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Research Original Article

Energy Audit and Electricity Load Prediction in Buildings using Artificial Neural Network Algorithm - A Case Study

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Abstract

The demand for electricity in Indonesia is continuously increasing due to the growing economy over time. In accordance with Presidential Instruction No. 10 of 2005 and Presidential Regulation No. 5 of 2006, regulations have been issued regarding energy conservation and national energy usage policies. Therefore, this paper discusses an electricity energy audit and predicts the electricity load at the PT. Telkom Indonesia Building in Lhokseumawe using Artificial Neural Network (ANN) algorithms. Energy audit involves the inspection, survey, and analysis of energy flows to identify energy-saving opportunities in buildings, aiming to reduce the input energy into the system without compromising system output. The research aims to identify electricity energy-saving opportunities. Additionally, the paper conducts predictions of electricity usage before and after the audit using the Artificial Neural Network (ANN) algorithm. Therefore, an audit of this load is needed. After inspecting the location, it was identified that the air conditioning units used exceed the required AC capacity. Consequently, a proposal for new devices is necessary to achieve potential electricity usage savings in the building. Based on the training and validation of the neural network using the Bilayered Neural Network (BNN) model with 3 layers, the most suitable model was obtained. The obtained values include an RMSE of 1210.7, R-Squared of 1.00, MSE of 1.4658e+06, MAE of 901.19, Prediction Speed ~1500obs/Sec, and Training Time of 4.8719 Sec. The results indicate potential savings of up to 17,023 kWh/month or 163,327 kWh/year. The required Payback Period to recover the invested capital is estimated at 14 months.

Keywords: Energy Audit; Energy Saving Opportunities; Regression Model; Artificial Neural Network

Introduction

The current electricity crisis in Indonesia must be a concern for many parties, as the demand for electricity continues to grow over time (Wijayanto & Sunitiyoso, 2019). It is feared that in the coming years, the demand for electricity will not be proportional to the electricity generated by existing power plants in Indonesia. Additionally, many remote villages still do not have access to electricity from the government, even though these villages have abundant energy sources that could be utilized by the government for local consumption. The excess electricity could also be distributed elsewhere, helping to alleviate the burden on existing power plants. Therefore, extensive research is needed by relevant parties to anticipate potential electricity shortages in the future, both from electricity service providers and consumers (PP, 2005), (of Sciences et al., 2017).

To address future electricity shortages, providers need to conduct research on the potential of renewable energy sources and assess the energy needs for the coming years (Siregar & others, 2019). This includes determining the most suitable type of power plant to build, ensuring a mutually beneficial relationship between companies like PT. PLN as providers and the government or the public as consumers (Hasibuan et al., 2022). On the consumer side, active participation is crucial in reducing electricity demand (Handbook, 2017). This involves researching ways to conserve energy consumption, both at home and in offices (Sivanandam et al., 2006), (Zhang et al., 2018). For example, replacing existing electrical appliances with energy-efficient ones can significantly reduce electricity consumption (PP, 2006).

This research focuses on conducting an electric energy audit in the PT. Telkom Indonesia Regional Office building in Lhokseumawe. The research aims to optimize electricity usage, reduce energy costs, and predict the building's load after implementing audit measures (Krarti, 2020), (Capehart et al., 2020). The optimization and reduction of electricity usage in the PT. Telkom Indonesia Regional Office building in Lhokseumawe will involve conserving and evaluating the largest energy consumers in the building. The prediction of the building's load before and after the audit will be carried out using the Artificial Neural Network (ANN) algorithm, incorporating necessary input data, with the assistance of MATLAB R2022a software (Heaton, 2015), (Fausett, 2006), (Tan et al., 2020).

Methods

A. Research Location

This research will be conducted at the PT. Telkom Indonesia Regional Office building in Lhokseumawe, consisting of three floors with a total building area of 2,032.09m2. Based on the standard calculation of Electric Energy Consumption Intensity, the value obtained is 401 kWh/m2/year. The IKE value for PT. Telkom Indonesia Regional Office in Lhokseumawe is considered very high, indicating significant energy consumption.

B. Data Collection

In this stage, data collection will encompass electricity bills, datasets of electronic devices, datasets of major PT. Telkom equipment, building layout plans, and other necessary data over a period of 70 months (March 2018 – December 2023). The data from 60 months (March 2018 – February 2023) will be utilized as input training data, while the data from the remaining 10 months (March 2023 – December 2023) will serve as testing data for evaluating the trained model's performance.

