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Frequency of Forced Outages for Subtransmission Circuit Breakers: Statistical Analysis of Data for the Period 2005-15

***Abstract**. This paper presents the results of the analysis of 2 124 forced outages for Eskom subtransmission circuit breakers recorded over the years 2005-15. Statistical techniques are used in the study. Firstly, the actual number of outages and outage rates are calculated and assessed for various event attributes. Further, the dependence between pairs of event attributes is evaluated graphically by plotting bivariate bar graphs and thereafter quantitatively by performing the chi-square test to assess the significance of the results. The insights gained are useful in the management of these breakers.*

Streszczenie.** W artykule przedstawiono analizę wymuszonych przerw w dostawie napięcia w sieci Eskom w latach 2005-2015. Przeprowadzono analizę statystyczną tych wydarzeń. Dodatkowo przeprowadzono nalizę korelacji tych zdarzeń. **Częstotliwość wymuszonych przerw w dostawie napięcia – analiza danych statystycznych w okresie 2005-2015

Keywords: Chi-square test, circuit breaker, forced outage.
Słowa kluczowe: przerwy w dostawach napięcia, wyłączniki, analiza statystyczna.

Introduction

Electrical energy and electrically-driven processes are at the core of virtually all human activities [1]. Studies by the World Energy Council [2] report that between 2004 and 2014, the globally installed power generation capacity rose from 3 800 GW to 6 180 GW. Furthermore, projections by the International Energy Agency (IEA) estimated that this installed capacity will reach 17 000 GW in 2030 and 30 000 GW in 2050 [3]. One of the main drivers for this growth will be a socio-economic demand for electricity due to human comfort needs and the needs arising from economic activities. Another key driver will be the introduction of electric vehicles as part of the drive towards the decarbonisation of the planet. This has already seen 1.2 million electric vehicles (EVs) and plug-in hybrid vehicles (PHEVs) sold globally in 2018 [4]. This number can reach 100 million per annum [5] by 2050, according to the IEA roadmap for electric vehicles, resulting in over a billion EVs/PHEVs on the road by that time.

This dependence on electricity means that electricity must not only be supplied in adequate quantities and in an economic manner, but must also meet minimum levels of reliability and quality of supply [6, 7]. Power systems are built in and span natural environments which expose them to a variety of factors such as animals, lightning, fire and pollution, to mention a few [8, 9]. These factors can initiate faults in the system, causing protection schemes to act to remove faulted components, thereby leading to forced outages.

Forced outages of power system equipment have adverse consequences for both the utilities and consumers of electricity. This leads to direct costs being incurred, where such costs, for example, include reimbursement payments, regulatory penalties, loss of revenue and equipment replacement costs [10]. Indirect costs, such as those associated with down time, loss of production and damage to sensitive equipment [11] may be precipitated by forced outages. Forced outages may [8] also affect the economy and jeopardize critical services such as transport, communication, emergency and security services. Breaker forced outages in particular [10] can result in serious injuries and death of people.

The frequency of forced outages is an important attribute [12, 13] as the cost of forced outages increases with the number of events. A literature review on publications related to the frequency of outages of circuit breakers was done to establish the developments in this in this area. The literature review was conducted by searching the IEEE and ScienceDirect databases for relevant publications. The relevant publications are summarized below.

In the work of Anders *et al.* [14], the number of outages and outage rates are used to analyse the frequency of forced outages of 230kV to 500kV air blast breakers, focusing on variables including age, voltage level, manufacturer and number of repairs. The analysis of frequency of forced outages for 245kV SF_6 breakers presented by Muratović *et al.* [15] used the outage rates per breaker component and number of operations. In a study by Suwanasri *et al.* [16], the forced outage data for 115kV, 230kV, and 500kV circuit breakers were analysed, focusing on the number of forced outages and failure rates to evaluate the influence of breaker components, voltage level and age on the frequency of forced breaker outages.

Using failure frequency, correlation coefficient, analysis of variance and box plots, Jürgensen *et al.* [17] assess the influence of various explanatory variables (including breaker type, planned maintenance and manufacturer) on failure rates of 40kV to 400kV circuit breakers. Lindquist *et al.* [18] analysed the frequency of forced outages of 110kV to 400kV SF6 breakers, with a focus on the impact of age, breaker function, manufacturer and voltage level on the risk of failure of breaker parts. Lindquist *et al.* [19] built regression models, with frequency of breaker forced outages as the dependent variable, to assess the impact of various explanatory variables (planned maintenance, age, voltage level and breaker type) on the frequency of forced outages of 80kV to 134kV circuit breakers.

The aim of this paper is to present a study on the analysis of the frequency of forced outages for Eskom subtransmission circuit breakers based on data for the years 2005 to 2015. The specific objectives and contributions of this work are as follows:

- To summarize the information on forced outages according to various variables of the events. The actual number of events and rate of events for various levels of variables are plotted.
- To assess the dependence between pairs of variables of events. Firstly, bivariate bar graphs are plotted to obtain a preliminary feel of the nature of dependence. This is followed by performing the chi-square test for dependence, a statistical technique for establishing the significance of the observed nature of dependence between variables.

The rest of the paper comprises of the following components. Firstly, the methods and tools for analysis are discussed. Thereafter, a discussion of data preparation and methodology of the study are presented. This is followed by the presentation and discussion of the results. Finally, the conclusions of the study are drawn.

Methods and Tools for Analysis

In this section, the theory of various techniques which will be used in the analysis of forced outages for subtransmission circuit breakers is discussed. This covers the approach used in analysing the frequency of events for individual event variables (or attributes) and the theory for testing for dependence between variables.

Both numerical descriptive statistics and graphical techniques can be used in summarizing and analysing the frequency of forced outages. Firstly, the actual number of forced outages for various levels of event variables can be calculated and then plotted graphically to see how the number of forced outages behaves across levels.

Secondly, further insight on variations of frequency across variables can be obtained by calculating the failure rate of levels of variables using

(1) $$FRL = \frac{NOL}{NBPL}$$

where: *FRL* – failure rate for some level of the variable, *NOL* – number of outages for some level for the period, *NBPL* – number of breakers in the population associated with some level.

The information on failure rates adds significant value to the simple frequency of forced outages as it becomes possible to compare frequencies of categories (or levels, to use statistical language) that may have completely different individual characteristics, e.g., number of equipment installed, resources and geography in a fairer way.

The application of the chi-square test is considered for a case where there are two or more independent comparison levels, especially when the outcome variable of interest is discrete with two or more levels for each variable. The main aim of the analysis is to compare the distribution of response variables to the discrete outcome variable among several independent levels. The chi-square test of independence is employed with the null hypothesis, as there is no difference in the distribution of responses to the outcome across levels. Independence in this case refers to homogeneity in the distribution of the variable among comparison levels. A description of independence is that it is the probability of a level of a variable or distribution of values of levels where one variable remains the same across all levels of another variable [20]. The chi-square test is a type of non-parametric statistical test, which works on the actual discrete type of data instead of the assumed parametric distributions. It can be performed on the outage data for different circuit breaker components from different categories to determine whether the outage data are statistically dependent on each other.

