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Applying a New Advanced Intelligent Algorithm for Optimal Distributed Generation Location and Sizing in Radial Distribution Systems

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Abstract: This paper presents a comparison between combination of heuristic search and PSO optimization methods and Modified Shuffled Frog Leaping Algorithm (MSFLA) for optimal location and sizing of distributed generation (DG) in a distribution network. The objective function consists of modified voltage profile and power losses. This proposed method is tested on the IEEE 33-bus system. This study includes a comparison between the proposed approaches. It shows the importance of installing the exact amount of DG in the best suitable location. Studies also show that if the DG units are connected at non-optimal locations or have non-optimal sizes, the system losses may increase. Test results show that MSFLA method can achieve better results than PSO and simple heuristic search method on the 33-bus radial distribution systems. The MSFLA can get maximum loss reductions for each three types of optimally placed multi-DGs. Furthermore, voltage profile improvement and branch current reduction will be obtained.

Key words: Distributed Generation; DG types; Optimal DG size; Modified Shuffled Frog Leaping Algorithm (MSFLA); Particle Swarm Optimization (PSO), Heuristic Search (HS),

INTRODUCTION

Distributed power generation (DG) refers to small generating units installed near local loads or load centers to avoid the need of the network expansions in order to cover new load areas or to support the increased energy transfer which would be necessary for satisfying consumers' demand. In other words, distributed generation (DG) is a small generator located in a power system network, providing the electricity to consumers' load, locally (Thomas Ackermann., *et al*. 2001). DG can be an alternative for residential, commercial, and industrial applications. DG uses the modern technology which is reliable, efficient, and simple, so it can compete with traditional large generating units in some areas (W. El-Khattam., *et al*. 2001). The artificial intelligence techniques are widely used to solve most of the optimization problems. These methods such as genetic algorithm, simulated annealing, and tabu search are still developing. The DG allocation using genetic algorithm (GA) has been published in (G. Celli., *et al*. 2001). Tabu search (TS) is used for DG allocation in distribution systems (K. Nara., *et al*. 2004). Analytical methods for minimizing the line losses and also for DG allocation have been provided in (C. Wang., *et al*. 2007). Also linear programming method coupled with power system studies has been used for DG applications in distribution systems (A. Keane., *et al*. 2005). In this paper, we assume that DG has a capability of supplying real power but consuming proportionately reactive power. As we need to find the optimal location and size of more than one DG, in this paper, we use a new method called "Modified Shuffled Frog Leaping Algorithm (MSFLA)" to determine the optimal location and size of multi- DGs to minimize the total real power losses and investment costs and improve voltage profile of the distribution systems. Also we use a load flow program based on backward-forward sweep (D. Shirmohammadi., *et al*. 1995) to solve the load flow problem in this paper. Different sections of this paper would be as follows:

Section 2 addresses the problem formulation. In section 3, we will explain the type of DG and heuristic search method. The MSFLA algorithm is presented in section 4. In section 5, the MSFLA computation procedure is presented for the OPDG problem. Simulation results on the test system are illustrated in section 6 and finally the conclusion will be presented in section 7.

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Problem Formulation:

The function that has to be minimized consists of three objectives:

Ii.1. Minimize the Active Power Losses:

The real power loss reduction in a distribution system is required for efficient power system operation. The loss in the system can be calculated by equation (1), given the system operating condition,

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} A_{ij} (P_i P_j + Q_i Q_j) + B_{ij} (Q_i P_j - P_i Q_j) \tag{1}$$

Where

$$A_{ij} = \frac{R_{ij} \cos(\delta_i - \delta_j)}{V_i V_j}$$

$$B_{ij} = \frac{R_{ij} \sin(\delta_i - \delta_j)}{V_i V_j}$$

Where, P_i and Q_i are net real and reactive power injection in bus '*i*'respectively, R_{ij} is the line resistance between bus '*i*'and '*j*', V_i and δ_i are the voltage and angle at bus '*i*' respectively.

The objective of the placement technique is to minimize the total real power loss. Mathematically, the objective function can be written as:

$$P_L = \sum_{k=1}^{N_{sc}} Loss_k \tag{2}$$

Subject to power balance constraints

$$\sum_{i=1}^{N} P_{DGi} = \sum_{i=1}^{N} P_{Di} + P_L \tag{3}$$

Where: $Loss_k$ is distribution loss at section *k*, N_{SC} is total number of sections, P_L is the real power loss in the system, P_{DGi} is the real power generation DG at bus *i*, P_{Di} is the power demand at bus *i*.

