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Full Length Research Paper

A new evolutionary algorithm based on data sharing concept for solving optimization problems

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In recent decades, evolutionary algorithms, as a powerful optimization tool, have been used in various areas of studies and applications. Some special features of these methods including vast ranges of applications, ease of use and their ability to yield results close to the real optimal solutions make them successful and popular. In optimization algorithms, despite lots of attentions paid to humans and other creature's biological evolutions less attention are paid to their social development, as the most complex and successful development mode. In this paper, a new algorithm inspired by human social evolution has been developed to solve the optimization problems. This algorithm has been obtained from a social behavior of human and it has very good capabilities as well as fast responses. The main idea of this algorithm which has very high impact in promoting of scientific studies of all students is originated from the collective studies of students and data sharing among them. This algorithm is applied in students' dormitories at exam season and it has been used to solve three well-known mathematical problems and one voltage profile optimization problem in electricity distribution network. To show the effectiveness of proposed method, the results are compared with the results obtained by genetic algorithm (GA) and honey bee mating optimization (HBMO) algorithm.

Key words: Evolutionary algorithms, data sharing algorithm, honey bee mating optimization algorithm, genetic algorithm.

INTRODUCTION

Evolutionary algorithms are widely used during past decades. Among them, genetic algorithm (GA) is broadly applied for solving optimization problems. Examples of GA applications can be found for either single objective optimization problems (Haghdar and Shayanfar, 2010; Farahani et al., 2010) or multi objective optimization problems (Taboada et al., 2008; Maghouli et al., 2009; Soares et al., 2009). Some other methods of optimization problems are originated from the behavior of social insects like ants and bees. The modeling of the behavior of these social insects can be used to solve optimization problems.

Ant colony algorithm has been proposed by Dorigo (Dorigo, 1992) and it is obtained by the studying of ants' behaviors when they are searching for food. This algorithm is used for solving various optimization problems such as traveling salesman problem (TSP) and other applications (Saber and Senjyu, 2007; Juang et al., 2008; Juang and Chang, 2010).

Another optimization technique is honey bee mating optimization (HBMO) algorithm and it can be considered as a general approach based on the bees behavior. The HBMO algorithm is derived from the honey bees mating process and it has been used for solving different optimization problems (Gavrilas et al., 2010; Horng et al., 2009; Marinakis and Marinaki, 2009). Although lots of attention are paid to modeling the behavior of insects and human physiology, less attention are given to social modeling of human as a most developed and complex creature.

In this paper, a new optimization algorithm based on data sharing and exchange of information among students has been developed and its

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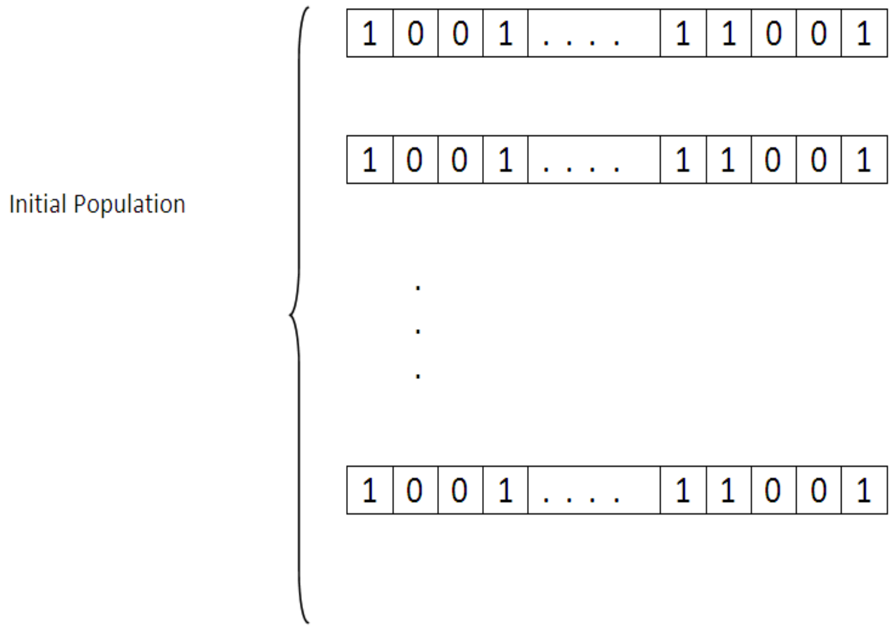

Figure 1. Initial population of DSA.

performance has been examined by using three well-known mathematical functions and one engineering problem for improving voltage profile in electricity distribution networks.

