

Received February 17, 2022, accepted March 9, 2022, date of publication March 14, 2022, date of current version March 24, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3158981

Design of 3D Wind Farm Layout Using an Improved Electric Charge Particles Optimization With Hub-Height Variety

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This work was supported by the Deputyship for Research & Innovation, Ministry of Education of Saudi Arabia and King Abdulaziz University, Jeddah, under Grant IFPRC-190-135-220.

ABSTRACT The limited resources of land and wind have increased the requirement for better designing of wind farm layouts in the wind industry. A three-dimensional layout of wind turbines (WTs) is proposed in this paper to optimize the horizontal and vertical layouts of wind farms. The issue of optimization is a highly challenging task as it involves many variables and requires handling conflicting criteria. Classical optimization algorithms cannot handle this problem due to discontinuity and nonlinear behavior. Considering this, a metaheuristic algorithm called improved electric charged particle optimization (ECPO) is developed and implemented in four different shapes and cases studies. All the scenarios implemented have the same wind distribution and obstacles. The result shows that ECPO achieves better performance in the case study when the maximum number of a wind turbine is the same as the number of grids when compared to three well-known metaheuristic algorithms, which are binary particle swarm optimization (BPSO), genetic algorithm (GA), and artificial bee colony (ABC). By implementing the three-dimensional WFLO, the levelized cost of energy (LCOE) will increase by 7% in the case of the optimal number of WT and 3% in the case of the fixed number of WT.

INDEX TERMS Electric charge particles optimization, wind farms, optimization.

I. INTRODUCTION

Wind energy has made significant development in recent years. According to the Global Wind Energy Council (GWEC), 2020 was the best year in history for the global wind industry as 93 GW of new capacity was installed, which resulted in a cumulative capacity of 743 GW [1]. To reduce the cost in terms of installation and maintenance costs, wind turbines are generally grouped into wind farms. However, the group of wind turbines will affect the amount of power produced owing to the wake effect within the wind farm, particularly in large wind farms that lead to considerable power loss [2]. Therefore, it is essential to design a wind farm layout that minimizes the wake effect while maximizing the expected power output that is generally called wind farm layout optimization (WFLO).

The associate editor coordinating the review of this manuscript and approving it for publication was Ton Duc Do¹.

The optimization design of a wind farm is a complex task owing to the presence of discontinuities caused by the wake effect of turbines and the large number of variables involved. These two factors make it difficult to solve the issue by using classical optimization methods, such as the mixed-integer non-linear programming (MINLP) or calculus-based method. Therefore, metaheuristic, the algorithm that has proven to handle the discontinuity of the optimization problem, has become the most popular and prominent method to solve WFLO problems.

Numerous researches have been conducted to optimize wind farm layout by using metaheuristic algorithms. Mossetti *et al.* [3] conducted the first research to solve the WFLO problem in which a genetic algorithm (GA) was used as the algorithm to place the turbine in a wind farm that consisted of 10×10 cells each. The total energy produced and the cost per year of the whole wind farm were designed as multi-objective functions. Grady *et al.* [4] improved the algorithm

proposed by Mossetti by implementing the total energy and production cost as the objective functions. This approach can produce greater total power production by adding more turbines in the layout with comparable efficiency by using more individuals to generate the fitness function in the GA. As a result, this study can decrease overall cost per unit power production as compared to the previous results using the algorithm developed by Mossetti.

Moreover, many researchers used GA to solve the WFLO problem with different objective functions. Mora *et al.* [5] used net present value (NPV) as the single objective function. Integer codification was used in the GA to investigate possible solutions to improve efficiency. In [6], the total energy produced and per unit value of cost per year of the whole wind farm is set as the objective function and solved by using multiobjective GA. Contrary to the objective function proposed by Mossetti *et al.* [3] and Gradi *et al.* [4], this author implemented the objective function that not only optimizes the placement of wind turbines but also controls the cost. Three types of variables, i.e., turbine location, turbine type, and hub height, were set as the control variable in [7], while NPV and investment cost are set as the objective functions, which is optimized using the GA. The author considers the uncertainty of wind direction and speed when evaluating the cost function. The probability optimization methodology is developed to consider various possible scenarios and their probability occurrence to obtain a behavior of the solutions under risk. Meanwhile, Wang *et al.* [8] proposed a GA to compare the performance of the optimization process between the grid-based method and unrestricted coordinate method.

In addition, two cost models (Mossetti's model [3] and Chen's model [9]) are compared to find the best optimization result. The result showed that the 20×20 grid-based model achieved better results than the unrestricted method and Mossetti's cost is more accurate than Chen's cost model. The author in [10] developed a single objective GA to minimize the cost of energy (COE) in a wind farm with 10×10 grid cells. Unlike the other research that mainly uses the Jensen wake model, in this research the author used the Gaussian wake model to evaluate the velocity deficit in wind farms. The proposed approach yields better objective function and lower computational time compared to the same scenario obtained by Gradi *et al.* [4].

PSO is also a popular algorithm that was adopted to solve WFLO problems. Chowdurri *et al.* [11] implemented a mixed-discrete PSO algorithm to solve unrestricted WFLO with the COE as the single objective function. The algorithm was developed to optimize the wind farm layout by allowing multiple types of commercial wind turbines with different rotor-diameters, hub-height, and performance characteristics. The author designed the diagonal site of a $2 \text{ km} \times 2 \text{ km}$ wind farm in [12] to increase the surface area exposed to the wind. In this study, COE is set as the single objective function. By implementing this design, the distance of adjacent WTs is longer and as a result, the power generated and the efficiency

of the wind farm was improved with a minimized objective function. The author in [13] implemented an adaptive PSO to optimize the levelized production cost (LPC) of the wind farm. The optimized control strategy was taken as the new consideration to increase the performance of the optimization process. The limitation of this design is that it is applicable only to the exact wake model. The electrical infrastructure, the location of the offshore substation, and the intra-array cable network are set as the new constraints in designing wind farm layout in [14]. In this research, the author implemented a PSO algorithm to optimize the levelized cost of energy (LCOE) as the single objective function in an offshore wind farm scenario. Meanwhile, Veeremachaneni *et al.* [15] developed a multi-objective PSO algorithm to minimize the layout cost and maximize the energy output of wind farms. The author proposed two different strategies to reduce the complexity of the optimization process, i.e., first come first removed strategy and worst first removal strategy.

