Siting and Sizing of Distributed Generation for Loss Reduction

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***Abstract*— The introduction of distributed generation (DG) onto distribution networks has a significant effect on losses. This effect cannot be characterized as a detrimental or beneficial but is dependent on the allocation of DG on each distribution network. This paper proposes a new method to calculate the optimal size and to identify the corresponding optimal location for DG placement (allocation) for minimizing the total power losses in distribution networks. The proposed (presented) algorithm is an evolutionary algorithm named Particle Swarm Optimization (PSO). The method is implemented and tested on a sample distribution network. The results show the importance of placement of DGs for minimizing losses.**

***Index Terms*—Allocation, Compensation, Distribution Network, Distributed generation, Loss Reduction, PSO Algorithm, Short Circuit Level, Transmission Capacity.**

I. Introduction

DISPERSED or distributed generation (DG) maybe defined as a generating resource, other than central generation station, that is placed close to load being served, usually at customer site. It can be renewable source based micro hydro, wind turbines, photovoltaic, etc or fuel based fuel cells, reciprocating engines, micro turbines, etc. In term of size, DG may range from a few kilowatts to over 100 Mega watts [1].

The share of DGs in power system world wide is increasing and their contribution in the future power system is expected to be even more [2]. The general belief is that the future of the power generation will be DGs. DGs come with opportunities as well as challenges. They in one hand, are expected to be the solution of most of the power system problems while, on the other hand, they add new problems.

DG will affect the electric power system in wide range. These effects can be detrimental or beneficial depending on where DG units are allocated. The proper placement of DG units will reduce losses and will free available capacity for transmission of power. Moreover, cost savings can be expected by deferring distribution system upgrading. While, improper placement of DG units will increase losses significantly [3].

Losses are an important consideration when designing and planning the distribution network. Losses are inevitable in any network; however, the amount can vary considerably depending on the design of the network. The level of losses is closely linked to the power flows. Therefore, in a distribution network utilizing distributed generation the allocation of DGs provides an opportunity to ameliorate losses.
Hence, utilities and distribution companies need tools to place DG units in their distribution systems.

A number of approaches to allocate DGs for loss minimization have been proposed. In [3] the authors propose an algorithm for allocating DG units in order to maximize power available for sale and minimize losses on the system. In [4] an analytical method is proposed for DG allocation. In this method the authors have derived an equation so that solving it would determine amount of real power that DG units have to produce at various locations so as to minimize the real loss. Then, by comparing the losses by putting DG of corresponding optimum size at various locations the authors solve the placement problem.

In [5] a methodology for optimal allocation of DGs in distribution networks has been developed by the authors. Some of considered constraints were voltage rise, thermal limit, short circuit capacity and short circuit level. In [6] authors derived an objective function that represents the amount of generation demanded from or exported to the transmission system. Then a linear programming is employed to maximize the objective function with respect to some constraints such as thermal limit, short circuit level, voltage rise and transformer rating.

In this paper, a new method for solving the problem of siting and sizing of DGs in distribution networks is proposed. The algorithm is based on Particle Swarm Optimization (PSO) algorithm. Lying somewhere between evolutionary programming and genetic algorithms, PSO is an optimization paradigm that mimics the ability of human societies to process knowledge. It has roots in two main component methodologies: artificial life (such as bird flocking, fish schooling and swarming), and evolutionary computation. PSO

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algorithm, with capability to optimize complex numerical functions, is initially developed as a tool for modeling social behavior [7-8]. Moreover, it is recognized as an evolutionary technique under the domain of computational intelligence [9]. It has been observed that the behavior of the individuals that comprise a flock adheres to fundamental rules like nearest-neighbor velocity matching and acceleration by distance. PSO belongs to the broad class of stochastic optimization algorithms and is a population-based algorithm that exploits a population of individuals to probe promising regions of the search space [10]. In this paper PSO algorithm is applied for finding location of DGs for minimum loss in distribution networks.