DATA SHARING ALGORITHM

As mentioned, the proposed algorithm uses the data sharing and exchange of information among students to solve optimization problems. In this algorithm, a special issue is discussed in the first step. Then, some students that have more knowledge about this particular subject share their information with other students. When, all students shared their opinions about a particular topic, the knowledge of all students is increased. Moreover, each student has the opportunity to have a private study. This algorithm can be summarized in seven main steps as follows:

(1) Create an initial population – this population includes a number of students which take part in discussions in order to promote their knowledge. Figure 1 shows that.
(2) Selecting top members to provide comments and information in rel ation to a particular subject - those students which have higher fitness function are introduced as top members.
(3) Training – Top members share their information with others. In each iteration, two top students are chosen to share their information. 20 percents of the bits from top students are randomly selected and exactly replaced in the same place to the other students' bits. It should be mentioned that top members are not trained. Figure 2 shows that.
(4) Learning–the learning possibility of each student in the previous steps is corresponding to their talents and previous knowledge. At this step, a random number in interval [0, 1] is assigned to each student. If the probability $P_i = e^{-|f_{best}-f_i|}$ is greater than the assigned number then the replacement of the bits are done and student is trained; otherwise, he/she is not trained. Figure 3 shows that. In the last equation, the value of f_{best} is the average of fitness function of superior members and is obtained according to the equation (1) .Also, f_i is the fitness function value of the other students.

$$f_{best} = \frac{f_{best1}+f_{best2}}{2} \qquad (1)$$

(5) Private study - in addition to participation in educational meetings, each student should spend some times for private studies to increase his/her information. At this stage, two percent of students' bits (except the top students) will be changed.
(6) If the scientific level of students has reached to the desirable level (stopping criterion met), go to step 7; otherwise, with the selection of new best members, keep training and go to step 2.
7 - End
(7) When students do not have any new information to share, the scientific level of most students

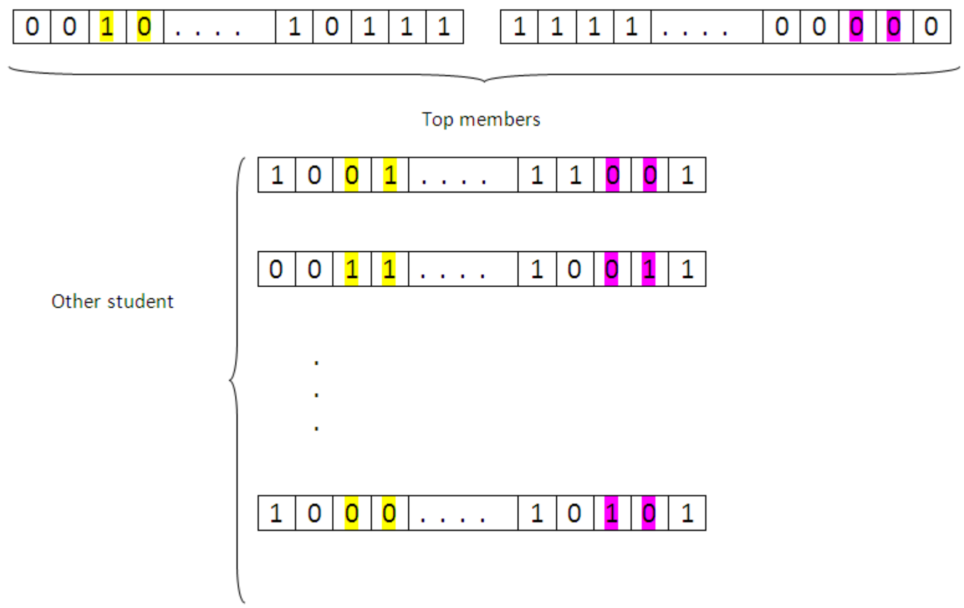

Figure 2. Training stage.

