Multi-objective wind farm layout optimization using evolutionary computations

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Article Info	ABSTRACT
	The usage of fossil fuels is actually not good for living nature and in future, this limited source of energy will vanish. Therefore, we need to go with the clean and renewable source of energy such as wind power, solar energy etc. In this paper, we are concentrating in wind power through optimizing the wind turbine placement in wind farm. The area-of-convex hull, maximize 'output power' and minimum spanning tree distance are our main objective topics, due to their effect in wind farm design. An implementation of modified version of the wind turbine (WT) placement model is uses to estimate the yields of the (wind farm) WF layouts and for simplifying the behavior of wind field, in this paper we use a simple wake approach. Moreover, to resolve the multi-objective problem here we proposed (Modified Genetic Algorithm) MGA, which is considerably better than the (Genetic Algorithm) GA and for evaluate the performance of MGA we use the multi-objective (EA) evolutionary algorithms such as; Genetic algorithm (GA) and SPEA2 and, produce different number of WT layouts. These methodologies are considered with various 'problematic specific operators' that are present in this paper.

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1. INTRODUCTION

The polluted environment is dangerous for humans' health, which has increased many public concerns. In the current society, fossil fuel is the main source of energy, which are not ecological and will be exhaust in future because of rapid consumption, limited resources, global warming, climate changing, etc. [1]. Meanwhile, many 'countries' are trying to replace the fossil fuels by the use of renewable energy to make better environment. Like wind energy, safety, clean and higher rate of conversion are its main advantages as compared with the other renewable types of energy [1-3]. In the global market of renewable energy, increment of wind power is very much important. Global-cumulative production-capacity has predicted to increment of 791.9 Gigawatts by the end of 2020. Last year (2016), the cumulative-capacity growth-rate was 14.8% and in the present year, it forecast to achieve 13.7% of cumulative-capacity growth-rate [4]. Figure 1 shows the Cumulative-market forecast by region 2016-2020.
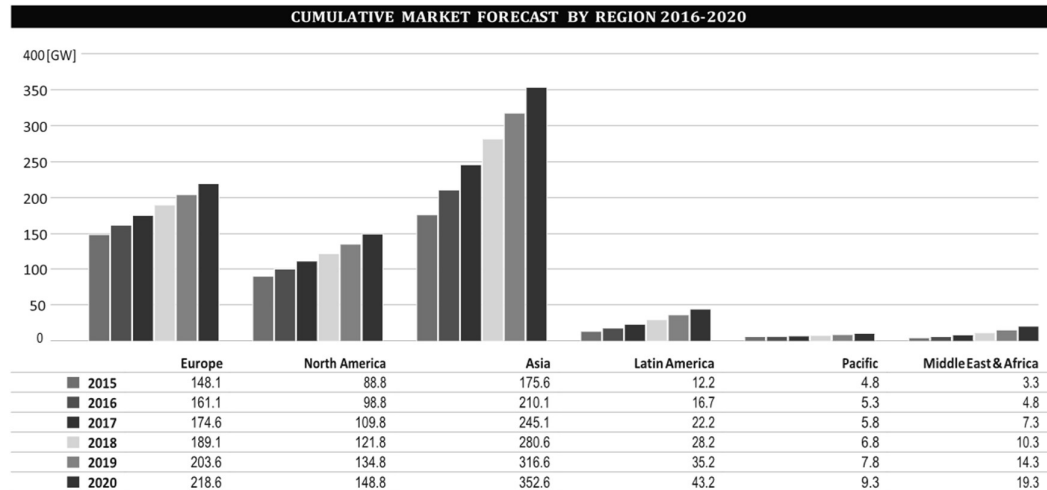
Figure 1. Cumulative market forecast by region 2016-2020 (source: Global Wind Energy Council)

Optimization in placement of wind turbine is the method of determining the wind turbines (WTs) placement in WF (Wind Farms). In the objective, yield optimization of WT placements, the WTs should place within an offshore area 'or' specific land, so that we can achieve the maximization in output power. Wind farms are now an integral part of electricity generation grids, numerous such systems like IEEE-Reliability Test System (IEEE-RTS), West Denmark Power System (WDKPS).

Here we will demonstrate the variant of multi-objective WT placement problem. The layout of wind farm is depend upon the "objective function". The four different combination of objective has consider; convex hull area with the minimum spanning tree, output power (yield) with the convex hull area, output power with EMST, and a combination of yield, convex hull area and EMST.

An implementation of modified version of the WT placement prototype [5] presented in [6] is uses to estimate yields of the WF arrangements. For simplify the behavior of wind field, in this paper we uses a "simple wake model". We use the multi-objective (EA) evolutionary algorithms such as Genetic algorithm (GA) [7] SPEA2 [8] and, proposed algorithm M-GA (Modified Genetic Algorithm [9]), to produce different number of WT layouts. These methodologies are considered with various 'problematic specific operators' that are present in this paper.

2. LITERATURE SURVEY

A new algorithm MORS has proposed by Ju Feng et al. [10] that help to optimize the wind farm layout and the WT numbers. Generalized algorithm can be considered for multi-objective (> 2 objectives) and logically deal with the different constrains. Normally, a simple algorithm needs only fewer parameters, which are ease to implementation and run. Generality of the algorithm should be maintain by considering simple algorithm. Here they consider 2 objectives (minimizing cable length and maximizing power) with 2 constraints (WT proximity and WF boundary). After the evaluation with popular multi-objective EA (Evolutionary Algorithm) NSGA- II, it has found that 'MORS' ('Multi-objective random search') performs better than Non-dominated sorted GA II, mostly in case of ideal test. Furthermore, MORS has the additional dealing advantage with a variable WT number. Under the actual test case of Horn Rev 1 'WF', MORS has shown the favorable performance. With the fixed number of wind turbines, that manages to get the shorter length cable and a little more production of power. The problem with variable number of WT's, they got an extensive range of the Pareto-optimal layouts with the variable WT numbers. For developing, the WF MORS is quite useful for developers. That can be further test and improved in the future studies, which will help to considering more number of realistic objectives.

