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PSO-Based Planning of Distribution Systems with Distributed Generations

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***Abstract*—**This paper presents a multi-objective formulation for optimal siting and sizing of distributed generation (DG) resources in distribution systems in order to minimize the cost of power losses and energy not supplied. The implemented technique is based on particle swarm optimization (PSO) and weight method that employed to obtain the best compromise between these costs. Simulation results on 33-bus distribution test system are presented to demonstrate the effectiveness of the proposed procedure.

***Keywords*—**Distributed generation, distribution networks, particle swarm optimization, reliability, weight method

I. Introduction

For many years, the distribution system has been planned, built and operated always in the same way. But in the last decade, the first signs of changes have appeared due to the liberalization of the electricity market, the governmental drive to reduce number and duration of long interruption and the growing presence of DG. In particular, if DG penetration reaches a high level, as predicted by many authors, distribution utilities will probably have to dismiss the traditional radial network operation, adopting a more flexible meshed structure. If DG is properly planned and operated, it may provide benefits to distribution networks (e.g., reduction of power losses, capacity saving, reliability and power quality improvement). The effect of adding DG on network indices will vary depending on its type and position and (forecast) load at the connection point. Consequently, one or more sites on a given network may be optimal.

There are many methods available for DG planning. Most of them has been considered only one objective function. [1] Presents an algorithm to determine the near optimal, with respect to system losses, placement of these units on the power grid. Further, the impacts of dispersed generation at the distribution level are performed with an emphasis on resistive losses, and capacity savings.

[2] proposed a strategic DG placement method to enhance the reliability and obtain the benefits for DG placement. [3] formulates and discusses a methodology for the optimal siting of distributed generators and reclosers, a security and reliability constrained distribution network can accept. Optimal siting is determined by sensitivity analysis of the power flow equations. The sizing method for a set of loading conditions, generation penetration level and power factor is formulated as a security constrained optimization problem. [4] minimizes the cost of active and reactive power generation based on GA and optimal power flow calculations. [5] presents a technique for assisting network planers determine the optimum rating and position of dispersed generators in an established distribution network, considering practical objectives and constraints over a number of planning years. The objectives considered were: the minimization of system losses, the minimization of disruption to the existing network, the minimization of costs and the maximization of the rating of the dispersed generators. The tool exploits conventional techniques in assessing the constraints imposed by the network, subsequently using Particle Swarm Optimization to provide an optimization of the decision making process.

In this paper, a PSO based multi-objective (MO) formulation is proposed to optimize cost of power losses and energy not supplied simultaneously. Then, a global non-inferior solution for MO problem is achieved by means of Genetic Algorithm. In a next stage, by using weight method, a set of non-inferior solutions can be produced with an iterative procedure in order to find the most compromised solution.

II. Multi-objective Programming

Recently, the liberalization of electric energy markets has brought important changes in the economic and technical aspects of power system planning and operation; the grids have to be managed according to new principles but taking into account the technical constraints. Therefore, it is necessary to change the methodologies and the algorithms used for the power system optimization. In particular, new tools that allow managing the system, complying with the rules of the electric market, must be available. The new scenario forces a change in the duties and objectives of the traditional planning and it compels to take into account several objectives that are likely to be in mutual conflict. The MO methodologies give a different solution that obtained by standard optimization methods. First of all, their intermediate results are not unique, but provide an infinite set of optimal solutions called Pareto set. Each point belonging to the Pareto set has an important characteristic: The improvement in one of the objectives results in the worsening of at least another objective. The general formulation of a MO problem is expressed by:

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$$\begin{aligned}&\min \quad [\, f_1(x),\ f_2(x),\ldots,\ f_m(x)]^T\\ &x \in \Omega\\ &g_j(x) = 0 \qquad j = 1,\ldots,\ n\\ &h_k(x) \le 0 \qquad k = 1,\ldots,\ p\end{aligned} \tag{1}$$

Where x represents a decision vector, f_i is the i_{th} objective function, Ω is the domain of solutions, g_j and h_k are the equality end inequality constraints, respectively.

