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24 HOURS PREDICTION OF HOT SPOT TEMPERATURE AND PERCENTAGE LOSS OF LIFE IN A 15MVA ELECTRICALTRANSFORMER USING ARTIFICIAL NEURAL NETWORK, MULTIPLE AND BAGGY REGRESSION

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Abstract

Distribution power transformers are very crucial to our modern society. They are expensive to install and maintain. All these factors contribute to continuous research being carried out in this field. One major phenomenon to consider is ageing of the transformer which depends on the condition of the solid insulation inside the transformer. Hence, the need to employ classical ageing models to predict the ageing based on parameters such as hotspot temperature and ambient temperature. Using24 hours reading (February 26th, 2018) of 15MVA 33/11kV distribution transformer in Ugbowo injection substation in Benin city, Nigeria as a case study, Artificial Neural Network (ANN), Multiple Regression (MR) and Baggy Regression (BR) models are used in predicting hotspot temperature based on loading and ambient temperature and loss of life of the distribution transformer. The results are obtained from measurement of oil temperature and winding temperature, ambient temperature and electrical load and utilization of Microsoft Excel to generate data and graphs. MATLAB (version R2015b) Neural Network Toolbox is also used to compute the models. The interpretation of the results shows that short term prediction of hotspot temperature and loss of life is essential in monitoring the thermal behavior and ageing of distribution transformers providing users information to ensure longer life span of distribution transformer. Having 88.37% MAPE Improvement and 0.013 loss of life, the Multiple Regression Prediction Tool is observed to be the most accurate.

Keywords: - loading, ambient temperature, Artificial Neural Network (ANN), Multiple Regression (MR), Baggy Regression (BR), distribution transformer, top oil temperature, hotspot temperature.

1.0 Introduction

Transformers are static devices that transfer electric energy from one circuit to another by magnetic coupling. They transfer energy between different voltage levels that allow choosing the most appropriate voltage for power generation, transmission and distribution separately. Transformers begin with the Generator Step Up (GSUs) that steps up generate output voltage to desired level for transmission, move on to system transformers in charge of interim voltage conversions and then delivery point (distribution) transformers. These are the transformer of popular nature and they step down the voltage from transmission system.

The delivery point transformer whose significance is often felt is the delivery point (distribution) transformer. That is, the transformers which are often found in various locality responsible for supply and end-users in either the residential, commercial and/or industrial ways and often times, especially in countries like Nigeria with little to no city planning, these transformers supply end-users electricity to serve all three purposes. Its failure may result in load interruption for hours and as long as its failure remains unattended to.

Just as the relevance of electricity is felt, so is the importance of the distribution transformer. As distribution transformers are the means by which end-users receive electricity, their sustained maintenance is very crucial. Their failure impacts service reliability and cuts across all works of life. Distribution transformer failure can directly or indirectly cause interruption.

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Observing their importance, studies are being done in order to understand thorough and intricate working of the distribution transformer. These studies are aimed with an end point providing information that aids distribution transformer failure and due to their costly nature, means of elongating their durability. This research aims at studying prediction tools for transformer loss of life. Short term prediction of hotspot temperature of electric power distribution transformers is aimed at predicting hotspot temperature with a loading time of one hour to twenty-four hours which is indispensable for convenient monitoring and protection of electric power transformers. Several things cause transformer failure such as overloading which increases oil and winding temperature. This causes the transformer to produce excessive amount of heat during their operation. Another implication is insulation failure that causes deterioration of the transformer [1].

Hence, all these factors create the need to predict the top oil temperature and hotspot temperature in order to control them below their benchmark value to enable transformers sustain their normal life expectancy. Measuring oil temperature and winding temperature using oil temperature indicators (OTIs) and winding temperature indicators (WTIs) alongside other parameters such as ambient temperature and electrical load with a loading time of one hour to twenty-four hours of the 15MVA 33/11kV Ugbowo distribution transformer is used as a case study. The results are collated and interpreted using the prediction tools; Artificial Neural Network (ANN), Multiple Regression (MR) and Baggy Regression (BR).

