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## Forecasting on Electrical Power Distribution Transformers

By

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### **ABSTRACT**

*Prediction of the remaining life of high-voltage power transformers is an important issue for energy usage because of the need for planning maintenance and capital expenditures. Lifetime data for such transformers are complicated because transformer lifetimes can extend over many decades and transformer designs and manufacturing practices have evolved. We were asked to develop statistically based predictions for the lifetimes of an energy company's fleet of high-voltage transmission and distribution transformers. Data were collected from the utility main-substation in Warri a city in Delta State, Nigeria with transformer rating: 2 x 15 MVA, with HV/LV of 33/11kV. These data were obtained from the log of daily recordings. These data collected were processed by using Excel Tools and Analysis ToolPak for over a year. The data obtained was observed that the oil and winding temperatures are almost constant as there are variations in the IN\_loads and OUT\_loads data for transformers 1 and 2. A statistical procedure, based on age-adjusted life distributions was developed, for computing a prediction interval for remaining life for two transformers in service. Extension of the idea provide predictions and prediction intervals for the cumulative number of failures, over a range of time, for the overall fleet of transformers.*

### **INTRODUCTION**

Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact forecasts. The process of forecasting can take on many different approaches that results in different methods. The approaches are appropriate for a given forecasting situation depends largely on the type of data available. Forecasting of electricity is one of the basic activities during energy sector planning process. Electricity consumption is observed within current and expected/planned development of economy with simultaneous observation of the influence of energy demand on economy development. The precise forecast is important for any organization because it determines the dynamics and characteristics of future construction of power facilities of the system. Precise forecasting requires both statistical data during forecasting period. Forecasts can be classified on short-term, mid-term and long-term forecasts with respect to forecasting period. Nowadays several methods for energy forecast are developed. References [1-3] give a large insight in possibility of application of different methodologies.

Electricity demand forecasting plays an important role for the management of power systems. A good electrical load forecast shows direct and significant impact on cost - generating unit start-ups and shutdowns, energy purchases, managing system demand as well as scheduling

system upgrades based on predicted load growth. Load forecasting can be classified as (a) short range (~day), (b) medium range (~1 week to 1 month) and (c) long range (several years). Long term forecasts of the electricity demand are required for capacity planning and maintenance scheduling. Medium-term demand forecasts are required for power system operation and planning. Short-term load forecasts are required for the control and scheduling of power systems. Each class of load forecasting uses different models to meet the specific objectives of the application. Load forecasting plays a pivotal role in the formulation of economic, reliable and secure operating strategies for the power system [4-5].

**METHODS**

Data were collected from the utility main-substation in Warri a city in Delta State, Nigeria with transformer rating: 2 x 15 MVA, with HV/LV of 33/11kV. These data were obtained from the log of their daily reading. The information of the name plate of the transformers includes the following: Phase: 3 – phase, Ampere: 787.3A, Connection: Delta – Star, Winding Temp: 60°C, Oil Temp: 55°C under load condition; 45°C under no load and Cooling nature: Oil natural and air natural (ONAN). These data collected were processed by using Excel Tools and Analysis ToolPak for weekly for over a year. The data obtained it can be observed that the oil and winding temperature are almost constant as there are variations in the IN loads and OUT loads data for transformers 1 and 2.

**Top oil power transformer temperature model**

The model for top oil temperature rise over ambient temperature captures that an increase in the loading current of the transformer will result in an increase in the losses within the device and thus an increase in the overall temperature. This temperature\_change depends upon the overall thermal time constant of the transformer, which in turn depends upon the heat capacity of the transformer, i.e. the mass of the core, coils, and oil, and the rate of heat transfer out of the transformer. As a function of time, the temperature change is modelled as a first-order exponential response from the initial temperature state to the final temperature state as given in the following equation [6].

