Australian Journal of Basic and Applied Sciences, 5(5): 635-641, 2011
ISSN 1991-8178

Optimal DG Allocation in Distribution Network Using A New Heuristic Method

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Abstract: This paper shows the results obtained in the analysis of the impact of Distributed Generation (DG) on distribution losses and presents a new algorithm to the optimal allocation of distributed generation resources in distribution networks. The optimization is based on a Shuffled Frog Leaping Algorithm (SFLA) aiming to optimal DG allocation in distribution network. Shuffled frog-leaping algorithm (SFLA) is a new memetic meta-heuristic algorithm with efficient mathematical function and global search capability. Through this algorithm a significant improvement in the optimization goal is achieved. The objective function is tested on the IEEE 34-bus and 69-bus system. With a numerical example the superiority of the proposed algorithm is demonstrated in comparison with the simple genetic algorithm.

Key words: Distributed Generation, Distribution Networks, Shuffled Frog Leaping Algorithm (SFLA), Genetic Algorithm,

INTRODUCTION

Nowadays the Distributed Generation (DG) is taking more relevance and it is anticipated that in the future it will have an important role in electric power systems. DG includes the application of small generators, scattered throughout a power system, to provide the electricity service required by the customers. DG can be powered by both conventional and renewable energy sources (H.L ,Willis, *et al*. 2000). Several DG options are fast becoming economically viable (R. C. Dugan, *et al*. 2002). Technologies of the DG allocation can be obtained by a complete enumeration of all feasible combinations of sites and sizes of DGs in the network. The artificial intelligence techniques are the most widely employed tool for solving most of the optimization problems. These methods (e.g. genetic algorithm, simulated annealing and tabu search) seem to be promising and are still evolving. The publications are on the DG allocation by application of genetic algorithm (GA) (G. Celli, & F. Pillo. 2001). Tabu Search (TS) algorithm is used for the DG allocation in distribution systems (K. Nara, *et al*. 2001). Analytical approaches minimizing line losses were also utilized for the DG allocation as provided in (C. Wang , *et al*. 2004). In (A. Keane, *et al*. 2005), the authors have integrated DG in distribution systems using power systems studies coupled with linear programming method. Analyzing these studies, the consideration of uncertainty in the DG allocation in distribution systems is neglected. Papers (L. F. Ochoa, *et al*. 2005)-(G. Celli, *et al*. 2005) utilized evolutionary programming for identifying the placement of DG in distribution systems. Shuffled frog leaping algorithm (SFLA) is a memetic meta-heuristic that is based on evolution of memes carried by interactive individuals and a global exchange of information among the frog population. It combines the advantages of the genetic-based memetic algorithm (MA) and the social behavior-based PSO algorithm with such characteristics as simple concept, fewer parameters adjustment, prompt formation, great capability in global search and easy implementation. Shuffled Frog Leaping Algorithm (SFLA) for evaluation of the DG site and size in MV networks is proposed. The SFLA is employed for the DG allocation. The results showed that the proposed method is better than the simple GA in terms of the solution quality and number of iteration.

Distributed generation:

Distributed generation is expected to become more important in the future generation system. In general, DG can be defined as electric power generation within the distribution networks or on the customer side of the network. A wide variety of DG technologies and types exists: renewable energy source such as wind turbines, photovoltaic, micro-turbines, fuel cells, and storage energy devices such as batteries. The importance of the DG is now being increasingly accepted and realized by power engineers. From the distribution system planning point of view, DG is a feasible alternative for new capacity, especially in the competitive electricity

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market environment and has immense benefit such as (N. Hadisaid, *et al*. 1999):
- Short lead-time and low investment risk since it is built in modules.
- Small-capacity modules that can track load variation more closely.
- Small physical size that can be installed at load centers and does not need government approval or search for utility territory and land availability.
- Existence of a vast range of the DG technologies for these reasons, the first signs of a possible technological change are beginning to arise on the international scene, which could involve in the future the presence of a consistently generation produced with small and medium size plants directly connected to the distribution network (LV and MV) and characterized by good efficiencies and low emissions. This will create new problems and probably the need of new tools and managing these systems.

