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Reliability Driven Reconfiguration of Rural Power Distribution Systems

Saikat Chakrabarti, Gerard Ledwich, and Arindam Ghosh
School of Engineering Systems
Queensland University of Technology
Brisbane, Australia
saikat.chakrabarti@qut.edu.au, g.ledwich@qut.edu.au, a.ghosh@qut.edu.au

Abstract—**This paper presents a reliability-based reconfiguration methodology for power distribution systems. Probabilistic reliability models of the system components are considered and Monte Carlo method is used while evaluating the reliability of the distribution system. The reconfiguration is aimed at maximizing the reliability of the power supplied to the customers. A binary particle swarm optimization (BPSO) algorithm is used as a tool to determine the optimal configuration of the sectionalizing and tie switches in the system. The proposed methodology is applied on a modified IEEE 13-bus distribution system.**

Keywords- Distribution system, Monte Carlo, particle swarm optimization, reconfiguration, reliability.

I. Introduction

In earlier days, power system reliability analysis was mainly involved with the reliability modelling and adequacy evaluation of the generating systems, since an outage or shortage of capacity in this part of the power system could have widespread consequences [1]. With the development of advanced technology and protection mechanisms for generating units and the associated transmission system, such events have become less frequent in the modern power systems. On the other hand, as a result of de-regulated electricity market scenario and rapidly increasing demand for electricity, distribution systems are being operated under highly stressed conditions, and thereby making them vulnerable to slight disturbances. The triggering events for a number of recent power system outages that involved subsequent outages of large generating capacities were located in the distribution segment of the corresponding power systems [2]. Statistically, majority of the service interruptions to customers come from distribution systems [1]. Detailed reliability evaluation of the distribution system is therefore very important both in the planning and the operating stage of a power system.

The distribution systems in the rural areas of a power network are mainly radial in nature, due to the sparsity of the customers and the large geographical distance from the substation. An outage or malfunctioning of any component tends to affect all the customers downstream. The overhead lines used in a rural distribution system are frequently vulnerable to faults due to their long exposed length. Rural power improvement programs are therefore initiated in different parts of the world to reduce the frequency and duration of power interruptions [3]. The major objectives of such programs are:

- To reduce the number of customers affected by individual faults.
- To reduce the time needed to locate and isolate a fault, thereby reducing the time required to restore power to the affected customers.
- To strengthen the rural power network by improving the existing power lines and installing new power lines and equipments, if required.

While reconfiguring the distribution networks, majority of the works reported in the existing literature aimed at minimizing the real power loss in the network and balancing the load [4]-[16]. An essential criterion for the reconfigured networks has been the preservation of the radial nature. There are mainly two types of switches in a distribution system: sectionalizing switches, that are normally closed and connect line segments; and tie-switches, that are normally open and can connect two feeders or substations or form a lateral loop. Distribution reconfiguration is essentially a combinatorial optimization problem where the best possible combination of switch status (open or close) has to be found so that the objective function (such as the total real power loss) is minimized. The frequently used constraints in this optimization process have been the maximum allowable voltage drop in the line, line current limits, transformer capacity limits, and any other possible network operational or planning constraints.

There have been mainly three approaches for solving the combinatorial optimization problem mentioned above: heuristic search [4]-[7], conventional optimization [8], and artificial intelligence based methods [9]-[16]. In the heuristic search approach, a branch exchange-based technique is usually employed to find the optimal network configuration, where an open switch is closed, and a closed switch is opened to maintain the radial configuration of the network. Simplified versions of power flow computation method that are suitable for radial networks are used to minimize the computational burden and speed-up the search process. The search process for finding the optimal network configuration is usually not

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exhaustive, and it does not guarantee convergence to a global optimum solution. An exhaustive search method can find the true optimal solution; however application of such methods to a large real world system is computationally extremely demanding, and therefore limited to small to medium sized systems only [6]. A linear programming based distribution system reconfiguration method is proposed in [8]. By using a modified simplex method, the optimal configurations of the switches, i.e., close or open status, are determined, so that the radial nature of the distribution system is maintained. Line capacity limits are incorporated in this approach, however it fails to accommodate the voltage constraints. The artificial intelligence based methodologies such as the use of fuzzy variables, genetic algorithm, simulated annealing, ant colony systems, and other evolutionary techniques have increasingly been used for distribution system reconfiguration problem [9]-[16]. The major advantage of these methods lies in their ability to avoid the local minima, if any, and find the global solution for the problem. Multiple objectives and constraints that are not always easy to formulate in a conventional optimization problem, can be easily handled in these methods.

