APPLYING PROBABILITY DISTRIBUTION FUNCTIONS TO MODEL SYSTEM FAILURES DUE TO ADVERSE WEATHER

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Abstract - **Power system reliability is an essential component of network design and planning. The risks to which power systems are exposed can be modelled according to the long term planning states of the system. Similarly, a reliability analysis during the operation stage of a system should cater for those risks relevant in the short term. It is however uncommon to use different reliability parameters for planning and operating reliability studies. This paper proposes an approach based on the Beta probability density function that is applicable to both short and long term reliability analyses. The approach and model developed account for variation in reliability inputs and also allow for better interpretation of reliability outputs.**

Keywords - Adverse weather, Reliability, Risk modelling, Probability distributions

1 INTRODUCTION

Power system reliability is an essential component of network design and planning. Reliability analyses are also important to electricity consumers who would prefer electricity to be provided at all times without any interruptions. Continuity of Supply (CoS) and Quality of Supply (QoS) are significant indicators of the performance of electrical utilities and in particular, the reliability or unreliability [1].

While QoS is usually measured in terms of acceptable values of voltage and frequency, CoS refers to uninterrupted electricity service [2]. Controllable and uncontrollable factors, referred to as network risks, limit QoS and CoS. Descriptions, definitions and analysis of network risks are available from many authors. According to Koonce et al [3], the event that occurs, the likelihood of it occurring and the assessment of its consequences constitute the risk. Falcao and Bollen [4] attempted to define risks regarded as ‘exceptional events’ or ‘force majeure events’.

All supply interruptions, regardless of their cause, reduce reliability. However, other drivers tend to increase the level of risk to power supply. Blake et al [5] describe the increased influence of a power network’s environment on its reliability. The risks to which power systems are exposed can be modelled according to the long term planning states of the system. Different approaches are usually implemented for short term analysis,.

The work presented here is limited to the external environment of power networks and, in particular, the sensitivity of component failure and repair rates to adverse weather and the effect of adverse weather on reliability. Repairs on a network, especially on transmission lines, usually commence after adverse weather subsides. Adverse weather elements follow seasonal patterns and although they occur for short periods of time, the physical stresses on the network components are much higher than those encountered under normal weather conditions. Koval et al [6] present the impact on failure rates of different adverse weather elements like lightning, wind and precipitation.

Unlike most conventional approaches, the approach described here can account for network risks that lead to N-n component outage states. Some recent examples of N-n component outage events related to severe-weather include:

- Strong winds, lightning and heavy rains blamed for outage that left over 60 million customers in Brazil and Paraguay without power in November 2009 [7]
- Hurricane-force winds in south-western France and northern Spain in 2009 left more than a million homes without electricity [8].
- In 2006, high pollution levels and misty conditions caused several lines into the Western Cape Province of South Africa to trip, resulting in a full blackout [9].
- Strong winds in Italy in September 2003 caused a blackout for about 60 million customers [10]

This paper presents an approach based on the Beta probability density function (PDF) to investigate the effect of normal, adverse and severe weather on the reliability of a network. While the analysis presented is on a short term basis, the approach is also consistent for long term reliability analyses. For network performance evaluation, utilities usually compare computed expected values with reliability index thresholds. This holds for an overview of network performance, but decisions with cost implications require more information, so computed reliability indices representing the cost at risk are presented as Beta PDFs to show how the approach leads to more useful outputs.

2 ADVERSE WEATHER MODELS

The bath tub curve is a common model of component failures; in which the failure rate initially decreases, stays constant and then increases. Most literature on reliability considers that period when component failures are deemed constant. However, using deterministic values to represent the failure rates of components is frequently unrealistic. One source of inherent uncertainty in network parameters is the network's environment, in particular occurrence of adverse weather elements such as lightning, strong winds and even geomagnetically induced currents [11].