Prediction tools can differ based on the time frame in consideration for prediction of hotspot temperature. It can be long term (one year to ten years), medium term (one week to few months) to short term (one hour to one week) and very short term (one minute to one hour). For this paper, short term prediction of a day is taken into consideration. It can be used for accurate power system operation. It represents a great saving potential for economic and secure operation of power systems. Generally, load forecasting methods are mainly classified into two categories; classical (traditional) approaches and ANN based techniques. Classical approaches are based on statistical methods and forecast future value of a variable by using a mathematical combination of the history information, for example time series model of Auto Regressive Integrated Moving Average (ARIMA) [2]. ANN based techniques make for smarter approaches to prediction. The drawback observed in these traditional models motivated proposal of models that are based on the thermal electrical analogy [3][4]. Their models were assumed to be an improvement on the IEEE models [5]. The models selected for this paper are the Artificial Neural Network ANN), Multiple Regression (MR) and Baggy Regression (BR).

Artificial Neural Network (ANN) is aimed to develop mathematical models of its biological counterpart in other to imitate the capabilities of biological neural structures with a view to design of intelligent control systems. They are essentially non-linear circuits that have demonstrated capability to do non-linear curve fitting. Hotspot temperature regression (Multiple Regression and Baggy Regression) are usually used to model the relationship of load consumption, transformer hotspot temperature and other factors such as day type, weather. Feed Forward Neural Network (FFNN) is used as a base to compare the Multiple Regression and Baggy Regression. Regression trees (CART) are statistical models with each step of evaluation involves examining the value of an input variable and posing a binary problem that divides the node into two child nodes [6]. Bagged Regression have observed values denoted as

$D=\frac{\{X_1,Y_1\}}{N}$

Where N is the number of observations (N=1, 2 …. N).

The goal of the predictive model is to estimate the value of an output value Y_1(radical displacement based on set of predictors), X_1(hotspot temperature, etc).

Multiple Regression is often an extension of simple linear regression hence why it is also called multiple linear regression. It is used to predict a variable based on two or more variables, one being the dependent variable. It helps to determine the overall fit of the model and the relative contribution of each of the predictors [7].

2.0 Materials and Methodology

Sample data was collected from the 15MVA 33/11kV distribution transformer substation Ugbowo, Benin City, Nigeria. The sample data include oil temperature, winding temperature measured by oil temperature indicators (OTIs) and winding temperature indicators (WTIs) respectively with an observation time of twenty-four hours. The parameters, electrical load, oil temperature, winding temperature and ambient temperature were recorded from the logbook and used for analysis. The ambient temperature was collected from National Energy Center in the premises of the University of Benin, Benin City, Nigeria. The data were logged in Microsoft Excel spreadsheets. MATLAB (version R2015b) by Math works Inc. computer software was used to create and implement the twenty-four hours' hotspot temperature prediction using the Neural Network Toolbox having built-in fumes and applications to assist in modeling non-linear systems. It supports Artificial Neural Network training, validation, testing and simulation with hardcode and Graphic User Interface (GUI) applications.

Table 1: Specification of a 15 MVA 33kV/11kV Power Transformer	
Rated voltage (HV)	$33kV$
Rated voltage (LV)	$11kV$
Rated Current (HV)	$787.27A$
Rated Current (LV)	$262.4A$
Weight of core and coil	$11530kg$
Weight of tank and fittings	$32850kg$
Weight of oil	$7080kg$
Rated top oil rise over ambient	60℃
Rated hot spot rise over top oil temperature	65℃
Ratio of load loss at rated load to no-load loss	2

Table 2: Cooling Equipment used in 15 MVA 33kV/11kV Power Transformer		
Oil Pumps & Fans	Pump (600gpm)	Fan (467 cum per min)
No of oil pumps and fans	4	10
(Running + Standby)	(2+2)	(8+2)

Table 3: OTI and WTI Auxiliary Contacts Settings of 15 MVA 33kV/11kV Power Transformer		
OTI	Alarm	95^0C
	Trip	100^0C
WTI	Fan Start	85^0C
	Pump Start	95^0C
	Alarm	115^0C
	Trip	125^0C

Table 4: Data Collected from the substation on Hourly Basis (Monday 26th February, 2021.)