The rest of this paper is organized as follows. Section II is devoted to exposition of losses in distribution networks. Section III presents the modeling of DG units. Then in section IV PSO algorithm is explained. Section V describes siting and sizing of DG units. Finally, in section VI, results of simulation are given.

II. Losses

The transmission of power will always incur certain amount of electrical losses. The integration of large amounts of DG is transforming distribution networks from what were traditionally energy delivery networks to networks that both deliver and harvest energy. A key element to the efficiency of this energy transmission is losses. The introduction of generation downstream will change the losses, with the losses initially decreasing until the load at the bus is met and then increasing as the excess power flows back up the line in the opposite direction [6].

The losses depend on the line resistance and currents are usually referred to as thermal losses. Therefore loss of any distribution system can be calculated as (1):

$$P_L = \sum_{j=1}^{m} R_j \left| I_j \right|^2 \qquad (1)$$

where

P_L is total system loss,

j is number of lines in the distribution network,

R_j is resistance of j^{th} line,

$\left| I_j \right|$ is absolute of j^{th} line current.

While the line resistances are fixed, the currents are a complex function of the system topology and the location of generation and load.

Consider the well-known power flow equations, with complex power $S_i = P_i + jQ_i$, injected at the bus i as

$$P_i = V_i \sum_{j=1}^{n} Y_{ij} V_j \cos\left(\delta_i - \delta_j - \gamma_{ij}\right) \qquad (2)$$

$$Q_i = V_i \sum_{j=1}^{n} Y_{ij} V_j \sin\left(\delta_i - \delta_j - \gamma_{ij}\right) \qquad (3)$$

where Y_{ij} is the magnitude of the $i-j^{th}$ element of the bus admittance matrix, V_i is the voltage magnitude at the i^{th} bus, γ_{ij} is the angle of the $i-j^{th}$ of the bus admittance matrix, and δ_i is the phase angle of the voltage V_i.

In this paper, only the real losses are considered. System losses can be calculated by subtracting total demand from total generation.

$$P_L = \sum_{i=1}^{n} P_{G_i} - \sum_{i=1}^{n} P_{D_i} \qquad (4)$$

In the above equation, P_L is the total loss of distribution system, P_{G_i} is generated power at i^{th} bus including distributed generations and P_{D_i} is demand at i^{th} bus. In this paper we use equation (4) to calculate system losses.

III. PSO Algorithm

PSO introduced by Kennedy and Eberhart [7] is one of the most recent and hopeful evolutionary metaheuristics which is inspired from the swarming behavior of and human social behavior. The general principles for the PSO algorithm are stated as below:

Similarly to evolutionary computation technique, the PSO maintains the population of particles, where each particle represents a potential solution to an optimization problem. Let K be the size of the swarm. Each particle i can be represented as an object with several characteristics.

Suppose that the search space is n-dimensional, then the i^{th} particle can be represented by a n-dimensional vector, $X_i = \left\{x_{i1}, x_{i2}, ..., x_{in}\right\}$, and velocity $V_i = \left\{v_{i1}, v_{i2}, ..., v_{in}\right\}$, where $i = 1, 2, ..., K$.

In PSO, particle i remembers the best position it visited so far, referred to as $P_i = \left\{p_{i1}, p_{i2}, ... p_{in}\right\}$, and the best position of the best particle in the swarm is referred as $G = \left\{G_1, G_2, ..., G_n\right\}$.

The PSO is similar to evolutionary computation algorithm and, in each generation t, particle i adjust its velocity v_{ij}^{t} and position x_{ij}^{t} through each dimension j by referring to, with random multipliers, the personal best position p_{ij}^{t-1} and the swarm's best position G_j^{t-1} using equations (5) and (6).

$$v_{ij}^{t} = v_{ij}^{t-1} + c_1 r_1 \left(p_{ij}^{t-1} - x_{ij}^{t-1}\right) + c_2 r_2 \left(G_j^{t-1} - x_{ij}^{t-1}\right), \qquad (5)$$

$$x_{ij}^{t} = x_{ij}^{t-1} + v_{ij}^{t} \qquad (6)$$

where c_1 and c_2 are the acceleration constants and r_1 and r_2

are random real numbers drawn from $U(0,1)$. Thus the particle flies through potential solutions toward P_i^t and G^t in a navigated way while still exploring new areas by the stochastic mechanism to escape from local optimum. Since there was no actual mechanism for controlling the velocity of a particle, it was necessary to impose a maximum value $V_{\max}$ on it. If the velocity exceeded this threshold, it was set equal $V_{\max}$, which controls the maximum travel distance in each iteration to avoid this particle flying past good solutions.

