Solution of The Capacitor Allocation Problem
Using A New Accelerated Particle Swarm Optimization Algorithm

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Abstract- Many nature inspired meta-heuristic algorithms have been attempted for reactive power compensation of radial distribution feeders. In this paper, we introduce and implement a novel accelerated particle swarm optimization technique. Results of the proposed approach are compared with previous methods to show the superiority of the proposed method using three actual distribution feeders (of 9 bus, 15 bus, and 69 bus feeders). This new simple technique has the ability to give the best results for maximum reduction in system losses and costs among all previous studied techniques.

Index Terms- Capacitor placement, accelerated particle swarm optimization technique, loss Reduction, Cost function.

I. INTRODUCTION

The installation of shunt capacitors on radial distribution systems is essential for power flow control, improving system stability, power factor correction, voltage profile management, and loss minimization. It is important to find the optimal size and location of capacitors required to minimize feeder losses (power and energy), and the suitable time to switch the capacitors on and off. The solution techniques for the capacitor allocation problem can be classified into four categories [1]: analytical, numerical programming, heuristic, and artificial intelligence-based (AI-Based). AI-based methods include genetic algorithms, simulated annealing, expert systems, artificial neural networks, and fuzzy logic. A survey of all capacitor allocation categories is presented in [1] and [2].

Heuristic search techniques have been introduced for distribution system loss reduction first by reconfiguration [3], [4]. Ref. [3] presents a formula for estimating the change in losses caused by the transfer of a group of loads from one feeder to another by the closing and opening of some connecting switches. Ref. [4] develops a feeder reconfiguration strategy using heuristics for the removal of transformer overloads and feeder constraint problems. Recently, the ideas presented in [3] and [4] were adapted to the field of capacitor placement for reactive power compensation in distribution feeders.

Ref. [5] presents a heuristic strategy to reduce system losses by identifying sensitive nodes at which capacitors should be placed. These nodes are determined by first identifying the branch in the system with largest losses due to reactive currents. Then the node, which contributes the largest load affecting the losses in that branch, is selected as the candidate node. The capacitor size is the value that gives minimum system real losses. A load flow is performed next to ensure that no voltage violation takes place. The process is repeated for the next candidate node until no further loss reduction is achieved. This method does not guarantee a minimization in the cost function or maximization in the net saving function. Ref. [6] modifies the method of [5] to overcome this disadvantage so their technique attained good results in both loss and cost reductions but this technique does not achieve the best reductions.

Ref. [7] proposes a method of minimizing the loss associated with the reactive component of branch currents by placing capacitors at optimal locations. The method first finds the location of the capacitors in a sequential manner (loss minimization by a singly located capacitor). Once each of the capacitor location is identified, the optimal capacitor size at each selected location for all capacitors are determined simultaneously, to avoid over-compensation at any location, through optimizing the loss saving equations. This involves the solution of a set of linear algebraic equations. The disadvantage of this method is that it neglects the cost-benefit analysis which in turn depends on the cost of the capacitor bank and energy saving.

Fuzzy systems-based methods have the advantage of accounting for uncertainty in data and the compromise between voltage profile improvements and cost and loss reductions. Ref. [8] presents a fuzzy based approach for capacitor placement for a 9-bus feeder. Two membership functions for real power losses and voltage sensitivity have been defined to reduce the effort of finding the optimal locations. The whole problem has been presented as a fuzzy-set optimization problem to minimize the real losses and capacitor cost with voltage limit constraints. They used the intersection principle in fuzzy logic as the fuzzy decision to find the capacitor location then a variational method has been used to find capacitor sizes to attain minimum cost without violating the voltage constraints.

In Ref. [9], exactly the same procedures using the same feeder have been implemented but with two different membership functions. In fact, their membership functions for real power losses and voltage are the fundamental part of the membership functions that have been used in [8].

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However, they have achieved relatively better results by introducing a certain constant in the real loss membership function depending on their experiences.

In Ref. [10], the authors used the membership functions forms of [8] but replacing the real losses by reactive losses and the intersection decision (using min. operator) by product decision. They used the product fuzzy decision to determine the location of the capacitors and find the capacitor sizes. They used an analytical method based on differentiating a well-defined net saving function of power and energy losses with respect to capacitor size, thus obtaining the optimum capacitor size.

