WIND ENERGY
Wind Energ. 2010; **13**:297–306
Published online 29 April 2009. DOI: 10.1002/we.339

RESEARCH ARTICLE

Optimal positioning of wind turbines on Gökçeada using multi-objective genetic algorithm

Sedat Şişbot[1], Özgü Turgut[1], Murat Tunç[1] and Ünal Çamdalı[2]

1 System Engineering Department, Engineering Faculty, Yeditepe University, Kayisdagi Cad., 34755 Istanbul, Turkey
2 Mechanical Engineering Department, Faculty of Engineering and Architecture, Abant Izzet Baysal University, Golkoy Campus, 14280 Bolu, Turkey

ABSTRACT

This paper addresses the problem of optimal placement of wind turbines in a farm on Gokçeada Island located at the north-east of Aegean Sea bearing full potential of wind energy generation. A multi-objective genetic algorithm approach is employed to obtain optimal placement of wind turbines by maximizing the power production capacity while constraining the budget of installed turbines. Considering the speed and direction history, wind with constant intensity from a single direction is used during optimization. This study is based on wake deficit model mainly because of its simplicity, accuracy and fast calculation time. The individuals of the Pareto optimal solution set are evaluated with respect to various criteria, and the best configurations are presented. In addition to best placement layouts, results include objective function values, total power output, cost and number of turbines for each configuration.

KEYWORDS
wind farms; multi-objective genetic algorithm; optimum localization; Gokçeada Island

Correspondence
Ü. Çamdalı, Mechanical Engineering Department, Faculty of Engineering and Architecture, Abant Izzet Baysal University, Golkoy Campus,14280 Bolu, Turkey.
E-mail: camdali_u@ibu.edu.tr

Received 11 July 2008; Revised 24 March 2009; Accepted 1 April 2009

1. INTRODUCTION

Wind power is increasingly becoming one of the fastest growing sustainable energy resources, as fossil and other carbon fuels are being rapidly depleted. Furthermore, these fuels are becoming more expensive, while the demand for energy consumption continues to expand in order to meet the fast growth of the world population. Energy generated by wind turbine is by far one of the cleanest energy resources. The term wind energy or wind power describes the process by which the wind is used to generate mechanical power or electricity. Wind turbines convert the kinetic energy in the wind into mechanical power, while a generator converts this mechanical power into electricity. Estimates of the wind resource are expressed in wind power classes[1] ranging from class 1 to class 7 with each class representing a range of average wind power density or equivalent average speed at certain specified heights above the ground. Areas classified as 4 or greater are sui and efficient for today's wind turbine technology. Power class 3 areas may be suitable for future technologies.

The factors that affect the production of wind power have been widely studied and explored in literature (see e.g. Manwell *et al.*,[2] Pasqualetti *et al.*[3] and Cavallaro and Ciraolo[4]). The power of a wind turbine is essentially proportional to the rotor surface area and the cube of the wind speed. Wind farms or wind power plants are the confined fields where wind energy within the field is harnessed by a set of wind turbines. Determining the optimum layout for the turbines in a farm involves many trade-offs. For example, placing turbines close together reduces the electrical cable cost; however, the total energy decreases because of the wake effect and the turbulence resulting to less overall lifetime. Several other such trade-offs exist and will be discussed in the following sections.

This paper focuses on a wind farm (study area) assumed to be on the north-west of Gokçeada Island which is located in the north-eastern part of the Aegean Sea where the annual average wind speed is recorded as 8.89 m s^{-1}. The wind speed sometimes reaches up to 25–30 m s^{-1}, especially during December and January of the year. These figures therefore promote power class of 5 and 6 for turbine selection.

The island is geographically positioned at latitude 40º09′49″ N, longitude 25º50′05″ E and has a surface area of 285.5 km^2. The maximum distance from east to west and north to south is 30 and 7 km, respectively. Its climate is mild, with a sufficient amount of rainfall. The average annual temperature is approximately 16ºC with an average annual humidity of 68.5%. The prevailing wind direction is noted as north-north-east (NNE).

The core topic of this paper is to place a set of turbines in the specified wind farm at Gökçeada by applying multi-objective genetic algorithm (MOGA) optimization techniques. As in many optimization studies, genetic algorithms (GAs) were employed to address the turbine placement problem[5] by using single objective function that lumps all different objectives into one. However, turbine placement problem is a multi-objective problem for which it is difficult to identify the true benefits and constraints mainly because of the uncertainty in future demands. Here, the objectives are set separately as total power obtained from the farm and cost of turbine investment including installation and commissioning. These objectives allow a decision maker to visualize the trade-offs between power and cost, and more importantly to consider uncertainty in future demands.

The MOGA applied in this work uses Pareto ranking as a means of comparing solutions across the objectives. The Pareto optimal set of a multi-objective optimization problem consists of all those vectors for which their components cannot be all simultaneously improved without having a detrimental effect on at least one of the remaining components. In addition to multi-objective criteria, we have considered the farm field of concern as an amorphous shape and the wind as random signal to agree with the real conditions.

This paper is organized as follows. The next, second section presents to certain details, sufficient to the proper perspective on the topic of wind farm modelling trade-offs including relevant information for site and turbine characteristics. The third section complements this presentation with the necessary outline discussion on engineering essentialities of multi-criteria genetic algorithms (MOGA) and the main performance criteria, which are considered to be most important for successful implementation and operation of the algorithms. The fourth section focuses on the discussions for the results achieved in several runs of MOGA. Finally, conclusion and references are given thereafter.

