ELECTRICAL ENGINEERING

Optimal allocation of remote control switches in radial distribution network for reliability improvement

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Received 21 April 2015; revised 5 September 2015; accepted 8 January 2016

Abstract This paper presents differential search algorithm in order to solve reliability optimization problem of radial distribution network. Remote control switches have been optimally allocated to improve reliability at a compromised cost. A multi-objective problem has been formulated and solved using differential search algorithm. The test systems considered in this paper are an 8 bus radial distribution network and a 33 bus radial distribution network. Simulation results obtained using differential search algorithm when applied to the test cases, have been compared with those obtained by particle swarm optimization. Differential search algorithm has been found to provide superior results as compared to particle swarm optimization.

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1. Introduction

Distribution system reliability has proved to be of great concern in the present days of power system operation. With the deregulation of power system and enhanced competitive environment, the demand for uninterrupted quality power has increased. As distribution system has the greatest contribution to the interruption of supply to a consumer [1]; hence, improving distribution system reliability is of serious concern in today’s power market. The enhancement of reliability always incurs a cost as it involves some additional preventive and corrective measures. So, the reliability improvement methods need to be adopted keeping in view the cost involved in the process. Failure rate, repair time and restoration time are some important parameters of defining reliability. Reducing the values of one or more of the above parameters can improve reliability considerably. Several approaches can be adopted to improve reliability, out of which, the present authors have adopted optimal placement of remote control switch (RCS) in the radial distribution network. RCSs are devices, which can isolate or connect a section of a network. Suitable locations of RCSs in a network may reduce the time to resume power and thus improve reliability. Placing one RCS at each segment of a network may improve reliability considerably.
network definitely improves reliability greatly, but at the same time it may incur a high installation and maintenance cost, as the number of RCSs required is large. Hence, a compromise is required, and here lies the importance of optimal allocation of RCSs. While adopting the present work, a number of literatures have been reviewed in which similar type of work has been done. Some of these are briefly discussed here.

An artificial intelligence technique with multi agent system was used by Bouhouras et al. [2] for performing cost/worth assessment of reliability improvement in distribution networks. Haifenga et al. [3] adopted Monte-Carlo simulation based approach for providing a basis for using a parallel computing environment in power system reliability and cost evaluations. Switch allocation problem has been a topic of research interest for decades and many studies have been performed [4–6]. RCSs are gaining importance in reliability improvement studies with the recent trend of automation. Some studies have been carried out in order to develop strategies for RCS without covering allocation of switches [7,8]. Allocation of switches has been considered in [9–12]. Optimal placement of switches and reclosers has been considered in [13–14]. Abiri-Jahromi et al. [15] utilized mixed integer linear programming (MILP) for optimal placement of sectionalizing switches. Viotto Romero et al. [16] proposed a dedicated Taboo Search (TS) algorithm for optimal switch allocation in distribution systems for automatic load transfer. Bernardon et al. [17] proposed a methodology to consider the impact of RCS when computing the reliability indices and the algorithm for multi-criteria decision making to allocate these switches. Benavides et al. [18] proposed a new iterated sample construction with path relinking (ISCPR) to solve distribution system switch allocation problem. Zheng et al. [19] studied the quantitative impact of automatic switches on the reliability of power distribution systems. Esmaeilian and Fadaeinedjad [20] adopted a Binary Gravitational Search Algorithm (BGSA) for network reconfiguration and capacitor placement in distribution system in order to improve reliability. Tippacon and Rerkpreedapong [21] adopted multiobjective ant colony optimization (MACO) whereas Pombo et al. [22] adopted a memetic algorithm combining Non dominated Sorting Genetic Algorithm II (NSGA-II) with a local search algorithm for switch and reclosure allocation in order to minimize the reliability indices namely average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI) as well as the cost of equipments. Golestani and Tadayon [23] used Linear Fragmented Particle Swarm optimization for optimal switch placement in distribution system. Assis et al. [24] proposed a memetic algorithm based optimization methodology to sectionalizing, tie, manual, and automatic switches in distribution networks. Amanulla et al. [25] used binary particle swarm optimization-based search algorithm to find the optimal status of the switches in order to maximize the reliability and minimize the real power loss. Zou et al. [26] adopted methods including feeder reconfiguration, recloser installation, recloser replacement, and distributed generation (DG) installation to minimize system average interruption duration index (SAIDI), an important reliability index. Brown et al. [27] used sequential feeder method and a multi-objective genetic algorithm (GA) together to solve the optimization of the feeder addition problem in an islanded distribution system with DGs. Vitorino et al. [28] presented the application of an improved genetic algorithm (IGA) to optimize simultaneously loss and reliability of a radial distribution system through a process of network reconfiguration as an optimization. Zhang et al. [29] proposed a reliability-oriented reconfiguration (ROR) method for improving distribution reliability and energy efficiency, based on interval analysis. Pitscher et al. [30] presented a new methodology for automatic reconfiguration of distribution network, in order to improve network performance indicators, such as losses and reliability. Kavoussi-Fard and Akbari-Zadeh [31] proposed a multi-objective distribution feeder reconfiguration problem for reliability enhancement as well as loss reduction. Raofat [32] adopted a GA based method to allocate DGs and RCSs simultaneously in order to reduce energy loss and improve reliability considering multilevel load.

