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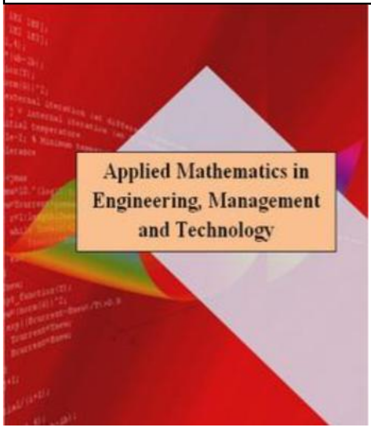
Optimal placement of distribution generation in power system by modified gravitational search algorithm

Hossein Nobakht Niri[1,2], **Aref Jalili**[1,2]
1- Department of Electrical Engineering, Ardabil Science and Research Branch, Islamic Azad University, Ardabil, Iran
2- Department of Electrical Engineering, Ardabil Branch, Islamic Azad University, Ardabil, Iran



Abstract

Today, by increasing of customers and producers in the power system the optimal system with least cost and most reliability is one of important goal of engineers. Basically, it may challenge with voltage drop and system instability. That is one of the best ideas why use of distributed generation (DG) sources. DG can consist of renewable or fossil resources, but the important goal is selection of best location and size to improve system performance. In this regard, in this paper to determine optimal location and size of them integrate power system, this problem is convert to an optimization problem that the target is reduction of power loss and improve voltage profile, but to solve this problem with these complexity and constraints a proper optimization algorithm is needed. For this reason, in this paper GSA optimization algorithm is employed to solve it, but it have some weaknesses in local search algorithm, therefore to improve its overall performance use chaos theory. The proposed algorithm is evaluated on the two test systems 13-bus and 34-bus. The simulation results show good performance in terms voltage profile and power loss minimization.

Keywords- GSA, DG, optimization, voltage profile, placement, loss minimization.

Introduction

The modern power distribution network is constantly being faced with an ever growing load demand, this increasing load is resulting into increased burden and reduced voltage [1]. The distribution network also has a typical feature that the voltage at nodes (nodes) reduces if moved away from substation. This decrease in voltage is mainly due to insufficient amount of reactive power. Even in certain industrial area critical loading, it may lead to voltage collapse. Thus to improve the voltage profile and to avoid voltage collapse reactive compensation is required [1-2]. The X/R ratio for distribution levels is low compared to transmission levels, causing high power losses and a drop in voltage magnitude along radial distribution lines [1- 3]. It is well known that loss in a distribution networks are significantly high compared to that in a transmission networks. Such non-negligible losses have a direct impact on the financial issues and overall efficiency of distribution utilities. The need of improving the overall efficiency of power delivery has forced the power utilities to reduce the losses at distribution level. Many arrangements can be worked out to reduce these losses like network reconfiguration, shunt capacitor placement, distributed generator placement etc. [1-3]. The distributed generators supply part of active power demand, thereby reducing the current and MVA in lines. Installation of distributed generators on distribution network will help in reducing energy losses, peak demand losses and improvement in the networks voltage profile, networks stability and power factor of the networks [3, 4][9-10]. Distributed generation (DG) technologies under smart grid concept forms the backbone of our world Electric distribution networks [5] [10]. These DG technologies are classified into two categories: (i) renewable energy sources (RES) and (ii) fossil fuel-based sources. Renewable energy source (RES) based DGs are wind turbines, photovoltaic, biomass, geothermal, small hydro, etc. Fossil fuel based DGs are the internal combustion engines (IC), combustion turbines and fuel cells [3] [6-7]. Environmental, economic and technical factors have a huge role in DG development. In accord with the Kyoto agreement on climate change, many efforts to reduce carbon emissions have been taken, and as a result of which, the penetration of DGs in distribution systems rises [8]. Presence of Distributed generation in distribution networks is a momentous challenge in terms of technical and safety issues [12- 14]. Thus, it is critical to evaluate the technical impacts of DG in power networks. Thus, the generators are needed to be connected in distributed systems in such a manner that it avoids degradation of power quality and reliability. Evaluation of the technical impacts of DG in the power networks is very critical and laborious. Inadequate allocation of DG in terms of its location and capacity may lead to increase in fault currents, causes voltage variations, interfere in voltage-control processes, diminish or increase losses, increase system capital and operating costs, etc. [13]. Moreover, installing DG units is not straightforward, and thus the placement and sizing of DG units should be carefully addressed [13-14]. Investigating this optimization problem is the major motivation of the present thesis research. DG allocation is basically a complex combinatorial optimization issue which requires concurrent optimization of multiple objectives [15], for instance minimizations of real and reactive power losses, node voltage deviation, carbon emanation, line loading, and short circuit capacity and maximization of network reliability etc. The goal is to determine the optimal location(s) and size(s) of DG units in a distribution network. The optimization is carried out under the constraints of maximum DG sizes, thermal limit of network branches, and voltage limit of the nodes [14-15]. In [17], sensitivity analysis had been used for finding the optimal location of DG. In [18], the optimal location of DGs was predicted by finding V-index. In [19], Loss sensitivity factor had been used for finding the optimal location of DGs. There are numerous optimization techniques used in the literature. In [16], an analytical approach to determine the optimal location of DG is presented. In most of the current works, population based evolutionary algorithms are used as solution strategies. This includes genetic algorithm (GA) [20-24], evolutionary programming [25], and particle swarm optimization [10] [26-28] etc. The advantages of population-based meta-heuristics algorithms such as GA and PSO are that a set of non-dominated solutions can be found in a single run because of their multi-point search capacity. They are also less prone to dimensionality problems; however, convergence is not always guaranteed.

