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# Optimal DG Placement for Power Loss Reduction and Improvement Voltage Profile Using Smart Methods

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**Abstract**

Distributed Generations (DGs) are utilized to supply the active and reactive power in the transmission and distribution systems. These types of power sources have many benefits such as power quality enhancement, voltage deviation reduction, power loss reduction, load shedding reduction, reliability improvement, etc. In order to reach the above benefits, the optimal placement and sizing of DG is significant. In this regard, this paper gets use of the Bacteria Foraging Algorithm (BFA) and Binary Genetic Algorithm (BGA) to investigate the DG placement with the purpose of power loss and voltage deviation reduction. The proposed method is applied on the 33-bus and 69-bus IEEE test systems and the optimal place and size of DGs from the power losses and voltage deviation minimization are assessed. Also, the performance of the above two algorithms are compared with each other.

*Keywords:* Bacteria Foraging Algorithm (BFA) and Binary Genetic Algorithm (BGA), Distributed Generation (DG), Voltage Deviation, Distribution Systems.



## 1. Introduction

In the first days of electrical networks, the power generation and transformation was done locally. With the network growth, as the result of several economical preferences, the local generations were replaced by the distribution generations. Nowadays, according to the technology developments as well as changes in the energy policy especially from the environmental point of view, Distributed Generations (DGs) have retained their valuable role in the power engineering. In fact, it is expected that a large portion of the electrical power would be supplied by DGs in the near future [1]. Until now, many different definitions have been assigned to DGs. In an overall definition neglecting the technology and capacity constraints, a DG is a power generation source which is connected to the distribution system or load side directly [2]. In this regard, different power sources such as Wind Turbines, Photovoltaics, Fuel Cells, Micro Turbines, etc can be utilized as DG. The energy of these power sources can be from the fossil fuel, renewable energy or storage devices which can vary from kW to several 10 MW. Some of the main benefits of DGs can be named as power generation cost reduction, power losses reduction, voltage deviation improvement, power quality enhancement, the possibility of producing both electrical and thermal energy in the form of combined heat and power (CHP), reducing Total Harmonic Distortion (THD), increasing the efficiency, positive effect on the environment, etc. The necessary factor to gain the above benefits is the optimal placement and sizing of DGs in the network. It is worth to note that misplacement of DGs can result to losing the above factors when resulting to instability of the system. In this paper, the two evolutionary algorithms of BFA and BGA are used to optimize the power losses and voltage deviation objective functions. The near optimal solutions obtained by both algorithms show the suitable and accurate implementation of these algorithms. In recent years, DG placement has been done with different objective functions. The LMP and MIP techniques are used to optimal placement and sizing of DGs [3]. A specific number of DGs are used to reduce the active power losses [4]. Distributed generation is obviously a new attraction for power industry, commercial and regulating systems [5]. The Genetic Algorithm (GA) is employed to handle the optimal DG placemen and sizing under different loading for power loss reduction [6]. The suggested approach is proposed to reach the maximum balance between the cost and benefits of using DG in the network [7]. The main purpose is to find the optimal place, size and type of DGs in the network [7]. The size and power factor for DG were found by using analytical expressions to minimize losses [8]. A multi-objective performance index-based determination of size and location of DG in distribution systems with different load models was presented by Singh et al. [9] and implemented using GA. A methodology based on GA was presented by Singh and Goswami to accommodate DG in distribution network by maximization of profit, reduction of losses and improvement in voltage regulation [10]. Dasan and Devi used fuzzy adaptation of evolutionary programming to find size of DGs [11].

## 2. Types of Distributed Generations

*First Type:* these types of DGs can just generate and supply active power. Photovoltaics (PVs) are among the most famous of these types. The output power of PVs will enter the storage batteries directly and so it can be stored as active power.

*Second Type:* these types of DGs can just generate reactive power. Synchronous condensers are from this category. Synchronous condensers are synchronous machines which connect to the network under no load condition to enhance the network situation. The amount of reactive power produced is determined by the control of the exciting system.

*Third Type:* these types of DGs can generate both active and reactive powers. Wind Turbines (WTs) belong to this category which gets use of induction motors to produce electrical power. Here reactive power is utilized to produce active power.

*Forth Type:* these types of DGs can adjust the bus voltage. In this type, the power unit will generate or consume reactive power to regulate the bus voltage. The active and reactive power sources used in this paper are as follows:

$0^{MW} \le P_{DG} \le 3^{MW}$ DG active power

$0^{MVAR} \le Q_{DG} \le 1^{MVAR}$ DG reactive power

This paper uses the third DG type which was mentioned above.

