Optimal Location of Shunt Faults in Distribution Networks using Non-dominated Sorting Particle Swarm Optimization

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Abstract

This paper presents the fault location in distribution systems as a multi-objective combinatorial optimization problem. In doing so, Non-dominated sorting particle swarm optimization (NSPSO) based on the concept of NSGA-II, has been proposed to alleviate the problems with conventional multi-objective evolutionary algorithms. The proposed algorithm estimates the location of shunt faults on radial distribution systems based on customer calls and their distance from the fault. Due to the presence of various conflicting objective functions, the fault location task is a multi-objective, optimization problem. The considered FSE problem should be handled using Multi objective Optimization techniques since its solution requires a compromise between different criteria. In this technique, the multi-objective nature of the fault section estimation problem is retained without the need of any tuneable weights or parameters. As a result, the proposed methodology is generalized enough to be applicable to any electric distribution network. The applicability of the proposed methodology has been demonstrated through detail simulation studies on different test systems. Results are used to reduce the possible number of potential fault location which helps and equips the operators to locate the fault accurately.

Keywords: Distribution Networks, Fault Location, NSPSO, NSGA-II, Particle Swarm Optimization.

1. Introduction

It is noted that the significant volume of literature exists for transmission line fault location; however, techniques developed for transmission systems are generally not applicable to distribution systems since distribution systems are inherently unbalanced and are equipped with very few recording devices, usually located at the main substation. The acrimony of these networks, like heterogeneity of feeders, unbalances due to the untransposed lines, presence of laterals along the main feeder, presence of the load taps along the main feeder and laterals and dynamic characteristics of the loads [1]:

Traditionally, fault diagnosis is performed off line by experienced engineers. Faulted section of the feeder is located generally using information of customer trouble calls. For estimation of fault section, the maintenance crews rely mainly on phone calls by customers and trial and error methods [2], [3]. But in this process, it takes several hours to identify the exact location of fault. Over the last three decades, due to technological progress in computers and electronics, power system has been equipped with digital relays.

The faulted feeder is energized section by section, using either remote control sectionalizers or auto reclosers until the protection relay trips again. When further energizing the feeder is not possible, the repair crew will patrol the feeder to locate the exact fault location. However, software tools for fault location have emerged in recent years. To improve the accuracy and speed of fault location the information is stored in a database and intelligent systems in a control centre and can be accessed for diagnosis of a fault event. Data recorded by recorders at substation, customer phone calls location and status of reclosers are used [3].

Researchers have done considerable work in the area of fault diagnosis particular to radial distribution systems.

Presently, the main methods of Fault Section Estimation can be classified into three categories:
- Analytic Calculation-Based Methods (ACBM),
- Reasoning-Based Methods (RBM), and
- Optimization-Based Methods (OBM).

ACBM identifies fault location through analytical calculation using information of current and voltage values available from Supervisory Control and Data Acquisition (SCADA) and Fault Recorders [1].

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In this class, one of the earliest fault-location algorithms belongs to Srinivasan et al. [4], in which the authors used the concept of simplified distributed parameters for fault location. The presence of load taps beyond the fault is treated by consolidating those load models with that of the remote end load. Taking the loads and their variable impedance behaviour into account was the main contribution which caused noticeable error reduction of the fault-location algorithm.

Other example of the most comprehensive works in the distribution fault location area goes to Aggarwala et al. [5]. The presented algorithm utilizes superimposed components to identify the fault location. Das et al. [6],[7] further developed the algorithm of Srinivasan et al. [4]. His method makes use of pre-fault data to estimate the load’s value when the fault occurs and then uses the simplified distributed parameter model for the construction of the fault-location algorithm. Furthermore, Das et al. assumes that all loads beyond the fault point are lumped together and placed at the end of the line. Their presented results showed good accuracy within the computer simulation environment.

J. Mora-Florez et al. [8] presented a detailed comparison of impedance based fault location methods for power distribution systems. The main drawback of the impedance-based methods is the multiple estimations due to the existence of multiple possible fault points at the same electrical distance from the measuring end.