2. WIND FARM MODEL, SITE AND TURBINE CHARACTERISTICS

Considerable research has gone into understanding wind flow within the wind farms during the last decade. Various models have been introduced in literature, and some of them have already been commercialized. Currently, there are three different wake models under use; Jensen model, the Ainslie model (eddy viscosity) and the Larsen model (Prandtl BL equations). All three wake models can be used for energy calculations, mean wind field calculations and with turbulence calculations. The models are varying in complexity from a simple empiric engineering model to an axi-symmetric CFD model. All the models still lack a structured validation and calibration for use on large farms. Traditional N.O. Jensen wake model[6,7] is more precise at predicting the observed wake loss than the other models and is also preferred in this study because of its simplicity and fast computation time. The wake model kinematics is first introduced by Jensen[7] and has been the fundamental conjecture for Mosetti *et al.*,[5] Katic *et al.*[6] and Grady *et al.*[8] It is also implemented in the commonly used wind farm program PARK.[9] The model assumes that the momentum is conserved in the wake. The downstream turbine speeds are calculated considering speed deficit including the distance from upstream turbine, rotor radius, axial induction factor, surface roughness and specific features of the turbines. The total power of the farm is then determined as the sum of individually calculated turbine powers. Another wake model is developed by Ainslie[10] (Ainslie model) which solves a simplified axial symmetric Reynolds equation to determine the development of the wake. It is therefore much more costly in terms of calculation time. G.C. Larsen model,[11] on the other hand, assumes axial symmetric flow and a single self-similar velocity profile for the whole wake. This model only considers the far wake region and turbulence created by the shear.

The second technique of farm modellers use various version of full CFD[12,13] which is based on parabolized Navier–Stokes equations. Turbulence is modelled by means of the *k*-epsilon turbulence model. Through the parabolization of the governing equations, it is assumed that there exists a dominant direction of flow, and that among others the downstream pressure field has little influence on the upstream flow conditions. In other words, the axial pressure gradients are neglected. These assumptions no longer hold in the near wake where additional modelling is necessary. In the ENDOW project,[14] this was accomplished by excluding the near wake and the solution procedure started at a fixed distance behind the rotor.

The third main technique was introduced by Ozturk and Norman[15] using a heuristic method for positioning wind turbines by considering multiple wind direction and intensity. The wind power calculations are independent of surface roughness. Here, the effect of turbines to each other is calculated using statistical reduction formulas which are only based on the difference between turbines and the wind direction.

The aerodynamic power P_W of a wind turbine was first formulated by Betz[16] as

$$P_W = \frac{1}{2}\rho\pi r^2 U^3 C_p \quad (1)$$

where ρ is the air density and equals to 1.225 kg m^{-3} at 16ºC, r is the turbine radius, U is the wind speed and C_p is the turbine power coefficient which represents the power

Wind Energ. 2010; **13**:297–306 © 2009 John Wiley & Sons, Ltd.
DOI: 10.1002/we

conversion efficiency. The coefficient C_p is a function of the tip-speed ratio, as well as the blade pitch angle in a pitch-controlled wind turbine and is proven to be maximum of 0.593.[2,16]

The wake deficit behind the front turbine using balance of momentum has been cited in many wake studies (e.g. Mosetti *et al.*,[5] Katic *et al.*[6] and Grady *et al.*[8]) that are fundamentally predicated on Jensen deficit model[7] as

$$\text{Deficit} = 1 - \frac{U}{U_0} = \frac{2a}{\left(1 + k\dfrac{x}{r}\right)^2} \tag{2}$$

where k is wake spreading or entrainment constant, a is axial induction factor and x is the distance from the turbines in front.

The axial induction factor is related to the turbine trust coefficient as[3]

$$a = \frac{1}{2}\left(1 - \sqrt{1 - C_T}\right) \tag{3}$$

where C_T is the trust coefficient which is determined by the turbine manufacturer.

The wake spreading constant is given empirically as

$$k = \frac{0.5}{\ln\left(\dfrac{z_H}{z_0}\right)} \tag{4}$$

where z_H and z_0 are hub height and surface roughness, respectively.[5,17]

The velocities in the downstream turbines caused by the wake effect determine the power generated by the turbine. A numerical model for prediction of the interaction of the wind turbines with the prevailing wind flow is to be determined. Assuming multiple turbines in the upstream of a turbine in concern and ignoring the non-linear near-wake region, the wake deficits are combined by summing the squares of the interacting deficits, as suggested by Katic *et al.*[6]

$$\left(1 - \frac{U}{U_0}\right)^2 = \sum_{i=1}^{N}\left[\left(1 - \frac{U_i}{U_0}\right)^2\right] \tag{5}$$

As a result of equations (2) and (5), it is obvious that the wind power harnessed by a set of wind turbines within the confined farm region is a function of local wind speed distribution throughout the farm, rotor diameter, hub height and surface roughness. Total power generated by a wind farm is the sum of the individual turbine powers, each of which is subject to different wind speeds caused by wake deficits and multiple wakes as given by equation (5).

