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Reliability Modeling and Simulation of Electric Substations – A Case Study

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Abstract: The main objective of power transmission and distribution companies is to provide reliable power with minimal Customer Interruptions (CI) and Customer Interruption Minutes (CMI). For these companies, processes and tools that accurately predict the reliability and availability is very important. Studies have shown that the Reliability Block Diagram (RBD) simulation methodology provides more precise results than other methods. Also, the use of field data produces specific and more accurate results than using generalized failure rates for the substation equipment. In this paper, we present how the RBD technique is used to develop precise reliability models for 120 substations using field data. Failure data from over 7000 pieces of equipment was collected, and Weibull distribution was used to create hazard functions for the models. Since substation equipment is repairable, the Restoration Factor (RF) played an essential role in the reliability analysis. A mixed analysis is used to calculate the RF. This paper presents the procedure and methodology used to develop the reliability models, perform a Monte Carlo Simulation, and calculate the CI and CMI for each substation. In addition, the case study shows how unique modeling and statistical methods can be used to perform reliability assessments when individual equipment failure data is not available.

Keywords: Monte Carlo simulation; Power law; Restoration factor; Weibull analysis.

1. INTRODUCTION

Any transmission and distribution company's goal is to ensure the distribution systems - particularly the substations - operate at peak reliability, thus minimizing Customer Interruptions (CI) and Customer Interruption Minutes (CMI). The loss of reliability has a significant impact on the production loss and customer satisfaction for the industries. Historically power system reliability analysts often use deterministic models with generalized failure data [1]. They usually consider specific configurations ignoring the stochastic nature of the power systems and the data requirements. Most engineers use generalized equipment failure data – either from benchmarking or from the equipment manufacturers - for performing the Reliability Availability and Maintainability (RAM) analysis. Moreover, manufacturers are either reluctant to share their data, or, in most cases, their data is inadequate or outdated [2]. One drawback of using generalized data is that the results will be the same for multiple substations if the substations are similar and use the same equipment type. Even though the equipment and systems are similar, each equipment has different age and is subjected to different stress levels (loading) due to power requirements. This plays a significant role in the reliability of individual equipment and substations. Hence, these deterministic models can only be used during the design phase of a system [3]. Appropriate methods, data, and analysis tools are needed to analyze operating substations with varied service parameters.

There are many methods and tools, such as Zone Branch, Reliability Block Diagram (RBD), Fault Tree, Boolean Algebra, Failure Mode, Effect, Criticality Analysis (FMECA), Cut Set, and others, are available to perform reliability assessment of complex systems. Out of these methods, Wang *et al*. applied and compared four methods - RBD, Zone Branch, Goal Oriented (GO), and Cut Set - to IEEE Std. 493 (The Gold Book) and concluded that the RBD method of modeling yields more accurate results [4]. RBD methodology is widely used in the manufacturing and service industries due to its simplicity and versatility. Many analytical methods provide approximate solutions; however, discrete simulation methods can be performed when exact analysis and results are required. RBD methodology is a powerful tool to evaluate complex systems [5]. Besides, using RBDs, engineers can model repairable systems, perform maintainability analysis, use multiple distributions without any restriction for failure times, and repair durations. Many reliability metrics can be easily developed, and what-if scenarios can be easily performed to develop optimum decisions.

Wang *et al*. presented a case study of a substation evaluating the four techniques but used published industry data for failure rates [4]. However, they determined that using field data with stochastic modeling will yield a robust model with accurate results for the specific substation. At the same time, proposing risk-based maintenance for navy vessels, Cullum *et al*. suggested the development of applications from the component level upwards [6].

Many reliability studies were conducted in the power sector, focusing on maintenance issues with electricity transmission lines [7]. Liao *et al*. performed a reliability assessment of transmission lines but encountered the same problem of lack of adequate field data [8]. Adelabu *et al*. performed a reliability assessment of a simple substation using qualitative fault tree and quantitative fault tree analyses [9]. They used Boolean algebra and probability expressions for qualitative analysis and simple reliability equations for quantitative analysis. Their analyses are limited to deterministic models without considering the stochastic nature of the substations. Verma *et al*. used the fuzzy fault tree approach for evaluating substations [10]. Most of the previous analyses were performed using only deterministic models, whereas, in this paper, we propose discrete simulation analyses using field data.

