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# Comparison Of The Power Flow Analysis Using A Deterministic Approach And Artificial Neural Network

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***Abstract*— In this paper, comparison of the power flow analysis using a deterministic approach and Artificial Neural Network (ANN) is presented. The algorithm and flowchart for the Gauss-Siedel power flow approach are presented. The key ANN power flow analysis model parameters settings and the ANN flowchart are presented. Power flow analysis is first conducted using the Guss-Siedel approach and then the output from the Guss-Siedel power flow analysis is used as the base case dataset for training the artificial neural network (ANN) power flow model. This min-max data normalization is adopted in the ANN model. Performance assessment of the ANN model is conducted in terms of the following three parameters, Mean-Squared Error (MSE), Mean-Absolute Error (MAE) and Coefficient of multiple determinations ($R^2$). The study is conducted using the IEEE 33 bus system with Bus as the slack bus. Both the ANN and Gauss-Siedel power flow models were simulated in MATLAB. The ANN model training gave satisfactory results after 7 iterations which took about 21 seconds with momentum constant of 0.000001. In all, with MSE of 0.001626 for bus voltage, 0.002427 for phase angle and not more than 1.5 for the bus powers, it can be concluded that the ANN model effectively estimated the power flow parameters presented as the base case dataset. Also, the high $R^2$ values, above 0.988 also confirms that the ANN model estimation of the base case parameter values is good and hence, the ANN model can be used to carry out power flow analysis on IEEE 33 bus system.**

***Keywords*— *Gauss-Siedel Method, Power Flow Analysis, Deterministic Power Flow Approach, Artificial Neural Network***

## 1.0 Introduction

Over the years, power system planning and design has evolved to accommodate diverse methodologies in handling the different aspects of the power system planning and design problem set. Analytical models have been widely applied in load forecasting, load flow analysis, voltage stability analysis and many other power system related issues [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]. Also, data driven models like the Artificial Neural Network (ANN) models has also emerged and evolved and have been employed in solving virtually all the power system problems to which analytical models are used [16,17,18,19,20]. The good side of the ANN model is that it can easily be adapted to diverse problem sets in any field and there also perform well when compared with various deterministic iterative algorithms that are used in various numerical analysis [21,22,23, 24,25,26, 27,28,29, 30,31,32, 33,34,35, 36,37, 38,39]. As such, today, ANN-based solution have been developed for application in telecommunications, in satellite communications, in social networking platforms, in Internet of Thing smart systems applications, as well as in web and mobile applications [40,41, 42,43, 44,45, 46,47, 48,49,50, 51,52, 53]. Also, many embedded systems and software solutions are based on ANN algorithms running at the backend and providing the requisite logics for the proper functioning of the software solution [54,55,56,57,58,59,60,61,62,63,64,65,66,67,68].

On the other hand, ANN is a data driven model [69,70,71]. As such, it can only be applied in the load flow analysis after it must have been trained with a load flow input and corresponding output dataset [72,73,74]. This is different from the deterministic approach which can on its own take load flow input data set and generate the corresponding load flow output data. However, after the ANN model is trained, it can then work like the deterministic model, whereby it takes load flow input dataset and generate the corresponding load flow output dataset. In order to compare the performance of a deterministic load flow model and a data-driven ANN model, in this paper, Gauss-Siedel deterministic load flow approach [75,76,77] is selected and compared with the ANN model. Specifically, the Newton Raphson load flow method is used to generate the base case load flow analysis input and expected output datasets and then the load flow analysis is conducted with Gauss-Siedel method and also with the ANN mode. The performance of the two methods with respect to the base case load flow datasets are determined and compared.

## 2. Methodology

### 2.1 The Gauss-Siedel power flow approach

In the Gauss-Siedel power flow approach, the bus power $P_i$ (real power) and $Q_i$ (reactive power) are computed using the static power flow equations which utilises the bus voltages, $V_i$ as follows [78];

$$P_i = \sum_{j=1}^{n} \left( |V_i||V_j||Y_{ij}| \left( \text{Cos}\, \theta_{ij} - \delta_i + \delta_j \right) \right) \tag{1}$$

$$Q_i = -\sum_{j=1}^{n} \left( |V_i||V_j||Y_{ij}| \left( \text{Sin}\, \theta_{ij} - \delta_i + \delta_j \right) \right) \tag{2}$$

where

$Y_{ij}$ is used to represent the admittance of the power line that links the ith bus with the jth bus

$\theta_{ij}$ is used to represent the phase angle of $Y_{ij}$

$\delta_i$ and $\delta_j$ are used to represent the phase angle of the ith and jth bus voltages

$V_i$ and $V_j$ are used to represent the bus voltage at the ith and jth bus

The algorithm for the Gauss-Siedel power flow approach is given in Procedure 1 while the flowchart is shown in Figure 1.