RBM reasons the fault section by using logical rules or connotative illation, including some techniques, such as Expert System (ES) [9], Artificial Neural Networks (ANN) [10], Fuzzy Logic (FL) [11] etc.

Fuzzy Logic aims to settle the incomplete and uncertain information problem with different degrees of success. These methods are satisfactory and efficient, and some have been used in practical systems. However, there are also some obvious shortcomings, which are weak in solving the problems of fault diagnosis in large-scale power systems. The greatest inconvenience of Fuzzy Logic approach lies in the choice of the membership functions, usually defined based on empirical data. This way, it is necessary to develop efficient algorithms for estimating membership functions in a coherent manner.

There is no doubt that fault location using ANN techniques is very fast and gives result without taking any time. But it is seen that the accuracy is very poor in comparison to other techniques. So in ANN based fault location techniques, more research is required to improve the accuracy.

The third technique is OBM, which formulates the FSE problem as a 0–1 integer optimization problem. It can then be solved by using a global optimization method such as Genetic Algorithm (GA) [12], Tabu Search (TS) [13] and PSO [14] etc. Diagnostic model based on optimization algorithms is most possibly practical because it has strict mathematical theory and given the global optimum or several possible results of part optimum under the circumstances of the complex fault.

More research work is required to make Genetic Algorithm more efficient and to improve the accuracy. To improve the performance of genetic algorithm technique, the elite-preserving operator, which favours the elites of a population by giving them the opportunity to be directly carried over to the next generation, should be used. It has been proved that GAs converges to the global optimal solution in the presence of elitism.

Zhengyou He et al. [14] proposed Binary Particle Swarm Optimization (BPSO) which takes the failure of protective relays or Circuit Breakers into account. Numerical results reveal that BPSO is superior to GA for the convergence speed and accurate estimation results.

In most of the reported methods, loads and laterals have not been considered during fault section estimation. None of the methods take into account the location of customer calls as one of the objectives, which is very practical and prevailing component of fault section estimation techniques. Moreover, effect of variation in the fault resistance has not been presented by most of the authors.

To alleviate the problems mentioned in the literature survey, a Non-dominated sorting particle swarm optimization (NSPSO) developed by X.Li [15] based on NSGA-II developed by K.Deb et al. [16] is presented for solving the fault section estimation problem in this paper. In this technique, the multi-objective nature of the fault section estimation problem is retained without the need of any tuneable weights or parameters. As a result, the proposed methodology is generalized enough to be applicable to any power distribution network. The applicability of the proposed methodology has been demonstrated through detail simulation studies on different test systems.

2. Overview of the Proposed Fault Location Method

A typical distribution system, which may include three-phase, two-phase, as well as one-phase laterals & loads, is depicted in fig.1. A fault section estimation method has been developed in which fault analysis is done by utilizing voltage and current measurements obtained at the local substation based on direct short-circuit analysis.

Fig.1. Sample radial power distribution system.

The multiple estimate of the location of fault, faulted phase and type of fault is obtained by existing method described in [7]. The selected system consists of an equivalent source, the line between nodes M and N and two laterals as shown in fig.2. Loads are tapped at several nodes
and conductors of different types are used on this circuit. Throughout the description, the term “node” will be adopted to represent a single-phase connection point, while a “bus” may contain one, two, or three nodes depending on the number of phases it contains. For example, a three-phase bus will have three nodes.

A detailed description of the technique is described in the next section.

2.1. Pre fault and Post fault Data acquisition

When a fault is detected, the fundamental frequency components of the pre-fault voltage and current phasors at node M are saved. The fundamental frequency components of voltage and current phasors at node M during the fault are estimated and the fault type is determined after a pre-set time has elapsed. These actions are taken on-line and are depicted in the fig.3. The pre-fault and fault data, along with line and load parameters, are used in an off-line mode to estimate the location of the fault. Necessary line and load parameters are obtained from a database.

