FAILURE RATE TRENDS IN AN AGING POPULATION – MONTE CARLO APPROACH

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ABSTRACT

This paper proposes a method to make future failure predictions from input data on population age distribution and failure rates, using a Monte Carlo approach. In contrast to many methods used today, the method in this paper is designed to address multiple properties and assumptions simultaneously, which makes the task complicated. For example, the component population is allowed to be divided into both age and different types. The time-dependent failure rates are defined separately for each individual type, can consist of a combination of multiple different failure rates for separate modes, and can be of practically any shape. Furthermore, a volatility measure for the failure rates is introduced and used to model the uncertainties in failure rate estimates. The method handles investment and reinvestment scenarios as well as different restoration models, such as replacing a failed component with a new component of a different type. As a part of the project, a stand-alone software tool was developed and presented in the paper. In the included case study, the method and the tool are shown to be useful when investigating reinvestment strategies to renew the population and decrease the expected number of future failures. The paper gives the reader useful information and understanding on how the problem of predicting the reliability of the future power system can be addressed and solved.

INTRODUCTION

While planning investments and reinvestments for power distribution systems, knowledge of the effects of an aging component population is important. To describe the probability of failure for components in the system, failure rates as a function of time are frequently used. With a well-defined failure rate for an evenly age-distributed population, the task of estimating the total future failure rate becomes fairly simple. However, it becomes more complicated to analytically compute the system future failure behaviour when the component population is more complex and diverse.

Methods to predict future failures for components in power system networks can be found in [1], [2] and [3], in which general guidelines are given. In [4] a method to include aging failures in standard methods are described, and the paper includes a real world case study. In [5] a third-party software tool, used by a large Swedish DSO, is discussed and the usage of the tool includes predicting future failures, with population and failure rates as input, by using simulation technique. One main usage of the tool in [5] is to compare different reinvestment scenarios. Another third-party tool that, among other things, uses population and failure rate data to predict the future failures, is the ABB Asset Health Center [6].

Studies based on predictive reliability models initially focused on estimating average system failure rate. But such estimates fail to reflect the effects of components with extreme performance, effects of maintenance etc. [7]. Following this, researches extended to count in the effect of age, maintenance, weather and environmental factors, system expertise etc., to improve the usability of respective estimates. For example, [8] counts in the information from available component inspection data so as to produce interruption distributions to replace average estimates.

There is a demand for advanced methods which makes use of already available system information and are not limited to specific systems for application. In this paper, the potential of available data in generating improved reliability models is identified by focusing on the complexities in component population present in power systems. Hence, the approach is generalizable and practical. Specifically, the proposed method is designed to handle:

- populations with an irregular age distribution,
- populations with components of different types and failure rate characteristics,
- a combination of different failure rates with different characteristics,
- failure rates with different levels of uncertainty in their estimates,
- failure rates corresponding to failures in the control equipment,
- investment and reinvestment scenarios, and
- different restoration models for failed components, such as minimal repair, perfect repair, and replacement with a new component of different type.

To solve the complexity in the problem, Monte Carlo simulation is used and the algorithms and methods are gathered in a useful standalone software tool.

METHOD

Probabilistic failure rate

Failure rates are widely used in power system reliability theory [9]. Failure rates in themselves behave probabilistic since they give a value of the *probability* of failure and not a value of how many components that *will* fail. In addition to this probabilistic nature we model the failure rate to have a stochastic nature between years. For example, in a population with 1000 components and a constant failure rate of 0.01 failures/year, the number of failures each year is expected to follow a binomial distribution $B(1000{,}0.01)$ with mean 10 failures and standard deviation $\sqrt{1000 * 0.01 * 0.99} = 3.14$ failures [10]. But if failure statistics show that the standard deviation is higher than what is expected from a binomial distribution, we propose to introduce an extra random factor drawn from log-normal distribution. The scale parameter σ of the log-normal distribution is chosen to fit the variance of the number of failures per year. The location parameter μ of the log-normal distribution is computed so that the arithmetic mean of the distribution is 1 and given by [10]:

$$\mu = \ln(e^{-\frac{1}{2}\sigma^2}). \qquad (1)$$

In our simulations, for each year, we sample a factor from this log-normal distribution and multiply the outcome k_{yf} with the failure rate to get a year-specific failure rate. So, if the failure rate for a component is denoted *f(x),* where *x* is the age, then we use the year-specific failure rate $k_{yf} \cdot f(x)$ for that particular simulation year.

