APPLICATION OF MONTE CARLO SIMULATION TO SUPPORT RISK-BASED DECISION MAKING IN MV DISTRIBUTION NETWORKS

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ABSTRACT

Asset management is currently a widely applied concept within distribution system operators (DSOs). The liberalization of the electricity sector and the introduction of regulatory agencies in the Netherlands motivated Dutch DSOs to implement this concept. Risk management is inseparable from asset management. It forms the basis for the decision-making process regarding the installed assets. With the introduction of PAS55 and ISO55000, there is an increasing need to apply probabilistic risk analysis (PRA). In this paper, the Monte Carlo Simulation (MCS) is applied for a part of the 10kV medium voltage grid of Dutch DSO, Stedin. The focus has been on predicting customer outages and developing a framework for the utilization of the results to support risk-based decision making.

INTRODUCTION

Asset management involves decision-making for investments where a balance between cost, performance and risk needs to be found [1]. PRA are relatively new for DSOs and have, so far, not been extensively applied and implemented. The main concern for DSOs is the reliability of supply of electrical energy to customers. Asset management decisions have been predominantly based on historical assessments which consists of analysing historical data. Predictive assessment can give an indication of future events and as a result preventive actions can be taken. Therefore, predictive assessment can provide valuable information for risk-driven asset management and can form a guide in the decision-making process for handling the physical assets. Predicting future customer interruptions using the Monte Carlo Simulation (MCS) is the focus of this research. The MCS is a probabilistic method for risk assessment which can provide results in the form of probability density functions.

MONTE CARLO SIMULATION

The MCS is a very powerful method that can be used for predictions [2]. MCS involves a series of experiments that is performed on the system in the form of simulations. Using this method, complete probability distributions of random variables associated with risks can be obtained and the system random behaviour can be reproduced. This is due to its ability to involve the variability of input parameters. MCS methods require high computing power and have become increasingly interesting due to the availability of high speed computers. The MCS method treats the input parameters, e.g. the time-to-failure (TTF), the fault restoration time, the time-to-repair (TTR), etc., as random variables and every possible probability distribution that describes their behaviour can be used. The values of each parameter are assigned by sampling methods and afterwards the system state can be derived. The process is repeated multiple times and complete probability distributions can be realized. Hence, the MCS method has the ability to analytically reflect all possible outcomes, even those considered to be too unlikely. The probability distributions of the outcome provide extra information on the possible risks of extreme events. Based on this information different decisions can be made than with single numerical results.

The risk assessment procedure using MCS for distribution networks involves the following steps [2]:

1. Specify a mission time for which the assessment must be done.
2. Specify the probability distributions for the TTF of each component.
3. Generate a uniform random number for each component.
4. Convert these random numbers into values of TTF according to the probability distributions specified for each component.
5. Compare the TTFs with the mission time. All TTFs smaller than the mission time will cause the respective components to be in a failure state during the mission time. For all TTFs larger than the mission time, the respective components are in an operating state during the mission time.

6. Evaluate the system state by incorporating the configuration. A failure state represents a state where customers experience a power interruption. A success state represents a state where all customers are supplied without interruption.
7. Repeat steps 3-6, cumulating the number of failures, until the desired number of simulations.
8. Display all the recorded results in a frequency histogram.

RESEARCH APPROACH

The study cases in this research are 12 radial feeder systems in a 10 kV sub-network of Stedin. The MCS is applied to investigate if failures in these feeder systems could have been predicted. Therefore, the applied strategy for the predictive assessment is to start a MCS at a starting year, chosen to be 2005, and to simulate for a mission time up to 2013, i.e. a mission time of 9 years. Through this strategy a prediction is made from the starting year and validation with the actual observed failure events recorded between 2005 and 2013 is possible.

Component failure behaviour

An important part of the MCS is modelling the system components. Since modelling every component in the network is a very comprehensive task, a statistical investigation is first performed to determine the critical components in the network, i.e. the components that fail most frequently and cause a customer outage. Through the statistical investigation of the customer outage data of the DSO, the critical components are found to be *cables* and *cable joints*. The failure behaviour of these components, more specifically, their time-to-failure (TTF) probability distributions, are inputs to the MCS. The probability distributions are assumed based on available failure data of the components and previous research using statistical life data analysis (LDA) to determine the failure probability distributions [3].