**PROCEDURE 1: The algorithm for the Gauss-Siedel power flow approach**

**Step 1:** Read the relevant power system dataset
**Step 2:** Form the admittance matrix (Ybus)
**Step 3:** Set the estimation accuracy tolerance, $\varepsilon$
**Step 4:** Set the iteration acceleration factor, $\alpha$
**Step 5:** Set the iteration counter, k = 0,
**Step 6:** Initialise $V_i$ the bus voltages for all the buses except the slack bus, such that $V_i = 1 \ < 0°$ $|V_i| = 1$ and the phase angle is 0° except the slack bus, that is set ${V_1}^k, {V_2}^k, {V_3}^k, \ldots, {V_n}^k = 1 < 0°$ except the slack bus
**Step 7:** Set the bus counter, i=1
**Step 8:** Check if it is a slack then jump to step 12 otherwise continue in the next step (step 9)
**Step 9:** Compute ${V_i}^{k+1}$
**Step 10:** Compute ${V_i}^{k+1} = {V_{iacc}}^{k+1} = {V_i}^k + \alpha\left[{V_i}^{k+1} - {V_i}^k\right]$
**Step 11:** Compute $\Delta {V_i}^k = {V_{iacc}}^{k+1} - {V_i}^k$
**Step 12:** Increase bus counter by 1; i = i +1
**Step 13:** Check if i < n then jump to step 8 otherwise continue in the next step (step 14)
**Step 14:** Find Maximum$\left(\left| \Delta {V_i}^k \right|\right) = \left|{V_{iacc}}^{k+1} - {V_i}^k\right|$ for i = 1,2,3,…,n
**Step 15:** Check if Maximum$\left(\left| \Delta {V_i}^k \right|\right) < \varepsilon$ then jump to step 18 otherwise continue in the next step (step 16)
**Step 16:** Increase iteration counter by 1; k = k +1
**Step 17:** Jump to Step 7
**Step 18:** Use the bus voltages to compute the line flows and slack bus power
**Step 19**: Stop