Monte-Carlo simulation

In a Monte-Carlo simulation approach [1, 2] the distribution of a sought entity is found by repeating samples from a given distribution. It is particularly useful when the resulting distribution is difficult, or impossible to find analytically. In this paper, we use the approach to find the distribution of future failures when the population age distribution is known and the assumptions for the failure rates described above are complied. For example, to predict the number of failures for one type of a component one particularly year, we let all the components either fail with probability p or not fail with probability *(1-p).* The probability p is computed for each component by $k_{yf} \cdot f(x)$, where x is the individual component's age. Through this we get a numerical result of the failures for that year and by repeating the procedure we get many results of the same entity, which together form a distribution. The mean from the distribution is our best guess on the number of failures that year, and the standard deviation of the results is one measure on the volatility.

Control equipment failure rate

Power system reliability calculations should consider the effect of control equipment failures especially when more automation is being introduced to the existing grid. Reference [11] identifies the requirement for including the failure effects of control equipment in probabilistic calculations to avoid sub-optimal system level evaluations. This is identified as a future potential of the developed tool as it can handle diverse component population. Controlled components such as circuit breakers can have complex active and passive failure rates [12]. Even advanced protection schemes experience unintentional breaker tripping and unknown open circuit conditions. Such automated components can be classified as a type which can be combined with complex failure behaviour (see section Input data description). The concept of co-simulation platform as in [13] can hence be comprised into the tool, and more improvements on this shall be introduced along future studies.

IMPLEMENTATION

To adequately implement the methods and for the method to be useful for decision makers, a stand-alone software tool was developed in MATLAB. The tool is designed to be simple to use and manage. The tool main window is shown in Figure 1, with a simplified example population imported. For the tool to work, the population and failure rate data are required to be stored in Excel data sheets (or database tables) with specific names and format.

Input data description

Population data sheet

Each row contains information about a number of components for one installation year and one component type. Column 1 is the installation year and column 2 is an id that identifies which type it is, which name is defined in the Types data sheet. Column 3 is the number of components for that year and type id.

Failure rates data sheet

Each row represents a failure rate. A failure rate defined here does not have to be used by a component type, and a failure rate can be used by many types. Two types of failure rates are allowed: Weibull-distribution-based or piece-wise constant. For Weibull-type failure rates, two parameters are expected: the scale and form parameter[1]. For constant failure rates, three parameters are expected: the start year, the end year, and the constant value within the interval. The start and end year parameters are used to be able to create a failure rate of any type from a combination of many piece-wise constant values. In addition, the failure rates can be given a volatile number, which states how uncertain the yearly failure rate value is, and is expressed as σ for the log-normal distribution introduce in section Probabilistic failure rate. The collection of failure rates defined in this data sheet can be combined (summed) in any combination to create a failure rate for a component type group. There is no limit on how many failure rates that can be combined, which makes it possible to define any form of failure rate for the component types. For example, bath-tube like failure rates can be constructed by a combination of different failure rates of Weibull-type and/or constant type. The links between component types and failure rates are defined in a data sheet called Type-FR.