Two types of cables are installed in the investigated area, i.e. PILC and XLPE cables. The average yearly failure rates of these components is calculated per km from outage data and are 0.0702/km/year and 0.0021/km/year, respectively. From this the exponential distribution with the parameter, the failure rate, is assumed to describe the TTF probability distribution of the cables.

Cable joints installed in the sub-network are of three types, namely oil-filled, resin-filled and synthetic joints. From a previous extensive analysis using statistical LDA [3], their probability distributions as function of age are determined. This indicates that the age of the joints is included in the failure behaviour. In order to customize the TTF probability distribution for each individual joint, the general probability distribution is left-truncated at the age of the joint at the starting year of the simulation. The assumed probability distributions are summarized in Table 1.

Table 1. The assumed TTF probability distributions and their parameters for 10 kV cables and 10 kV cable joints at age 0.

	Assumed probability distribution	***Parameters***
PILC cable	Exponential	λ =0.0702
XLPE cable	Exponential	λ=0.0021
Oil-filled joint	Normal	μ=54.03 σ=15.02
Resin-filled joint	Weibull	β=4.93 η=69.95
Synthetic joint	Weibull	β=4.48 η=52.39

Network data acquisition at starting year

Data of the installed components in the radial feeder systems at the starting year 2005 is essential to start the simulation. Since historical data is often missing while the currently installed components are well-known, a backwards reasoning method is developed to recover the data. This first step is to perform a check to determine the components that were installed after 2005. The older components installed before 2005 surrounding the newer components installed after 2005 are analysed. From the analysis, assumptions are made based on the older component types and ages in the radial feeder system. These assumptions are justified since the cable systems were normally installed in the same year.

Monte Carlo Simulation algorithm

The algorithm for the MCS is programmed in Matlab. The flowchart shown in Figure 1 presents the principle of operation of the Matlab code.

The input data required for a study case is the simulation data and the system data. The simulation data includes the mission time (9 years) and the number of runs (5000). The system data consists of the installed cable length and type, the installed number of joint, their types and ages.

The simulation starts with the generation of random failures of every component in the radial feeder system. This is done in the Matlab engine 'TTF generator' where a random number for the random variable TTF is generated from the associated probability distribution of the component.

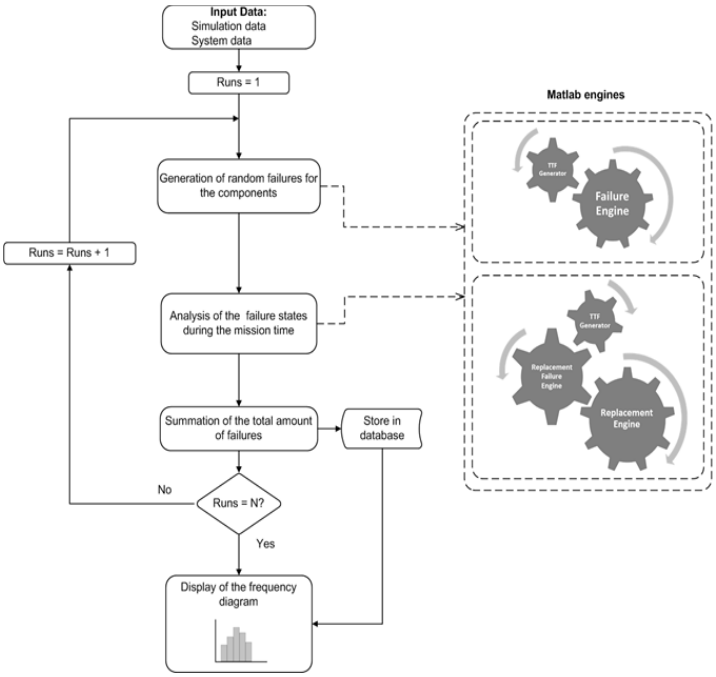

Figure 1. Flowchart representing the principle of operation of the MCS algorithm.