Amin I et al. [9] proposed the model of NSGA-III, which outperformed the paternal algorithm in-terms of achieved solutions precision and the convergence. Increasing in objectives numbers, the Elite NSGA III corresponding performance significantly better than of NSGA-III in almost every instance. Furthermore, they influence on the exclusive population archive. The proposed algorithm capability in persevering elite population diverse sets and hence causes the improvement in offspring population diversity. For the further

improvement, this study extends to investigate the elite-population archive impact, when the alternative recombination operators have used (e.g., (DE) differential evolution instead of the polynomial-mutation-operators and SBX). Secondly, investigation of elite-population archive impact when the neighboring solutions of elite has used to build offspring population. Lastly, consequently methodologies to avoid the build solutions has attracted towards some reference points. George Cristian et al. [11] proposed a WF layout optimization problem (WFLOP). The WFLOP objective is to determine the WT optimal placement within a WF. In this paper, they have focused on to maximize the power production. Wake effect is the major reason to significant losses of the power production; therefore, they used a discrete representation of WF. By using heuristic algorithms, the farm area is decomposed into cells set, where every cell having only one WT. In future, solution that is more exact and multiple optimized solution for the larger size problem is need.

Markus Wagner et al. [12], focus on evolutionary based turbine placement with the enhanced wake fed prototype under real-world wind flow. They modeled real world geo-constraints data from the open Street Map. Moreover, the geo-constraints and realistic wakes modeling, the paper focus on comparison of the various approaches of evolutionary optimization. The proposed evolutionary strategies of four variants with the turbine-oriented operators and compared with the state-of-art optimizers. For the future work this can be extend to further scenarios of experimental analysis. In specific largescale, scenarios and offshore turbines placement with the ground and constraint like ship route. Important parts are constraints in realistic scenarios which, shown in result that the constraints produce problem in order to optimize the problem. It can be further concentrate on more developed constraint handling techniques. J. Day et al. [13] represent the effective and speedy algorithm for the huge type of wind farms layout enhancement. This consider problem specific feature and that can help to decrease the complexity of computation under considering Park Wake model. The result of that, algorithms achieves better quality of results than the existing approaches. The effective obtain speed is very less, in order of minutes 'or' hours instead of weeks or days. Parallelization approach can speed up the computation process and furthermore it can improve in future. Although here they consider a selected wake model (Park Wake model), and it is important that the optimized algorithm is very easy to applied to the different "Wake models" (such as the deep array 'wake model' [14]). Michele S. et al. [15] describes the "WFLOP" (wind farm layout optimization problem), which is critical problem that is necessary to solved during wind farm design. The better layout design tends to give a more profit and higher energy production. Only the several scientific communities have given consideration to such kind of constraints to this operational research area. In this, they have given the mathematical model that used to calculate the wake effect impact on production of energy.

Main motive of the wind farm developer is to minimize the road network, but the connection should be done properly. Such that one can reach, one point to any other point short of passing through the public roads. In that case, the cranes easily install the wind turbines and can easily move through the road network. This type of road network has built by subnetworks, which are separate from the public road. Initially, the 'cranes' need to move throughout the passenger road to reach next address. Unfortunately, the turbines are huge and the assembled one cannot transport through public roads. Therefore, it is necessary to disassemble, to transport over public road to another sub-network and, after that reassemble. Although, it is difficult to get information about operation cost (developers of WF do not publicize the cost information), it has estimated around tens thousands of dollars.

W. Tong et al. [16] proposed a MOWFD ('Multi-objective WF Design') approach, which integrates and analyzes the several type of impact factors on the wind farms design. This methodology comes with three main advancement of WF design paradigm: first, one provides an understanding of key factor impact over performance of WF under the various wake model use. Second explores the important tradeoffs between COE (cost of energy), usage of area in WF layout optimization, and energy production. Third built an original advancement on the mixed-discrete PSO (particle swarm optimization) algorithm through concept of multi-domain diversity preservation for solving a difficult multi-objective optimization ('MOO') problem. A complete sensitivity analysis of WF power generation has performed to make understand and differentiate the land configuration impact, incoming speed of wind, installed capacity decisions and, ambient turbulence on conventional array layouts performance. Such that array WF, each factor are relatively important and vary considerably with the wake model choice, i.e., acceptable differences in sensitivity (up to 70%) were detect across the various wake models. Considering, optimized WF layouts, the selection of wake model has not much significant effect on the indices sensitivity.

3.   PROPOSED METHODOLOGIES

In the following, the different constraints and objectives are outline, which we consider for optimization of wind farm. Let $A = \{A_1, \ldots, A_n\}$ and $B = \{B_1, \ldots, B_n\}$ are set of the coordinates x and y of n WT in the plane. Our objective is to obtain such coordinates set that the whole

WF output is maximize. At same time, the whole cable length essential to inter-connect the turbines, also the necessary area for the WF, which should be minimum. Moreover, the layout developer has to pay certain attention towards constraints. Every aforesaid combined objective is set to solution as distinct objectives.

