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New approach on optimization in placement of wind turbines within wind farm by genetic algorithms

Alireza Emami [a,*], Pirooz Noghreh [b]

[a] Department of Electrical Engineering, Ferdowsi University of Mashhad, Islamic Republic of Iran
[b] Department of Mechanical Engineering, Mazandaran University, Islamic Republic of Iran

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ABSTRACT

In the present study, the placement of wind turbines in wind farm has been resolved with a new coding and also a novel objective function in Genetic algorithm approach. In comparison to previous works, the results have been noticeably improved. The presented objective function, with its adjustable coefficients, provides more control on the cost, power, and efficiency of wind farm in comparison with earlier objective functions. Furthermore, in earlier jobs it was required to consider some subpopulations as well as individuals. However, there is no need to use the subpopulations in recent research by applying new coding approach in solving this problem. Therefore, running genetic algorithm only once for each case is sufficient. In this approach, three cases are considered (a) unidirectional uniform wind, (b) uniform wind with variable direction, and (c) non-uniform wind with variable direction. In Case (a), 10 individuals evolve over 150 generations. Case (b) has 20 individuals evolve for 150 generations. Case (c) starts with 20 individuals evolve for 100 generations. In addition to optimal configurations, results include fitness, total power output, efficiency of output power, number of turbines and objective function coefficients for each configuration.

1. Introduction

Wind is one of the oldest widely used sources of energy. Although its use is many centuries old, it has not been a dominant factor in the energy picture of developed countries for the past 50 years because of the abundance of fossil fuels. Recently, the realization that fossil fuels are in limited supply has awakened the need to develop wind power with modern technology on a large scale. Consequently, there has been a tremendous resurgence of effort in wind power in just the past few years. Wind energy is one of the lowest-cost forms of renewable energy. In 1995, more than 1700 MW of wind energy capacity was operating in California, generating enough energy to supply a city the size of San Francisco with all its energy needs [1]. European capacity was almost the same.

The fundamental principles of wind power technology do not change and are discussed here.

In optimized placement of wind turbines the following statements must be considered:

- The influence of wind turbines on each other (the wake)
- The variation of wind in direction and intensity
- The final placement for wind turbines should produce the maximum energy with the minimum cost for installation and terrain.

In present study, the wind farm modeling has been made using the RISO approach reported in Refs. [2,3], the same as Mosseti et al. approach, and the optimization procedure is based on a genetic algorithm. The optimization is performed in MATLAB Text Based environment by employment of new coding and objective function in comparison with previous studies.

2. Past approaches

Many attempts have been made in optimizing wind turbines positioning. As Bansal et al. claim in their essay, 10 ha/MW can be taken as the land requirement of wind farms, including infrastructure [4]. Of course many conditions, like the morphology of the terrain, the speed and the direction of the wind and also the turbine size will specify the spacing between the wind turbines in a wind farm.

When installing a cluster of machines in a wind farm, certain spacing between the wind towers must be maintained to optimize

* Corresponding author. No. 6, 8th Bahonar Ave., Vakil Abad Blvd., Islamic Republic of Iran.
E-mail addresses: emami112@yahoo.com, emami112@hotmail.com (A. Emami), pnoghreh@yahoo.com (P. Noghreh).

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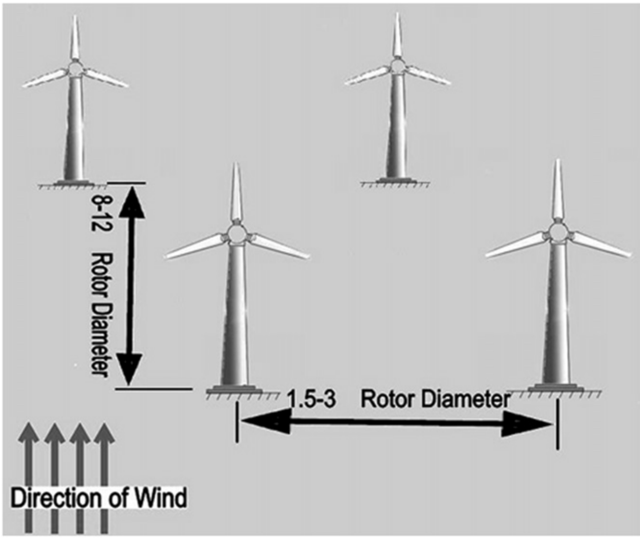

Fig. 1. Optimum tower spacing in wind farms in flat terrain.