2.1 Discrete (N-n) Adverse Weather States Models

The main model used when considering adverse weather is the two weather state representation shown in Figure 1; a normal-weather stage and an adverse-weather stage are defined.

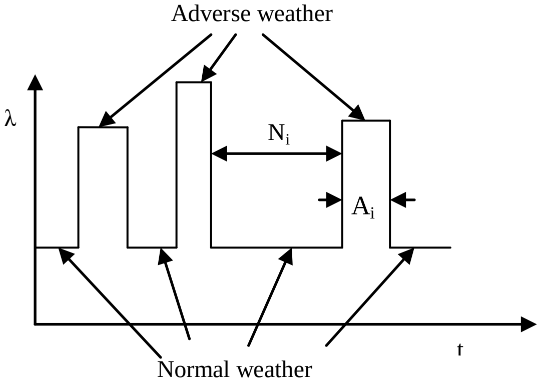

Figure 1: Random failure rate history [12]

λ = failure rate

A_i = duration of i[th] adverse weather period

N_i = duration of i[th] normal weather period

Component failure rates are assumed constant during normal weather conditions. Different constant failure rates apply for the duration of adverse weather conditions. This allows the probability distributions associated with the failure and duration parameters to be negatively exponential. Sannino and Bollen [13] use this model to analyze the effect of adverse weather on the voltage dip mitigation capability of a static transfer switch.

The two state adverse weather model is limited as it disregards changes in severity of adverse weather elements. According to Makkonnen [14], the data sets used to develop previous weather models, in particular for freezing precipitation, seldom include extreme situations. The IEEE Standard 346 [15] proposes the division of a network's weather environment into three categories: normal, adverse and major adverse weather, illustrated in Figure 2. In which a, m and n are transition rates between adverse, major adverse and normal weather states.

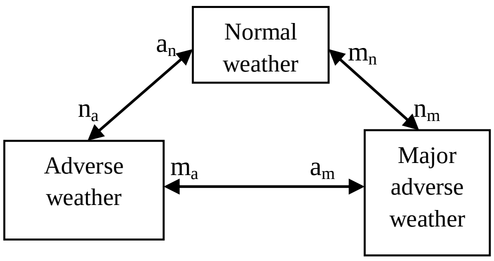

Figure 2: Three weather state model [12]

Failures occurring in major adverse weather are not combined with adverse weather failures but considered separately.

2.2 Stochastic Adverse Weather State Models

Using constant values in the models neglects the variability of network component failure and repair rates during each weather state. This makes discrete models inflexible and limiting for weather related reliability assessments. Stochastic adverse weather state models are based on the randomness of the adverse weather element being investigated.

Alvehag and Soder [16] propose a stochastic weather dependent reliability model to investigate the effect of variable failure and restoration times of a radial distribution network, due to adverse wind, on the interruption cost. The failure rate during adverse conditions, $\lambda_a(w)$, is modelled through the wind speed as shown in Eq 1 for wind speeds greater than the critical wind speed, w_c.

$$\lambda_a(w) = (1 + k(\frac{w(t)^2}{w_c^2} - 1))\lambda_n \qquad (1)$$

λ_n = constant normal weather failure rate

k = scaling parameter

w(t) = varying wind speed

Carer and Briend [17] also apply a constant failure rate during normal wind conditions and consider an exponential growth in failures for wind speeds greater than w_c.

The stochastic nature of weather means that the distributions representing the failure and repair rates can be skewed in any form. Within the limited scope of this paper, variation is considered under normal and adverse weather conditions.

3 TIME DEPENDENT ADVERSE WEATHER MODEL

Previous research cited in this paper carried out analyses on an annual basis. However, weather patterns vary according to seasonal changes and the network risk arising from adverse weather occurs only for short periods during a year. According to Alvehag and Soder [16], failures of overhead lines increase with the weather intensity level.

