Placement Optimization for Renewable Energy Sources: Ontology, Tools, and Wake Models

MUHAMMAD YOUSAFA KHAN(1,2), (Member, IEEE), MUDASSAR ALI(3), (Member, IEEE), SAAD QAIJAR(4,5), (Senior Member, IEEE), MUHAMMAD NAEM(6), (Senior Member, IEEE), CHYRSTOMOS CHYRSTOMOU(2), (Member, IEEE), AND MUHAMMAD IQBAI(6)

1Department of Electrical and Electronics Engineering, Universiti Teknologi Petronas, Seri Iskandar 32610, Malaysia
2Department of Electrical and Computer Engineering and Informatics, Frederick University, 1036 Nicosia, Cyprus
3Department of Telecommunication Engineering, University of Engineering and Technology, Taxila 47050, Pakistan
4Department of Electrical Engineering, School of Electrical Engineering and Computer Science, National University of Science and Technology, Islamabad 44000, Pakistan
5Department of Electrical Engineering, University of Jeddah, Jeddah 23218, Saudi Arabia
6Department of Electrical Engineering, COMSATS University Islamabad, Wah Campus, Wah 47040, Pakistan

Corresponding authors: Mudassar Ali (mudassar.ali@hotmail.com) and Muhammad Naeem (muhammadnaeem@gmail.com)

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ABSTRACT Due to intermittent nature of renewable energy sources (RESs) and their strong dependence on various environmental factors, it is imperative to carefully deploy these sources. A survey of recent works published in the area of optimal deployment of RESs is presented in this article. The existing works are categorized according to the type of energy source, objective function and model of operation. An optimal mix of hybrid-RESs along with energy storage system (ESS) is presented as solution to overcome the randomness and inconstancy of a single RES such as wind or solar power. We outline mathematical formulations for different objective functions, i.e., minimization of cost, maximization of power generation, maximization of the average cosine efficiency and minimization of the distribution losses. We present different wake models and simulation tools being used for the wind form layout optimization. These simulation tools are used to grade particular RESs according to technical and financial feasibility. This review paper depicts multifaceted coverage of the subject to provide the readers with state of the art developments in the area and can serve as a foundation for further research in the area. In addition, it can be used to find optimal mix of RESs for particular geographical area to satisfy the energy demands of that particular area.

INDEX TERMS Renewable energy, placement optimization, positioning, wake models.

I. INTRODUCTION

Renewable energy is the energy that originates from the renewable resources which are naturally restored such as wind, sunlight, tidal waves etc. Constant increase of world wide energy consumption is depleting the fossil based oil, coal and gas reserves on one hand and producing huge amount of carbon dioxide on the other hand. To cater for the afore mentioned problems, researchers and practitioners are searching for cost efficient placement of RESs. Power generation from RESs such as wind and solar is difficult to estimate due to its strong dependence on the climate, ambient temperature, season, time and geographical location. Therefore, the optimal placement of the renewable sources provides numerous technical benefits like reducing losses, improving voltage profile and power quality [11–3]. It is therefore, imperative to optimally place the RESs in the power systems in order to maximize power generation and minimize the losses. This paper presents an insight into the recent work published in the area of optimal placement of RESs in different practical scenarios. In the preceding, we show the trend of research community with respect to geographical area, with respect to specific RES and with respect to different wake effect model.

A. WORLD RESEARCH TREND TOWARDS RES DEPLOYMENT

Due to changing techno-economic and environmental preferences, the world is focussing on RESs as an alternative to the fossil fuel power plants [4–6]. Optimal deployment of RESs...
is a critical issue which influence various factors including but not limited to energy yield, continuity of supply, operation and maintenance cost, and infrastructure cost. In this section, we have analyzed the existing literature focused on optimal deployment of RESs. The analysis has been carried out to show the trend of the research community in the areas of optimal RESs deployment with respect to the geographical area, type of RESs and wind flow models. Following is the detail of each aspect.

1) DEPLOYMENT TREND WITH RESPECT TO GEOGRAPHICAL AREA

Articles relating to optimal deployment of RESs have been analyzed with respect to the affiliation of the authors to different countries as shown in Fig. 1. It is evident from Fig. 1 that half of the research is carried out in China, North America and Western Europe in the area of optimal deployment of RESs. The research in the aforementioned area is being lead by USA with 16% contribution. So it can be inferred from this analysis that the USA is eying to achieve the projected goal [7] of meeting most of its energy needs through RESs by year 2050. China is also desperately trying to change their energy mix due to two reasons firstly to reduce carbon dioxide emission which is currently almost 50% of the world’s total carbon dioxide emissions [8] and secondly, to cope with the increasing demand of energy to satisfy its ever increasing industrial growth. The other major contributing countries are Canada, Greece, India, Australia, Italy, Korea, Turkey and Iran. Where as, rest of the world jointly contribute 19% of the research activities in the area of optimal deployment of RESs.

2) DEPLOYMENT TREND WITH RESPECT TO RENEWABLE RESOURCES

Potential yield of electricity from different renewable resources depend on various factors including but not limited to geographical location, season of the year, type of renewable resource, area available for installation and capacity of the generating units. Problem of selecting appropriate renewable resources and their relative location can be modeled as optimization problem which can be solved by using state of the art optimization algorithms, to minimize cost associated with the deployment, operation and maintenance.

![FIGURE 1. Distribution of articles on renewable energy deployment with respect to geographical areas.]

3) RESEARCH INTEREST WITH RESPECT TO WAKE EFFECT MODELS USED IN DEPLOYMENT OPTIMIZATION

Harnessing of wind energy has been renewed since late 1970s [11] and ever since lot of research efforts have been made towards the wind turbine wakes. The term wake effect originates from the wake behind a ship [12]. In wind turbines, wake effect encompasses the decrease in wind speed and reduced energy content possessed by the wind after leaving a particular wind turbine. As the wind passes through the turbine, the volume of air downwind of the turbine has a lower wind speed and more turbulence than the wind in the freestream; therefore reducing the energy yield of the downwind turbines. Wake effect is influenced by various factors including but not limited to environmental and atmospheric...
conditions, the model of the wind turbine, blade characteristics [13] and distance between wind turbines [14]. Optimal deployment of wind turbines is obtained by considering appropriate wake effect model [15]. Fig. 3 shows trend of different wake effect models being considered while optimal deployment of wind turbines for maximizing the energy yield and minimizing the cost. Jensen wake model (JWM) has been considered in most of the articles while optimal deployment of wind turbine has been achieved by using different optimization algorithms. The other wake models namely, linear wake flow model (LWFM), Jensen/Katic (J/K), park wake model (PWM), dynamic wake model (DWM), Frandsen wake model (FWM), Katic wake model (KWM), non linear wake expansion model (NLWEM), turbulence and turbulence generated structural loading (T&TGSL) and sum of square wake model (SWM) have been used less commonly.

B. EXISTING SURVEYS RELATED TO THE OPTIMAL DEPLOYMENT OF RESs

A snapshot of the existing surveys in area of RESs and their placement is shown in Table 1. It can be observed from the Table 1 that no comprehensive survey exist that covers the deployment issues related to different renewable resources in real-life scenarios. For example, Iqbal et al. presented in [5] a generalized review of the work related to optimization of RESs without specifically considering the deployment issues. Problems related to optimized design of wind farm with micro sitting perspective has been discussed in [16]. Optimization techniques generally applied to renewable and sustainable energy have been reviewed in [17], [18] providing a clear vision of latest research advances in this field. In [19], the authors have investigated the problem of optimal placement of wind turbines to minimize the cost per unit of power. Optimal deployment of stand alone hybrid renewable systems based on wind and solar sources have been discussed in [20], [21] to provide an insight into the maximization of the generation capacity. Optimization techniques related to optimal deployment and operation of solar system have been summarized in [22], [23]. A review of the deterministic and stochastic models used for forest bio-energy supply chain has been presented in [24]. The problems related to optimal design and deployment of wind form have been elaborated in [25]–[29]. Optimization problems related to the design of micro-grids consisting of hybrid renewable resources namely wind and solar have been reviewed in [30]–[33]. The authors in [34] summarize the optimization techniques applied to deal with the problem of placement as well as sizing of dispersed power generation systems based on RESs. The authors in [35] outline optimization methods for reliability in seaward renewable energy units, and argue that reliability based optimization methods can be used to reduce cost for seaward renewable energy units.

Rest of the article is organized as follows: Section II discusses the placement scenarios of different type of RESs. This section also classifies exiting literature according to optimization models as well as software and simulation tools being used for placement of different types of RESs. Section III gives the optimization ontology, summarizing the mathematical formulations for different objective functions, i.e., minimization of cost, maximization of power generation, maximization of the average cosine efficiency and minimization of the distribution losses. Section IV presents different wake models and simulation tools being used for the wind form layout optimization. These simulation tools are used to grade particular RESs according to technical and financial feasibility. Section V concludes the article.