Chromosome1	101	0101010	Offspring1	101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
	101	0101010		101	0101111
Chromosome2	111	0101111	Offspring2	111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010
	111	0101111		111	0101010

Fig. 3. Uniform crossover operator in Genetic Algorithm.

the power cropping. The spacing of a cluster of turbines in a wind farm depends on the terrain, direction and speed of the wind, and the turbine size. The optimum spacing is found in rows 8–12-rotor diameters apart in the wind direction, and 1.5–3-rotor diameters apart in the crosswind direction (Fig. 1) [5].

In 2002, Ammara et al. proposed a dense and staggered scheme in sparse wind farms by considering the performance losses associated with the wake effects, which are significant in dense arrangement. The first approach, which used the Genetic algorithm in optimization, was made by Mosetti et al. and then Grady et al wrote a computerized a program that used genetic algorithm in MATLAB Software.

The present study is based on the same models that Mosetti et al. and Grady et al. used and we attempt to obtain more optimal and effective results than these two essays by using a different objective function and novel coding with respect to capability of MATLAB in working with matrix.

3. Wake and cost modeling

The assumption which has been made here are the same as Mosetti et al and Grady et al; therefore, the result of optimization are comparable with the previous studies. The model used here is similar to the wake decay model developed by N.O. Jensen [2].

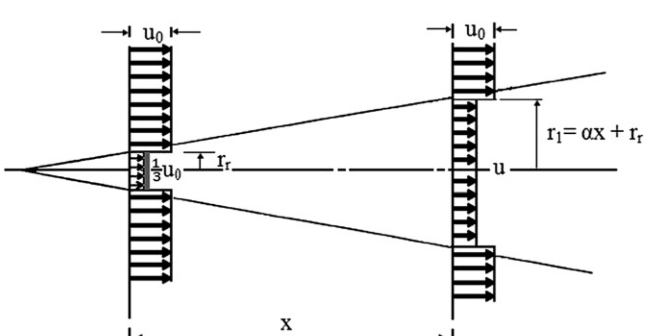

Fig. 2. Schematic of wake model.

By considering some assumption, the wake model has been simplified and by applying the continuity equation in the control volume in the Fig. 2 is given as:

$$\rho u_0 A_0 = \rho(u_1)A_1 = \rho u_i A_i \tag{1}$$

and assuming that the speed of wind, immediately after passing the blades of turbine, will reduce to 1/3 of its quantity:

$$\rho((1/3)u_0)A_r + \rho u(A_1 - A_r) = \rho u A_1 \tag{2}$$

where $A_1 = \pi r_1^2$, $A_r = \pi r_r^2$, $r_1 = \alpha x + r_r$ and substituting in Eq. (2):

$$u = u_0\left[1 - \left[(2/3)(r_r/(\alpha x + r_r))^2\right]\right] \tag{3}$$

then assume $a = 1/3$:

$$u = u_0\left[1 - \left((2a)/[1 + \alpha(x/r_1)]^2\right)\right] \tag{4}$$

where u_0 is the mean wind speed, a is the axial induction factor, x is the distance downstream of the wind turbine, r_r is the downstream rotor radius and α is the entrainment constant (see Fig. 2).

The downstream rotor radius r_1 and the turbine coefficient C_T are related to the rotor radius, r_r, and the axial induction factor a through the Betz relations:

$$r_1 = r_r\sqrt{((1-a)/(1-2a))}, \quad C_T = 4a(1-a) \tag{5}$$

The entrainment constant is given empirically as:

$$\alpha = (0.5)/(\ln(z/z_0)) \tag{6}$$

where Z is the hub height of the wind turbine and Z_0 is the surface roughness.

Assuming that the kinetic energy deficit of a mixed wake is equal to the sum of the energy deficits, the resulting velocity downstream of N turbines can be calculated using the following expression:

$$\left(1 - \frac{\overline{u}}{u_0}\right)^2 = \sum_{i=1}^{N}\left(1 - \frac{u_i}{u_0}\right)^2 \tag{7}$$

The extracted electrical power from the wind turbine depends on direction, intensity and probability of occurrence of the wind.