Ref. [11] introduces a study of previous work using fuzzy and heuristic strategies. The effect of varying some parameters in the membership functions to get better results is discussed. Also the effect of selection of parameters that should be used in fuzzy modelling is investigated. The advantages of fuzzy and heuristic methods presented are combined in a new fuzzy-heuristic idea. This combined technique is verified, by the application to test feeders, to give better results. Different fuzzy decision-making forms are applied to the fuzzy modelling problem. Finally a recommendation is made for the most efficient way to get a solution equal or very close to the optimal.

Ref. [12] aims to study distribution system operations by the ant colony search algorithm (ACSA). The objective of this study is to present new algorithms for solving the optimal feeder reconfiguration problem, the optimal capacitor placement problem, and the problem of a combination of the two.

In Ref. [13], Differential Evolution (DE) Algorithm along with Dimension Reducing Distribution Load Flow (DRDLF) has been used. This load flow identifies the location of the capacitors and the Differential Algorithm determines the size of the capacitors such that the cost of the energy loss and the capacitor to be minimum.

Ref. [14] presents a refined genetic algorithm which uses prim's algorithm in order to obtain spanning trees (radial configuration), with random costs for every branch. At every generation, the power flow calculations are made only if the candidate solution is unique.

In Ref. [15], Self Adaptive Hybrid Differential Evolution (SAHDE) along with sensitivity factors algorithm has been proposed to solve the capacitor placement problem. The purpose of the loss sensitivity factors is to identify the sensitive buses of the distribution system. With the integration of (SAHDE), the amount of capacitors to be included at the identified locations has been found.

A two-stage methodology is used in [16] for the optimal capacitor placement problem. In the first stage, fuzzy approach is used to find the optimal capacitor locations and in the second stage, an artificial bee colony algorithm is used to find the sizes of the capacitors. The sizes of the capacitors corresponding to maximum loss reduction have been determined.

The work presented in [17] introduces a new algorithm based on a combination of fuzzy, Dynamic Programming (DP), and Genetic Algorithm (GA) approaches for capacitor allocation in distribution feeders. The proposed method of this article uses fuzzy reasoning for sitting of capacitors in radial distribution feeders, (DP) for sizing and finally (GA) for finding the optimum shape of membership functions which are used in fuzzy reasoning stage.

In Ref. [18], capacitor placement and sizing are done by loss sensitivity factors and particle swarm optimization respectively, but the disadvantage of this method is that it narrows the search space for the possible capacitor locations.

Ref. [19] presents a fuzzy and Particle Swarm Optimization (PSO) method for the placement of capacitors on the primary feeders of radial distribution systems to reduce the power losses and to improve the voltage profile. A two-stage methodology is used for the optimal capacitor placement problem. In the first stage, fuzzy approach is used to find the optimal capacitor locations and in the second stage, Particle Swarm Optimization method is used to find the sizes of the capacitors. The sizes of the capacitors corresponding to maximum annual savings are determined by considering the cost of the capacitors. Also this technique narrows search space for possible capacitor locations which results in not reaching maximum system losses reduction.

Ref. [20] presents an approach for capacitor placement in radial distribution feeders to reduce the real power losses and to improve voltage profile. The location of the nodes where the capacitors should be placed is decided by set of rules given by the fuzzy expert systems [FES]. Then sizing of capacitors is modeled as an optimization problem and objective function is solved using a Hybrid Particle Swarm Optimization (HPSO) technique.

In Ref. [21], reactive power is minimized using particle swarm optimization (PSO) algorithm. It is applied to standard reactive power with voltage deviation problem by combining of two objective functions; real power loss and voltage profile improvement.

In this paper, we review and implement accelerated particle swarm optimization (PSO) algorithm applied to three actual distribution feeders. This technique is not a trial and error optimization technique. It is set of definite arranged procedures guaranteed to lead to the global optimal solution. This new method has the ability to give the best results concerning maximum reduction in system losses and costs with voltage profile improvement without voltage violations.