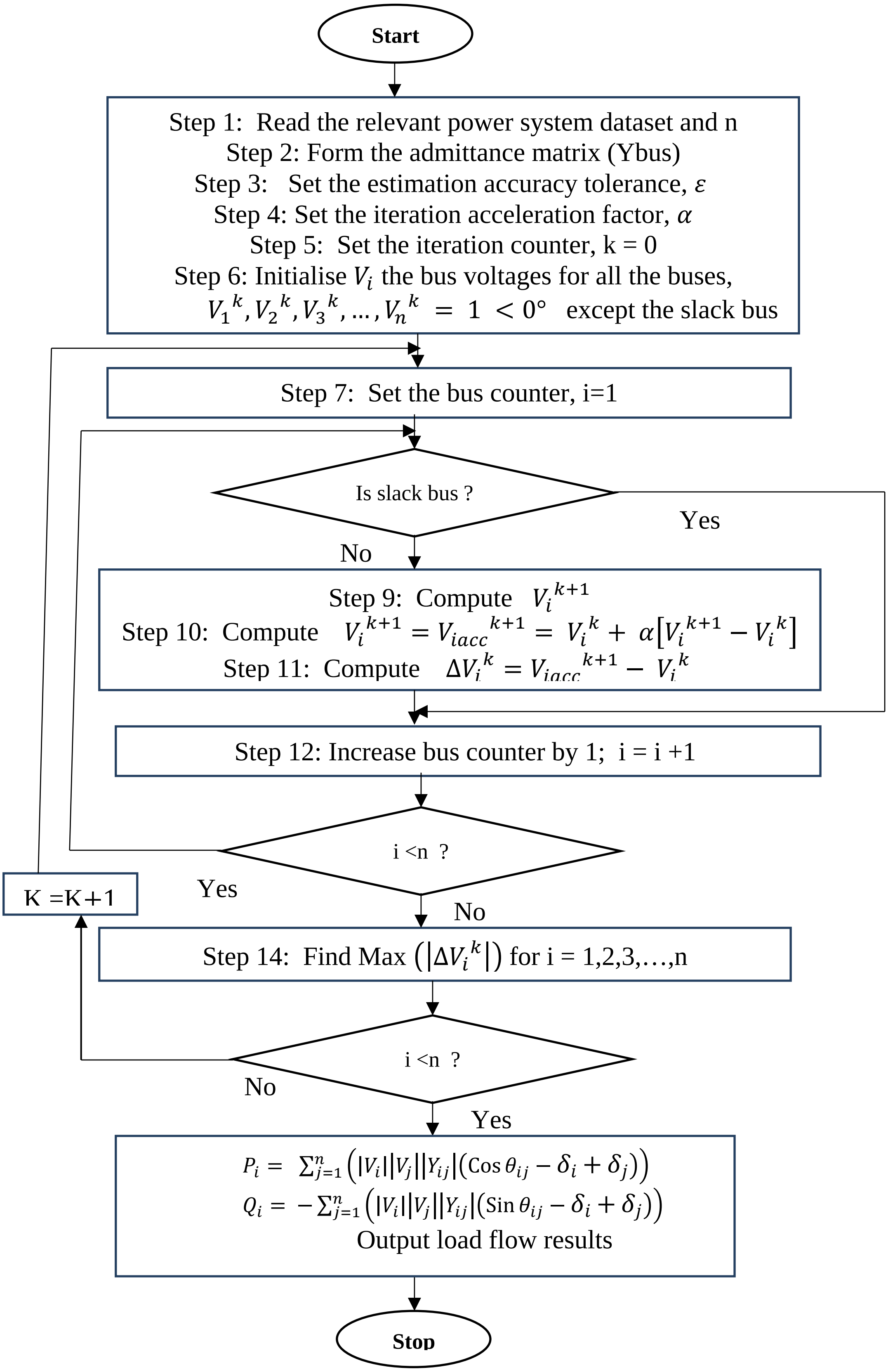


**Figure 1 The flowchart for the Gauss-Siedel power flow approach**

### 2.2 The Artificial Neural Network Power flow Approach

The key ANN power flow analysis model parameters settings that are used in the study are shown in Table 1 while Figure 2 shows the flowchart of the ANN power flow analysis model.

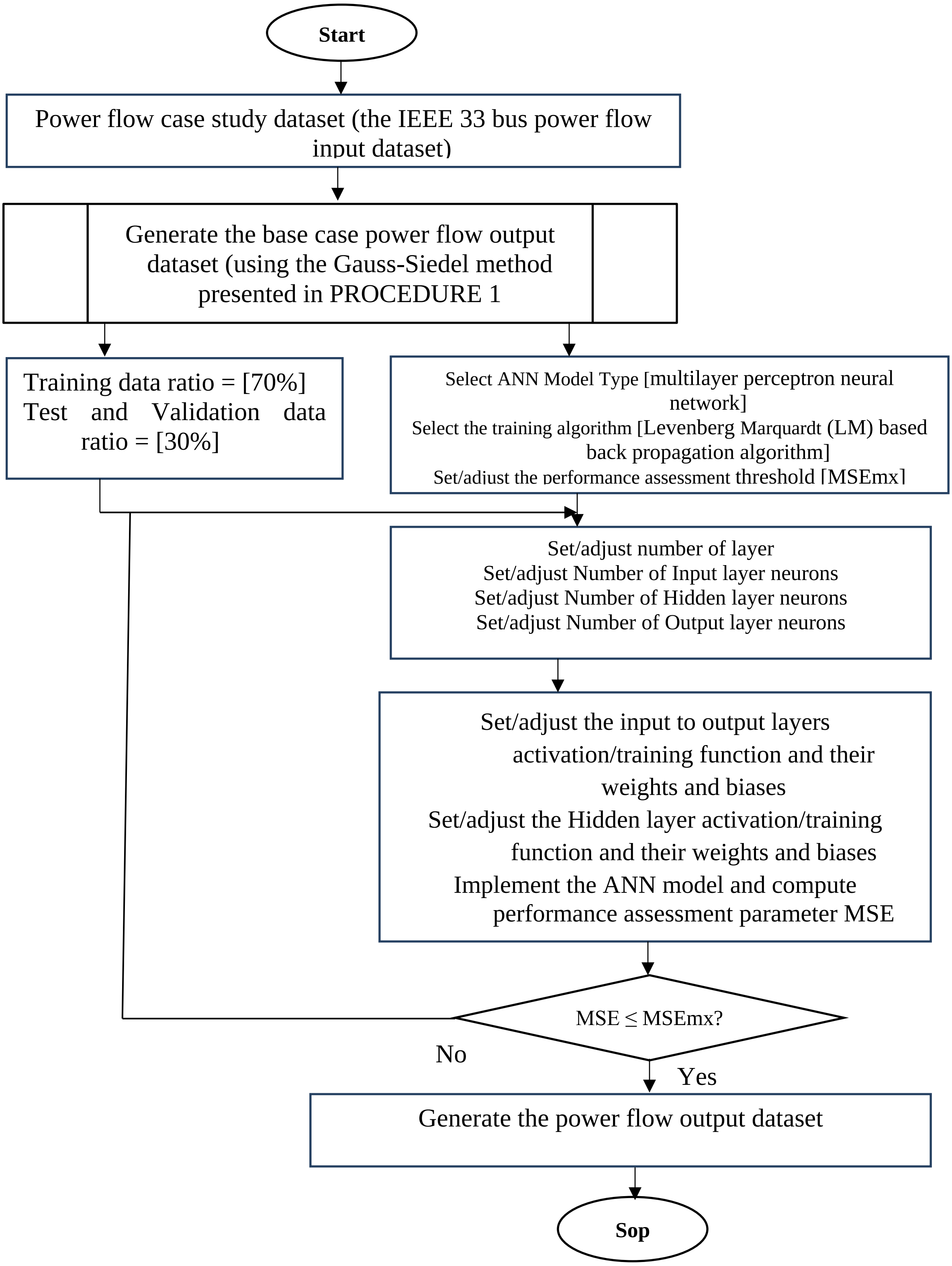


**Figure 2 The flowchart of the ANN power flow analysis model**

**Table 1 The key ANN power flow analysis model parameters settings that are used in the study**

| **ANN Configuration / Parameter Description** | **ANN Configuration /Parameter Value** |
|---|---|
| ANN Model type | Multilayer perceptron neural network (MLPNN) |
| The number of layers | 3 |
| Input layer neurons | 66<br>Note : Each input layer neuron represents the input features which are the real and reactive powers for the thirty-three (33) load buses in the IEEE 33-bus system |
| Hidden layer neurons | 120 |