But the above algorithms cannot best solution for optimization of Hydro-turbine governing, so this paper a new optimization algorithm based on the law of gravity, namely Gravitational Search Algorithm (GSA) for problem solving is proposed [29]. This algorithm is based on the Newtonian gravity: ‘‘every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them”.

Problem formulation

The problem is formulated with a objective functions, the real power loss reduction in a distribution system is required for efficient power system operation. The loss in the system can be calculated, given the system operating condition [11].

$$SLOSS = Sij + Sji$$

$$Sloss = \sum_{j=1}^{n} Zj * Ij^2$$

$$PLOSS = real(Sloss) \qquad QLOSS = image(Sloss)$$

$$Sltotal = \sum_{j=1}^{n} Slossj$$

$$INDEX = A * Sltotal + B * \sum_{j=1}^{n} (1 - |Vj|)^2 \tag{1}$$

where, SLOSS, PLOSS and QLOSS are power loss, active and reactive power loss for power system network, respectively. The A and B is penalty factor for INDEX objective function to voltage profit improvement and minimize total loss. This penalty factors define based operator for minimize loss or modified voltage profile [12]. Also, they are different value for test systems. This problem contains some constrains such as:

(a) Power balance constraint

$$\sum_{DG=1}^{n_{DG}} P_{DG} + \sum_{G=n_{DG}+1}^{n_G} P_G = P_D + P_L \tag{2}$$

(b) Generation and voltage limits constraints

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i \in 1,2,...,\alpha$$

$$V_i^{\min} \le V_i \le V_i^{\max} \qquad i \in 1,2,...,\alpha \tag{3}$$

The active power transmission loss PL can be calculated by the network loss formula:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}\,(P_i P_j + Q_i Q_j) + B_{ij}\,(Q_i P_j - P_i Q_j) \tag{4}$$

where,

$$A_{ij} = \frac{R_{ij}\cos(\delta_i - \delta_j)}{V_i V_j}$$

$$B_{ij} = \frac{R_{ij}\sin(\delta_i - \delta_j)}{V_i V_j} \qquad (5)$$

where, Pi and Qi are net real and reactive power injection in bus ‘i’ respectively, Rij is the line resistance between bus ‘i’ and ‘j’, Vi and δi are the voltage and angle at bus ‘i’ respectively.

Gravitational search algorithm

The gravitational search algorithm is constructed based on the law of gravity and the notion of mass interactions. The GSA algorithm uses the theory of Newtonian physics and its searcher agents are the collection of masses. In GSA, we have an isolated system of masses. Using the gravitational force, every mass in the system can see the situation of other masses. The gravitational force is therefore a way of transferring information between different masses. In GSA, agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. Hence, masses cooperate using a direct form of communication, through gravitational force. The heavy masses - which correspond to good solutions - move more slowly than lighter ones, this guarantees the exploitation step of the algorithm [29, 30]. In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function.

In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, we expect that masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space. The GSA could be considered as an isolated system of masses. It is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion. More precisely, masses obey the following laws: Law of gravity: each particle attracts every other particle and the gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the distance between them, R.

