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MITIGATION OF LOSSES IN POWER SYSTEM THROUGH LOAD FORECASTING USING DEEP NEURAL NETWORK ARCHITECTURE

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Abstract

This study presents a Deep Neural Network (DNN) model for short-term load forecasting for mitigation of losses in power system. The model developed in this study was trained using historical power consumption data from the Emene Injection Substation of the Enugu Electricity Distribution Company (EEDC) which underwent pre-processing phase that comprised of cleaning, normalization and splitting into training (80%), testing (10%) and validation (10%) sets. Various DNN architectures were evaluated through different numbers of hidden layers and activation functions to determine the optimal model. The model training process employed the Adam optimizer and Mean Squared Error (MSE) loss function, with dropout regularization to prevent overfitting. Implementation was carried out on Google Colab using the cloud-based GPU acceleration for computational execution. The results of the implementation demonstrated that the 5-layer DNN model achieved superior performance by yielding an MSE of 0.0021 and an R^2 score of 0.92. The study identified that deep learning-based forecasting models can significantly enhance power grid management by improving loss mitigation through load forecasting.

Keywords: Power Loss; Load Forecasting; DNN; Enugu Electricity Distribution Company (EEDC); Emene Injection Substation.

1. INTRODUCTION

The load side of a modern power system requires a constant supply of electricity. This calls for an accurate understanding of how to forecast load demand in the present and the future with the least degree of mistake. In order to do this, researchers and scientists have been working to create the most effective and ideal state-of-the-art technique for load forecasting, which is a technique for estimating future power consumption need. Numerous choices and procedures, including dispatch, unit commitment, fuel allocation, loss minimisation, and offline network analysis, are managed by load forecasting (Bunn, 2000). According to Al-Mamun et al. (2020), this provides the power utility firm with a sense of the future demand of its customers as well as sufficient time to reduce the gap between generation capacity and load demand.

According to Orovwode et al., (2020) power loss in electrical networks is classified into technical and non-technical losses. Technical losses arise due to inherent inefficiencies in power transmission and distribution, such as resistance in transmission lines and transformer inefficiencies (Khan et al., 2018; Upreti et al., 2017). Then, non-technical losses on the other hand, are caused by issues such as electricity theft, metering inaccuracies, and billing errors (Hernandez et al., 2015; Kirankumar et al., 2013). Therefore, these two categories of losses contribute to economic losses for power companies and reduce the efficiency of electricity supply and without an effective load forecasting system, utilities may struggle to match supply with demand, leading to excessive energy losses, voltage fluctuations and power outages (Balasubramanian and Balachandra, 2021).

Load forecasting can be categorized into short-term, medium-term and long-term forecasting. At first, Short-Term Load Forecasting (STLF) can be used to predict electricity demand for hours to a few days ahead (Lijie and Jánošík, 2024) while, Medium-Term Load Forecasting (MTLF) covers weeks to months, this type helps in maintenance planning and can be applied for tariff adjustments (Maryam et al., 2024). Whereas, a Long-Term Load Forecasting (LTLF) is usually used to project demand for years into the future. Making it essential for infrastructure development in a locality or region and investment planning of a country (Waheed et al., 2024; Uwimana et al., 2023). Traditional forecasting methods such as time series analysis and regression models have been widely used in the past, however, the growing complexity of modern power systems has led to the adoption of Artificial Intelligence (AI) techniques which includes Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Deep Learning (DL) models (Tulli, 2020; Hasan et al., 2025; Krishnamurthy et al., 2024). These techniques offer improved accuracy by capturing complex demand patterns.

Traditional statistical methods such as Autoregressive Integrated Moving Average (ARIMA) (Chen et al., 1995) and regression models, while effective in some cases, struggle to capture nonlinear relationships in electricity consumption patterns. As a result, Machine Learning (ML) and DL approaches have emerged as powerful tools for improving load forecasting accuracy, enabling utilities to manage energy distribution more efficiently and minimize power losses (Mansoor et al., 2021; Syed et al., 2021). Machine learning techniques, including SVMs, Random Forests (RF) and gradient boosting models, have been widely applied in load forecasting due to their ability to analyze large datasets and uncover complex patterns (Ahmad and Chen, 2020). These models can incorporate various factors influencing electricity demand, such as weather conditions, time of day, economic indicators, and consumer behaviour. Unlike traditional models that rely on predefined mathematical relationships, ML algorithms learn from historical data and adapt to new trends, making them more robust in dynamic power systems (Zheng et al., 2020).