As pointed earlier, reliability evaluation is an integral part of the planning and operation of a modern-day power distribution system. Consequently, in recent years, there has been significant amount of effort devoted by the researchers on addressing the reliability issues while reconfiguring the distribution networks [17]-[20]. The maximization of the reliability of the supplied power is being considered as the objective of the distribution system reconfiguration problem, as an alternative to, or in addition to the objectives such as the minimization of the real power loss, equipment cost or the voltage sag. Artificial intelligence based methods such as immune algorithm [17], particle swarm optimization [18], ant-colony optimization [19], and greedy algorithm [20] are generally used to obtain the optimal switch configurations that maximizes the reliability of the system. At each stage of the iteration, one or more reliability indices are used to evaluate the reliability of the system configuration at that stage. The expected energy not supplied (EENS), expected outage cost (ECOST), and system average interruption duration index (SAIDI) are some of the widely used reliability indices in this approach.

The basic philosophy behind the reliability evaluation method followed so far in distribution reconfiguration problem has been the use of *N*-1 criterion, where the effect of failure of a component on the power supplied to the load or customer is quantified [21]. The failure rate of the component is usually obtained from the past measurements. However, to predict the performance of the system in future, one needs to rely on probabilistic description of various failure events [22]. *N*-1 criterion fails to account for different probabilities of various contingencies to occur. Also, it does not take into consideration the factors such as the risks associated at various operating stages and times of a power system, the aging of equipments, and the growth of loads.

In the present paper, a distribution system reconfiguration methodology is proposed, which maximizes the reliability of the system. The probabilistic models of the distribution system components are considered, and the reliability is computed by using the Monte Carlo simulation technique [23]. Binary particle swarm optimization (BPSO) technique is used to determine the optimal configuration of switches in the network.

Section II gives an overview of the Monte Carlo simulation technique used in this paper. Section III briefly describes the BPSO algorithm. The formulation of the optimization problem is presented in Section IV. Simulation results are presented in Section V, and Section VI concludes the paper.

II. Reliability Assessment using Monte Carlo Simulation

The Monte Carlo simulation technique [23] is used in this work to assess the reliability of the distribution system. The probabilistic reliability models of various components such as feeders, transformers, breakers, switches and lines are considered. The system state sampling approach is followed while evaluating the reliability of a system [24]. This sampling approach has the advantage of reduced computational burden and less memory requirement, compared to the other approaches, viz., state duration sampling, and system state transition sampling approach. The basic methodology of reliability assessment by Monte Carlo simulation using state sampling approach is briefly described in the following [24]:

Let the state of a system containing m components be denoted by,

$$\mathbf{S} = (s_1, s_2, ..., s_m) \tag{1}$$

where the elements of **S** are assigned values according to the outcomes of a random experiment as follows:

$$s_i = \begin{cases} 0 & \text{if } r_i \geq PF_i \\ 1 & \text{if } 0 \leq r_i < PF \end{cases} \tag{2}$$

Here s_i is the state of the ith component. $s_i = 0$ implies that the component is in 'down' state, and $s_i = 1$ implies the component is in 'up' state. r_i is a random number drawn from the uniform distribution in the range [0,1]. PF_i is the probability of failure for the ith component.

Let $P(\mathbf{S})$ be the probability of the system of being in state **S**, and $F(\mathbf{S})$ be the corresponding reliability index for the state. The mathematical expectation of the reliability index is given by,

$$E(F) = \sum_{\mathbf{S} \in G} F(\mathbf{S}) P(\mathbf{S}) \tag{3}$$

where G is the set of system states.

Let N be the total number of Monte Carlo trails, and $n(\mathbf{S})$ be the total number of occurrences of the state **S**. The probability of occurrence of the state **S** is therefore given by,

$$P(\mathbf{S}) = \frac{n(\mathbf{S})}{N} \tag{4}$$

Consequently, the expected value of the reliability index is given by,

$$E(F) = \sum_{\mathbf{S}\in G} F(\mathbf{S}) \frac{n(\mathbf{S})}{N} \tag{5}$$

The expected value of the reliability index, $E(F)$ is used to rank various possible configurations of the distribution system, and to find the optimal configuration having maximum reliability among the alternatives. The search of the optimal configuration among various alternatives is carried out with the help of an enhanced binary particle swarm optimization (BPSO) technique. The essential features of the BPSO and the techniques used for its enhancement are described in the next section.

