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A Novel and Efficient Hybrid Optimization Approach for Wind Farm Micro-siting

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Abstract: Due to increasing penetration of wind energy in the recent times, wind farm owners tend to generate increasing amount of energy out of wind farms. In order to meet targets, many wind farms are operated with a layout of numerous turbines placed close to each other in a limited area leading to greater energy losses due to ‘wake effects’ instead of generating more power. To solve the problem in the most optimal way, these turbines need to satisfy many other constraints such as topological constraints, minimum allowable capacity factors, inter-turbine distances etc. Existing methods to solve this complex turbine placement problem typically assume knowledge about the total number of turbines to be placed in the farm, which might be unrealistic. This study proposes a novel hybrid optimization methodology, a combination of evolutionary and classical optimization approaches, to simultaneously determine the optimum number of turbines to be placed in a wind farm along with their optimal locations. Application of the proposed method on a representative case study yields 43% higher Annual Energy Production (AEP) than the results found by one of the existing methods.

Keywords: Wind energy systems engineering; micro-siting optimization; genetic algorithms; gradient based optimization.

1. INTRODUCTION

Wind energy has turned out to be a promising alternative energy source in order to compete with the depleting conventional sources. Due to its wide-scale availability, low cost and environment friendly operation, the idea of utilizing wind power at a massive scale has become a primary focus in the power industry, government policies and academic research (Chowdhary et al. 2012, Khan and Rehman 2013, Duan et al. 2014). According to the Global Wind Energy Council (GWEC, 2014), the global cumulative installed wind capacity is expected to nearly double from today’s capacity (~300GW) by the end of 2018. Wind farm micro-siting is the process of determining optimal layout of turbines in a wind farm to extract maximum energy out of it. However, the predictions of the commercial software’s for designing the layout of turbines in a wind farm are still not up to the mark and need human intervention to reduce the installation and operational costs for yielding the maximum energy and efficiency of wind farm after tackling the wake effects (Khan and Rehman, 2013). These facts set the importance of solving the complex micro-siting problem considering various practical aspects of it.

Many research articles are available, where binary–coded Genetic Algorithms (GAs) have been used to maximize the net Annual Energy Production (AEP) while minimizing the installation cost over fixed number of turbines in a wind farm (Gonzalez, 2014). Apart from GAs, evolutionary strategy based multi-objective algorithm (maximization of expected energy and minimization of constraint violation) has been proposed and the effect of wake loss with increasing number of turbines in a wind farm has been studied (Gonzalez, 2014). Ant Colony Optimization and Particle Filtering Approach have also been tested to deal with the optimal placement of turbines in a wind farm layout (Gonzalez, 2014). Recently, Chowdhary et al. (2012) attempted to maximize the power and efficiency of a wind farm with identical and non-identical turbines using Particle Swarm Optimization (PSO). Zhang et al. (2014) presented Constrained Programming and Mixed Integer Programming models to maximize the total farm-level energy produced for simple to complex wind scenarios. Most of these existing models deal with the micro-siting problem with a fixed number of turbines. However, wind farm developers are not sure of the maximum number of turbines that can actually be fitted in a farm to attain the maximum net AEP. Recently, Kulkarni and Mittal (2014) developed a novel heuristic approach where the optimal number of turbines and their optimal locations can be found out simultaneously in order to maximize the net AEP and minimize the wake losses in a wind farm. It suffers from the drawback of grid-based methods i.e. since all candidate turbine-locations lie on the grid, possibly better locations lying between grid-points can never be chosen. Moreover, refining the grid resolution to better represent the wind farm area may make the problem computationally very demanding. Another limitation of this approach is that the performance of the algorithm is driven by the selection of the starting solution. To overcome these limitations, a novel hybrid methodology has been proposed in this work which makes use of a bi-level optimization formulation. GA has been used in the first level to determine the number of turbines out of certain number of possible candidate locations (a discrete formulation) whereas a classical optimization technique improves those locations in the second level assuming the number of turbines in the layout as obtained from the first level are fixed (a continuous formulation). The paper is organized as follows. Section II describes the problem formulation, AEP and wake calculations in the model. The proposed methodology is explained in section III, whereas section IV presents the results of a representative case study. Conclusions along with the scope of future work is given in section V.