The timing of an outage has a significant bearing on the consequences for a utility and its customers. The power network in South Africa is loaded most heavily during winter, such that outages during this season affect the reliability of an already strained network. This suggests the time of occurrence of network interruptions must be included in any weather related reliability model.

3.1 The Beta PDF

The distributions of failure rates are skewed because of the variability of failures due to adverse weather. Using or deriving information about the skewness or dispersion of a given parameter is impossible if only average values are used..

The Beta PDF can represent skewed data describing network failures caused by adverse weather. Unlike other distribution functions, the Beta PDF can be used to represent several common shapes, as shown in Figure 3. The Gamma and Weibull PDFs can also represent various shapes, but the Beta PDF has an advantage when the data being described is within a finite range.

The shape of a Beta PDF is described by two parameters, α and β, which can be computed using Eq 2 and 3 from the mean, variance, and scaling factor of measured or computed data [18].

$$\alpha = \frac{(C\mu - \mu^2 - \sigma^2)}{C\sigma^2} \tag{2}$$

$$\beta = \frac{(C - \mu)(C\mu - \mu^2 - \sigma^2)}{C\sigma^2} \tag{3}$$

μ = mean of data; σ^2 = variance; C = scaling factor

The Beta PDF has been used to compute voltage drop along distribution feeders [19] but it has not otherwise been used much in electrical engineering. As far as reliability analyses are concerned, Nadarajah and Kotz propose a generalized beta-exponential distribution [20], but this is limited to applications that consider constant failure rates. Preliminary work has shown the suitability of the Beta PDF for reliability data fitting [18, 21].

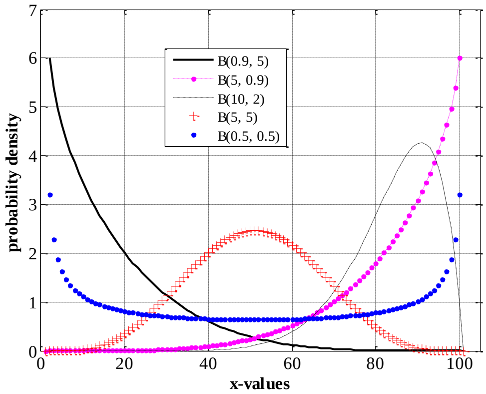

Figure 3: Different beta PDF shapes, B(α,β)

3.2 Time-dependent characterization of network interruptions

Although adverse weather parameters are stochastic; varying for different lengths of time and having variable severity levels, adverse weather is mostly associated with specific seasons of the year such that a pattern can be attached to its occurrence. Also, some interruptions have specific time dependence. According to Naidoo et al [22], faults due to pollution and to bird streamers occur at similar times during the day."

Data from the South African Weather Service shows that lightning activity in South Africa is more likely to occur on summer afternoons. For the Western Cape, cold fronts are especially severe at night during the winters [23]

The approach proposed here associates seasonal and time-of-day intervals with component failure and repair rates. A possible arrangement is shown by the 4 x 4 matrix in Table 1, and smaller or larger matrices are possible [24]. The seasons need not be annual seasons, and could define daily, weekly, monthly or annual periods. The duration of each time interval can also vary. To apply the approach, utilities require extensive historical data of the season and time of failure, possibly broken down for the cause of failure and geographic location. The larger the number of cells in the matrix and the categories for which separate matrices are identified, the more source data is needed to give statistically relevant parameters in each cell.