| | |
|---|---|
| Output layer neurons | 64<br>Note : Each output layer neuron represents the output variables |
| ANN performance parameter | MSE |
| Hidden layer | Hyperbolic tangent sigmoid (tansig) |
| Activation function used between the input and output layers | Purely linear (purelin) |
| Training algorithm | Levenberg-Marquardt-based back-propagation algorithm |
| Data normalisation model | min-max data normalization |
| **Performance Assessment parameters** | i. Mean-Squared Error (MSE)<br>ii. Mean-Absolute Error (MAE)<br>iii. Coefficient of multiple determinations (R^2) |

### 2.3 Data normalisation and Performance Assessment for the ANN Model

**Data normalization:** This min-max data normalization is adopted in the ANN model input dataset. The normalization process scales the input data ($X_i$) to a normalized data $Z_i$ whose value is between zero and one using the following expression;

$$X_{i(max)} = maximum\ (X_i)\ for\ i = 1,2,3, \dots, n \quad (3)$$

$$X_{i(min)} = minimum\ (X_i)\ \ for\ i = 1,2,3, \dots, n \quad (4)$$

$$Z_i = \frac{X_i - X_{i(min)}}{X_{i(max)} - X_{i(min)}} \quad (5)$$

**Performance assessment:** Performance assessment of the ANN model is conducted in terms of the following three parameters;

i. Mean-Squared Error (MSE)
ii. Mean-Absolute Error (MAE)
iii. Coefficient of multiple determinations ($R^2$)

The parameters are computed in terms $Y_{ANN}$ (the ANN model predicted value) and $Y_{BaseCase}$ (the base case value which is the equivalent power flow parameter value generated using Gauss-Siedel power flow approach ) as follows;

$$MSE = \left(\frac{1}{n}\right)\left[\sum_{i=1}^{n}(Y_{ANN} - Y_{BaseCase})^2\right] \quad (6)$$

$$MAE = \left(\frac{1}{n}\right)\left(\sum_{i=1}^{n}|Y_{ANN} - Y_{BaseCase}|\right) \quad (7)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(Y_{ANN} - Y_{BaseCase})^2}{\sum_{i=1}^{n}(Y_{BaseCase})^2}\right) \quad (8)$$

### 2.4 The simulation and dataset

The comparison of the deterministic (Gauss-Siedel) approach and Artificial Neural Network power flow approach is conducted using the IEEE 33 bus system. The slack bus is assigned to Bus 1 of the IEEE 33 bus network. Both the ANN and Gauss-Siedel power flow models were simulated in MATLAB. The Gauss-Siedel power flow analysis was first conducted and the results were used along with the input dataset to train and validate the ANN model. The ANN model training gave satisfactory results after 7 iterations which took about 21 seconds, as shown in Figure 3. Also, Figure 3 show that the gradient obtained at the 7th epoch is 0.00164 while the momentum constant is 0.000001. The screenshot in Figure 4 shows that the gradient became very small as the training reaches a best of its performance at epoch 7. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease, in this case the validation check was 6, as shown in Figure 4. Also, Figure 5 shows the regression values for the model training, testing and validation phases.

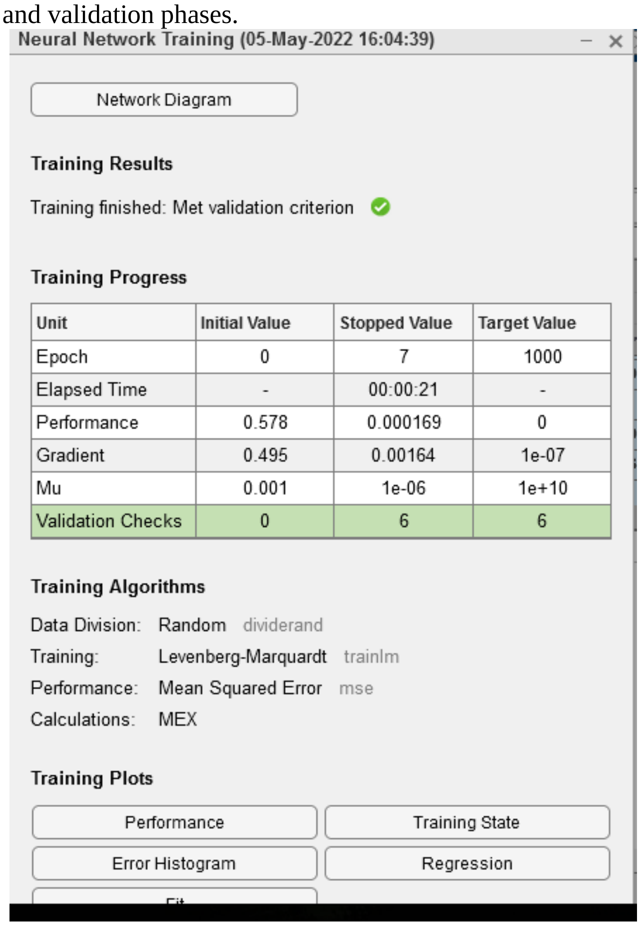

Figure 3.: The Artificial neural network training result interface


Figure 4. The screenshot show how the gradient and momentum constant vary with the iterations/epoch