2. PROBLEM FORMULATION

The development of mathematical model for wind farm micro-siting is limited to certain assumptions (A1 – A5). A1: N number of wind turbine locations are described as (x_i, y_i) where i = 1,…, N; A2: In order to maintain consistency in a problem, homogenous wind turbines are considered; A3: For simplicity, a widely used and well-known Jensen (1983) wake model is used to calculate the velocity deficit due to wake effects; A4: For a specific direction, height and location, wind speed follows a two parameter Weibull distribution $C_v(u, A, k) = 1 - \exp(-(u/A)^k)$, where A is the scale parameter and k is the shape parameter and Cv (.) is the cumulative distribution function, which is a well-accepted concept worldwide (Kulkarni and Mittal, 2014); A5: Power and thrust coefficient curve is used to evaluate the power and coefficient of thrust (CT) for the corresponding wind speed. (Fig. 1).

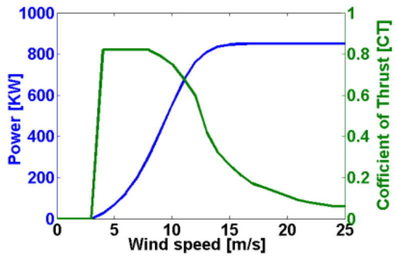

Fig. 1. Power and CT curve for Vestas-V52 850 kW (Kulkarni and Mittal, 2014)

Mathematically, the problem can be represented as:

$$\textit{Objective Function}: \quad \underset{N_t}{Max}\ \underset{x_i, y_i}{Max} \sum_{1}^{N_t} AEP(x_i, y_i) \tag{1}$$

Subject to two inequality Constraints:

$$g_1(x_i, y_i) = n_{space} * D - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq 0, \quad j \neq i, i, j = 1, \ldots, N_t \tag{2}$$

$$g_2(x_i, y_i) = OCF^{\lim} - \sum_{1}^{N_t} AEP(x_i, y_i) / (8766) * N_t * \Pr \leq 0 \tag{3}$$

Here $g_1(x_i, y_i)$ is the inter turbine distance (ITD), which is considered to keep enough spacing between turbines (3 times the rotor diameter of the turbines) in order to minimize the wake loss and fatigue loads. Another constraint $g_2(x_i, y_i)$ is overall capacity factor (OCF), which is a measure of wind farm performance and defined as a ratio of overall power generated in wind farm to the power generated if all turbines were at their rated capacity. Here, the limit for OCF is decided by a wind farm owner (Eq. 3). In this case study, n_{space} is 3, D is the diameter of turbine in consideration, $OCF^{\lim}$ is assumed to be 20% and $\Pr$ is rated power of turbine's (850 kW). Also the overall number of turbines (N_t) is taken as upper level decision variables and the location co-ordinates of these turbines (x_i, y_i) are considered as lower level decision variables whereas the geographical boundary limits are described by lb and ub . For a regular shaped rectangular 500×500m^2 grid farm considered here, lb and ub for (x_i, y_i) can be 0 and 500, respectively.

This problem is mixed integer nonlinear programming problem (MINLP) in nature which are generally very hard (NP-hard) to solve due to the combinatorial complexity involved. Due to discontinuous nature of the energy calculation step in the above formulation, it is difficult to solve this problem using efficient MINLP solvers such as DICOPT and others available in the GAMS environment.

