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A Review of Wind Farm Layout Optimization Techniques for Optimal Placement of Wind Turbines

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Abstract- In this paper, different optimization techniques for Wind Farm Layout Optimization (WFLO) are reviewed for the optimal placement of wind turbines. After reviewing the recent approaches, the most important considerations for the WFLO work are outlined, and the future objectives are mentioned. Wind is inexpensive, and renewable source of electricity. Wind energy seems to have the ability to reduce greenhouse gas emissions and slow down climate change. Wind energy lowers dependency on depletable, non-renewable energy sources like fossil fuels. Generation of wind energy is affected by the presence of wind. Wind turbines requires a lot of space, that can cause problems for people who do not want large wind farms next to their homes and for the safety of wildlife and environment. Researchers are attempting to find solutions to problems with wind farms like WFLO and the best locations for wind turbines in terms of cost and power output. Different optimization techniques have been discovered and proposed for the identified objectives.

Keywords Wind power, Wind farm layout optimization, Wind turbines, Optimization Techniques, Metaheuristics.

1. Introduction

A pure and cost-free energy source is Wind Power (WP). The earth's rotation generates wind, which can be utilized to produce electricity [1]. The current global energy crisis has highlighted the ongoing risks of depending only on fossil fuels for our energy requirements. WP is safe for the environment because it causes no harmful effects like the greenhouse effect or pollution. WP can be used to power vehicles, water pumps, grain mills, and windmills. WP is generated by Wind Turbines (WTs) [2]. WTs run entirely on the energy of the wind which utilized from several years. The investment cost, power production cost, longevity, and maintenance cost of a Wind Farm (WF) are the four primary components of a WP projects. Through WTs, WP is converted into electricity. WTs are considered the most significant source of renewable energy [3]. In opposed that, WTs are also considered to be harmful to birds and other species of birds, and they also make noise. Storms, thunder, and strong winds harm WT. A hybrid metaheuristic is employed to solve the WT optimization problem [4]. WP is an extremely fast source of power generation since its operational costs are almost zero after installation. The cost of installing a WT involves manufacturing, transportation, and installation expenses. WP is produced in WFs. WF occupies a very limited size of land in comparison to their ability to produce renewable energy, and it is independently connected to the electrical grid. WFs are constructed in areas that are known to be windy on a regular basis. WFs can be utilized for power generation. Small WFs may consist of only a few turbines but rather large WFs have hundreds of turbines. WP is the most rapidly expanding energy source with zero cost. Wind generators are used to generate maximum power. Table 1 lists some historical examples of WTs. To maximize energy production, WTs are located in regions with strong and consistent wind patterns, such as windy plains or coastal regions. There are three types of WFs: on-shore, off-shore, and near-shore. The on-shore WF is at least three kilometers inland from the shore [5].

The offshore WF is situated in lakes or the open ocean. The near-shore WF is less than 3 kilometers from the shore. A large amount of energy is produced by on-shore and off-shore WFs. Metaheuristic approaches are employed to Wind Farm

Layout Optimization (WFLO) to identify the best locations for WTs, minimize energy and wake losses, and increase the WFs energy output. When improving the layout of WFs, multi-objective optimization problems are frequently solved using these algorithms. Artificial neural networks are applied on WFs to increase power efficiency [6].

Table 1. Wind turbines

S. No.	Wind Turbine (WT)	Inventor	Year
1	Automatic WT	Charles F. Brush	1888
2	Electricity Generating Wind Turbine	Poul la Cour	1891
3	Electrical Power Plan	Poul la Cour	1895
4	Darrieus Wind Turbine	Georges Jean Marie Darrieus	1931
5.	Smith-Putman Wind Turbine	Palmer Cosslett Putnam	1941
6.	Commercial Wind Turbine Rotors	--	1980
7.	NASA Wind Turbine Program	NASA	1987
8.	E-126	Enercon Company, Germany	2008
9.	Off-shore Wind Turbine	Statoil	2009

The first WF was located in the USA. Table 2 represents different WFs and their power capacities.

