Fuzzy Logic-Based Characterization And Forecasting Of Transformer Failure Rate For A District Electricity Distribution Network

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***Abstract*— In his paper, fuzz logic-based characterization and forecasting of transformer failure rate for a district electricity distribution network is presented. The model is used for the prediction and forecasting of the total number of transformers installed, the total number of customers, the total number of failed transformers, the total outage due to transformer faults and the transformer failure percentage. A five years transformer failure performance dataset for 2016 to 2020 for an injection substations in the Aba electricity distribution network is used for the study. The model performance parameters used are Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Percentage Error (MPE). The model prediction performance for total number of transformers installed is such that, $MSE = 0.75272$, $RMSE = 0.86759$, $MAPE = 0.00046$, $MPE = -0.00918$, and $MAD = 2.27 \times 10^{-14}$. The model prediction performance for failed transformers is such that $MSE = 0.2599$, $RMSE = 0.5098$, $MAPE = 0.00193$, $MPE = -0.0387$, and $MAD = 0$. Also, the model prediction performance for total outage due to transformer faults is such that $MSE = 22.05$, $RMSE = 4.6957$, $MAPE = 0.00023$, $MPE = -0.00457$, and $MAD = 7.27 \times 10^{-12}$. In all, the forecast results show that with respect to the base year of 2016, in 2023 the total number of transformers installed will increase by 24%, the total number of customers will increase by 10%, the failed transformers will increase by 80%, the total outage due to transformer faults will increase by 43% and the transformer failure percentage will increase by 61%.**

Keywords:* *Fuzz Logic, Transformer Failure Rate, Reliability Index, Time Series Model, Outage Due To Transformer, Transformer Failure Percentage

1. INTRODUCTION

Over the years, the Nigerian national power industry has been plagued with diverse challenges that made it difficult to meet the energy demand of the nation [1, 2,3,4]. Notably, large chunk of the population do not have access to the national grid [5,6,7]. A significant portion of those that are connected to the national grid are faced with the challenges of epileptic power supply due to several factors such as transformer failure, load shedding, vandalization, among others [8,9,10,11].

Moreover, in most of the electric power distribution networks across Nigeria, the issues of power theft and illegal connections cause overloading of the transformers which in turn cause transformer failure and power outages [12,13,14]. In view of this, power distribution networks acquire relevant data that can be used to effectively characterize the distribution network reliability; such data items include transformer faults, customer base and power outage due to transformer failure, among others. Accordingly, in this paper fuzz logic models for the characterization and forecasting of transformer failure and related transformer parameters in a distribution network and other related parameters that impact on the performance of the network are presented. This parameters considered are essential for the evaluation of the various distribution network reliability indices. The model development is based on the dataset of a case study distribution network in Aba, Abia State Nigeria.

2. METHODOLOGY

2.1 The fuzzy model for the prediction

The data collated for the transformer parameter prediction is the summary of total feeder-wise transformer outage and transformer failure data for 2016 to 2020 as presented in Table 1. The block diagram for the fuzzy logic system is presented in Figure 1. The fuzzy logic starts with the input of the data set for the five years (2016-2020). During fuzzification, the membership functions are established.

The graphs of the computed membership functions obtained for the various transformer parameters are shown in Figure 2, Figure 3, Figure 4, Figure 5, and Figure 6, for inputs.
As shown in Figure 1, the proposed prediction model takes in five set of independent inputs, computes the respective membership function, then the fuzzy controller with the help of well-defined rules generates crisp output for each of the selected inputs. A total of twenty-five (25) rules were formulated for the process and the input-output response based on the rules can be seen in Figure 7.

Table 1: Summary of total feeder-wise transformer outage and transformer failure data for 2016 to 2020

TOTAL	Total No. of Transformer (Ntf)	Total No of Customers (Ni)	Total Outage due to Transformer Fault (λf)	Total Outage Duration due to Transformer Fault (Df)	Total Transformer failure percentage (%)	Total Customer Hrs due to Transformer Fault (Ni*Df)	Total Customer Frequency due to Transformer Fault (Ni*λf)
2016	830	129,498	102	8,879	15.4	77,157,872	933,124
2017	830	130,516	101	7,798	15.0	63,306,989	859,568
2018	835	131,637	109	8,745	13.9	77,197,952	1,013,876
2019	853	134,778	123	8,889	19.6	85,156,308	1,140,322
2020	885	135,098	162	10,990	28.3	96,008,136	1,522,318

