Research Journal of Applied Sciences, Engineering and Technology 2(8): 832-837, 2011
ISSN: 2040-7467

Received: July 26, 2011 Accepted: August 17, 2011 Published: August 30, 2011

PSO Based Multiobjective Approach for Optimal Sizing and Placement of Distributed Generation

Mohammad Mohammadi and M. Akbari Nasab
Department of Engineering, Aligoudarz Branch, Islamic Azad University, Aligoudarz, Iran

Abstract: Distributed Generation (DG) is a promising solution to many power system problems such as voltage regulation, power loss, reliability, power quality, etc. This paper presents a new methodology using Particle Swarm Optimization approach (PSO) for the placement of Distributed Generators (DG) in the radial distribution systems to reduce the real power losses and to improve the system reliability. A hybrid objective function is used for the optimal DG placement. It has two parts, in first part the power loss purpose as one index named Power Loss Reduction Index is considered .in second part the effect of DG on reliability improvement of system has been considered and it is considered as one index named as Reliability Improvement Index. The proposed method is tested on standard IEEE 12 bus test system and the results are presented and compared with different approaches available in the literature. The proposed method has outperformed the other methods in terms of the quality of solution and computational efficiency.

Key words: Distributed generation, distribution system, particle swarm optimization, power loss, reliability

INTRODUCTION

Distribution system provides a final link between the high voltage transmission system and the consumers. A radial distribution system has main feeders and lateral distributors. The main feeder originates from substation and passes through different consumer loads. Laterals are connected to individual loads. Generally radial distribution systems are used because of their simplicity. Power loss in a distribution system is high because of low voltage and hence high current that don't consider in Keane and O'Malley (2005). The overall efficiency can be improved using DG units. Utilities are continuously planning the expansion of their existing electrical networks in order to face the load growth and to properly supply their consumers. Distribution system provides a final link between the high voltage transmission system and the consumer. Electricity networks are in the era of major transition from stable passive distribution networks with unidirectional electricity transportation to active distribution networks with bidirectional electricity transportation. Distribution networks without any DG units are passive since the electrical power is supplied by the national grid system to the customers embedded in the distribution networks. It becomes active when DG units are added to the distribution system leading to bidirectional power flows in the networks (Zareipour *et al*., 2004). In an active distribution network the amount of energy lost in transmitting electricity is less as compared to the passive distribution network, because the electricity is generated very near the load center, perhaps even in the same building. Active Distribution Network has several advantages like reduced line losses, voltage profile improvement, reduced emission of pollutants, increased overall efficiency, improved power quality and relieved T&D congestion. Hence, utilities and distribution companies need tools for proper planning and operation of Active Distribution Networks. The most important benefits are reduction of line losses and voltage stability improvement. They are crucially important to determine the size and location of DG unit to be placed. Studies indicate that poor selection of location and size would lead to higher losses than the losses without DG (Kim, 2001a, b). In EI-hattam and Salma (2004), an analytical approach has been presented to identify appropriate location to place single DG in radial as well as loop systems to minimize losses. But, in this approach, optimal sizing is not considered. Loss Sensitivity Factor method (LSF) (Graham *et al*., 2000) is based on the principle of linearization of the original nonlinear equation (loss equation) around the initial operating point, which helps to reduce the amount of solution space. The LSF method has widely used to solve the capacitor allocation problem. Optimal placement of DG units is determined exclusively for the various distributed load profiles to minimize the total losses. They have iteratively increased the size of DG unit at all buses and then calculated the losses; based on loss calculation they ranked the nodes. Top ranked nodes are selected for DG unit placement. The Genetic Algorithm (G.A) based method to determine size and

Corresponding Author: Mohammad Mohammadi, Department of Engineering, Aligoudarz Branch, Islamic Azad University, Aligoudarz, Iran

location of DG unit is used in (Ault and McDonald, 2000; Caisheng and Nehrir, 2004). They have addressed the problem in terms of cost, considering cost function may lead to deviation of exact size of the DG unit at suitable location. It always gives near optimal solution, but they are computationally demanding and slow in convergence. In this paper, a new objective function to calculate optimal location and optimum size value for DG is proposed. The DG is considered to be located in the primary distribution system and the objective of the DG placement is to improve the voltage profile and short circuit level at each bus of system. The cost and other associated benefits have not been considered while solving the location and sizing problem.