The PSO algorithm is terminated with a maximal number of generations or the best particle position of the entire swarm that cannot be improved further after a sufficiently large number of generations.

The aforementioned problem was addressed by incorporation a weight parameter for the previous velocity of the particle. Thus, equation (5) and (6) are changed to the following ones.

$$v_{ij}^t = \chi\left(\omega v_{ij}^{t-1} + c_1 r_1\left(p_{ij}^{t-1} - x_{ij}^{t-1}\right) + c_2 r_2\left(G_j^{t-1} - x_{ij}^{t-1}\right)\right) \quad (7)$$

$$x_{ij}^t = x_{ij}^{t-1} + v_{ij}^t \quad (8)$$

where ω is called inertia weight and is employed to control the impact of the previous history of velocities on the current one. Accordingly, the parameter ω regulates the trade-off between the global and the local exploration abilities of the swarm. A large inertia weight facilitates global exploration, while a small one tends to facilitate local exploration. A suitable value for the inertia weight ω usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iteration required to locate the optimum solution.

χ is a constriction factor which is used to limit velocity.

The PSO algorithm has shown its robustness and efficacy in solving function value optimization in real number spaces, only a few researches have been conducted for extending PSO to combinational optimization problems on the binary form.

IV. Modeling of DG units

DGs can be divided into two parts from the energy source viewpoint. One is non-renewable energy including cogeneration, fuel cells and micro turbine systems and the other is renewable energy including photovoltaic, wind, geothermal, biomass and so on [11].

A constraint for DG source, similar to central generation, is active power constraint. It can be formulated as below:

$$P_{g_{\min}} \le P_g \le P_{g_{MAX}} \quad (9)$$

The reactive power output of DG units is also important and must be considered. Small and medium sized DG units mostly use asynchronous generators that are not capable of providing reactive power. Several options are available to solve this problem. On the other hand, DG units with a power electronic interface are sometimes capable to deliver a certain amount of reactive power [12]. These interfaces (or power converters) can generate and inject Q to the network, but ratings of elements will increase [13]. The reactive power generation of DG units which use synchronous generators, depends on reactive power control strategy. There are two control strategies for this group [14]:

a. Constant Q/constant power factor mode.
b. Voltage regulated mode.

Considering this point, the bus connected to the DG can be modeled as a PQ or PV bus, depending on control strategy. In this paper, DG buses can be considered as a PQ or a PV bus.

V. Siting and Sizing of DG units

Distribution system planners need to have powerful tools for finding and identifying optimum size and location of DG resources in a given (existent) distribution networks. Because of some limitations in traditional procedures, experts have applied evolutionary algorithm to solve siting and sizing of DG units' problem. These evolutionary algorithm include Genetic Algorithm (GA) [15-17], Hereford Ranch Algorithms [18] or PSO.

In this study, PSO algorithm is used for finding optimum size and location of DG units. Every particle is a $1\times n$ vector representing an answer. Each particle conveys information on location and size of DG. The particle has 3 variables for each DG unit. First variable is number of bus that DG located there. The second one represents real power of each DG. The last one depends on the type of DG. If DG is modeled as a PQ bus, it indicates reactive power must be generated by DG. If DG is modeled as a PV bus, it shows voltage of bus DG is connected to. Length of each particle is dependent on number of DG units that must be located. For example if 2 DG units are located in network, length of each particle must be 6. A particle is shown for a DG modeled as a PV bus in Fig. 1.