II.2. Voltage Profile Improvement:

$$F_2 = \sum_{i=1}^{N} | V_i - V_{i,ref} | \tag{4}$$

Voltage constraints:

$$| V_i |^{\min} \leq | V_i | \leq | V_i |^{\max} \tag{5}$$

Current limits:

$$| I_{ij} | \leq | I_{ij} |^{\max} \tag{6}$$

DG Type:

Here, we consider that the DG will supply real power and in turn will absorb reactive power. In case of the wind turbines, induction generator is used to produce real power and the reactive power will be consumed in the process (D. Shirmohammadi., *et al*. 1995). The amount of reactive power they require is an ever increasing function of the active power output. The reactive power consumed by the DG (wind generation) in simple form can be given as in equation (7) as in the case of (R.H. Lasseter., 1998)

$$Q_{DG} = -(0.5 + P_{DG}^2) \tag{7}$$

The loss equation will be modified. After following the similar methodology of the first two types, optimal DG size can be found by solving equation (8).

$$P = 0.0032A_{ii}P_{DGi}^3 + P_{DGi}[1.004A_{ii} + 0.08A_{ii}Q_{Di} - 0.08Y_i] + (X_i - A_{ii}P_{Di}) = 0 \tag{8}$$

Equation (8) gives the amount of real power that a DG should produce when located at but *'i'*, so as to obtain the minimum system loss whereas the amount of reactive power that it consumes can be calculated from equation (7).

IV. Modified Shuffled Frog Leaping Algorithm (MSFLA):

IV.1 Shuffled Frog Leaping Algorithm (SFLA):

Shuffled Frog Leaping Algorithm (SFLA) is a heuristic search algorithm presented for the first time by Eusuff and Lansey in 2003 (M. M. Eusuff., *et al*. 2006). The main purpose of this algorithm was achieving a method to solve complicated optimization problems without any use of traditional mathematical optimization tools. In fact, the SFL algorithm is combination of "meme-based genetic algorithm or Memetic Algorithm" and "Particle Swarm Optimization (PSO)". This algorithm has been inspired from memetic evolution of a group of frogs when seeking for food. In this method, a solution to a given problem is presented in the form of a string, called "frog" which has been considered as a control vector in this paper as follows in (9). The initial population of frogs is partitioned into groups or subsets called "memeplexes" and the number of frogs in each subset is equal. The SFL algorithm is based on two search techniques: local search and global information exchange techniques. Based on local search, the frogs in each subset improve their positions to have more foods (to reach the best solution). In second technique, obtained information between subsets is compared to each other (after each local search in subsets). The procedure of SFL algorithm will be as follows:

1) An initial population of "*P*" frogs (*P* solutions) created randomly which considered in this paper as follows: (9)

$$Population = \begin{bmatrix} X_1 \\ . \\ . \\ X_P \end{bmatrix}_{(p)\times(2\times N_{tie})} \tag{9}$$

$$X = [Tie_1, Tie_2, ..., Tie_{N_{tie}}, Sw_1, Sw_2, ..., Sw_{N_{tie}}]$$

2) The entire population is divided into m subsets (m memeplexes), each containing n frogs (i.e., P = m × n), in such a way that the first frog of sorted population goes to the first memeplex, the second frog goes to the second memeplex, frog m goes to m memeplex, and frog m+1 goes to the first memeplex again, etc. therefore, in each memeplex, there will be n frogs.
3) This step is based on local search. Within each local memeplex, the frogs with the best and the worst fitness are identified as and, respectively. Also, the frog with the global best fitness (the best solution) is identified as. Then, the position of the worst frog is updated (based on frog leaping rule) as follows:

$$D_i = rand \times (X_b - X_w)$$
$$X_w(new) = X_w(old) + D_i \qquad (10)$$
$$(-D_{\min} \le D_i \le D_{\max})$$

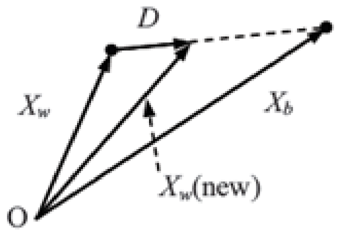

Fig. 1: The original frog leaping rule.