In the IEEE model, the final (ultimate) temperature rise depends upon the loading and approximately can be obtained by the following equation [7]:

$$\Delta_{ou} = \Delta_{fi} \left[ \frac{K^2 * R + 1}{R + 1} \right]^n \tag{1}$$

Where  $\Delta_{fi}$  is the full load top oil temperature rise over ambient temperature obtained from an off-line test.  $R$  is the ratio of load loss at rated load to no-load loss.  $K$  is the ratio of the

specified load to rated load  $K = \frac{I}{I_{rated}}$  and  $n$  is an empirically derived exponent that depends on the cooling method. The top-oil time constant at the considered load is given by the equation below:

$$T_{To} = \frac{C_{th.oil} * \Delta_{Toil}}{q_{tot.rated}} * 60 \tag{2}$$

Where  $T_{TO}$  is the rated top-oil time constant in minutes,  $\Delta_{n\ Toil}$  is the rated top-oil temperature rise over ambient temperature,  $q_{tot.rated}$  is the total supplied losses (total losses) in watts (W), at rated load and  $C_{th.oil}$  is the equivalent thermal capacitance of the transformer oil (Wh/°C). The equivalent thermal capacitance of the transformer oil is given by the following equation (2) as below [8]:

$$C_{th.oil} = 0.48 * M_{oil} \tag{3}$$

Where  $M_{oil}$  is the weight of the oil in kilograms (kg).

**ANALYSIS AND SIMULATIONS OF LOAD FORECASTING FOR WARRI UTILITY POWER DISTRIBUTION TRANSFORMERS**

The major part of the current electrical network of Warri utility power distribution has been built in the 60s. A lot of the electrical equipment in the network is reaching the end of its lifetime in the coming years. Therefore, and due to the historical developments in the network structure, reliability is low compared to Nigerian electricity regulation commission (NERC). Also the operation of the network and detection of faults is difficult this was due to incessant power outages from natural causes or man-made. The forecasting of electrical load for Warri utility power distribution system is fulfilled for the period from September 3, 2016 to December 23, 2017. The forecast of consumption of the Warri utility power system in graphical view for different scenarios of the economic development can be seen in Figures 5.

For forecasting of Latvian Republic electrical load must take into account:

1. the actual load of 2 x 15 MVA transformers substations by measurements for the period under consideration;
2. load of consumers growing by years includes Ogunu, Road Bendel and GRA all in Warri;
3. marketable power of new objects;
4. Technical possibilities to cover new declared powers and other factors.

The variants of forecast are taken for:

1. 3% - percent year load growing, beginning the period under consideration;
2. 2% - percent year load growing in disadvantaged scenario due to incessant power outages from natural causes or man-made.

The deteriorating economic situation leads to the need to periodically adjust the previously made predictions.

**Table 1:** IN\_load forecast for Transformer 1

Month	Average Data	Forecast Data	Column1	Lower Bound	Upper Bound
Aug/2016	1065.86				
Sep/2016	1102.96				
Oct/2016	1085.96				
Nov/2016	1037.17				
Dec/2016	1082.55				

Jan/2017	1082.17	1082.17	1082.17		
Feb/2017		1075.36	1075.36	1028.42	1122.31
Mar/2017		1077.22	1077.22	1029.35	1125.08
Apr/2017		1079.07	1079.07	1029.21	1128.94
May/2017		1080.93	1080.93	1027.69	1134.17
Jun/2017		1082.79	1082.79	1024.68	1140.89
Jul/2017		1084.64	1084.64	1020.17	1149.11
Jul/2017		1086.38	1086.38	1014.62	1158.14