## 3. Problem Formulation (Power losses, voltage deviation, objective function)

Reducing the active power losses is a significant factor in the proper performance of the power system. The power losses in a system can be evaluated as follows (1):

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} A_{ij}(P_iP_j + Q_iQ_j) + B_{ij}(Q_iP_j - P_iQ_j) \tag{1}$$

The objective function is as follows (2):

$$FitnessFunction = Minimize(w_1.\frac{P_L}{P_{L,Normal}} + w_2.\sum_{i=1}^{N}(\frac{(1-V_i)}{(1-V_i)_{Normal}}) \tag{2}$$

The first term of above equation is the objective function which is calculated as follows (3):

$$P_L = \sum_{k=1}^{N} Loss_k \tag{3}$$

The second term of the objective function is the voltage deviation. The coefficients w1 and w2 are found experimentally to balance the objective function which are 96.252 and 11.8 for the 33-bus and 64.269 and 26.8 for the 69-bus system [5]-[12].

In Eq. 1, $P_i$ & $P_j$ are the active power of the $i^{th}$ and $j^{th}$ buses; $Q_i$ and $Q_j$ are the reactive power of the $i^{th}$ and $j^{th}$ buses, respectively. The power and voltage constraints are as follows (4,5,6):

$$\sum_{i=1}^{N} P_{DGi} = \sum_{i=1}^{N} P_{Di} + P \tag{4}$$

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max} \tag{5}$$

$$|I_{ij}| \le |I_{ij}|^{\max} \tag{6}$$

Where $V_i$ is the voltage of the $i^{th}$ bus and $I_{ij}$ is the current flowing between the $i^{th}$ and $j^{th}$ buses.

## 4. Test systems

This paper uses the 33-bus and 69-bus test systems as the case studies. The total active and reactive loads for 33-bus system are 6.627 MW and 4.376 MVar, respectively. Also, the initial active and reactive power losses neglecting DGs are 18 kW and

12 kVar, respectively. In the case of 69-bus test system, the amounts of active and reactive power loads are 3.811 MW and 2.694 MVAR respectively. The total active and reactive power losses neglecting DGs are 225 kW and 102 kVar respectively.

## 5. The proposed algorithms

### *5.1. Bactria Foraging Algorithm*

Natural selection tends to eliminate animals with poor foraging strategies and favour the propagation of genes of those animals that have successful foraging strategies. The Escherichia coli (E. coli) bacteria that are present in our intestine also undergo these foraging strategies. The social foraging behaviour of E. coli bacteria has been used to solve optimization problems. The optimization in BFA comprises the following process: chemotaxis, swarming, reproduction, elimination and dispersal. The chemotaxis is the activity that bacteria gathering to nutrient-rich area naturally. The characteristic of E. coli bacteria is: the diameter is 1µm, the length is 2µm, and under appropriate conditions can reproduce (split) in 20 min. The move of the E. coli is done with flagellum.

### *5.2. Chemotaxis step*

The process in the control system is achieved through swimming and tumbling via flagellum. To represent a tumble, a unit length random direction, say $\varphi(j)$, this will be used to define the direction of movement after a tumble, then:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + c(i)\varphi(j)$$

Where $\theta^i(j,k,l)$ is the position of the $i^{th}$ bacterium at $j^{th}$ chemotaxis step, $k^{th}$ reproduction step and $l^{th}$ elimination and dispersal step.

$c(i)$ is the size of step taken in the random direction that specified by the tumble(run length unit). If the new position of bacterium

$\theta^i(j+1,k,l)$ is better than the old position, then the bacterium will keep taking successive step in that direction. The number of iteration chemotaxis step is NC. And the maximum number of permissible successive steps is Ns.

### *5.3. Swarming step*

The bacteria in times of stresses release attractants to signal bacteria to swarm together. It however also releases a repellent to signal others to be at a minimum distance from it. Thus all of them will have a cell to cell attraction via attractant and cell to cell repulsion via repellent. The mathematical representation for swarming can be represented by:

$$J_{cc}(\theta) = \sum_{i=1}^{s} J_{cc}^i(\theta) = \sum_{i=1}^{s}\left[-d_{attract}\, exp\left(-w_{attract}\sum_{j=1}^{p}\left(\theta_j-\theta_j^i\right)^2\right)\right] + \sum_{i=1}^{s}\left[-d_{repellant}\, exp\left(-w_{repellant}\sum_{j=1}^{p}\left(\theta_j-\theta_j^i\right)^2\right)\right]$$

Where:
$d_{attract}$: depth of the attractant
$w_{attract}$: measure of the width of the attractant
$h_{repellant}$: height of the repellant effect
$w_{repellant}$: measure of the width of the repellant
p: number of parameters to be optimized
S : total number of bacteria
$J_{cc}$: the cost function to be added to the actual cost function to be minimized, to present a time varying cost function.