Table 2. Wind farms and their power capacity

S. No.	Wind Farm	Location	Power Capacity
1	Smith-Putman Wind Turbine	1941, USA	1.5 mw
2	First Wind Farm	1980, USA	30 KW each
3	Second Wind Farm	1981, USA	10 MW

This paper examines and identifies the strengths and shortcomings of the most promising and workable WFLO techniques. The article is structured as follows. General framework of Wind Farm Optimization (WFO) is given in section 2. WFLO objective is presented in section 3. WFLO techniques are discussed in section 4. The key conclusions are summarized in section 5.

2. Wind Farm Optimization (WFO)

Increasing a WFs productivity and efficiency is referred to as WFO. For highest power output in the wind project, Wind Farm Layout (WFL) and design play a major role. Before a WF is set up land quality investigation is very important. The performance of the turbines will be influenced by the geography and wind flow, therefore selecting the appropriate location for the WF is crucial for optimization. Maximum power output depends on the WTs location and size. WTs are heavy in size; land must have the ability to support WTs weight. WF location also plays a major role in maximum power output. WTs produce maximum energy when they face the strongest winds. Depending on their size, WFs can have several WTs. WFs are designed in such a way they are cost-effective and reliable. Maintaining the balance between wind energy generation and distribution is crucial. WFs are considered successful when they produce and distribute enough energy. The final WFL must be designed after comparing various wind farm layouts. A WFL must minimize investment costs while maximizing power output Running WFs requires a careful land project plan as well as the location of WTs in the suitable location.

2.1. Wake Effect in WF

Wake Effect (WE) limit power production in WF. WE slows the wind down. Wake is created, when turbulence is caused by a free stream of wind passing through the WT's rotor. The WE can be minimized and energy output maximized by using WFO techniques like wake management. The development of various wake models are listed in Table 3. Researchers frequently utilise the 1983-built Jensen wake model to determine WE in WFs [7, 8]. To reduce the WE WTs optimal positioning is important. Jansen's wake model shown in Figure 1 is a simplistic analytical wake model that produces results quickly and accurately.

Table 3. Wake effect models

S. No.	Popular Wake Models	Year
1	Jensen Wake Model [4]	1983
2	Ainslie Eddy Viscosity Model	1985
3	Katic Park Model [3]	1986
4	Dynamic Wake Meandering	2007

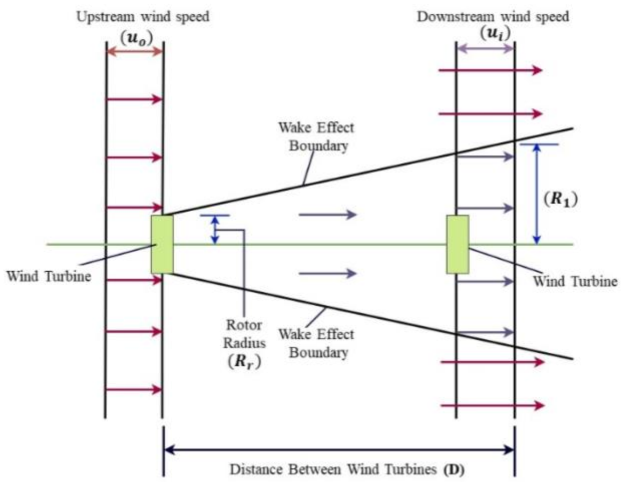

Fig. 1. The Jensen WE model

In the renewable energy industry, the Jensen wake model is extensively used for WF design, optimization, and management. Jensen's model can work with both radial and

axial directions using a cylindrical coordinate system. Jensen considered the wake behind the WT as a stormy wake, excluding the vortex shedding effect, which is only relevant in the local wake region [9].
Equation (1) represents the non-WE, which happens when the wind speed is equal for all WTs.

$$u_o = u_i \tag{1}$$

Using the Jensen model [10], the wake speed is calculated from the current free wind speed for i-th WT in wake area is expressed in equation (2).