After this, the failure states are determined using the 'Failure Engine' to define if the failures occurred within the mission time. All failures outside the mission time are neglected. For failures within the mission time a replacement is performed. A failure of either a cable or a joint leads to the replacement with two new synthetic joints and a small length of XLPE cable. In order to check if these newly installed components fail within the remaining mission time, a TTF is generated and analysed for these component.

All simulated failures within the mission time are summated and stored in a database. The whole process is repeated 5000 times and finally the results are shown in a frequency plot of the amount of customer outages is. Due to the series configuration of the radial feeder system, a component failure will immediately cause a customer interruption and therefore a component failure is assumed equal to a customer interruption.

RESULTS

The frequency plot of simulated customer outages compared to the actual number of outages for feeder system 2 is shown as an illustration in Figure 2. From this plot, several statistical summary measures can be derived. The summary measures, used to describe the probabilistic results, are the (arithmetic) mean, the standard deviation, the median, the mode and the 90th percentile. The results of the 12 feeder systems investigated, are shown in a Box-and-Whisker plot in Figure 3.

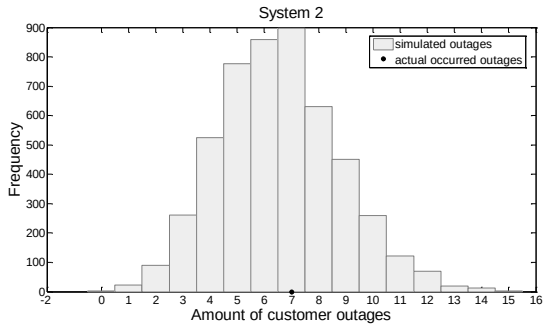

Figure 2. Frequency plot of MCS result for feeder system 2 including the actual occurred number of outages of 7. The actual number of outages corresponds to the mode of the histogram.

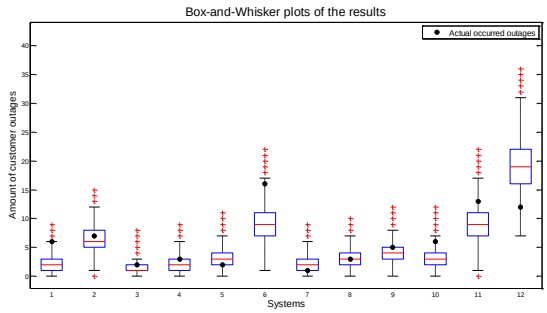

Figure 3. Box-and-Whisker plots of the results for the MCS of the 12 systems in comparison with the actual occurred amount of customers outages. For 7 systems, the actual occurred outages fall within the interquartile range (IQR), defined by the box. The actual occurred outages of the remaining 6 systems fall within the whiskers, representing rare events. All the actual occurred outages are captured by the probability distributions of the predicted customer outages through the MCS.

From the observations in Figure 3 it can be seen that all the actual number of outages were included in the predictions using the MCS. Therefore it can be concluded that the MCS can be of great value in predicting future outages. From the graphs, however, it is clear that the actual occurred outages have very different probabilities of occurrence as predicted through the MCS. The 90th percentile of the predictions indicates an event with the probability of occurrence of less than 0.1 and these events are labelled as extreme events. From the results of the MCS of the feeder systems in a sub-network of Stedin, 33% of actual failures occurred with a probability of less than 0.1. These extreme events are further analysed by investigating the influence of the cable length, the number of joints in the feeder systems, the soil type and the average component age. From this analysis it is found that these factors have an influence on the occurrence of extreme events. The result of the analysis was that systems with cable length larger than 10 km, systems with more than 50 joints and systems installed in peat soil

are more likely to encounter extreme events. Furthermore, the higher the average component age in the feeder system the higher the probability of extreme events. From these results it is clear that other factors influencing the behaviour of the system should be included in the way the MCS results are interpreted.

