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WEEKEND PREDICTION OF HOT SPOT TEMPERATURE AND PERCENTAGE LOSS OF LIFE IN A 15MVA ELECTRIC POWER TRANSFORMER USING ARTIFICIAL NEURAL NETWORK, MULTIPLE REGRESSION, AND BAGGY REGRESSION

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Abstract

Power transformers for distribution are extremely important in today's world. They are costly to set up and maintain. All of these elements contribute to ongoing study in this subject. The ageing of the transformer, which is dependent on the state of the solid insulation inside the transformer, is an important factor to consider. As a result, standard ageing models must be used to predict the future. As a result, standard ageing models must be used to anticipate ageing based on data such as hotspot temperature and ambient temperature. Using Weekend reading (march 3rd & 4th , 2018) of 15MVA 33/11kV distribution transformer in Uselu 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 data and graphs were generated using Microsoft Excel after measuring the oil temperature and winding temperature, as well as the ambient temperature and electrical load to get the predicted result. MATLAB (version R2015b) Neural Network Toolbox is also used to compute the models. The results suggest that weekend prediction of hotspot temperature and loss of life is critical in monitoring the thermal behavior and ageing of distribution transformers, providing users with information to guarantee that distribution transformers have a longer life span. 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

The power transformer is one of the most significant, as well as one of the most expensive, components of the power grid. They use magnetic coupling to transmit electric energy from one circuit to another. Only the use of power transformers allows for efficient transmission and distribution of electricity across multiple voltage levels. Any failure of this component might jeopardize the network's dependability and have a significant financial impact on the system. [1][2][3]Transformers start with power step up, which raises the output voltage to the necessary level for transmission, then go on to system transformers, which handle interim voltage conversions, and finally delivery point (distribution) transformers. These are common transformers that scale down the voltage from the transmission system.

A distribution transformer, also known as a service transformer, is a transformer that provides the last voltage transformation in an electric power distribution system, lowering the voltage used in distribution lines to the level used by

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customers [4]The Distribution transformer is a type of transformer whose importance is frequently felt. That is, transformers, which are responsible for supplying electricity to end-users in either the residential, commercial, or industrial ways, and in some countries these transformers frequently used to serve all three purposes, due to lack of proper planning. Its failure may cause load disruption in the supply of power for hours, depending on how long it goes untreated.

Because of their relevance, research is being conducted in order to fully comprehend the distribution transformer's complicated operation. These researches are aimed at giving knowledge that can help prevent failure of these distribution transformers and, because these transformers are expensive, ways to extend their lifespan are also being researched. The main goal of this project is to look at techniques for predicting transformer failure. The goal of short-term hotspot temperature prediction for electric power distribution transformers is to anticipate hotspot temperature with a loading time of one weekend, which is crucial for efficient monitoring and management of electric power transformers.

The hotspot is located on the conductor, and it has a temperature of θ_{HST}. The conductor comes into touch with oil as a cooling fluid, which has a temperature range that is lower than the hot-spot temperature at various spots. Because of the flow of oil in the transformer, the hottest part of the oil should be closer to the top. The top-oil temperature (θ_{TOT}) is the name given to this temperature. Hot-spot temperature rise (θ_{HST}) is the difference between the hot-spot temperature and the top-oil temperature.

Overloading power transformers raises the operating temperature. The operating temperature has a known effect on the aging of power transformers.[5]

As a result of all of these circumstances, it is necessary to estimate top oil temperature and hotspot temperature in order to keep them below their benchmark value and allow transformers to continue to operate normally.

The 15MVA 33/11kV Uselu distribution transformer is used as a case study. 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 weekend. The Artificial Neural Network (ANN), Multiple Regression (MR), and Baggy Regression prediction tools are used to compile and evaluate the findings (BR).

Predictive models might vary depending on the time frame taken into account for predicting hotspot temperature. It might be long, medium, short, or extremely short term. A weekend short-term forecast is taken into account in this article. It may be utilized to run a power system with precision. It has a significant cost-cutting possibility for the efficient and safe running of power systems.

In general, load forecasting techniques are divided into two groups: classical (conventional) approaches and ANN-based strategies.

Traditional techniques are based on statistical methods and anticipate future value of a variable by applying a mathematical combination of historical data [6]such as the time series model of the Auto Regressive Integrated Moving Average (ARIMA). Techniques based on artificial neural networks (ANNs) allow for more intelligent prediction. The shortcomings of previous models prompted [7]Lehn et al. and Lehtonen et al. to develop models based on the thermal electrical analogy. Their models were seen to be superior to the IEEE models. The Artificial Neural Network (ANN), Multiple Regression (MR), and Baggy Regression models were chosen for this study (BR).

