Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **61**, *4*, pp. 338–342, Bucarest, 2016

OPTIMAL ALLOCATION OF DISTRIBUTED GENERATION UNITS BASED ON TWO DIFFERENT OBJECTIVES BY A NOVEL VERSION GROUP SEARCH OPTIMIZER ALGORITHM IN UNBALANCED LOADS SYSTEM

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Key words: Optimal distributed generation allocation, Group search optimizer, Unbalanced distribution network

In this paper, distributed generation (DG) units are optimally allocated in a network containing unbalanced loads. To do this, parametric and cost functions have been formulated for this problem. A novel technique is used to solve the unbalanced load flow problem group search optimizer (GSO) algorithm is one of the new swarm intelligence algorithms which is modified in this paper and results are investigated. We simulated a real network of Iranian's north-west power network and IEEE standard test system. Each objective function is configured for one these networks. For each network two allocating scenarios are proposed: one for the number of DGs and the other for the locations of DGs. In case studies, the results from impoved GSO (iGSO) are compared with simple GSO and particle swarm optimization (PSO) algorithms results.

1. INTRODUCTION

There are many different definitions of DG. It can be defined as generating electric power in distribution network or in demand side [1] or using small size generation units to generate power in places near the consumers [2]. References are categorized to demonstrate one of the main features of our study which is the novel technique for solving the problem. Therefore, the references are divided into four sections: evolutionary techniques, swarm intelligence, heuristic approaches and fuzzy algorithms.

In literatures, three methods are proposed mostly to solve the DG allocation problems. Evolutionary programming (EP) [3], immune algorithm [4] and genetic algorithm (GA) [5]. Swarm intelligence is based on the social behavior of swarms in decentralized self-organizing systems. Many examples of these swarms could be observed in the nature such as ant colony, bird flocks, animal herds, masses of bacteria and fish flocks. Artificial bee colony is used in [6], while Ref. [7] applies honey bee mating optimization (HBMO) algorithm to solve the problem and in [8] swarm particle optimization (PSO) algorithm solves the problem of DG optimal capacity and place allocation.

Evolutionary techniques are used in [9–12] to solve this problem. Variety of methods have been used in these papers such as combination of algorithms [10], defining vulnerable buses from voltage stability point of view and finding DG places by dynamic programming search [11], sensibility test and heuristic curve-fitted technique [12] and straightforward algorithm. The fuzzy algorithm goes beyond "zero and one" values in traditional programming and opens new horizon in programming and computer world.

References [13] use fuzzy algorithm to find optimum place and capacity for DGs. Authors in [14] applied mixed integer non-linear programming (MINLP) algorithm to overcome the problem.

In this paper, best places of DGs in unbalanced radial distribution network are found by a novel optimization algorithm. The reminder of this paper is organized as follows: in Section 2, two objective functions are introduced for DG allocation in unbalanced distributed network. Proposed load flow for unbalanced loads is discussed in Section 3. Concept and structure of GSO, applied modifications and the methodology to solve the problem are presented in Section 4. Results of several scenarios and cases for test systems have been illustrated in Section 5. This work has been conclude in Section 6.

2. FORMULATING THE PROBLEM

2.1. COST OBJECTIVE FUNCTION

In formulating the objective function, two challenges rise which both have cost fabric: minimizing the cost from power losses and the cost from capital investment and operating the DG units. Therefore, the objective function is introduced as follows:

$$COF = SP \cdot K_p \sum_{i=1}^{NB} P_{loss,i} + K_{DG} S_{DG}, \tag{1}$$

where SP is the length of period (it is 7840 hours for one year). K_p and P_{Loss} are the costs caused by power losses and total power loss of the network. K_{DG} and S_{DG} represent the DGs installation and operation costs and the total apparent power respectively. NB is the number of buses. The constrains which should be all satisfied could be found in [15].

