Reliability enhancement of a radial distribution system using coordinated aggregation based particle swarm optimization considering customer and energy based indices

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ABSTRACT

This paper describes an algorithm for optimum modifications for failure rate and repair time for a radial electrical distribution system. The modifications are with respect to a penalty cost function minimization. The cost function has been minimized subject to the energy based and customer oriented indices, i.e. AENS, SAIFI, SAIDI and CAIDI. Coordinated aggregation based particle swarm optimization (CAPSO) has been used for optimization. The algorithm has been implemented on a sample radial distribution system. The results obtained have been compared with those obtained using PSO.

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1. Introduction

Reliability evaluation of distribution systems has received considerable attention and played important role in quantitative assessment of the adequacy of the system from consumer’s viewpoint [1–5]. Important reliability indices for a distribution system are system failure rate, outage duration and annual outage time. All these three indices are average values from respective probability distribution functions and represent the long term performance of the distribution systems. The above mentioned reliability indices are of fundamental importance, they may not always depict a complete characterization of adequate performance of the system. Since these indices do not account number of customers and load at various load points, in order to reflect severity of an outage customer oriented and energy based indices are evaluated, e.g. SAIFI, SAIDI, CAIDI and AENS. Usually distribution system is constructed as a radial distribution system. Further there are many other systems which are constructed as meshed systems but operated as single radial feeder systems by applying open points in the mesh. In such systems an adequate performance of the distribution system is achieved by maintaining desired level of the reliability indices. In such situation it is required to intensify fault avoidance measures and measures to reduce repair time for each distributor segment of the distribution system. These measures in turn modify failure rate and repair time of each segment and thus improve the reliability indices. Sallam et al. [6] described an algorithm for evaluating optimum value of reliability indices for distribution system using gradient projection method. The objective function is the minimization of interruption cost subject to constraints on reliability indices. Chang and Wu [7] used a primal dual interior point algorithm for optimum reliability design of a distribution system. Chowdhury and Custer [8] described a value based approach for designing an urban distribution system. Bhoomik et al. [9] presented a distribution network planning algorithm by considering a non-linear objective function with linear and non-linear constraints for a radial distribution system. Developed strategy includes substation as well as feeder optimization. Modified genetic algorithm has been used by Su and Lii [10] for reliability design of a meshed distribution network. Arya et al. [12] used particle swarm optimization (PSO) for failure rate and repair time allocation for a radial distribution system applying decomposition. Bouguerra and Habi [11] developed an algorithm of reliability improvement of industrial electric network fed by two sources. Ganguly et al. [19] presented an algorithm expansion planning of...


2. Electrical distribution network using particle swarm optimization, Nicabadi et al. [20] developed a new variant of PSO using a newly proposed inertia weight approach.

All the papers cited above considered system failure rate, outage duration and annual outage duration for reliability enhancement. None of these have considered customer oriented and energy based reliability indices for reliability optimization. As mentioned earlier in order to have adequate performance of the distribution these need to be considered in the reliability improvement algorithm. In view of this discussion in this paper an algorithm has been presented for reliability improvement of a radial distribution system accounting constraints on energy based and customer oriented indices using a variant of particle swarm optimization (PSO) known as coordinated aggregation based particle swarm optimization (CAPSO). PSO and its variants are being applied to various engineering applications because of ease of implementation, mechanization and having better chances of obtaining global optimal solution [16,17].

2. Customer oriented and energy based reliability indices

Various customer oriented reliability indices have been identified and are being used for predictive performance evaluation by distribution utilities. A survey by EPRI (Electric Power Research Institute) has identified that most frequently used customer oriented indices are SAIFI, SAIDI, CAIDI and AENS. These indices are defined as follows [1,18]

System average interruption frequency index (SAIFI)

\[ \text{SAIFI} = \frac{\sum \lambda_{\text{sys}}, N_i}{\sum N_i} \]  \hspace{1cm} (1)

System average interruption duration index (SAIDI)

\[ \text{SAIDI} = \frac{\sum U_{\text{sys}}, i N_i}{\sum N_i} \]  \hspace{1cm} (2)

Customer average interruption duration index (CAIDI)

\[ \text{CAIDI} = \frac{\sum U_{\text{sys},i} N_i}{\sum N_i} \]  \hspace{1cm} (3)

where \( \lambda_{\text{sys},i} \) is the system failure rate at ith load point, \( N_i \) is number of customers at load point \( i \), \( U_{\text{sys},i} \) is system annual outage duration at ith load point.