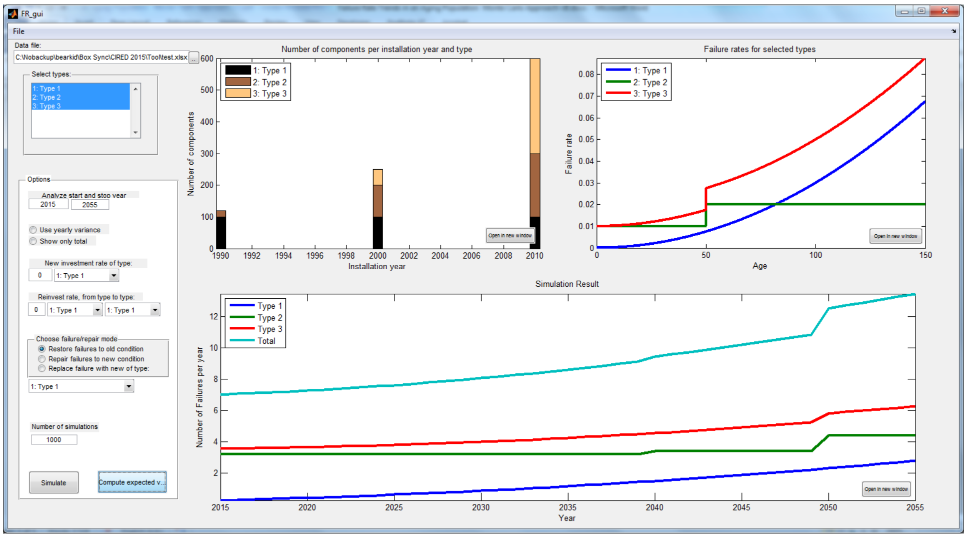

Figure 1 The main window of the tool. A simplified example population is shown in the upper left graph window and the corresponding failure rates in the upper right window. To the left import button and options are shown and a simulation result is shown in the lower graph window.

Tool simulation options

The tool has a number of options for the user to choose from when performing a simulation, which can be seen in the left part of the tool main window in Figure 1. The first option is to choose the simulation start and stop year. That is, between which years to simulate the future failure rate for the population. Next, two radio buttons give the user the option to use yearly variance (see section Failure rate data sheet) and to only show the total resulting number of failures (as opposed to show the resulting number of failures for all the included component types separately). Furthermore, the user can choose to include a new investment scheme and/or a reinvestment scheme. They are defined as a percentage of the total population and are modelled to be performed once at the end of each year. In addition, the user can choose three different repair modes to be used in the algorithm. Finally, the user have the option to choose the number of simulation runs the tool will use if the simulate button is pressed. If the button named compute expected value is pressed, the tool only computes expected values, which makes the number of simulations button obsolete and leads to results without uncertainty.

Tool simulation algorithm and result

Once a file with the population data and corresponding failure rates is imported by simply browsing the file system to the correct file, the population and failure rates are shown in respective graph window. Pressing the simulation button starts the simulation algorithm with the chosen options. The simulation algorithm output is an m-by-n-by-p array of numbers (of failures), here called A_{ijk}. The number m is the number of analysed years, n the number of analysed types and p the number of simulation runs. Thus is i the year, j the type and k the simulation run number; For example, $A_{3,2,999} = 3$ means that for the third analysed year, the second type and the 999:th simulation run the result was 3 failed components. The simulation algorithm is briefly described in the flow chart in Figure 2.