Original Offspring 1	1010101010	Mutated offspring 1	1010101000
	1010101011		1110101011
	0010101110		0010101110
	1010111010		1010111010
	1010101011		1010101001
	0010101010		0010101010
	0010101111		0010101111
	1010101010		1010101010
	0011101010		0011101010
	1010101011		1010101011
Original Offspring 2	1100101111	Mutated offspring 2	1000101111
	0110101101		0110101101
	1100101011		0100101001
	0100101111		0100101111
	1110100101		1110100101
	0110101111		0110101111
	1110101101		1110101101
	0110101110		0110101110
	1000101010		0000101010
	1010101101		1010101101

Fig. 4. Mutation operator in Genetic Algorithm.

Furthermore, thrust coefficient, hub height and rotor diameter also affect the power extracted.

The power equation presented in Mosetti for the turbine under consideration yields the following expression for power:

$$P_{\text{total}} = \sum_{i}^{N} 0.3u_i^2 \tag{8}$$

In order to calculate the total cost, the investment cost has been modeled in such a way that only the number of turbines need to be considered. Mosetti et al. assumed that the non-dimensionalized cost/year of a single turbine is 1, and that a maximum cost reduction of 1/3 can be obtained for each turbine, if a large number of wind turbines are installed. Therefore, the total cost/year of a wind farm can be expressed as follows:

$$\text{cost} = N\left(\frac{2}{3}+\frac{1}{3}\exp^{-0.00174N^2}\right) \tag{9}$$

And the efficiency of the wind turbine can be calculated using the following expression:

$$\text{efficiency} = \frac{\sum_{i=1}^{N} 0.3u_i^3}{N(0.3u_0^3)} = \frac{p_{\text{total}}}{N(0.3u_0^3)} \tag{10}$$

The objective function that will lead us to the optimal result (minimum cost per unit of energy produced) is the following expression:

$$g = w_1 \cos t_m + w_2 \frac{1}{P_{\text{total}}} \tag{11}$$

$$w_1 + w_2 = 1 \tag{12}$$

where P_{total} is the total energy produced in one year (MWatt), W_1 and W_2 are arbitrarily chosen weights, and cos t_m is the per unit value of cost/year of the whole wind farm.

In contrary to the previous objective functions which were presented by Mosetti et al. and Grady et al. [6,7], this objective function not only optimize the placement of wind turbines but also has control on cost. In fact, this objective function is a multi-objective function which can optimize the placement of wind turbine by considering constraint and limitation on cost value. Such a constraint on cost is more tangible in real environment where limitation on financial resources is inevitable. In addition, with employing this function and novel coding of the placement of wind turbine problem, the results in the cases (b) uniform wind with variable direction, and (c) non-uniform wind with variable direction has been improved in comparison with Mosseti results.

4. Genetic algorithm and optimization

The wind farm positioning problem is a typical discrete problem and solving the optimization by using classical methods are more complicated and require to use more variables, for instance, non-uniform wind with variable direction. Genetic algorithms are capable of efficiently finding an optimal solution for complex problems. The genetic algorithm only requires information from the objective function.

The basic processes that can occur in the construction of a new chromosomal string are random mutation of a gene, an exchange of genetic information between the reproducing parents and an inversion of the chromosomal string. In a binary coded genetic algorithm, individuals are strings comprised of ones and zeros. Several individuals make up a population, and within this population, parent individuals are reproduced. The fittest individuals will be selected, and parent pairs will be reproduced by crossover. In a uniform crossover operation, any point in the string has potential to become a crossover point. Crossover points are chosen randomly, with each parent having equal probability of contributing variables to the offspring [8]. Mutation is the random switching of a bit in the individual string to the opposite value and ensures that the genetic algorithm does not locate a false minimum as the solution. Figs. 3 and 4 illustrate crossover and mutation operations.