Expressions for the evaluation of \( \lambda_{\text{sys},i} \) and \( U_{\text{sys},i} \) for each load point are given as follows

\[ \lambda_{\text{sys},i} = \sum_{k \in S} \lambda_k r_k \]  \hspace{1cm} (4)

\[ U_{\text{sys},i} = \sum_{k \in S} \lambda_k r_k \]  \hspace{1cm} (5)

where \( \lambda_k \), \( r_k \) denote failure rate and average repair time of kth distributor segment respectively. \( S \) denotes the set of distributor segments connected in series up to ith load point.

One of the most important energy based indices is average energy not supplied (AENS) which is given as follows

\[ \text{AENS} = \frac{\sum L_i U_{\text{sys},i}}{\sum N_i} \]  \hspace{1cm} (6)

where \( L_i \) is average load connected at ith load point, which may be obtained from load duration curve. Constraint is imposed on AENS by selecting a threshold value of this index.

3. Problem formulation

A cost is associated with modifications in failure rates and repair times. The preferred approach is to formulate the cost function using previous data analysis, and relationship may be obtained between cost of improvement and failure rate (repair time) modifications. Usually such cost function is not available. Hence in this paper a cost function in penalty form has been assumed and is given as follows

\[ J = J_1 + J_2 \]  \hspace{1cm} (7)

where \( J_1 \) represents total penalty on modifications in failure rates at each distributor segment and is expressed as

\[ J_1 = \sum_{i=1}^{NC} \left[ \frac{\lambda_0 - \lambda_i}{\lambda_i - \lambda_{i,\text{min}}} \right] \]  \hspace{1cm} (8)

where \( \lambda_0 \), \( \lambda_{i,\text{min}} \) and \( \lambda_i \) are current, minimum achievable and modified failure rate of ith segment respectively. \( NC \) denotes total number of distributor segments.

Expression (8) indirectly reflects cost (penalty) on failure rate modification. As failure rate reduces penalty increases. It is assumed that failure rates will take values lower than current values.

Similarly \( J_2 \) represents cost of modification in repair time for all the distributor segments and is given as follows

\[ J_2 = \sum_{i=1}^{NC} \left[ \frac{r_i^0 - r_i}{r_i - r_{i,\text{min}}} \right] \]  \hspace{1cm} (9)

where \( r_i^0 \), \( r_i \) and \( r_{i,\text{min}} \) represent current, modified and minimum achievable repair time for ith segment. It is obvious that the lesser is the value of repair time the more is the penalty. It is assumed that modified repair time of a component is less than the current value.

Finally the objective function (7) is written as follows

\[ J = \sum_i \frac{\lambda_0 - \lambda_i}{\lambda_i - \lambda_{i,\text{min}}} + \sum_i \frac{r_i^0 - r_i}{r_i - r_{i,\text{min}}} \]  \hspace{1cm} (10)
The objective function as given by (10) is minimized subject to following constraints

(i) Inequality constraint on SAIFI

\[ \text{SAIFI} \leq \text{SAIFI}_d \]  

(ii) Inequality constraint on SAIDI

\[ \text{SAIDI} \leq \text{SAIDI}_d \]  

(iii) Inequality constraint on CAIDI

\[ \text{CAIDI} \leq \text{CAIDI}_d \]  

(iv) Inequality constraint on AENS

\[ \text{AENS} \leq \text{AENS}_d \]  

(v) Inequality constraints on failure rate and repair time of each component

\[ \lambda_{i,\text{min}} \leq \lambda_i \leq \lambda_{i,\text{max}}, \quad r_{i,\text{min}} \leq r_i \leq r_{i,\text{max}}, \quad i = 1, \ldots, NC \]

where \( \text{SAIFI}_d, \text{SAIDI}_d, \text{CAIDI}_d \) and \( \text{AENS}_d \) are desired values of SAIFI, SAIDI, CAIDI and AENS, respectively.

