TIME SERIES ANALYSIS OF OUTAGES IN FOUR NIGERIAN CITIES

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ABSTRACT

With the best maintenance policy and strategy, there is bound to be outages. The operation manager must be able to predict outages on the electric power distribution system in order to minimize outage time (mean time to repair) on the system. The occurrence of outages in four electric power distribution centers are studied. Outage data for ten years at each of the distribution were collected and analyzed. Autoregressive Moving Average (ARMA) models were developed to each of the centers using eight years of data. The model was used to predict two years ahead and the result obtained compare with two years of data. It was discovered that the prediction is accurate within 95% boundary and highly correlated with the original data. It was concluded that if operators can predict faults occurrence on their system, it will enhance fault management strategies thereby reducing outage time.

TIME SERIES MODEL[2]

Because of the uncharacterized relationship between all the variables contributing to faults in an electricity distribution dam, a model is developed which exhibits the same essential characteristics as the process under study, without attempting to identify the casual nature of the relationships between the various relevant interacting variables.

The dynamics of many physical systems can be expressed in terms of a differential equation of the form (1)

$$(1 + c_1 D + c_2 D^2 + \cdots)Y = (1 + d_1 D + d_1 D^2 + \cdots)X \qquad (1)$$

where Y is the output variable,
X is the input variable,
D is the differential operator, and
the c's and d's are constants.

Such structurally simple models can often describe complex systems adequately, even when the true nature of the system is not understood.

In the discrete-time case in which observations are taken at equally spaced intervals, the above differential equation evolves into a difference form as (2)

$$(1 + c_1 + c_2 \nabla^2 + \cdots)Y_t = (1 + d_1 + d_2 \nabla^2 + \cdots)X_t \qquad (2)$$

where ∇ denotes the backward difference operator, defined by $\nabla = Y_t - Y_{t-1}$

Similarly, the complex stochastic behavior of a random process $\{z_t\}$ can often be successfully described in terms of a difference equation relating $\{z_t\}$ to a much simpler random process – a "white noise" process, $\{a_t\}$, having zero mean, constant variance, and no correlation among its members:

$$(1 + c_1 + c_2 \nabla^2 + \cdots)z_t = (1 + d_1 + d_2 \nabla^2 + \cdots)a_t \qquad (3)$$

Assuming that there are a finite number of c's and d's. it is convenient here to introduce the backward shift operator B, where B is defined by $Bz_t = z_{t-1}$, and $B = 1 - \nabla$:

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)z_t = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)a_t \qquad (4)$$

Applying the polynomial operators to z_t and a_t, we may write this model as

$$z_t - \phi_1 z_{t-1} - \cdots - \phi_p z_{t-p} = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (5)$$

or

$$z_t = \phi_1 z_{t-1} + \cdots + \phi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (6)$$

This equation defines the basic model investigated by Box and Jenkins. It implies that the current observation can be represented as a finite linear combination of previous observations, plus a white noise error term associated with the current time period, plus a finite linear combination of white noise term associated with previous time periods.

Let Φ(B) and Θ(B) be polynomials as defined by equations 7 and 8

$$\Phi(B) = 1 - \phi_1 B - \cdots \phi_p B^p \qquad (7)$$

and

$$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \qquad (8)$$

Then the model of equation 4 may be re-expressed as

$$\Phi(B)z_t = \Theta(B)a_t \qquad (9)$$

The general model (9) is called a mixed autoregressive moving average (ARMA) process.

CAUSES OF INTERRUPTIONS

Some of the most common causes of failure [1].

1. Ageing: Every component has a specific useful life. Thus, even operating under ideal conditions, a component tends to wear-out and fail. Ageing is one of the most common factors causing in equipment failure and customer interruptions.
2. Loading/ Increased activity: Due to increased customer

demand during the hot season, the loading on the distribution equipment is increased. This in turn increases the operating temperatures of the equipment like distribution transformers, thereby making them more susceptible to failure. Increased activity in case of protective equipment like reclosers tend to make them prone to failure due to mechanical wear out that occurs in the moving parts.