II. PLACEMENT SCENARIOS

The placement scenarios of different type of RESs not only influence the power generation capacity but also the operation and maintenance cost of the source. RES wise review of the work is provided in this section. Table 2 tabulates some commonly used optimization tools used to simulate different RESs under various practical constraints.

A. WIND

Wind is considered as major contributor in providing renewable energy. Wind turbines are used for converting kinetic energy from the wind into electrical power. It is also known as aerofoil–power generation because in process no wind turbine is used. In field of renewable energy research, wind energy has its significant part. With industry perspective a lot of production is being done in this part. Array of large turbines is known as wind farms, are emerging as important source of renewable energy and are used by many countries as part of strategy to reduce their reliance on non-renewable energy resources.

1) BIOLOGICALLY INSPIRED MODELING TECHNIQUES

Mankind has always been learning from the nature to solve its problems and the solutions derived are often based on simple laws, yet they can be applied to the complex problems efficiently. A number of problems of the modern
era are solved by modeling aspects of the natural world. From large set of these evolutionary algorithms there are few which also address the topic of micro-siting of wind turbines.

In [36], ant colony algorithm [37] is applied for optimizing the wind farm siting by maximizing the expected energy output. The algorithm convergence design is inspiration from ant food searching behavior. Another bio-inspired meta-heuristic

| Article | Technologies | Planning | Micrositing | Optimization | Wake Models | Software Tools | Remarks |
|---------|--------------|----------|-------------|--------------|-------------|----------------|---------|
| [5]     | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This article was meant to carry a general review of RESs. |
| [16]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The article highlighted the problems by identifying the most relevant issues involved in the optimized design of wind farm with micro siting perspective. |
| [17]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | Computational optimization methods applied to renewable and sustainable energy are reviewed in this article, offering a clear vision of the latest research advances in this field. |
| [18]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The work discusses the most popular distributed renewable generation placement methods. The study highlighted the features specific to every technique. |
| [19]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | Main objective of this study was to find most optimal solution for cost per unit power. For achieving this objective number of wind turbine placement techniques are analyzed and summarized with respect to its advantages and disadvantages to figure out the most optimal technique for deployment of a wind farm in a region of Pakistan. |
| [20]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This article discusses the exiting simulation tools along with optimization techniques that are required to design and simulate stand alone hybrid systems for power generation. |
| [22]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This work gives a review of stochastic methods for the optimization of solar systems. |
| [23]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The study discusses the tilt angle optimization which is most important factor in deployment of a solar panel and which is site specific. This paper is a review of various optimization techniques of determining the tilt angle. |
| [24]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This paper describes review on the deterministic and stochastic models used for forest bio-energy supply chain in literature. |
| [25]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This article provides a summary of different methods used for designing and optimizing wind farms. |
| [26]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The article has reviewed the relevant literature on economic preferences for wind power, both on and offshore, while focusing on the spatial dimensions that influence those preferences. |
| [27]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The paper presents a review of the optimization techniques and strategies applied to wind turbines performance optimization. Different optimization problems like airfoil shape optimization, wind turbine blade performance optimization and wind turbine optimization has been discussed in this work. |
| [28]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | This paper gives an overview of existing commercial as well as non-commercial decision support models along with their main characteristics. |
| [29]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The work briefly outlines the design issues and constraints involved in the wind farm layout design by using multi objective formulations. |
| [30]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | In this author highlighted the bottom-up model for community energy planning. |
| [31]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | In the context of computational optimization, a technical literature about optimization techniques applied to micro-grid planning have been reviewed and the guidelines for innovative planning methodologies focused on economic feasibility can be defined. |
| [32]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The review article discusses the optimum design of hybrid renewable energy systems moreover the study includes the detailed analysis of such optimum sizing approaches of hybrid renewable energy systems which enhances their applicability for giving a boost to economy. |
| [33]    | ✔            | ✔        | ✔           | ✔            | ✔           | ✔              | The study has briefed on Hybrid Renewable Energy System, the system metrics utilized for developing optimization objectives and software tools/algorithms employed to optimized the system. |
TABLE 2. Simulation and Optimization Tools for RESs.

| S.No. | Organization       | Tool               | Specifications                                                                                                                                                                                                 | Use/Application                                                                                     |
|-------|--------------------|--------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| 1     | MathWorks          | Simulink           | It is a graphical programming language tool, which have customizable block diagrams and block libraries. [http://www.mathworks.com/products/simulink/](http://www.mathworks.com/products/simulink/) | It is used for modeling and simulating dynamic systems.                                               |
| 2     | MathWorks          | MATLAB             | MATLAB is a high-level technical computing language and provides interactive environment. [http://www.mathworks.com/help/matlab/](http://www.mathworks.com/help/matlab/) | MATLAB can be used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. |
| 3     | DigSILENT GmbH     | DigSILENT Power Factory | It contains advance tools for visualizing network structures, power supply planning and restoration mechanisms, enhanced reliability assessment for balanced and unbalanced networks, voltage profile optimization for bi-directional power flows. [http://www.digsilent.de/index.php/products-powerfactory.html](http://www.digsilent.de/index.php/products-powerfactory.html) | DigSILENT PowerFactory caters for all standard power system analysis needs, including high-end applications in new technologies such as wind power and distributed generation and the handling of very large power systems. |
| 4     | Meteodyn           | Meteodyn WT        | Meteodyn WT solves the equations of Fluid Mechanics, i.e. the averaged equations of mass and momentum conservations (Navier-Stokes equations). [http://meteodyn.com/en/logicelcs/cfd-wind-modelling-software-meteodynwt/#_VP3dH3yU35w](http://meteodyn.com/en/logicelcs/cfd-wind-modelling-software-meteodynwt/#_VP3dH3yU35w) | It is used to estimate wind resource, to evaluate the Annual Energy Production, to analyze site suitability and to optimize the energy production. |
| 5     | AWS Truepower      | OpenWind           | Openwind is a software with GIS-based interface providing professional wind developers the tools they need to design, analyze and optimize a wind farm. [http://software.awstruepower.com/](http://software.awstruepower.com/) | Using an intuitive GIS-based interface, users can optimize for cost of energy, assess deep array impacts, define and analyze strategies for managed shut-down of turbines, and manage uncertainty. |
| 6     | ReSoft Limited     | Windfarm           | WindFarm has advanced graphics, and can be used to perform various calculations namely, wind flow and noise. It can also measure, correlate, predict and analyze the data of wind speed. [http://www.reso.co.uk/](http://www.reso.co.uk/) | It can be used to calculate the energy yield of a wind farm while considering the demographic and wake effects. It can facilitate the optimal deployment of turbine under various constraints, namely natural, planning and some design constraints. |
| 7     | DNV GL             | Windfarmer         | WindFarmer offers advanced, validated wake models suitable for all types of wind farms. This allows for the most accurate energy predictions. [https://www.dnvgl.com/services/windfarmers-3766](https://www.dnvgl.com/services/windfarmers-3766) | Software tool for designing, optimizing and analyzing the wind farm.                                    |
| 8     | EMD International  | WindPRO            | WindPRO is a complete software for designing both single WTG and large wind farms. [http://www.emd.dk/windpro/](http://www.emd.dk/windpro/) | The software can resolve various issues including, expected energy potential of any site, optimal utilization of the site and techno-economic trade-off while connecting the RESs with the national grid. |
| 9     | WindSim AS         | WindSim            | WindSim is based on a 3D Reynolds Averaged Navier Stokes (RANS) solver. Solving the non-linear transport equations for mass, momentum and energy makes WindSim a suitable tool for simulations in both complex terrain, and in situations with complex local climatology. [https://www.windsim.com/](https://www.windsim.com/) | WindSim optimizes park layouts by identifying turbine locations with the highest wind speeds but with low turbulence to maximize energy production while minimizing turbine load problems. |

technique for optimized placement of wind turbines by Coral Reef Optimization at off-shore is proposed [38]. This technique is based on artificial simulations of the coral reefs formation and reproduction process. The work was also practically tested in designing of an offshore wind farm in northern Europe and also compared with other biological inspired approaches. In [39] viral based optimization is used to find the optimal placement solution for the wind turbines by considering the constant wind speed and unidirectional uniform wind. The optimal layout (farm size and position of turbines) is analyzed on MATLAB.