The optimization is performed in MATLAB Text Based environment by employment of new coding in comparison with previous studies. Matrix binary chromosomes have been chosen instead of numerical binary chromosomes. This type of coding has an undeniable impact on reducing the time of calculation and optimizing the results. In this study, the available terrain has been divided into cells where a turbine could be installed. In fact, the chromosomes

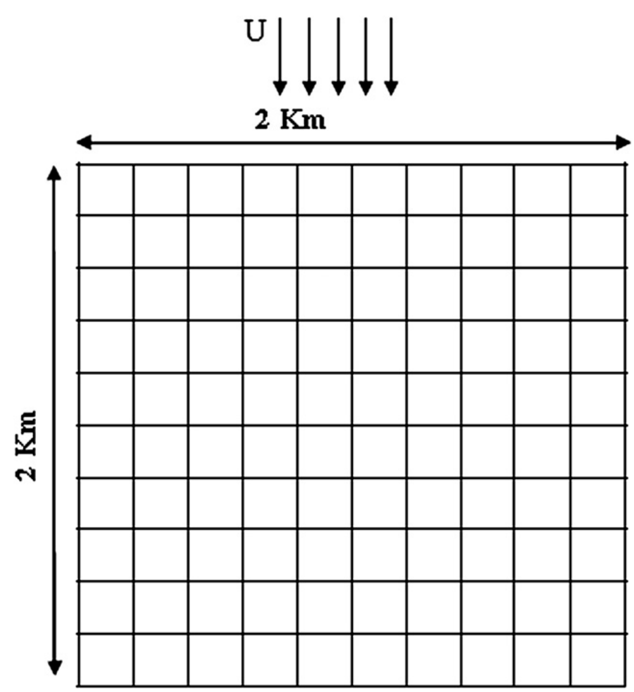

Fig. 5. Subdivided wind farm.

Table 1
Wind turbine properties.

Hub height (z)	60 m
Rotor radius (r_r)	40 m
Thrust coefficient (C_T)	0.88

are 10 by 10 matrixes that representation of a wind farm can be easily found: 1 means that in the relative cell a turbine exists, 0 means that no turbine.

5. Numerical procedure

In this project, a square grid has been used, which was divided into 100 possible turbine locations. The total length of each side corresponds to a length of 2 km. Every cell, in the center of which we can place a wind turbine, has a width that is equal to five rotor diameters, $5D$, or 200 m. So the total domain dimension is $50D \times 50D$ (2 km $\times$ 2 km) as it shown in Fig. 5.

The width of each cell, in the center of which a turbine would be placed, is equal to five rotor diameters, or 200 m. Therefore, the wake of a column of turbines would not affect turbines in an adjacent column.

We use a specific type of wind turbine with the characteristics shown in Table 1.

The C_T thrust coefficient will be considered constant throughout the processes.

Three cases have been assessed. The first case, (a), is the case of uniform wind direction with a wind speed of 12 m/s, as shown in Fig. 6. The only change in wind speed for this case would occur in the wake of the wind turbines. The second case, (b), is the case of multi-directional wind with a mean wind speed of 12 m/s. Each of the 36 angles under consideration represents 10° increments from 0 to 360°, in which has an equal fraction of occurrence. The third case, (c), is that of wind having multiple directions and variable speeds of 8, 12, and 17 m/s. The fraction of occurrence for each angle at each wind speed is shown in Fig. 6, where the sum of occurrences is unity.

6. Results

6.1. Case (a)

This case consists of uniform wind direction with a wind speed of 12 m/s. The only change in wind speed for this case would occur

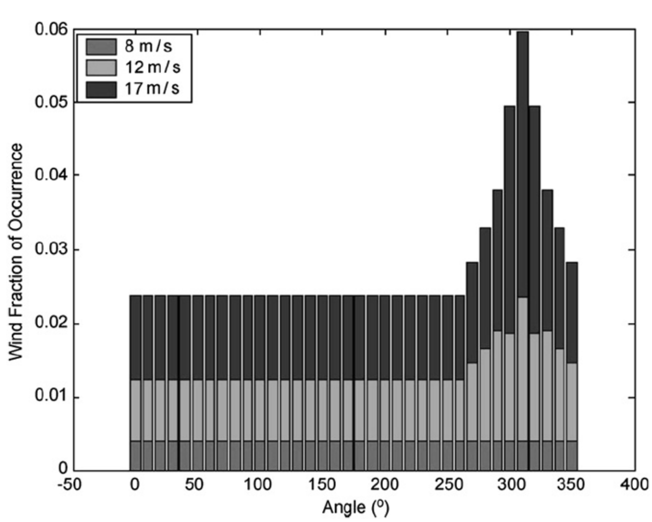

Fig. 6. Case (c): variable direction, variable wind speed.