In this study a multi objective function consist of reliability and power loss function is considered and in follow solved with PSO. This study proposes a Particle Swarm Optimization (PSO) algorithm for optimal placement of Distributed Generation (DG) in a primary distribution system to minimize the total real power loss. The PSO provides a population-based search procedure in which individuals called particles change their positions with time.

Modeling:

Power loss reduction: DG sources are normally placed close to load centers and are added mostly at the distribution level. They are relatively small in size (relative to the power capacity of the system in which they are placed) and modular in structure (Takahashi *et al.*, 2006; Goldberg, 1989). A common strategy for sizing and placement of DG is either to minimize system power loss or system energy loss of the power systems. The voltage at each bus is in the acceptable range and the line flows are within the limits. These limits are important so that integration of DG into the system does not increase the cost for voltage control or replacement of existing lines. The formulation to determining the optimal size and location of DG in a system is as follows:

Loss Reduction Factor Index per node is defined as the ratio of percentage reduction in loss from base case when a DG having size DGS KW is installed at bus i, to the DG size at that bus. Power Loss Reduction Index (PLRI) is expressed as:

$$PLRI = \frac{PIoss_{Bas} - PIoss_{DGi}}{PIoss_{Base}} \quad (1)$$

where After the iterative solution of bus voltages, line flows and line losses can be calculated. The complex powers Sij from bus I to j and Sji from bus j to i are:

$$Sij=V_i I^*ij$$
$$Sij=V_j I^*_{ji} \quad (2)$$

The power loss in line i-j is the algebraic sum of the power flows determined from the above equations.

$$pIoss = \sum_{i=1}^{N-bus} \sum_{j=1}^{N-bus} \mathrm{Re}\left\{S_{ji} + S_{ij}\right\} \quad (3)$$

Reliability improvement: In order to guaranty the reliability of system, the paper calculates the power not supplied after the three phases short-circuit. In (Goldberg, 1989; Ault and McDonald, 2000; Baran and Wu, 1989; Rau and Wan, 1994), the more detail rate values for calculating the reliability are not yet available. So we just consider the time after fault clearing assuming that all DG are in ready state. The momentary interruption due to DG ready state is neglected. Reliability Improvement Index (RII) is illustrated as:

$$RII = \left\{\frac{AENS_T - AENS_i}{AENS_T}\right\} \quad (4)$$

where,

ENS_T : The total average energy not supplied when the fault happened in sequence in all the sections in the case of without DG.

ENS_i : The total average energy not supplied when the fault happened in sequence in all the sections with the i-combination of DG.

which

$$AENS = \frac{\sum L_a(i) u_i}{\sum N_i} \quad (5)$$

which,

N_i Number of customer at i^{th} load point

U_i HInterruption duration at i^{th} load point

$L_a(i)$ Average load at i^{th} load point

Multiobjective based problem formulation: The multiobjective index for the performance calculation of distribution systems for DG size and location planning with load models considers all previous mentioned indices by giving a weight to each index. The PSO-based multiobjective function (MOF) is given by:

$$MOF = W_1^* PLRI + W_2^* RII \quad (6)$$

where,

$$W_1 + W_2 = 1 \quad (7)$$

These weights are indicated to give the corresponding importance to each impact indices for the penetration of DG with load models and depend on the required analysis (e.g., planning, operation, etc.). The weighted normalized

indices used as the components of the objective function are due to the fact that the indices get their weights by translating their impacts in terms of cost. It is desirable if the total cost is decreased. In this work, due to more important the reliability factor respect to power loss reduction pupose, these weights are assigned as $W_1 = 0.65$ and $W_2 = 0.35$. However, these values may vary according to engineer's concerns, Subjected to various operational constraints to satisfy the electrical requirements for distribution network. These constraints are the following:

