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Applying Marine Predators Algorithm for Optimizing the Layout of Wind Turbines

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Abstract- The extracted power from wind is clean, plentiful, and completely renewable. All over the world, researchers keep looking for the best layouts of wind parks to maximize captured energy. To design wind farms suitably, forecast their performance, and understand the strain loads of wind turbines, there is a persistent need to catch a perfect wake model. Wind turbine wakes are one of the most vital factors in the meteorology of wind power due to reducing the power production and the necessity to raise the downstream capacity of wind turbines. This study is divided into two main aspects: firstly, enhancing the optimal layout for the wind turbines at a farm using Marine Predators Algorithm (MPA). The Jensen wake model is applied to get the extracted power for each turbine, which is one of the mutual analytic models used to reach the optimized layout. By comparing the performance of the proposed algorithm with the previous studies achieved by several techniques, the obtained results revealed that the MPA achieves promising results. Secondly, the proposed algorithm is applied for four sites in Egypt as the fraction of occurrence for the selected locations has been adequately calculated using wind speed over five years.

Keywords- Jensen wake model, Marine Predators Algorithm (MPA), Optimal layout of wind turbines, Wind farm.

1. Introduction

There are many ways to generate electricity like nuclear reactors, thermal power plants, and renewable energy sources. Nowadays, renewable energy is the most vital source of electricity generation that plays a significant role in avoiding environmental impacts all over the world [1]. Wind energy is one of the fastest developing renewable resources, so a rapid growth in energy production from wind parks has occurred worldwide in the last years [2]- [3].

Wind turbines should be appropriately distributed in a farm to increase the production of energy output and reduce the cost of operation, installation, and maintenance. Because of turbine-to-turbine interaction and wind speed reduction in the wake, large amounts of wind energy are missing in parks. Therefore, wind farm optimization is essential to reach the maximum possible power from the wind; the other meaning of wind farm optimization is to build up more wind turbines in a limited location [4]. The traditional way of placing wind turbines in a park, illustrated in Fig. 1, is achieved according to Patel's rule; 8–12 rotor diameters in rows in the same wind direction and 3–5 rotor diameters in columns in the crosswind direction [5].

Many researchers have studied the distribution of wind turbines and planned to increase annual energy production besides decreasing the cost. Several optimization methods were applied in previous studies to get the optimal layout of wind farms. The first study was in 1994 by Mosseti [6]. It proposed to mix a Weather Research and Forecasting mesoscale model with the genetic algorithm (GA). The GA is also used in [4] to obtain the optimal location for the wind turbines in three cases of wind speed and direction. Monte Carlo simulation algorithm was applied by [7] to optimize the wind turbine location in a farm, and the achieved results were better than those [6] and [4]. Also, a modified code of GA is suggested in [8] to solve the location of wind turbines inside the wind park for three cases. It is compared with [4] and the results in the three cases indicated that [8] has given better results than [4]. The particle swarm optimization (PSO) method was utilized in [9] with more improved results than the earlier studies. In [10], an evolutive algorithm was introduced for wind farm layout optimization based on wind farm cost using the primary investment and the annual net cash flow present value. The lazy greedy algorithm is also utilized in [11] for placing wind turbines in a wind farm. The results showed that it reaches a superior solution in less time. The binary PSO with time-varying acceleration coefficients is also applied in [12] to get the optimal location of wind turbines.

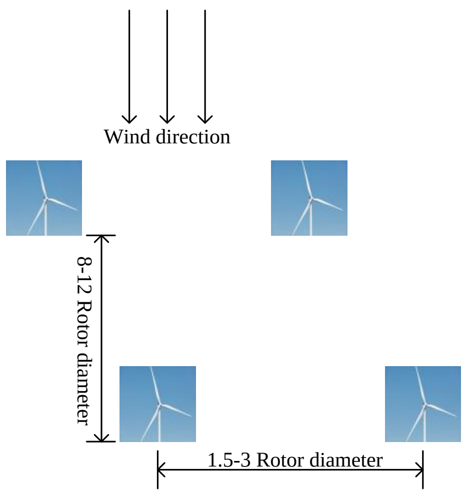


Fig. 1. Spacing between wind turbines in the traditional layout of a wind farm.

Optimizing the dimensions for wind farm space to reduce the cost per power is also presented in [13]. The lightning search algorithm is applied in [1] while minimizing the overall area of the wind park, the annual energy production cost, and the losses of the wake effect. Another algorithm, called the adaptive differential evolution algorithm, is utilized in [14] as its main advantage is that it has automatic adjustment for the parameters in the crossover and mutation to reach the optimal design. Biogeographical-based optimization is also applied as an evolutionary algorithm and has generated excellent results for different benchmarks [15].

Different wake models have been developed from simple to complex models requiring extensive calculations. Selecting the wake model is not an easy mission because of the advantages and drawbacks of each model. Larsen, Frandsen, Jensen, and Jensen–Gaussian models are the most common analytical model types [16]. GA is applied in [17] using a model for linear wake decay. Using the Jensen wake model, the optimal wind farm layout has been achieved by the binary real-coded GA in [18] for regular and irregular landscapes. Four cases considering multiple wake effects using the Jensen wake model are discussed in [19], where a model of nonlinear mathematics for wind turbines' layout optimization has been introduced. A mixed discrete PSO algorithm is applied in [20] to solve the problem of uniform and non-uniform park layouts with different sizes, various wake models, and wind conditions.

In 2020, Marine Predators Algorithm (MPA) was introduced [21], and used for two problems design. One problem was the ventilation areas, and the other was optimizing building energy. The results indicated that MPA achieves high performance compared with the previous algorithms. In [22], a scheme that depends on the MPA is developed to determine the optimal parameters of a photovoltaic system. The results of several carried-out tests have presented a better performance of this algorithm compared with some present algorithms for the photovoltaic model. To improve the voltage profile and reduce the losses in the power system, MPA is applied to optimize the location, size, and parameters of the fractional-order capacitor in the power system [23]. The achieved results ensured that MPA presents strong and promising performance.

Because of the encouraging results of MPA indicated in the previous studies, MPA is selected for optimizing wind farm layout in this paper. The Jensen wake model will be applied with the model for the sum of squares for the proposed approach using MATLAB software. The proposed method will obtain the optimum locations of wind turbines for maximum production capacity while limiting the number of turbines installed. Besides, it will be compared with several algorithms applied in previous studies. The MPA presented better results compared to other algorithms. Therefore, the proposed approach will be investigated for four real locations in Egypt that have not been studied in the literature.

