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# **Interpretation of the Concept of Particle Swarm Optimization for Power Compensation**

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**ABSTRACT** :This paper represents the introduction of particle swarm optimization and its application for the placement of capacitors in radial feeders in order to improve voltage profile and reduction of active power losses. The optimal location of capacitors and sizing of capacitors are done by loss sensitivity factors and particle swarm optimization respectively. Loss sensitivity factors can be determined using single base case load flow study. Particle swarm optimization technique is well applied and found to be much effective in radial distribution systems. This method places capacitors at less number of locations with optimum sizes and offer more saving in initial investment and regular maintenance.

**KEYWORDS:** CAPACITOR PLACEMENT, RADIAL DISTRIBUTION SYSTEMS, LOSS SENSTIVITY FACTORS AND PARTICLE SWARM OPTIMIZATION (PSO).

#### I. INTRODUCTION

As the demand of electricity is rising day by day, due to which distribution systems are growing large and being stretched too far. As a result, the system losses become higher and lead to poor voltage regulation. Therefore, it becomes imperative and important to make the distribution systems efficient and effective. In regard to this, installment of capacitor banks is one of the effective methods for power factor correction, loss reduction and voltage profile improvement.

For the placement of capacitors, many techniques have been developed. But now-a-days optimization techniques are the latest trend to minimize the losses and maximize the benefits. Particle Swarm Optimization (PSO) is the most popular among all techniques and still under research. Many researchers gave their own point of view about different capacitor installment techniques through research papers. In the 80's, Grainger [1],[2] and Barun Wu [3],[4] represented the capacitor placement as a mixed integer non-linear program. In the 90's combinational algorithms were introduced as a mean of solving the capacitor placement problem and neural network technique were formulated [5] & [6]. A solution approach to the capacitor placement based on fuzzy logic was represented by Ng. & Salama [7]. Chin [8] formulated a fuzzy dynamic programming model in which it was explained that how to express real power loss, voltage, deviation and harmonic distortion in fuzzy set notation. A genetic algorithm was used by Sundharajan and Pahwa [9] for capacitor placement.

Particle Swarm Optimization(PSO) is a robust meta-heuristic optimization technique which was developed by James Kennedy (social Psychologist) and Russel Eberhart(Electrical Engineer)[10] in 1995. It is a multi-agent parallel search technique which maintains a swarm of particles and each particle represents a potential solution in the swarm. All particles fly through a multi-dimension search space where each particle is adjusting according to its own.experience and that of neighbors. Shi and Eberhart [11] uses the concept of an extra inertia weight which is used to scale down the velocity of each particle.

#### **II.** Swarm Particle Optimization (PSO)

To get familiarize with PSO, one must be well known to certain terms and analysis of PSO, such that its successful research can be carried out.

Let us assume  $x_i^t$  denotes the position vector of particle i in the multi-dimensional search space ( where each particle is adjusting its position according to its own experience and that of the neighbors) at the time step t, then the position of each particle is updated in the search space given by:



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 $x_i^{t+1} = x_i^t + v_i^{t+1}$  with  $x_i \sim u(x_{min}, x_{max})$ 

(1)

(2)

#### where

 $v_i^t$  = the velocity vector of particle I that drives the optimization process and reflects both the own experience knowledge and social experience knowledge from all particles.

 $u(x_{\min}, x_{\max})$  = the uniform distribution where  $x_{\min} \& x_{\max}$  are its minimum and maximum values respectively.

Therefore, in a PSO method, all particles are initiated randomly and evaluated to compute fitness together with finding the personal best(best value of each particle) and global best(best value of particle in the entire swarm). After that a loop starts to find a optimum solution, first the particles velocity is updated by the personal and global bests and then each particle's position is updated by current velocity. The loop is ended with a stopping criterion pre-determined in advance.

Elements of a PSO are:[12]

**Particle** x(t): It is a k-dimensional real value vector which represents the candidate solution. For an i<sup>th</sup> particle at a time t, the particle is described as  $x_i(t) = \{x_1(t), x_2(t)...x_n(t)\}$  where  $x_i(t)$  gives the ith dimensional value and hence positional placement of particle can be determined.

**Population:** It is a set of 'n' number of particles at a time t described as  $\{x_1(t), x_2(t), ..., x_n(t)\}$ .

**Swarm:** It is apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in random direction.

**Particle velocity v(t):** It is the velocity of the moving particle represented by a k-dimensional real valued vector  $v_i(t) = \{v_1(t), v_2(t), \dots, v_n(t)\}$ .

**Particle best**( $\mathbf{p}_{best}$ ): When a particle moves through the search space, it compares its fitness value at the current position to the best value it has ever attained at any time up to the current time. The best position that is associated with the best fitness arrived so far is termed as individual best or particle best.

