Hybrid Fuzzy Monte Carlo and Logic Programming Model for Distribution Network Reconfiguration in the Presence of Outages

Zita VALE, Bruno CANIZES, João SOARES, Pedro OLIVEIRA, Tiago SOUSA, Marco SILVA, Alexandre SOEIRO, Hussein KHODR
GECAD – Knowledge Engineering and Decision-Support Research Center
Polytechnic of Porto - Rua Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal
{zav, bmrc, japs, pmro, tas, masi, aso, hmk} @isep.ipp.pt

ABSTRACT

This paper presents a methodology for distribution networks reconfiguration in outage presence in order to choose the reconfiguration that presents the lower power losses. The methodology is based on statistical failure and repair data of the distribution power system components and uses fuzzy-probabilistic modelling for system component outage parameters. Fuzzy membership functions of system component outage parameters are obtained by statistical records. A hybrid method of fuzzy set and Monte Carlo simulation based on the fuzzy-probabilistic models allows catching both randomness and fuzziness of component outage parameters.

Once obtained the system states by Monte Carlo simulation, a logical programming algorithm is applied to get all possible reconfigurations for every system state. In order to evaluate the line flows and bus voltages and to identify if there is any overloading, and/or voltage violation a distribution power flow has been applied to select the feasible reconfiguration with lower power losses.

To illustrate the application of the proposed methodology to a practical case, the paper includes a case study that considers a real distribution network.

INTRODUCTION

The reliability of power systems is the ability to deliver electricity to all delivery points within acceptable levels of quality at the minimum cost. These are conflicting goals, as to increase the quality of energy to provide to customers will necessarily increase the cost of investment in networks as well as the operation cost. The task of planners and operators is to find the adequate balance, taking into account the uncertainties of future conditions.

Conventionally, the performance of power systems is evaluated using deterministic methods. The most popular deterministic method is known as N-1 criterion. Probabilistic methods are gaining more importance over deterministic ones due to being more effective in dealing with uncertainties [1, 2]. There are two types of uncertainties in power systems: randomness and fuzziness [3]. It has been recognized that failure frequencies or probabilities of transmission overhead lines are related to weather conditions [4, 5]. Weather conditions are often described in fuzzy words like: heavy, medium or light rain [3]. This classification is obviously vague or fuzzy. The failure frequencies or probabilities of distribution lines are also impacted by the environment (such as tree falling or animal activities) and operational conditions (such as load levels). A probability model cannot be used since there are little statistics available; some utilities have a good judgment on the range of outage parameters (such as repair time). For all of these cases, a fuzzy approach allows to obtain adequate models [3].

The reliability criteria can be deterministic and/or probabilistic. In both cases a consistent data base and an exhaustive statistical analysis of all the available information, such as failure rate (λ) and the average repair times (r) of each power systems component, are needed. On the other hand, maximizing reliability in power systems implies the minimization of unserved energy and therefore of load curtailment, avoiding an important monetary loss by undelivered energy, economy damage and an inconvenient to the consumers.

The method proposed in this paper is based on statistical failure and repair data of a distribution network. Fuzzy-probabilistic modeling is used for system component outage parameters. Using statistical records allows developing the fuzzy membership functions of system component outage parameters. To catch both randomness and fuzziness of component outage parameters, a hybrid method of fuzzy set and Monte Carlo simulation based on the fuzzy-probabilistic models is proposed. Once obtained the system states by Monte Carlo simulation in MATLAB, logic programming (using PROLOG) is used to determine all possible network reconfigurations for all system states guaranteeing the radial operation, ensuring that there are not isolated buses and that all loads are fed. A network contingency analysis is made for each reconfiguration in order to evaluate the line flows and bus voltages and to identify if there is any overloading, and/or voltage violation. At the end, the reconfiguration which presents the minimum losses without violating network constraints is selected.

This paper is organized as follows: Section "Methodology" depicts an explanation of the proposed methodology to obtain the reconfiguration that presents the lowest power loss. Section "Case Study" presents a case study based on a real network and a brief analysis of the obtained results. Finally, the last section presents the most relevant conclusions.

