# A STOCHASTIC APPROACH FOR ANALYSING AVAILABILITY OF ELECTRICITY SUPPLY

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## ABSTRACT

Good electricity supply availability is turning out to be more and more important for today's society as the electricity dependability increases. Furthermore, high availability of electricity supply is one of the commonly recognized targets of Smart Grid visions. Enhancing the supply availability call for technology investments and reorganization of network operation both typically requesting considerable amounts of money. Due to the regulated nature and capital intensity of the electricity distribution business, the investments and reorganisations have to be carefully considered. Thus, novel approaches are needed for evaluating the reliability of electricity distribution and the availability of supply in distribution network planning. This paper introduces a stochastic supply availability analysis method aiming for considering the supply availability at single customer level.

## 1 INTRODUCTION

The availability of electricity supply depends from the reliability, resiliency and operational security of the electricity distribution network. Moreover, the reliability of network structures and the organisation's ability to response to the disturbance situations affect strongly to the availability of the network service. In distribution network planning, the supply availability is traditionally approached through deterministic reliability analyses and depicted with average indicators like customer interruption costs and customer based reliability indices SAIFI (System average interruption frequency index), SAIDI (System average interruption duration index), MAIFI (Momentary average interruption frequency index) [1] and many more system level indices. The system level reliability indices and deterministic analysis do not describe the supply availability from single customer viewpoint or give information of the annual or customer specific variation of supply reliability. As a result, there can be several sections in the network, where the supply reliability is considerably worse than in average. This may not be noticed during the network planning.

The Finnish Energy Industries association (ET) together with electricity distribution companies has decided to start monitoring the customer specific cumulative sum of durations of sustained customer interruptions and the cumulative number of momentary (<3 min) interruptions. Spatial limits, called the supply availability criteria, will be set on the magnitude of these figures. A target of the criteria is to guide both the development of the network operating process and the development of the distribution network structures. The criteria set a new boundary condition for the network planning process, objective of which is to ensure a certain minimum level of supply availability for all the customers on a supply area. [2]

An analysis methodology is needed for defining socio-economically reasonable supply reliability criteria based on supply area specific customer expectations. Respectively a method is also required for depicting supply availability of single customer and its annual deviations in network planning process. A stochastic reliability analysis is able to produce probability distribution of possible outcomes [3]. It enables the analysis of the confidence of a certain supply availability level and, hence, point out the risk areas on the supply area of a network more precisely than the deterministic analysis. Especially the possibility to perform statistical risk assessments already during network planning makes the stochastic analysis powerful tool in strategic decision making.

The proposed stochastic reliability analysis is based on a Monte Carlo simulation algorithm. The algorithm is used for simulating the annual customer interruptions on the basis of the probability distributions of fault frequencies, switching times and fault repair times of the network structures. As result, the simulations produce the probability distributions of the numbers and the durations of customer specific supply interruptions. These results enable distribution companies to define how the requirements of the supply availability criteria can be fulfilled most efficiently and what the risk of a criteria violation is. Furthermore, the method is suitable for benchmarking different network development strategies and, for instance, reorganisation plans of the fault repair process.

As disadvantages, more detailed initial information and exhaustive computation is required in the stochastic analysis compared to the deterministic. In addition, interpretation of the sensitivity to small changes in the system is hampered due to the natural random variation of the results of each calculation round. [3]

## 2 SUPPLY AVAILABILITY

Reliability and availability are central terms when the service quality of electricity supply is estimated. Power quality as a whole is presented in Figure 1. The introduced analysis method focus on assessing the risk related with reliability and availability.

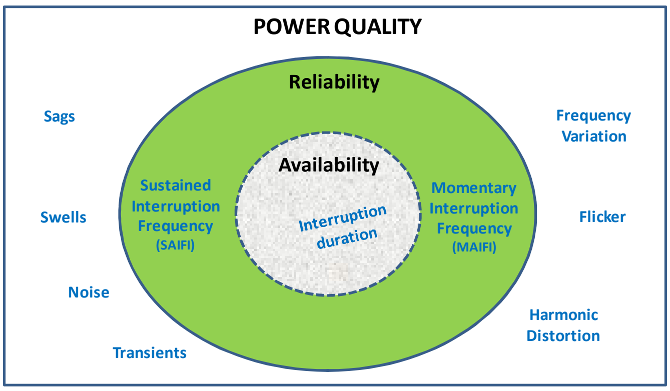



*Figure 1 Power quality and reliability [3].*

Reliability of electricity distribution, or more precisely, the reliability of electricity supply, can be defined based on the numbers and durations of interruptions in customer's voltage supply. The concept of supply reliability has to be separated from the concept of network reliability. The reliability of the electricity distribution depends on the reliability of the network and the security of operating the network.

Availability describes the time a voltage supply to a customer is uninterrupted within considered time period. Commonly availability is given as percentage of the total time period. [3] Availability can be, for instance, defined on annual basis or as the mean value over a set of years. When considering the supply availability experienced by a customer, a statistical distribution having a mean value and a standard variation can be defined based on annual variation. Therefore, also a confidence level can be related with the supply availability. The concept of availability is the most basic aspect of reliability [3], but when supplemented with the numbers of momentary customer interruptions and considered at single customer level, it can also reveal the reliability performance of the distribution system on the most crucial way; just as it is seen by the customers.

The customer interruptions can be divided into scheduled and unexpected events. Scheduled interruptions are due to normal operation of the system and typically caused by system maintenance. Unexpected interruptions, on other hand, are caused by faults or incorrect system operation. Furthermore, the unexpected interruptions can be divided into momentary interruption events and sustained interruptions. Momentary interruption events consist of one or more momentary interruptions within a time window, e.g. sequential operation of a recloser [3]. A typical time window is 3 minutes. Correspondingly, in sustained interruptions a customer is de-energised for more than 3 minutes.

