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A comparative study of RSM, ANN and ANFIS models for predicting circuit Thevenin voltage

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ABSTRACT

Manual reduction of complex circuits using the conventional Thevenin's theorem is a time consuming, laborious, and prone-to-mistakes task. Computational intelligence-based techniques have been successfully used in the prediction of process variables, albeit in fields other than circuit reduction. It is therefore necessary to test the suitability of these computational intelligence techniques in circuit analysis, for the elimination of the highlighted challenges of the Thevenin's theorem. This research paper presents a comparative study of the Response Surface Methodology (RSM), Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System models for predicting the circuit Thevenin voltage. The Taguchi orthogonal array has been utilized in designing the experiment with three levels for each of the three control resistor variables. The Levenberg-Marquardt training algorithm has been implemented in the ANN modelling. Based on the Mean Absolute Percentage Error (MAPE), the ANN and RSM predicted values have been compared to each other. Research results show that the RSM, ANN and ANFIS models have prediction accuracies of 90.13%, 93.35% and 95.33% respectively, in predicting circuit Thevenin voltage. The results show that ANFIS has a higher prediction accuracy of 99.86% when using training data set. Based on the Student's t-test, the research revealed that the mean values of RSM and ANN predicted Thevenin voltages are not significantly different at $p < 0.05$. The results are a clear exhibition of the superiority of ANN and ANFIS over the RSM model in circuit Thevenin voltage estimation. Based on the outcome, it is concluded that computational intelligence-based techniques can be reliably used in circuit reduction.

Keywords: Thevenin Voltage, ANN, ANFIS, RSM, Computational Intelligence and Prediction Accuracy

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1. INTRODUCTION

The conventional circuit reduction method that scientists are introduced at elementary level is the Thevenin's theorem. However, this method is laborious, time consuming and prone to mistakes when dealing with complex electrical circuits. It is therefore imperative to search for alternative methods that are in sync with current technology trends. In this research, the suitability of the Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Response Surface Methodology (RSM) as alternatives for the Thevenin theorem is explored.

Researchers have invented clever alternative supplements to the conventional Thevenin theorem (Hashemian, 2009; Sun, et al., 2018). Despite the invention of these alternatives, the suitability of computational intelligence-based techniques has not been assessed. Hence, this study seeks to bridge this gap. An experimental approach has been taken to generate modelling data in this investigative study. The experimentally observed data has been used to formulate RSM, ANN and ANFIS models, and subsequently validating the models. Based on the Mean Absolute Percentage Error (MAPE), the accuracy of the models in predicting equivalent circuit Thevenin voltage has been assessed. For the utilization of the experimental approach in data generation, a leaf has been borrowed from research aimed at enhancing large and complex circuits (Gunaratne, et al., 2010).

The RSM is a popular statistical analysis method employed for experimental use. With this technique, mathematical model coefficients are determined based on statistically designed experiments, followed by response prediction and efficiency checks. Chamoli (2015) postulated that, RSM is functional in modelling and predicting the response variable of a multi-input system. This study has used a three-input variable and one single variable model.

An ANN is a mathematical model that closely mimics the functional attributes of a biological neural network. It utilizes a multilayer feed-forward learning algorithm. The ANN consists of an input layer, one or more hidden layers and an output layer. During the learning process, inter-layer activation functions and the comparable influence of each neuron are determined. This study employed the MATLAB ANN toolbox for the development and validation of the ANN model.

The ANFIS model determines a learning algorithm based on the connection between input and output parameters (D'Amato, et al., 2014). This is achieved through mapping of input parameters into corresponding input membership functions, followed by transformation of the membership functions to sets of rules. These sets of rules are transformed to output membership functions and subsequently to crisp outputs. In this paper, the experimental setup and procedure are discussed, followed by a presentation of results and their analysis. Lastly, the study conclusion is given.

2. Thevenin's Theorem

Thevenin's Theorem states that "Any linear circuit containing multiple voltages and resistances can be replaced by a single voltage in series with a single resistance connected across the load" (Adebayo, et al., 2019). The ever-increasing addition of components on the grid has motivated the need for a method to accurately determine power grid status. This method comes in the form of the Thevenin theorem. The Thevenin theorem reduces a complex power circuit into an equivalent simpler power circuit. The Thevenin theorem makes use of principles derived from Ohm's and Kirchhoff's laws. The Thevenin's theorem has diverse applications in power systems that include short circuit current calculation in a distribution power system.