A preliminary assessment of independence between two variables can be performed by plotting a bivariate bar graph and assessing the patterns as described above. The chi-square test for independence is conducted by following the steps below.

The above process is then followed by conducting a chi-square test for independence in order to draw inferences on the independence of two variables and whether variations exist among population variables. The methodology of the test can be summarised as follows:

- Step 1: Express the null and alternative hypotheses
- Step 2: Calculate the test statistic for the test
- Step 3: Determine the rejection region of the test
- Step 4: Draw conclusion on the null hypothesis

1) Step 1: Express the Null and Alternative Hypotheses

The null hypothesis for independence will specify that two variables are independent, whereas the alternative hypothesis states that one variable affects the other. These hypotheses, i.e., the null hypothesis, H_0, and alternative hypothesis, H_1, may be expressed as follows:

H_0: The two variables are independent.
H_1: The two variables are dependent.

2) Step 2: Calculate the chi-square test statistic for the test

The chi-squared test statistic has a sampling distribution that asymptotically approaches a chi-squared distribution. The chi-squared distribution is mostly used to compare some cross-classification table with a theoretical model. This entails a comparison of observed frequencies and expected frequencies, with the latter obtainable from

(2) $$e_{ij} = \frac{row\ i\ total\ * column\ j\ total}{sample\ total}$$

The expected frequencies [21] are those that would be obtained if the variables were independent. To compare the observed and expected frequencies, the chi-squared statistic is calculated using

(3) $$x^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\left(\frac{f_{ij}-e_{ij}}{e_{ij}}\right)$$

where: x^2 – test statistic that asymptotically approaches a chi-square distribution, f_{ij} – observed frequency of the i^{th} row and j^{th} column, *r* – number of rows in the contingency table, and *c* – number of columns in the contingency table.

3) Step 3: Determine the rejection region of the test

The degrees of freedom of a chi-squared statistic and the test itself must be known in order to determine the rejection region. For a cross-tabulation table consisting of *r* rows and *c* columns, its number of degrees of freedom, *υ*, can be calculated from

(4) $$\upsilon = (r-1)(c-1)$$

A type 1 error is made when the null hypothesis is rejected when in fact it is true, i.e., a conclusion is reached that the variables are dependent when in fact they are not. The significance level, *α*, is the probability of making a type 1 error. The chance of committing this type of error can be reduced by using a smaller value of *α*. In this way there will be a smaller chance of committing a type 1 error, but the probability of committing a type 2 error will be increased, i.e., rejecting the null alternative hypothesis when it is true, i.e., not accepting that there is dependence between variables when there is dependence.

The choice of the significance level is thus a compromise between the probabilities of making the two types of errors. Traditionally, the significance level is set at α=0.1, α=0.05 and α=0.01. Variations that occur with a probability less than the selected significance level are said to be statistically significant at the chosen significant level.

The rejection region of the null hypothesis occurs when

(5) $$\chi^2 \geq \chi^2_{\alpha,\upsilon}$$

where $\chi^2_{\alpha\upsilon}$ – critical value of the chi-square distribution for the chosen significance level α and the degrees of freedom, *υ*. Alternatively, one can calculate the probability value, *p*, of the Kruskal-Wallis Test statistic H, and use it to determine the rejection region null hypothesis. If the *p*-value is less than significance level, *α*, of the test, then the null hypothesis is rejected, otherwise it is not rejected.

4) Step 4: Draw conclusion on the null hypothesis

When equation (5) is valid, the null is rejected and the alternative hypothesis is confirmed. The difference between the observed and the expected frequencies is statistically significant. Thus, the conclusion is that there is a dependence between the variables. If the equation is not valid, the difference between the observed and expected frequencies is not statistically significant. Therefore, the conclusion is drawn that there is insufficient evidence of dependence between variables. The practical implication of dependence between two random variables is that one could alter the outcome or behaviour of one variable by modifying that of the other variable in the pair of dependent variables.

Data Preparation and Methodology of Analysis

Over the period 2005 to 2015, 2 124 forced outages were recorded for Eskom subtransmission circuit breakers. These outages include emergencies and faults. Only sustained outages, i.e., with durations greater than 5 minutes are of concern here. Various attributes were recorded for each event and in this paper the attributes assessed are Operating Unit (OU), kV level of breaker (kV), Manufacturer (Mfr), Breaker Function (BF), Age (Age), Month of the Year (MoY) and Day of the Week (DoW) [22, 23].

Results and Discussion

In this section, the results of the analysis of frequency of forced outages are presented. Firstly, the number of forced outages and the rates of forced outages are presented and discussed for various levels of variables. Thereafter, the results for the graphical analysis and the tests for dependence between pairs of variables are also presented and discussed.

Numbers and Rates of Forced Outages

The number of forced outages and the associated rates for various operating units are shown in Fig. 1. Operating units *c*, *b*, *f*, and *h* in that order, have the highest number of forced outages. Although having the lowest number of forced outages, attention should also be paid to operating unit *d* as it has the highest forced outage rate. The geographic variation in the numbers and rates of forced outages tallies with findings made by Abdelfatah *et al.* [24] in their analysis of power transformer outage data for the different zones. They attributed this to factors that vary across zones including, inter alia, environmental conditions, qualifications, experience, skills and expertise of employees.

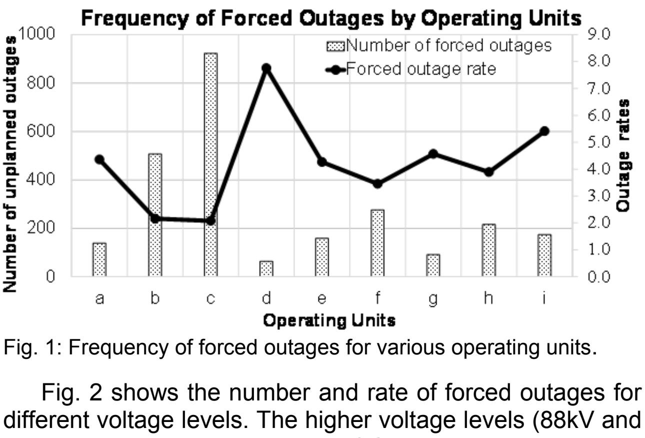

Fig. 1: Frequency of forced outages for various operating units.

Fig. 2 shows the number and rate of forced outages for different voltage levels. The higher voltage levels (88kV and 132kV) have higher numbers of forced outages than the lower voltage levels. The rate of forced outages was the highest for 44 kV circuit breakers. Other studies, such as those by Lindquist *et al.* [19], Norris [25], Koval [26] and Fletcher and Degen [27], also found that breakers operating at higher voltages tended to experience significantly higher numbers of forced outages.