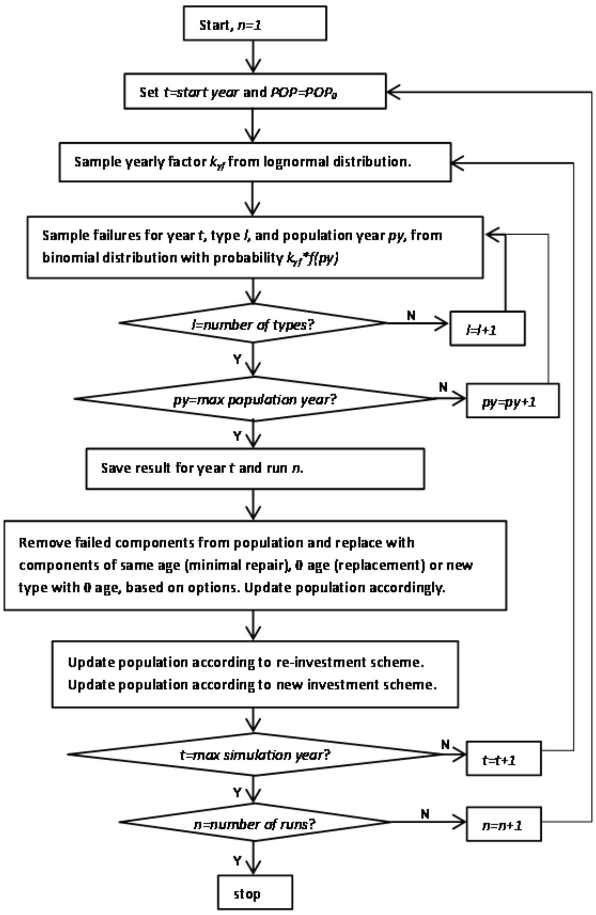

Figure 2 Flow chart of the used algorithm.

In Figure 2, *POP* stands for the updated population matrix (*POP_0* for the original, not updated, population), k_{yf} stands for the outcome of a sample of the yearly failure rate factor. Furthermore, *t* stands for simulation year (e.g. a year in the future), *py* stands for the population installation year, *f(py)* stands for the value of the failure rate for installation year *py* and simulation year *t*. Some additional notes on the algorithm is given below:

- The k_{yf} factor is sampled from a log-normal distribution with location parameter according to (1) and scale parameter taken from input data.
- The re-investment update function updates the population with new components of the type and with the percentage of the total population as specified in options. Also the same amount of the oldest components of the type specified is removed.
- The new investment update function updates the population with new components of the type and with the percentage of the total population as specified in options.

CASE STUDY

The methods and the tool are exemplified through a case study with data for cables and cable joints in the 10 kV urban distribution network of Gothenburg, owned by Göteborg Energi. At the time of writing this paper, no division in types of the cables and cable joints were possible. Thus, cable and cable joints were chosen to be treated as two types of the cable system and the input age distributions of the two types are shown in Figure 3. The feeding cables are presented in units of 100 m, in contrast to standard, so that the number of cable units and joints are of the same magnitude.

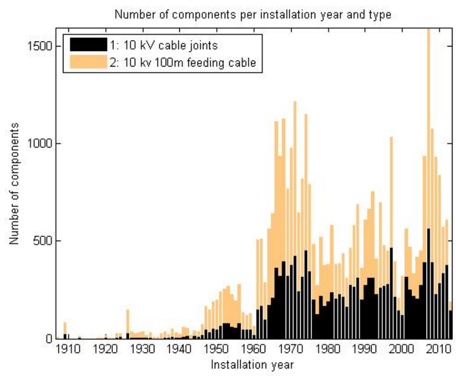

Figure 3 The population age distribution in the Göteborg Energi 10 kV cable system

In another unpublished project the failure rate for the cables and cable joints were estimated by analysing the failures in the network in the year 2012. Only failures that could not be explained by outer factors (such as digging accidents) were included in the analysis and in total there were 17 failures in the cables and 25 failures in the cable joints. Since the numbers of failures are low, compared to the number of components, the estimates of the failure rate were produced as constant values per 25 year intervals. The computed failure rates for the oldest intervals were set as the failure rates for ages older than the oldest component in the population. This is a conservative assumption, since the failure rate for both cables and especially cable joints show an increasing trend, but the approach was chosen not to overestimate trends based on few data points. The failure rates can be seen in Figure 4.