Law of motion: the current velocity of any mass is equal to the sum of the fraction of its previous velocity and the variation in the velocity. Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by mass of inertia [29].

In the GSA algorithm particle researcher, is sum of all mass. We define the position of the i_{th} agent by:

$X_i = (x_i^1 \ldots x_i^d \ldots x_i^N)$ for i = 1, 2, 3… N (6)

In the Eqs.1 x_i^d is the position of ith agent in the dth dimension. N is total of agent. At a particular time (t), we have define the force acting on mass (i) from mass (j) as pursuing:

$F_{ij}^d(t) = G(t)\,(M_{pi}(t) – M_{aj}(t))/(R_{ij}(t)+\varepsilon)\times(X_j^d(t) - X_i^d(t)$ (7)

M_{aj} (t) is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, G (t) is gravitational constant at time t, ε is a small constant, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j:

$$R_{ij} = \left\| X_i(t), X_j(t) \right\|_2 \qquad (8)$$

To give a chromatic characteristic to GSA algorithm, suppose that the total force that acts on agent i in a dimension d be a randomly weighted sum of dth components of the forces exerted from other agents:

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} rand_j F_{ij}^d(t) \qquad (9)$$

where $rand_j$ is generate random in the interval [0, 1]. by the law of motion, the acceleration of the agent i at time t, and in direction dth, $a_i^d(t)$, give from:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \qquad (10)$$

In the equation (4) M_{ii} is the inertial mass of ith agent. Velocity for next step will update from equation 11 it is similar to PSO algorithm, because any particle get a new vector of velocity for generate new population. After update velocity vector for agents the position of any agent get from equation 12. The equation for give new velocity and new position following:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{11}$$

$$x_i^d(t+1) = x_i^d(t) + \upsilon_i^d(t+1) \tag{12}$$

With attention to Eqs.11, the next velocity of an agent is considered as a fraction of its current velocity added to its acceleration. $rand_i$ is a uniform random variable in the interval [0, 1]. For give a randomized characteristic to the search used this random number.

The gravitational constant, G, is initialized at the beginning and will be reduced with time to control the search accuracy. In other words, G is a function of the initial value (G0) and time (t):

$$G(t) = G(G0, t) \tag{13}$$

Gravitational and inertia masses are simply calculated by the fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and walk more slowly. Assuming the equality of the gravitational and inertia mass, the values of masses are calculated using the map of fitness. We update the gravitational and inertial masses by the following:

$$M_{ai} = M_{pi} = M_{ii} = M_i, i = 1, 2, ..., N \tag{14}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{15}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_i(t)} \tag{16}$$

Fitness value of the agent i at time t show with fit_i (t) and, worst (t) and best (t) are defined as follows (for a minimization problem):

$$best(t) = \min_{j \in \{1,2,...,N\}} fit_j(t) \tag{17}$$

$$worst(t) = \max_{j \in \{1,2,...,N\}} fit_j(t) \tag{18}$$

It is to be noted that for a maximization problem, Eqs. (17) and (18) are changed to Eqs. (13) and (14), respectively:

$$best(t) = \max_{j \in \{1,2,...,N\}} fit_j(t) \tag{19}$$

$$worst(t) = \min_{j \in \{1,2,...,N\}} fit_j(t) \tag{20}$$

For getting best performed with desirable compromise between exploration and exploitation, one way is to reduce the number of agents with lapse of time in Eq. (8). For getting that target, suggest set an agent with bigger mass apply their force to the other. However, we should be careful of using this policy because it may reduce the exploration power and increase the exploitation capability. We remind that in order to avoid trapping in a local optimum the algorithm must use the exploration at beginning.

By lapse of iterations, exploration must fade out and exploitation must fade in. To improve the performance of GSA by controlling exploration and exploitation only the K_{best} agents will attract the others. K_{best} is a function of time, with the initial value K0 at the beginning and decreasing with time. In such a way, at the beginning, all agents apply the force, and as time passes, K_{best} is decreased linearly and at the end there will be just one agent applying force to the others. Therefore,:

$$F_i^d(t) = \sum_{j \in K_{best}, j \neq i}^{N} rand_j F_{ij}^d(t) \tag{21}$$

where K_{best} is the set of first K agents with the best fitness value and biggest mass.

GSA based DG placement

The GSA technique for solving the optimal placement and capacitor sizing DG problem to minimize the loss may be constructed with the following main stages:

Set power system: Input line and bus data, and bus voltage limits.