Table 1: Time windows for failure and repair rates

Season	Period			
	00-06 hrs	**06-12 hrs**	**12-18 hrs**	**18-24 hrs**
1	$\alpha_{11}\ \beta_{11}$	$\alpha_{12}\ \beta_{12}$	$\alpha_{13}\ \beta_{13}$	$\alpha_{14}\ \beta_{14}$
2	$\alpha_{21}\ \beta_{21}$	$\alpha_{22}\ \beta_{22}$	$\alpha_{23}\ \beta_{23}$	$\alpha_{24}\ \beta_{24}$
3	$\alpha_{41}\ \beta_{31}$	$\alpha_{42}\ \beta_{32}$	$\alpha_{43}\ \beta_{33}$	$\alpha_{44}\ \beta_{34}$
4	$\alpha_{41}\ \beta_{41}$	$\alpha_{12}\ \beta_{42}$	$\alpha_{13}\ \beta_{43}$	$\alpha_{14}\ \beta_{44}$

Beta PDF shape parameters are then computed for the failure and repair data collected per interval. To illustrate the approach, an analysis was carried out considering only season 1 (2week period) and variations in the failure rates of overhead lines during different time intervals.

Only two weather elements, strong wind and lightning, were considered in this analysis and they were assumed to be independent of each other. The Beta PDFs shown in Figure 4 represents the failure rates due to lightning (and a similar set of parameters would describe the failures due to wind) during season 1 at different time intervals. Each PDF represents the failure rate of only those overhead line failures during that season and time of day, possibly collected over many years, but in this example hypothetical data was used. Similar curves were developed for component repair rates.

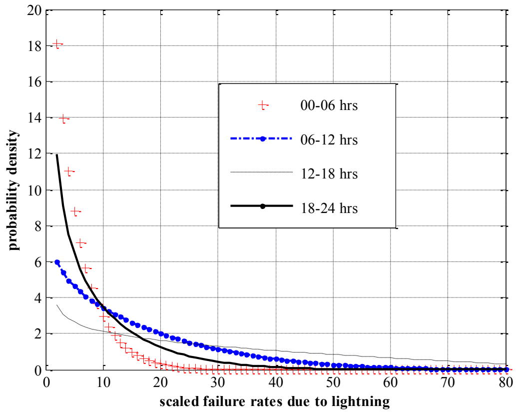

Figure 4: Assumed Beta PDFs representing failure rates due to lightning

The PDFs in Figure 4 depict that high failure rates due to lightning are more likely in the afternoon compared to other time intervals.

Figure 5 shows the Beta PDFs developed for components exposed to both wind and lightning. The curves were developed by computing the average of the means and sum the variances of corresponding distributions lightning and wind, and deriving the Beta PDF using Eq 2 and 3.

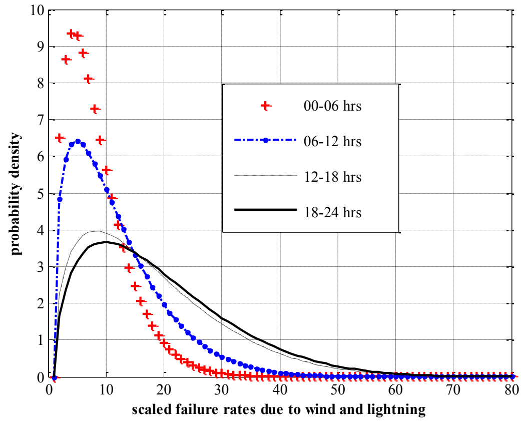

Figure 5: Failure rate PDFs for components exposed to both wind and lightning.

It is important to note the change in the basic shape of the resultant distributions shown by the Beta PDFs in Figure 5, and the increase in the relative probability of incidents between 1200-2400 hrs.

The PDFs represent failures during adverse weather. Normal weather can be included by developing new sets of PDFs from failure data that incorporates normal weather failures.

4 THE TEST SYSTEM

Most published work reports the effect of adverse weather on distribution networks that are confined to small geographic areas, so that all the components are exposed to the same weather element at any given time. Transmission networks usually traverse different geographical areas such that different sections could be affected by different weather elements.

The pseudo test network shown in Figure 6, similar to a portion of the real South African transmission network, shows two overlapping regions representing exposure to adverse weather during a particular period. The network components in one area are exposed to strong winds and in the other to lightning, and in the overlapping area the network is exposed to both adverse weather elements.