Artificial Neural Networks (ANNs) are designed to create mathematical models of their biological counterparts in order to mimic the capabilities of organic neural structures in order to construct intelligent control systems. They're basically non-linear circuits that have been shown to be capable of non-linear curve fitting. Modelling the link between load consumption, transformer hotspot temperature, and other parameters such as day type and weather is commonly done using hotspot temperature regression (Multiple Regression and Baggy Regression). The Multiple Regression and Baggy Regression are compared using a Feed Forward Neural Network (FFNN) as a basis.

[8originally presented regression trees (CART), which entail analysing the value of an input variable and asking a binary dilemma that separates the node into two child nodes at each stage of assessment.

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

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

The predictive model's purpose is to forecast the value of an output value Y1 (radical displacement based on a set of predictors), and X1 (hotspot temperature, etc).Multiple Regression is commonly referred to as multiple linear regression since it is an extension of simple linear regression. It's a technique for predicting a variable using two or more variables, one of which is the dependent variable. It aids in determining the model's overall fit as well as the relative contribution of each predictor (Leard Statistics, n.d).

2.0 Materials and methodology

The 15MVA 33/11kV distribution transformer substation Uselu in Benin City, Nigeria was used to collect data. The sample data includes oil temperature, winding temperature, and winding temperature indicators (WTIs), all of which were monitored using oil temperature indicators (OTIs) and winding temperature indicators (WTIs), respectively, over a weekend period. The logbook's metrics, such as electrical load, oil temperature, winding temperature, and ambient temperature, were recorded and analyzed. The ambient temperature was taken at the National Energy Center on the University of Benin's campus in Benin City, Nigeria. The information was entered into Microsoft Excel files. Mathworks Inc.'s MATLAB (version R2015b). The Neural Network Toolbox, which has built-in components and applications to aid with modeling non-linear systems, was used to build and implement the weekend hotspot temperature forecast. With hardcode and Graphic User Interface (GUI) applications, it allows Artificial Neural Network training, validation, testing, and simulation.

Table 3.1 : Specification of a 15 MVA 33kV/11kV Power Transformer	
Rated voltage (HV)	$33kV$
Rated voltage (LV)	$11kV$
Rated Current (HV)	$787.27A$A
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 3.2 : 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 (Running + Standby)	4 (2+2)	10 (8+2)

Table 3.3 : OTI and WTI Auxiliary Contacts Settings of 15 MVA 33kV/11kV Power Transformer		
OTI	Alarm Trip	95^0C 100^0C
WTI	Fan Start Pump Start Alarm Trip	85^0C 95^0C 115^0C 125^0C

Table 3.4: Data Collected from the substation on Hourly Basis (Saturday 3th march, 2018.)

Date	Hour Check (Hr)	Ambient Temperature Readings (℃)	Oil Temperature Readings (℃)	Winding Temperature Readings (℃)	Load Readings (A)
03/03/2018	1	37.5	36.5	23.9	843.56
03/03/2018	2	37	36	23.3	858.51
03/03/2018	3	36.5	35.5	23.7	873.47
03/03/2018	4	36	35	22.8	888.43
03/03/2018	5	36	35	23.1	918.29
03/03/2018	6	37	35	22.3	979.14
03/03/2018	7	38	36	21.6	1005.08
03/03/2018	8	38	36	21.9	886.16
03/03/2018	9	38	36	23.9	840.24
03/03/2018	10	38.25	36.5	27.2	859.57
03/03/2018	11	38.5	37	29.8	878.89
03/03/2018	12	38.75	37.5	31.4	898.23
03/03/2018	13	39	38	32.5	917.53

03/03/2018	14	39.25	38.5	33.7	936.87
03/03/2018	15	39.5	39	34.4	956.19
03/03/2018	16	39.75	39.5	33.7	975.52
03/03/2018	17	40	40	33.4	994.84
03/03/2018	18	40	40	32.3	1041.92
03/03/2018	19	40	40	29.8	1022.29
03/03/2018	20	40.33	40	28.2	948.91
03/03/2018	21	40.67	40	27.5	875.52
03/03/2018	22	41	40	27.2	802.14
03/03/2018	23	40	39	25.8	776.43
03/03/2018	24	40	38	24.3	749.71

Table 3.5: Data Collected from the substation on Hourly Basis (Sunday 4th march, 2018.)