We propose a methodology for evaluating the stochastic nature of the substations using the RBD method. We present how field data was used to develop hazard functions and RBD models for 120 substations with a case study. We also present a technique for calculating the Restoration Factor (RF) from qualitative methods. The project was completed in 2012. The objective was to accurately predict the CI and CMI for the years 2013 to 2022 using proposed statistical methods and modeling with data from 1985 to 2012, which was available at that time. This model provided results that aligned very closely with the distribution company's historical data.

2. THEORY

CI and CMI are defined as follows:
Customer Interruptions (CI): Number of times the substation equipment failures interrupt the service to the customers. Natural disasters such as storms and lightning are not considered in this measure.

$$CI = N_f \times N_c \tag{1}$$

where N_f is the total number of failure events during a given period and N_c is the number of customers served.
Customer Interruption Minutes: Total number of minutes the customers are affected by the system failures. This is calculated as follows:

$$CMI = CI \times D_a \tag{2}$$

where D_a is the average repair duration (average duration of interruption).

Since each substation serves multiple circuits, the CI and CMI are calculated for each circuit and summed to obtain the total values for a given substation. The CI and CMI are calculated using the output of the dynamic model 'Number of Failures' and 'Down Time'. One drawback of using field data for each individual equipment is that it may not be available, accurate, or adequate. To overcome this problem, failure data was collected from over 800 substations, similar equipment grouped, and innovative methods were developed to evaluate these substations. The technique used is described in the Methodology section.

Most equipment in electric substations is repairable. When evaluating such repairable equipment's reliability, Life Data Analysis (LDA) cannot be used. Instead, a General Renewal Process (GRP) should be used. In the GRP process, the repair time is ignored so that the process can be treated as a point process [11]. While the LDA process assumes that the failures are independent and time between failures follows the same distribution, the GRP assumes that the failures are dependent [12]. The time between the successive failures is not uniform and varies based on the type of repairs performed. GRP model describes the rate of occurrence of events over time, which may be more useful to an engineer rather than knowing when the first failure will occur, as in the case of the LDA process. Also, GRP modeling facilitates the estimation of reliability and maintainability of repairable systems [13].

In 1986, Kijima and Sumita suggested two models – Type I and II - for evaluating the repairable components with the GRP. The GRP model is based on the component or equipment's Virtual Age (VR) [14]. This methodology is used to determine the amount of life of a component that is reduced or restored after a repair. The two models suggested are:

- Kijima Type I: The repair will restore life from the last repair only
- Kijima Type II: The repair will restore all the life after the repair

For Kijima Type I model, the virtual age is given by:

$$v_i = v_{i-1} + qx_i \tag{3}$$

and For Kijima Type II model as:

$$v_i = q\,(v_{i-1} + x_i) \tag{4}$$

where v_i is the virtual age of the system after the i-th repair, q is the Action Effective Factor = (1-RF), x_i is the time between the repairs and v_{i-1} is the virtual age at $(i-1)$th repair.

The quality of repairs can be described by a measure called Restoration Factor (RF). The RF is defined as the amount of original life of a component or equipment restored after a repair. An RF of 1 indicates that the equipment is repaired to an "as-good-as-new" condition. An RF of '0' means the equipment is "as-bad-as-before", and the repair did not restore any of its life. The amount that is not restored, which we denote with q, is thus (1-RF). q is called the 'Action Effectiveness Factor', which contributes to the component's virtual age.

The assumptions – "as-bad-as-old" (Type I), and "as-good-as-new" (Type II) - assume extreme conditions rather than a norm. Generally, they are the upper and lower "limiting" conditions to which a system could be restored [15]. However, in real life, the repairs are not perfect, and the RF falls between 0 and 1. These repairs are called imperfect repairs. There is no closed-form solution for calculating the expected number of failures or RF [16]. Instead, a stochastic method is typically used. Duane and Crow developed models for evaluating such repairable systems. Duane's model suggests that the cumulative failures versus time when plotted on a log-log scale will be a straight line [17].