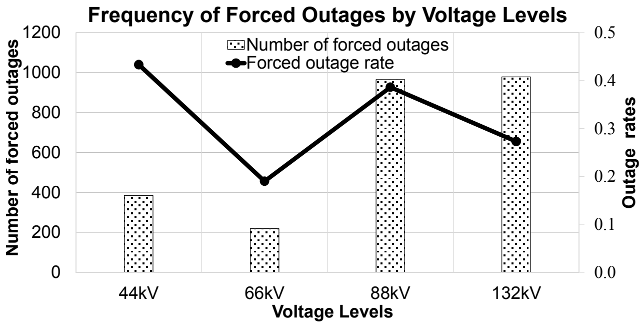

Fig. 2: Frequency of forced outages for various voltage levels.

The number and rate of forced outages for various manufacturers are shown Fig. 3. Manufacturers 1 and 3 have the highest numbers of forced outages, in that order. However, real concern should be with manufacturer 7 as its rate is the highest. The result here tallies with those from a statistical analysis of forced outages of Hydro One's carried out by Anders *et al.* [14, 28]. Their analysis showed that the forced breaker outage rates of different manufacturers varied.

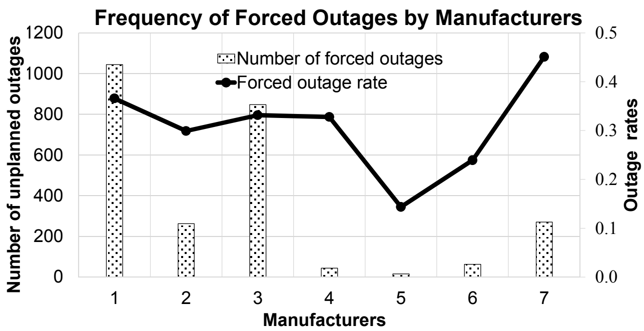

Fig. 3: Frequency of forced outages for various manufacturers.

Fig. 4 presents the number and rates of forced breaker outages by the type of equipment the breakers protect. The lines and transformers have the highest number of forced outages. The forced outage rates for capacitor and traction are the highest, with those for bus coupler breakers being the lowest. The research by Janssen *et al.* [29] and Lindquist *et al.* [18] also found that the forced outage rates of circuit breakers varied according to the equipment the breakers protect.

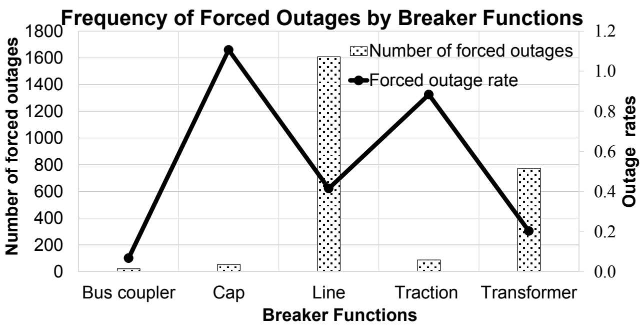

Fig. 4: Frequency of forced outages for various breaker functions.

The number and rates of forced outages by age of breakers are shown in Fig. 5. The number of outages peaked in the 1990s and 2000s. However, the forced outage rate by age shows a decreasing trend over time. The research by Jürgensen *et al.* [17] and that of Zhang *et al.* [30] also shows that ageing has an adverse effect on the forced outage rate of breakers.

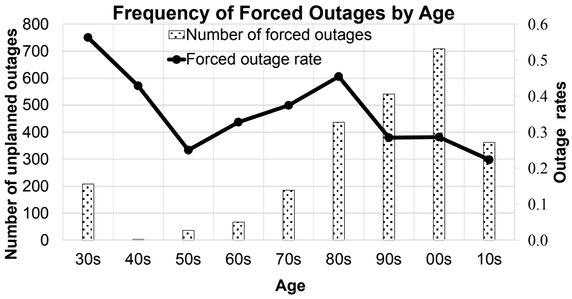

Fig. 5: Frequency of forced outages for various ages.

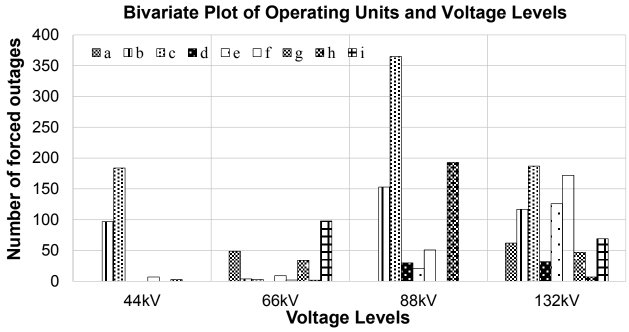

Fig. 8: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various kV levels.

In Fig. 6, the forced outages for breakers by months of the year are presented. The frequencies of forced outages are higher during the months of October to March. These observations align with findings by Vosloo [31] who noted that there were seasonal variations in fault frequencies associated this with seasonal variation in weather patterns, such as change in amount of rainfall, frequency of thunderstorms and lightning activity.

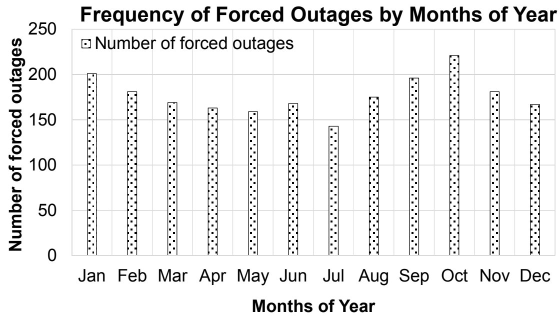

Fig. 6: Frequency of forced outages for various months of the year.

The number and rates of forced outages for various days of the week is presented in Fig. 7. It can be seen that more outages occur over weekdays compared to weekends. This tallies with the research done by Zachariadis and Poullikkas [30] who maintained that fewer sectors of the economy operate over weekends, or operate at lower capacities. As a result, less equipment tends to experience forced outages over weekends compared to weekdays.

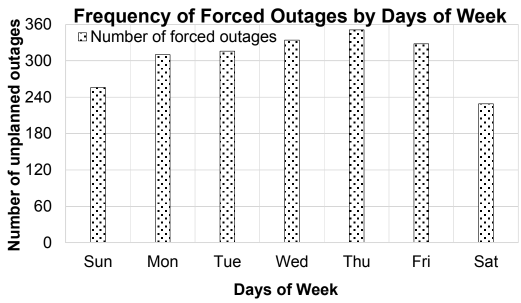

Fig. 7: Frequency of forced outages for various days of week.

Dependence between Variables

The results of graphical analysis for the evaluation of and statistical test for dependence between various pairs of attributes of forced outage events are presented in this section. The results are presented for various null and alternative hypotheses assessed. The level of significance assumed for the test is 5%.

H_0: There is no dependence between the OU and kV.
H_1: There is dependence between the OU and kV.

The bivariate bar graph of OUs against kVs is shown in Fig. 8. The distribution of the number of outages for OUs seems to vary as the levels of the kV variable change, suggesting dependence between OU and kV variables.

