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Reliability Optimization of a Radial Distribution System Using Bacterial Foraging Algorithm Based on Customer and Energy Based Indices

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Abstract – **In this paper, a methodology has been developed for reliability evaluation of radial distribution system by determining the optimal values of repair times and failure rates of each section. Failure rate and repair time based on penalty cost function has been constructed. Constraints on customer and energy based indices i.e. SAIFI, SAIDI, CAIDI, AENS, and ASAI are considered. A decomposed approach, which optimizes failure rate and repair time separately satisfying the constraints, is used. A recently developed bacterial foraging algorithm is employed to solve the optimization problem. The proposed algorithm has been implemented on an eight node distribution network. The obtained results are compared with PSO, CAPSO, FDR PSO and DE algorithms.**

Keywords - **Distribution Systems, Reliability Indices, Bacterial Foraging Algorithm.**

I. INTRODUCTION

It is of great significance to evaluate reliability of individual customer service which can significantly affect the design and operating characteristics of power systems, especially distribution systems. Analysis of customer failure statistics indicates that distribution systems make a significant individual contribution to overall customer supply unavailability. Approximately 80% of all customer interruptions occur due to failures in the distribution system [1]. The reliability assessment is concerned with the system performance at customer end, which could be considered as the system load point's indices. The primary customer load point reliability indices are the average outage duration and the annual outage duration. Conventional reliability analyses are normally only concerned with evaluating the expected or average value of a particular index. Despite the considerable growth in the field of distribution system reliability assessment, service continuity indices [2] continue to be measured almost exclusively by average indices. In order to reflect severity of an outage, customer oriented and energy based indices are evaluated. Most frequently used indices by utilities are (i) SAIFI, (ii) SAIDI, (iii) CAIDI, (iv) AENS and (v) ASAI [2].

Distribution system reliability performance is optimized with respect to failure rate and repair time allocation to each distribution segment. Failure rate and average repair time are reduced by intensifying fault avoidance and corrective repair measures. In the literature, many researchers have attempted the optimization of distribution system performance using various algorithms such as gradient projection method [3], primal dual interior point algorithm [4], value based approach [5], modified genetic algorithm [6]. Chandra Mohan et al. [7] minimized operating cost of radial distribution system in deregulated electricity market via reconfiguration. Mendoza et al. [8] proposed a multiobjective approach based on a micro genetic algorithm for reconfiguration in distribution networks to minimize the power losses and reliability indices.

All these methodologies successfully obtains optimum failure rate and repair time for reliability enhancement. In all these articles, constraints are considered only on primary reliability indices i.e. system failure, average interruption duration and unavailability. But it should be noted that these indices may not give true picture of severity of an outage as the number of customers and average load at various load points are not included in these indices [2].

Swarm optimization methods are very popular in recent days because they have information sharing and conveying mechanisms. Among swarm optimization methods, bacterial foraging [10] is very promising. This paper focuses on bacterial foraging algorithm to solve the problem of radial distribution system reliability performance on accounting customer and energy based reliability indices. The results obtained using proposed algorithm has been compared with that of PSO and its variants CAPSO, FDR PSO, and DE algorithm with respect to the solution quality.

The problem is decomposed into two sub-problems. One of it optimizes failure rate and the other one determines optimum repair time satisfying customer and energy based reliability constraints.

II. CUSTOMER-BASED RELIABILITY INDICES

The most widely used reliability indices are averages that weight each customer equally. Customer-based indices are popular with regulating authorities since a small residential customer has just as much importance as a large industrial customer. They have limitations, but are generally considered good aggregate measures of reliability and are often used as reliability benchmarks and improvement targets. A survey by Electric Power Research Institute (EPRI) has identified that most frequently used customer oriented indices are SAIFI, SAIDI, CAIDI, AENS and ASAI. These indices are defined as follows [2].