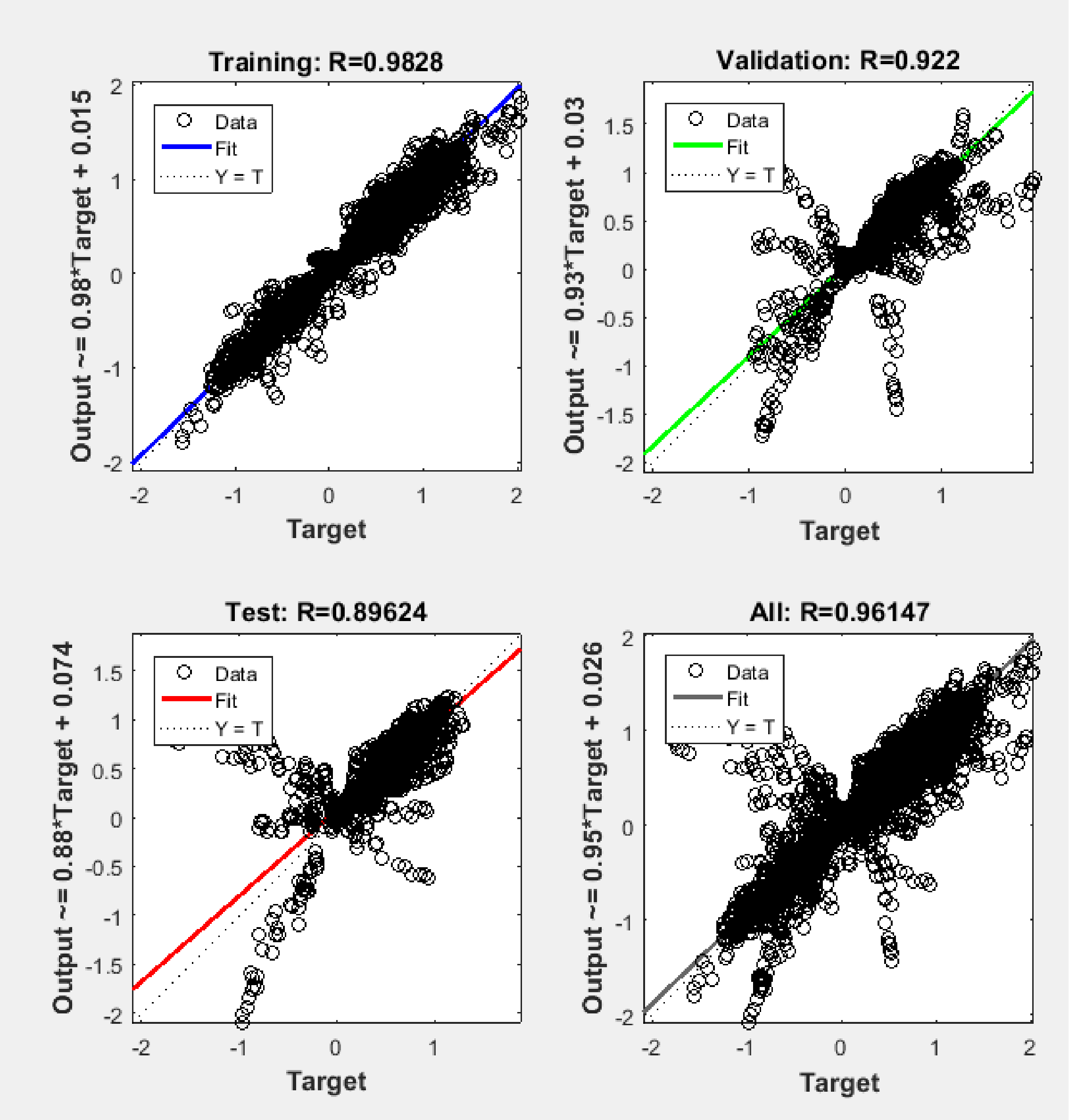


Figure 5: The learning curve of the ANN model

## 3. Results and Discussion

The results of comparison of the base case voltage [P.U.] by the Guss-Siedel model and the predicted voltage [P.U.] by the ANN model are shown in Table 2 and Figure 6. Similarly, the results of comparison of the base case phase angle in radians by the Guss-Siedel model and the predicted phase angle in radians by the ANN model are shown in Table 3 and Figure 7. Furthermore, the results of comparison of the base case load and generator active and reactive power by the Guss-Siedel model and the predicted values by the ANN model as shown in Table 4 while the results on the prediction performance of the ANN model for the voltage, phase angle, and power in terms of MSE, MAE and $R^2$ values as shown in Table 5.