Therefore a new objective function should be defined as follows:

$$POF = \frac{P_{loss,a}}{P_{loss,b}} + \frac{VB_a}{VB_b}, \tag{2}$$

where, the indexes a and b are the values before and after allocation, respectively. VB is the voltage deviation. With this technique, the parameters of POF are normalized in an acceptable range and their effects on objective function would be directly of their variations not their real values. This objective function is a step forward than the cost objective function and it is more practical.

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3. **GROUP SEARCH OPTIMIZER ALGORITHM**

3.1. RUNNING THE GSO ALGORITHM [16]

In GSO, each group contains three types of members; the members with best outcome for objective function are considered as leaders. Some of members are defined as explorer. If the best position delivers a better result compared to current position, then the particles moves to that position or stays at its current position and follows a new head angle. If a leader could not find a better region after few explorations, then it gets back to zero head angle.

The iteration value is initially set to zero ($K = 0$) and all the members of random initial matrix X_i and head angle φ_i are initialized. The population of GSO is called a group and each particle in this group is a member. In a n-dimension search space, the i^{th} member in k^{th} iteration has the current position of X_i^k ($Z_i^k \in R^n$) and head angle of δ_i^k ($\delta_i^k = (\delta_{i1}^k, \ldots, \delta^k_{i(n-1)}) \in R^{n-1}$). Exploration path of the i^{th} member which is a unit vector (based on problem matrix dimensions) could be calculated by a polar to Cartesian transformation.

$$d_{i_1}^k = \prod_{q=1} \cos(\delta_{i_q}^k), \tag{3}$$

$$d_{i_1}^k = \sin(\delta_{i(j-1)}^k).\prod_{q=1} \cos(\delta_{i_q}^k) \quad (j = 2, \ldots, n-1), \tag{4}$$

$$d_{i_1}^k = \sin(\delta_{i(j-1)}^k). \tag{5}$$

Each member in the group goes through following seven processes:

Step I. Selecting the leader: finding the leader of group X_p which has the best possible result.

Step II. Starting the search procedure: Leader is scanned at zero angle, then by applying following equations three points will be sampled in scanned area. In K^{th}, the position of leader is defined based on $X_p^k = (x_{p1}^k, \ldots, x_{pn}^k)$ vector. This vector explores three neighboring points to find a better possible position. First (X_F), second (X_R) and third (X_L) leaders scan points in front, right and left, respectively:

$$X_F = X_P^K + r_1 l_{\max} D_P^K(\delta^K), \tag{6}$$

$$X_R = X_P^K + r_1 l_{\max} D_P^K(\delta^K + r_2\theta_{\max}/2), \tag{7}$$

$$X_L = X_P^K + r_1 l_{\max} D_P^K(\delta^K - r_2\theta_{\max}/2), \tag{8}$$

where r_1 is a random number from normal distribution with mean value and standard deviation equals to 1. r_2 is a random number between 0 and 1 with normal distribution. θ_{max} is the maximum-pursuit angle and l_{max} is the maximum length:

$$l_{\max} = \|U - L\| = \sqrt{\sum_{j=1}^{n}(U_j - L_j)^2}. \tag{9}$$

In (9), U_j and L_j are upper and lower boundaries of search space. If the best point has a better reference regarding to current position, the point moves toward the leader. If not, it stays at the current point and finds its path by (10). If the position of one of three points becomes better than the current position of leader, then leader moves to that point and its angle could be found by (9).

$$\delta^{K+1} = \delta^K + r_2\alpha_{\max}, \tag{10}$$

where, α_{max} is the maximum-pursuit angle.

Step III. If aforementioned situation does not happen then leader stays at its current position. If the leader fails to find a better position in a^{th} iteration, it scans opposite leader applying (11):

$$\delta^{K+a} = \delta^K. \tag{11}$$

Step IV. Running the exploration (search): remaining 80 % members are initialized randomly to start the search.

Step V. Running distribution: remaining members are scattered randomly, to do this, based on (10), a head angle should be generated for random movement, and l_I which is a random distance obtained by (12) so the particle moves to new position using (13).

$$l_i = ar_1 l_{\max}, \tag{12}$$

$$X_i^{K+1} = X_i^K + l_i D_i^K(\varphi^{K+1}). \tag{13}$$

Step VI. Fitness calculation: calculating fitness for current member $f(Z_i)$.