Date	Hour Check (Hr)	Ambient Temperature Readings (℃)	Oil Temperature Readings (℃)	Winding Temperature Readings (℃)	Load Readings (A)
26/02/2018	1	36	38	24.3	861.29
26/02/2018	2	36	38	23.7	851.56
26/02/2018	3	36	38	23.1	852.85
26/02/2018	4	36	38	23.4	867.29
26/02/2018	5	36	38	23.6	881.73
26/02/2018	6	36	38	22.8	896.14
26/02/2018	7	36	38	22.7	910.57
26/02/2018	8	36	37.76	23.3	913.71
26/02/2018	9	36	37.53	23.7	881.86
26/02/2018	10	36	37.29	25.3	892
26/02/2018	11	36	37.06	29.3	865
26/02/2018	12	36	36.82	32.4	900
26/02/2018	13	36	36.59	33.9	937.57
26/02/2018	14	36	36.35	34.3	975.14
26/02/2018	15	36	36.12	34.7	1012.71
26/02/2018	16	36	35.88	34.5	1050.29
26/02/2018	17	36	35.65	34.3	1072.86
26/02/2018	18	36	35.41	32.4	1153.43
26/02/2018	19	36	35.18	30.3	1167.43
26/02/2018	20	36	34.94	28.4	1095.85
26/02/2018	21	36	34.71	27.1	1010.28
26/02/2018	22	36	34.47	25.7	960.57
26/02/2018	23	36	34.24	25.7	910.87
26/02/2018	24	36	34	23.8	861.14

The transformer ageing equations were based on hotspot temperature and top oil temperature. In order to calculate the hotspot temperature, the values of the parameters recorded hourly is used.
The top-oil temperature rise $\Delta\theta_{TOT}(t)$was computed using the given expression

$$\Delta\theta_{TOT}(t) = [\Delta\theta_{TOT}(u) - \Delta\theta_{TOT}(i)]\left[1 - e^{t/T_{TOT}}\right] + \Delta\theta_{TOT}(i) \quad (1)$$

Where $\Delta\theta_{TOT}(i)$ is the oil temperature (OTI) and $\Delta\theta_{TOT}(u)$ is the final rise in the oil temperature and is given as

$$\Delta\theta_{TOT}(u) = \Delta\theta_{TOT}(r)\left[\frac{K^2R+1}{R+1}\right]^n \quad (2)$$

where$\Delta\theta_{TOT}(r)$ is the full load top oil temperature rise over ambient temperature in ℃, 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, n is an empirically derived exponent that depends upon the cooling method. The IEEE loading guide recommends the use of n=0.8 for natural convection and n=0.9 to1.0 for forced cooling. [8] The top oil time constant at the considered load is given by

$$T_{TOT} = 60 \times \frac{C_{th-oil} \times \Delta\theta_{TOT}(r)}{q_{tot}} \quad (3)$$

Where q_{tot} represents the total supplied losses in W, and C_{th-oil} is the equivalent thermal capacitance of the transformer oil inW_h/℃.
The equivalent thermal capacitance of the transformer oil is given as

$$C_{th-oil} = 0.48 \times M_{oil} \quad (4)$$

Where M_{oil} is the weight of the oil in kg.
The hot-spot temperature rise $\Delta\theta_{HST}(t)$ was computed using the given expression

$$\Delta\theta_{HST}(t) = [\Delta\theta_{HST}(u) - \Delta\theta_{HST}(i)]\left[1 - e^{t/T_{HST}}\right] + \Delta\theta_{HST}(i) \quad (5)$$