Calculate fitness based load flow: Calculate the loss using distribution load flow based on backward-forward sweep.

Initial population: Randomly generates an initial population (array) of particles with random positions and velocities on dimensions in the solution space. Set the iteration counter k = 0. In the other hand, in this step, an initial population based on state variable is generated, randomly. That is formulated as:

$$D = [D_1, D_2, D_3, ..., D_n] \qquad D_i = (d_i^1, d_i^2, ..., d_i^m) \tag{22}$$

Calculate fitness: For each particle if the bus voltage is within the limits, calculate the total loss. Otherwise, that particle is infeasible.

Updating: update population with GSA explore engine.

Finish: If the iteration number reaches the maximum limit, go to next Step. Otherwise, set iteration index k = k + 1, and go back to Step 4.

Results: Print out the optimal solution to the target problem. The best position includes the optimal locations and size of DG or multi-DGs, and the corresponding fitness value representing the minimum total real power loss.
The flowchart of the proposed GSA algorithm is shows in Fig .1.

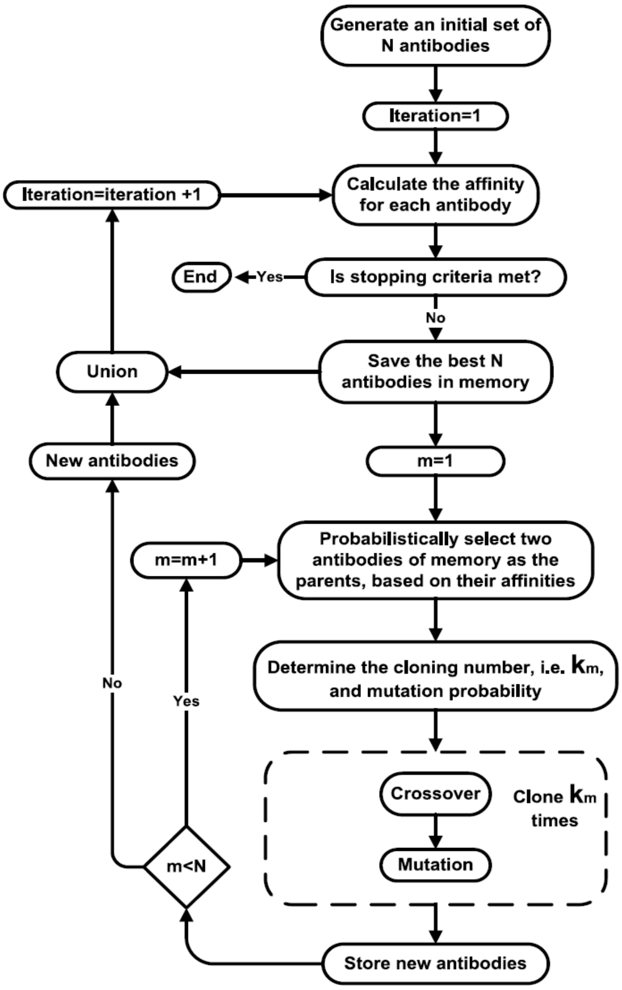


Figure 1. GSA based on DG computational procedure

Simulation Results

For the testing of proposed technique two case studies are considered as; mat power 13 and 34 bus power system. For both of the case studies, the DGs are considered with 5-50 MW and 1-10 Mvar. Also the proposed technique considered 5 source of DGs to power systems. Table. 1-2, shows the numerical results of DGs in system.

In the mentioned tables, the active and reactive powers are presented for 5 optimized buses. Fig. 2-3, shows the system response with 5 sources and without sources. It is clear that by increasing the number of DGs in power system, the stability, losses decreasing and improving of voltage profile will be appropriate. The presented figures show the losses and voltage of active and reactive power in proposed case studies.