Where rand is a random number between 0 and 1; $D_{\max}$ is the maximum allowed change in frog's position. If this process produces a better solution $(X_w(new))$, new position of the worst frog), it replaces the worst frog's position $(X_w(old))$. Otherwise, the calculations in equations 1 and 2 are repeated with respect to the global best frog (i.e. replaces). If no improvement becomes possible in this case, then a new solution is randomly generated to replace the worst frog (X_w) . Because of all arrays in X are integers, obtained solutions from equations 1 and 2 must be rounded after each iteration.

4) Continue of previous step for a number of predefined iterations.
5) After improvement in frog's positions, new population is sorted in a descending order according to their fitness.
6) If the convergence criteria are satisfied, stop. Otherwise, go to step 2 and repeat again.

IV.2. Modified Shuffled Frog Leaping Algorithm (MSFLA):

According to previous section, the worst frog in each memeplex improves its position toward the best frog's position or the global best position in the same memeplex. But according to equations 9 and 10 and Fig. (1), the possible new position of the worst frog is restricted in the line segment between its current position (X_w) and the best frog's position (X_b), and the worst frog will never jump over the best one (see Fig. (2)). these limitations not only slow down the convergence speed, but also cause premature convergence. Hence, the equations 1 and 2 must be replaced by new equations as follows:

$$D_i = rand \times C(X_b - X_w) + W$$
$$W = [r_1 w_{1,\max}, r_2 w_{2,\max}, \ldots, r_{N_{tie}} w_{N_{tie},\max}]^T \qquad (11)$$

$$X_w(new) = \begin{Bmatrix} X_w + D & if\ |D| \le D_{\max} \\ X_w + \dfrac{D}{\sqrt{D^T D}} D_{\max} & if\ |D| \ge D_{\max} \end{Bmatrix} \qquad (12)$$

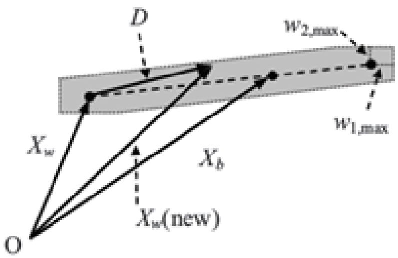

Fig. 2: The new frog leaping rule.

Where rand is a random number between 0 and 1; C is a constant in the range between 1 and 2; r_i are random numbers between -1 and 1; $w_{i,\max}$ are the maximum allowed perception and action uncertainties in the *ith* dimension of the search space; $D_{\max}$ is the maximum allowed change in frog's position. Because of all arrays in X are integers, obtained solutions from equations 3 and 4 must be rounded after each iteration. By applying equations 3-4, local search space in each memeplex increases. Therefore, the convergence speed increases and convergence probability to achieve the best solution will increase. For applying MSFL algorithm to a reconfiguration problem, following steps must be taken:

1) In this step, required parameters and information such as branch impedance, switch positions, number of memeplexes, number of frogs and etc, are defined and determined.
2) The constrained objective function is converted to an unconstrained objective function according to:

$$F(x) = f(x) - k(\sum_{j=1}^{N_{eq}} (h_j(x))^2) - k_2(\sum_{j=1}^{N_{ueq}} (Max[0 - g_i(x)])^2) \tag{13}$$

Above formula is objective function of OPDG problem where N_{eq} and N_{ueq} are the number of equal and unequal constraints, respectively. Also, $g_i(x)$ and $h_i(x)$ are equal and unequal constraints, respectively. k_1 , k_2 (k_1 , $k_2 > 0$) are penalty factors which must have a large value.

V. MSFLA Procedure:

The MSFLA-based approach for solving the OPDG problem to minimized consists of three objectives 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 is within the limits, calculate the total loss in equation (9).Otherwise, that memplex is infeasible.
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:

$$\begin{aligned} &B_i = rand(.) \times (X_b - X_w) \\ &new\ X_w = old\ X_w + B_i \quad (-B_{max} \le B_i \le B_{max}) \end{aligned} \tag{14}$$

Where rand (.) is a random number between1 and 0 and Bmax 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 (14) 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 step 4.

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. The best position includes the optimal locations and size of DG or multi-DGs, and the corresponding fitness value representing the minimum total real power loss and improvement in voltage profile.

Simulation Result:

The distribution test systems are the 33 bus systems (M. Ermis, *et al*. 1992). The original total real power loss and reactive power loss in the system are 221.4346 kW and 150.1784 kVar, respectively. The 33 bus system has 68 Sections with the total load of 3.80 MW and 2.33 MVar, shown in Figure 3. The original total real and reactive power losses of the system are 230.0372 kW and 104.3791 kVar, respectively.