The objective function (10) is minimized subject to constraints (i)–(v). It is assumed specifically in radial (series) system, that by intensifying preventive and corrective repair measures, one reduces the failure rate \( \lambda_i \) and repair time \( r_i \) from their current values. In view of this the value of objective function, as given by relation (10) will be increasing as \( \lambda_k \leq \lambda_0 \) or \( r_k \leq r_0 \). This is dictated by constraints as given by relation (15). Hence the objective is to minimize the increase in total penalty cost (objective function) subject to satisfaction of constraints as given by relations (11)–(15).

4. Overview of particle swarm optimization (PSO) and coordinated aggregation based particle swarm optimization (CAPSO)

Particle swarm optimization (PSO) is a member of various methods developed based on swarm intelligence for obtaining global optimum solution. The method was originally proposed by Kennedy and Eberhart [13]. This methodology is population based, where the procedure is initialized with a population of random particles and the algorithm updates the population. Assume that search space is \( n \)-dimensional. The position of the \( i \)-th particle is represented by an \( n \)-dimensional vector as

\[ S_i = (s_{i1}, s_{i2}, \ldots, s_{in}), \quad i = 1, \ldots, m \]

where \( m \) denotes the size of swarm or population. The velocity of the particle (agent) is represented by another \( n \)-dimensional vector

\[ \rho_i = (\rho_{i1}, \rho_{i2}, \ldots, \rho_{in}), \quad i = 1, \ldots, m \]

The fitness of each particle is evaluated using objective function. The best position of particle is in terms of objective function and is denoted as \( P_{best,i} \). The position of the best individual of the whole swarm is named as global best position, \( G_{best} \). At each iteration the velocity and position of particle is updated as follows

\[ \rho_{iter}^i = w \rho_{iter}^{i-1} + c_1 \text{rand}_1 (P_{iter}^{i-1} - s_{iter}^i) + c_2 \text{rand}_2 (G_{iter}^{i-1} - s_{iter}^i) \]

\[ s_{iter}^i = s_{iter}^{i-1} + \rho_{iter}^i \]

where \( w \) is termed as inertia weight which controls the impact of previous velocity on its current velocity. \( \text{rand}_1 \) and \( \text{rand}_2 \) are random digits in the range [0,1]. \( c_1 \) and \( c_2 \) are positive constants known as acceleration coefficients and hence control maximum step size. In PSO, relation (16) is applied for the calculation of new velocity according to its previous velocity and to the distance of its current position from both its own best position and global best position. Then the particle flies toward a new position according to relation (17). The process is repeated until a user defined stopping criterion is satisfied. Further a suitable magnitude of inertia weight provides balance between global and local exploration abilities. The procedure is modified by varying \( w \) in each iteration according to the following relation [14]

\[ w_{iter} = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \]

where \( iter_{max} \) denotes maximum number of iterations specified, \( w_{max} \) and \( w_{min} \) are maximum and minimum values specified of inertia weight. Inequality constraints are accounted by a fly back mechanism [15]. Whenever an updated particle exits feasible region it is put back to its previous position. It is assumed that the population is initialized in feasible region. Hence flying back to its previous position will assure that particle is always in feasible region.

Various PSO algorithms differ the way swarm is updated in feasible search space. A co-ordinated aggregation (CA) based approach has been proposed and applied to solve a steady state optimization problem related to power network [16]. In CAPSO a new operator has been introduced in the swarm, where each agent moves considering only the positions of agents with better achievement in terms of objective function than its own, with the exception of the best particle which moves randomly exhibiting craziness. The CA may be conceived as a type of active aggregation where particles are attracted where availability of food is most. Achievement factor \( \alpha_i \) is the ratio of differences between the achievement of particle-\( i \), \( J(S_{iter}^{i-1}) \) and better achievements by particle-\( j \) \( J(S_{iter}^{j-1}) \) to the sum of all of these differences. \( \alpha_i \) is calculated as

\[ \alpha_i^{iter-1} = \frac{J(S_{iter}^{i-1}) - J(S_{iter}^{j-1})}{\sum_{j \in T_i} [J(S_{iter}^{j-1}) - J(S_{iter}^{j-1})]} \]

where \( T_i \) represents the set of particle-\( j \) with better achievements in terms of objective function. The velocities of the particles except the best achievement are updated using following relation.

