Optimal Placement Of Capacitors For Voltage Profile Improvement And Loss Reduction In A Radial Distribution System Using Shuffled Frog Leaping And Particle Swarm Optimization Algorithms

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***Abstract*—A new and efficient approach for capacitor placement in radial distribution systems is proposed for determining the optimal locations and size of capacitor with an objective of improving the voltage profile and reduction of power loss. The solution is presented in two parts: at first the loss sensitivity factors are used to select the candidate locations for the capacitor placement and then a new algorithm that employs Shuffle Frog Leaping Algorithm (SFLA) and Particle Swarm Optimization are used to estimate the optimal size of capacitors at the optimal buses. One of the advantages of this method is not using any external control parameters. Handling the objective function and the constraints separately is the other advantage, which avoids the trouble to determine the barrier factors. Finally, simulation results for the IEEE 45-bus system using the proposed method are presented.**

Keywords—Voltage Profile, Capacitor placement, loss reduction, Loss sensitivity factors, SFLA, PSO

I. INTRODUCTION

As studies indicated nearly 13% of total power generated is wasted in the form of losses at the distribution level. In addition, although the trend towards distribution automation will require the most efficient operating scenario for economic viability variations, the loss minimization in distribution systems has assumed greater significance [1]. One of the most efficient ways to mitigate these losses is the installation of shunt capacitor bank on distribution primary feeders.

Adding shunt capacitor banks have several advantages such as improving the power factor and feeder voltage profile, reducting power loss and increaseing available capacity of feeders. The aforementioned assets dramatically relys on the placement and size of the capacitor.

Many optimization techniques and algorithms have been proposed in order to optimally determine the locations of installation and the sizes of capacitors, as they are the general problems related to capacitors. Schmill [2] presented his well known 2/3 rule for the placement of one capacitor assuming a uniform load and a uniform distribution feeder. Duran *et al* [3] considered the capacitor size as a discrete variable and implemented dynamic programming to solve the problem. Grainger and Lee [4] developed a method in which capacitor location and capacity were supposed to be continuous variables. Grainger *et al* [5] proposed decoupled solution methodology for general distribution system by formulating the capacitor placement and voltage regulators problem. Baran and Wu [6, 7] proposed a method with mixed integer programming. Sundharajan and Pahwa [8] have used the genetic algorithm approach for obtaining the optimal placement of capacitors based on the mechanism of natural selection. One of the drawbacks of the major previously aforementioned methods is that the capacitors are often assumed as continuous variables. This is mainly based on the notion that selecting integer capacitor sizes closest to the optimal values that are found by the continuous variable approach, may not guarantee an optimal solution [16]. To address this deficiency, in this paper the optimal capacitor placement is considered as an integer-programming problem, and capacitors are assumed to have discrete values. Consequently, the solution searching process becomes heavy burden since a large number of possible solutions will be created. In this paper, Loss Sensitivity Factors and Shuffled Frog Leaping Algorithm (SFLA) are used to solve Capacitor Placement and Sizing problem respectively. The loss sensitivity factor can predict that placing a capacitor will cause the biggest loss reduction in which buses. Therefore, these sensitive buses can serve as candidate locations for the capacitor placement.

To improve the voltage profile of the system, SFLA is used to estimate the required level of shunt capacitive compensation. The proposed method is tested on IEEE 45 bus system and results are very promising. The Shuffled frog leaping algorithm (SFLA) 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; in addition it does not need any external parameters such as crossover rate, mutation rate, etc.

The paper is developed into 7 sections. Besides introduction of the paper was delivered in section I, description of the problem is presented in section II; Section III explains sensitivity analysis and loss factors; Section IV gives brief description of the shuffled frog leaping algorithm; Section V develops the test results and Section VI gives conclusions.

II. PROBLEM FORMULATION

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) [17], 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,

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

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

Pi and *Qi* are net real and reactive power injection in bus *'i'* respectively, *Rij* is the line resistance between bus *'i'* and *'j'*, *Vi* and *δi* are the voltage and angle at bus *'i'* respectively.

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

Minimize:

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

Subject to power balance constraints:

$$\sum_{i=1}^{N} Q_{Capacitori} = \sum_{i=1}^{N} Q_{Di} + Q_L \tag{3}$$

Voltage constraints:

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max} \tag{4}$$

Current limits:

$$|I_{ij}| \le |I_{ij}|^{\max} \tag{5}$$

Where, $Loss_k$ is distribution loss at section k, NS_C is total number of sections, P_L is the real power loss, $P_{Capacitori}$ is the reactive power generation Capacitor at bus i, P_{Di} is the power demand at bus i.