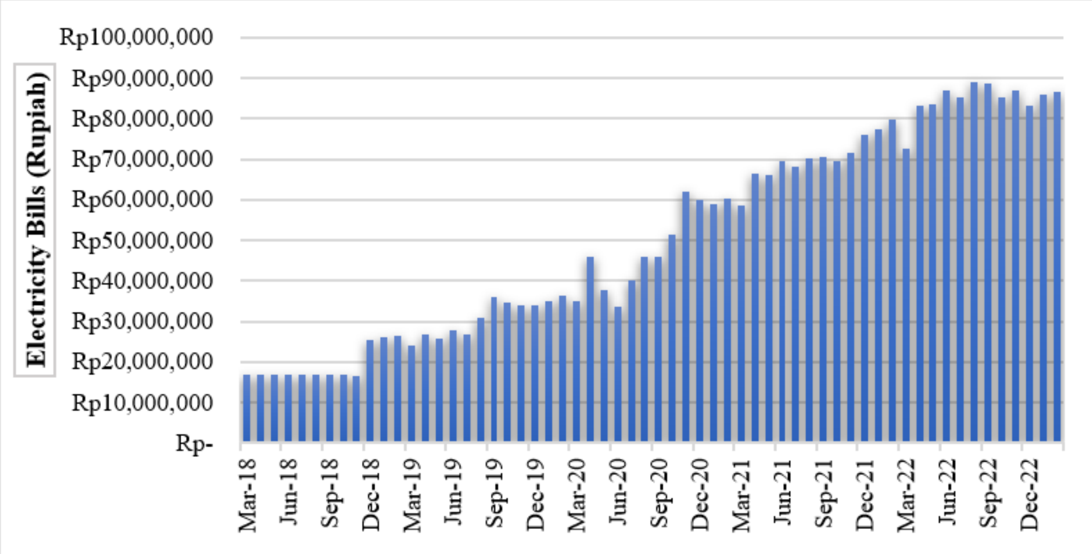

Figure 1. Electricity Bills Over 5 Years (March 2018 – February 2023)

On the above figure, it can be observed that the electricity bills are continuously increasing over time. From the data above, it can be concluded that an energy audit at the PT. Telkom Indonesia Building in Lhokseumawe is highly necessary to derive benefits from the obtained audit results.

C. Site Inspection

During this phase, a direct inspection is conducted at the research site, encompassing factors that influence electricity consumption such as potential energy wastage, air leaks, and any issues with heating or cooling systems (Olajire, 2020). Subsequently, determining and ensuring the steps to be taken to enhance energy efficiency and analyzing the results of the site inspection are carried out. Following the site inspection and the collection of electricity load data at the Telkom Building in Lhokseumawe, the electricity load profile data is obtained, as shown in the table 1 below.

Table 1. Electronic Device Data in Buildings

No	Device Name	Power (W)	Percentage
1	Air Conditioner (AC)	102740	61.08%
2	Main Telkom Device	49025	29.15%
3	Computer	3200	1.90%
4	Lights	2957	1.76%
5	Dispenser	2750	1.63%
6	Printer	1800	1.07%
7	Refrigerator (Fridge)	1400	0.83%
8	TV	1050	0.62%
9	Laptop	780	0.46%
10	Mobile Phone (HP)	625	0.37%
11	Wifi Adapter	500	0.30%
12	CCTV	500	0.30%
13	Smoke Detector	396	0.24%
14	Landline Phone	275	0.16%
15	Exhaust Fan	200	0.12%

In Table 1 above the devices used in the PT. Telkom Indonesia building. It is evident that the air conditioner (AC) has the highest percentage of electricity consumption in the building, reaching 61.08%. Therefore, it is crucial to conduct an audit on this device with the expectation of reducing the electricity load in the building. As for the main Telkom device (29.15%), no audit is conducted to maintain the stability and uninterrupted output quality of the system. Other devices also do not undergo an audit because their electricity load is relatively small, ranging from 1.90% to 0.12% of the total load.

D. Determining Recommendations

In this stage, the recommended audit action is the evaluation of the air conditioning system. As explained in the previous stages, an audit of the air conditioning system (AC) is necessary because it constitutes the largest load in the PT. Telkom Indonesia Building in Lhokseumawe, and it is expected to yield energy-saving opportunities for the building. The evaluation of the air conditioning system is carried out by calculating the air conditioning needs for the rooms in the Telkom Building (Nugraha et al., 2020). The calculation of the air conditioning needs for a room is determined using the formula:

$$Q = (P \; x \; L \; x \; T \; x \; I \; x \; E) \;/\; 60 \tag{1}$$

Where:

- Q is the heat load in British Thermal Units per hour (BTU/hr).
- P is the length of the room in feet.
- L is the width of the room in feet.
- T is the height of the room in feet.
- I is For insulated rooms (enclosed by other rooms or located on lower floors), the value is 10, while for uninsulated rooms (rooms on upper floors), the value is 18.
- E is values based on the direction of the longest wall. Facing north is valued at 16, facing east is valued at 17, facing south is valued at 18, and facing west is valued at 20.

E. Selection of ANN Regression Model

In the MATLAB 2022a application (Syahputra et al., 2018), there are several options for models or types of networks that can be used, namely Narrow Neural Network (NNN), Wide Neural Network (WNN), Medium Neural Network (MNN), Bilayered Neural Network (BNN), and Trilayered Neural Network (TNN) (Westfall, 2020). Below, you can see the default settings for testing the ANN Regression model in MATLAB R2022a (Nugraha, 2019).

Table 2. Default Settings for Model Testing

Type Network	*Number Layers*	*Neuron*	*Activation*	*Iteration Limit*	*Standarize Data*
NNN	1	10	ReLU	1000	Yes
MNN	1	25	ReLU	1000	Yes
WNN	1	100	ReLU	1000	Yes
BNN	2	20	ReLU	1000	Yes
TNN	3	30	ReLU	1000	Yes

F. Training and Testing Neural Network

At this stage, training is conducted on the neural network selected in the previous phase. Training is performed using the Bilayered Neural Network (BNN) model. In the training of this model, testing is carried out using 1 Layer, 2 Layers, and 3 Layers to achieve more optimal results (Hasibuan & others, 2011). The table below shows the testing settings for the BNN model.