Another frequently used biological inspired technique for finding the optimal solution is Particle Swarm Optimization (PSO) [40]. In wind turbine placement problem, Chowdhury et al. [41] and Gu et al. [42] uses PSO for finding the optimal solution for the micro-siting problem. The first study [41], that gives layout of wind farm the as well as optimally selects the turbines by using constrained PSO. The study concludes that designing a wind farm with differed rotor size can improve the farms efficiency. The performance of the study is analyzed by comparing the size of rotors with number of turbines to be placed in a farm. In [42], a detailed analysis for placement of wind turbines with irregular boundary has been done. The work differs from the former works because in most of the approaches the shape of the farm is considered as square or circle. To test the effectiveness of the proposed boundary constraint model, simulation of four commercial wind farms are performed, which verifies the significance of irregular-shaped wind farm micro-siting optimization problem. The authors in [43] propose a biogeography based optimization (BBO) algorithm to solve the wind farm layout optimization problem (WFLOP) using wake model. The authors in [44] propose modified BBO algorithm named Fitness Difference Based BBO (FD-BBO) to solve
the WFLOP. The authors claim that FD-BBO an efficient and accurate algorithm and prove their claim using graphical and statistical analysis. In [45], location optimization of wind turbines in a wind farm is solved by the PSO, which is biological inspired algorithm. IEEE 69 bus system is used to analyze the efficiency and feasibility of the proposed algorithm. Genetic Algorithm (GA) is a search heuristic algorithm, which belongs to a larger class of evolutionary algorithms. In the problem of optimal siting of wind turbine, GA and its variants are mostly used (approaches) for solution finding. Although there is a number of variants evolving from the classical GA, the conventional one still has great significance and it is frequently practiced for the solution finding.

In [46], bionic method for the micro-grid layout optimization is used. The purpose of this micro-siting is to maximize the output power. For solution finding GA is used. The bionic method can be applied in high resolution with low maintenance and deployment cost. Furthermore, an optimal design process with implementation numerical methods to determine the turbine spacing that results reliable efficiency in a wind farm is presented in [47]. The wake effect in the model is adjusted by Ainslie’s wake model [48]. The optimal inter-turbine distance is predicted by using classical GA for maximizing the efficiency of the wind farm. This approach concluded that the placement of first two turbines has impact on the efficiency of the entire wind farm’s performance. In another study [49], GA is used to place wind turbines optimally. The uniqueness of this study is that it presents the lightning aware placement. This technique compute the right location of the wind turbine in the wind farm by considering the past data of lightning strikes.

In [50], authors presented an optimal off shore wind farm layout designing approach, which strongly considers the wake decay loss. A non-linear wake expansion model was introduced into the calculation in flat or lightly undulated topography. Cost benefit model results in increasing the number of turbines. Biological inspired GA is used for enumerating the optimal solution. In [51], a new coding approach and novel objective function for solving the problem of wind turbine placement in wind farm using GA has been introduced. For verification process three different cases are considered: uni-direction uniform wind, uniform wind with variable direction and non-uniform wind with variable direction. These different configurations were first practiced in a classical optimal siting approach [52]. The optimal configuration out-turns the output power efficiency, optimal number of turbines for each configuration.

A budget constrained placement of wind turbines through GA and Branch and Bound (B&B) [53] has been proposed for minimizing and maximizing the cost and power, respectively [54]. The proposed formulation contributes a more convenient way of considering resources (number of turbines) and budget bounds (available budget). The study analyzed and demonstrated that GA outperforms B&B for the specific problem. In [55] new approaches to enhance the effectiveness of multi-objective evolutionary algorithms have been investigated. The authors adopted a meta-heuristic approach: non-dominated sorting GA-II (NSGA-II) [56]. The problem is designed and analyze on several number of perimeters for eg., convergence efficiency and diversity metrics. The resulting Pareto-Optimal maps provide useful guidelines for both optimization researchers and land use planners, by exhibiting the practical implications of such methodologies.

A case study for optimal offshore deployment wind mills in Hong Kong is done in [57] by using Multi-Population GA (MPGA) [58]. The layout configuration is designed by considering the hourly wind data of last 10 years (2002-2011), economic analysis and monthly power generation. The outcome of the study finds that power production is highest in the month of October (46.46%) and lowest in August (7.93%). The work also calculated the effective area for deploying of wind farms in Hong Kong i.e. 357 Km², which is 21.68% of Hong Kong water area. In another technique [59], optimal layout designing is performed. Unlike the previous techniques, the optimal placement is computed by considering the turbines layout with electrical and civil infrastructure as a whole. The work contributes with cash flow presentations between incomes and sue to energy selling and the ordinary maintenance and operation cost for rest of life of the farm.

The variants of GA also proved to be effective in providing wake decay constrained optimal solution in problem of wind turbine micro-siting. In [60], real-coded GA is utilized to solve the problem of wind farm optimal placement. The speciality of this approach is the wind turbine position that can be easily adjusted within a predefined cell for maximizing the produced energy. Different wind directions are considered The present study aimed at improving the wind farm efficiency to extract more energy from the farm. In another study [61], an efficient method for optimal large offshore wind farm design by improved GA (iGA) with aiming the maximizing the economic profitability of the project is presented. The study contributed with a complete economic model for the optimal farm designing. In addition, number of optimal wind farm layout designing techniques like [62] and [63] are proposed in past times. For optimal solution finding, Double-stage GA and adapter GA are used in [62] and [63] respectively. In double stage GA method, optimal positions of wind mills for complex terrains within the realistic available area in Serbia are obtained. This approach’s outcome is accurate placement and reduction of problem dimensionality. Land costs and availability, local and access roads, the environmental impacts, forbidden areas are considered as constraints in computation of the optimal solution. On the other side, Adaptive GA is a heuristic technique of layout problem, which minimizes the wake decay effect of an offshore wind farm. The study is experimentally verified at different wind speeds. The wake decay is modeled by JWM [64].
2) LARGE SCALE GRADIENT BASED MODEL
The optimal siting is aimed for efficient usage of the recycled energy. In [65], a gradient based optimization algorithm, Sequential Quadratic Programming (SQP) [66], is applied for the optimization process of wind farm placement. In this model, geographic location of each turbine is presented in terms of longitude and latitude. The proposed model aimed at optimal location and size of wind farm by minimizing the cost of electricity.

3) CLOSELY SPACED WIND TURBINE CONFIGURATION MODEL
For knowing the benefit closely spaced wind turbines, In [67], a realtime model was proposed and experimentally verified with micro-turbines in Ottawa, Canada. The study shows that in closely spaced wind turbines environment while having tested boundary layers, the performance benefits with a smooth boundary layer. These results lead to new wind farm design methodology which states that wind farms can be closely spaced in lateral direction in order to obtain substantial increase in power.

4) GREEDY ALGORITHM BASED PLANNING
Classical greedy algorithm is a method that follows the problem solving heuristic of first finding the locally optimal solution with the aid of finding a global optimum [68]. The study in [69] reveals a wind turbine positioning algorithm for complex terrains which finds the optimal value of the OF by using lazy greedy algorithm. The proposed method claims the comparatively better computing time for getting an optimal solution. Later on an LWFM based on classical greedy algorithm is given by Chen et al. [70]. This wind turbine positioning model solves the problem, with the target of maximizing the total power output of wind farm. The problem was formulated for both single and multiple wind directions. In an another technique [71] based on global greedy algorithm, authors introduced turbine site matching factor as OF to solve the problem. The placement of turbines in this study was controlled by the height of turbines.

5) ETHICAL PLANNING
The evidence of compelling that extended use and production of renewable energy is enhanced, is globally responsible for the serious deterioration of physical environment and climate change. In [72], a planning scenario NIMFY (Not in my front Yard), is advised, which considers public likeness for installation of wind farm. The study explored community attitude towards existing and proposed wind turbine placement techniques. The study resulted from response of community living in a close proximity to a wind farm which states that the community usually supports the deployment of such farms in their areas, but community also appear to accept the construction of additional wind parks under the restriction of their establishment away from their residence.

6) MONTE CARLO SIMULATIONS
Aiming at finding the most suitable result for any problem, Monte Carlo simulation (MCS) method [73] is frequently used in modern days studies. One application of MCS is used for solving optimization problems. The method is also used to address the issue of micro-siting of wind turbines. In [74], Marmidis et al. compute the solution for placement of wind turbines in a wind park. The purpose of study was to maximize the energy production and to minimize the cost. Another model of wind turbine placement by MCS is proposed in [75]. The model was validated by experimental testing in wind tunnel. Study results with less than 4% error rate with comparison to real time deployment which optimizes the cost and power for the wind turbine deployment process. Wake decay loss is considered as a major constraint in the study.

7) DATA ENVELOPMENT BASED TECHNIQUE
Data envelopment analysis (DEA) based technique for multi-criteria location selection of wind turbines is developed in [76]. The proposed approach uses different criteria for decision making: population of the area where wind farm is deployed, labor availability, density of the distribution network, land cost, average wind blow, intensity of natural disasters, quantity of proper geological areas and proper topographical areas. The prescribed method was empirically verified in 25 different cities of Iran.