The *p*-value returned by the chi-square test is 0.01%, which is less than the 5% level of significance, providing enough evidence to reject the null hypothesis. The conclusion is made that there is dependence between kVs and OUs.

H_0: There is no dependence between the OU and Mfr.
H_1: There is dependence between the OU and Mfr.

The bivariate bar graph of OUs and manufacturers is shown in Fig. 9. The distribution of the number of outages for OUs seems to differ across the levels of the manufacturer variable, indicating that there might be dependence between OU and manufacturer variables. The *p*-value from the test statistic is 0.01%, which is less than the 5% level of significance of the test, providing enough statistical evidence to reject the null hypothesis. The conclusion is that there is dependence between the two variables.

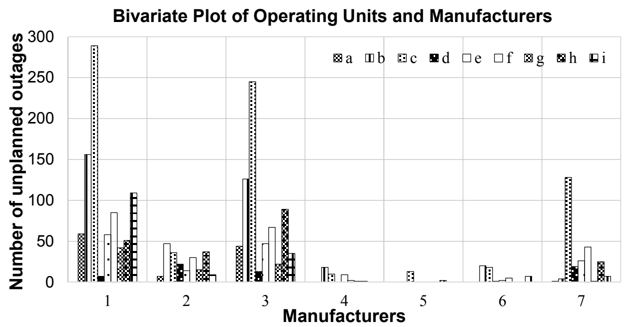

Fig. 9: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various manufacturers.

H_0: There is no dependence between the OU and BF.
H_1: There is dependence between the OU and BF.

The bivariate bar graph of OUs and breaker functions is shown in Fig. 10.

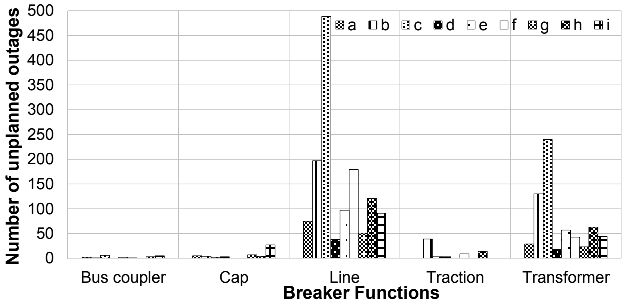

Fig. 10: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various breaker functions.

The distribution of the number of outages in various OUs seems to change as the breaker function varies, suggesting a potential dependence. The *p*-value from the chi-square test for independence is 0.01%, which is less than the 5% level of significance. There is thus enough evidence to reject the null hypothesis and conclude there is dependence between OUs and breaker functions.

H_0: There is no dependence between the OU and Age.
H_1: There is dependence between the OU and Age.

Fig. 11 shows the bivariate bar graph OUs for various ages of breakers. Visually, there seems to be an observable variation in the distribution of the number of forced outages as the ages of the breakers change. The chi-square test for dependence gives a *p*-value of 0.01%, which is less than the 5% level of significance. A conclusion of dependence between OUs and age is thus made.

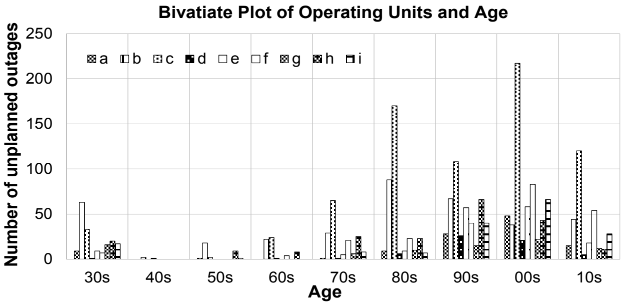

Fig.11: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various ages.

H_0: There is no dependence between the OU and MoY.
H_1: There is dependence between the OU and MoY.

The bivariate plot of forced outages for OUs versus months of the year is presented in Fig. 12. Visual inspection of the graph does not immediately suggest dependence between variables as the distribution of OU frequencies seems to be the same for various months of the year. The *p*-value of the chi-square test for dependence of 0.83%, which is less than the 5% level of significance, indicating enough evidence to reject the null hypothesis. The conclusion of dependence between OUs and months of the year is reached.

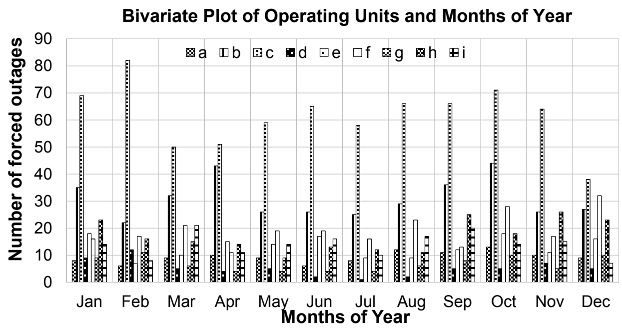

Fig.12: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various months of the year.

H_0: There is no dependence between the OU and DoW.
H_1: There is dependence between the OU and DoW.

The bivariate bar graph of the number of forced outages for OUs versus days of the week is shown in Fig. 13. Visually, there seems to be no appreciable variation in the pattern of forced outages as the days change, suggesting no dependence exists. The *p*-value from the test statistic is 37%, which is greater than the 5% level of significance of the test, providing enough statistical evidence to accept the null hypothesis. The conclusion is that there is no dependence between the two variables.

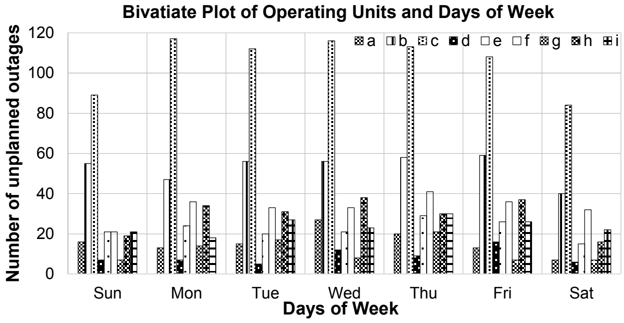

Fig.13: Bivariate bar chart of number of forced outages for various OUs against the number of forced outages for various days of the week

H_0: There is no dependence between the kV and Mfr.
H_1: There is dependence between the kV and Mfr.

The bivariate bar graph of kVs versus manufacturers is depicted in Fig. 14 suggests a possible dependence between these variables as a noticeable change in the distribution pattern of kVs is observed for manufacturers. The test returned a *p*-value of 0.01%, which is less than the 5% level of significance. There is thus enough evidence to reject the null hypothesis and conclude that there is dependence between kVs and manufacturers.

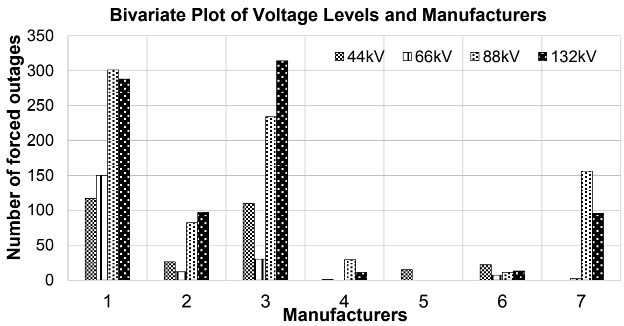

Fig.14: Bivariate bar chart of number of forced outages for various kVs against the number of forced outages for various manufactures.