A. System Average Interruption Frequency Index (SAIFI)

SAIFI is a measure of how many sustained interruptions an average customer will experience over the course of a year. For a fixed number of customers, the only way to improve SAIFI is to reduce the number of sustained interruptions experienced by customers.

$$\mathrm{SAIFI} = \frac{\text{Total number of customer interruptions}}{\text{Total number of customers served}}$$

$$\mathrm{SAIFI} = \frac{\sum \lambda_{sys,i} N_i}{\sum N_i} \qquad (1)$$

B. System average interruption duration index (SAIDI)

SAIDI is a measure of how many interruption hours an average customer will experience over the course of a year. For a fixed number of customers, SAIDI can be improved by reducing the number of interruptions or by reducing the duration of these interruptions. Since both of these reflect reliability improvements, a reduction in SAIDI indicates an improvement in reliability.

$$\mathrm{SAIDI} = \frac{\text{Sum of all customer interruption durations}}{\text{Total number of customer served}}$$

$$\mathrm{SAIDI} = \frac{\sum U_{sys,i} N_i}{\sum N_i} \qquad (2)$$

C. Customer average interruption duration index (CAIDI)

CAIDI is a measure of how long an average interruption lasts, and is used as a measure of utility response time to system contingencies. CAIDI can be improved by reducing the length of interruptions, but can also be reduced by increasing the number of short interruptions. Consequently, a reduction in CAIDI does not necessarily reflect an improvement in reliability.

$$\mathrm{CAIDI} = \frac{\text{Sum of all customer interruption duration}}{\text{Total number of customer interruptions}}$$

$$\mathrm{CAIDI} = \frac{\sum U_{sys,i} N_i}{\sum \lambda_{sys,i} N_i}$$

(3)

D. Average energy not supplied (AENS)

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

$$\mathrm{AENS} = \frac{\text{Sum of system annual outage duration at load point}}{\text{Sum of average load point}}$$

$$\mathrm{AENS} = \frac{\sum L_i U_{sys,i}}{\sum N_i} \qquad (4)$$

E. Average Service Availability Index (ASAI)

ASAI is the customer-weighted availability of the system and provides the same information as SAIDI. Higher ASAI values reflect higher levels of system reliability, with most US utilities having ASAI greater than 0.999.

$$\mathrm{ASAI} = \frac{\text{Customer hours service availability}}{\text{Customer hours sevice demand}}$$

$$\mathrm{ASAI} = [(8760\text{-}\mathrm{SAIDI})/8760]*100 \qquad (5)$$

where L_i is average load connected at i^{th} load point, which may be obtained from load duration curve, $\lambda_{sys,i}$ is the system failure rate at i^{th} load point, N_i is number of customers at load point i and $U_{sys,i}$ is system annual outage duration at i^{th} load point.

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

$$\lambda_{sys,i} = \sum_{k \in s} \lambda_k \qquad (6)$$

$$U_{sys,i} = \sum_{k \in s} \lambda_k r_k \qquad (7)$$

λ_k, r_k denote failure rate and average repair time of k^{th} distributor segment respectively. S denotes the set of distributor segments connected in series up to i^{th} load point.

III. PROBLEM FORMULATION

A penalty cost is associated with reduction in failure rate and repair time of each distributor segment from their current values. The preferred approach is to formulate the cost function using previous data analysis and relationship may be obtained between costs of improvement of failure rate (repair time) reductions. In this paper, penalty cost function has been assumed to be indirectly reflect the cost of modifications of failure rate or repair time. Increased investment is necessary in order to reduce failure rate or repair time, which in turn improves reliability of the system. The general trend shows that incremental cost to achieve a given decrease in failure rate or repair time increases as the modification level increases. Low failure rate or repair time (near minimum reachable values) is expensive to achieve. This is reflected from penalty functions (8) and (11). In the absence of field data, penalty functions of the form given by (8) and (11) have been assumed. Indirectly these functions represent cost of investment for a specific decrement in failure rate or repair time. Large is the decrement higher will be penalty, which will reflect the cost of investment. Optimization will provide changes in failure rates or repair times of component with lesser penalties (indirectly investment cost) and significant contribution to the reliability indices. If field data in terms of cost are available then the penalty function can be calibrated in terms of actual cost investment. Further, the problem formulation is decomposed in two stages. One sub-problem optimizes failure rates and other optimizes repair times satisfying inequalities on customer and energy based reliability indices described in previous section. The following sub sections describe the formulation of two sub problems.