Finally, the rest of the paper is presented in five main consecutive tracks. The first one is the methodology of the Jensen wake model. After that, the problem formulation and MPA methodology will be fully discussed. The third one will present the analytical procedure of the model used in the optimization. The fourth one will discuss the obtained results for using the proposed algorithm compared with some previous studies. Lastly, MPA is applied to optimize the wind farm layout in four different sites in Egypt.

2. Applied Methodology

This section clarifies in detail the procedure to reach the optimal layout for the wind turbines location at any wind park in three main issues:

- Firstly, the applied mathematical wake model, the Jensen wake model, is fully described.
- Secondly, the problem formulation is defined to get the optimum wind farm layout with minimum wake interaction between wind turbines.
- Thirdly, the procedure to apply the MPA technique to get the optimum wind farm layout is briefly displayed.

2.1. Jensen Wake Modeling

The wake effect produced by the wind turbines is the main factor in reducing the total energy from a wind farm. So, the wake effects should be considered by an adequate mathematical wake model as the accurate estimation of the produced power in any wind farm is directly affected by the prediction of wake losses. Based on the previous studies [18], [24], the Jensen wake model can be considered one of the most straightforward wake models and the most-popular mathematical models due to the simplification of wind velocity deficit calculation [4]. Accordingly, the Jensen wake model, shown in Fig. 2 [18], will be the wake model applied in this paper.

The idea of the Jensen wake model depends on the distance behind the wind turbine rotor [19]. By the Jensen wake model, the wind speed at the downstream turbine (Vi) affected by the wake; is estimated using Equation (1) [25]. Where; V is the undisturbed wind speed, A denotes the factor of axial induction, WE specifies the wake enlargement, $R1$ designates the rotor radius at the downstream wind turbine, and finally, X is the distance between the upstream wind turbine and the downstream wind turbine.

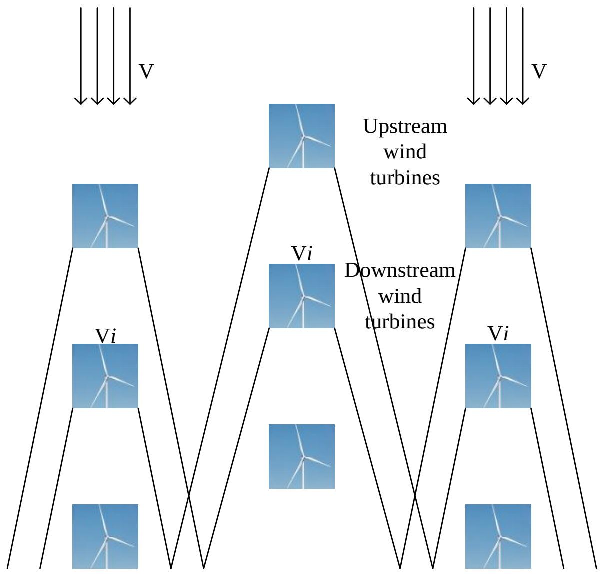


Fig. 2. Jensen wake model.

$$Vi = V\left[1 - 2A\left(\frac{R1}{R1 + WE \times X}\right)^2\right] \quad (1)$$

Where:

- Equation (2) is applied to get the factor of axial induction (A) for a given thrust coefficient (CT).
- To get the wake enlargement (WE); Equation (3) is applied, where z indicates the hub height while zo designates the surface roughness.
- Equation (4) is applied to get the rotor radius at the downstream wind turbine ($R1$), by known $R0$, which is the rotor radius of the upstream wind turbine [18].

$$A = 0.5 - 0.5\sqrt{1 - CT} \quad (2)$$

$$WE = \frac{0.5}{\ln(z/zo)} \quad (3)$$

$$R1 = R0\sqrt{\frac{1 - A}{1 - 2A}} \quad (4)$$

Equation (5) estimates the wind speed Vi at turbine i; located in multiple wakes from a number n of upstream wind turbines [8]. The sum of squares method is applied by summing up the velocity deficit squares of all upstream wakes. In Equation (5), Vij indicates the wind speed at turbine i because of the wake from a turbine j, which means that when i =1, $V1 = V$. Hence, the presence of Vj ensures the recursive function of the model.

$$Vi = V \times (\,1 - \sqrt{\sum_{j=1}^{n}\left(1 - \frac{Vij}{Vj}\right)^2}\,) \quad (5)$$

2.2. Problem Formulation

The power of a wind turbine is achieved by the relation $P = 0.3 \times Vi^3$ kW, and consequently; the total power produced from the wind park ($Ptot$) will be obtained using Equation (6), where N designates the number of wind turbines installed in the farm [4], [8], [18], [19].

$$Ptot = \sum_{i=1}^{N} 0.3 \times Vi^3 \times fraction\ of\ occurrence \quad (6)$$

The cost is another parameter that affects the optimization of the wind farm layout. According to previous studies, the main factor that should be considered to calculate the annual wind farm cost is the total number of wind turbines. The study in [6] has assumed that the cost per year for any single wind turbine is one, while the total cost is decreased by 1/3 if there are many wind turbines. Consequently, the total cost per year for a wind farm can be estimated by Equation (7) [4], [8], [18], [19].

$$COST = N\left(\frac{2}{3} + \frac{1}{3}e^{0.00147N^2}\right) \quad (7)$$

Finally, optimizing the wind farm layout depends on the objective function in Equation (8), which minimizes the cost while maximizing the total power produced:

$$Objective\ function = Minimizing(\frac{COST}{Ptot}) \quad (8)$$

2.3. Marine Predators Algorithm

For this paper, Marine Predators Algorithm (MPA) is applied to optimize the wind farm layout. MPA is inspired by nature. Till now, it has only been implemented for limited engineering applications, one of them is the ventilation areas, and the other is the energy performance of a building. The procedure to implement the MPA technique as an efficient method for metaheuristic optimization is summarized in the following three main issues [21].

2.3.1 Formulation procedure

In this algorithm, both the predators and prey are named search agents. The predator is searching for prey while the prey is searching for food. The first solution is equal spread in the search space like different population-based methods; it is the first experiment as expressed in Equation (9).

$$x_0 = x_1 + ran(x_2 - x_1) \quad (9)$$

Where x_1 designates the lower bound, x_2 designates the upper bound, and ran specifies a random value between 0 and 1.

