RESEARCH REVIEW

A novel review on optimization techniques used in wind farm modelling

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The important interest and efforts devoted by industries and academic research institutions to electricity production from renewable and clean energy with the maturity of existed technologies justify the biggest exploitation of wind energy over the recent years. With the reduction in oil prices, renewable energy is way forward for efficient and environment friendly energy generation. Out of all existing available renewable energy, Wind Energy is the front runner owing to its ability of efficient power generation and to produce energy at large scale. Due to the non linear nature of wind energy, Optimization techniques are extremely critical as they are solely responsible for building an effective wind farm. Layout optimization is performed by using soft computing techniques and are extensively studied in the available literature. Therefore, this review paper highlights the significant research works of wind farm modelling using optimization techniques. This work also addresses the new approaches used in wind farm modelling. Further, it also presents a critical evaluation of existing research methodologies used for wind farm layout optimization. Hence, the objective of this work is to benefit scientists and new entrants in the field of modelling and layout optimization of the wind farm.

Introduction

In today's world, the atmosphere is getting polluted with carbon-dioxide and other global warming emissions, which trap heat and hence steadily increase the average temperature of the planet which creates a harmful impact on human health, environment and climate. On the other hand, many sectors of energy are facing a global recession due to the COVID 19 pandemic and also many other factors. A typical example of the above statement is the oil and gas sector, which is facing an appalling crisis due to fall in oil price per barrel. The world is focused on increasing renewable energy sources due to the reduction in oil prices. Renewable energy and oil/gas energy sources focus on different markets, economics of renewable energy are improving, the global dynamics of energy is changing, renewable energy is larger, cleaner and hence they provide a welcome diversity to the energy supply.

Renewable energy is mainly used to supply cleaner and efficient electrical power. There are many types of promising renewable energy sources such as wind, solar, fuel cells, micro-hydro, etc. Among all, wind energy is now growing exponentially and has an impact with great potential. Electrical energy demand is met by means of wind turbine due to its multiple advantages like low cost and very robust in nature.

In the modern world, the undisputed form of electrical energy generation is the wind energy. The growth of wind farms is

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enormous which grew in size and ratio from very small wattage to megawatts size. The conversion of wind energy to electrical energy involves primarily two phases: the first stage is the conversion of kinetic energy to mechanical energy for the wind generator of the shaft to be driven. The critical converting devices in this phase are the wind blades. The second stage is the mechanical energy captured by wind blades and are further converted to electrical energy via wind generators. The grid connection is highly driven by the converter, it is extremely important to maximize the performance of the first conversion, what can be done by using variable speed generators as the conversion efficiency is very low [1]. The most sort after research in wind farm technology are performed on the areas, (a) wind farm layout optimization [2–5] (b) Modelling approaches of wind turbines [6–8] (c) Cost reduction (d) Grid planning and operation (e) Energy and power management [9].

Recently, a number of numerical tools are under development, some based on stochastic mathematical models, each presenting specific features in terms of accuracy, convergence, stability, robustness, and calculation speed [10]. Among the most promising methods which have applied wind farm layout optimization, are Greedy Algorithm [5,121], Multilevel Extended pattern search algorithm [11] and Sequential convex programming (SCP) [12]. As of now, there is no single research article which summarizes the research of wind farm layout optimization. Hence, a detailed analysis of the existing technologies related to modelling techniques, wind farm layout optimization and new approaches adopted in wind farm technology are presented in this paper. This paper will also highlight the significant concepts and governing equations of the types of models in a wind farm.

This work will also critically analyze the existing methodologies in wind farm technology and provide possible solutions. The objective of this paper is to provide a one stop solution to practicing researchers and new entrants in the field of wind farm modelling and wind farm layout optimization. The following sections are divided as follows: Sections ''Modelling approaches used in wind farm technology'' explains the modelling approaches used in Wind Farm Technology. Section ''Objective function'' expounds the important inventions in objective functions. Section ''Wind farm layout using several optimization techniques'' elucidates the prominent works in wind farm layout optimization. Section ''Novel approaches in wind farm optimization'' elucidates the novel approaches used in wind technology. Section ''Critical evaluation of existing research methodologies used for wind farm layout optimization'' presents a Critical evaluation of existing research methodologies used for wind farm Layout Optimization and conclusion of the article is presented in Section ''Conclusions''.

Modelling approaches used in wind farm technology

Wind turbines use the heavy winds to generate electricity. A wind turbine is a machine that has a rotor with the propeller blades. For the electricity generation, the blades are systematically arranged in a horizontal orientation. The wind farms are placed in areas with high wind velocity. As the velocity of the wind is higher, the blade spin will be faster, thereby increasing the rotor speed to transmit electricity to the generator. This produced electricity is supplied to different stations through the electric grid. A wind farm consists of many wind turbines that normally are 50 m long each in height [13,14]. Air circulation increases with the increase in altitudes. Hence, Wind turbines are generally constructed at higher altitudes. It is noteworthy to mention that the mechanical power during higher wind speeds must be controlled and maintained. Fig. 1 illustrates the wind turbine system architecture. The figure illustrates the various parts of Wind turbine system such as the gear box and machine connected to the grid. The figure also highlights the stages of conversion such as primary conversion and secondary conversion.

The basic characteristics of the wind turbine system are presented in Fig. 2. The gearbox mechanism is responsible for the conversion of low speed, high torque mechanical power to electrical power. This conversion of mechanical to electrical power is performed by the power electronic converters, transformers and circuit breakers [15].

Different modelling approaches used in wind farm technology

Over many decades, there has been a genuine interest in Wind farm modelling research. The important types of wind farm modelling are broadly classified as follows and its detailed governing equations of each model are presented in this section.

Governing equations in wind speed profile in the wind farm model

The governing equations in wind speed profile of the wind farm model are detailed below [16]:

Logarithmic Law

$$u = u_{ref} \log(h/z_0)/\log(h_{ref}/z_0) \quad (1)$$

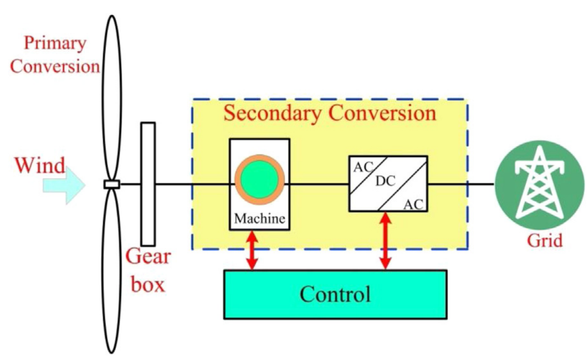

FIG. 1
Wind turbine system architecture.