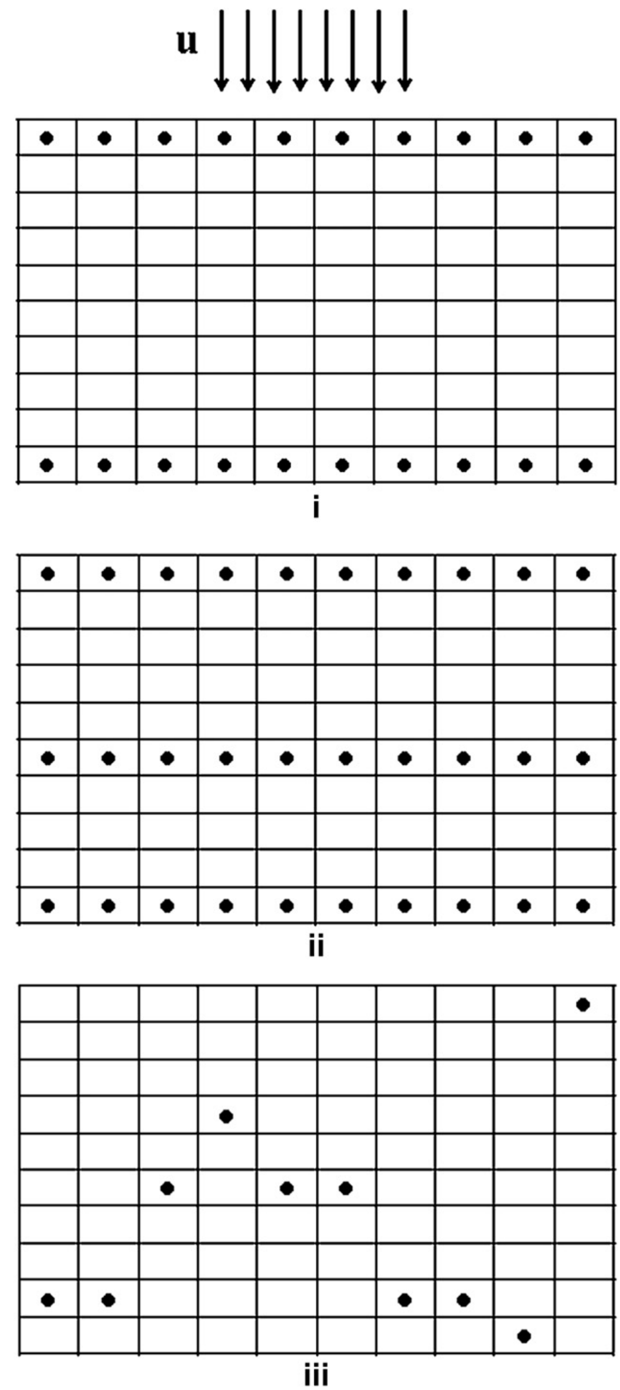

Fig. 7. Optimal configuration in case (a) for: (i) cost lower than 17, (ii) cost lower than 23, (iii) cost lower than 10.

Table 2
Results of case (a) uniform wind direction.

	i	ii	iii
Fitness value	0.1514	0.12217	0.1633
Total power (kW/year)	10,164	14,310	5184
Efficiency (%)	98	92	100
Number of turbines	20	30	10
Cost	16.65	22	9.47
W_1	0.35	0.2	0.6
W_2	0.65	0.8	0.4

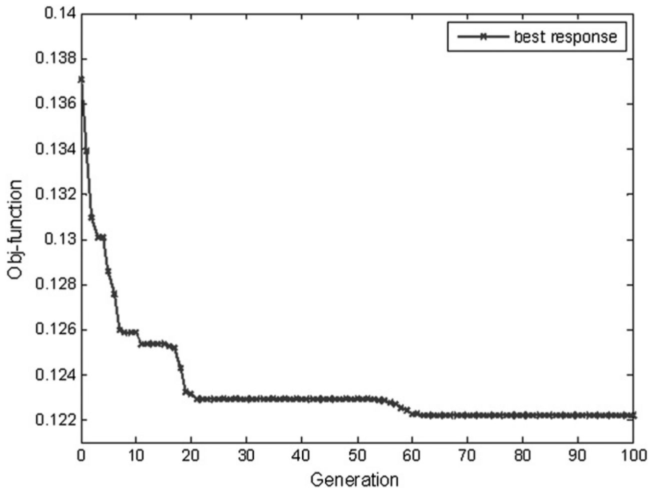

Fig. 8. Case (a), (ii) case cost lower than 23.