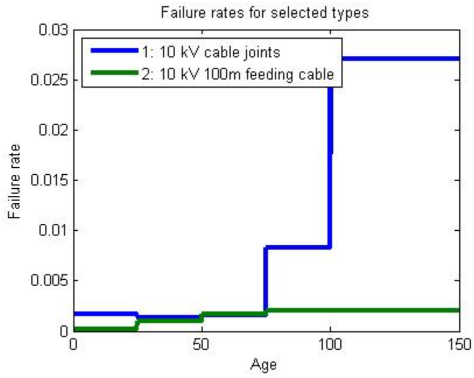

Figure 4 The failure rates for 100 m cables and cable joints for the population in the case study. The failure rate is stated in failures per year and per cable joint or 100 m cable.

In this particular case study, it was decided to simulate the future failures for 25 years, starting at 2015, for the base scenario with no investments and compare it with the scenario with reinvestments of 1% of the population per year for the next 10 years. 1000 simulation runs were used and a failed component was modelled to be replaced in the population with minimal repair. In practice, the components to be replaced are chosen to be the oldest cables and the joints connected to them. It is assumed that it means that also the oldest and the same percentage of the joints are replaced. 1% of the cable joints mean 154 cable joints per year and 1% of the cables means 21 km. The resulting expected values for future failures with no replacement are shown in Figure 5. The resulting expected values for future failures when 154 cable joints and 21 km cable are replaced during the first 10 future years, is shown in Figure 6.

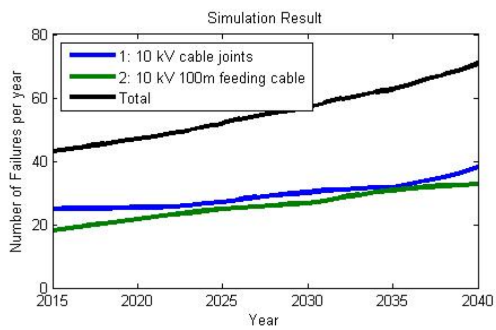

Figure 5 Expected values for future failures for the case study data, with no replacement.

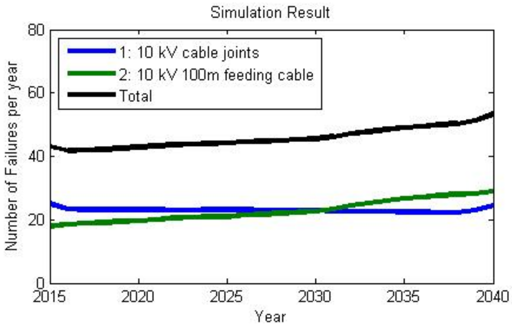

Figure 6 The resulting expected values for future failures for the case study, with 154 cable joints and 21 km cable replaced the first 10 future years.

It can be seen in Figure 6 that the failures for cable joints are held under 25 and the number of failures for cables are held under 29 during the 25 years of analysis when 1% of components are replaced per year. This can be compared with the case with no replacement in Figure 5 where the number of failures continuously increases to its maximum value of 38 and 32 respectively, the year 2040. After the replacements, the oldest cable joint has its installation year in 1964 and the oldest cable in 1954, compared to 1907 for both types as in the original population.

DISCUSSION AND CONCLUSION

In this paper, we have described an approach to predict the future failures in an aging population. The presented tool was shown to be useful understanding the effect of applying a replacement scheme to an aging population of cable joints. A natural extension of the case study would be to analyse the effect of also replacing cables, which would have decreased the future expected number of failures even more. Also, the failure rates used in the case study were conservative regarding the values for components older than 100 years. Extrapolation of the trend beyond the age of 100, seen in Figure 4, would have made the expected future number of failures more extreme than was seen in Figure 5. In future projects we would like to make a complete analysis of the data and also develop the tool to be able to handle the needs for such analysis. We believe that this paper gives the reader a better understanding of what to expect in terms of future failures, when dealing with an aging and complex component population, and therefore will aid in the process of making better investment decisions

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