H_0: There is no dependence between the kV and BF.
H_1: There is dependence between the kV and BF.

The bivariate bar graph of the number of forced outages for kV levels against those for various breaker functions is presented in Fig. 15. Visually, there is a possibility of dependence between the variables as the kV distribution pattern seems to change with function, with distributions for bus couplers and capacitors that are different from each other and are in turn different from those of the remaining equipment.

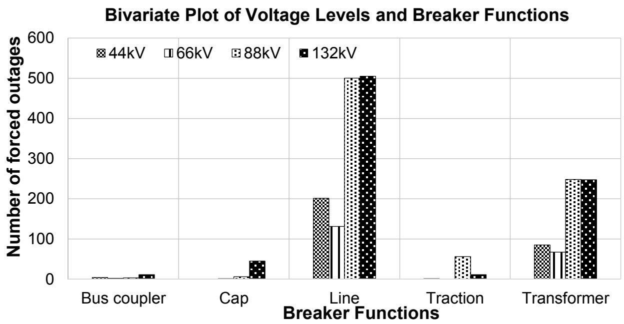

Fig.15: Bivariate bar chart of number of forced outages for various kVs against the number of forced outages for various breaker functions.

The *p*-value from the chi-square test is 0.01%, which is less than the 5% level of significance of the test, providing of enough evidence to reject the null hypothesis. The conclusion is made that there is dependence between kVs and breaker functions.

H_0: There is no dependence between the kV and Age.
H_1: There is dependence between the kV and Age.

Fig. 16 is the bivariate bar graph of forced outages for voltage levels against ages. The distributions tend to differ from one type of equipment to another.

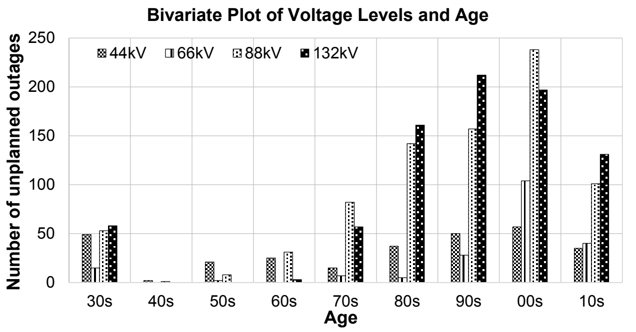

Fig. 16: Bivariate bar chart of number of forced outages for various kVs against the number of forced outages for various ages.

The chi-square test for independence results in a *p*-value of 0.01%, which means there is enough evidence to reject the null hypothesis. The conclusion is that there is dependence between the two variables.

H_0: There is no dependence between the kV and MoY.
H_1: There is dependence between the kV and MoY.

Fig. 17 shows a bivariate bar graph of kVs versus months of the year. Except for minor, observed variations, the distribution of voltages seem to remain unchanged over various months of the year.

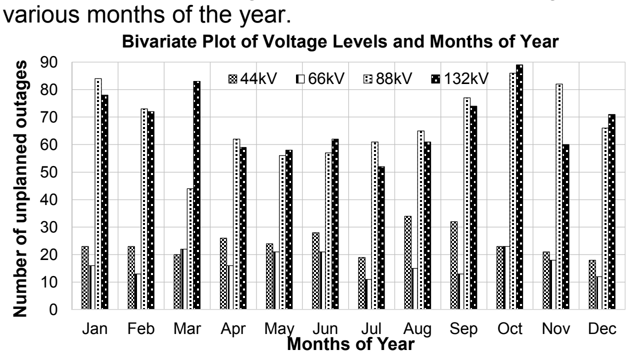

Fig.17: Bivariate bar chart of number of forced outages for various kVs against the number of forced outages for various months of the year.

The *p*-value from the test is 11%, which implies there is not enough evidence to reject the null hypothesis. It is concluded that there is no dependence between kVs and months of the year.

H_0: There is no dependence between the kV and DoW.
H_1: There is dependence between the kV and DoW.

The bivariate bar graph in Fig. 18 is a plot of forced outages for kVs against the days of week. Except for slight variations in the numbers for 88kV and 132kV, the profiles of the number of kV forced outages remains largely unchanged over the days of the week. The chi-square test performed at 5% level of significance returned a *p*-value of 23%, indicating inadequate evidence to reject the null hypothesis. A conclusion is reached that there is no dependence between kVs and days of week.

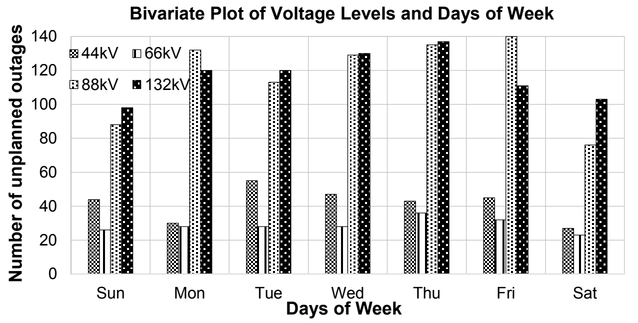

Fig. 18: Bivariate bar chart of number of forced outages for various kVs against the number of forced outages for various days of the week.

H_0: There is no dependence between the Mfr and BF.
H_1: There is dependence between the Mfr and BF.

The bivariate bar graph of manufacturer and breaker function levels is shown in Fig. 19. The distribution of the number of outages for manufacturers seems to vary across the levels of the breaker function variable, suggesting dependence between manufacturer and breaker function variables. This dependence is further confirmed by the results of the chi-square test in Table 1, which determines that dependence exists at 5% level of significance.

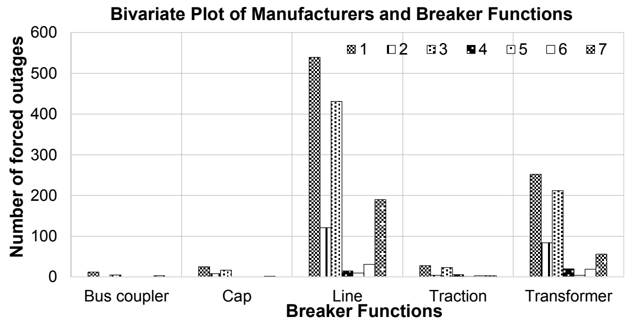

Fig.19: Bivariate bar chart of number of forced outages for various manufacturers against the number of forced outages for various breaker functions.

H_0: There is no dependence between the Mfr and Age.
H_1: There is dependence between the Mfr and Age.