Problem Formulation:
Iii.1. Objective Function:

The problem is to determine allocation and size of the DGs which minimizes the distribution power losses for a fixed number of DGs and specific total capacity of the DGs. Therefore, the following assumptions are employed in this formulation (J.O. Kim, *et al*. 1997):
- The maximum number of installable DGs is given (D) .
- The total installation capacity of the DGs is given (Q) .
- The possible locations for the DG installation are given for each feeder.
- The upper and lower limits of node voltages are given.
- The current capacities of the conductors are given.

The objective function in this optimization problem is:

$$OF = \sum_{i=1}^{n} P_i \tag{1}$$

Where, P_i is the nodal injected power at bus i, and n is the total number of buses.

If the total injected power of distributed generation was constant as C MW, this equality constraint should be expressed in form of a penalty function as shown (J.O. Kim, *et al*. 1997).

$$OF = \sum_{i=1}^{n} P_i + \alpha(\sum_{K=1}^{L} P_k - C) \tag{2}$$

Iii.2. Constraints:

1. Maximum number of DGs:

$$\begin{aligned} &\Delta V \\ &I_i \le I_i^{\max} \\ &(k = 1,2,...,L, l = 1,2,...,M, g = 1,2,...,N) \\ &P_k \\ &G_g \\ &l^{th} \\ &n_{gl} \end{aligned} \tag{3}$$

2. Total capacity of DGs:

$$\sum_{l=1}^{M} \sum_{g=1}^{N} G_g n_{gl} \le Q \tag{4}$$

3. One DG per installation position:

$$\sum_{g=1}^{N} n_{gl} \le 1 \sum_{g=1}^{N} n_{gl} \le 1 \tag{5}$$

4. Upper and lower voltage limits:

$$V_i \le V_n \pm \Delta V \tag{6}$$

5. Current capacity limits:

$$\begin{aligned} & I_i \le I_i^{\max} \\ & (k = 1, 2, ..., L, l = 1, 2, ..., M, g = 1, 2, ..., N) \end{aligned} \tag{7}$$

Where,
P_i : Nodal injection of power at bus i,
P_k : Load power of bus k,
V_i : Magnitude of voltage of bus i,
V_n : Nominal magnitude of voltage in the network,
G_g : Capacity of g^{th} DG,
n_{gl} : 0-1 variable for determining whether one DG with g^{th} capacity is allocated at l^{th} location (1: allocated, 0: not allocated),
L : Total number of load buses,
M : Total number of DG location candidates,
N : Total number of capacity types of DGs,
Q : Total installation capacity of DGs,
D : Maximum number of installable DGs,
α : Penalty weight of equality constraint,
C : Total injected dispersed generation for network,
ΔV : Maximum permissible voltage deviation,
I_i : Current of section i,

$I_i^{\max}$: Maximum current capacity of section i.

Shuffled Frog Leaping Algorithm (SFLA):

