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Asset maintenance planning in electric power distribution network using statistical analysis of outage data

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ABSTRACT

The problems faced by electric power utilities in developing countries today is that the power demand is increasing rapidly whereas the supply growth is constrained by aging generating and distributing assets, scarce resources for constructing new ones and other societal issues. This has resulted in the need for constructing new additional generating plants and a more economic ways of planning and maintaining existing Generating and Electric power distribution assets. System planning and maintenance that is based on reliability – centred asset management approach had been adopted in this paper.

Maintenance of critical asset is an essential part of asset management in distribution network. In most Electric utilities, planning for maintenance constitutes an essential parts of asset management. In this paper, an enhanced RCM methodology that is based on a quantitative statistical analysis of outage data Performed at system/component level for overall system reliability was applied for the identification of distribution components critical to system reliability. The conclusion from this study shows that it is beneficial to base asset maintenance management decisions on processed, analyzed and tested outage data.

1. Introduction

Asset management (AM) is one of the hottest topics on everyone's mind. AM is not something new. In fact AM has been with us since the inception of creation [1].

The problem is that we have been making decisions about assets without the benefit of having thought of a formal strategy regarding asset maintenance, repair and replacement before now. We have relied heavily on the frequency of occurrences of unplanned and unscheduled repair events to drive our thought process.

In many situations, decisions regarding equipment maintenance, repair or replacement have been made in the heart of a crisis, usually at the time when one critical equipment has failed and requires immediate attention [2].

Most often, due to lack of planning, managers had to rely on a personal account of an event or history of failures to justify costly and untimely maintenance or replacement decisions.

Even with well-documented equipment repair and maintenance history records, we find ourselves planning for the future by looking in the rearview mirror [3].

We have lacked a process that would provide information that could be used to estimate the remaining useful life of an asset and allow us to optimize our decisions about deploying resources in the most effective and efficient manner.

Asset management is about decision-making. It is a disciplined, deliberate, and systematic approach to making informed decisions about assets. Asset management is a cost of doing business and also a great liberator [4].

By defining and then focusing on the core mission of the system and the level of service, we become free to prioritize our level of maintenance effort vis-avis our assets. We can then focus on those assets that are critical to our mission and give less attention to those that are less critical.

In this paper, a statistical analysis for determining and identifying the critical asset for distribution components in power system had been presented. The presented method is able to deal with uncertain outage parameters and to maximize the possibility of reliability improvement and loss reduction. The graphical and statistical results show that the proposed statistical analysis method is an efficient tool for identifying critical distribution component that will require more suitable maintenance strategy. The maintenance outage data collection method is presented in Section 2 and this is followed by the mathematical processing technique in Section 3. The discussion and analysis of the results followed by the achievements and conclusions are presented in Sections 4 and 5 respectively.

2. Data collection methods

Maintenance of critical equipment is an essential part of power systems. In today's competitive power utilities, planning for

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maintenance constitutes an essential part of asset management. However, in most developing countries, this essential part of asset management may receive no attention at all or at best may receive very limited interest from owners of these utilities.

The foundation of this process is in the collection of all types of observed failure data. This data set then constitutes the failure sample space. It is the subsequent statistical analysis of the data that will provide valuable insight into the failure rate and time to failure. These two are the essential building blocks of any predictive maintenance planning program.

A good data mining techniques to the failure data space can transform the maintenance planning program from a preventive plan or time based maintenance into a condition based maintenance or predictive one that will attempt to arrest system failures before they even occur. Preventive maintenance is required in order to prevent failures and significant damage or even destruction of equipment or component. A strategic maintenance method that require the use of condition based maintenance leads to high availability with moderate maintenance costs [5] and is mainly used within EHV- and HV grids [6]. Nowadays a lot of utilities try to adopt this approach also for the medium voltage level. Reliability Centred Maintenance (RCM) is one of the maintenance strategy used to determine the maintenance requirements of any physical asset in its operating context [7]. The RCM method facilitates among several other functions, the selection of applicable and effective maintenance tasks. It is this function of the RCM that is utilized in this paper.

2.1. Outage data gathering

The starting point for an effective maintenance program using information from failure data is to first decide which data to collect and the method of collecting it. In some organisations, this effort is almost institutionalized; however, in the distribution company of Power Holding Company of Nigeria (PHCN), this critical and all important aspect of maintenance planning is almost non-existent [8]. What is practised here is breakdown maintenance. After a reasonable amount of data has been collected, the datasets to be used for analysis are then obtained after pre-filtering and removal of extraneous events. These events include outage due to scheduled maintenance and those due to load shedding.

We then consider the properties of the aggregate system component outage failure data, deriving simple empirical relationships from the data sets before delving into the statistical analysis of the constituting components.

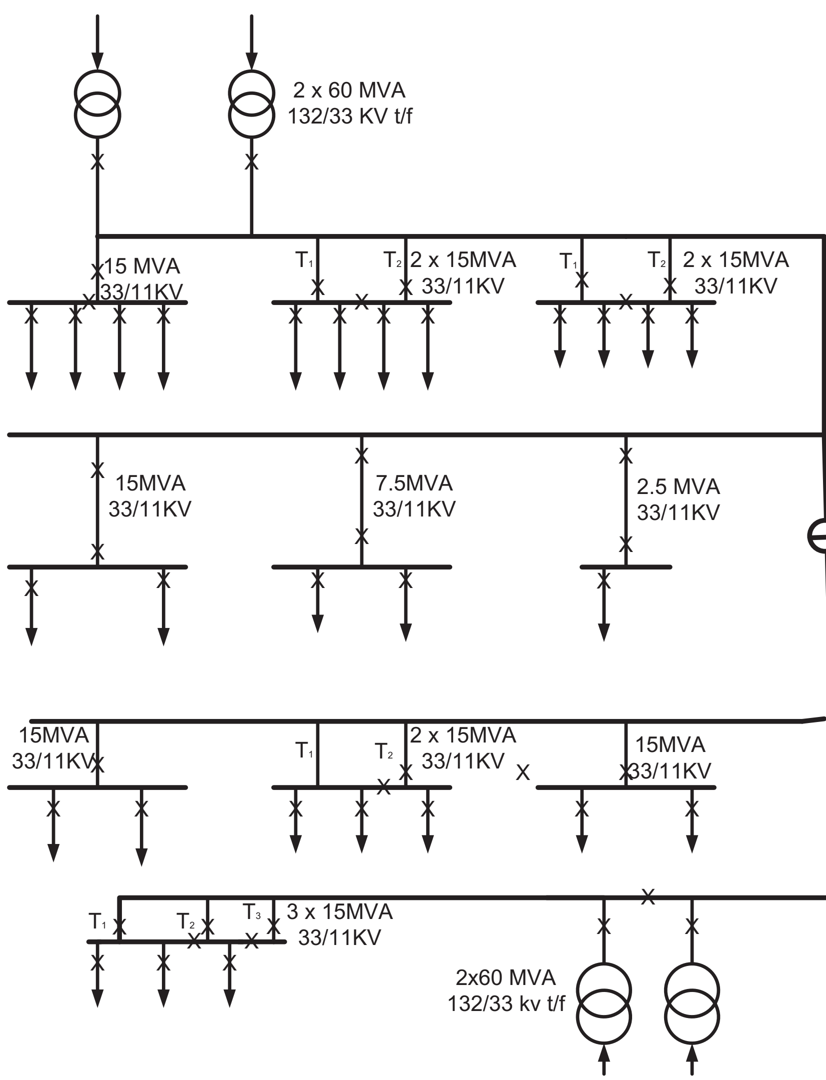

Fig. 1. Line diagram showing Ikeja distribution zone.