Numerous researchers have used different optimization algorithms and techniques to solve WFLO problems. A multi-objective evolutionary strategy algorithm is developed by the author in [16] to solve the transformed bi-criteria optimization problem, while the objective functions are energy output and constraint violation. In the algorithm, all the constraints are transformed to formulate the second objective function, which would be minimized to zero. Bilbao *et al.* [17] used simulated annealing (SA) to maximize the wind farm annual profit. This approach gave better performance in terms of total power produced and computational time as compared to distributed genetic algorithm (DGA). A lazy greedy algorithm was implemented to optimize the placement of WTs in a wind farm by setting COE as the objective function [18]. This study adopted the submodular property of the cell when designing the turbine position in a wind farm to reduce the computational time with the guaranteed quality of the result. Chen *et al.* [19] implemented the greedy algorithm to find the best position of WTs in wind farms where LCOE was used as the objective function. The incremental calculation method and repeated adjustment strategy were implemented in this study to accelerate the calculation of wind power and improve the result in the optimization process. The author in [20] implemented an extended pattern search (EPS), multiagent system (MAS) optimization approach to optimize the position and size of a wind turbine, including rotor diameter and hub height in the wind farm to maximize the profit. In this research, the author proposed the advanced modeling system for the cost, wake effect, atmospheric condition, and power generation for real-world applications.

In another study, Ramli and Boucekara [21] implemented a new algorithm called the binary most valuable player algorithm (BMVPA) with COE set as the single objective function. In this study, the grid was treated as a matrix to reduce the design variables. The optimization results showed that the new algorithm is better when being compared to GA and PSO with the objective function value. Wang *et al.* [22] used a differential evolution algorithm with a new encoding mechanism

to solve the WFLO to maximize the power output. In the new encoding mechanism, each wind turbine was considered to be an individual and all the wind turbines as the population. By implementing this technique, the efficiency and effectiveness of the algorithm were increased. In a recent study (2021), a lightning search algorithm with multi-objective function was applied to solve WFLO by minimizing annual energy production, wind farm area, and wake effect losses [23]. The author implemented nacelle's rotation modeling to address all variations of wake effect in each wind turbine as a function of the wind direction that can represent the real scenario of the wind farm. A biogeography based optimization (BBO) algorithm was presented by Aggarwal *et al.* [24] to evaluate the COE as the single objective function. A modified objective function by adding the weightage of the wind farm efficiency is adopted to reduce wake loss per turbine and to obtain better wind farm efficiency. The result is then compared with PSO, GA, and ACO showing that BBO achieves a better fitness function than these two algorithms.

Several studies on WFLO have been conducted by using different sets of variables and the position of the wind turbine as the main variable. Chen *et al.* [9] analyzed the impact of the hub height variation for WFLO by using a nested GA in which power output is set as the single objective function. The result shows that the power output will increase when using different hub heights as compared to the fixed hub heights. A three-dimensional greedy algorithm was implemented by the author in [25] by optimizing the hubheight as one of the variable control. The result shows that the total power output increases when using multiple hub heights and the cost per unit power output will decrease particularly for the complex terrain wind farm. The effect of hub height optimization on the annual energy production (AEP) in WFLO problem was studied in [26]. In this case, the other variables such as the position, the rotor diameter, and the total number of WT are fixed. The result shows that multiple hub height wind farms can increase the annual energy production by 2% when compared to single hub height. The WTs type and hub height are set as an optimization variable in [27]. The LCOE is set as the single objective function that is optimized using a GA. The result showed that height variability is useful in wider offshore cases. Meanwhile, Wang *et al.* [28] implemented the different hub heights in the range 40–80 m and the result showed that the application of different hub heights achieves better optimization results with higher power production and higher efficiency. A more advanced optimization process was presented by Huang *et al.* [29] where the wind turbine rotor diameter that influences the height of the turbine is designed as the optimization variable by using the NSGA II algorithm. The optimization process consists of a nested loop that optimizes the selection of WT type and the layout of wind farms separately. The result showed that the WT selection decreased the LCOE, which are set as an objective function. Moreover, in a recent study (2021), Xu *et al.* [30] used differential evolution and greedy algorithm to design wind farm layout with multiple hub heights of WTs. The results show

that by using multi hub height, it can reduce the LCOE by 13.96%, 12.54%, 8.22%, 6.14%, and 7.77% for the number of WT of 5, 10, 30, and 50, respectively. Moreover, Zhu [31] confirmed the result shown in the previous research wherein the adaptive differential evolution with the greedy method is used to solve the WFLO problem. The result showed that the multiple hub heights of WTs can increase the output power by approximately 5.59%, 1.16%, 0.18%, 0.22%, and 0.63% when the WT is 5, 10, 20, 30, and 50, respectively.

Improving the performance of wind farms in terms of the COE and power produced, in addition to the other aspects such as the location of the wind turbine, hub height, rotor diameter, or the wind turbine type, is crucial. However, the addition of variables will make the optimization more complex and will require more computational time, particularly for a large number of wind turbines. This paper will involve two variables: a wind turbine location and hub height to optimize the WFLO with an ingenious idea. This consists of bundling the two variables in one packet optimized simultaneously in the optimization algorithm. The ingenious idea will reduce the complexity of the WFLO problem, while the optimization only runs once for each iteration.

As reported in the literature, a metaheuristic algorithm is one of the best options to solve the WFLO problem due to the ability to handle the discontinuity and many variables involved. Based on The No Free Lunch (NFL) theorem that states that no algorithm is best for solving all optimization problems [32], many new algorithms, especially metaheuristic algorithms, have recently been developed with specific advantages and drawbacks based on their application. One of the most recently published algorithms is electric charge particle optimization (ECPO) that has shown excellent performance to solve mathematical benchmark problems for optimization, in sidelobe level reduction for circular antenna array (ECPO) [33], and to find moving targets using unmanned aerial vehicles (UAV) [34]. In this present study, the improved version of the ECPO algorithm was developed to solve the three-dimension WFLO problem where the binary version of ECPO is used to optimize the layout of the wind farm and the continuous version is implemented to optimize the hub height of the wind turbine.

The main contribution of this paper can be summarized as follows:

1. An improved and efficient ECPO algorithm to solve WFLO problem is proposed by simultaneously optimizing WTs' position and the hub height.
2. Reducing the complexity of the WFLO problem consists of more than one variable control by bundling into one variable and simultaneously optimizing it.
3. Wind farm layout is designed by solving the WFLO problem with various type of shapes and different maximum number of WTs.

The remainder of this paper is organized as follows. Section II describes the theoretical model of wind farm layout models. Section III proposes the mathematical model of the

WFLO problem. Section IV describes the improved ECPO algorithm to solve the WFLO problem. Section V will present the scenario, results, and discussion, while a conclusion is provided in Section VI.