III. Binary Particle Swarm Optimization

The basic principles of PSO are taken from the collective movement of a flock of bird, a school of fish, or a swarm of bees [25]- [27]. A number of agents or particles are employed in finding the optimal solution for the problem under consideration. The movement of the particles towards finding the optimal solution is guided by both individual and social knowledge of the particles. As shown below, the position of a particle at any instant is determined by its velocity at that instant and the position at the previous instant.

$$\mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{v}_i(t) \ , \tag{6}$$

where $\mathbf{x}_i(t)$ and $\mathbf{x}_i(t-1)$ are the position vectors of the ith particle at the instant t and t-1 respectively, and $\mathbf{v}_i(t)$ is the velocity vector of the particle.

The velocity vector is updated by using the experience of the individual particles, as well as the knowledge of the performance of the other particles in its neighbourhood. The velocity update rule for a basic PSO is,

$$\begin{aligned}\mathbf{v}_i(t) = \mathbf{v}_i(t-1) + \varphi_1.r_1.(\mathbf{pbest}_i - \mathbf{x}_i(t-1)) \\ + \varphi_2.r_2.(\mathbf{gbest} - \mathbf{x}_i(t-1))\end{aligned} \ , \tag{7}$$

where φ_1 and φ_2 are adjustable parameters called individual and social acceleration constant respectively; r_1 and r_2 are random numbers in the range [0, 1]; $\mathbf{pbest}_i$ is the best position vector found by the ith particle; $\mathbf{gbest}$ is the best among the position vectors found by all the particles.

The vectors $\mathbf{pbest}_i$ and $\mathbf{gbest}$ are evaluated by using a suitably defined fitness function. φ_1 and φ_2 are usually defined such that $\varphi_1 + \varphi_2 = 4$, with $\varphi_1 = \varphi_2 = 2$. The maximum and minimum values of the components of velocity are limited by the following constraints to avoid large oscillations around the solution.

$$v_{ij} = \begin{cases} -v_{\max} & \text{if } v_{ij} < -v_{\max} \\ v_{\max} & \text{if } v_{ij} > \ v_{\max} \end{cases} , \tag{8}$$

For the problem under investigation in this paper, $v_{\max}$ is taken to be equal to 4 [25].

A. Binary PSO

In a BPSO, each element of the position vector can take only binary values, i.e., 1 or 0. At each stage of iteration, the elements of the position vector $\mathbf{x}_i$ are updated according to the following rule:

$$x_{ij}(t) = \begin{cases} 1 \text{ if } \ \rho_{ij} < s(v_{ij}) \\ 0 \text{ otherwise} \end{cases} , \tag{9}$$

where ρ_{ij} is a random number in the range [0, 1], $s(v_{ij})$ is a sigmoidal function defined as,

$$s(v_{ij}) = \frac{1}{1+\exp(-v_{ij})} , \tag{10}$$

B. Enhanced PSO

The enhancement to the basic PSO proposed in [28] is used in this work for increasing the efficiency of the search process. The rules, additional to the one described in (7) for updating the velocity vector, are as follows:

1. If the individual best solution found by the particle, $\mathbf{pbest}_i$, and the best solution found by all the particles, $\mathbf{gbest}$ are both feasible solutions in terms of satisfying all the constraints for the problem, then the velocity of the particle is updated according to (7).
2. If the particle has not found a solution, i.e., $\mathbf{pbest}_i$ is not feasible, but the global best solution $\mathbf{gbest}$ is feasible, its velocity is updated by the following rule:

$$\mathbf{v}_i(t) = \mathbf{v}_i(t-1) + \varphi.r.(\mathbf{gbest} - \mathbf{x}_i(t-1)) \ , \tag{11}$$

where $\varphi = \varphi_1 + \varphi_2$, r is a random number in the range [0,1].

3. If none of the particles has found a solution so far, i.e., both $\mathbf{pbest}_i$ and $\mathbf{gbest}$ are infeasible, the components of the velocity of the particle are set to random fractions of the maximum values of the corresponding components as shown below.

$$\mathbf{v}_i(t) = [rn_1.v_{1\max}, rn_2.v_{2\max}, ..., rn_D.v_{D\max}] \ , \tag{12}$$

where $rn_j, \forall j = 1,...,D$ are random numbers in the range [-1, 1]; $v_{j\max}, \forall j = 1,...,D$ are the maximum specified values of the velocity components; D is the dimension of the velocity vector.

The main principle behind the enhanced PSO is that, when an individual particle is not able to find a feasible solution, it should use the knowledge of the feasible solution, if any, found by some other particle. When none of the particles has found a feasible solution, a random search enhances the possibility of quickly finding a feasible solution.