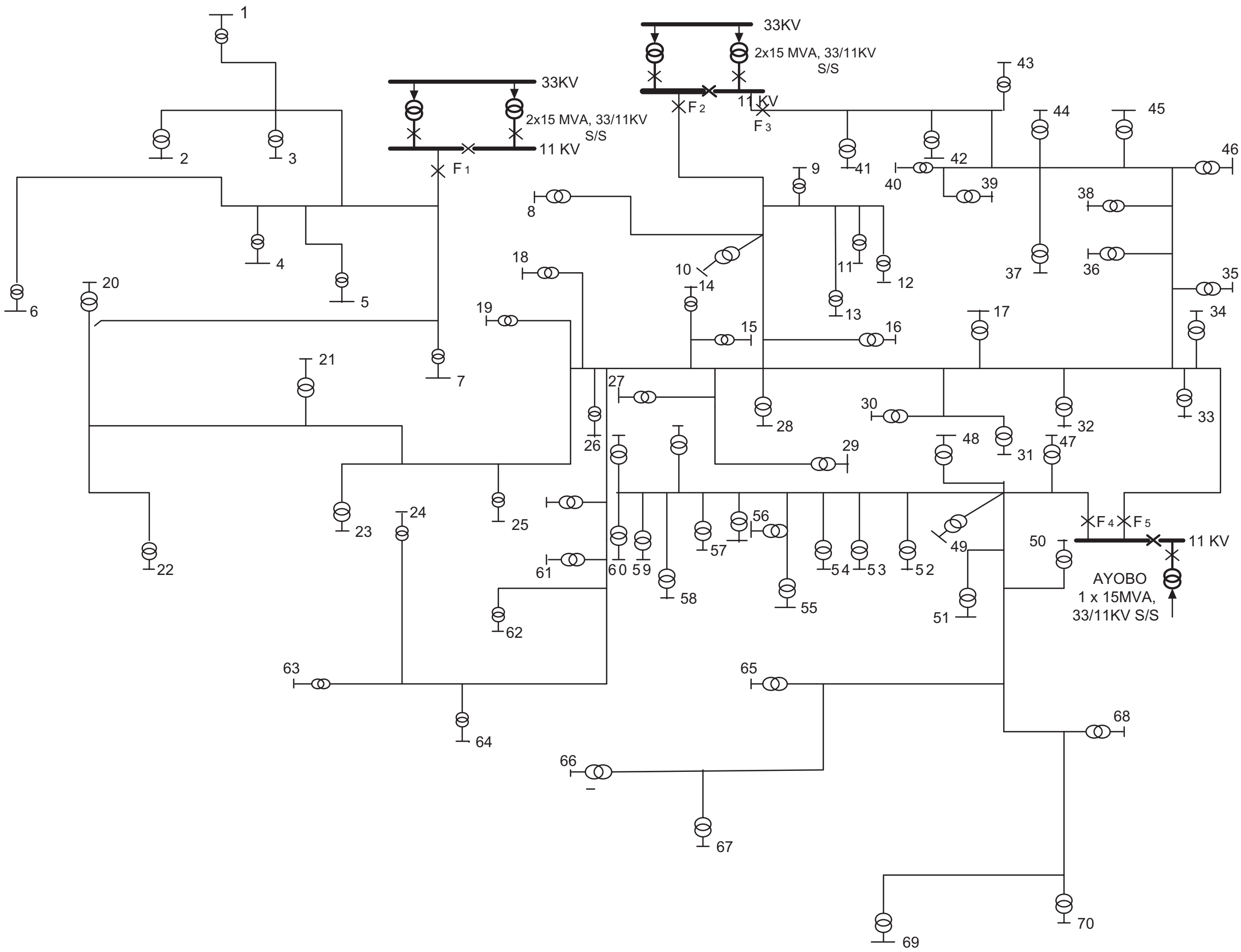

Fig. 2. A section of the Abule Egba distribution business unit.

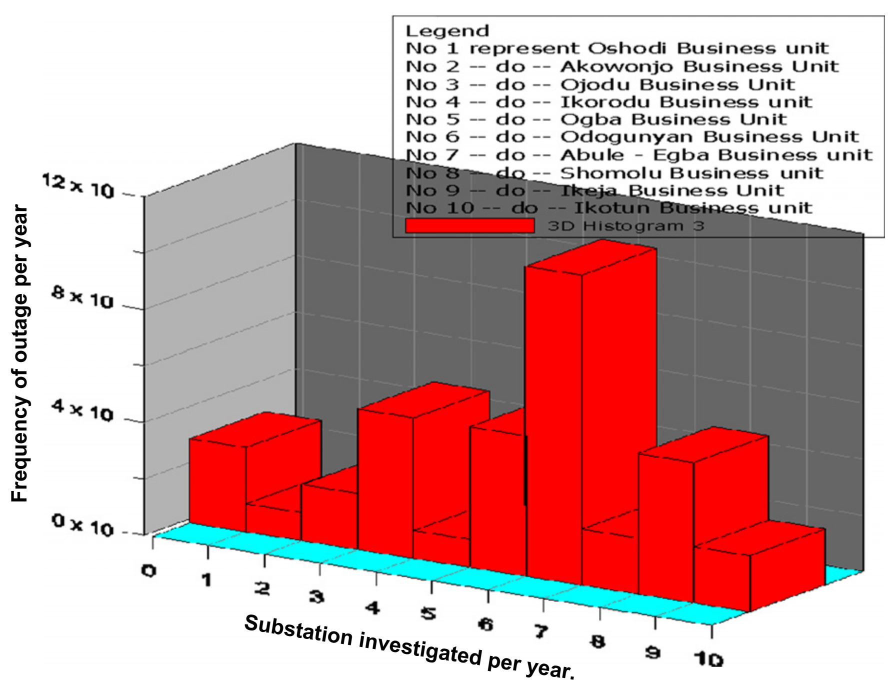

Fig. 3. Processed 2004 outage data for Ikeja distribution zone.