2.2. Estimation of the faulted section

The sequence voltages and currents at node M, before and during the fault, are calculated from the estimated phasors. A preliminary estimate of the location of the fault is made, say between nodes x and x+1 (=y) as shown in fig.2. Line parameters, the type of fault and the phasors of the sequence voltages and currents are used to obtain this estimate. Impedance, measured at the terminal, could point to multiple locations in the system, if it has laterals. Steps C to F are applied using each of the apparent locations.

2.3. Modification in radial distribution system

All laterals between node M and the apparent location of the fault are ignored and the loads on a lateral are considered to be present at the node to which the lateral is connected. For example, load at nodes K and L are lumped with the load at node x – 1.

2.4. Modeling of loads

All loads up to node x are considered independently and the loads beyond the fault, node F, are assumed to be consolidated with the load at the remote node, N. Non-linear models of loads are used to take into account their dependency on voltage. The constants of load models are computed from the pre-fault load voltages and currents.

2.5. Estimating sequence voltages and currents at the fault and at remote node

Using the voltage-dependent load model, determined in Step D, sequence voltages and currents, at node x during the fault, are computed taking into account the load currents. The sequence voltages at the remote end are taken calculated as a function of the distance of the fault from node x. The sequence voltages and currents at the fault node, F, are also obtained as functions of distance of the fault from node x and the impedance of the consolidated load at the remote node.

2.6. Estimating the distance of fault from node x

The relationships between the sequence voltages and currents at the fault are used to estimate the distance of the fault from node x. The first estimate of the distance is obtained using the pre-fault sequence admittance of the consolidated load at node N. Subsequently, the value of the admittance is updated using the net values of the sequence voltages at node N and voltage dependent load model determined in Step D. The procedure is repeated until a converged solution is obtained.

An attempt is made to obtain two additional estimates, for the fault location by considering that the fault is either located between the nodes x – 1 and x or between the nodes x + 1 and x + 2. The most plausible solution is selected and

Fig.2. Single line diagram of a distribution system experiencing a fault [7].
the location of the fault from the measurement node $M$ is estimated.

3. **Voltages and Currents at the Fault and Remote End**

The sequence currents at node $F$ for the network shown in fig. 3, and the sequence voltages at nodes $F$ and $N$ during the fault are estimated using the voltages and currents at node $x$. The sequence voltages and currents at node $R$ during the fault are calculated by using the voltages and currents at $M$ and the load models. The sequence components of load currents are estimated. The currents at node $N$ flowing towards the fault, are then calculated. The sequence voltages and currents at node $x$ during the fault are calculated using procedure given in [7] for each sequence component and for all sections up to node $x$. The sequence voltages and currents at node $F$ during the fault are estimated by assuming that all loads beyond node $x$ are consolidated into a single load at $N$, as shown in fig. 3.

The voltages and currents at nodes $F$ and $x$, related by

\[
\begin{bmatrix}
V_f \\
I_{f_x}
\end{bmatrix}
= 
\begin{bmatrix}
1 & -sB_{xy} \\
sC_{xy} & -1
\end{bmatrix}
\begin{bmatrix}
V_x \\
I_{sf}
\end{bmatrix}
\]  

(1)

where, '$s'$ is the per unit distance to node $F$ from node $x$, $B_{xy}$ and $C_{xy}$ are the constants of section between the nodes $x$ and $x+k(=y)$.

3.1. **Converting Multiple Estimates to Single Estimate**

The proposed fault estimation technique could provide multiple estimates if the distribution system has laterals. The number of estimates, for a fault, depends on the system configuration and the location of the fault. It is, therefore, necessary to convert the multiple estimates to a single estimate.

To further nail down the most potential fault location, Non-dominated sorting particle swarm optimization (NSPSO) developed by X. Li [15], have been applied in the following section. The proposed algorithm estimates the location of shunt faults on radial distribution systems including customer calls as one of the objectives.

4. **Problem Formulation of Fault Section Estimation**

Fault location problem is formulated as multi objective function problem. These objective functions [17] will use the data collected, such as current and voltage measurements and customer phone calls to create a list of most potential fault locations and verify them with the available multiple estimates from the iterative approach as described in section 2 and 3.