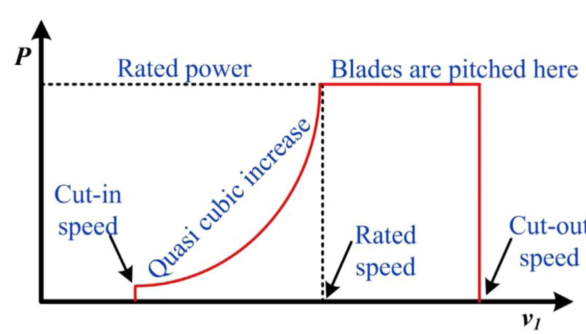

FIG. 2
Power output of Wind Turbine.

TABLE 1

Description of the model/governing equations in model.

Reference	Type of model	Description of the model/ governing equations of the model
[6,23,24]	Objective model	In this works, the authors have addressed the problem of multiple objectives by combining it into a single formulation. $Objective = \frac{\sum_i^{N_T} Costi}{P_{tot}}$ (7) The cost model is shown in the numerator and the denominator is the total power output
[7]	Particle wake model	In this paper, the authors have deduced the particle wake model which is primarily used to understand the momentum diffusion process.

where $u - speed of the wind$, u_{ref} refers to the speed of the wind at the reference height, z_0 refers to the ground roughness and h_{ref} is the reference height and h refers to the hub center height.

Governing equations in linear wake model

The governing equations and most significant equations in the linear wake model are as follows [6–20].

$$u = u_0\left[1 - \frac{2a}{\left(1 + \alpha\frac{x}{r_1}\right)^2}\right] \tag{2}$$

$$a = \frac{1 - \sqrt{1 - C_T}}{2} \tag{3}$$

$$r_1 = r\sqrt{\frac{1-a}{1-2a}} \tag{4}$$

$$\alpha = \frac{0.5}{\ln(h/z_0)} \tag{5}$$

where u_0– Speed of wind, x – downstream distance from the wind turbine that generates the wake, r_1– Wake radius, a – Induction factor, C_T – Thrust exerted on wind rotor by air, R_w represents the radius of the wake region at a specified section along the cross-wind, calculated by

$$R_w = \alpha x + r_1$$

where α = entrainment constant, r = Turbine radius.

The wake flow equation can be given as follows:

$$u_i = u_{0i}\left(1 - \sqrt{\sum_{j=1}^{N_T}\left[\frac{A_{ij}}{\pi r_i^2}\left(1 - \frac{u_{ij}}{u_{0j}}\right)\right]^2}\right) \tag{6}$$

where u_{0i} and u_{0j} are the wind speeds at the i_{th} and the j_{th} turbines positions, respectively. They are equal to the inlet speed (u_0) of wind farm. (u_{ij}) is the wind speed at the wind rotor of i_{th} turbine in the wake region of the j_{th} turbine. N_T is the number of wind turbines in wind farm. r_i is the rotor radius of the i_{th} turbine. A_{ij} is the rotor area of the turbine inside i_{th} and the j_{th} turbine's wake.

The description and the governing equations of the other two models are detailed in Table 1. The prominent works by authors in wind farm models are detailed in Table 2.

Objective function

A correct definition of the objective function is essential to solve a complex non-linear problem. The following section discusses about the formulation of objective function.

TABLE 2

Prominent works of authors in models used in wind turbine technology.

Reference	Type of make/model of wind technology	Remarks
[10]	Turbine layout optimization model	This paper presents a modified version of the Jensen wake model. Simulated data collected from six wind locations, all offshore, were used to conduct numerical experiments.
[25]	Wake interaction model	The paper uses energy balance to create a mechanistic, linear model for the wake interactions. This method can be used with standard mathematical programming methods.
[26]	5 kW simulated wind power generator	This paper describes a simulation system for the research and development of wind power optimization using grid-connected power generator. The simulations can produce fluctuant power that meets the demand of optimization of wind power flow systems.
[27]	Mathematical model	The author addresses the design thickness of the airfoil, by increasing the thickness, better aerodynamic performance is observed. The optimal design takes into account the complicated requirements and still shows an overall improvement in the airfoil performance.
[28–31]	Surrogate modelling	The paper uses surrogate modelling to optimize the layout of hydrokinetic turbine layout. The method uses surrogate model construction, experiment design, simulations of computational fluid dynamics analyze the various parameter combinations and satisfy the optimal criteria at a very reasonable computational time.

Energy cost minimisation

The cost of the wind farm (WF) divided by the total power production [20], is widely used in literature and is the most commonly used objective function:

$$Cost\,of\,Energy = \frac{\mathrm{Cost}}{P_{tot}} \tag{8}$$

where 'Cost' represents the cost of the wind farm, $\mathrm{P_{tot}}$ is the total power production modelled by a simple function which only depends on the number of wind Turbines:

$$\mathrm{Cost} = N_{wt} = \left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N_{wt}^{2}}\right) \tag{9}$$

The cost of energy is extremely important. The power improvements, thereby improving energy efficiency in wind farm technology have eventually resulted in lower costs [21,22].

Maximization of annual energy production

The maximum of annual energy for a given distribution was investigated in the following references [32–41]. Integration of the wind turbine power combined with a wind speed distribution over the wind speed spectrum can be defined as the annual energy.

$$AEP = \int_{V_{\min}}^{V_{\max}} P(V)f(V)dV \tag{10}$$

where *P(V)* is the power curve of the wind turbine, *f(V)* is the wind speed distribution.

Wind farm layout using several optimization techniques

Wind farm layout design optimization has taken number one priority in the recent times and soft computing techniques are being preferred to solve nonlinear problems compared to classical analytical optimization techniques. It involves several constraints like legitimacy and social issues, engineering and design that may be logistic, economic, technical or environmental [42]. The main area of concern is placement of wind turbines, optimization of objective functions for energy maximization and cost minimization. Additionally the constraints involve turbine proximity, farm boundary, initial investment, noise emission level, hub height, number of turbines and the type of turbine. The prominent works in optimization techniques using several optimistion techniques are detailed below (Table 3).

TABLE 3

Cost element contribution to CAPEX, DECEX, and OPEX.

Cost element	CAPEX	DECEX	OPEX	Sensitivity to output
Turbine supply	ˇ	–	–	Low
Turbine Installation	ˇ	–	–	Medium
Foundation concept	ˇ	–	–	Medium
Operations and maintainence	–	–	ˇ	Medium

Genetic algorithm

Genetic algorithm is used to improve population of random candidate solutions, best known as chromosomes by repeated application of selection, crossover, and mutation operators. In every cycle, the fitness of the said chromosome in the population is estimated using an objective function. The genomes, also known as the decision variables of the designated chromosomes are changed after a series of crossover and mutation operators, to create new chromosomes for the subsequent generation. The crossover probability enunciates the probability of each designated chromosome to be mated with a different chromosome. Ideally, two parents produce two offsprings, with some exceptions [43].