III. SENSIVITY ANALYSIS AND LOSS SENSIVITY FACTORS

Loss sensitivity factors are used to determine the candidate nodes for the placement of capacitors. One of the advantages of this method is, reducing the search space for the optimization procedure.

Consider a distribution line with an impedance *R+jX* and a load of $P_{eff} + jQ_{eff}$ connected between *'r'* and 's' buses as given in Fig. 1.

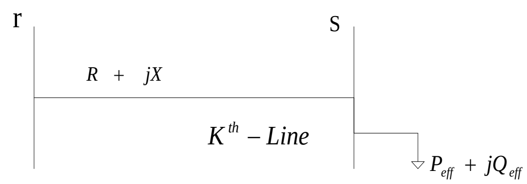


Fig. 1. Distribution line

Active power loss in the k^{th} line is given by, $[I^2_k]*R[k]$ which can be expressed as,

$$P_{lineloss}[s] = \frac{(P^2_{eff}[s] + Q^2_{eff}[s])\, R[k]}{(V[s])^2} \tag{6}$$

Similarly the reactive power loss in the k^{th} line is given by

$$Q_{lineloss}[s] = \frac{(P^2_{eff}[s] + Q^2_{eff}[s])\, X[k]}{(V[s])^2} \tag{7}$$

Where, *Peff [s]* = Total effective active power supplied beyond the node 's'.

Qeff [s] = Total effective reactive power supplied beyond the node *'s'*.

Now, both the Loss Sensitivity Factors can be obtained as shown below:

$$\frac{\partial P_{lineloss}}{\partial Q_{eff}} = \frac{(2 * Q_{eff}[s] * R[k])}{(V[s])^2} \tag{8}$$

$$\frac{\partial Q_{lineloss}}{\partial Q_{eff}} = \frac{(2 * Q_{eff}[s] * X[k])}{(V[s])^2} \tag{9}$$

Candidate Node Selection using Loss Sensitivity Factors:

The Loss Sensitivity Factors ($\partial P_{lineloss} / \partial Q_{eff}$) are calculated from the base case load flows and the values are arranged in descending order for all the lines of the given system. To store the respective 'end' buses of the lines arranged in descending order of the values ($\partial P_{lineloss} / \partial Q_{eff}$), a vector bus position 'bpos[*i*]' is used. The descending order of ($\partial P_{lineloss} / \partial Q_{eff}$) elements of "bpos[i]' vector will decide the sequence in which the buses are to be considered for compensation. This sequence is purely governed by the ($\partial P_{lineloss} / \partial Q_{eff}$) and hence the proposed 'Loss Sensitive Coefficient' factors become very useful in capacitor Placement. At these buses of 'bpos[*i*]' vector, normalized voltage magnitudes are calculated by (norm[*i*]=*V*[*i*]/0.95), where 0.95 is the base case voltage magnitude. If norm[i] value is less than 1.01 at any bus, that bus is considered as the candidate bus requiring the Capacitor Placement. These candidate buses are stored in 'rank bus' vector. If norm[*i*]>1.01, this means the voltage at a bus in the sequence list is healthy and no compensation needs at that bus and it will not be listed in the 'rank bus' vector. The 'rank bus' vector gives the information about the possible potential or candidate buses for capacitor placement. The sizing of Capacitors at buses listed in the 'rank bus' vector is done by using Shuffled Frog Leaping Algorithm.

IV. OPTIMIZATION METHODS

A. Shuffled Frog Leaping Algorithm

The SFLA is a meta heuristic optimization algorithm which aims to mimic the behavior of frogs searching for food laid on stones randomly located in a pond. The algorithm contains elements of local search and global information exchange [18]. In the SFLA, a population of possible solutions is composed of a set of virtual frogs that is partitioned into subsets designated as memeplexes. Through a process of memetic evolution, the idea of a frog in a memplex can be evolved by influencing of other frogs' idea in that memplex.