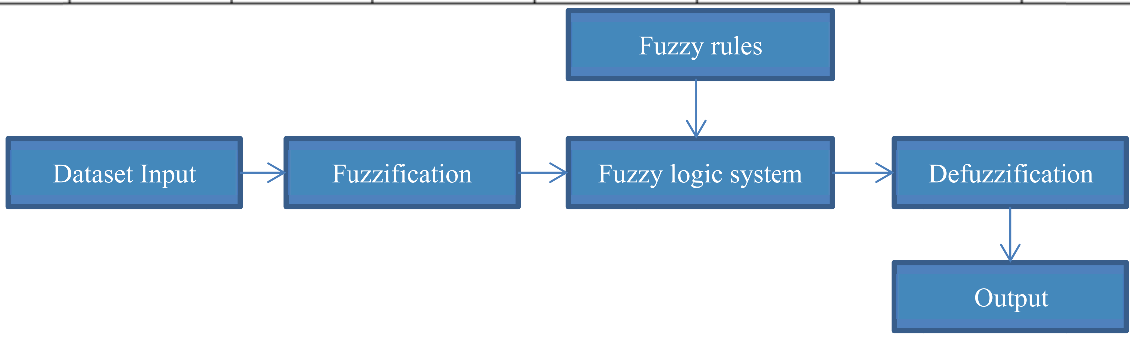

Figure 1: Block diagram for the fuzzy logic system

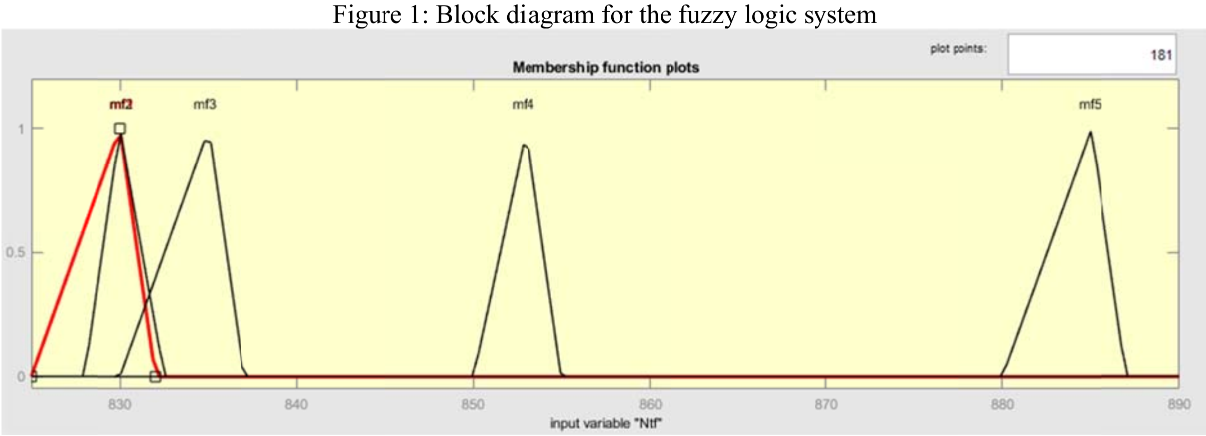

Figure 2: Membership function for number of transformers installed (Ntf)