Additionally, the Thevenin theorem is utilized in simplifying complex circuits. It has been successfully used in fault detection in power circuits, load matching for maximum power transfer, battery charge state estimation, voltage stability margin adjustment and renewable energy penetration to grid study (Hashmi et. al., 2015).

2. MATERIALS AND METHODS

The first stage in the research is the design of the experiment. The design has three control parameters (circuit resistances) and one response variable (Thevenin voltage). To minimize the number of experiments, the Taguchi L(9) orthogonal array design has been adopted. The control parameters were varied up to three levels for each factor as illustrated in Table 1. For instance, the values of R_1 have been judiciously varied at 6Ω, 12Ω and 20Ω. Only experiment numbers 1-9 have been designed using the Taguchi orthogonal array. Five supplementary experiments were conducted for the purposes of creating data for model validation. These experiments with their corresponding results are presented in the results section in Table 2. The data for Thevenin voltage model development is experimentally obtained by reducing the three-resistor circuit into an equivalent Thevenin circuit, followed by connecting a voltmeter across points XY shown in Figure 1. Figure 1 shows the connection of the three resistors R_1, R_2 and R_3 and their connection to the input voltage V_{in}. Each set of resistor combination and its corresponding Thevenin voltage are tabulated. These experimentally obtained results are used to formulate RSM, ANN and ANFIS models linking circuit resistance to Thevenin voltage. Each model's predicting accuracy is determined by the Mean Absolute Percentage Error Method (MAPE). The mean absolute error value is obtained by the absolute difference between actual Thevenin voltage (V_a) and the estimated Thevenin voltage (V_E) and dividing the result by the actual Thevenin voltage. The MAPE Equation is shown by (1). The experiment setup is illustrated by Figure 1. The value of V_{in} is kept constant at 48V. This value has been selected judiciously.

$$MAPE = \left|\frac{V_a - V_E}{V_a}\right| \times 100 \qquad [1]$$

Table 1: Control variables and their levels

Variables	Levels		
	Low	Medium	High
R1 [KΩ]	6	12	20
R2 [KΩ]	5	8	12
R3 [KΩ]	2	4	6

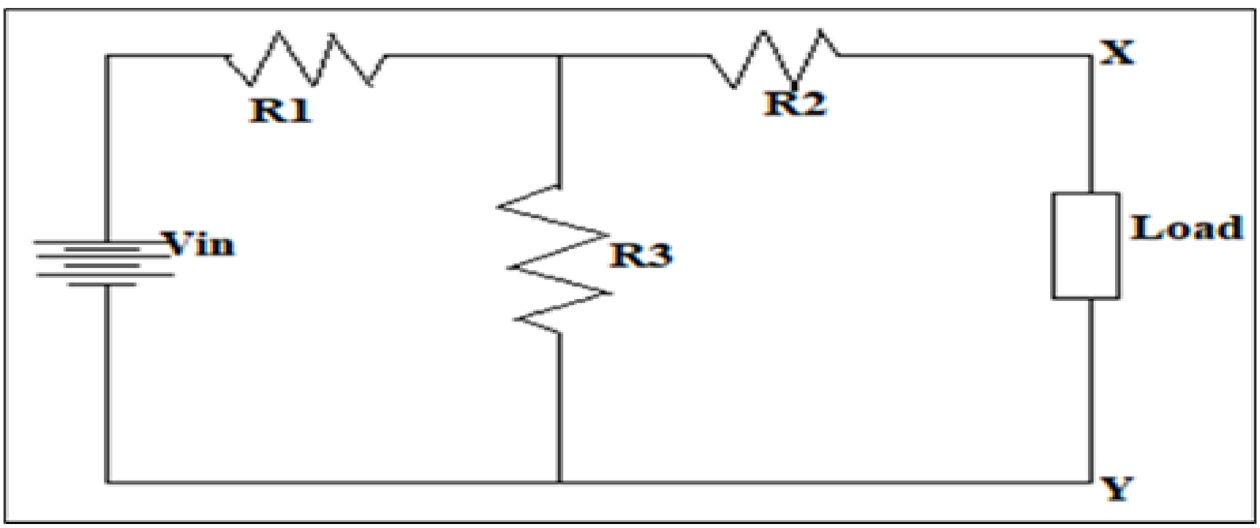

Figure 1: Experiment Setup

3. RESULTS AND DISCUSSION

Response Surface Methodology modelling of the data yields equation 1. RSM modelling shows that R_2 is not a significant predictor for V_{TH} due to a p-value >0.05. Therefore, it has been excluded from the RSM model.

$$V_{Th} = 13.05 - 0.73\, R_1 + 2.17\, R_3 \quad [1]$$

The RSM model's R square (R^2) value equals 0.944. This means that the predictors (R_i) explain 94.4% of the variance of V_{Th}. Adjusted R square value equals 0.934. The coefficient of multiple correlation (R) equals 0.971. This value is an indication of a very strong agreement between the predicted V_{Th} and the experimentally observed V_{Th}. The experimental and predicted V_{Th} results are presented in Table 2.