In contrast, the Crow AMSAA model assumes that the instantaneous failure intensity of the underlying Poisson distribution is a straight line when plotted on a log-log scale [18, 19]. Crow also determined that all repairable equipment failures follow a Power Law. The Power Law is also termed as a Non-homogenous Poisson Process (NHPP). In the NHPP model, the instantaneous failure rate is not uniform and varies from failure to failure. Thus, the failure intensity depends on how well the equipment is repaired and restored to its original condition. Also, Crow observed that the Duane model could be evaluated stochastically using the Weibull process for complex repairable systems, and the time for the first failure in the Power Law follows a Weibull distribution [20].

Thus, in the Crow AMSAA or Power Law model, the first failure is determined by the Weibull distribution, and subsequent failures are governed by the RF and the virtual age function. RF plays a vital role in the number of failures and, therefore, on the system's availability. Figure 1 is an example that shows the impact of RF on the cumulative number of failures of a component for the same Weibull location parameter ($\beta = 3.5$) and scale parameter ($\eta = 703$ days).

As stated earlier, a closed-form solution does not exist for calculating the expected number of failures in a GRP model with imperfect repairs. Only the time to the first failure can be determined analytically. Inversely, no closed-form analytical solutions are available in the literature to calculate the RF for repairable systems. It can be calculated only either stochastically or iteratively using Equations (3) and (4) [16, 21]. Yu *et al*. [22] proposed an analytical method that replaces the simulation to predict the number of failures. In either case, simulation or analytical, the repair history of each piece of equipment is needed to use the GRP model to calculate the Weibull parameters and the RF. The distribution company kept good records of the fleet's equipment failures, but not on each piece of equipment. Hence, the RF could not be calculated stochastically. Therefore, the team had to develop a mixed-method (qualitative and quantitative) to calculate the RF. The method is explained in the methodology section.

3. METHODOLOGY AND TECHNIQUE

An electric substation can be very simple, as shown in Figure 2, or very complex, as in Figure 3. A substation consists of many pieces of equipment such as transformers, breakers, switchgear. This equipment consists of different designs and models by various manufacturers. Each manufacturer produces equipment with its own design and unique model numbers. However, the equipment is interchangeable between the substations with the same ratings and configurations, even though they are from different manufacturers. When a piece of equipment such as a transformer or a breaker fails, it is replaced with a repaired or new equipment from the warehouse. The failed equipment is then repaired, tested, and put back into stock for future use at any of the substations. The average age of the equipment in these substations was around 40 years, with the oldest being 74 years old.

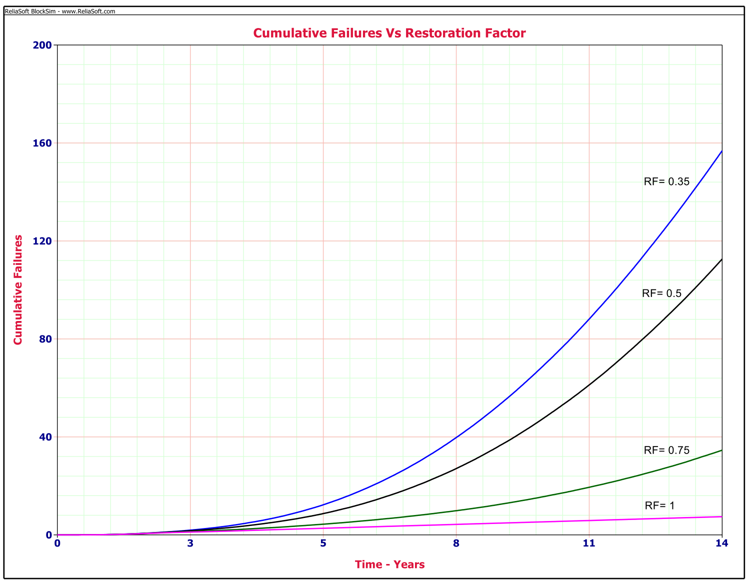

Figure 1. Example of cumulative failures vs. time for various Restoration Factors