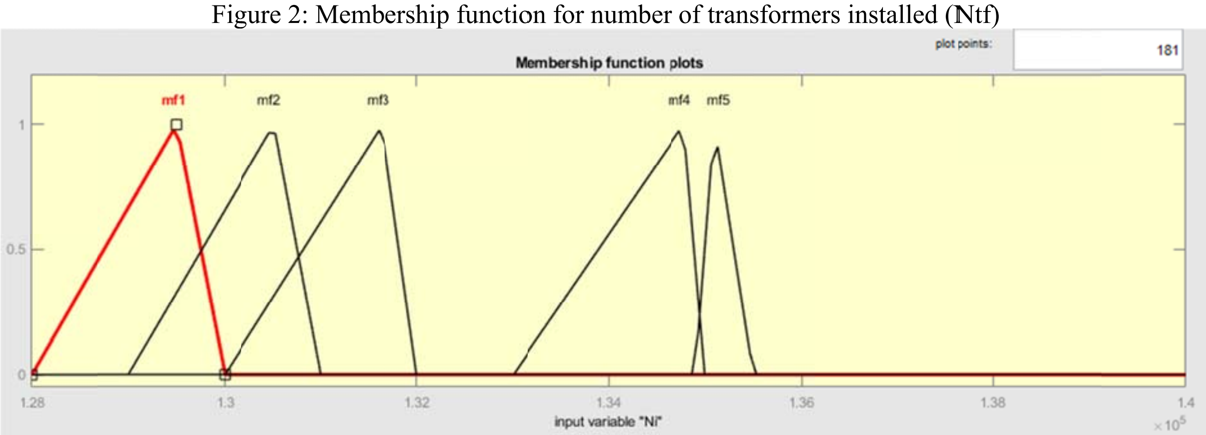

Figure 3: Membership function for number of customers

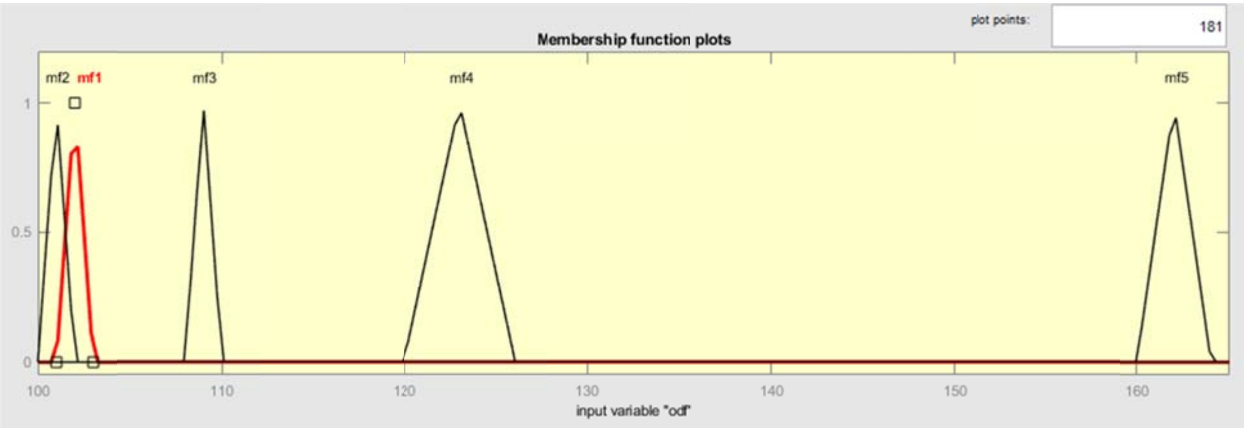

Figure 4: Membership function for total number of failed transformers

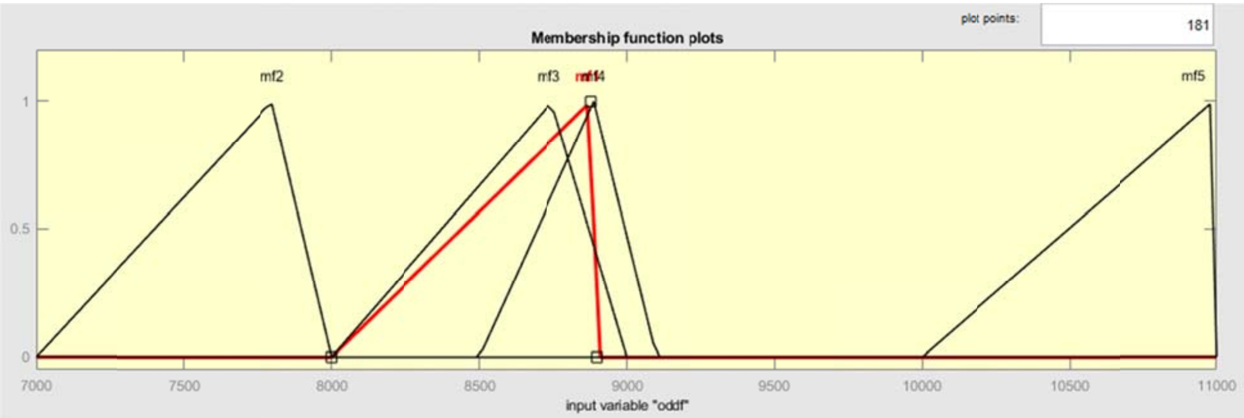

Figure 5: Membership function for total outage due to transformer faults

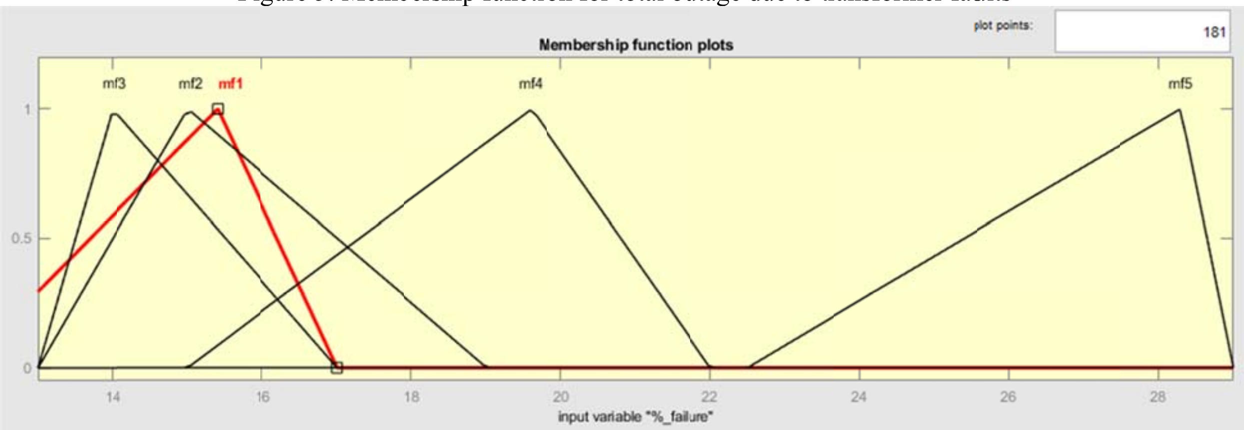

Figure 6: Membership function for transformer failure percentage

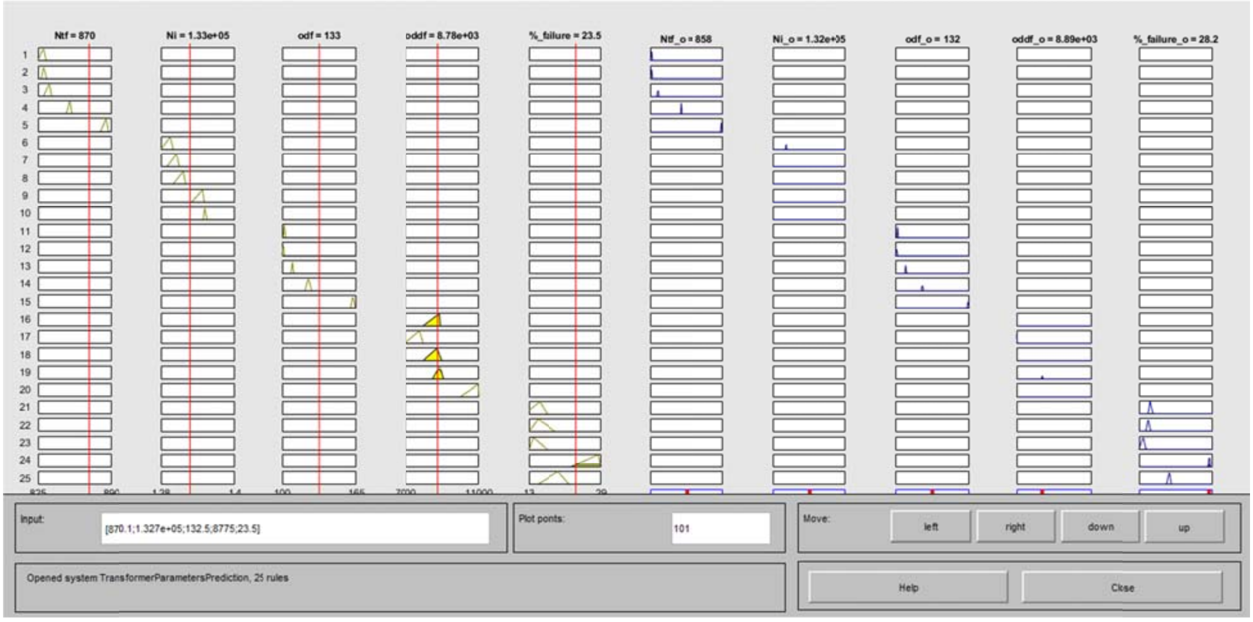

Figure 7: Fuzzy based rule viewer for the proposed model

2.2 The Model Error Analysis

Let the model prediction error be denoted as e which is defined as shown in Equation 1

$$e = P_{actual} - P_{predicted} \quad (1)$$

Where P denotes any parameter for test or evaluation

The Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE) of the prediction are presented in Equation 2 and Equation 3, respectively

$$MSE = \left(\frac{1}{n}\right)\left(\sum_{t=1}^{n}\left(e_{(t)}\right)^2\right) \quad (2)$$

$$RMSE = \sqrt[2]{\left[\left(\frac{1}{n}\right)\left(\sum_{t=1}^{n}\left(e_{(t)}\right)^2\right)\right]} \quad (3)$$

The Mean Absolute Percentage Error (MAPE) and Mean Percentage Error (MPE) are expressed as follows;

