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Weekly Forecast of Electrical Power Distribution Transformers in Warri Metropolis

Dr. Eyenubo, Ogheneakpobo Jonathan
(Department of Electrical/Electronic Engineering, Delta State University, Oleh Campus, Nigeria).
Corresponding Author: Dr. Eyenubo

ABSTRACT: There is no single forecast that can satisfy all of the needs of utility. A common practice is to use different forecasts for different purposes. With so many applications, it is unrealistic to establish a forecasting problem for each application. Therefore, we have to take a scientific approach to classifying the load forecasting problems. The classification of various forecasts not only depends upon the business needs of utilities, but also on other factors that drive the electricity consumption. Data was 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. Forecasting of power transformer reliability or more accurately forecasting power transformer failure probability presents a predictive model.

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I. INTRODUCTION

In electrical power transmission and distribution networks power transformers represent a crucial group of assets both in terms of reliability and of investments. The major concerns which drive asset managers to decisions are related either to the age of equipment or to the power demands that have increased over the years. In order to safeguard the required quality at acceptable cost, it is of great importance to base decisions on a reliable forecast of future behaviour. Most transformer lifetime models developed arelimited to the degradation of the transformer winding insulation. Developing an integral transformer lifetime model involves all relevant degradation mechanisms for relevant subsystems, applicable to individual power transformers and transformer populations and allowing for a variety of external input (measured data, historical information) to improve the forecast accuracy [1-4].

Forecast is known as the capability to predict conditions and events in the future. Its main purpose is the reduction of the risk involved in decision making. Load forecasting, also referred to as electricity demand forecasting, is being used within all sectors of the electric power industry, including generation, transmission and distribution. It could be generalized into threecategories which are long-term, medium-term, and short-term forecast. The long-term forecast is intended for capital investment studies and it covers a range from 1 to 10 years. The medium-term forecast focus on fuel scheduling and maintenance for several years in intervals of one month. The short-term forecast involves knowledge of the demand from minutes to a few days. Information resulting from the short-term forecast is fundamental to the system operations in terms of demand scheduling of generation units and economic and secure operation of power systems [6-5].

II. METHODOLOGY OF LOAD FORECASTING ON TRANSFORMER

Load forecast is used to provide decision-making support for several aspects of utility power supply that includes the integrated resource plan, revenue requirements, rate design, system planning then operations and service plans. Ranges in the load forecasts referred to as uncertainty bands are developed using simulation methods (Excel Tools and Analysis ToolPak). These bands represent the expected ranges around the annual reference load forecasts at certain levels of statistical confidence. This forecast is produced because there may be uncertainty in the variables that predict future loads and in the predictive powers of the forecasting models. The demand is based on estimating the future demands of larger customers which are driven by future market conditions and company-specific production plans. Load forecasting on transformers at constant oil and winding temperature can be expressed the relation below [9-10].

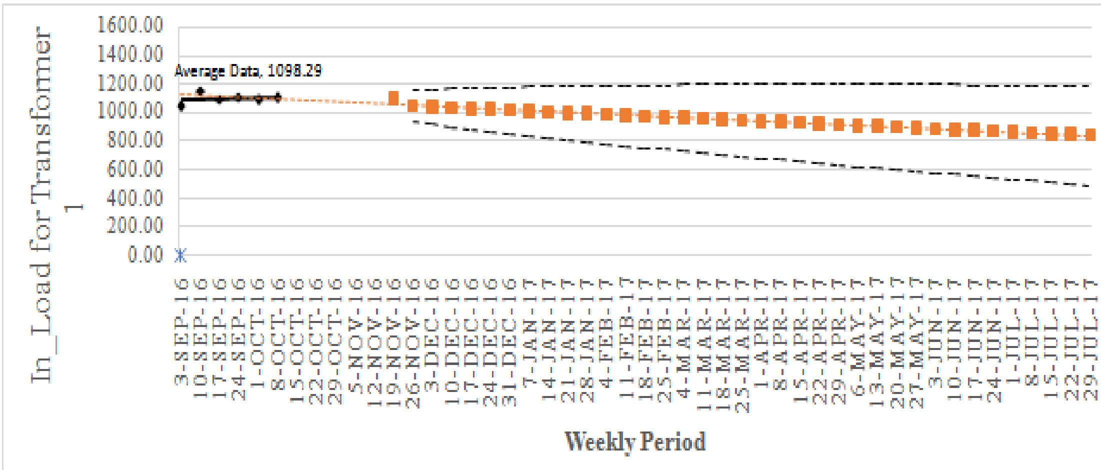
Forecasting is made for 2 x 15 MVA transformers in the main power station. The perspective transformer substations can appear with irregular growing of load in different districts of state or if the load of existing transformer substation is not enough due to big load compactness in the district. The data provided include: Electricity load demand recorded every day from August, 2016 to January, 2017. The task is to supply the prediction of maximum weekly values of electrical loads and evaluation of submissions would mainly depend on the results [11].