4.1 **Objective functions**

4.11. **Minimization of difference of measured and calculated fault current**

\[
\min f_1 = \sum_{n=1}^{N} \sum_{l=1}^{NF} (I_{M} - I_{C})
\]  

(2)

The first objective function compares the calculated fault currents with the measured fault current value. Note that the pre-fault load current must be added to fault currents calculated by the fault analysis routine. Locations where the calculated fault current is within a specified range of the measured current are listed as potential fault locations. It is assumed that the difference between the calculated and measured values were within 1-2%.

4.12. **Minimization of distance between customer fault location and predicted fault location**

\[
\min f_2 = \sum_{n=1}^{N} \sum_{l=1}^{NF} L_{CC-F}
\]  

(3)

The second objective function minimizes the distance between the location of customer phone call and existing fault to further reduce the list of potential fault locations.

4.13. **Minimization of pre fault voltage and voltage during fault**

\[
\min f_3 = \sum_{n=1}^{N} \sum_{l=1}^{NF} (V_r - V_f)
\]  

(4)
where, 
\( f_1, f_2, f_3 \): the defined fitness function  
\( N \): number of buses  
\( NF \): number of faults  
\( NC \): number of customer calls  
\( I_m \): measured fault current  
\( I_c \): calculated fault current as obtained from eqn. (1)  
\( L_{c,c,f} \): distance between customer call location and predicted fault locations as obtained from customer call input file.  
\( V_i \): pre fault voltage as obtained from buffer memory.  
\( V_f \): voltage during fault as obtained from eqn. (1)

The minima of single objective function converted from these multiple objectives using non-dominated sorting concept [16], correspond to the most likely fault locations. The optimization algorithm and fitness function evaluation are described in detail in the following section. By decreasing the search area for the maintenance crew the time required to find the exact location of the fault can be highly reduced.

Also if estimation is started with only the critical components rather than all the components in the circuit, much smaller number of potential fault locations can be obtained. The critical components are defined as the ones that are the most likely to fail, based on the historical observations by the distribution utility.

5. Particle Swarm Optimization

Kennedy and Eberhart [18] proposed an approach called particle swarm optimization (PSO) in 1995. The particle swarm optimization (PSO) algorithm is a population-based search algorithm based on the simulation of the social behaviour of birds within a flock or fishes in a school. In PSO, individuals, referred to as particles, are “flown” through hyper dimensional search space. Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbours. The consequence of modelling this social behavior is that the search process is such that particles stochastically return toward previously successful regions in the search space. The concept of PSO is simple and is easy to implement. Thus, the PSO is a powerful algorithm to aid and speed up the decision-making process for service restoration problem to identify the best switching strategy.

In PSO, in each iteration, each agent is updated with reference to two “best” values: \( pbest \) the best solution (in terms of fitness) the individual particle has achieved so far, while \( gbest \) the best obtained globally so far by any particle in the population. Each agent seeks to modify its position using the current positions, current velocities, the distance between the current position and \( pbest \), and the distance between the current position and \( gbest \). Almost all modifications vary in some way the velocity update equation as given in eqn. (5):

\[
\begin{align*}
    v_i^{k+1} &= w_i v_i^k + c_1 r_1 \text{rand} \ast (pbest - x_i^k) + c_2 r_2 \ast (gbest - x_i^k) \\
    x_i^{k+1} &= x_i^k + v_i^{k+1}
\end{align*}
\]

In eqn. (5), \( c_1 \) and \( c_2 \) are positive constants, defined as acceleration coefficients, \( w_i \) is the inertia weight factor and it is used to control the balance between exploration and exploitation of velocity; \( rand_1 \) and \( rand_2 \) are two random functions in the range of [0-1]; \( x_i \) represents the \( i \)th particle and \( pbest_i \) is the best previous position of \( x_i \); \( gbest \) is the best particle among the entire population; \( v_i \) is the rate of the position change (velocity) for particle \( x_i \). Velocity changes in the eqn. (5) comprise three parts, i.e. the \textit{momentum} part, the \textit{cognitive} part, and the \textit{social} part. For number of particles, the typical range is 20 – 40 [19]. This combination provides a velocity getting closer to \( pbest \) and \( gbest \). Every particle’s current position is then evolved according to the eqn. (6), which produces a better position in the solution space.