Recently, Pinar Civicioglu [33] introduced a new algorithm named differential search (DS) algorithm to solve the problem of transforming geocentric cartesian coordinates into geodetic coordinates and compared its performance with classical methods and other computational intelligence algorithms. DS algorithm adopts the seasonal migration behavior of many organisms where they shift from one habitat to a more efficient one, in terms of efficiency of food areas. The individual organisms form a Superorganism which as a whole move toward more efficient area. The effectiveness of DS algorithm has already been compared with other algorithms such as artificial bee colony algorithm (ABC), self-adaptive differential evolution algorithm (JDE), adaptive differential evolution algorithm (JADE), strategy adaptation based differential evolution algorithm (SADE), differential evolution algorithm with ensemble of parameters (EPSDE), gravitational search algorithm (GSA), particle swarm optimization (PSO) and covariance matrix adaptation evolution strategy (CMA-ES). DS algorithm has been found to solve the problem at a very high level of accuracy [33]. Unlike other algorithms such as differential evolutionary algorithm (DE), JDE, and ABC, DS algorithm may simultaneously use more than one individual during updating steps. An important advantage of DS algorithm over many other algorithms is that DS algorithm has no inclination to correctly approach the best possible solution. Therefore, exploration ability of the algorithm is significantly improved compared to many other existing algorithms. Hence, it may be proved to be a successful strategy for solution of multimodal functions.
As DS algorithm has proved to be a new and effective evolutionary algorithm [33], the present authors have adopted this algorithm with a view to test its computational efficiency to solve a multi-objective function in order to enhance system reliability at a reduced cost. The objective of this paper was to solve a multi-objective function in order to find a compromised solution both to enhance the reliability by optimal allocation of RCSs and to minimize the cost incurred. In most of the previous work, where optimal placement of switches has been considered, number of RCS has been taken as fixed. In some literature where number of RCS has been considered as variable, multi-objective problem formulation has not been considered. In the present paper, both number and position of RCS have been considered as variable and a multi-objective problem formulation has been formulated. The outcome of the proposed technique has been compared with a well known and widely used optimization technique, PSO.

Section 2 of the paper provides a brief description of the function of RCS in radial distribution system and its impact on the reliability parameters. Section 3 describes mathematical formulation of the optimization problem. Section 4 presents the DS algorithm and the steps involved to solve the optimal RCS allocation problem in order to enhance distribution system reliability. Simulation studies are presented and discussed in Section 5. The conclusion is drawn in Section 6.

2. RCS in radial distribution network and reliability indices

With the recent trends of automation of distribution networks, RCS is proved to be very convenient as its switching time is very less. RCS may be sectionalizing-switch (normally closed) or tie-switch (normally open). In the present work, the RCS considered for installation is normally closed type. In radial network, normally closed RCS can be operated to isolate a faulty section from the rest of the network. The location of RCS can contribute to enhance the reliability of a network to a great extent.

The basic reliability indices commonly used are failure rate, repair time, restoration time and outage duration. Failure rate denotes the frequency of occurrence of failure. Repair time represents the time required to repair a faulty section after a fault occurs. Restoration time represents the time required to restore service after an interruption occurs. Outage duration represents the annual duration of outage and is given either by the product of failure rate and repair time or by the product of failure rate and restoration time, as applicable.

While RCS does not affect the failure rate, however, it can have a considerable impact on the outage duration. Optimal placement of RCSs can reduce the outage duration to a considerable extent, thus improve the reliability. If there is a fault, located at downstream to the load point, and if there is no switch in between the fault and the load point of consideration, time to restore power to the load point will be equal to the time needed to repair the fault i.e. repair time. On the other hand, a switch in between the load point of consideration and fault location (downstream to the load point) can reduce this time to the operating time of the switch i.e. restoration time, as the opening of switch will isolate the faulty segment from the healthy portion and power can be restored to the healthy portion.