## 2.1 Availability metrics

Customer-based supply availability gives the probability of a customer network being energised. It is commonly defined as a percentage of the year while the customer network is supplied by the distribution system, as presented in (1). Its complement is the unavailability that can be directly computed from customer specific cumulative interruption durations $T_{\text{cumulative}}$. [3]

$$A_i = \left(1 - \frac{T_{\text{cumulative}\,i}}{8760}\right) \cdot 100\,[\%] \tag{1}$$

According to (1), the supply availability can directly be described with the customer specific cumulative time of supply unavailability. The cumulative sum of the durations of the interruptions experienced by a customer can be defined, as follows.

$$T_{\text{cumulative},i} = \sum_{k=1}^{K} T_{\text{int}\,i,k} \left[\frac{\text{hours}}{\text{year}}\right], \tag{2}$$

where $T_{\text{int}}$ is the interruption duration at customer $i$ due to outage $k$, and $K$ is the total amount of outages over a year. The interruption duration experienced by the customer $i$ due to a single fault $k$ in the network can be defined with (3).

$$T_{\text{int}\,i,k} = T_{\text{repair}\,i,k} + T_{\text{manual}\,i,k} + T_{\text{remote}\,i,k} \left[\frac{\text{hours}}{\text{interruption}}\right], \tag{3}$$

where $T_{\text{repair}}$ stand for the sum of fault repair and reconnection time experienced by the customer, $T_{\text{manual}}$ is the time of manual separation of the faulted section, and $T_{\text{remote}}$ represent the time of remote controlled separation of the faulted section.

The unexpected momentary interruption events and both the number and duration of unexpected sustained interruptions are typically focused in the reliability benchmarking of different network structures. As the supply availability depend both from the duration and number of single interruption events, such indices like SAIDI, MAIFI and customer outage costs are able to describe it on system level. The annual variations, for instance, in the SAIDI of existing network structures, can be defined based on statistical studies and stochastic analysis methods [3][4]. However, the problem in this approach is the lack of single customer perspective that is on the other hand required if customer specific supply availability is considered

## 2.2 Supply availability criteria

The development of the supply availability criteria stems from the willingness to ensure a minimum supply availability level for all the customers. Also the lack of standardized minimum requirements has encouraged the utilities to resolve reasonable guidelines for them selves. The criteria have been established in close collaboration of ET, distribution utilities and technical universities. The definition work included analysis of the expectations of the society and the impacts on the electricity distribution business. [2]

The criteria for the availability of electricity supply concern interruptions caused by faults in electricity distribution networks. In this context, an electricity distribution network refers to an entity comprising primary substations, medium-voltage networks and low-voltage networks. The monitored figures are the cumulative sum of the durations of the unexpected sustained interruptions and the number of momentary interruptions which are traced annually. The same customer may exceed the recommended target values only once within a reference period of three years. If the criteria limits are exceeded multiple times during the reference period, the criteria will be violated. The criteria refer to the target level of service reliability applied in network planning. The principle of this planning criterion is that an interruption caused by a very severe single fault or a large-scale blackout can be allowed once during the reference period, whereas from the perspective of an individual customer, events within normal operating conditions may not lead to exceeding of the target values. [2]

The target values are mostly linked on the electricity supply availability expectations of the society at different residential environments (city, urban, rural), not to the performance of the existing distribution network structures. Determination of the rural limits is, however, partially based on analysing the probability of violating the principles of the criteria with different limit values when the network is constantly developed on economical basis. The stochastic analysis methodology introduced in this paper was used in the analysis. The recommended target levels of the criteria are presented in Table 1 and discussed further in [2].

*Table 1 Target level for the reliability of supply in different areas. [2]*

| Criteria | City | Urban area | Rural area |
|---|---|---|---|
| Total interruption time | 1 hour in a year at max. | 2–3 hours in a year at max. | 4–6 hours in a year at max. |
| Number of short interruptions (< 3 min) | No short interruptions | ≤ 10 interruptions in a year | ≤ 60 interruptions in a year |

## 2.3 Availability in network planning

Reliability analysis is essential part of modern medium voltage (MV) network planning process. Reliability analyses are especially emphasized during the strategic planning and the detailed long-term planning. The objective of the planning assignment is the total cost minimisation, where the investment costs, operational costs (maintenance, losses, etc.) and outage costs (customer interruptions, repairing, standard compensations, etc.) are taken into account over the lifetime of the network as presented by equation (4) [5].

$$C_{\text{tot}} = \int_0^T \left( C_{\text{cap}}(t) + C_{\text{opex}}(t) + C_{\text{out}}(t) \right) dt \,, \tag{4}$$

where $C_{\text{tot}}$ is the total costs of a network over time, $C_{\text{cap}}$ is the capital costs, $C_{\text{opex}}$ is the operational costs, and $C_{\text{out}}$ is the costs due to outages. The sum of previous is integrated over the utilisation period $T$ of the network.

In Finland, the economical regulation of distribution business encourages the utilities to consider the reliability of supply through the outage costs in network planning [2]. Typical boundary conditions of the planning assignment are related with the technical capacity of the designed network. In addition, the reliability of the system can be approached by suppressing the optimisation under additional boundary conditions, such as target values of the customer supply availability.

Applying only the average results of the reliability assessments in the planning of network investments include an economical risk. First of all, the statistical confidence of the average indices based on deterministic analyses is not revealed. Secondly, the system level indices lack ability to address the supply availability of a single customer. The stochastic reliability analysis is able to reveal the risk related with the annual variation of the supply availability from a single customer perspective. Questions related to the probability of exceeding a certain level of outage costs or to the capital needed for meeting the predefined reliability requirements with certain confidence level can be answered on the grounds of the customer-based statistical supply availability analysis.

If the supply availability criteria are not included in the network planning as a boundary condition task, some customers may become discriminated in a sense of interruptions when the distribution company is optimising the financial performance of the network. The desired impact of the supply availability criteria on cost optimisation of the network structures is illustrated in Figure 2.