$$u_i = u_o\left(1 - \frac{2a}{1+\alpha\,(D/R_1)^2}\right) \tag{2}$$

Where 'a' is the [0.2-0.4] range's axial induction factor, $'\alpha'$ is entrainment constant. The Equation (3) demonstrates the wake boundary expansion rate with respect to D [11].

$$\alpha = \frac{0.5}{\mathrm{In}\left(\frac{Z}{Z_o}\right)} \tag{3}$$

Where, 'Z' is the height of the hub, $'Z_o'$ is WF surface roughness, and 'Z_o' is 0.3 m and varies according to the location for plain territories [12]. The WT rotor is damaged by the upstream WE when a part of it is partially inside the WE boundary, [13] that is expressed in equation (4).

$$u_i = u_o\left(1 - \frac{2a}{1+\alpha\,(D/R_1)^2}\right)\frac{A_{T,wake,i}}{A_{T,total,i}} \tag{4}$$

Where $A_{T,wake,i}$ is the rotor portion that is damaged by the wake, $A_{T,total,i}$ is total rotor area. Equation (5) describes the full wake effect that WTs experience, which includes both upstream and downstream wake effect [14].

$$u_i = u_o\left[1 - \sqrt{\sum_{j=1}^{m_i}\left(1 - \frac{2a}{1+\alpha\,(D/R_1)^2}\right)_j}\right] \tag{5}$$

Where m_i is total number of WT with WE. The following other formulas are taken into consideration for analytical purposes are given in equation (6), (7) and (8):

$$R_d = R_d = R_r\left[1 - \sqrt{\frac{1-a}{1-2a}}\right] \tag{6}$$

$$R_1 = aD + R_r \tag{7}$$

$$C_t = 4a(1-a) \tag{8}$$

Where R_d is downstream rotor radius, R_r is rotor radius and C_t is trust coefficient.

2.2. Scenarios for Wake Effect (WE)

Due to the WE, wind speed decreases and power output is reduced to a minimum. The WE can be reduced through WF evaluation, advancements in WT design, wind speed directions, and turbine location that is optimum. Wake management and wake merging are two strategies that can be used to reduce the effect of one turbine on the power generation of downstream turbines. In order to calculate the WE in the WF, several sceneries are taken into account. The three wind speed combinations are Uniform Wind Speed (UWS) and Uniform Wind Direction (UWD), Uniform Wind Speed (UWS) and Variable Wind Speed (VWS) with Variable Wind Direction (VWD). The wind speed and direction in the first scenario UWS-UWD are both constant at 12m/s. In the second UWS-VWS scenario, even when the wind direction is shifting, the wind speed remains the same. In the third case, the wind's direction and speed are both variables. VWS-VWD. The total Power that can be extracted using WT is expressed in equation (9) as:

$$\mathrm{Power} = \frac{1}{2}\, c_p \rho A U^s \tag{9}$$

Where 'c_p' is power extracted by WT, 'ρ' is air intensity, 'U^s' upstream wind speed.

3. Wind Farm Optimization Objectives

WFLO's goal is to improve power output from the WF while taking into account a range of limitations, such topography, impact on the environment, wind direction, and others. The prime target is to harness WE as much as possible. The WF optimization objective is to maintain WFs at a reasonable value while reducing overall investment costs [15]. The WFL is designed to deploy WTs where they will produce the most power. The proper type and size of turbines must be chosen for the specific site conditions in order to maximize energy output. The WF is considered successful if it minimizes total power generation and minimize investment costs [16].

3.1 WFLO Problem

The purpose is to increase power generation while decreasing costs and harmful effects on the environment. WF electricity output is reduced by the WE. WTs are also affected by wind speed. Strong winds and storms can damage WTs. If a WF is not optimized, production power will decrease, and operating and maintenance costs will increase.