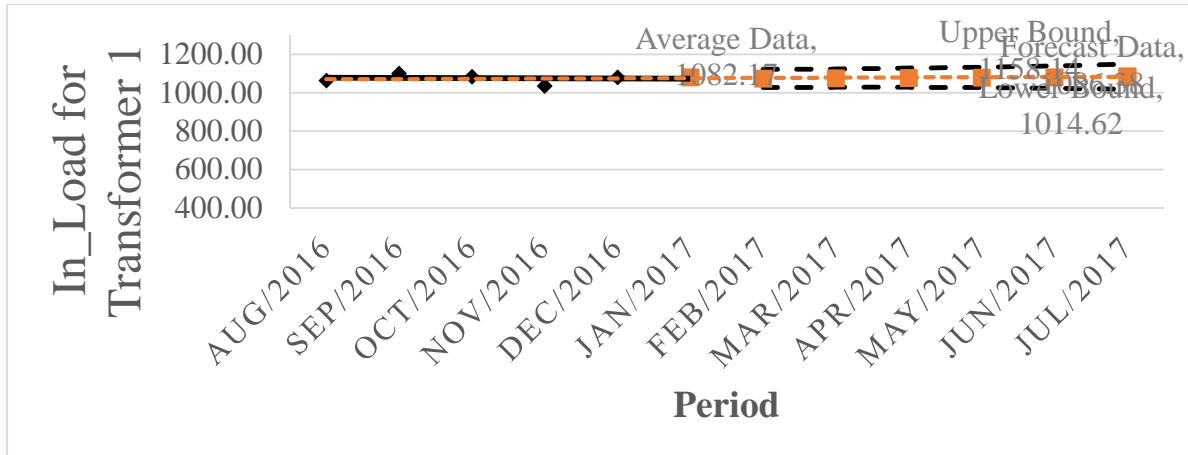


Figure 1: shows average IN\_load of transformer 1 showing the IN\_load data not fitting into the regression line while the forecasted load with upper and lower band as the forecasted data fitting into the regression line.

Table 2: OUT\_load forecast for Transformer 1

Month	Average Data	Forecast Data	Column1	Lower Bound	Upper Bound
Aug/2016	681.53				
Sep/2016	714.95				
Oct/2016	707.05				
Nov/2016	719.61				
Dec/2016	760.30				
Jan/2017	694.23	694.23	694.23		
Feb/2017		724.56	724.56	669.92	779.20
Mar/2017		728.94	728.94	672.61	785.27
Apr/2017		733.33	733.33	675.34	791.32
May/2017		737.71	737.71	678.10	797.33
Jun/2017		742.10	742.10	680.89	803.30
Jul/2017		746.48	746.48	683.71	809.25
Jul/2017		750.72	750.72	686.46	814.99

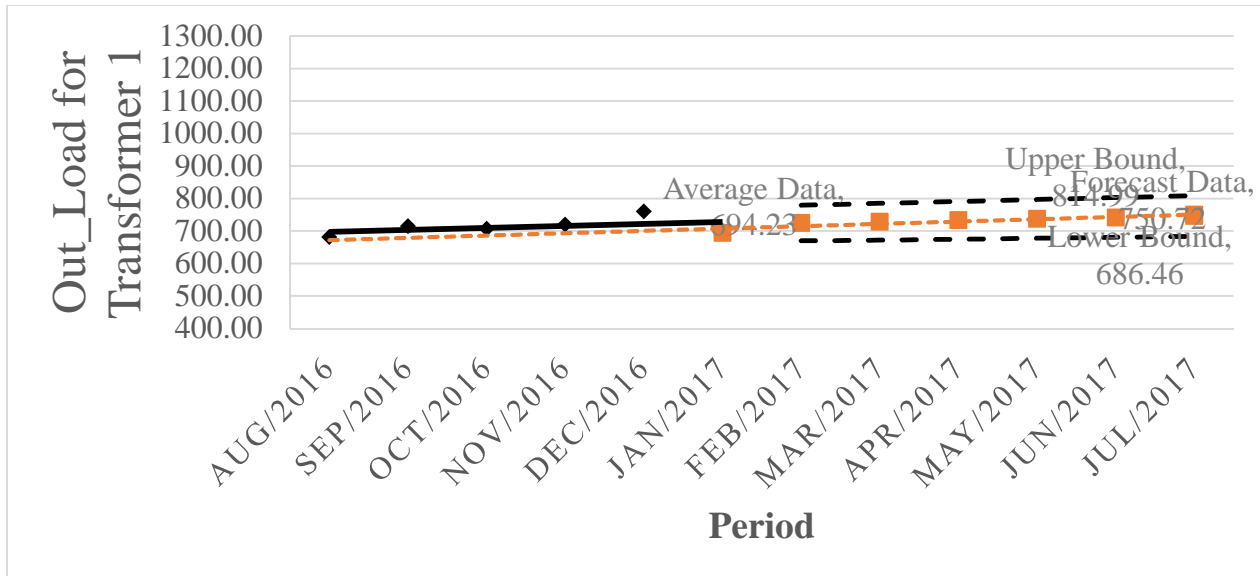


Figure 2: shows average OUT\_load of transformer 1 showing the OUT\_load data not fitting into the regression line while the forecasted load with upper and lower band as the forecasted data fitting into the regression line.