3.1. Energy output

The overall output energy of the WF varies, depending upon the selected coordinates, because here we considering wake effects into the account. In reference [17], it has already declared that an efficiency of wind turbine would be decrease after putting into a WF with other turbine, because of wake effect. Wind flows over a WT; the kinetic energy part has transferred to turbine blades. Because of that wind speed is reduce by the blades, it generates an expansion of volumetric regarding to the mass accumulation earlier the blades. Wake model can be simplify by without considering the intensity of nearest turbulence. That effect has assumed to propagate linearly and continuously as shown in Figure 2. Increment in wake effect when more wakes have apply to same WT. The analytical wake effect model is consider in this paper that was 1st developed by the Jensen [18] is known as park wake model.
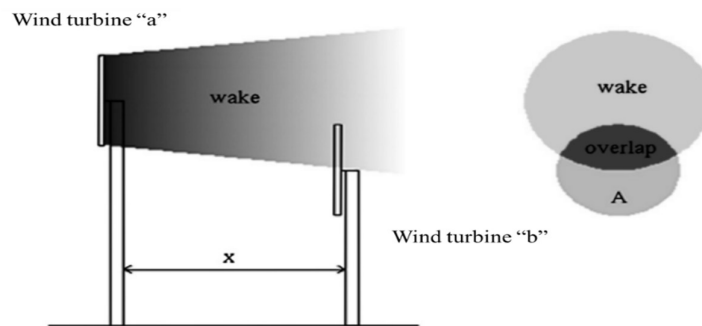

Figure 2. Schematic of a wake model involving wind turbines with different hub heights

The Park wake prototype, it is a trade-off between the computationally very expensive simulations and simplifying wake models, which has based upon the dynamics of fluid. The effects of wake upon a turbine n has change the available wind resource to another direction, through decreasing the scale parameter p of 'Weibull Distribution' predicted for the whole farm that called as free-stream 'wind resource'. This wind resource has reliant on its address and rest turbines location. Through, we have a p_n scale parameter for every turbine n: it is having complex computation and involves $Sdef_a$ velocity deficits, which the n turbine experiences the influence due to other.

Algorithm 1: Wake effects evaluation procedure ("Park model") [19, 20]
a. Providing $\{A, B\}$ as the locations and thrust-coefficient K_T is given for the WT, wake spreading factor s that is landscape-specific and, rotor diameter D;
b. $t = 1 - \sqrt{1 - K_T}$, $b = s / D$, $u =$ unit step function;
   $m = (B_n - B_a)sin\theta + (A_n - A_a)cos\theta$;
c. $d_{n,a} = \|m\|$, $z = \tan^{-1} s$;
d. **for** $n = 1$ to turbines number **perform**
e. **for** $\theta = 0^0$ to 360^0 **perform**
f. **for** $a = 1$ to $x - 1$; also $a \neq n$ **perform**

g. $\delta_{n,a} = \cos^{-1}\left(\dfrac{m + D/k}{\sqrt{\left(A_n - A_a + \frac{D}{s}\cos\theta\right)^2 + \left(B_n - B_a + \frac{D}{s}\sin\theta\right)^2}}\right)$;

h. $Sdef_{(n,a)} = u\left(\delta_{n,a} - z\right)\dfrac{z}{(1+bd_{n,a})^2}$;

i. $Sdef_n^\theta = \sqrt{\sum_j\left(Sdef_{(n,a)}^\theta\right)^2}$;

j. $p_n(\theta) = p_n(\theta) \times (1 - Sdef_n)$;

Turbines $n, a \neq n$ (see Algorithm 1). We refer to [19] for the detailed demonstration on a parameter computation, since the "wake effects" present in the Park wake effect approach. In terms, the predictable energy output η of all WF is given thru the (1).

$$T^{wf}[\eta] = \sum_n \int_\theta^i H(\theta) \int_v^i H(y(\theta)), p_n(\theta, A, B), s(\theta) \beta^n(y). \tag{1}$$

Here, y is 'wind speed', and the function $\beta^n(y)$ describes the *'power curve'* for n turbine. However, Wind speed y is random variable as per a 'Weibull distribution'. Which has projected from resource data wind and, using A and B considers as the 'wake effect'. That type of distribution is a wind direction function, in which θ varies from the $0^0 - 360^0$. Here the wake effects is not disturbing the Weibull distribution. Moreover, a flow of wind from a specific direction having some probability $H(\theta)$.

3.1.1. Constraints

Here we are following some constraints that placed on our "optimization function". The upper bound WF area has taken as the first constraint. This ensures that a turbine n place within a "certain area". The length F_l and width F_w for a rectangular wind farm, this constraint should satisfy.

$$0 \leq A_n \leq F_l \text{ and } 0 \leq B_n \leq F_w, 1 \leq n \leq x.$$

The damage risk increase through turbulences, when turbines placed too close. Spatial proximity is the second constraint. The equation is given as

$$\sqrt{(A_n - A_a)^2 + (B_n - B_a)^2} \geq u \cdot D, 1 \leq n \neq a \leq x$$

Here, u is a 'proximity factor' and D is a 'rotor radius'. We consider $u = 8$ as per the industry standard.

3.2. Euclidean Minimum Spanning Tree (EMST)

The EMST has used to compute a minimal cable length necessary to link the all WTs in a particular WF layout. It can calculated by the first complete construction graph that represent the WT set of points. Edge costs has calculated by Euclidean distance between the any turbines pair. For this graph minimal spanning tree distance is calculated and used as a main objective, which representing the cable length costs. Figure 3 displays a layout of wind turbine, and minimal spanning tree, which has denoted by lines joining to each WT. Shown turbines has enclosed thru a 'rectangular area', which presented by grey color. This theoretical EMST is calculated using formula 22 in [19] equation as

$$L^{EMST} = (x - 1) \times 38.5 \times 8.0 \tag{2}$$

Where, the Turbine RR (Rotor Radius) proximity constraint is 38.5 m and n is the number of turbines in the wind farm. The area enclosed by dash line is represents convex hull area. The joining lines shows the edges of EMST, or cables. The drawn circles visualize the least safety distance imposed by the proximity constraint (twice the rotor radius of turbine).
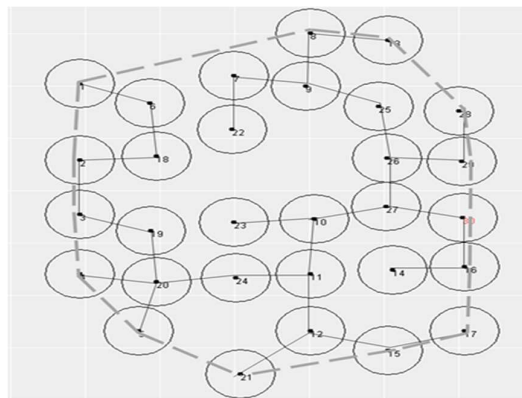