A. Sub-problem-I: Optimum failure rate allocation.

It is observed that the SAIFI depends only on failure rate of distribution system segments. Hence this sub-problem considers inequality constraints on SAIFI and bounds on failure rate modifications. Following form of penalty cost function is selected which is a function of failure rates of each distributor segment.

$$J_1 = \sum_{K=1}^{NC} \left[\frac{\lambda_k^0 - \lambda_k}{\lambda_k - \lambda_{k,min}} \right] \qquad (8)$$

λ_k^0, $\lambda_{k,min}$ and λ_k are current, minimum achievable and modified failure rate of k^{th} distributor segment respectively. Expression for J_1 indirectly reflects cost of failure rate modifications. As failure rate reduces from its current value, cost increases. It is further assumed that failure rate will take values lower than current values. The objective function (8) is minimized subject to following constraints.

(i) $\text{SAIFI} - \text{SAIFI}_d \leq 0$ (9)

SAIFI_d is specified desired value of SAIFI

(ii) $\lambda_{k,min} \leq \lambda_k \leq \lambda_k^0$, k=1,…. NC (10)

NC denotes total number of distributor segments.

Objective function (8) is minimized subject to constraints (9) and (10) and optimum failure rates are determined. It is stressed here that there are various failure modes, which contributes to overall failure rate of a section. Some failure modes may belong to categories of random failures and contributes to a low constant failure rate. Some others may give rise to increasing failure rate. Such type of failure mode requires preventive maintenance and replacement of sub-components in time to have overall failure rate practically constant. The optimization in this paper has been carried out with respect to overall/crude failure rate, which is aggregation of failure rates due to various failure modes [3, 4, 6]. One important objective of such failure rate optimization is to assign target to the crew involved in preventive maintenance and persons involved in related managerial activities. Thus at a later stage target may be assigned to reduce the failure rates by various modes (root causes). Modes having higher contribution (based on field data) to overall failure rate should be given large weightage in preventive maintenance efforts.

B. Sub-problem-II: Optimum repair time allocation.

Cost function J_2, which accounts penalty on repair time modification is selected as follows

$$J_2 = \sum_{K=1}^{NC} \left[\frac{r_k^0 - r_k}{r_k - r_{k,min}} \right]$$

(11) r_k^0, $r_{k,min}$ and r_k are current, minimum achievable and modified repair time for k^{th} section. It is obvious that smaller is the value of repair time larger is the value of objective function. It is assumed that modified repair time of a component is less than the current value. The objective function J_2 is minimized subject to following constraints.

(i) $\text{SAIDI} - \text{SAIDI}_d \leq 0$ (12)
(ii) $\text{CAIDI} - \text{CAIDI}_d \leq 0$ (13)
(iii) $\text{AENS} - \text{AENS}_d \leq 0$ (14)
(iv) $r_{k,min} \leq r_k \leq r_k^0$, k=1,……. NC (15)

Objective function (11) is minimized subject to constraints (12)–(15). SAIDI_d, CAIDI_d and AENS_d are the desired threshold value of indices SAIDI, CAIDI and AENS respectively.

In these formulations, it is stressed that the penalty function indirectly represents the cost of modifications of failure rate or repair time of each section. Further the inequality constraints implicitly represent the various associated costs which may be mitigated by selecting adequate desired values of the customer and energy based indices. Consider for example the constraints on SAIFI, which represent the cost proportional to system failure rate [6] with a relative weightage to customers at load points. Similarly the constraints on SAIDI represent the initial interruption cost which involves the product of system failure rate and average down time ($\lambda_{sys,q}$, $r_{sys,q}$). Further constraints on CAIDI represent adequate performance or customer satisfaction. Average energy not supplied (AENS) represents cost of energy not supplied to consumer and it is an indication of not only customer satisfaction but also represents loss of revenue to the utility. Hence a target value of AENS is fixed. Lesser is this target value higher will be cost of failure rate/repair time modification which is exhibited in penalty functions. ASAI is the customer-weighted availability of the system. Higher ASAI values reflect higher levels of system reliability. Thus optimization of objective function in penalty form subject to constraints on SAIFI, SAIDI, CAIDI, AENS, and ASAI represent the optimal performance of the distribution system.