Table 3: IN\_load forecast for Transformer 2

Month	Average Data	Forecast Data	Column1	Lower Bound	Upper Bound
Aug/2016	1113.29				
Sep/2016	1025.41				
Oct/2016	1001.37				
Nov/2016	1064.02				
Dec/2016	1089.48				
Jan/2017	1138.61	1138.61	1138.61		
Feb/2017		1153.56	1153.56	1050.01	1257.12
Mar/2017		1171.73	1171.73	1032.33	1311.12
Apr/2017		1189.89	1189.89	1022.09	1357.69
May/2017		1208.06	1208.06	1015.96	1400.15
Jun/2017		1226.22	1226.22	1012.53	1439.91
Jul/2017		1244.38	1244.38	1011.04	1477.73
Jul/2017		1261.37	1261.37	1011.03	1511.74

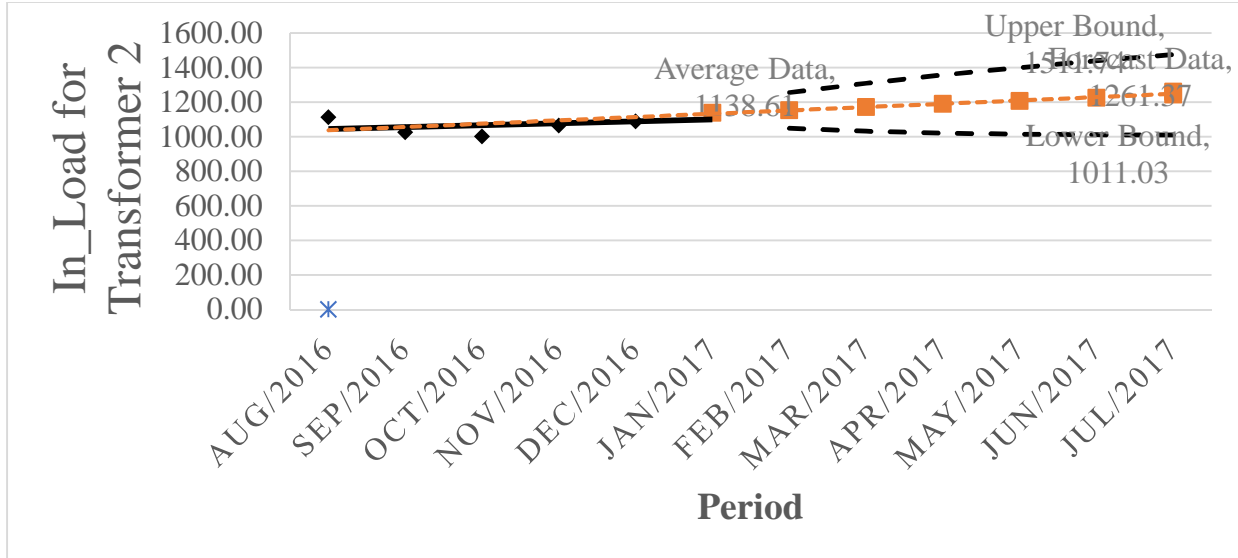


Figure 3: shows average IN\_load of transformer 2 showing the IN\_load data not fitting into the regression line while the forecasted load with upper and lower band as the forecasted data fitting into the regression line.

