithms describe a technique that achieve the minimum and maximum of a function using ideas influenced by natural genetics rather than natural transformation processes [17]. Their guiding idea is the preservation of a sequence of population which changes with time, trying to lead population its best.The input sequence can be determined by chance or by heuristics.

2.2.2. Pseudo-random number generation

It's an iterative approach based on deterministic functions, that are frequently used to generate pseudo-random numbers based on recurrent patterns [27] like,

$$X(N+1) = (aX(N) + b) mod[NC + 1] \quad (12)$$

Where NC is the total amount of turbines which does not surpass NC and a ,b are positive integers. This indicates that the components of this series are the remainders of dividing mostly on divisor NC+1, while simultaneously picking non-zero integers a and b;

2.2.3. GA involving Boolean code modification

The assignment probability in the binary-coded GA is a constant P_i= P. As a consequence, using a Boolean code, the order and number of turbines will be distributed evenly that optimizes the starting population's variety [26]. The mutation involves converting the output of even a bit to inverse. For each bit, the mutation site is picked at random with equal probability (p). Mutation is vital in GAs because it introduces new genes into the population, preventing the algorithm from reaching a premature local optimum solution. The classic mutation procedure, on the other hand, still attempts to balance the amount of both 1s and 0s there in code. To eliminate this detrimental consequence, different mutation rates are utilized for codes, as follows: The real code for such an N-bit code has c number of 1s. Whereas if the rate of mutation is p, then p 0 in the Boolean code represents the mutation rate at 0 and p1 represents the mutation rate for 1. The following describes the link between p, p 0, and p 1:mutation rate for 1. T.

$$p = \frac{(N-c)p_0 + cp_1}{N} \quad (13)$$

2.2.4. Partical swarm optimization

The metaheuristic called PSO is an optimization tool depending on individual participation. The concept of this optimization algorithm PSO is that we can reach a global organization of unintelligent individuals [29]. All particles of the swarm gradually converge to a global minimum.The principal gain of this metaheuristic is that it is easy to implement because it does not require many parameters. In a PSO, each particle in the swarm remembers its best position as well as the best position of its neighbor because each particle has a large memory capacity if compared with other metaheuristic methods such as the genetic algorithm (GA). Initially, each particle takes its place in the search space whether randomly or not. Following each iteration, a particle will be moved according to three components: the current velocity V_k,the greatest solution P_k and the greatest solution collected in its vicinity P_G. The relationship between the different parameters of the metaheuristic (PSO) are expressed by the two (14),

$$\begin{cases} v_{t+1} = c_1 v_t + c_2(p_{i,t} - x_t) + c_3(p_{g,t} - x_t) \\ x_{t+1} = x_t + v_{t+1} \end{cases} \tag{14}$$

V_t : the velocity gathered at time t, x_t: the particle's placement at time t, $p_{i,t}$: the greatest previous placement at time t, $p_{g,t}$: the greatest vicinity's previous best at time t.c_1,c_2 and c_3 are the coefficients of social/cognitive confidence.

2.3. Problem formulation

The primary purpose of this research is to increase farm productivity by selecting the ideal position for each turbine, a location which the wake effect is minimal. Mosetti *et al*. jumped to a conclusion concerning the cost of wind turbines as a whole [16]. This assumption shows that a single wind turbine has an unsized cost per year that is one, with a maximum cost decrease of one-third for each additional rotor. Therefore, the normalized cost is expressed as a function of turbine's number,

$$Cost = N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) \tag{15}$$

N denotes the farm's turbine number. The production that a wind turbine configuration can generate is,

$$P_T = \sum_{k=1}^{360}\sum_{i=1}^{N} f_k P_i(u_i) \tag{16}$$

Table 1 shows the incidence rate to every angle and for each wind speed, with the sum of occurrences equal to unity $\sum_{k=0}^{360} f_k = 1$ (Where f_k is the wind frequency distribution).