As these indices do not take into account the number of customers and load connected, the severity of the fault is not revealed by these indices. To get a clear picture of the severity of the fault, customer oriented indices are derived from the basic indices. Among several customer oriented indices, expected energy not supplied (EENS) is the index of concern in this work which is given by

\[
EENS = \sum L_j U_j
\]

where

\[
U_j = \sum_{i=1}^{n_j} \lambda_i rep_i + \sum_{i=1}^{n_j} \lambda_i res_i
\]

\[
\lambda_i \text{ and } rep_i \text{ denote the failure rate and repair time of } i^{th} \text{ distributor segment, and } n_j \text{ denotes the total numbers of segments where the fault has occurred and power can be resumed to the } j^{th} \text{ load point only after repairing of those faults. } \lambda_i \text{ and } res_i \text{ denote the failure rate and switching time or restoration time of } i^{th} \text{ distributor segment, and } n_j \text{ denotes the total number of segments where the fault has occurred and power can be restored to the } j^{th} \text{ load point through switching operation before repairing of those faults. } U_j \text{ denote the annual outage duration for } j^{th} \text{ load point. } L_j \text{ is the average load connected at } j^{th} \text{ load point.}
\]

2.1. Logic for energy interruption duration calculation of a given load point

Distribution segments are branches of a distribution network. The failure rate (\(\lambda\)), repair time (\(rep\)) and restoration time (\(res\)) of distribution segments affect the reliability of load points. A load point experiences interruption of power for a failure in any segment if either

(a) The segment is in the path between the source and the load or
(b) The segment is not in the path between the source and the load but there is no fuse in between the segment and the load point.

After a failure occured in such a distribution segment, the time to resume power in the load point may be repair time or restoration time. This can be selected using following conditions:

(i) If the segment is in the path between the source and the load, time to resume power will be repair time.
(ii) If the segment is not in the path between the source and the load and there is no RCS (remote control switch) in between the segment and the load point, time to resume power will be repair time.
(iii) If, the segment is not in the path between the source and the load and there is at least one RCS in between the segment and the load point, time to resume power will be restoration time i.e. switching time.

EENS of a particular load point is obtained by the multiplication of annual outage duration and load of that load point. The annual outage duration is obtained by the multiplication...
of failure rate and time to resume power (either repair time or restoration time, as applicable), as presented in (2). Hence, the failure rate and repair time/restoration time of distribution segments have a direct impact on the EENS of a load point. With the increase of the failure rate and repair time/restoration time, EENS also increases.

3. Problem formulation

In this paper, the objective was to obtain the optimum number and location of RCS in radial distribution system. Increasing the number of RCS may reduce the EENS but at the same time, it may increase the cost involved. A multi-objective formulation is developed with a view to reduce the EENS cost without excessive increase in RCS cost. Here, the target is to find a compromised solution such as to improve the reliability (by reducing equivalent cost of EENS) without excessive increase in RCS cost.

The objective function to reduce EENS is

\[
J_1 = \sum_{j=1}^{n} EENS_j \times C_1 \times CPV_1
\]  

where \(EENS_j\) corresponds to the EENS of \(j^{th}\) load point, \(n\) corresponds to the total number of load points, \(C_1\) stands for per unit cost of EENS (\$/kW h) and \(CPV_1\) is the cumulative present value (CPV) of EENS cost. The CPV method converts all costs and benefits of a plan during the lifecycle to the first year of operation and thus helps to evaluate the total costs and benefits during the economic lifecycle of the equipments [32]. \(CPV_1\) is calculated as follows:

\[
CPV_1 = \frac{1 - (PV_1)^{EL}}{1 - PV_1} \quad (4)
\]

where

\[
PV_1 = \frac{(1 + I_{int})(1 + LG)}{(1 + I_{int})}, \quad (5)
\]

\(EL\) is the economic lifetime of the equipments, \(I_{int}\) is the inflation rate, \(I_{int}\) is the interest rate and \(LG\) is the load growth rate.

The objective function to reduce RCS cost is

\[
J_2 = n_{RCS} \times (C_i + C_m \times CPV_2)
\]

where \(n_{RCS}\) denotes the total number of RCS present in the system. \(C_i\) stands for the installation cost and \(C_m\) stands for the maintenance cost of each RCS. \(CPV_2\) is the cumulative present value (CPV) of maintenance cost of RCS cost which is expressed as follows:

\[
CPV_2 = \frac{1 - (PV_2)^{EL}}{1 - PV_2} \quad (7)
\]

where

\[
PV_2 = \frac{(1 + I_{int})}{(1 + I_{int})} \quad (8)
\]

Therefore, the overall objective function to represent multi-objective formulation is expressed as

\[
J = w \times J_1 + (1 - w) \times J_2 \quad (9)
\]

where \(w\) is a weightage value assigned to a single objective, in order to find the Pareto optimal solution. Here, both the number of RCS and position of RCS have been considered as variable while minimizing the objective function.