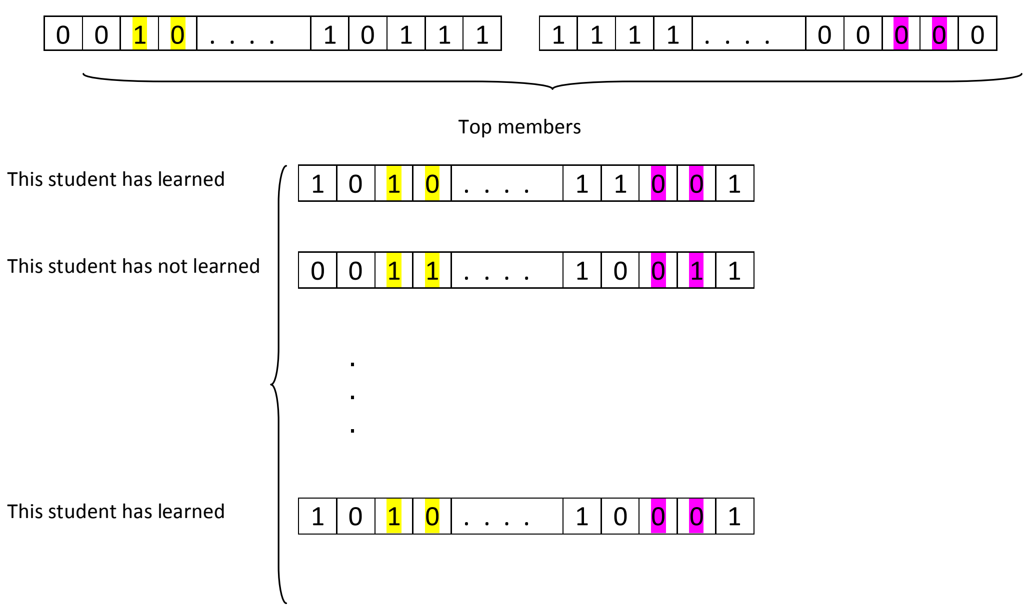

Figure 3. Learning stage.

has reached to its optimum solution.

MATHEMATICAL EXAMPLES

Unconstraint sinusoidal function

The First numerical example is the maximization of following unconstrained sinusoidal function [14].

reached to its suitable level and the problem has Equations (2), (3) and (4) show objective function, the permitted range for variables x_1 and x_2, respectively. This function has the following formulation:

$$Max\ f(x_1,x_2) = 21.5 + x_1 \sin(4\pi x_1) + x_2 \sin(20\pi x_2) \quad (2)$$

$$-3 \leq x_1 \leq 12.1 \quad (3)$$

Table 1. The values of objective function and decision variables in HBMO algorithm.

Variable	i-th run									
	1	2	3	4	5	6	7	8	9	10
Objective function	38.8502	38.8502	38.8502	38.8502	38.8502	38.8502	38.8502	38.8502	38.8502	38.8502
First variable	11.6255	11.6255	11.6257	11.6255	11.6255	11.6255	11.6254	11.6255	11.6254	11.6256
Second variable	5.7250	5.7250	5.7250	5.7250	5.7250	5.7250	5.7250	5.7250	5.7250	5.7250

Table 2. The values of objective function and decision variables in DSA.

Variable	i-th run									
	1	2	3	4	5	6	7	8	9	10
Objective function	39.1176	39.1176	39.1176	39.1176	39.1176	39.1176	39.1176	39.1176	39.1176	39.1176
First variable	12.0262	12.0262	12.0262	12.0262	12.0262	12.0262	12.0262	12.0262	12.0262	12.0262
Second variable	5.6255	5.6255	5.1270	5.6255	5.6255	5.6255	5.6255	5.6255	5.6255	5.6255

Table 3. Statistical parameters of objective function and decision variables for HBMO algorithm in 10 runs.