3. AEP CALCULATION AND WAKE MODELLING

3.1 AEP Calculation

To calculate the energy produced accurately, the spatial and the temporal distribution of wind resource must be known which is generally expressed in terms of Wind Resource Grid (WRG) that stores information about Weibull parameters at a given location. The net AEP (kWh) at a given location of wind farm can be expressed as (Kulkarni and Mittal, 2014):

$$AEP = (8766) \sum_{i=1}^{360^\circ} \sum_{j=1}^{u_{\max}} Pwr(\theta_i, u_j)\ p(\theta_i)\ p(u_o) \Delta\theta_i\ \Delta u_j \tag{4}$$

Where, $p(\theta_i)$ and $p(u_o)$ determine the probability that the wind blows in direction θ_i at free-stream wind speed u_o and are obtained from Wind Resource Grid (WRG) data (Kulkarni and Mittal, 2014). Depending on whether a turbine is affected by wake and the number of upstream turbines generating the wake, the reduced velocity u_j at the turbine affected by wake is calculated. The corresponding power $Pwr(\theta_i, u_j)$ for that particular speed can be calculated using the turbine power curve (Fig. 1). Here the WRG data is adapted from WindRose and contains the spatial distribution of speed and direction at regularly spaced points in the form of A , k and f parameters. The two-parameter Weibull distribution is used to calculate the probability of wind speed at given locations $p(u_o)$ by using (5) and (6)

$$W_{cum}(u, A, k) = 1 - \exp\left(-(u / A)^k\right) \tag{5}$$

$$p(u_o) = W_{cum}\left(u_o + u_{step} / 2,\ A, k\right) - W_{cum}\left(u_o - u_{step} / 2,\ A, k\right) \tag{6}$$

Where, W_{cum} is the cumulative probability distribution and $p(\theta_i)$ is extracted from parameter f given in WRG which represents the percentage of total time when wind blows in a particular direction at a given location.

3.2 Wake model and calculation

In a wind farm, different turbines interact with each other due to wake effect that upstream turbines create on downstream turbines. Among various wake models reported in the literature, a widely accepted Jensen (1983) wake model has been adopted here .An expression for the reduced wind-speed of downwind turbines due to wake-effects can be expressed as follows:

$$\Delta u_{ij} = u_o\left(1 - \sqrt{1 - C_T}\right)\ \left(R_o / R_o + k_w d_{ij}\right)^2\ \left(A_{ij} / A_j\right) \tag{7}$$

The following nomenclature is followed in the above equation assuming 'i' and 'j' as an upwind and downwind turbine respectively. Δu_{ij} : Reduction in the wind speed on 'j'; CT : Coefficient of thrust (Fig 1); R_o : Rotor radius; k_w :Wake decay constant for Jensen model; d_{ij} : Distance between upstream and downstream turbines (Fig. 2),; A_{ij}: Overlapped area (Chowdhary et al., 2012) varies depending on type of wake effect on downwind turbine and A_j : Downwind turbine area. In reality, a downwind turbine may be under the influence of multiple upwind turbines. In that case, (7) can be modified as follows:

$$U_j = u_o\left(1 - \sqrt{\sum_{k=1,k\neq j}^{N_{upwind}} \left(\Delta u_{ij}\right)^2}\right) \tag{8}$$

where, U_j is the effective wind-speed at turbine 'j' while account for all wake effects and N_{upwind} is the number of upwind turbines. Velocity deficit, Δu_{ij} in (8) (Kulkarni and Mittal, 2014), is a function of location coordinates (x_i, y_i) as well as wind direction.

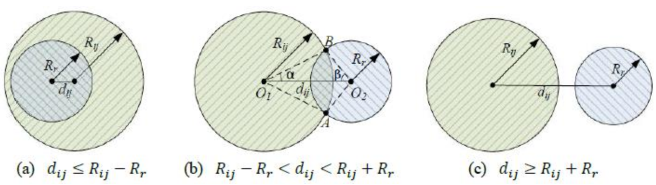

Fig. 2 : Schematic view of affected area of turbine in wake effects of turbine in 3 situations (a) full wake or complete wake, (b) partially wake, (c) no wake (Feng and Shen, 2014)