II. WIND TURBINE MODEL

A. WIND TURBINE AND WAKE EFFECT MODEL

The characteristic of a wind turbine is related to the power curved parameter that involves cut-in speed, cut-out speed, nominal speed, and nominal power. The relation between those parameters is shown in (1) [2].

$$P(v) = \begin{cases} 0 & \text{if } V < V_{cut-in} \\ \lambda v + \eta & \text{if } V_{cut-in} < V < V_{rate} \\ P_{rate} & \text{if } V_{rate} < V < V_{cut-out} \end{cases} \quad (1)$$

When the wind speed is greater than the cut-in speed, the blades of wind turbine will spin and generate power. The power increases until the wind speed reaches the nominal speed and remains constant until the speed reaches the cut-out speed. If the wind speed exceeds the cut-out speed, the wind turbine will stop spinning to prevent the wind turbine from getting damaged. λ and η are the slope and the intercept parameter, respectively used to calculate the power in each wind speed between cut-in and cut-out speeds.

Wind turbines will extract energy from the wind, and the wind speed behind the blades are slower and more turbulent. This phenomenon is called the wake effect and the area behind it is called the wake region. This phenomenon has been studied and modeled by many researchers. One of the prominent models is the Jensen Katic model, which was first proposed by Jensen [35] and improved by Katic [36]. The representation of the wake effect by using the Jensen-Katic model is shown in Figure 1.

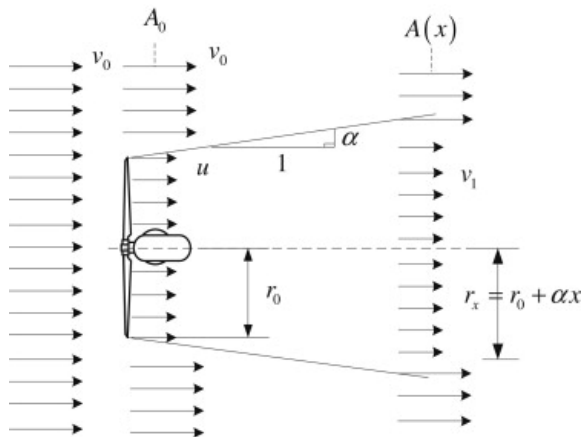


FIGURE 1. Representation of the wake effect.

For any two turbines located (x_j, y_j) that have hub height (H_j) , the velocity of the wind due to the wake effect of all the

surrounding wind turbine can be formulated using (2).

$$v^j = v^0 \left[1 - \sum_n^{i=1} \left(1 - \sqrt{1 - C_T} \right) \left(\frac{r_j}{r_i + kd_{ij}} \right)^2 \frac{A_s}{A_j} \right] \left(\frac{H_j}{H_i} \right)^a \quad (2)$$

B. ENERGY CALCULATION

The wind farm’s energy production is determined by the wind speed and wind direction distribution. In this research, Weibull distribution is used as the distribution of the wind. The expected energy production from a wind turbine is calculated by using (3) [37].

$$E = 8760 \int p(\theta) \int p_v(v; c_i; k_i | \eta(v)) \quad (3)$$

The total energy produced by the wind farm is the sum of the energy produced by the individual wind turbine.

C. LCOE MODEL

Cost of energy (COE) [\$/KWh] is defined as the cost per kWh of energy converted from the wind. This parameter is generally used to represent the price of energy where the operation of the wind farm for its operational life will not have either economic profit or economic losses [38]. The levelized COE (LCOE) is similar to CoE, but the difference is that LCOE differentiates between fixed and variable costs. The LCOE will include the time variation of money represented by the interest and the inflation rate, and will be related to life cycle cost that can be modeled using (4).

$$C_{cost} = \frac{c_T n + c_s \left[\frac{n}{L_m} \right] + c_{OM} n}{(1 - (1 - r)^{-y}) / r} \quad (4)$$

In the three dimension layout optimisation, the different height will contribute to the cost, by referring to literature [27], the increase of 1 meter of the tower can contribute to around 1/200 of the total cost, so, the wind farm cost with the variable of the hub height can be modeled in (5)

$$C_{cost} = C_{cost}(H_{ref}) \left(1 + \frac{1}{200} \left(\sum_{i=1}^N \frac{(H_i - H_{ref})}{N} \right) \right) \quad (5)$$

So, LCOE as the main objective function can be modeled in as follows.

$$LCOE = \left(\frac{C_{cost}}{P_{total}} \right) \quad (6)$$

III. MODELING OF 3-D LAYOUT OPTIMIZATIONS

A. DESCRIPTION

WFLO mainly includes the selection of the wind turbine capacity, wind turbine diameter and height, and wind farm’s location, including the area size, terrain, obstacles, and wind distributions. After the required data is gathered, the optimization process can begin. This paper proposes the variable combining method where the wind turbine location and hub height are combined into one package variable that will be

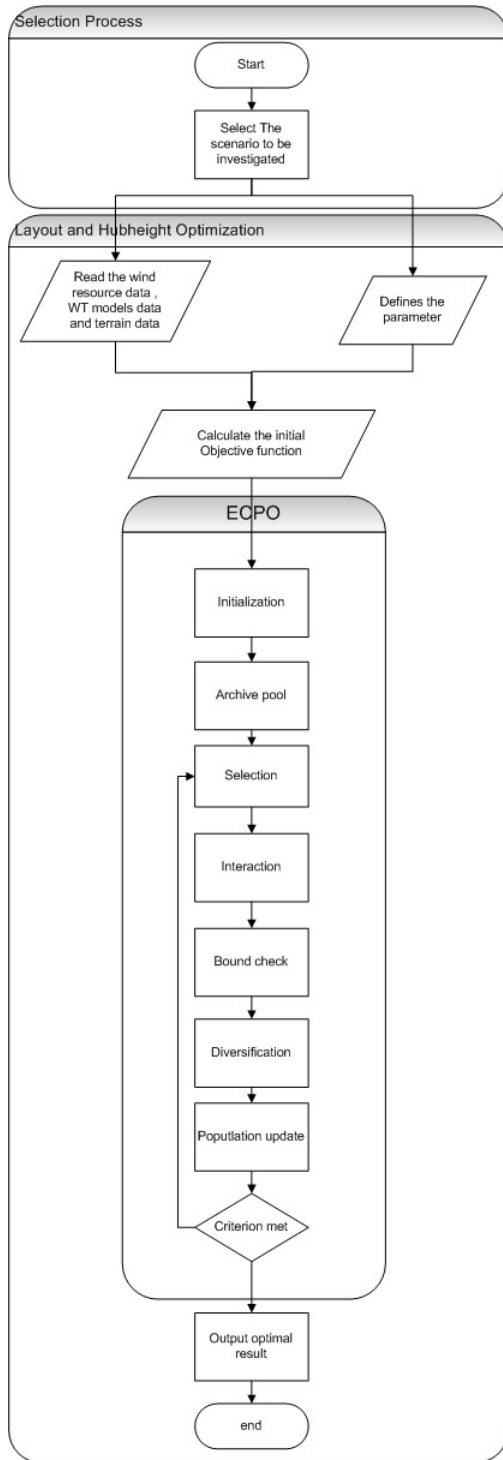


FIGURE 2. 3D WFLO Flow Cart.

optimized to minimize the wind farm’s LCOE. The entire procedure of optimization is illustrated in Figure 2.