3.2 Wind Farm Cost Calculation

The location of the WT is extremely important in WFs for maximum power output. WF construction and maintenance cost. A WF's overall cost varies depending on its size, location, and equipment in addition to other elements including infrastructure development, rules, and demand. Cost functions are used to calculate the total cost WF. The most popular objective function used in WFLO for cost minimization is written in equation (10) as follows:

$$\text{Min:}\quad f(x) = \frac{\mathrm{Cost}}{P_T} \tag{10}$$

In equation (6) WF cost is divided by the total energy generation. Where, one of the design variable's vectors is x, cost denotes the WF cost, and P_T is the total power produced by the WF. A WFs cost can be estimated by considering in a number of factors, such as the cost of the turbines, structures, generators, highways, and other equipment needed. Due to recent drops in price, the cost of wind energy can sometimes exceed that of conventional energy sources like coal and natural gas. WT's construction and installation cost, The cost is determined by how many WTs are deployed overall in each WF. The cost of a WF is calculated using a cost model. Investment cost function is written in equation (11) as:

$$\mathrm{Cost} = \mathrm{N_{WT}}\left(\frac{2}{3} + \frac{1}{2}\, e^{-0.00174 \mathrm{N_{WT}^2}}\right) \tag{11}$$

Where 'N_{WT}' represents total number of WTs purchased.

3.3 Wind Farm Power Calculation

The placement of the WFs turbines, which must be regulated based on the flow patterns, may also have an impact on power generation. The quantity of power produced by a WF can be calculated using the formula below presented in equation (12) and (13) as:

$$\mathrm{P_U} = \frac{1}{2}\,\rho A u^3 \tag{12}$$

$$\mathrm{P_G} = \eta \frac{1}{2}\,\rho A u^3 \tag{13}$$

Where, air density is ρ, swept area is A, and wind speed is u. The WTs utilizable power and generated power is given in equation (8), and (9) respectively. Where η is considered as WT efficacy. If $\eta = 40\%$, total power generated by WT is calculated in equation (14) and (15) as:

$$\mathrm{P_G} = \frac{40}{100} \times \frac{1}{2} \times\ 1.2\ \times \pi \times (20)^2 \times u^3 \tag{14}$$

$$\mathrm{P_G} = 301 \times u^3\ \mathrm{W} = 0.3\ u^3\ \mathrm{Kw} \tag{15}$$

4. Wind Farm Optimization Techniques

Proper wind data and analysis are important for calculating energy production and improving turbine location and design. By modifying the blade height or rotor speed, active power control techniques can be used to maximize the energy generation of single turbines. Massive amounts of data from WF operations can be evaluated using machine learning algorithms and data analytics to find ways to improve efficiency. For maximum power output, optimal placement of WTs is required. Kunakote. T. (2022), compared twelve metaheuristics for WFLO problems. The fundamental flow method for WFLO using metaheuristics is shown in Figure 2 and schematic representation of WFLO using metaheuristics is shown in Figure 3. The design problem for the optimal WF layout is expressed in terms of cost minimization, total power maximization, noise minimization, and performance are tested on 12 different metaheuristic algorithms [17].