II. PROBLEM FORMULATION

A. Basic Concept of Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based optimization technique that is originally inspired by the sociological behavior associated with bird flocking and fish schooling [22]. One of the main advantages of PSO is that it needs no gradient information derived from the objective function. The aforementioned feature is a common property of all evolutionary algorithms (EA), including PSO, allowing them to be used on functions where the gradient is either
unavailable (due to the discontinuity of most of real functions), or computationally expensive to obtain.

The main idea of the PSO algorithm is to maintain a population of particles (agents), referred to as “swarm”, where each particle represents a potential solution to the objective function under consideration. Each particle in the swarm can memorize its current position that is determined by evaluation of the objective function, velocity, and the best position visited during its flying tour in the problem search space referred to as “personal best position” (pbest). The personal best position is the one that yields the highest fitness value for that particle. For a minimization task, the position having a smaller function value is regarded to as having a higher fitness. Also the best position visited by all the particles are memorized, i.e. the best position among all pbest positions referred to as “global best position” (gbest). The particles of the swarm are assumed to travel the problem search space in a discrete rather than continuous time steps. At each time step (iteration), the velocity of each particle is modified using its current velocity and its distance from pbest and gbest according to:

\[
v_i^{k+1} = v_i^k + c_1 \cdot \text{rand()} \cdot \frac{(pbest_i - s_i^k)}{\Delta t} + c_2 \cdot \text{rand()} \cdot \frac{(gbest_i - s_i^k)}{\Delta t} \tag{1}
\]

where:
- \(v_i^k\) is the \(i^{th}\) velocity component at iteration \(k\)
- \(\text{rand()}\) is random number between 0 and 1
- \(s_i^k\) is the current position in the \(i^{th}\) dimension
- \(c_1, c_2\) are the acceleration coefficients
- \(pbest_i\) is the personal best position in the \(i^{th}\) dimension
- \(gbest_i\) is the global best position in the \(i^{th}\) dimension
- \(\Delta t\) is the time step

Usually the value of the velocity is clamped to the range \([-v_{\text{max}}, v_{\text{max}}]\) to reduce the possibility that the particle might fly out of the search space. If the space is defined by the bounds \([-x_{\text{max}}, x_{\text{max}}]\), then the value of \(v_{\text{max}}\) is typically set so that \(v_{\text{max}} = k v_{\text{max}}\), where \(0.1 \leq k \leq 1\) [14]. After that, each particle is allowed to update its position using its current velocity to explore the problem search space for a better solution as follows:

\[
s_{i}^{k+1} = s_{i}^{k} + v_{i}^{k+1} \cdot \Delta t \tag{2}
\]

It is a common practice in PSO literatures to choose a unity time step (\(\Delta t\)), accordingly (\(\Delta t\)) is set to one throughout this work. The personal best position is updated after the \(k^{th}\) iteration according to:

\[
pbest_i^{k}= \begin{cases} pbest_i^k & \text{iff } f(s_i^{k+1}) \geq f(pbest_i^k) \\ s_i^{k+1} & \text{iff } f(s_i^{k+1}) < f(pbest_i^k) \end{cases} \tag{3}
\]

Referring to (1), the velocity update equation has three terms; the first term represents the particle’s memory of its current velocity (change in position) in the different dimensions of the search space, the second term is associated with “cognition” since it only takes into account the particle’s own experience, while the third one represents the “social interaction” between the particles. These three components are shown in Fig. 1 [23]. Each agent updates each location according to the interaction of the above three components, as illustrated in Fig. 2.

A better way to understand the mechanism of the stochastic search done by PSO is to think of each iteration not as a process of replacing the previous population with a new one (death and birth), but rather as a process of adaptation [22].

Attempting to increase the rate of convergence of the standard PSO algorithm to a global optimum, the inertia weight has been introduced in the velocity update equation [24]. The inertia weight is a scaling factor associated with the velocity during the previous time step. According to this modification proposed, equation (1) is modified to:

\[
v_i^{k+1} = w v_i^k + c_1 \cdot \text{rand()} \cdot \frac{(pbest_i - s_i^k)}{\Delta t} + c_2 \cdot \text{rand()} \cdot \frac{(gbest_i - s_i^k)}{\Delta t} \tag{4}
\]

where \(w\) is the inertia weight.