4. Solution methodology using DS algorithm

DS algorithm simulates the Brownian-like random-walk movement used by an organism to migrate [33]. Due to periodical climatic changes, many organisms show seasonal migration behavior where they shift from one habitat to a more efficient one with respect to capacity and efficiency of food areas. In the process of migration, the species undergoing migration forms a Superorganism consisting of a large number of individuals and the Superorganism changes its position toward more fruitful areas.

The artificial organisms (i.e. \(X_y, y = 1, 2, 3 \ldots N\)) constituting a Superorganism contain members equal to the size of the problem (\(X_y, y = 1, 2, 3 \ldots D\)). \(D\) is the size of the problem and \(N\) denotes the number of elements in a Superorganism. In initial position, a member of an artificial organism is given by

\[
X_y = rand(up_{y} - low_{y}) + low_{y} \quad (10)
\]

The Superorganism migrates toward global minimum and during this process, the members search for some randomly selected position suitable to stop over temporarily and on finding such position, the members of the artificial Superorganism immediately settle there and continue their migration from this position onward.

In order to discover site, randomly selected individuals move toward the targets of donor [\(X_{Random\_shuffling}y\)]. The extent to which the change occurs is controlled by a scale value. The Stopoversite position is given as

\[
Stopoversite = Superorganism + Scale \times (donor - Superorganism) \quad (11)
\]

The members to participate in search process are selected by random process of specific structure. If any element goes beyond the limits of habitat, the element is randomly deferred to another position. Software code of the algorithm of DS algorithm can be found in [34].

4.1. Sequential steps of DS algorithm

The stepwise DS algorithm is mentioned as follows:

<table>
<thead>
<tr>
<th>Required:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(N): size of Superorganism, where (y = {1, 2, 3, \ldots N})</td>
</tr>
<tr>
<td>(D): The dimension of the problem</td>
</tr>
<tr>
<td>(G): No. of maximum generation</td>
</tr>
</tbody>
</table>

(1) Initialize Superorganism, where Superorganism is termed as Artificial Organism, 
(2) For \(i = 1 : N\) 
(3) \(y_i\): Evaluate objective function corresponding to Artificial Organism, 
(4) end for
(5) For cycle 1:G, do 
(6) Random shuffling of Superorganism, i.e. \(Donor = Superorganism_{Random\_shuffling}\) 
(7) Calculate Scale = rand[2 rand1] (rand2 – rand3)
The sequential steps of the DS algorithm applied to find optimum number and location of RCS of a radial distribution system are as follows.

Required: N: size of Superorganism, where $i = \{1, 2, 3, \ldots, N\}$, $D$: The dimension of the problem, $G$: No. of maximum generation.

Step 1: Read input data: $L_p$, $rep_p$, $res_p$, $\lambda_s$, inflation rate ($I_{inf}$), interest rate ($I_{int}$), load growth rate ($LG$), economic lifetime of equipments ($EL$), total number of load points ($n$), the DS algorithm parameters like control parameters $c_1$ and $c_2$ etc.

Step 2: Initialize the value of $w = 0$, where $w$ is the weightage factor.

Step 3: Initialize Superorganism by generating Artificial organism which contains either 0 or 1. 0 represents no RCS and 1 represents presence of RCS in a distribution segment. Generate Artificial organism using (10), where $up_j$ and $low_j$ are 1 and 0 respectively.

Step 4: Evaluate the objective function $J_1$ and $J_2$ using (3) and (6) respectively for each initially generated Artificial organism, set as per following steps:

$$
\text{StopoverSite}_{i} = \text{Superorganism} + \text{Scale} \times \text{(donor – Superorganism)}
$$

(9) $p_1 = c_1 \times rand_4$ and $p_2 = c_2 \times rand_4$, where $c_1$ and $c_2$ are control parameters.

(10) If $rand_1 < p_1$, then

(11) If $rand_2 < p_1$, then

(12) $r = \text{rand}(N, D)$

(13) for Counter1: $N$, do

(14) $r (\text{Counter}1,:) = r (\text{Counter}1,:) < rand_4$

(15) end for

(16) else

(17) $R = \text{ones}(N, D)$

(18) for Counter2: $1: N$, do

(19) $r (\text{Counter}2, \text{rand}(D)) = r (\text{Counter}2, \text{rand}(D)) < rand_{10}$

(20) end for

(21) end if

(22) else

(23) $r = \text{ones}(N, D)$

(24) for Counter3: $1: N$, do

(25) $d = \text{rand}(D, [1, \text{rand}, \text{rand}(D)])$

(26) end for

(27) $r (\text{Counter}4, d(\text{Counter}4)) = 0$

(28) end for

(29) end for

(30) end if

(31) $\text{Individual}_{ij} = r_{ij} > 0 \text{ if } i \in \{J\}, j \in \{D\}$

(32) $\text{StopoverSite}(\text{individual}_{ij}) = \text{Superorganism}(\text{individual}_{ij})$

(33) If StopoverSite crosses the limits, set

$\text{StopoverSite} = \text{rand}(up – low) + low_j$.