$$MAPE = \left(\frac{1}{n}\right)\left(\sum_{t=1}^{n}\left(\frac{P_{a(t)} - P_{p(t)}}{P_{a(t)}}\right)\right) \quad (4)$$

$$MPE = \left(\frac{100}{n}\right)\left(\sum_{t=1}^{n}\left(\frac{P_{a(t)} - P_{p(t)}}{P_{a(t)}}\right)\right) \quad (5)$$

The Mean Absolute Deviation (MAD) is expressed as follows;

$$MAD = \left(\frac{1}{n}\right)\left(\sum_{t=1}^{n}\left|P_{a(t)} - \overline{P_a}\right|\right) \quad (6)$$

3 RESULTS AND DISCUSSION

The results obtained from the model prediction for the total number of transformers installed is presented in Table 2, while the graph of the actual and predicted values of the total number of transformers installed is presented in Figure 8. The results showed that by the end of 2021, the total number of transformers installed will rise to 934.71 which is about 11% from the start year (2016), it will rise to 1003.62 in 2022 which is about 17% from the start year, and it will rise to 1095.12 in 2023 which is about 24% increase from the start year. The model prediction performance for total number of transformers installed is such that $MSE = 0.75272$, $RMSE = 0.86759$, $MAPE = 0.00046$, $MPE = -0.00918$, and $MAD = 2.27 \times 10^{-14}$. The graph of the comparison between the actual and predicted total number of transformers installed is presented in Figure 8.