The shuffled frog leaping algorithm (SFLA) (M. M. Eusuff, *et al*. 2006) is a metaheuristic optimization method inspired from the memetic evolution of a group of frogs when seeking for food. The SFLA draws its formulation from two other search techniques: the local search of the 'particle swarm optimization' technique; and the competitiveness mixing of information of the 'shuffled complex evolution' technique. This combined strategy enables a SFLA to search for a suboptimal solution and to avoid local extremes. The SFLAs have been used to solve discrete as well as continuous optimization problems. Eusuff and Lansey (M. M. Eusuff, *et al*. 2006) used a SFLA for determining optimal discrete pipe sizes for new pipe networks and for network expansions. Amiri *et al*. (Amiri, M, *et al*. 2007) proposed an application of SFLA on data clustering. In (M. M. Eusuff, *et al*. 2006), the authors proposed a hybrid multi-objective algorithm based on SFLA and bacteria optimization to solve a mixed-model assembly line sequencing problem. Elbeltagi *et al*. (A. Rahimi-Vahed, *et al*. 2007) compared SFLA to other evolutionary-based algorithms such as genetic algorithms (GA), memetic algorithms (MA), particle swarm optimization (PSO), and ant-colony optimization (ACO). The comparison reveals that the SFLA is a relatively good optimization technique. It has similar performance as PSO and outperforms GA in term of success rate, solution quality and processing time. The SFLA is thus a promising approach for optimal tuning of controller parameters, in general, and multivariable PID controller gains, in particular. The SFLA involves a population of possible solutions defined by a set of virtual frogs that is partitioned into subsets referred to as memeplexes. Within each memeplex, the individual frog holds ideas that can be influenced by the ideas of other frogs, and the ideas can evolve through a process of memetic evolution. The SFLA performs simultaneously an independent local search in each memeplex using a particle swarm optimization like method. To ensure global exploration, after a defined number of memeplex evolution steps (i.e. local search iterations), the virtual frogs are shuffled and reorganized into new memeplexes in a technique similar to that used in the shuffled complex evolution algorithm. In addition, to provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions. The local searches and the shuffling processes continue until defined convergence criteria are satisfied. The flowchart of the SFLA is illustrated in Fig. 1. The SFLA is described in details as follows. First, an initial population of N frogs $P = \{X_1, X_2, ..., X_N\}$ is created randomly. For S-dimensional problems (S variables), the position of a frog i_{th} in the search space is represented as $X_i = [x_1, x_2, ..., x_{is}]^T$. A fitness function is defined to evaluate the frog's position. For minimization problems, the frog's fitness can be defined as

$$fitness = 1/[f(x)+C] \tag{8}$$

and for maximization problem, the frog's fitness can be simply defined as

$$fitness = F(X)+C \tag{9}$$

where $f(X)$ is the cost function to be optimized, and C is a constant chosen to ensure that the fitness value is positive. Afterwards, the frogs are sorted in a descending order according to their fitness. Then, the entire population is divided into m memeplexes, each containing n frogs (i.e. $N=m\times n$), in such a way that the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m_{th} frog goes to the m_{th} memeplex, and the $(m+1)_{th}$ frog goes back to the first memeplex, etc. Let M_k is the set of frogs in the K_{th} memeplex, this dividing process can be described by the following expression:

$$M_k = \left\{ X_{k+m(l-1)} \in P \mid 1 \le k \le n \right\}, (1 \le k \le m) \tag{10}$$

Within each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. Also, the frog with the global best fitness is identified as X_g. During memeplex evolution, the worst frog X_w leaps toward the best frog X_b. According to the original frog leaping rule, the position of the worst frog is updated as follows:

$$D = r.(X_b - X_w) \tag{11}$$

$$X_w(new) = X_w + D, (\|D\| < D_{\max}) \tag{12}$$

where r is a random number between 0 and 1; and $D_{\max}$ is the maximum allowed change of frog's position in one jump. Fig. 2 demonstrates the original frog leaping rule. If this leaping produces a better solution, it replaces the worst frog. Otherwise, the calculations in (11) and (12) are repeated but respect to the global best frog (i.e. X_g replacesX_b). If no improvement becomes possible in this case, the worst frog is deleted and a new frog is randomly generated to replace it. The calculations continue for a predefined number of memetic evolutionary steps within each memeplex, and then the whole population is mixed together in the shuffling process. The local evolution and global shuffling continue until convergence criteria are satisfied. Usually, the convergence criteria can be defined as follows:

I. The relative change in the fitness of the best frog within a number of consecutive shuffling iterations is less than a pre-specified tolerance;
II. The maximum user-specified number shuffling iterations is reached. The SFLA will stop when one of the above criteria is arrived first.