IV. BACTERIAL FORAGING ALGORITHM

BFA is an optimization method developed by Kevin M. Passino (2002) [9], based on the foraging strategy of Escherichia Coli (E. Coli) bacteria, bacteria that live in the human intestine. Foraging strategy is a method of animals for locating, handling and ingesting their food. The structure of E. Coli bacteria is such that it has a “body” which is constructed from a plasma membrane, cell wall and capsule that contains the cytoplasm and nucleoid. Furthermore, E. Coli bacteria have flagella that can move in a rotation manner and used for locomotion: if the flagella moves counter clockwise it makes bacteria to move forward with large displacement namely “swim” and if the flagella moves clockwise it makes the bacteria move in an uncertain direction with very small displacement called “tumble”. The size of E. Coli bacterium itself is very tiny, about 1μm in diameter, 2μm in length, 1 picogram in weight with about 70 % of it being water. The foraging strategy is governed basically by four processes namely Chemotaxis, Swarming, Reproduction, Elimination and Dispersal.

F. Chemotaxis

Chemotaxis process is the characteristics of movement of bacteria in search of food and consists of two processes namely swimming and tumbling. A bacterium is said to be 'swimming' if it moves in a predefined direction, and 'tumbling' if moving in an altogether different direction. Let j be the index of chemotactic step, k be the reproduction step and l be the elimination dispersal event. Let θ^i (j,k,l) is the position of i^{th} bacteria at j^{th} chemotactic step, kth reproduction step and lth elimination dispersal event. The position of the bacteria in the next chemotactic step after a tumble is given by

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i)\bullet\Delta(i)}} \qquad (16)$$

If the health of the bacteria improves after the tumble, the bacteria will continue to swim to the same direction for the specified steps or until the health degrades.

G. Swarming

Bacteria exhibits swarm behavior i.e. healthy bacteria try to attract other bacteria so that together they reach the desired location (solution point) more rapidly. The effect of Swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density.

$$\begin{aligned} J_{cc}(\theta,P(j,k,l)) &= \sum_{i=1}^{n} J_{cc}\left(\theta,\theta^i(j,k,l)\right) \\ &= \sum_{i=1}^{s}\left[-d_{attract}\exp\left(-w_{attract}\sum_{i=1}^{n}(\theta_m-\theta_m^i)^2\right)\right] + \\ &\quad \sum_{i=1}^{s}\left[-d_{repellant}\exp\left(-w_{repellant}\sum_{i=1}^{n}(\theta_m-\theta_m^i)^2\right)\right] \end{aligned} \qquad (17)$$

Reproduction

In this step, population members who have had sufficient nutrients will reproduce and the least healthy bacteria will die. The healthier half of the population replaces with the other half of bacteria which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

H. Elimination and Dispersal

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.

Following is the step by step procedure of Bacterial Foraging Algorithm:

Initialize parameters:

p	Dimension of search space.
S	Number of bacteria in the population.
Nc	Number of chemotaxis steps.
Ns	Number of swimming steps
Nre	Number of reproduction steps
Ned	Number of elimination and dispersal steps
Ped	Elimination and dispersal probability
C(i)	Unit run-length

Step 1: Elimination and dispersal loop l = l+1

Step 2: Reproduction loop l = l+1

Step 3: Chemotaxis loop j = j+1

a. For i= 1, 2, 3.....S, a chemotaxis step for ith bacterium will be as follows:

b. Calculate fitness function J(i,j,k,l).
Let *J(i,j,k,l)=J(i,j,k,l)+Jcc(θ^i(j,k,l),P(j,k,l))* is cell to cell attractant effect to the nutrient concentration).

c. Let $J_{last} = J(i,j,k,l)$

d. Tumble: generate a random vector Δ(i)εR^p with each element $\Delta_m(i)$, m = 1,2,…..P a random number on [-1,1]

e. Move: Let
$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i)\bullet\Delta(i)}}$$
The step of size C(i) in the direction of the trumble for bacterium i.

f. Compute *J(i,j+1,k,l)* and let *J(i,j+1,k,l)= J(i,j,k,l)+Jcc(θ^i(j+1,k,l),P(j+1,k,l))*

g. Swim: Let m=0
While m<Ns
Let m=m+1
If $J(i,j+1,k,l) < J_{last}$
Let $J_{last} = J(i,j,k,l)$ & let
$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i)\bullet\Delta(i)}}$$
And use this θ^i(j+1,k,l) to compute the new *J(i,j+1,k,l)* as same in step (f) Else, let m= Ns. This is the end of the while statement.

h. Go to next bacterium (i+1), if i≠S go to step (b)

Step 4: If j< Nc, go to step 3 for next chemotaxis step as the chemotaxis process not complete.