Table 2: Comparison between the actual and predicted total number of transformers installed

Year	Year index (t)	Total number of actual transformers installed (Ntfa)	Predicted number of transformers installed (Ntfp)
2016	1	830	830.00
2017	2	830	830.94
2018	3	835	835.32
2019	4	853	853.24
2020	5	885	885.44
2021	6		934.71
2022	7		1003.62
2023	8		1095.12
$MSE = 0.75272$	$RMSE = 0.86759$	$MAPE = 0.00046$	$MPE = -0.00918$
$MAD = 2.27 \times 10^{-14}$			

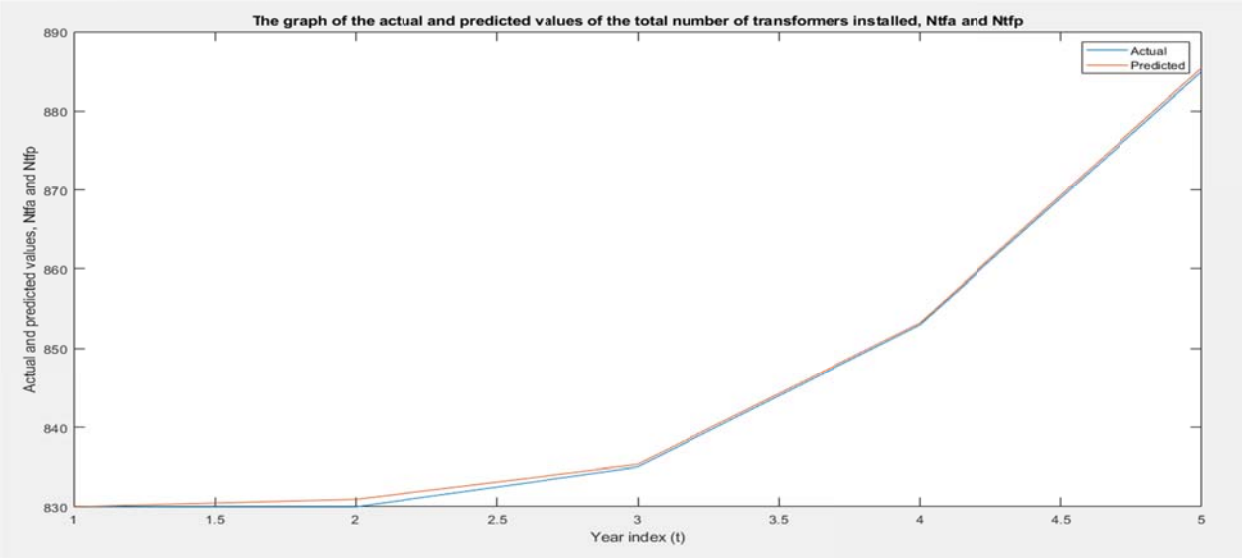

Figure 8: The graph of the actual and predicted values of the total number of transformers installed, Ntfa and Ntfp

Again, the results obtained from the model prediction for the total number of customers is presented in Table 3, while the corresponding graph is presented in Figure 9. The results showed that by the end of 2021, the total number of customers will rise to 137,217.52 which is about 6% from the start year (2016), it will rise to 141,326.12 in 2022 which is about 8% from the start year, and it will rise to 143,219.31 in 2023 which is about 10% increase from the start year. The model prediction performance for total number of customers is such that the $MSE = 67289.28$, $RMSE = 259.40$, $MAPE = 0.000859$, $MPE = 0.0172$, and $MAD = 5.82 \times 10^{-12}$.

Table 3: The total number of customers

Year	Year index (t)	Total number of actual customers (Nia)	Predicted number of customers (Nip)
2016	1	129,498	129,498.00
2017	2	130,516	130,520.24
2018	3	131,637	131,684.19
2019	4	134,778	134,098.20
2020	5	135,098	135,146.33
2021	6		137,217.52
2022	7		141,326.12
2023	8		143,219.31
$MSE = 67289.28$	$RMSE = 259.40$	$MAPE = 0.000859$	$MPE = 0.0172$
$MAD = 5.82 \times 10^{-12}$			