In all, with MSE of 0.001626 for voltage, 0.002427 for phase angle and not more than 1.5 for the bus powers, it can be concluded that the ANN model effectively estimated the power flow parameters presented as the base case. Also, the high $R^2$ values, above 0.988 also confirms that the ANN model estimation of the base case parameter values is good and hence, the ANN model can be used to carry out power flow analysis on IEEE 33 bus system.

**Table 2 Comparison of the base case voltage [P.U.] by the Guss-Siedel model and the predicted voltage [P.U.] by the ANN model**

| Bus No. | Base Case Voltage [P.U.] By Guss-Siedel Model | Predicted Voltage [P.U.] by ANN Model | Bus No. | Base Case Voltage [P.U.] By Guss-Siedel Model | Predicted Voltage [P.U.] by ANN Model |
|---|---|---|---|---|---|
| 1 | 1 | 1 | 17 | 0.715 | 0.67563 |
| 2 | 0.9862 | 0.989117 | 18 | 0.717 | 0.719333 |
| 3 | 0.927 | 0.88199 | 19 | 0.9821 | 0.94807 |
| 4 | 0.8924 | 0.949953 | 20 | 0.9543 | 0.96655 |
| 5 | 0.8607 | 0.69591 | 21 | 0.9486 | 0.968141 |
| 6 | 0.7693 | 0.7658 | 22 | 0.9432 | 0.951852 |
| 7 | 0.7277 | 0.745394 | 23 | 0.9198 | 0.86059 |
| 8 | 0.7236 | 0.69307 | 24 | 0.9094 | 0.960634 |
| 9 | 0.7036 | 0.67375 | 25 | 0.9042 | 0.90216 |
| 10 | 0.6954 | 0.71951 | 26 | 0.7635 | 0.71304 |
| 11 | 0.6981 | 0.67778 | 27 | 0.7568 | 0.72754 |
| 12 | 0.7032 | 0.6927 | 28 | 0.7226 | 0.69275 |
| 13 | 0.7077 | 0.710519 | 29 | 0.7025 | 0.719124 |
| 14 | 0.7053 | 0.716383 | 30 | 0.6971 | 0.66862 |
| 15 | 0.7085 | 0.68604 | 31 | 0.6815 | 0.713388 |
| 16 | 0.7135 | 0.72818 | 32 | 0.6776 | 0.64318 |
| 17 | 0.715 | 0.67563 | 33 | 0.6746 | 0.6746 |

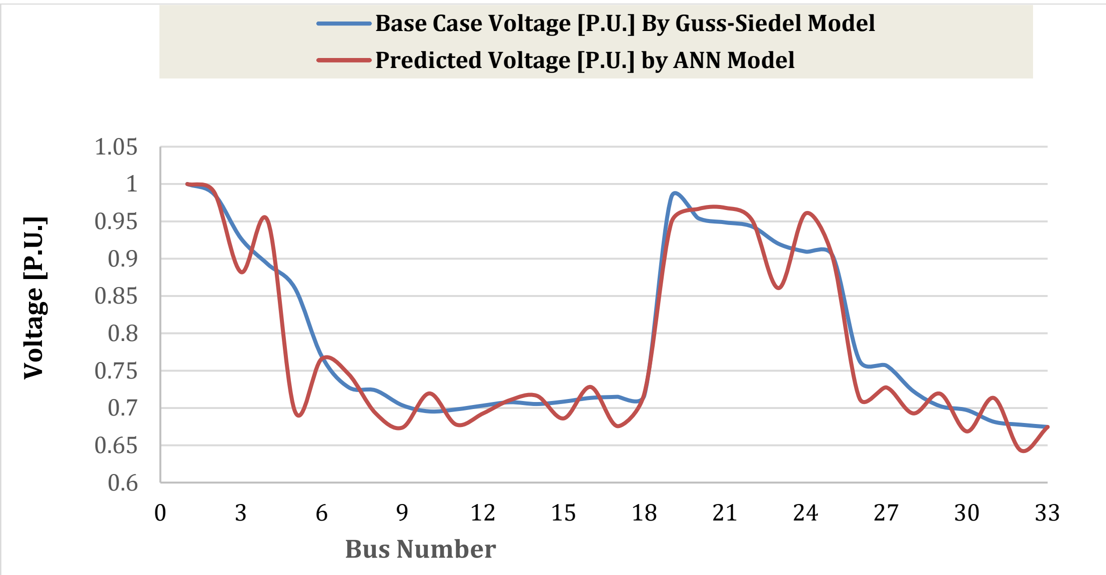


**Figure 6 Comparison of the base case voltage [P.U.] by the Guss-Siedel model and the predicted voltage [P.U.] by the ANN model**