There are primarily two methods, arithmetic and linear crossover. While two parents produce two offsprings in the first one, the two parents produce three offspring in the latter. Once produced, the two fittest offsprings replace their parents in the population [44,45]. The purpose of mutation is to generate new genetic material in the population and preserve the population diversity. This usually amounts to changing a random part of a gene of an arbitrarily picked chromosome. The most widely used method is the uniform mutation operator where a random element of the chosen chromosome is switched to another feasible arbitrary value [44]. As only characteristics of fitter chromosomes have a higher chance of being passed on to the following generation, the gross fitness of the population betters over time. The algorithms continues until the maximum number of generations have been created or an acceptable fitness value has been attained. The authors have used the parallel selection method in multi objective genetic algorithm (MOGA) in which the initial step is to create some starting individuals arbitrarily. Following which the genetic algorithm will separate them into two equal halves, out of which one is used for calculation of farm efficiency and the other is for calculation of cost per unit power.

A fixed percentage of the individuals will be picked for the crossover mutation, usually the random mate selection method in MOGA is deployed for this purpose. The highest probability of selections is given to the individuals with the best fitness in the sub-population, these designated individuals are then combined into a single population for crossover and mutation. While we cannot presume that with this selection method the fitness value in each generation will definitely improve, it will most certainly prevent false convergence or premature phenomena. This will, however, ensure that the MOGA will reach global search and optimization [46]. The downside of using random mate selection method is, one cannot prevent the participation of poorer individuals in the selection process, since the distance between the champion and medicore could have a large euclidean distance. Although, it does have advantages of avoiding premature as compared to other selection methods [46].

Related works:

The authors in Refs. [2,3] investigates the effect of pursuing different aspects of internal structural geometry as compared to a sequence of wind turbine blade design created with altering structural configurations. The main considerations of investigation are the geometry of the structural spar done by changing the width of the spar caps along with the number and location of shear webs that are inclusive if the span wise starting and ending location.

In Ref. [4] authors developed a structurally optimized model for wind turbine composite blades considering a parametric FEA (finite element analysis) model and GA (genetic algorithm) model. The idea of the optimization model is to minimize the mass of the composite blades with multiple criteria, constraint, like, number of unidirectional piles, thickness of shear webs and locations of spar cap which are considered as the design variables. The mass of the optimized blade has been lowered by 17.4% compared to the intial design, now weighing 228 kg, which indicates that blade mass can be considerably reduced by using the current optimization model. The model is also capable of perfectly determining the optimal structural lay-up of composite blades as demonstrated in the paper.

In paper [6] the use of different hub heights for wind turbines is assessed. Using Genetic algorithm for various wind conditions proved that optimizing the height will yield more power with the same number of turbines. The below figure is plotted between power output (MW) and generations. Fig. 3 below clearly shows that with increase in height, the output of power is higher. Further, the genetic algorithm with definitive point selection is implemented by author in Ref. [47].

Greedy algorithm

The layout of the wind turbine is optimised by the usage of the greedy algorithm [48]. Most of the research considered identical hub height for the wind turbine and used two dimensional grid system to identify the position of the wind turbines.

Related Works:

The author in Ref. [5] uses the greedy algorithm to explain the wind turbine layout optimization with multiple hub heights. The two models, linear wake model and particle wake model are used to estimate the wake flow calculation over flat and complex terrain respectively.

Using the greedy algorithm over the genetic algorithm incurs low computational cost and gives better results, as the layouts with multiple hub heights can increase the total power output and reduce the cost per unit output significantly, essentially for complex terrain wind farms. The flowchart representation of greedy algorithm is presented in Fig. 4. The flowchart details each process flow of the algorithm.

In greedy algorithm a set of resources are recursively divided based on the maximum, immediate availability of that resource at any given stage of execution.

Two conditions define the greedy paradigm.

- Each stepwise solution must structure a problem towards its best-accepted solution.
- It is sufficient if the structuring of the problem can halt in a finite number of greedy steps.

Important characterstics of greedy algorithm

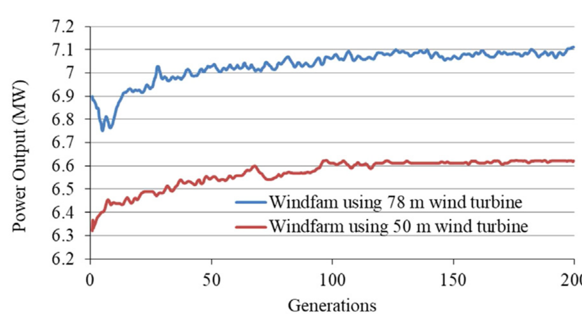

FIG. 3
Power output Vs generations.

- There is an ordered list of resources, with costs or value attributions. These quantify constraints on a system.
- You will take the maximum quantity of resources in the time a constraint applies.
- For example, in an activity scheduling problem, the resource costs are in hours, and the activities need to be performed in serial order.

E_n, E_r are the set of normal and abnormal links in the road network, $i = 1,2,3, \ldots m$; m is equal to the number of links belonging to E_r. $i = 1,2,3,\ldots,m$; m is equal to the number of links belonging to E_r. I_e' is the ratio of c^i_e to $c^i_{e'}$ it represents the importance of a given link *e*. c^i_e *is* system-wide travel cost after repairing *i* links and link *e* is repaired in the last. *E* is the set of all links in the road network.

Multilevel extended pattern search algorithm

A pattern search can be defined as a purely deterministic search algorithm [49,50] which uses a defined set of pattern directions to traverse potential solutions. To aid the escaping of local minima,

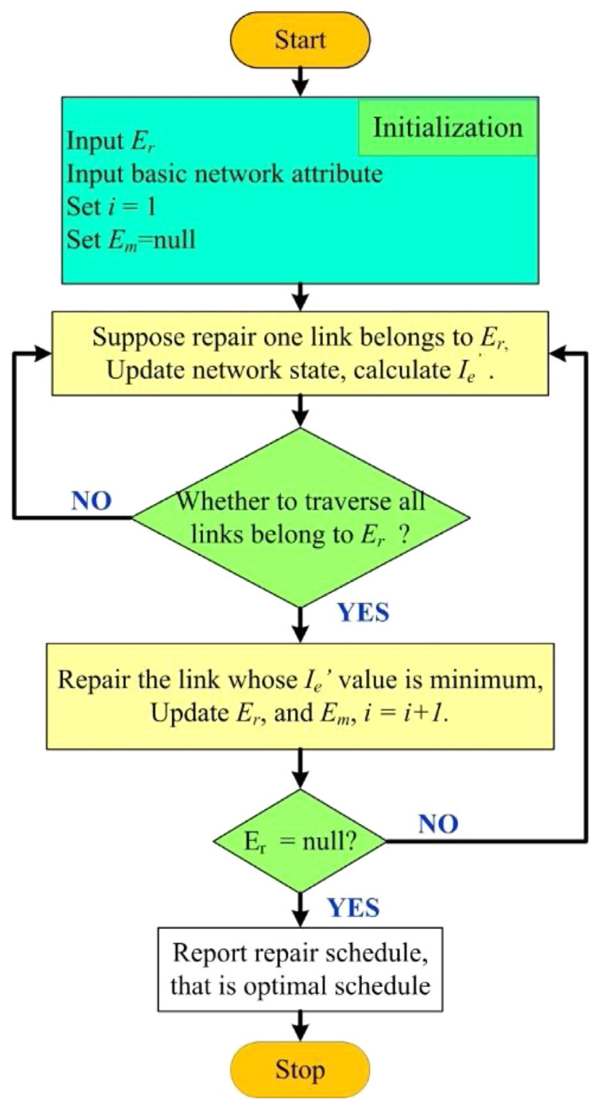

FIG. 4
Greedy Algorithm.

attributes are infused stochastically into the search which are the extensions provided to the EPS.