8) MISC
In [77], optimal siting is achieved by simulated annealing. The models follows the KWM for constraining the wake decays. Simulated Annealing is meta-heuristic for global optimization, by searching in the large landscape for possible solutions. The model is analyzed by several case studies according to different wind conditions. In [78], the study presents a comprehensive analysis and comparison levelised cost of energy for the offshore floating wind turbines. The finding of study stated that deployment cost significantly affected by depth and distance from shore, due to mooring costs and export cable length, respectively. Aiming the objective of optimal design of wind farm Chen et al., presented an electrical layout design for a wind farm in [79], which is based on fuzzy c-means (FCM) and binary integer programming (BIP). The proposed system can automatically allocate wind turbines to the nearest substations and obtain the topology structure of cables utilized to connect with turbines and substation. The proposed system is analyzed on the base of connection cost and the transmission power losses.

In another study [80], authors have proposed a novel method to find the optimal location of wind turbines with in a fixed geographical area to maximize profit under stochastic wind conditions. For handling the non linearity of aerodynamic mixed integer programming (MIP) and constraint programming (CP) is use to incorporate the nonlinearity. The problem is addressed with varying wind scenario complexity, turbine numbers, and wind farm grid resolution.
The inclusion of landowner participation is also considered while formulating this method. The robustness of technique is tested by comparison of four different models on twelve problem instances, with varying wind scenario complexity, and number of wind turbines. The research resulted that proposed technique is computational efficient with more power production than other conventional models.

B. SOLAR

In the solar thermal applications the energy is optically concentrated before being converted into heat. The optical collection can be oriented by reflection or refraction of solar radiation employing reflectors, refractive optics or combinations of mirrors and lenses. The orientation of a solar panel is an important factor in deploying a solar power plant [81], but selecting the right location and position still has great significance for getting maximum efficiency of the plant.

Unique feature of the renewable energies such as solar energy is expected to take increasing role in the future energy consumption. Solar energy production have a great potential. In order to minimize the effect of solar energy resources number of work has been done to solve this issue. Some of the selected works are given below:

1) CASE STUDY FOR SOUTH-EASTERN SPAIN

In order to obtain an optimal location, robust enough to consider multiple criteria, in [82] Lozano et al. aware stated geographic information system (GIS) and multi-criteria decision making (MCDM) based model. The model calculates an optimal design based on constraints restrictive criteria and weighting factor, which prevents on adding such areas for consideration that are not fit for solar plants deployment. The criteria are extracted from legislation (planning regulations, protected areas, road networks, railways, etc.). The weighting factor in the model specifically target the location, geomorphological, environment and climatic criteria. For calculation and analysis purpose two reliable classical algorithms, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Analytical Hierarchy Process (AHP), are used. TOPSIS is multi-criteria decision making approach which identifies solutions that are as close as possible to an ideal solution, while AHP evaluate the possible alternatives, which aim at determining the weight of the criteria or factors in our decision problem. The model has restriction on deployment like if site plot is already occupied. The study concluded on suggesting “area of catagena (South-East Spain)” as optimal location of deployment of the solar plant. The weakness of this model is certain other factors like agrology capacity, orientation etc.

2) LEVELIZED COST MODEL FOR A CASE STUDY IN CHILE

Solar power generation depends upon the light radiation emitted by sun on a specific region. In [83], A levelized energy cost (LEC) analysis of solar power plants deployed in 16 different locations in Chile has been done. The analysis includes the solar plants different capacities.

The purpose of study was to prove Chile as a potential venue of deployment of solar energy power plants with comparison to other developed countries e.g., Spain and USA. Moreover, hourly beam radiation for Chile is also studied, which shows the solar energy electricity production potential of any specific area. For empirical verification purpose, solar panels are deployed in Atacama Desert, which gives the LEC of 19 centsUS$/kWh [83] with a gas fired backup and thermal energy storage systems. The value increases to approximately 28 centsUS$/kWh [83], if plant is not supported by any back up.

3) BIOLOGICAL IMPACT AWARE SITING

There was a great need to plan the siting of solar panels problem by looking at its biological impact on the surrounding environment. So, in [84] a spacial multi-criteria analysis method for modeling risk of conflict with biological resources is proposed. The model is also implemented for practical verification at California deserts. The major reason for choosing this venue was due to high frequency of conflicts arising. The entire study suggest sufficient compatible land exists in flat non-urban areas to meet the future targets of the region. It suggests the right placement areas in the region of solar panels with conservation of biological resources and the appropriate size of the farm. The model is very comprehensive assessment of biological conversation value but still it fulfilling the objectives of environmental groups which is an encouraging aspect. The study concludes that solar panels to be sited close to roads and transmission infrastructure, accompanying the Off-Site Impacts criterion. The use of degraded lands for such projects is also encouraged in the study. By applying win-win strategy [ref] land out side the urban areas and steep terrain are highly compatible for the solar farm deployment.

4) HILLSIDE DEPLOYMENT OF SOLAR PLANTS

Another study has been done in [85] for developing a model and tool used for hillside central receiver site selection. A thorough case study has been done by changing the beam of solar radiations. The objective of this placement is to minimize the cosine losses. In this study, for approximating the efficiency of a heliostat field some factors like: cosine efficiency, i.e., the ratio of the projected heliostat area in the direction of beam insolation to the surface area, shading and blocking losses due to nearby hill side are considered for the optimal placement of solar cells. The measured yearly cosine coefficient helps in the designing methodology of solar farm by uniformly designating a suitable hillside location by considering the shading by earth and blocking factors.

5) A FUZZY DATA ENVELOPMENT TECHNIQUE FOR ARTIFICIAL NEURAL NETWORKS

A technique of solar plant placement approach composed of artificial neural network (ANN) [86] and fuzzy data envelopment analysis (FDEA) [87] is proposed in [88]. A set of technical geological and social factors (population and
human labor, distance of power distribution networks, land cost, solar global radiation, quantity of available water) for location optimization of solar power units are considered in this work. FDEA-ANN proved to be a flexible approach which is proposed in this work for location optimization of the solar plants. In comparison to DEA the FDEA is robust, because it easily handles the uncertainty and noise in the input data, which may lead to misleading decisions. This proposed technique is used for solar power plant location optimization in Iran.

6) POSITIONING OF SOLAR PANELS TO MAXIMIZE ENERGY EXTRACTIONS
The authors in [89] propose GA based optimization for positioning of the solar panels so that shadow losses are minimized. The authors demonstrate location specific tuning of the solar power generation by appropriately orienting solar panels in a solar tree. The author in [90] demonstrated a mechanism to optimize solar energy extraction by using a automatic sun tracking system, where a pilot is used to track the sun and a panel is used to rotate. The authors in [91] discuss the row-spacing and tilt trade-off, and the east west orientation methods. They claim that these methods can be used to optimally design solar system layouts taking into account practical limitations and constraints.

C. BIO-FUELS ENERGY
Biomass is also very useful, green and economical source of energy production. Biogas is methane produced by the process of anaerobic digestion of organic material by anaerobes. With time the contribution of biomass in energy production is increasing, which is considered as an important step towards sustainable development in trending RESs [92]. Moreover, using biomass as an RESs, can be a new source of income to farmers and rural communities, and it also can play its part in reducing global warming [93]. In the agricultural countries like Pakistan, Bangladesh, India, etc., ample amount of biomass is generated from agricultural crops and debris, forest wood and leave residues, mill residues, animal waste and municipal solid wastes (MSW). Biofuels can help such agricultural countries meet their energy needs partly [94], [95]. Promoting Bio-ethanol and biodiesel in agricultural countries, which are importing oil to meet energy demands, can improve the foreign exchange reserves.

The complex supply chain of forest biomass is significantly affected by its characteristics, e.g., low density and unpredictable quality, makes the generation cost higher than that of other traditional RESs [24].

D. DISTRIBUTED GRID
A new Pareto-based multi-objective problem is proposed in [96] for the placement and sizing of multiple distributed energy resources (DERs) to improve the transient stability index, rates of fault occurrence in the different locations. The proposed model is demonstrated on a 33-bus distribution system for analyzing the performance in DigSILENT in power factory software. The solution is computed by PSO and Shuffled Frog Leaping (SFL).

In [97], a probabilistic multi-objective framework for optimal distributed energy resources planning is presented. Problem is formulated with nonlinear programming (NLP) computation. The approach aim at minimizing the monetary cost and minimizing the emission of pollutants constraining with electrical loads as well as market prices uncertainties. A hybrid approach FCM/ MCS is used for solution finding. The presented planning model is applicable on different DERs: wind turbines, photovoltaic (PV), fuel cell, micro turbine, gas turbine and diesel engines. A methodology of optimal sizing and placement of DERs on electrical distribution feeders based on technical and economic consideration is proposed in [98]. DERs (Wind, PV-Solar cells and Fuel Cells) placement is evaluated on IEEE 34-bus system. Similarly in [99], a simple method for optimizing cost and optimal placement of generators (wind and solar) by using a meta-heuristic approach namely Shuffled frog leaping algorithm is presented. A 38 bus distribution is used as a platform for implementing a vector based load flow technique. The study contributed an efficient algorithm of placement of DERs in the radial distribution systems to reduce the real time power losses and cost. Furthermore, enhancing this work, authors proposed another method of optimal placement considering active and reactive power losses, voltage power, and the line loading of the system in [100]. The main objective of this work is to optimize the power system that models multi-DER location and size, while minimizing system real reactive losses and to improve voltage profile and line loading by considering the bus available limit of the renewable DERs, like wind mills and PVs.