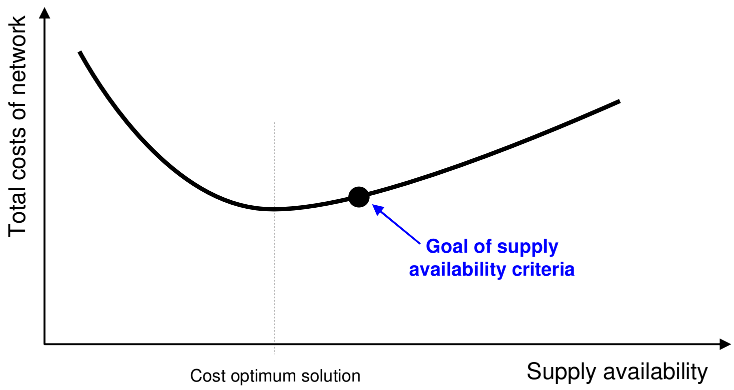



*Figure 2* *Target of supply availability criteria as boundary condition in cost optimum based network planning*

## 3 STOCHASTIC RELIABILITY MODEL

The proposed stochastic supply availability analysis method was developed during the determination of the supply availability criteria. The main objective was to develop a tool for estimating the risks of setting the criteria and also for considering the criteria in network planning. In the rural networks, the feeder lengths can be long (from 20 to over 100 km), and hence, the supply availability of the customers situated to different locations of the network varies considerably. Also the deviation in the interruption durations is large due to varying operational conditions. Therefore, the statistical risk analysis of the supply availability was considered necessary. Figure 3 presents the situation on a long feeder from the cumulative interruption duration viewpoint.

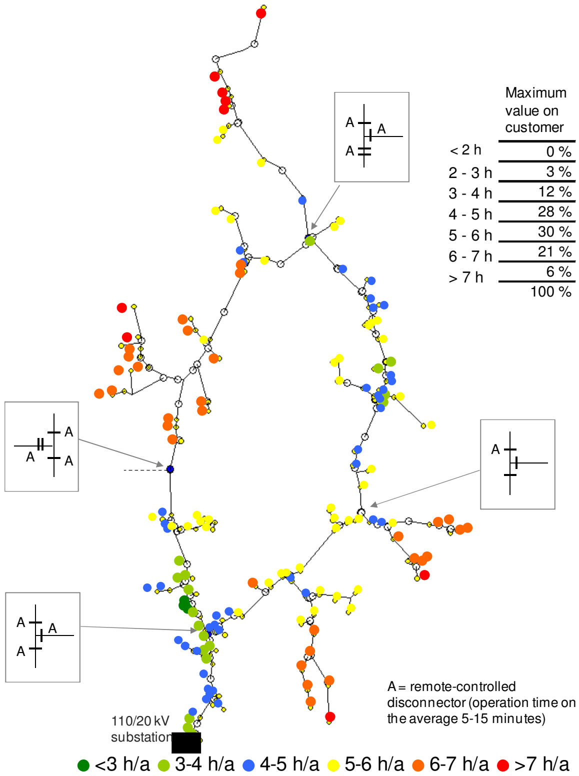



*Figure 3* *A rural MV feeder and estimated distribution-substation-based cumulative interruption durations.*

The developed analysis method is based on Monte Carlo simulation algorithm, which provides an opportunity to assess statistically the reliability performance of a network. The simulation algorithm is used for simulating the annual customer interruptions. Real networks from a Finnish distribution company have been modelled for the simulations, which provide an opportunity to compare simulated results with actual measured reliability data. The presented simulation model considers, at the moment, only the fault events of the MV-network, neglecting the faults in the high and low voltage networks. The MV-network is in major role when assessing the supply availability experienced by the customers on a supply area of a primary substation. When the rural distribution system is considered, by far the most of the customer interruptions are caused by outages in the MV-network.

## 3.1 Initial data analysis

Reliable fault event simulation requires huge amount of statistic data from a long period. Modern network information systems enable gathering detailed statistics of the behaviour and operation of the distribution system in versatile situations. This statistical data creates the basis for probability distributions required in stochastic analysis. Probability distributions of the fault rates of different components, switching times of disconnecting devices and fault repair times are needed in the stochastic supply availability analysis.

The first step in the initial data determination is to define fault rates for different line constructions in different operating conditions for the analysed network. First, the categorisation is done according to the outage duration (sustained or momentary). Then the fault frequencies have been divided into seven categories; overhead line in forest, road side and field; covered conductor line in forest, road side and field; and underground cables in general. This categorisation derives from the varying of the fault rates due to the different impact of environmental conditions on the performance of different network structures.

After definition of the fault rates the next step is evaluation of the duration of the outages. The total duration of an outage caused by a fault comprises of the duration of switching events aiming for separation of the faulted section of the network, the duration of the fault repair, and the duration of re-energising the faulted section. Large enough statistical outage data provides an analysis where all kind of interruptions are represented; not only the regular outages but also the long ones, which can be very rare. The duration of the fault repair process forms typically the largest proportion of the total outage time caused by a single fault event. Also the deviation in the fault repair times is large as it is strongly affected by the cause, type and location of the fault (forest or road side, overhead line or underground cable, amount of trees fallen on an overhead line, etc.), environmental and operational conditions (climate, number of simultaneous faults, size of the supply area, etc.) and overall operational situation of the organisation (available personnel, mobility, time of day, etc.). Figure 4 presents an example of the fault repair times in a rural overhead line structured distribution network. The data consist of the distribution of actual faults (over 5000 fault cases in 8 years, the repair time being 3 hours on average).