The farm area of our interest is assumed to be on the north-west of Gokçeada.[18] The monthly average speeds between the years of 1994 and 2002 have been supplied

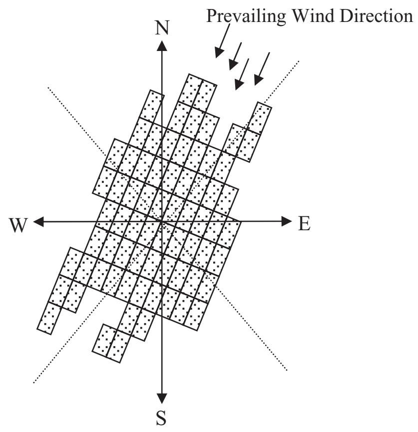

Figure 1. Position of the land and prevailing wind direction.

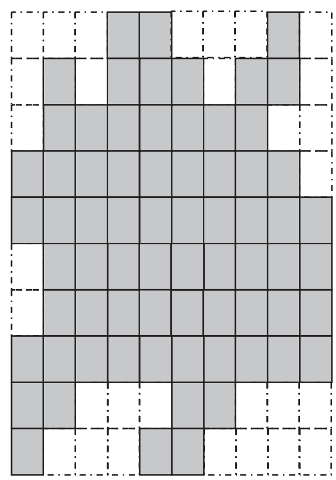

Figure 2. Partitioned representation of region.

by Eskin *et al.*,[19] and annual average speed has been given as 8.89 m s^{-1}.

The prevailing wind direction is noted as NNE. Figure 1 illustrates the farm geography together with prevailing wind direction and wind distribution. The farm terrain is divided into 100 equal rectangular cells, some of which are omitted to adapt the geometry to existing land geography (see Figure 2 for the details). The turbines are assumed to be placed at the centre of each cell. The lengths of the cells are determined according to the minimum spacing rule.[20] When distances are shorter than certain values, this will cause potential turbine damage caused by the large wake decay effects. The minimum spacing distances are $8D$ and $2D$ for prevailing wind and crosswind, respectively, where D is the diameter of the rotor. Grid area is therefore chosen as rectangle which allows more efficient use of the area as shown in Figure 3.

We have assumed that a single type of a turbine would be employed in the farm. The selected turbine for this study

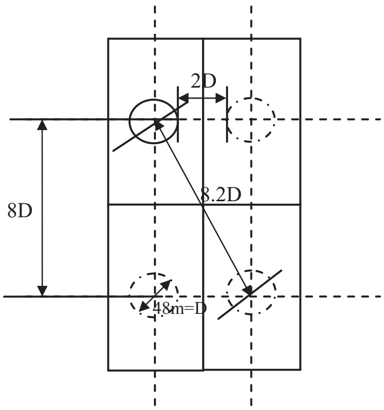

Figure 3. Neighbouring grid distances.

Table I. Properties of turbine used for this study.

Rated power	800 kW
Rotor diameter	48 m
Swept area	1810 m^2
Cut-out wind speed	28–34 m s^{-1}
Hub height	50 m
Power coefficient	0.44
Number of blades	3
Trust factor	0.52
Orientation	Upwind

Table II. Used parameters during the calculations.

Turbine power (W)	$P = 487.8U^3$
Axial induction factor	$a = 0.1535$
Hub height (m)	$z_H = 50$
Surface roughness (m)	$z_0 = 0.005$
Wake spreading constant	$k = 0.054$

is Enercon E-48 turbine. A few important properties of this turbine are given in Table I. Note that the turbine has 48 m rotor diameter and placed over on a 50 m hub with power coefficient and thrust coefficient of 0.44 and 0.52, respectively, for the average of 8.89 m s^{-1} wind speed.

In the lights of above formulas and discussions, the following will prevail for furthering the process of optimization. The parameters used in our calculations are given in Table II.

3. MOGA OPTIMIZATION FOR TURBINE PLACEMENT

Turbine placement may seem as a rather straightforward task at first glance if a smooth convex area is of concern. However, when the balance between cost and extracted power is considered, this issue becomes an optimization problem. In addition to conflicting attributes of cost and power, the power of each and every individual turbine is determined by the wake effects caused by the turbines at the proximity; this problem can be considered in the field of combinatorial optimization where the set of feasible solution is discrete or can be reduced to discrete one. Consequently, solving the problem with a heuristic search method is appropriate.

The GA is a proven method to solve optimization problems including non-linear problems. GAs are search and optimization methods based on natural evolution. They consist of a population of bit strings transformed by three genetic operators: selection, crossover and mutation. Each string (chromosome) represents a possible solution for the problem being optimized, and each bit (or group of bits) represents a value for a variable of the problem (gene). These solutions are classified by an evaluation function, giving better values, or fitness, to better solutions. The advantage of GAs is their use of stochastic operators instead of deterministic rules to search for fitness solutions. The search process jumps randomly from point to point, thus avoiding the local optimum, in which other conventional optimization algorithms might land. Therefore, the GA is a very promising method to deal with complex, multi-variable optimization problems. It should, however, be noted that GA cannot always find the exact solution, but the best solution and is relatively slow compared to other optimization techniques. These disadvantages can partly be avoided using different techniques. Based on a GA approach, an effective and efficient optimization platform is applied for the turbine placement for Gökçeada wind farm in this paper.