The authors in [101] present different types of distribution network architectures being used, i.e., ring, mesh and radial. The performance of distribution network architectures is compared in terms of power quality, load and reliability, is discussed. They propose a novel, aromatic distribution network based on chemical structures of benzene and dichlorodiphenyltrichloroethane, which improves the drawbacks of existing networks.

E. HYBRID
Hybrid renewable energy systems can overcome the randomness and inconstancy of a single renewable energy source such as wind or solar power, and more than 80% of them are off-grid systems [102]. In this article we consider hybrid renewable energy systems without hydropower.

1) PV-WIND POWER SYSTEM
In [103] a PV-wind power system is installed in the very challenging ambient conditions at French-Italian Antarctic Base. There was a need of deployment scenario such a stress place. The size of wind plant is calculated by the data collected from the site. The model was analytically verified by Simulink and then implemented. Entire data for designing the farm resulted by the empirical data collection of one year. This was the
first attempt to study the deployment of a RES in very hard conditions, like Antarctic Base.

Another study [104] presents the real time environment based PV-wind placement scheme. In this approach each PV and wind unit is defined based on real environment conditions. The authors in [105] propose PV-wind hybrid power system using electronic converter topology. They use voltage-source rectifier (VSR) to excerpt the power from the wind source, while the voltage source inverter (VSI) is used to harvest the maximum power from PV source. The authors in [106] present PV-wind power system for energy demand in Makadi Bay, Hurgada, and Egypt. The authors in [107] present a hybrid power plant consisting of an off-grid PV and wind energy generator to fulfill the demand of energy for the research center in Libya. The authors propose a crow search method to decrease the capital expenditures (CAPEX) and operating expenses (OPEX) by optimally sizing the both parts of the hybrid system. They optimized the powers of wind turbines and the number of PV modules required.

2) PV-ENERGY STORAGE SYSTEM
Energy storage system (ESS) is necessary to overcome the intermittent nature of PV output. A combination of PV and energy storage can be used to store the energy generated by PV during the daytime, which is used during night time to fulfill the load demand. The authors in [108] propose an algorithm for sizing of batteries for the grid integration of PV energy plants. The authors in [109] present a novel approach to combine PV-generator and ESS, to handle the power flows in a large building, while considering ESS state of charge and the load demand.

3) WIND-ENERGY STORAGE SYSTEM
In off-grid or on-grid wind-ESS systems, energy storage is necessary to stabilize the real time fluctuations of wind energy generator. In addition, ESS stores the excess energy produced by wind generator, to meet load demands in peaks hours or transmits it into the power grid. The authors in [110] discuss the installation of compressed air energy storage systems (CAES) deployed in large underground caverns in Germany. The author suggest to combine CAES with wind parks, leading to quasi-conventional power plants. The author in [111] assess the value of wind-ESS projects in China using net present value and real options. They claim that wind-ESS will be commercially feasible for the future power market in China.

III. OPTIMIZATION ONTOLOGY
The optimization is an integral part of any RES placement paradigm. The generic optimization for renewable energy placement problem includes three main segments: (1) inputs, (2) required output or objectives to achieve, and (3) constraints. Fig. 4 shows different possibilities for each part of the problem. In the generic renewable energy placement problem, the input parameters/decision variables are set by the power network operators or the regulatory authorities. The most important segment the optimization problem is its objective function and constraints. In this section, we will briefly describe commonly used objective functions (OFs) and constraints in renewable energy placement problems.

A. COST-POWER FUNCTION
The most common objective used in optimal placement of RES (mostly in wind mill planning) is cost power objective. Which was firstly used by [52]. The purpose of this OF was to find the optimal placement with perspective of cost and power. OF $O$ is stated as:

$$O = \text{min} \frac{C}{P}$$  \hspace{1cm} (1)

where $C$ is cost and $P$ is power. Minimization of the objective function mentioned above leads to a solution with lowest investment cost per unit of energy production. The total cost per year of the entire wind park of $N$ turbines can be expressed as:

$$C = N \left( \frac{2}{3} + \frac{1}{3} e^{-0.00174 N^2} \right)$$  \hspace{1cm} (2)

The total power production by $N$ number of turbines is:

$$P = 0.3 \sum_{i}^{N} \left( u_0 \left[ 1 - \sum_{i=1}^{N} \left( 1 - \frac{u}{u_0} \right)^2 \right] \right)^3$$  \hspace{1cm} (3)

where $u$ is the downstream velocity. Another pioneer work for optimal placement of any RES was done in [112], where weighted cost-power OF was presented as given below:

$$O = \text{min} \left\{ \frac{1}{P} w_1 + \frac{C}{P} w_2 \right\}$$  \hspace{1cm} (4)

Later on, a number the new models based on cost-power functions was proposed with little modifications. A few of them have been stated as follows.

- In [69], a lazy greedy algorithm based method is used for optimal portioning of wind turbine by aiming the objective to minimize the cost per unit while maximizing the power.
- Annualized cost and power is optimized in [65] by using gradient based optimization method.
- Another study [47] performs the optimization of cost-power objective function by considering the number of wind turbines and azimuthal rotor sections.
- In [50], [113], the authors optimized cost-power function by minimizing the total investment cost and maximizing the total power generation. The solution of OF in [113] is provided by a biologically inspired algorithm, PSO.
- The cost-power objective is optimized by weighting the objectives with arbitrary weights for different wind conditions has been done in [51]. While, in another technique [54], the cost-power objective is also achieved by weighting the objective function and considering resources available (number of turbines) and wind speed at each turbine.
In [74] and [77], problem of optimal wind turbine placement is achieved by successfully optimizing the cost-power objective, where in former technique installation cost is considered as objective for optimal placement while in later the total cost (deployment and maintenance) of wind turbine per year was considered.

In [83], solar power plants are designed by aiming the cost-power objective considering the levelized energy cost.

Similarly, in [57] and [71], the authors performed optimal placement of wind turbines by minimizing the deployment cost and maximizing the power produced.

### B. COST FUNCTION

For renewable resources deployment planning, cost is the most important factor that effectively improves the reliability of the solution proposed. Many techniques has been proposed, which aimed at cost optimization, solely. In [114], a multi-objective function is presented which two objectives, namely, costs and emissions. The cost function includes DER installation and electricity cost, operating, feeding and substation reinforcement cost. Other objective function in this solution comprises of total emission produced by the grid. OF is given below:

\[
O = \min \{C_g + C_l + C_o + C_i + C_e\} \quad (5)
\]

where \(C_g\) is grid cost, \(C_l\) is electricity cost, \(C_o\) is the DER operating cost, \(C_i\) is total feeder reinforcement cost and \(C_e\) is substation reinforcement cost. In an another work [104], a method is developed to optimize system (deployment) cost of different RESs like hydel, solar and wind power sources by using GA. The objective function is stated as:

\[
O = \min_{l=1}^{L_{\text{max}}} (C_l) = \min_{l=1}^{L_{\text{max}}} (C^l) \times \frac{\min(C^l)}{\min(C^d)} \quad (6)
\]

In equation (6), \(l\) is the location number of the unit, \(C^l_{\text{nc}}\) and \(C^l_{c}\) are total system costs without and with the consideration of load shedding, respectively.

Optimal layout of wind turbine is made possible by using Adaptive Genetic Algorithm (AGA) in [63]. In this study, the authors aimed at minimizing the wake decay effect of an off shore wind using following OF.

\[
P = \sum_{v} \sum_{\theta} f_\theta(v, \theta) P_{G(\theta, v)} \quad (7)
\]

where in (7), \(f_\theta(v, \theta)\) is the two dimensional possibility distribution function of wind over wind speed \(v\) and wind direction \(\theta\). \(P_{G(\theta, v)}\) is the total power generated under the condition of wind speed to be \(v\) and direction to be \(\theta\). Total power generated is defined in (8) for \(N\) number of turbines.

\[
P_{G(\theta, v)} = \sum_{i=1}^{N} P_{G_i(\theta, v)} \quad (8)
\]

In [83], an LEC analysis of solar power plants deployed has been done. LEC is calculated as:

\[
L = \frac{A}{E} \quad (9)
\]

where \(A\) and \(E\) are annualized cost and annual electricity generation, respectively. Annualized cost \(A\) can be calculated as:

\[
A = T \frac{(1 + r)^n r}{(1 + r)^n - 1} \quad (10)
\]

where \(r\) is the discount rate, \(n\) is the life time of plant in years and \(T\) presents the “total investment costs and variable costs.” For empirical verification purpose, solar panels are deployed in Atacama Desert, which gives a reliable LEC measure with and without a backup. Moreover, this work contributed with a suitable plant size and configuration for a cost effective power generating solution in a specific region (Chile).
C. POWER FUNCTION

As RESs are deployed to extract energy from renewable resources, the key parameter for measuring the efficiency of deployment planning is power produced with respective to resources utilized. A large number of techniques has proposed of modeling a farm layout from which few are described here.