Therefore, to solve a MO problem it is necessary to follow these steps: a) define the useful objectives; b) find the Pareto set and c) choose a solution from Pareto set. Step c) is the most important, because the final solution depends on the point of view of the decision maker who has to take into account the relative importance of the conflicting objectives. There are various techniques for generating non-inferior solutions (Non-inferiority means that improvements in one objective are attained only at the cost of some sacrifice in the other objective functions). The method presented and used in this paper is the Weight Method. It transforms the MO optimization problem into a traditional problem: the different objective functions are weighted and added to form a single objective function to be optimized. The optimization problem can be defined as follows:

$$\min \sum_{i=1}^{k} w_i f_i(\bar{x}) \tag{2}$$

Where $w_i \ge 0$ are the weighting coefficients representing the relative importance of the objectives. It is usually assumed that

$$\sum_{i=1}^{k} w_i = 1 \tag{3}$$

The main strength of this method is its efficiency (computationally speaking) and its suitability to generate a strongly non-dominated solution that can be used as an initial solution for other techniques [6].

III. Problem Formulation

The main goal of this paper is to determine optimal locations and sizes for new generators by minimizing the cost of energy losses and cost of energy not supplied subject to bus voltages limits, DG power limit, short circuit currents and network power flow equations.

In the following, each cost function is described in detail under the assumption of a linear load growth during the whole planning period.

A. Cost of Energy Losses (CL)

The losses of distribution system depend on the line resistance and currents and are usually referred to as thermal losses. While the line resistances are fixed, the currents are a complex function of the system topology and the location of generation and load.

In this work, only the real power injections as they relate to distribution losses are of concern. The system losses at the beginning of the planning period can be expressed as

$$P_{0L} = \sum_{i=1}^{n} P_{G_i} - \sum_{i=1}^{n} P_{D_i} \tag{4}$$

Where P_{0L} is the real power loss, P_{Gi} is the real power generated at the i_{th} bus, P_{Di} is the real power required at the i_{th} bus. All of the above parameters are calculated by power flow program. The net present value of the power losses cost in the whole planning period can be calculated as follows:

$$\begin{aligned}&C_L = 8760 \times U_E \times \sum_{h=1}^{Ny} B^h . P_{0L} .(1+\gamma)^h\\ &B = \frac{1+f}{1+\mu}\end{aligned} \tag{5}$$

Where B is a economic factor for converting costs to present value, f and μ are inflation and interest rate respectively, γ is a load growth rate per year, U_E is cost of energy($/kWh) and N_y is planning period. In eq. (5) it has been assumed that DG units operate 24 h/day at their rated power. That's why coefficient of 24*365=8760 h/year has been used.

B. Cost of Energy Not Supplied (CENS)

In order to calculate the cost of energy not supplied the duration of a branch fault is usually divided into two phases: fault location and fault repair. Automatic sectionalizers and reclosers can restrict the area of influence of a fault, reducing the number of customers affected by long-term interruptions during the fault location phase. In this stage, intentional islanding may be used to supply unfaulted portions of the network automatically separated from the faulted section. The repair stage consists of the time required to isolate the faulted branch, connect any emergency ties and repair the fault. DG, enabling power to be restored to the nodes downstream the sectionalized branch, can lead to significant reliability improvements. Load flow studies should be performed to check that voltages and currents are within their operative ranges and that DG units have a sufficient probability to pick up the loads in the islanded network. Equation (6) gives the cost of energy not supplied of the j_{th} network branch.

$$C_{0aj} = 8760 \times U_E \lambda_j L_j \times (\sum_{i=1}^{Nloc} P_{0i} . t_{loc} + \sum_{i=1}^{Nrep} P_{0i} . t_{rep}) \tag{6}$$

Where λ_j is the branch fault rate (number of faults per year and km of feeder), L_j is the branch length (km), N_{loc} and N_{rep} are the number of nodes isolated during the fault location and repair stages, respectively, P_{0i} is the node power (kW) at the beginning of the planning period, and t_{loc} and t_{rep} are the durations of the fault location and repair stages (h), respectively.