METHODOLOGY

A methodology aiming at minimizing the losses cost in distribution network reconfiguration in the presence of an outage is presented in this paper.
Figure 1 presents the basic idea of the proposed method.

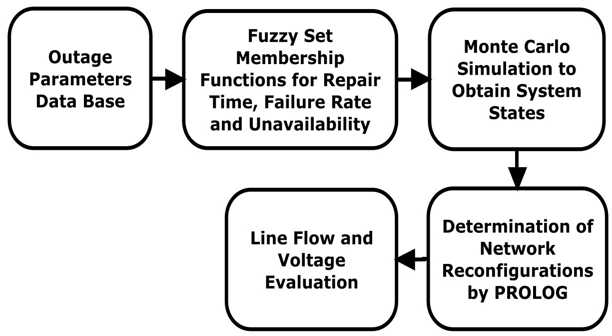

Figure 1: Diagram of the proposed methodology

- Outage parameters data base

With all available information like repair times, number of repairs, number of failures, number of reparable failures, and time periods it is possible to develop a consistent data base and to undertake an exhaustive statistical analysis.

- Fuzzy set functions for $\bar{r}$, λ and U

It is extremely difficult to precisely distinguish the effects of the weather conditions, and environment and operational conditions on the outage data of individual components using a probability model since there are no or little statistics available. The failure frequency or probability of distribution power systems are directly impacted by these conditions. It is also very common that a large number of utilities do not have sufficient statistical records of outage parameters.

Membership function for repair time – $\bar{r}$

A direct average of repair times in different outage events can be calculated by equation (1). Where $\bar{r}$ is the point estimate of repair time, r_i is the ith repair time, and n is the number of repair times in the outage data.

$$\bar{r} = \frac{1}{n}\sum_{i=1}^{n} r_i \tag{1}$$

A *t*-distribution can be used to estimate the confidence interval of the expected repair time, so:

$$r_2 = \bar{r} - t_{\alpha/2}(n-1)\frac{s}{\sqrt{n}} \tag{2}$$

$$r_3 = \bar{r} + t_{\alpha/2}(n-1)\frac{s}{\sqrt{n}} \tag{3}$$

$$r_2 \le \mu \le r_3 \tag{4}$$

The real expected repair time (μ) is located between the lower (r_2) and higher bound (r_3) as it can be seen in equation (4). A triangle membership function for repair time r (in hours per failure) can be easily created using the point and interval estimates [3]. So:

Failure frequency - f / failure rate - λ

Failure frequency is estimated as average failures per year over a time period for individual components. Where R_f is the number of component repairable failures in time period T (in years).

$$f = \frac{R_f}{T} \tag{5}$$

Developing a theoretical accurate method for failure frequency estimation is not easy. Fortunately, statistics theory can be used to estimate the confidence interval of the failure rate, which can be approximately considered as an interval estimate of failure frequency, as they are numerically close in most cases [6].
In the failure data processing a relationship between Chi-Square distribution (χ^2) and the Poisson distribution can be considered. For a given significant level α the failure rate λ falls into the random confidence interval (6) with the probability of $1-\alpha$ [6]:

$$\frac{\chi^2_{1-\alpha/2}(2\cdot F)}{2\cdot T} \le \lambda \le \frac{\chi^2_{\alpha/2}(2\cdot F)}{2\cdot T} \tag{6}$$

F is the statistical number of failures within the time T in data samples.
The two bounds of failure rate can be estimated by equation (7):

$$\lambda_2 = \frac{\chi^2_{1-\alpha/2}(2\cdot F)}{2\cdot T} \tag{7}$$

$$\lambda_3 = \frac{\chi^2_{\alpha/2}(2\cdot F)}{2\cdot T} \tag{8}$$

$$\lambda_2 \le \lambda \le \lambda_3 \tag{9}$$

A triangle membership function of failure rate can be easily created using the point and interval estimates of failure rate.