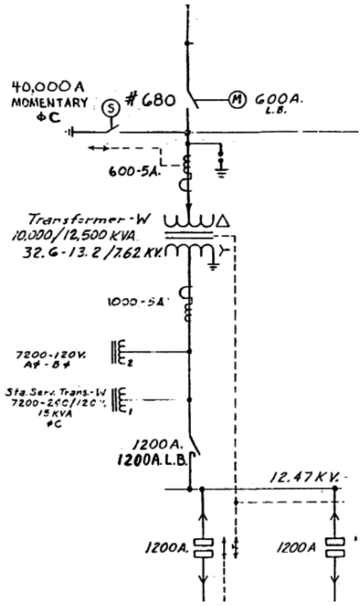

Figure 2. A simple substation configuration

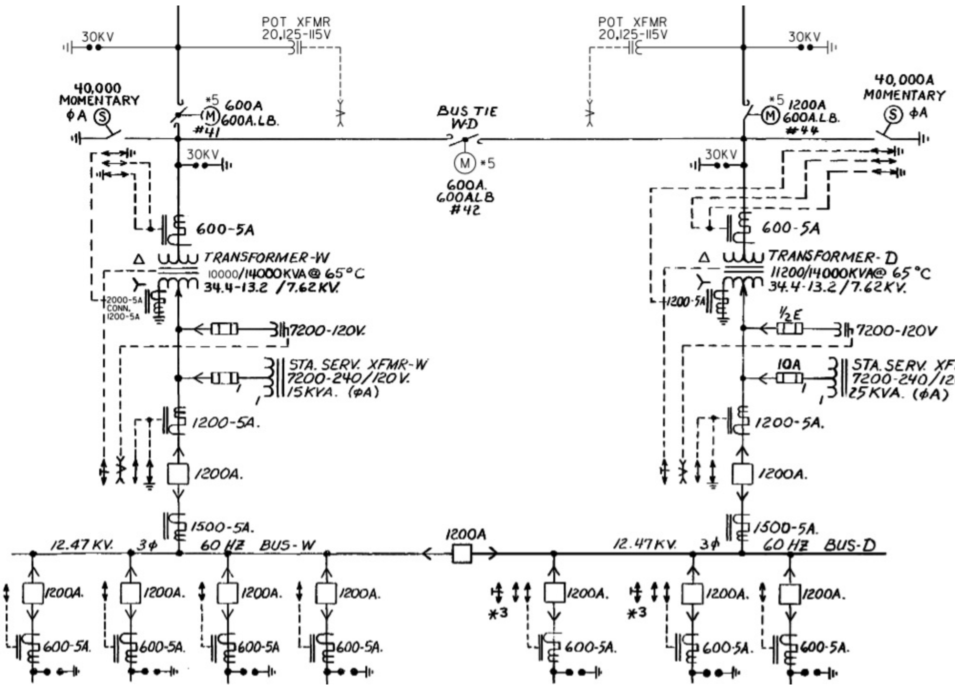

Figure 3. A complex substation configuration

The configurations of many of the 120 substations are the same but have a different combination of equipment. Also, each substation serves various parts of the region, population, and customers. Hence, models must be constructed for each of the 120 substations individually.

The company kept good records of when the equipment failed at each of the substations. However, the repair history of individual equipment based on the serial numbers was not available. Since individual equipment history was not available, the team decided to develop fleet models instead of individual equipment models. The equipment was then grouped into 68 groups based on their type, rating, and function, such as breakers (BR), Transformers (TR), Reclosers (RC), and others, irrespective of the model numbers and manufacturer. A sample of the groups is shown in Table 1.