Then, the most suitable solution is filtered as the superior predator to build a matrix named Elite (E). The arrays of the Elite matrix observe the search to find the prey according to the information on the prey location [26].

$$E = [Y_{1,1}^V\ Y_{1,2}^V\ Y_{1,D}^V; \dots; Y_{Nag,1}^V Y_{Nag,2}^V Y_{Nag,D}^V] \quad (10)$$

Where Nag describes the number of search agents, D is the size of the dimensions, and Y^V refers to the vector of the top predators to build up the E matrix.

Upon any iteration, the Elite matrix is updated with better predators. Then, the $Prey$ matrix is arranged in the same manner as the dimension of the E matrix; so the positions of predators are updated by the following equation:

$$Prey = [Y_{1,1}Y_{1,2}Y_{1,D}; \dots.; Y_{Nag,1}Y_{Nag,2}Y_{Nag,D}] \quad (11)$$

Where $Y_{I,J}$ is the J-th dimension for the I-th $Prey$, and thus the optimization process depends on the matrices E and $Prey$.

2.3.2 Optimizing procedure

The second main issue is for the MPA optimizing procedure, which is divided into three phases taking into consideration the variance of the velocity ratio and the imitating of the whole life of the prey and predator [26]:

- Phase 1- when the movement of the prey is faster than the predator (high-speed ratio), where $Iter < 1/3\ Max\_Iter$:

$$\overrightarrow{Step_{\chi}} = \overrightarrow{Rand_{\beta}} \otimes (\overrightarrow{E_{\chi}} - \overrightarrow{Rand_{\beta}} \otimes \overrightarrow{Prey_{\chi}}) \quad x = 1, \dots Nag \quad (12)$$

$$\overrightarrow{Prey_{\chi}} = \overrightarrow{Prey_{\chi}} + (Y.\overrightarrow{Ran} \otimes \overrightarrow{Step_{\chi}}) \quad (13)$$

Where $\overrightarrow{Rand_\beta}$ is the vector consisting of a random number that showed at the Brownian movement, Y is a fixed number (0.5), $\overrightarrow{Ran}$ means the vector of a constant random number from [0, 1], $Iter$ represents the current iteration, Max_Iter represents the maximum number of iterations, and finally, the symbol $\otimes$ displays the entry wise multiplications.

- Phase 2- when the movement of the predator and the prey is roughly the same speed (the speed ratio is unity), where $1/3\, Max\_Iter < Iter < 2/3\, Max\_Iter$:
  - For the first half of the population, it will be expressed by:

$$\overrightarrow{Step_\chi} = \overrightarrow{Rand_v} \otimes \left(\overrightarrow{E_\chi} - \overrightarrow{Rand_v} \otimes \overrightarrow{Prey_\chi}\right) \quad x = 1, \dots Nag/2 \tag{14}$$

After that, Equation (13) is applied to update the prey matrix.

  - For the second half of the population, it will be expressed by:

$$\overrightarrow{Step_\chi} = \overrightarrow{Rand_\beta} \otimes \left(\overrightarrow{E_\chi} \otimes \overrightarrow{Rand_\beta} - \overrightarrow{Prey_\chi}\right) \quad x = Nag/2, \dots Nag \tag{15}$$

$$\overrightarrow{Prey_\chi} = \overrightarrow{E_\chi} + \left(Y.CO \otimes \overrightarrow{Step_\chi}\right) \tag{16}$$

$$CO = \left(1 - \frac{Iter}{Max\_Iter}\right)^{\frac{2\times Iter}{Max\_Iter}} \tag{17}$$

Where $\overrightarrow{Rand_v}$ is the vector that contains the random number according to Levy motion and CO is the parameter that controls the step size of the predator motion.

- Phase 3- when the movement of the predator is faster than the prey (low-speed ratio), where $Iter > 2/3\, Max\_Iter$:

$$\overrightarrow{Step_\chi} = \overrightarrow{Rand_v} \otimes \left(\overrightarrow{E_\chi} \otimes \overrightarrow{Rand_v} - \overrightarrow{Prey_\chi}\right) \quad x = 1, \dots Nag \tag{18}$$

Then, the prey matrix is updated using Equation (16).

The abovementioned three phases are determined by the rules that govern the nature of prey and predator movement. According to the rules, the percentage of the Levy movement and Brownian movement is the same throughout the predator's lifetime. In the first phase, the movement of the predators is zero; but in the second phase, the movement of predators is Brownian, and in the third phase, it is presented by the Levy technique. This procedure has also occurred in the prey movement as the prey is considered another predator.

2.3.3 The memory of marine predators

The third main issue for the MPA procedure is the memory of marine predators, which is very good to remember the place that has the best foraging. The model is estimated for fitness to upgrade the Elite after upgrading the procedure of the Fish Aggregating Devices (FAD) effect. So, the final point for the MPA procedure is the environmental matters affected by the behavior of predators like FAD effects and eddy formation. It is considered that FAD is a local optimum, and thus it made a blockade at some points in the search space. The long jump at the simulation is deliberated to bypass the recession that occurs at the local optima. For every step in the optimization technique, the fitness of the current iteration is compared with the previous iteration to replace the solution with a more fitted one. This procedure is used to improve the quality of solutions.

Finally, the procedures to apply the MPA technique are summarized in the flowchart displayed in Fig. 3.