\[ \rho_i^{iter} = w \rho_i^{iter-1} + \rho_i^{iter-1} + \text{rand}_2 \alpha_i^{iter-1} [S_{iter-1}^{j} - S_{iter-1}^{j}] \]

where \( \text{rand}_2 \) is a random digit in the range [0,1]. Velocity of the best particle \( (S_{iter-1}^{i}) \) in the swarm is updated using relation given below

\[ \rho_i^{iter} = w \rho_i^{iter-1} + \rho_i^{iter-1} + \text{rand}_2 [S_{iter-1}^{i} - S_{iter-1}^{i}] \]

where \( S_{iter-1}^{i} \) is the position of randomly selected particle from the swarm. The updating of the best particle behaves like a crazy way and helps the swarm escape from local minima. The difference \( (S_{iter-1}^{i} - S_{iter-1}^{i}) \) is termed as random co-ordinator. Positions of all the particles are updated using relation (17). The reliability optimization problem as formulated in Section 3 is solved using CAPSO and the details of the computational algorithm as given in next section.

5. Computational algorithm

The CAPSO technique is implemented in the following steps to obtain optimum failure rates and repair times with respect to the formulated problem.
Table 1
System data for sample radial distribution system.

<table>
<thead>
<tr>
<th>Distributor segment</th>
<th>#1</th>
<th>#2</th>
<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_i^0 ) failure/year</td>
<td>0.4</td>
<td>0.2</td>
<td>0.3</td>
<td>0.5</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>( r_i^0_{\text{avg}} ) repair time</td>
<td>10</td>
<td>9</td>
<td>12</td>
<td>20</td>
<td>15</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>( \lambda_i^\text{max} ) failure/year</td>
<td>0.2</td>
<td>0.05</td>
<td>0.1</td>
<td>0.1</td>
<td>0.15</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>( r_i^\text{min} )failure/year</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>8</td>
<td>7</td>
<td>6</td>
<td>6</td>
</tr>
</tbody>
</table>

Step-1 Initialization: Generate swarm of \( m \) particles in terms of initial velocities and positions as follows

\[
S^0_i = [x_{i1}^0, x_{i2}^0, \ldots, x_{iNC}^0, y_{i1}^0, y_{i2}^0, \ldots, y_{iNC}^0]^T, \\
r^0_i = [x_{i1}^0, x_{i2}^0, \ldots, x_{iNC}^0, y_{i1}^0, y_{i2}^0, \ldots, y_{iNC}^0]^T; \quad i = 1, \ldots, m
\]

A particle in the swarm consists of \( 2NC \) decision variables. \( x_{ij}^0 \) and \( y_{ij}^0 \) represents starting values of failure rate and repair times respectively. Initial components \( x_{ij}^0 \) and \( y_{ij}^0 \) are selected from uniform distribution between \( [\lambda_i^\text{min}, \lambda_i^0] \) and \( [r_i^\text{min}, r_i^0] \) respectively satisfying inequality constraints as given by relations (11)–(14).\#3 Such initial solutions are generated. Initial velocity \( x_{ij}^0 \) and \( y_{ij}^0 \) of each particle is generated using random digits in the range

\[
\lambda_i^\text{min} - \lambda_i^0 \leq x_{ij}^0 \leq \lambda_i^0 - \lambda_i^\text{min} \\
r_i^\text{min} - y_{ij}^0 \leq y_{ij}^0 \leq y_i^0 - r_i^\text{min}
\]

Step-2 Set \( \text{iter} = 1 \)
Step-3 Calculate objective function as given by relation (10) for all particles in the swarm. Identify the best particle in swarm based on the objective function.
Step-4 Calculate achievement factors \( \alpha_{ij} \) using the relation (19).
Step-5 Update position and velocity of each particle except the best one using relations (17) and (20) respectively.
Step-6 Velocity of the best particle is updated using a random co-ordinator given by relation (21). Position of this particle is updated using relation (17).
Step-7 If any decision variable \( x_{ij} \) and \( y_{ij} \) in an updated solution violates the limits as given by relation (15), it is set to previous value.
Step-8 Each updated solution is applied to inequality constraints given by relations (11)–(14). If any of the updated solution does not satisfy these constraints, then the particle is brought back to its previous position (15).
Step-9 Calculate global optimum solution up to current iteration. \( \text{iter} = \text{iter} + 1 \)
Step-10 If \( \text{iter} > \text{iter}_{\text{max}} \)
Stop, otherwise repeat from step-4.