Variable	Minimum	Maximum	Medium
Objective function	38.8502	38.8502	38.8502
First variable	11.6254	11.6257	11.6255
Second variable	5.7250	5.7250	5.7250

Table 4. Statistical parameters of objective function and decision variables for DSA in 10 runs.

Variable	Minimum	Maximum	Medium
Objective function	38.6176	39.1176	39.0676
First variable	12.0262	12.0262	12.0262
second variable	5.1270	5.6255	5.5757

$$4.1 \leq x_2 \leq 5.8 \qquad (4)$$

This Multi-Modal function includes two decision variables and its best response by the using genetic algorithm is as follows [14].

$$f(11.631407, 5.724824) = 38.818208 \qquad (5)$$

The results of data sharing algorithm (DSA) and HBMO algorithm are listed in Tables 1 to 4. In these tables, at the end of the 10th run, the values of objective function and other variables are very close together and their standard deviation errors are very small. It can be seen, the objective function and other variables produced by DSA and HMBO algorithm are very close together. This fact shows the ability of proposed method for solving problems with several local maximums and minimums. Figure 4 shows the structure of unconstraint sinusoidal function.

ACKLEY FUNCTION (ACKLEY)

In this section, the accuracy of DSA is tested by Ackley function. The second example of unconstrained optimization is Ackley's function. This test function is continuous and multi-modal which it is obtained by modulating an exponential function with a cosine wave with the moderate amplitude.

The definition of Ackley function is as follows:

$$Min\, f(x_1, x_1) = -c_1 . \exp\left(-c_2 \sqrt{\frac{1}{2}\sum_{j=1}^{2} x_j^2}\right) - \exp\left(\frac{1}{2}\sum_{j=1}^{2} \cos(c_3 x_j)\right) + c_1 + e \qquad j = 1,2 \qquad (6)$$

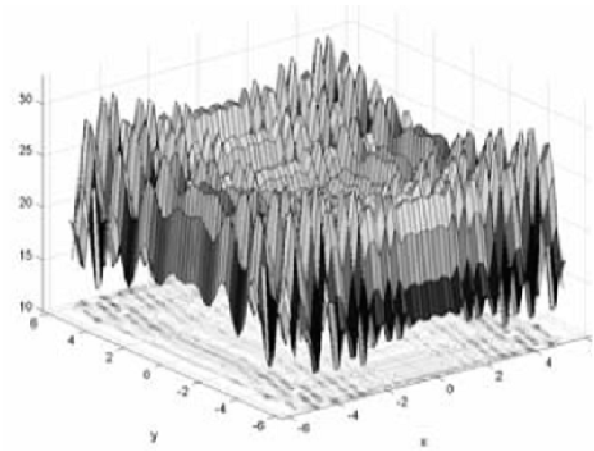

Figure 4. Unconstraint sinusoidal function.

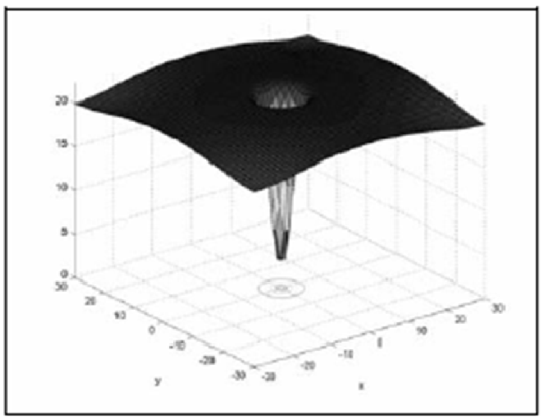

Figure 5: Ackley function in the range [-30,30]