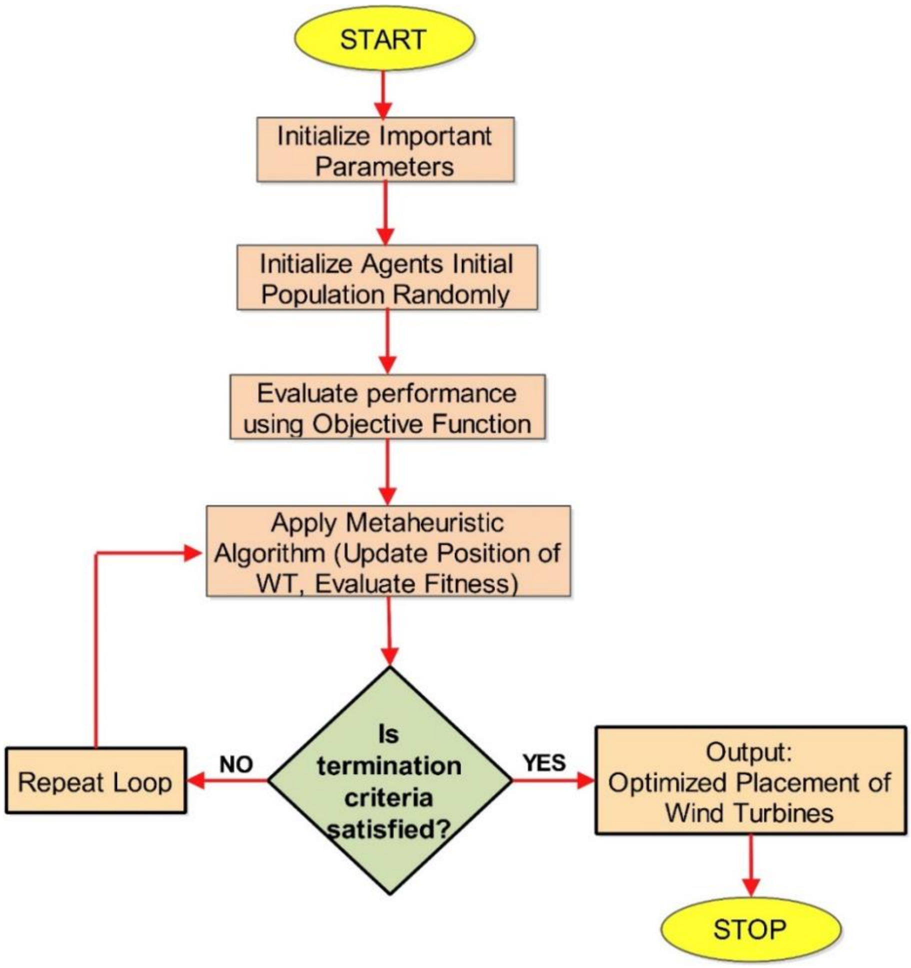

Fig. 2. Basic flow process to solve WFLO using metaheuristics

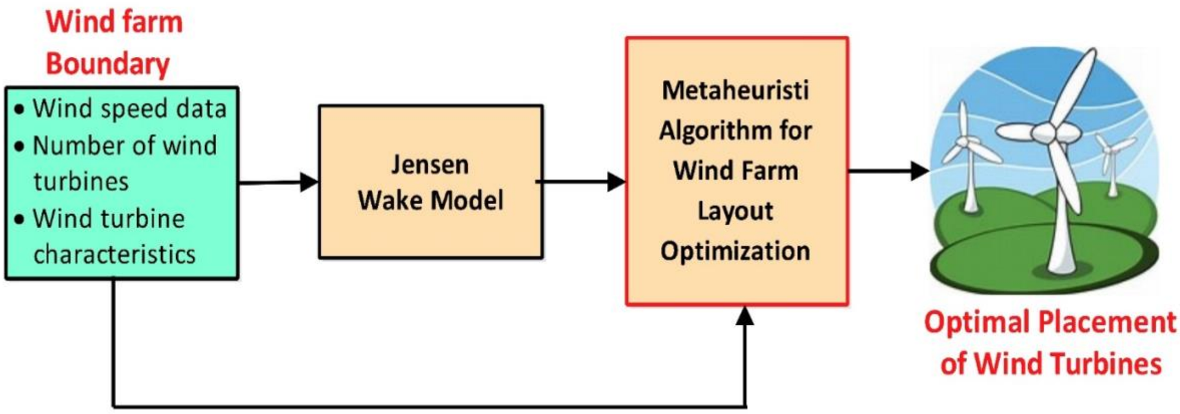

Fig. 3. Schematic representation of WFLO using metaheuristics

The layout optimization of a WF is an example of a large-scale problem that can improve by the use of metaheuristic optimization techniques. The researcher applied metaheuristic algorithms to overcome WFLO issues because they are the best at solving engineering design objective functions. The review of some of the most notable works in optimization techniques are enumerated in Table 4.