Date	Hour Check (Hr)	Ambient Temperature Readings (℃)	Oil Temperature Readings (℃)	Winding Temperature Readings (℃)	Load Readings (A)
04/03/2018	1	38	36	24.3	728.86
04/03/2018	2	38	36	24.4	730.71
04/03/2018	3	38	36	23.2	732.57
04/03/2018	4	38.43	36.57	22.2	773.43
04/03/2018	5	38.86	37.14	22.5	814.29
04/03/2018	6	39.29	37.71	22.3	855.14
04/03/2018	7	39.71	38.29	22.2	896
04/03/2018	8	40.14	38.86	22.2	946
04/03/2018	9	40.57	39.43	24.4	976
04/03/2018	10	41	40	28.1	995.01
04/03/2018	11	41	40	30.2	872.99
04/03/2018	12	41	40	32	830
04/03/2018	13	42	41	33.2	833.5
04/03/2018	14	43	42	34.2	837
04/03/2018	15	43	42	34.9	825.5
04/03/2018	16	41	40	34.9	880.5
04/03/2018	17	41	40	34	922
04/03/2018	18	41	40	32.3	992.5
04/03/2018	19	44	42	30.1	1032.29
04/03/2018	20	44	42	28	1052.57
04/03/2018	21	44	42	26.9	995.86
04/03/2018	22	41.75	40	26.2	972.28
04/03/2018	23	39.5	38	24.8	948.72
04/03/2018	24	37.25	36	25.3	925.14

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

$$\Delta\theta_{TOT}(t) = [\Delta\theta_{TOT}(u) - \Delta\theta_{TOT}(i)]\left[1 - e^{t/T_{TOT}}\right] + \Delta\theta_{TOT}(i) \qquad (3.1)$$

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

$$\Delta\theta_{TOT}(u) = \Delta\theta_{TOT}(r)\left[\frac{K^2R+1}{R+1}\right]^n \qquad (3.2)$$

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 [9] recommends the use of n=0.8 for natural convection and n=0.9 to1.0 for forced cooling. The top oil time constant at the considered load is given by

$$T_{TOT} = 60 \times \frac{C_{th-oil} \times \Delta\theta_{TOT}(r)}{q_{tot}} \qquad (3.3)$$

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

$$C_{th-oil} = 0.48 \times M_{oil} \quad (3.4)$$

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

$$\Delta\theta_{HST}(t) = [\Delta\theta_{HST}(u) - \Delta\theta_{HST}(i)]\left[1 - e^{t/T_{HST}}\right] + \Delta\theta_{HST}(i) \quad (3.5)$$

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

$$\Delta\theta_{HST}(u) = \Delta\theta_{HST}(r)[K]^{2m} \quad (3.6)$$

Where $\Delta\theta_{HST(r)}$the rated hot spot temperature is 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

$$T_{HST} = 2.75 \times \frac{\Delta\theta_{HST}(r)}{(1+P_e)J^2} \quad (3.7)$$

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

$$\theta_{HST}(t) = \theta_A(t) + \Delta\theta_{HST}(t) + \Delta\theta_{TOT}(t) \quad (3.8)$$

Where θ_A is 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} is theultimate 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. The formula includes;

$$\text{MAPE}= \frac{100}{N}\sum_{i=1}^{N}\frac{|y_{predicted}-y_{actual}|}{y_{actual}} \quad (3.9)$$

$$\text{RMSE}= \sqrt{\frac{(y_{predicted}-y_{actual})^2}{N}} \quad (3.10)$$

3.0 Results and discussion

Using the three predicting tools to predict the weekend hot-spot temperature and the resultant loss of life of the investigated distribution transformer, Saturday 3rd and Sunday 4th of march 2018, are the weekend days chosen for this prediction and the results obtained are as shown below.

