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Research Article

Optimized Power Loss Prediction in IEEE 118 Bus Network using Multilayered Feed-Forward Neural Networks

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Special Issue
A Themed Issue in Honour of Professor Onukwuli Okechukwu Dominic (FAS).

This special issue is dedicated to Professor Onukwuli Okechukwu Dominic (FAS), marking his retirement and celebrating a remarkable career. His legacy of exemplary scholarship, mentorship, and commitment to advancing knowledge is commemorated in this collection of works.

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Optimized Power Loss Prediction in IEEE 118 Bus Network using Multilayered Feed-Forward Neural Networks

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Abstract

Accurate power loss estimation is crucial for efficient power system operation and planning. Traditional methods rely on assumptions, leading to inaccuracies. This study employed Multilayered Feed-Forward Neural Networks (MFNNs) to develop a model that estimates real and reactive power losses in power lines. Load flow techniques were used to obtain variables for training several models. The desired model was selected after adjusting neuron numbers and comparing the performance indicators of other models. The 118-Bus IEEE test network was modelled using MATPOWER. The Levenberg-Marquardt backpropagation algorithm trained the model on generated data. Results show that the 25-neuron model performed best, achieving the least mean square error (0.00047543) at 1000 epochs. Correlation coefficients revealed a 0.99999 value for 20-neuron and 25-neuron models. The analysis identified the 25-neuron-based trained model as the most accurate for predicting power losses. It was observed that the 25-neuron model achieved optimum performance with the highest correlation coefficient (0.99999) recorded and the Least mean square error (0.00047543) at 1000 epochs. This study demonstrates the effectiveness of ANNs in estimating power losses in transmission lines. The recommended 25-neuron-based trained model provides the best predictions from studied models, enhancing power system efficiency and planning.

Keywords: Neural Network, Neurons, Load flow, Levenberg-Marquardt, Newton Raphson

1. Introduction

The power grid serves the important role of delivering electricity from power plants to consumers (Hasanuzzaman, et al. 2017, Madueme and Onyegbadue 2018). Nonetheless, losses occurring in the transmission lines can considerably affect the efficiency and reliability of the system. It is important to effectively detect and minimize real and reactive power losses to enhance the system's overall performance (Ismail, et al. 2020, Bayat and Bagheri 2019). Tools for modelling power system networks have become more important due to the increasing energy generation and demand (Yekini, et al. 2024, Deng and Lv 2020). The growing complexity of the electricity system requires new tools for power system modelling (Deng and Lv 2020). Transmission companies continuously seek ways to reduce line losses and meet operating secure and reliable limits and power transfer restrictions (Ufa, et al. 2022). In the past, determining real and reactive power losses on an electrical transmission line network was typically done through manual calculations based on complex mathematical equations (Saddique, et al. 2022).

This process was time-consuming, prone to errors, and could not account for various system conditions and dynamic changes. Traditionally, power losses on a transmission line network are calculated using mathematical equations based on the line parameters and load characteristics (Shaikh, et al. 2021, Onyegbadue and Madueme 2014). However, these methods often rely on simplifications and assumptions that may not accurately represent real-world scenarios and require significant computational resources. To overcome the limitations of traditional methods, an AI model can be developed to accurately determine power losses on an electrical transmission line network (Ozcanli, Yaprakdal and Baysal 2020). The model can be trained using historical data that includes line parameters, load characteristics, and corresponding power losses. The AI model can utilize various machine-learning techniques, such as neural networks or support vector machines, to study the intricate relationships existing between the various transmission line parameters and line losses (Strielkowski, Civin, et al. 2021). By analyzing the training data, the model can identify patterns and correlations that may not be apparent through traditional methods (Zhao, et al. 2021). The advancement of artificial intelligence (AI) has opened up new possibilities in various industries, including the field of electrical engineering (Ahmad, Zhang, et al. 2021). One area where AI can be particularly beneficial is in determining real and reactive power losses on an electrical transmission line network. This article explores the development and implementation of an AI model for accurately calculating power losses in such networks. With advancements in artificial intelligence (AI) and machine learning (ML) techniques, researchers have been able to develop intelligent models that can accurately predict and determine real and reactive power losses on electrical transmission line networks (Abdalla, et al. 2021). These models utilize large datasets, historical information, and advanced algorithms to analyze and predict power losses. The AI model for determining real and reactive power losses on an electrical transmission line network uses a combination of supervised and unsupervised learning techniques (Taghvaie, et al. 2023).

The model is trained using historical data that includes variables such as line characteristics, load profiles, weather conditions, and system operating parameters. The model utilizes regression analysis to create a mathematical relationship between the input variables and the real and reactive power losses. It then uses this relationship to predict power losses for future data. The accuracy of the model is continuously improved through iterative training and validation processes. Supervised learning is a type of machine learning where the algorithm is trained on labelled data (Suyal and Goyal 2022). Labelled data refers to a dataset that includes input variables (features) and the corresponding output variable (target) (Xu, et al. 2019). The algorithm learns from this labelled data to make predictions or classify new, unseen data (Guo, et al. 2020). In supervised learning, the algorithm is provided with a set of input-output pairs, and it learns to map the pairs by finding patterns and relationships between the variables. The goal is to find a generalized model that can make accurate predictions on unseen data.

Artificial Intelligence (AI) has become a transformative force in various industries, including electrical power systems research (Cheng and Yu 2019). A comprehensive review of AI shows how extensive the application of AI techniques in optimizing Electrical power systems, bolstering grid stability, enabling the seamless introduction of renewable energy, and enhancing overall system performance can be (SaberiKamarposhti, et al. 2024). The electrical power sector is undergoing a significant overhaul driven by the demand for more efficient, reliable, and sustainable power systems (Bhusal, et al. 2020). The integration of renewable energy sources, the escalating electricity demand, and the ageing infrastructure pose challenges that necessitate innovative solutions (Alotaibi, et al. 2020). The unique capabilities of AI, such as analyzing vast datasets, uncovering hidden patterns, and intelligent decision formulation, have the potential to transform the electrical power system landscape, enabling innovative design, real-time monitoring, and optimized operations (Ahmad, Madonski, et al. 2022).

One predominant application of AI in electrical power systems is in optimization (Chen, et al. 2022). Employing AI algorithms, such as Genetic Algorithms (GA), Neural Networks (NN), and Fuzzy logic, power flow, voltage control, and energy scheduling have been optimized (Abdolrasol, et al. 2021). These techniques have proven to minimize system losses, reduce operating costs, and enhance the overall efficiency of power systems. Grid stability is imperative for ensuring the reliable operation of power systems (Gu and Green 2022). AI-based techniques, such as Machine Learning algorithms and predictive analytics, can predict and prevent grid disturbances, voltage fluctuations, and power outages (Mazhar, et al. 2023). By analysing real-time data from sensors and control devices, AI can provide early warnings and recommend corrective actions to maintain grid stability (Afridi, Ahmad and Hassan 2022).

The combination of renewable energy sources, such as solar and wind power, presents challenges owing to the intermittent nature of these energy sources (Husin and Zaki 2021). AI can aid in forecasting renewable energy generation, optimizing energy storage systems, and managing the variability of renewable energy output (Boza and Evgeniou 2021). By leveraging AI algorithms, power systems can efficiently integrate renewable energy sources while upholding grid stability and reliability (Chandratreya 2024). AI also significantly enhanced the overall efficiency of electrical power systems (Abdalla, et al. 2021, Onyegbadue, Ogbuka and Madueme 2022). Through the analysis of historical data, AI algorithms can identify inefficiencies, predict equipment failures, and optimize maintenance schedules (Zonta, et al. 2022). This proactive approach can curtail downtime, boost system reliability and extend the lifespan of power system components (Mohamed, et al. 2019). The prospects of AI in power systems research are promising, with the potential to create smarter, more resilient, and sustainable power systems (Guo, et al. 2023).

Neural networks, inspired by the human brain's neural network system, have emerged as a powerful tool in electrical power systems research, providing innovative solutions to various challenges in the field (Xu, et al. 2021).
One of the key advantages of using neural networks in electrical power systems research is their ability to model complex, nonlinear relationships that traditional analytical methods may struggle to capture (Strielkowski, Vlasov, et al. 2023). This allows researchers to create more precise and effective models for different components and operations within the power system. Neural networks have been successfully employed in load forecasting, where they can analyse historical load data and predict future electricity demand with high accuracy (Vanting, Ma and Jorgensen 2021). This is crucial for utilities to optimize their generation schedules and ensure grid stability. In fault diagnosis, neural networks can analyse real-time data from power system sensors to quickly detect and locate faults, helping operators take corrective actions promptly and minimize downtime (Almasoudi 2023). This can significantly improve the reliability and efficiency of power systems.

Moreover, neural networks can be used for power system control, where they can optimize the operation of generation units, transmission lines, and distribution networks to ensure reliable and cost-effective power delivery (Pandey, et al. 2023). This can help utilities to better manage their resources and reduce operational costs. The future of neural networks in electrical power systems research looks promising (Rahman, et al. 2021). Advances in supervised learning techniques, such as convolutional neural networks and recurrent neural networks, are facilitating more sophisticated and accurate power system dynamics modelling (Miraftabzadeh, et al. 2021). Furthermore, integrating neural networks with other advanced technologies will likely lead to even more innovative approaches for enhancing power systems (Zhu, et al. 2022).

1.1 Overview of Artificial Neural Network

Artificial Neural Networks (ANNs) are biologically inspired paradigms that emulate the structural as well as the functional properties of the brain of human, exhibiting superior performance in pattern recognition and data classification tasks within machine learning and data analysis frameworks (Prieto, et al. 2016). A typical architecture of ANN is contained in Figure 1 (Moon, et al. 2019)

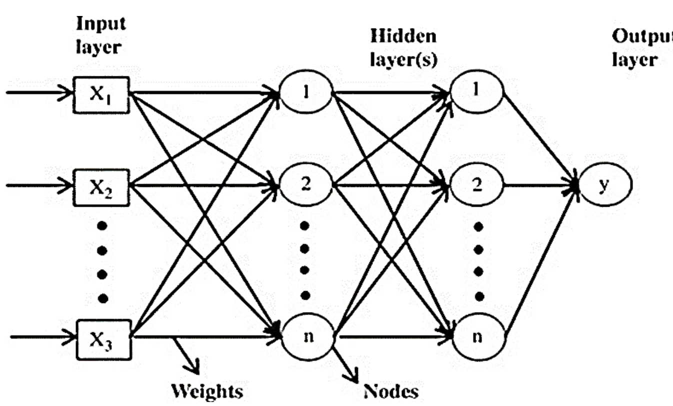

Figure 1: A Typical ANN Architecture (Moon, et al. 2019)

1.1.1 Some of the Key Algorithms in Artificial Neural Networks:

a. Feedforward Algorithm

The feedforward algorithm is the most widely used and straightforward approach in Artificial Neural Networks (ANNs). It is defined by a one-way flow of information, moving from the input layer to the output layer, and lacks any feedback loops (Calzolari and Liu 2021, Shahidehpour, Yamin and Li 2002). Empirical studies on artificial neural networks have consistently demonstrated the efficacy of feedforward algorithms in solving complex classification and regression tasks (Ojha, Abraham and Snavsel 2017). This algorithmic framework relies on the sequential transmission of information across layers, where each neuron processes inputs from preceding layers and projects outputs to subsequent layer. Figure 2 shows a typical Feedforward Architecture (G. Yang 2019, Medus, et al. 2019).

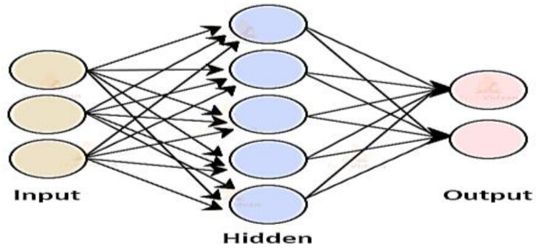

Figure 2: Feedforward Architecture (G. Yang 2019, Medus, et al. 2019)

b. Backpropagation Algorithm

Backpropagation, a fundamental technique in supervised learning, utilizes gradient descent to optimize artificial neural network (ANN) performance by reducing prediction errors (Alsadi, et al. 2022). Backpropagation is a process that entails propagating the error backwards from the output layer to the input layer and simultaneously adjusting the weights and biases of the neurons along the way. (Chen, et al. 2021). Figure 3 shows a typical Feed backward Architecture (Krestinskaya, Salama and James 2018).

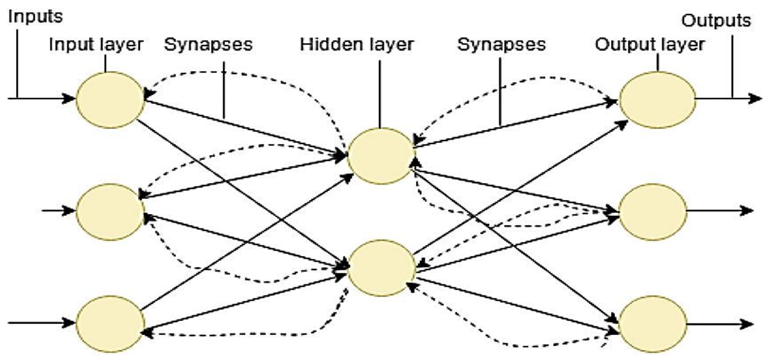

Figure 3: Feed backward Architecture (Krestinskaya, Salama and James 2018)

c. Convolutional Neural Network (CNN) Algorithm

Convolutional Neural Networks (CNNs), a subclass of Artificial Neural Networks (ANNs), are extensively employed for image and video processing tasks (Stadelmann, et al. 2019). The architectural framework of CNNs comprises convolutional layers, pooling layers, and fully connected layers (Albawi, Mohammed and Al-Zawi 2017). Convolutional layers extract features using filters, pooling layers reduce spatial dimensions, and fully connected layers handle classification. CNN algorithms excel at image recognition and object detection. Figure 4 Convolutional Neural Network Architecture (Wu 2017).