PSO-based optimization method: Particle Swarm Optimization, as an optimization tool, consists of a characteristic called particle (Mithulananthan *et al*., 2000). Each particle in order to move to optimum position, changes its position with time.Particles move around in a multi dimensional search space, during flight. Each particle according to its own experience, and the experience of neighboring particles, adapt its position. Other characteristic in the PSO approach is called swarm. A swarm consists of a set of particles, neighboring the particle and its history experience. X represents a vector that shows various positions of particle. So, the dth particle in a k-dimensional space is represented as:

$$Xd = (x_{dk}, x_{dk}, \ldots, x_{dk}) \tag{8}$$

In order to achieve to optimum position, the best previous position is recorded as:

$$Qbest_d = (qbest_{d1}, q\ qbes_{d2}, \ldots, qbest_{dk}) \tag{9}$$

In Eq. (33), the "sbestd" is represented as index of the best particle among all the particles in the swarm. Another characteristic defended in the PSO approach is called velocity. The velocity of the dth particle is expressed as:

$$Vd = (vd1, vd2, vd3, \ldots, vd4) \tag{10}$$

In order to search the better velocity and position, in the next iteration, velocity and position of each particle may be obtained by using current velocity and position as expressed by:

$$\begin{aligned} Vr+1 = {} & w.v^{r+1}{}_{dk} + C_1{}^{*}rand(\ ) \\ & {}^{*}\left(qbest_{dk} - x^{y}{}_{dk}\right) + C_2 \\ & {}^{*}rand(\ )^{*}\left(sbest_{dk} - x^{y}{}_{dk}\right) \end{aligned} \tag{11}$$

$$\begin{aligned} & x^{r+1}{}_{dk} = x^{y}{}_{dk} + v^{r+1}{}_{dk} \\ & d = 1,2,\ldots,D \quad K = 1,2,\ldots,m \end{aligned} \tag{12}$$

That D indicates the number of particles in a group; m is the population size in a particle, r is the number of iterations (generations), w indicates the weight factor, c1, c2 are the acceleration constants. Moreover in above equations the Rand (), rand () are the uniform random values in the range [0, 1], $x^{y}{}_{dk}$ is the position of the kth member in the dth particle at iteration r and finally $x^{y}{}_{dk}$ represents the velocity of the kth member in the dth particle at iteratio r.

It is notable that $V^{\min}{}_{d} \le V^{r}{}_{dk} \le V^{\max}{}_{d}$ .The parameter $V^{\max}$ determines the resolution, or fitness, showing which regions are to be searched between the present position and the target position. If $V_{\max}$ is very high, particles might fly past good solutions. Similarly if $V^{\max}$ is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, $V^{\max}$ was often set at 12–25% of the dynamic range of the variable on each dimension. The parameters c1 and c2 represent the weighting of the stochastic acceleration terms. High values result in abrupt movement toward, or past, target regions. On the other hand, low values allow particles to roam far from the target regions before being tugged back. Hence, according to past experiences, the acceleration constants c1 and c2 were often set to be 2.0.

Suitable choice of the inertia weight w can supply a balance between global and local explorations. In general, the inertia weight w is adjusted according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{13}$$

In this equation itermax represents the maximum number of iterations, and iter indicates the current number of iterations.