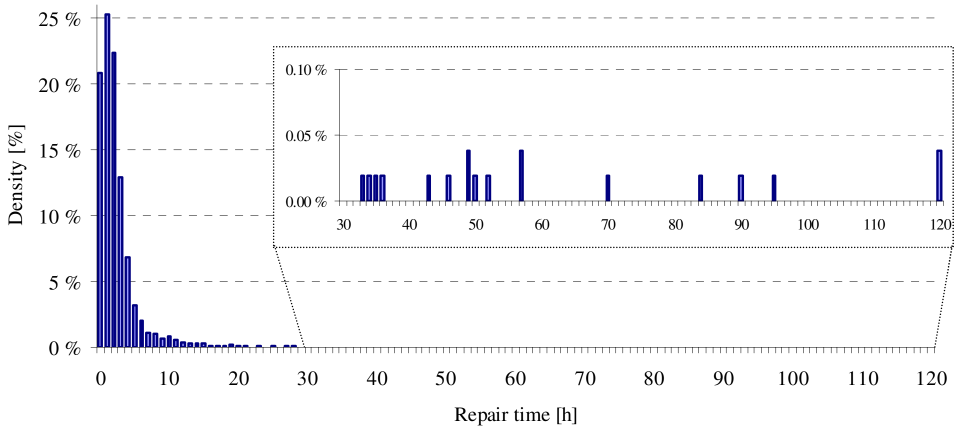



*Figure 4* *Density of fault repair times in a rural network based on dataset including outage times of over 5000 fault events.*

For the stochastic analysis, a probability distribution function is fitted to the statistical data. Both fault repair time and fault frequencies are deviated around the mean values. The switching times of both manual and remote controlled couplings can also be described with probability distributions. Weibull distribution can be adapted to almost any kind of statistical data [6], and it is widely used in engineering. Weibull distribution is selected to be used in the introduced algorithm due to its flexibility and ease of fitting on the statistical data. The equation of Weibull distribution function is written, as follows

$$F(x,\alpha,\beta) = 1 - e^{-(x/\beta)^{\alpha}} \tag{5}$$

and Weibull probability density function

$$f(x,\alpha,\beta) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{k-1} e^{-(x/\beta)^{\alpha}}\ , \tag{6}$$

where $\alpha$ is the shape parameter and $\beta$ is the scale parameter. They can be defined with the least-squares fit from the initial data. The estimations of the Weibull parameters are given by

$$\alpha = \frac{k\sum_{j=1}^{k} x_j v_j - \left(\sum_{j=1}^{k} x_j\right)\left(\sum_{j=1}^{k} v_j\right)}{k\sum_{j=1}^{k} x_j^{\,2} - \left(\sum_{j=1}^{k} x_j\right)^2}, \tag{7}$$

$$\beta = \exp\left(\frac{\left(\sum_{j=1}^{k} v_j\right)\left(\sum_{j=1}^{k} x_j^{\,2}\right) - \left(\sum_{j=1}^{k} x_j\right)\left(\sum_{j=1}^{k} x_j v_j\right)}{-\alpha\left(k\sum_{j=1}^{k} x_j^{\,2} - \left(\sum_{j=1}^{k} x_j\right)^2\right)}\right), \tag{8}$$

where variables $x_j = \ln(t_j)$ and $v_j = \ln(\ln(1/(1\text{-}P))$. $P$ can be written as $(j - 0.3) / (k + 0.4)$ [7], [8]. In these parameters $t_j$ is the duration of interruption $j$ and $k$ is the number of interruptions.

For the Weibull function fitting, the repair time data is sorted to form a cumulative distribution. The cumulative Weibull distribution function is then fitted to the data. Figure 5 presents an example of an actual fault repair time distribution and corresponding Weibull fit. The background data includes outage times over a single year comprising of 487 separate data points.

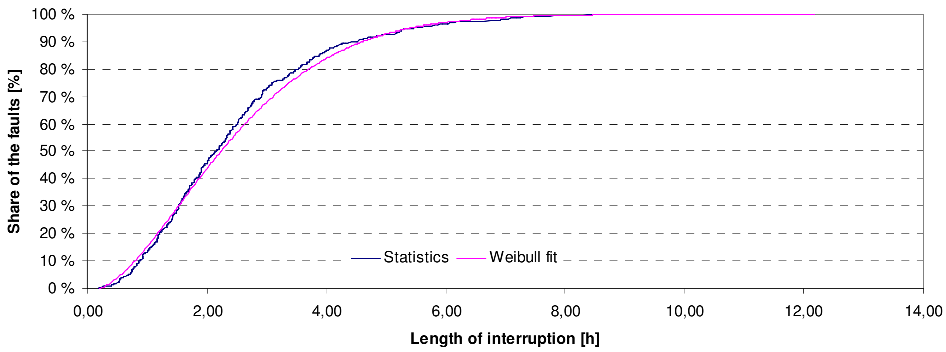



*Figure 5* *An example distribution of fault durations, which consists of 487 separate interruptions.*

As shown in Figure 5, a Weibull distribution fit to the statistical data quite accurately. The fitted cumulative distribution function (CDF) represents the probability of exceeding a fault repair time. For instance, according to the CDF the probability of exceeding the repair time of five hours is round 8 %. It means that 92 % of repair times are shorter than five hours.

After fitting the CDF to the statistic data, it is possible to determine the probability density function (PDF). The PDF provides opportunity to determine the probability of a fault repair time. The PDF is needed in the Monte Carlo simulation of the outage durations. Figure 6 presents the PDF corresponding to the CDF of Figure 5.