The inertia weight governs how much of the previous velocity should be retained from the previous time step. The inertia weight is set to decrease linearly from 0.9 to 0.4 during the course of a simulation. This setting allows the PSO to explore a large area at the start of the simulation (when the inertia weight is large), and to refine the search later by using a small inertia weight. In addition, damping the oscillations of the particles around gbest is another advantage gained by using a decreasing inertia weight. These oscillations are recorded when a large constant inertial weight is used. Accordingly, damping such oscillations assists the particles of the swarm to converge to the global optimal solution. In brief, the inertia weight can be likened to the temperature parameter encountered in simulated annealing [22].

In brief, the PSO algorithm can be summarized as follows [25]:

1. Create an initial swarm, with a random distribution and random initial velocities.
2. Calculate a velocity vector for each particle, using the particle's memory and the knowledge gained by the swarm.
3. Update the position of each particle, using its velocity vector and previous position.
4. Update the personal best position of each particle, and the global best position of all particles.
5. Go to step 2 and repeat until convergence, or the termination criteria is met.

It is important to realize that the velocity term models the rate of change in the position of the particle. Therefore, the changes induced by the velocity update equation represent acceleration, which explains the name of acceleration coefficients for the constants \( c_1 \) and \( c_2 \). The acceleration coefficients can be thought of as a balance between exploration (searching for a good solution) and exploitation (taking advantage of someone else's success). Too little exploration and the particles will all converge on the first good solution encountered, while too little exploitation and the particles will never converge, i.e. they will just keep searching. There is another way of looking at this rather than behaviors (exploration and exploitation). What must be properly balanced is individuality and sociality, i.e. traits that influence behavior. Ideally, individuals prefer being individualistic yet they still like to know what others have achieved so that they can learn from.

\[
\begin{align*}
\text{Original velocity} & \quad \text{Velocity towards } p_{best} \\
\text{Velocity towards } g_{best} & \quad \text{Resultant velocity}
\end{align*}
\]

Fig. 1 The three components of the velocity update equation.

Fig. 2 The position updates operation of agents.

B. Accelerated Particle Swarm Optimization

From Ref.[26] it is shown that the standard particle swarm optimization (PSO) uses both the current global best \( g^* \) and individual best \( S_i^* \). The reason of using the individual best is primarily to increase the diversity in quality solutions, however, this diversity can be simulated using some randomness. Subsequently, there is no compelling reason for using the individual best.

A simplified version which could accelerate the convergence of the algorithm is to use global best only. Thus in the accelerated particle swarm optimization, the velocity vector is generated by a simpler formula

\[
v_{i}^{k+1} = v_i^k + \alpha * (e - 0.5) + \beta (g^* - s_i^k)
\]

(5)

where \( e \) is a random variable with values from 0 to 1. Here the shift 0.5 is purely out of convenience. We can also use a standard normal distribution \( \alpha e \) where \( e \) is drawn from \( \mathcal{N}(0,1) \) to replace the second term.

Now the update of position is simply

\[
s_i^{k+1} = s_i^k + v_i^{k+1}
\]

(6)

In order to increase the convergence even further, we can also write the update of the location in single step

\[
s_i^{k+1} = (1 - \beta) s_i^k + \beta g^* + \alpha e
\]

(7)

This simpler version will give the same order of convergence. The typical values for this accelerated PSO acceleration constants are \( \alpha \approx 0.1 \sim 0.4 \) and \( \beta \approx 0.1 \sim 0.7 \) it is worth pointing out that the parameters \( \alpha \) and \( \beta \) should be in general related to the scales of the independent variables \( S_i \) and search domain.

A further improvement to accelerated PSO is to reduce the randomness as iterations proceed. This means that we can use a monotonically decreasing function such as
\[
\alpha = \alpha_0 \gamma^t
\]
(8)
where \( \alpha_0 \approx 0.5 \sim 1 \) is the initial value of randomness parameter. Here \( t \) is the number of iterations or time steps. \( 0 < \gamma < 1 \) is a control parameter.