(34) Evaluate $\text{StopoverSite}$, $\text{yStopoverSite}$

(35) Modify $\text{ySuperorganism}$ by $\text{yStopoverSite}$, if

$\text{yStopoverSite} < \text{ySuperorganism}$. 

(36) Artificial organism$_i = \{ \text{StopoverSite}_i \text{ if } \text{yStopoverSite}_i < \text{ySuperorganism}_i \}$, else

For the bi-objective function, evaluate the overall objective function for each set of initially generated Artificial organism$_i$ using (9).

Step 5: Perform steps 3 to 30 of Section 4.1.

Step 6: If any variable $j$ of StopoverSite (generated using (11)) crosses the respective limits, set the value of that variable as $\text{StopoverSite}_i,j = \text{rand}(up_j – low_j) + low_j$.

The upper limit of variable $j$ is 1 and the lower limit is 0. These are discrete variables which can have values of either 0 or 1. It is assumed that a maximum of one RCS can be installed at each distribution segment. The total number of variables is equal to the total number of distribution segment in a system. A zero represents no RCS in a particular segment and 1 represents presence of RCS in that segment.

Step 7: Evaluate objective function of StopoverSite i.e. $\text{yStopoverSite}$ as given by Eqs. (3) or (6) or (9), as performed in Step 4.

Step 8: Modify $\text{ySuperorganism}_i$ by $\text{yStopoverSite}_i$ if objective function of $\text{StopoverSite}_i$ is less than cost function of Superorganism$_i$.

Step 9: $\text{Artificial organism}_i = \{ \text{StopoverSite}_i \text{ if } \text{yStopoverSite}_i < \text{ySuperorganism}_i \}$, else

Step 10: In case of the bi-objective problem, increment the value of $w$ in steps of 0.1 and repeat steps 3–8. Repeat the process until the value of $w$ reaches 1.
Step 11: Best compromise solution- the algorithm described above generates the non-dominated set of solutions known as the Pareto-optimal solutions. The decision-maker (power system operator) may have imprecise or fuzzy goals for each objective function. To aid the operator in selecting an operating point from the obtained set of Pareto-optimal solutions, the fuzzy logic theory is applied to each objective function to obtain a fuzzy membership function as given below [35]:

\[
\mu_{J_i} = \begin{cases} 
1 & \text{if } J_i \leq J_i^{\min} \\
\frac{J_i^{\min} - J_i}{J_i^{\max} - J_i^{\min}} & \text{if } J_i^{\min} < J_i < J_i^{\max} \\
0 & \text{if } J_i \geq J_i^{\max}
\end{cases}
\]

(12)

The best non-dominated objective function can be found when (13) is a maximum, where the normalized sum of objective function values for all objectives is highest:

\[
\mu^* = \frac{\sum_{i=1}^{Q} \mu_{J_i}}{\sum_{i=1}^{M} \mu_{J_i}}
\]

where \(Q\) denotes the total number of individual objective function in (9), and \(M\) is the number of non-dominated solutions. After completion of the process, the best solution of the problem is obtained.

5. Results and discussions

The DS algorithm has been implemented on two test systems and its performance has been compared with PSO for verifying its feasibility for solving optimization problems of distribution system reliability. The algorithms have been coded in MATLAB software (version 7.10.0) on a processor of specification Intel (R) Core (TM) i7-2600 CPU 3.40 GHz with 2 GB RAM.

5.1. Description of the test system

1) Test Case I: An 8-bus radial test system as shown in Fig. 1 has been considered. The system consists of seven feeder segments and contains a circuit breaker at the beginning of the network. The RCSs are considered to be allocated at the beginning of any distribution segment. Numbering of distribution segments is done in the following manner: distribution segment preceding load point 2 is numbered as distribution segment 1; preceding load point 3 is numbered as distribution segment 2, and so on. The failure rate and repair time of the segments are considered as in Table 1. The restoration time has been considered to be 5 min. Table 2 gives the peak loads of different load-points as considered in the present work. Three different load levels are considered as in Table 3. The per kilowatt cost of EENS is considered to be 55 for all the load levels; and the installation and maintenance cost of one RCS has been considered to be 18,000$ and 2000$ respectively. The interest rate, inflation rate and load growth rate have been considered as 0.05, 0.08 and 0.05 respectively.