As a first step, a broad range of turbine locations is established using a randomized initial layout of turbines which do not specifically assign starting locations. Secondly, to avoid favoring individual turbine movement the search order is randomized. Lastly, to pick the weakest turbines, a popping algorithm is used and it tries to assign a new random location to the selected turbines until a certain number of attempts are complete or the superior global evaluation is used for the relocation of the turbine [49,50].

Related Works:

The authors in paper [11] discuss a system of modelling advances that can be used for computational optimization of wind plants. This technique involves accurate cost and power modelling, effects of varying atmospheric stability and partial wake interaction. This algorithm is used to validate this advanced modelling system for multiple wind scenarios. The multi level pattern algorithm is presented in Fig. 5.

Particle swarm optimization (PSO)

The PSO algorithm mimics the behavior of a swarm as a simplified social system, mainly inspired by the swarm intelligence of birds flocking or fish schooling [51,52].

Related Works:

The authors [53,54] uses model predictive control and a binary particle swarm optimization (BPSO) system with time-varying acceleration coefficients (TVAC) to address the optimal placement of wind turbines within the farm. The aim being extraction of maximum turbine power output with a minimum investment cost, the BPSO-TVAC algorithm takes into account uniform and non-uniform wind speeds with variable direction characteristics and applies to a 100 square cells test site.

The authors in paper [55] attempts to optimize offshore wind farm layouts, by optimizing the position of the wind turbines in the wind farm to ensure maximum energy production. A penalty function method is introduced in this paper to account for a restricted zone due to limiting factors of wind turbine placement like marine traffic, shipwrecks or seabed conditions. The particle swarm optimization algorithm with multiple adaptive methods (PSO-MAM) is a stochastic algorithm that can simulate a layout to find a feasible solution which can out-do the baseline layout of a reference wind farm (RWF).

The Unrestricted wind farm Layout Optimization (UWFLO) is a novel approach [56] which determines both optimal farm layouts as well as selection of suitable turbines based on the rotor diameter which will enhance the net power generation.

Ant colony algorithm (ACO)

Ant colony optimization (ACO) has been yet another algorithm developed to address discrete optimization problems [57], the algorithm reproduces the behavior of a real ant and the colony in the process of looking for food [58].

Related Works:

The authors in Ref. [59] adapt the ant colony algorithm for maximizing the desired energy output, it takes into account wake loss which is determined by wind turbine location and wind direction. The results show this method produces better results than evolutionary algorithm. The ant colony algorithm is presented in Fig. 6. The flowchart details the steps presented in the algorithm.

Characteristics of Ant colony algorithm

The Ant colony algorithm mimics the real ant colony behaviour while they look for food.

- Ants randomly explore the area to find food.
- After finding a source, the ant returns back to its nest.
- During traversing, ants leave a trail of pheromones.
- Pheromone quantity increases according to food quantity
- The follower ants of the first ant go after the pheromones deposited by the first ant.
- As a result of this transaction, the deposition of the pheromone on the trail will be strengthened.
- The quantity of pheromones in each traversal will evaporate.
- If there are two paths to get to the same source of food, the ant finds the shortest path between their nest and food with the help of the freshpheromones.

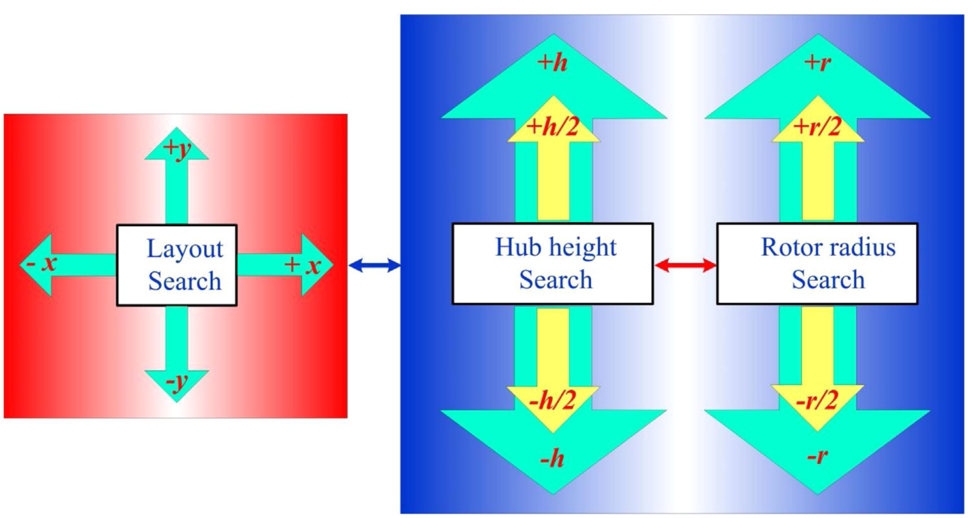

FIG. 5
Multi level pattern algorithm.

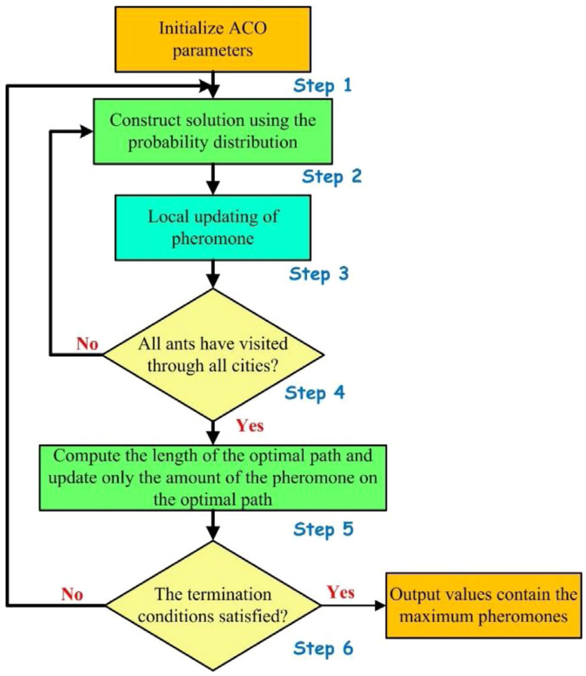

FIG. 6
Ant colony algorithm.