The pseudo network is composed of 36 buses with a total load of 6.3 GW. The maximum generating capacity is 2.2 GW with make-up infeed (slack-bus) from Terminal 01. The base voltage and power for the network is 400 kV and 100 MW respectively.

Only 1st order contingencies were considered i.e. only system states composed of single component outages were analyzed. Loads were fixed at their maximum values.

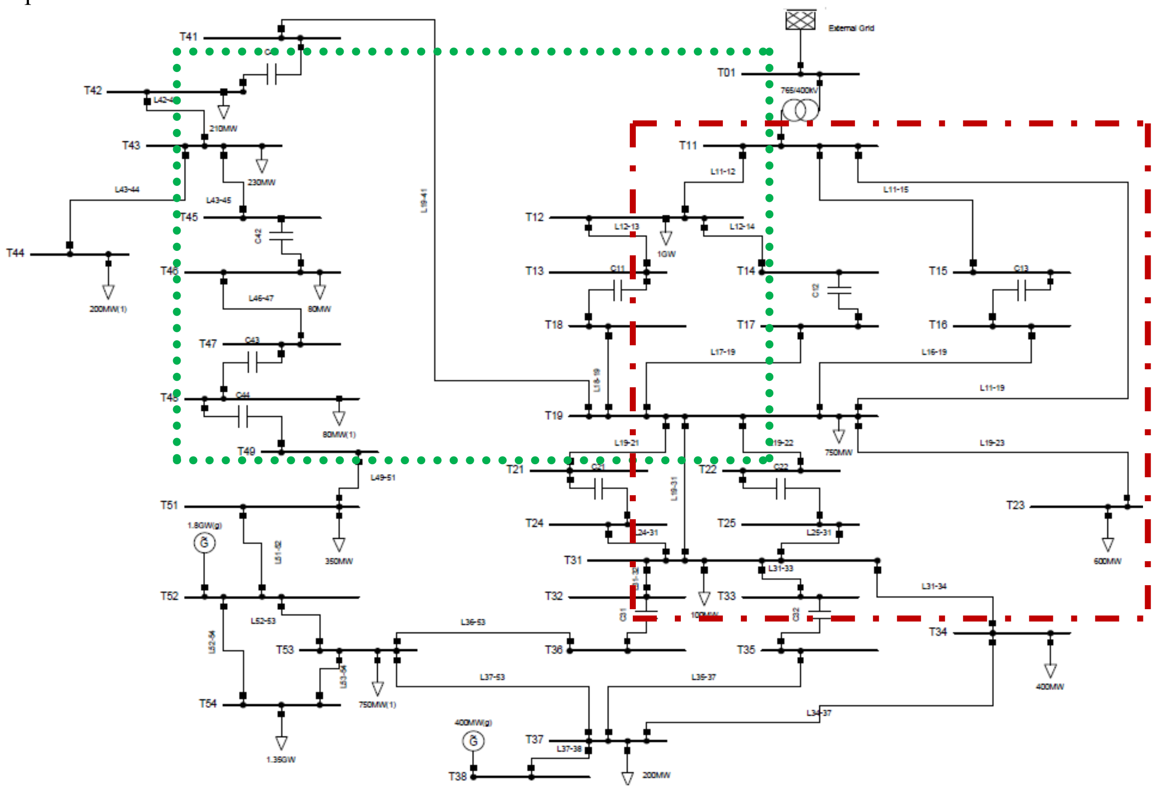

Figure 6: Pseudo Network used as test system

5 NETWORK SIMULATIONS

The analysis was carried out in two parts; power flow simulations and reliability simulations.