2) Test Case II: A 33-bus radial test system as shown in Fig. 2 has been considered, where there is a circuit breaker (CB) at the beginning of the network and fuses at the starting point of each lateral branch. The test system consists of 32 distribution segments and 33 loads points. Like the earlier case, the RCSs are considered to be allocated at the beginning of any distribution segment, except first distribution segment of branches as there is a fuse. Numbering of distribution segment is done as in the previous test case. The loads, failure rate, repair time and restoration time of distribution segments have been considered same as presented in [32]. Here also, three different load levels are considered as in Table 3. The per kilowatt cost of EENS is considered to be 8$ and the installation and maintenance cost of one RCS has been considered to be 18,000$ and 2000$ respectively. The interest rate, inflation rate and load growth rate have been considered same as in test case I.

5.2. Comparative study

5.2.1. Solution quality

Tables 4 and 5 present the best objective function values and the corresponding number and location of RCS as obtained by DS algorithm and PSO for the 8 bus distribution system for minimizing EENS cost and RCS cost respectively. It is obvious that minimizing RCS cost leads to no RCS installation in the network. Therefore, no improvement is possible in the network.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Failure rate and repair time of different segments (Test case I).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distribution segment no.</td>
<td>Failure rate, ( \lambda ) (f/yr.)</td>
</tr>
<tr>
<td>1</td>
<td>0.4</td>
</tr>
<tr>
<td>2</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>0.3</td>
</tr>
<tr>
<td>4</td>
<td>0.5</td>
</tr>
<tr>
<td>5</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Peak loads of different load points (Test case I).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load point</td>
<td>Load (kW)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1000</td>
</tr>
<tr>
<td>3</td>
<td>700</td>
</tr>
<tr>
<td>4</td>
<td>400</td>
</tr>
<tr>
<td>5</td>
<td>500</td>
</tr>
<tr>
<td>6</td>
<td>300</td>
</tr>
<tr>
<td>7</td>
<td>200</td>
</tr>
<tr>
<td>8</td>
<td>150</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Different load levels.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load level</td>
<td>Duration (h)</td>
</tr>
<tr>
<td>1</td>
<td>340</td>
</tr>
<tr>
<td>2</td>
<td>5500</td>
</tr>
<tr>
<td>3</td>
<td>2920</td>
</tr>
</tbody>
</table>

Please cite this article in press as: Ray S et al., Optimal allocation of remote control switches in radial distribution network for reliability improvement, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.01.001.
Table 4  Best results for EENS cost minimization obtained using different methods (Test case I).  

<table>
<thead>
<tr>
<th>Method</th>
<th>No. of RCS</th>
<th>RCS position (distribution segment no.)</th>
<th>Objective function</th>
<th>Corresponding RCS cost ($)</th>
<th>Total cost ($) (EENS cost + RCS cost)</th>
<th>Simulation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>6</td>
<td>2–7</td>
<td>EENS cost ($)</td>
<td>1,414,165</td>
<td>328,860</td>
<td>1.0402</td>
</tr>
<tr>
<td>PSO</td>
<td>6</td>
<td>2–7</td>
<td></td>
<td>1,414,165</td>
<td>328,860</td>
<td>1.3245</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Table 5  Best results for RCS cost minimization obtained using different methods (Test case I).  

<table>
<thead>
<tr>
<th>Method</th>
<th>No. of RCS</th>
<th>RCS position (distribution segment no.)</th>
<th>Objective function</th>
<th>Corresponding EENS cost ($)</th>
<th>Total Cost ($) (EENS cost + RCS cost)</th>
<th>Simulation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>0</td>
<td>–</td>
<td>RCS cost ($)</td>
<td>0</td>
<td>4,198,200</td>
<td>1.0013</td>
</tr>
<tr>
<td>PSO</td>
<td>0</td>
<td>–</td>
<td></td>
<td>0</td>
<td>4,198,200</td>
<td>1.2872</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Figure 2  Thirty-three bus network (Test case II).

Figure 3  Convergence characteristic for EENS cost minimization obtained by DS and PSO for Test case I.

Figure 4  Convergence characteristic for RCS cost minimization obtained by DS and PSO for Test case I.
from reliability point of view. Hence, for minimizing RCS cost, same result is obtained by DS and PSO. Similarly, EENS cost minimization will lead to installation of RCS in almost all the segments. The solutions obtained by DS and PSO are same which is quite logical. Figs. 3 and 4 show the respective convergence characteristics of minimizing EENS cost and minimizing RCS cost for the eight bus network (test case I). The results show that minimum output is same in both the cases, but the solutions converge to final results comparatively faster using DS compared to PSO, which is evident from Figs. 3 and 4. Table 6 presents the best objective function values and the corresponding number and location of RCS as obtained by DS algorithm and PSO for the multi-objective formulation of test case I. Best non-dominated values of EENS cost and RCS cost are obtained by the multi-objective formulation. The results show that EENS cost and total cost are quite less with DS than that obtained by PSO keeping the RCS cost same. A comparison of solutions for the multi-objective formulation obtained using DS algorithm and PSO is drawn in Table 7. The Pareto optimal front obtained by DS algorithm and PSO for simultaneous minimization of EENS cost and RCS cost for test case I is shown in Fig. 5.