**Table 3 Comparison of the base case phase angle [Radian] by the Guss-Siedel model and the predicted phase angle [Radian] by the ANN model**

| Bus No. | Base Case Phase Angle [Radian] By Guss-Siedel Model | Predicted Phase Angle [Radian] by ANN Model | Bus No. | Base Case Phase Angle [Radian] By Guss-Siedel Model | Predicted Phase Angle [Radian] by ANN Model |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 17 | 0.8631 | 0.70765 |
| 2 | 0.011602 | 0.021227 | 18 | 0.870032 | 0.783312 |
| 3 | 0.074328 | 0.151325 | 19 | 0.0116 | -0.03176 |
| 4 | 0.1218 | 0.05871 | 20 | 0.0124 | 0.00978 |
| 5 | 0.1739 | 0.17273 | 21 | 0.0118 | 0.050785 |
| 6 | 0.2954 | 0.303566 | 22 | 0.011 | -0.01982 |
| 7 | 0.3218 | 0.2762 | 23 | 0.0769 | 0.04851 |
| 8 | 0.3904 | 0.3485 | 24 | 0.08 | 0.112665 |
| 9 | 0.4948 | 0.44191 | 25 | 0.0814 | 0.081692 |
| 10 | 0.5951 | 0.57216 | 26 | 0.3074 | 0.29758 |
| 11 | 0.6094 | 0.56536 | 27 | 0.322316 | 0.320176 |
| 12 | 0.632917 | 0.633014 | 28 | 0.3739 | 0.3529 |
| 13 | 0.7334 | 0.68868 | 29 | 0.408764 | 0.358984 |
| 14 | 0.773222 | 0.700792 | 30 | 0.427247 | 0.404697 |
| 15 | 0.8019 | 0.71256 | 31 | 0.455514 | 0.411184 |
| 16 | 0.8253 | 0.7869 | 32 | 0.46178 | 0.4333 |
| 17 | 0.8631 | 0.70765 | 33 | 0.465189 | 0.465189 |

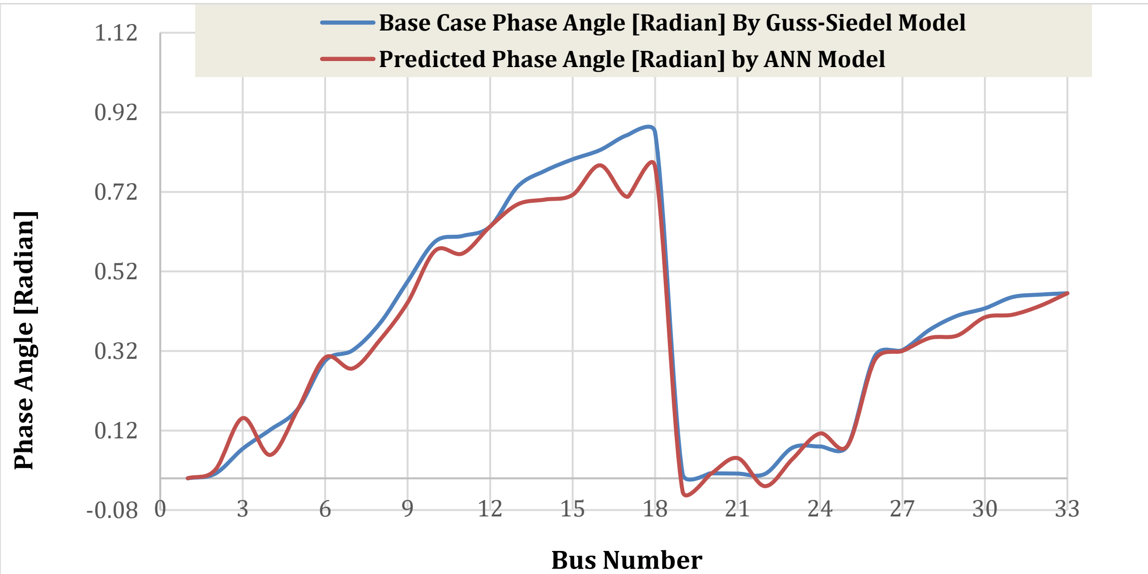


**Figure 7 Comparison of the base case phase angle [Radian] by the Guss-Siedel model and the predicted phase angle [Radian] by the ANN model**