The net present value of the cost of energy not supplied due to a fault in the j_{th} branch during the planning period is calculated with the following expression:

$$C_{ENS\,j} = \sum_{h=1}^{Ny} C_{0a\,j} \times (1+\gamma)^h \times B^h \qquad (7)$$

The cost of energy not supplied (C_{ENS}) is then obtained as the sum of the $C_{ENS\ j}$ for each branch in the whole planning period.

C. Problem Constraints

Two above objectives were subject to the following constraints:

1. The network voltage levels should be held within specified limits.
2. The short circuit limitations of network plant needed to be respected.
3. DG real and reactive power capabilities needed to be respected.

These are represented by the following equations:

$$\begin{aligned}
&V_{\min} \le V_i^n \le V_{\max} \quad n = 1,\dots,N\\
&S_{\min}^b \le S_i^b \le S_{\max}^b \quad b = 1,\dots,B\\
&P_{DG\min}^k \le P_{DGi}^k \le P_{DG\max}^k \quad k = 1,\dots,K\\
&Q_{DG\min}^k \le Q_{DGi}^k \le Q_{DG\max}^k \quad k = 1,\dots,K
\end{aligned} \qquad (8)$$

Where N is the number of nodes in the network, K is the number of DG units and B is the number of branches (transformers and lines), V_i is the node voltage in year i, $P^k{}_{gi}$ and $Q^K{}_{gi}$ are real and reactive power generated by generator k in year i respectively and $S^b{}_i$ is the apparent power flowing in branch b in year i.

IV. PSO Implementation

In this paper, a PSO optimization technique has been used for finding the non-inferior solutions of the MO optimization algorithm.

The particle swarm optimization (PSO) algorithm was first proposed by Kennedy and Eberhart [7], and had exhibited many successful applications, ranging from evolving weights and structure for artificial neural networks [8], manufacture end milling [9], reactive power and voltage control [10], to state estimation for electric power distribution systems [11]. The convergence and parameterization aspects of the PSO have also been discussed thoroughly [12]. The PSO is inspired by the observations for bird flocking and fish schooling. A number of birds/fishes flock synchronously, change direction suddenly, and scatter and regroup together. Each individual, called a particle, benefits from the historical experience of its own and that of the other members of the swarm during the search for food. The PSO models the social dynamics of birds/fishes and serves as an optimizer for nonlinear functions.

The PSO proceeds as follows. Given an optimization function f(P) where P is a vector of n real-valued random variables, a swarm of particles is generated at random for targeting the optimum solution P*. Each particle is represented as Pi = (pi1,pi2, . . . ,pin), i = 1,2, . . . ,S, where S is the swarm size. The particle is a candidate solution in the n-dimensional real number space and iteratively moves in the problem space. The PSO enriches the swarm intelligence by storing the best solutions seen by every particle. In particular, particle i remembers the best position it visited so far, referred to as pbesti, and the best position by its neighbors. There are two versions for defining the neighbors' best position, namely lbest and gbest. In the local version, each particle keeps track of the best position lbest attained by the particles within its topological neighborhood. For the global version, the best position gbest is determined by any particles in the entire swarm. Hence, the gbest model is a special case of the lbest model. The PSO is an iterative evolutionary algorithm. At each iteration, particle i adjusts its velocity v_{ij} and position p_{ij} through each dimension j by referring to the personal best position ($pbest_{ij}$) and the swarm's best position ($gbest_j$, if the global version is adopted) using Eqs. (4) and (5) as follows:

$$v_{ij} = k(v_{ij} + c_1 r_1 (pbest_{ij} - p_{ij}) + c_2 r_2 (gbest - p_{ij}))$$

and

$$p_{ij} = p_{ij} + v_{ij}$$

where c1 and c2 are the acceleration constants, r1 and r2 are random real numbers drawn from U(0, 1), and K is the constriction factor. Clerc and Kennedy [12] has pointed out that the use of a constriction factor is needed to insure convergence of the PSO, and it is determined by

$$k = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}$$

where $\varphi = c_1 + c_2 \succ 4$ .Typically, φ is set to 4.1 and k is thus 0.729.