Table 3. Metaheuristics used for WFLO

S. No.	Metaheuristics	Problem	Research Work
1	PSO	WFLO	Philip et. al. [18]
2	SSA	WT Placement	Kumar et. al. [32]
3	GA	WFLO	Majid et. al. [33]
4	ACO	WFLO	Eroğlu Y et. al [34]
5	TLBO	WFLO	Patel J et. al. [35]
6	GWO	WF Energy Production	Kiji, Sareta et. al [36]
7	ABC	WFLO	Patel J et. al. [35]
8	GOA	WF Energy Production	Fathy Ahmed Et. al [37]
9	FA	WF Energy Production	R. I. Putri et al [38]
10	DE	WFLO	Hen, L et. al. [39]
11	CSA	WFLO	S. Rehman et, al. [40]
12	BA	WFLO	Qi, Yuanhang et. al. [29]
13	DA	WFLO	Rahman et. al. [30]

In terms of quality and convergence ratio, metaheuristic approaches produce the best results. Different metaheuristics are applied to solve WFLO problems including particle Swarm Optimization (PSO) [18], Sparrow Search Algorithm (SSA) [19], Genetic Algorithm (GA) [20], Ant Colony Optimization (ACO) [21], Teaching Learning Based Optimization (TLBO) [22], Grey Wolf Optimization (GWO) [23], Artificial Bee Colony (ABC) Optimization [24], Grasshopper Optimization Algorithm (GOA) [25], Firefly Algorithm (FA) [26], Differential Evolution (DE) [27], Cuckoo Search Algorithm (CSA) [28], Bat Algorithm (BA) [29], Dragonfly Algorithm (DA) [30], etc.

4.1 Particle Swarm Optimization (PSO)

PSO is inspired by the birds flocking behavior [18]. PSO mimics the behavior of a group of birds in the search for food. In PSO, possible solutions are represented by moving particles in a search space, with each particle's velocity and position constantly updated in accordance with its own and other particles' interactions. PSO is used to solve various constraint and unconstraint optimization problems. WTs are placed at optimal locations using the PSO algorithm. For efficient optimal output power, PSO is applied on WF layout. To check the PSO's efficiency, the author [31] considers three scenarios, including CWS-CWD, CWS-VWD, and VWS-VWD. Table 5 displays the WFLO PSO performance [31].

Table 5. PSO results for the WFLO problem

S.No	Parameter	PSO results [31]	
		Case 1: CWS-CWD	Case 2: CWS-VWD
1	Wind Turbines	32	19
2	Total Power	16326.59 kW	9741.30 kW
3	Cost	0.00140	0.00164
4	Wake loss	262.20 kW	108.30 kW
5	Efficiency	98.42%	93.90%

4.2 Sparrow Search Optimization (SSA)

SSA algorithm is inspired by sparrow bird foraging behavior in nature [19]. SSA is used to position WTs in wind farms in the best possible way. To examine the effectiveness of WT in a 2 km by 2 km flat region, author [32] takes into consideration two scenarios, including CWS-VWD and VWS-VWD. WT's optimal placement is done within the WF reduces overall cost. In contrast to other metaheuristics like GA and Randon Search Algorithm (RSA), the SSA provides better results for 2 cases (CWS-VWD and VWS-VWD). Table 6 presents SSA performance on two cases for WFLO [32].

Table 6. SSA results for the WFLO problem

S.No	Parameter	SSA results [32]	
		Case 1: CWS-VWD	Case 2: VWS-VWD
1	Wind Turbines	40	39
2	Total Power	17.781 MW	32.49 MW
3	Cost	0.0000015461	8.377e-7
4	Efficiency	85.74%	86.11%

4.3 Genetic Algorithm (GA)

GA use crossover, mutation, and selection operators to find the best solution [20]. Natural selection is the foundation for GA. It uses a population of potential solutions that are combined and modified to produce new solutions until an ideal solution is found. To optimize small WFL as well as large WFL, the author [33] used two-step optimizations based on GA. Table 7 presents GA performance on different parameters for WFLO [33].