Unavailability – U

Failure frequency (failure rate) and repair time are used to determine the unavailability (U) or forced outage rate:

$$U \cong \lambda \times r \tag{10}$$

The interval calculation rules for a given membership function grade are used to obtain the unavailability membership function.

- Monte Carlo simulation

Components in distribution systems can include overhead lines, cables, transformers, capacitors, circuit breakers and reactors. A two-state (up and down) model can be used to represent these components. Nonsequential Monte Carlo can be used to create the two-state models for distribution components with the objective to obtain a sample of states for the distribution system.

Let S_i denote the state of the ith component and Q_i its failure probability. After generating a random number R_i distributed uniformly between [0, 1] for the ith component, the state (success or failure) of R_i can be determined according to (11):

$$S_i = \begin{cases} (success) & if \quad R_i > Q_i \\ (failure) & if \quad 0 \leq R_i \leq Q_i \end{cases} \qquad (11)$$

The system state containing N components is depicted by the vector S as in (12):

$$S = (S_1, \ldots, S_i, \ldots, S_N) \qquad (12)$$

- Reconfiguration

To determine all possible network reconfigurations for all system states a logic programming based algorithm is used (see figure 2), always guaranteeing the radial operation and ensuring that there are no isolated buses or islands.

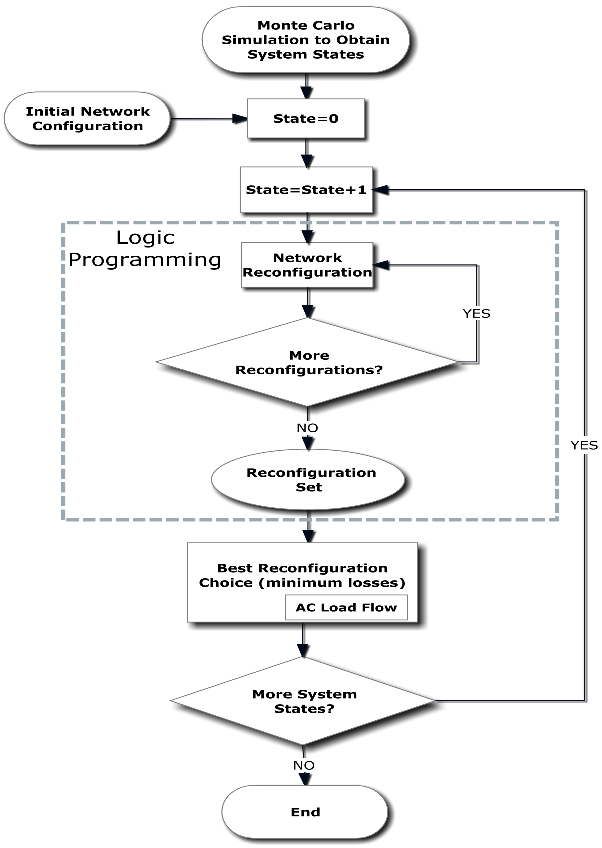

Figure 2: Reconfiguration flowchart

- Load flow

Load flow calculation allows to obtain the line power flows, bus voltages and to identify any overloading and/or voltage violation. For each state, the reconfiguration which presents the minimum losses is selected.

CASE STUDY

This section uses a real 30kV distribution network to illustrate the application of the proposed methodology. This distribution network has one substation, 6 feeders, 940 buses, 465 load points, 16 switches, and 946 lines – cables and overhead lines whose historic fault data base is used for Monte Carlo Simulation (MCS).

Equations (2), (3), (4) and (7), (8), (9) are used to obtain the membership functions for repair time and failure rate. Equation (10) is used to obtain the membership function of unavailability.

100,000 cycles have been used for MCS leading to an accuracy level of 7×10^{-4} which has been considered adequate. MCS took 7 seconds to perform 100,000 cycles.

As a result, MCS generates 786 different system states. One of these states is a state for which there is not any failure, thus we have 785 different system states with at least one component in down state. The probability of all components being in up state is 94.5%

For the states with components in down state a logic programming based algorithm, developed in PROLOG, is used to determine all possible network reconfigurations, ensuring that there are no isolated bus or islands and guaranteeing the radial operation.