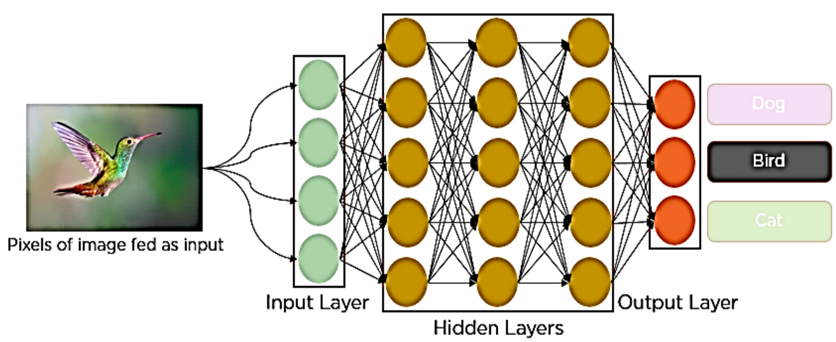

Figure 4: Convolutional Neural Network Architecture (Wu 2017)

d. Recurrent Neural Network (RNN) Algorithm

This is a distinct category of artificial neural networks developed to manage sequential data, like tasks related to natural language processing. (Yang, Jiang and Guo 2019). RNNs employ feedback connections to interpret data from earlier time steps. The primary algorithm implemented in RNNs is LSTM, which is capable of preserving information for extended durations, making it ideal for tasks that require significant memory, such as speech recognition and language translation (Yang and Kim 2018).
Figure 5. shows the Recurrent Neural Network Architecture (Mishra, Agarwal and Puri 2018).

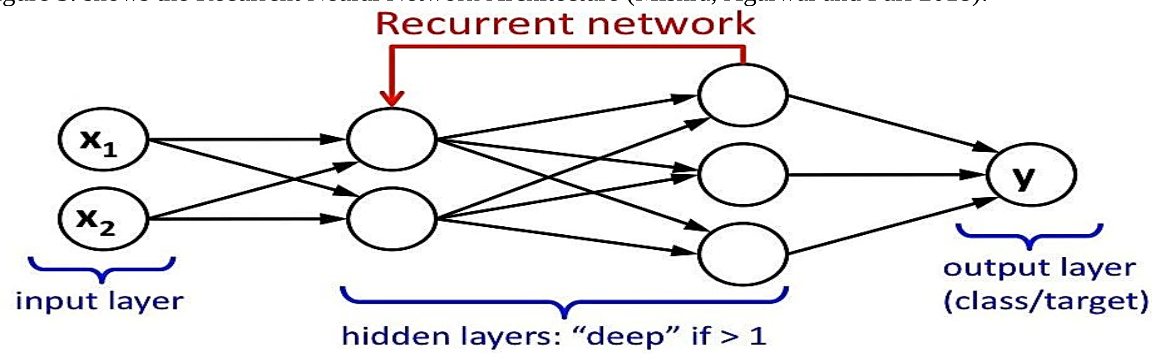

Figure 5: Recurrent Neural Network Architecture (Mishra, Agarwal and Puri 2018)

e. Reinforcement Learning Algorithm

Reinforcement learning is machine learning where an agent learns to engage with its environment to optimize a reward signal. In reinforcement learning that utilizes artificial neural networks, the algorithm employs the concepts of neural networks to make choices and adjust according to the feedback obtained from the environment. (Elavarasan and Vincent 2020). The algorithm explores different actions, evaluates their outcomes, and adjusts its behaviour accordingly. Reinforcement learning algorithms have been successful in tasks like game playing and robotic control. Figure 6 shows the Reinforcement Learning Architecture (Gu, Yang and Ji 2020).

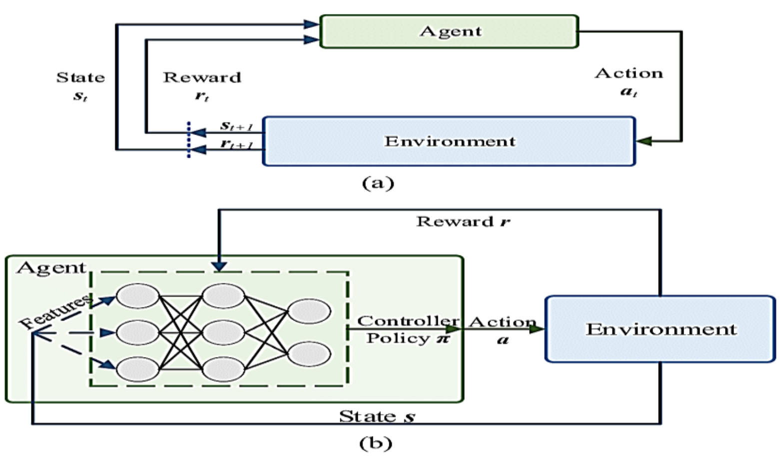

Figure 6: Reinforcement Learning Architecture (Gu, Yang and Ji 2020)

The algorithms used in artificial neural networks are vital to the network's learning processes. Each has unique characteristics and applications, from feedforward and backpropagation algorithms to specialized algorithms like CNNs, RNNs, and reinforcement learning algorithms. These algorithms have revolutionized machine learning and driven advancements in various fields. (Shrestha and Mahmood 2019).

2.0 Methods

The initial stage in this work is to determine the dependent and independent variables used in the model. The dependent variables are the real and reactive power loss along the transmission lines, which is the difference between the power injection from the sending bus and the power injection from the receiving bus. These variables represent the amount of power dissipated as losses in the transmission network. The independent variables consist of various parameters that influence the power losses in the network. These include the branch resistance, reactance, and susceptance. The resistances represent the opposition to the flow of current in the branches, while the reactance represents the opposition due to the inductance or capacitance of the branches. The susceptance represents the opposition due to capacitive or inductive elements in the branches. In addition to these branch parameters, the real and reactive power injection from the sending buses are also included as independent variables. These values represent the amount of power at the respective buses in the branched network.

The dependent variables were acquired from the Newton Raphson and Fast Decoupled Load Flow methods. A 118 IEEE test network with an initial real and reactive power demand of 4242.0 MW and 1438.0 MVAr was modelled for load flow studies using MATPOWER. The real power was gradually increased in steps of 20 MW and all input and targets were obtained. This approach was considered necessary due to the requirement of generating a significant amount of data for the Lavenberg-Marquardt backpropagation algorithm in the Artificial Neural Network (ANN).

The results obtained from the Lavenberg-Marquardt backpropagation algorithm will be compared for different numbers of neurons. By utilizing the Lavenberg-Marquardt backpropagation algorithm, the model will be trained on a set of data samples that include these independent and dependent variables. The algorithm adjusts the weights and biases of the neural network to minimize the difference between the power losses that were predicted and actual power losses in the training data. Once the model is trained, it can be used to predict the power losses in the network for new data samples. The values of the independent variables were applied to the trained model and the real and reactive power losses were estimated. Figure 7 represents a block diagram for the methodology adopted.

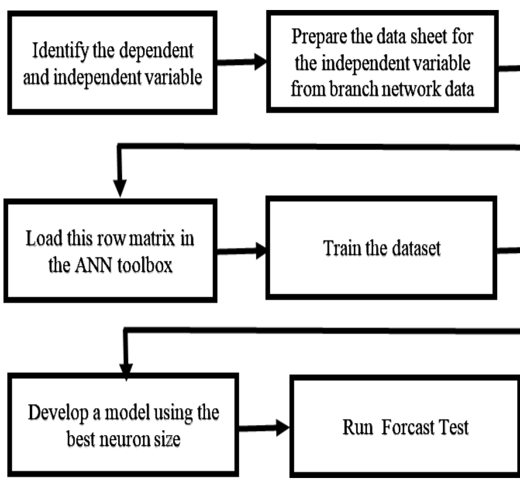

Figure 7: Block Diagram for the methodology adopted

2.1 Data Collection for Artificial Neural Network (ANN)

Data collection plays a pivotal role in the effectiveness and efficiency of ANN models, enabling them to learn, adapt, and make predictions with precision (G. Yang 2019). It is crucial to consider that the accuracy and effectiveness of these networks are heavily influenced by the quality and volume of the data they receive. Data collection is fundamental in shaping the training of ANN models by equipping them with the diverse and pertinent datasets needed to comprehend intricate patterns and connections (Medus, et al. 2019). The data sets concerning real and reactive power losses on transmission lines, including line resistance, reactance, and susceptance, are important for creating precise ANN models with Newton-Raphson and Fast Decoupled methods (Alsadi, et al. 2022). The Newton-Raphson method is a robust and widely used technique for solving nonlinear power flow equations, providing accurate estimates of bus voltage magnitudes and angles. The Fast Decoupled method, on the other hand, offers a computationally efficient alternative for solving power flow equations, particularly suitable for large-scale power systems. By utilizing both methods, a comprehensive dataset is generated, capturing the intricate relationships between transmission line parameters, bus voltage profiles, and power flow patterns. This dataset serves as the

foundation for training the ANN model, enabling it to learn complex patterns and make accurate predictions of transmission line losses (Onyegbadue, Ukagu and Okonkwo 2024, Fernandes, et al. 2019).
Real and reactive power losses on transmission lines are key indicators of system efficiency and performance (Chen, et al. 2021). By analyzing these losses, areas of inefficiency can be identified and corrective measures taken to improve overall system reliability.

The characteristics of the transmission line, including resistance, reactance, and susceptance, directly impact power flow and losses (Krestinskaya, Salama and James 2018). Understanding these parameters enables the optimization of the transmission network operations. The Newton-Raphson method is a powerful numerical technique to solve power flow equations in electrical networks (Vysocky, et al. 2022). By incorporating data sets related to power losses and line parameters, ANN models can be trained to predict power flow behaviour accurately and efficiently. The Fast Decoupled method simplifies power flow calculations by decoupling the real and reactive power equations (Fernandes, et al. 2019). Data sets on transmission line losses and parameters serve as input for ANN models trained using the fast decoupled method, enabling rapid and reliable power flow predictions.

2.2 Mathematical Formulation

To mitigate computational complexities associated with traditional load flow methods, the fast decoupled power flow algorithm is employed, leveraging its superior computational efficiency and diminished storage requirements. This methodology is predicated upon two fundamental insights:

i. Modifications in voltage angle (δ) at a given bus predominantly influence the real power (P) flow within transmission lines, whereas reactive power (Q) flow remains relatively unaffected (Anderson, et al. 2022).
ii. Variations in voltage magnitude (|V|) at a given bus predominantly influence the reactive power (Q) flow within transmission lines, whereas real power (P) flow remains relatively insensitive (Ismail, et al. 2020).

$$P_i = f_1(\delta, |V|) \tag{1}$$
$$Q_i = f_2(\delta, |V|) \tag{2}$$

For an n-bus power system with Bus 1 serving as the slack bus, the mathematical relationships governing the interaction between active and reactive power variations and bus voltage magnitude and angle can be concisely represented by the following equations;

$$\Delta P_i = \sum_{p=2}^{n} \frac{\partial P_i}{\partial \delta_p} \Delta\delta_p + \sum_{p=2}^{n} \frac{\partial P_i}{\partial |V_p|} \Delta|V_p| \tag{3a}$$
$$\Delta Q_i = \sum_{p=2}^{n} \frac{\partial Q_i}{\partial \delta_p} \Delta\delta_p + \sum_{p=2}^{n} \frac{\partial Q_i}{\partial |V_p|} \Delta|V_p| \tag{3b}$$

ΔP_i and ΔQ_i represents the changes in the specified and the calculated values of P_i and Q_i.
For convenience, $\Delta|V|$ can be replaced by $\frac{\Delta|V|}{|V|}$ in equation (3)

$$\Delta P_i = \sum_{p=2}^{n} \frac{\partial P_i}{\partial \delta_p} \Delta\delta_p + \sum_{p=2}^{n} \frac{\partial P_i}{\partial |V_p|} |V_p| \frac{\Delta|V_p|}{|V_p|} \tag{4a}$$
$$\Delta Q_i = \sum_{p=2}^{n} \frac{\partial Q_i}{\partial \delta_p} \Delta\delta_p + \sum_{p=2}^{n} \frac{\partial Q_i}{\partial |V_p|} |V_p| \frac{\Delta|V_p|}{|V_p|} \tag{4b}$$

Equations (4a) and (4b) are thus;

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} H & N \\ J & L \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \frac{\Delta|V|}{|V|} \end{bmatrix} \tag{5}$$

Where;
$H_{ip} = \frac{\partial P_i}{\partial \delta_p}$,
$N_{ip} = \frac{\partial P_i}{\partial |V_p|} |V_p|$,
$J_{ip} = \frac{\partial Q_i}{\partial \delta_p}$,
$L_{ip} = \frac{\partial Q_i}{\partial |V_p|} |V_p|$.