Table 3. BNN Model Testing Configuration

Type Network	*Number Layers*	*Neuron*	*Activation*	*Iteration Limit*
BNN 1 Layers	1	10	ReLU	1000
BNN 2 Layers	2	20	ReLU	1000
BNN 3 Layers	3	30	ReLU	1000

G. Electrical Load Prediction

At this stage, the prediction of electrical load for PT. Telkom Indonesia Area Lhokseumawe is conducted based on the predetermined audit actions from the previous phase. Prediction is performed by inputting the data into the trained and validated ANN model from the earlier stages (Hasibuan et al., 2021). The electrical load prediction utilizes data before and after the recommended audit actions have been implemented.

H. Data Analysis

In this phase, an analysis is carried out on the five trained ANN Regression models, and an evaluation is performed on the obtained results to select the best regression model for this research. Additionally, a calculation of the payback period for the investment cost incurred in the recommended actions from the previous phase is conducted using the formula:

$$Payback\ Periode = \frac{Investment\ Cost}{Savings} \quad (2)$$

Where:

- Investment Cost: Total cost incurred for the recommended actions.
- Savings: The financial savings or benefits achieved as a result of the implemented actions.

The data analysis will lead to conclusions drawn from the research. These conclusions may include insights into the performance and effectiveness of the different ANN Regression models, the success of the audit recommendations in predicting and managing electrical load, and the feasibility of the investment in terms of the calculated payback period. The conclusions will provide a comprehensive understanding of the outcomes of the research and may guide future actions or improvements in the context of electrical load prediction and management for PT. Telkom Indonesia Lhokseumawe Area.

Results and Discussion

A. Results of Site Inspection

After conducting on-site observations to identify potential energy-saving opportunities, the electrical load distribution in the building is as follows: Air Conditioning (AC) System constitutes 61%, Main Telkom Devices (Rectifier) 29%, Computers & Lights 4%, Dispenser & Refrigerator 2%, Printers & TV 2%, and Other Electronic Devices 2%. Based on it can be concluded that an evaluation is needed for the air conditioning (AC) system as it represents the largest electricity load in the building. No evaluation is conducted for the main Telkom devices to ensure the uninterrupted operation of the Telkom main system.

Table 4 below provides the calculation of the AC requirements for each room in the PT. Telkom Indonesia Area Lhokseumawe building. The server room is not included in the calculation because the temperature in the server room differs from that in regular rooms. Adhering to standard room specifications for the server room could impact the temperature of Telkom devices, potentially disrupting the Telkom system's output. The server room is equipped with 8 units AC Standard 2 HP, 3 units AC 5 HP, and 2 units AC 20 HP.

Table 4. Calculation of AC Requirements (BTU/h)

Name Room	P (ft)	L (ft)	T (ft)	I (ft)	E (ft)	BTU/h Requirements	BTU/h Existing	Description
Meeting Room	18.70	23.29	11.48	10	17	14161.87	36000	Overload
Warehouse Meeting Room	18.70	16.40	11.48	10	16	9386.49	18000	Overload
CME Staff Room	17.71	17.06	11.48	10	17	9826.17	18000	Overload
Kandatel Meeting Room	8.20	17.71	11.48	10	17	4724.12	9000	Overload
Prayer Room (Mushala)	16.40	21.32	11.48	10	20	13379.86	9000	Less
Kandatel Room	13.12	17.71	11.48	10	17	7558.59	18000	Overload
Customer Asman Room	13.12	16.40	11.48	10	20	8233.76	18000	Overload
Guest Room	9.84	16.40	11.48	10	20	6175.32	9000	Overload
Service Room	26.24	22.96	11.48	10	17	19596.35	36000	Overload
Plasa Supervisor Room	13.12	11.48	11.48	10	17	4899.09	9000	Overload
CSR Room	13.12	11.48	11.48	10	17	4899.09	9000	Overload
GSD Room	16.40	18.04	11.48	10	17	9623.21	18000	Overload

Based on the data in Table 4 above, it can be observed that all non-server rooms in the building do not meet the standard AC (BTU/h) requirements. The recommended audit based on the obtained data is to propose more energy-efficient AC devices. In Tables 5 below, a comparison of power between the old Standard AC devices and the proposed Inverter AC devices is presented. By utilizing inverter technology, inverter ACs can adjust the compressor speed according to the needs, avoiding energy-consuming on-off cycles, and providing more consistent temperature maintenance. Thus, inverter AC become more energy-efficient and efficient in the long term compared to non-inverter AC. Despite the higher initial cost of inverter AC, the energy savings they produce make them a more economical and sustainable choice over a longer period. The table below presents the recommendations based on the calculation and evaluation of AC requirements (BTU/h) in the previous Table 4.