The first step consists of initialization of the pheromone trail. Each ant constructs a complete solution to the problem according to a probabilistic state transition rule which depends mainly on the state of the pheromone. Finally, quantity of pheromone is updated in two phases; an evaporation phase where a fraction of the pheromone evaporates, and a reinforcement phase where each ant deposits an amount of pheromone which is proportional to the fitness of its solution. This process is iterated until a stopping criterion.It is shown in below in the form of pseudocode.

m = number of ants in population, T is number of iterations (generations), ij = portion of entire solution (trail), N_i = neighborhoods of location i, l indicates number of neighborhoods, $\prod_{ijt}$ = amount of pheromone on trail ij at time t, $\Delta\prod_{ijt}$ = addition of pheromone on trail ij at time t, ρ = evaporation factor ($0 < \rho < 1$), η_{ij} = heuristic regarding trail ij, α, β are relative importance of pheromone and heuristic respectively.

Sequential convex programming (SCP)

SCP is applied to maximize the objective function and to study the optimal wind farm layout problem.

Related Works:

The energy production of downstream wind turbines in a wind farm reduces due to wind speed and elevated levels of turbulence caused by wakes from the upstream wind turbines, which reduce the overall efficiency of the farm due to the wake interference. The authors in Ref. [12] present an efficient solution to optimize the placement of wind turbines to generate maximum wind farm power output.

Random search algorithm

The random search (RS) algorithm for wind farm layout optimization in the previous study [60] was based on a continuous formula and refines the results obtained by GA [61] for an ideal test problem presented in Ref. [20]. While in this study, adaptive mechanisms are added to the algorithm to the same problem and subsequently for the Horns Rev 1 WF. To minimize the computational cost, a strategy similar to that adopted by Wagner et al. [62,63], is applied to evaluate the layouts.

Related Works:

The random search (RS) algorithm [64] is based on a continuous formulation which begins from an initial feasibility layout and proceeds to improve the layout iteratively in the feasible solution space by adding adaptive mechanisms.

Evolutive algorithm

Evolutive algorithms mainly consider two operators to generate new individuals or potential solutions. The method is the roulette wheel wherein the parents with the highest NPV have a higher chance of selection. The paper describes five types of crossover operators applied in a random way [65].

Related Works:

The authors discuss optimum wind farm configuration problem along with evolutive algorithm to optimize the layout [66]. The results are compared with previously published works and test cases used as performance evaluation of the proposed algorithm.

Novel approaches in wind farm optimization

This section will describe the approaches that will use optimization techniques along with a specific method. This section will help the readers to understand the usage of specific methods such as mixed Linear Programming methods and mathematical programming techniques. Also, this section highlights more practical case studies of usage of optimization techniques in Wind Farm modelling.

The authors in Ref. [67] have applied wind farm optimizations for lands that are owned by different people which includes a traditional penalty technique that depends on the type of wind farm land division. The traditional approach could be quite cumbersome in the case of complex divisions, a new method is discussed in this reference. The approach is to repair infeasible solutions prior to fitness evaluation rather than having a penalizing term during evaluation of the fitness function. Results from three types of farm divisions were compared to prove the efficacy of the method proposed. In Ref. [68], the authors developed a novel mathematical programming technique for layout optimization. To account for the multi-turbine wake effects the authors consider the Jensen's wake decay model.

In Ref. [69], A mixed Integer Linear Programming method (MILP) should be used to solve two fold problems that deal with investment cost and operation cost, this is a better approach than solving them as independent issues. The MILP is a reliable and effective approach. Cost of energy loss must not be neglected as they influence the financial results, the expense is comparable to cable laying and influences the design approved for the internal network. The algorithm has practical use in the design process of the wind farm.

In Ref. [70], a brand new method which involves simultaneous layout plus control optimization are followed by the authors. The results are compared to various other approaches as layout and control optimization using both grid based and unrestricted coordinate design methods for both ideal and also realistic wind conditions. The technique yields close to 1–3 kW more power for each turbine as compared to self optimum control technique whereas unrestricted coordinate method produces 1–2 kW more power for each turbine turbine when compared with the grid based method.

In Ref. [71], the authors consider the landowner participation as well as a number of turbines as a binary string variable, in cases where continuous availability of land for wind farm construction cannot be assumed. The authors provide an enhanced levelled wind farm cost model which takes into account remittance fees to decide the optimal placement of turbines in three landowner involvement scenario and couple of land-plot shapes. The system-level cost-of-energy (COE) optimization model is tested for the two different shapes of the plot, i.e., equal sized square plot and unequal rectangular plots. The results produced were realistically comparable to the original COE data. Irregularly shaped land plots too are handled easily by the model and result show landowner remittance fee accounts for close to 10% of all the operating costs. Larger plots always incur higher remittance costs. This particular model helps wind farm developers locate crucial plots for successful layouts and optimal positioning of the turbines with actual estimates of profit and cost.

In Ref. [72], the current trend involves researchers focusing on advancing optimization algorithms and enhancing wind farm models based on two designing methods, i.e., grid based method and unrestricted coordinate method. These two methods are explained in the paper by taking three unique grid situations for producing best optimization solutions using grid based methods and pitched against the results obtained from the unrestricted coordinate method. Additionally, cost models like Mosetti's and Chen's model are employed to study the impact on the results of optimization.

In Ref. [73], A parametric aerodynamic optimization study is discussed to produce the blade design for a unique implementation of a vertical axis wind turbine, the technique was put on to enhance the cross-sectional and two-dimensional geometry of the blades in the turbine. In order to compare the geometries, a non dimensional coefficient of energy was used as the fitness function, to assess the blade performance unsteady viscous computational fluid dynamic simulations were employed as well as to accommodate the transient nature of the given physical process moving meshes were considered. For the blade cross sections a unique parameterized approach which involves circular arcs was developed. The entire optimization process was created in 2 stages: Experiments designed based on response surface fitting to explore the parametric design space and use of Nelder Mead simplex gradient based optimization procedure.

In Ref. [74], the current model uses turbine induction factor as a function to calculate the wind velocity for the wake behind the turbine, this factor is usually considered as 0.324 in all previous approaches. But as an improvement the induction factor is calculated for the wind turbines based on Blade Element Momentum theory. This accounts for the blade profile, wind speed and the angular velocity of the turbine. The important conclusion of this method is that varying blade profiles and differing operational conditions obtain different induction factors, this greatly affects the calculated power gain from a farm. Hence, influencing the farm layout in the optimization process.