In this optimization problem with n type candidate of energy source for planning, a particle in order to represents the added capacity in planning horizon will be defined by:

$$q_{i,d} = [(q^{1}{}_{d1}, q^{2}{}_{d1}, \ldots, q^{t}{}_{d1}) \ldots\ldots (q^{1}{}_{dn}, q^{2}{}_{dn}, \ldots, q^{T}{}_{dn})] \tag{14}$$

$$q^{t}{}_{i} = [q^{t}{}_{d1}, q^{t}{}_{d2}, \ldots, q^{t}{}_{dn} \tag{15}$$

where, qd,i is the dth particle vector that represents the added capacity of different type energy source of the ith energy source in planning horizon. Also,$q^{t}{}_{dn}$, , as a member of the dth particle, relates to the added capacity of the nth type of the energy source at period t. It should be noted that the planning horizon of energy source planning is split into T2-year periods. After preparing particles and swarm, the fitness value should be calculated. In this study, the fitness value is equal to the value of objective function, shown in Eq. (5). In order to

comparing of particles with together and also speeding up the convergence of the iteration procedure, the fitness value is normalized between [0, 1] based on the following equation that is given by

$$f'^{(i)} = \frac{f(i) - f_{\max}}{f_{\max} - f_{\min}} \tag{16}$$

where, f(i) is the fitness value,f_{min},f_{max}, represent the minimum and maximum fitness value in a iteration, f(i) indicates the normalized fitness value.

Once the fitness value is calculated, the regional constraints must be checked. Hence a modified fitness value, mf (i), is defined by using a penalty factor. If a particle satisfy the all of constraints of regional level, then mf (i) is equal to f (i), otherwise, the penalty factor is subtracted from f(i). So, the mf (i) and penalty factor (pf) is expressed as:

$$mf(i) = \begin{matrix} f^{(i)} \; if \; constrainsatisfie \\ f^{(i)} - pf \; otherwise \end{matrix} \tag{17}$$

$$pf = \frac{f'(i)}{\gamma} \tag{18}$$

It is notable that is a constant value. It is set to a value that the mf becomes near to zero in an attempt to reduce the effectiveness of particles not satisfying the regional level constraints. With this consideration, the particles that satisfy the constraint will have a significant mf as compared to that of offender particles. In order to better clarify, the solution of optimization problem in regional level with PSO can be presented by an algorithm in five steps as follows:

Step1: Initialization γ: In this step d, n, T, itermax, w, c1, c2 and velocities are assigned. In this step, the lower and higher bound of regional constraints is specified too. Based above d initial particles are generated in random in the range of regional constraint. Set iteration = 1.

Step2: Objective function calculation: In this step the objective function and fitness value of each particle qi,d is calculated. Compare fitness value of each particle with its qbest.The best fitness value among qbest is denoted as sbest.

Step3: Velocity modification: In this step the velocity of each particle is modified based on bellow equation, and then generate the new particles based follow equation:

$$V^{t}_{dn}{}^{r+1}=W.V^{r}_{dk}+C_1{}^{*}rand()^{*}(qbest_{dk}-q^{t}_{dn}{}^{®)})+C_2{}^{*}Rand()*(Sbest_d-x^{y}_{dk}) \tag{19}$$

$$q^{t}_{dn}{}^{(r+1)=}q^{t}_{dn}{}^{(r)+}V^{t}_{dn}{}^{®+1)} \tag{20}$$

In these equations $q^{t}_{dn}{}^{(r)}$ is a part of abobe equation in the rth iteration. It should be noted that $q^{t}_{dn}{}^{(r)}$ is defined earlier, ifV^{t}_{dn} reaches to its boundary values, it will be adjust to the extreme values. In other words, If $V^{t}_{dn} > V^{max}$ then $V^{t}_{dn} = V^{max}$. Similarly, If $V^{t}_{dn} > V^{min}$ then $V^{t}_{dn} > V^{mun}$. Finally the all of regional constraints are checked and the offender particles are penalized with the penalty factor expressed by above equation:

Step4: Upgrading of qbest, sbest: If the fitness value of each particle is better than the previous qbest,then qbest is updated with the current value.If the best qbest is better than sbest, then sbest will be substituted with the best qbest. This is the end of iteration. Set iteration = iteration+1.
If iteration>itermax then the algorithm is stopped unlessitiscontinue bygoing to step2.Otherwise step 5.