The partial derivatives H, N, J, and L are real functions of the admittance matrix and the bus voltages. The decoupling principle involves neglecting the sub-matrices N and J in equation (5), resulting in two separate equations.

$$[\Delta P] = [H][\Delta\delta] \tag{6a}$$

$$[\Delta Q] = [L]\left[\frac{\Delta|V|}{|V|}\right] \tag{6b}$$

That represents admittance in the line;

$$|Y_{ip}|\varepsilon^{j\gamma_{ip}} = G_{ip} + jB_{ip} \tag{7}$$

G and B are line conductance and susceptance respectively.
From the load flow equation,

$$P_i - jQ_i = V_i^* \sum_{p=1}^{n} Y_{ip}V_p \tag{8}$$

Where;
$V_i = |V_i|\varepsilon^{j\delta_i}$,
$V_i^* = |V_i|\varepsilon^{-j\delta_i}$
$V_p = |V_p|\varepsilon^{j\delta_p}$
$Y_{ip} = |Y_{ip}|\varepsilon^{j\gamma_{ip}}$.
Substitute these values into equation (8).

$$P_i - jQ_i = |V_i|\varepsilon^{-j\delta_i} \sum_{p=1}^{n}(|Y_{ip}|\varepsilon^{j\gamma_{ip}})(|V_p|\varepsilon^{j\delta_p}) \tag{9}$$

Differentiating partially with respect to δ_p, $p \neq i$, we have;

$$\frac{\partial P_i}{\partial \delta_p} - j\frac{\partial Q_i}{\partial \delta_p} = j(|V_i|\varepsilon^{-j\delta_i})(|Y_{ip}|\varepsilon^{j\gamma_{ip}})(|V_p|\varepsilon^{j\delta_p}) \tag{10}$$

Rewriting equation 10

$$\frac{\partial P_i}{\partial \delta_p} - j\frac{\partial Q_i}{\partial \delta_p} = j|V_i||V_p|\varepsilon^{j(\delta_p - \delta_i}(|Y_{ip}|\varepsilon^{j\gamma_{ip}}) \tag{11}$$

Substitute the value of ($|Y_{ip}|\varepsilon^{j\gamma_{ip}}$) in equation (7) into equation (11)

$$\frac{\partial P_i}{\partial \delta_p} - j\frac{\partial Q_i}{\partial \delta_p} = j|V_i||V_p|\varepsilon^{j(\delta_p - \delta_i)}(G_{ip} + jB_{ip}) \tag{12}$$

Since the angle $(\delta_p - \delta_i)$is small, $\varepsilon^{j(\delta_p - \delta_i)} \cong 1$ then

$$\frac{\partial P_i}{\partial \delta_p} - j\frac{\partial Q_i}{\partial \delta_p} = j|V_i||V_p|(G_{ip} + jB_{ip}) \tag{13}$$

Separating the real and imaginary parts noting that $p \neq i$

$$H_{ip} = \frac{\partial P_i}{\partial \delta_p} = -|V_i||V_p||B_{ip}| = L_{ip} \tag{14}$$

For $p = i$

$$H_{ii} = \frac{\partial P_i}{\partial \delta_i} = -|V_i|^2|B_{ii}| = L_{ii} \tag{15}$$

Hence, equation (6) can be represented as;

$$[\Delta P] = [|V||B'||V|][\Delta\delta] \tag{16}$$

$$[\Delta Q] = [|V||B''||V|]\left[\frac{\Delta|V|}{|V|}\right] \tag{17}$$

The elements of matrices B' and B'' are the elements of $|-B_{ip}|$matrix.

2.3 IEEE 118 Bus Network Summary

Table 1 (Anderson, et al. 2022) contains details of the bus network considered.

Table 1: Bus Network Summary (Anderson, et al. 2022)

S/No.	Item	Value
01	Buses	118
02	Generators	54
03	Committed Generators	54
04	Load Buses	100
05	Fixed Load	100
06	Dispatchable Load	0
07	Shunts	14
08	Bus Area	1
09	Branches	186
10	Transformer	11

2.4 Artificial Neural Network for the Prediction of Transmission Line Losses in IEEE 118 Bus Network

This study employed a multilayer feedforward neural network (MFNN) to intricately model the relationship between electrical network parameters and power losses. The MFNN was configured with a five-dimensional input vector comprising: branch resistance (R), branch reactance (X), branch susceptance (B), real power injection (P) and reactive power injection (Q). The corresponding target output vector consisted of two variables: real power loss (Ploss), and reactive power loss (Qloss).

A dataset of 2,233 samples was utilized for training, with input and target data represented as column matrices to facilitate efficient computation and minimize numerical instability. To mitigate the multidimensional mapping problem inherent in this task, the MFNN was designed with a hidden layer having sigmoidal neurons to introduce nonlinear transformations and a linear output layer to ensure accurate prediction of power losses The Lavenberg-Marquardt backward propagation algorithm was used for training, leveraging its ability to optimize network performance through efficient memory utilization and adaptive learning rate adjustment.
Network Specifications are thus;
Number of Input layer neurons: 5 neurons
Number and Type of Hidden layer neurons: sigmoidal neurons (n = 10)
Number and Type of Output layer neurons: 2 linear neurons
Training algorithm: Lavenberg-Marquardt backward propagation
Training dataset: 2,233 samples
Memory size: 1024 MB

Figure 8 shows the Neural Network for the prediction model

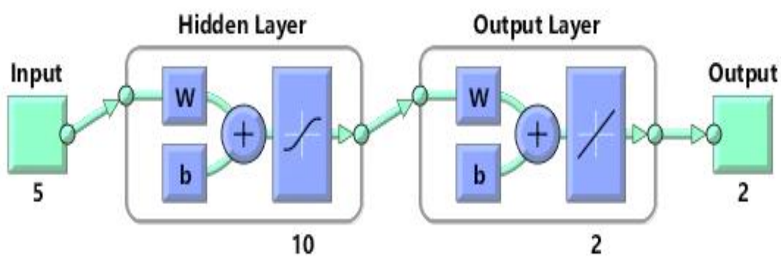

Figure 8: Neural Network Diagram for the Prediction Model

Table 2 contains the simulation parameters for the model that was trained.

Table 2: Simulation Parameters

S/No.	Parameter	Descriptions
1	Number of Layers	Two
2	Layers	Hidden and Output
3	The Hidden Layer Activation Function	Sigmoid
4	the Output Layer Activation Function	Linear
5	Input Sample Size	2232 samples of 5 variables
6	Target Sample Size	2232 samples of 2 variables
7	Sample representation format	Row Matrix
8	The number of neurons at the start in the hidden layer	10
9	Number of neurons at the start in the output layer	2
10	Training Algorithm	Levenberg Marquardt
11	Training Data Set	70%
12	Validation Data Set	15%
13	Testing Data Set	15%
14	Data selection mode	Random

3.0 Result and Discussion

The load flow studies were done with FDXB and NR and Table 3 compares the results of load flow studies conducted for varying network loads.

Table 3: Comparison of Load Flow Techniques Adopted for this Study.

S/No.	Load	Method	No. of Iterations	Maximum Mismatch (pu)		Time of Convergence (Sec)	Losses	
				P	Q		Real (MW)	Reactive (MVAr)
1	4242 MW/1438 MVAr	***FDXB***	***8P/7Q***	***1.70E-09***	***7.65E-10***	***0.54***	***132.86***	***783.79***
		NR	3	1.50E-12	1.50E-12	0.01	132.86	783.79
2	4242 MW/1458 MVAr	***FDXB***	***8P/7Q***	***1.70E-09***	***7.67E-10***	***0.02***	***132.86***	***783.76***
		NR	3	1.51E-12	1.51E-12	0.01	132.86	783.76
3	4262 MW/1438 MVAr	***FDXB***	***7P/6Q***	***7.26E-09***	***4.50E-09***	***0.02***	***133.84***	***786.01***
		NR	3	1.76E-12	1.76E-12	0.02	133.84	786.01
4	4242 MW/1478 MVAr	***FDXB***	***8P/7Q***	***1.68E-09***	***7.58E-10***	***0.02***	***132.87***	***783.87***
		NR	3	1.52E-12	1.52E-12	0.01	132.87	783.87
5	4282 MW/1438 MVAr	***FDXB***	***7P/6Q***	***9.34E-09***	***6.65E-09***	***0.02***	***135.02***	***789.75***
		NR	3	3.01E-12	3.01E-12	0.01	135.02	789.75
6	4302 MW/1438 MVAr	***FDXB***	***8P/7Q***	***2.02E-09***	***2.20E-09***	***0.02***	***136.40***	***795.03***
		NR	3	6.41E-12	6.41E-12	0.01	136.404	795.03

The results of the load flow study indicate that Newton-Raphson's approach required fewer P and Q iterations than FDLF. NR technique converged faster than FDLP, taking approximately 0.01 seconds. Furthermore, the P and Q mismatch was smaller with the NR technique. However, the P and Q losses obtained were the same in both techniques.

3.1 Prediction Model Using Artificial Neural Network

An Artificial Neural Network was employed to estimate the real and reactive power losses in the transmission network of the IEEE 118 bus network. The size of the neurons varied between 10 and 25 in increments of 5. For each neuron size, the model was trained and retrained four times, and the efficacy of the model was evaluated. Figure 9a - Figure 9e show the error histogram of the trained and retrained models for the model with ten neurons.