Table 3
Results of case (b).

Fitness value	0.1028
Total power (kW/year)	17,335
Efficiency (%)	90.4
Number of turbines	37
Cost	25.8
W_1	0.14
W_2	0.86

Table 4
Comparison of solution characteristics – Case (b), (i) Grady, (ii) present study.

	i	ii
Number of turbines	39	37
Total power (kW/year)	17,220	17,335
Efficiency (%)	85.174	90.4

in the wake of the wind turbines. In order to prove the capability of new objective function in controlling the cost, three cases are considered: (i) cost lower than 17, (ii) cost lower than 23, (iii) cost lower than 10. The optimized result obtained in case (ii) is the same as result in Grady's, which shows that this function is also able to reach the optimum result by choosing sufficient coefficient (Fig. 7.). Table 2 is a comparison of the fitness value, total power output, efficiency of power output and number of turbines for each configuration. In the present study, only 20 individuals were allowed to evolve over 100 generations. For instance, Fig. 8 illustrates objective function evolution for case (a) (ii) over 100 generations. It is obvious that although the new coding has kept its effectiveness, it has reduced number of individuals and required generations.

6.2. *Case (b)*

Case (b) is the case of multi-directional wind with a mean wind speed of 12 m/s. Each of the 36 angles under consideration represents 10° increments from 0 to 360°, that each one has an equal chance of occurrence.

In comparison with the Grady's results, results have been improved by using the new coding besides the new objective function in the present study.

Table 3 includes the values for the fitness value, total power, Efficiency, number of turbines, cost, and coefficients W_1 and W_2. In Table 4 the optimal configuration of Grady for this case with the optimal configuration of the present study has been compared (Fig. 9).

In the present study, 20 individuals were allowed to evolve over 150 generations (Fig. 10). It is obvious that the new configuration got more total power by using fewer turbines. In new optimized configuration, we reduce the number of turbines from 39 to 37, increase the efficiency from 85.17% to 90.4%, and get 115 kW more for the total power.

6.3. *Case (c)*

In Fig. 11 both arrangement of turbine in the wind farm for recent study and Grady study have been shown. Fig. 11(i) shows the

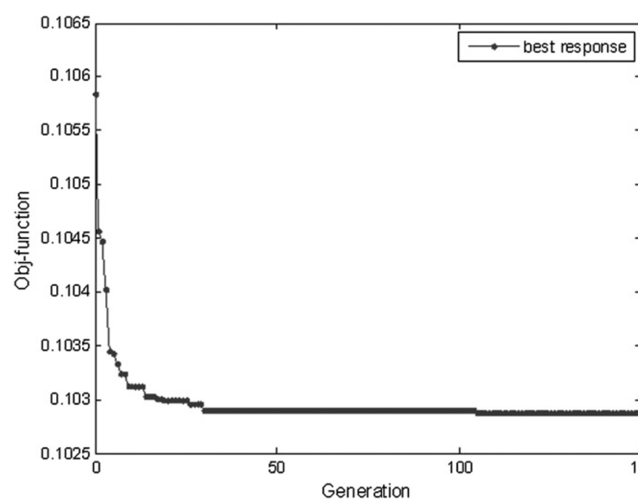

Fig. 10. Fitness curve for Case (b).

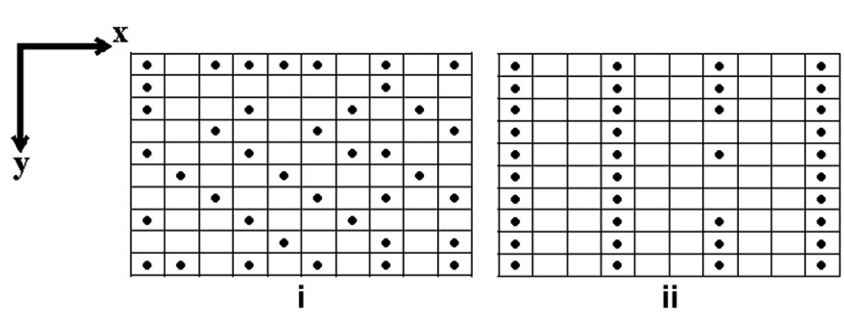

Fig. 9. Case (b), optimal configuration (i) Grady, (ii) present study.