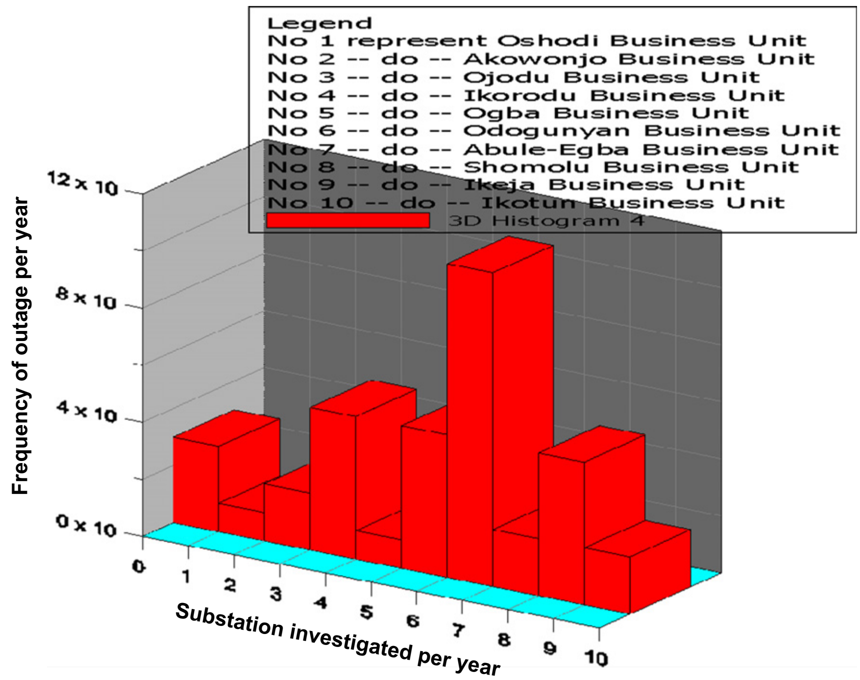

Fig. 4. Processed 2005 outage data for Ikeja distribution zone.

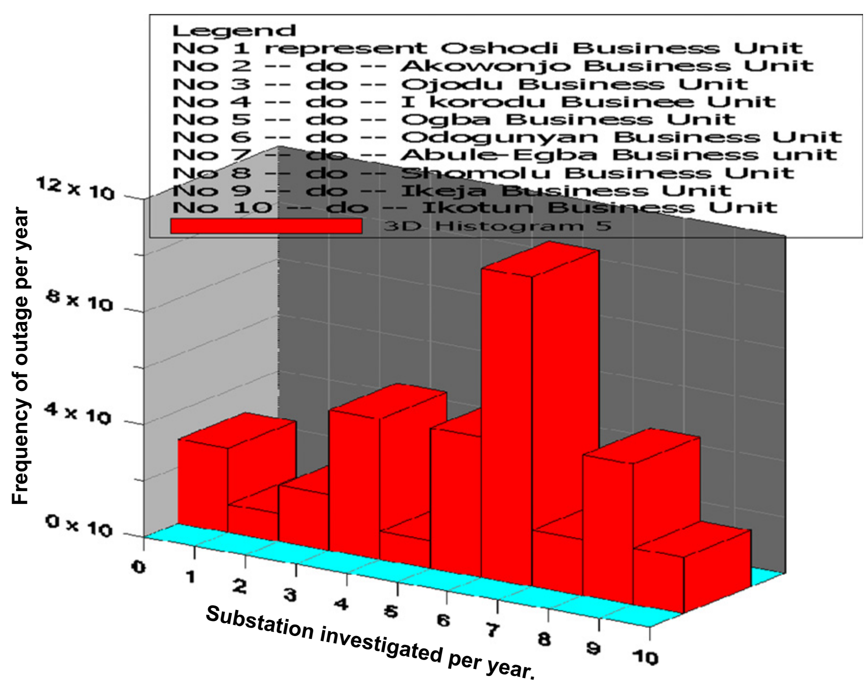

Fig. 5. Processed 2006 outage data for Ikeja distribution zone.

2.2. Source of outage data

The data were collected from Ikeja distribution Zone with particular emphasis on Abule-Egba Business units that are made up of Industrial, Commercial and Residential customers. This utility unit is made up of ten (10) busbars normally referred to as injection Substations. These injection substations are fed by 4×60 – MVA, 132-/33-kV transformers from different substations located within the Zones. These ten injection substations in turn feed 27 11-kV different customer feeders with 647 different loads – points. The line diagram for this representation is shown in Fig. 1.

A typical distribution system showing a section of the Ikeja Zones Network is represented in a line diagram in Fig. 2. Power Holding Company of Nigeria (PHCN) called this section ''Ikeja Distribution Zone''.

The raw outage data collected on the entire Zone was processed and then plotted on a histogram. The feeder with the highest failure rate was selected for a more critical analysis. In this case the

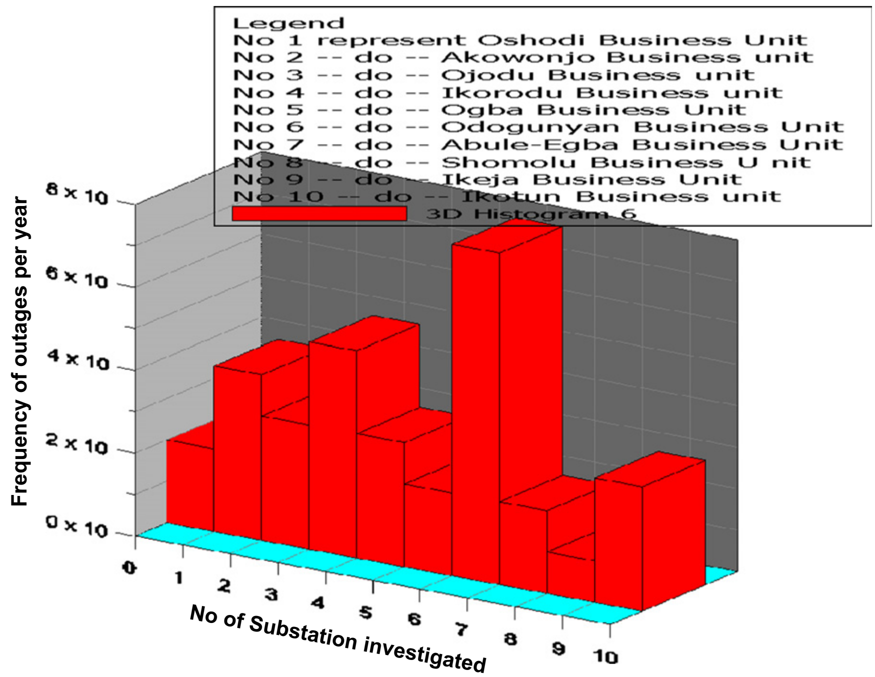

Fig. 6. Processed 2007 outage data for Ikeja distribution zone.

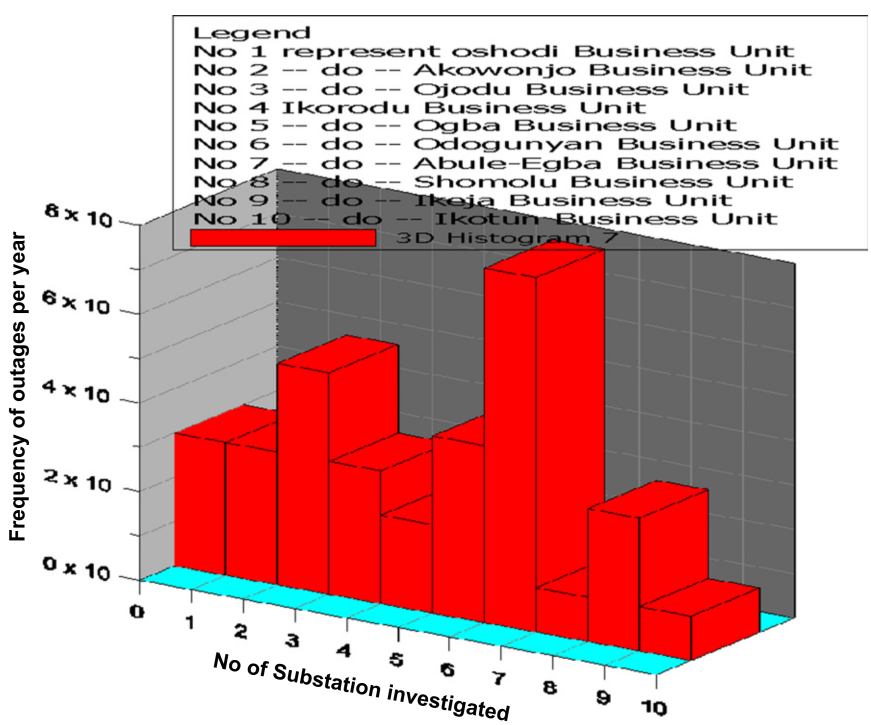

Fig. 7. Processed 2008 outage data for Ikeja distribution zone.