As such, the particle flies through candidate solutions toward $pbest_i$ and *gbest* in a navigated way while still could explore new potential solutions by the random multipliers to escape from local optima. The PSO algorithm is terminated with a maximal number of iterations or the best particle position of the entire swarm cannot be improved further after a sufficiently large number of iterations.

If the network structure is fixed, all the branches between nodes are known, and the evaluation of the objective functions described above depend only on the size and location of DG units. For this reason two control variables were identified for each solution vector. These were the position and size of DG units. A node chosen for installation of a generator was treated as a PV bus, thus the node active power and voltage values had to be specified within their specified limits.

The fitness function was derived from the objective function by transforming it so that the minimization problem became a maximization problem. The following transformation was used:

$$\begin{aligned} &Min = C \\ &C = w_1 C_L + w_2 C_{ENS} \end{aligned} \tag{9}$$

Where C is weighted sum of C_L and C_{ENS}.

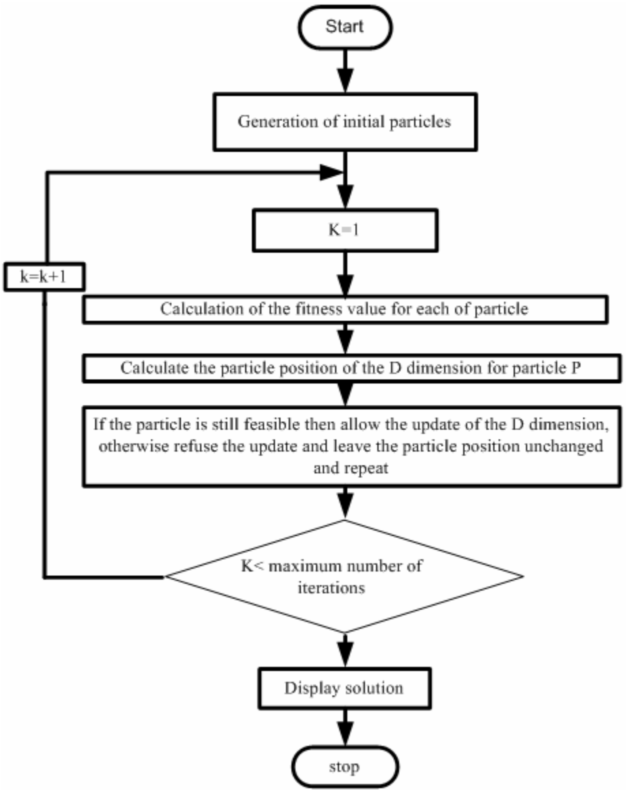

Fig. 1 Optimization process block diagram in sizing and placement of DG units

The block diagram of the described MO optimization algorithm is depicted in Figure 1.

V. Results and Discussion

In order to show the capability of the proposed algorithm to solve the problem of the optimal DG allocation, a 33 bus distribution test system has been considered. A fast decoupled power flow program for radial distribution systems has been developed and used for simulation of proposed method [13]. The period taken into consideration for the planning study is 10 years long, with all nodes existing at the beginning of the period. For each node a constant power demand growth rate of 5% per year has been assumed. The inflation and interest rate has been considered 7% and 10% respectively. The cost of energy has been assumed 4.2 ¢/kWh.

The total cost of the network during the assigned study period is equal to k$486.5 (see Table I.) without any operating DG. Such a high generalized network cost is due to the significant growth rate of the demand, which requires the enforcement of a large number of branches. The attempt to minimize the global cost has led to a solution with many lines operate close to their maximum capacity and for this reason the cost of the energy losses counts for a significant percentage of the generalized cost of the network. The use of DG as an electric supply option can reduce both costs.

Very often the planner needs more alternatives to evaluate and sometimes he can prefer to reduce the cost of losses instead of improving service quality, depending on strategic decisions, regulatory directives regarding the electric service, and budget restrictions. As showed in the following examples, the proposed MO optimization process permits of finding out alternative configurations, characterized by different costs for each single function constituent of the global cost. In each optimization stage the MO algorithm looks for alternative solutions according to weighting coefficient of objective functions.