Table 5. Device AC Existing

Merk	AC Existing		
	Total Unit	Power Per Unit (W)	Total Power (W)
AC Standard 1 HP	5	900	4500
AC Standard 2 HP	17	1920	32640
Total Power	22	2820	37140

Table 6. Device AC Proposed

Merk	AC Proposed		
	Total Unit	Power Per Unit (W)	Total Power (W)
AC Inverter ½ HP	3	310	930
AC Inverter ¾ HP	1	510	510
AC Inverter 1 HP	2	500	1000
AC Inverter 1½ HP	3	900	2700
AC Inverter 2 HP	10	1240	12400
AC Inverter 2½ HP	1	1520	1520
Total	20	4980	19060

From Tables 5 and Tabel 6 it can be observed that by proposing the replacement of existing AC units with more energy-efficient Inverter AC units, a power saving of 48.68% is achieved for the replacement of 1 HP and 2 HP AC units. For existing 5 HP AC (3 units) and 20 HP AC (2 units), no replacement is recommended as there are no available Inverter AC units for these capacities. The audit recommendations suggest using the data from the new AC proposals to predict the electrical load in the building for the coming years. The calculation will determine how long the invested capital will be recovered with the obtained savings.

B. Neural Network Training

The neural network training is conducted using MATLAB R2022a software. For neural network training, input data and desired output data (target) are required. The training input data include monthly data on the number of days, number of employees, and all electronic devices in the PT. Telkom Indonesia Area Lhokseumawe building from March 2018 to February 2023 (5 years). This data is chosen as input because it is closely related to the desired output data (monthly kWh). Validation training data span from March 2023 to December 2023 (10 months). In this study, the desired output target is the monthly kWh data after the energy audit recommendations for the PT. Telkom Area Lhokseumawe building, spanning from January 2024 to December 2024 (12 months). Neural Network training is repeated in the MATLAB R2022a software until obtaining good training and validation results, making the trained neural network ready for predicting the desired data.

C. Training and Validation Results

Based on observations after training and validation on the training data, it is found that the Bilayered Neural Network (BNN) model is the best fit for the dataset. The BNN model exhibits the smallest Root Mean Square Error (RSME), a common metric used in statistics and machine learning to measure how well a model predicts data with observational datasets. Therefore, it can be concluded that the training results from the BNN model are the best.

Table 7. Comparison of Validation Results

Type Network	**RSME**	**R-Squared**	**MSE**	**MAE**	**Training Time (s)**
BNN	**1237.5**	**1**	**1.53E+06**	**938.37**	**10.17**
NNN	1583.8	0.99	2.51E+06	1221.3	8.49
TNN	1609.6	0.99	2.59E+06	1014.3	8.72
MNN	2209	0.99	4.88E+06	1353.4	7.54
WNN	2235.5	0.99	5.00E+06	1459.1	10.87

From Table 7 above, it can be seen that the best regression model for the given dataset is the Bilayered Neural Network (BNN) regression model, obtaining results for Root Mean Square Error (RMSE), R-Squared, Mean Squared Error (MSE), and Mean Absolute Error (MAE). RMSE is a common metric used in statistics and machine learning to measure how well a model predicts data with observed dataset observations. R-Squared values range from 0 to 1, where a value of 1 indicates that the model fully explains the variability in the data, while a value of 0 indicates that the model provides no explanation at all. MSE measures the average of the squared differences between predicted and observed values, giving more weight to large differences as they are squared. MAE measures the average of the absolute differences between predicted and observed values. Based on the validation results comparison, the Bilayered Neural Network (BNN) model is chosen for training the neural network and subsequently used as a model to predict electricity consumption before and after energy audit actions in the PT. Telkom Indonesia Building in the Lhokseumawe. On the other hand, the Wide Neural Network

(WNN) model shows the least favorable results. The comparison of validation results leads to the selection of the Bilayered Neural Network (BNN) model for neural network training.

The training is conducted with different layer configurations: BNN 1 Layer, BNN 2 Layers, and BNN 3 Layers. The activation function used in each training session is "ReLU." ReLU is chosen for its ability to address the vanishing gradient problem that can occur in sigmoid or hyperbolic tangent functions in deeper neural networks. Additionally, ReLU tends to provide faster convergence during training due to its simplicity and computational efficiency. The iteration limit is set to "1000" to prevent unlimited execution or optimize the process to stop after reaching a specific number of iterations. Data Standardization is set to "Yes" to ensure that all variables have a similar scale, preventing any variable from dominating its influence solely based on a larger scale value.

a) Bilayered Neural Network (BNN) 1 Layer

In the training of BNN 1 Layer, the settings used were as follows: Input Layer: 33x60 data, 1 Fully Connected Layer: 10 neurons, Output Layer: Monthly kWh, Activation Function: ReLU, Iteration Limit: 1000, Data Standardization: Yes.

Table 8. Summary Training of BNN 1 Layers

Training Results	
RSME (Validation)	1511.3
R-Squared (Validation)	0.99
MSE (Validation)	2.2841e+06
MAE (Validation)	1040.7
Prediction Speed	~970obs/sec
Training Time	7.2695 sec

In the above table 8, a summary of the training based on the validation is provided. The best RMSE obtained is 1511.3, R-Squared is 0.99 (approaching perfection), MSE is 2.2841e+06, MAE is 1040.7, Prediction Speed ~970obs/Sec, Training Time is 7.2695 Sec.