In Ref. [75], When considering an offshore wind farm, the port should be installed and designed in an efficient way to minimize factors like transportation cost of required components within the port. Two MILP are developed to establish the optimized port layout in which the shape of the internal areas present in the port maybe rectangular with the possibility of other dimensional configurations. The final shape of the required port area may be treated as a convex or a concave polygon. For small-sized problems, MILP can be used while for medium-sized problems while for medium sized issues, Meta heuristic methods like variable neighborhood search (VNS) can be applied. These methods are used on random data sets.

In Ref. [76], the authors approach the optimum layout design for onshore farms in which the wind load is decided based on stochastic fields. Metaheuristic search algorithms designed around discrete variants of harmony search are employed. Wake effects and influence of wind direction are considered to solve the optimization problem. The results show the efficiency and applicability of putting together metaheuristic optimization along with stochastic methods of implementing wind loads for an optimized wind farm layout.

In Ref. [77], The author covers an approach that include both warm and cool thermal packed beds where the heat engine as well as pump function on a reciprocating Joule cycle which makes use of argon as dealing solution. Results mainly focus on trade surfaces for complete efficiency, power and energy density, this is conveyed as fairly dull effectiveness vs. energy density trade off. This is used to guarantee a heightened storage density that could be accomplished by using a reduced efficiency penalty. Loss thanks to irreversible heat transfer and pressure fall within the winter reservoir are negligent. Hence, the effectiveness is primarily affected by processes of expansion and compression.

In Ref. [78], Computational fluid dynamics is used to simulate the output of two straight-bladed vertical-axis wind turbines and further analysed and optimized by adapting the Taguchi method. There are various factors considered like the incoming flow angle (b), turbine spacing (S/d), tip speed ratio (k), blade angle (/) and rotational direction (RD). In addition, there are four levels taken into account to influence the output of the dual turbine system. Based on this, an orthogonal array of L16 is designed. The factors stated above are ranked in the order of the strength as $k > b > RD > S/d > /$. After analysing the signal-to-noise (S/N) ratio, it is deduced that the five factors can be optimized to maximize the power generated by the system, and this optimum solution occurs at $k = 2$, $b = 120$ either counter-clockwise or clockwise, $/ = 0$ and $S/d = 3$. The flow velocity can be enhanced in the regions that are beyond, between and beyond the two turbines but drops significantly in the wake regions. As compared to a single turbine system, using the optimum conditions and factors for the dual turbine system can improve the mean power coefficient by 9.97%.

In Ref. [79], the stability is discussed by the authors and reactive power management through an isolated hybrid type of the Offshore wind-diesel-tidal turbine, this system is prone to losing stability due to uncertain input parameters and load, hence making reactive power management an urgent requirement. This power management is made possible through the use of FACTS devices.

In Ref. [80], the authors describe a maintenance model which will evaluate the joint redundancy as well as formulate the imperfect block opportunistic model, hence reducing the loss of load probability and the total life cycle cost for a wind farm. The approach is to enable different thresholds of reliability for imperfect maintenance that include failed and working turbines, preventive and proactive dispatching of the maintenance team. Additionally, to evaluate the performance metrics of the farm like the various types of turbines, delays in the maintenance, activation, duration and considering the limitation on availability of maintenance teams. Sensitivity analysis is performed on this data and the multi-objective particle swarm optimization algorithm is used to drive pareto optimal solutions. A comparative study with the current policies show the advantages of the proposed system.

In Ref. [81], The application discussed in this paper addresses a gradient based optimization algorithm to solve previously constrained physical model. In every iteration, the performance and flow of array configuration are predicted using a two-dimensional finite element shallow water model. Using the fraction of time used by the flow the power is extracted using the turbine position and tuning parameters. The solution is derived by solving the associated adjoint equations. The method is designed to backtrack the computation to tuning parameters and turbine positions, making the gradient almost independent of the number of turbines.

In Ref. [82], the authors present a non-linear mathematical programming model to solve land-use constraints and other heavy constraint practical problems using a continuous-variable layout optimization of the wind farm. This effective method makes use of the accurate gradient data pertaining to the problem constraint and objective. The results are then compared to the genetic algorithm in certain wind farm layout optimization test cases. When the method is applied to cases of high dimensionality and constraints proves effective reduction in computational cost and an increase in wind farm efficiency.

In Ref. [83], the paper talks about a hybrid evolutionary method or a quadratic assignment problem-genetic algorithm to solve restrictions due to a turbine arrangement in farms with the candidate selection approach. Initial candidate point selection approach discussed, is adapted by four cases to show optimal design efficiency. Along with previously addressed wake effects, rotor diameter and turbine hub height, the algorithm accounts for restrictions on prohibiting places for placement, load bearing capacity and changing wind direction and velocity. The approaches show a 3% improvement in efficiency for one case and reasonable impact on the remaining.

In Ref. [84], The author propose a definite point selection algorithm and an area rotation method to ascertain optimal dimensions for the wind farm, thereby facilitating the farm to face maximum free stream velocity. The points are used for the placement of the turbines for maximum efficiency while allowing for the minimum safety operation distance. This method has the potential to identify zero-wake effects points in the farm. This provides better overall power for a fixed number of turbines as compared to previous methods.

In Ref. [85], The paper describes the optimization of blade development process by considering the trailing edge flap controllers and individual pitch to estimate the impact they have on energy cost. The parameters considered are twisted, blade chord, material distribution, width of the spar cap and also includes costs of the turbine to create a mass model from the present simulation codes. Constraints considered are fatigue damage, resonant frequency, rotor thrust and ultimate stresses. NREL 5 MW was used as the reference turbine to estimate the gain of this optimization, estimating to 1.05% levelized cost of energy with collective pitch control and 1.17% with individual pitch control. Using trailing edge flaps additionally increases it to 1.27%. The main parameters of consideration for optimizing the design are ultimate stresses in the spar cap, rotor thrust and blade deflection.

In Ref. [86], particle filtering approach is discussed which describes an optimized model for wind farms that have least wake effect and most power generation, although the constraints are the farm boundary and gap between two adjacent turbines which are factored into the solution. It has been used to optimize cases with different wind speed and direction distribution. This method shows results comparable to evolutionary strategy and colony algorithms discussed above.

In Ref. [87], deep learning can be used in Wind farm optimization. The primary contributions of the experts are automated suggestion process for harm detection in drone inspection pictures, accuracy in the suggestion model attained through skilled details augmentation and publication of wind generator inspection information sheet. Vestas is one of the leading companies in R&D of Wind farm technology. Vestas product portfolio covers all wind classes across the world and ambition to lower the cost of energy faster than anyone in wind energy through various optimization techniques [88]. The author in Ref [110]. presents a novel approach based on the characteristics of all Wind turbines effectively available in the market, thus mainly focussing on Wind turbine selection rather than on mere wind turbine best allocation.