Table 1. Non-uniform wind speed, changeable direction probability density wind distribution

	u_0 = 8 m/s	u_0 = 12 m/s	u_0 = 17 m/s
k	0-360	[0-270, 280, 290, 300, 310, 320, 330, 340, 350, 360]	[0-270, 280, 290, 300, 310, 320, 330, 340, 350, 360]
f_k	0.0042	[0.0084, 0.0107, 0.0126, 0.0149, 0.0149, 0.0195, 0.0149, 0.0149, 0.0126, 0.0102]	[0.0112, 0.0135, 0.0163, 0.0191, 0.0302, 0.0358, 0.0307, 0.0191, 0.0163, 0.0135]

Since it is an optimization method, it is clear that we must define an objective function. The purpose of this study is to achieve the greatest quantity of electrical energy at the lowest feasible cost. So, the objective function is expressed,

$$Objective = \frac{Cost}{P_T} \tag{17}$$

To give a logical comparison of data obtained from previous research on the difficulties of avoiding the wake effect by improving wind turbine siting and the current study based on particle swarm metaheuristics (PSO), we use a model similar to the one of the previous studies: it is a representation of a wind farm by 10×10 square cells which depict a wind farm site of 2000×2000 m as seen in Figure 3. Each wind farm cell can be configured with or without wind turbines. Based on this model, a single wind turbine can have 100 locations. In Figure 3, we can pinpoint potential wind turbine locations. Wind speed and direction are the two wind parameters. Formally or informally, the wind direction can be distributed. As shown in Figure 3 the wind distribution is done on 36 directions. The initial direction will be equal to 0°, we denote it θ_0. Then, to identify the abscissa and ordinate of the position of wind turbine i, we use the formula,

$$\begin{cases} x(\theta_i) = x(\theta_0)\cos\theta_i + y(\theta_0)\sin\theta_i \\ y(\theta_i) = -x(\theta_0)\sin\theta_i + y(\theta_0)\cos\theta_i \end{cases} \quad (18)$$

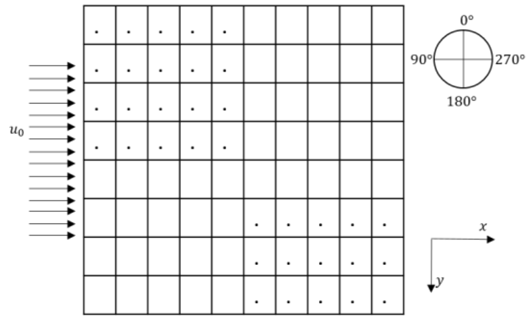


Figure 3. Divided wind farm site which is considered for case study

3. RESULTS AND DISCUSSION

A rectangular shape ground of 2 kilometers by 2 kilometers on which turbines will be placed has been investigated in myriads of previous studies. In this study, we have adopted the same condition and turbine type in order to achieve a plausible comparison. Figure 4 depicts the suggested algorithm's flow chart.

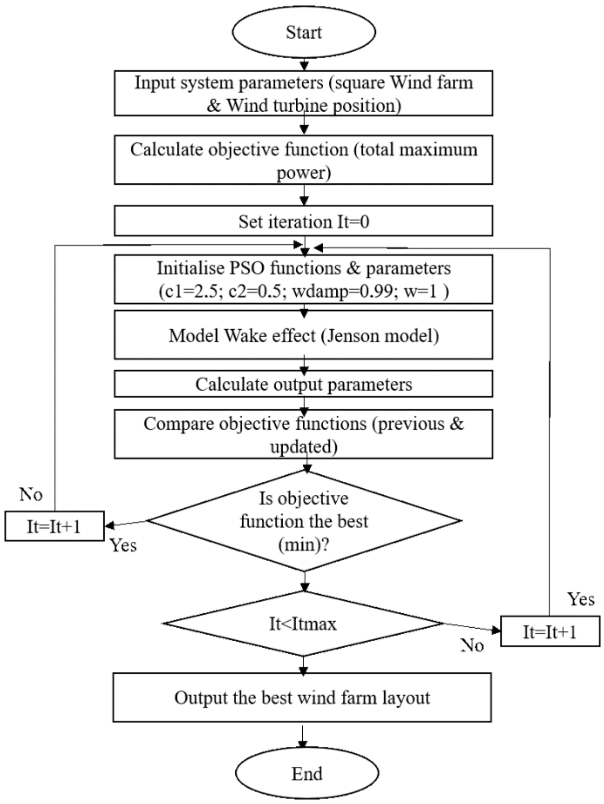


Figure 4. The suggested algorithm's flowchart

The study offered three instances categorized according to the number of turbines,