Table 6  Best results for multi-objective problem obtained using different methods (Test case I).

<table>
<thead>
<tr>
<th>Method</th>
<th>No. of RCS</th>
<th>RCS position (distribution segment no.)</th>
<th>Objective function</th>
<th>Total ($) (EENS cost + RCS cost)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>2</td>
<td>2, 4</td>
<td>1,820,000</td>
<td>1,929,620</td>
</tr>
<tr>
<td>PSO</td>
<td>2</td>
<td>3, 4</td>
<td>1,980,200</td>
<td>2,089,820</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Table 7  Comparison of solution among different methods after 50 trials (Multi-objective problem) (Test case I).

<table>
<thead>
<tr>
<th>Methods</th>
<th>Minimum ($)</th>
<th>Maximum ($)</th>
<th>Average ($)</th>
<th>Simulation time (s)</th>
<th>No. of hits to optimum solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>1,929,620</td>
<td>1,929,620</td>
<td>1,929,620</td>
<td>10.0924</td>
<td>50</td>
</tr>
<tr>
<td>PSO</td>
<td>2,089,820</td>
<td>2,341,640</td>
<td>2,104,929</td>
<td>13.1625</td>
<td>47</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Table 8  Best results for EENS cost minimization obtained using different methods (Test case II).

<table>
<thead>
<tr>
<th>Method</th>
<th>No. of RCS</th>
<th>RCS position (distribution segment no.)</th>
<th>Objective function</th>
<th>Corresponding RCS cost ($)</th>
<th>Total Cost ($) (EENS cost + RCS cost)</th>
<th>Simulation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>27</td>
<td>2–11, 13–17, 19–21, 23–24, 26–32</td>
<td>6,591,615</td>
<td>1,479,900</td>
<td>8,071,515</td>
<td>3.7720</td>
</tr>
<tr>
<td>PSO</td>
<td>27</td>
<td>2–11, 13–17, 19–21, 23–24, 26–32</td>
<td>6,591,615</td>
<td>1,479,900</td>
<td>8,071,515</td>
<td>4.9021</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.
those where fuses are installed. Table 9 shows the results of minimizing RCS cost by DS and PSO, and Fig. 7 shows the corresponding convergence characteristic. Here also, due to obvious reasons as discussed in the earlier test case, the results obtained by DS and PSO are same. The convergence characteristics as shown in Figs. 6 and 7 reveal a faster convergence of DS algorithm as compared to PSO. Table 10 presents the best objective function values and the corresponding number and location of RCS as obtained by DS algorithm and PSO for the multi-objective formulation. The results show that though EENS cost obtained by DS algorithm is somewhat more, the RCS cost is quite less compared to that obtained by PSO. A comparison of solutions for the multi-objective formulation obtained using DS algorithm and PSO is presented in Table 11. As the multi-objective function provides a compromised solution, it may be proved to be more realistic than the single objective formulation of minimizing either EENS cost or RCS cost. The Pareto optimal front for simultaneous minimization of EENS cost and RCS cost, in case of DS algorithm and PSO is shown in Fig. 8. The Pareto optimal front presents a smoother characteristic in case of DS algorithm than in PSO.

5.2.2. Computational efficiency

Time taken by DS algorithm to reach the minimum solution for EENS cost minimization is 1.0402 s for test case I and 3.7720 s for test case II. Whereas, PSO takes 1.3245 s and 4.9021 s for EENS minimization of test case I and test case II respectively. For RCS cost minimization, DS algorithm takes 1.0013 s and PSO takes 1.2872 s for test case I. For test case II, DS algorithm takes 2.0054 s and PSO takes 3.0352 s for RCS cost minimization. PSO takes Time taken by DS algorithm to reach the best solution for the multi-objective formulation of test case I is 10.0924 s and that for test case II is 34.7621 s. For same objective formulation, time required by PSO to reach best solution is 13.1625 s and 41.3287 s for test case I and test case II respectively. These are quite prominent from Tables 4, 5, 7–9 and 11. The results show superior computational efficiency of DS algorithm.

5.2.3. Robustness

Performance of any heuristic algorithm cannot be judged by the results of a single run. Normally their performance is judged after running the programs of those algorithms for several numbers of trials. Many numbers of trials should be made to obtain a useful conclusion about the performance of the algorithm. The results show that those who perform well in one run are likely to perform well in another run also.

Table 9 Best results for RCS cost minimization obtained using different methods (Test case II).