To conclude, this section outlays the various novel works carried out in the field of Wind farm optimization.

Critical evaluation of existing research methodologies used for wind farm layout optimization

Due to the ever increasing power demands and concern over the environmental impact of conventional fossil fuelled power plants, Wind energy has rapidly developed [111]. Wind energy has experienced an amazing expansion in the previous years. The global collective capacity of wind power development has amplified twenty times in a 10 year period and is anticipated to get much more quicker in the future [89]. Most developed countries are in the mission to produce 20% of electricity by wind energy by the year 2030. Hence, wind energy is the next potential replacement source of clean energy.

Wind Farm optimisation is very important in offshore platforms. Accurate optimization of wind farms in offshore platforms help in high cost reduction and also energy savings. There are many works from authors [115–120] which highlight the importance of energy yields based on control strategy and accurate wind farm layout optimization.

It is important to mention that there is very little uniformity of wind farm modelling proposed by all researchers. Also, there is no in-depth information about the constraints used and codes of the various algorithms. Also, the manufactures data sheet gives only limited values. This section will present an evaluation of all the research performed on wind farm layout optimization. The performance parameters such as (1) algorithm complexity, (2) Convergence speed and computational domain, (3) soft computing techniques, (4) comments on wind farm optimisation using MPPT approach, (5) hardware implementation, (6) Cost statistics of wind farm optimization are selected to generally categorize the methods. Table 4 summarizes all the discussed optimisation techniques into catergories such as convergence speed, Wind Behaviour, complexity level, computational domain and Hardware Implementation.

Cell technologies

There are five types of modelling approaches used for wind farm technology. The first type of model is the wake interaction model which is linear or mechanistic in nature. Most authors have used the linear wake. The other four types of models namely the turbine layout optimization model, simulated wind power generator model, mathematical model and surrogate model are not widely used for wind farm layout optimization as it is more complicated in nature for real time implementation.

Convergence Speed and computational domain

The primary cause is the fact that the dynamic and static characteristics of large scale wind turbines differ from the traditional power plant systems. Thus, novel theories for modeling wind generator methods are required. Optimization techniques are a solution to solve this complex problem due to its non-linear and dynamic nature. Hence, optimization techniques with faster convergence speeds are necessary.

The convergence quickness is very dependent on the specific set of constriants. Hence, it is noteworthy to mention that conventional algorithms and methods is very limited as known set of constriants and values are used. If we deeply analyse we can also understand optimization techniques are comparable to adaptive conventional algorithms in terms of performance. It is due to changes in steps, constraints and values, we notice an enhanced and better performance. In Refs. [2–4] GA is implemented for standalone wind systems; convergence is accomplished at less than 0.3 s with less steady state oscillations. Recently new domains of evolutionary algorithms have emerged to handle Wind Farm applications. Among all the algorithms presented in the previous section, the greedy algorithm [5,121] stands tall in terms of convergence value and It is noteworthy to mention that theoretical error in this method is 0.0001%. In the evolution algorithm [65] the convergence characteristics are achieved in very less generations and very minimum computational effort.

There are four types of objective functions used for wind farm layout optimization. The first objective function is the minimization of the cost of energy which has been predominately used in most papers. The second objective function is Maximization of Annual Energy Production, the third objective function is Minimization of Blade Mass and the fourth objective function is multidisciplinary optimization. Minimization of the cost of energy is the objective function used in most papers due to its manifold advantages such as computational speed and less complexity compared to the other objective functions.

Algorithm complexity

The complexity ranking for soft computing techniques on the basis of algorithm complexity can be expressed in terms of the amount of computation involved, complexity and number of steps, although this would be an indirect comparison. Essentially, multilevel extended pattern search algorithm occupies highest complexity ranks while factoring in the computational time and memory.

According to procedural and implementation complexity the following soft computing wind farm optimization layouts techniques are ranked. (1) Multilevel extended pattern search algorithm [11] (2) Greedy Algorithm [5,121] (3) Ant Colony algorithm [58] (4) Quadratic Interpolation Optimization [90] (5) Particle Swam optimization [53] (6) Binary Particle Swarm Optimization [54] (7) Genetic Algorithm [2,112] (8) Definite Point Selection [91] (9) Evolutive algorithm [92] (10) Random Search [93] (11) Simulated Annealing [94].

Comments on soft computing techniques

PSO has been employed to solve the majority of the control issues of energy development for MPPT or perhaps Maximum Power

TABLE 4

Summary of Optimization Techniques in Wind Farms.

S. no	Name of the method	Convergence speed	Wind behaviour	Level of complexity	Computational domain	Hardware implementation
1	Genetic algorithm [2,3,4,6]	Normal	Mean	Moderate	Discrete	Difficult
2	Particle swarm ptimization [51,52,113]	Good	Mean	Moderate	Continuous	Moderate
3	Binary Particle swarm optimization [54]	Good	Mean	Moderate	Continuous	Moderate
4	Multilevel extended pattern search algorithm [11]	Good	Mean	High	Continuous	Difficult
5	Greedy Algorithm [5,121]	Good	Mean	High	Continuous	Moderate
6	Ant Colony Algorithm [58]	Good	Mean	High	Continuous	Moderate
7	Random Search Algorithm [93]	Good	Mean	Low	Continuous	Easy
8	Evolutive Algorithm [65]	Good	Mean	Moderate	Continuous	Moderate
9	Definite point selection [84]	Normal	Mean	Moderate	Discrete	Moderate
10	Quadratic Interpolation Optimization [90]	Normal	–	High	Discrete	Difficult
11	Simulated Annealing [94]	Good	Mean	Low	Not Specified	Easy

Point Tracking. This is completed for each fixed and adjustable speed wind turbines, the concept is usually to estimate the correct tip speed ratio for adjustable wind generator and rotor velocity for repaired wind turbines to produce optimum energy annually [95]. Additionally, PSO shows simpler implementation and faster convergence compared to GA [96]. The best way to go is Hybrid algorithms to address the complexity of power system problems. Existing algorithms take considerable computational time to provide in-depth analysis, while what essentially is required is a turn around time in milliseconds. This prospect of parallel processing has great scope for improvement [97]. Power supply systems must be reliable as they are critical for renewable sources that mainly depend on the weather [98], hence digital control [99] or intelligent control based on Neural Networks [100,101] should be used as control strategies for the optimal sizing of renewable generators.

Comments on wind farm optimization using MPPT approach

Most wind farm optimizations are conducted making use of the optimum power point method. It is conducted using the wake design and is very associated with distant relative positions of the wind generator and input wind velocity. Thus, additionally, it justifies the choice of the wind farm area. Installation and wind turbine placement is dependent on the wind direction [105]. The wake loss can go down when the distance between wind turbines along prevailing wind direction must be greater compared to the vulnerable wind direction [106].