Table 2: Experimental and Predicted RSM Results

Exp. No.	R1 [KΩ]	R2 [KΩ]	R3 [KΩ]	Exp. V_{Th} [V]	RSM Pred. V_{Th} [V]	Absolute Error (%)
1	6	5	2	12.0	13.01	8.47
2	6	8	4	19.2	17.36	9.56
3	6	12	6	24.0	21.70	9.54
4	12	5	4	12.0	12.98	8.18
5	12	8	6	16.0	17.32	8.30
6	12	12	2	6.9	8.63	25.17
7	20	5	6	11.1	11.48	3.49
8	20	8	2	4.4	2.79	36.44
9	20	12	4	8.0	7.14	10.72
10	7	6	3	14.4	14.46	0.41
11	8	7	4	16.0	15.90	0.60
12	9	9	5	17.1	17.34	1.43
13	13	11	6	15.2	16.59	9.19
14	18	12	3	6.9	6.42	6.81
Mean Absolute Error (%)						**9.87**
Prediction Accuracy (%)						**90.13**

Based on the results presented in Table 2, it is evident that there is a difference between experimental and predicted Thevenin voltage values. However, there is need to ascertain the significance of the difference between the two sets of values.

During ANN modelling, the entire dataset spectrum has been divided into three groups, viz. training, validation, and testing. These groups have been assigned 10, 2 and 2 datasets, respectively. The most accurate ANN has been utilized at this stage. The training algorithm utilized in this study is the Levenberg-Marquardt, while performance has been measured using the Mean Squared Error (MSE). MSE is defined as the average squared difference between outputs and targets. Lower values of MSE are better and zero values indicate the absence of errors. Table 3 gives the experimental and predicted ANN results.

Table 3: Experimental and Predicted ANN Results

Experiment Number	R1 [KΩ]	R2 [KΩ]	R3 [KΩ]	Experimental V_{Th} [V]	ANN Predicted V_{Th} [V]	Absolute Error (%)
1	6	5	2	12.0	12	0.00
2	6	8	4	19.2	17.83	7.14
3	6	12	6	24.0	22.2	7.50
4	12	5	4	12.0	11.16	7.00
5	12	8	6	16.0	14.48	9.50
6	12	12	2	6.9	5.77	16.37
7	20	5	6	11.1	11.23	1.17
8	20	8	2	4.4	4.36	0.90
9	20	12	4	8.0	7.68	4.00
10	7	6	3	14.4	13.15	8.68
11	8	7	4	16.0	14.48	9.50
12	9	9	5	17.1	19.03	11.28
13	13	11	6	15.2	16.16	6.31
14	18	12	3	6.9	6.64	3.76
Mean Absolute Error (%)						**6.65**
Prediction Accuracy (%)						**93.35**

The Thevenin voltage results are compared based on their MAPE values. The ANN model yields a higher prediction accuracy in comparison to the RSM model. Therefore, the ANN model is an appropriate substitute for the manual classical method. A pictorial presentation of the variations of both models' results is given in Figure 2. The RSM predicted values are higher than the ANN predicted values between experiment number 3-7 and 9-12.