### *5.4. Reproduction*

After NC chemotaxis step, a reproductive step is occurs. The fitness of bacteria is calculated, that is, during all chemotaxis steps:

$$J_{health} = \sum_{i=1}^{Nc} J(i,j,k,l)$$

Then this fitness is sorted in ascending order. The least healthy bacteria die and the other bacteria, each bacterium split into two bacteria, thus the size of the population is constant.

### *5.5. Elimination and dispersal:*

The chemotaxis step provides a basis for local search, and the productive step speeds the convergence. While to a large extent, only chemotaxis and reproduction are not enough for global optima searching. Then an elimination and dispersal event is necessary.

For each elimination and dispersal event each bacterium is eliminated with a probability $P_{ed}$, and dispersed them to a new environment. The selection of $P_{ed}$, play an important role in convergence of the algorithm. If $P_{ed}$ is large, the algorithm can degrade to random exhaustive search. If however, it is chosen appropriately, it can help the algorithm jump out of local optima and into a global optimum.

*Pseudo Code for BFA:*

The algorithm is discussed here.
[step1]: Initialization

1. p: number of parameter that be optimized
2. S: the total number of bacteria
3. NC, Nre, Ned: the number of chemotaxis steps, the number of reproduction steps, the number of elimination and dispersal events, respectively.
4. Ns: the maximum number of permissible successive steps
5. the values of : $d_{attract}$, $w_{attract}$, $h_{repellant}$, $w_{repellant}$
6. $P_{ed}$: the probability of elimination and dispersal event
7. C(i) : the step size

[step2]: Elimination and dispersal loop: l=l+1
[step3]: Reproduction loop: k=k+1
[step4]: chemotaxis loop: j=j+1
[a]. for i = 1,2,…,N take a chemotaxis step for each bacterium i as follows:
[b]. compute fitness function, $J(i, j, k, l)$
Let
$J(i, j, k, l) = J(i, j, k, l) + J_{cc}$
[c]. let $J_{last} = J(i, j, k, l)$ to save this value since we may find a better cost via a run.
[d]. Tumble: generate a random vector $\Delta(i)$ that $1 \le \Delta(i) \le -1$
[e]. Move: Let

$$\theta^{i}(j+1, k, l) = \theta^{i}(j, k, l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}}$$

[f]. compute J(i,j+1,k,l) and let
$J(i, j, k, l) = J(i, j, k, l) + J_{cc}$
[g]. swim
i) Let m = 0(counter for swim length)
ii) While m<$N_s$
● Let m=m+1
● If *J(i,j+1,k,l)* < $J_{last}$ (if doing better), Let $J_{last}=J(i,j+1,k,l)$ and

$$\theta^{i}(j+1, k, l) = \theta^{i}(j, k, l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}}$$

● Else let m = $N_s$
[h]. Go to next bacterium (i+1) if i $\neq$ N
[step5]. If j<NC, go to step 3.
[step6]. Reproduction
[a]. for the given k and l, and for each i = 1,2,…,N , Let

$$J^{i}_{health} = \sum_{i=1}^{Nc+1} J(i, j, k, l)$$

Sort this fitness in order of ascending.
[b]. The Sr bacteria with the highest $J_{health}$ values die, the remaining Sr bacteria with the best values split
[step7]. If k < Nre, go to step 3.
[step8]. Elimination and dispersal
For i=1,2,…,N, with probability $P_{ed}$, eliminate and disperse each bacterium, and this result in keeping the number of bacteria in the population constant.
To do this, if a bacterium is eliminated, simply one to a random location on the optimization domain.
If l< Ned, then go to step 2; otherwise END.

## 6. Binary genetic algorithm (BGA)

This algorithm mimics the behaviour of natural evolvement [13]. At first, some binary strings are generated randomly. Each of these strings simulates a chromosome and a set of chromosomes construct the population. By forming the population, the search for the optimal solution starts. According to the fitness of the chromosomes, the most suitable chromosomes are chosen to generate the next generation. The BGA has special operators to increase the algorithm performance which is described below.