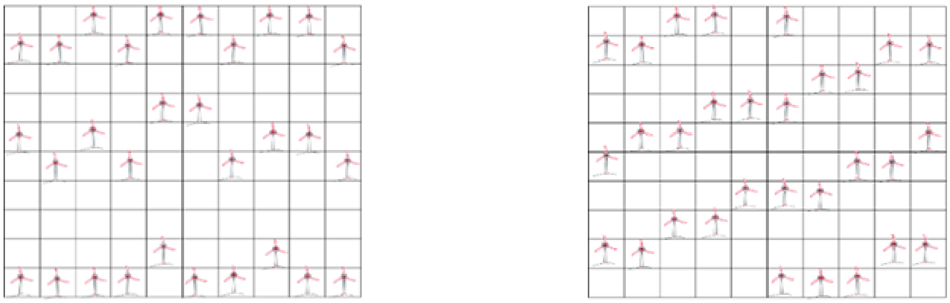
– Case 1: the wind blows in one direction (θ_i = 0 ∀ i) and at a specific speed (for example u_0 = 12 m/s = constant). Whenever it relates to air flow, we use the direction of the ordinate vector.
– Case 2: In this case, we conserve a constant value of speed (for example u_0 = 12 m/s) and we adopt the scenario of multiple direction.

– Case 3: Such as previous work, this study will employ three alternative wind speed values: 17 m/s, 12 m/s, and 8 m/s. For every value of speed, the direction angle θ_i can take 360 values (from 0° to 360°).

In the three cases, the number of populations will be taken such as previous studies, which mean 30 and 39 turbines.

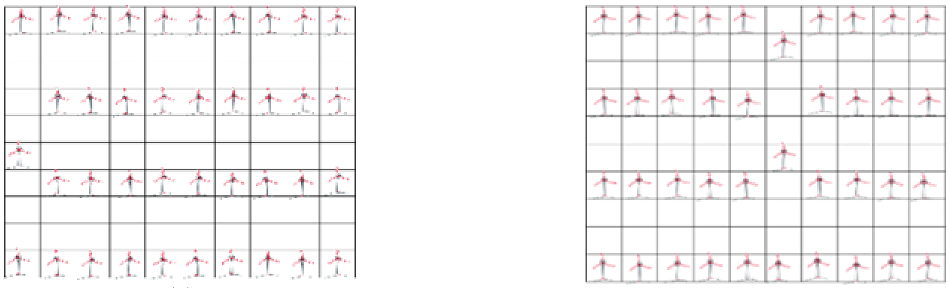
3.1. Case 1: uniform wind speed and uniform direction

For the case of 30 turbines, the use of PSO gave a minimal objective compared to the Pseudo-random Number Generation as shows in Table 2. The turbines configuration is presented in Figure 5 (a) and (b). Comparing the results obtained for each method in case 1 for a population of 39 mentioned in Figure 6 (a) and (b), in the PSO approach Figure 6 (b), the objective function has the lowest value as the first case. The resulting energy is 15058 kW.



(a) (b)

Figure 5. Optimal turbine's configuration by Zergane *et al*. (a) [27] current study and (b) using 30 turbines



(a) (b)

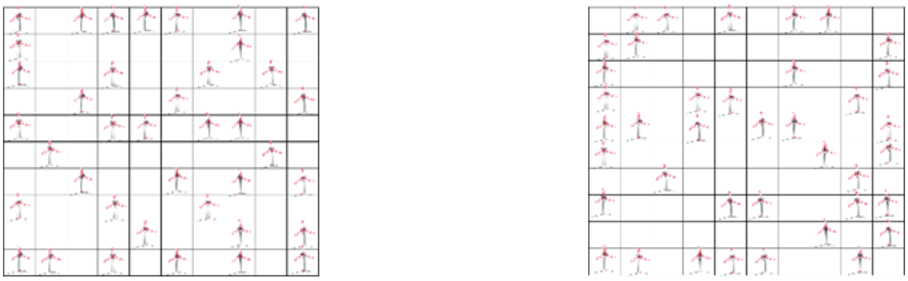
Figure 6. Optimal turbine's configuration by Yang *et al*. (a) [26] current study and (b) using 39 turbines

Table 2. Comparison results between PSO, pseudo-random number generation and GA Boolean

	Number of turbines	Objective (10−3)	P (kW)
Modified genetic algorithm based on Boolean code [26]	39	1.515	17,768
current study	39	1.389	18,861
Pseudo-random Number Generation [27]	30	1.543	14,310
current study	30	1.463	15,058