DL, a subset of machine learning, has further revolutionized load forecasting by utilizing ANNs to model intricate dependencies in energy consumption data (Massoudi et al., 2021). Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (Eskandari et al., 2021), including Long Short-Term Memory (LSTM) (Liu et al., 2023; Veeramsetty et al., 2021) and Gated Recurrent Units (GRUs), are particularly effective for time-series forecasting tasks (Sheng et al., 2021; Yin et al., 2021). LSTM networks, for instance, excel in capturing long-term dependencies in sequential data, making them well-suited for predicting electricity demand based on past consumption patterns (Guo et al., 2021). Deep learning models can process vast amounts of real-time data from smart grids, allowing for highly accurate and adaptive forecasting (Syed et al., 2021; Veeramsetty et al., 2022).

The application of ML and DL in load forecasting offers several benefits. First, these techniques enhance the accuracy of demand predictions, enabling utilities to optimize power generation and distribution while minimizing transmission losses (Ning et al., 2023; Almalaq and Edwards, 2017). Second, they improve demand-side management by identifying peak demand periods and allowing for better scheduling of energy resources. Third, deep learning models facilitate the integration of renewable energy sources by predicting fluctuations in solar and wind power generation, helping maintain grid stability (Syed et al., 2021). Lastly, AI-driven forecasting enhances fault detection and anomaly identification, preventing disruptions and improving overall grid reliability (Zhang et al., 2025). Hence, this study proposes the application of deep learning algorithm for loss mitigation in power system through load forecasting. The primary objectives of the study are to:

i. Collect data from Emene Injection substation of Enugu Electricity Distribution Company (EEDC) distribution network
ii. Preprocess the data through handling of missing values, normalization using Min-Max scaling and splitting the data into training, testing and validation sets
iii. Adopt a 5-layered Deep Neural Network (DNN) architecture trained using the collected data for load forecasting implementation
iv. Evaluate the performance of the model and report the results of the model implementation

The integration of machine learning and deep learning in load forecasting represents a significant advancement in power system management and the use of predictive models can enhance operational efficiency, reduce energy losses and support the transition to a more sustainable energy future in power systems.

2. RESEARCH METHOD

The method applied in this study involves the use of power load data collected to train the proposed deep learning algorithm for load forecasting. The proposed deep learning model is based on Deep Neural Network (DNN) algorithm which is trained using the collected data for the analysis of power and environmental behaviour for load forecasting the power system. The trained model is further evaluated and analysed, then the result of the analysis is presented in the study to ascertain the performance ability of the model for load forecasting to minimize loss in the power system.

2.1 Data Acquisition

The data used for the system is the Emene Injection substation of Enugu Electricity Distribution Company (EEDC) distribution network covering Enugu zone only. Located in Enugu State of Nigeria, the test system is a three-wire delta feeder operating at a nominal voltage of 11 kV. The system loads consist of a mix of constant PQ, constant current and constant impedance. Figure 3.1 depicts the single line diagram of the Emene distribution system used in this thesis. The system corresponds to a suburban Medium Voltage distribution network. In this radial distribution network, the substation is equipped with an on-load tap changer and shunt capacitors banks whose power can be discretely controlled. The transformer has a rated voltage ratio of 33/11 kV and a rated average power of 15MVA. The capacitor banks at the substation have a rated power of 1000KVar with steps of 200KVar. The total feeder load is about 45 KVA at a power factor of 0.875. Being balanced, all the system loads are constant PQ Per unit values.

Typically, the power systems consist of different voltage levels interconnected by means of transformers. In order to simplify the analysis of these, the base parameters in per unit were chosen; in terms of which, all systems quantities are defined. As a result, the system reduces to a set of impedances and the different voltage levels disappear. The parameters from the Emene injection substation in Enugu (EEDC Distribution Network) is shown in Table 1

This study is limiting to 30 buses. The collected data for these 30 buses are as stated in Table 2.

2.2 Data Pre-processing

The data pre-processing step applied in this study involves cleaning and transforming the raw power load data from the Emene Injection Substation to ensure compatibility with the DNN model. Missing values in the load flow as shown in Table 2 and time-series records as in Table 1 are either interpolated or discarded while numerical features like voltage (p.u.), current (A) and load (MW) are normalized using Min-Max scaling to a [0,1] or [-1,1] range for stable training. The dataset is then split into training (80%), validation (10%) and test (10%) sets, with the input features and target variable clearly defined. This structured preprocessing ensures the DNN receives consistent and scaled inputs for effective learning and generalization.