Figure 3. An example wind turbine layout

3.3. Area of convex hull

Area that cover all the set of points is known as area of convex hull. The occupied area is the minimal land area, which has needed for an optimal WF layout. Here convex hull area can be computed by the Graham's scan model [20]. Figure 3 displays a layout of WT, and the convex hull area (cost) enclosed by dash grey line. If the outline is 'non-intersecting polygon' with x vertices, then the area of convex hull can be compute.

$$A^{CH} = \frac{1}{2}\sum_{n=0}^{x-1}(A_n B_n + 1 - A_n + B_n) \qquad (3)$$

3.4. Variation operators for the turbine placement

In this section, the multi-objective WT placement framework problems and problem-specific-variation operators are outline. Because of the large turbines number, the problem is more constrained. Therefore, the operator has to confirm the feasible placements of turbines.

3.4.1. Movement mutation

Local changes of current solution is done by the mutation operator, i.e. turbines placement on the given land area. The 'mutation operator' (i.e Movement Mutation Algorithm 2) randomly selects turbine moves in a particular proportion of specified solution. Subject to constrains, the movement direction and distance is determined randomly.

Algorithm (2): Mutation operator (i.e. Movement Mutation)
   a. The S_p selected as in with turbine with locations $\{A, B\}$;
   b. Consider turbine location $Q = \{x, y\}$ is chosen, $Q \in C, x \in A \ and \ y \in B$;
   c. Here, S_d = protection distance;
   d. Set R_h is 'movement range' in horizontal direction of Q and R_v is the movement range' in vertical direction of Q;
   e. **for each** $Q' = \{x', y'\} : \{y - S_d < y' < y + S_d\}$
   f. **if** x' is near to x on nonnegative way;
   g. Perform
   h. Save x' to x_{S_p};
   i. **if** x' is near to x on non-positive direction;
   j. Perform
   k. Save x' to x_x;
   l. R_h varies from $x_{S_p} - S_d$ to $x_x + S_d$;
   m. Re-do the steps v to xii to get the R_v;
   n. **Return** $Q^x = \{x^x, y\}: (x^x \in R_h) \ or \ Q^x = \{x, y^x\}: (y^x \in R_v)$;

In order to get the feasible solution, the max distance that WT can move in every (each) has computed. This can be done thru examine a designated surrounded area, with movement of x-axis and y-axis. In the checkup area, WT whose safety rotor margins has found to be overlap, limit the movement constraints for particular turbine. The defined designated area is two times of 38.5-meter safety margin, originating each direction perpendicular to the travel axis. To get valuable placement after the turbines movements, R_v and R_h (movement ranges) has computed, which has based on the placement of neighboring turbines. Afterwards, the MM (Movement Mutation) approach not give an infeasible individual child and algorithm 2 shows the MM operation algorithm, which is based on the simple single loop calculation.

3.4.2. Block swap crossover

Block Swap Crossover (BSC) has considered to produce the two children from randomly selected two parents from each block, each child having varying information from their parents. A wind farm is a rectangular area block, entire wind farm enclosed by the boundary to provide protection [20]. The first parent basis is uses by the first child. A randomly block has chosen from 2nd parent to copying 1st child, consequently, the boundaries of the block has extended afar the proximity constraint of each turbines through the twice rotor radius value (i.e. 38.5 meters). This will help to get a safety distance between turbines that are outside of these circle bounds.

Algorithm 3: 'BSC' (Block Swap Crossover)
   a. Consider S_{p1} and S_{p2} are chosen as parents, with in the turbine locations;

    b.   **for** $n = 0$ to T
    c.   Rectangular area A_{r1} is generated randomly a in WF area;
    d.   Turbines in S_{p1} are separated into two sets, I_1 for turbines insideA_{r1} and $\Theta_1$for ones outside of A_{r1};
    e.   Modify A_{r1} to A'_{r1} in that every edge keeps a protected space to the 'adjacent turbine' in I_1;
    f.   Considering A'_{r1}on S_{p2} to get I_2 and Θ_2;
    g.   **if** $|I_2| \geq |I_1|$ **then**
    h.   Move x = $|I_2| - |I_1|$ turbines from Θ_1 into I_1;
    i.   Set the turbine locations in I_1 as in I_2;
    j.   Return S_{p1} as child number one;
    k.   **Else**
    l.   Process continue;
    m.   Provide above on the S_{p2}, to obtain the 2nd child number;

Then the child boundary is used to get the area, which is totally replaced through the turbine $2nd$ parent. This method has continued for the operation of 2nd child, which is basis on information of second parent. The process of copying turbine position is straightforward, in which the child holds equal or lesser turbines related to their parents has replaced at in destination area. A newly boundary is selected randomly until the case condition is not satisfy. Even if the appropriate block has not obtain for the copying child, then its parent will appear as the operation result. This thing indicates the failure in crossover operation. If destination turbines number are matches with the source area, the operation ends. Then the randomly selected child destination area from outside has to be moved into destination area like as substitute. Which confirms the turbine number is equal in both destination and source.

4.   PROPOSED METHODOLOGIES

There are many proposed Genetic Algorithm (GA), but the basic framework remains same as the original GA [7] with some significant alterations in its "selection mechanism". According from G.C Ciro. [21] it is found that the 'MGA' has performed superior than the GA, if the problem is multi-objective. Adoption of MGA is to solve problems, which more than two 'objective' due to the classification of solution with some reference point and selection of best qualified for 'next population'. Through altering some selection mechanism here, we proposed an MGA. The steps define in algorithm 4 describes the MGA.