The CAPSO algorithm may even be terminated before \( \text{iter}_{\text{max}} \) if no improvement in objective function is observed in a pre-specified number of iterations.

6. Results and discussions

The CAPSO based algorithm developed in this paper for reliability enhancement has been implemented on a radial distribution system shown in Fig. 1. The system has in all seven load points (LP). The system contains seven feeder segments. Table 1 gives current failure rate \( \lambda_i^0 \) and average repair time \( r_i^0 \) for each distributor segment. The same table also gives minimum reachable values of these variables. Table 2 gives average loads and number of customers \( (N_i) \) at each load point. A swarm of hundred particles was generated in the range of decision variables dictated by constraint (15). Maximum 800 iterations were specified and carried out as well. Thirty independent runs have been carried out with different initial swarms. Maximum and minimum inertia weights were selected as 1.0 and 0.1 respectively. Table 3 gives best final fitness value (objective function), average of best final fitness values

Table 2
Average load and number of customers at load points.

<table>
<thead>
<tr>
<th>Load point LP-k</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average load ( L_i ), kW</td>
<td>1000</td>
<td>700</td>
<td>400</td>
<td>500</td>
<td>300</td>
<td>200</td>
<td>150</td>
</tr>
<tr>
<td>Number of customers ( N_i )</td>
<td>200</td>
<td>150</td>
<td>100</td>
<td>150</td>
<td>100</td>
<td>250</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 3
Statistics of best fitness function values as obtained using PSO and CAPSO based on 30 numbers of runs.

<table>
<thead>
<tr>
<th>Statistics technique</th>
<th>PSO</th>
<th>CAPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average value of best fitness function values</td>
<td>19.2545</td>
<td>19.0522</td>
</tr>
<tr>
<td>Standard deviation (( \sigma ))</td>
<td>0.1445</td>
<td>0.0252</td>
</tr>
<tr>
<td>Minimum value of best fitness function</td>
<td>19.0738</td>
<td>19.0214</td>
</tr>
<tr>
<td>Maximum value of best fitness function</td>
<td>19.5737</td>
<td>19.1230</td>
</tr>
</tbody>
</table>
as achieved out of the 30 independent runs. The same table also presents other related statistics, i.e. standard deviation, and maximum value of best fitness values obtained in 30 runs. Further results have also been obtained using standard PSO method as given by relations (16) and (17). Statistical parameters for PSO method have also been provided in Table 3. It is observed that standard deviation and range of value of objective function is smaller in CAPSO than that obtained in PSO. Further in 30 runs the difference between maximum value of sample and minimum value of sample is less as obtained using CAPSO. Figs. 2 and 3 show the relative frequency distribution plots of best fitness value as obtained using 30 runs by CAPSO and PSO respectively. The class interval in each case has been selected using Sturge’s relation [18]. It is further observed that frequency distribution plot as obtained by CAPSO is more skewed towards the least minimum value. Fig. 4(a)–(d) shows the evolution of best fitness value (objective function), the worst fitness value, average fitness value, and standard deviation as obtained by PSO and CAPSO respectively. These evolutions have been presented for run which gives least value of objective function out of 30 runs. It is observed that CAPSO creates some solutions with very high fitness value as opposed to PSO. This is observed owing to (i) random co-ordinator aggregation as given in Eq. (20) and (ii) the way the best position of swarm is updated using relation (21). The updating of the best particle behaves like a crazy way and helps the swarm to get better fitness value [16]. Table 4 provides execution time for both the methodologies on Core2Duo processor 2.93 GHz with 2 GB RAM. Fastest and average execution times of 30 runs have been provided. The difference between fastest and the average times differ for the same algorithm (PSO or CAPSO) because of randomly generated initial swarm for each run. Table 5 shows the optimized set of decision variables, i.e. λr, r along with least values of objective function as obtained by PSO and CAPSO. These values are with respect to the best run in each case. It is to be noted that the optimized result have been presented as obtained after executing maximum number of iterations specified, i.e. 800 in this paper. No significant change has been observed after 480 iterations with both PSO and CAPSO. Table 6 shows un-optimized and optimized values of the reliability indices. This table also shows desired values of the indices. It is observed from this table that all the indices are less than the threshold values specified. The reliability optimization problem as formulated in Section 3 has been solved using one of the popular non-linear optimization techniques known as Davidon–Fletcher–Powell’s (DFP) method and accounting inequality constraints by an exterior penalty function method [21–23]. The gradient based technique has been extensively used for non-linear optimization problem solution in power system studies. Mechanization of DFP method is much more involved (as details may be seen in Refs. [21,23]) than PSO/CAPSO techniques. Various related sensitivities are required to determine the gradient vector. A exterior penalty parameter is selected at a low initial value say 0.5 and