Several methods for adapting GAs to cope with the simultaneous optimization of a problem over a number of dimensions have been proposed, including the use of Pareto ranking.[21] The MOGA applied in this work uses Pareto ranking as a means of comparing solutions across multiple objectives. The Pareto optimal set of a multi-objective optimization problem consists of all those vectors for which their components cannot be simultaneously improved without having a detrimental effect on at least one of the remaining components. This is known as the concept of Pareto optimality, and the solution set is known as the Pareto optimal set (or non-dominated set).

Because GA is a population-based algorithm, it has been recognized to be well suited to multi-objective optimization as described in literatures.[22,23] One way of dealing with multiple objectives is to give a weight to each of the objectives. On the other hand, MOGAs adopt the other method and do not impose an ill-informed weighting process on the task of selecting a single optimal solution, but instead, the concept of Pareto ranking can be applied in order to deliver a set of candidate solutions.

In this study, a controlled elitist GA has been used. An elitist GA always favours individuals with better fitness value (rank), whereas a controlled elitist GA also favours individuals that can help to increase the diversity of the population even if they have a lower fitness value. It is very important to maintain the diversity of population for convergence to an optimal Pareto front. This is done by controlling the elite members of the population as the algorithm progresses.[24]

Wind Energ. 2010; **13**:297–306 © 2009 John Wiley & Sons, Ltd.
DOI: 10.1002/we

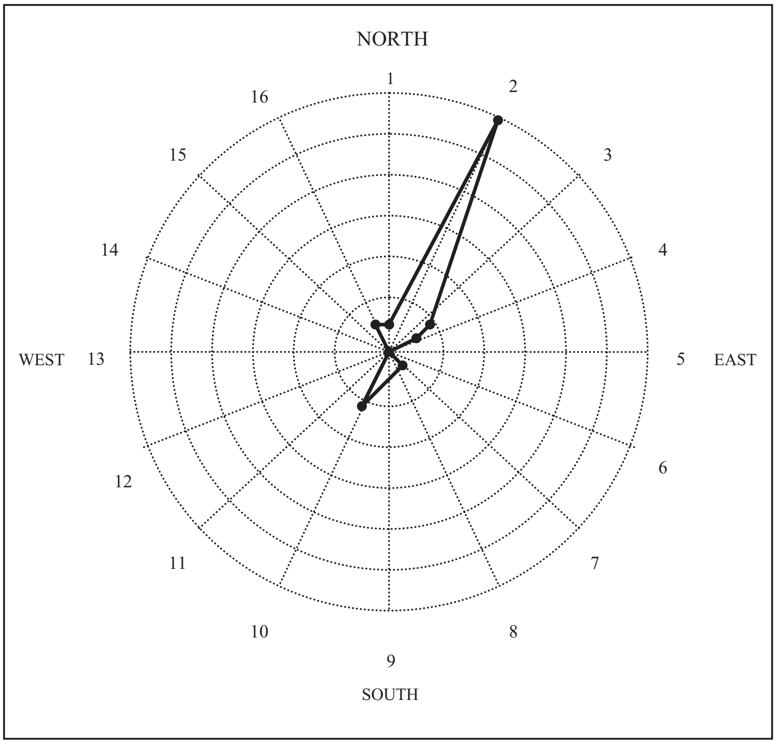

Figure 4. Prevailing wind direction on Gökçeada Island.

In our study, prevailing wind direction is regarded as NNE as shown in Gokçeada wind rose diagram as seen in Figure 4,[18] and the wind speed is assumed to be constant at the yearly average of 8.89 m s^{-1}.

Our first objective function was predicated on the cost of the configuration. Kiranoudis *et al.*[25] offered a detailed cost analysis that is tuned for the Enercon turbines. We have evaluated this cost structure for our cost objective function. Equations (6)–(11) provide the base equations for the cost calculation.

$$c_0 = c_{01}e^{-c_{02}N} \tag{6}$$

$$b_0 = b_{01}e^{b_{02}N} \tag{7}$$

$$c_{\mathrm{op}} = b_0 + (b_1 - b_0)\left(1 - e^{-b_2\delta}\right) \tag{8}$$

$$C_{\mathrm{cp}} = c_0 P^{c_1} N^{c_2} + C_{\mathrm{p}} \tag{9}$$

$$C_{\mathrm{op}} = c_{\mathrm{op}} NP \tag{10}$$

$$\text{Total Cost} = \ell C_{\mathrm{cp}} + C_{\mathrm{op}} \tag{11}$$

where C_{cp} and C_{op} are the installation cost and the operational cost, respectively, and N is the number of turbines. The other parameters related to Enercon E-48 turbines used in this study are given in Table III.

Our algorithm is designed to eliminate the individuals who have higher costs than our budget constraint of \$20M. It manages this through assigning large values as the first objective fitness value for infeasible individuals in terms of budget. One can buy at most 25 turbines with \$20M according to our cost function. Thus, the configurations having more than 25 turbines are forced to exhaust according to our first objective function.

Table III. Constants of cost equations.

Name of the constant	Value
P	800 W
C_1	0.948
C_2	0.102
c_{01}	0.824
c_{02}	0.000138
B_1	80.1
b_2	0.00107
b_{01}	4.09
b_{02}	0.000154
λ	0.1
δ	4

Our second objective function was the power extracted from the farm. This function was designed to find the most effective design in terms of power with the budget. In order to do this, we first calculate an upper bound for the power that will be extracted from a farm with 25 turbines without any wake effect. This value comes up to be 8568.5 kW. The total power of the farm is the sum of the individual powers of the turbines as a result of GA allocation where

Table IV. Properties of multi-objective genetic algorithm.