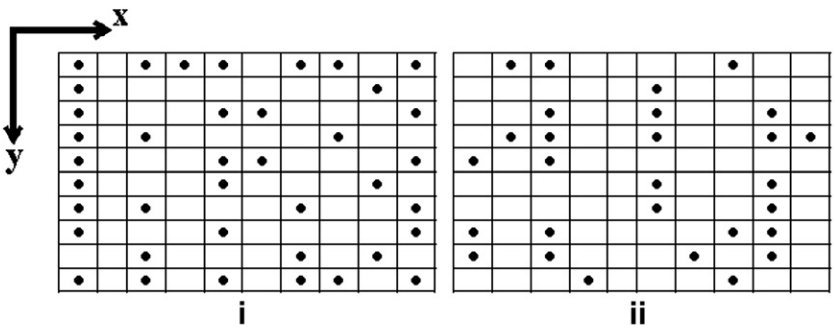

Fig. 11. Case (c), optimal configuration (i) Grady, (ii) present study.

Table 5
Results of case (c).

Fitness value	0.05475
Total power (kW/year)	32,261.63
Efficiency (%)	91
Number of turbines	28
Cost	21.0522
W_1	0.1
W_2	0.9

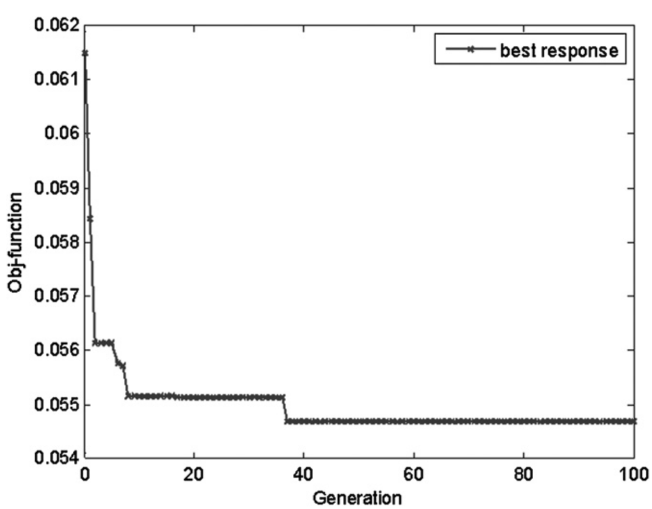

Fig. 12. Fitness curve for Case (c).

Table 6
Comparison of solution characteristics – Case (b), (i) Grady, (ii) present study.

	i	ii
Number of turbines	39	28
Total power (kW/year)	32,038	32,261.6
Efficiency (%)	86.619	91

optimized configuration obtained by Grady et al., and Fig. 11(ii) shows the optimized configuration obtained in this study. Table 5 includes the values for the fitness value, total power, Efficiency, number of turbines, cost, and coefficients W_1 and W_2. In the present study, 20 individuals were allowed to evolve over 100 generations (Fig. 12). Table 6 is a comparison of total power output, efficiency of power output and number of turbines between present study and Grady's.

7. Conclusions

In present study a new coding approach and a novel objective function for solving the problem of wind turbine placement in wind farm using genetic algorithms has been introduced. With help of new coding and the objective function the obtained results noticeably improved in comparison with previous works. Since MATLAB is powerful software in working with matrix, in this research binary matrix chromosomes were replaced with binary number chromosomes. Hence, considering some subpopulations and running genetic algorithm in each subpopulation for reaching to the final result is not required. Moreover, in recent study a new objective function has been employed. One of the major properties of this objective function is its capability to control the cost of wind farm construction. In fact, in real world sometimes the limitation of financial resources may be considerable, hence, this objective function with its adjustable coefficients provide required tools for solving the wind turbine problem with any constraint on cost. Previous studies and their objective functions just optimized the configuration of wind turbines in a wind farm regardless of cost limitation.

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