distribution components listed in numbers 1–5 below were investigated using the outage data recorded for the identified critical feeder for years being considered.

(1) Lines' conductors (lines, poles and related items).
(2) Cables (cables, junctions and related items).
(3) Breakers.
(4) Transformers.
(5) Disconnectors, isolators and bus bars.

For the purpose of this study, outage data that results in system failure because of the failure of any of the above listed components were collected from the outage log book. Only those components listed in numbers 1–5 found to be critical to the functionality of the system and which are also affected by maintenance were analyzed.

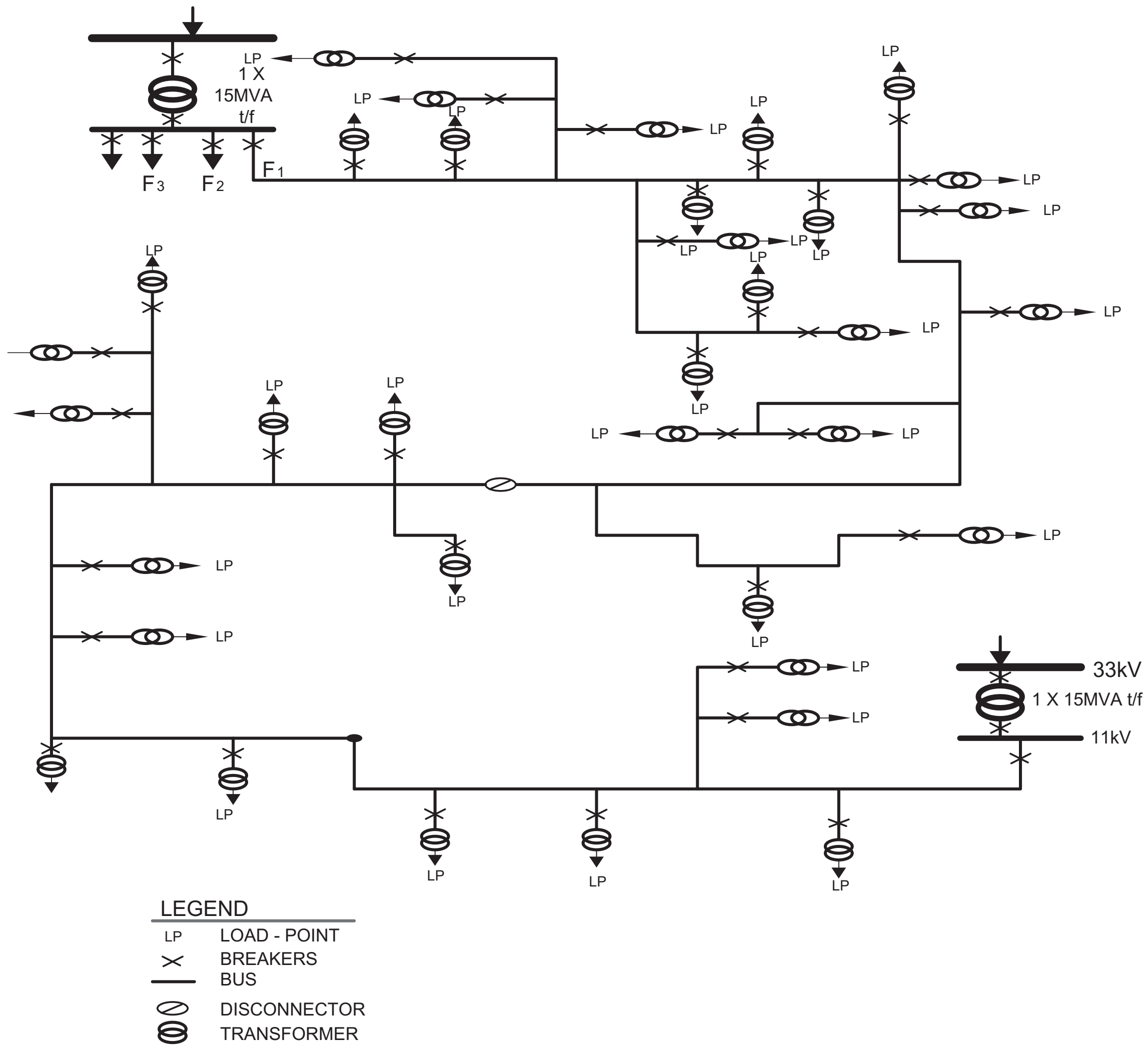

Fig. 8. A typical section of Abule-Egba business unit.

3. Collected raw maintenance data processing and testing

In this section, 5 years of outage data collected from Abule-Egba business unit which is one of the PHCN business units in Ikeja Zone Distribution Company in Nigeria are analyzed to test assumptions about failure rate and repair duration models. The data included 9500 faults after excluding those occurring as a result of load shedding due to insufficient generation as a result of poor planning and lack of maintenance culture.

The most basic statistic that can be extracted from the failure data is the measure of center [9] for the variable under consideration. It is also called the sample mean. This is the arithmetic average of the n failure observations.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{1}$$

where n is the number of observations in the sample space, x_i the number of aggregate failure/day, y_i the time between failure on the system components, and z_i the time taken to repair failed components.

Using the sample mean, we can easily estimate

$\bar{x} = \lambda$ as the mean number of failure occurrence per given time,
$\bar{y}$ = Mean time between Failure (MTBF) and
$\bar{z}$ = Mean time to repair (MTTR).

For a system that has a good maintenance record, this simple analysis can be performed on different components that perform the same function and very easily the feeder that contain the component prone to failure can be identified. In modern distribution systems, data uncertainties become an unprecedented challenge because of human involvement in the collection and demand side responses [10]. To deal with these uncertainties and give credence to the data used in this work, the collected data were first processed and then subjected to the following **important statistical b**asic tests.

The **first step** in the analysis of outage data is to determine whether the system reliability changes with time. The Laplace test is an efficient mathematical method for testing for trend [11,12]. If $T_i, T_i, \ldots\ldots\ldots T_m$ are a set of chronologically arranged outage times, the Laplace test statistic is calculated as

$$U_L = \frac{\left[\frac{1}{m-1}\sum_{i=1}^{m-1} T_i\right] - \frac{1}{2}T_m}{T_m\sqrt{\frac{1}{12(m-1)}}}. \tag{2}$$

The conclusions drawn from this calculation are:

- $U_L = 0$ indicates lack of trend. We then assume HPP.
- $U_L > 0$ indicates that interarrival time trends are decreasing, indicating system deterioration with time

- $U_L < 0$ indicates that interarrival time trends are increasing, indicating system improvement, or reliability growth with time [11,13].