**Global best**( $g_{best}$ ): It is the best position among all the individual  $p_{best}$  of the particles.

**Velocity Updation:** Using the global best and individual best, the i<sup>th</sup> particle velocity is updated according to the following equation:

$$v_{ij}^{t+1} = v_{ij}^{t} + c_1 r_{1j}^{t} [p_{best,i} - x_{ij}^{t}] + c_2 r_{2j}^{t} [g_{best} - x_{ij}^{t}]$$

where

 $v_{ij}^{t+1}$  = velocity vector of particle i in dimension j at time t,

 $x_{ij}^{t}$  = position vector of particle i in dimension j at time t,

p<sub>best</sub>=the personal best position of particle i in dimension j found from initialization through time t,

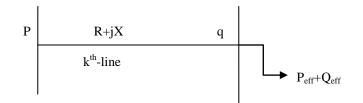
G<sub>best</sub>= the global best position of particle I in dimension j found from the initialization through time t,

 $c_{1,c_{2}}$  = positive acceleration constant which are used to level the contribution of the cognitive and social components respectively

 $r_{1i}^{t} \& r_{2i}^{t}$  random numbers from uniform distribution U(0,1) at time t;

#### **III. LOSS SENSITIVITY FACTORS**

Loss sensitivity factors helps to determine the candidate nodes for the placement of capacitors. The estimation of these candidate nodes basically helps in the reduction of the search space for the optimization procedure. Consider a distribution line connected between 'p' and 'q' buses.





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Active power loss in the k<sup>th</sup> line is given by  $[I_k^2] * R[k]$  which can be expresses as [12],

$$P_{\text{lineloss}} = \frac{(P_{\text{eff}}^2[q] + Q_{\text{eff}}^2[q]) \cdot R[k]}{(V[q])^2}$$

$$Q_{\text{lineloss}} = \underline{(P_{\text{eff}}^2[q] + Q_{\text{eff}}^2[q]) \cdot X[k]}$$
(3)
(4)

 $Q_{\text{lineloss}} =$ 

Where.

P<sub>eff</sub>[q]=total effective active power beyond the node 'q' Q<sub>eff</sub> [q]=total effective reactive power beyond the node 'q' Now both the loss sensitivity factors can be calculated by[12]:

(V[q])

$$\frac{\partial P_{\text{lineloss}}}{\partial Q_{\text{eff}}} = \frac{(2*Q_{\text{eff}}[q]*R[k])}{(V[q])^2}$$
(5)

$$\frac{\partial Q_{\text{lineloss}}}{\partial Q_{\text{eff}}} = \frac{(2^* Q_{\text{eff}}[q]^* X[k])}{(V[q])^2}$$
(6)

The loss sensitivity factors are calculated from the base case load flows and the values are arranged in descending order for all the lines of the given system.

#### **IV. POWER COMPENSATION**

Resistive, inductive and capacitive are the three type of loads. Among which inductive load is the most common as it is used in transformers, fluorescent tubes etc. All inductive loads require two kinds of power to work properly: active power (actually perform the function) and reactive power(sustains the electromagnetic field). As an example with an unloaded AC motor, one might expect the no-load current to drop near zero. In reality, however, the no-load current will generally show a value between 25% and 30% of full load current. This is due to continuous demand for magnetizing current by an induction load.

Capacitance is considered as a reactive power component, but in fact, it's characteristics in an electric circuit is to neutralize or compensate for the inductive reactive power. Thus, we have an item of electrical equipment which can be used to effectively offset a proportion of reactive power drawn from the supply.

#### V. ANALYSIS OF PSO IN RADIAL FEEDERS

The following algorithm is to be used for the placement of capacitors while using the particle swarm optimization:

Step 1: Run the base case distribution load flow and determine the active power loss.

Step 2: Identify the candidate buses for placement of capacitors using Loss Sensitivity Factors.

Step 3: Generate randomly 'n' number of particles, where each particle is represented as

particle[i]= $\{Q_{c1}, Q_{C2}, \dots, Q_{Cn}\}$  number of candidate buses.

Step 4: Generate the particle velocities

Where, v<sub>max</sub> =(Capmax,Capmin)/N

Capmax= maximum capacitor rating in kvar

Capmin= minimum capacitor rating in kvar

N= number of steps to move the particle from one position to the other

**Step 5:**Set the iteration count, iter=1.

Step 6: Run the load flows by using newton rephson method byplacing a particle 'i' at the candidate bus for reactive power compensation and store the active power loss.

Step 7: Evaluate the fitness value of the particle 'i'and compare the previous particle best(pbest) value. If the current fitness value is greater than its p<sub>best</sub> value ,then assign the p<sub>best</sub> value, then assign the p<sub>best</sub> value to the current value. Step 8: Determine the current global best(gbest) maximum value among the particles individual best(pbest) values.



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Step 9: Compare the global position with the previous global position. If the current global position is greater than the previous, then set the global position to the current global position.

**Step 10:** Update the velocities by using the equation (2) as mentioned above in the paper.

**Step 11:** If the velocity  $v_{ii}$  violates its limits( $-v_{max}, v_{max}$ ), set it at its proper limits.

**Step 12:** Update the position of the particle by adding the velocity  $v_{ii}$  to it.

**Step 13:** Now run the load flow and determine the active power loss with the updated particle.

Step 14: Repeat step 7 to step 9.

Step 15: Repeat the same procedure for each particle from steps 6 to 13.

**Step 16:** Repeat steps from 6 to 13 until the termination criteria are achieved.

#### VI.ADVANTAGES OF PSO AS COMPARED TO CLASSICAL TECHNIQUES

1.PSO algorithm is a derivative free algorithm.

2. It is easy to implement, so it can be applied both in scientific research and engineering problems.

3. It has a limited number of parameters and the impact of parameters to the solution is small compared to other optimization techniques.

4. Calculation of PSO algorithm is very simple.

5. There are some techniques which ensure convergence and the optimum value of the problem calculates easily within a short time.

#### VII. CONCLUSION

Particle swarm optimization technique can be preferred over the other heuristic techniques for the placement of capacitors in radial feeder distributors because of its simple concept, easy implementation, robustness to control parameters and better computational efficiency.

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