IV. Optimal Reconfiguration using BPSO

The distribution reconfiguration problem is essentially the determination of status (open or close) of the switches in the system, depending on desired performance criterion, which, in this case, is the reliability of the power supplied to the customers. The reconfiguration can be an operational or planning problem. In the operating state of a distribution system, the existing sectionalizing and tie switches constitute the set of switches for which the optimal statuses are to be determined. In the planning stage, along with the existing switches in the system, potential locations where new switches may be installed need to be identified. For the present work, it is assumed that the locations of the existing switches and the potential new switches are known. The BPSO algorithm searches through various possible set of switch configurations. At each stage of the search process, reliability of the reconfigured system is evaluated in terms of the chosen reliability index. Constraint imposed on the feasibility of a set of switch configuration is that the system should be radial, and that the electrical connection from the feeder to the end load should be maintained.

In the proposed implementation of the BPSO, the position vectors of the particles represent the potential solutions for the distribution system reconfiguration problem. A fitness function needs to be defined to evaluate the suitability of the solutions found by the particles at each stage of iteration. The individual best position vector of a particle, $\mathbf{pbest}_i$, and the global best position vector $\mathbf{gbest}$ are evaluated based on this fitness function. The objective of the distribution system reconfiguration problem in this paper is to maximize the reliability of the power supplied to the customers. The fitness function therefore should evaluate, for the position vector of each particle, (1) whether the reconfigured system is feasible in terms of network constraints, and (2) in case it is feasible, what is the reliability of the power supplied to the customers. The reliability indices used in the present work are the following [24]:

1. *LOLE*: Loss of load expectation (LOLE) is defined as the average number of hours or days in a given period in which the hourly or daily peak load exceeds the available generating capacity. This is a measure of the adequacy of the power supplied by one or more feeders to the distribution system.
2. *LOEE*: Loss of energy expectation (LOLE) is the expected energy (in MWHr) not supplied due to the loads exceeding the available power supplied by the feeders.

The fitness function $J(\mathbf{x})$ for using the BPSO is formulated as follows:

$$J(\mathbf{x}) = \begin{cases} K & \text{if the configuration is not feasible} \\ w_1 J_1 + w_2 J_2 & \text{if the configuration is feasible} \end{cases}, \quad (13)$$

where K is a large number assigned to the fitness function if the position vector representing the set of switch configurations is not feasible (i.e., the reconfigured system is not radially connected); w_1 and w_2 are two weights with values such that $w_1 J_1$ and $w_2 J_2$ are comparable in magnitude. J_1 and J_2 are the reliability indices as shown below:

$$J_1 = LOLE\,, \quad (14)$$

$$J_2 = LOEE \quad (15)$$

The number of elements in the binary position vector $\mathbf{x}$ is equal to the number of switches in the system. The elements of $\mathbf{x}$ are defined as follows:

$$x = \begin{cases} 1 & \text{if the switch is closed} \\ 0 & \text{if the switch is open} \end{cases}, \quad (16)$$

The search process starts with a randomly selected binary position vector $\mathbf{x}$, i.e., each element of $\mathbf{x}$ is randomly assigned a value of either 0 or 1. Using this switch configuration, it is examined whether the network constraints are being satisfied or not. If the switch configuration fails to render a connected and radial network, it is considered an infeasible solution, and a large numerical value, K is assigned to the fitness function. When the switch configuration satisfies the network constraints, a Monte Carlo simulation is performed, and the reliability indices *LOLE* and *LOEE* are evaluated based on the reliability models of the components that are involved in the network. The fitness function is the weighted sum of *LOLE* and *LOEE*, as mentioned in (13).

V. Case Studies

The proposed methodology of reliability-based distribution system reconfiguration is applied on the modified 13-bus distribution system shown in Fig. 1 [29]. The four switches in the system are denoted by SW1,…, SW4. Loads LD1,…, LD6 are assumed to be lumped at the buses shown in the figure.

Risk_A, a software tool for power system reliability assessment and risk analysis from Manitoba HVDC Research Centre Inc., is used in this work for performing the Monte Carlo analysis and computing the reliability indices [22]. The reliability models of the components, i.e., transformers, circuit breaker, bus-bars, transmission lines, and switches are specified in terms of parameters such as the failure and recovery rate, maintenance and recovery rate, derating rate and its recovery rate, derated power levels (for transformers), end of life probability of a component, and starting and ending time for seasonal derating [22]. Loads are represented by the nominal values multiplied by the normalized load curves for 24 hours of a day, and 365 days of year. Fig. 2 shows sample normalized load curves for the first day of each month in a year. Months of January to December are enumerated as 1 to 12. The nominal values for the loads used in this study are shown in Table 1.