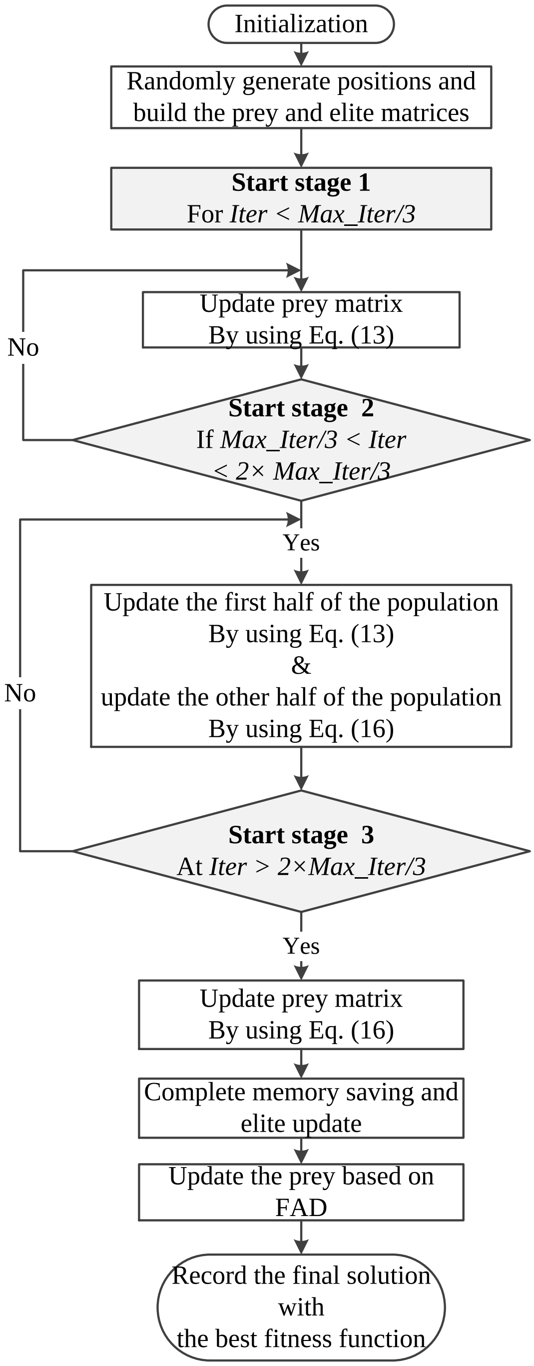


Fig. 3. Implementation procedures for MPA.

3. Analytical Model and Achieved Results

Most of the published papers studied the layout of wind farms with regular square land space as in [4], [6], [8], [18], where the side length of the farm is assumed 2 km; and divided into 100 squares. Each square has a side length of five rotor diameters of the wind turbine (5D), where the rotor diameter of the wind turbine equals 40 m. These 100 squares indicate 100 possible wind turbine locations and are used as the computational domain. Consequently, it will be like a matrix 10×10, as shown in Fig. 4.

These previous studies have considered some other parameters for the model. The rotor diameter (R) is 40 m, the hub height (z) is 60 m, the thrust coefficient (CT) is 0.88, the surface roughness (zo) is 0.3, and finally, the power curve is displayed in Fig. 5. Accordingly, these same parameters are used in this paper to reach the same baseline for a fair comparison with other algorithms implemented for wind farm layout optimization.

3.1. Tested Scenarios

Most of the published papers have discussed three scenarios when optimizing the wind farm layout as follows [4], [6]:

- The first scenario presents the constant wind direction with a constant wind speed value of 12 m/s. The variation in this scenario is the wind speed only that would happen in the wake behind the wind turbine.
- The second scenario presents different wind directions with a constant wind speed of 12 m/s. The wind direction changes from 0° to 360° angles with an equal fraction of occurrence.
- The third scenario presents several wind speeds of 8, 12, and 17 m/s, and different wind directions with variable fractions of occurrence. Any angle at each wind speed has a fraction of occurrence, as displayed in Fig. 6, and applied in [4], [6], [18], where the sum for the fraction of occurrence is one.

The following sections present the results of applying MPA compared with the previously published studies in [4], [6], [7], [9], [10], [11], [12], [13], [19], [27] for the three different tested scenarios to investigate the performance of the proposed algorithm.

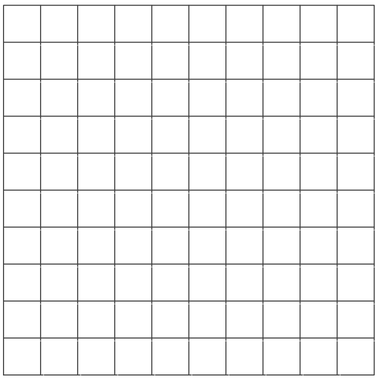


Fig. 4. A regular square wind farm of 2 km side length.

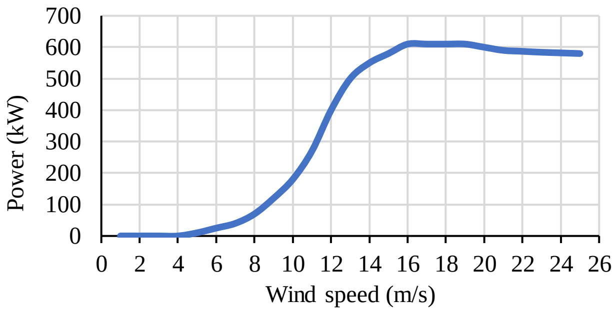


Fig. 5. Wind turbine power curve.

3.2 Results of 1st Scenario: Constant Wind Speed with Constant Wind Direction

In this scenario, the wind farm speed is maintained constant at 12 m/s besides the wind direction is uniform. The wind farm layout optimization is accomplished by maximizing the total power produced from the wind farm and reducing the cost of the farm. So, the comparison is carried out by getting the best objective (cost/power).

According to the results of previous studies displayed in Table 1, it can be deduced the highest total power for this 1st scenario is 18065 kW which is revealed by [10]. But, the least objective function of 0.00136 (cost/kW) is attained using the nonlinear mathematical method suggested in [19]; nevertheless, the introduced method in [19] has only produced a total power of 16163 kW from 30 wind turbines at the farm.

On the other hand, the proposed optimization algorithm has succeeded in enhancing the objective value in this scenario to be reduced to 0.001302 cost/kW, which is better than the other published studies, but with a total power of 13135 kW smaller than the corresponding one in [19] as the number of wind turbines becomes 29. Thus, the MPA has achieved an objective value lower by 4.3% than the method in [19]. Figure 7 presents the optimal distribution for the wind turbines for this scenario by using MPA.

3.3 Results of 2nd Scenario: Constant Wind Speed with Different Wind Directions

In this scenario, the wind speed is still maintained constant at 12 m/s while the wind direction applied to the wind farm is multidirectional. The angles of the wind directions are divided into 36 angles from 0° to 360° degrees. Every angle with 10 degrees has a fraction of occurrence while the fraction of occurrence is supposed to be equal in this scenario.