3.2. Case 2: Changeable direction and constant speed

The wind direction will be incremented by 10° from 0° to 360° and for a constant wind speed, which is equal to 12 m/s. The algorithm proposed by this study has given significant results and the objective function is minimal when compared with that found in the case of the genetic algorithm. A number of turbines are located around the periphery of the wind farm, and the wind dispersion is uniform throughout the site, therefore, these turbines are directly confronted with a freewind speed, so they can provide a significant power output and higher than others. Figure 7 (a) and (b) depicts the optimal wind farm arrangements. The turbines of the farm are symmetrically positioned Figure 7 (b). To prevent the creation of the wake effect, each wind turbine is kept above a certain spacing from the others. Since the wake impact is significant in the zone, whatever of directions, the wind farm's center is not entirely filled in. Table 3 presents the results of each method.



(a) (b)

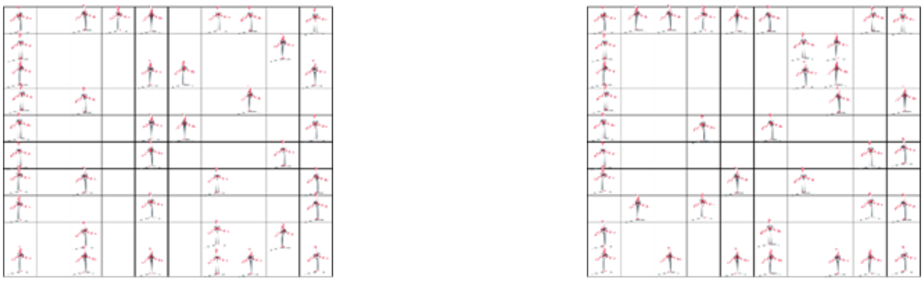
Figure 7. Optimal turbine's configuration by Grady *et al*. (a) [17] current study and (b) using 30 turbines

Table 3. Comparison results between PSO and GA

	Number of turbines	Objective (10−3)	P(kW)
Genetic Algorithm [17]	39	1.567	17,220
current study	39	1.376	20,187

3.3. Case 3: Variable direction as well as speed of wind

The third instance is the most challenging, since it is reliant on the fluctuation of both: wind speed and flow direction (Three speeds are taken into account in this research): 17, 12 and 8 m/s). Figure 8 shows how the turbines in the three-optimization methods are placed in the park boundaries to avoid the wake effectas much as possible. In addition, the Table 4 shows that the objective function adopted in the study is minimal in the case of the PSO algorithm (lower than that of GA by 0.0008403).Therefore, the output production of the wind site is the highest in the case of the algorithm proposed by this study (since the turbines are positioned around the site's perimeter, facing a free wind directly towards them).In addition, the locations of the wind turbines within are dispersed, It has the potential to lessen wake impacts. Table 4 shows the comparison with previously reported results. The suggested approach increases overall energy output while decreasing cost per unit of electrical generation. Figure 8 (a) and (b) depicts the optimal turbine designs. Because the most common occurrence of wind in the current research is between 270 and 360 degrees, as indicated in Table 1, the algorithm put the turbines in the upper left and lower right sides, which are linked with lesser wake impact.



(a) (b)

Figure 8. Optimal turbine's configuration by Grady *et al*. (a) [17] current study and (b) using 39 turbines

Table 4. Comparison results between PSO and GA

	Number of turbines	Objective (10−3)
Genetic Algorithm [17]	39	0.8403
current study	39	0.776

4. CONCLUSION

The presented work concerned the optimization of the wind turbine's location within the park. The goal of this article was to increase the energy efficiency of this wind farm while lowering the system cost. However, the wind device to be optimized involves several strongly coupled physical phenomena such as the wake effect. The study focused on the use of the swarm particle algorithm; the results are precisely improved compared to the same GA method that was previously used. As demonstrated throughout the study, the algorithm integrates several aspects that tremendously ameliorate the performance of the previously described literature while simultaneously contributing to the betterment of output production with the fewest turbines. The results were initially compared favorably with previously published studies. The suggested algorithm's performance and suitability for determining the optimal wind farm configuration have been demonstrated. To solve more complex cases, there is ample scope for further research in this area to investigate the problem of turbine placement optimization when the turbine height is different from one turbine to the other in the same sit.

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