The bivariate bar graph of forced outages for manufacturers versus age of breakers is shown in Fig. 20. There are observable variations in the pattern of frequencies of manufacturers as the breaker function changes. The chi-square test returned a *p*-value of 0.01%, which is less than the 5% level of significance. This indicates the existence of adequate evidence to reject the null hypothesis. It is concluded that there is dependence between the two variables.

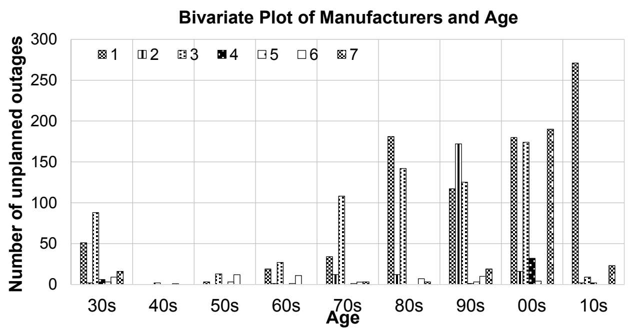

Fig. 20: Bivariate bar chart of number of forced outages for various manufacturers against the number of forced outages for various ages.

H_0: There is no dependence between the Mfr and MoY.
H_1: There is dependence between the Mfr and MoY.

Fig. 21 is a bivariate plot of the number of outages for various manufacturers against the months of the year. Visually, there does not seem to be a change of pattern of the frequency of forced outages for manufacturers with months of the year.

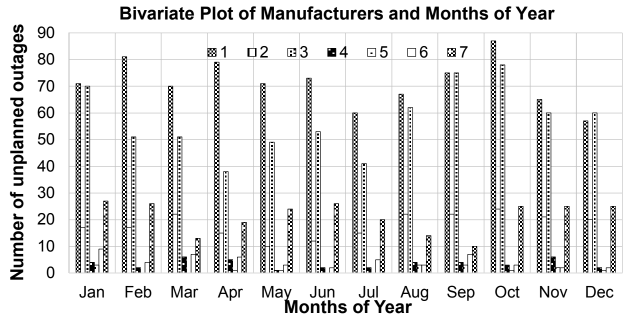

Fig. 21: Bivariate bar chart of number of forced outages for various manufacturers against the number of forced outages for months of the year.

Furthermore, the chi-square test for independence returned a *p*-value of 31%, which is higher than the 5% level of significance of the test, indicating there is enough evidence to accept the null hypothesis. It is concluded that there is no dependence between the variables.

H_0: There is no dependence between the Mfr and DoW.
H_1: There is dependence between the Mfr and DoW.

The bivariate bar graph of the number of forced outages for various manufacturers for various days of the week is plotted in Fig. 22. The distribution of the number of outages for manufacturer does not vary with days of the week.

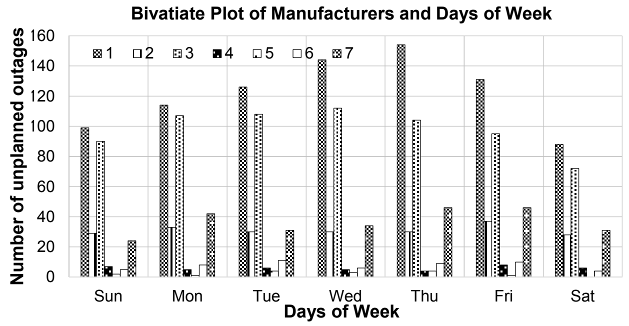

Fig. 22: Bivariate bar chart of number of forced outages for various manufacturers against the number of forced outages for various days of the week.

The chi-square test resulted in a *p*-value of 73%, which is more than the 5% level of significance. This indicates that there is enough evidence to accept the null hypothesis and conclude there is independence between variables.

H_0: There is no dependence between the BF and Age.
H_1: There is dependence between the BF and Age.

In Fig. 23, a bivariate bar graph of breaker forced outages by breaker function versus age is presented. The distribution of frequencies of forced outages by breaker functions during 1940-59 seems to differ from that of other periods. The chi-square test for independence returns a *p*-value of 0.01%. Since this is less than the 5% level of significance, there is enough evidence to reject the null hypothesis. It is concluded that there is dependence between variables.

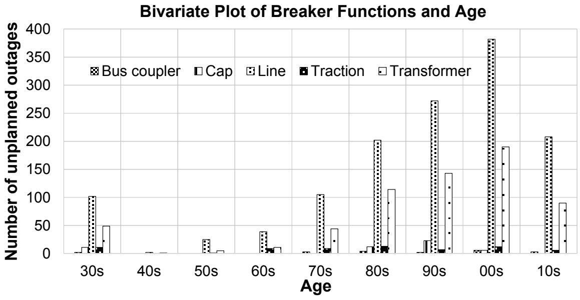

Fig. 23: Bivariate bar chart of number of forced outages for various breaker functions against the number of forced outages for various ages.

H_0: There is no dependence between the BF and MoY.
H_1: There is dependence between the BF and MoY.

The bivariate bar graph of forced outages for breaker functions against months of the year is shown in Fig. 24. The patterns of forced outages for breaker functions seem to vary for months of the year, with frequency of capacitor breaker outages changing erratically compared to other frequencies.

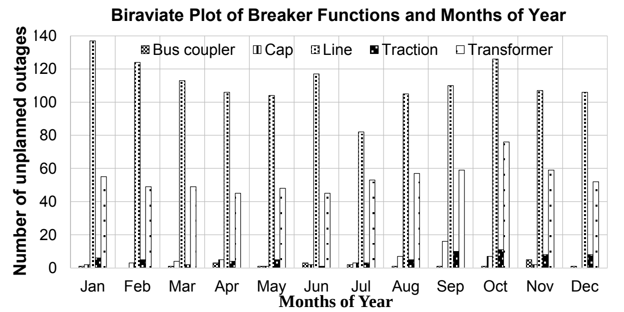

Fig. 24: Bivariate bar chart of number of forced outages for various breaker functions against the number of forced outages for various months of the year.

The *p*-value from the chi-square test for independence is 1.1%, which is less than 5% level of significance. This means there is enough evidence to reject the null hypothesis and conclude that there is dependence between the variables.

H_0: There is no dependence between the BF and DoW.
H_1: There is dependence between the BF and DoW.

The bivariate bar graph of breaker functions and days of the week is shown in Fig. 25. The distribution of the frequencies of outages for breaker function does not seem to vary for days of the week. Against the 5% level of significance the test returns a *p*-value of 45%. This indicates there is enough evidence to accept the null hypothesis and conclude that there is independence between variables.

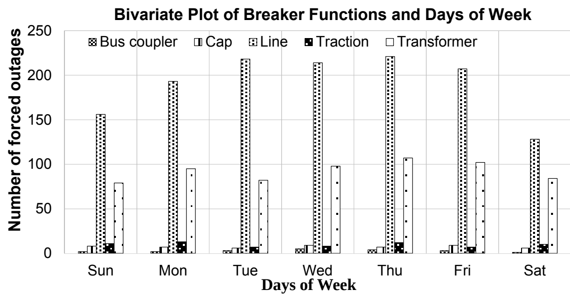

Fig. 25: Bivariate bar chart of number of forced outages for various breaker functions against the number of forced outages for various days of the week.