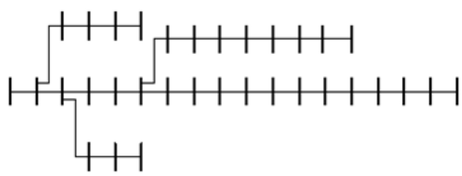

Fig. 3: The 33 bus radial distribution system.

Table 1: PSO result of the 33 bus test system

Algorithms	Total Power Loss (kW)(Min)	Total Power Loss (kW) (Avg)	Total Power Loss (kW) (MAX)	Average Time (sec)
heuristic search	164.6975	177.4055	286.8644	5.6135
PSO	162.1489	175.8621	203.7605	5.1611
MSFLA	158.8167	172.1938	279.3904	4.8841

The convergence characteristic of the best solution of MSFLA is shown in Figure 4. The average CPU time is 4.1267 second.

For a better insight of the solutions supplied by the three methods, a voltage level analysis is made in Figure 5, showing the voltage levels in the network for one DG unit.

For the 33 bus systems, in Tables 2-4, the MSFLA can obtain the same optimal size and location as the heuristic search and PSO algorithm.

Conclusion:

In this paper, This paper has proposed a new evolutionary algorithm known as SFLA to solve the UC problem. The combination of the local search with information exchange of groups results in performance improvement of SFLA. The MSF algorithm for optimal placement of multi-DGs is efficiently minimizing the total real power loss and voltage improvement, satisfying transmission line limits and constraints. The methodology is fast and accurate in determining the sizes and locations. The proposed method has been compared with other methods. The simulation results show that the computation times and Loss of SFLA are less than other algorithms such as Heuristic Search and PSO.

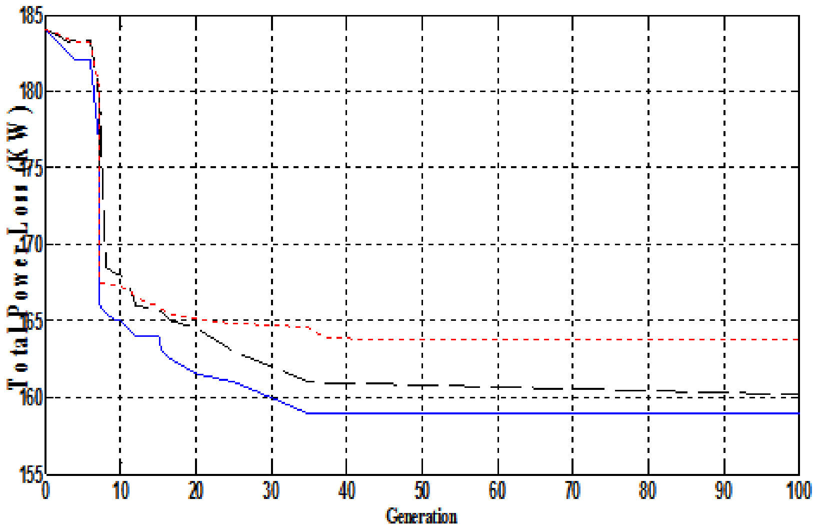

Fig. 6: Convergence characteristic of the 33 bus test system. Solid (MSFLA), Dashed (PSO),Dot(HS).

Table 2: Optimal DG placement for DG type 3

system	Method	Bus No.	DGSizeMW	BusNo.	DGSize MW	BusNo.	DGSize(MW)	P_{loss} (Kw)	Q_{Loss}(Kw)	Loss Reduction%	
										Real	Reactive
33 bus	Load Flow Analysis	-	-	-	-	-	-	221.4342	150.1783	-	-
	Heuristic Search	14	1.9933	-	-	-	-	163.8515	115.5283	27.03	23.07
	PSO	14	1.9354	-	-	-	-	163.8976	115.9445	26.03	23.07
	PSO	3	1.3163	14	2.1826	-	-	164.4311	115.9619	25.71	23.06
	PSO	2	1.1141	14	2.6882	3	0.7912	166.1743	117.1713	24.53	22.03
	MSFLA	12	2.7756	-	-	-	-	159.7913	116.5516	30.45	29.25
	MSFLA	2	1.4812	12	2.7003	-	-	159.9346	117.1211	30.75	29.47
	MSFLA	3	0.8107	12	2.5931	2	0.8918	158.0867	118.2128	30.86	31.04

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