The Genetic Algorithm operators:

*Reproduction:* In this step, the previous chromosomes with the most fitness are utilized as the next parents. The most famous method for this process is the roulette wheel mechanism.

*Crossover:* After selecting parents, the children chromosome should be constructed. The crossover operator should mix the parents' chromosome to produce new children. Generally, the crossover coefficient is selected around 0.8 to 1.

*Mutation:* The mutation operator is utilized to avoid the premature convergence and escaping from local optima. This process is implemented by converting some binary numbers from 0 to 1 and vice versa. The mutation coefficient is usually between 0.001 and 0.1.

1- Generation of the initial population.
2- Evaluating the fitness of each chromosome according to the objective function.
3- Constructing new chromosomes by the use of old ones.
4- Applying the mutation and crossover operators
5- Omitting some chromosomes to make space for the new ones.
6- Evaluating the fitness of the new chromosomes according to the objective function and transferring them to the population.

If the termination criterion is satisfied then finish the algorithm else return to step 3.

## 7. Simulation Results

This paper uses the BFA and BGA to reduce the power losses and enhance the voltage deviation objective functions. Both of the algorithms are applied to the 33-bus and 69-bus IEEE test systems and the optimal places and sizes are evaluated. The simulations are in the MATLAB package using Newton-Raphson load flow method. The output power generation capacities of the DGs are as follows:

$0^{MW} \le P_{DG} \le 3^{MW}$ Active power

$0^{MVAR} \le Q_{DG} \le 1^{MVAR}$ Reactive power

In the first part, the optimal allocation of one DG in the 33-bus system is assessed. In the next part, 2 DGs are assessed. The simulation results are shown in Table.1.

As it can be seen from Table.1, the amount of power losses in the 33-bus network using 2 DGs is reduced effectively. Also, it can be seen that BFA has better performance in searching the optimal operating point than BGA. In the case of using 2 DGs by BFA, the percent of active and reactive power reduction are 84.4% and 83.3% respectively. In the case of BGA, the percent of active and reactive power reduction are 82.7% and 80.8% respectively. The results of voltage profile enhancement can be deduced from Fig.1 and 2. As it can be seen, utilization of DG has resulted to better voltage level. In Fig.3, the voltage deviation after using one DG in the 33-bus test system by both BFA and BGA is shown. As it can be seen from Fig.3, the voltage profile in both case are to some extent similar.

Table.1
The simulation results for the 33-bus IEEE test system

| Test System | The proposed algrotihm | Operation status | DG place | DG value (MW) | DG value (MVAR) | DG place | DG value (MW) | DG value (MVAR) | Ploss (KW) | Qloss (KVAR) | Power loss reduction | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | Active % | Reactive % |
| 33-bus | BFA | Normal | | | | | | | 18 | 12 | | |
| | | 1 DG | 30 | 1.512 | 1 | | | | 6.8 | 5.1 | 62.2 | 57.5 |
| | | 2 DG | 30 | 1.1735 | 0.997 | 14 | 0.8273 | 0.4195 | 2.8 | 2 | 84.4 | 83.3 |
| | BGA | Normal | | | | | | | 18 | 12 | | |
| | | 1 DG | 30 | 1.5396 | 0.9941 | | | | 6.9 | 5.1 | 61.6 | 57.5 |
| | | 2 DG | 30 | 1.3636 | 0.9013 | 12 | 0.8473 | 0.6168 | 3.1 | 2.3 | 82.7 | 80.8 |