Number of Bus	Real Power	Voltage

Fig. 1. a particle in PSO algorithm

The type of particle used is suitable for every kind of network structure (radial, meshed, etc.). But the algorithm has been applied to a radial distribution network, which are usual in Iran.

In the first step, after determination of number of DGs and maximum active and reactive power of each DG and model of DG (PV or PQ), an initial population of possible solutions is randomly generated. These random solutions must satisfy the constraints that will be discussed in Appendix. If an answer violates the constraints, it will be regenerated until the constraints are satisfied. Number of population in each generation is at least 5 times greater than total variables in problem. For instance, for a network with 3 DG units, total variable of network is 12 and minimum population is:

$$(4\times 3)\times 5 = 60 \quad (10)$$

At the second step, the power flow program calculates the total loss of system for each answer. Then the loss of each answer attribute to it as fitness. At the next step, PSO algorithm begins. At the end the best answer is introduced as optimum answer. PSO achieves the optimum point very fast and captures global optimum with high probability.

VI. Results and Discussion

A. Results

The structure of distribution network in Iran is radial or open loop MV ring. The medium voltage network is three-wire 20 kV. The 20 kV in HV/MV substation has been considered as slack bus and in the MV/LV substations and other nodes, the loads are modeled as a constant balanced PQ loads. The case study is an MV feeder with 11 buses (nodes) and 11 branches. It is assumed that the voltage of slack bus is 1.0 p.u. and 5% voltage deviation is permissible.

Based on the proposed method, optimum location of DG is bus 8 with real power 3.95 MW and reactive power 2.40 MVAR. Losses before DG allocation are 94.58 kW and after DG allocation it decreases until 8.88 kW.

Fig. 2 shows voltage profile of the network before and after DG allocation.

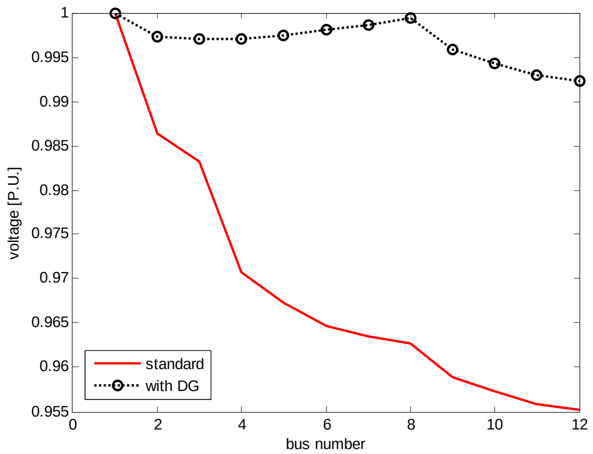

Fig. 2 voltage profile before and after DG allocation

In Fig. 3 the apparent power through lines of network is depicted.

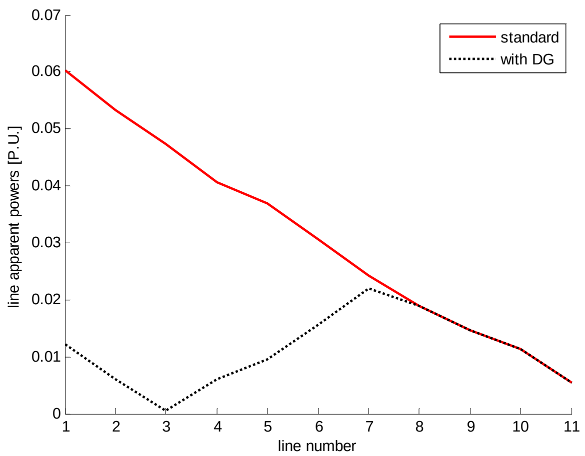

Fig. 3. apparent power of lines

The losses can be reduced 90.60% and the constraints are satisfied.

The proposed method is tested in another loop network that has 2 generators and 3 compensating capacitors. Originally this case is IEEE 14 bus that 20 branches. The total loss in base case is 13.39 MW. The optimum place for DG unit is at bus 3 with 139.63 MW and 58.62 MVAR. The total loss changes to 5.867 MW. Voltage profile of network after allocating DG unit is shown in Fig. 4.