B. OBJECTIVE FUNCTION

The main objective of WFLO is to minimize LCOE, where $C_T = \$750,000$, $C_s = \$8,000,000$, $m = 4$, $r = 3\%$, $y = 20$ years and $C_{OM} = \$20,000/\text{year}$.

C. DESIGN VARIABLE

The design variables in this WFLO problem are

$$\text{Minimize } F(n, x_i, y_i, H_i) = \min(LCOE) = \min\left(\frac{C_{cost}}{P_{total}}\right) \tag{7}$$

Subject to $D_i \in D_f, H_i \in H_f, (x_i, y_i) \in S$

$$\begin{aligned} x_{min} &\leq x_i \leq x_{max} \\ H_{min} &\leq H_i \leq H_{max} \end{aligned} \tag{8}$$

D. CONSTRAINTS

There are several constraints to be considered in the WFLO problem. The first constraint is the minimum distance between the turbine (D_{min}). In this research, D_{min} is five times the rotor radius that can be formulated as below.

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq 5D_i, \quad i \neq j \in [1, n] \tag{9}$$

The other constraint is the hub height, the minimum hub height is 50 m, and the maximum is 80 m, which can be formulated as follows:

$$50 \leq H_i \leq 80 \tag{10}$$

The other constraint is that the location of wind turbines should be in the wind farm area, which can be formulated in (11) as follows:

$$\begin{aligned} x_{min} &\leq x_i \leq x_{max} \\ y_{min} &\leq y_i \leq y_{max} \end{aligned} \tag{11}$$

Furthermore, the last constraint is the obstacle where the wind turbine area cannot be installed; in this research, we implement an obstacle’s in the same size and location for all scenarios.

$$\forall \in [1n] \notin [X_{oL}, X_{oU}] \notin [Y_{oL}, Y_{oU}] \tag{12}$$

IV. ELECTRIC CHARGED PARTICLES OPTIMIZATION

A. STANDARD ELECTRIC CHARGED PARTICLES OPTIMIZATION

The ECPO is a population-based metaheuristic algorithm inspired by the interaction of electrically charged particles. ECPO have some internal parameters used as follows: nECP is the total number of ECPs; MaxITER is the maximum number of iterations; nECPi is the number of ECPs interacting in one of the three strategies; and naECP is the archive pool size. The charged particle interacts using a selected strategy where the best particle will attract the worst, and the worst particle will repel the best one.

Initialization: The first step of ECPO is generating nECP charged particles within the search space by using a random normal distribution. Then, all the particles are sorted according to their fitness.

Archive Pool: A separated naECP (archive pool) is created. Then, the best ECPs will be saved and updated for each iteration based on the size of the archive.

Selection: This is the most crucial step in ECPO that will determine the performance of the optimization process. The number of ECPs in interaction (nECPi) are arbitrarily selected from the population generated. The ECPs selected are then sorted from the best to the worst and done interaction.

Interactions: The selected nECPi article then interact among themselves based on the one of three strategies which are detailed as follows.

Strategy 1: Only the best ECP gets interacts with another ECP. This strategy will generate (n-1) new ECPs called ECPnew1 and ECPnew2 in which n is the number of nECPi selected.

Strategy 2: The ECPbest does not interact with all of the remaining ECPs. It is instead associated with selected ones. All the three ECPs will interact with other ECPs, except ECPbest and create n number of ECPnew.

Strategy 3: Strategy one and two are combined in this strategy. The interaction product is called the new population of ECPs (newECP) which have sizes similar to the original population size for all numbers of the nECPi chosen or the different chosen interaction strategies.

Checking the Bounds: In this step, any ECPnew created in the interaction step will be checked. If any article is found outside the search space, it will be bounced back to the sign boundary.

Diversification: In this step, the new ECP population will be diversified using a specific probability called the probability of diversification (Pd). Then, the information from the newECP and achievedECP will be collected by the diversity operator.

Population update: In this stage, the new population from rank 1 to nECP is modified and stored in the archive pool.

B. IMPROVED ELECTRIC CHARGED PARTICLES OPTIMIZATION

To reduce the computation time, the type of variable is optimized based on the application. In this WFLO application, two types of variables will be optimized. The first variable is the location of the wind turbine, and the second variable is the height. A binary version of the variable will be implemented for the location, while for the height of the wind turbine, the continuous version will be adopted.

For the initial form of the ECPO algorithm, each type of variable will be optimized separately and will consume twice the time if two types of variables are optimized. However, in this study, these two variables will be set as a bundle of variables optimized simultaneously. Therefore, an improved version of ECPO was developed.

To design the improved version of ECPO, the ECP is created to combine two variables. The first ECP is set from [0,1] and the second ECP is set in the minimum and maximum height of the wind turbine. Then, these two variables are bundled into one package of variables that will be optimized using the algorithm. After identifying the best package of variables, the bundled variable is separated again to evaluate the objective function. This improved ECPO algorithm will

reduce time, while consuming half the time compared to the standard version of the ECPO algorithm.

V. APPLICATION AND RESULTS

A. CASE STUDY

Four WFLO problems are proposed in this study that can be detailed as follows.

Case 1. The design problem is posed to find the location of the wind turbine in a selected area where the hub height of a wind turbine is fixed. The maximum number of wind turbines is the total number of the grid. For convenience, this case is also called 2D WFLO with an optimal number of WTs.

Case 2. The design problem is set to find the location of wind turbines in the selected area where 30 is set as the number of the WTs which are located in the wind farm. The hub height of the wind turbine is set to constant. For convenience, this case is also called 2D WFLO with a fix number WTs.

Case 3. The design problem is posed to find the location and hub height of wind turbines where the maximum number of wind turbines is the total number of grids. For convenience, this case is called 3D WFLO with optimal number of WTs

Case 4. The design problem is set to find the location and hub height of wind turbines in the selected area where 30 is set as the number of the WTs which are located in the wind farm. For convenience, this case is called 3D WFLO with fixed number of WTs.

B. INVESTIGATED SCENARIO

This study will investigate four sites with the same large but different shapes. All the sites are assumed to have the same wind distribution and obstacles. The areas in the investigated sites are:

Sites A: 2000 m × 2000 m, Sites B: 1000 m × 4000 m, Sites C: 800 m × 5000 m, Sites D: 400 m × 10000 m

Site A which is the square site is the standard site that used by many previous researchers to validate and compare the result of different algorithm WFLO. This type of site was first developed by Mosseti [3] and followed by the next researcher to find a better algorithm to solve the WFLO problem. This site has 100 grids where each grid has a size of 200 m × 200 m. Site B, C, and D which are the rectangular sites have the same large and number of grids but different widths and lengths compare to site A.