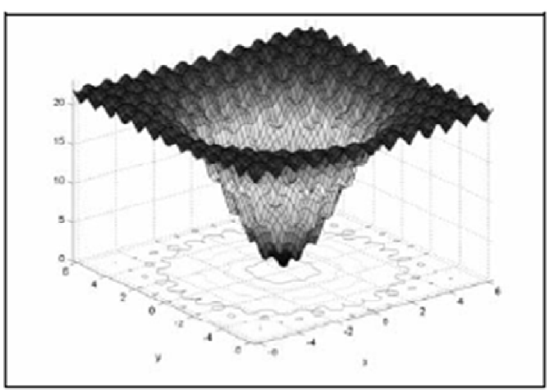

Figure 6: Ackley function in the range [-6, 6]

$$-5 < x_j < 5 \quad (7)$$

Where $c_1 = 20$, $c_2 = 0.2$, $c_3 = 2\pi$ and $e = 2.71282$. This

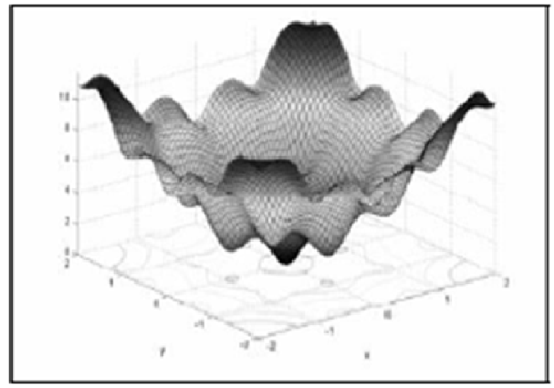

Figure 7: Ackley function in the range [-2,2]

function with different decision variables has been plotted in Figures 5 to 7. Also, it has been formed by an exponential operator and a series of cosine waves with an average magnitude. This function has a relatively smooth surface including a minimum. This function has difficulties in searching for answer because since the function has many local optimum points it might be caught in one of them. The solution of this problem by the use of Genetic Algorithm has been reported as $f(x_1^*, x_2^*) = -0.00545$ (Gen and Cheng, 1997). The results of DSA and HBMO algorithms are in Tables 5 to 8.

CONSTRAINED POWER FUNCTION

Another example discussed in this section is a nonlinear optimization of a continuous function with two decision variables. Equations (8), (9) and (10) describe this function.

$$Min\ f(x_1, x_1) = (x_1^2 + x_2 - 11)^2 + (x_2^2 + x_1 - 7)^2 \quad (8)$$

$$g_1(x) = 5.059 - x_1^2 - (x_2 - 2.5)^2 \geq 0 \quad (9)$$

$$g_2(x) = (x_1 - 0.05)^2 + (x_2 - 2.5)^2 - 4.84 \quad (10)$$

$$0 \leq x_1 \leq 6,\ 0 \leq x_2 \leq 6 \quad (11)$$

The function surfaces have been depicted in Figures 8 to 10.

The constraint objective function $f(x_1, x_1)$ includes an absolute minimum with the value of zero at point (3, 2). However, with the given constraints this answer is not possible and the allowed optimal answer is $f^* = 13.5908$ at point $x^* = (2.2468, 2.3818)$. The results of HBMO algorithm and DSA are in listed in Tables 9 to 12.

Table 5. The objective function and decision variables values of HBMO algorithm.

Variable	i-th run									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Objective function	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054
First variable	0	0	0	0	0	0	0	0	0	0
Second variable	0	0	0	0	0	0	0	0	0	0

Table 6. The objective function and decision variables values of DSA.

Variable	i-th run									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Objective function	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054
First variable	0	0	0	0	0	0	0	0	0	0
Second variable	0	0	0	0	0	0	0	0	0	0

Table 7. Statistical parameters of objective function and decision variables for HBMO algorithm.

Variable	Minimum	Maximum	Medium
Objective function	-0.0054	-0.0054	-0.0054
First variable	0	0	0
Second variable	0	0	0

Table 8. Statistical parameters of objective function and decision variables for DSA.