Aiming to extract maximum powers from a wind farm by considering minimum resources and boundary constraints, Ergüloğlu et al. optimized the OF of power in [36] and [115] by using ant colony algorithm and particle filtering approach, respectively. OF is presented as:

$$\max \sum_{i=1}^{N} E(P_i)$$  \hspace{1cm} (11)

where $E(P_i)$ is the power output of $i^{th}$ turbine of $N$ units.

Distance between two turbines in limited to $8R$, where $R$ is diameter of rotor.

Moreover, placement of off-shore wind turbine, authors in [116] computed the optimal solution by intelligently tuned harmony search algorithm (ITHS). Power function used in this work is stated as:

$$O = \frac{1}{1 + \Delta P}$$  \hspace{1cm} (12)

where $\Delta P = |P_o - P_n|$ is difference between power determined in the old iteration $P_o$ and power determined in new iteration $P_n$.

In [75], a new procedure for optimizing wind farm turbines placement by mean of MCS method is presented. The objective of this study is to maximize the energy production by determining the optimal turbine position in farm. The OF is constrained by wake decay loss, annual wind intensities, wind directions and wind turbine interactions. Further, power efficient deployment is performed in [71] by applying greedy algorithm considering the towers height and wake effect. In another study [41], layout of the rectangular wind farm is optimized to achieve maximum power generation. The OF is defined as:

$$\max f(V) = \eta_f$$  \hspace{1cm} (13)

where $\eta_f$ is effective wind farm efficiency defined as:

$$\eta_f = \frac{P_f}{N \sum P_j}$$  \hspace{1cm} (14)

where $P_f$ is the collective power generated by entire farm, and $P_j$ is the power that Turbine-$j$ would generate if operating as a stand-alone entity considering uniform wind speed.

D. WIND FARM EFFICIENCY

In [60], Wan et al. utilized real-coded GA to optimize the wind turbine placement in a wind farm. The objective function is given as:

$$\eta = \frac{P}{P_0}$$  \hspace{1cm} (15)

where $P$ is the total power of wind turbine evaluated in [52] and $P_0$ is the represents the ideal total power of the wind farm in absence of wake decay effect.

E. AVERAGE COSINE EFFICIENCY

In [85], a tool is proposed for locating the right placement solar PV cells in hillside terrain to get maximum efficiency. The objective of this study is to maximize the annual average cosine efficiency i.e., the ratio of projected of heliostat area in the direction of beam insolation to the surface area. Of is stated:

$$\eta_{c,y} = \frac{\sum_{d=1}^{365} \int_{r_s}^{r_o} \eta_c(t)q_b(t)dt}{\sum_{d=1}^{365} \int_{r_s}^{r_o} q_b(t)dt}$$  \hspace{1cm} (16)

where $c$ is cosine, $y$ is year, $d$ is day, $r$ is sunrise, $s$ is sunset and $b$ represents beam. The average cosine efficiency is the irradiation weighted mean of instantaneous cosine efficiency integrated for each tabulated value. This instantaneous beam radiation is calculated using meteorological radiations model for direct beam irradiance in clear sky conditions. The yearly cosine coefficient helps in the design methodology of solar farm by uniformly designating a suitable hillside location considering the earth shading and blocking factors.

F. COMPUTATIONAL ANNUAL ENERGY PRODUCTION

Computational Annual Energy Production (CAEP) of $ij_{th}$ turbine denoted by $E_{ij}$, is calculated by using Double Genetic Algorithm (DGA) in [62]. The OF is expressed as:

$$E_{ij} = \left[ T \sum_{s=1}^{12} \int_{t_{ij}}^{V_{co}} F(w(s) \cdot t_{ij} \cdot V) \cdot f_a(s, V) dV \right] \cdot p_{ij}$$  \hspace{1cm} (17)

where $T = 8760$ h of a year, $s$ is the section of wind rose and $f(s)$ is the frequency of wind occurrence in section. Moreover, $V_{ci}$ and $V_{co}$ is the cut-in and cut-out wind speed, respectively. $F(V)$ is the power curve of the wind turbine, where $w$ is the element of wake matrix, $t$ is the topography matrix element and $f_a(s, V)$ is the Weibull distribution of wind speed $V$ in section $s$, and $p$ is priority element matrix. The study concluded with optimal position with increasing accuracy of the solution with comparison to traditional techniques.

G. INDUCED VOLTAGE LIGHTENING

Lighting strikes significantly affect the performance of wind turbines by damaging their circuitry. A mechanism of lightning aware optimal deployment is proposed in [49], which solves the issue by using GA. The OF is given below:

$$\min (0.05 \times 10^{-7} \frac{dl}{dt} \ln (\frac{D + 0.025}{D}))$$  \hspace{1cm} (18)

where voltage is a function of the rate of change of lightning current and distance of loop from the site and where, $D$ is the distance from the lightning strike which increases the induced voltage. The OF in the study aim at minimizing the induced voltage by lightening in the loop circuitry by
closely observing the past data of lightning strikes in North America.

H. DISTRIBUTION LOSSES FUNCTION

Distribution loss in wind turbines is featured in [45] for layout optimization. The OF is solved by PSO for finding the optimal locations of wind turbines in distribution systems. The OF is to minimize the distribution network loss, while satisfying the operational constraints. \( P_{\text{loss}} \) is the total line loss with \( NB \) admittance of branch \( i-j \) and \( V_i \) is the voltage at \( i_{th} \) bus. Furthermore, \( \theta_{ij} = \theta_i - \theta_j \) is the angle of voltage.

\[
\min \ P_1 = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{B} \text{Re}[Y_{ij}][|V_i|^2] + |V_j|^2 - 2|V_j||V_i|\cos\theta_{ij}
\]

(19)

Constraints of the above objective are the feeder capacity limits, bus voltage profile and load balance. The proposed model in the study combines PSO with load flow algorithm to result the proper site selection of wind turbines which can be used to reduce system losses and maintain the voltage profile.

In another work [117], the total distribution losses are minimized where \( V_G \) and \( \delta \) are the voltage and phase angles of the generators, respectively. \( N_G \) is the number of generator nodes and \( N_L \) is the number of loads nodes in the system.

\[
\min \ P_1 = \sum_{i=1}^{N_G} P_{L}^{(i)}(\delta_G, \delta_L, V_G, V_L)
- \sum_{i=1}^{N_L} P_{L}^{(i)}(\delta_G, \delta_L, V_G, V_L)
\]

(20)

I. MULTI-OBJECTIVE

In some mathematical optimization problems, multiple criteria are considered for decision making known as Multi-Objective Optimization problems [118]. In these types of problems, more than one OF to be optimized simultaneously. In RESs placement, a considerable number of studies came up with solution involving multiple objectives.

Kusaik et al. presented a multi-objective evolutionary strategy algorithm [119] for designing wind farm layout, aiming at capturing the maximum wind energy. The first objective is to maximize the energy output expressed as:

\[
\max \sum_{i=1}^{N} E(P)
\]

subject to:

\[
\begin{align*}
\text{s.t.} & \quad (x_i)^2 + (y_i)^2 \leq r^2, \ i = 1 \ldots N \\
& \quad (x_i - x_j)^2 + (y_i - y_j)^2 \geq 64R^2 \quad i, j = 1 \ldots N, \ i \neq j
\end{align*}
\]

(21)

where

\[
E(P) = \int_{0}^{360} \ p_\theta(\theta)E(P, \theta) \ d\theta
\]

(22)

\( E(P) \) is the expected energy produced and \( \theta \) ranges from \( 0^\circ \) to \( 360^\circ \). In (22), the wind speed is integrated from 0 to infinity, which is equivalent to integrating the wind speed from 0 to the cut-out speed. Once the wind speed is greater than the cut-out speed, a wind turbine is shut down for safety and it produces zero energy. \( r \) is the radius of the wind farm.

\[
\min \ \{O_1, O_2\}
\]

where:

\[
\begin{align*}
O_1 &= \frac{1}{N} \sum_{i=1}^{N} E(P_i) \\
O_2 &= \sum_{i=1}^{N} \max\{0, x_i^2, y_i^2 - r^2\}
+ \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \max\{0, 64R^2
- (x_i-x_j)^2 - (y_i-y_j)^2\}
\end{align*}
\]

(23)

\( O_1 \) is for maximizing the expected energy output and the minimum of \( O_2 \) is zero when all constraints are satisfied. To solve this multi-criteria problem evolutionary strategy algorithm [120], is used. This algorithm matches the complexities of the underlying problem.