Table 1. Sample of equipment grouping

Equipment Type	Model Number	Model Type Grouping No.	Equipment Type	Model Number	Model Type Grouping No.
Metal clad switchgear	MI	7	XFMR	TR5	19
Breaker	BR1	14	XFMR	TR6	20
Breaker	BR2	36	XFMR	TR7	20
Breaker	BR3	41	XFMR	TR8	24
Breaker	BR4	42	XFMR	TR9	45
XFMR	TR1	16	Breaker	BR5	27
XFMR	TR2	16	Metal clad switchgear	MCS1	30
XFMR	TR3	18	Recloser	RC1	11
XFMR	TR4	18	Recloser	RC2	31

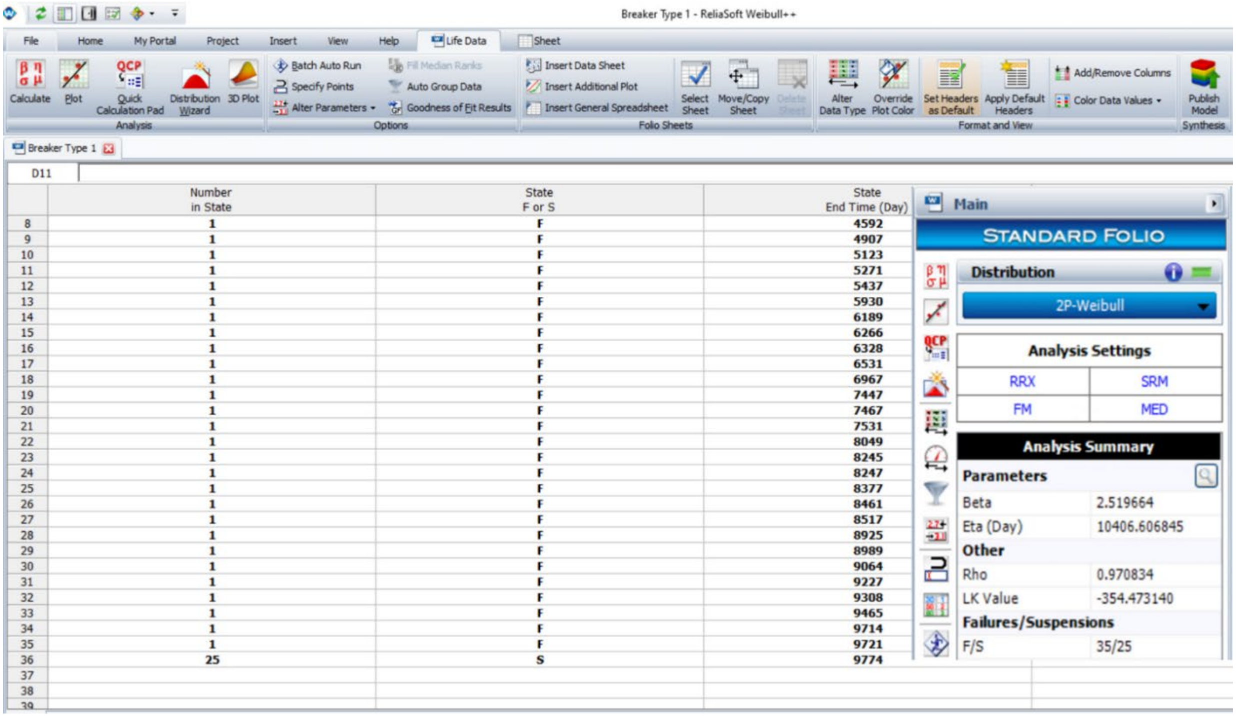

Figure 4. Weibull analysis of Type 1 breaker

Twenty-seven years of failure data - from January 1985 to December 2012 - for 7,000 pieces of equipment from approximately 800 substations was collected and populated into these 68 equipment groups (Types). While performing the analysis, the team found that the equipment's failures were more discrete than recurring. So, after further discussion, the group decided to perform a Life Data Analysis (LDA), rather than a recurring data analysis using power law. Weibull distribution was used to develop hazard functions for all the equipment based on goodness of fit. The team used the Weibull++ software from ReliaSoft Corporation to perform the Weibull analysis. An example of a life data analysis performed on a Type 1 Breaker is explained next. Twenty-seven years of failure data were collected for each type of breaker. Type 1 breakers had 37 failures in 27 years, with 25 breakers still operating beyond the observation end date of December 31, 2012. These 25 breakers were right-censored. Figure 4 shows a sample Weibull analysis and the Weibull parameters for Type 1 breaker. Failure rates were calculated using the Quick Calculation Pad (QCP) in the Weibull++ software. A sample of failure rate curves for four types of breakers is shown in Figure 5.