Algorithm 4: Modified Genetic Algorithm (MGA)
    a.   Reference point number is calculate to place on a '$hyper-plane$'
    b.   Random generation of initial population with considering the resources assignment constraints.
    c.   Recognize the sorting of non-dominated population
    d.   **For** $the\ n = 1\ stopping\ criteria$ **do**
    e.   Using tournament method select the two parents S_{p1} and S_{p2},
    f.   The crossover is apply between S_{p1} and S_{p2},with a $p(c)$ probability,
    g.   Recognize the sorting of non-dominated population,
    h.   Normalize the $'population\ members'$,
    i.   Associate the reference points with the population member,
    j.   Apply the ($counter$) niche preservation
    k.   Keep the obtained niche solution for the $"next\ generation"$
    l.   **End for**.

4.1. Reference points determination on a hyper-plane

We must have to define a reference points set to confirm the obtained solution diversity. On the standardized hyper-plane, the different points set are place, which have the identical orientation in all axis. The reference point's number (G) defined as

$$G = \binom{e + N_g - 1}{N_g} \qquad (4)$$

Where e is number of the objective function and N_g is divisions number, which consider on each objective axis. After the placement of reference point, the created reference points is consider to associate the solution.

4.2. Population members normalization

The ideal point must be determined from the current population, so that we identify the minimum objective value of each function. In order to create the hyper-plan, we are following the steps, which has proposed by Jain and Deb et al. [22].

4.3. Associate the reference points with the population member

When each objective function has normalized, it is essential to associate every population member with the reference. Reference line is defined for joining the point with initial point. Afterwards, perpendicular distance between each reference line and each population member is define. Lastly, the point of reference that are close to reference line from the individual population has allowed being the population member.

4.4. Niche preservation operation

A reference point set can be relate to the one 'or' more members of solution, but here we take that solution which is closer to point (the perpendicular distance from origin line [22])

4.5. Genetic operators

The generation of children is the same operation, which were also using in genetic algorithm. According to Jain and Deb [22], we have fixed the size of population (SOP) close to a reference point's number (G) to provide the importance to every population member.

5.   RESULT ANALYSIS

In this paper, we consider the variation operator and multi-objective EAs (evolutionary algorithms) to solve the multi-objective WT placement problems. The 3-multi-objective EAs are consider such as; MGA [9], SPEA2 [8] and GA [7], and the execution has done in the '$jMetal$ framework' [4]. The simulation has done using Matlab 2016b, the system configurations is 8 GB RAM, Windows 10 and Intel i5 processor. To evaluate the performance of our proposed approach we used wind-Scenario-2 [23]. Scenario 2 can be consider as complex scenario and the prevailing direction of wind covers a sector broad about 105◦. There are two cases, first when wind is coming from only one direction and second when wind is coming from different directions. As per intensity of wind, the direction has consider thru "Weibull distributions" at both considered cases, which results there is non-zero probability for the second case. Hence, the layout optimization is necessary to work within the minimal wake loss with all wind direction. Finally, the turbine rotor radius $D = 38.5m$ is use for proximity constraints. In wind scenario, here we are computing the yield (power) that can be used as an main objective to our WF optimization. The convex hull area and EMST are the other objectives, which we are considering to minimize the cost of wind farm. In our experiment, we used the multi-objective GA, MGA, and SPEA2 optimization algorithms with our proposed operators. In every instance of simulation, 50-population size has utilized with over 10,000 generations. The MM operator has applied with $p(m) = 0.7$ probability in the individual iteration. Similarly, the block swap (BS) 'crossover operator' has provided with $p(c) = 0.3$ probability (based upon the initial testing both value were selected/chosen). The following objective combinations are:

a. Maximizing the yield and, minimizing the 'area of convex-hull'
b. Maximizing the yield and, minimizing the EMST
c. Minimizing the area of the 'convex hull' and, EMST
d. Also the combination of yield, convex hull area and, the EMST.

For analyzing the better performance of evolutionary algorithms, here we taken the three scenarios of turbines. In first scenario, we took the four turbines for placement on the given area (Area size = 3000×3000 m^2). In second scenario, we took the twenty turbines for placement on same area. In last case, we took thirty turbines at same given area. Considering these following objective mixtures with the variation operators, the enhanced location of wind turbine can be obtained.

5.1. Scenario one for wind turbines placement

The placement of wind turbines is critical task. As we earlier mentioned that in scenario one we are taking 4-turbines to place on rectangular land area (9 Km^2). In according to the variation operator and objective combination the placement of wind turbines are carried out. Combinational objective has shown in Figure 4, which has combination of all three main objectives (yield, convex hull area and, the EMST). X-axis represent the area in m^2, Y-axis represent the yield in kW and Z-axis represent for EMST in meter. In Figure 6, three different color represent for three different evolutionary algorithms. Blue color represents for M-GA, green color for GA, and red color for SPEA2.

Through using these combinational objectives, we got our turbine placement location. The circle shows the minimal distance of safety that has imposed by proximity constraint. Figure 5 shows the 4-turbines placement using M-GA, Figure 6 shows the four turbines placement using GA algorithm, and Figure 7 shows for turbine placement using $SPEA-2$. In each Figure 5 to Figure 7 the turbine placement is different, which causes the differences in objectives values.
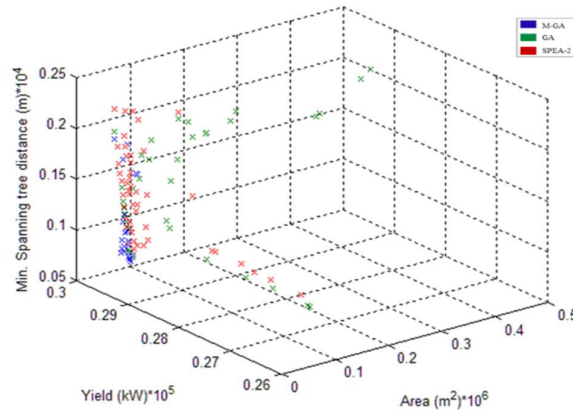