4. HYBRID METHODOLOGY

The proposed hybrid approach is a combination of probabilistic GAs and deterministic gradient search based methods. The problem of simultaneous determination of optimal number and layout of turbines is decomposed into two sub-problems that can be solved in sequence. In the first step, the regular rectangular wind farm is converted into a finite number of grid-points and the optimal turbine number and locations are simultaneously determined from a selected finite number of possible locations (grid cross points) through GAs. In the second step, the turbine number is fixed at the value obtained in the first step and the turbine co-ordinates are improved through classical gradient-based optimization techniques. The first sub-problem solves an integer programming problem over the possible turbine locations as signified by the grid cross-points through binary variables 0 and 1 that signify absence and presence of turbine at different locations, respectively. Based on number of possible locations, the number of binary variables are determined. The second sub-problem is a continuous nonlinear programming problem where the total number of turbines is fixed, as determined in the first step, and the focus is on determining optimal turbine coordinates given the turbine number. The proposed hybrid methodology can start the search procedure using one of the feasible heuristic outcomes (Kulkarni and Mittal, 2014) as initial guess and the cycle between evolutionary and gradient approach (Fig. 3) is continued until a predefined termination criteria is met. The proposed hybrid methodology comprises five important components

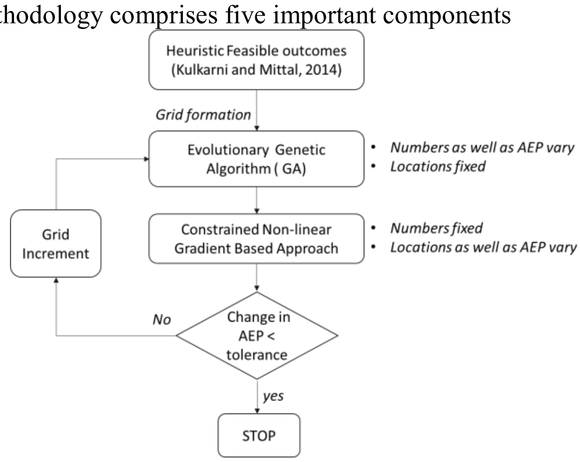

Fig. 3: Schematic Representation of Hybrid Methodology

4.1 Heuristic Approach

The proposed hybrid methodology starts with a heuristic approach (Kulkarni and Mittal, 2014) where the given rectangular layout is divided into a fine grid and the points where the grid lines cross each other can be considered as possible turbine locations. Subsequently, turbines are placed in these possible locations one by one starting with the point where the gross AEP is maximum. The subsequent turbines are placed at locations where AEP will be the best and none of the constraints such as ITD, OCF will most likely be violated. The algorithm is implemented as follows. In the first step, a point is selected based on the gross AEP and added to the accepted turbine location matrix (M). In the next step, other locations surrounding the accepted location and violating other constraints are discarded and are added up to the rejected turbine location matrix (V). The left over locations are next updated as available locations. Now, the next turbine can again be added at the location that shows highest gross AEP value in the map and no constraint violation among all available locations. This way of adding turbines is continued till the search on all possible candidate locations is exhausted. Fig. 4 shows the schematic view of this methodology. It can be seen that the matrices M and V are updated at each iteration.

4.2 Grid Formation

The rectangular (500×500 m^2) wind farm is converted into a finite number of grid-points (7×7) leading to 49 possible locations for turbines. Though grids are formed for both approaches, grid resolution of heuristic approach and hybrid methodology are not necessarily same. So, the final solutions of the heuristic approach may not belong to the set of grid points of the hybrid approach. After obtaining a heuristic outcome (say 8 turbines can be feasibly located), the starting matrix of candidate turbine location in GA is formed by adding these 8 locations to 49 grid cross points. Using these 57 locations, a location index array with unique index for each location is formed (Fig. 5). Each location can be represented by 0 or 1 depending on the absence or presence of turbines in that location (binary array).