Iv.1. sfla procedure for opdg problem:

The MSFLA-based approach for solving the OPDG problem to minimized objective takes the following steps:

Step 1: Input line and bus data, and bus voltage limits.
Step 2: Calculate the loss using distribution load flow based on backward-forward sweep.
Step 3: Create an initial population of k frogs generated randomly.
Step 4:Sort the population increasingly and divide the frogs into p memplexes each holding q frogs such that $k=p\times q$. The division is done with the first frog going to the first memplex, second one going to the second memplex, the *pth* frog to the *pth* memplex and the *p+lth* frog back to the first memplex.
Step 5: For each memplex if the bus voltage and other constraint are within the limits, calculate the equation (1). Otherwise, that memplex is infeasible.

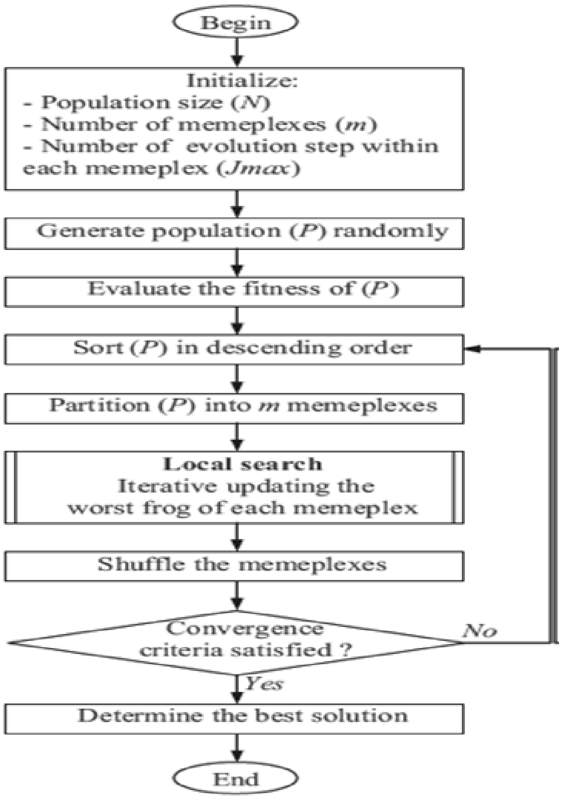

Fig. 1: Flowchart of the SFLA

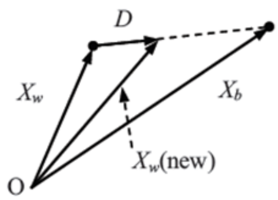

Fig. 2: The original frog leaping rule

Step 5-1: Set p_1=0 where p_1 counts the number of memeplexes and will be compared with the total number of memeplexes p. Set y_1=0 where y_1=0 counts the number of evolutionary steps and will be compared with the maximum number of steps (y_{max}), to be completed with in each memeplex.
Step 5-2: Set p_1=p_1+1.
Step 5-3: Set y_1=y_1+1
Step 5-4: For each memplex, the frogs with the best fitness and worst fitness are identified as X_w and X_b, respectively. Also the frog with the global best fitness X_g is identified. Then the position of the worst frog X_w for the memplex is adjusted as follows:

$$B_i = rand(.) \times (X_b - X_w)$$
$$new\ X_w = old\ X_w + B_i \quad (-B_{max} \le B_i \le B_{max}) \tag{13}$$

Where rand (.) is a random number between 1 and 0 and B_{max} is the maximum allowed change in the frogs position. If the evolutions produce a better frog (solution), it replaces the older frog. Otherwise, X_b is replaced by X_g in (13) and the process is repeated. If non improvement becomes possible in this case a random frog is generated which replaces the old frog.
Step 5-5: If $P_1 \le P$, return to step5-2. If $y_1 \le y_{max}$, return to step 5-3. Other wise go to step4.
Step 6: Check the convergence. If the convergence criteria are satisfied, stop. Otherwise, consider the new population as the initial population and return to the step4.The best solution found in the search process is considered as the output results of the algorithm.