For time-series, data are extracted for entries for the period of August 28, 2016 to January 21, 2017 to form the validation set for evaluation and simulation. The performance is decided by averaging the IN_loads, the forecast for average IN_loads for transformers 1and 2 and the averaging the OUT_loads, the forecast for average OUT_loads for transformers 1and 2.

Table 1: from 28th August, 2016 to 7th January, 2017 are the obtained loads from the transformers; while from 8th January, 2017 to 21st January, 2017 are the predicted loads.

WEEKLY MEAN DATA FROM 28 AUGUST 2016 TO 21 JAN 2017								
Ordinal Week	Interval	Week Ending	Average IN_Load_1 (MW)	Average OUT_Load_1 (kV)	Average IN_Load_2 (MW)	Average OUT_Load_2 (kV)	Average XT_Oil Temp	Average XT_Winding Temp
1	28 Aug 16 - 3 Sep 16	3-Sep-16	1040.26	694.07	1068.63	780.02	48.00	51.00
2	3 Sep 16 - 10 Sep 16	10-Sep-16	1153.13	745.31	1069.95	797.00	48.00	51.00
3	11 Sep 16 - 17 Sep 16	17-Sep-16	1092.54	702.60	1071.84	795.67	48.00	51.00
4	18 Sep 16 - 24 Sep 16	24-Sep-16	1110.74	708.07	945.84	762.74	48.00	51.00
5	25 Sep 16 - 1 Oct 16	1-Oct-16	1090.73	696.23	1024.95	728.66	50.23	50.63
6	2 Oct 16 - 8 Oct 16	8-Oct-16	1098.29	715.43	1059.14	765.86	52.17	51.80
7	9 Oct 16 - 15 Oct 16	15-Oct-16	1112.07	704.15	1024.22	753.38	49.96	49.96
8	16 Oct 16 - 22 Oct 16	22-Oct-16	1045.45	690.76	938.43	746.59	50.11	49.94
9	23 Oct 16 - 29 Oct 16	29-Oct-16	1065.03	711.96	1013.54	761.17	50.44	50.44
10	30 Oct 16 - 5 Nov 16	5-Nov-16	1061.44	731.38	907.26	820.62	51.51	51.52
11	6 Nov 16 - 12 Nov 16	12-Nov-16	957.37	776.54	1010.96	822.43	47.88	48.08
12	13 Nov 16 - 19 Nov 16	19-Nov-16	1096.03	706.28	1121.43	792.86	48.18	48.30
13	20 Nov 16 - 26 Nov 16	26-Nov-16	1078.65	684.57	1150.85	728.08	46.23	45.79
14	27 Nov 16 - 3 Dec 16	3-Dec-16	1079.73	712.29	1105.69	780.73	50.99	50.98
15	4 Dec 16 - 10 Dec 16	10-Dec-16	1068.09	723.53	1110.30	778.02	49.40	48.98
16	11 Dec 16 - 17 Dec 16	17-Dec-16	1132.35	761.71	1031.95	798.52	50.00	50.17
17	18 Dec 16 - 24 Dec 16	24-Dec-16	1098.00	785.70	1024.82	801.13	50.01	50.58
18	25 Dec 16 - 31 Jan 16	31-Dec-16	1004.51	785.25	1170.55	803.18	49.06	49.23
19	1 Jan 17 - 7 Jan 17	7-Jan-17	1082.17	694.23	1138.61	662.39	51.63	51.66
20	8 Jan 17 - 14 Jan 17	14-Jan-17	1082.17	694.23	1138.61	767.29	51.63	51.66
21	15 Jan 17 - 29 Jan 17	21-Jan-17	1098.00	696.23	1105.69	766.61	51.51	51.78

Figure 1: shows average IN_load of transformer 1 showing the IN_load data not fitting into the regression line with the forecasted load at 1098.29 MW.