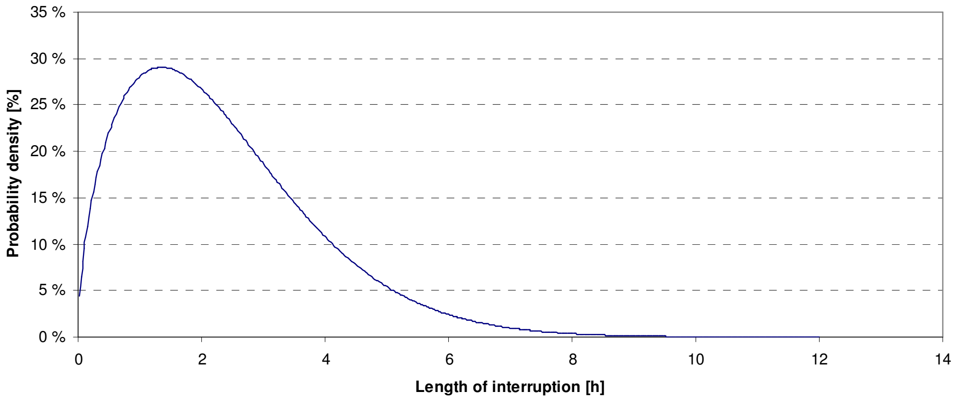



*Figure 6* *Weibull probability density function, based on the parameters found by fitting the cumulative distribution function to the data presented in Figure 5.*

When the size of the statistical data is reduced, also important information will be lost. This is easily noticed by comparing the density function of Figure 6 with the statistical data presented in Figure 5. In this case, the density function based on smaller statistical base data does not describe the probability of the long over 120 hour repair times. These long repair times are due to the major storms that happen only once between every 5-10 years. Therefore, it is essential to have statistical data from a long time period for including also the possibility to the rare events in the simulations.

Reliable fitting of the Weibull probability distribution functions requires large statistical data sets describing several key parameters. Complete data is not necessarily available in all cases. In the Monte Carlo simulations a lacking probability distribution function of a variable can be replaced with a constant average parameter describing the variable. However, this reduces the statistical confidence of the results, which has to be remembered in further analysis of the simulation results. Recognizing the correct level of details in the initial data is important for reducing the calculation time and the need to deal with exhaustive statistics, and yet achieving useful results.

## 3.2 Monte Carlo simulation algorithm

The hearth of the proposed stochastic analysis method is the time domain Monte Carlo simulation algorithm used for randomising event occurrences within boundaries characterised by the probability density functions of initial parameters. The target is to produce the customer specific probability distributions for the cumulative duration of the sustained interruptions and for the number of momentary interruptions. The Monte Carlo approach is often used in the simulation of the reliability performance of power systems. Numerous papers deal with the application of Monte Carlo simulation methodology for modelling different cases [1], [3], [9], [10].

In this study, the sequential Monte Carlo method has been chosen as the basis of the stochastic model. Sequential simulation attempts to model the fault events just as they occur in the real networks. The simulation sequence, typically a year, is formed by random events building upon each other over the time. Because of this, the simulation sequence is divided into small time slices. For instance, modelling of a year can be carried out with a one-hour resolution by dividing it into 8760 time slices [3]. Figure 7 presents the principle of slicing the upper level simulation sequence into smaller pieces in time domain.

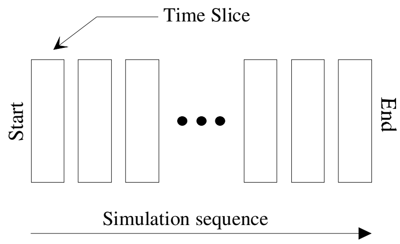



*Figure 7 Time slices in sequential Monte Carlo simulation [3].*

In addition to the time domain slicing, the network comprises of hundreds of sections linking the nodes of the network together. All the sections have their own expected fault rate, probability of outage duration, and other individual properties. Simulating the fault occurrences section by section increases the accuracy of the results. For each section and time slice, the number and the duration of fault events is randomised independently. Fault events are not mutually exclusive in this kind of simulation enabling simultaneous fault occurrences. The variation of the fault rates or the repair times over a year is not considered, that is, one of the development needs of the proposed model for the future. Figure 8 presents a simulation sequence for MV networks.

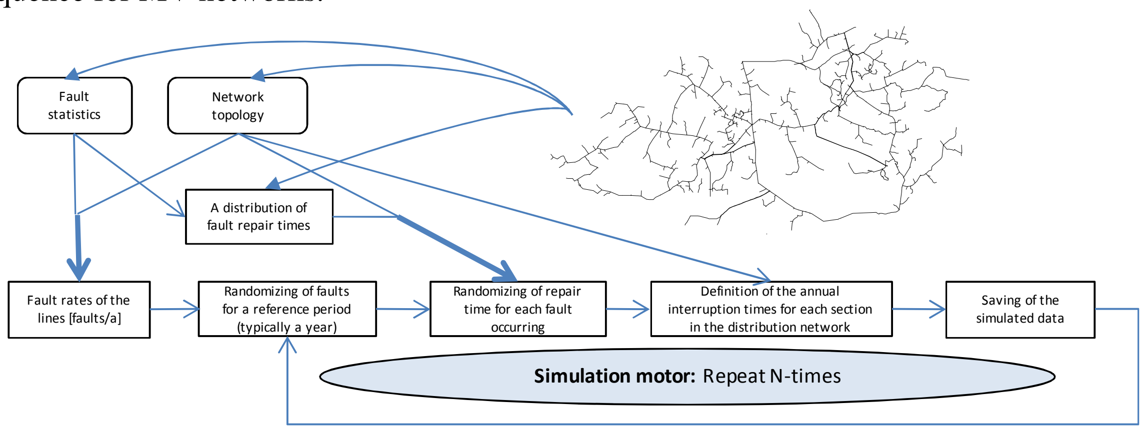



*Figure 8 Fault simulation sequence of the MV-network. One loop in the simulation corresponds a year.*

In the Monte Carlo simulation, huge amount of simulation sequences are done, which all corresponds to a year. These simulated years form an artificial interruption statistics for each customer in the simulated network. The algorithm used for randomising the faults for each section of the network and time slice is presented in Figure 9. All the time slices for a selected section of the network are simulated consecutively, followed by the simulations for the next section of the network and so forth, until all the sections have been gone through.