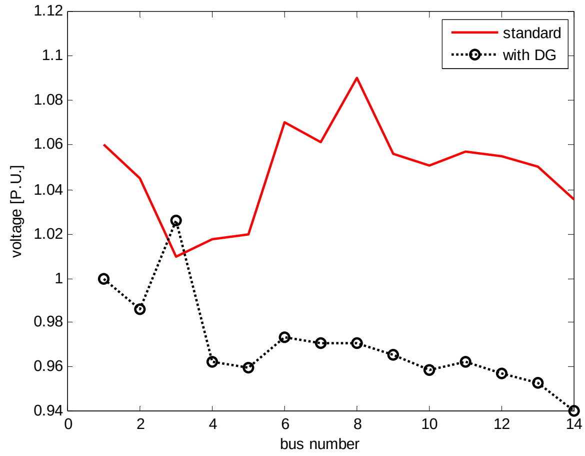

Fig. 4. voltage profile after installing DG unit

In Fig. 5 apparent power in lines is shown.

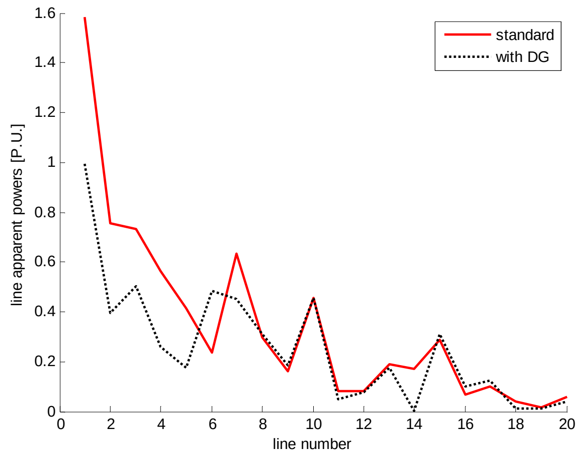

Fig. 5. apparent power in lines.

In Fig. 5, it is obvious that line apparent power in line 1 reduces because part of power is delivered by DG.

Short circuit level of buses is shown at Fig. 6. As could be seen, short circuit level increases due to installing DG units.

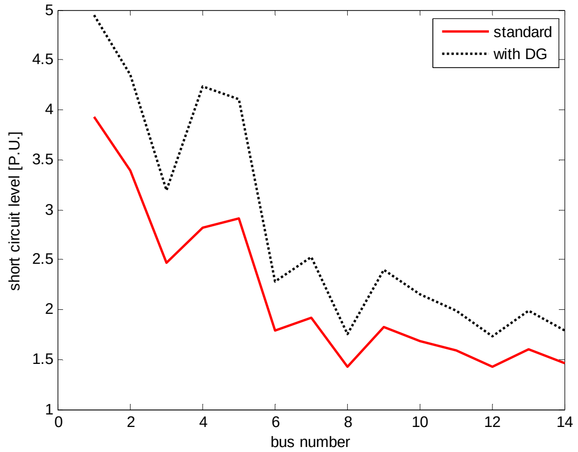

Fig. 6. short circuit level of network buses

It is noticeable in prepared computer program, in addition to DG allocation an option is considered for allocating capacitors. 3 capacitors and 1 DG have allocated in mentioned network. Losses are reduced to 4.973 MW. This shows reduction in losses approximately 65.85%. Results are briefly shown in table (1). Voltage profile of network is depicted in Fig. 7.