3. Weather: Another important factor that influences the useful life of a component is its environment. Dusty and moist climates in general increase the tendency of all equipment to fail. Adverse weather conditions like lightning and wind storms increase the chances of equipment failure.
4. Vegetation: Trees are one of the greatest contributors to failures in distribution systems in the forest zone. Every year utilities spend a large portion of their investment to prevent trees and vegetation from growing into power lines [3]. Apart from causing outages due to faults arising from parts of trees touching the lines, growth of trees into the lines can cause increased momentary interruptions, increase in line losses and in some cases even catastrophic forest fires.
5. Animals and Pests: Increased animal activity near power equipment often results in outages that are hard to prevent. Animals like squirrels, snakes and birds often get trapped near power lines resulting in faults and interruptions. Other common causes include ants, termites etc.
6. Human Factors: Failures also arise due to human factors, some of them intentional while the others are unintentional. While the intentional ones like maintenance are often scheduled and the customer is informed, events like diggings, switching errors, accidents, etc. are unintentional and lead to failures.

As in other systems, in the electric power distribution system, effective management can only be attained by having empirical insight into the direction systems parameters are going. Managing faults on the system will involve deploying maintenance personnel and equipment, spare inventory control and staff training amongst others. Being able to know how many faults are currently on the system and if possible what is the likely number and types of faults in a short or long term will help the manager make informed decisions that will be profitable to the utility company and the consumers.

DATA COLLECTION FOR MODEL DEVELOPMENT

The dearth of electric distribution faults data in Nigeria is not an isolated case. Like in most countries, distribution authorities in Nigeria do not keep and /or release accurate fault data to outsiders. This is due to a number of factors that include the non-existence of such data and the fear that if long outages are reported, there may be backlash from government who is at present the sole owner of these utilities.

The fault data for the distribution systems at Abuja, Ilorin, Lagos Island and the Ikeja were collected over a period of thirteen years (1989 – 2002). Data was collected in the format shown in Table 3.1 below.

MODEL DEVELOPMENT

A plot of the original normalized data and an estimated linear trend for the distributions are shown in Figures 1 to 4. The difference

In order to remove the trend, a lowpass filter was designed to remove the trend from the system before analysis. The transfer function of the first order digital filter is given as

$$H(z) = z/(z-a) \qquad (10)$$

Transforming to time domain,

$$za/(z-e^{-saT}) = y_k / u_k \qquad (11)$$

$$\hat{y}_{k+1} = \beta\hat{y}_k + \alpha\hat{y}_{k+1} \qquad (12)$$

where

$$\alpha = \ln\beta$$

$$\beta = e^{-sat}$$

After many trials, it was discovered that a value of 0.8 for α gives a very reasonable estimate. Figure 1 to Figure 4 shows the plot of the estimated trends, original data and the residue for Abuja, Ikeja, Ilorin and Lagos.

Table 1: Part of Fault Records for Ilorin (First 4 Months)

Month	S	D	T	WC	WS	B	**FB**	**G**	**Total Faults**
1	3	1	6	2	3	1	4	1	21
2	4	2	5	1	2	1	1	2	18
3	5	1	4	3	1	1	2	1	18
4	3	1	3	2	1	3	3	2	18

S – Single Phase Fault; D – Double Phase Fault; T – Three Phase Fault; WC – Wire Cut; WS – Wire Twisted; B – Blown Feeder Pillar; FB – Fuse Blown

A – Grounded Phase

By inspecting the autocorrelation plots, the partial autocorrelation plots and the spectrogram of the residues it was observed that it can be predicted by an ARMA series of order 4.

The estimation of the parameters of the time series was done in MATLAB using the Systems Identification toolbox.

The first hundred months of the residues used to estimate model parameters. After estimation, the models were examined for stability by examining the transient responses and the poles and zeroes. All the models were found to be stable.