5.1 Non-dominated Sorting Particle Swarm Optimization (NSPSO)

NSPSO algorithm developed by X. Li [15] is based on the same non-dominated sorting concept used in NSGA-II [16]. This approach ensures more non-dominated solutions discovered through the domination comparison operations. Instead of comparing solely on a particle’s \( pbest \) with its potential offspring, the entire population of \( N \) particles’ \( pbest \) and \( N \) of these particles’ offspring are first combined to form a temporary population of \( 2N \) particles. After this, the non-dominated sorting concept is applied, where the entire population is sorted into various non-domination fronts. The first front being completely a non-dominant set in the current population and the second front being dominated by the individuals in the first front only and the front goes on so on. Each individual in each front is assigned fitness values or based on front in which they belong to. Individuals in the first front are given a fitness value of 1 and individuals in second are assigned a fitness value of 2 and so on. In addition to the fitness value, two parameters called crowding distance and niche count [15] is calculated for each individual to ensure the best distribution of the non-dominated solutions. The crowding distance is a measure of how close an individual is to its neighbours and Niche count provides an estimate of the extent of crowding near a solution. The \( gbest_i \) for the \( i \)th particle \( x_i \) is selected randomly from the top part of the first front (the particle which has the highest crowding distance). \( N \) particles are selected based on fitness and the crowding distance to play the role of \( pbest \). Such as, when the first front has more than \( N \) particles, we select the particles that have the highest distance [16].
The complete algorithm is also put in plain words with the help of flow chart shown in fig.4.

![Flowchart of NSPSO](image)

Fig.4. Flowchart of NSPSO [20].

6. Implementation of NSPSO in FSE Problem

In this paper, the input to the algorithms is given as binary string. For example, line section 9(LS9) between the nodes 7 and 10 as shown in fig. 5 is coded as [0 1 0 0 1]. Similarly other sections are coded as given in Appendix A. The bits in the string will increase according to the increase in number of buses for different test systems. The voltage, current and impedances are calculated with respect to these nodes and line sections. Customer call input file is given in Appendix A. Initial population is generated randomly. This is the simplest method, in which no knowledge about the network is required.

NSPSO have already been discussed in detail in [15] hence it is not repeated here.

6.1 Non Dominated Sorting Particle Swarm Optimization (NSPSO) Algorithm for FSE

Algorithmic Steps for implementation of NSPSO based Fault Section Estimation:

Step 1 : The information available to the algorithm are, i) system data, ii) pre fault configuration iii) post fault configuration. iv) customer calls input file.

Step 2 : Generate initial swarm Ri, initial velocity Vi, maximum velocity Vmax and initial position xi randomly and code the Line section as binary string, for ex. LS5 is coded as [0 0 1 0 1].

Step 3 : Evaluate fitness values using objective functions from eqns. (2), (3), and (4) and initialize pbest and gbest values.

Step 4 : Calculate new velocity Vi+1 and update particle’s position using eqns. (5) and (6).

Step 5 : Calculate new fitness value in the next iteration and if the new fitness value is better than the current one, update pbest otherwise go to step 4. Determine gbest.

Step 6 : Rk=x1.Upbesti.(combine the current solution and all personal best).

Step 7 : F is non dom sort (Rk) i.e. implement the non-dominated sorting on Rk.

Step 8 : pbest=i+1; until |pbest| + |Fi| N (until the pbest is filled);

a) i = i+1;

b) calculate the niche count and crowding distance for each particle in Fi;

c) pbestk+1 = pbestk+1 UFk;

Step 9 : Sort F in descending order.