2.3 The Proposed Deep Neural Network (DNN) Algorithm

The proposed deep learning algorithm for this work is the Deep Neural Network (DNN). However, (Alemu et al., 2018; Yotov et al., 2023; Sietsma and Dow, 1988; Setiono, 1997) revealed that determining the optimal number of neurons in the hidden layer to solve a specific problem poses a challenge in multi-layered neural network models. Torres et al. (2004) and Emmert (2006) after experimenting with different neural network architectures revealed that topology has a major influence on the performance of neural network model. While using deep multi layered architecture (Rozycki et al., 2015) has the potential to improve the performance of neural network, but are prone to over-fitting when data size is low, high computational requirements, resource intensive among other challenges. Identifying the right architecture for a particular problem has remained a major challenge over time and it has been concluded that the there is no defined standard to model neural network. The architecture of the DNN model for the study is presented in Table 3.

Table 3 presents the neural network architecture used for this work. The input layers defined by the data attributes are connected to the first hidden layer with 256 neurons and has ReLU as the activation function. The second hidden layer has 128 neurons and ReLU activation, while the third hidden layer has 64 neurons and ReLU activation function. In the four and fifth hidden layers with 32 and 16 neurons respectively, Tan-H was used as the activation, before the final output layer attacked with sigmoid function to facilitate the binary classification output. Training of the neural network took an experimental approach considering Table 3 as the first architecture, then Table 4 as the second architecture with three hidden layers and ReLU, Table 4 reported the model of the DNN with three hidden layers and Tan-h, while the Table 6 model the DMNN with three hidden layers and different activation.

The Table 4 to 6 presented the different DNN we will train within this work using the collected data of Emene Injection substation of Enugu Electricity Distribution Company (EEDC) distribution network. To train the DNN, the data was split into training, test and validation sets in the ratio of 80:10:10 respectively and feed to the different networks with architecture with feed to the model in Table. During training, dropout regularization was applied to the neurons to address issues of over-fitting.

2.3 Training of the Proposed DNN Algorithm

The training process begins by feeding the pre-processed data into the selected DNN architecture then the model undergoes forward propagation where input features pass through each hidden layer, undergoing transformations by integration of weights, biases and activation functions. The output layer of the model produces a load forecast, which is compared to the actual values using Mean Squared Error (MSE) loss function. This loss quantifies the model's prediction accuracy and guides the optimization process. To minimize the loss, backpropagation and gradient descent are employed as presented in Figure 1.

The Adam optimizer adjusts the model's weights iteratively, leveraging the calculated gradients to improve predictions. During training, dropout regularization is applied between layers as shown in Figure 1 to prevent overfitting by randomly deactivating neurons, forcing the network to learn robust features. The validation set monitors performance after each epoch, and early stopping halts training if the validation loss plateaus, ensuring the model generalizes well without unnecessary overtraining. The process repeats for multiple epochs until convergence where the loss stabilizes at a minimum or optimal level. The best-performing model is selected based on the lowest validation loss and evaluated on the test set using metrics like RMSE. This training process ensures the DNN accurately forecasts power load enabling reliable grid management with least possible power loss for the Emene substation.