Step VII. These seven steps are performed on all the particles. The termination criterion (number of iterations) is then checked, if it is satisfied the algorithm stops.

3.2. MODIFIED GSO ALGORITHM

In this version, initial matrix (Par) with the dimension of population and number of variables is randomly generated. For each person (row) an objective function is introduced and they organized descending and consequently Par is organized accordingly. Persons (code strings) are generated with (14)– (16):

$$X'_F = r_1 l_{\max} D_P^K(\delta^K), \tag{14}$$

$$X'_R = r_1 l_{\max} D_P^K(\delta^K + r_2\theta_{\max}/2), \tag{15}$$

$$X'_L = r_1 l_{\max} D_P^K(\delta^K - r_2\theta_{\max}/2), \tag{16}$$

in which the elements of D matrix are calculated by equations (6)–(8).

Then new parameters are generated as follows:

$$X''_F = \mathrm{Min}\{Par(1,:),[1 - Par(1,:)], Z'_F\} \tag{17}$$

$$X''_R = \mathrm{Min}\{Par(1,:),[1 - Par(1,:)], Z'_R\} \tag{18}$$

$$X''_L = \mathrm{Min}\{Par(1,:),[1 - Par(1,:)], Z'_L\}. \tag{19}$$

Objective function is calculated based Z_F, Z_R and Z_L, each one of these or the $Par(1,:)$ that delivers better objective function is selected as the code of next level. This string goes to next level unchanged. Other strings are calculated and substituted as:

$$X'_P = r_2(Par(1,:) - Par(P,:)), \tag{20}$$

$$X''_P = \mathrm{Min}\{Par(1,:) - [1 - Par(P,:)], Z'_P\}, \tag{21}$$

$$X_P = Par^K(P,:) + Z''_P. \tag{22}$$

In these equations, *Par(1,:)* and *Par(P,:)* are the best and non-best codes. The angles are calculated as follows: If *Par(1,:)* is lower than X_F, X_R and X_L then the angle is obtained from equation (14) in which $\alpha = \pi/2(N+1)$ and N is the number of variables. After a^{th} iteration, if *Par*(*1,:*) could not reach the optimum position and the angle of Eq.(15), for non-optimal codes, δ should be calculated by Eq.(23):

$$\delta(P,:) = \delta(P,:) + r_2\sqrt{N+1}\,. \qquad (23)$$

3.3. SOLVING PROBLEM

First we should feed the input data. There are two types of data in our problem: first, network data, including base voltage (20 kV) and power, resistance and inductance as well as the diagram of the network and next, data needed for GSO algorithm: bus voltage magnitude and total power loss before running the optimization process on the network, initial population generated in initial matrix based on the nature of the problem and grid characteristics. When adding a DG to the network, a particle adds to the network and the proposed algorithm should be implemented to find the optimal DG allocation. Next, DG installation cost is calculated for each particle of generation and objective function. The particles of matrix are introduced and organized based on the objective function. When the optimization process starts, the proposed algorithm runs to find better particles from initial population and next, load flow should be performed for each particle to evaluate power losses. Objective function is then calculated based on the load flow results. Substituting old particles with new results from the algorithm operators, the objective function is reorganized and best results are selected for it. This procedure goes on until the criteria are met.

4. **CASE STUDY**

The case studies are performed on two networks; a 25 bus standard test system (Fig.1) and a real 37 (Fig.2) bus system. In these figures, white and black ground show reactive and actives powers, respectively. For each network, two scenarios are considered: Number of DGs and allocating the place of DG installation. Showing the advantages of proposed iGSO in solving the problem and investigating the effects of more DGs on parameters of objective function are the main purpose of first and second scenarios, respectively. In each scenario the following parameters are surveyed: power loss, objective function, capacity and location of installed DGs and grid voltage profile. Energy loss cost is 0.6 $/kWh and DG units installation cost is 400,000 $/MW [17]. Unit of each quantity is considered as follows: power loss (kW), voltage (per unit), cost function ($), parametric function (without unit), active capacity (kW) and reactive capacity (kvar).