Like particle swarm optimization method, the SFLA performs simultaneously an independent local search in each memeplex. After a defined number of memeplex evolution steps, in a technique similar to that used in the shuffled complex evolution, the virtual frogs are shuffled and reorganized into new memeplexes algorithm, to ensure global exploration. If the local search cannot find better solutions, new random population is generated and substituted in the population to provide the opportunity for random generation of improved information. The local searches and the shuffling processes continue until defined convergence criteria are satisfied. The flowchart of the SFLA is illustrated in Fig. 2.

As it is shown in Fig. 2, First, an initial random population of *N* frogs *P*={*X*1,*X*2,...,*XN*} is created. For S variables, the position of a frog i^{th} in the search space is represented as $X_i=(x_1,x_2,\ldots,x_{is})^T$.

After that, according to frogs' fitness, they are sorted in a descending order. Then, the entire population is divided into *m* memeplexes, each containing *n* frogs (i.e. N=m×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:

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

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:

$$D = r.(X_b - X_w) \quad (11)$$

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

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.

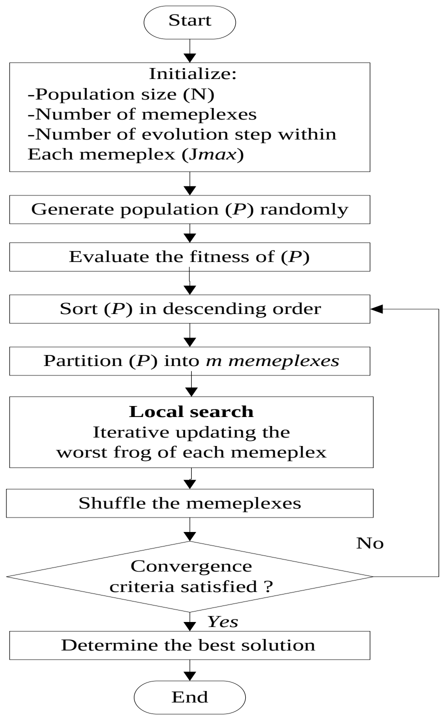


Fig. 2. SFLA flow chart

B. Particle Swarm Optimization Algorithm

PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995 [19-20]. The PSO algorithm is based on the social behavior of bird flocking or fish schooling. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas [21].

PSO optimizes a problem by having a population of particles, and moving these particles around in the n-dimensional search-space according to simple mathematical formulae. The state of each particle is represented by its position $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ and velocity $v_i = (v_{i1}, v_{i2}, ..., v_{in})$, the states of the particles are updated. According to (13), The update procedure is done in tree steps, at first the inertial constant w, controls how much the particle remembers its previous velocity [21]. Then the acceleration constant C_1, controls how much the particle heads toward its personal best position. After that, the acceleration constant C_2, controls the particle toward swarm's best ever position. The flow chart of the procedure is shown in Fig. 3.

During each iteration, each particle is updated by two "best" values. The first one is the position vector of the best solution (fitness) this particle has achieved so far. The fitness value $p_i = (p_{i1}, p_{i2}, ..., p_{in})$ is also stored. This position is called pbest. Another "best" position that is tracked by the particle swarm optimizer is the best position, obtained so far, by any particle in the population. This best position is the current global best $p_g = (p_{g1}, p_{g2}, ..., p_{gn})$ and is called gbest. At each time step, after finding the two best values, the particle updates its velocity and position according to (13) and (14).

$$v_i^{k+1} = wv_i^k + c_1 r_1 (pbset_i - x_i^k) + c_2 r_2 (gbset_k - x_i^k) \quad (13)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (14)$$

V. SIMULATION RESULT

The proposed algorithms applied to the IEEE 45 bus system. This system has 44 sections with 16.97562MW and 7.371194MVar total load as shown in Fig. 4. The original total real power loss and reactive power loss in the system are 2.05809MW and 4.6219MVR, respectively.

Fig. 5 shows the convergence of proposed SFL and PSO algorithms for different number of capacitors. It is observed that the variation of the fitness during both algorithms run for the best case and shows the swarm of optimal variables.

The improvement of voltage profile before and after the capacitors installation and they're optimal placement is shown in Fig. 6.

According to tables 1- 4 it is observed that the ratio of losses reduction percentage to the total capacity of capacitors which is one of the capacitors economical indicators. Also by comparing the voltage profile curves in the four cases with the curve before capacitors installation, it is observed that the voltage profile in the four cases is improved.