5.1 Power flow simulations

The failure states of the test network were identified through power flow simulations. DIGSILENT software package was used for this purpose. The procedure included:

1) Build network in DIGSILENT and run power flow to ensure network is stable
2) Disconnect component and run power flow. Failure state is one that meets the following conditions:
    - Capacity deficiency in the system due to component outage(s)
    - Voltage collapse at system buses
    - MVAR limit violations
    - Failure of load flow to converge due to voltage and power limits
3) Reconnect component. Repeat steps 1-2 for all components

5.2 Monte Carlo Simulations (MCS)

MATLAB software package was used to carry out probabilistic reliability simulations. This work uses sequential MCS. Sequential MCS accounts for the stochastic nature of real power networks.

1) Each simulation process involved generating probabilistic component up and down states. These were dependent on the failure and repair rate PDFs.
2) The component life cycles were then combined to derive a system state.
3) This system state was then compared with the failure states obtained from the power flow analysis
4) Reliability indices were computed if failure state was identified
5) Beta PDFs attached to the respective indices

The data flow diagram in Figure 7 shows the sequential MCS algorithm applied. U_i represents a random number generated for component i, while λ and μ represent the failure and repair rates of a given component. Time, T, is the analysis period.

5.3 Simulation results

This analysis did not consider a bus priority order for load curtailment purposes such that only overall system performance indices were computed. The indices computed for each time interval include:

- Probability of Load Curtailment (PLC)
- Frequency of Load Curtailment (FLC)

The indices are presented as PDFs thus allowing for the variability in performance indices to be investigated. This would not be possible with average values. The level of skewness of the index PDFs provides information useful to network planners and operators.

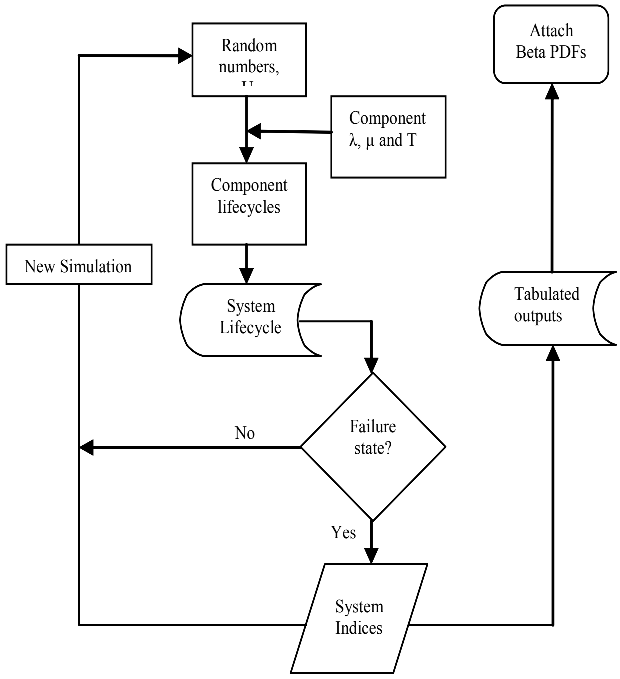

Figure 7: Data flow of applied MCS algorithm

Attempting to make a power system 100% reliable is not economically sound. Planners and utility owners usually have to determine the network reinforcement, cost and risk associated with each alternative. Realistic and accurate reliability analyses are critical to such decision making. As an example, reliability analyses are used to determine where in a power grid the probability of demand exceeding electricity supply is high or low. These decisions are based on index values that have confidence limits attached.

Using average values, such as SAIFI, means planners and utilities are allowing for a 50% risk on the values used. In many cases, this is not good enough, where PDFs can represent reliability at various levels of risk.

Figures 8 and 9 show the index PDFs for the probability and frequency of load curtailment associated with each of the time intervals considered. It is clear from the shapes that the consideration of variability in the inputs of the reliability analysis leads to changes in the performance indices computed. From these PDFs, 10% and 50% risk levels were selected for each index as shown in Tables 2 and 3. Risk levels show the level of confidence in a computed value. At 10% risk level, there is a 10% chance the index value will be exceeded. A 50% risk level value allows for 50% chance of exceedance. A 50% risk level value corresponds to the mean of the data described by the PDF.