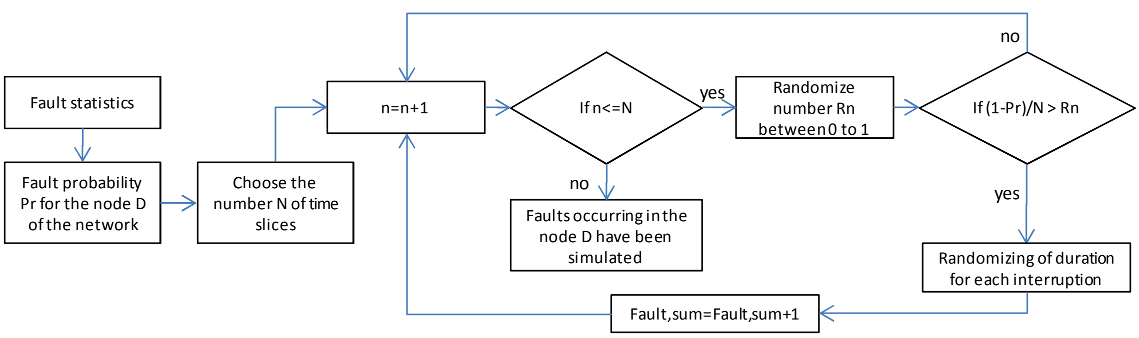



*Figure 9 Randomising algorithm for faults.*

The above presented simulation algorithm is repeated as many times as complete annual simulations is needed for achieving large enough statistical basis for further analysis. The selection of the required number of needed rounds is based on the convergence of the mean (expected) value of the simulation results, that is, the difference in the mean values of two successive sets of simulations.

### 3.3 From system outages to customer interruptions

The locations of the disconnectors and the circuit reclosers have a key role in the determination of the customer interruptions caused by the simulated fault incidents in the analysed network. Therefore, they have to be carefully taken into account. Because of the sequential algorithm, each fault situation is processed individually. A detailed model of the analysed network enables to allocate the interruptions into the right customers and to set the duration of an interruption into correct scale depending on the location of the switching devices. Figure 10 presents an example where the duration of an interruption has been divided to three phases, which each contains different number of interrupted sections and customers.

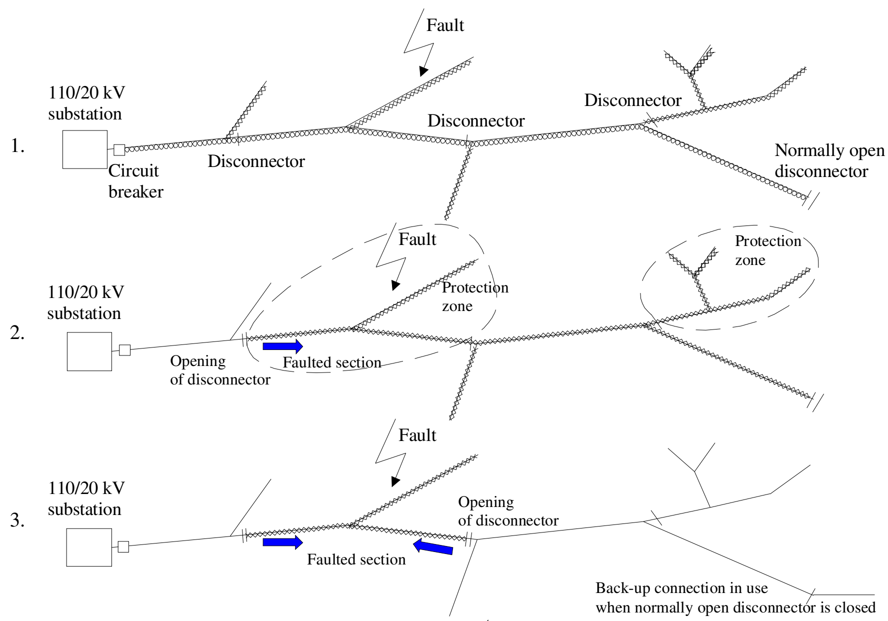



*Figure 10 A fault isolation process. In the 1st step circuit breaker has been operated. In the 2nd step disconnector in front of the fault has been opened. In the 3rd step a disconnector after the fault has been opened and the back-up switch has been closed.*

The influences of the interruptions into the customers have been defined utilizing the method presented in Figure 10. The differences of the disconnector types have been notified in the switching times. For instance, for a remote-controlled disconnector a switching time is only some minutes when for a normal disconnector it can be more than hour.

## 4 ANALYSIS OF SIMULATION RESULTS

The analysis of the simulation results has been divided into two parts; model verification and supply unavailability risk assessment. The main focus has been put on the criteria concerning the cumulative interruption time experienced by the customers due to the fault occurrences in MV-network, and on the methodology of the risk assessment of the criteria violation. Both the risk of the criteria limit violation and the impacts of network development actions on the risk were assessed during criteria establishment.

The introduced Monte Carlo simulation results the MV-network based statistical distributions for the duration and the number of interruptions for each distribution transformer. Weibull distributions are fitted on the distribution substation specific simulated interruption data. Figure 11 presents an example distribution of the cumulative interruption durations for a distribution substation in the analysed network.