Three cases with different weighting coefficients have been investigated. In the first case study (see Table II. and Table III.), the power losses cost has been regarded and a larger weighting coefficient has been given to it. The value assumed by the cost of the power losses in the initial network configuration is equal to k$227.4. Three consecutive steps of iteration have been run. In the first iteration, the power losses cost and energy not supplied cost reduced in percentage of the 23% and 5.3% respectively. The total cost also reduced 13.6%. This cost reduction is obtained resorting to a DG penetration level (DG% is the ratio between the DG capacity and the power of load) of 15.98%. In the second iteration, the cost of C_L decreases from the value of k$175.1 to the value of k$152.5. The penetration level of DG increases from the value of the 15.98% to the value of 26.67%. Finally, in the third iteration a new optimal solution has been achieved and C_L decreases to k$138.7 with DG penetration level of 37.34%.

In the second case study, the cost of service interruptions C_{ENS} has been regarded with larger weighting coefficient. In this case the planner aims at reducing the number and the duration of service interruptions by positioning DG in suited locations. Even though many standards and almost all the distributors do not generally allow resorting to "intentional islanding" operation, in order to emphasize the effect of DG it has been hypothesized that this practice can take place. In the proposed example, the capability of optimizing the location of DG has been advantageously used to find a network arrangement able to give the customers a much more reliable service avoiding the construction of new emergency ties.

The starting network configuration is equal to the previous case study, where the C_{ENS} cost has the value of k$259.1. With the first optimization step this value is reduced to k$198.6 (see Table IV. and Table V). A further optimization permits reducing C_{ENS} up to k$169.3 thanks to a new allocation of DG. It is worth noticing that in this case generators are located at the end of long and heavy loaded lateral edges to serve as back up energy sources during upstream faults. Global benefits on energy not supplied and cost of not supplied energy are clearly recognizable, but benefits are much more significant for those customers that suffer for poor quality due to their position in the network.

In the third case, the weighting coefficient for both of costs has been considered the same and equal to 0.5. The results of optimization process were represented in Table VI. and Table VII.

TABLE I
COST OF DISTRIBUTION NETWORK BEFORE DG INSTALLATION

C_L(k$)	C_{ENS} (k$)	C_{TOT} (k$)
227.4	259.1	486.5

TABLE II
COST PROGRESSION IN MO ITERATIVE PROCEDURE (CASE 1)

W_1=0.75 ,W_2=0.25			
Iteration No.	C_L(k$)	C_{ENS} (k$)	C_{TOT} (k$)
1	175.1	245.2	420.3
2	152.5	230.4	382.9
3	138.7	221.5	360.2

TABLE III
DG LOCATION AND DG% (CASE 1)

Iteration No.	DG Location (Bus No.)	DG (%)
1	8,31	15.98
2	24,25	26.67
3	8,24,31	37.34

TABLE IV
COST PROGRESSION IN MO ITERATIVE PROCEDURE (CASE 2)

W_1=0.25 ,W_2=0.75			
Iteration No.	C_L(k$)	C_{ENS} (k$)	C_{TOT} (k$)
1	220.8	198.6	419.4
2	205.5	180.2	385.7
3	198.2	169.3	367.5

TABLE V
DG LOCATION AND DG% (CASE 2)

Iteration No.	DG Location (Bus No.)	DG (%)
1	8,14	24.89
2	8,30,32	30.23
3	7,8,30,32	40.9

TABLE VI
. COST PROGRESSION IN MO ITERATIVE PROCEDURE (CASE 3)

W_1=0.5 ,W_2=0.5			
Iteration No.	C_L(k$)	C_{ENS} (k$)	C_{TOT} (k$)
1	208.3	240.7	449
2	194.9	230.6	425.5
3	183.9	213.2	397.1

TABLE VII
DG LOCATION AND DG% (CASE 3)

Iteration No.	DG Location (Bus No.)	DG (%)
1	8,32	14.22
2	8,25	24.89
3	8,24,25	33.78

VI. CONCLUSIONS

The values of Distributed Generation are very dependent on its type, size and location as it was installed in distribution feeders. Hence, a PSO based multi-objective optimization for siting and sizing of distributed generation resources in distribution systems has been performed in order to minimize the cost of power losses and energy not supplied. Simulation results on 33-bus distribution test system have been presented for three case studies. The results show 25.96%, 24.46% and 18.37% reduction on total cost for case1, case2 and case3, respectively.