Step5: Results of PSO: The particle that generates the latest sbest is the optimal solution of PSO

SIMULATION AND RESULTS

The proposed methodology is tested on test systems to show that it can be implemented in distribution systems of various configuration and size. The test system is a 12 bus system with the total load of 761.04 KW and 776.50 KVAR and base voltage 11KV. A single line diagram of the test system is shown in Fig. 1.

A computer program has been written in MATLAB 7.6 to calculate the optimum location and sizes of DG at various buses using GA and reparative load flow method

Table 1: Optimal DG unit sizes for 12-bus radial distribution system

Test system	Optima locations l	Optimum DG Size in KW	Power loss Without DG	Power loss With DG	AENS Without DG	AENS With DG
12 bus	3	437.21		200.20		45.3
	6	450.65	280.8	210.87	75.7	54.7
	7	477.00	KW	230.45	kwh/yr	66.2
	11	513.07		240.45		70.7

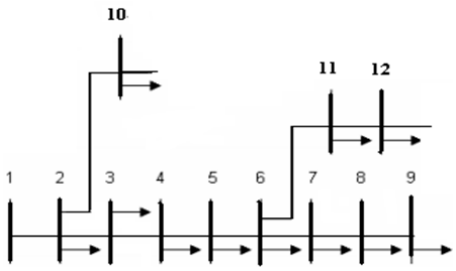

Fig. 1: Test distribution system

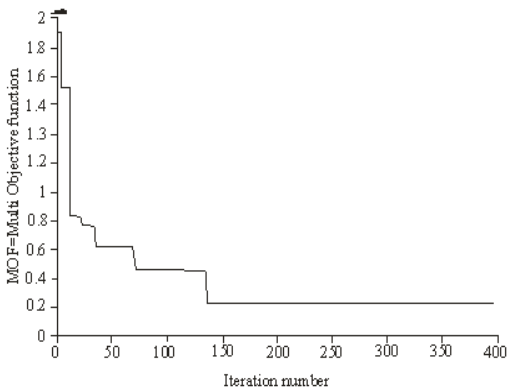

Fig. 2: Multiobjective function optimally minimized value versus iteration number

to identify the best location and size of DG. A complex Newton based load flow program is used to solve the load flow problem. The multiobjective function optimally minimized is shown in Fig. 2.

By using the method described here, the best location in 12 bus system, as listed in Table 1, is in the order 3, 6, 7 and 11 and corresponding optimal sizes are 437.21, 450.65, 477.00 and 513.07 KW for reducing power loss and reliability improvement. Simulation results show that the average energy not supplied with installing DGs reduces, so the reliability of system increases. By using the method described here, the best location in 12 bus system is in the order 3, 6, 7 and 11 and corresponding power loss are 200.2, 210.87, 230.45 and 240.45 KW, also corresponding average energy not supplied are 45.3, 54.7, 66.20 and 70.7 kwh/yr.

Figure 3 gives voltage profile of each bus in 12 bus radial system. The result shows the voltage level before and after installing DG. Before DG installation, voltage level from bus number 6-12 is lower than 0.92 p.u. After DG installation, the voltage levels of these buses are improved with minimum of 0.96 p.u. for bus number 8. Further more if multiple DGs are installed, voltage level will be higher than the previous levels.