Where $\Delta\theta_{HST(i)}$ is the recorded winding temperature (WTI).$\Delta\theta_{HST(u)}$ is the final rise in the winding temperature and is given as

$$\Delta\theta_{HST}(u) = \Delta\theta_{HST}(r)[K]^{2m} \quad (6)$$

Where $\Delta\theta_{HST(r)}$ represents the rated hot spot temperature rise over top oil temperature and m is an empirically derived exponent that depends on the cooling method. The winding hot spot time constant is given as

$$T_{HST} = 2.75 \times \frac{\Delta\theta_{HST}(r)}{(1+P_e)J^2} \quad (7)$$

WhereT_{HST} is the winding hot spot time constant in minutes at the rated load, P_e is the relative eddy current losses (W), is the current density in A/mm2 at rated load.
The hot-spot temperature is given as

$$\theta_{HST}(t) = \theta_A(t) + \Delta\theta_{HST}(t) + \Delta\theta_{TOT}(t) \quad (8)$$

Where θ_A represents the recorded ambient temperature in ℃ extracted from the logbook of the National Energy Centre premises in the University of Benin and is shown in Table 3.4. θ_{HST} represents the ultimate hot spot temperature in ℃.
The Multiple Regression and Baggy Regression analysis algorithm script were written in MATLAB.
Error analysis was performed using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to evaluate the measure of performance of a forecasting/predicting method. These analysis tools compare results and evaluate the advantages and disadvantages of the three predicting tools (models) used. [9]The formula includes;

$$\text{MAPE}= \frac{100}{N}\sum_{i=1}^{N}\frac{|y_{predicted} - y_{actual}|}{y_{actual}} \quad (9)$$

$$\text{RMSE}= \sqrt{\frac{(y_{predicted} - y_{actual})^2}{N}} \quad (10)$$

3.0 Results and discussion

Following the computation of top oil temperature (TOT) and hotspot temperature of the 15MVA 33/11kV distribution transformer, the data were collated on the MATLAB (version R2015b) by Mathworks Inc.'s Neural Network Toolbox computer software. The results were logged into the Microsoft Excel and the graphs below we're generated.

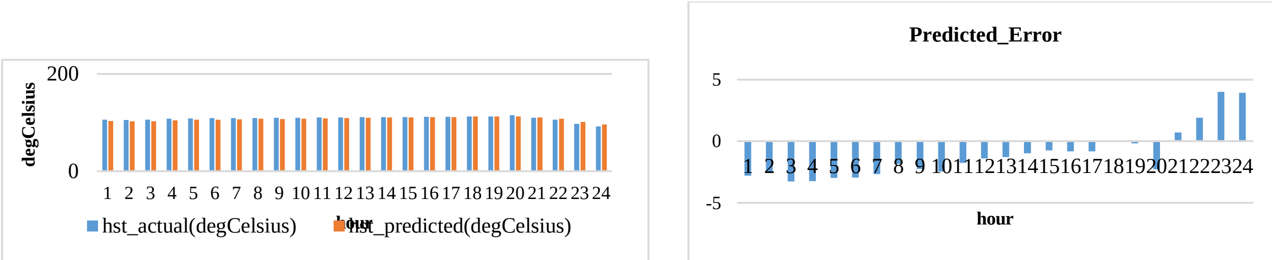
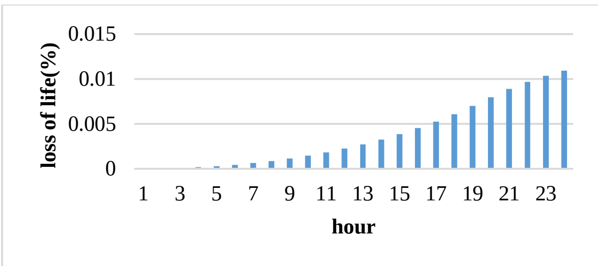


Figure 1: A Day Ahead Predicting Result for ANN (FFNN)



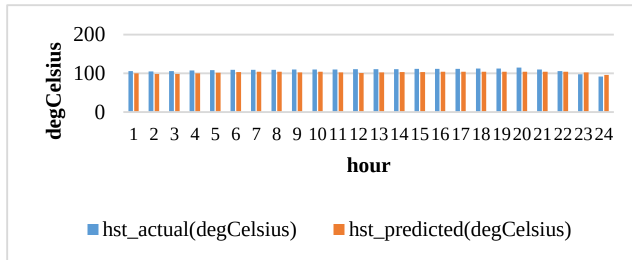


Figure 2: A Day Ahead Loss of Life Result for ANN (FFNN)