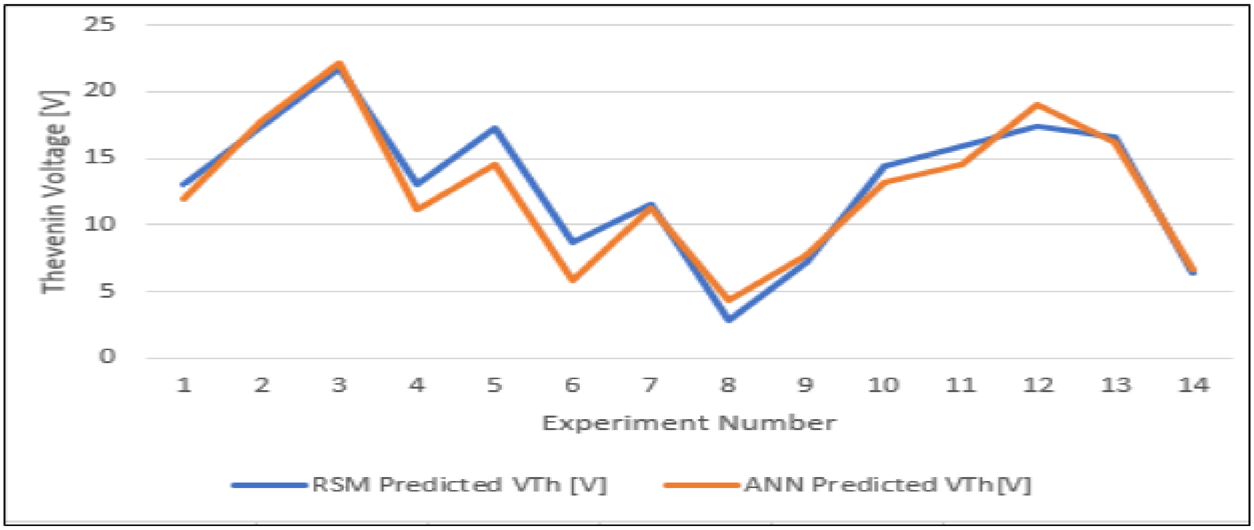

Figure 2: Variation of V_{TH} values

The results have revealed that there is a difference between RSM and ANN model accuracy. However, it is necessary to ascertain whether the difference between the mean of RSM predicted values and the mean of ANN predicted values is significant or not. The student's t-test has used to determine if the mean of two data sets differ significantly. A t-test summary is presented in Table 4. The critical value is 2.056 and the calculated t-value is 0.2499. The calculated t-value is smaller than critical value, signifying that the means are not significantly different. Hence, the means of RSM and ANN predicted Thevenin voltages are not significantly different at $p < 0.05$.

Table 4: t-Test Summary

Statistical Parameter	**RSM**	**ANN**
Mean	13.08	12.58
Variance	27.60	27.65
Standard Deviation	5.25	5.26
Total Number of Values	14	14
t-value	**0.2499**	
Degrees of Freedom	**26**	
Critical Value	**2.056**	

The MATLAB ANFIS toolbox using a trapezoidal membership function has the attributes presented in Table 5. A membership function with three inputs has been utilized since it yielded the highest accuracy in determining Thevenin voltage.

Table 5: ANFIS learning information

Learning Scenario	Value
Number of Nodes	78
Number of Linear Parameters	36
Number of Non-Linear Parameters	54
Total Number of Parameters	90
Number of Training Data Pairs	9
Minimal Training RSME	0.026352
Number of Fuzzy Rules	9

Table 5 shows that the ANN utilized has 78 nodes, 36 linear parameters and 54 non-linear parameters. Additionally, 9 training data pairs yielded 0.026352 RSME. Figure 3 is a screen shot of the ANFIS test plot against training data. The circles in the plot represent experimentally determined Thevenin voltage values. The stars represent ANFIS predicted Thevenin voltage values. The total overlapping of the circles and stars in the screen is an indication of high prediction accuracy. Table 6 represents an assessment of ANFIS prediction accuracy based on MAPE. The prediction accuracy of ANFIS on training datasets is 99.86%.

Figure 3: Fuzzy inference system plot against training data

Table 6: Thevenin voltage prediction using training data

Experiment Number	Measured V_{Th} [V]	Predicted V_{Th} [V]	Absolute Error (%)
1	12.0	12.0	0.00
2	19.2	19.2	0.00
3	24.0	24.0	0.00
4	12.0	12.0	0.00
5	16.0	16.0	0.00
6	6.9	6.9	0.00
7	11.1	11.1	0.00
8	4.4	4.4	0.00
9	8.0	7.9	1.25
Mean Absolute Error (%)			**0.14**
Prediction Accuracy (%)			**99.86**

The prediction accuracy value is an exhibition of ANFIS's high prediction power. A plot of ANFIS predicted Thevenin voltage values against testing data is shown in Figure 4. The dots in the plot represent experimentally determined Thevenin voltage values. The red stars represent ANFIS predicted Thevenin voltage values. The overlap between the dots and the red stars is an indication of the model's high prediction accuracy. Table 7 is a presentation of ANFIS prediction accuracy on Testing Data. Based on the MAPE method, ANFIS has a prediction accuracy of 95.33%.