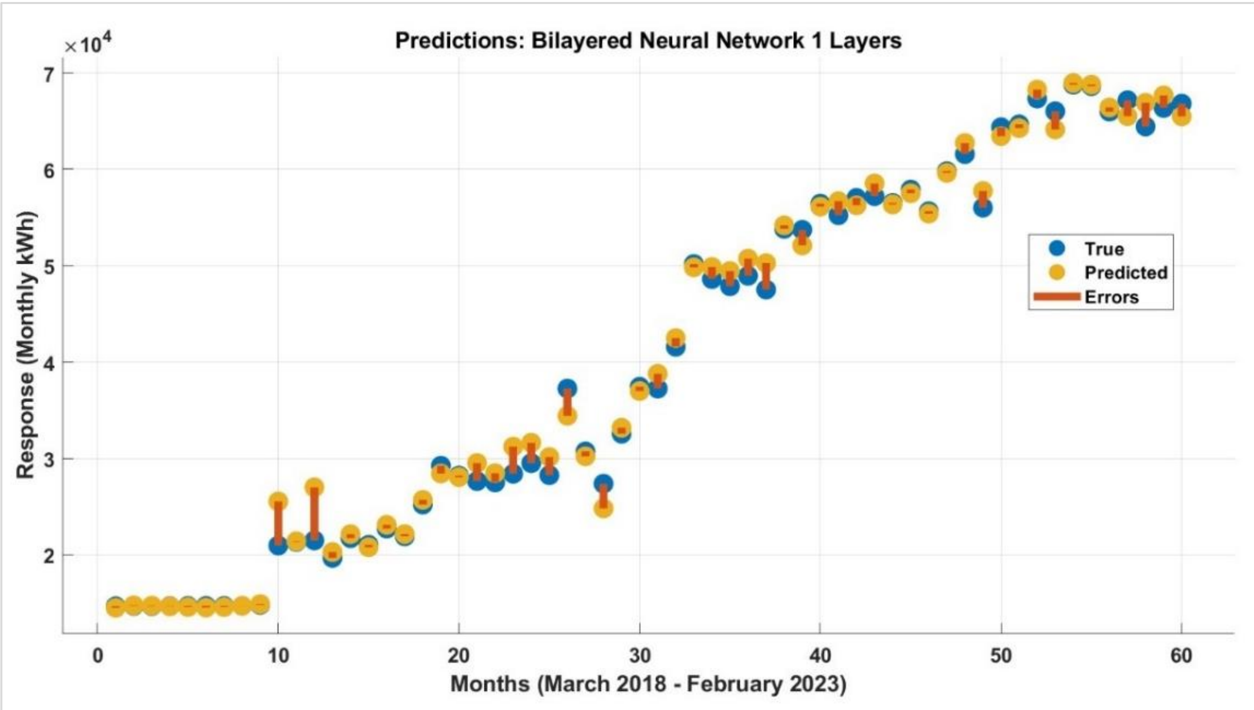

Figure 2. Actual Data vs. Prediction BNN 1 Layers

In the above figure 2, the graph of actual data and predictions, along with the differences (errors) between actual and predicted data, is presented. Blue dots represent actual data, yellow dots represent predicted data, and the red line indicates the difference between actual and predicted data. Based on the image, it can be observed that the predicted data can follow the pattern of the actual data, but there are still significant differences at some points.

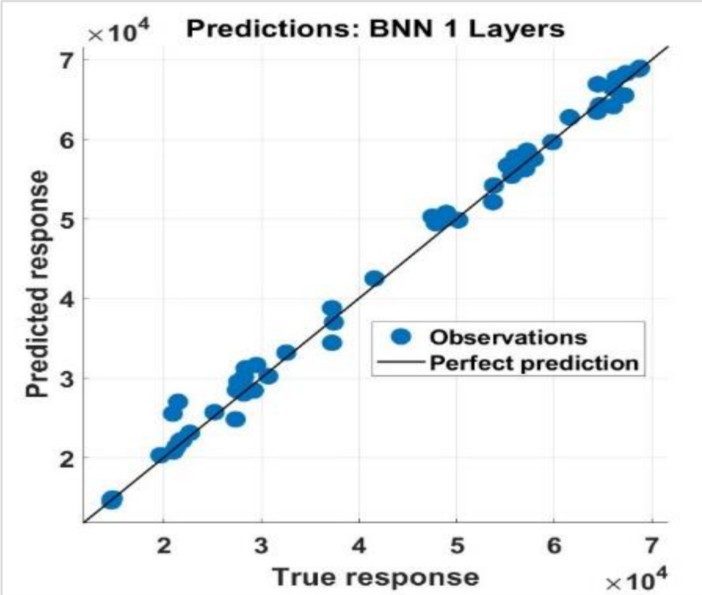

Figure 3. Plot of Actual Data and Prediction BNN 1 Layers

In figure 3 above, the relationship between predicted data (blue dots) and actual data (black line) is shown. The figure indicates that the predictions are close to the actual data, but some data points still appear far from the actual data.