All the case studies will be implemented to site A to compare the LCOE, while for the three remaining sites, only 3D WFLO (case 3 and 4) will be implemented. By comparing the LCOE and power production, the effect of the shape of the area will be investigated. The obstacles for all the sites are the same. Moreover, the wind distribution is also set to be the same for all the scenarios.

C. RESULT AND DISCUSSION

All the investigated scenarios are optimized by using three different strategies of ECPO. To validate the proposed

algorithm, three popular metaheuristic algorithms (BPSO, ABC, and GA) are also simultaneously implemented to solve the scenarios with the same parameter involved. The result is then compared to assess the best algorithm among them. Six algorithms are simultaneously simulated using parallel computation to solve 4 different cases of wind farm. The experiment was run on an i9-11900F Intel processor at 2.50 GHz with 32 GB RAM.

The first site to be elaborately investigated is site A with a 2 km × 2 km area. The six algorithms were run simultaneously to optimize four case studies that detailed in previous section. In this model site, 100 grids are formed and the size of each grid is 200 m × 200 m. For cases 1 and 3, the maximum number of WTs is 100, while for case 2 and 4, the number of WTs is set to 30. The result for all the case studies represented by LCOE as the objective function are tabulated in Table 1.

TABLE 1. LCOE obtained for the investigated scenarios using different algorithms.

| Cased Study | | | | |
|--------------------------|---------|---------|---------|---------|
| LCOE($\times 10^{-4}$) | Case 1 | Case 2 | case 3 | case 4 |
| ECPO1 | 21,8605 | 43,2833 | 20,4616 | 42,0441 |
| ECPO2 | 21,7636 | 43,2833 | 20,2972 | 42,1036 |
| ECPO3 | 21,8142 | 43,2833 | 20,6414 | 42,0277 |
| BPSO | 25,5592 | 42,0764 | 22,1392 | 41,679 |
| ABC | 25,6342 | 42,22 | 23,2466 | 42,1323 |
| GA | 21,8259 | 42,1339 | 20,6448 | 42,1094 |

Table 1 shows the comparison of the best LCOE achieved in six different algorithms implemented for four case studies. ECPO with all types of strategies yields better results as compared to the three algorithms: BPSO, GA, and ABC for cases 1 and 3. Moreover, for cases 2 and 4, BPSO achieved better performance than ECPO, but ECPO is better than GA and ABC in case 4. Cases 1 and 3 compare 2D and 3D in the case of an optimal number of WTs, where cases 2 and 4 limit the number of WTs. For the best result of ECPO, the 3D WFLO can improve the LCOE by 7% for an optimal number of WTs and 3% for a fixed number of WT.

The LCOE of a wind farm depends on the power produced by the wind farm and the number of wind turbines. So these two factors can also be used to evaluate the performance of the optimization algorithm to find the best wind farm layout. Table 2 shows the power produced by each algorithm and case study. For cases 1 and 3, ECPO achieves the highest power produced compared to the three other algorithms. On the

TABLE 2. Power produced for the investigated scenarios using different algorithms.

| Cased Study | | | | |
|-------------|--------|--------|--------|--------|
| Power (MW) | Case 1 | Case 2 | case 3 | case 4 |
| ECPO1 | 0,4113 | 0,1778 | 0,4736 | 0,2031 |
| ECPO2 | 0,4151 | 0,1778 | 0,4822 | 0,2017 |
| ECPO3 | 0,4131 | 0,1778 | 0,4715 | 0,2035 |
| BPSO | 0,3213 | 0,2024 | 0,4474 | 0,212 |
| ABC | 0,333 | 0,1991 | 0,4265 | 0,2011 |
| GA | 0,4126 | 0,201 | 0,4665 | 0,2016 |

other hand, for cases 2 and 4, BPSO produces the highest power in comparison to all the algorithms, but the ECPO is better than the ABC and GA algorithms in these case studies. The total number of wind turbines in the wind farm is shown in Table 3. For the optimal number of wind turbines (case 1 and 3), ECPO with all strategies yields the highest number of wind turbines compared to the other algorithms. A large number of wind turbines will give the highest power produced, thus producing the lower LCOE compared to the other algorithms as shown in Figure 3. However, in the case of a fixed number of wind turbines (case 2 and case 4), the power produced by the wind farm using the ECPO algorithm is just better to compare with ABC and GA algorithm, PSO becoming the highest one, thus make PSO have the lowest LCOE followed by ECPO algorithm as shown in Figure 4

TABLE 3. Number of wind turbines for the investigated scenarios using different algorithms.

| Cased Study | | | | |
|-------------|--------|--------|--------|--------|
| n | Case 1 | Case 2 | case 3 | case 4 |
| ECPO1 | 89 | 30 | 89 | 30 |
| ECPO2 | 89 | 30 | 89 | 30 |
| ECPO3 | 89 | 30 | 86 | 30 |
| BPSO | 59 | 30 | 72 | 30 |
| ABC | 65 | 30 | 66 | 30 |
| GA | 89 | 30 | 88 | 30 |

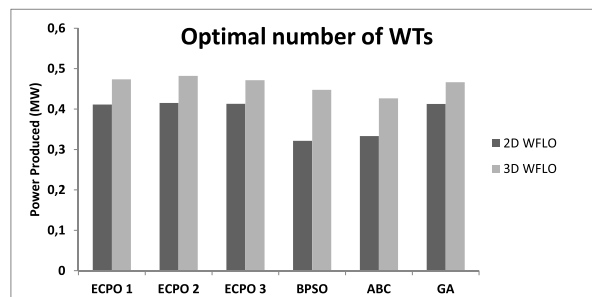


FIGURE 3. Power produced comparison between different algorithm in the case of optimal number of WTs.

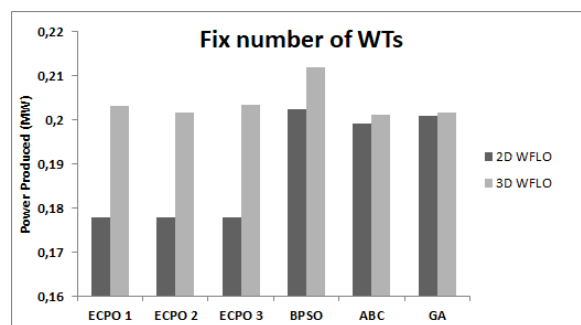


FIGURE 4. Power produced comparison between different algorithm in the case of fix number of WTs.