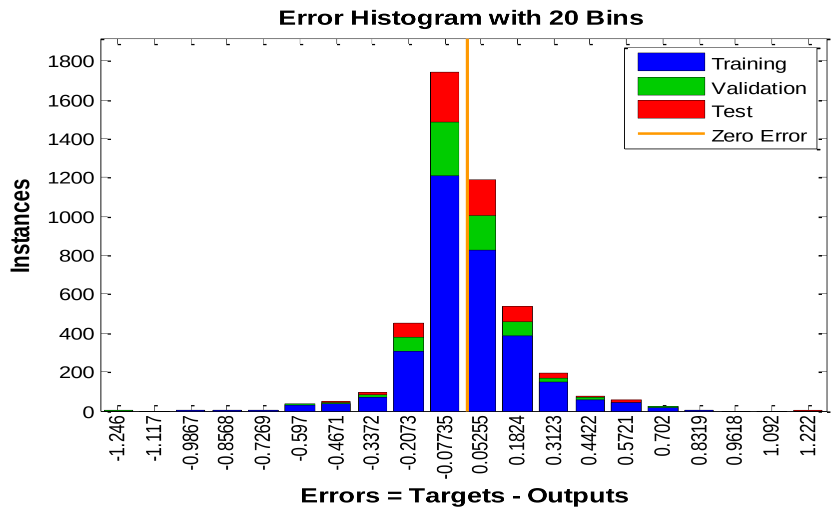

Figure 9a: From the Trained Model

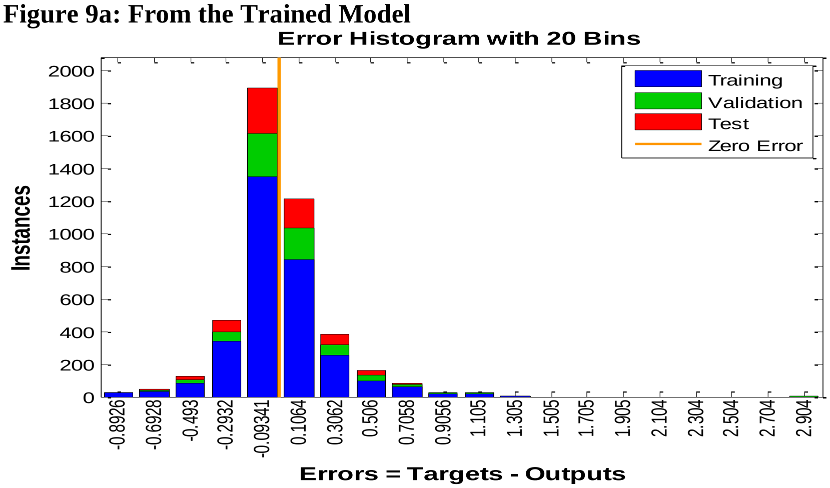

Figure 9b: Ist Retrained Model

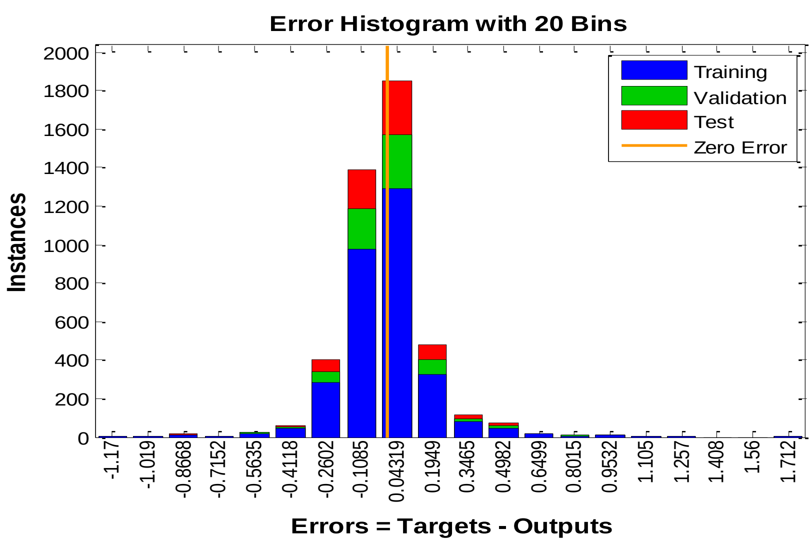

Figure 9c: 2nd Retrained Model

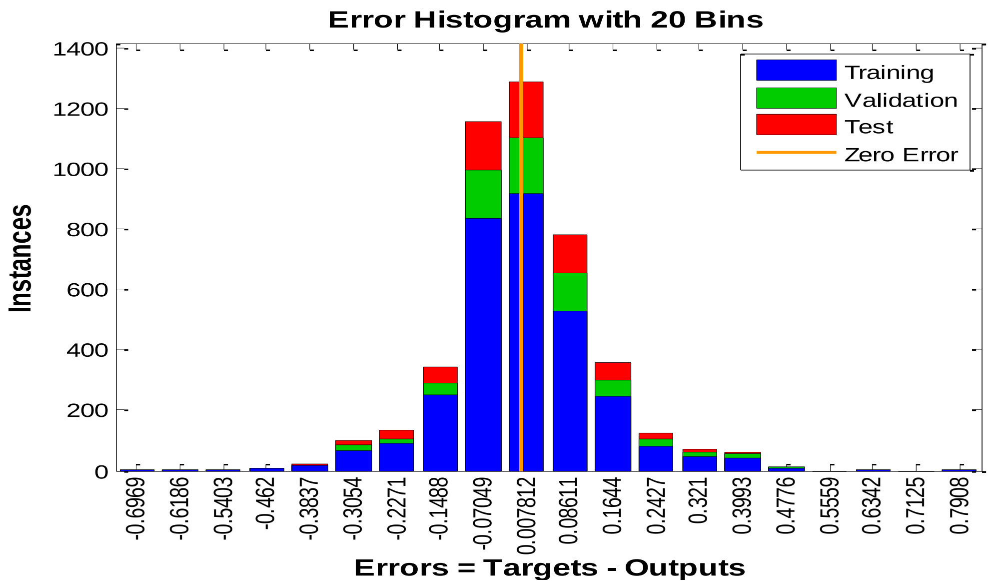

Figure 9d: 3rd Retrained Model

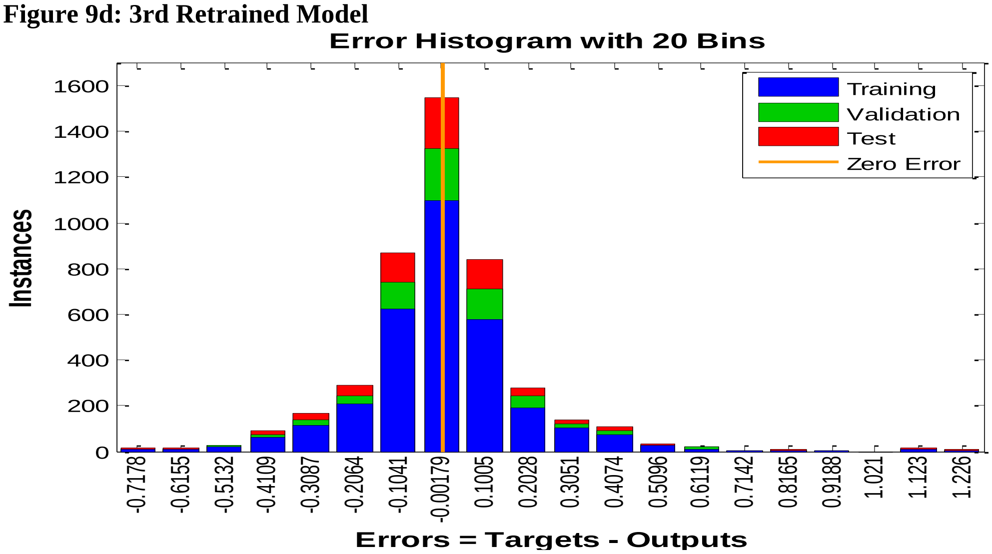

Figure 9e: 4th Retrained Model

Upon examining the error histograms of the trained and retrained models in Figure 9, it was discovered that the outliers remained significantly reduced throughout the retraining process. Additionally, it was noted that all histograms displayed a noticeable skew towards both the right and left sides. Lastly, the fourth retrained model exhibited a greater concentration of data points along the zero-error mark, as evidenced by the central placement of the modal bar on the said mark.

Figure 10a - Fig 10e show the error histogram of the trained and retrained models for the model with fifteen neurons.

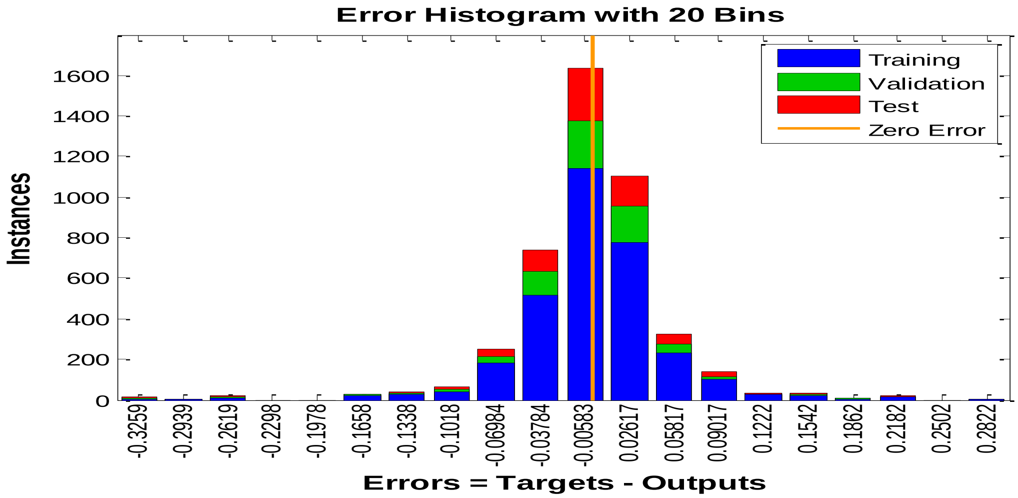

Figure 10a: From the Trained Model

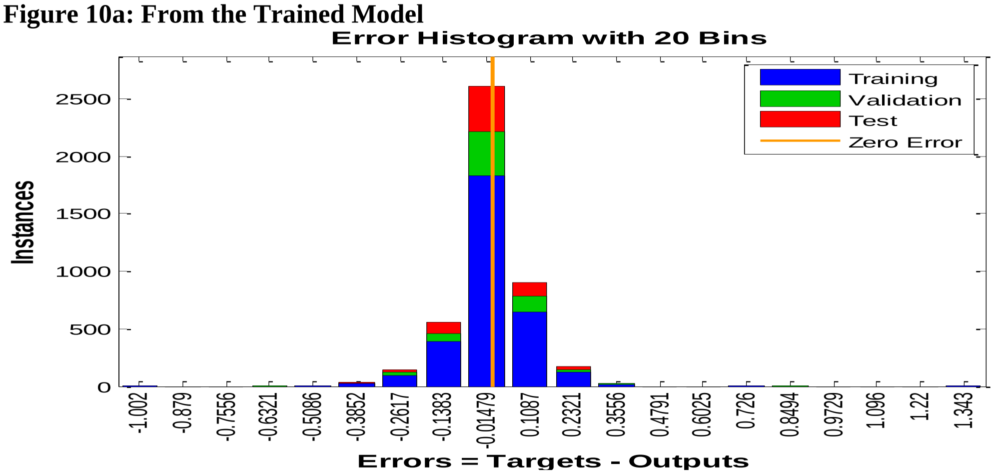

Figure 10b: Ist Retrained Model

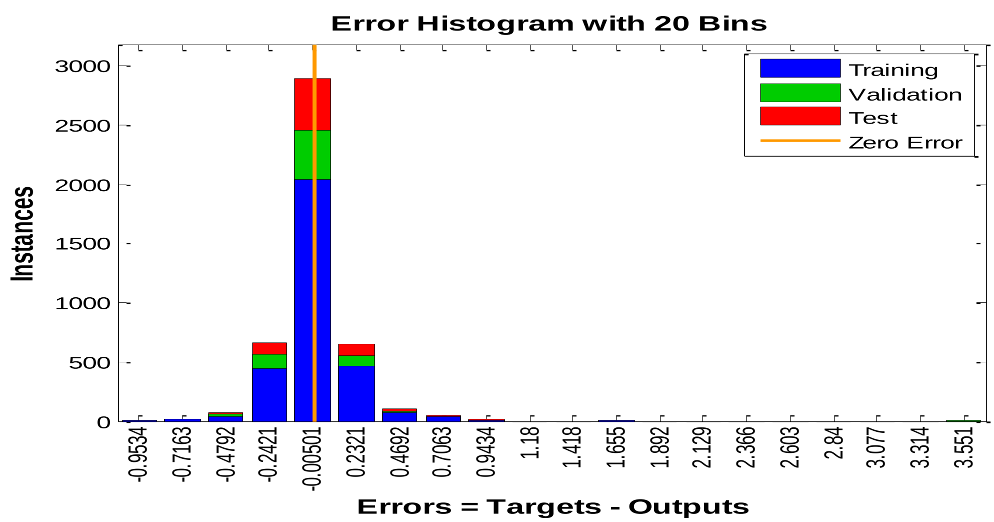

Figure 10c: 2nd Retrained Model

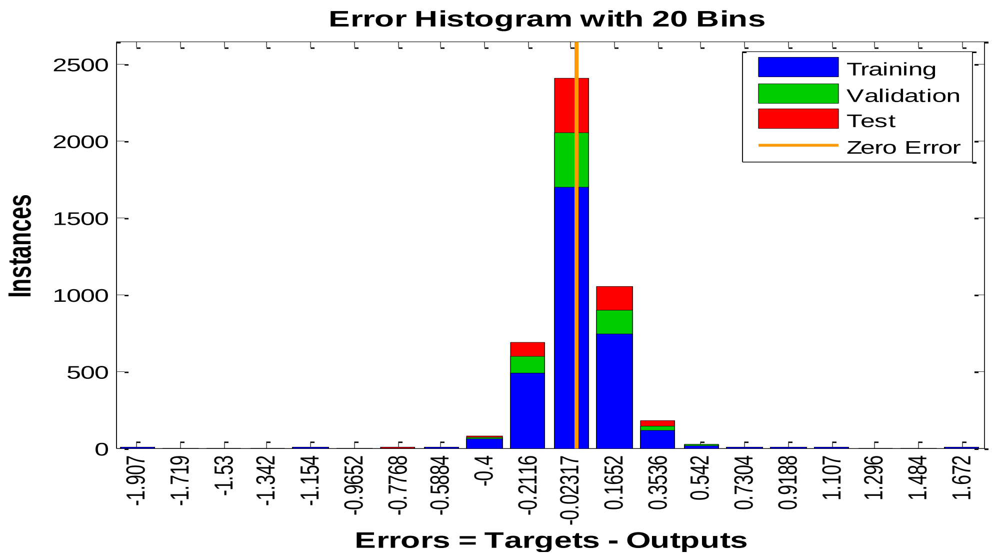

Figure 10d: 3rd Retrained Model

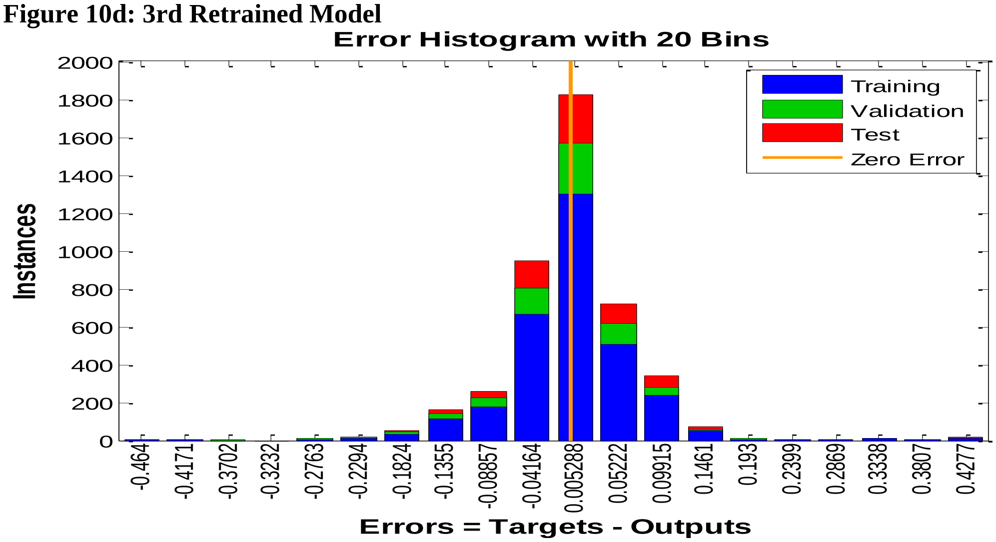

Figure 10e: 4th Retrained Model

Compared to the 10-neuron test, the 15-neuron test error histogram as represented in Figures 10a-10e showed intriguing results across its five runs. Notably, the trained model displayed some distinct outliers on the chart. Even after four retrained models, the outliers persisted but diminished. However, the second retrained model produced a more favourable outcome. This particular model exhibited a higher concentration of data points near the zero-error mark, as evidenced by the central placement of its modal bar. Nevertheless, all models featured data points that skewed towards both the left and right sides of the modal class. Figure 11a - Figure 11e show the error histogram of the trained and retrained models for the model with twenty neurons.