ASSET MANAGEMENT ADDED VALUE

The results of the MCS as presented in this paper can be of great value in the decision-making process within asset management. The conceptual framework proposed to support decision making based on the MCS results is presented in the following steps and illustrated in Figure 4.:

- The utility must set clear reliability objectives on behalf of the acceptable amount of customer interruptions in a certain period of time.
- The asset manager must decide which summary measures (mean, mode, median, 90th percentile, etc.) are appropriate as the critical measure for the feeder systems. This choice may differ for different systems. For example, a on choosing the 90th percentile can be made when the system exists mainly in peat soil and a decision on choosing the mean value might be made when the system exists in clay. Also it can be decided to make use of the 90th percentile if the system consists of more than 10 km of cable or more than 50 joints. Another factor could be the number of customers connected to the system. If this number is large, the asset manager can decide to avoid the worst-case scenario and take the 90th percentile value as a criterion.
- When the objectives and critical summary measures for the feeder systems are defined, the MCS can be performed and the outputs compared. The systems, for which the summary measures result in higher values than the utility objectives, are considered critical systems. The asset manager can decide to invest in these systems.
- The investment for cable systems consist of replacement of components in the system, adding components for redundancy or planning offline and online diagnostic and condition monitoring inspections. After the decisions for improvement of the critical systems are made, the reduction of the system risk of customer outages can be validated by incorporating the improvements in the MCS and performing the simulation another time. The outcome of the simulations can provide a decision tool for investment in the systems.

CONCLUSIONS

The MCS results, applied to predict future customer outages, have proven that the actual occurred events were included in the outcomes. This implies that the MCS can provide good estimations on the future events. It must be noted that modelling the component failure behaviour and describing it by a probability distribution is the key to perform the MCS. The component TTF probability distributions are of major importance as input to the MCS. Therefore historical data is indispensable and DSOs should be driven to keep up their databases in order to perform predictive assessments.

The utilization of the results in the decision-making process is possible if clear targets are set and assumptions on the appropriate summary measures for different systems are set.

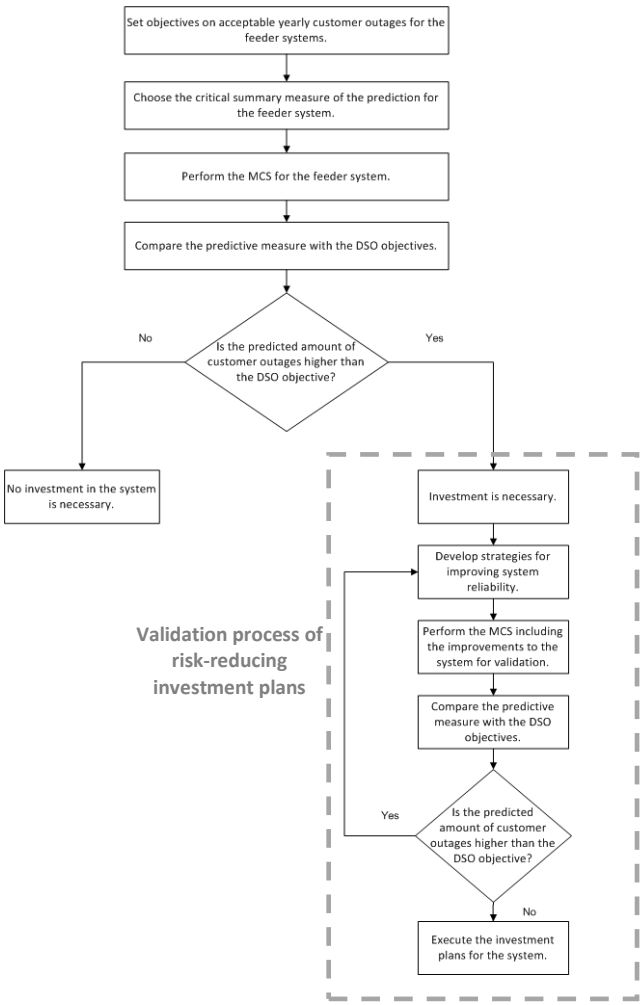

Figure 4. Framework for implementing the MCS in the decision-making process.

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