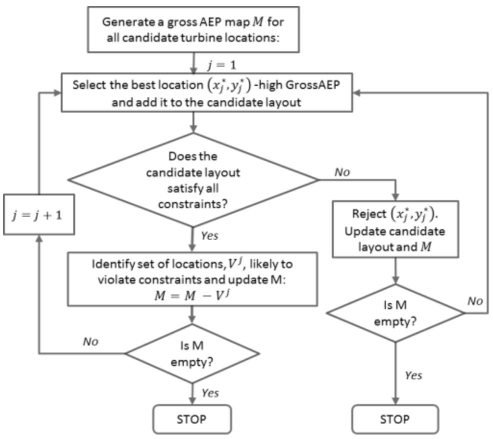

Fig. 4: Flowchart of Heuristic Approach (Kulkarni and Mittal, 2014)

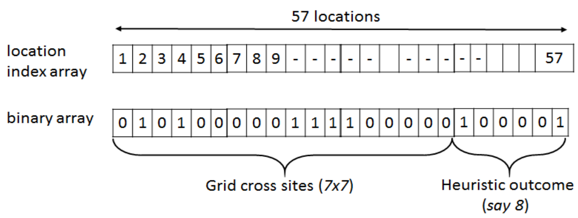

Fig. 5: Binary array and location index array at grid formation step.

4.3 Evolutionary Algorithm

An elitist version of binary coded genetic algorithm has been used here.

<u>Step I (Initialization):</u>

First, an initialization matrix is formed which has number of rows based on the number of populations $Npop$ in a generation (Table 1) and each of its rows is denoted by the *binary array*. Each of the rows in the initialization matrix, therefore, represents a particular layout and $Npop$ such layouts are considered to start with. The initialization matrix can be populated in a random way or a feasible layout found from the heuristic algorithm can be represented in the similar 0 - 1 manner and can be added in the matrix as a row. Each of these rows in the initialization matrix can be termed as a chromosome in GA. Fig. 6 shows the formation of $Npop \times 57$ size of population matrix.

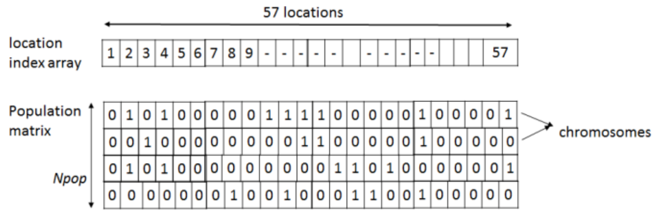

Fig. 6: Population matrix formed at initialization step.

<u>Step II (Modified Function Evaluation):</u>

The constrained optimization problem has been converted into an unconstrained optimization problem in order to reduce the complexity of constraint handling in GA. The constraints are first normalized and added to the objective function to form a modified unconstrained objective function that can be represented as

$$Modified\ Obj.:\ \underset{N_t}{Max}\ \underset{x_i,y_i}{Max}\sum_{1}^{N_t} AEP(x_i,y_i) - NormConstraints \quad (10)$$

Here, *NormConstraints* is a summation of all inequality constraints that are normalized to represent them in scales of similar order of magnitude. As our main objective is to maximize both the number of turbines as well as the net AEP, *NormConstraints* are subtracted from the objective function to obtain the modified objective function. Objective function is not modified when a particular solution is feasible. After modifying the objective function for each chromosome, the corresponding modified function value is calculated and stored in the initialization matrix as an additional column.

<u>Step III (Cross-over and mutation)</u>:

The current population (called as 'parents') undergoes cross-over and mutation to generate a new set of solutions (called the 'children'). Cross-over and mutation (Deb, 2001) are applied over the population according to the user defined cross-over and mutation probability (Table 1). A uniform type of cross-over is used and the cross-sites for crossover operation are selected between two chromosomes randomly. Modified objective functions are obtained for the children population in the similar manner as the parent population. Next, both these populations are merged together to form a population matrix of double size (2*Npop*) and finally a tournament selection method is applied to find the best *Npop* candidates out of them. Here a pair of two random chromosomes are picked and the one with higher modified objective value is selected. In this way, feasible points are preferred to infeasible points and infeasible points with lesser degree of infeasibility are preferred to that of a point with higher degree of infeasibility. Finally, an updated initialization matrix with rows and columns is obtained and this process is repeated till the convergence is reached.