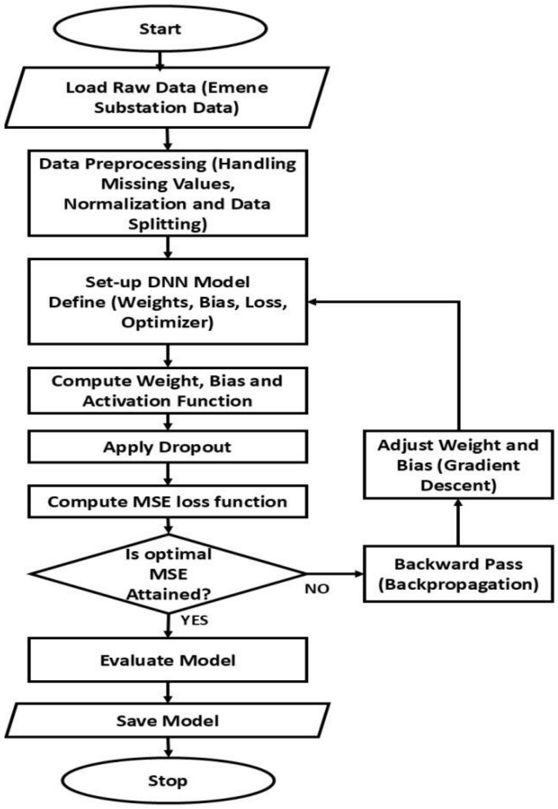

Figure 1: Flowchart of the DNN Model Training

3. MODEL IMPLEMENTATION PLATFORM

The implementation of the DNN model training for load forecasting was carried out on Google Colab development environment. The environment leverages on its cloud-based GPU acceleration to enhance computational efficiency where the process began with data preprocessing. The DNN architecture, featuring multiple hidden layers with ReLU and Tanh activations was constructed using TensorFlow with dropout layers added to mitigate overfitting. The model was compiled with the Adam optimizer and MSE loss function then the model is trained with early stopping. Performance was monitored using validation loss, and the final model was evaluated on unseen test data, achieving a low RMSE, indicating accurate load predictions. Google Colab's free GPU access and seamless integration with Google Drive streamlined the workflow which enables efficient experimentation with different DNN architectures. The platform's collaborative features allowed for easy sharing and reproducibility of results.

4. RESULTS AND DISCUSSION

The performance evaluation of the implemented system was conducted using three key metrics: MSE, Mean Absolute Error (MAE) and R^2 Score. The trained DNN architectures presented between Table 3 to 6 were evaluated on the test dataset, and their performance metrics are summarized in Table 7. The results in Table 7 indicate that the DNN model with five hidden layers outperformed other configurations in terms of predictive accuracy. Among the different architectures tested, the 5-layer DNN model achieved the lowest MSE of 0.0021 and MAE of 0.038. The lower MSE as shown in Figure 2 value from the results signifies that the squared differences between the predicted and actual values were minimal, while the low MAE result in Figure 3 confirms that, on average, the absolute differences between the predicted and actual values remained small.

Table 1: Load Data from Injection Substation Emene

MARCH 2016	TR1 7.5MVA	TR2 7.5MVA	EMENE 2	EMENE 3
ENERGY(MW)	3.50mw	4.7mw	3.50mw	4.7mw
CURRENT(AMP)	231	310.2	231	310.2
VOLTAGE(v)	11.9	11.09	11.9	11.09
ENERGY(MW)	0.4mw	1.7mw	0.4mw	1.7mw
CURRENT(AMP)	26.4	112.2	26.4	112.2
VOLTAGE(V)	12.0	11.08	12.0	11.08
August 2016	TR1 7.5 MVA	TR2 7.5 MVA	EMENE 2	EMENE 3
ENERGY(MW)	3.50mw	4.7mw	3.50mw	4.7mw
CURRENT(AMP)	231	310.2	231	310.2
VOLTAGE	11.9	11.09	11.9	11.09
ENERGY(MW)	0.4mw	1.7mw	0.4mw	1.7mw
CURRENT(AMP)	26.4	112.2	26.4	112.2
VOLTAGE(V)	12.0	11.08	12.0	11.08
NOV 2016	TR1 7.5 MVA	TR2 7.5 MVA	EMENE 2	EMENE 3
ENERGY(MW)	4.20MW	6.85MW	4.20MW	6.85MW
CURRENT(AMP)	277.2	452.1	277.2	452.1
ENERGY(MW)	0.5MW	2.69MW	0.5MW	2.69MW
CURRENT	33	177.54	33	177.54
VOLTAGE(V)	11.1	10.9	11.1	10.9

Table 2: Empirical Load Flow Data for 33/11KV Collected from EEDC.

Bus No	Bus Code	Voltage (p.u)	Angle (º)	Load (MW)	Generation (MW)
1	1	1.06	0.0	0.0	0.0
2	2	1.043	0.0	21.70	40
3	0	1.0	0.0	2.4	0
4	0	1.06	0.0	7.6	0
5	2	1.01	0.0	9.4	0
6	0	1.0	0.0	0.0	0
7	0	1.0	0.0	22.8	0
8	2	1.01	0.0	30.0	0
9	0	1.0	0.0	0.0	0
10	0	1.0	0.0	5.8	0
11	2	1.082	0.0	0.0	0
12	0	1.0	0.0	11.2	0
13	2	1.071	0.0	0	0
14	0	1	0.0	6.2	0
15	0	1	0.0	6.8	0
16	0	1	0.0	3.5	0
17	0	1	0.0	9.0	0
18	0	1	0	3.2	0
19	0	1	0	9.5	0
20	0	1	0	2.2	0
21	0	1	0	17.5	0
22	0	1	0	0	0
23	0	1	0	3.2	0