Table 4: OUT\_load forecast for Transformer 2

Month	Average Data	Forecast Data	Column1	Lower Bound	Upper Bound
Aug/2016	792.35				
Sep/2016	772.35				
Oct/2016	753.45				
Nov/2016	795.33				
Dec/2016	792.27				
Jan/2017	662.39	662.39	662.39		
Feb/2017		693.46	693.46	615.74	771.17
Mar/2017		676.98	676.98	599.27	754.70
Apr/2017		660.51	660.51	582.79	738.22
May/2017		644.03	644.03	566.32	721.75
Jun/2017		627.56	627.56	549.84	705.28
Jul/2017		611.08	611.08	533.37	688.80
Jul/2017		595.14	595.14	517.42	672.86

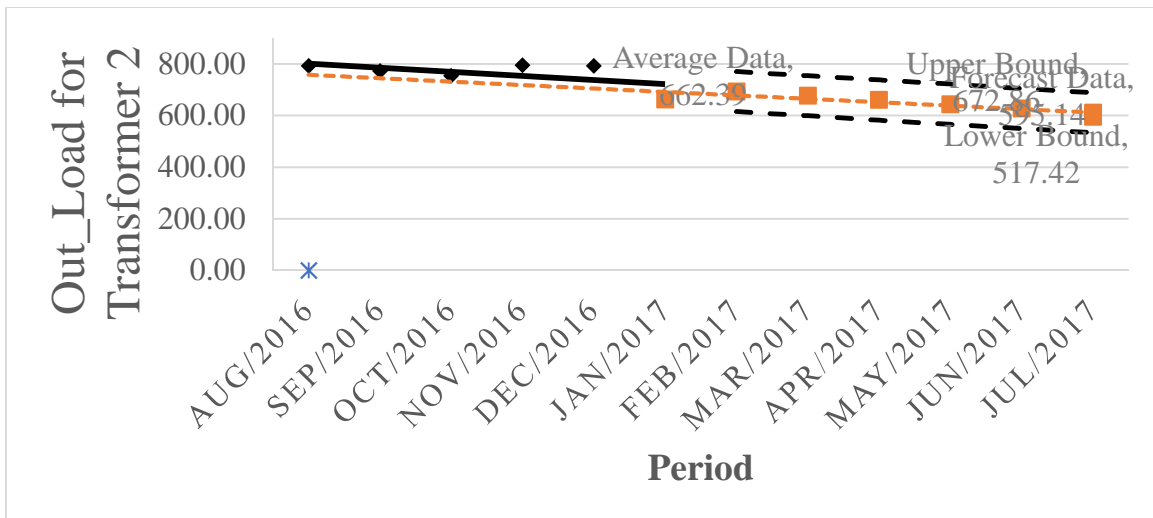


Figure 4: shows average OUT\_load of transformer 2 showing the OUT\_load data not fitting into the regression line while the forecasted load with upper and lower band as the forecasted data fitting into the regression line.

Table 5: Regression table for Transformers 1 and 2.

**REGRESSION FOR IN\_LOAD AND OUT\_LOAD (T<sub>1</sub> AND T<sub>2</sub>)**

MONTH	Average IN_Load_1 (MW)	Average OUT_Load_1 (kV)	Average IN_Load_2 (MW)	Average OUT_Load_2 (kV)
Aug 16	1065.86	681.53	1113.29	792.35
Sep 16	1102.96	714.95	1025.41	772.35
Oct 16	1085.96	707.05	1001.37	753.45
Nov 16	1037.17	719.61	1064.02	795.33
Dec 16	1035.82	707.69	1009.71	747.36
Jan 17	1082.17	694.23	1138.61	662.39