In another work [100], Yammani et al. presented a multi-objective function for the purpose of solving the optimal placement problem by GA. Authors constructed a multi-objective function by combining all the indices with appropriate weights. OF is given below:

\[
O = ((W_1 \ast L_p) + (W_2 \ast L_q) + (W_3 \ast I_c) + (W_4 \ast I_c))
\]

(24)

where \( W_1, W_2, W_3 \) and \( W_4 \) are weights where \( W_k \in [0, 1] \). Further more, \( L_p \) and \( L_q \) are real and reactive power loss indices, respectively. \( I_c \) is the capacity index. The OF in (24) states that the power system that models multi DERs location and size is optimized, while minimizing system real, reactive losses and voltage profile and line loading are improved by considering the bus available limit of the renewable DERs, like wind mills and PV cells. Again Yammani et al. in [99], presented DERs placement by solving the problem with Shuffled Frog Leaping Algorithm targeting the optimal cost and placement. The OF comprises of generated power by DER (\( P_d \)) and cost of DER (\( C_d \)). \( w \) is the weighting factor and \( P_L \) is power loss in (25), stated below:

\[
O = C_d(P_d + wP_L)
\]

(25)

In [96], a pareto-based multi-objective problem for placement and sizing of DERs is presented. The proposed model contains three different OFs (\( O_1, O_2 \) and \( O_3 \)) for minimizing the power loss, improving the voltage profile and the transient stability. The OFs are given as follows

\[
O_1 = \min P_L^1 + P_L^2
\]

(26)
where

\[ f_3 = \frac{\sum_{b=1}^{N} p_b T}{\sum_{b=1}^{N} p_b} \]

\( P^i_t \) and \( P^j_t \) are power losses by transmission line and transformer, respectively, \( V_b \) and \( V_r \) are nominal voltage of the bus and voltage of \( b^{th} \) bus of the system. \( T \) is fault duration for which a system is transiently stable and \( p_b \) is the fault occurrence rate. System is constrained by limited voltage, DER technical constraints and branch power flow limit of the DERs.

**J. MISC**

Wake effect can affect the performance of wind farm significantly. In [121] wake effect mathematical programming approach is proposed for wind farm layout optimization. Multi-turbine wake effect Jensen’s wake decay model [64] is used. For optimization, a mixed integer non-linear programming (MINLP) and quadratic optimization based formulation is developed and applied to different layout cases presented in [52] and [112], for testing the robustness of the formulations.

\[
O_2 = \min \sum_{b=1}^{b=N} (V_b - V_r)^2
\]

\[
O_3 = \min \left\{ \frac{f_{\min,3}}{f_3} \right\}
\]

\( f_3 = \frac{\sum_{b=1}^{N} p_b T}{\sum_{b=1}^{N} p_b} \)

**IV. WAKE MODELS**

Though renewable energy has been used for centuries, but now trends are heading in the favor of wind energy source. As air flows through a wind turbine and energy is extracted from it, some of the properties of the flow decrease the performance of wind turbine by decelerating the rotor speed. One of these performance degradation factor, which is the region in the flow behind of wind turbine, is wake of the wind turbine, and the effect caused is commonly know as wake effect. Normally due to limitation of space, wind turbine are planned to placed closely in a group in large farms. For getting maximum output from the farm, site section is the most important step of its planning. Once you the site is selected, wind farm owner cannot afford it to place the wind turbines far from each other if general rule of thumb of wake effect is followed; i.e. turbines are to be spaced more than 10 rotor diameter from each other [122]. For minimizing the land cost and maximizing the output power produced, researchers modeled the influence of wind turbine on each other (wake effect). For analyzing the effect of wake effect, different software tools are used (mentioned in Table 2). A large number of models has been proposed by different designers and researchers for modeling this effect to make the planning process more efficient (cost and power output perspective). Few of them are discussed in this section.

Factors affecting the wake are

- Environment, weather seasons and complex terrain
- Blade characteristics
A. JENSEN WAKE MODEL

JWM [64] (also known as Park wake model or linear wake model) is the most commonly used wake model by the researchers for estimating the wake effect (see Fig. 3). This model was first utilized by Mosetti et al., and Graddy et al., in [112] and [52], respectively. The model is based on the assumption that the momentum is conserved inside the wake, and radius of wake is also assumed to be same as radius of rotor.

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

(32)

where \( u_0 \) is the average wind speed, \( a \) is the axial induction factor, \( x \) is the distance downstream of the turbine, \( r_1 \) is the downstream rotor radius, and \( \alpha \) is the entrainment constant. The entrainment constant, \( \alpha \) is calculated as done in [123], shown below:

\[ \alpha = \frac{0.5}{\ln(z/z_0)} \]  

(33)

where \( z \) is hub height of the wind turbine and \( z_0 \) is the surface roughness.

In the case of encountering with multiple wakes, kinetic energy of the mixed wake can be assumed to be equal to the sum of the kinetic energy deficits. Summarizing the energy of the mixed wake can be assumed to be equal to roughness.

The main loop hole in the basic JWM is that it neglects yaw misalignment, which change wind speed in the wind wake [124], addressed later on by the researchers.

B. EDDY VISCOSITY MODEL

A single wake model has been presented in [48], which calculates the wake velocity behind a wind turbine by considering all the environmental influence parameters. The author claim that model is comparatively simple and computationally efficient to the other classical approaches. The model can be used for getting a reliable measure of wake deficits in planning and designing a wind farm. The hub height of the wind turbine and surface roughness are also taken into account. The equation for the model is given as:

\[ \epsilon = Fk_1 \left( \frac{b}{D} \right) \left[ 1 - \frac{U_c}{U_H} \right] + Fk_2 \frac{\epsilon}{\ln \left( \frac{z_H}{z_0} \right)} \]  

(35)

where \( U_H \) is free speed at hub height, \( k_1 \) is dimension less constant and \( b \) is known as wake width occurred due to a wind turbine. In equation 35, \( D \) is given as wind turbine’s rotor diameter. \( U_c \) and \( U_H \) are wake centerline velocity and free stream wind speed at hub height, respectively. Rest of the parameters like \( k, z_H, z_0 \) are Von Karman Constant (taken as 0.4 in the study), wind turbine hub height and roughness length, respectively.

The effect of a build up turbulence appears consistent with a filter function \( F \), which is used in equation (35) and is calculated as:

\[ F = \begin{cases} 0.65 + [(x - 4.5)/23.32]^{1/3} & \text{if } x > 5.5 \\ 1 & \text{if } x < 5.5 \end{cases} \]  

(36)

The simplest form of the model gives eddy viscosity as:

\[ \epsilon = F[k_1 b(U_o - U_c) + K_M] \]  

(37)

where \( U_o \) is free stream wind speed, and \( K_M \) is eddy diffusivity of momentum.

This numerical wake model can be used to calculate the wake velocity field for wind turbines over a range of sizes and in a variety of meteorological conditions.

C. KATIC WAKE MODEL

In [125], Katic et al., modeled the wake decay. The model is very similar to JWM [64] and is considered as one of the pioneer studies of modeling wake decay effect. The model gives a theoretical calculations for cluster configuration of wind farm. It intelligently calculate the optimized configuration of wind turbine by taking its different characteristic into account, which makes it sophisticated.

The KWM propose that the deficit of equivalent speed can be calculated by using the average quadratic sum of the deficits produced by each turbine separately, as shown in (38).

\[ (U - U_o)^2 = \sum_i \frac{A_{o,i}}{\pi r^2} (U_i - U_o)^2 \]  

(38)

where \( U \) is the speed to be considered in the turbine downstream, \( U_i \) is the speed of the air due to wake of turbine \( i \), \( r \) is the radius of rotor girths being analyzed, \( A_o \) is the overlapped area by the wake, and \( U_o \) is speed of incident wind.

The model shows that wind speed is linearly reduced to transversal position located four times away the rotor’s diameter (4D). This model has been used in several well known studies like in [59], [77] and [61].