C. The Algorithm Steps

The algorithm steps can be summarized as:

a. Perform a load flow calculation for the uncompensated feeder and determine active power losses. Define the cost function. We will define the cost function as the form used in [14], which depends on system losses \( P_{loss} \), capacitor size \( Q_c \), and capacitor cost \( K_c \), as follows:

\[
\text{Cost} = K_c^p \cdot P_{loss} + \sum_{j=1}^{k} K_c^j \cdot Q_c^j
\]
(9)

Where \( K_c^p \) is the cost per power loss ($/kW/year),

b. Initialize the swarm by generating randomly \( n \) iterations, and voltage -

c. Evaluate fitness value (objective function) of each particle

d. If fitness (x) > fitness (pbest), then pbest = x

e. If fitness (x) > fitness (gbest), then gbest = x

f. Run the load flow for reactive power compensation and store objective function value

g. Update iteration counter

h. Update the particles velocities using equation (5)
i. Calculate particles new positions using equation (7)
j. Check that there is no violation to the specified constraints.

k. Re-evaluate fitness value of each particle at the new locations & corresponding the current global best

l. Now, run the load flow for reactive power compensation with updated particles.

m. If the iteration number exceeds the maximum number of iterations, then Output the optimal solution. otherwise go to step (c)

From this algorithm, we note that attention is placed on power loss reduction, cost minimization and voltage profile improvement without voltage violations.

III. IMPLEMENTATION AND RESULTS

A. The First Feeder

The 9-bus radial distribution feeder of [8] is the first feeder to be studied. The rated voltage is 23 kV. The system is shown in Fig. 3. The feeder data is given in [8].

From load flow solution for this feeder, before compensation, the total active and reactive loads are 12367.6 kW and 4188.3 kVAr. The cost function and the total power losses are $ 131,675 and 783.8 kW respectively.

The objectives of capacitor placement are to reduce the power loss and keep voltages within prescribed limits with minimum cost. Considering investment cost, there are a finite number of standard capacitor sizes that are integer multiples of the smallest size \( Q_c \). The cost per kVAr varies from one size to another. Generally, larger sizes are cheaper than smaller ones. Let the maximum permissible capacitor size be

\[
Q_c \text{ max} = L \cdot Q_c
\]
(10)

Where L is an integer. Then at each selected location, there are L sizes to choose from. For the test feeder, K\(^p\) is selected to be $ 168/kW [27]. Commercially available capacitor sizes with $/kVAr are used in the analysis. Table I shows an example of such data. For reactive power compensation, the maximum capacitor size \( Q_c \text{ max} \) should not exceed the reactive load, i.e. 4186 kVAr. This results in 27 possible capacitor sizes shown in Table II with their corresponding cost/kVAr. The values of the 27 choices are derived from Table II by assuming a capacitor life expectancy of 10 years (the operating costs are neglected) [27].

<table>
<thead>
<tr>
<th>Size (kVAr)</th>
<th>150</th>
<th>300</th>
<th>450</th>
<th>600</th>
<th>750</th>
<th>900</th>
<th>1200</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ($)</td>
<td>750</td>
<td>975</td>
<td>1140</td>
<td>1320</td>
<td>1650</td>
<td>2040</td>
<td></td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Size (kVAr)</th>
<th>15</th>
<th>30</th>
<th>45</th>
<th>60</th>
<th>75</th>
<th>90</th>
<th>105</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ($/kVA)</td>
<td>.197</td>
<td>.188</td>
<td>.170</td>
<td>.183</td>
<td>.187</td>
<td>.211</td>
<td>.176</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
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<th>15</th>
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<th>45</th>
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<th>75</th>
<th>90</th>
<th>105</th>
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<td>.170</td>
<td>.183</td>
<td>.187</td>
<td>.211</td>
<td>.176</td>
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TABLE I

Available 3-phase capacitor sizes and cost

<table>
<thead>
<tr>
<th>Size (kVAr)</th>
<th>15</th>
<th>30</th>
<th>45</th>
<th>60</th>
<th>75</th>
<th>90</th>
<th>120</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ($/kVA)</td>
<td>.197</td>
<td>.188</td>
<td>.170</td>
<td>.183</td>
<td>.187</td>
<td>.211</td>
<td>.176</td>
</tr>
</tbody>
</table>

TABLE II

Possible choices of capacitor sizes and cost/kVAr
maximum and minimum bus voltage magnitudes are 0.9929 and 0.8375 pu respectively, where the voltage of the substation (bus no. 0) is assumed to be 1 pu, thus we have generally 0.8375 ≤ Vᵢ ≤ 1.0 pu.