The wake effect reduces the power produced by the wind farm and thus reduces the efficiency. By using an optimization algorithm, the reducing power due to the wake effect can

be minimized by optimizing the wind turbine's location. The increasing number of wind turbines reduces the efficiency of a wind farm by only optimizing the WTs does not prevent the reduction of efficiency of the wind farm. So, another factor should be added as the control variable to maintain the wind farm's efficiency. In the present research, the hub height of wind turbine is the variable besides the location that be optimized, and the effect of the number of the wind turbine on the efficiency of a wind farm for both scenarios, which are only location (2D WFLO) and both location and hub height (3D WFLO) optimized is shown in Figure 5. The blue and red lines show the 3D and 2D WFLO, respectively. From the trend, it proves that the 3D WFLO can maintain the efficiency of the wind farm in the value around 90 – 95%, while for 2D WFLO, the efficiency is reducing until the value of 70% when the number of wind turbines near the maximum number of wind turbines in the wind farm. Thus, the efficiency affects the LCOE of the wind farm. The higher the efficiency yield, the lower LCOE as the power produced by the wind farm increases. The overall trend of LCOE in the various number of wind turbines is shown in Figure 6. The figure shows that 3D WFLO has a lower LCOE than 2D WFLO.

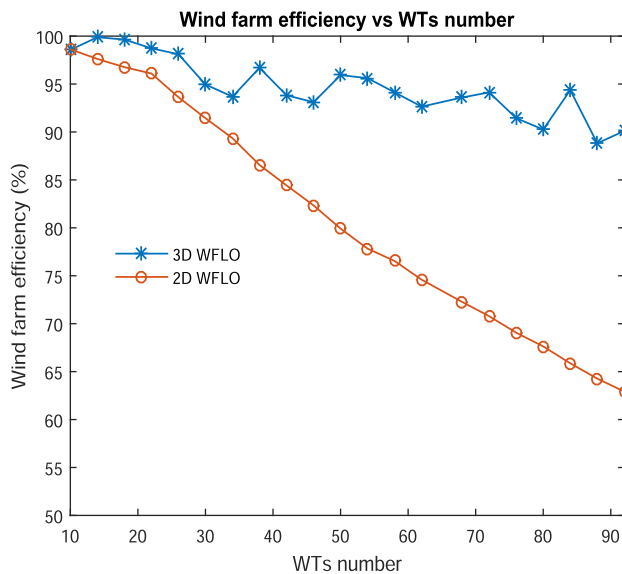


FIGURE 5. Efficiency pattern for different maximum number of WTs.

The performance of the optimization algorithm to find the best solution can be assessed by tracking the algorithm's search history. The first indicator that can be evaluated is the simulation time required to find the best objective function. The second indicator is the search pattern to find if the algorithm is either trapped in the local optima or successful in finding the optimum global value. Figure 7 shows the search histories for all algorithms in the case of 3D WFLO with the optimal number of wind turbines. All ECPO strategies show the fastest simulation time to find the global optimum of LCOE compared to the other algorithms. Moreover, the ECPOs also yield the most minimum value of LCOE. For the fixed number of 3D WFLO, ECPO is just better than

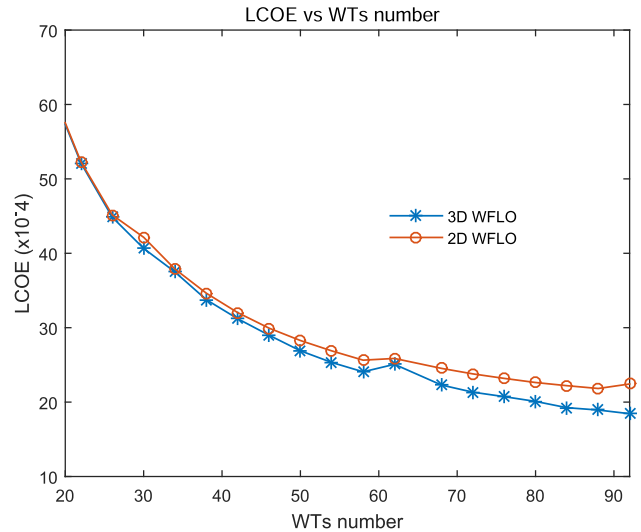


FIGURE 6. LCOE pattern for different maximum number of WTs.

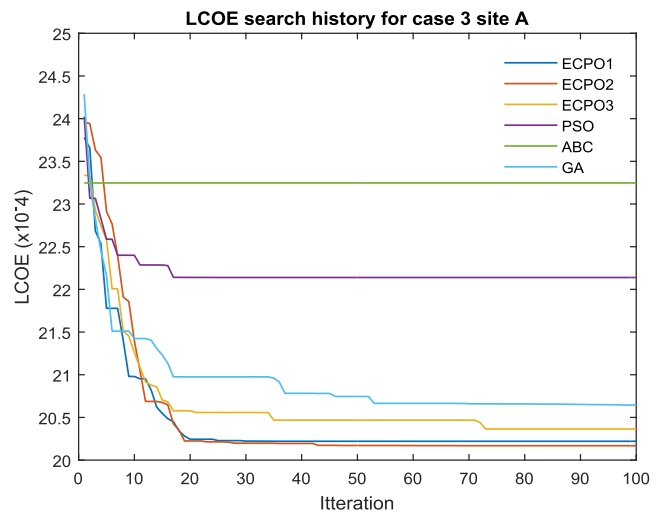


FIGURE 7. LCOE search history 3D WFLO for the optimal number of WTs - Site A.

GA and ABC, as shown in Figure 8. BPSO achieves better performance than ECPO in terms of the value of objective function and simulation time.

The best layout of the 3D wind farm for optimal (case 3) and fix number (Case 4) of WTs are shown in Figure 9 and Figure 10, respectively. The red rectangle indicates the WTs position, which is the center of each grid. For case 3, The 2 km × 2 km wind farm area consists of 72 Wind turbines scattered in all positions of the wind farm. The different pattern is shown for case 4, where 30 WTs fulfills the edge and the center of the wind farm. The pattern was formed due to the direction of the wind farm that is in the horizontal line of the wind farm so that the optimization process would locate the WTs in the longest possible distance. For case 4, in which the number of WTs is limited by only 30, the longest possible distance is half of the width of the wind farm by which each row of the wind farm in vertical line can load 10 WTs

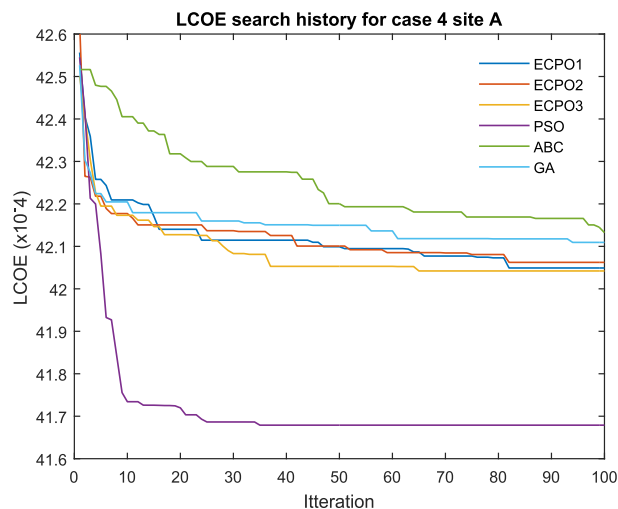


FIGURE 8. LCOE search history 3D WFLO for a fixed number of WTs - Site A.