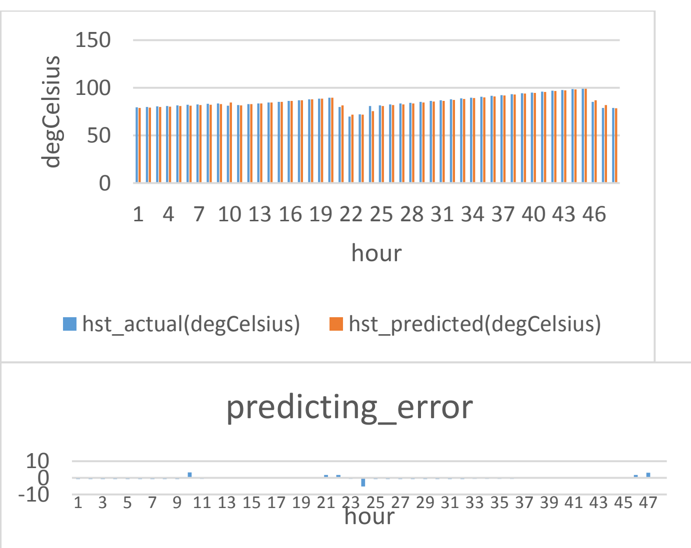

Fig.3.1: A Weekend Hot-spot Temperature Result for ANN(FFNN)
(Saturday 3rd and Sunday 4th March, 2018)

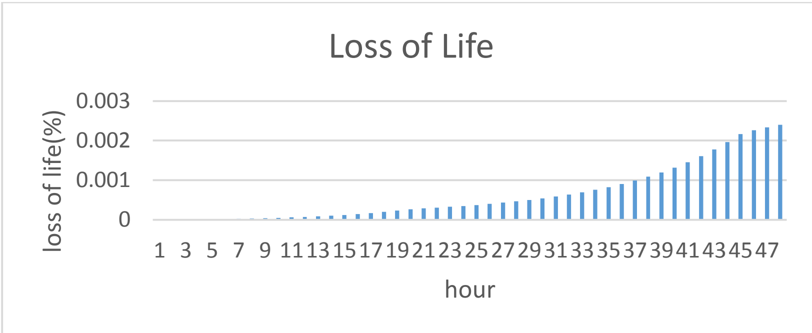

Fig.3.2: A Weekend Loss of Life Result for ANN(FFNN)
(Saturday 3rd and Sunday 4th March, 2018)

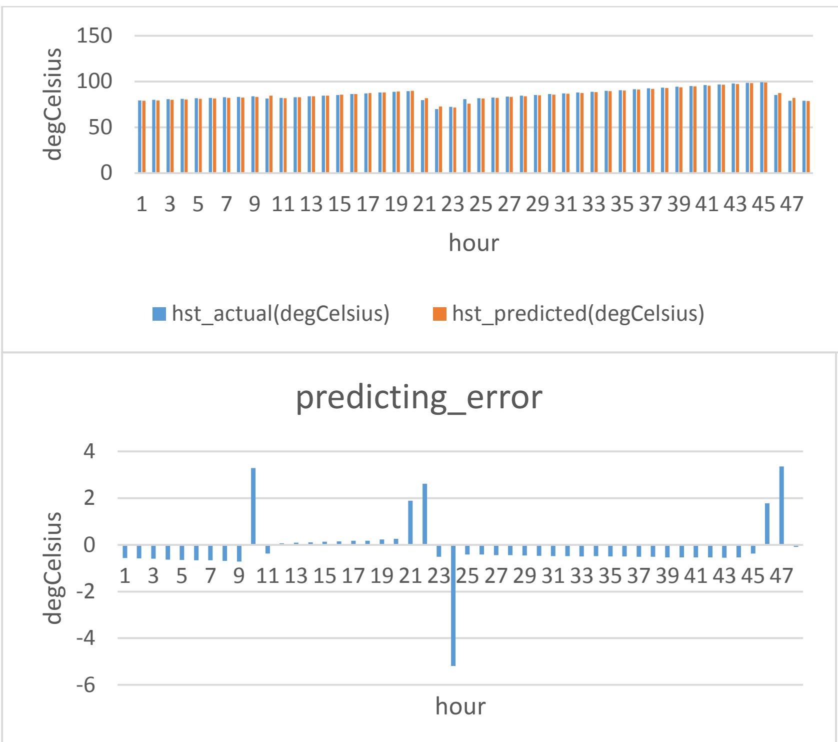

Fig.3.3: A Weekend Hot-spot Temperature Result for Multiple Regression
(Saturday 3rd and Sunday 4th March, 2018)

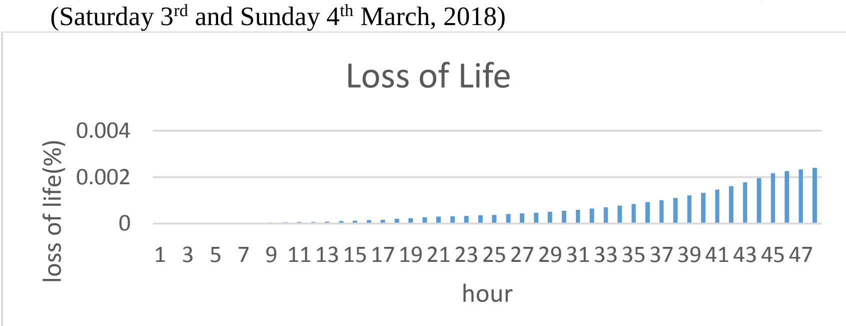

Fig.3.4: A Weekend Loss of Life Result for Multiple Regression
(Saturday 3rd and Sunday 4th March, 2018)