4.1. PARAMETRIC OBJECTIVE FUNCTION IN 25 BUS NETWORK

4.1.1. **Optimal number of DGS**

Single-line diagram and corresponding information of this network are presented in [18] and Fig. 1. In Table (1), DG allocation results from proposed iGSO, simple GSO and PSO algorithms from first scenario are presented to show the advantages of the iGSO algorithm regarding to two other algorithms.

Table 1

Optimal DG allocation in IEEE 25 bus test system

Tech-nique	Power loss	Minimum voltage (pu)			Size		POF
		Phase a	Phase b	Phase c	Active	Reactive	
Without	150.1225	0.928431	0.928444	0.931182	-	-	2.0000
PSO	91.0915	0.949964	0.949690	0.949494	793	742	1.4416
GSO	79.1369	0.969965	0.969703	0.969511	519	351	1.3564
iGSO	58.7825	0.969969	0.969748	0.969579	381	262	1.2205

From the data in this table we could conclude that proposed algorithm delivers better results and this is achieved by lower DG capacity. In comparison with required active capacity, lower reactive capacity resulted by iGSO is more significant when comparing with two other algorithms. The simple GSO is still better than PSO. Capacity and location of installed DGs are shown in Fig. 2.

Considering Fig. 1, we could observe that iGSO resulted in 2 and 6 units less DG units compared two algorithms, respectively, but it is also capable of delivering the best possible results by allocating these units on most sensitive place.

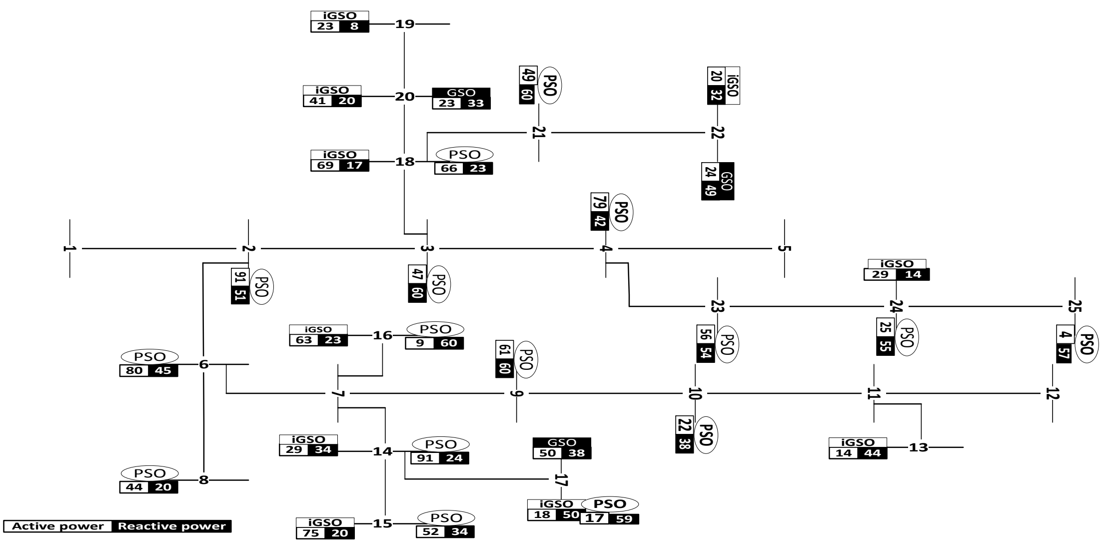

Fig. 1 –DG Placement on 25-bus system.

4.1.2. **Optimal number of DGS**

In second scenario, to investigate the effects of DGs quantity on objective function and power loss, DG number varies from 1 to 25 and results from iGSO algorithm optimization are indicated in Fig. 3. Regarding to different scales of power loss and objective function, they are divided by corresponding value before DG allocations. On the other hand, the voltage variations are very small, so we neglect voltage deviations in Fig. 2.