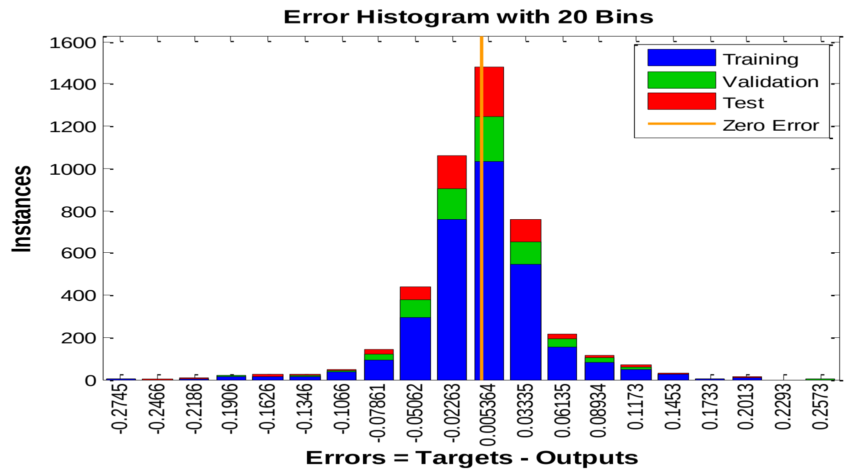

Figure 11a: From the Trained Model

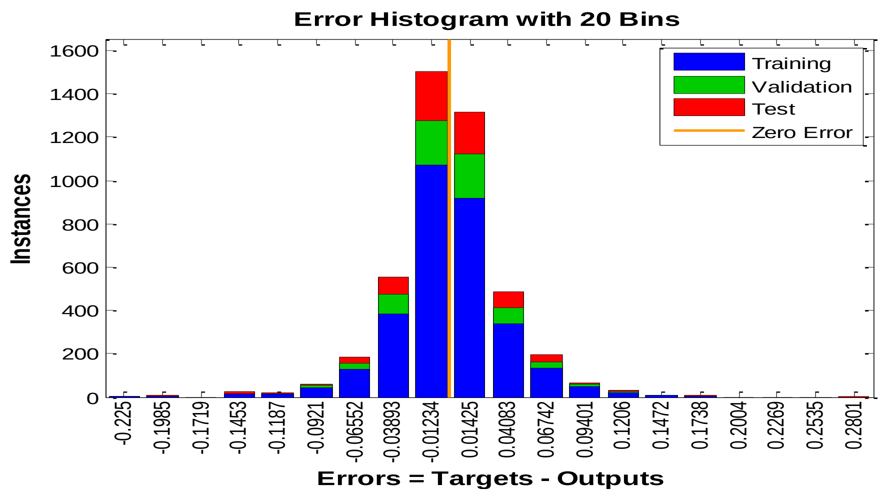

Figure 11b: Ist Retrained Model

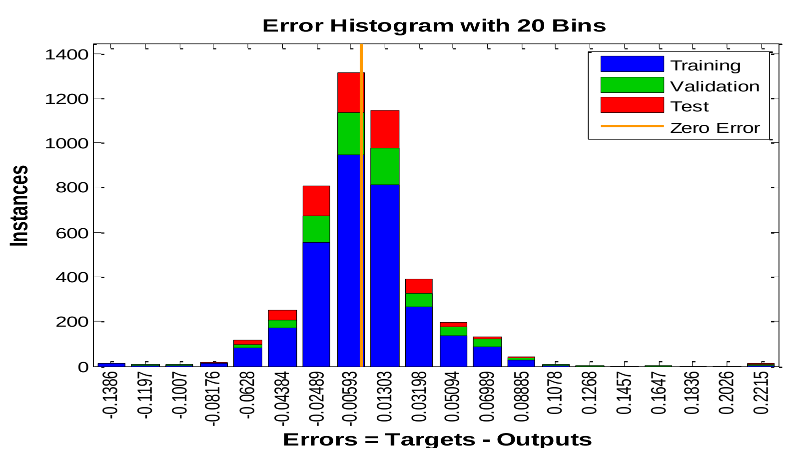

Figure 11c: 2nd Retrained Model

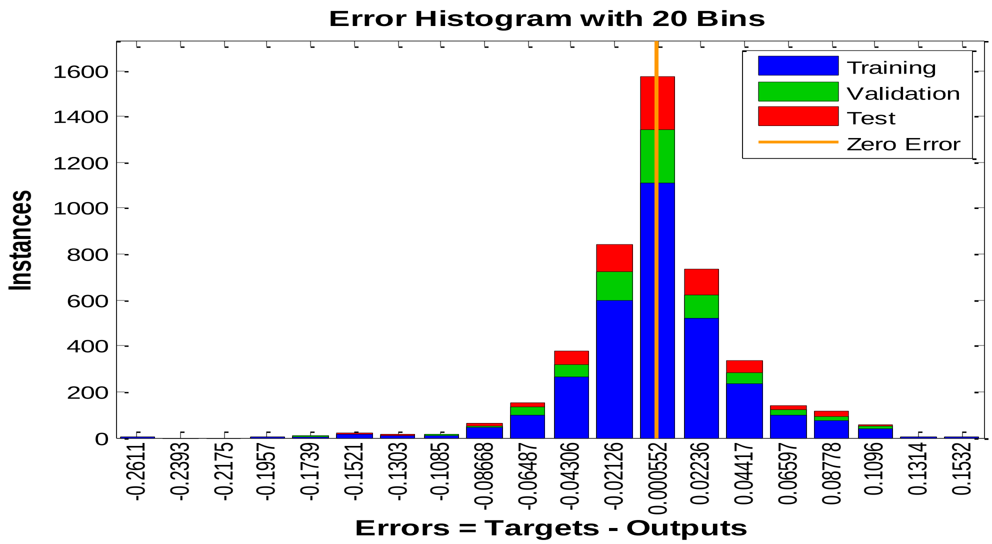

Figure 11d: 3rd Retrained Model

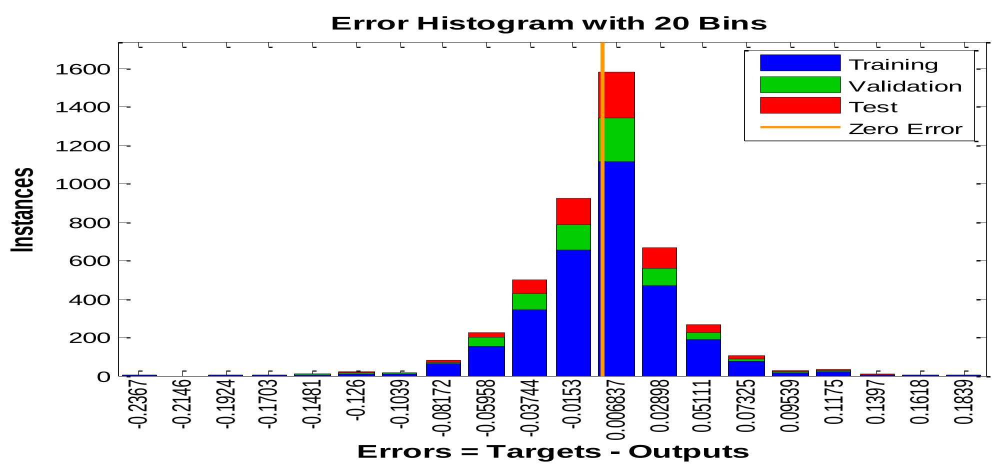

Figure 11e: 4th Retrained Model

The third retrained model for the 20-neuron test outperformed the other neuron tests by providing the most accurate results with the least error, especially in its modal class. However, similar to the other tests, the data distribution was skewed towards both the right and left sides of the modal class. Outliers diminished in all models.

Figure 12a - Figure 12e show the error histogram of the trained and retrained models for the model with twenty-five neurons.

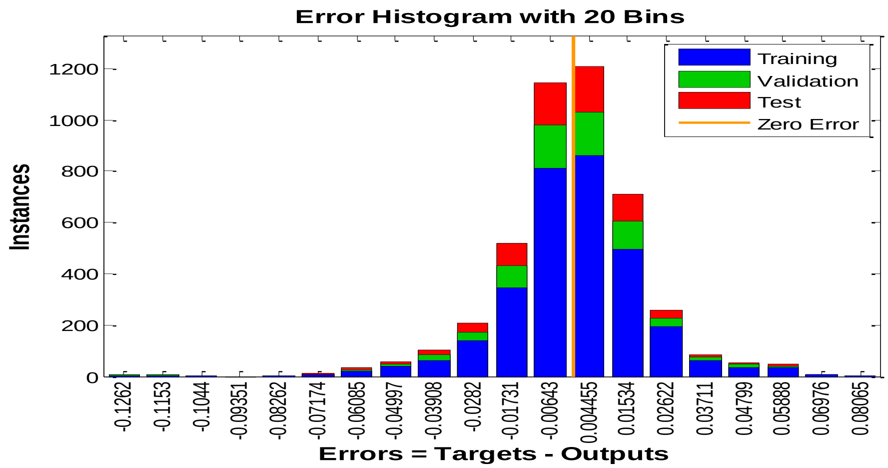

Figure 12a: From the Trained Model

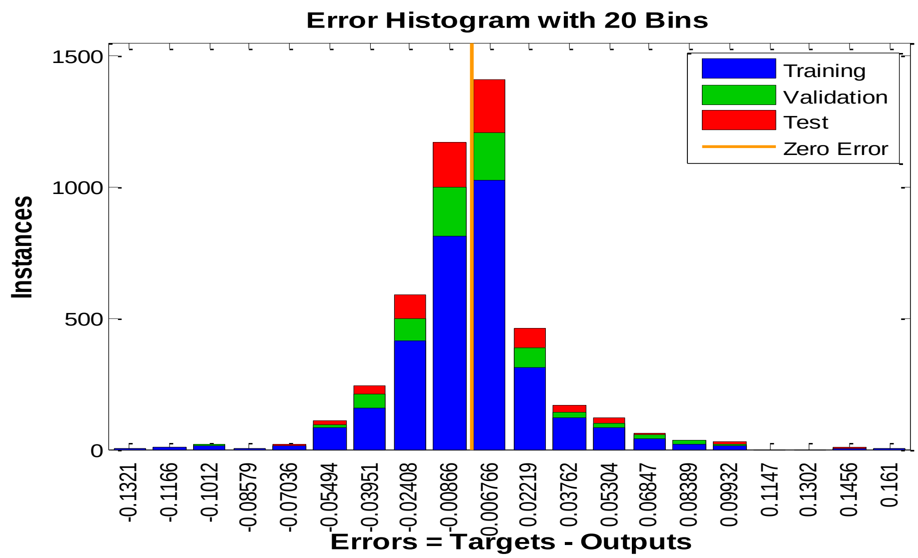

Figure 12b: Ist Retrained Model

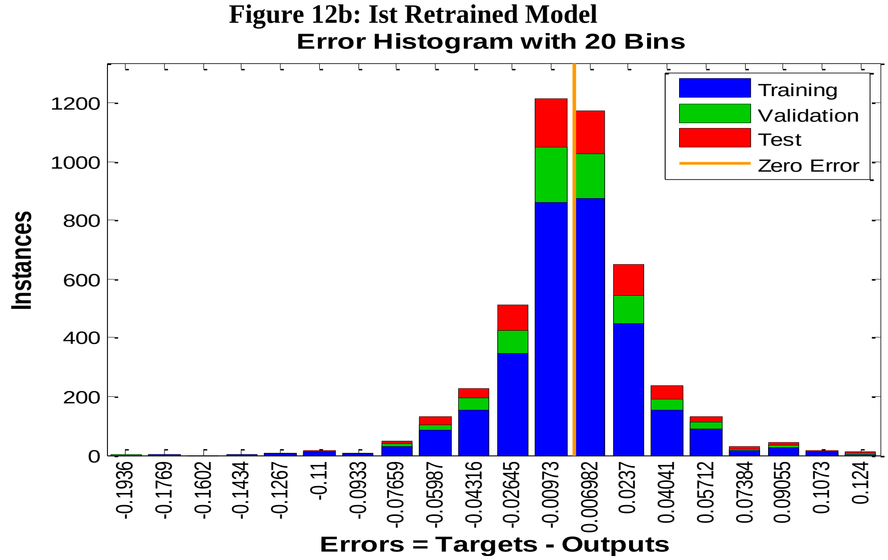

Figure 12c: 2nd Retrained Model

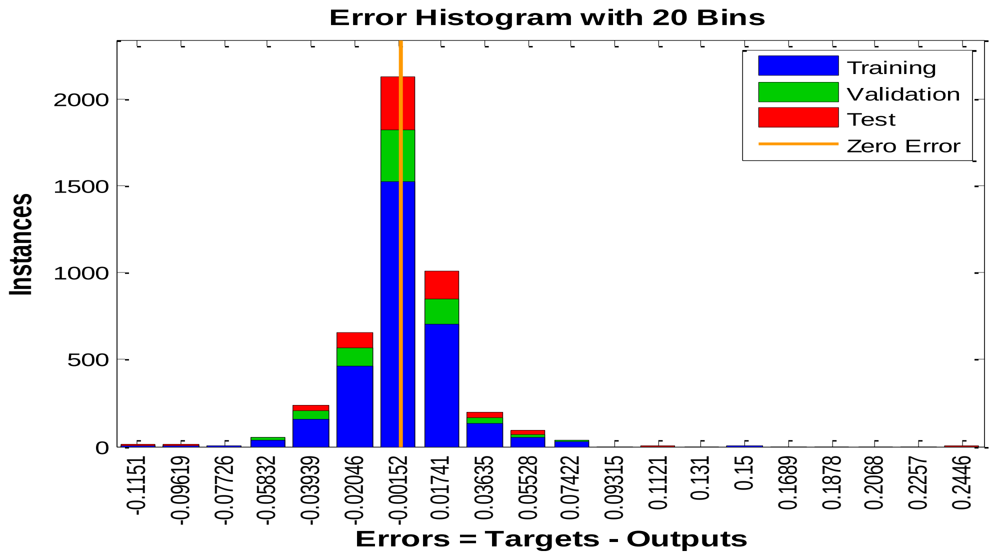

Figure 12d: 3rd Retrained Model

The fourth model that went through retraining for the 25-neuron test dominated by providing the most precise results with few errors. This is especially true in its modal class, which is positioned centrally at the zero-error mark. Nonetheless, like the other tests, the distribution of data was inclined towards both the right and left sides of the modal class. Outliers diminished in all models.