Creation function	Uniform
Crossover function	Scattered crossover
Crossover fraction	0.8
Distance measure function	Distance crowding, phenotype
Elite count	5
Fitness scaling function	Rank scaling
Maximum generations	2000
Migration direction	'Forward'
Migration fraction	0.2
Migration interval	50
Mutation function	Gaussian
Pareto fraction	0.35
Population size	250
Selection function	Stochastic (uniform)
Limit generation of unchanging objective values	50
Limit time of unchanging objective values	100
Change tolerance	1,00E-8

the power of downstream turbines is calculated from the multiple wake models as given in equation (1).

$$P_{\mathrm{TOTAL}} = \sum_i P_{\mathrm{W}i} \tag{12}$$

Based on these calculations, our second objective function was the absolute difference between P_{TOTAL} and the upper bound value. So, the algorithm also tries to minimize the distance between the ideal case value and the expected power output of each configuration.

The important properties and parameters of MOGA are given in Table IV. Creation function is the property that indicates the way we used to create initial population. Elite count is the number specifying how many individuals in the current generation are guaranteed to survive to the next generation. We have used scaling according to the rank to scale fitness functions. The term 'maximum generations' indicates the positive integer specifying the maximum number of iterations before the algorithm halts. Migration fraction is the fraction of individuals in each subpopulation that migrates to a different subpopulation. Migration interval is the number of generations that take place between migrations of individuals and between subpopulations. Mutation children are produced using Gaussian methods. Pareto fraction is the fraction of individuals to keep on the first Pareto front while the solver selects individuals from higher fronts. The population size was chosen as 250, which is the number of binary variables. Parents of crossover and mutation children are chosen uniformly. The algorithm stops if there is no improvement in the objective function for 50 consecutive generations or within 100 s. Fitness function algorithm is introduced in Figure 5.

Figure 2 shows the farm region details with equal rectangular cells (10×10). The cells which are not suitable to place a turbine are left blank implying out-of-farm region. The forbidden cells are introduced to the algorithm as constraints within the fitness function.

4. RESULTS AND DISCUSSION

The population of 250 has been allowed to evolve for 2000 generations. Average change in value of the spread of Pareto set over the last 50 generations came up to be less than 10^{-8}, and iteration has ended after producing around 300 generations. Our run has ended up with a Pareto optimal solution set consisting of 450 individuals. Since there are two objective functions, i.e. cost and difference of power and upper bound, it is possible to evaluate the individuals in the resultant population from different aspects. However, in our case, our main concern is finding the best layout in terms of power based on the budget constraint at our hand. So, the ranking according to the second objective is the main interest. On the other hand, the individuals are also ranked according to ratio in order to validate the results of our algorithm. The results are presented in Tables V and VI in three layouts at each with number of turbines they include. Table V presents the first three best layouts sorted for power objective, and Figure 6 shows the turbine distribution in the area of interest corresponding to this layout, where the 1s represent the cells having a turbine, while 0s no turbine cells. These configurations are the best candidates for uni-directional wind with constant intensity. In case of power maximization, the emphasis is naturally given to power. In the maximum power criterion, the number of turbine has reached up to 25, which is the maximum number of turbines being purchased within our \$20M budget.

In the final evaluation, we have pursued a criterion for validating our algorithm by presenting our results about the ratio of power over cost in order to compare the results with the previous studies. Table VI presents the three best results, and Figure 7 gives the corresponding optimal turbine placement under this criterion. It is important to note that the evaluation with this criterion has been applied after the algorithm evolved based on Pareto optimality, and produced a Pareto optimal solution set according to two objectives, namely cost and power. As discussed in the previous sections, similar studies[5,8] which have found reasonable recognition considered the same ratio as an objective function to determine the optimal layout. In case of uni-directional wind, they presented similar result of placing turbines in a row or almost in a row and reaching to the total turbine count as 26–30. Here, we found only 10 turbines (layout 7) having the maximum power/cost ratio of 0.402305798. When only the power is considered and constrained by the budget, our results showed that the turbine count reaches up to 25 (layout 4). The number of turbines satisfying objective functions of cost and power separately differs significantly. As expected, the best results for one objective yield the worst results for the other objective. The differences between our study and previous studies are caused by the multi-objective nature