Variable	Minimum	Maximum	Medium
Objective function	-0.0054	-0.0054	-0.0054
First variable	0	0	0
Second variable	0	0	0

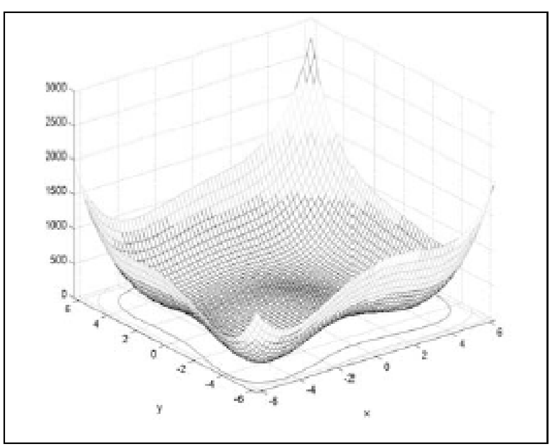

Figure 8: Power function surface

OPTIMAL LOCATION OF DISTRIBUTED GENERATION UNITS FOR IMPROVING VOLTAGE PROFILE

Some of the buses in Figure 11 are outside the limited boundary of 5% and consequently the network is not stable. In order to ensure the stability of this network, the installation of the distributed production units is done. The aim of this problem is finding the optimal locations and capacities of production units so that all bus voltages stay within permitted ranges. This objective function of this problem is given by equations (12) and (13). The purpose of this example is the minimization of these equations.

$$\Delta V = \sum_{i=1}^{n} \Delta V_i \qquad (12)$$

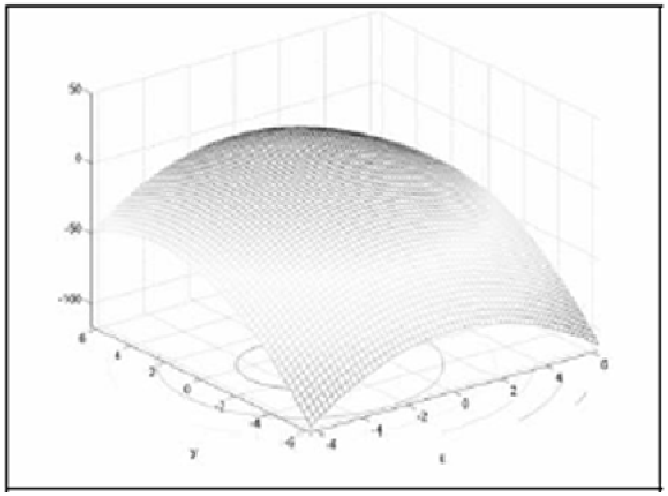

Figure 9: g_1 (x) surface

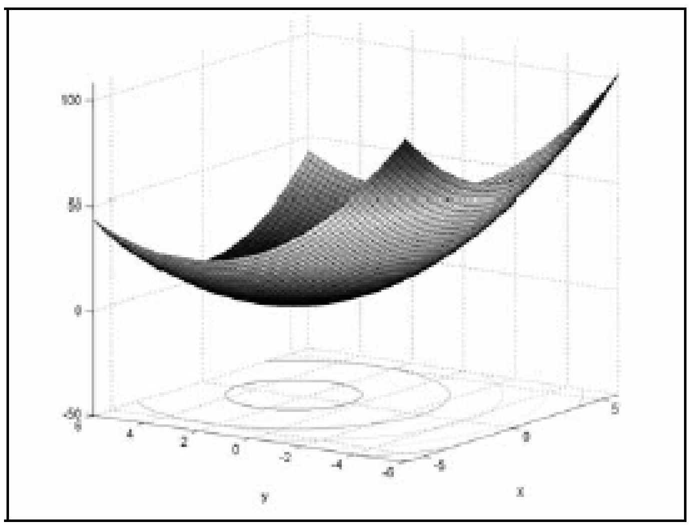

Figure 10: $g_2(x)$ surface

$$\Delta V_i = |1^{pu} - V_i| \quad (13)$$

By using the proposed algorithm, all the bus voltages stay in the desirable ranges of $0.95^{pu} \leq V_i \leq 1.05^{pu}$. By using the proposed algorithm, the optimal locations and capacities of the distributed generation (DG) will be achieved. Table 13 shows these results. The characteristics of this DG unit are expressed by equations (14) and (15)

$$1.4^{pu} \leq P_{DG} \leq 2^{pu} \quad (14)$$

$$0^{pu} \leq Q_{DG} \leq 0.5^{pu} \quad (15)$$

The buses voltages that are outside the permitted range before and after DG installation are given in Table 14.