For example, at the 95% confidence level, if $U_L > 1.96$, them the system reliability is deteriorating with time, while system reliability is improving if $U_L < -1.96$.

For the 5 year's outage data collected on the system under consideration, $U_L = 2.33$, indicating that at 95% confidence level, the system reliability is deteriorating with time. The existence of a trend requires the need for a time-dependent model of failure and repair rate.

After system failure data have been collected and trend tests conducted, maintenance strategy based on the condition of the equipment can now be apply to any critical distribution component that was identified from the statistical analysis.

The **second step** in the data analysis is to test if the times – between – faults (tpfs) are independent. This can be evaluated using the serial correlation coefficient of the tbf data. The tbf data is independent if the correlation coefficient is equal to 0, has perfect positive correlation if it is 1.0, and has perfect negative correlation if it is −1.0 [14].

The definition of linear correlation used here assumes that each set of data has exactly n samples. This means that the numbers of outage data collected from all feeders in the zone investigated were collected at the same time period when they were all subjected to the same climatic and operational conditions. The linear

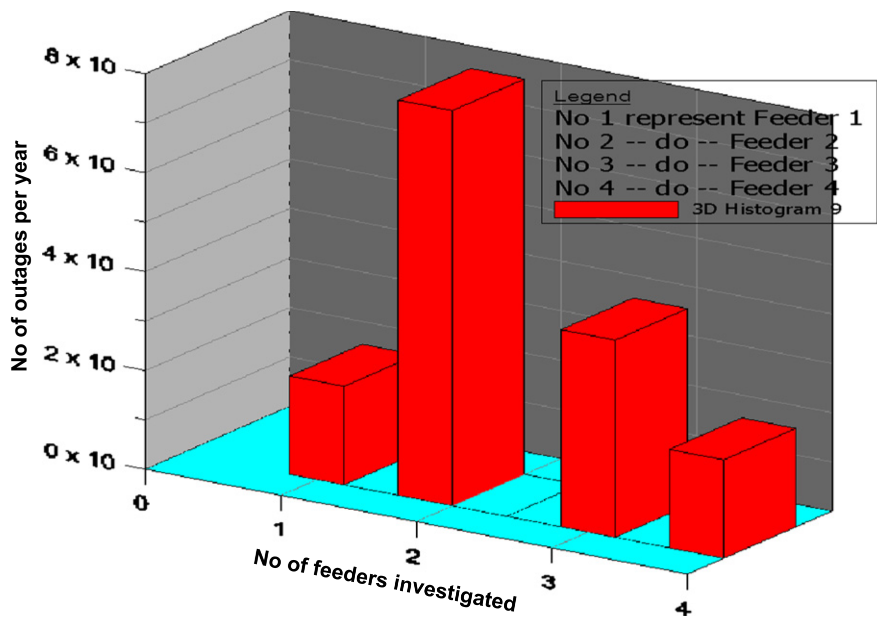

Fig. 9. Processed outage data for Ijaye Ojokoro feeders for 2004.

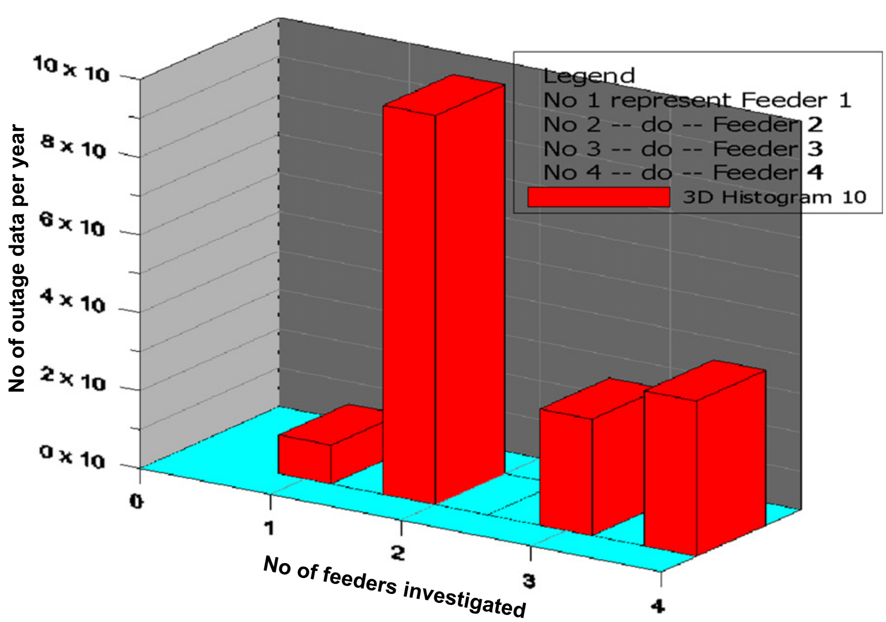

Fig. 10. Processed outage data for Ijaye Ojokoro feeders for 2005.

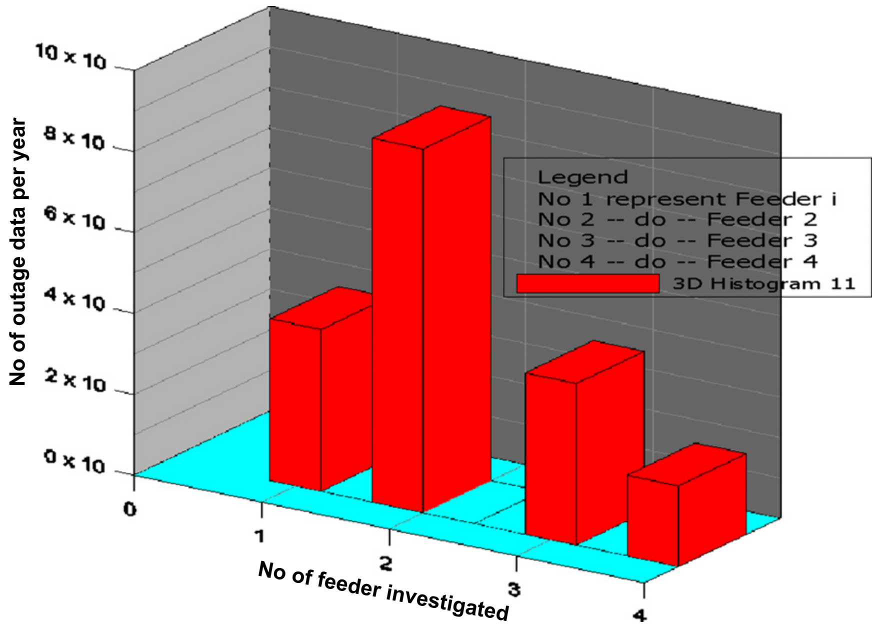

Fig. 11. Processed outage data for Ijaye Ojokoro feeders for 2006.

correlation (referred to in the statistical literature as Pearson's r) is obtained from

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}, \quad (3)$$

where $\bar{x} = \frac{1}{n}\sum_{i=1}^{n}(x_i)$ and $\bar{y} = \frac{1}{n}\sum_{i=1}^{n}(y_i)$

Since the observed sample values are random, the calculated value of r is also random [15]. When n is large (say, greater than 500), the distribution of r is approximately Gaussian [16].