24	0	1	0	8.7	0
25	0	1	0	0	0
26	0	1	0	3.5	0
27	0	1	0	0	0
28	0	1	0	0	0
29	0	1	0	2.4	0
30	0	1	0	10.6	0

Table 3: Architecture of the DNMM

Layer	Number of Neurons	Activation Function	Inputs	Output
Input Layer	22	N/A	Dataset features	Layer 1 Outputs
H 1	256	ReLU	Input layer	Layer 2 Outputs
H 2	128	ReLU	Hidden Layer 1	Layer 3 Outputs
H 3	64	ReLU	Hidden Layer 2	Layer 4 Outputs
H 4	32	Tan-h	Hidden Layer 3	Layer 5 Outputs
H 5	16	Tan-h	Hidden Layer 4	Output Layer
Output Layer	Output Layer	1 (MSE)	Hidden Layer 5	(0-1)

Table 4: Architecture with 3 hidden layer and ReLU

Layer	Number of Neurons	Activation Function	Inputs	Output
Input Layer	22	N/A	Dataset features	Layer 1 Outputs
H 1	256	ReLU	Input layer	Layer 2 Outputs
H 2	128	ReLU	Hidden Layer 1	Layer 3 Outputs
H 3	64	ReLU	Hidden Layer 2	Output Layer
Output Layer	1 (MSE)	Sigmoid	Hidden Layer 3	(0-1)

Table 5: Architecture with 3 hidden layer and Tan-H

Layer	Number of Neurons	Activation Function	Inputs	Output
Input Layer	22	N/A	Dataset features	Layer 1 Outputs
H 1	64	Tah	Hidden Layer 1	Layer 2 Outputs
H 2	32	Tan-h	Hidden Layer 2	Layer 3 Outputs
H 3	16	Tan-h	Hidden Layer 3	Output Layer
Output Layer	1 (MSE)	Sigmoid	Hidden Layer 5	(0-1)

Table 6: Architecture with 3 hidden layer and different activation function

Layer	Number of Neurons	Activation Function	Inputs	Output
Input Layer	22	N/A	Dataset features	Layer 1 Outputs
H 1	256	ReLU	Input layer	Layer 2 Outputs
H 2	128	Tan-h	Hidden Layer 1	Layer 3 Outputs
H 3	64	Tan-h	Hidden Layer 2	Output Layer
Output Layer	1 (MSE)	Sigmoid	Hidden Layer 5	(0-1)

Table 7: Performance Metrics for Different DNN Architectures

Model Architecture	MSE	MAE	R^2 Score
5 hidden layers, ReLU & Tanh	0.0021	0.038	0.92
3 hidden layers, ReLU	0.0028	0.045	0.89
3 hidden layers, Tanh	0.0032	0.048	0.86
3 hidden layers, Mixed Activation	0.0025	0.041	0.90