Figure 4. Turbine-4, a combination of power, convex hull area and minimum spanning tree
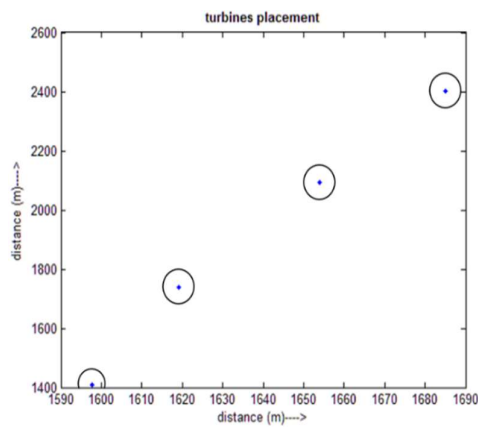
Figure 5. Turbine-4 placement using MGA
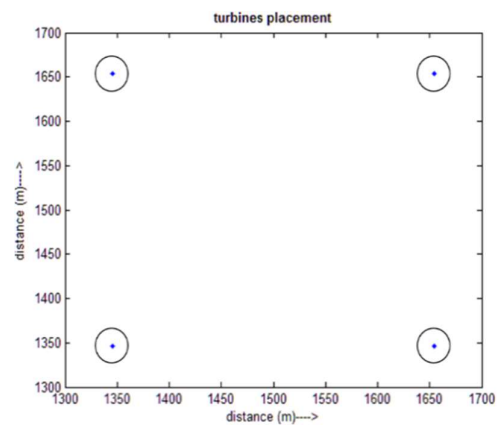
Figure 6. Turbine-4 placement using GA
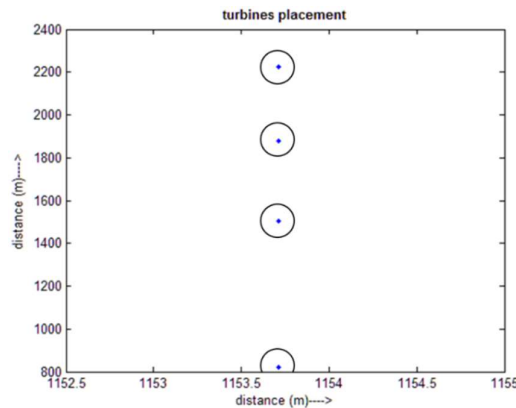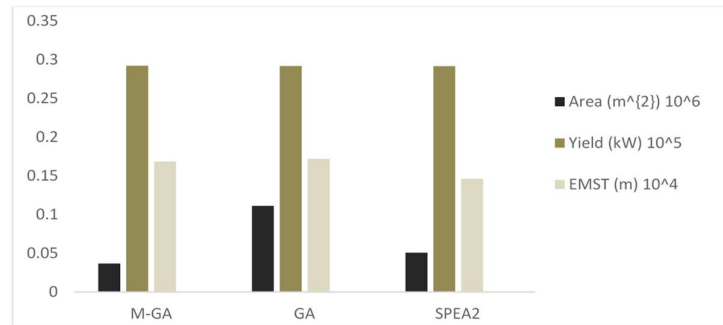

Figure 7. Turbine-4 placement using SPEA2

Figure 8 shows the presentation of Yield (kW), Area of convex hull (m^2) and EMST (m) using evolutionary algorithms $M-GA$, GA and $SPEA-2$. The presented results show that M-GA of $0.04\ Km^2$ occupying 66.93% less area when compared to GA ($0.11\ Km^2$) and 27.72% less area compared to SPEA-2 ($0.05\ Km^2$). A 0.2% more yield produced by M-GA ($29.22\ MW$) compared to SPEA-2 ($29.17\ MW$) and 0.08% more yield compared to the GA ($29.20\ MW$). The minimal spanning tree distance is also the important factor in which SPEA-2 ($1.46\ Km$) doing well in lesser number of turbines. SPEA-2 require 13.2% less cables to connect all the WT compared to M-GA ($1.68\ Km$) and 14.85% less cable length compared to GA ($1.71\ Km$) is reported.

Figure 8. Turbines-4, representation of Yield (kW), Area of convex hull (m^2) and EMST (m).
Using evolutionary algorithms MGA, GA and SPEA2

5.2. Scenario two for wind turbines placement

In scenario two, we are taking twenty turbines; same as the previous scenario here we are following same procedure to get optimized result from WF. A combination objective of power, EMST and convex hull area is shown in Figure 9. For every population (population size =50) the objectives values are plotted. From Figure 9, we can say that GA and SPEA-2 having more variation in every population with compared to M-GA. That combinational objective will help to place the turbines effectively. Therefore, we should get maximum power output from the wind farm, with lesser, EMST and convex hull area.

The placement of 20 turbines has shown in Figure 10 to Figure 12 with using of different evolutionary algorithms. Location of turbines from algorithm MGA, GA and SPEA-2 are different from each other, which means the area covered by the turbines are not the same. The area given to place turbines is $9\ km^2$, which is a rectangular area. More area in wind farm indicates the more initializing cost. A less convex hull area is always desired objective parameter and this parameter considered in our paper for optimization.