Step 10 : Select randomly gbest for each particle from a specified top part (e.g. top 5%) of the first front i.e. F1.

Step 11 : pbestk+1 |pbestk+1| (Ni= |pbestk+1|) (choose the first Ni= |pbestk+1| elements of F1).

Step 12 : Verify the customer call from customer call input file in pbestk+1. Check the radiality of the solutions in pbestk+1 and modify them, if necessary.

Step 13 : Update particle’s position, xik, using eq. (5) and (6) and using the new pbest and gbest.

Step 14 : Choose the gbest after calculating the performance metric values as described in [15] for best solution.

Step 15 : Test for convergence, using if (iter<itermax), stop otherwise go to Step 5.

Step 16 : If algorithm converges write the fault location report.

The following inertia weight is used in the implementation of NSPSO

\[ w_i = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \]  \hspace{1cm} (7)

where, \( w_{min} \) is the initial weight, \( w_{max} \) the final weight, \( iter_{max} \) is the maximum iteration number, \( iter \) is the current iteration number.

The values of \( w_{max} \) and \( w_{min} \) are 0.9 and 0.4 respectively. Other parameters of NSPSO algorithm are:

- No. of iterations = 100, Acceleration Coefficients, \( c_1 = 2.0, c_2=2.0, \) Number of particles (or swarm size) \( Np=20 \).

Flowchart of Non-dominated sorting particle swarm optimization algorithm for FSE is shown in fig.7.

7. Results and Discussion

The proposed approach is applied on a test radial distribution system as shown in fig.5 and described in Table.1. The approach described in section 2 has been used for fault analysis and to find the multiple estimates of fault location. To further narrow down the most potential fault sections, NSPSO based optimization techniques have been used as described in sections 5.1, 6.1 and 6.1 respectively. The performance of NSPSO has been compared with NSGA-II [16] and another existing technique using Binary particle swarm optimization developed by Zhengyou.et al [14]. Zhengyou.et al used weighted sum approach for converting multi objective PSO into single objective PSO. It is to be noted that, for any particular radial distribution
system under test, the algorithm parameters like population size, crossover probability, mutation probability, swarm size and no. of iterations have been kept same in all the three algorithms.

Different types of faults like LG, LLG, LL faults have been simulated at all nodes of the distribution circuit shown in fig.5. Different fault resistance values were used in these simulations. The results indicate that the distances of the faults, estimated by the proposed technique i.e. NSPSO are substantially more accurate than the distances estimated by the NSGA-II and BPSO based algorithms.

As shown in fig.5, every line section (part of line between two nodes or buses) has been assigned a number and distance of the buses is measured in kms from substation. This is done to locate the accurate distance of fault location from substation.

For system-A, it is assumed that the fault has occurred between nodes 10 and 12 and this location is LS11. The distance of line section LS11, where the fault has occurred, is 11.57-16.07 kms from substation.

Additionally, 1% and 2% measurement error has been assumed for voltage and current measurements. As seen from the results shown in Table.3, even with these errors the algorithm is able to capture the exact potential fault location. From Table.3, it is clearly seen in the results that component LS11 is faulty and the exact location of the fault is at a distance of 14.27 kms for LG and LL faults and 14.17 kms from substation for LLL faults. To develop the NSPSO algorithm for FSE, MATLAB 7.11[22] has been used and for simulating the different type of faults, PSCAD simulation software [23] is used.

<table>
<thead>
<tr>
<th>Table.1 Brief summary of the test system [21].</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>System</strong></td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>A</td>
</tr>
</tbody>
</table>

Table.2. showsthe results obtained from iterative procedure as explained in section 2. The algorithm NSPSO produces the most potential faulted section but the distance in p.u. from previous node or bus has been verified from results obtained from iterative procedure .The distance in

![Fig.5. Radial Distribution System-A under test [21].](image)
Table 2. Fault Location Multiple Estimates resulted without NSPSO in System-A