As a result of the placement of DG units in the system, the short circuit level at most of the system buses

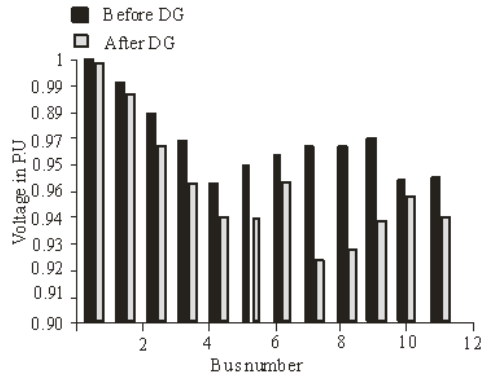

Fig. 3: Voltage profile before and after DG injection having optimum value

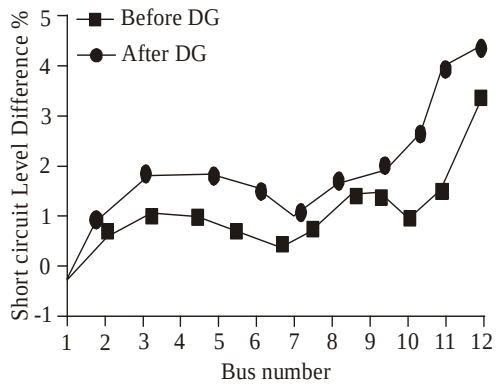

Fig. 4: The short circuit level difference of the system at each bus

was increased. Figure 4 shows the difference between the short circuit level at each bus of the system with and without DG as a percent of the value of short circuit level before placement of DG units in the system. As shown in figure, the maximum increase is very low where a maximum difference of 3.92% occurred at bus 4.

CONCLUSION

A PSO based distributed generator placement technique in a distribution system for reducing the total real power losses and improve system reliability in the system is presented in the paper. The PSO approach gives both optimal size and the locations as outputs. This study shows that the proper placement and size of DG units can have a significant impact on system loss reduction. It also shows how improper choice of size would lead to higher losses than the case without DG. However, in practice there will be many constraints to be considered in selecting the site. In this paper an objective function with aim to minimizing power loss and minimizing energy not supplied following fault is distribution system is considered and with PSO is optimized.

REFERENCES

Ault, G.W. and J.R. McDonald, 2000. Planning for distribution generation within distribution networks in restructuted electricity markets. IEEE Power Eng. Rev., 20: 52-54.

Baran, M.E. and F.F. Wu, 1989. Network reconfiguration in distribution systems for loss reduction. IEEE Trans. Power Delivery, 4(2): 1401-1407.

Caisheng, W. and M.H. Nehrir, 2004. Analytical approaches for optimal placement of distributed generation sources in power systems. IEEE Trans. Power Sys., 19(4): 27-34.

EI-hattam, W. and M.M.A. Salma, 2004. Distributed generation technologies, definitions and benefits. Electric. Power Sys. Res., 71: 119-1283.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley, Long man Publishing Co. Inc., Boston, MA, USA.

Graham, W., A. James and R. Mc-Donald, 2000. Optimal placement of distributed generation sources in power systems. IEEE Trans. Power Sys., 19(5): 127-134.

Keane, A. and M. O'Malley, 2005. Optimal allocation of embedded generation on distribution networks. IEEE Trans. Power Sys., 20(3): 1640-1646.

Kim, T.E., 2001a. A method for determinig the introduction limit of distributed generation system in distribution system. IEEE Trans. Power Delivery, 4(2): 100-117.

Kim, T.E., 2001b. Voltage regulation coordination of distributed generation system in distribution system. IEEE Trans. Power Delivery, 6(3): 1100-1117.

Mithulananthan, N., O. Than and L. Van-Phu, 2004. Distributed generator placement in power distribution system using PSO algorithm to reduce losses. Thammasat Int. J. Sc. Tech., 9(3): 55-62.

Rau, N.S. and Y.H. Wan, 1994. Optimal location of resources in distributed planning. IEEE Trans. Power Sys., 9: 2014-2020.

Takahashi, C., R.S. Rodney and M.N. Oriane, 2006. Electric distribution network multi objective design using a problem-specific genetic algorithm. IEEE Trans. Power Delivery, 21(2): 157-164.

Zareipour, H., K. Bhattacharya and C.A. Canizares, 2004. Distributed generation: Current status and challenges. IEEE Proce. NAPS, 21(2): 157-164.