Regarding the performance of the previous studies, as demonstrated in Table 1, the lowest cost per power is accomplished by [12] with the value of 0.001476 cost/kW, besides the highest value of the total power was 18623 kW is also achieved in [12] by using 35 wind turbines. However, the proposed algorithm gives a better result than these studies, which is 0.001372 cost/kW improved by about 0.000104 cost/kW, and the total power is also enhanced significantly to 25211 kW with 37 wind turbines (higher than the method in [12] by 35.4%). For this scenario, Fig. 8 presents the output of the proposed method for getting the optimal layout for the wind turbines at the wind farm.

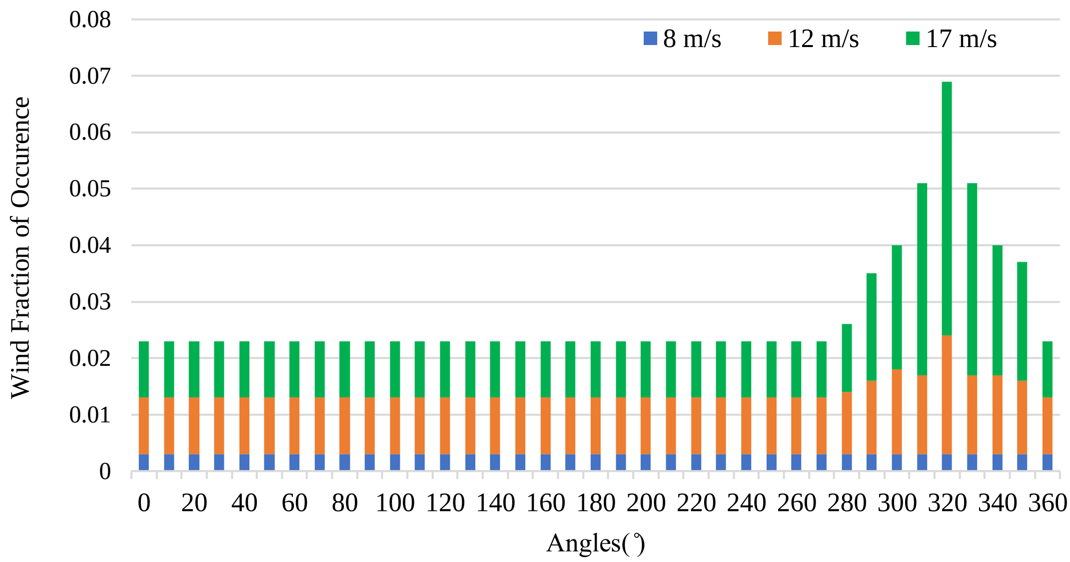


Fig. 6. Fraction of occurrence of wind speed at different wind directions for the third scenario.

Table.1 Comparing the achieved results by the proposed scheme against other published studies for three tested scenarios.

Different studies			**Objective (cost/kW)**			**Total power (kW)**			**Number of wind turbines**		
Reference/ Year		**Applied Method**	**Scenario #**			**Scenario #**			**Scenario #**		
			1st	**2nd**	**3rd**	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
[6]	**1994**	GA	0.00157	0.0018	0.0036	12375	8711	3695	26*	19*	15*
[4]	**2005**	GA	0.00154	0.0016	0.0008*	14310	17220	32038	30	39	39
[7]	**2008**	Monte Carlo simulation algorithm	0.00142	–	–	15164	–	–	29	–	–
[9]	**2010**	PSO	0.00154	–	–	12819	–	–	26*	–	–
[10]	**2010**	Evolutive algorithm	0.00154	0.0015	–	18065*	16464	–	30	39	–
[27]	**2010**	GA	0.00202	0.0015	0.0008*	16014	17259	33262	32	38	41
[11]	**2011**	Lazy greedy algorithm	0.00154	0.0015	0.0008*	14310	17611	33553	30	39	39
[12]	**2013**	Binary PSO	0.00154	0.001476	0.0008*	14310	18623	39359*	30	35	46
[13]	**2015**	GA	0.00153	–	–	13636	–	–	32	–	–
[19]	**2019**	Nonlinear mathematical model	0.00136	0.0015	0.001	16163	16134	26932	30	36	36
Proposed Scheme	**2023**	**MPA**	**0.001302***	**0.001372***	**0.000799***	**13135**	**25211***	**31650**	**29**	**37**	**42**

Where: the symbol (−) means that the scenario is not tested in that study & the symbol (*) indicates for best value per column for each scenario.

3.4 Results of 3rd Scenario: Different Wind Speeds with Different Wind Directions

The wind speed for the wind farm in this scenario is variable at 8, 12, and 17 m/s. The wind direction for the wind farm is also multidirectional, and the angles are divided by 36° angles as implemented in the 2nd Scenario, but the fraction of occurrence is not equal. Each angle has a different fraction of occurrence as illustrated in Fig. 6 [4], [6], [8], [18]. As displayed, the high wind speeds are dominant, especially between the angles from 270° to 350° degrees. It is worth mentioning that the direction of the angular measurement reference has not been identified in the previous studies which may lead to ambiguity and confusion [27].

As demonstrated in Table 1, the lowest result of the total power obtained from the previous studies is 3695 kW which is achieved in [6] using only 15 wind turbines. On the other hand, the maximum total power obtained was 39359 kW by [12] using the largest number of turbines of 46 turbines.

By comparing the achieved results using the MPA with the previous studies for this scenario, the total power is 31650 kW from 42 wind turbines with a value of 0.000799 cost/kW. As shown, the cost/power is slightly lower than the minimum value achieved previously in [4], [11], [12], [27], (0.0008 cost/kW), as revealed in Table 1. Finally, the accomplished optimal location for the wind turbines at the wind farm for this scenario is presented in Fig. 9.

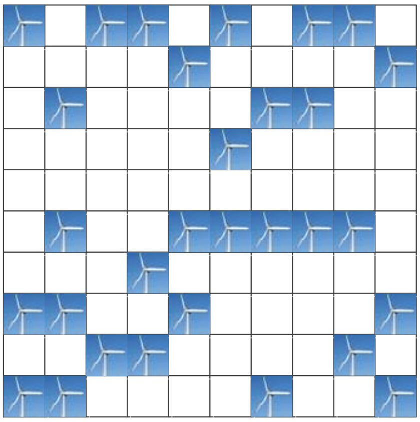


Fig. 7. Optimal location for wind turbines for 1st scenario.