The class with the bin equally divided by the zero-error mark was identified. Also, the model with a test result having fewer outliers was identified. The class with the largest bin size among all bins was singled out. We examined the shape of the skewness and chose the best model (bell-shaped skewness). Consider Table 4 showing the best-performed model according to the earlier displayed error histogram.

Table 4: A summary table of the best model based on the analysed error

S/No.	No. of Neurons	Modal Class Centred along the zero-error	Diminished Outliers	Most Significant Modal Class	Bell-Shaped Skewness
1	10	4th retrained	All models	1st and 4th retrained	All
2	15	2nd retrained	All models	2nd retrained	All
3	20	3rd retrained	All models	3rd retrained	All
4	25	4th retrained	All models	4th retrained	All

From all the trained models, the second retrained model of the 15-neuron test performed the best from the error histogram.

The graphical representations of the validation performance of the models were obtained. Figure 13a – Figure 13e illustrate the graphical representation of the validation performance of the 10-neuron-based model.

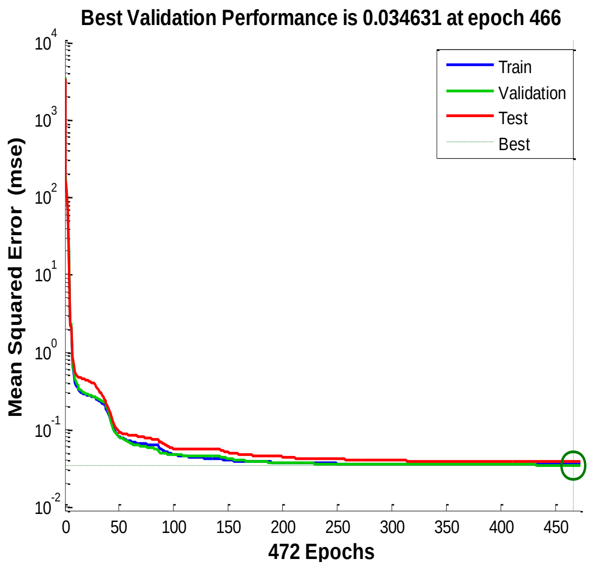

Figure 13a: Trained Model

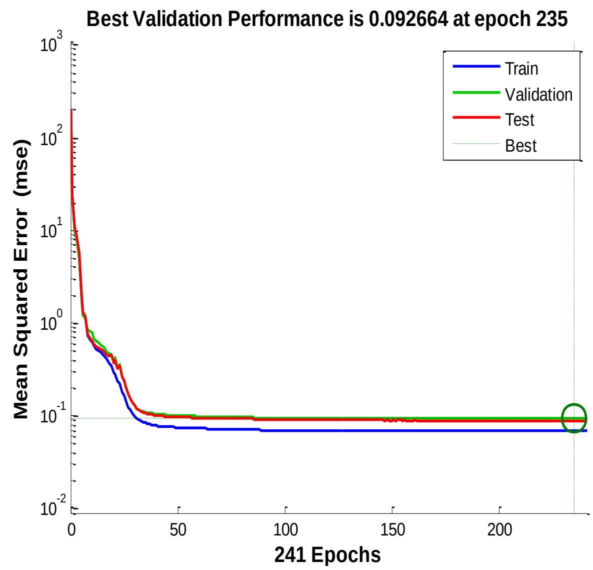

Figure 13b: Ist Retrained Model

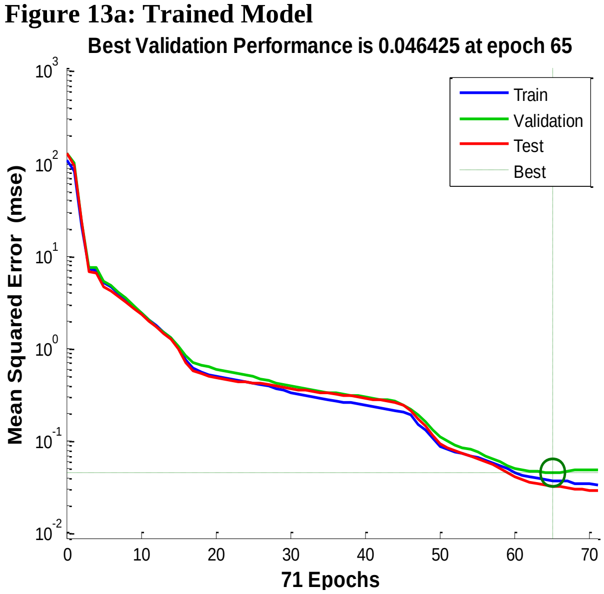

Figure 13c: 2nd Retrained Model

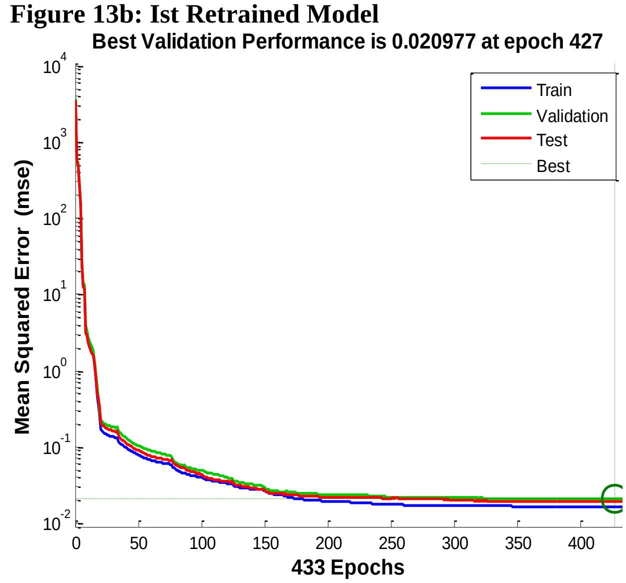

Figure 13d: 3rd Retrained Model

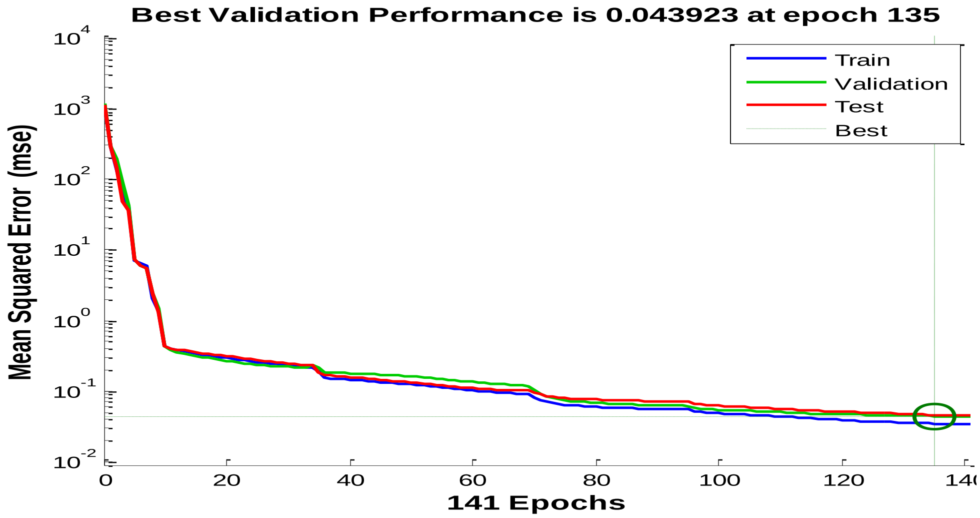

Figure 13e: 4th Retrained Model

The graphical representations of the validation performance show that the 3rd retrained model has the least mean square error and was regarded as the best model with 10 neurons.

Figure 14a – Figure 14e illustrate the graphical representation of the validation performance of the 15-neuron-based model.

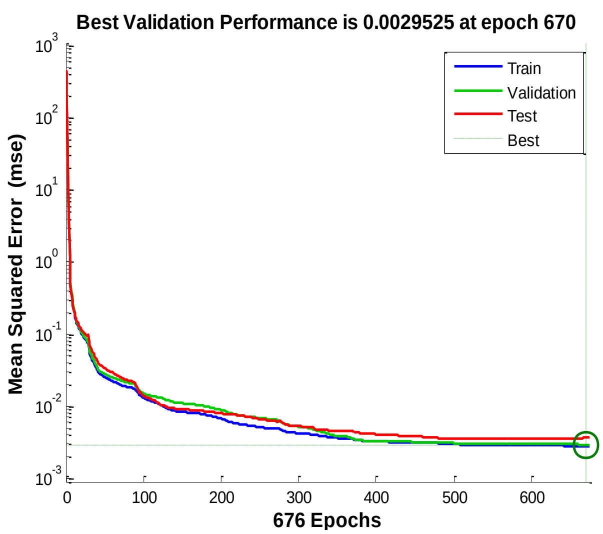

Figure 14a: Trained Model

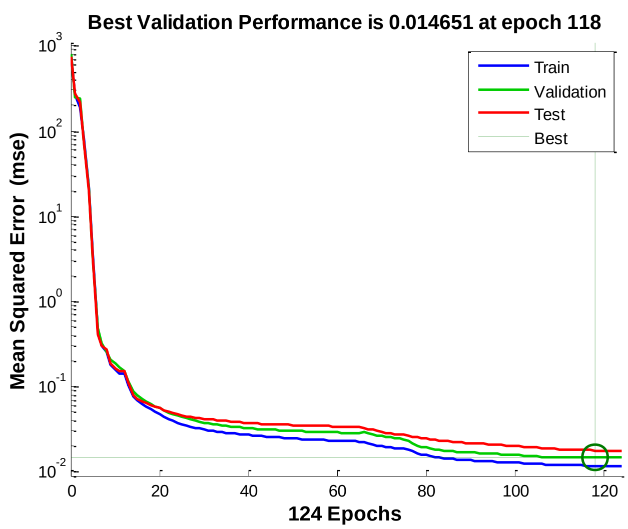

Figure 14b: Ist Retrained Model

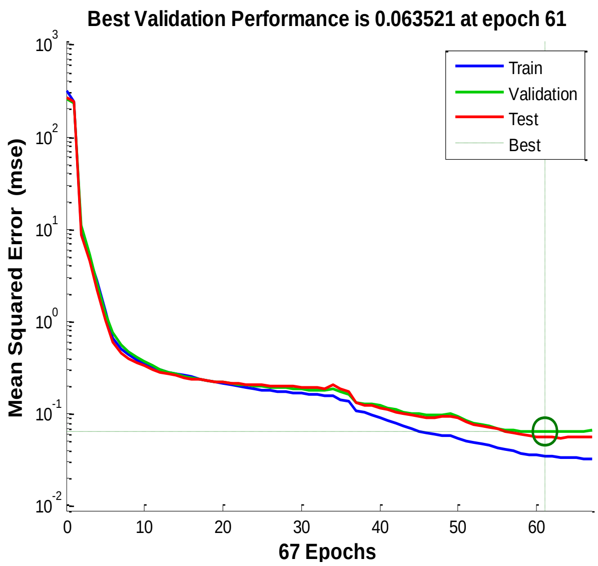

Figure 14c: 2nd Retrained Model

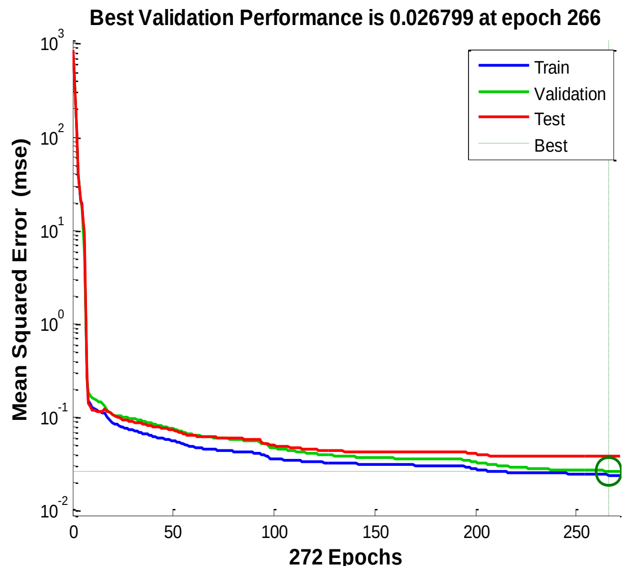

Figure 14d: 3rd Retrained Model

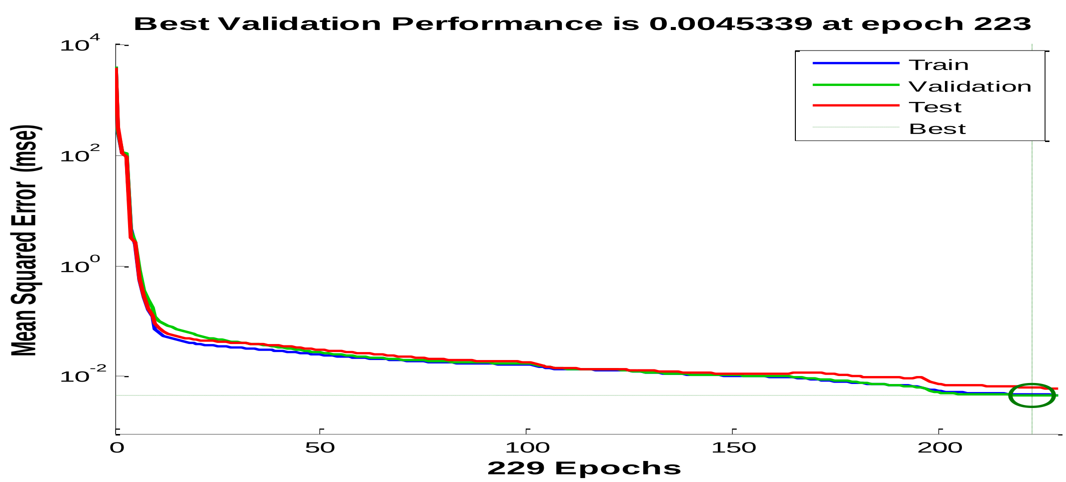

Figure 14e: 4th Retrained Model

The graphical representations of the validation performance show that the trained model has the least mean square error and was regarded as the best model with 15 neurons.