The representation of convex hull area, EMST and yield is shown in Figure 13 for the 20 turbines. The presented result exhibit A^{CH}>1.4Km^2 considering M-GA, SPEA-2 and GA models. The more area is achieved by GA, which is 10.74% more compared to M-GA model of $1.48\ km^2$. SPEA-2 model occupying area of $1.49Km^2$ that is 0.74% more A^{CH} compared to M-GA model. The highest yield is achieved by the M-GA of 127 MW that is 1.42% more compared to SPEA-2 model of 125 MW. A 0.19% more yield is obtained by M-GA compared to the GA. The increment in turbine numbers and area of convex hull will affect on EMST (L^{EMST}) values. As per the obtained result, the maximum length is obtained by SPEA-2 of 6.2 Km, which is 3.65% more compared to M-GA. The minimum EMST obtained by the M-GA of 5.9 Km that is 3.33% less than GA of 6.1 Km is reported.
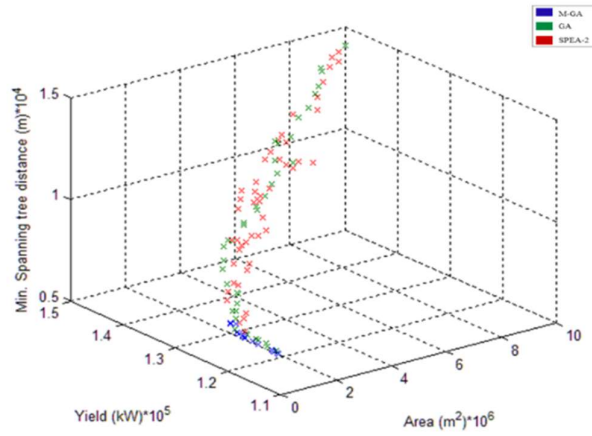
Figure 9. Turbine-20, a combination of power, convex hull area and minimum spanning tree
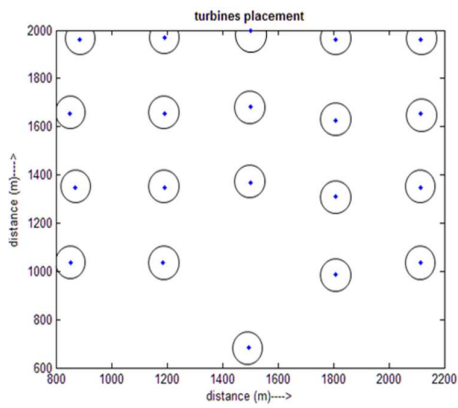

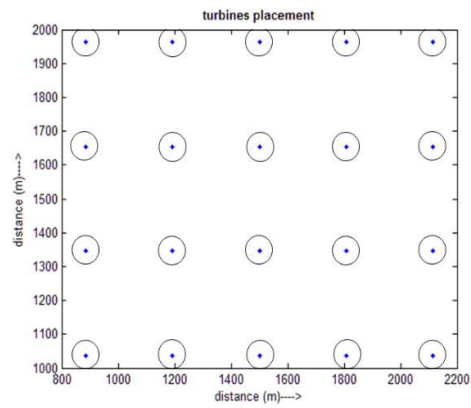Figure 10. Turbine-20 placement using MGA

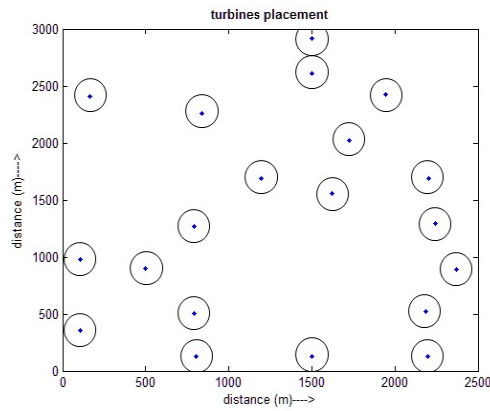

Figure 11. Turbine-20 placement using GA

Figure 12. Turbine-20 placement using SPEA2
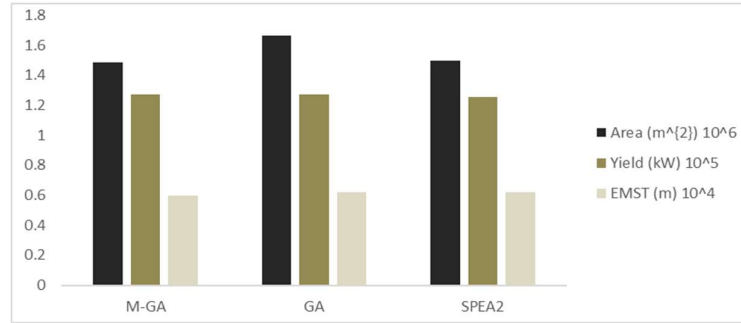
Figure 13. Turbines-20, representation of Yield (kW), Area of convex hull (m^2) and EMST (m).
Using evolutionary algorithms MGA, GA and SPEA2

5.3. Scenario three for wind turbines placement

Same as the other two scenario here we showing the combinational objective of thirty turbines in Figure 14. Turbines placement using M-GA is shown in Figure 15, in which the blue dot represent the turbines and circle around that blue dot represent the safety distance between the turbines in wind farm. 30 Turbines placement using the GA is shown in Figure 16 and Figure 17 show the turbines placement using SPEA-2 model. The turbines placement has done randomly by the variation operators. The performance of all wind turbines model is evaluated on basis of optimized objective parameters.
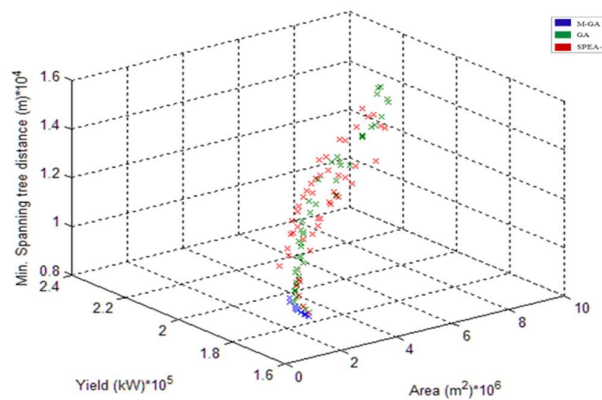