The group statistical parameters (characteristics) were then used for each equipment in developing the reliability models for the substations. Since LDA is used instead of the GRP methodology, the RF must be calculated using different means. A Subject Matter Expert (SME) was consulted to generate the RFs for the different equipment types. The SME provided the average life of each equipment after corrective maintenance was performed. These years of life between repairs (restored life) are then converted to RF as a percentage and used in the model. A sample of calculations is shown in Table 2.

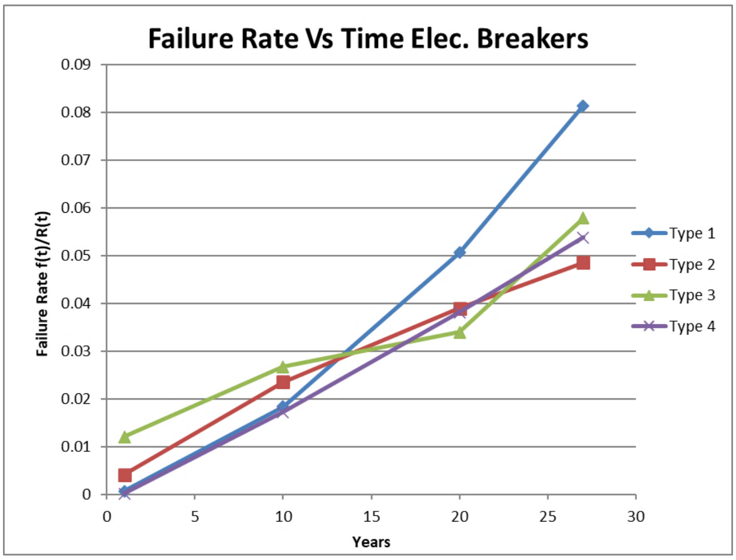

Figure 5. Failure rate curves for different types of breakers

Table 2. Calculation of RF – Qualitative method

Equipment Type	No. of Events	Model Grouping No.	Age in Years as of Observation End Date 'A'	Corrective Jobs 'B' (%)	Renewal Years 'A' x 'B'	Recommended RF (%)	Used in Model (%)
Switchgear	18	7	46	4	1.8	4	5
Breaker	32	14	21	30	6.3	36	40
Breaker	25	36	18	5	0.9	4	5
Breaker	49	41	47	10	4.7	10	10
Breaker	40	42	5	99	5.0	100	100
XFMR	14	16	15	50	7.5	57	60
XFMR	35	18	47	10	4.7	10	10
XFMR	1	20	10	99	9.9	100	100
XFMR	101	24	48	8	3.8	8	10
XFMR	7	45	45	5	2.3	4	5
Breaker	0	27	51	6	3.1	4	5
Switchgear	0	30	40	5	2.0	4	5
Recloser	31	11	40	8	3.2	20	20

After calculating the RFs for all the model groups, RBDs, which became a practical methodology in industry and power systems, were developed for all the 120 substations. An RBD represents a system where each piece of equipment is connected reliability wise [23]. In an RBD, each block represents a component of the system, in this case, a substation. An RBD differs from a flow or one-line diagram in that an RBD connects the equipment based on their functional impact on the system rather than how materials or components flow [24]. The equipment can either be connected in series, parallel, or a combination of the two based on the impact of a component on the whole system. The equipment's reliability-wise arrangement is directly related to the mathematical description of the system [25]. The mathematical relationship of the components is the reliability function $R(t)$ of the entire system. Examples of RBDs for a simple and complex substation are shown in Figures 6 and 7 respectively.