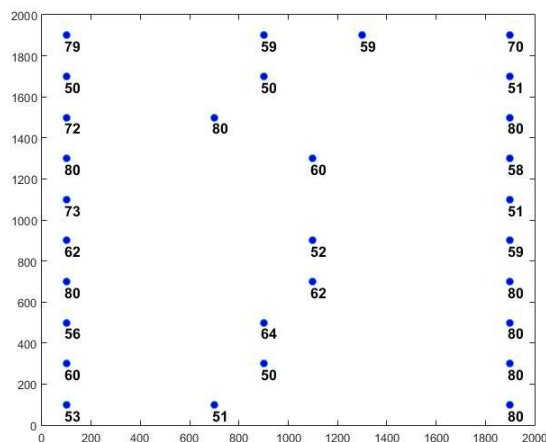


FIGURE 10. Best layout of 3D WFLO by a fixed number of WTs.

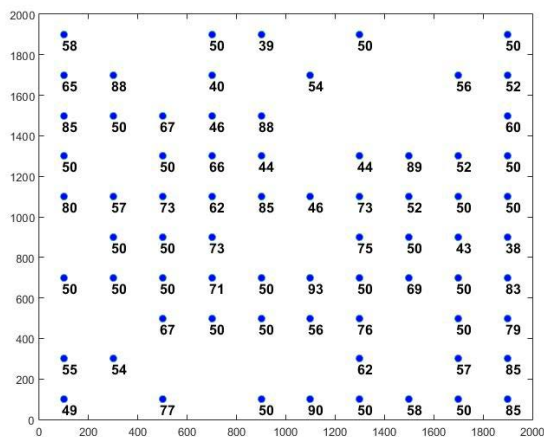


FIGURE 9. Best layout of 3D WFLO by the optimal number of WTs.

each. Figures 9 and 10 also show the height distribution of WTs. The hub height is set between 50 – 80 m. The variable of hub height maintains the efficiency of the wind farm by minimizing the overlapping area of the wake effect. The result show in which the number of WTs is limiting, the variance of hub height is lower because the distance of each WTs is higher.

After the initial site of the wind farm with 2 km × 2km size optimized, various shapes of the wind farm are evaluated. In this research, 3 different rectangle shapes with the same large are optimized to evaluate the effect of the shape of the wind farm on the layout and the objective function. The sites' size is 1 km × 4 km, 800 m × 5 km, and 400 m × 10 km. All the shapes have the same grid size, 200 m × 200 m. All the sites are optimized using case 3 and case 4, which are explained in the previous section. The best-optimized layout is shown in Figure 13 and Figures 14. Compared with the

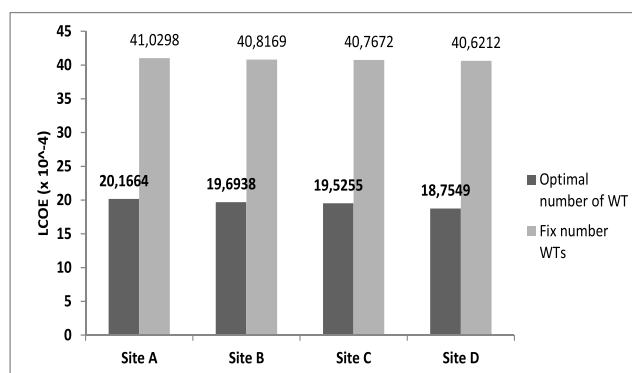


FIGURE 11. Comparison of LCOE for different shape of wind farm.

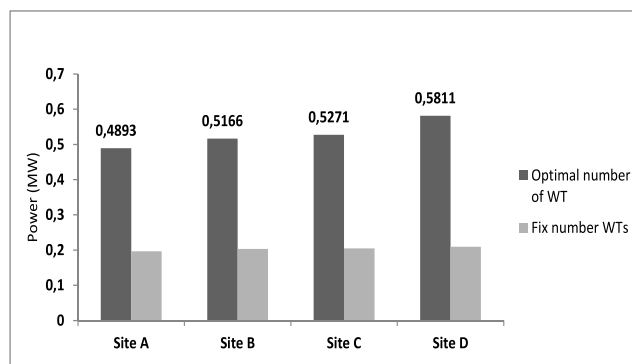


FIGURE 12. Comparison of Power produced for different shape of wind farm.

three shapes of the layout, the smallest width shapes consist of the most WTs.

The comparison of LCOE for different shapes of wind farms is shown in Figure 11 and Figure 12. Site A is the initial shape of a wind farm with a square shape, while sites B, C, and D are rectangular shapes of wind farms with the same large area. Site D has the lowest width with only 400 m

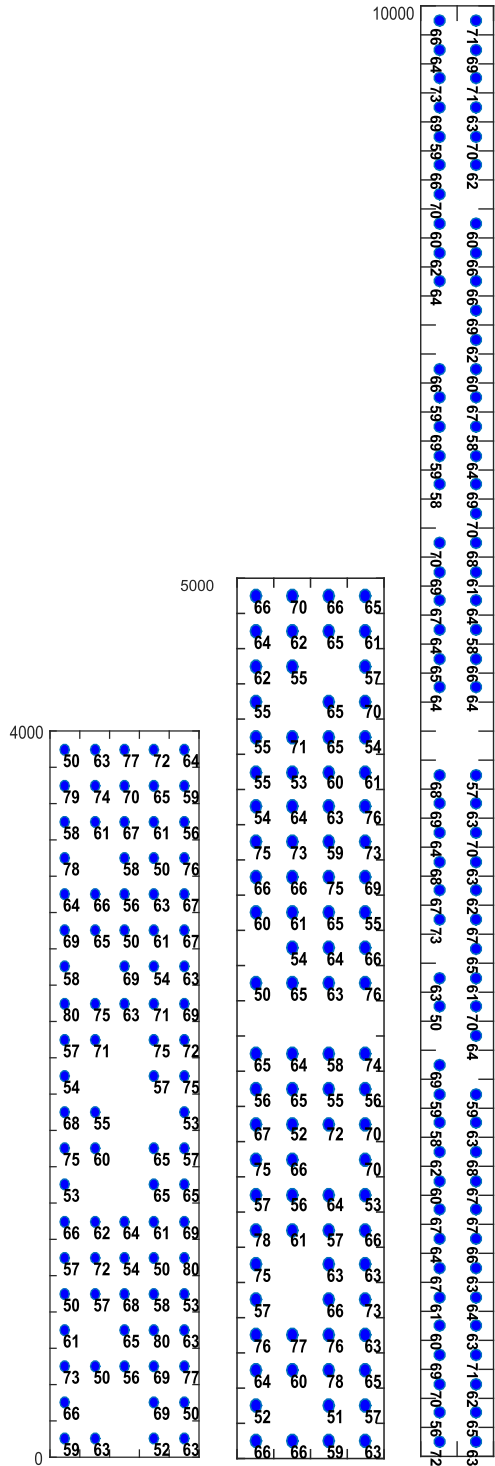


FIGURE 13. 3D WFLO for various layout shape with optimal number WT.

width, while site B and site C have 800 m and 1 km width. The result shows that site D with the lowest width achieves the best LCOE compared to the other shapes. The result is suitable with the number of WTs where shape D consists of the most number of WTs.