4.4 Gradient Based Approach

Though GA can solve the problem of optimal number and location of turbines simultaneously, it performs a search for certain number of fixed locations (grid cross points). If GA is employed to solve the problem with finer grids, the size of the problem (number of binaries) increases with increase in number of grid cross sites, thereby making the GA runs computationally expensive. The first sub-problem involving GA should, therefore, be solved for a relatively coarser grid which can later be fine-tuned by solving the second sub-problem over the continuous x-y coordinate space. Finally, GA declares the chromosome with the maximum modified function value among all generations as the final solution. The final GA outcome of a feasible layout is next passed as an initial guess to a gradient based solver.

Table 1: Evolutionary GA and Gradient based approach specification

Genetic Algorithm (GA) specifications	
Algorithm Type	Elitist-Tournament selection
Number of Population (*Npop*)	100
Number of Generations (*Ngen*)	150
Crossover Probability (pc)	0.80
Crossover Type	Uniform
Mutation Probability (pm)	0.01
Gradient Based solver	
Solver	fmincon MATLAB®
Algorithm	Interior Point

A well-known constrained nonlinear optimization routine of MATLAB®, *fmincon*, (Table 1) has been utilized for this purpose. In this step, the only decision variables are location coordinates of the turbines keeping the total number of turbines as constant and the search is performed between the upper and lower bounds of regular rectangular boundary. Since a continuous optimization problem is solved in this step, it searches for coordinates in addition to the points present on the grid for which further improved AEP can be obtained.

4.5 Grid Increment

As mentioned in the section above, the outcomes of the gradient based search method can bring in coordinates that may not be present in the set of grid cross points. As the last step in the hybrid approach, these additional coordinates are added into the candidate location matrix and the binary array is updated accordingly. This is done to provide more coordinate locations to be searched by GA in the next turn. For example, if the number of old locations were 57 and gradient search provided 10 new locations as outcome, the new index array will have total 67 locations which are uniquely indexed. After an updated index matrix is obtained, GA run is performed again using the new index array. Further, the outcome of GA is passed as a starting point to gradient based approach and the cycle is continued until a stabilized AEP is obtained as well as the location coordinates for three consecutive iterations are not changed.

Table 2: Wind farm, wind turbine and wake model specifications (Kulkarni and Mittal, 2014).

Wind farm Information	
Farm area (m^2)	500 x 500
Wind turbine specifications	
Turbine Type	Vestas V52-850 KW
Turbine Rated Capacity (KW)	850
Turbine Diameter (m)	52m
Wake model Information	
Jensen Constant (k_w)	0.075

5. RESULTS AND DISCUSSIONS

The wind farm considered here has a uniform distribution of Gross AEP over the given geographical boundary. All information regarding case studies are provided in (Table 2). Two different case studies have been discussed below on which the proposed methodology has been applied.

Case 1: GA initialization with one feasible chromosome from heuristics

Here, the outcome from the heuristic algorithm (H0) is added as one of the chromosome in the initial population. Since this outcome has 8 turbines in place, rest of chromosomes are created randomly but restricting them to have a total of 8 turbines in each one of them. The outcome of GA (A1) is passed as starting point to gradient based approach which improves locations further with better net AEP. This cycle is continued until the stabilization of AEP and no further change in location coordinates for three consecutive runs are attained. (Table 3) shows the outcome obtained by the hybrid approach for each cycle.