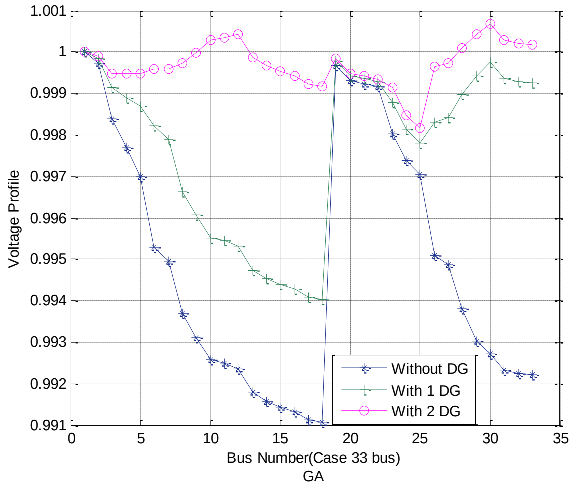


Fig.1. The voltage deviation in the 33-bus IEEE test system using BGA

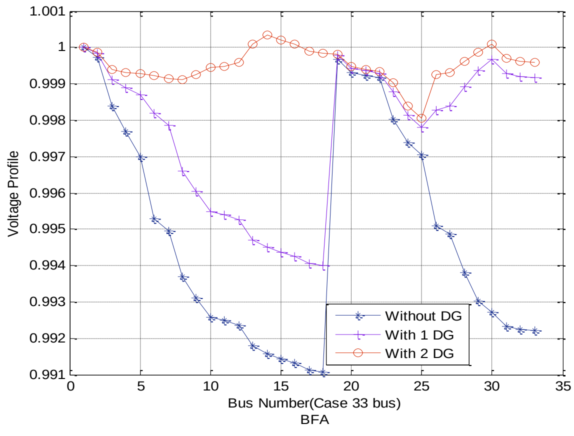


Fig.2. The voltage deviation in the 33-bus IEEE test system using BFA

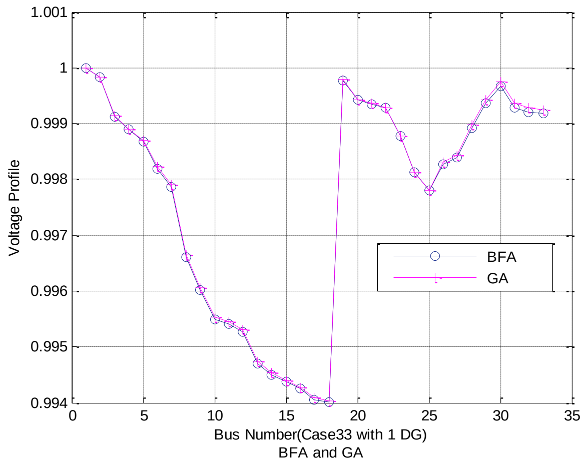


Fig.3. Comparison of the voltage deviation of the 33-bus test system in the case of 1 DG using both BFA and BGA

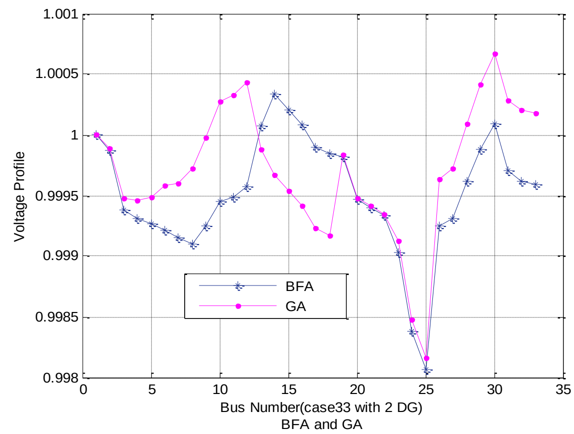


Fig.4. Comparison of the voltage deviation of the 33-bus test system in the case of 2 DGs using both BFA and BGA