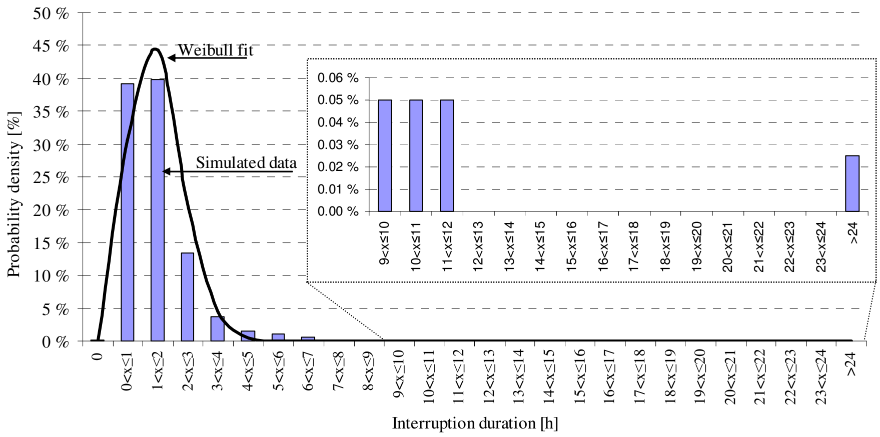



*Figure 11 Simulated density function for MV-network origin cumulative interruption durations for a distribution substation in the test network.*

The distribution transformer specific probability distributions (both PDF and CDF) enable definition of the expected unavailability of the supply corresponding to a statistical confidence level. Probability functions have also been calculated for SAIFI, SAIDI and number of reclosing events.

### 4.1 Model verification

During the model development and parameterisation, the model was verified against the existing statistical data and the results of the deterministic calculations. If the model and its parameterisation are correct, the mean values of simulation results should approach the measured data. The values of SAIDI and SAIFI of an example network were used as the basis of model verification. The number of simulation sequences was chose to be 4000, that is more than enough for the statistical base of further analysis.

The network used in testing of the model is a typical rural area network in Finland. Almost all the lines are overhead structured and the network is mainly located to forests (over 75 %). Hence, only one density function for the fault repair time was decided to be used. The average fault rate for the test network is about 5 $^{\text{faults}}/_{\text{100 km}}$. The analysed network is presented in Figure 12.

The feeders in the analysed network are quite long, which corresponds to the high probability of long customer interruptions at the outskirts of the network. The density of switching devices is quite good and many of them are remote controlled. Thus, this provides an opportunity to separate the faulted section to a small area within a short time period. However, the total impact of switching possibilities depends on the existence of the back-up connections. This culminates especially on the feeders without back-up connection to the neighbouring feeders, which is the situation on couple of feeders.

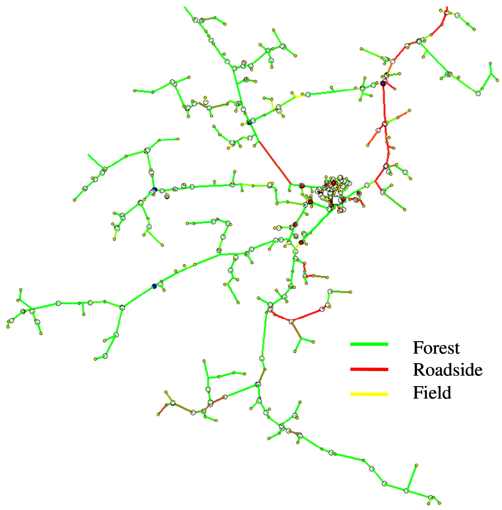



*Figure 12 Analysed network.*

The simulated reliability indices match quite well with the deterministically calculated target values as can be noticed from the values presented in Table 2. Measured values of SAIFI for a year were also available. The measured values fit well between the simulated and targeted deterministic values.

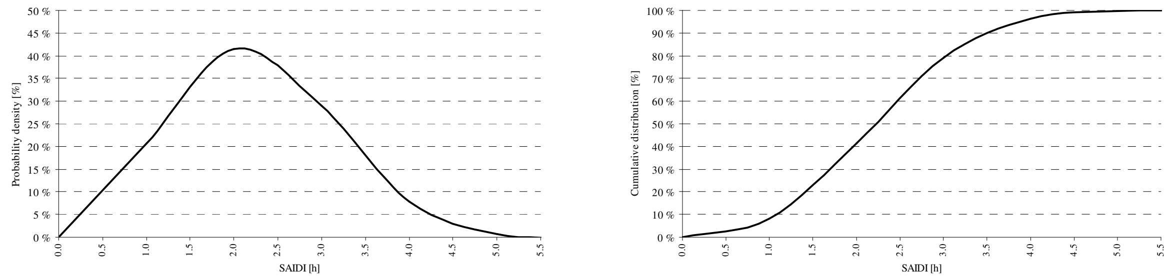
*Table 2 Comparison of simulated and actual SAIFI and SAIDI*

| Feeder | Target values | | Simulated values | |
|---|---|---|---|---|
| | SAIFI | SAIDI | SAIFI | SAIDI |
| Feeder 1 | 2,2 | 1,8 | 2,0 | 1,6 |
| Feeder 2 | 6,5 | 2,5 | 6,2 | 2,2 |
| Feeder 3 | 2,6 | 3,9 | 2,5 | 3,0 |
| Feeder 4 | 1,7 | 2,6 | 1,6 | 2,0 |
| Feeder 5 | 3,9 | 3.0 | 3,8 | 2,6 |
| Feeder 6 | 2,2 | 2,6 | 2,1 | 2,0 |

## 4.2 Risk analysis

The probability of a certain supply unavailability levels were analysed in the risk assessment. The statistical confidence of both the system level unavailability, described by the SAIDI, and the customer specific (distribution substation specific) unavailability, described by the annual cumulative interruption time, were studied. Figure 13 presents PDF and CDF of SAIDI for a feeder in the example network.