Step 7: Print out the optimal solution to the target problem. Fitness value representing the minimum total real power loss.

Case study:

In order to test the proposed algorithm, the 33 and 69 node distribution test feeder has been considered. Figure 3 and Figure 4 shows the convergence process of the GA and SFLA when employed to solve the optimization problem of 33 and 69 node test network, respectively.

Conclusion:

In this paper the results of application of SFL algorithm to the optimal allocation of DGs in distribution network is presented. The effectiveness of the proposed algorithm to solve the DG allocation problem is demonstrated through a numerical example. The IEEE 33 and 69 node distribution test feeders have been solved with the proposed algorithm and, the simple genetic algorithm. The results in table 1 and table 2 demonstrated the better characteristics of the SFL algorithm in comparison with the GA specially in terms of solution quality and number of iterations.

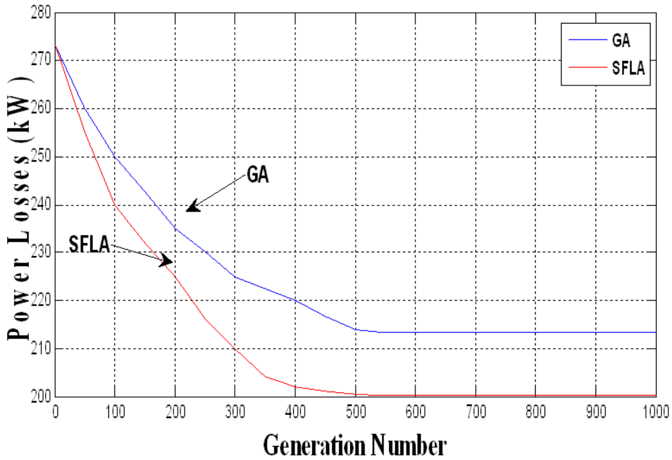

Fig. 3: Power losses reduction with generation number for IEEE 33-node system

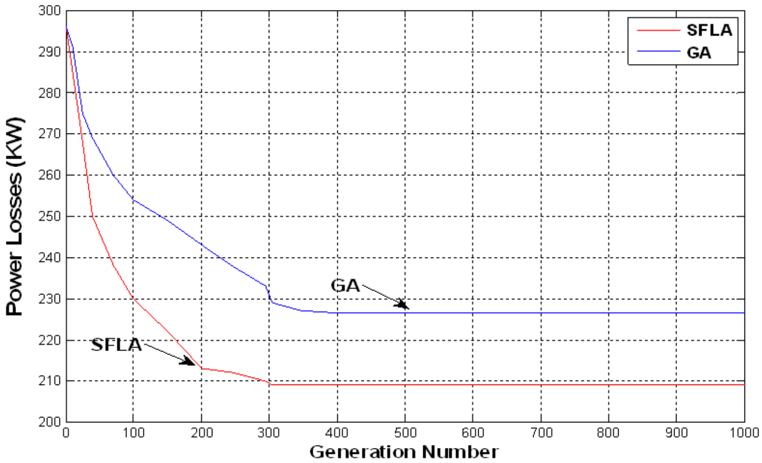

Fig. 4: Power losses reduction with generation number for IEEE 69-node system

Table 1: Comparison of GA & SFLA results for IEEE 33-node

Algorithms	Total Capacity of Installed DGs (kW)	Power Losses (kW) with DG
GA	200	212.52
SFLA	200	200.09

Table 2: Comparison of GA & SFLA results for IEEE 69-node

Algorithms	Total Capacity of Installed DGs (kW)	Power Losses (kW) with DG
GA	200	226.52
SFLA	200	209.67

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