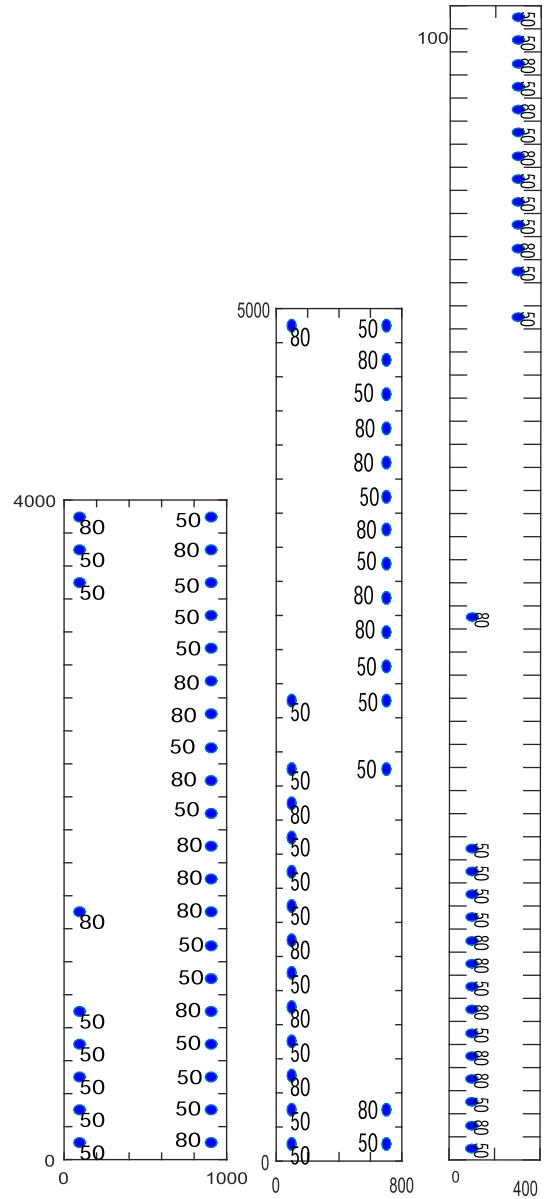


FIGURE 14. 3D WFLO for various layout shape with fix number WT.

TABLE 4. LCOE Comparison of 3D WFLO by using different sites in the case of an optimal number of WTs.

| Algorithm | LCOE | | | |
|-----------|---------|---------|---------|---------|
| | Site A | Site B | Site C | Site D |
| ECPO1 | 20,6753 | 19,9408 | 20,2293 | 19,0254 |
| ECPO2 | 20,1664 | 19,6938 | 19,5255 | 18,7549 |
| ECPO3 | 20,3215 | 20,4089 | 19,6167 | 18,8535 |
| BPSO | 21,799 | 22,5516 | 23,6616 | 21,5411 |
| ABC | 23,9598 | 23,7539 | 23,7557 | 23,4854 |
| GA | 20,6489 | 20,1326 | 19,6342 | 18,9646 |

The comparison of LCOE for all sites, including 1 square and 3 rectangular sites in 2 different scenarios and 6 different algorithms, is shown in Table 4 and Table 5. For case 3 with optimal number of WTs, ECPO with strategy 2 achieves the lowest LCOE compared to the other algorithm for all shapes.

TABLE 5. LCOE Comparison of 3D WFLO by using different sites in the case of a fixed number of WTs.

| Algorithm | LCOE | | | |
|-----------|---------|---------|---------|---------|
| | Site A | Site B | Site C | Site D |
| ECPO1 | 41,0007 | 40,8467 | 40,7705 | 40,6204 |
| ECPO2 | 41,0298 | 40,8169 | 40,7672 | 40,6212 |
| ECPO3 | 41,0077 | 40,8275 | 40,7785 | 40,6232 |
| BPSO | 41,0548 | 40,6352 | 40,6046 | 40,5668 |
| ABC | 41,0827 | 40,9215 | 40,8498 | 40,6124 |
| GA | 41,0285 | 40,8399 | 40,7739 | 40,621 |

Moreover, in case 4 with a fixed number of WTs, BPSO achieves better LCOE than ECPO, but ECPO is still better than the ABC and GA algorithm. Furthermore, the results also confirm that for all algorithms implemented, reducing the width of the wind farm decreases the LCOE and increases the number of WTs.

VI. CONCLUSION

This paper proposes an efficient algorithm using an improved version of the ECPO algorithm to solve the 3D WFLO layout optimization problem. Wind turbine position and hub height are two variables control to minimize the Levelized cost of energy (LCOE) while considering some conflicting constraints: the distance between the turbines, the minimum and maximum hub height, and the wind turbine locations. The ECPO algorithm is implemented in 16 different scenarios based on four case studies and four different shapes of the wind farm. Three popular metaheuristic algorithms are simultaneously implemented to solve all the scenarios to validate the result. The result is then compared to find the better algorithm. Furthermore, different shapes of wind farms with the same large were compared to evaluate the effect of the shapes on the LCOE of the wind farm.

The result shows that by implementing the 3D WFLO, the LCOE of the wind farm increases by 7% in the case of the optimal number of WTs and 3% in the case of a fixed number of the wind turbine. This result is consistent by using all types of algorithms while ECPO achieved the best performance in terms of the LCOE in the case of an optimal number of WTs. Moreover, the performance of LCOE can also increase by changing the shape of the wind farm. The result shows that the wind farm's rectangular shape has better LCOE than a square shape wind farm. The LCOE of the wind farm in most rectangular shapes reduces by 8% compared with the square shape wind farm.

Considering future work, a multiobjective optimization problem can be implemented to minimize other objective functions such as noise level and the total area used. Moreover, the different terrains can be set as another constraint for the WFLO.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia for funding this research work through the project number IFPRC-190-135-2020 and King Abdulaziz University, DSR, Jeddah, Saudi Arabia.

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