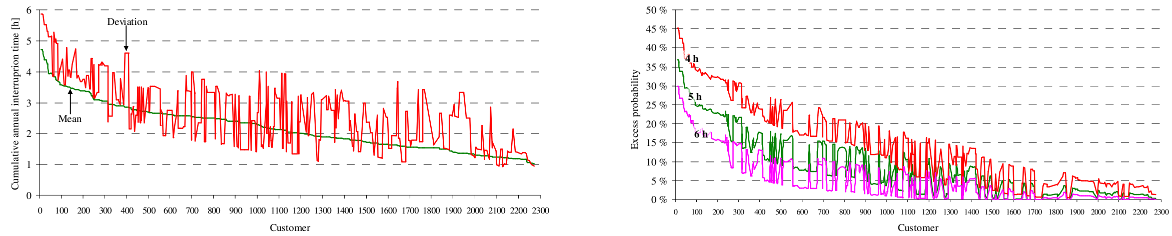
According to the probability distributions presented in Figure 13, with 90 % statistical confidence SAIDI of the feeder will land between 50 minutes and 230 minutes. Correspondingly, with 38 % statistical confidence SAIDI will remain between two and three hours, which indicate that SAIDI will be outside that region roughly five times within eight year period. The excess probability of three hours is 21 % and the probability of less than two hours is 41 %. The average SAIDI of the feeder is 2.2 hours.




a) b)

*Figure 13 Probability density function and cumulative distribution function of SAIDI for a feeder in the test network based on the simulated interruption data.*

A probability distribution has been assigned for all the substations allowing similar risk assessment to be made for each of them as was presented above for SAIDI. The distribution substations can also be arranged to performance order based on the expected value (mean) of the cumulative interruption time. Figure 14 a) presents the average cumulative interruption duration and its standard deviation for the supply areas of the distribution transformers in the analysed network. Figure 14 b) presents the excess probability of a specified cumulative interruption time. From the figure it is immediately seen that the standard deviation is larger than the expected mean value for a large number of customers. This means that the average mean value, approaching the deterministically calculated one, can in some circumstances be exceeded considerably. If a limit is set on the cumulative interruption time, there is high probability of exceeding the limit on worst performing areas. For instance, according to Figure 14 b) the customers in the supply area of the worst performing distribution substation are expected to exceed the 6 h limit in average once in three years.




a) b)

*Figure 14 a) Simulated cumulative interruption time and b) time limit excess probabilities for 4, 5 and 6 hour limits.*

The Figure 14 b) does not yet indicate how often the limit of the supply availability criteria is expected to be violated or what is the group of customers violating the limit. At this point it is important to remember that the cumulative duration limit (i.e. 6 h) can be exceeded once during the reference period without violating the criteria [2]. Thus, from the reliability criteria perspective, it is interesting to know, what is the probability of exceeding criteria limit more than once during the three-year reference period and who are the customers expected to violate the criteria? As each year can be considered independently from the previous ones, the binomial distribution can be used to describe the probability of an event to happen multiple times within a certain time interval. The function of binomial distribution is given by (9).

$$F(x) = \sum_{k=0}^{x} \binom{n}{k} \cdot p^k \cdot (1-p)^{n-k} \tag{9}$$

Figure 15 presents the probability of exceeding the limit of 4, 5 or 6 hours at least twice within a three year period, based on the binomial distribution and excess probabilities presented in Figure 14 b). Now it is possible to determine the customers who will most likely violate the criteria limit and how often.

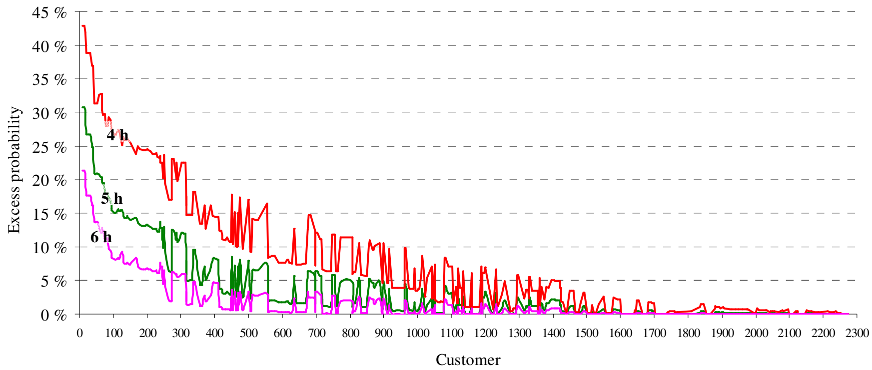



*Figure 15 Probability of the annual cumulative customer interruption time to exceed 4, 5, or 6 hour time limit at least twice within a three year period.*

The expected number of customers violating the criteria limit can be defined by integrating the excess probability curve (calculating the area bounded by the x-axis and the curve). For instance, in the test network the annual interruption time of 40 customers (~2 %) is expected to exceed the six hour limit at least twice within the three year reference period. Furthermore, the criteria will be violated at least once within four successive reference periods at the worst case distribution substation.

As can be concluded based on [2], the criteria limits will be fulfilled at most of the customers already due to the cost optimum based network development. However, the stochastic analysis is needed in network planning to recognise those customers whose supply availability will repeatedly be lower than recommended. The consequences due to the risk of criteria violation can then be weighted against the additional investments required on top of the cost optimum ones to patch the situation.

## 5 CONCLUSIONS

The presented stochastic supply availability analysis method can provide important information for network planning process. For instance, the possibility to analyse the customer specific statistical distributions of the numbers and durations of the interruptions enables consideration of the customer-based supply availability criteria in the network planning process. Presented stochastic analysis provides information of the risk related with the reliability impacts of network development alternatives. Knowing the risk help in ranking the development alternatives and controlling the uncertainties in the reliability analysis and investment decisions.

The sequential Monte Carlo method enables modelling the fault occurrences and the system behaviour almost precisely according to reality. The modelling accuracy depends on the qualities of the initial data and the algorithm's ability to internally define the interdependencies of different variables. As a down side, the stochastic methodology is computing intensive and requires more initial data compared with deterministic one. Carefully gathered statistical data of the behaviour of the existing network structures are vital for achieving useful results.

In future, the method will be tested further in versatile planning assignments for analysing the economical benefits gained through the risk assessment from business perspective. The model will also be developed by improving the initial data processing abilities and by testing different stochastic randomisation methods for achieving higher calculation efficiency. Further statistical analysis are also needed for considering the dependencies of fault frequencies, repair times and switching times from the overall surrounding situation and personnel resources.

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