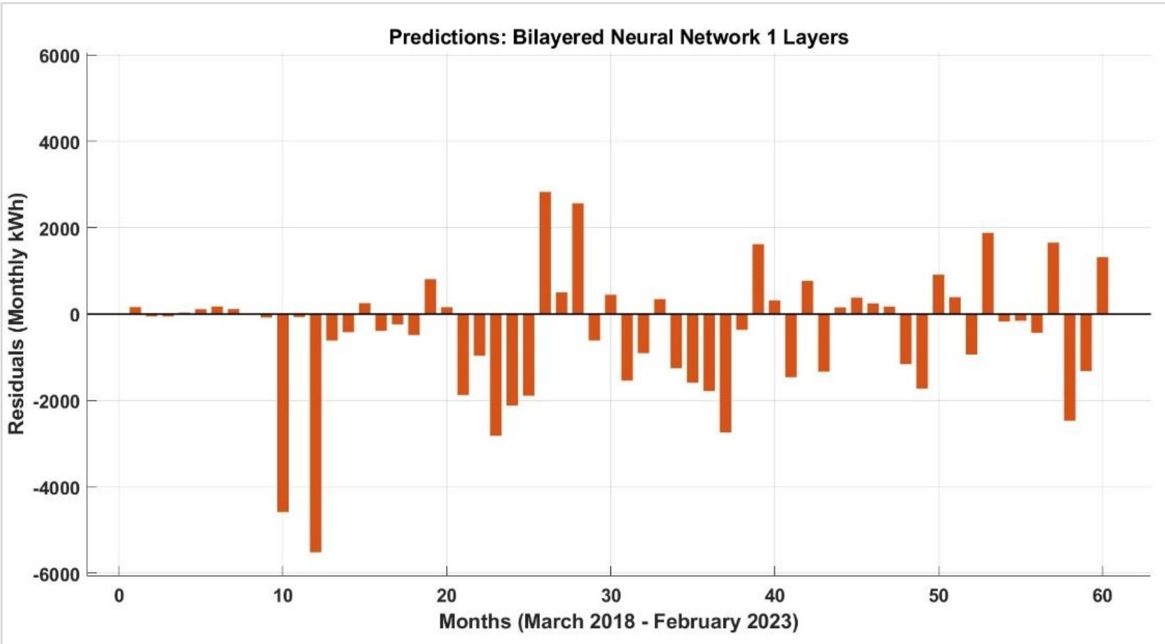

Figure 4. Residual between Actual Data and Prediction 1 Layers

In figure 4 above, the residual between actual data and predictions is shown, with the largest reaching -5516.28 and 2826.58. The average difference is 1151.3 (RSME).

b) Bilayered Neural Network (BNN) 2 Layers

For BNN 2 Layers training, the settings include 33 input layers (33x60 data), 2 fully connected layers (10 neurons each layer), an output layer (Monthly kWh), ReLU activation function, Iteration Limit = 1000, Standardization of Data = Yes. The results obtained from these settings are summarized in the table 9.

Table 9. Summary Training of BNN 2 Layers

Training Results	
RSME (Validation)	1237.5
R-Squared (Validation)	1.00
MSE (Validation)	1.5314e+06
MAE (Validation)	938.37
Prediction Speed	~610obs/sec
Training Time	10.172 sec

In table 9 above, a summary of the training based on validation is provided. The RMSE is 1237.5, R-Squared is 1.00 (perfect value), MSE is 1.5314e+06, MAE is 938.37, Prediction Speed is ~610obs/Sec, and Training Time is 10.172 Sec. The training results obtained for BNN 2 Layers are better than those for BNN 1 Layers.

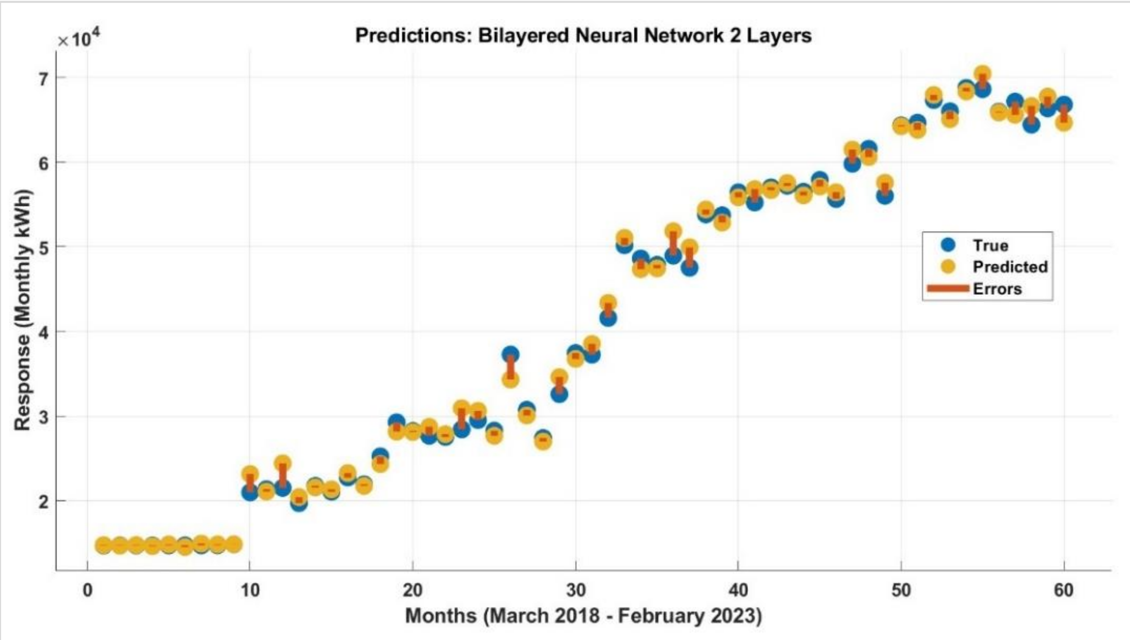

Figure 5. Actual Data vs. Prediction BNN 2 Layers

In the above figure 5, the plot between actual data and predicted data, along with the differences between actual and predicted data, is presented. The color blue represents actual data, yellow represents predicted data, and the red line represents the difference between actual and predicted data. Based on the image, the difference between the predicted data and the actual data is not too large, unlike the training of BNN 1 Layers.