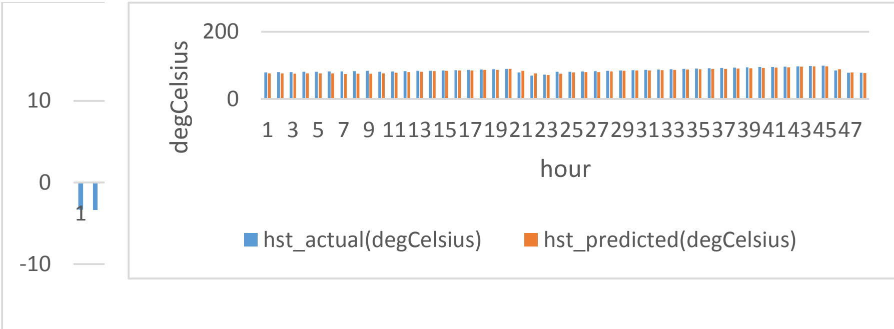

Fig.3.5: A Weekend Hot-spot Temperature Result for Baggy Regression
(Saturday 3rd and Sunday 4th March, 2018)

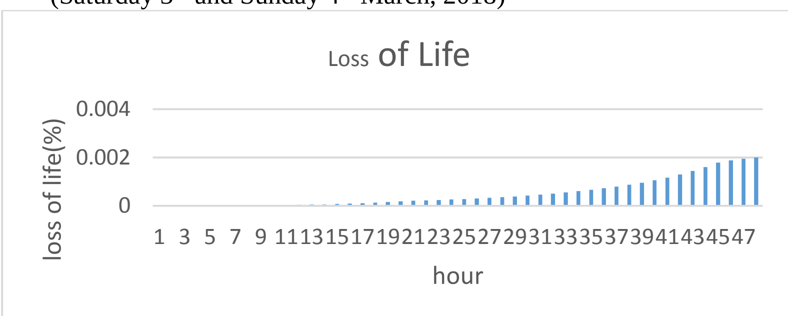

Fig.3.6: A Weekend Loss of Life Result for Baggy Regression
(Saturday 3rd and Sunday 4th March, 2018)

Table 3.6 shows the comparison between the three predicting tools for predicting hot spot temperature Error analysis was done on the basis of Mean Absolute Percentage Error(MAPE), another parameter calculated for error analysis is the Root Mean Square Error(RMSE) $\%MAPE_{inprovement} = 100 - \frac{MAPE_{low}}{MAPE_{high}} \times 100$

Table 3.6: Comparison between the three predicting tools			
	MAPE	RMSE	Improvement
Baggy Regression	3.4280	3.4965	00.00%
Multiple Regression	0.9195	1.2249	73.18%
ANN(FFNN)	0.9033	1.1927	73.66%

ANN has produced best results with 73.66% improvement over MR with performance enhancements of 73.18%. The two predicting tools gives the best performance during peak hours. Overall, the performances of these two predicting tools for weekends have forecasted better results. Fig.3.7 shows a comparison between the predicting error performance of MR, BR, ANN while Fig.3.8 shows that of transformer's loss of life.

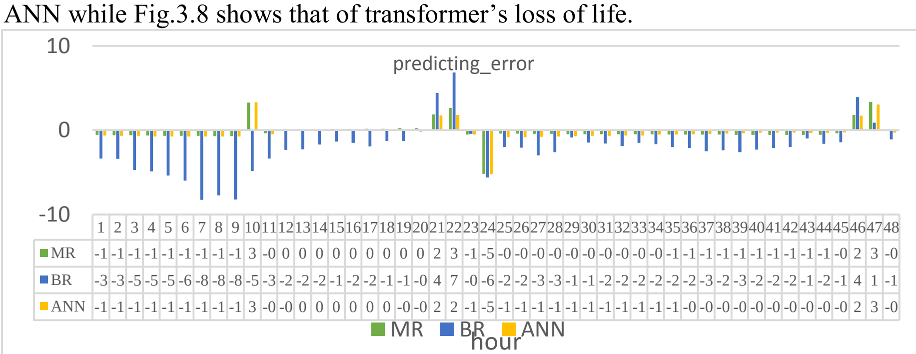

Fig.3.7: A Weekend Predicting Error Result comparison between the three predicting tools: Multiple Regression (MR), Baggy Regression (BR) and Artificial Neural Network (ANN (FFNN)) (Saturday, 3rd and 4th March, 2018)