The serial correlation coefficient for the data collected from the PHCN distribution systems used for the example data has a value of 0.388, indicating that the tbfs are largely independent. Strong evidence of correlation, positive or negative, would require a model incorporating interaction among faults.

4. Discussion and analysis of results obtained

The data structure has to be well thought out to be able to extract reasonable information from the collected data. The starting point for the statistical analysis is to attempt to gain a better understanding of properties of the raw data usually by imposing the corresponding empirical distribution of each of the component

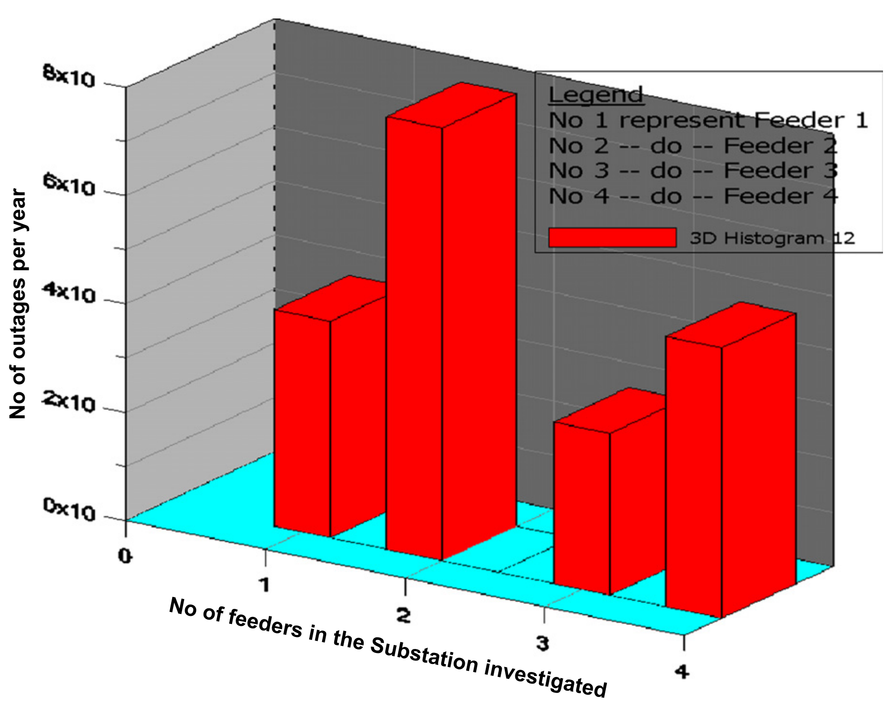

Fig. 12. Processed outage data for Ijaye Ojokoro feeders for 2007.

failure data. This was achieved by constructing a histogram over the sample space. Of the entire ten Business unit that made up the zone that was investigated, one of them was found to have the highest failure rate as revealed from the histogram plotted from the collected outage data for a period of 5 years (2004–2008). The graphical illustration of the outage data in Figs. 3–7 clearly shows that Abule-Egba Business unit recorded the highest failure rate. This Business Unit with the highest failure rate was selected for a more critical analysis.

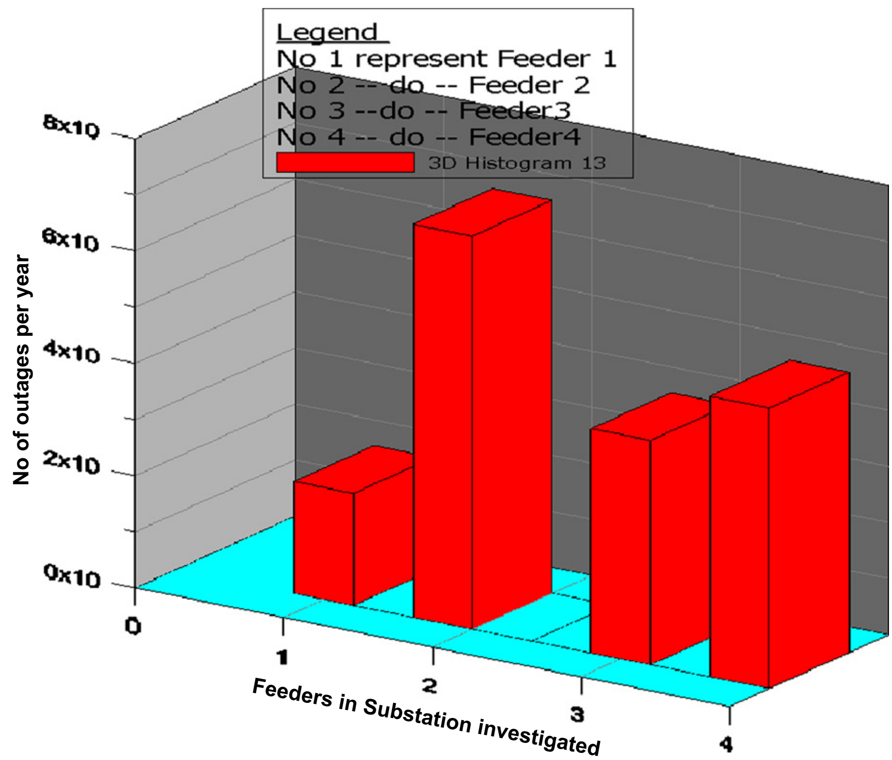

Fig. 13. Processed outage data for Ijaye Ojokoro feeders for 2008.

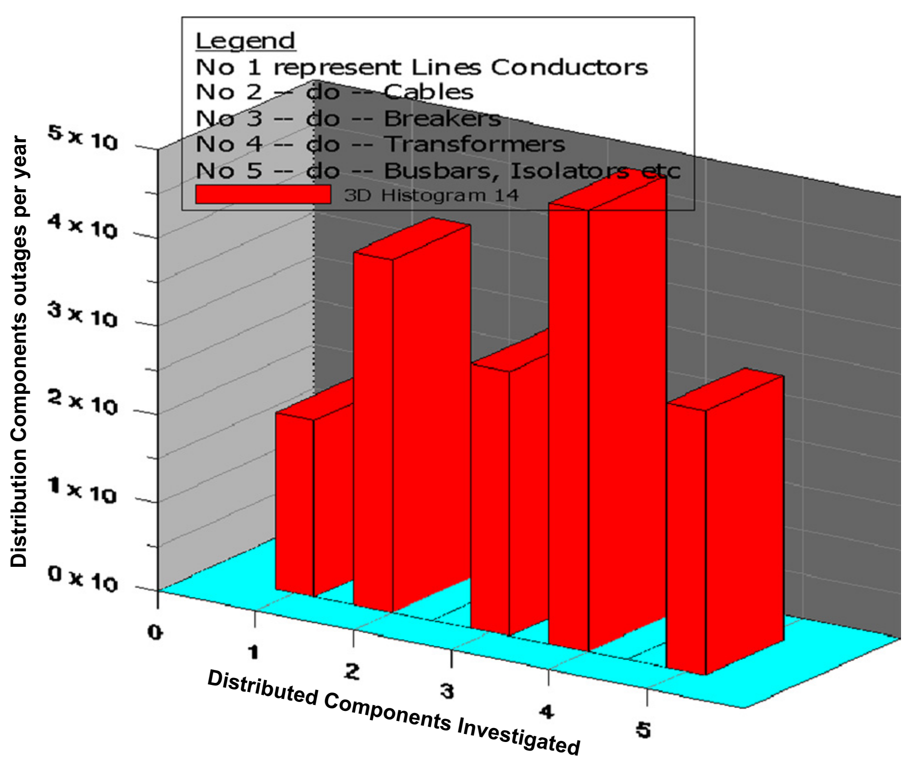

Fig. 14. Processed distribution components outages for 2004.