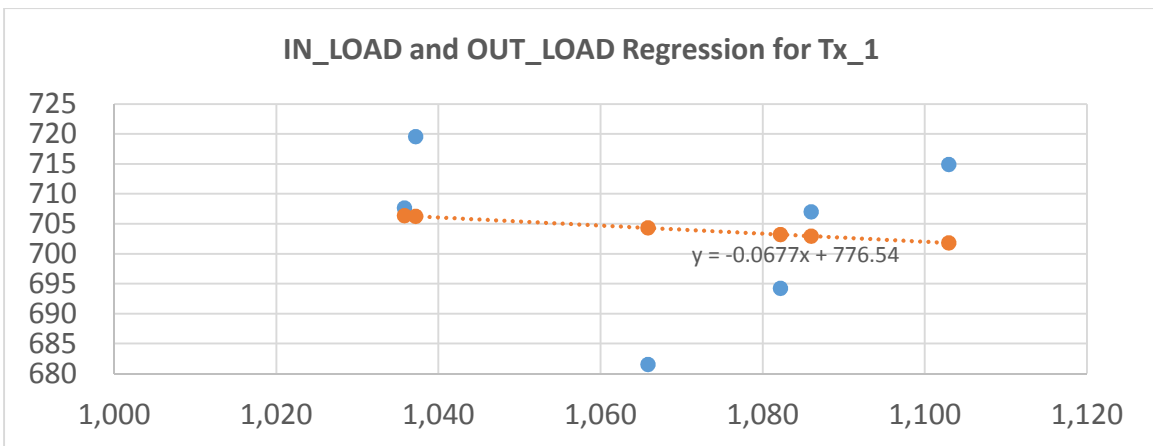


Figure 5: Regression analysis carried out on IN\_ and OUT\_load Transformer 1

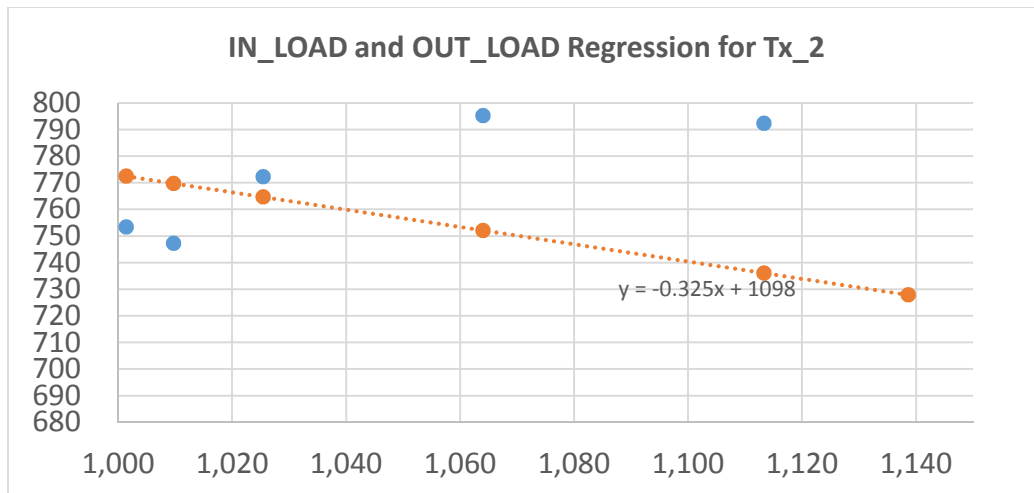


Figure 6: Regression analysis carried out on IN\_ and OUT\_load Transformer 2

Loading considerations for paralleling transformers are simple unless kVA, percent impedances or ratios are different. When paralleled transformer turn ratios, and percent impedances are the same, there will be equal load division on each transformer. When paralleled transformer kVA ratings are the same, but the percent impedances are different, then unequal load division will occur. The same is true for unequal percent impedances and unequal kVA. Circulating currents only exist if the turn ratios do not match on each transformer. The magnitude of the circulating currents will also depend on the X/R ratios of the transformers. Delta-delta to delta-wye transformer paralleling should not be attempted.

## CONCLUSION

Prediction intervals for the individual transformers are often too wide to be directly useful in determining when a transformer should be replaced, the quantitative information does provide a useful ranking for setting priorities in maintenance scheduling and for selecting transformers that need special monitoring attention or more frequent inspections to assess their health. The prediction intervals for the cumulative number of failures over time for the population of the transformers are useful for capital planning.

The prediction intervals for individual transformers tend to be wide. If usage and/or environmental information for the individual transformers were available (e.g., load, ambient temperature history, and voltage spikes, etc.).

Further developments may be needed to compute appropriate prediction interval procedures. If engineering knowledge can provide information about the shape parameter of the lifetime distribution of the transformer or regression coefficients could be used to take advantage of the prior information and could narrow the width of the prediction intervals. Regression analysis can be done directly on remaining life.



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