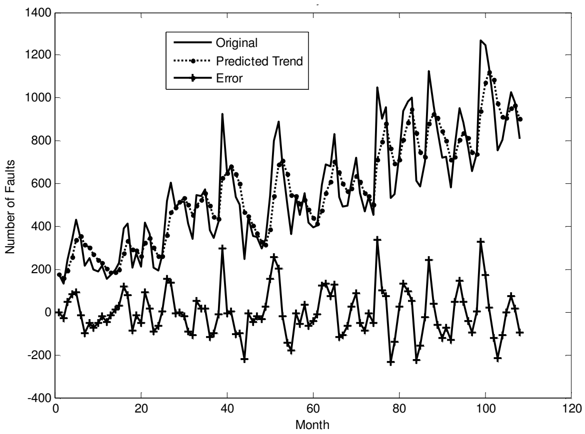

Figure 1. Plot of estimated trends, original data and the residue for Abuja

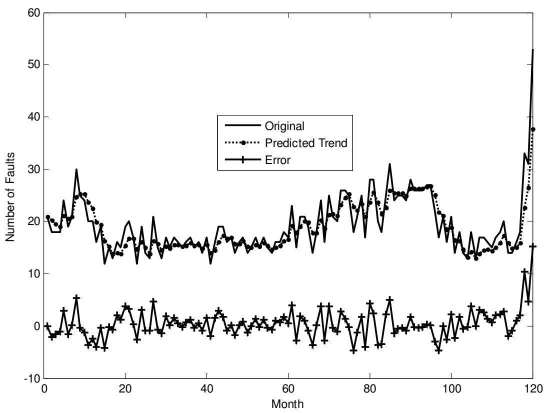

Figure 2. Plot of estimated trends, original data and the residue for Ikeja

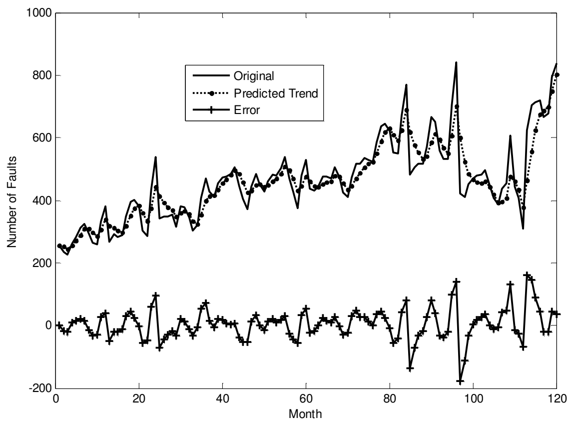

Figure 3. Plot of estimated trends, original data and the residue for Ilorin

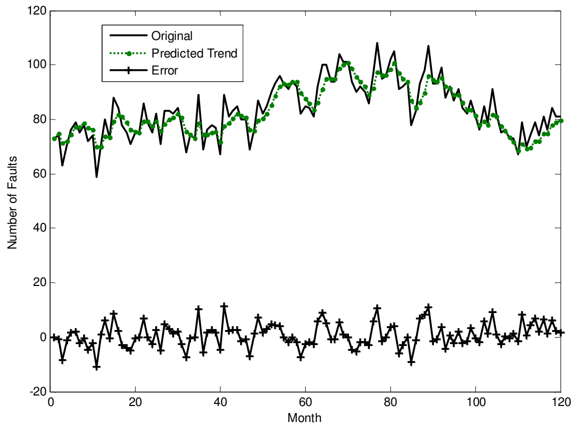

Figure 4. Plot of estimated trends, original data and the residue for Lagos

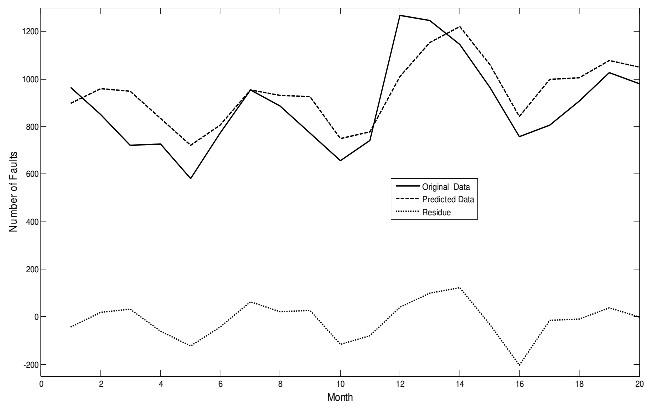

Figure 5. Plot of original data, predicted data and the residue for Abuja.

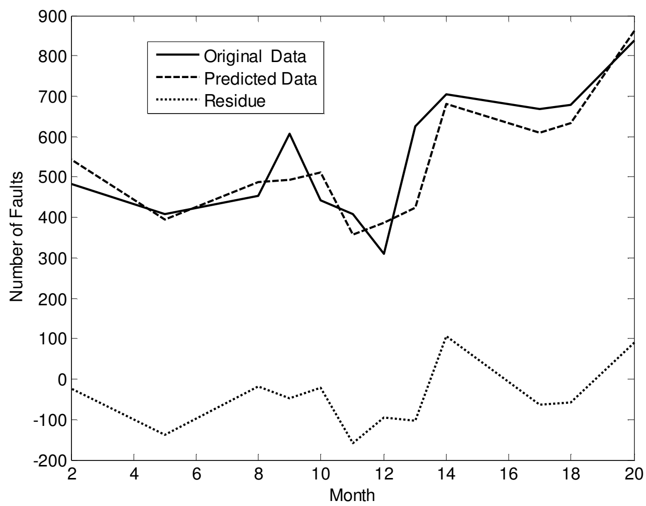

Figure 6. Plot of original data, predicted data and the residue for Ikeja.