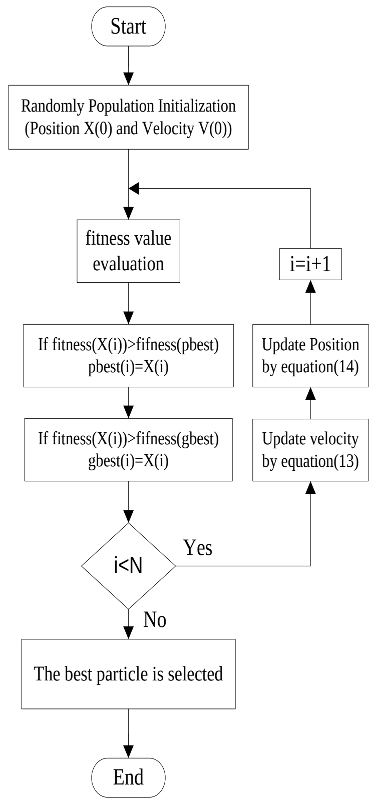


Fig. 3. PSO flow chart

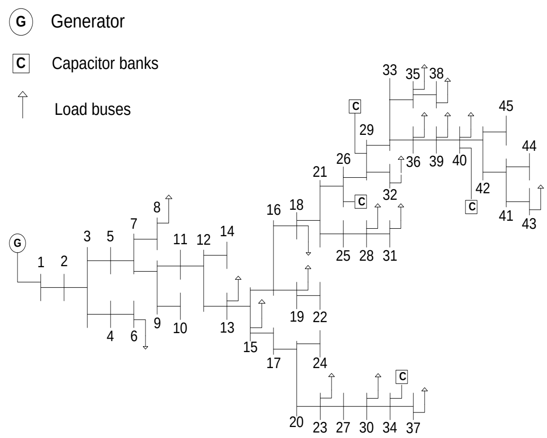
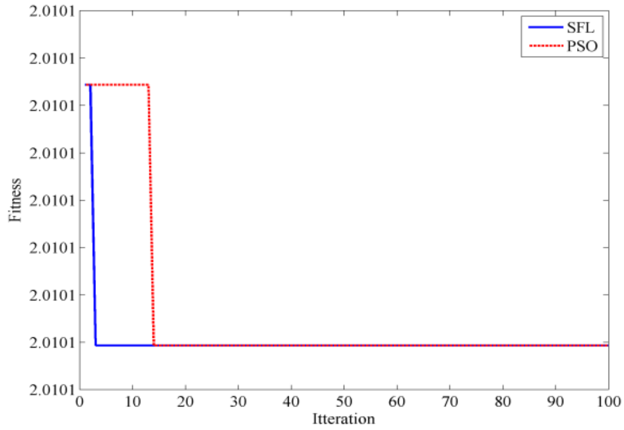
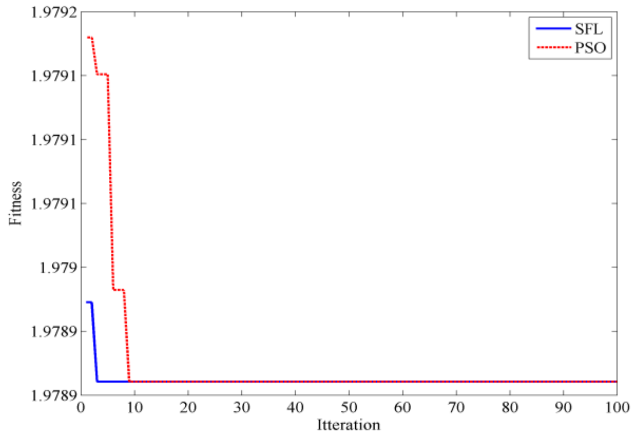


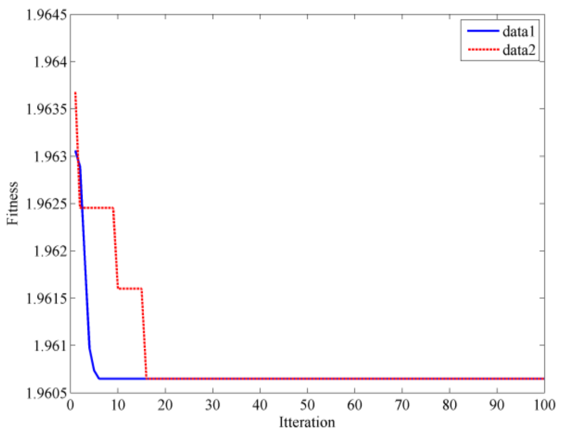
Fig. 4. The IEEE 45 bus radial distribution system