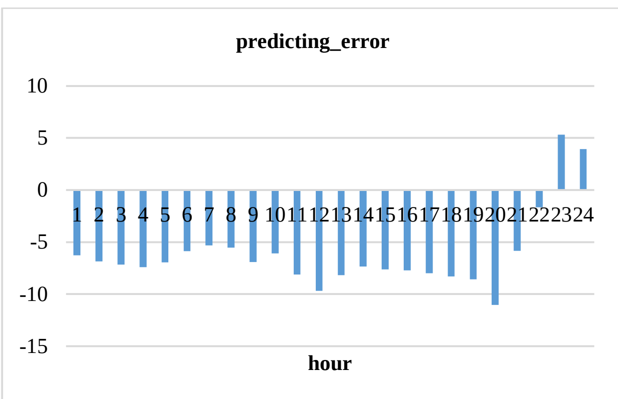


Figure 3: A Day Ahead Predicting Result for Baggy Regression

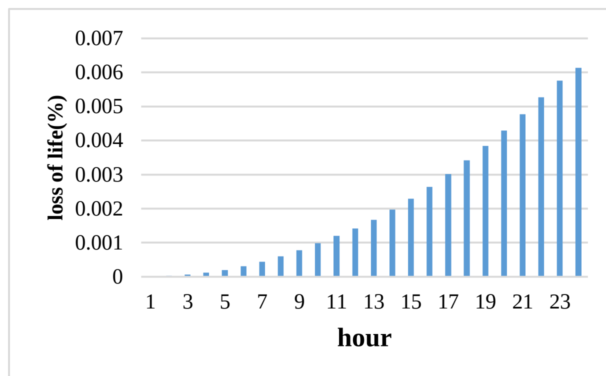


Figure 4: A Day Ahead Loss of Life Result for Baggy Regression

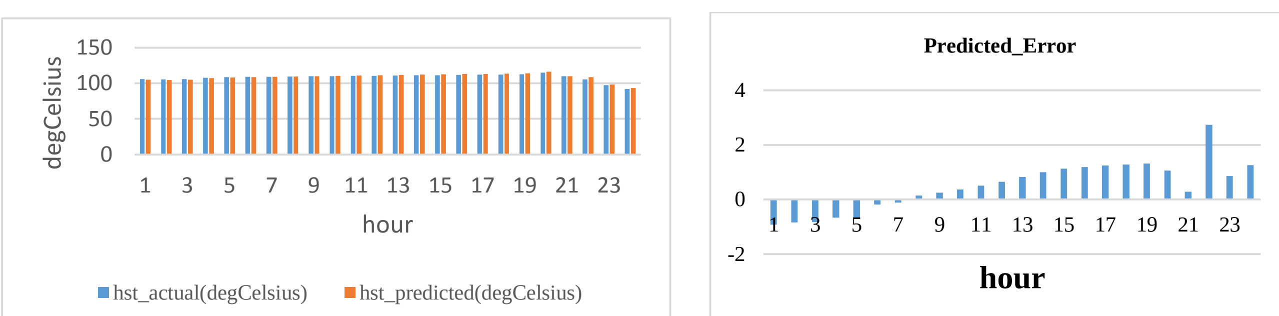


Figure 5: A Day Ahead Predicting Result for Multiple Regression

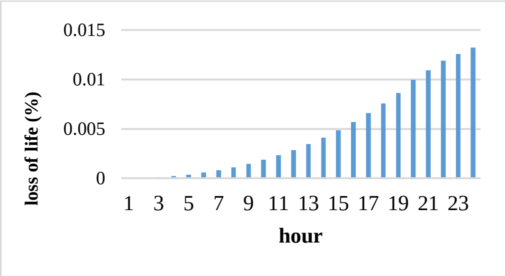


Figure 6: A Day Ahead Loss of Life Result for Multiple Regression

A comparative analysis of all three predicting tools is done. Table 5 shows the MAPE and RMSE of each predicting tool used for predicting the hot-spot temperature for February 26, 2018. The improvement expression of each predicting tool used is given as

$$\%MAPE_{inprovement} = 100 - \frac{MAPE_{low}}{MAPE_{high}} \times 100 \qquad (11)$$