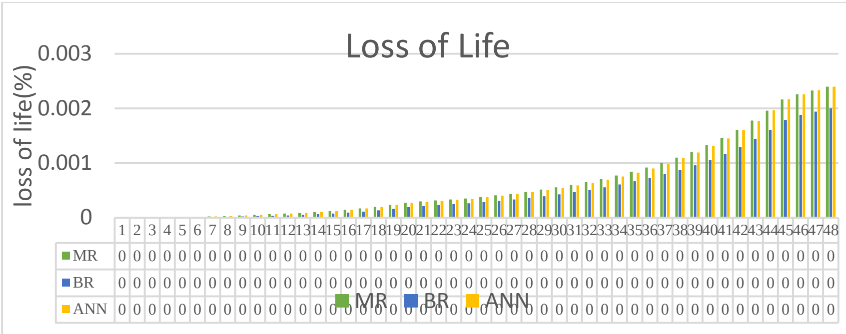

Fig.3.8: A Weekend Loss of Life Result comparison between the three predicting tools: Multiple Regression (MR), Baggy Regression (BR) and Artificial Neural Network (ANN(FFNN)) (Saturday 3rd and Sunday 4th , March, 2018)

4.0 Conclusion

For weekend prediction the BR has the worst performance among the three predicting tools. While the ANN has the best Performance .BR performance is taken as a base and an improvement of each network over BR is given along with the summary of error performances.

The predicting error for ANN ranges from -5.3pu to 3.42pu and a minimum error of 0.01%. Its MAPE is 0.9033%. MR has the same error variation with the same minimum error as ANN. It suppresses forecasting errors during the starting and ending hours of both Saturday and Sunday as a result produce lower MAPE of 0.9195%. The loss of life for the three predicting tools are as shown in Fig.3.2 Fig.3.4 and Fig.3.6 respectively. The transformer's loss of life values is 0.0024, 0.0024 and 0.0020 for ANN, MR and BR respectively which means that the load demand for Saturday and Sunday was lower compared with the load demand during the weekdays.

Furthermore, in terms of the transformer loss of life, the MR with the best preforming MAPE produces the best acceptable loss of life computation of 0.0024% for weekend.

5.0 References

[1] Heathcote, M.J. J & P Transformer Book; Newnes: Oxford, UK, 2007

[2] Bayliss, C.R.; Hardy, B.J. Power Transformers. In Transmission and Distribution Electrical Engineering, 4th ed.; Bayliss, C.R., Hardy, B.J., Eds.; Newnes: Oxford, UK, 2012; pp. 543–614

[3] Degeneff, B.C. 3—Power Transformers. In The Electrical Engineering Handbook; Chen, W.-K., Ed.; Academic Press: Burlington, VT, USA, 2005; pp. 715–720

[4] Harlow, James H. (2012). *Electric Power Transformer Engineering, Third Edition, Volume 2*. CRC Press. ISBN 143985629X.

[5] Sen, P.K.; Pansuwan, S. Overloading and loss-of-life assessment guidelines of oil-cooled transformers. In Proceedings of the 2001 Rural Electric Power Conference, Little Rock, AR, USA, 29 April–1 May 2001.

[6] Amjady, N. (2001). Short Term Hourly Load Forecasting Using Time Series Modeling with Peak Load Estimation Capability. *IEEE Transactions Power Systems***16** (7);98-805.

[7] Lehn, W., Molinski, S.T. and Swift, G. (2001). A Fundamental approach to transformer thermal modeling .I. theory and equivalent circuit. *Power Delivery, IEEE Transactions* **16**; 171-175.

[8] Lehtonen, M., Nordman, H. and Susa, D. (2005). Dynamic thermal modeling of power transformers. *Power Delivery, IEEE transactions***20**; 197

[9] Breiman, L., Friedman, H.J., Olsen, R.A and Stone, C.J(1984). *Classification and Regression Trees*, Wadsworth and Brooks, Monterey, CA.

[10] IEEE (1995). IEEE Standard C57.115-1995. IEEE Guide for Loading Mineral Oil-Immersed Power Transformer.