<table>
<thead>
<tr>
<th>Method</th>
<th>No. of RCS</th>
<th>RCS position (distribution segment no.)</th>
<th>Objective function RCS cost ($)</th>
<th>Corresponding EENS cost ($)</th>
<th>Total Cost ($) (EENS cost + RCS cost)</th>
<th>Simulation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>0</td>
<td>–</td>
<td>0</td>
<td>8,271,100</td>
<td>8,271,100</td>
<td>2.0054</td>
</tr>
<tr>
<td>PSO</td>
<td>0</td>
<td>–</td>
<td>0</td>
<td>8,271,100</td>
<td>8,271,100</td>
<td>3.0352</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Table 10 Best results for multi-objective problem obtained using different methods (Test case II).

<table>
<thead>
<tr>
<th>Method</th>
<th>Variables</th>
<th>Objective function</th>
<th>Total ($) (EENS cost + RCS cost)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of RCS</td>
<td>EENS cost ($)</td>
<td>RCS cost ($)</td>
</tr>
<tr>
<td>DS</td>
<td>7</td>
<td>2,6,20,24,27,30,32</td>
<td>6,948,400</td>
</tr>
<tr>
<td>PSO</td>
<td>10</td>
<td>2,3,7,17,20,24,27,29,31,32</td>
<td>6,833,100</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.

Table 11 Comparison of solution among different methods after 50 trials (Multi-objective problem) (Test case II).

<table>
<thead>
<tr>
<th>Methods</th>
<th>Minimum ($)</th>
<th>Maximum ($)</th>
<th>Average ($)</th>
<th>Simulation time (s)</th>
<th>No. of hits to optimum solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>7,332,080</td>
<td>7,332,080</td>
<td>7,332,080</td>
<td>34.7621</td>
<td>50</td>
</tr>
<tr>
<td>PSO</td>
<td>7,381,210</td>
<td>7,383,813</td>
<td>7,381,574</td>
<td>41.3287</td>
<td>43</td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.
algorithm. As DS algorithm is a stochastic optimization technique, randomness is obvious and many trials are required to obtain the optimum result. In this study, 50 trial runs were carried out to obtain each result in order to take into consideration the stochastic nature. An algorithm is said to be robust, if it gives consistent result during these trial runs. Table 7 shows a comparison of the solution of DS algorithm and PSO for the multi-objective formulation for test case I, where former one proves to be better in terms of robustness. Table 11 shows the comparison of the solution for test case II. Here also, DS algorithm outperforms PSO in terms of robustness. Both Tables 7 and 11 reveal that out of 50 numbers of trials, the number of hits to reach the minimum solution is 100% using DS algorithm, which signifies robustness of the algorithm.

Therefore, the above results establish the enhanced ability of DS algorithm to achieve superior quality solutions, in a computational efficient and robust way for solving reliability problem.

Table 12 Influence of DS parameters on multi-objective problem value (After 50 trials) (Test case II).

<table>
<thead>
<tr>
<th>Superorganism size</th>
<th>$c_2$</th>
<th>$c_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td></td>
</tr>
</tbody>
</table>

Bold signifies the best results in terms of quality of solution and computational efficiency.
5.3. Tuning of parameters for DS algorithm

To get optimum solution using DS algorithm, it is necessary to get proper values of parameters $c_1$ and $c_2$. Moreover, value of the cost function may vary with the Superorganism size also. For different values of these parameters, minimum value of cost function is evaluated for the multi-objective function of test case II. For a single value of one parameter, the other parameters have been varied for their all possible combinations. The results of the tuning procedure are presented in Table 12.

Too large or small value of Superorganism size may not be capable to get the minimum value of cost. For each Superorganism size of 20, 50, 100 and 200, 50 trials have been run. After a rigorous tuning procedure, it has been found that the best value is obtained with $c_1 = 0.3$ and $c_2 = 0.3$ with a Superorganism size 50. For Superorganism size more than 50, there is no improvement in the result. Moreover, beyond Superorganism size of 50, simulation time also increases. The variation of results obtained by DS algorithm with variation in Superorganism size for test case II is shown in Table 13.

6. Conclusion

In this paper, DS algorithm has been successfully implemented to find optimum number and location of RCS in a radial distribution feeder. The performance of DS algorithm has been compared with that of PSO algorithm. Both single objective and multi-objective formulations are considered and multi-objective formulation proves to provide more realistic solution set, by compromising reliability improvement with the cost incurred. Analyses of all the simulation results reveal that the performance of DS algorithm in all respect is better in comparison with the PSO. Thus, DS algorithm may be considered as an efficient tool to solve multi-objective reliability optimization problems. In future, DS algorithm may be tried to solve much more complex reliability optimization problem, considering optimal placement of both RCSs and distributed generators together.

References


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