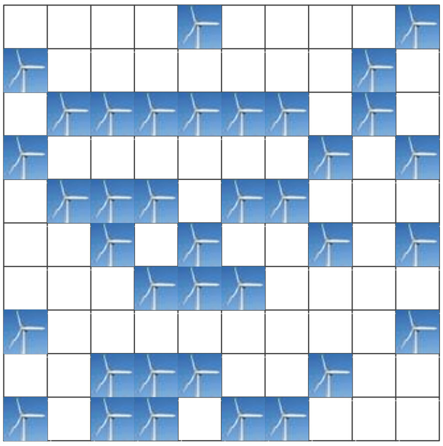


Fig. 8. Optimal location for wind turbines for 2nd scenario.

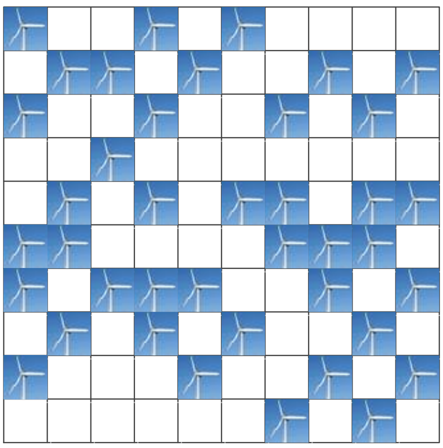


Fig. 9. Optimal location for wind turbines for 3rd scenario.

3.5 Discussion

The detailed comparison of the proposed scheme using the MPA against several previous studies for the three tested scenarios is tabulated in Table 1. It includes comparing the achieved objective (cost/kW), produced power (kW), and the number of turbines. Besides, for quick interpretation of the results, the achieved objective value (cost/kW) as an effective index for comparison is illustrated in graphical form in Fig. 10. Accordingly, some findings can be highlighted as follows:

- The results showed that the MPA for the 1st scenario is less than [19] by 0.000058 cost/kW and less than [6] by 0.000268. It ensured good results of the objective function in that scenario.
- As some studies did not apply the 2nd and 3rd scenario such as [7], [9], [13], the achieved results of MPA is only compared in the 2nd scenario with the studies in [4], [6], [10], [11], [12], [19], and [27]. The achieved results indicated better performance of MPA for the 2nd scenario compared with these studies regarding the objective (cost/power). It is lower than [6] by 23.7% and lower than [19] by 8.53%. Moreover, for the 3rd scenario, the previous studies in [4], [11], [12], and [27] have the same objective value which is close to the achieved value by the MPA, but [6] has resulted in a higher value than the MPA by 0.0028 cost/kW.
- According to the total power produced through the three tested scenarios, the 3rd scenario by using MPA has resulted in higher than the total power in the 1st scenario by 140.95%.
- Figure 10 ensures that MPA has given great results and thus, it is suitable for the optimization of wind turbines' locations inside the wind farm.

4. Applying the Proposed Scheme in Four Places in Egypt

To address the global energy crisis and protect the environment, different public authorities worldwide have long prioritized renewable energy sources [28]. Developed countries focus on using renewable energy to produce green and sustainable energy for a better future [29]. Egypt has several encouraging areas for installing wind farms. Different cardinal directions like North, South, East, and West with different wind speeds have been chosen to test the MPA's utilization to get the optimum wind farm layout. Based on the recent research study in [30], the potential of wind energy is comprehensively evaluated for four selected locations in Egypt with two different wind classes: Ras El-Hekma and Nuweiba with a moderate class of wind, while Farafra and Aswan belong to the marginal wind class.

Figure 11 displays the location of these areas. Ras El-Hekma is placed on the northern coast (coordinates 31.24° N and 27.85° E), Farafra is placed in the Western Desert of Egypt (coordinates 27.06° N and 27.97° E), Nuweiba is placed in the eastern of Sinai Peninsula on the Gulf of Aqaba (coordinates 29.2° N and 34.40° E), and finally, Aswan is located in the south of Egypt (coordinates 24.05° N and 32.53° E). Merra website is used to get wind speed at these four locations for five consecutive years from 2015 to 2020. EWT-DW61/22 wind turbine has been used in this study because it gives the lowest cost of energy in the four sites based on the study. This wind turbine's cut-in, rated, and cut-out speed is 2.5, 10, and 25 m/s respectively [30].

The fraction of wind speed occurrence for these selected sites is displayed in Fig. 12, which has been extensively calculated according to the optimal hub height for EWT-DW61/22 wind turbine for different wind directions (wind direction at these four locations is defined in 36 sectors from 0° to 360°). It is worth mentioning that the optimal hub heights for EWT-DW61/22 wind turbine have been previously estimated in [30] and the achieved results were 65, 55, 58, and 58 m for Ras El-Hekma, Farafra, Nuweiba, and Aswan respectively.