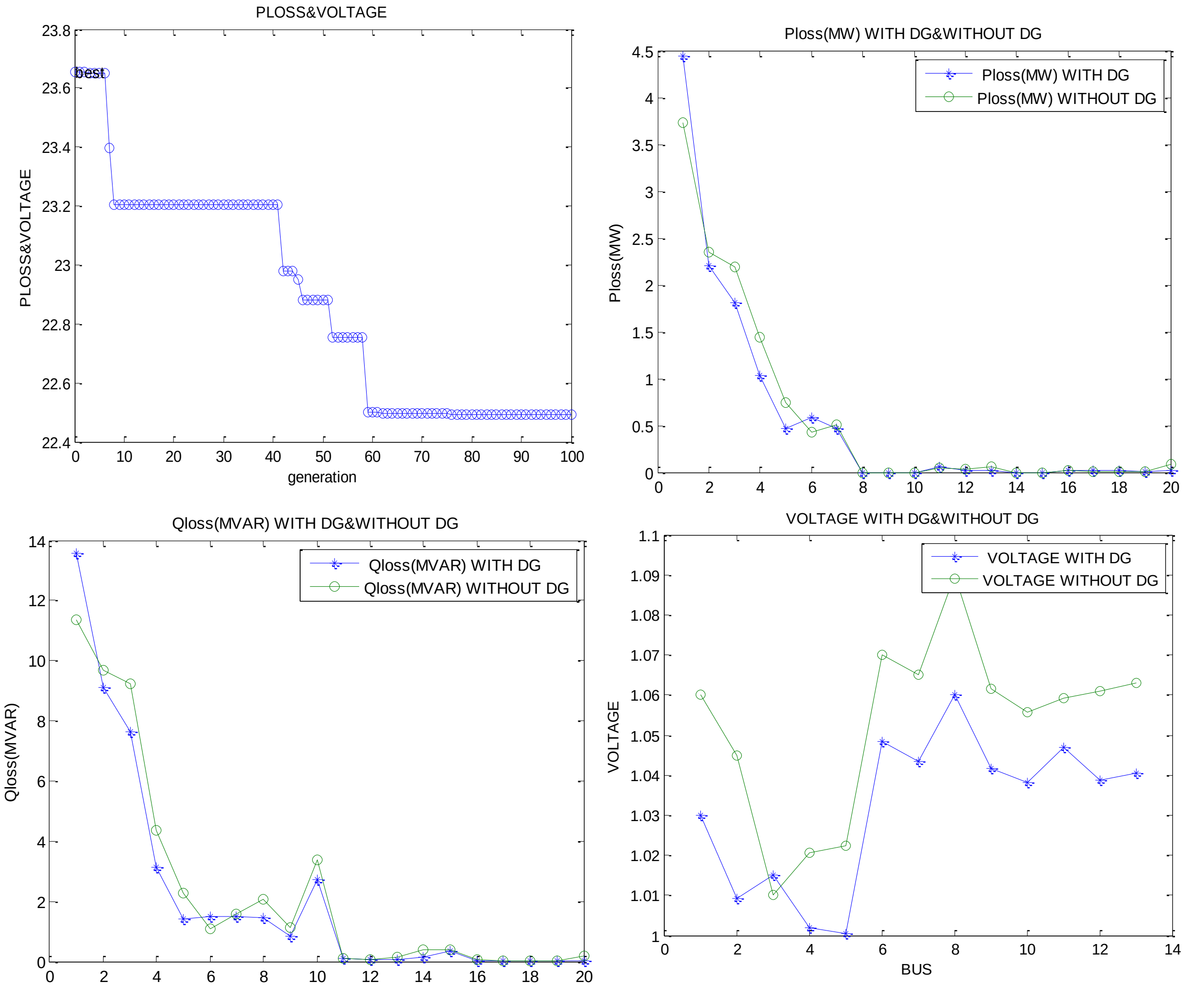


Figure 2. The losses and voltage of active and reactive power in 30- bus system.

Table 1. The results of 30 bus Power System

system	No DG	Without DG		With DG		Proposed algorithm			Fitness
		P(MW)	Q(MVAR)	P(MW)	Q(MVAR)	BUS	P(MW)	Q(MVAR)	
13	1	0.281	0.22	0.171	0.13	9	3.2	0.02	0.15183