The average simulation run-time for a season lasting 30 and 14 days was 2.5 and 1.2 seconds respectively.

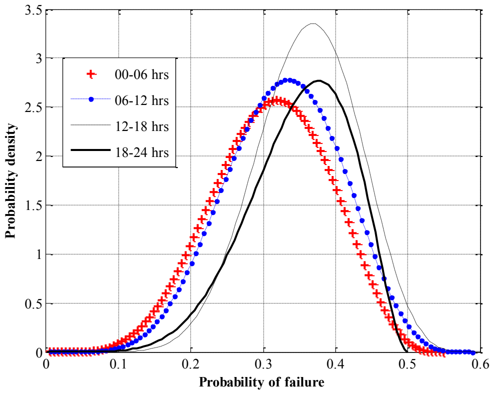

Figure 8: Probability of load curtailment (PLC) PDFs at different time intervals

Table 2: PLC values per time interval for two risk levels

Risk Level	Period			
	00–06 hrs	06-12 hrs	12–18 hrs	18–24 hrs
10%	0.42	0.43	0.45	0.44
50%	0.32	0.33	0.36	0.35

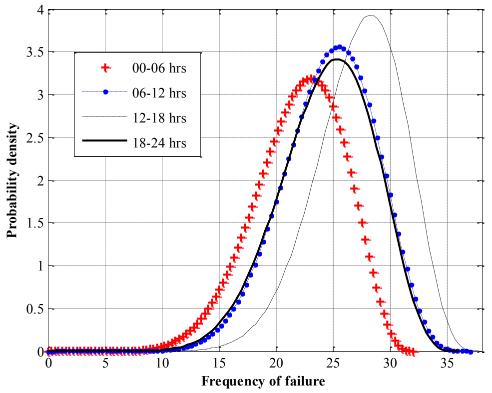

Figure 9: Frequency of load curtailment (FLC) PDFs at different time intervals

Table 3: FLC values per time interval for two risk levels

Risk Level	Period			
	00–06 hrs	06-12 hrs	12–18 hrs	18– 24 hrs
10%	26.9	29.7	32.0	29.6
50%	22.0	24.7	27.3	24.5

The Beta PDFs in Figures 8 and 9 clearly show the variation in the indices computed; incorporating inherent skewness. Thus, it is unrealistic to use a single deterministic value to represent a given reliability index. The results show that use of the Beta PDF based approach allows one to investigate variations in network performance (index values) for different periods (daily, monthly or even annually) and different time intervals during the given season. The approach is also applicable to cases when network components are exposed to several risks at a given time.

Tables 2 and 3 show significant differences between 10% and 50% (average) risk level values.

The results show that network planners and operators can obtain a range of index values, with different risk levels attached, when PDFs are used. Using single deterministic (average) values discards useful information. It is important for network planners and operators to know the risk level attached to the values on which they are basing their decisions. The use of a given risk level will depend on the application. By comparing low risk index values with a minimum accepted (threshold) regulatory target, a utility can, for example, determine what significant improvement (if any) can be achieved by proposed network reinforcement measures. Improvement in network reliability usually has cost implications. The greater the percentage difference between the index value and threshold, the easier it is to justify investment in the network.

For the operational purposes, the approach can be used to improve short-term management of reliability.

6 CONCLUSION

This paper applied a Beta PDF based approach to reliability analysis of a pseudo-real network. Beta PDF models can be used to account for faults due network risks such as adverse weather, that occur for short periods of time. Thus, the approach has high potential for network operation reliability analyses but can easily be extended to long term analyses (planning). The use of Beta PDFs improves on the interpretation of reliability indices. The analysis showed that not only are reliability index values per risk level provided, but any inherent skewness in the index distributions is described by the Beta PDF.

The reported work will continue with the sorting of collected fault data into 16-cell incident matrices and application to larger networks of the approach described here.

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