<table>
<thead>
<tr>
<th>Faulted Section (Line Section)</th>
<th>Fault Type</th>
<th>Fault Location (p.u.)</th>
<th>Fault Distance from Substation (kms)</th>
<th>Fault Resistance (Ω)</th>
<th>FL Estimate Error (%)</th>
<th>Estimated Fault Resistance (Ω)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-4 (LS₁₁)</td>
<td>LG</td>
<td>0.6</td>
<td>4.27</td>
<td>50</td>
<td>0.01</td>
<td>50.00</td>
</tr>
<tr>
<td></td>
<td>LL</td>
<td>0.5</td>
<td>4.90</td>
<td>5</td>
<td>0.01</td>
<td>5.00</td>
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<tr>
<td></td>
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<td>0.5</td>
<td>4.90</td>
<td>[0.5, 0.5, 50]</td>
<td>0.01</td>
<td>[0.50, 0.50, 49.99]</td>
</tr>
<tr>
<td></td>
<td>LLL</td>
<td>0.8</td>
<td>6.01</td>
<td>[1, 2.5, 4]</td>
<td>0.02</td>
<td>[1.00, 2.50, 4.00]</td>
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<tr>
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<td>LG</td>
<td>0.2</td>
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<td>1</td>
<td>0.01</td>
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<td></td>
<td>LLL</td>
<td>0.9</td>
<td>11.28</td>
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<tr>
<td></td>
<td>LL</td>
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<td>14.27</td>
<td>5</td>
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</tr>
<tr>
<td></td>
<td>LLL</td>
<td>0.8</td>
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<td>[5, 5, 5]</td>
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<td>[5.00, 5.00, 5.00]</td>
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<td></td>
<td>LL</td>
<td>0.8</td>
<td>21.59</td>
<td>1</td>
<td>0.01</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>LLG</td>
<td>0.8</td>
<td>21.59</td>
<td>[1, 1, 50]</td>
<td>0.01</td>
<td>[1.00, 1.00, 50.00]</td>
</tr>
</tbody>
</table>

Table 3. Impact of Measurement errors on Fault Location Estimates in System-A

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Fault Resistance (ohm)</th>
<th>Fault Location (p.u.)</th>
<th>Fault Location Estimate Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>With 1% Voltage error</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>With 2% Voltage error</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>With 1% Current &amp; Voltage error</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>With 1% Current &amp; Voltage error</td>
</tr>
<tr>
<td>LG</td>
<td>50</td>
<td>0.2</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.16</td>
</tr>
<tr>
<td>LL</td>
<td>1</td>
<td>0.6</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>1.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.25</td>
</tr>
<tr>
<td>LLL</td>
<td>[1, 1, 50]</td>
<td>0.7</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.32</td>
</tr>
<tr>
<td>LLL</td>
<td>[5, 5, 5]</td>
<td>0.9</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.19</td>
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<td></td>
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<td></td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.51</td>
</tr>
<tr>
<td>LLG</td>
<td>[1, 1, 10]</td>
<td>0.9</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.53</td>
</tr>
</tbody>
</table>

Table 4. Potential Fault Location using NSPSO in System-A

<table>
<thead>
<tr>
<th>Technique</th>
<th>Number of Line Sections</th>
<th>Potential Faulted Section</th>
<th>Distance of Fault location From Substation (kms)</th>
<th>Run Time of Algorithm (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSPSO [Proposed]</td>
<td>16</td>
<td>10-12 (LS₁₁)</td>
<td>LG</td>
<td>14.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LL</td>
<td>14.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LLL</td>
<td>14.17</td>
</tr>
<tr>
<td>NSGA-II [26]</td>
<td>16</td>
<td>10-12 (LS₁₁)</td>
<td>LG</td>
<td>14.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LL</td>
<td>14.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LLL</td>
<td>14.92</td>
</tr>
<tr>
<td>Binary PSO [24]</td>
<td>16</td>
<td>10-12 (LS₁₁)</td>
<td>LG</td>
<td>14.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LL</td>
<td>14.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LLL</td>
<td>14.74</td>
</tr>
</tbody>
</table>

7. Conclusion

This paper presents analytical fault analysis and iterative procedure to get the multiple estimates of fault location and NSPSO based optimization algorithm to further nail down the exact fault location. The proposed technique fully consider loads, laterals and customer trouble calls in radial distribution systems, take into account for all types of faults, and allow for different fault resistances values.