Table 5: Comparison of Predicting Tools

Predicting Tools	MAPE	RMSE	Improvement (%)
Baggy Regression	6.7482	7.6352	0.00
Multiple Regression	0.7845	1.0060	88.37
ANN (FFNN)	2.0949	2.5899	68.96

When compared, the RMSE proves that it provides higher index for the prediction tools than the MAPE. This is seen to be the general case as seen in [9]. The table above shows Multiple Regression with the best overall performance of 88.37%, followed by Artificial Neural Network of 68.96% and Baggy Regression of 0.00%.

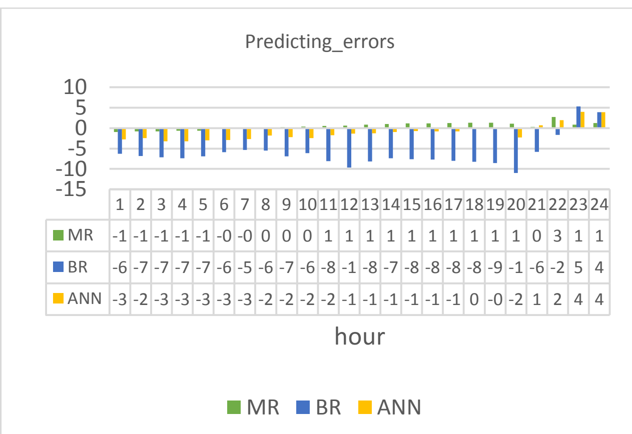


Fig.4.6: A Day Ahead Predicting Error Result comparison between the three predicting tools: Multiple Regression (MR), Baggy Regression (BR) and Artificial Neural Network(ANN-FFNN)

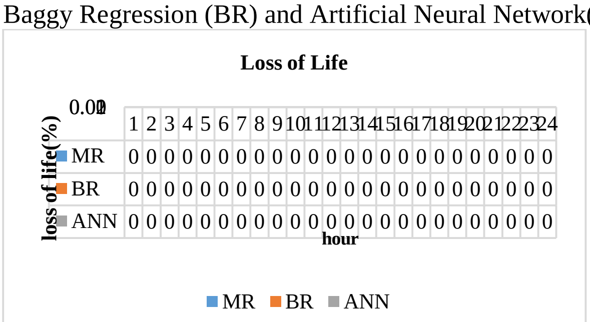


Fig.4.7: A Day Ahead Loss of Life Result comparison between the three predicting tools: Multiple Regression (MR), Baggy Regression (BR) and Artificial Neural Network (ANN-FFNN)

4.0 Conclusion

There are various models used to carry out Short term prediction of hotspot temperature and loss of life in an electric power distribution transformer. The models selected for this research are the Artificial Neural Network (ANN), Multiple Regression (MR) and Baggy Regression (BR). The Artificial Neural Network (ANN) designs used in this work start from the most commonly used Feed Forward Neural Network (FFNN) which served as a base to compare the performances of the Multiple Regression (MR) and Baggy Regression (BR). The performances were evaluated on the basis of Mean Absolute Percentage Error (MAPE) with comparisons made between the three predicting models; ANN (FFNN), MR and BR. The results show the Multiple Regression (MR) gives the best overall performance with0.7485 MAPE 88.37% MAPE Improvement, followed by the Artificial Neural Network (ANN) with 2.0949 MAPE 68.96% MAPE Improvement and then the Baggy Regression (BR) with6.7482 MAPE and 0.00% MAPE improvement. In terms of transformer loss of life, Multiple Regression with the best performing MAPE produces the best acceptable loss of life computation of 0.013% in lieu of Artificial Neural Network's 0.011% and Baggy Regression's 0.006%. Through computation, it is observed that the Multiple Regression Prediction Tool is the most accurate for Short term prediction of hotspot temperature and loss of life in an electric power distribution transformer**.**

5.0 References

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