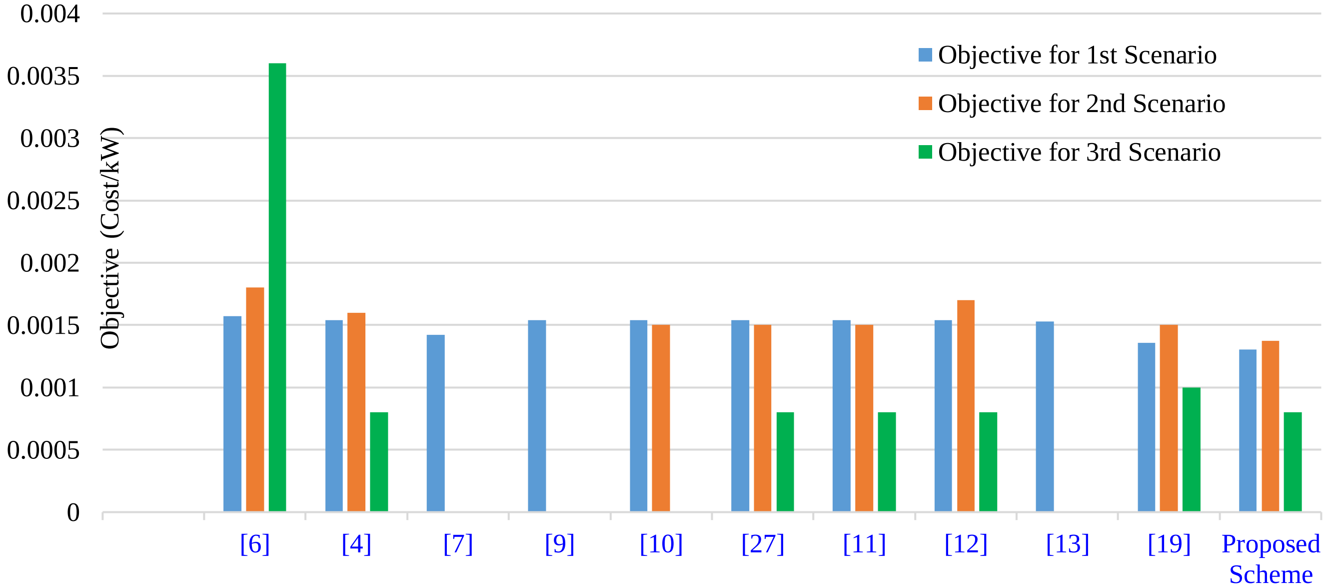


Fig. 10. The objective values for different studied scenarios.

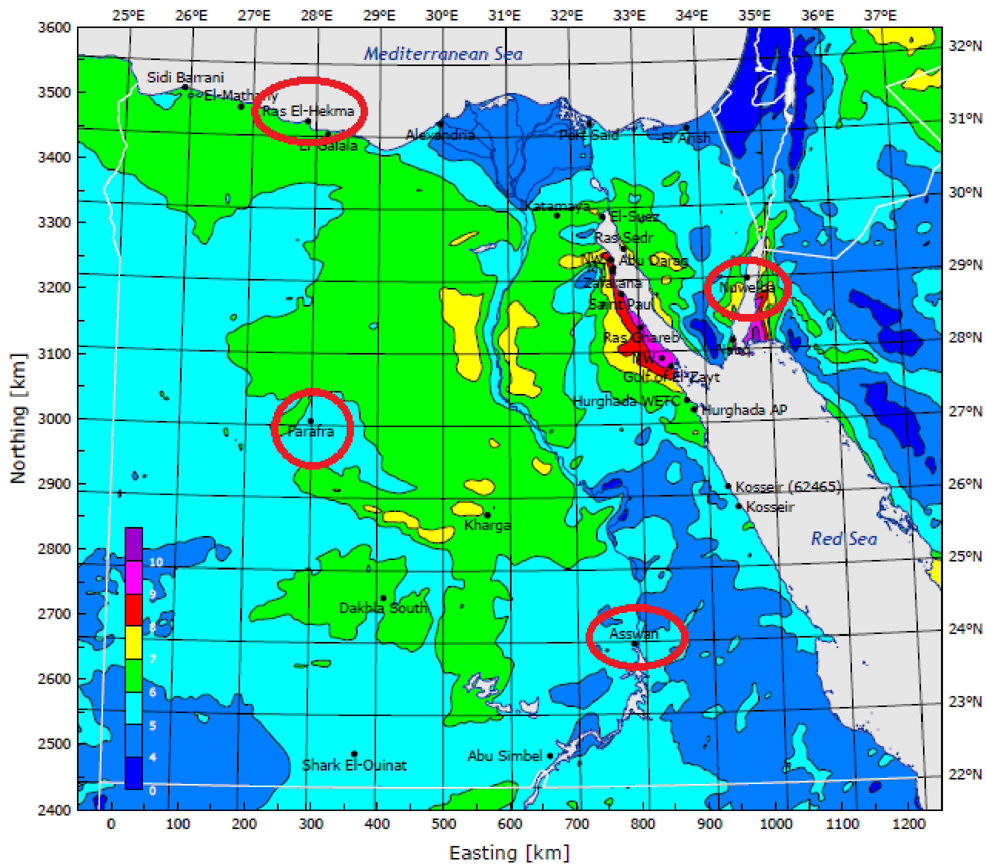


Fig. 11. Egypt wind atlas shows the promising area of Ras El-Hekma, Farafra, Nuweiba, and Aswan.