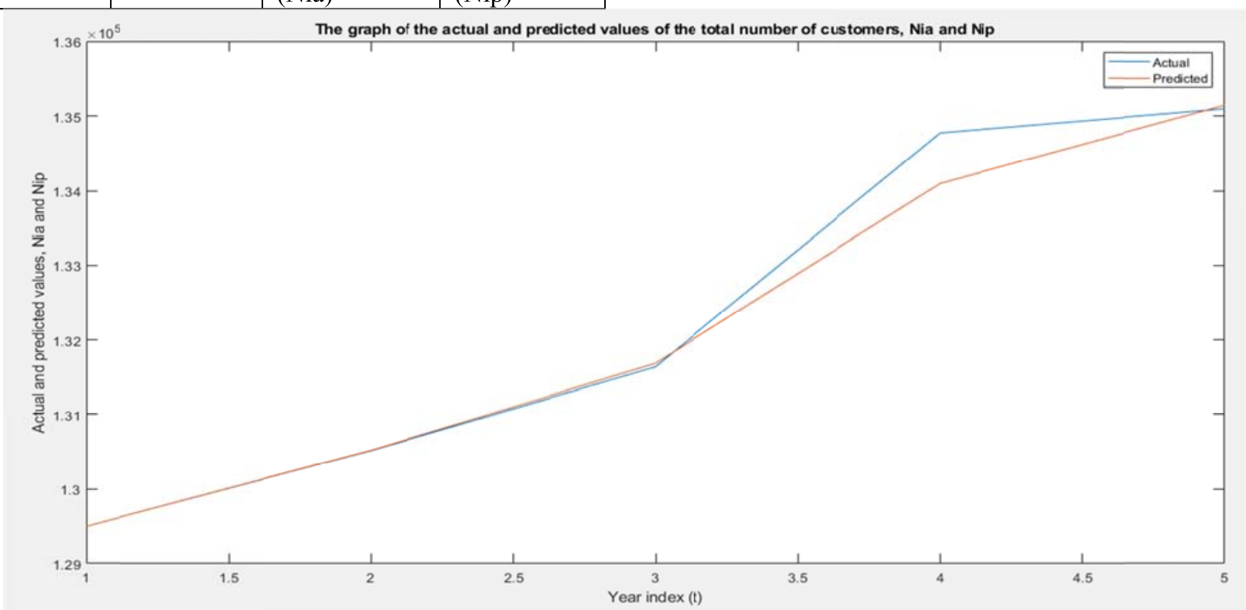

Figure 9: The graph of the actual and predicted values of the total number of customers

Furthermore, the results obtained from the model prediction for the total number of failed transformers is presented in Table 4, while the corresponding graph is presented in Figure 10. The results predicts by the end of 2021, the total number of failed transformers will rise to 225.48 which is about 55% from the start year (2016), 304.21 in 2022 which is about 66% from the start year, and 503.22 in 2023 which is about 80% increase from the start year . The model prediction performance for failed transformers is such that, $MSE = 0.2599$, $RMSE = 0.5098$, $MAPE = 0.00193$, $MPE = -0.0387$, and $MAD = 0$.

Table 4: The total number of failed transformers

Year	Year index (t)	Total number of failed transformers (actual)	Total number of failed transformers (predicted)
2016	1	**102**	102.00
2017	2	**101**	101.33
2018	3	**109**	109.40
2019	4	**123**	123.10
2020	5	**162**	162.31
2021	6		225.48
2022	7		304.21
2023	8		503.22
$MSE = 0.2599$	$RMSE = 0.5098$	$MAPE = 0.00193$	$MPE = -0.0387$
$MAD = 0$			