Table 7. GA results for the WFLO problem

S.No	Parameter	GA results [33]	
		Case 1: X=372.8, Y=186.4	Case 2: X=186.4, Y=372.8
1	Wind Turbines	56	48
2	Total Power	10441 kW	8834.9 kW
3	Fitness value	0.0036	0.0036
4	Normalized Cost	37.41	32.29
5	Efficiency	89.54%	88.39%

4.4 Ant Colony Optimization (ACO)

ACO algorithm is inspired by ants foraging behavior in real life [21]. The algorithm is used to determine the optimal solution. In ACO, artificial ants are used to generate a series of solutions, each of which is a sequence of moves all around the problem space, to identify a problem's answer. The quality of each solution is evaluated, and this evaluation is used to guide the ants' movement toward better solutions. One of the many applications of ACO is in the optimization of WFL.

Table 8. ACO results for the WFLO problem

S. No	Parameter	ACO results [34]		
		First Scenario	Second Scenario	Third Scenario
1	Wind Turbines	8	8	8
2	Total Power	111589.7 kW	56453.73 kW	105238.261 kW
3	Wake loss	776.20	2071.71	2445.73
4	Efficiency	99.30%	96.46%	97.73%

Author [34] uses ACO for WFLO. For the three scenarios CWS-CWD, CWS-VWD, and VWS-VWD, the WFL is tested. For maximum power generation problem, ACO performs better than the existing methods. Table 8 presents ACO performance on 3 scenarios for WFLO problem.

4.5 Teaching Learning Based Optimization (TLBO)

TLBO algorithm is stimulated by teaching learning behavior in real life [22]. In TLBO, a teacher imparts knowledge to a group of students, who then utilize that knowledge to enhance their own solutions to a particular optimization problem. On the basis of the student's performance, the teacher improves his knowledge. TLBO has been used to tackle a range of optimization issues and has been effective in a number of contexts. The WFLO problem was solved using both basic and enhanced TLBO by the author [35]. The author tests the proposed methodology on the WFLO problem as well as 10 different real-life engineering design challenges. Table 9 presents TLBO performance on two cases considering CWS-VWD and VWS-VWD for WFLO problem [35].

Table 9. TLBO results for the WFLO problem

S.No	Parameter	TLBO results [35]	
		Case 1: CWS-VWD	Case 2: VWS-VWD
1	Wind Turbines	39	39
2	Total Power	18401 kW	33137 kW
3	Cost	0.001463	0.000812
4	Efficiency	91.01%	89.58%

4.6 Grey Wolf Optimization (GWO)

GWO algorithm is stimulated by grey wolf leadership and hunting behavior in real life [23]. By mimicking wolf behaviors, The GWO algorithm is utilized to effectively resolve optimization issues. GWO has been used to handle a range of optimization issues and has shown progress in a variety of fields. The author [36] applied modified GWO to address the problem of energy production at WFs. When compared to other metaheuristics like GWO, PSO, and Safe Experimentation Dynamics (SED) Methods, Modified GWO produces the greatest energy generation results. Table 10 presents GWO performance for WFLO problem [36].

Table 10. GWO results for the WFLO problem

S.No	Parameter	GWO results [36]	
		Modified GWO [36]	Conventional GWO [23]
1	Mean MW	4.76484157	4.76483905
2	Best MW	4.764841572	4.76484129
3	Worst MW	4.76484157	4.76483393
4	Standard Deviation	6.678×10^5	1.3615

4.7 Artificial Bee Colony (ABC) Optimization

Honey bee foraging behavior in nature serves as an inspiration for the ABC algorithm [24]. ABC simulates the behavior of honeybees to identify the optimal solution to optimization difficulties. ABC is able to handle high-dimensional operational problems. The author [35] researched a wind farm having 10 WTs that is located in southern Turkey. In a real WF, energy production is optimized by eliminating the WE. Energy production is increased annually and costs are reduced when the ABC algorithm is used. Table 11 presents ABC performance on two cases for WFLO [35].