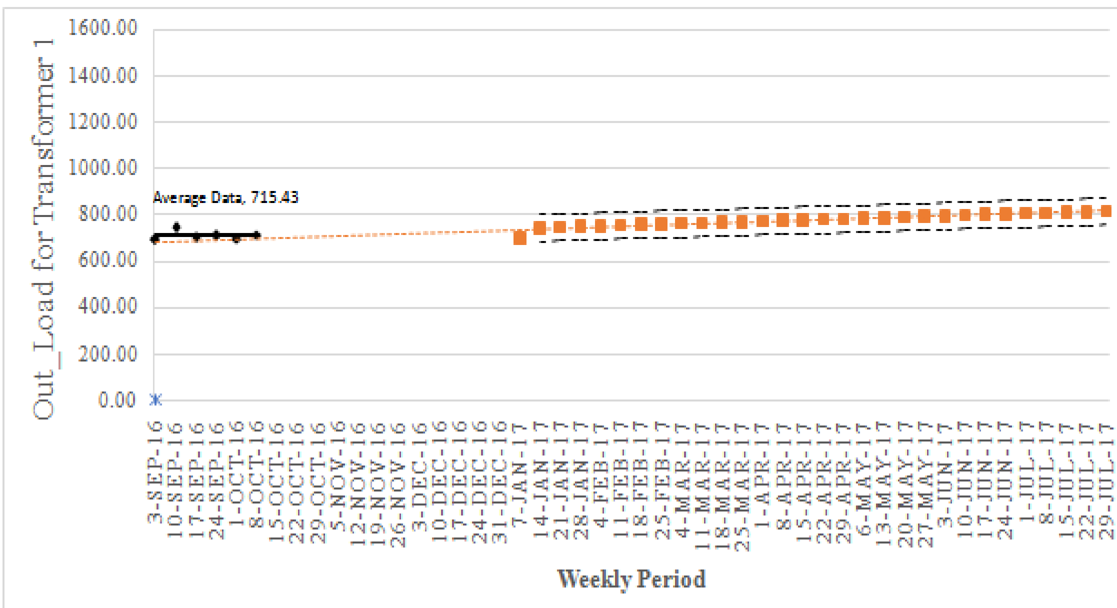


Figure 2: shows average OUT_load of transformer 1 showing the OUT_load data not fitting into the regression line with the forecasted load at 715.43MW.