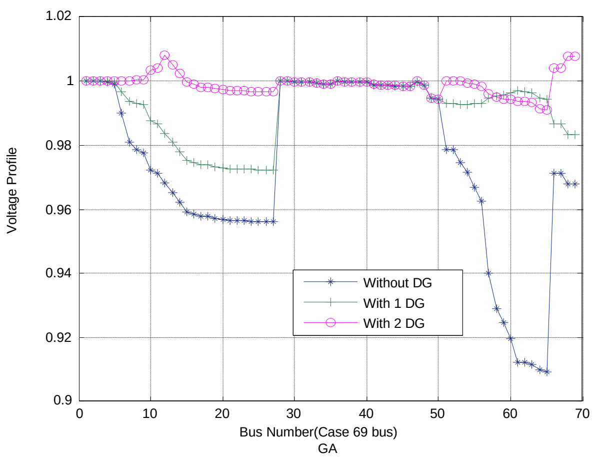


Fig.5. The voltage deviation of the 69-bus IEEE test system using BGA

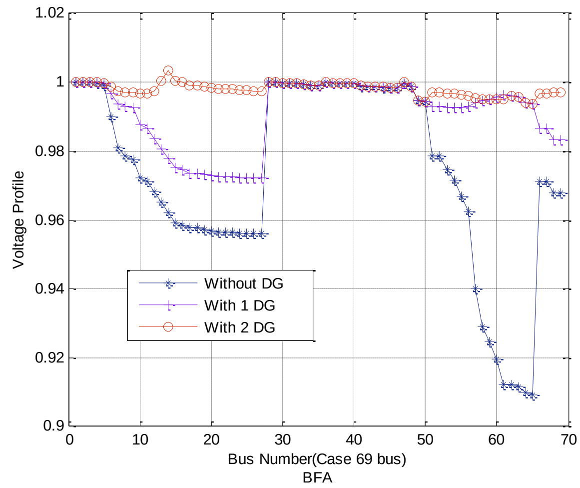


Fig.6. The voltage deviation of the 69-bus IEEE test system using BFA

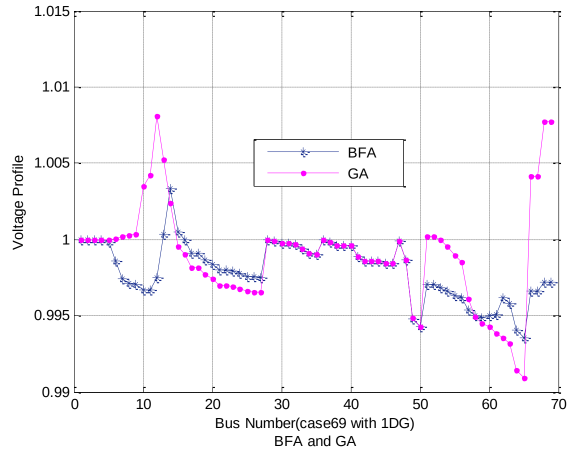


Fig.7. Comparison of the voltage deviation of the 69-bus test system in the case of 1 DG using both BFA and BGA

Fig.4 shows the voltage profile after using 2 DGs for the 33-bus test system for BFA and BGA. As it can be seen, at some points, BFA is better when BGA is better in some others. For the 69-bus test system, 2 DGs are considered. Table. 2 shows the results associated with the existence of 1 DG and 2 DGs in the network. The total power loss of the 69-bus test system considering 2 DGs has reduced notably. This power loss reduction is much for the BFA than the BGA. For example, by the use of 2 DGs in the network, the percentage of active and reactive power loss reduction for BFA are 94.6% and 90.29% respectively when for BGA are 93.2% and 89.8% respectively. As it can be seen, the amount of power loss reduction is more using BFA than BGA. The simulation results for the voltage profile for both BGA and BFA are shown in Fig.5 and 6. In Fig.9, the voltage deviations of the system after using 1 DG in the 69-bus test system for both BFA and BGA are shown. As it can be seen, utilization of DG has reduced the voltage deviation.

As it can be seen from Table.2, after using DG, the amount of power loss is reduced effectively. For instance, utilization of DG (by BFA) in the 69-bus test system has reduced the initial active and reactive power losses from 225 kW and 102 kVar to the suitable values of 26 kW and 16 kVar respectively. Similar results can be deduced for the BGA case for both active and reactive power losses.

## 8. Conclusion

This paper utilizes BFA and BGA to optimize the total power losses as well as the voltage deviation of buses on both 33-bus and 69-bus IEEE distribution test systems. Using DG in the network results to notable reduction in the power losses and enhancing the voltage profile simultaneously. The near optima solutions found by both algorithms show the proper and accurate implementation and ability of BFA and BGA in DG optimal placement and sizing problem. Technically, BFA has better performance and could achieve to more optimal solutions in regard to BGA. If the optimal DG placement is not implemented properly, the final result can be a network with more power losses and even voltage instability. However, in this paper, the total situation of the networks from power loss and voltage profile points of view is enhanced effectively.

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Table.2
The simulation results for the 69-bus IEEE test system

| Test System | The proposed algrotihm | Operation status | DG place | DG value (MW) | DG value (MVAR) | DG place | DG value (MW) | DG value (MVAR) | Ploss (KW) | Qloss (KVAR) | Power loss reduction | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | Active % | Reactive % |
| 69-bus | BFA | Normal | | | | | | | 225 | 102 | | |
| | | 1DG | 61 | 1.8516 | 1 | | | | 26 | 16 | 88.4 | 84.3 |
| | | 2DG | 62 | 1.6547 | 0.9938 | 14 | 0.7396 | 0.4634 | 12 | 9.9 | 94.6 | 90.29 |
| | GA | Normal | | | | | | | 225 | 102 | | |
| | | 1DG | 61 | 1.8915 | 0.9521 | | | | 26 | 16 | 88.4 | 84.3 |
| | | 2DG | 61 | 1.4985 | 0.9726 | 12 | 1.3050 | 0.8143 | 15.2 | 10.4 | 93.2 | 89.8 |