APPENDIX

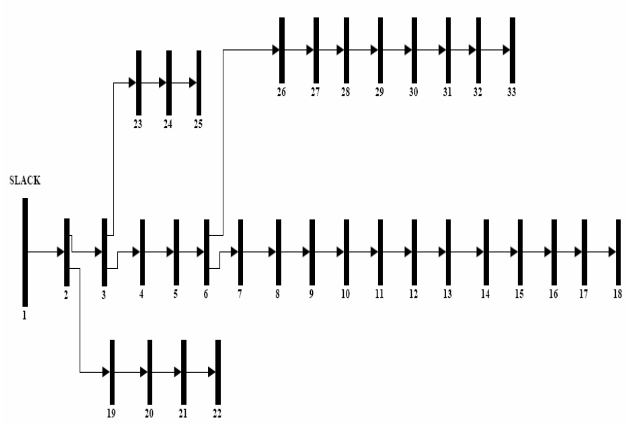

Fig. 2 The 33-bus radial distribution test system diagram

TABLE VIII
LINE LENGTH FOR 33-BUS TEST SYSTEM

Line No.	Length (km)	Line No.	Length (km)	Line No.	Length (km)
1	0.103	12	0.125	23	0.650
2	0.350	13	0.427	24	0.641
3	0.335	14	0.452	25	0.270
4	0.279	15	0.457	26	0.390
5	0.134	16	0.245	27	0.194
6	0.560	17	0.300	28	0.449
7	0.540	18	0.120	29	0.304
8	0.453	19	0.224	30	0.496
9	0.510	20	0.512	31	0.187
10	0.306	21	0.423	32	0.192
11	0.200	22	0.198	-	-

TABLE X
LOAD AND LINE DATA FOR TEST SYSTEM BEFORE DG INSTALLATION

Parameter	Overhead Lines
λ	1.2 $(\text{year.km})^{-1}$
t_{loc}	2 h
t_{rep}	6 h

TABLE IX
DATA USED FOR RELIABILITY CALCULATION

Sending Bus	Receiving Bus	R (Ω)	X (Ω)	Load at Receiving Bus	
				P (kW)	Q (kVAr)
1	2	0.0922	0.0477	100	60
2	3	0.4930	0.2511	90	40
3	4	0.3660	0.1864	120	80
4	5	0.3811	0.1941	60	30
5	6	0.8190	0.7070	60	20
6	7	0.1872	0.6188	200	100
7	8	1.7114	1.2351	200	100
8	9	1.0300	0.7400	60	20
9	10	1.0400	0.7400	60	20
10	11	0.1966	0.0650	45	30
11	12	0.3744	0.1238	60	35
12	13	1.4680	1.1550	60	35
13	14	0.5416	0.7129	120	80
14	15	0.5910	0.5260	60	10
15	16	0.7463	0.5450	60	20
16	17	1.2890	1.7210	60	20
17	18	0.7320	0.5740	90	40
2	19	0.1640	0.1565	90	40
19	20	1.5042	1.3554	90	40
20	21	0.4095	0.4784	90	40
21	22	0.7089	0.9373	90	40
3	23	0.4512	0.3083	90	50
23	24	0.8980	0.7091	520	200
24	25	0.6960	0.7011	320	200
6	26	0.2030	0.1034	60	25
26	27	0.2842	0.1447	60	25
27	28	1.0590	0.9337	60	20
28	29	0.8042	0.7006	120	70
29	30	0.5075	0.2585	200	600
30	31	0.9744	0.9630	250	70
31	32	0.3105	0.3619	210	100
32	33	0.3410	0.5302	60	40

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