Step 5: Reproduction. With current values of k, l, compute overall fitness (cost function) $\sum_{j=1}^{Nc} P^{i,j,k,l}$ for each ith bacterium and sort the fitness in descending order. Higher value of cost function means less fitness.

Step 6: Half of the bacteria with less fitness will die and the other half will reproduce. They will split into two and placed at the same locations of their parents. So, population remains constant.

Step 7: If k< N_{re}, go to step 2. Increment the reproduction counter and start new chemotaxis process.

Step 8: Elimination-dispersion. Eliminate the bacterium with probability P_{ed} and disperse one at a random location in the optimization space.

Step 9: If l< N_{ed}, go to step1. Otherwise end.

V. RESULTS AND DISCUSSIONS

Bacterial foraging algorithm was used to solve the reliability optimization problem on a sample 8 node radial distribution system [11], which is shown in fig 2. The system has seven distributor segments. Each load point (LP) connected to lateral distributor via pole mounted transformers (33/0.4 kV) where a fuse gear is installed. In case a short circuit occurs on a lateral distributor, causes fuse to blow. It does not affect or cause the disconnection of any other load point. Hence reliability of 33 kV load point is unaffected. Appendix A.1 gives current and minimum values of failure rate of average repair time for each segment. Appendix A.2 shows average load and number of customers at various load points.

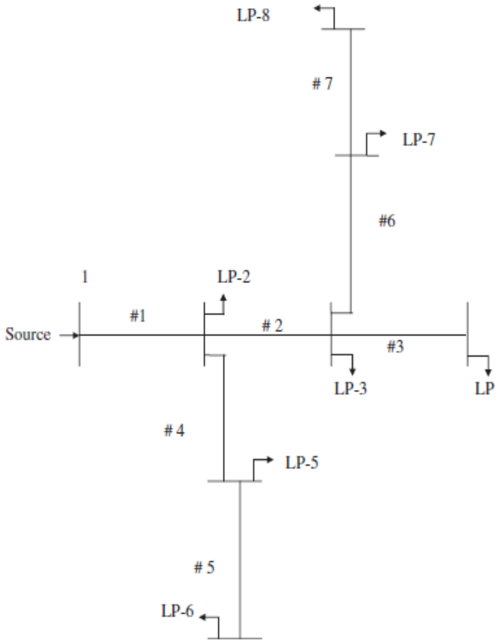


Fig.2. Eight node distribution network

The two sub problems were solved by using the proposed algorithm. The optimum values of failure rate and repair times of each feeder segment are given in table 1. To validate the proposed method, the obtained results are compared with that of PSO, CAPSO, FDR PSO and DE algorithms and the comparison is given in table 1. It is observed that the results of all the four methods are in close agreement. CPU times required to solve the problem by these four methods are given in table 2 and it is observed that BF algorithm takes much less time than other algorithms. Figs.3 and 4 show the best value of objective function of failure rates and repair times respectively. Table 3 provides reliability indices as obtained using BF algorithm along with the threshold values.

Table I: Optimized values of failure rates and repair times as obtained by BFA

Variables	Magnitudes as obtained by				
	PSO [11]	CAPSO [11]	DE [11]	FDR PSO [12]	**BFA**
λ_1 (yr)	0.2701	0.2678	0.2706	0.2531	0.2532
λ_2 (yr)	0.1294	0.1324	0.1316	0.1975	0.1343
λ_3 (yr)	0.2862	0.2938	0.3000	0.2904	0.2700
λ_4 (yr)	0.3018	0.3001	0.2882	0.2215	0.2145
λ_5 (yr)	0.1991	0.2000	0.2000	0.1982	0.1722
λ_6 (yr)	0.0993	0.1000	0.1000	0.0995	0.0955
λ_7 (yr)	0.0986	0.1000	0.1000	0.0983	0.0993
r_1 (h)	6.1671	6.1429	6.1775	6.4356	6.7356
r_2 (h)	6.3033	6.4103	6.3525	6.4189	6.6413
r_3 (h)	4.6629	4.7310	4.5345	4.5039	4.5039
r_4 (h)	8.5466	8.4723	8.6180	8.6018	8.4018
r_5 (h)	7.8077	8.0240	7.9474	7.9361	8.0361
r_6 (h)	6.5526	6.6173	6.6789	6.1964	6.9964
r_7 (h)	7.5168	8.0184	7.5878	7.4328	7.9328
Total Penalty, $J = J1 + J2$	82.1877	82.4892	77.3953	72.0832	69.2643

Table II: CPU times required for convergence

Technique	PSO [11]	CAPSO [11]	DE [11]	FDR-PSO [12]	**BFA**
CPU Time (ms)	6829	5063	328	302	297

Table III: Current and optimized reliability indices for radial distribution system.