Figure 15a – Figure 15e illustrate the graphical representation of the validation performance of the 20-neuron-based model.

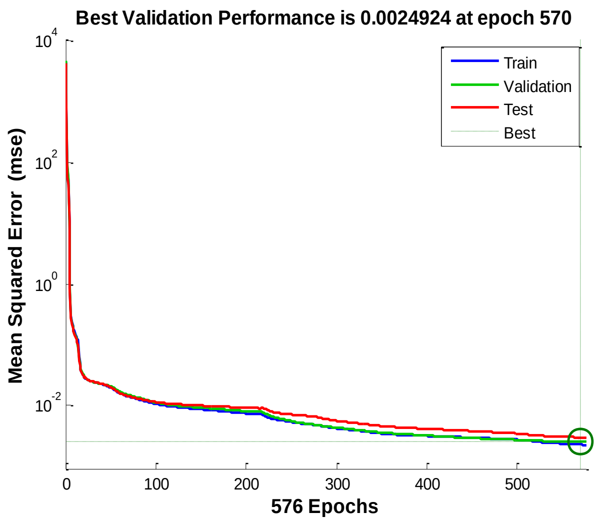

Figure 15a: Trained Model

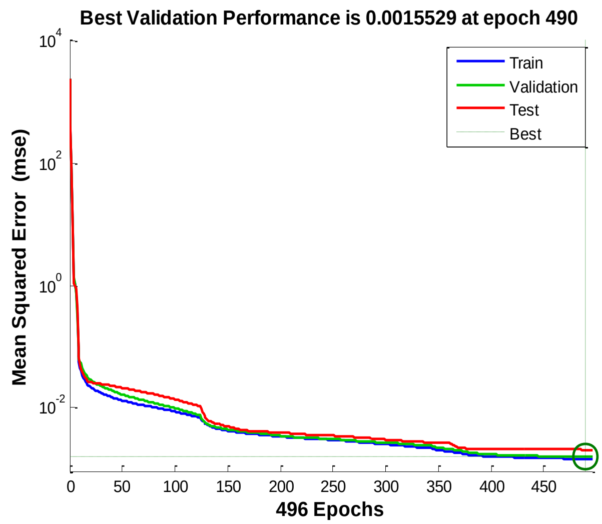

Figure 15b: Ist Retrained Model

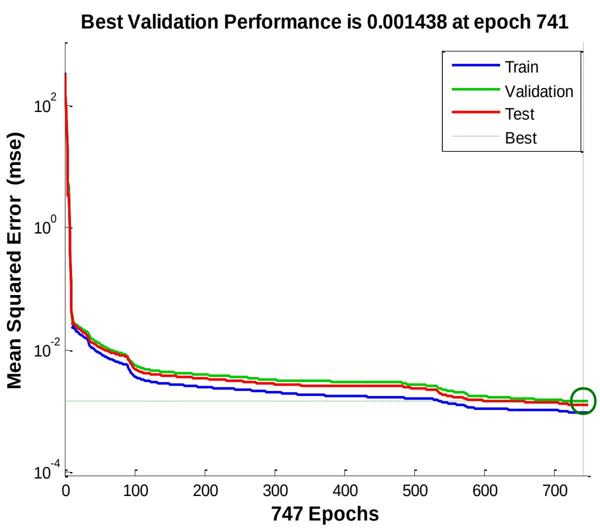

Figure 15c: 2nd Retrained Model

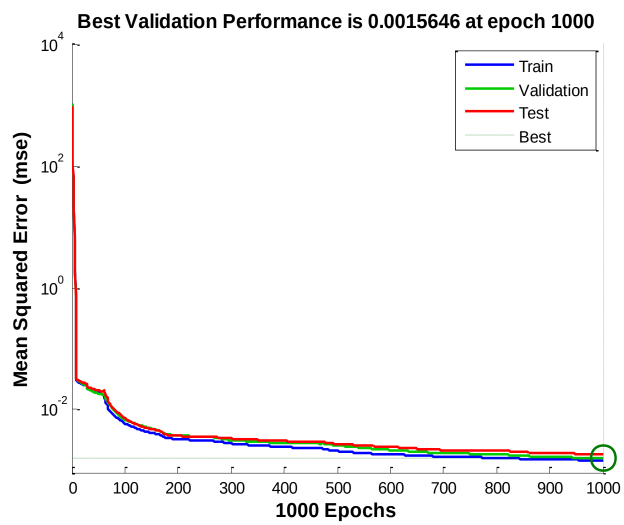

Figure 15d: 3rd Retrained Model

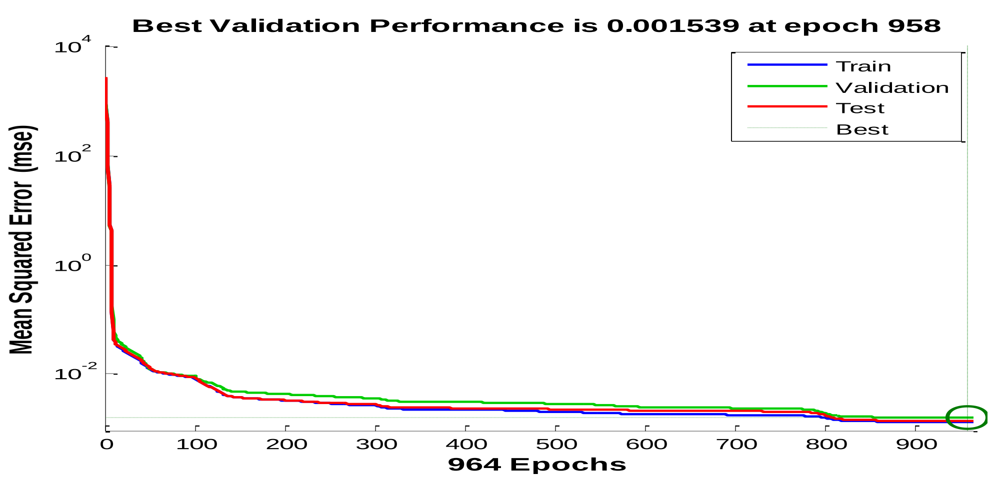

Figure 15e: 4th Retrained Model

The graphical representations of the validation performance show that the 2nd retrained model has the least mean square error and was regarded as the best model with 20 neurons.

Figure 16a – Figure 16e illustrate the graphical representation of the validation performance of the 25-neuron-based model.

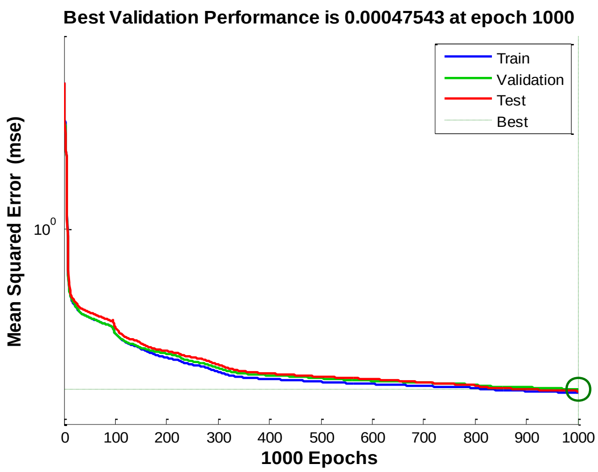

Figure 16a: Trained Model

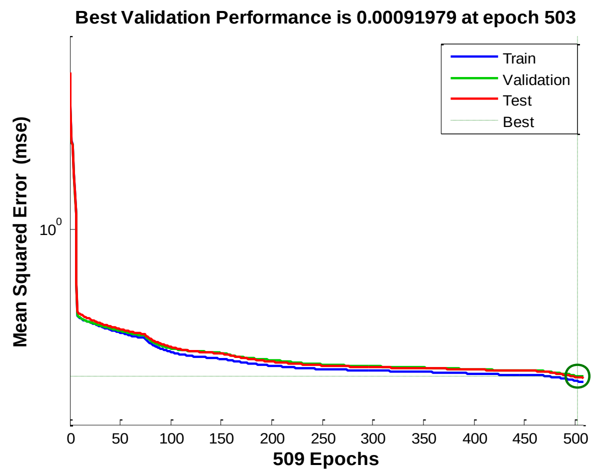

Figure 16b: Ist Retrained Model

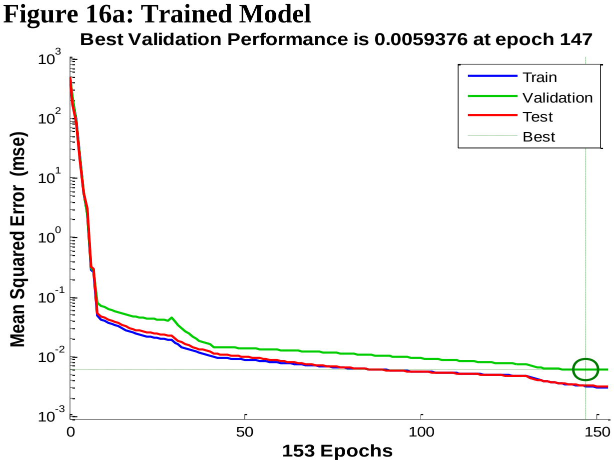

Figure 16c: 2nd Retrained Model

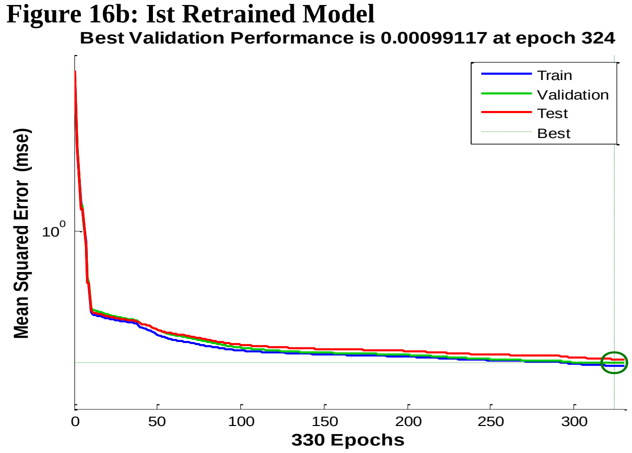

Figure 16d: 3rd Retrained Model

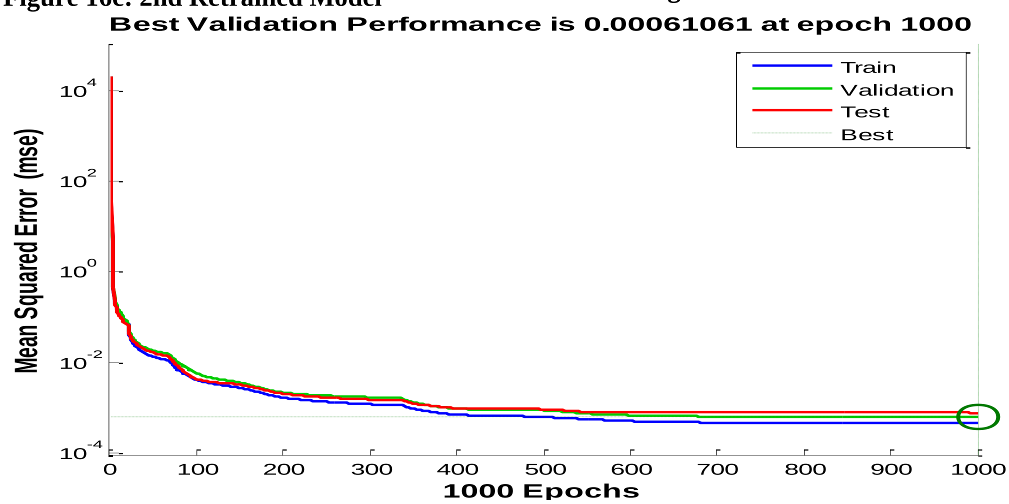

Figure 16e: 4th Retrained Model

The graphical representations of the validation performance show that the trained model has the least mean square error and was regarded as the best model with 25 neurons.