Wind Energ. 2010; **13**:297–306 © 2009 John Wiley & Sons, Ltd.
DOI: 10.1002/we

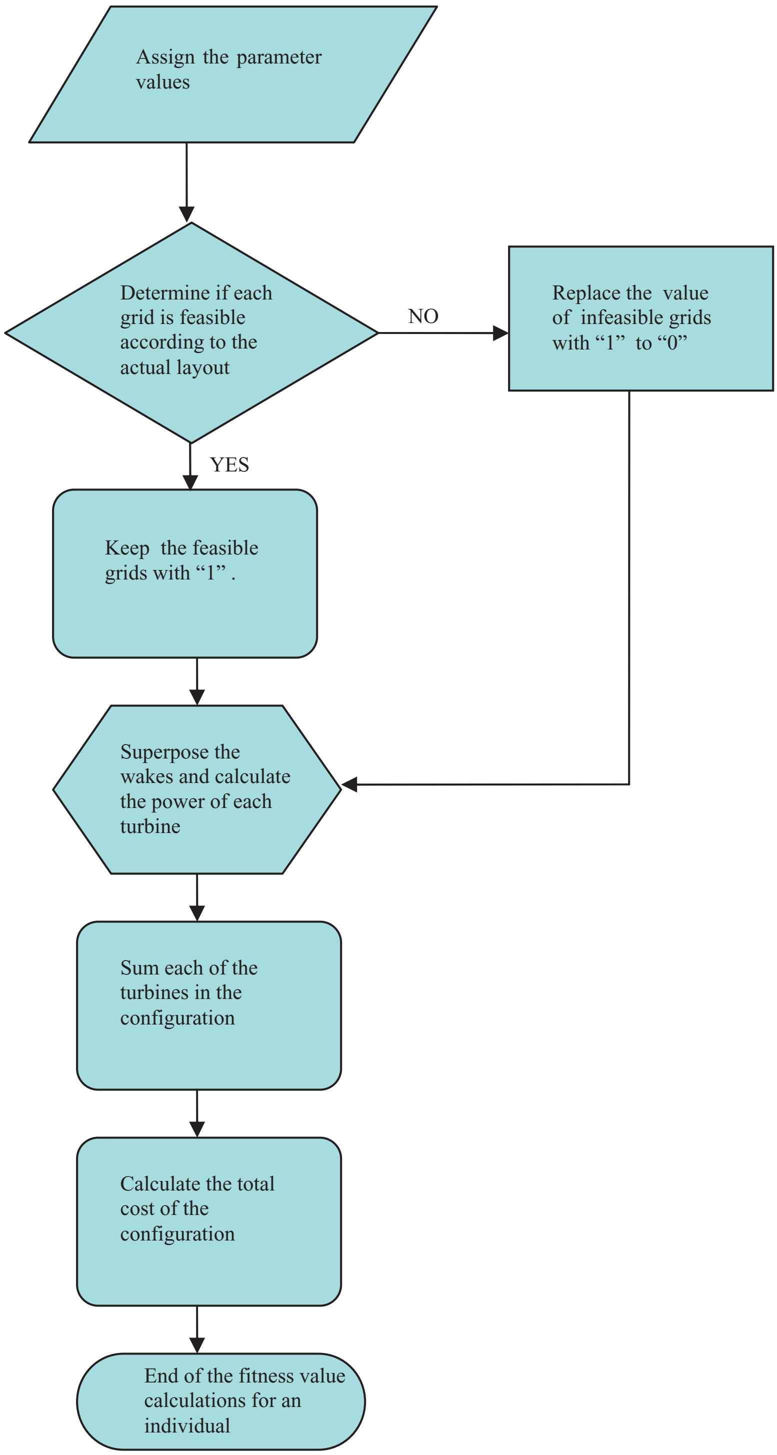

Figure 5. Algorithm of fitness function.

of our approach and the dissimilar cost function. Multi-objective criteria method offers more flexibility by creating the chance of adding realistic constraints to the placement problem.

The budget allows maximum of 25 turbines to be placed in the defined farm area. These turbines can be placed intuitively as 10 turbines to front cells and 10 to back cells of each column so that minimum wake effect consequently maximum power will be experienced. The remaining five turbines are hard to be positioned exactly. At least, we cannot expect adding more than one turbine in each column in the mid-part of the region; it would otherwise be four turbines in some columns, which will eventually reduce the expected power because of the intense wake. Moreover, the third turbine in the mid-part should be as far as possible to the front and back turbines. The good guess is to place the remaining turbines to the longest columns. When examined carefully, it can be seen that these intuitions are closely observed in layouts 7–9 as a result of many runs of the MOGA algorithm. It is apparent that MOGA allows us to introduce more stringent constraints so that intuition may not be as smooth as in this case.

Table V. Layouts for power objective.

Layout no.	Cost ($)	Power (W)	Number of turbines
4	19.960.950,0	7.220.743,0	25
5	19.162.477,0	7.020.217,0	24
6	18.364.008,0	6.804.834,0	23

Table VI. Layouts for power/cost ratio objective.

Ratio ranking				
Layout no.	Cost ($)	Power (W)	Power/cost ratio	Number of turbines
7	7.984.336,0	3.212.145,0	0,402305798	10
8	7.186.010,0	2.890.930,0	0,402299767	9
9	6.387.694,0	2.569.716,0	0,402291593	8

5. CONCLUSION

It is necessary to evaluate potential fields for renewable energy generation to meet the growing electric power demand, and economics dictate that wind power is the most promising source wherever it is applicable. In this study, an onshore wind farm field having amorphous shape on the Island of Gökçeada has been considered. Based on the wind data history record, the average wind velocity in