The case study has used a PC compatible with one processor Intel Xeon W3520 2.67GHz with 4 cores, 3GB of Random-Access-Memory (RAM) and Windows 7 Professional 64-Bit Operating System.

An AC distribution power flow method [7] is applied to ensure that reconfigurations meet network constrains. In the present case study 1569 reconfigurations were obtained from logic programming algorithm with an average time of 2 seconds each. The power flow took an average time of 0.8 seconds for each reconfiguration to check for network constraints. In table 1 it is depicted these reconfiguration statistics. It can be noted that only 70 out of 785 MCS obtained states were possible to reconfigure with all loads supplied. However, 10 out of these 70 states have all reconfigurations violating network constraints.

Table 1: Reconfiguration statistics

Reconfiguration statistics	
Average number of reconfigurations per state	2
Minimum reconfigurations per state	0
Maximum reconfigurations per state	6
Average reconfiguration time per state	2 seconds
Possible states reconfigurations	70 out of 785
Bus voltage violations	6 out of 70
Lines thermal capacity violations	4 out of 70

The system state in MCS with highest probability of occurrence only has one component in down state which is line 698. For that reason this state reconfiguration's result was chosen as an example to display in this paper. With this component in down state, 6 reconfigurations were obtained in PROLOG. This can be seen in table 2. The initial configuration is also displayed in this table. The switches that are turned on are marked with an "X".

Table 2: Reconfiguration with line 698 in down state

Switch ID	Initial configuration	Component 698 failure (reconfiguration)					
		1	2	3	4	5	6
1	X	X	X	X	X	X	X
2							
3	X	X	X	X			X
4	X	X	X	X	X	X	X
5					X	X	X
6	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X
8		X		X	X		X
9			X	X		X	X
10	X	X	X		X	X	
11	X	X	X	X	X	X	X
12							
13	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X
15	X	X	X	X	X	X	X
16							

Table 3 presents the results for the initial network configuration and for all possible reconfigurations with component 698 in down state. It can be seen that the reconfiguration with the lowest power loss is the reconfiguration number 6. This reconfiguration presents respectively 2.80MW and 0.26MVAr for active power loss and reactive power loss.

Table 3: Reconfiguration results

	Reconfiguration						
	Initial	**1**	**2**	**3**	**4**	**5**	**6**
Loss (MW)	2.58	5.54	3.30	3.10	3.48	3.15	2.80
Loss (MVAr)	0.28	0.86	0.41	0.42	0.50	0.48	0.26
Load (MW)	58.23						
Load (MVAr)	21.65						
Supply (MW)	60.8	63.8	61.5	61.3	61.7	61.4	61.0
Supply (MVAr)	21.9	22.5	22.1	22.1	22.2	22.1	21.9
Supply (MVA)	64.6	67.6	65.4	65.2	65.6	65.3	64.8

CONCLUSIONS

This paper proposes a hybrid fuzzy Monte Carlo method for generating a sample of system states according to the historic fault data base. This method is combined with a logic programming algorithm, developed in PROLOG, to determine all the possible reconfigurations for each obtained system state. The proposed method allows modeling both randomness and fuzziness of component outage parameters.

An AC load flow is used to identify possible constraint violations in order to choose the reconfiguration that is feasible that presents the lower power losses.

The presented case study considers a real 30kV distribution network with 940 buses, 465 load points, 946 lines and 16 switches. The system state with higher failure probability has been selected for presenting more detailed results. For this state, 6 reconfigurations were obtained by PROLOG and compared. The reconfiguration with the lowest power losses was the 6th reconfiguration with 2.80MW and 0.26MVAr power loss. This method proved to be a good basis for a network operator decision support tool, allowing supporting operator's choice concerning the best reconfiguration in the presence of an outage.

Acknowledgments

The authors would like to acknowledge FCT, FEDER, POCTI, POSI, POCI, POSC, and COMPETE for their support to R&D Projects and GECAD.

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