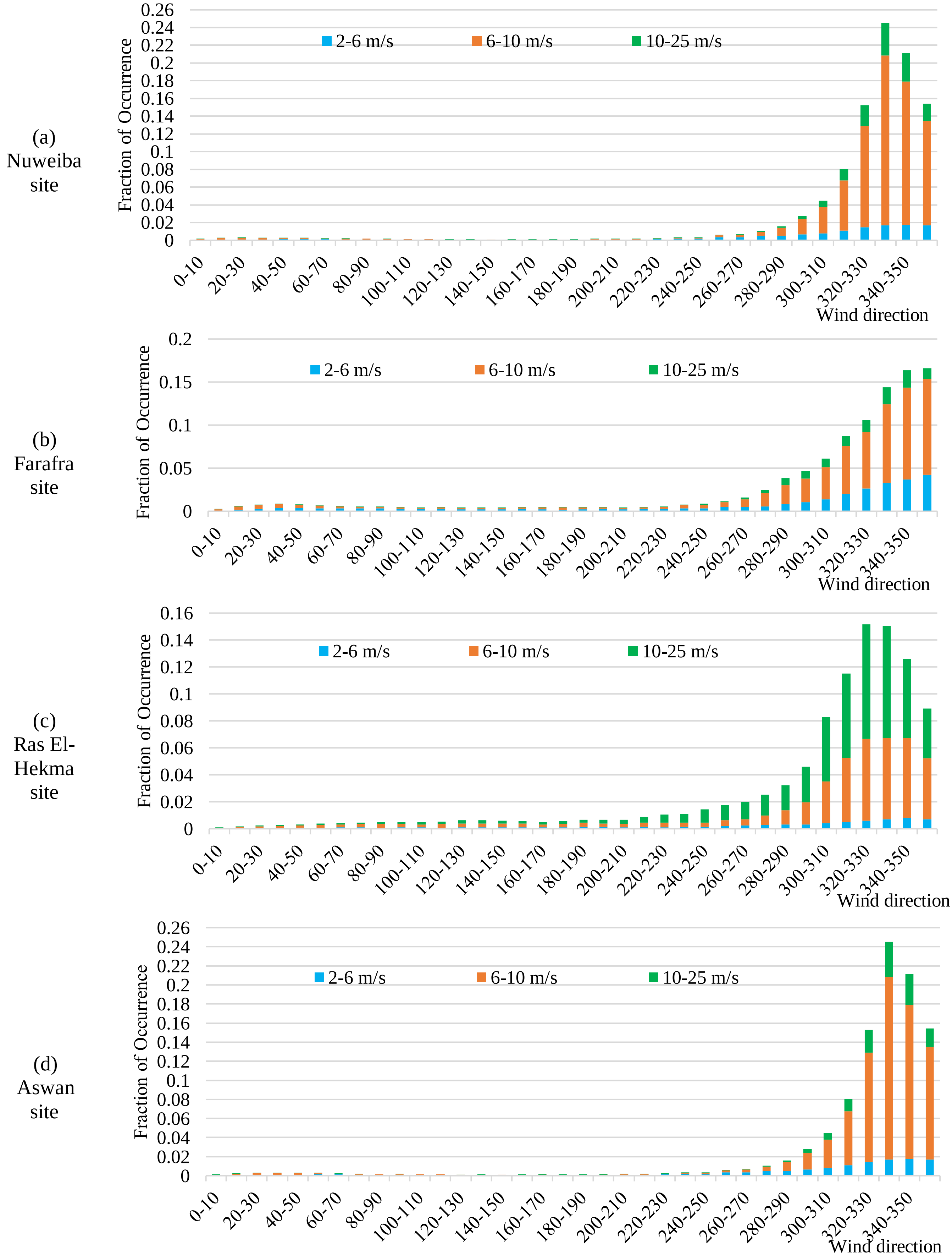


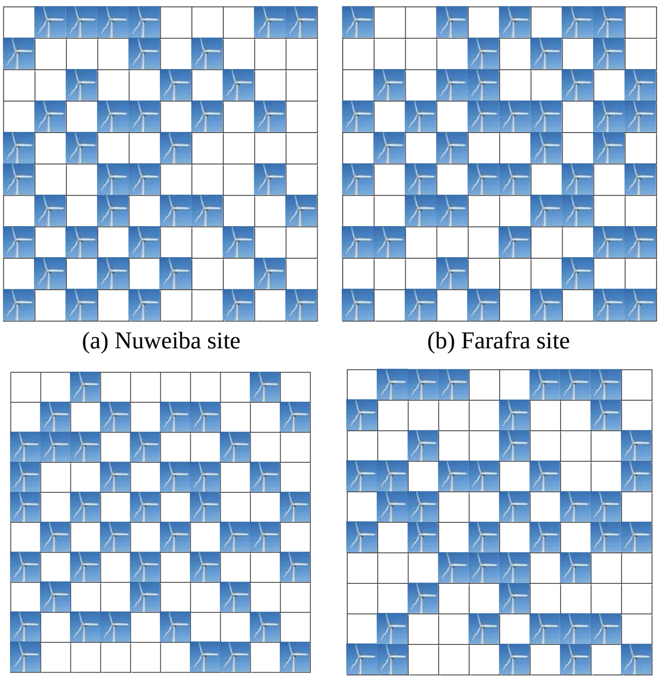
Fig. 12. The estimated fraction of occurrence for the four tested locations in Egypt.

Consequently, the MPA is applied here for optimizing wind turbines' layout in wind farms located at the four mentioned places in Egypt as tested locations. The maximum iteration for the model is 500, and the number of search agents is 50. Regular square land space is assumed where the side length of the farm is 2 km and the third scenario is applied to get the optimal layout at the selected locations with different ranges of wind speed: 2-6 m/s, 6-10 m/s, and 10-25 m/s at different wind directions. Table 2 summarized the obtained results of the cost/power, power, and the number of turbines in each site. As shown, the lowest cost per power is achieved at the Ras El-Hekma location with a value of 0.000586 cost/kW, it has slightly increased at the Nuweiba location by only 0.000033 cost/kW. Besides, the value for the cost per power for both the Farafra site and Aswan site is significantly close as the difference between them is just about 0.00002 cost/kW. The maximum total power is attained at the Ras El-Hekma location by using 44 wind turbines. It is higher than the Nuweiba location by 5.72 % (using 42 wind turbines), larger than the Aswan location by 11.39 % (using 45 wind turbines), and more than the Farafra location by 14.86 % (using 47 wind turbines).

Finally, for the estimated number of wind turbines at the wind park at the four tested locations, Fig. 13 illustrates the optimum layout for locating the turbines using the proposed scheme by applying MPA.

Table.2 Results of applying MPA for the four tested locations in Egypt

Location	Nuweiba	Farafra	Ras El-Hekma	Aswan
Objective (Cost/kW)	0.000619	0.000673	0.000586	0.000653
Power (kW)	20410	18786	21577	19371
No. of turbines	42	47	44	45



(a) Nuweiba site (b) Farafra site

(c) Ras El-Hekma site (d) Aswan site

Fig. 13. The optimum location of wind turbines for the four tested sites in Egypt.

5. Conclusions

Optimizing the wind farm layout depends on maximizing the total power produced from the farm while minimizing its cost. Thus, the objective function (cost/power) needs to be optimally minimized while considering the effects of multiple wakes. The wake effects are incorporated into the suggested model according to Jensen`s wake model, and accordingly, three scenarios have been extensively evaluated. The first scenario is assessed with a fixed wind speed and wind direction. The second scenario is examined at a fixed wind speed, whereas the wind direction changes between 0° to 360° with an equal fraction of occurrence. The third scenario is studied for variable wind speed with variable wind direction and dissimilar fractions of occurrence. MPA is proposed as an effective algorithm to solve the wind farm layout problem and accurately determine the optimal configuration for the wind farms. The achieved results for utilizing MPA compared to different algorithms applied in the literature confirm its superior results in the first and second scenarios; however, in the third tested scenario, MPA reaches a slightly improved result. Thus, it is deduced that the proposed scheme can be considered an acceptable method for solving the problem of the distribution of wind turbines to increase the production of annual energy besides decreasing the cost.

As a practical application for the proposed method, four promising locations in Egypt are tested where the fraction of wind speed occurrence has been comprehensively calculated over five years. Then, MPA is applied to get the best-optimized objective function from these sites and the optimal distribution of wind turbines. According to the accomplished results, the Ras El-Hekma site has ensured the lowest objective value and the highest produced power compared with the other tested locations Farafra, Nuweiba, and Aswan. Therefore, it is concluded that Ras El-Hekma is the most promising location to build a wind farm out of the four selected sites.

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