Conclusions

According to the various optimization problems such as single objective optimization or multi objective optimization, constraint bounds and discrete or continuous variables, it is necessary that in the early stages of the development of each algorithm, the performance and accuracy of the algorithm is checked. It should be noted that this algorithm can be

Table 9. The values of objective function and decision variables for HBMO algorithm in 10 runs.

Variable	i-th run									
	1	2	3	4	5	6	7	8	9	10
Objective function	14/3496	14.4334	14.3653	14.6226	13.8670	13.9973	13.9083	14.1874	13.9815	13.7719
First variable	2.2334	2.2334	2.2332	2.2301	2.2400	2.2381	2.2393	2.2355	2.2383	2.2416
second variable	2.2289	2.2203	2.2275	2.2032	2.2899	2.2700	2.2832	2.2462	2.2726	2.3073

Table 10. values of objective function and decision variables for DSA in 10 runs.

Variable	i-th run									
	1	2	3	4	5	6	7	8	9	10
Objective function	13/6149	13/6149	13/6149	13.6268	13.7874	13.6149	13.6149	13.6149	13.6149	13.6149
First variable	2.2463	2.2463	2.2463	2.2463	2.2463	2.2463	2.2463	2.2463	2.2463	2.2463
second variable	2.3871	2.3871	2.3871	2.3930	2.4399	2.3871	2.3871	2.3871	2.3871	2.3871

Table 11. Statistical parametersof objective function and decision variables for HBMO algorithm.

Variable	Minimum	Maximum	Medium
Objective function	13.7719	14.6226	14.1484
First variable	2.2301	2.2416	2.2362
Second variable	2.2032	2.3073	2.2549

Table 12. Statistical parameters of objective function and decision variables for DSA.

Variable	Minimum	Maximum	Medium
Objective function	13.6149	13.7874	13.6333
First variable	2.2463	2.2463	2.2463
Second variable	2.3871	2.4399	2.3929

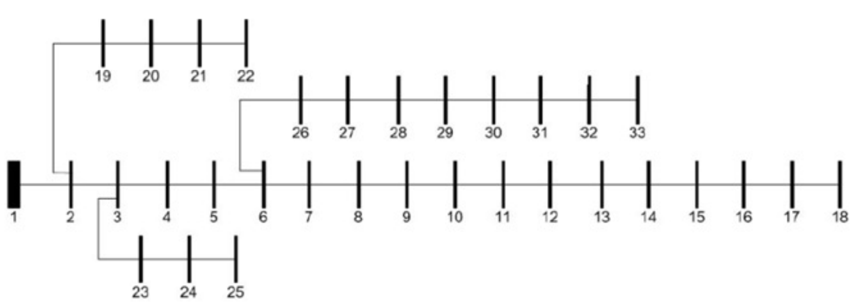

Figure 11. The 33 buses network.

developed further according to the results of above mentioned examples. These results of proposed method are quite comparable with the results of GA and HMBO algorithm.

Table 13. The optimal location and capacity of DG to improve the voltage profile in 33 Buses networks.

Optimum DG location	Optimal active power capacity DG (pu)	Optimal reactive power capacity of DG (pu)
Bus 12	1.6710	0.5

Table 14. Buses voltages before and after DG installation.

Bus number	Bus voltages before DG installation	Bus voltages after DG installation
6	0.9497	0.9783
7	0.9462	0.9789
8	0.9413	0.9820
9	0.9351	0.9898
10	0.9292	0.9780
11	0.9284	0.9991
12	0.9269	1.0020
13	0.9208	1.0155
14	0.9185	1.0134
15	0.9171	1.0121
16	0.9157	1.0100
17	0.9137	1.0090
18	0.9131	1.0085

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