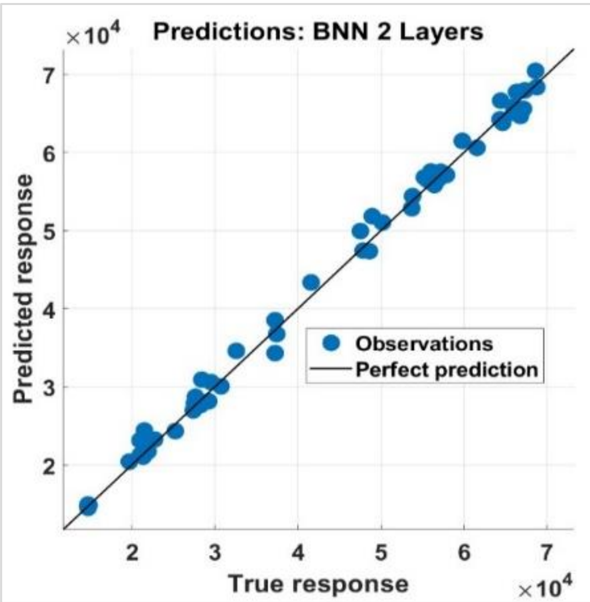

Figure 6. Plot of Actual Data and Prediction BNN 2 Layers

In the above figure 6, the relationship between predicted data (blue dots) and actual data (black line) is shown. The figure indicates that the predictions are close to the actual data, and the distance is closer compared to the training of BNN 1 Layers.

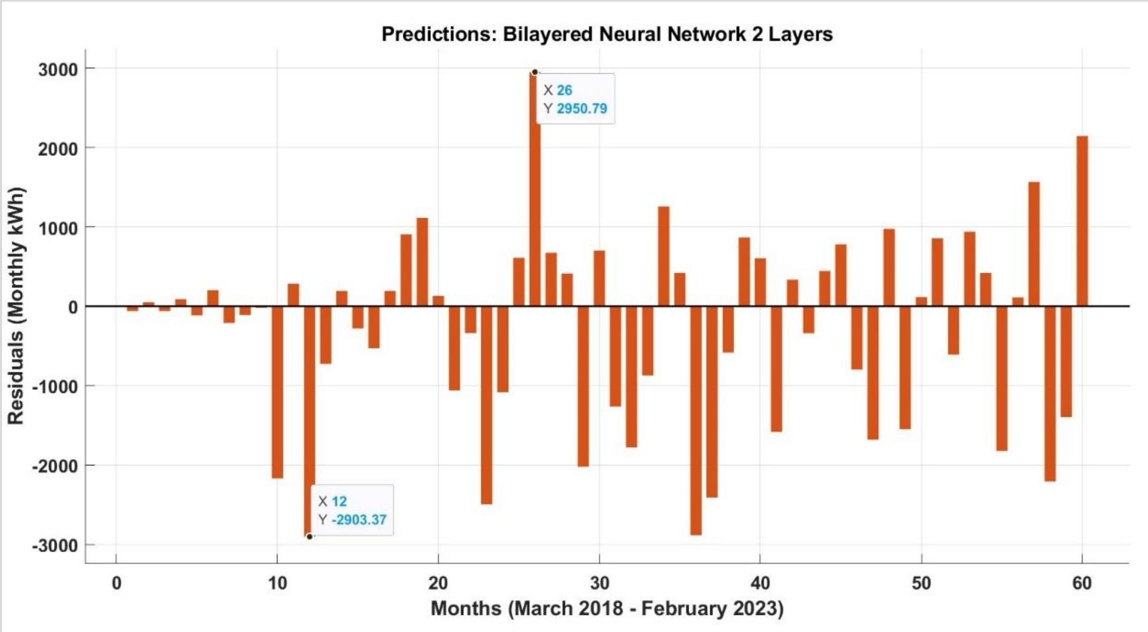

Figure 7. Residual between Actual Data and Prediction BNN 2 Layers

In the above figure 7, the residual between actual data and predictions is shown, with the largest reaching -2903.37 and 2950.79. The average difference is 1237.5 (RSME). Based on the generated residuals, it can be observed that the distance of the residual data is not too far, as seen in the residuals of the BNN 1 Layers training.

c) Bilayered Neural Network (BNN) 3 Layers

For BNN 3 Layers training, the settings include 33 input layers (33x60 data), 3 fully connected layers (10 neurons each layer), an output layer (Monthly kWh), ReLU activation function, Iteration Limit = 1000, Standardization of Data = Yes. The results obtained from these settings are summarized in table 9.