Table 11. ABC results for the WFLO problem

S.No	Parameter	ABC results [35]	
		Case 1: CWS-VWD	**Case 2: VWS-VWD**
1	Wind Turbines	39	39
2	Total Power	18062 kW	33652 kW
3	Objective function	0.001490	0.0008
4	Efficiency	89.34%	90.97%

4.8 Grasshopper Optimization Algorithm (GOA)

GOA is inspired by grasshopper swarm behavior in nature [25]. By mimicking the movement of grasshoppers using the approach, optimization issues are resolved as effectively as possible. GOA is appropriate for highly complicated optimization problems. The maximum energy production of the WF under various wind conditions at various sites in Saudi Arabia is determined by the author [37] and is shown in Table (12). Compared to the other alternatives, The electricity produced by the WE system can be increased more successfully using the suggested methods. Table 12 presents GOA performance on different locations for WFLO in Saudi Arabia WF [37].

Table 12. GOA results for the WFLO problem

S. No	Location	GOA results [37]	
		Mechanical Power (kW)	**Maximum Power (Kw)**
1	Sakaka	1.5023	40.3462
2	Dumat Al-Jandal	1.5024	40.1940
3	Qurayyat	1.0919	64.9912
4	Tabarjal	1.7860	49.2735

4.9 Firefly Algorithm (FA)

FA is stimulated by fireflies flashing behavior [26]. By mimicking the behaviors of fireflies. The algorithm is employed to address optimization issues in the best possible way. In FA, the optimal solution is discovered by using a population of fireflies. FA has been used to resolve numerous optimization issues. Furthermore, FA is exploited to resolve large-scale optimization difficulties. Author [38] applied modified FA for maximum power extraction. Modified FA provides better results as compared with PSO and other methods. Table 13 presents modified FA performance on two cases for WFLO [38].

Table 13. FA results for the WFLO problem

S. No	Metaheuristic	Wind Speed	Efficiency
1	Modified FA [38]	7 m/s	94.10%
2		8 m/s	93.16%

4.10 Differential Evaluation (DE)

DE is a heuristic optimization algorithm that simulates natural selection and evolution to find the best solution to optimization problems [27]. In 1997, Storn and Price invented the population-based optimization algorithm known as Differential Evolution (DE). The author [39] applied DE to solve the WFLO issues. DE is a hybrid that uses a brand-new bilevel programming model to produce the most power possible.

4.11 Cuckoo Search Algorithm (CSA)

Yang and Deb [28] first introduced the CSA algorithm as a tool for numerical functions and continuous problems. The method is based on cuckoo species that brood parasitically in their natural habitat. The CSA algorithm is contrasted with the widely used PSO and GA methods for WFL design [40]. According to empirical findings, the presented CSA algorithms performed better than the PSO and GA algorithms for the specified test scenarios in terms of annual power output and efficiency. Table 13 presents CSA performance on two cases for WFLO [40].

Table 13. CSA results for the WFLO problem

S. No	Parameter	CSA results [40]	
		Case 1: CWS-VWD	**Case 2: VWS-VWD**
1	Wind Turbines	39	39
2	Total Power	17861	34548
3	Efficiency	88.34	87.82
4	Run time	2428 sec	5271 sec

4.12 Wind Turbines Optimal Placement Techniques

The location of the WTs is determined by the precise design requirements as well as offshore and on land. Sites with average winds of more than 10 m/s are often seen as ideal locations for WTs [41, 42]. Placements of WTs are usually constructed in areas with the stable, regular wind [43]. The WT placement problem in wind farms is solved using a variety of metaheuristics, including SSA, Water Cycle Optimization (WCO) [44], Binary Invasive Weed Optimization (BIWO) [45], GA [46, 47], and PSO [48].

5. Conclusion

By producing recyclable, reusable, reasonably priced, and renewable electricity, wind farms can reduce reliance on scarce and non-renewable energy sources, such as fossil fuels. This paper reviews existing research on WFLO problems using various metaheuristic optimization techniques along with Jensen WE model. Different research works performed by researchers for the optimization of wind farm layouts are highlighted. The performance of several metaheuristics for WFLO optimization problems is reviewed and mentioned with results. To get better results, further research on various cutting-edge methods, including hybrid approaches, can be chosen. This work will be beneficial to exist researchers and newcomers to the field of studying WFLO.

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