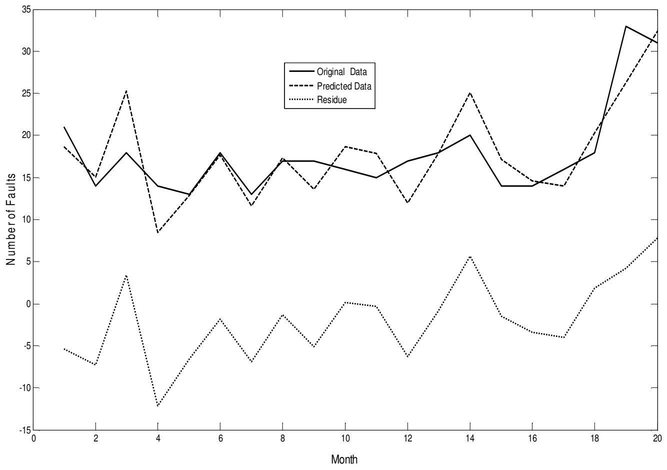

Figure 7. Plot of original data, predicted data and the residue for Ilorin.

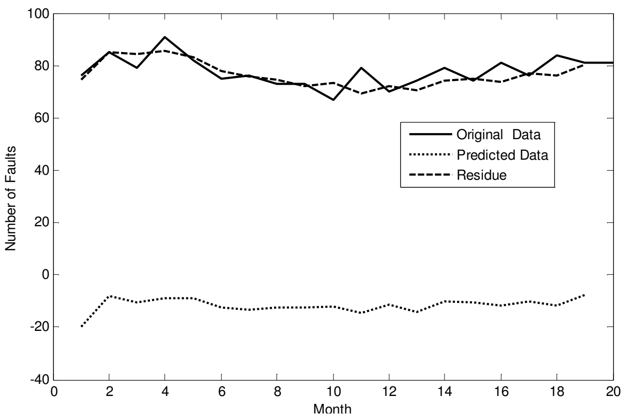

Figure 8. Plot of original data, predicted data and the residue for Lagos.

The estimates for the trends are as in equation (12).
The models for the difference in filtered data and the original data are given as $A\, z_t = C\, a_t$ as in equation 9.

The models for the different cities are given in equations 13 to 17.

For Abuja,
$A = 1+ 1.155\ B^{-1} + 1.027\ B^{-2} + 0.6776\ B^{-3} + 0.9146\ B^{-4}$
$C = 1 + 1.445\ B^{-1} + 1.456\ B^{-2} + 1.245\ B^{-3} + 0.9038\ B^{-4}$
For Ikeja,

$A = 1 - 1.01\ B^{-1} + 0.5431\ B^{-2} + 0.335\ B^{-3} - 0.4686\ B^{-4}$
$C = 1 - 0.606\ B^{-1} + 0.584\ B^{-2} + 0.4132\ B^{-3} + 0.05118\ B^{-4}$
For Ilorin

$A = 1 - 1.752\ B^{-1} - 0.05355\ B^{-2} + 1.752\ B^{-3} - 0.846\ B^{-4}$
$C = 1 - 1.106\ B^{-1} + + 0.5044\ B^{-2} + - 1.122\ B^{-3} + 0.782\ B^{-4}$

For Lagos,
$A = 1 - 1.37\ B^{-1} + 0.9214\ B^{-2} - 0.2404\ B^{-3} - 0.3287\ B^{-4}$
$C = 1 - 1.012\ B^{-1} + 0.6311\ B^{-2} + 0.08123\ B^{-3} - 0.5308\ B^{-4}$

The models were used to predict the next twenty months and the results of the predictions are as shown in Figure 5 to Figure 8

CONCLUSION

Time series models were developed for number of faults on four distributions. From the results, even though the data were from different environments, it is possible to accurately predict the number of faults that will occur in a utility. This can help managers to plan for stock acquisition, staff training and equipment, as such the time to repair faults can be considerably shortened

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3. Yuan L., (2005). "Risk Based Asset Management for Utility: Preventive Maintenance Resource Allocation"; M.S. Dissertation, Iowa State University.