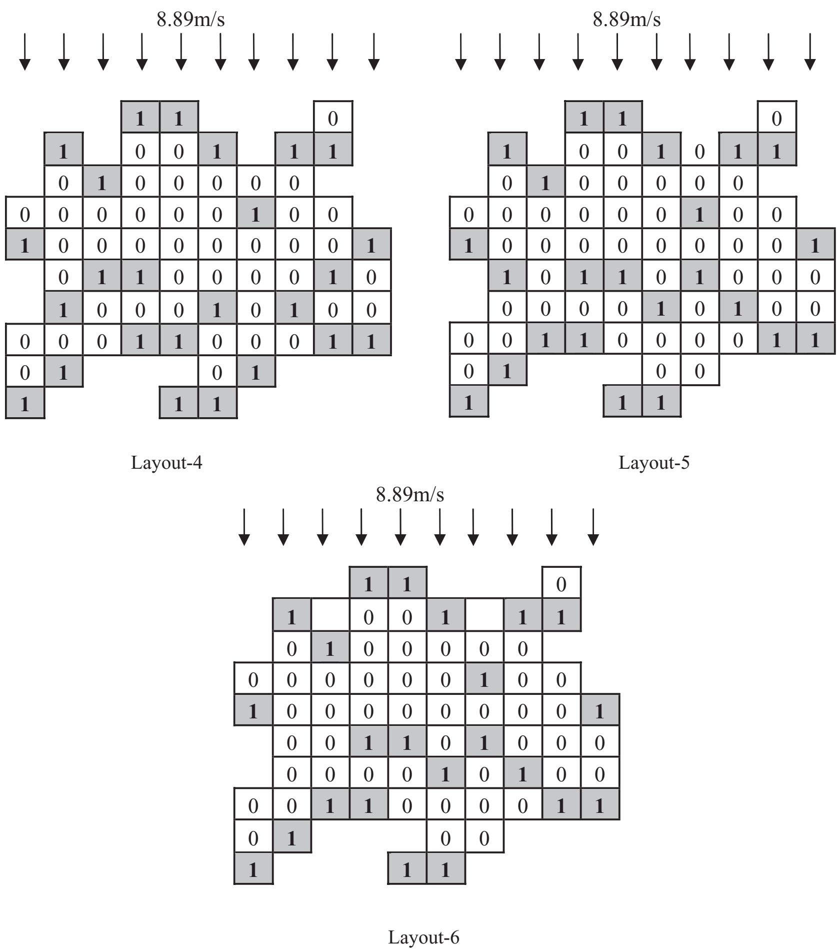

Figure 6. Turbine placement for Table V.

Wind Energ. 2010; **13**:297–306 © 2009 John Wiley & Sons, Ltd.
DOI: 10.1002/we

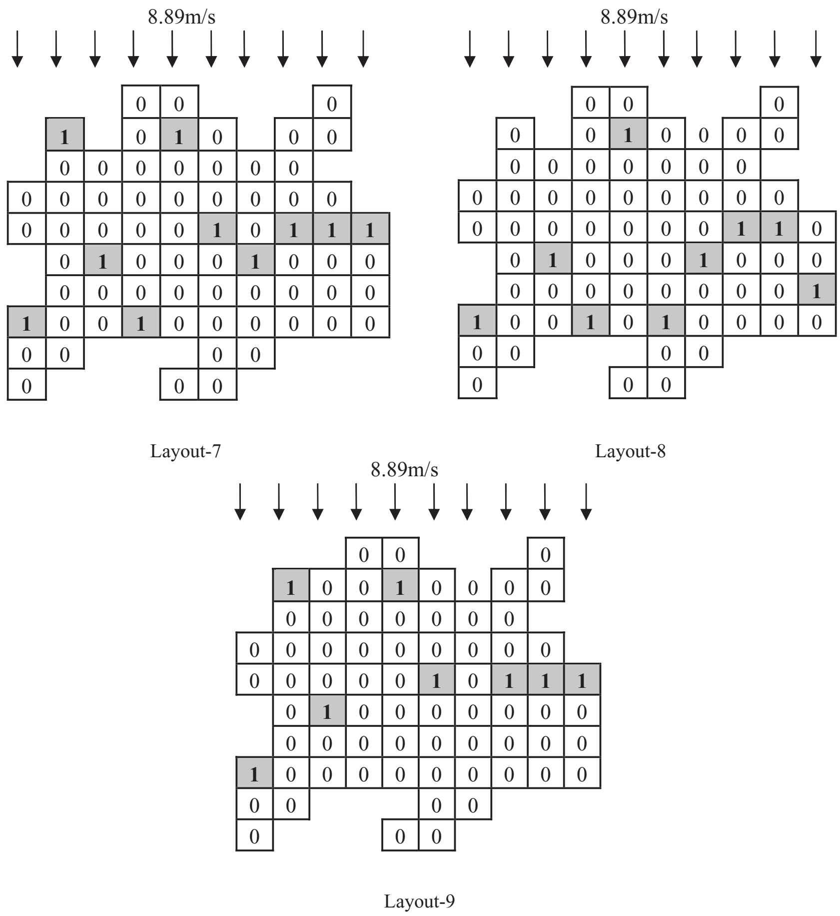

Figure 7. Turbine placement for Table VI.

the island is measured as 8.89 m s^{-1} (at 50 m), and prevailing direction is observed as NNE. Located in the north-east of the Aegean Sea, Gökçeada is therefore a very promising place for wind power plant construction.

The results of this work have revealed that MOGA with Pareto optimality criteria could also predict optimal turbine placement. The cost of investment and the power to be harnessed from the farm field have been set separately as two major criteria. The objectives under consideration conflict with each other. For multiple-objective problems, the objectives are generally conflicting, preventing simultaneous optimization of each objective. The first objective was the cost, and a total budget of \$20M was allocated. While trying to minimize the cost, this objective acted as the limiting constraint that punished the individuals; those cost more than our budget. The second objective function was the difference between the power that would be extracted from the layout of each individual and the power of ideal case, which was nominated as an upper bound. So, the second objective function served as to maximize the total power output of the layout. As a result of the wake deficit and surface roughness, the total power in a wind farm was as expected lower than of the case with a free air mass throughout the farm. The power in the downstream turbines was calculated by the multiple wake interactions using fundamental velocity relationship. These two criteria have generated a Pareto optimal solution set consisting of 450 individuals. The best three layouts have been shown according to power in tables. Moreover, making various evaluations using different criteria was possible among these configurations.