Table 3 : Outcome of hybrid methodology case 1

Cycle	Algorithm	Outcome	Number of turbines / feasible locations	AEP (Kwh)
1	**Heuristic**	H0	8	1360.00
	GA	A1	10	1732.58
	Gradient	B1	10	1764.86
2	**GA**	A2	10	1769.86
	Gradient	B2	10	1786.26
3	**GA**	A3	11	1909.89
	Gradient	B3	11	1941.42
4	**GA**	A4	11	1942.01
	Gradient	B4	11	1943.47
5	**GA**	A5	11	1943.50
	Gradient	B5	11	1943.49

It has been found due to the combinatorial complexity and non-linearity involved in the problem, GA takes more time to execute, and further increment is reported on increase in binary array size. While the solution is moving towards a stabilized value, the execution time of gradient approach decreases. All calculations are performed on Intel® Xeon® CPU E5-2690 0 @ 2.90GHz (2 processors) 128 GB RAM machine. Fig. 7(a) shows the final superimposed accepted and rejected location coordinates or number of turbines on gross AEP contour plot obtained for the given boundary. The proposed methodology is able to place more number of turbines with much improvement in AEP (1943 Kwh) as compared to the results obtained from the heuristic approach (1360 Kwh).

Case 2: GA initialization with one feasible chromosome and rest randomly placed without restriction on total number of turbines

This case is similar to the previous case, where GA initialization is performed with one of the chromosomes coming from heuristics (H0). Rest of the chromosomes are generated randomly, but there is no limit of total number of turbines on them (as 8 in case 1). It can be seen (Table 4) that

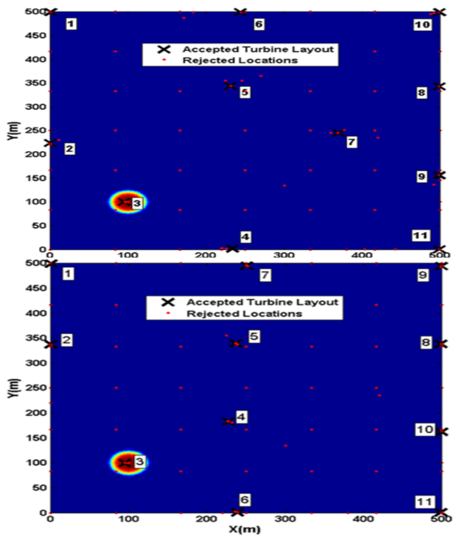

Fig. 7 Comparison of accepted turbines superimposed on gross AEP contour for (a) analysis 1 and (b) analysis 2.

Table 4: Outcome of hybrid methodology case 2

Cycle	Algorithm	Outcome	Number of turbines / feasible locations	AEP (Kwh)
1	Heuristic	H0	8	1360.00
	GA	A1	11	1917.98
	Gradient	B1	11	1931.79
2	GA	A2	11	1931.85
	Gradient	B2	11	1933.56
3	GA	A3	11	1932.24
	Gradient	B3	11	1933.38
4	GA	A4	11	1933.46
	Gradient	B4	11	1933.40

due to increase in diversity during initialization, GA is able to place 11 turbines in first cycle itself whereas AEP takes more cycles to get stabilized. In this case, the produced AEP is quite close to case 1 though the coordinate locations are different in both cases (Fig. 7). However, AEP generated for both case 1 (1943 Kwh) and 2 (1933 Kwh) are individually better than that of heuristic case (1360 Kwh). It has been found that both the constraints play an important role in solving the micro-siting problem. Considering only the ITD constraint, at most 14 turbines can be placed inside a wind farm, but due to the involvement of the OCF constraint, the number has been reduced to 11 in both the cases.

6. CONCLUSIONS

Simultaneous maximization of overall number of turbines and AEP is carried out in order to obtain the optimal number and location coordinates of wind turbines in a wind farm. A hybrid methodology, based on the concept of decomposition of the decision variable set, is proposed for solving the NP-hard MINLP, which utilizes the merits of GA and interior point based classical gradient based approach. Proposed methodology is applied on a case study and it has been shown that the proposed methodology works better (~43% improvement in AEP) than the existing heuristics based method.

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