H_0: There is no dependence between the MoY and Age.
H_1: There is dependence between the MoY and Age.

The bivariate bar graph of forced outages for months of the year versus those for age of circuit breakers is plotted in Fig. 26. The frequencies of the number of outages for the months of the year seem to change as age varies.

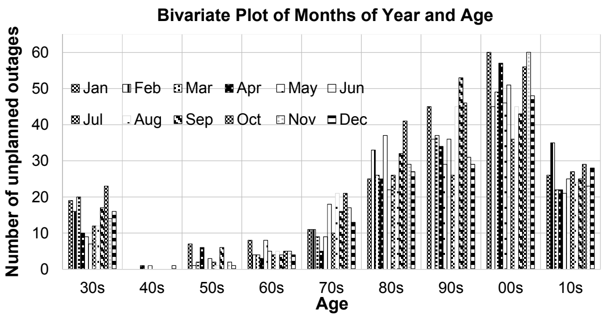

Fig. 26: Bivariate bar chart of number of forced outages for various months of the year against the number of forced outages for age.

The chi-square test for independence give the *p*-value of 11%, against the 5% level of significance. Thus, there is enough evidence to accept the null hypothesis and conclude there is independence between variables.

H_0: There is no dependence between the DoW and Age.
H_1: There is dependence between the DoW and Age.

Fig. 27 presents a bivariate bar graph of forced outages for days of the week versus age. The patterns of frequencies for days of the week seem to vary with age.

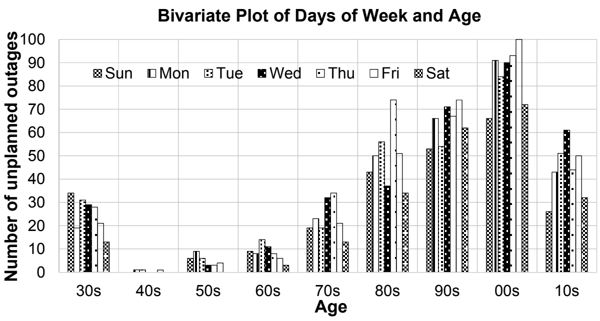

Fig. 27: Bivariate bar chart of number of forced outages for various days of the week against the number of forced outages for various ages.

The chi-square test for independence returns a *p*-value of 0.7%, which is below the 5% level of significance. This indicates that there is adequate evidence to reject the null hypothesis and conclude that dependence between the variables exists.

H_0: There is no dependence between the DoW and MoY.
H_1: There is dependence between the DoW and MoY.

A bivariate bar graph of days of the week against months of the year is presented in Fig. 28.

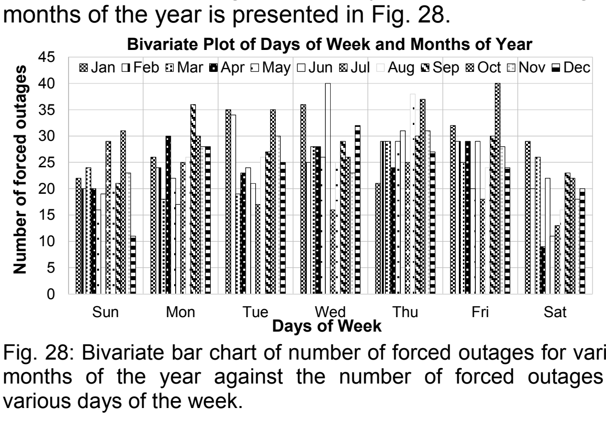

Fig. 28: Bivariate bar chart of number of forced outages for various months of the year against the number of forced outages for various days of the week.

There is no obvious dependence between the variables. The chi-square test was performed and returned a *p*-value of 21%, which is higher than the 5% level of significance. There is thus not enough evidence to reject the null hypothesis. It is concluded that there is independence between the variables.

A summary of results for the chi-square tests for independence performed for various pairs of variables is presented in Table 1. The practical value of the results can be described by the way of an example.

Table 1: Summary of results for chi-square test for independence at 5% significance level for various pairs of variables or attributes of forced outage frequencies.

Pair No.	Pair	*p*-value	Null	Conclusion
1	OU and kV	0.01%	Reject	Dependence
2	OU and Mfr	0.01%	Reject	Dependence
3	OU and BF	0.01%	Reject	Dependence
4	OU and Age	0.01%	Reject	Dependence
5	OU and MoY	0.83%	Reject	Dependence
6	OU and DoY	37%	Accept	**Independence**
7	kV and Mfr.	0.01%	Reject	Dependence
8	kV and BF	0.01%	Reject	Dependence
9	kV and Age	0.01%	Reject	Dependence
10	kV and MoY	11%	Accept	**Independence**
11	kV and DoW	23%	Accept	**Independence**
12	Mfr. and BF	5%	Reject	Dependence
13	Mfr. and Age	0.01%	Reject	Dependence
14	Mfr. and MoY	31%	Accept	**Independence**
15	Mfr. and DoW	73%	Accept	**Independence**
16	BF and Age	0.01%	Reject	Dependence
17	BF and MoY	1.1%	Reject	Dependence
18	BF and DoW	45%	Accept	**Independence**
19	Age and MoY	11%	Accept	**Independence**
20	Age and DoW	0.7%	Reject	Dependence
21	MoY and DoW	21%	Accept	**Independence**

Consider rows 1 to 6, in which the significance of the dependence between variable OU and other variables is assessed. Rows 1 to 5 show that there is significant dependence between OU and variables including kV, manufacturer, breaker function, age and month of the year. There is no dependence between OU and day of the week, as shown by the results in row 6. The practical significance of these observations is that the number of forced outages in various OUs can be altered by taking the initiative to alter the number of forced outages for various categories of kVs, manufacturers, breaker functions, ages and months of the year.

Conclusion

In this paper, the authors have analysed the frequency of forced outages recorded over the years 2005 to 2015 for the 44kV to 132kV Eskom circuit breakers. The frequency and rate of forced outages were calculated and enabled the identification of levels of variables that were the largest contributors to forced outages.

Next, the dependence between pairs of variables was studied by first plotting bivariate bar graphs to get a preliminary view on dependence. This was followed by performing a chi-square test to test quantitatively for significance of dependence. This enabled the identification of specific variables that had dependence with a particular variable, where these specific variables could be manipulated to alter the outcomes of a particular one.

The paper contributes to the discourse on asset management in the power system by carefully documenting an approach and statistical techniques for the analysis of the frequency of forced outages. Furthermore, the results obtained are a useful input in planning initiatives for reducing the frequency of forced outages. Finally, the insights obtained can be an input into asset management of equipment, in general, and 44-132kV circuit breakers in particular.