A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. Instead of determining a single objective at the outset, MOGA algorithm allowed us to make no clear preference between power and cost relative to each other. Furthermore, each objective has its own constraints designed for its specific needs. Here, we have performed the evaluation of the results according to ratio of these two objectives, which could also be considered as the validation of the algorithm. For furthering this study, one can also evaluate the results based on energy requirements, multiple wind direction and land usage.

REFERENCES

1. National Renewable Energy Laboratory. Wind Power Class-National Wind Technology Center. [Online]. Available: http://www.nrel.gov/wind. (Accessed 1 July 2008)
2. Manwell JF, McGowan JG, Rogers AL. *Wind Energy Explained, Theory, Design and Application.* Wiley: Amherst, USA, 2002.
3. Pasqualetti MJ, Gipe P, Righter RW. *Wind Power in View.* Elsevier: San Diego, USA, 2002.
4. Cavallaro F, Ciraolo LA. Multicriteria approach to evaluate wind energy plants on an Italian Island. *Energy Policy* 2005; **33**: 235–244.
5. Mosetti G, Poloni C, Diviacco B. Optimization of wind turbine positioning in large wind farms by means of a genetic algorithm. *Journal of Wind Engineering and Industrial Aerodynamics* 1994; **51**: 105–116.
6. Katic I, Hojstrup J, Jensen NO. A simple model for cluster efficiency. *European Wind Energy Association Conference and Exhibition*, Rome, 1986; 407–410.
7. Jensen NO. *A Note on Wind Generator Interaction.* Riso National Laboratory: Roskilde, 1983.
8. Grady SA, Hussaini MY, Abdullah MM. Placement of wind turbines using genetic algorithms. *Renewable Energy* 2005; **30**: 259–270.
9. Katic I. *Program PARK, Calculation of Wind Turbine Park Performance, Release 1.3++*. Risø National Laboratory: Roskilde, 1993.
10. Ainslie J. Calculating the flow field in the wake of wind turbines. *Journal of Wind Engineering and Industrial Aerodynamics* 1988; **27**: 213–224.
11. Larsen GC, Højstrup J, Madsen HA. *Wind Fields in Wakes.* EUWEC '96: Gothenburg, 1996.
12. Réthoré P-E, Bechmann A, Sørensen NN, Frandsen ST, Mann J, Jørgensen HE, Rathmann O, Larsen SE. A CFD model of the wake of an offshore wind farm: using a prescribed wake inflow. *Journal of Physics, Conference Series* 2007; **75**: 012047.
13. Barthelmie RJ, Rathmann O, Frandsen ST, Hansen K, Politis E, Prospathopoulos J, Rados K, Cabezón D, Schlez W, Phillips J, Neubert A, Schepers JG, van der Pijl SP. Modelling and measurements of wakes in large wind farms. *Journal of Physics: Conference Series* 2007; **75**: 012049.
14. ENDOW. Efficient development of offshore wind farms. [Online]. Available: http://www.risoe.dk/Research/sustainable_energy/wind_energy/projects/endow.asp. (Accessed 1 July 2008)
15. Ozturk UA, Norman BA. Heuristic methods for wind energy conversion system positioning. *Electric Power Systems Research* 2004; **70**: 179–185.
16. Betz A. (Randall DG, trans.) *Introduction to the Theory of Flow Machines.* Pergamon Press: Oxford, 1966.
17. Frandsen S. *On the Wind Speed Reduction in the Center of a Large Cluster of Wind Turbines.* EEC'91: Amsterdam, 1991.
18. Odyakmaz O. Energy production and control at power plants by renewable energy sources. PhD Thesis, Yildiz Technical University, 2008.
19. Eskin N, Artar H, Tolun S. Wind energy potential of Gokceada Island in Turkey. *Renewable and Sustainable Energy Reviews* 2008; **12**: 839–851.
20. Patel MR. *Wind and Solar Power Systems.* CRC Press: Boca Raton, FL, 1999; 85–86.
21. Fonseca CM, Fleming PJ. An overview of evolutionary algorithms in multiobjective optimization. *Evolutionary Computing* 1995; **3**: 1–16.
22. Fonseca CM, Fleming PJ. Genetic algorithms for multiobjective optimization: formulation, discussion and generalization. *Proceedings of 5th International Conference on Genetic Algorithms*, San Mateo, CA, 1993; 416–423.
23. Horn J, Nafpliotis N, Goldberg DE. A niched Pareto genetic algorithm for multiobjective optimisation. *IEEE Conference on Evolutionary Computation* 1994; **1**: 82–87.
24. Kalyanmoy D. *Multi-objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons: New York, USA, 2001.
25. Kiranoudis CT, Voros NG, Maroulis ZB. Short-cut design of wind farms. *Energy Policy* 2001; **29**: 567–578.

Wind Energ. 2010; **13**:297–306 © 2009 John Wiley & Sons, Ltd.
DOI: 10.1002/we