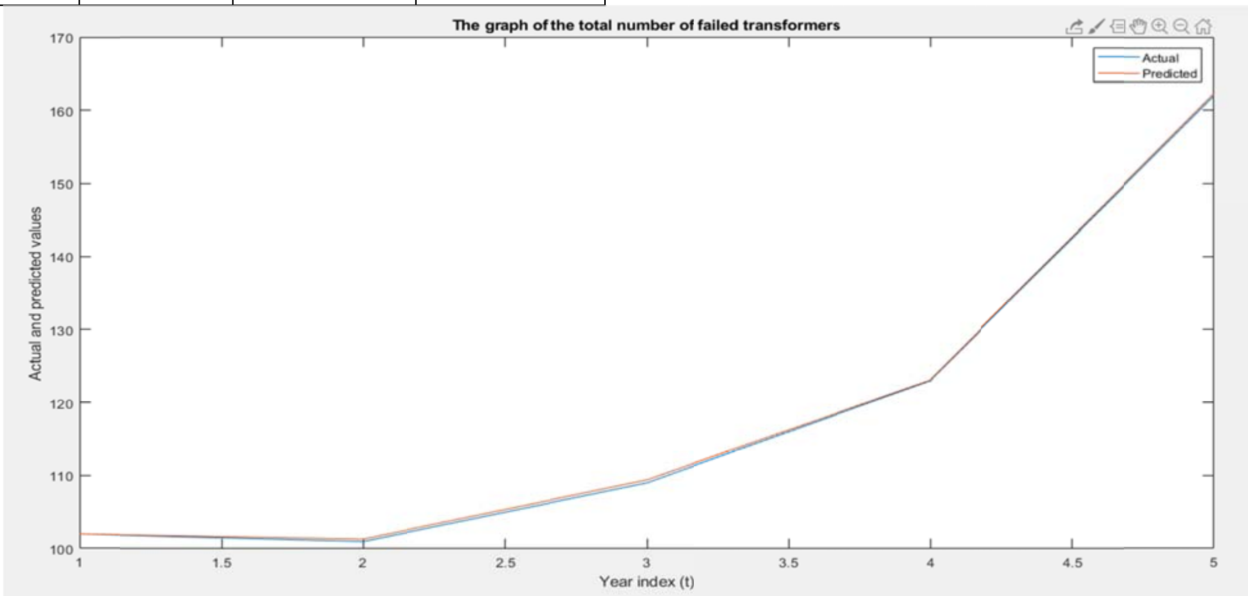

Figure 4.10: The total number of failed transformers

In addition, the results obtained from the model prediction for the total outage due to transformer faults is presented in Table 5, while the corresponding graph is presented in Figure 11. The results showed that by the end of 2021, the total outage due to transformer faults will rise to 12102.52 which is about 27% from the start year (2016), it will rise to 15561.33 in 2022 which is about 43% from the start year, and it will rise to 17633.41 in 2023 which is about 50% increase from the start year. The model prediction performance for total outage due to transformer faults is such that $MSE = 22.05$, $RMSE = 4.6957$, $MAPE = 0.00023$, $MPE = -0.00457$, and $MAD = 7.27 \times 10^{-12}$.

Table 5: Total outage due to transformer faults

Year	Year index (t)	Total outage due to transformer faults (actual)	Total outage due to transformer faults (predicted)
2016	1	**8,879**	8879.00
2017	2	**7,798**	7795.99
2018	3	**8,745**	8750.46
2019	4	**8,889**	8895.22
2020	5	**10,990**	10990.83
2021	6		12102.52
2022	7		15561.33
2023	8		17633.41
$MSE = 22.05$	$RMSE = 4.6957$	$MAPE = 0.00023$	$MPE = -0.00457$
$MAD = 7.27 \times 10^{-12}$			