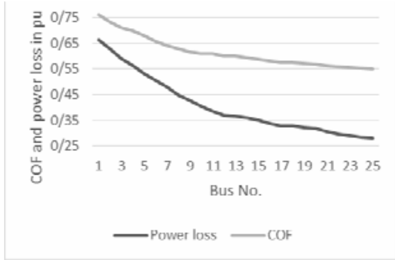

Fig. 2 – Optimal values variations in 25 bus.

Table 2

Optimal DG allocation in 37 bus real system

Technique	Power loss (kW)	Minimum voltage (*pu*)			Size		COF
		Phase a	Phase b	Phase c	Active	Reactive	
Without DG	173.4624	0.927323	0.969858	0.922313	-	-	911718
PSO	93.1497	0.940655	0.976798	0.935739	825	481	897867
GSO	86.6433	0.949964	0.949696	0.949502	820	523	844435
iGSO	62.1134	0.949970	0.949731	0.949564	675	392	767634

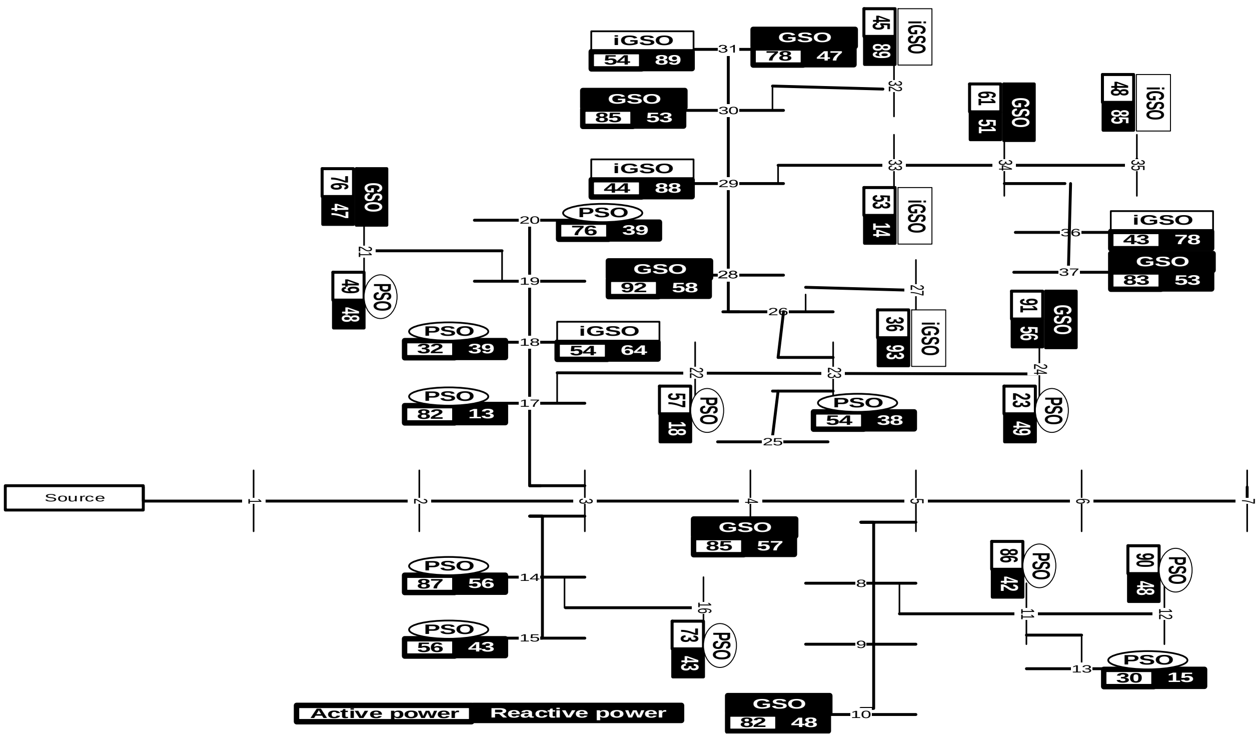

Fig. 3 – DG placement in 37 bus real system.