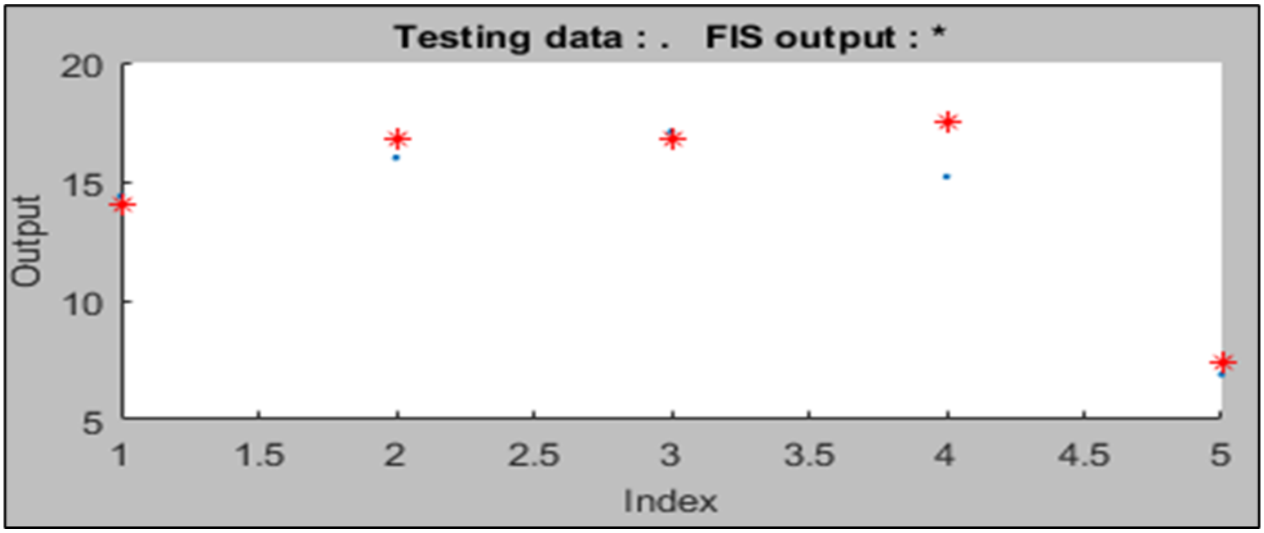

Figure 4: Fuzzy inference system plot against testing data

Table 7: Thevenin voltage prediction using testing data

Experiment Number	Measured V_{Th} [V]	Predicted V_{Th} [V]	Absolute Error (%)
10	14.4	14.0	2.77
11	16.0	15.70	1.85
12	17.1	16.80	1.75
13	15.2	17.5	15.13
14	6.9	7.03	1.88
Mean Absolute Error (%)			**4.67**
Prediction Accuracy			**95.33**

A comparison of ANFIS's prediction accuracy on training datasets and testing datasets reveals that the model has a higher prediction accuracy on training data than on testing data. This is understandable, since a small training dataset has been used. Generally, a larger dataset enhances the accuracy of the RSM model. In real life, there are instances when large datasets are not available for prediction purposes. The highest MAPE value of 15.13% is obtained on experimental run 13 while the lowest MAPE value of 1.75% is attained on experimental run 12. The Prediction accuracy of ANFIS on testing datasets is

95.33%. This value is within the upper quartile region, hence ANFIS is classified as being an accurate prediction model.

4. Conclusion

This study presented a comparative study of the RSM, ANN and ANFIS models for predicting circuit Thevenin voltage. The experiments have been designed by the Taguchi orthogonal array with three levels for each of the resistor control variables. The research results have revealed that the order of increasing prediction accuracy is as follows: RSM, ANN and ANFIS. RSM has a prediction accuracy of 90.13% while ANN and ANFIS have prediction accuracies of 93.35% and 95.33% respectively. The study also revealed that ANFIS predicts Thevenin voltage more accurately when using training datasets than when using testing datasets. ANFIS yields prediction accuracy of 99.86% on training datasets and a prediction accuracy of 95.33% on testing datasets. Since these values are in the upper quartile region, both prediction accuracy values are classified as good, hence ANFIS can be reliably employed to predict Thevenin voltage. Based on the Student's t-test, the research has also revealed that the mean values of RSM and ANN predicted Thevenin voltages are not significantly different at $p < 0.05$. Generally, computational intelligence-based models are superior to RSM model. Further studies to compare the performance of ANFIS and other computational intelligence techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are recommended, and the author is currently working on the research.

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