D. FRANDSEN WAKE MODEL

As its often the need for offshore wind farms, the model handles a regular array of geometry with straight rows of wind turbines and equidistant spacing between units in each row in a rectangular considered geometry by defining three flow regimes. For accommodating the above problem, in [126], Frandsen et al. modeled the speed deficit of the wind turbine by employing the control volume concept that relates the thrust and power coefficient to the velocity decay.
TABLE 3. Abbreviations.

| Abbreviation | Description |
|--------------|-------------|
| AGA          | Adaptive Genetic Algorithm |
| AHP          | Analytical Hierarchy Process |
| AIC          | Annualized cost |
| ANN          | Artificial neural network |
| B&B          | Branch and Bound |
| BBO          | Biogeography based optimization |
| BIP          | Binary integer programming |
| CAEP         | Computational Annual Energy Production |
| CAES         | Compressed air energy storage systems |
| CFD          | Computational fluid dynamics |
| CP           | Constraint programming |
| DEA          | Data envelopment analysis |
| DERS         | Distributed energy resources |
| DGA          | Double Genetic Algorithm |
| DWM          | Dynamic wake model |
| ESS          | Energy storage system |
| FCM          | Fuzzy c-means |
| FDBO         | Fitness Difference Based BBO |
| FDDEA        | Fuzzy data envelopment analysis |
| FWM          | Frandsen wake model |
| GA           | Genetic Algorithm |
| GIS          | Geographic Information System |
| IWM          | Jensen wake model |
| JK           | Jensen/Katic |
| KWM          | Katic wake model |
| LEC          | Levelized energy cost |
| LEC          | Levelized energy cost |
| LWFM         | Linear wake flow model |
| MCDM         | Multi-criteria decision making |
| MCS          | Monte Carlo simulation |
| MIP          | Mixed integer programming |
| MPGA         | Multi-Population genetic algorithm |
| MSW          | Municipal solid waste |
| NLP          | Nonlinear programming |
| NLWEM        | Nonlinear wake expansion model |
| NSGA-II      | Non-dominated sorting genetic algorithm-II |
| OF           | Objective function |
| PSO          | Particle Swarm Optimization |
| PV            | Photovoltaic |
| PWE          | Park wake model |
| RESs         | Renewable energy sources |
| SFL          | Shuffled Frog Leaping |
| SQP          | Sequential Quadratic Programming |
| SWM          | Sum of square wake model |
| TICVC        | Total investment costs and variable costs |
| TaTGSIS      | Turbulence and turbulence generated structural loading |
| TOPSIS       | Technique for Order of Preference by Similarity to Ideal Solution |
| VSI          | Voltage source inverter |
| VSR          | Voltage-source rectifier |
| WFLOP        | Wind farm layout optimization problem |

The increase of wake front right after the rotor of wind turbine $i$ is presented as

$$D_{w,i} = (1 + 2\alpha \bar{s}) \tag{39}$$

where $\bar{s} = s/D_i$ and $D_{w,i}$ is the diameter of the expanding wake front at a distance $s$ behind the wind turbine $i$. $\alpha$ represents the wake spreading constant, which can be computed as:

$$\alpha = \frac{0.5}{\ln z_H/z_0} \tag{40}$$

where $z_H$ and $z_0$ are the average hub height and the average surface roughness of wind farm region, respectively. This model is applicable on both single and multiple wake cases and has been practiced by number researchers for getting adjusting the wake velocity deficit into their studies [41], [127].

E. COMPUTATIONAL FLUID DYNAMIC MODEL

Various computational fluid dynamic (CFD) techniques for modeling the wind turbine wake effect have been proposed (e.g. Kinematic, Blade Element Momentum, Vortex Lattice, Panels, Generalized Actuator, Direct [128]) by the designers and researchers for improving the performance of wind turbines [129]. By using CFD it is possible to do wake turbine computations efficiently [130], which allows larger problems to have a refined solution.

F. DYNAMIC WAKE MODEL

The key issue in wind farm designing is finding computationally efficient tool for modeling its wake deficit. The need for this model is due to unsteady wind farm flow behavior and is modeled by treating wind turbines wakes as passive tracers transported downstream using a meandering process driven by the low frequent cross wind turbulence components [131], [132].

G. MISC

A part from the above models other models are also proposed with time. In [50], a non-linear wake expansion model is presented on the base of classical linear model [52], which takes the realistic characteristics of the actual wake that develops non-linearity along the axial distance.

V. CONCLUSION

This article provides a survey of the recent works related to the optimal deployment of RESs in different practical scenarios. It gives a tabular summary of the simulation tools, which are used to grade the RESs with respect to technical and financial feasibility. The existing works in this area are categorized according to the type of objective function, RES, and model of operation. Different wake models being used for the wind farm layout optimization are discussed in detail. This article gives the reader an insight to the state-of-the-art developments in the area and provide a foundation for further research. In addition, it can be used to find optimal mix of RESs for particular geographical area to satisfy the energy demands of that particular area.

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M. Yousaf Khan et al.: Placement Optimization for RESs: Ontology, Tools, and Wake Models
MUHAMMAD NAEEM (Senior Member, IEEE) received the master’s and Ph.D. degrees in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2000 and 2005, respectively, and the Ph.D. degree from Simon Fraser University, Burnaby, BC, Canada, in 2011. From 2012 to 2013, he was a Postdoctoral Research Associate with the Wireless Networks and Communications Research (WINCORE) Laboratory, Ryerson University, Toronto, ON, Canada. From 2013 to 2016, he was an Assistant Professor, and since 2016 he has been an Associate Professor with the Department of Electrical Engineering, COMSATS University Islamabad, Wah Campus, Wah, Pakistan. Since 2013, he has been a Research Associate with the WINCORE Laboratory. From 2000 to 2005, he was a Senior Design Engineer with Concept (Pvt.) Ltd., Islamabad, Pakistan, where he participated in the design and development of smart card-based GSM and CDMA pay phones with the Department of Design. He is also a Microsoft Certified Solution Developer. His research interests include the optimization of wireless communication systems, non-convex optimization, resource allocation in cognitive radio networks, and approximation algorithms for mixed integer programming in communication systems. He was a recipient of the NSERC CGS Scholarship.

MUHAMMAD IQBAL was born in Multan, in October, 1976. He received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Lahore, in 1999, the M.S. degree in telecommunication engineering from the University of Engineering and Technology, Peshawar, in 2007, and the Ph.D. degree from the Beijing University of Posts and Telecommunications, China, in 2011. He served in the state owned telecommunication company for more than seven years. He rejoined COMSATS and till date working as an Assistant Professor with Electrical Engineering Department, CIIT, Wah Campus. His research interests include signal and information processing, wireless communication, smart grid, and applied optimization.

SAAD QAI SAR (Senior Member, IEEE) received the master’s and Ph.D. degrees in electrical engineering from Michigan State University, USA, in 2005 and 2009, respectively. He is currently serving as an Assistant Professor with the School of Electrical Engineering Computer Science (SEECS), National University of Sciences Technology (NUST), Pakistan. He is the Lead Researcher and the Founding Director of the CoNNeKT Lab: Research Laboratory of Communications, Networks and Multimedia, National University of Sciences Technology (NUST), Pakistan. As of September 2011, he is the Principal Investigator or Joint Principal Investigator of seven research projects spanning cyber physical systems, applications of wireless sensor networks, network virtualization, communication and network protocol design, wireless and video communication, Internet measurements analysis, multimedia coding, and communication. He has published over 45 articles at reputed international venues with a vast amount of work in pipeline.

CHRYSOSTOMOS CHRYSOSTOMOU (Member, IEEE) received the B.Eng. degree (Hons.) in electronic and electrical engineering and the M.Sc. degree in telecommunications (telecommunications and software) from the University of Surrey, Surrey, U.K., in 1998 and 1999, respectively, and the Ph.D. degree in the area of computer networks from the University of Cyprus, Nicosia, Cyprus, in 2006. He is currently an Assistant Professor with the Department of Electrical and Computer Engineering and Informatics, Frederick University, Nicosia, Cyprus. He is the Coordinator of the Computer Systems and Networks Academic Domain Unit within the Department and the Director of the Networks Research Laboratory (NETLAB). Prior to his current appointment, he served in a number of positions with the Department of Computer Science, University of Cyprus, from September 1999 to September 2008. In particular, he was a Research Associate and a Special Scientist in several research projects, and further, he worked as a Special Teaching Staff, and also as a Visiting Lecturer. His research work has been published in more than 50 articles in international peer-reviewed scientific book chapters, journals, and conferences (more than 900 citations with H-index: 15, source: Google Scholar) and he has given presentations in various international scientific conferences. His research interests include quality-of-service (QoS) provisioning in mobile/wireless networks, including the Internet-of-Things architectures, communication technologies for smart systems, Device-to-Device (D2D) Communications in 5G Networks for energy and spectrum efficiency, millimeter wave communication, and cooperative multihop 5G D2D communication with energy harvesting capabilities for public safety networks. In addition, his research work has been conducted in the mobility support in wireless sensor networks, in intelligent, QoS-aware mechanisms in vehicular ad hoc networks, and in the application of computer networking principles and techniques in the field of high-performance computer architecture (network-on-chip architectures). He actively serves as a member of several technical program committees of international scientific conferences and as a Referee for international scientific journals and conferences. Moreover, he is involved in the organization of international conferences. Since 2001, he has been actively involved in several European (FP5, FP6, FP7, H2020, Interreg, Cost Actions) and National funded research projects.