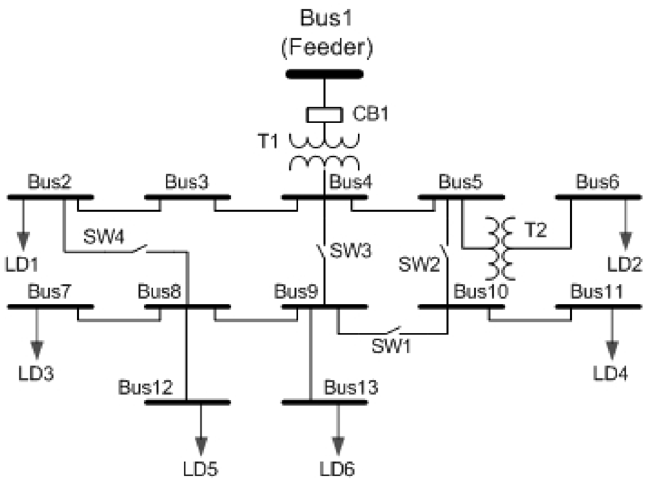

Fig. 1. Modified IEEE 13 bus test feeder

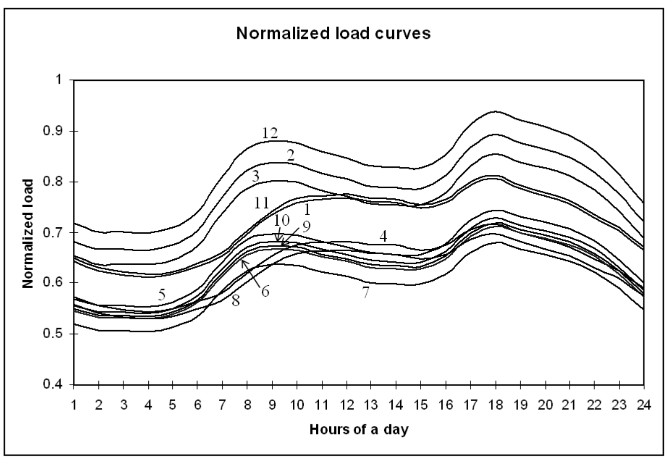

Fig. 2. Normalized load curves for the first day of each month in a year

TABLE I
NOMINAL VALUES OF LOADS

Load	**MW**
LD1	35
LD2	32
LD3	25
LD4	21
LD5	45
LD6	27

Table II shows the chosen values of the parameters for the BPSO. These values are chosen after multiple runs of the algorithm, and offer best performance in terms of finding the optimal switch configuration and computational time. In Table II, N_{SW} denotes the number of switches in the system.

TABLE II
BPSO PARAMETERS

Parameter	Optimal value
Number of particles	5^*N_{SW}
Individual acceleration constant (φ_1)	2
Social acceleration constant (φ_2)	2
Number of iterations after which the search is stopped if no better solution is found	5
Maximum number of iterations	100^*N_{SW}

Table III shows the optimal configuration of the switches for the 13-bus system. The switches SW1 and SW4 are closed, and the switches SW2 and SW3 are kept open so that the radial nature of the system is maintained, and the reliability of the power supplied to the loads is maximized. The reliability is evaluated in terms of *LOLE* and *LOEE* by using Risk_A software.

TABLE III
OPTIMAL SWITCH CONFIGURATION FOR THE 13-BUS TEST SYSTEM

Switch	Optimal Configuration
SW1	Closed
SW2	Open
SW3	Open
SW4	Closed

The Monte Carlo simulation is performed for a period of one year, and each simulation consists of 10^3 trials based on the random samples drawn from the probabilistic reliability models of the participating components in the system.

VI. CONCLUSION

This paper presents a distribution system reconfiguration methodology aimed at maximizing the power supplied to the customers. The existing reliability-driven distribution system reconfiguration methods assess the reliability of the system by utilizing the past performance record of various components involved. In the present work, probabilistic reliability models of the components are used to estimate the future behavior of the distribution system in terms of the reliability of supplying power to its customers. This method has the advantage of taking into account the aging of the equipments, the stochastic nature of their availability, the probability of various failure events to take place, and the changing nature of the load with time. An enhanced binary particle swarm (BPSO) algorithm is used to determine the optimal statuses of the switches in the distribution system. The Monte Carlo simulation is used to evaluate the loss of load expectation (LOLE) and the loss of energy expectation (LOEE) at the load points. The proposed method is applied on the modified IEEE 13-bus test system to determine the optimal switch configuration.

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