From the entire graphical representations of the validation performance, the trained model with 25 neurons performed best with the least mean square error 0.00047543 at 1000 epoch.

The regression plot was also used to evaluate the performance of the model. The R-values or correlation coefficients for the various models were obtained and compared. A value closer to 1 indicates a strong correlation between the variables (outputs and target).

Table 5 illustrates the representation of the correlation coefficient for the trained model with 10, 15, 20 and 25 neurons. The R-values included that for the Training, validation and test data. However, attention was given to the representation tagged ‘All’.

Table 5: The Correlation Coefficient for the Model with 10, 15, 20 and 25 Neurons

			Coefficient of Correlation			
S/No.	No. of Neurons	Model	Training	Validation	Test	All
1	10	Trained	0.99958	0.99958	0.9995	0.99957
		Ist Retrained	0.99914	0.99902	0.99902	0.99909
		2nd Retrained	0.99948	0.99957	0.99967	0.99953
		3rd Retrained	0.99979	0.99974	0.99981	0.99979
		4th Retrained	0.99956	0.99957	0.99945	0.99954
2	15	Trained	0.99997	0.99994	0.99995	0.99996
		Ist Retrained	0.99985	0.99985	0.9998	0.99984
		2nd Retrained	0.99956	0.99936	0.99954	0.99949
		3rd Retrained	0.99969	0.99956	0.99969	0.99967
		4th Retrained	0.99994	0.99997	0.99987	0.99994
3	20	Trained	0.99997	0.99996	0.99996	0.99997
		Ist Retrained	0.99998	0.99998	0.99998	0.99998
		2nd Retrained	0.99999	0.99998	0.99998	0.99999
		3rd Retrained	0.99998	0.99998	0.99997	0.99998
		4th Retrained	0.99998	0.99999	0.99998	0.99998
4	25	Trained	1.000000	0.99999	0.99999	0.99999
		Ist Retrained	0.99999	0.99999	0.99999	0.99999
		2nd Retrained	0.99996	0.99994	0.99995	0.99996
		3rd Retrained	0.99999	0.99999	0.99998	0.99999
		4th Retrained	0.99999	0.99999	0.99999	0.99999

Based on the correlation coefficient for various models, the highest correlation coefficient recorded was 0.99999. This value was recorded by the following models: 20-neuron-based 2nd retrained model, 25-neuron-based trained, 1st retrained, 3rd retrained and 4th retrained models.

Throughout the neural network training process, three key indicators that showed the state of the models were carefully monitored. These indicators include the gradient, momentum coefficient, and validation error check. The gradient is a measurement of the network error rate of change, and it adjusts the ANN's weight to reduce the error. This adjustment results in a more accurate model.

The momentum coefficient ranges from zero (0) to one (1) and incorporates the historical weight updates into the current update. This prevents weight update oscillation and improves the convergence speed.

The validation error check uncovers failed validation tests and guarantees that the iterative process terminates once the maximum number of consecutive failed validations has been reached.

Table 6 illustrates these parameters and their values at the end of the training process.

Table 6: The indicators that show the state of the models

S/No.	No. of Neurons	Model	Epoch	Model States indicators		
				Gradient	Momentum Coefficient	Validation Error Check
1	10	Trained	472	0.067507	0.0000001	6
		Ist Retrained	241	0.037737	0.0001	6
		2nd Retrained	71	0.55049	0.0001	6
		3rd Retrained	433	1.1381	0.000001	6
		4th Retrained	141	0.30776	0.0001	6
2	15	Trained	676	0.060413	0.000001	6
		Ist Retrained	124	0.070419	0.0001	6
		2nd Retrained	67	0.14381	0.001	6
		3rd Retrained	272	7.427	0.00001	6
		4th Retrained	229	0.19983	0.0001	6
3	20	Trained	576	0.38128	0.00001	6
		Ist Retrained	496	0.018079	0.00001	6
		2nd Retrained	747	0.10338	0.00001	6
		3rd Retrained	1000	0.003132	0.00001	0
		4th Retrained	964	0.085078	0.00001	6
4	25	Trained	1000	0.003732	0.00001	0
		Ist Retrained	509	0.63559	0.00001	6
		2nd Retrained	153	0.049449	0.0001	6
		3rd Retrained	330	0.24893	0.00001	6
		4th Retrained	1000	0.008004	0.00001	0

After analyzing the state of the model throughout the training and retraining process, some models performed better than others. Specifically, the 20-neuron-based trained model, 20-neuron-based 1st retrained model, 25-neuron-based trained model, and 25-neuron-based 4th trained model all had a few validation errors, as indicated by red spots on the validation graphs. Out of all these models, the 25-neuron-based trained model performed the best. Therefore, it is the recommended model for predicting real and reactive power losses on the transmission network described earlier.
The Artificial Neural Network utilized for prediction demonstrated that the error histogram obtained for all tested models indicated good prediction models. However, the validation performance graph differed from the error histogram, implying that only a few models performed better. The correlation of the coefficient curve and the state of the training models graph provided a clearer view of the model with the best predictive characteristics for losses in the IEEE 118-bus transmission network.
Sample data was collated and classified (A-F) to test the adopted model.
The sample data is contained in Table 7

Table 7: Sample Data

Class	Br_Resistnce (Ohm)	Br_ Reactance(Ohm)	Susceptance (Ohm)	Real Power Injection (MW)	Reactive Power Injection (MW)
A	0.0303	0.0999	0.0254	-12.35	-13.04
B	0.0129	0.0424	0.01082	-38.65	-17.06
C	0.00176	0.00798	0.0021	-103.23	-26.79
D	0.0241	0.108	0.0284	-68.11	-14.49
E	0.0119	0.054	0.01426	88.47	4.11
F	0.00459	0.0208	0.0055	35.54	-4.77

The bar charts in Figure 17 and Figure 18 were used to compare the real and reactive power losses respectively.

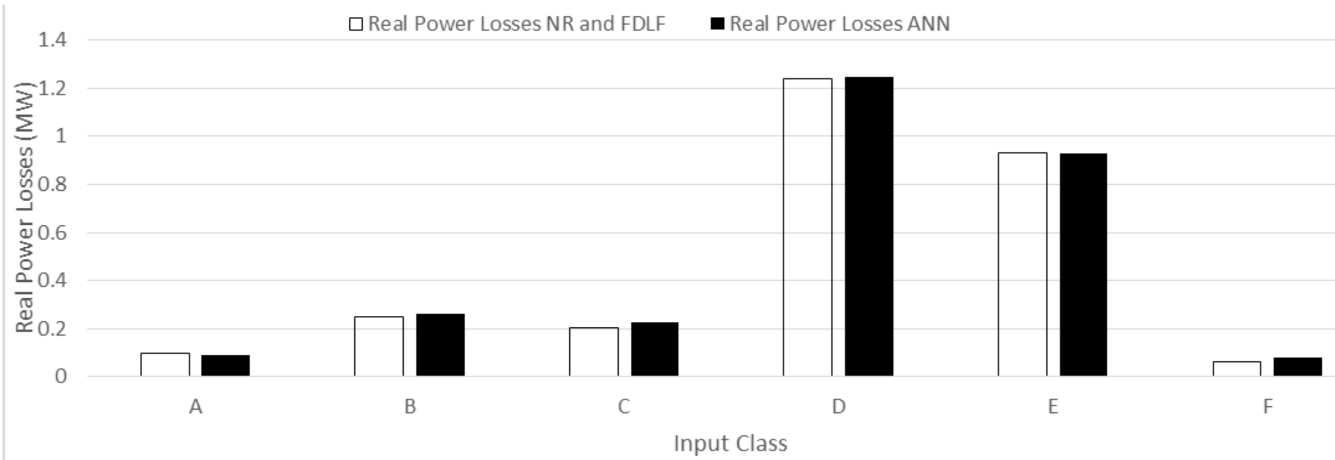

Figure 17: Compared Real Power Output from the Load flow Techniques and ANN

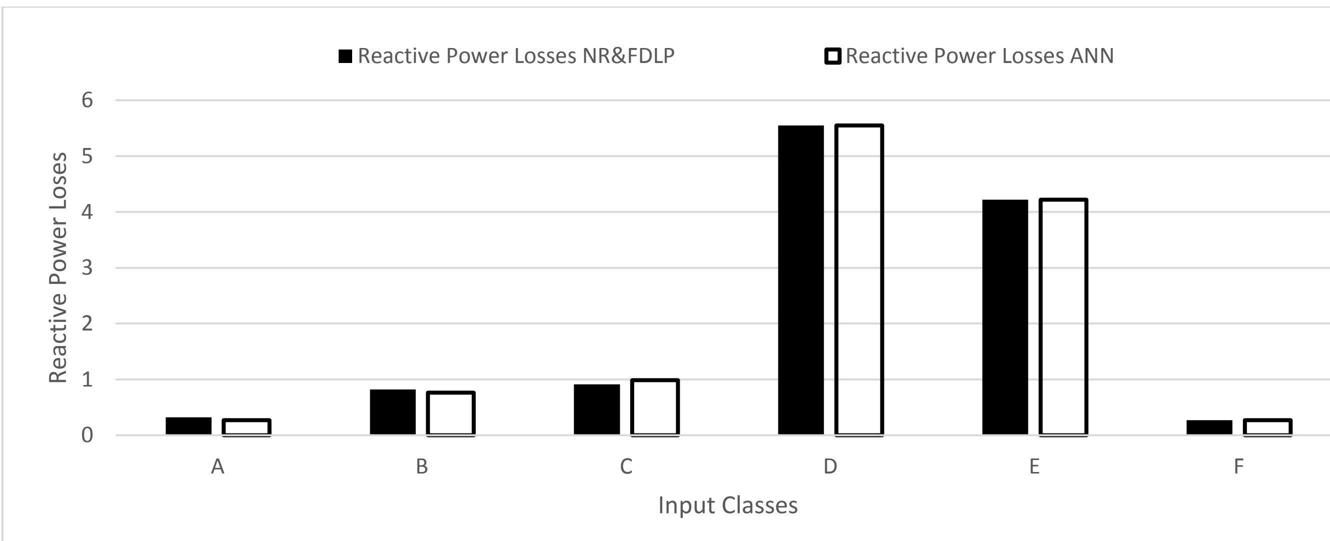

Figure 18: Compared Reactive Power Output from the Load flow Techniques and ANN

The bar chart depicts a comparison between conventional load flow techniques and the Neural Network technique. It indicates that there is little variation, suggesting that the Neural Network model can be utilized to obtain network losses on the IEEE 118 bus network.

4.0 Conclusions

The purpose of this study was to analyze the real and reactive transmission line losses in the IEEE 118 bus network. To achieve this, an Artificial Neural Network (ANN) model was created using data obtained from two load flow techniques, namely the Newton-Raphson's technique and the Fast decoupled technique. Different ANN models were tested and evaluated, and the most optimal model was determined by comparing its performance with the others. The error histogram for each tested model indicated good prediction, while the validation performance graph showed that only a few models performed better. The correlation of the coefficient curve and the training model state graph was used to identify the model with the best predictive characteristics for the network's losses. The development of an Artificial Neural Network (ANN) model for predicting real and reactive power losses in transmission lines produced promising results. By training the model with data obtained from Newton-Raphson (NR) and Fast Decoupled Load Flow (FDLF) techniques, we have been able to create a tool for estimating power losses in transmission lines. The model's performance was evaluated using various neuron sizes, and the optimal model was selected based on its efficiency and accuracy.

Validation is important to ensure that the ANN model is reliable and accurate in different conditions. A larger dataset can be used to test the model and compare predicted results with actual field measurements. Sensitivity analysis can help identify key parameters that influence power losses in transmission lines, improving system efficiency. Integrating the ANN model with real-time monitoring systems in power grids can enable continuous monitoring and prediction of power losses, contributing to proactive maintenance and optimization of transmission line operations. Collaboration with industry partners and utilities to implement the model in practical settings can provide valuable feedback and insights for further improvements. Future research could explore advanced machine learning techniques and optimization algorithms for more accurate and efficient prediction of power losses in transmission lines. Overall, the ANN model is a significant step towards enhancing the efficiency and reliability of power systems. By implementing the recommendations provided, we can further contribute to the sustainable operation of power grids.

5.0 Recommendation

The development of an Artificial Neural Network (ANN) model for predicting real and reactive power losses in transmission lines has yielded promising results. To further enhance the efficiency and reliability of power systems, it is recommended that the ANN model be integrated into real-time monitoring systems in power grids, enabling continuous monitoring and prediction of power losses. Additionally, exploring advanced machine learning techniques and optimization algorithms can lead to more accurate and efficient predictions. Furthermore, testing the model with a larger dataset and comparing predicted results with actual field measurements will ensure the model's reliability and accuracy in various conditions.

6.0 Abbreviations

i. ANN- Artificial Neural Network
ii. MFNNs- Multilayered Feed-Forward Neural Networks
iii. NR- Newton Raphson
iv. FDLF- Fast Decoupled Load Flow
v. AI - Artificial Intelligence
vi. ML- Machine Learning
vii. CNN- Convolutional Neural Network
viii. RNN- Recurrent Neural Network
ix. Fast Decoupled Reactance and Susceptance (FDXB)

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