Fig. 8 represents the line diagram of this identified Abule-Egba Business unit that was found to contribute more to the outage data recorded when compared to other Business unit in the Zone. This unit containing four customers' feeders was identified as the most contributors to system failure and was therefore selected for more critical analysis to find out the Substation within this Business unit that could be responsible for this high rate of failure. From the analysis of the data collected from this unit, estimates of mean time between failures (MTBFs), failure rate [λ] and mean time to repair (MTTR) were determined for the whole Business unit containing this four customer's feeders [17]. The performance statistics from the synthesized failure data set for 5 years 2004–2008 is shown in Tables 1–5. The histogram plotted from the outage data as shown in Figs. 9–13 and the result of the failure rate shown in Tables 1–5 indentified that the feeder labeled 2 contributed more to the high rate of outages recorded in the Business unit. This Ijaye

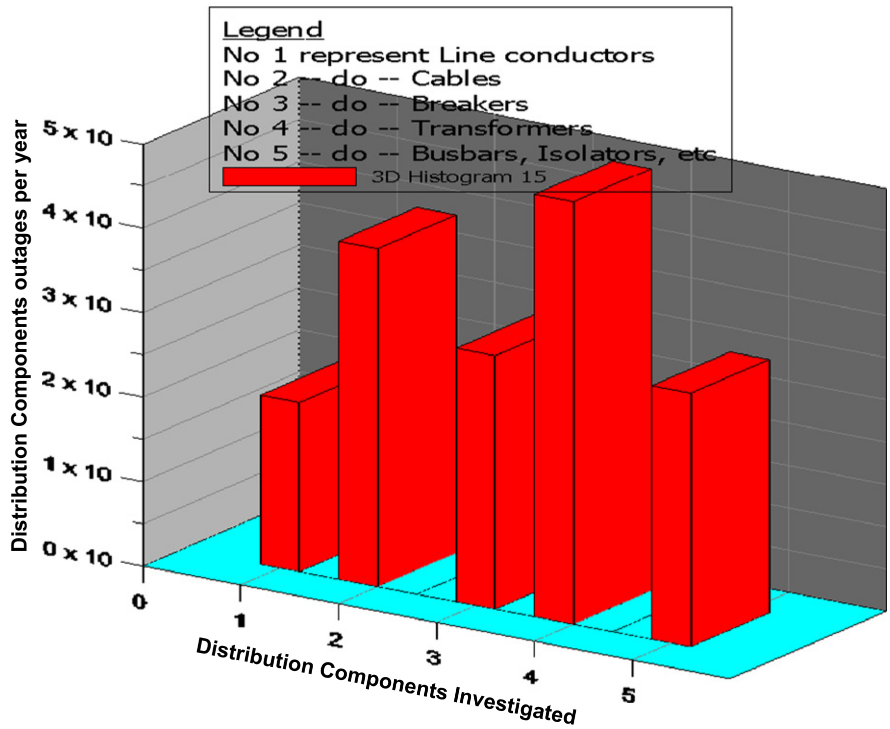

Fig. 15. Processed distribution components outages for 2005.

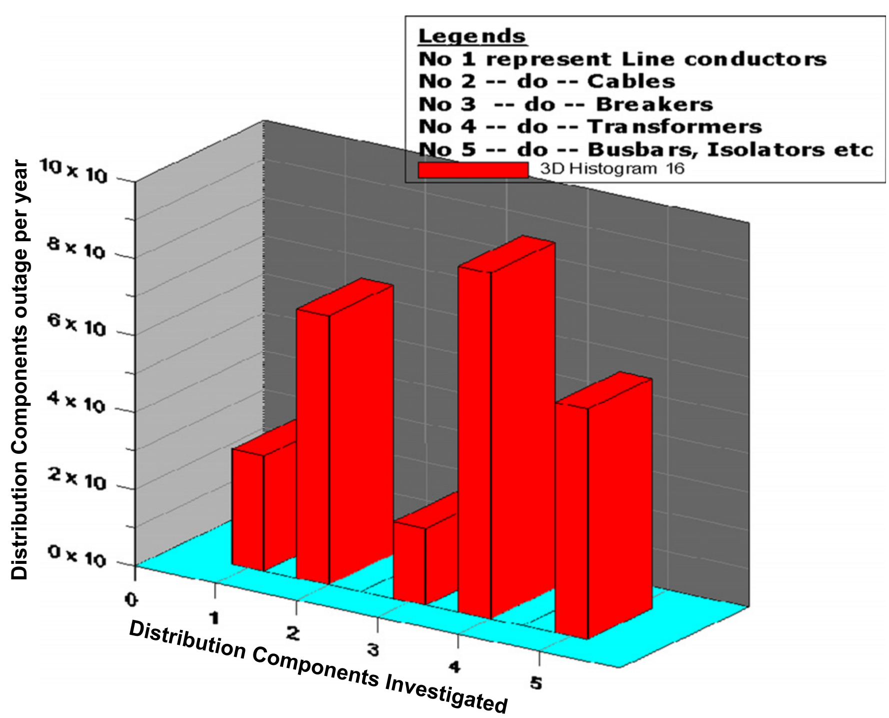

Fig. 16. Processed distribution components outages for 2006.