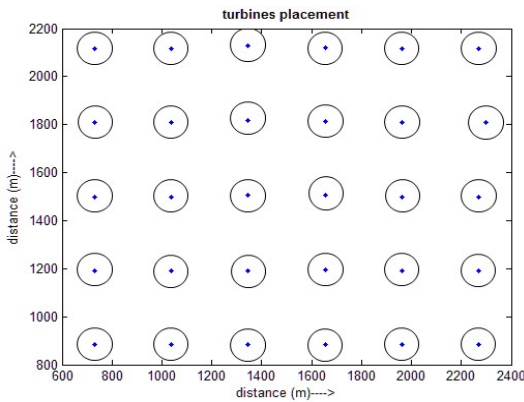Figure 14. Turbine-30, a combination of power, convex hull area and minimum spanning tree

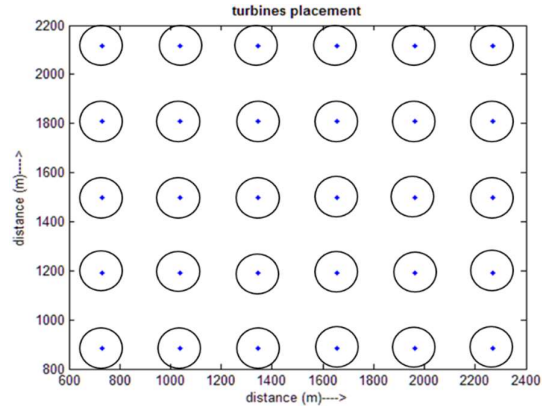Figure 15. Turbine-30 placement using MGA

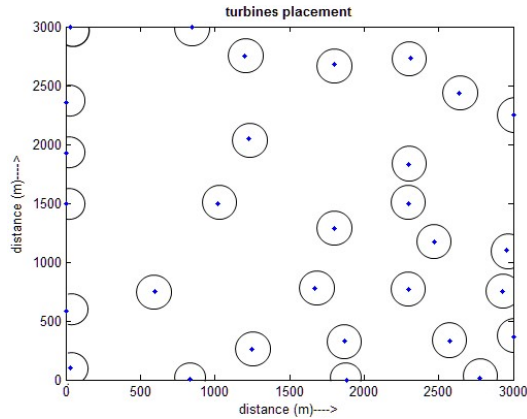Figure 16. Turbine-30 placement using GA

Figure 17. Turbine-30 placement using SPEA2

Figure 18 shows the presentation of Yield (kW), Area of convex hull (m^2) and EMST (m) using evolutionary algorithms $M - GA, GA$ and $SPEA - 2$. The result presented exhibit more convex hull area ($A^{CH} > 2.30 Km^2$) considering M-GA, GA and SPEA-2 models. The lowest A^{CH} achieved in M-GA model of $2.30 Km^2$, which is 3.9% less compared to GA ($A^{CH} = 2.39 Km^2$) and 6.52% less compared to SPEA-2 model of $2.46\ Km^2$. The result exhibits more yield > 180 MW considering evolutionary algorithm models [8-10]. A 0.94% more yield is produced by M-GA of $182\ MW$ compared to GA model ($180.6\ MW$) and 1.06% more yield compared to the SPEA-2 model ($180.4\ MW$). As increasing in turbine numbers, the cable length will also increase. The obtained result exhibits $L^{EMST} < 9.3$ Km considering SPEA-2, GA and M-GA model. Considering all the algorithm models minimum L^{EMST} is obtained by M-GA of 9.04 Km, which is 1.22% less compared to the GA model ($L^{EMST} = 9.15\ Km$) and 1.75% lesser than the SPEA-2 model ($L^{EMST} = 9.15\ Km$). This means M-GA exhibits better performance in all optimized objective parameter is very efficient for every scenarios of WF.
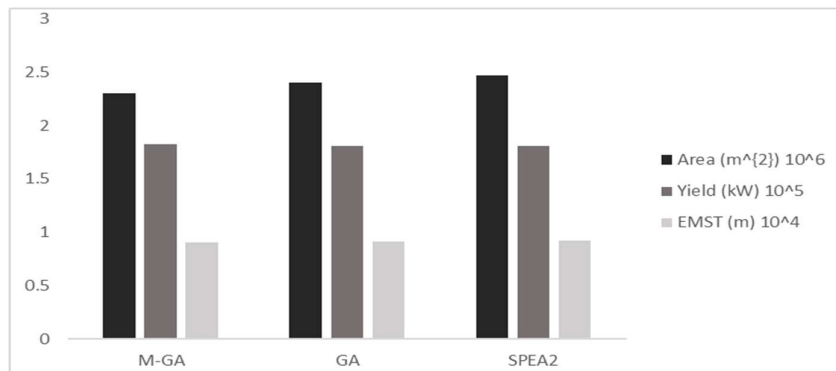

Figure 18. Turbines-30, representation of Yield (kW), Area of convex hull (m^2) and EMST (m).
Using evolutionary algorithms MGA, GA and SPEA2

6.   CONCLUSION

In this paper, we are concentrating in wind power through optimizing the wind turbine placement in wind farm. In proposed wind scenario, we computed the yield (power) that has used as one of the main objective in our WF optimization. The convex hull area and EMST are the other objectives, which we are considering to minimize the cost of wind farm. The multi-objective GA and, SPEA2 optimization algorithms has compared with our proposed MGA for analyzing the better performance of evolutionary algorithms, here we taken the three scenarios of turbines. In first scenario, we took the four turbines for placement on the given area (Area size= 3000×3000 m^2). In second scenario, we took the twenty turbines for placement on same area. In last case, we took thirty turbines at same given area. At each scenario, the turbines placement is

shown in the given area; also, we provide the representation of Yield (kW), Area of convex hull (m^2) and EMST (m) using evolutionary algorithms MGA, GA and SPEA2. Taking average from three scenarios, proposed MGA produce 0.89% more yield than SPEA2 and 0.403% more yield than GA, which is considerable improvement in WF optimization process.

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