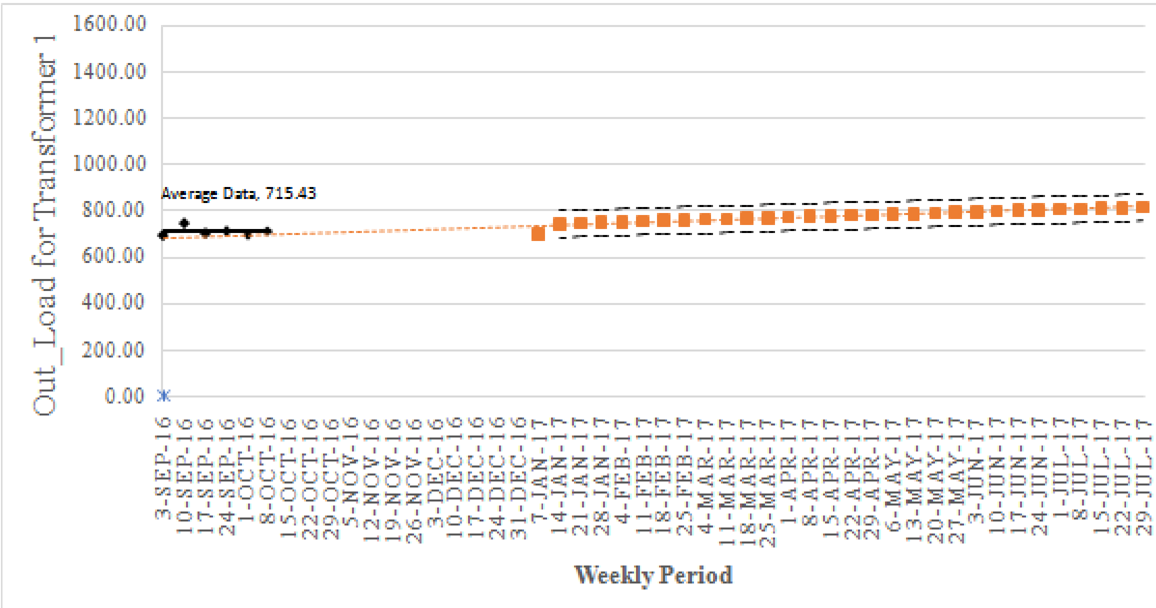


Figure 3: shows average IN_load of transformer 2 showing the IN_load data not fitting into the regression line with the forecasted load at 715.43MW.

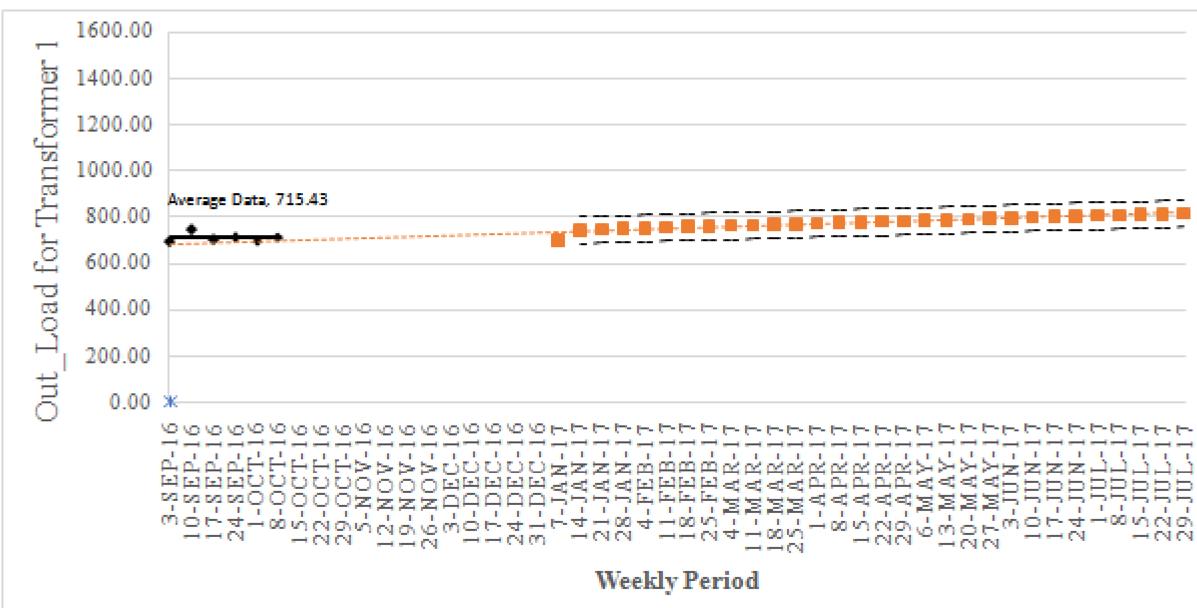


Figure 4: shows average OUT_load of transformer 2 showing the OUT_load data not fitting into the regression line with the forecasted load at 1059.14MW.

III. DISCUSSION

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. It can be seen that the OUT_load of transformer 1 shows the same output with IN_load of transformer 2; the oil temperature was at the same condition while the IN_load of transformer 1 and the OUT_load of transformer 2 are slightly different.

IV. CONCLUSIONS

The concept of an integral transformer lifetime model is presented and illustrated by modelling thermal degradation of paper insulation. The modelling concept is based on a physical description of the process but adds a probabilistic approach and incorporates externally measurable parameters and a feedback loop to limit the inaccuracy inherent to degradation process modelling. It is demonstrated that the probabilistic approach adopted enables to predict future life in terms of a time dependent failure probability. As compared to the standard loading guide approach the accuracy is significantly improved by the incorporation of externally measurable quality parameters. Repeated measurement of quality parameters may further enhance the accuracy. Further improvement is also possible by using a feedback loop which reveals the dominant sources of uncertainty. The approach presented provides a more accurate tool for the asset manager to predict future failure probability, and to base decisions on a realistic prediction rather than on a worst case.

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