The equipment in Figures 6 and 7 are connected both in parallel and series. How the equipment is connected affects the overall availability and reliability of a system. For example, in Figure 7, two parallel systems A and B, with a common tie breaker, serve four feeder breakers 1 to 4. Each feeder breaker serves a different number of customers. Average repair durations for each equipment type were calculated from the historical data. The statistical parameters, average repair durations, and the RFs were then entered into the RBDs. A discrete event simulation (Monte Carlo simulation) was performed on all the 120 substation models. A total of 2000 simulations for a simulation period of ten years were performed on each model. A Discrete Event Simulation allows the inclusion of repair and maintenance characteristics in the analysis. This is particularly useful when analyzing aging repairable systems where a repair will not restore the equipment to its original condition; either the repair partially restores the equipment to the original condition, or the repair removes all or part of the damage. Many computer software packages, such as GoldSim, BlockSim, Crystal Ball, MatLab, TRYDYN, are available to perform Monte Carlo simulations on sophisticated systems. The team used BlockSim software from ReliaSoft Corporation to create RBDs and perform Monte Carlo simulations.

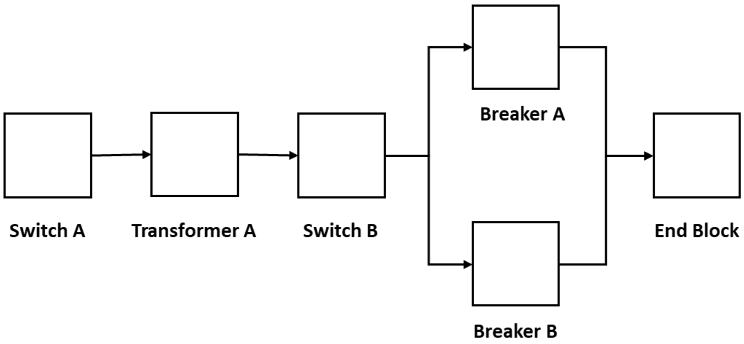

Figure 6. RBD of a simple substation shown in Figure 1

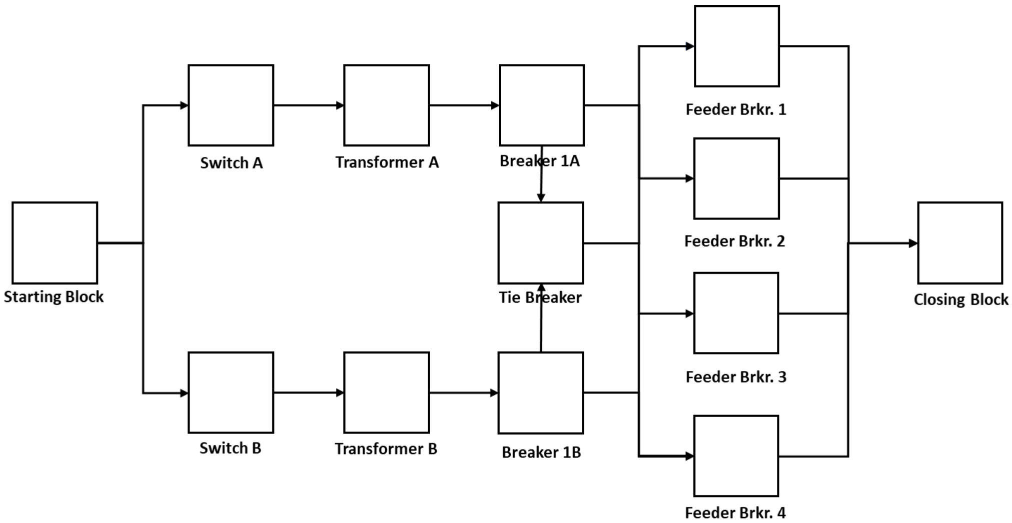

Figure. 7: RBD of a complex substation shown in Figure 2

4. RESULTS

The simulation's output provided the Expected Number of Failures and Expected Down Time for the sample substation shown in Figure 7. The CI and CMI for each equipment are calculated from these values, as shown in Table 3. The simulation output showed an overall substation availability of 99.9% because of significant redundancies built into the systems. However, feeder breakers 1 to 4 do not have any redundancy. If any of these breakers failed, the customers in that particular community would be affected. Therefore, in addition to understanding the reliability of the entire system, it is also critical to know how the individual equipment directly impacts the customers. Table 4 shows the CI and CMI results for the top ten substations, out of 120, ranked by CMI.