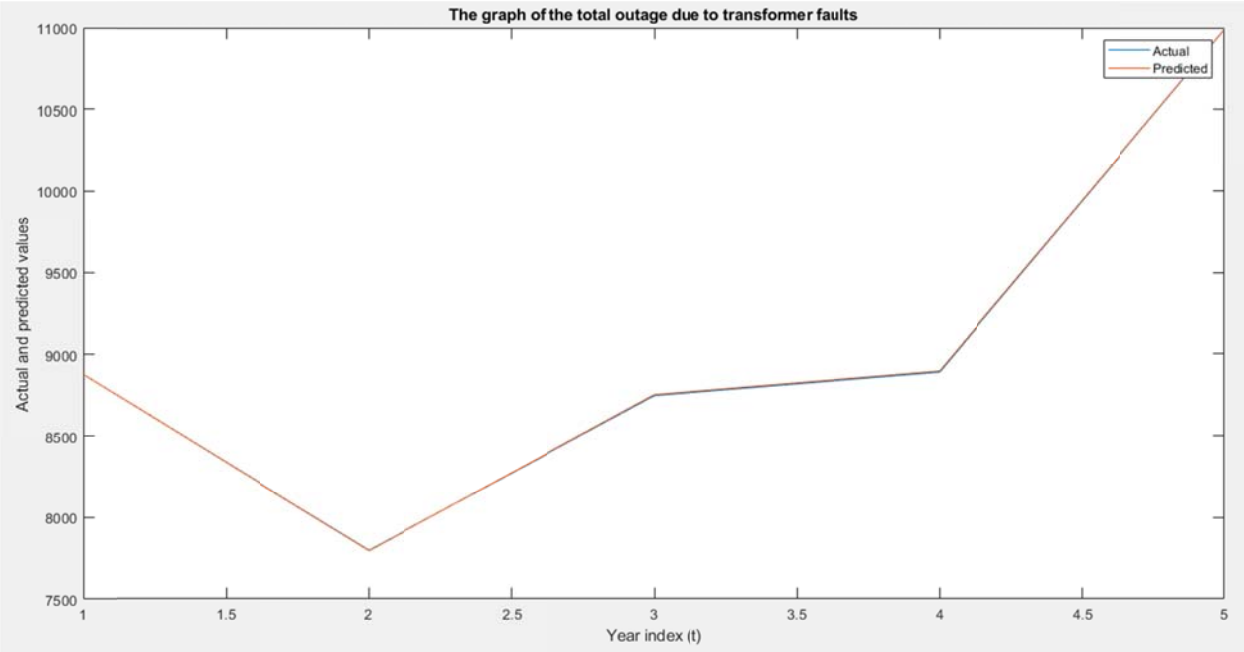

Figure 4.11: Total outage due to transformer faults

Finally, the results obtained from the model prediction for the transformer failure percentage is presented in Table 6, while the corresponding graph is presented in Figure 12. The results showed that by the end of 2021, the transformer failure percentage will rise to 41.66 which is about 26% from the start year (2016), it will rise to 58.33 in 2022 which is about 43% from the start year, and it will rise to 76.41 in 2023 which is about 61% increase from the start year. The model prediction performance for transformer failure percentage is such that $MSE = 0.3125$, $RMSE = 0.5590$, $MAPE = 0.01932$, $MPE = 0.3863$, and $MAD = 0$

Table 6: The transformer failure percentage

Year	Year index (t)	Transformer failure percentage (actual)	Transformer failure percentage (predicted)
2016	1	**15.4**	15.40
2017	2	**15**	14.10
2018	3	**13.9**	13.32
2019	4	**19.6**	19.41
2020	5	**28.3**	28.72
2021	6		41.66
2022	7		58.33
2023	8		76.41
$MSE = 0.3125$	$RMSE = 0.5590$	$MAPE = 0.01932$	$MPE = 0.3863$
$MAD = 0$			

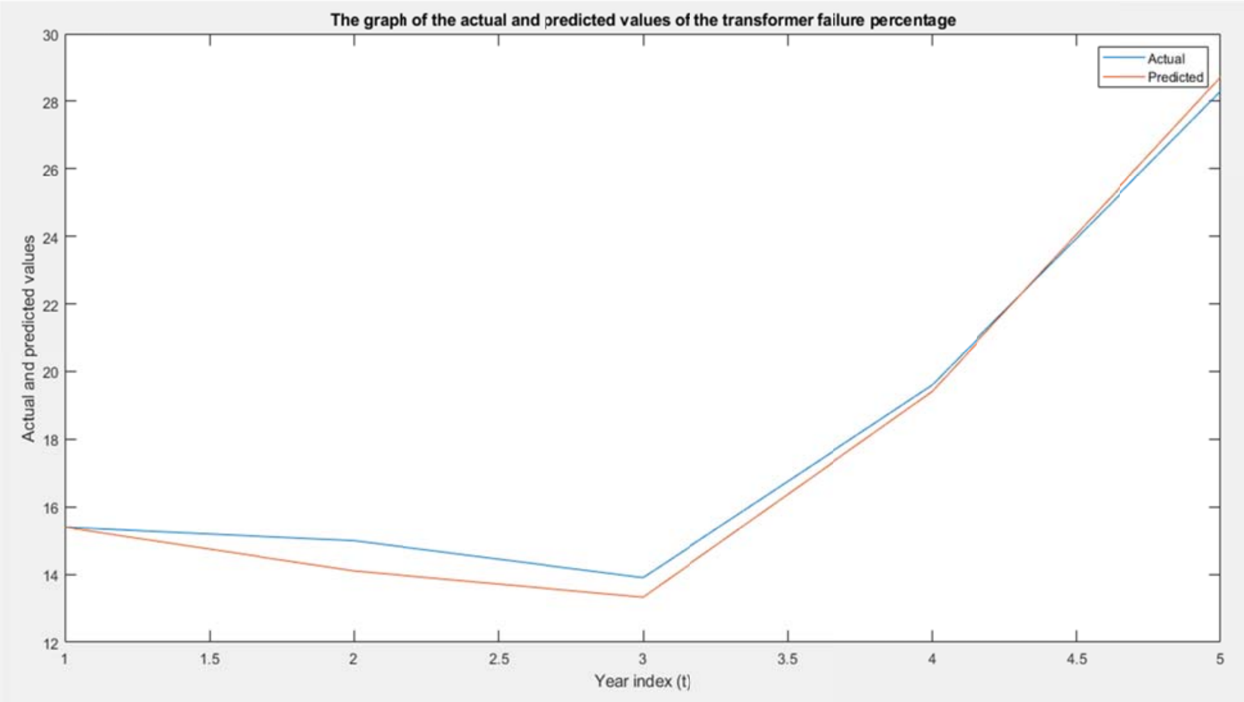

Table 12: The transformer failure percentage

4. CONCLUSION

The Fuzz logic model for the prediction and forecasting of transformer failure rate for a district electricity distribution network is presented. The model is used for the prediction and forecasting of the total number of transformers installed, the total number of customers, the total number of failed transformers, the total outage due to transformer faults and the transformer failure percentage. The model performance parameters used are Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Percentage Error (MPE). The fuzzy logic model results were compared with those of regression model.

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