TABLE I
RESULTS FOR ALLOCATION OF 3 CAPACITORS AND 1 DG

	Bus	P	Q	V
DG	3	154	21	1.01
Capacitor	5	0	16.47	0.98
Capacitor	9	0	17	1.02
Capacitor	13	0	10	1.02

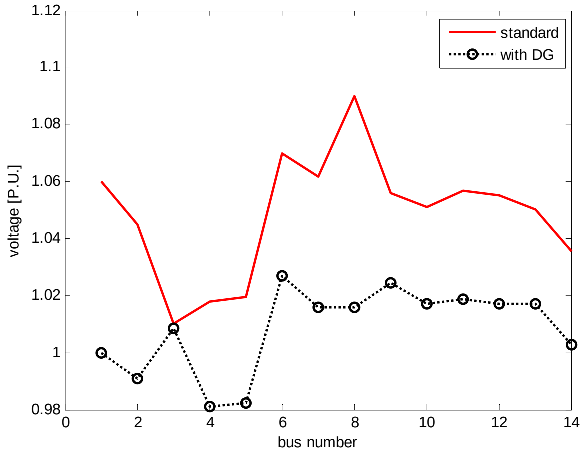

Fig. 7. voltage profile for sample network with 3 capacitor and 1 DG

Table I shows possible reduction of losses for proper allocation of DG units. Comparison between optimum case and original case shows that applied technique can results in considerable saving.

Trend of converging in proposed algorithm for 5 executions of program is presented in Fig. 8. From this figure, one can see a high convergence rate in the algorithm. This point is merit of PSO algorithm in suggested technique of this paper.

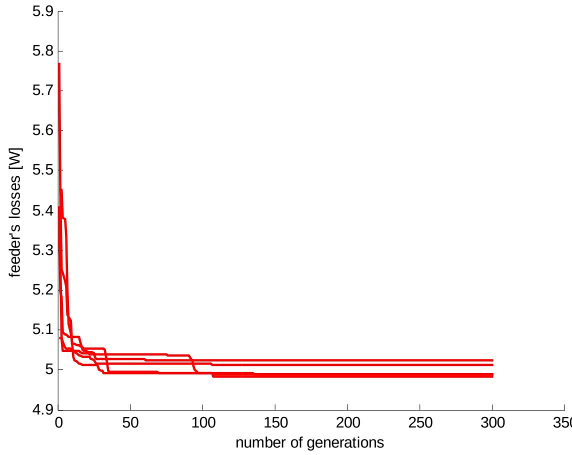

Fig. 8: trend of convergence in PSO algorithm for 5 executions

VII. CONCLUSION

Size and location of DG are crucial factors in the application of DG for loss minimization. This paper presents a new algorithm to calculate the optimum size of DG and find the best location corresponding to the optimum size for reducing total power losses in primary distribution network. In this paper, PSO is used as optimization algorithm. This algorithm has enough ability to solve the problem accurate and fast with the view of minimizing total losses. The paper considers technical constraints in DG siting and sizing. As a result, it is shown that used technique can allocate and find size of DG units to reduce losses significantly. In radial networks proposed algorithm can reduce losses by 90% and in loop network the losses can be reduced to 66%.

VIII. APPENDIX

A. Thermal Constraint:

$$S_i \prec S_i^{Rated} \qquad i \; \forall \; N$$

where S_i is the apparent power flowing through line i, S_i^{Rated} is the maximum apparent power for line i. N is number of branches in distribution network.

B. Voltage Limit:

$$0.94 \le V_j \le 1.06 \;\; p.u. \qquad j \; \forall \; M$$

where V_j is voltage of j^{th} bus. 6% deviation is allowed. M is number of buses in the network.

C. Short Circuit Level

$$\frac{MVA_{Base}}{Z_{jj}} = SCL_j \le SCL_{MAX} \qquad j \; \forall \; M$$

where MVA_{Base} is base apparent power in network. Z_{jj} is the element which is located on row j^{th} and column j^{th} of Z_{bus} matrix. SCL_j is short circuit level of j^{th} bus and SCL_{MAX} is maximum allowed short circuit level in distribution network.

D. Back Power Flow

$$\sum P_{DG} \leq \sum_{j=1}^{M} P_{L_j}$$

where $\sum P_{DG}$ is total active power generated by distributed generation allocated in distribution network and $\sum_{j=1}^{M} P_{L_j}$ is total load in system. This constraint checks that the power always flow from upper network to lower network. Violation of this constraint will result in protection malfunctions.

IX. References

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