Regarding Fig. 2, two curves behave almost the same. Obviously, after 10 DGs, the curve descending slows down, and it shapes a linear line more or less. This is more obvious if we compare the trend in first 5 DGs and last 5 DGs.

4.2. COST OBJECTIVE FUNCTION IN 37 BUS REAL SYSTEM

The results in Table 2 are presented to show the capability of proposed iGSO algorithm in solving the DG allocation problem in unbalanced grid as well as the real power grid and the results are compared to GSO and PSO algorithms.

From Table 2 we could conclude that the iGSO algorithm is able to significantly reduce the overall grid costs by decreasing the power loss with even less DG units. Also, we could see that the voltage minimum is not much improved due to long abnormal structure of studied network. Optimal capacity and place of DG units allocated in first scenario of the real system is represented in Fig. 3.

In this figure, we could observe that the number of DG units resulted by iGSO, GSO and PSO are 8, 9 and 13, respectively and obviously the iGSO algorithm delivers lower required capacity. Also, in the iGSO solution the DG units are installed at end busses which have more sensitivity.

4.2.1. **Optimal number of DG units**

Like 25 bus test system, second scenario is applied to the 37 bus real system and results are presented in Fig. 4. It can be seen in this figure that power loss variation and decrease is much more intense compared to objective function. Actually the behaviors of objective function and power loss are opposite.

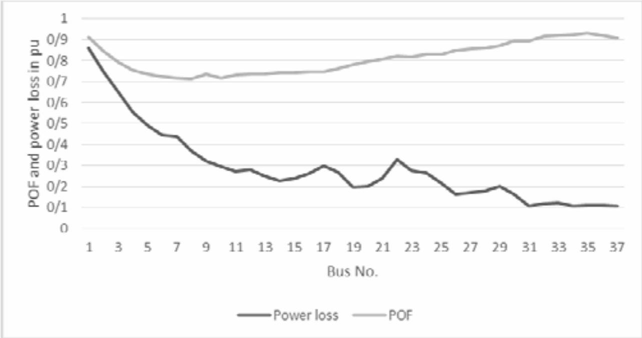

Fig. 4 – Optimal values variations in 37 bus.

5. **CONCLUSION**

In this paper, we proposed iGSO algorithm for DG optimal allocation in a grid with unbalanced loads pursuing two different objective functions. By comparing iGSO algorithm with GSO and PSO, the advantage of the iGSO algorithm could be proven. Regarding to table 1 and 2 we could see the results from iGSO is 18.11 % and 11.13 % better than PSO and GSO in parametric objective function, respectively. For cost objective function these reductions are 16.97 % and 10.00 %.

The proposed algorithm delivers better results with fewer DG units and lower capacity. Fewer DG units are highly demanded by grid designer due to high operation costs and capital investments. From Figs. 2 and 4 it can be seen that better place allocation of DG units is the other important aspect of the iGSO algorithm compared to other algorithms. This algorithm placed the DG units in most sensitive and strategic busses of the network, and hence the parameters of the grid improved. Fewer number of DG units has lots of financial, technical and environmental advantages. Increasing the number of DGs from the optimum number, lowers the rate of improvement in objective function to installed capacity.

In other words, the number of DGs is different from the capacity of DGs. Therefore in DG unit allocation, the number and the capacity of DGs should be studied separately. In number-based allocating optimization, if the number of DG units is predefined compared to the case that it should be found, the results from the former is better.

In both objective function the power loss shows a descending behavior (Figs. 2 and 4), although this trend is more linear in cost objective function, while it has some fluctuations in parametric objective function. From Figs. 2 and 4 it can be seen that the two objective functions behave contrary and that is due to the parameters and formulations in these functions. Terms in parametric objective function are normalized and higher number of DG units lowers the voltage deviation and power loss. On the other hand, in cost objective function, the costs would increase with the increase in the number and capacity of DG units.

Received June 15, 2015

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