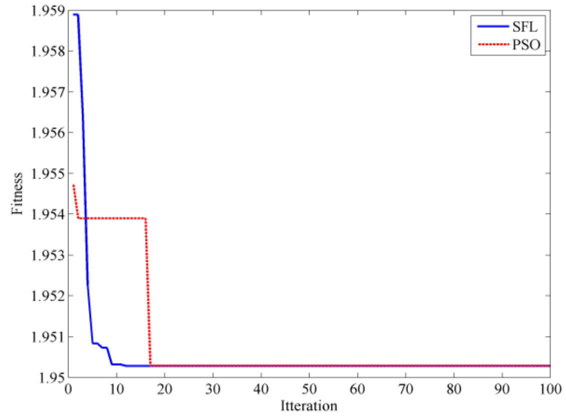
(a)



(b)



(c)



(d)

Fig. 5. Convergence of the optimization of algorithms. (a). With 1 capacitor, (b). With 2 capacitors, (c). With 3 capacitors, (d). With 4 capacitors

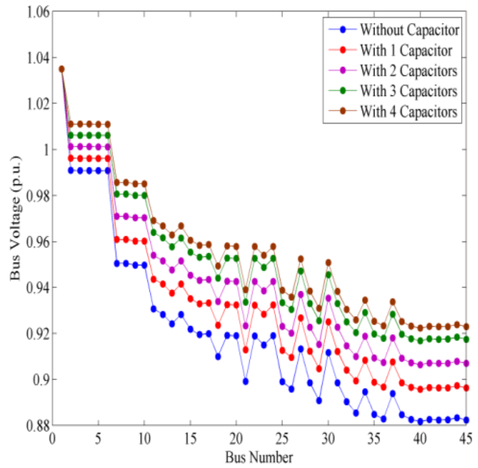


Fig. 6. Bus voltage before and after capacitor installation with SFL and PSO algorithms

VI. CONCLUSION

In this paper, the shuffled frog leaping (SFL) algorithm and particle swarm optimization (PSO) algorithm for optimal placement of multi-capacitors is efficiently minimizing the total real power loss satisfying transmission line limits and constraints. Capacitor regulating bus voltage will be considered in future research work.

With comparing results and application of the two algorithms we should say that as it is observed the acquired voltage profile of the result of SFL algorithm is better than PSO algorithm. However the main superiority of this algorithm is in acquiring the best amount. Because SFL algorithm find the correct answer in the first repeating that are done to be sure of finding the best correct answer and the probability of capturing in the local incorrecting answers is very low. Also it is worthy or mentions that the time of performing this algorithm is faster.

Finally we can say that SFL as compared with PSO is more efficient in this case.

Table 1. Optimal capacitor placement for 1 capacitor with SFL and PSO algorithms

Method	Capacitor Size (MVAR)	Bus No	Losses Without Capacitor		Losses With Capacitor	
			MW	MVAR	MW	MVAR
SFLA	1*1.2	12	2.058	4.6219	2.0101	4.5160
PSO						

Table 2. Optimal capacitor placement for 2 capacitors with SFL and PSO algorithm

Method	Capacitor Size (MVAR)	Bus No	Losses Without Capacitor		Losses With Capacitor	
			MW	MVAR	MW	MVAR
SFLA	2*1.2	9	2.058	4.6219	1.9789	4.4476
PSO		12				

Table 3. Optimal capacitor placement for 3 capacitors with SFL and PSO algorithms

Method	Capacitor Size (MVAR)	Bus No	Losses Without Capacitor		Losses With Capacitor	
			MW	MVAR	MW	MVAR
SFLA	3*1.2	7	2.058	4.6219	1.9606	4.4092
		9				
PSO		11				

Table 4. Optimal capacitor placement for 4 capacitors with SFL and PSO algorithms

Method	Capacitor Size (MVAR)	Bus No	Losses Without Capacitor		Losses With Capacitor	
			MW	MVAR	MW	MVAR
SFLA	3*1.2	7	2.058	4.6219	1.9606	4.4092
		9				
PSO		11				

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