Table 3. Model output and calculation of CI and CMI for sample substation for the period 2013 - 2022

Type	Customers Served (N_c)	Expected No. of Failures (N_f)	Expected Down Time (min) EDT= $N_f \times D_a$	CI (No.) ($N_f \times N_c$)	CMI (min) ($N_c \times$ EDT)
Switch A	-	0	0	0	0
Switch B	-	0	0	0	0
Transformer A	-	0.004	2.9	0	0
Transformer B	-	0.084	60.5	0	0
Breaker 1A	-	0.865	311.4	0	0
Breaker 1B	-	0.632	227.5	0	0
Tie Breaker	1,808	0.185	66.6	334	120,413
Feeder Breaker 1	417	0.952	342.7	397	142,906
Feeder Breaker 2	645	0.147	52.9	95	34,121
Feeder Breaker 3	501	0.149	53.6	75	26,854
Feeder Breaker 4	512	0.174	62.6	89	320,512
Total	**3,883**	**3.192**	**1,180.7**	**2,682**	**965,297**

Table 4. CI and CMI results for the top ten substations 2013 - 2022

Station	Type	CI (No.)	CMI (min)
Station A	1	23,046	23,898,281
Station B	3	15,907	16,944,040
Station C	4	25,192	13,650,229
Station D	15	12,929	9,584,107
Station E	4	9,277	8,679,875
Station F	15	10,436	8,219,366
Station G	5	11,543	6,614,848
Station H	2	5,361	5,935,697
Station I	3	11,422	5,872,756
Station J	1	7,188	5,798,524

4.1 Validation

The distribution company kept good records of CI and CMI data for all the substations in their system. They use this information to identify issues and take proactive measures. However, the company could not share this information with the team as it was proprietary and confidential. Instead, the team ran the models for the previous five years (2008 to 2012), calculated the CI and CMI, and provided the results to the company. In turn, the company compared the model predictions with their historical data and confirmed that the results matched very closely with the actual values.

4.2 Outcomes

The outcomes from the analysis are:

a) The distribution company was able to develop its long-term replacement strategy based on the criticality of equipment and substations.
b) The company was able to obtain necessary approvals from the regulatory body for incurring the expenditure
c) The output of the models provided the company with projections of CI and CMI, which gave them the impact of their actions on specific communities and businesses
d) The stochastic nature of the modeling allowed the company to perform what-if scenarios to choose different options for repair or replacement of equipment and the optimum time to perform these tasks.
e) The process showed how accurate results could be obtained where the data is limited. Specifically, the methodology proved that an LDA could be used to calculate the time to the first failure, and a qualitative method can be used to calculate RF when individual equipment history is not available.
f) The CI and CMI values calculated from the models matched very closely with the company's actual data validating the model and methodology.

5. CONCLUSION

Minimizing CI and CMI is a significant objective for power transmission and distribution companies. Hence accurate and fact-based methods and processes are needed for evaluating the substations. Many reliability practitioners use static methods or general failure data in their analyses and assume the equipment repairs are as-bad-as-before. Studies have shown that using field data and performing Monte Carlo simulations allow for including repair and maintenance data into the analysis and providing realistic results. In this paper, we presented a methodology using field data to generate hazard functions through a case study.

Discrete reliability assessment methods exist to perform reliability analysis of substations. The proposed process is simple, and the RBD technique used is more accurate than other methods. This methodology fully addresses the stochastic nature of the substations by using discrete simulation analysis. A reliability assessment of 120 substations was performed in 2012 to predict the number of power interruptions to the customer (CI) and the total minutes of interruptions (CMI). The objective of the assessment was to make these predictions for the future years 2013 to 2023. Twenty-seven-years of equipment failure data from approximately 800 substations and 7,000 pieces of equipment were collected for the assessment. Since individual equipment failure and repair history were not available, the equipment was grouped into 68 equipment groups, based on their function and ratings. This data was used in reliability modeling. The restoration factor plays a vital role in the assessment of repairable items. As there is no closed-form solution for calculating the RF, a mixed methodology was used to compute the quantitative restoration factor from qualitative analysis. Through a case study, the authors demonstrated how critical systems' reliability assessment using the General Renewable Process (GRP) could be performed when individual equipment failure data is not available. The distribution company validated the models by comparing the results with their actual CI and CMI data.

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