**Table 4 Comparison of the base case load and generator active and reactive power by the Guss-Siedel model and the predicted values by the ANN model**

| | Guss-Siedel Model | | | | ANN Model | | | |
|---|---|---|---|---|---|---|---|---|
| **Bus No.** | **Base Case Load Active Power (MW) By Guss-Siedel Model** | **Base Case Load Reactive Power (MVar) By Guss-Siedel Model** | **Base Case Gen. Active Power. (MW) By Guss-Siedel Model** | **Base Case Gen. Reactive Power (MVar) By Guss-Siedel Model** | **Predicted Load Active Power (MW) by ANN Model** | **Predicted Load Reactive Power (MVar) by ANN Model** | **Predicted Gen. Active Power (MW) by ANN Model** | **Predicted Gen. Reactive Power (MVar) by ANN Model** |
| 1 | 0.000 | 0.000 | 260.950 | -17.010 | 0.000 | 0.000 | 258.772 | -16.944 |
| 2 | 21.700 | 12.700 | 40.000 | 48.826 | 21.581 | 12.676 | 39.784 | 48.781 |
| 3 | 2.400 | 1.200 | 0.000 | 0.000 | 2.263 | 1.136 | 0.000 | 0.000 |
| 4 | 7.600 | 1.600 | 0.000 | 0.000 | 8.026 | 1.695 | 0.000 | 0.000 |
| 5 | 94.200 | 19.000 | 0.000 | 35.995 | 87.615 | 17.740 | 0.000 | 33.643 |
| 6 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 7 | 22.800 | 10.900 | 0.000 | 0.000 | 23.162 | 11.112 | 0.000 | 0.000 |
| 8 | 30.000 | 30.000 | 0.000 | 30.759 | 28.481 | 28.588 | 0.000 | 29.342 |
| 9 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 10 | 5.800 | 2.000 | 0.000 | 0.000 | 5.952 | 2.060 | 0.000 | 0.000 |
| 11 | 0.000 | 0.000 | 16.113 | 0.000 | 0.000 | 0.000 | 15.510 | 0.000 |
| 12 | 11.200 | 7.500 | 0.000 | 0.000 | 10.938 | 7.351 | 0.000 | 0.000 |
| 13 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 14 | 6.200 | 1.600 | 0.000 | 0.000 | 6.245 | 1.617 | 0.000 | 0.000 |
| 15 | 8.200 | 2.500 | 0.000 | 0.000 | 7.871 | 2.409 | 0.000 | 0.000 |
| 16 | 3.500 | 1.800 | 0.000 | 0.000 | 3.542 | 1.828 | 0.000 | 0.000 |
| 17 | 9.000 | 5.800 | 0.000 | 0.000 | 8.428 | 5.452 | 0.000 | 0.000 |
| 18 | 3.200 | 0.900 | 0.000 | 0.000 | 3.183 | 0.899 | 0.000 | 0.000 |
| 19 | 9.500 | 3.400 | 0.000 | 0.000 | 9.091 | 3.266 | 0.000 | 0.000 |
| 20 | 2.200 | 0.700 | 0.000 | 0.000 | 2.210 | 0.706 | 0.000 | 0.000 |
| 21 | 17.500 | 11.200 | 0.000 | 0.000 | 17.713 | 11.376 | 0.000 | 0.000 |
| 22 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 23 | 3.200 | 1.600 | 0.000 | 0.000 | 2.967 | 1.489 | 0.000 | 0.000 |
| 24 | 8.700 | 6.700 | 0.000 | 0.000 | 9.117 | 7.045 | 0.000 | 0.000 |
| 25 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 26 | 3.500 | 2.300 | 0.000 | 0.000 | 3.239 | 2.137 | 0.000 | 0.000 |
| 27 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 29 | 2.400 | 0.900 | 0.000 | 0.000 | 2.437 | 0.917 | 0.000 | 0.000 |
| 30 | 10.600 | 1.900 | 0.000 | 0.000 | 10.077 | 1.813 | 0.000 | 0.000 |
| 31 | 3.500 | 2.400 | 0.000 | 0.000 | 3.634 | 2.501 | 0.000 | 0.000 |
| 32 | 8.700 | 3.500 | 0.000 | 0.000 | 8.185 | 3.305 | 0.000 | 0.000 |
| 33 | 3.500 | 2.400 | 0.000 | 0.000 | 3.470 | 2.388 | 0.000 | 0.000 |

**Table 5 The results on the prediction performance of the ANN model for the voltage, phase angle, and power in terms of MSE, MAE and $R^2$ values**

| | Voltage | Phase Angle | Load Active Power | Load Reactive Power | Gen. Active Power | Gen. Reactive Power |
|---|---|---|---|---|---|---|
| MSE | 0.001626 | 0.002427 | 1.442858 | 0.123011 | 0.15618 | 0.228672 |
| MAE | 0.027499 | 0.036631 | 0.404515 | 0.154788 | 0.090818 | 0.117576 |
| $R^2$ | 0.997473 | 0.9882 | 0.995513 | 0.997674 | 0.999925 | 0.99838 |

4. Conclusion

Power flow analysis is conducted using the Guss-Siedel approach and then the output from the Guss-Siedel power flow analysis is used as the base case dataset for training an artificial neural network (ANN) power flow model. The main mathematical expressions for Guss-Siedel power flow are presented along with the flowchart and algorithm. Also, the key ANN parameters settings are presented along with the flow chart for the ANN power flow model. The models are implemented using MATLAB program and IEEE 33 bus system data. The results of the bus voltages and also the phase angles as well as the load and generator powers obtained from the power flow analysis using the two models are compared and the prediction performance results show that the ANN is suitable for effective power flow analysis.

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