**Table 4**

<table>
<thead>
<tr>
<th>Technique</th>
<th>Execution time in s</th>
<th>Fastest</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>2.6590</td>
<td>2.6630</td>
<td></td>
</tr>
<tr>
<td>CAPSO</td>
<td>1.8750</td>
<td>1.9780</td>
<td></td>
</tr>
<tr>
<td>DFP</td>
<td>9.5890</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Actual time of a run.

**Table 5**

Optimized values of failure rates and repair times as obtained by PSO, CAPSO, and DFP techniques.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Magnitudes as obtained by</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>CAPSO</td>
</tr>
<tr>
<td>λ1</td>
<td>0.2395</td>
</tr>
<tr>
<td>λ2</td>
<td>0.0991</td>
</tr>
<tr>
<td>λ3</td>
<td>0.2065</td>
</tr>
<tr>
<td>λ4</td>
<td>0.1831</td>
</tr>
<tr>
<td>λ5</td>
<td>0.1956</td>
</tr>
<tr>
<td>λ6</td>
<td>0.1000</td>
</tr>
<tr>
<td>λ7</td>
<td>0.0999</td>
</tr>
<tr>
<td>r1</td>
<td>6.9454</td>
</tr>
<tr>
<td>r2</td>
<td>7.9565</td>
</tr>
<tr>
<td>r3</td>
<td>7.7388</td>
</tr>
<tr>
<td>r4</td>
<td>11.5192</td>
</tr>
<tr>
<td>r5</td>
<td>11.3236</td>
</tr>
<tr>
<td>r6</td>
<td>8.0000</td>
</tr>
<tr>
<td>r7</td>
<td>12.0000</td>
</tr>
<tr>
<td>Objective function</td>
<td>19.0738</td>
</tr>
</tbody>
</table>

**Table 6**

Current and optimized reliability indices.

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Index</th>
<th>Current values</th>
<th>Optimized values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>PSO</td>
</tr>
<tr>
<td>1</td>
<td>SAIFI interruptions/customer</td>
<td>0.7200</td>
<td>0.4150</td>
</tr>
<tr>
<td>2</td>
<td>SAIDI hrs/customer</td>
<td>8.4500</td>
<td>3.3056</td>
</tr>
<tr>
<td>3</td>
<td>CAIDI hrs/customer interruption</td>
<td>11.7361</td>
<td>7.9657</td>
</tr>
<tr>
<td>4</td>
<td>AENS kWh/customer</td>
<td>26.4100</td>
<td>10.0000</td>
</tr>
</tbody>
</table>
if violations are observed then this parameter is increased in step size say by 10% each time till all inequality constraints are satisfied. Table 4 provides CPU time required using DFP method. The CPU time required by DFP method is sufficiently large as compared to that required by CAPSO and PSO. Since DFP is an analytical technique only one CPU time has been provided. Table 5 provides optimized values of failure rates and repair times as obtained using DFP method along with objective function (J). The results are in close agreement with those obtained using CAPSO and PSO techniques. Further Table 6 provides the optimized values of reliability indices as obtained using DFP. The optimized reliability indices are within limits.

7. Conclusions

Customer and energy based reliability indices are of great significance in predictive reliability performance assessment of a distribution system. These indices are extensively used in power industry. All such indices depend on failure rate and repair time of each segment of distribution systems. An optimization method has been presented using co-ordinated aggregation based particle swarm optimization (CAPSO) to obtain optimum failure rate and repair times so as to achieve desired levels of the indices. A penalty cost function has been used for this purpose. CAPSO, variant of PSO is found to be computationally effective over the standard PSO.

References