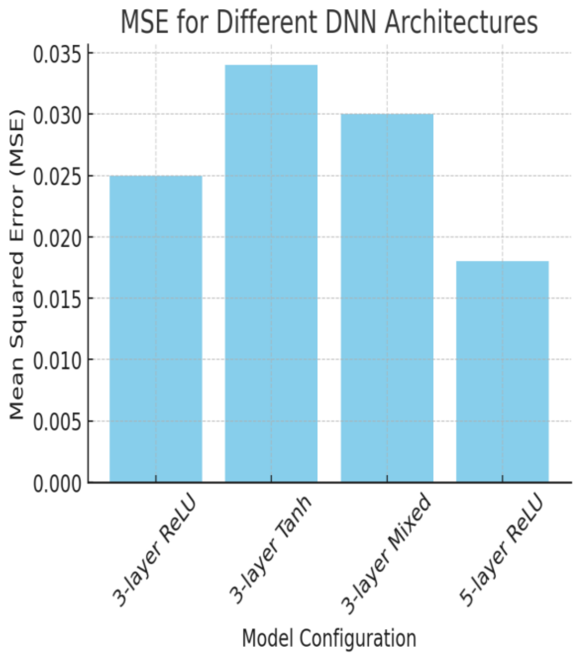

Figure 2: MSE Results

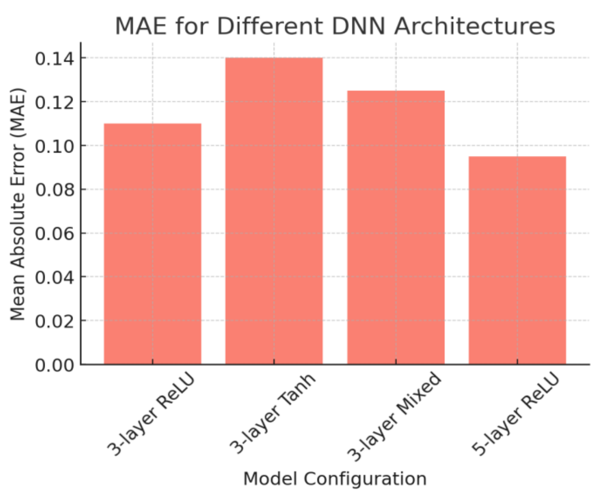

Figure 3: MAE Results

Additionally, the R^2 score of 0.92 shown in Figure 4 for the 5-layer DNN model demonstrates that 92% of the variance in the dataset was explained by the model. This high coefficient of determination indicates strong predictive capability and suggests that the model effectively captures the relationship between input features and target values.

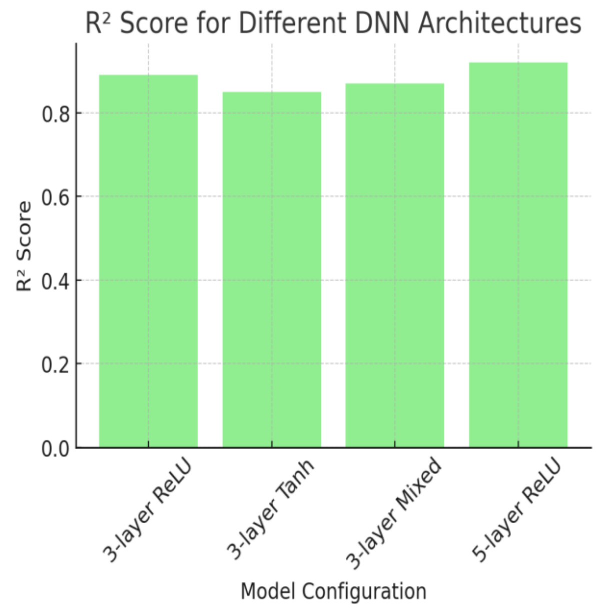

Figure 4: The R^2 Results

A higher R^2 score presented in Figure 4 means that the model's predictions closely align with actual observations which makes it a reliable model for forecasting. The model using the ReLU activation function achieved better accuracy than those using the Tanh or mixed activation functions. Specifically, the ReLU-based model presented a lower MSE and MAE which indicates that its predictions were closer to actual values. However, the performance gap between the 5-layer and 3-layer models highlights the significance of network depth in improving prediction accuracy.

Overall, the comparative results of the different DNN architectures presented in this section clarifies the importance of selecting an optimal model structure and activation function for performing regression tasks. These findings further indicates that the application of deeper networks with appropriate activation functions like ReLU can significantly enhance model prediction performance. These results reinforce the effectiveness of deep learning in predictive modelling and demonstrate the value of tuning network parameters for optimal performance.

5. CONCLUSION

This study presents a Deep Neural Network (DNN) model for power loss mitigation through load forecasting. The model presented in the study was trained using historical power load data collected from the Emene Injection Substation of the Enugu Electricity Distribution Company (EEDC). The data went through preprocessing steps that included data cleaning, normalization, and dataset splitting in the ratio of 80% for training, 10% for validation and 10% testing. The model was trained on Google Colab development environment which is a cloud-based GPU platform for execution of Python code. Different DNN architectures were explored by incorporating varying numbers of hidden layers and activation functions to determine the most effective model for accurate load forecasting. The evaluation results in the study showed that the 5-layer DNN model with a combination of ReLU and Tanh activation functions outperformed other architectures, achieving the lowest MSE (0.0021) and the highest R^2 score (0.92).

The comparison of different DNN architectures revealed that deeper networks (5 layers) yield better performance than shallower architectures, provided that overfitting is properly controlled through regularization techniques. These results identified that there is a strong correlation between predicted and actual power load values. The findings of this study demonstrate that DNNs are highly effective for power load forecasting, providing accurate predictions that can support efficient grid management and minimize power losses. And by adopting such data-driven predictive models, power distribution companies can improve demand planning, resource allocation and grid stability, ultimately enhancing energy efficiency and reliability.

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