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REFERENCES

[1] O. Dzobo, T. Gaunt, and R. Herman, "Reliability worth assessment of electricity consumers: a South African case study." *Journal of Energy in Southern Africa*, vol. 23, no. 3, pp. 31-39, 2012.
[2] World Energy Council. Variable renewables integration in electricity systems: How to get it right. World Energy Perspectives: Renewables Integration, 2016. [Online]. Available: https://www.worldenergy.org/. Last accessed 27 February 2019.
[3] Global Energy Systems based on 100% Renewables-Power Sector. November 2017. [Online]. Available: https://www.google.co.za/search?q=drivers+for+global+electricity+demand+pdf&ei=7MUKXbj7J46Y1fAP5LWrqA0&start=10&sa=N&ved=0ahUKEwi4odmU2vbiAhUOTBUIHeTaCtUQ8tMDCJkB&biw=1138&bih=526. Last accessed 27 February 2019.
[4] International Renewable Energy Agency (IRENA) Report: global energy transformation: A roadmap to 2050, 2018. [Online]. Available: https://www.irena.org/publications/2018/Apr/Global-Energy-Transition-A-Roadmap-to-2050. Last accessed 26 September 2019.
[5] S. Agalar, and Y. A. Kalan, "Power quality improvement using STS and DVR in wind energy system." *Renewable Energy,* vol. 118, no. 1, pp. 1031-1040, 2018
[6] A. Rozanskiene, and L. Markevicius, "Evaluation of electromagnetic processes in high voltage OHL by transient fast analysis models." *Przeglad Elektrotechniczny*, R. 94 NR 2/2018, pp. 74-78, 2018.
[7] P. J. Maliszewski, E. K. Larson, and C. Perrings, "Environmental determinants of unscheduled residential outages in the electrical power distribution of Phoenix Arizona." *Reliability Engineering and System Safety,* vol. 99, pp. 161-171, 2012.
[8] U. J. Minnaar, C. T. Gaunt, and F. Nicolls, "Characterisation of power system events on South African transmission power lines." *Electric Power Systems Research,* vol. 88, pp. 25-32, 2012.
[9] S. Natti, M. Kezunovic, and C. Singh, "Sensitivity analysis on the probabilistic maintenance model of circuit breaker." In *9th International Conference on Probabilistic Methods Applied to Power Systems*, Stockholm, Sweden, 2006, pp. 1-7.
[10] R. J. Campbell, "Weather-related power outages and electric system resiliency." *Congressional Research Service*, August 28, 2012.
[11] M. Shuai, W. Chengzhi, Y. Shiwena, G. Hao, Y. Jufang, and H. Hui, "Review on economic loss assessment of power outages." *Procedia Computer Science*, vol. 130, pp. 1158-1163, 2018.
[12] EPRI's Consortium for Electric Infrastructure for a Digital Society (CEIDS), The Cost of Power Disturbances for Industrial and Digital Economy Companies, EPRI, 2001.
[13] G.J. Anders, H. Maciejewski, B. Jesus, and F. Remtulla, "A comprehensive study of outage rates of air blast breakers." *IEEE Transactions on Power Systems,* vol. 21, no. 1, pp. 202-210, 2006.
[14] M. Muratović, K. Sokolija, and M Kapetanović, " Modelling of high voltage SF_6 circuit breaker reliability based on bayesian statistics." In *2013 7th IEEE GCC Conference and Exhibition (GCC)*, Doha, Qatar, 2013, pp. 303-308.
[15] C. Suwanasri, T. Suwnansri, and W. Srisongkram, "Analysis of failure data to determine the failure pattern of HV circuit breaker components." In *2014 International Electrical Engineering Congress (iEECON)*, Chonburi, Thailand, 2014, pp. 1-4.
[16] J. H. Jürgensen, L. Nordström, P. Hilber, E. Andreasson, and A. L. Brodersson, "Assessment of explanatory variables on the failure rate of circuit breakers using the proportional hazard mode." In *2018 Power Systems Computation Conference (PSCC)*, Dublin, Ireland, 2018, pp. 1-8.
[17] T. M. Lindquist, L. Bertling, and R. Eriksson, "Circuit breaker failure data and reliability modelling." *IET Generation, Transmission & Distribution,* vol. 2, no. 6, pp. 813-820, 2008.
[18] J. H. Jürgensen, L. Nordström, P. Hilber, E. Andreasson, A. L. Brodersson, and L. Goel. "Modelling of recurrent circuit breaker failures with regression models for count data." In *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Boise, USA, 2018, pp. 1-6.
[19] C. L. Atwood, J. L. LaChance, and H. F. Martz, "Handbook of parameter estimation for probabilistic risk assessment." NUREG/CR-6823, 2002.
[20] Electricity Supply - Quality of Supply, NRS 048-6, 2009.
[21] IEEE Guide for Electric Power, Revision of IEEE Std 1366-2003, 2012.
[22] M. Abdelfatah, M. EL-Shimy b, and H. M. Ismail, "Outage data analysis of utility power transformers based on outage reports during." *Electrical Power and Energy Systems,* vol. 47, pp. 41-51, 2013.
[23] A. Norris, "Report of circuit breaker reliability survey of industrial and commercial installations." In *Industrial and Commercial Power Systems Technical Conference*, Chicago, USA, 1989, pp. 1-16.
[24] D. O. Koval, "Transmission equipment reliability data from Canadian Electrical Association." In *IEEE Industrial and Commercial Power Systems Technical Conference*, San Antonio, Canada, 1995, pp. 1431-1439.
[25] P. L. Fletcher, and W. Degen, "A summary of the final results and conclusions of the second international enquiry on the reliability of high voltage circuit breakers." In *Reliability of Transmission and Distribution Equipment Second International Conference*, Coventry, UK, 1995, pp. 24-30.
[26] H. Anders, H. Maciejewski, B. Jesus, and F. Remtulla, "Analysis of failure rates of air blast breakers as a function of age and usage." In *2003 IEEE Bologna PowerTech Conference*, Bologna, Italy, 2003, pp. 1-8.
[27] A. Janssen, D. Makareinis, and C. E. Sölver, "International surveys on circuit-breaker reliability data for substation and system studies." *IEEE Transaction on Power Delivery,* vol. 29, no. 2, pp. 808-814, 2014.
[28] X. Zhang, E. Gockenback, Z. Liu, H. Chen, and L. Yang, "Reliability estimation of high voltage SF_6 circuit breakers by statistical analysis on the basis of the field data." *Electric Power Systems Research,* vol. 103, pp. 105-113, 2013.
[29] H. F. Vosloo, "The need for and contents of a life cycle management plan for Eskom transmission line servitudes." MSc dissertation, Dept. of Geography, Environmental and Energy Studies, Rand Afrikaans Univ., Johannesburg, South Africa, December, 2004.
[30] T. Zachariadis and A. Poullikkas, "The costs of power outages: A case study from Cyprus." *Energy Policy*, vol. 51, pp. 630-641, 26 September, 2012.
[31] M. Yue, and X. Wang, "Outage data collection and parameter estimation for an improved probabilistic contigency analysis." In *2015 IEEE Power & Energy Society General Meeting*, Denver, USA, 2015, pp. 1-5.