We implemented our proposed accelerated PSO method and the results were promising. The real power loss has been reduced from its initial configuration loss of 783.8 kW to 677.9 kW. Also the annual cost per year has been reduced from 131,675 K$ to 115,619 K$. Also the minimum voltage in pu is 0.9 and the maximum voltage in pu is 1.005.

The optimal size of the capacitors at the buses 2, 4, 6, 9 is 4050, 3150, 1650 and 150 kVAr, respectively. Our optimized result has been compared with the previous published works for the capacitor placement problem and results are shown in Table III

Total annual cost for PSO in [18] is calculated according to Table II.

B. The Second Feeder

The second feeder, shown in Fig. 4, is 11 kV and consists of 15 buses. The data of this feeder is given in [29]. The power factor is 0.7. The total apparent power 1752 kVA. Total active and reactive power losses of this system are 61.79 kW and 57.3 kVAr respectively. The voltage range is 0.946 ≤ Vᵢ ≤ 1.0 p.u. Here voltage profile improvement is not a target. Figure 5 shows that our proposed method leads to better results compared with the PSO method used in [18] regarding the active power losses (kW) of the system. The optimal sizes of the capacitors at buses 3, 6, 12 are 900, 300 and 150 kVAr, respectively. The active power losses after compensation is 32.3 kW with total capacitor size installed of 1350 kVAr. The total annual cost ($/year) is calculated and found to be 5,771 $.

C. The Third Feeder

The third test feeder is a 12.66 kV, 69-bus distribution feeder. The feeder consists of main feeder and seven laterals. The scheme of this feeder is shown in figure 6. The data of this feeder is given in [18]. Before compensation, the cost is $37,653; this is based on the previously defined cost function, and the total active and reactive loads are 3802.2 kW and 2694.6 kVAr. The active and reactive losses are 224.1 kW and 101.7 kVAr respectively. The voltage range is 0.9093 ≤ Vᵢ ≤ 1.0 p.u.

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TABLE IV
SYSTEM CONDITIONS WITHOUT AND WITH
CAPACITORS PLACEMENT USING DIFFERENT
OPTIMIZATION METHODS FOR THE 69 BUS SYSTEM

<table>
<thead>
<tr>
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<th></th>
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</thead>
<tbody>
<tr>
<td>Final power loss (kW)</td>
<td>224.1</td>
<td>147.96</td>
<td>146.79</td>
<td>145.2</td>
</tr>
<tr>
<td>Total Capacitor Size (kVAR)</td>
<td>–</td>
<td>1400</td>
<td>1500</td>
<td>2400</td>
</tr>
<tr>
<td>Total Annual cost ($/year)</td>
<td>–</td>
<td>30,293</td>
<td>28,607</td>
<td>24,986</td>
</tr>
<tr>
<td>Min. Bus voltage</td>
<td>0.9093</td>
<td>0.9296</td>
<td>0.9309</td>
<td>0.933</td>
</tr>
<tr>
<td>Max. Bus voltage</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

In Fig. (7), the total annual cost of the capacitors using our proposed accelerated particle swarm optimization is compared with PSO in [18], Genetic Algorithms, GA in [30] and DE in [13]. As shown, our proposed technique gives the least annual costs.

IV. CONCLUSIONS

This paper ensures that the accelerated particle swarm technique can be considered powerful for solving the capacitor allocation problem for radial distribution feeders. Regardless of the feeder nature, our proposed method gives the maximum power loss and cost reduction accompanied by better voltage profile improvement without buses voltage violation. The technique converges to the optimal solution with high quality. Also the coding of accelerated PSO is simple and gives more accurate results.

V. REFERENCES