Simulation studies have demonstrated that proposed technique produces accurate and speedier results and are quite robust to voltage and current measurement errors. Speedy and precise fault location plays an important role in the fast fault location process. The simulation results prove that the proposed method is accurate, faster and robust to voltage and current measurement errors.
role in accelerating system restoration, reducing outagetime and significantly improving system reliability. Compared with the genetic algorithm, NSPSO for fault-section estimation has got advantages that it uses smaller population size, more rapid convergence and diversity in Pareto optimal solution, which is the main goal of any multi objective optimization problem. The proposed algorithm is compared with two of the most complete methods published to date to confirm the superiority of the work in terms of accuracy.

Appendix

Table 5. List of Customer trouble calls experiencing outage for System-A

<table>
<thead>
<tr>
<th>Line Section(s)</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS_{10}</td>
<td>11:00 AM</td>
</tr>
<tr>
<td>LS_{11}</td>
<td>11:02 AM</td>
</tr>
<tr>
<td>LS_{12}</td>
<td>11:03 AM</td>
</tr>
<tr>
<td>LS_{13}</td>
<td>11:05 AM</td>
</tr>
<tr>
<td>LS_{14}</td>
<td>11:09 AM</td>
</tr>
<tr>
<td>LS_{15}</td>
<td>11:10 AM</td>
</tr>
<tr>
<td>LS_{16}</td>
<td>11:12 AM</td>
</tr>
<tr>
<td>LS_{17}</td>
<td>11:14 AM</td>
</tr>
<tr>
<td>LS_{18}</td>
<td>11:15 AM</td>
</tr>
<tr>
<td>LS_{19}</td>
<td>11:18 AM</td>
</tr>
</tbody>
</table>

Table 5. shows the list of Customer trouble calls experiencing outage for System-A. Customer trouble calls those who are experiencing outage, are from the loads connected to particular bus/node. Line sections consist of two node/bus(s) as shown in fig.5.

A.2 Test data of System - A

The source impedance is given in sequence domain as follows [21]:
Positive-sequence: 0.23+ j2.10 Ω,
Zero-sequence : 0.15+ j1.47 Ω

The feeder impedance matrices in Ohms/km are given as follows:
For main feeder, the impedance matrix is

\[
\begin{bmatrix}
0.3465 + j1.0179 & 0.1560 + j0.5017 & 0.1580 + j0.4236 \\
0.1560 + j0.5017 & 0.3375 + j1.0478 & 0.1535 + j0.3849 \\
0.1580 + j0.4236 & 0.1535 + j0.3849 & 0.3414 + j1.0348
\end{bmatrix}
\]

For the three-phase lateral, the impedance matrix is

\[
\begin{bmatrix}
0.7526 + j1.1814 & 0.1580 + j0.4236 & 0.1560 + j0.5017 \\
0.1580 + j0.4236 & 0.7475 + j1.1983 & 0.1535 + j0.3849 \\
0.1560 + j0.5017 & 0.1535 + j0.3849 & 0.7436 + j1.2112
\end{bmatrix}
\]
For the two-phase lateral, the impedance matrix is
\[
\begin{bmatrix}
1.3294 + j1.3471 & 0.2066 + j0.4591 \\
0.2066 + j0.4591 & 1.3238 + j1.3569
\end{bmatrix}
\]

For the single-phase lateral, the impedance matrix is
\[
[1.3294 + j1.3471]
\]

The length of the line sections has already been labelled in the figures of the systems A.A power factor of 0.9 is assumed for all type of loads. Single or double-phase laterals are indicated in the figure, while others are of the three phases.

The magnitudes of short circuit currents (fault currents) have been computed by simulating different type of faults using PSCAD [23].

References