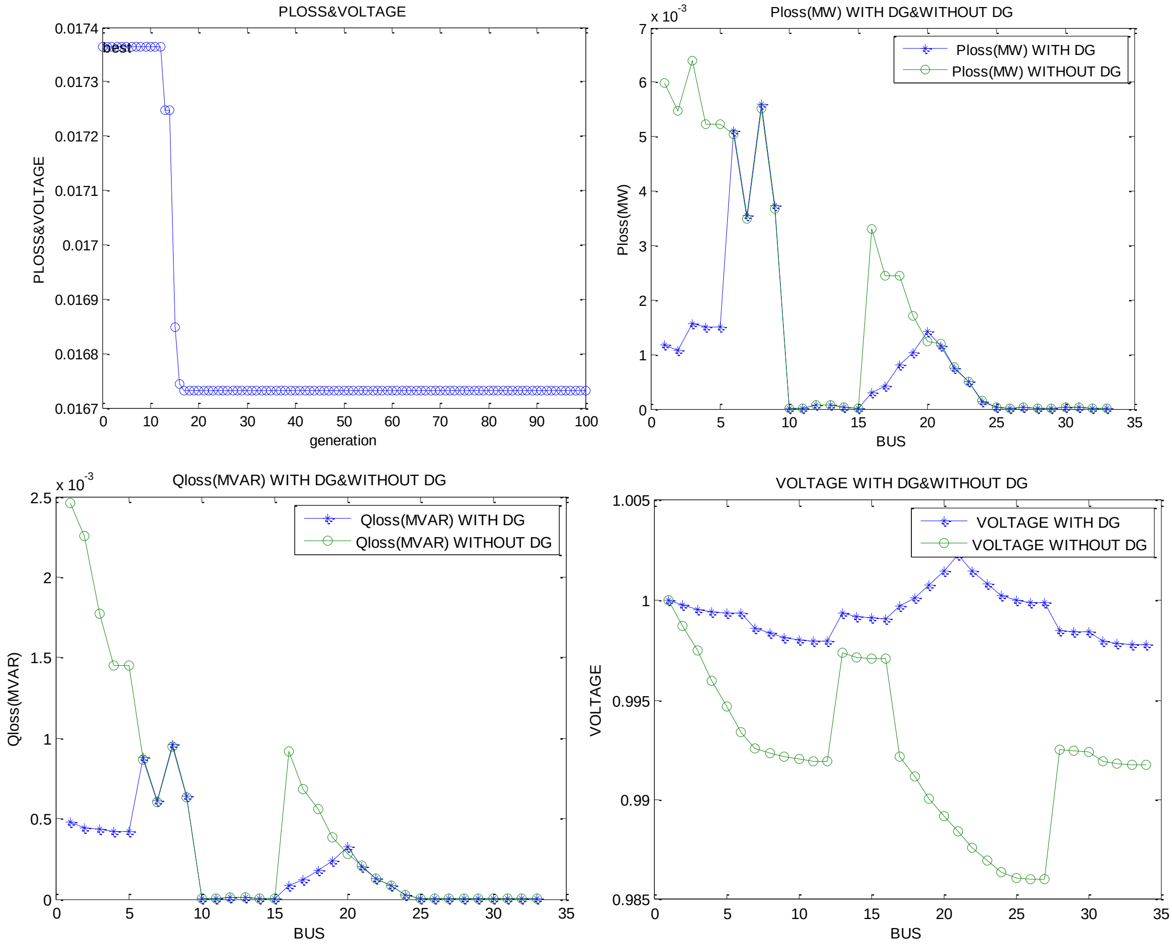


Figure 2. The losses and voltage of active and reactive power in 34- bus system.

Table 2. The results of 34 bus Power System

system	No DG	Without DG		With DG		Proposed algorithm			Fitness
		P(MW)	Q(MVAR)	P(MW)	Q(MVAR)	BUS	P(MW)	Q(MVAR)	
34	1	0.06	0.02	0.03	0.01	21	3.2	0.02	0.01699

Conclusion

The installation of DG units in power distribution networks is becoming more prominent. Consequently, utility companies have started to change their electric infrastructure to adapt to DGs due to the benefits of DG installation on their distribution systems. These benefits include reducing power losses, improving voltage profiles, reducing emission impacts and improving power quality. Additional benefits are avoiding upgrading the present power systems and preventing a reduction of T&D network capacity during the planning phase. Nevertheless, achieving these benefits depends highly on the capacity of the DG units and their installation placement in the distribution systems. In this paper, an innovative approach for management of DG power is represented. The proposed method deals with optimal selection of nodes for the placement and size of the DG by using GSA. The load flow problem has been solved by forward/backward load flow methodology. The rating and location has been optimized using GSA. In GSA, coding is developed to carry out the allocation problem, which is identification of location and rating by one dimensional array. The effectiveness of the approach is demonstrated on the IEEE 13-node and 34-node test systems. The numerical results demonstrate that the proposed method has better ability in finding optimal answers and possibility of particle placed in local zone. Moreover, the proposed strategy has simple structure, easy to implement and tune and therefore it is recommended to generate good quality and reliable electric energy in the restructured power systems.

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