Hardware implementation

The authors in Refs. [107] present a series of studies of various optimization techniques showing processor speed, function calls, number of cores used, and total Random Access Memory (RAM) installed in the system. The inference deduced from this study is the conventional algorithms such as the basic genetic algorithm and simple particle swarm optimization approach are simpler, less complex and require less memory. Whereas advanced algorithms and methods such as preconcoditioned sequential quadratic programming require higher memory but have faster convergence. It's also noteworthy to point out that the gradient based strategies have done much better in finding the relative optima particularly for scaled-down wind farm sizes. Also, latest research shows that wind farm using optimisation techniques are extensive in the offshore region [102]. The energy production in offshore wind farms are highly dependent on the model type (wake interaction model, turbine layout optimisation model, simulated wind power generator, mathematical model and surrogate model), control strategy and optimisation technique [103,104].

Hence, the algorithms categorised are easy, moderate and difficult in Table 4. This categorisation is based on the number of steps the algorithm takes for execution, computational time and convergence speed. Hence, the algorithms with least number of execution steps, least computational time and faster convergence speed is categorised as 'Easy'. The algorithms with high number of execution steps, high computational time and slow convergence speed is categorised as 'difficult'.

Cost statistics of wind farm optimization

The algorithmic optimizations have been thorough in the prior sections. This section will detail on the price degree optimizations on Wind Farm. The estimated price of wind farms is based on the following factors such as the turbine supply, turbine installation etc. Each cost element is decided to becoming a part of the capital spending (CAPEX) and the functional expenditure (Decommissioning expenditure or opex) (DECEX) [109].

Turbine supply

The rotary engine costs are decided based upon the worth per turbine in concert with tower. The turbine producers have furnished these values through various considerations with the policy makers of the offshore wind business. This value thus does not vary due to the layout unless the whole range of turbines or perhaps invest capability changes.

Turbine installation

The rotary engine installation costs are backed promote values for vessel costs as well as capacities. These costs are modelled by scheming the anticipated time required to invest all of the turbines at the specific locations. The value design differs from typical methods through the work of the algorithms.

Foundation concept

The cost of transition piece and delivery of an invented foundation to the set up port are embodied by the foundation conception prices. Wind power facility layout improvement tools are generally deployed in first stages of the wind farm design at the objective elaborate the value of soil testing. Soil surveys are very crucial prior to the assembly of the wind farm as soil that is loose is able to damage or perhaps collapse the wind farm. Hence, economical models are needed dependent on correct soil surveys.

Maintenance and operations

The maintenance and operations costs are supported anticipated maintenance and operations expenses, is within the 5–100 MW to 1000 MW. The maintenance and operations costs are classified as operational expenditure as these are incurred annually during the time of operation. Fig. 7 details the areas of concentration to reduce and optimise wind farm cost.

Future research trends in wind farm technology

Within the last 15 years, maturity has been reached by turbine technology. The developments in horizontal turbine performance

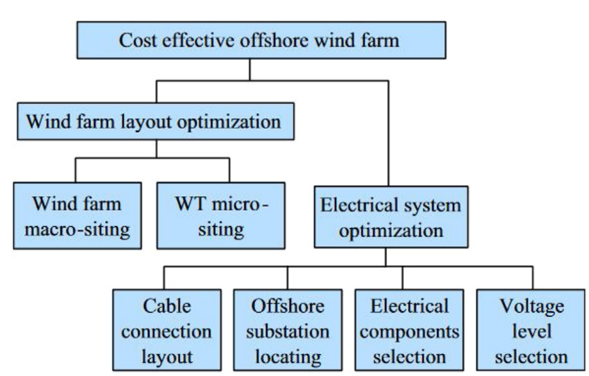

FIG. 7
Cost effective wind Farm structure.

methods as well as strategies are able to end up to more cost reductions and within the near future, wind energy will have the ability to replace Gas and Oil. The main conclusion that will be obtained from this particular assessment would be that the amount of analysis documents that will utilize optimization strategies to unravel for the maximum horizontal turbine blade, aerofoil type and rotor like challenges have exaggerated significantly in the recent past. The authors anticipate long haul optimization challenges are likely to be set as multi disciplinary problems. Thus, to place the final remarks, the writers have broadly classified the future research trends in wind farm technology.

1 The majority of the papers presented illustrates the works contemplating optimizing the power system topology and the mechanics topology. The two factors are co related that ought to be considered at exactly the same period in wind farm planning stage, therefore, in the future, a general cost effective wind farm may be found. Efforts should be put on the information exchange, along with an alternative management system to verify the collaboration between different sections. General electric along with the wind farm industry is switching to some digitization stage where together with the assistance of analytics and data for creating superior design for better problem solving. Customized aerodynamic efficiency and analytics platform upgrades the trouble shooting and enhances better and efficient usage of the wind Farm [108].
2 Exhaustion load is the change seen in a material under the influence of stress created during cyclic stacking. It causes the decrease of wind farm lifetime because of the wake turbulence. In the event that closer dispersing is orchestrated between two Wind turbines, the weakness burden will increment. Expository models are expected to assess the weariness heap of the entire wind farm in the future.
3 Unwavering quality is a significant factor for the exhibition of wind farm at Offshore. Since the activity and support is expensive and tedious for offshore wind farm, it is important to have a safe electrical framework. In any case, greater unwavering quality consistently reacts to greater venture. Henceforth, the electrical framework configuration should find the trade off as indicated by the down to earth necessities.
4 Heuristic calculation and scientific programming strategy are both pertinent in fathoming the wind farm enhancement. For wind farm with a predetermined number of Wind turbines, numerical programming strategy has its one of a kind focal points as fast convergence and robustness. The improvement of offshore wind farm is towards enormous limit within excess of 100 Wind turbines. In such a case, the heuristic calculation will show its preferred position since it can get another ideal arrangement quicker, and adopting innovation can be effectively received to additional computational speed.
5 Wind farm noise control is another area interest in the present trend and will continue further [114]. Previous research on wind farm layout optimization has been generally aimed at achieving the minimum investment costor maximum captured energy. The approach in Ref. [114] focuses on an optimal layout for a wind farm considering its noise, without sacrificing power production.

Conclusions

Wind farm increasingly attracts worldwide attention due to its contributions in reducing carbon emission as well as the potential value of higher energy production efficiency. In this paper, the most important papers on wind farm layout optimization techniques are systematically reviewed. The concepts behind types of models used in wind technology are highlighted as well. The different works on soft computing techniques for wind farm layout modelling are elaborated in detail. In the critical evaluation section, the research methodologies are reviewed in terms of base factors such algorithm complexity, computational speed, objective functions, optimization techniques, cost statistics and hardware implementation. Hence, this paper will be useful to the researchers and new entrants as it is one step solution for the research of wind farm layout optimization.

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