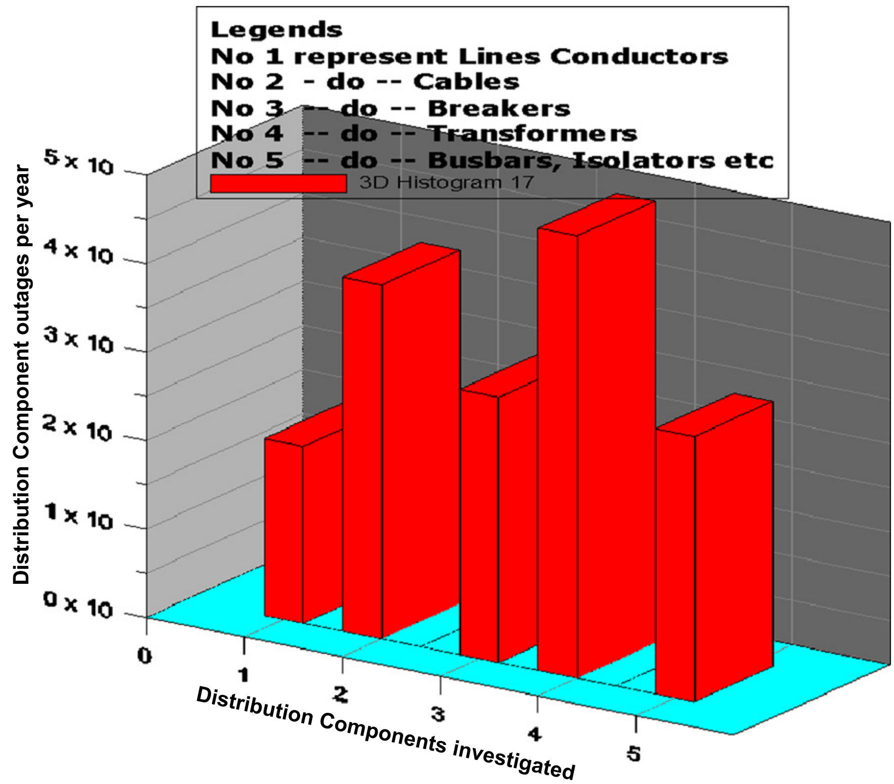

Fig. 17. Processed distribution components outages for 2007.

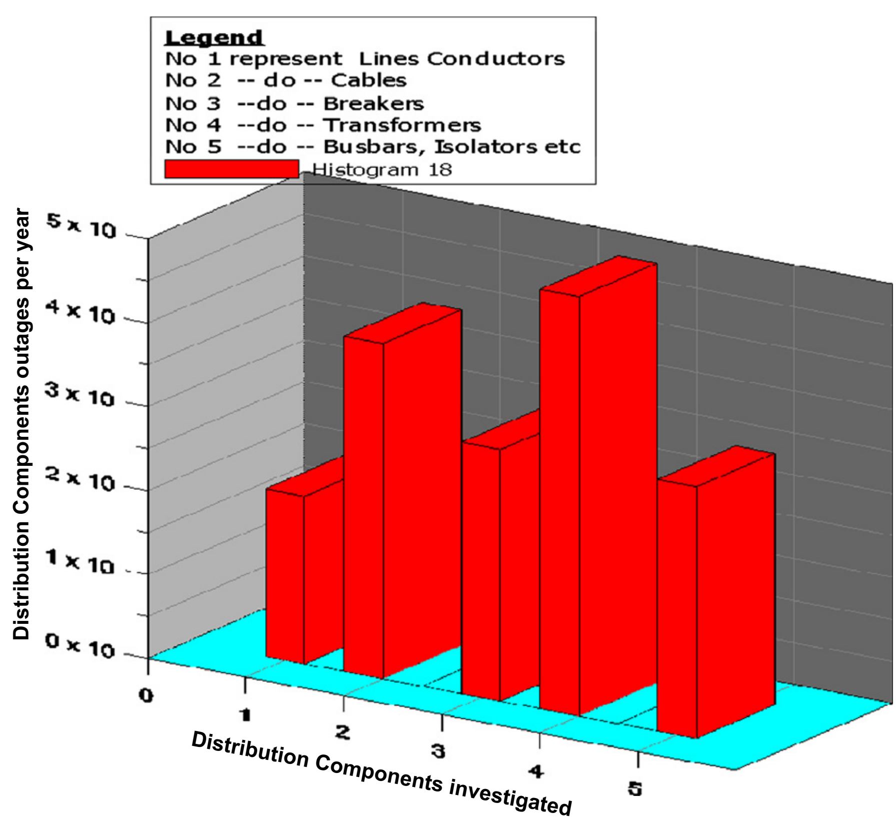

Fig. 18. Processed distribution components outages for 2008.

Table 1
Statistical Parameters from Outage Data for 2004.

	F_1	F_2	F_3	F_4	Total Substation
MTBF(days)	3.3	3.1	3.2	3.2	0.97
Failure rate λ (Failures/yr)	0.304	0.320	0.309	0.310	1.24
MTTR(days)	5.0	5.8	5.1	5.2	0.94

F_1, F_2, F_3, F_4, and F_5 represent Feeder_1, Feeder_2, Feeder_3, Feeder_4 and Feeder_5 respectively.

Table 2
Statistical Parameters from Outage Data for 2005.

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	1.6	1.5	2.6	1.6	0.99
Failure rate λ Failure/year	0.63	0.65	0.39	0.64	2.31
MTTR (days)	6.2	6.3	4.2	6.7	0.94

F_1, F_2, F_3, F_4, and F_5 represent Feeder_1, Feeder_2, Feeder_3, Feeder_4 and Feeder_5 respectively.

Table 3
Statistical Parameters from Outage Data for 2006.

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	1.7	1.65	2.63	1.69	**0.998**
Failure rate λ (Failures/year)	0.593	0.606	0.381	0.590	2.17
MTTR (days)	9.7	11.3	6.1	9.5	0.904

F_1, F_2, F_3, F_4, and F_5 represent Feeder_1, Feeder_2, Feeder_3, Feeder_4 and Feeder_5 respectively.

Table 4
Statistical Parameters from Outage Data for 2007.

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	2.06	1.65	2.67	1.72	0.998
Failure rate λ (Failures/year)	0.485	0.608	0.375	0.582	2.05
MTTR (days)	6.67	8.0	5.03	7.84	0.928

F_1, F_2, F_3, F_4, and F_5 represent Feeder_1, Feeder_2, Feeder_3, Feeder_4 and Feeder_5 respectively.

Table 5
Statistical Parameters from Outage Data for 2008.

	F_1	F_2	F_3	F_4	Total for Substation
MTBF (days)	2.17	2.15	3.07	2.31	0.97
Failure rate λ (Failures /year)	0.461	0.466	0.326	0.432	1.69
MTTR (days)	3.77	3.87	2.85	3.73	0.96

F_1, F_2, F_3, F_4, and F_5 represent Feeder_1, Feeder_2, Feeder_3, Feeder_4 and Feeder_5 respectively.

Ojokoro Injection substation (feeder No. 2) was now subjected again to a more critical analysis to find out which of the distribution components listed in Section 2.3 could be responsible to this high rate of failure recorded in feeder 2. The outage data collected from this particular feeder 2 was again processed and plotted as shown in Figs. 14–18. It was these plots that identified the component labeled 4 (transformer) as the major contributor to the outage data recorded in this feeder 2. This RCM approach had therefore facilitated the selection or identification of a transformer as the critical distribution components that possess the highest risk index to system reliability. The asset manager or maintenance personnel based on his knowledge of the criticality of the identified component will now make an informed decision as to the type of strategic maintenance method that can be adopted on this transformer that will lead to high availability with moderate maintenance costs.

5. Conclusion

In this work, an effective Maintenance planning program using statistical analysis of failure data as well as deciding which failure data are relevant using Laplace test analysis and Serial Correlation Coefficient techniques has been presented.

Various estimates of sample mean from failure data such as failure rate (λ), mean time between failures (MTBFs) and mean time to repairs (MTTRs), which are tools for reliability analysis yield immediate insight into the group of distribution feeders or components that are prone to failures.

This will aid in the selection of the critical components that possess the highest risk index to the system reliability and to recommend the maintenance strategy for tackling that critical component.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ijepes.2012.10.061.

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