Index	SAIFI (interruptions /customer)	SAIDI (h/customer)	CAIDI (h/customer interruption)	AENS (kWh/customer)	ASAI
Current values	0.7200	8.4500	11.7361	26.4100	-----
DE [11]	0.5000	3.2855	6.6710	10.0000	-----
PSO [11]	0.5000	3.2806	6.5611	9.9994	-----
CAPSO [11]	0.5000	3.2854	6.5708	9.9999	-----
FDRPSO [12]	0.5000	3.3309	6.6198	9.9731	99.9
BFA	0.4585	3.1464	6.8620	9.5313	99.9
Threshold values	0.5000	4.0000	8.0000	10.0000	-----

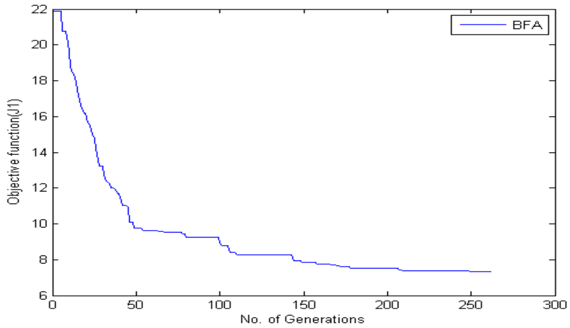


Fig.3. Best value of objective function for failure time

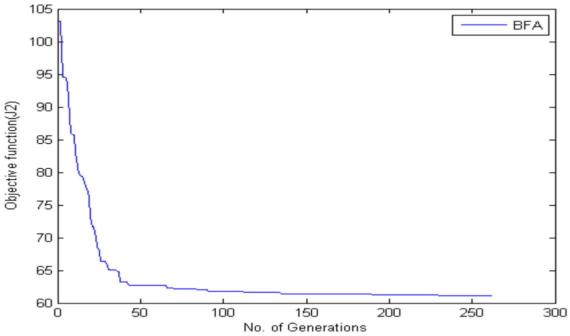


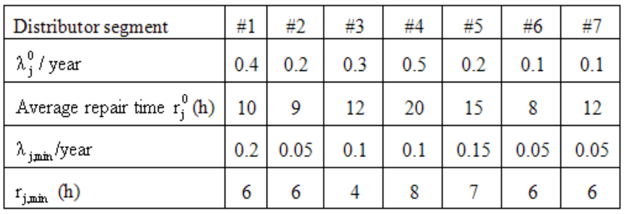
Fig.4. Best value of objective function for repair time

VI. CONCLUSION

A methodology for the computation of customer and energy based reliability indices are sufficient to evaluate predictive performance of distribution systems. An application of BFA has been successfully employed to evaluate optimum failure rate and repair time for each section to achieve desired reliability goals in terms of the mentioned indices. The problem has been solved in two stages, one optimizes failure rate and other optimizes repair time. The main advantage of the proposed model has been compared with other four algorithms based on PSO, CAPSO, FDR PSO and DE. From the comparison it is referred that the BFA gives desired results with less computational time than other methods.

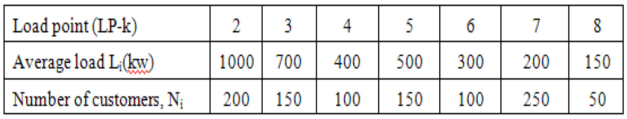
APPENDIX

A.1 System data for sample radial distribution system



Distributor segment	#1	#2	#3	#4	#5	#6	#7
λ_j^0 / year	0.4	0.2	0.3	0.5	0.2	0.1	0.1
Average repair time r_j^0 (h)	10	9	12	20	15	8	12
$\lambda_{j,min}$/year	0.2	0.05	0.1	0.1	0.15	0.05	0.05
$r_{j,min}$ (h)	6	6	4	8	7	6	6

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



Load point (LP-k)	2	3	4	5	6	7	8
Average load L_i(kw)	1000	700	400	500	300	200	150
Number of customers, N_i	200	150	100	150	100	250	50

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