Table 10. Summary Training of BNN 3 Layers

Training Results	
RSME (Validation)	1210.7
R-Squared (Validation)	1.00
MSE (Validation)	1.4658e+06
MAE (Validation)	901.19
Prediction Speed	~1500obs/sec
Training Time	4.8719 sec

In table 10 above, a summary of the training based on validation is provided. The RMSE is 1210.7, R-Squared is 1.00 (perfect value), MSE is 1.4658e+06, MAE is 901.19, Prediction Speed is ~1500obs/Sec, and Training Time is 4.8719 Sec. The training results obtained for BNN 3 Layers are significantly better than those for BNN 1 Layers and slightly better than BNN 2 Layers.

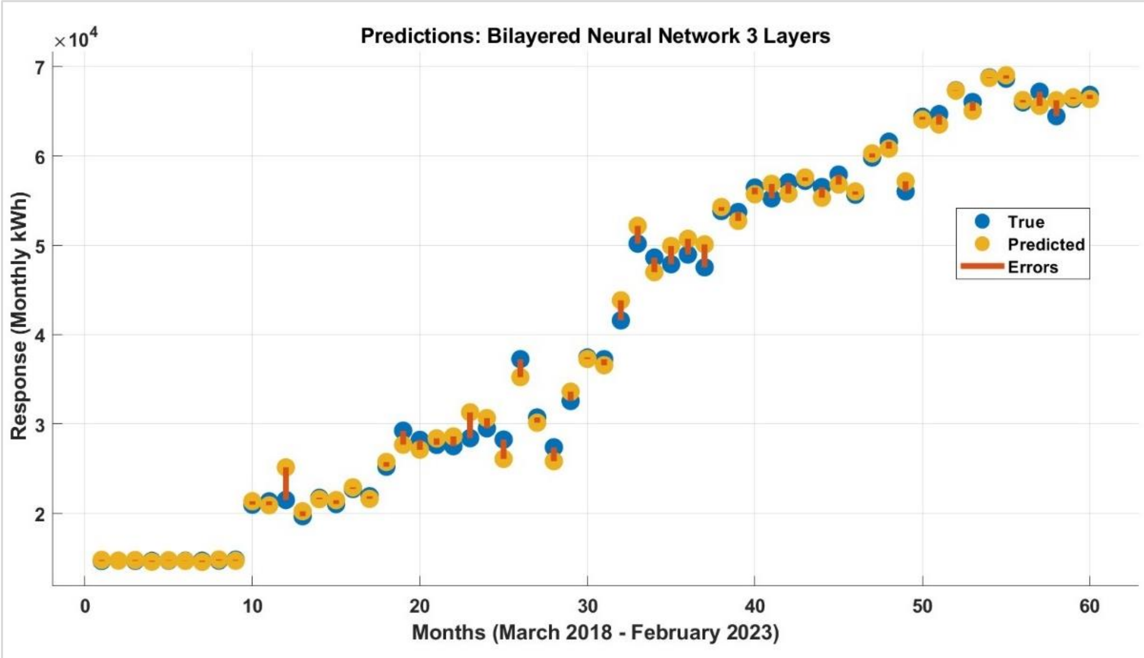

Figure 8. Actual Data vs. Prediction BNN 3 Layers

In the above figure 8, the plot between actual data and predicted data, along with the differences between actual and predicted data, is presented. The color blue represents actual data, yellow represents predicted data, and the red line represents the difference between actual and predicted data. Based on the image, the difference between the predicted data and the actual data is not too large, similar to the training of BNN 2 Layers.

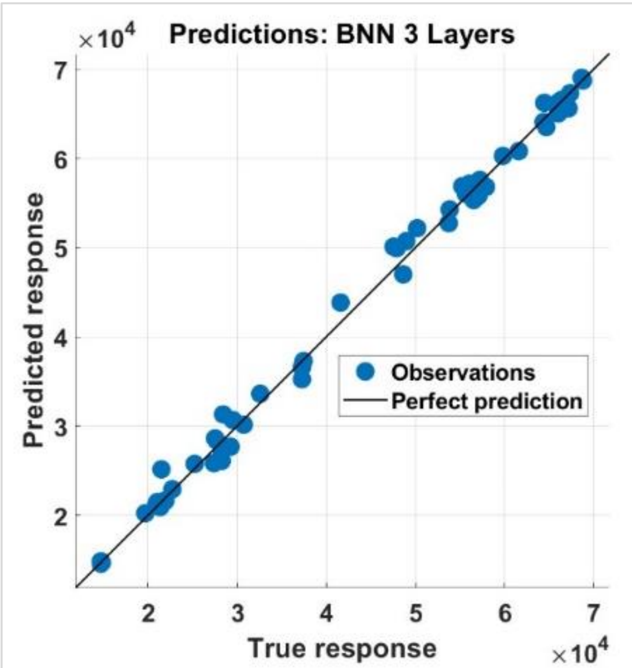

Figure 9. Plot of Actual Data and BNN 3 Layers Prediction

In figure 9 above, the relationship between predicted data (blue dots) and actual data (black line) is shown. The figure indicates that the predictions are close to the actual data and the distance is closer compared to the training of BNN 1 Layers and slightly better than the training of BNN 2 Layers.

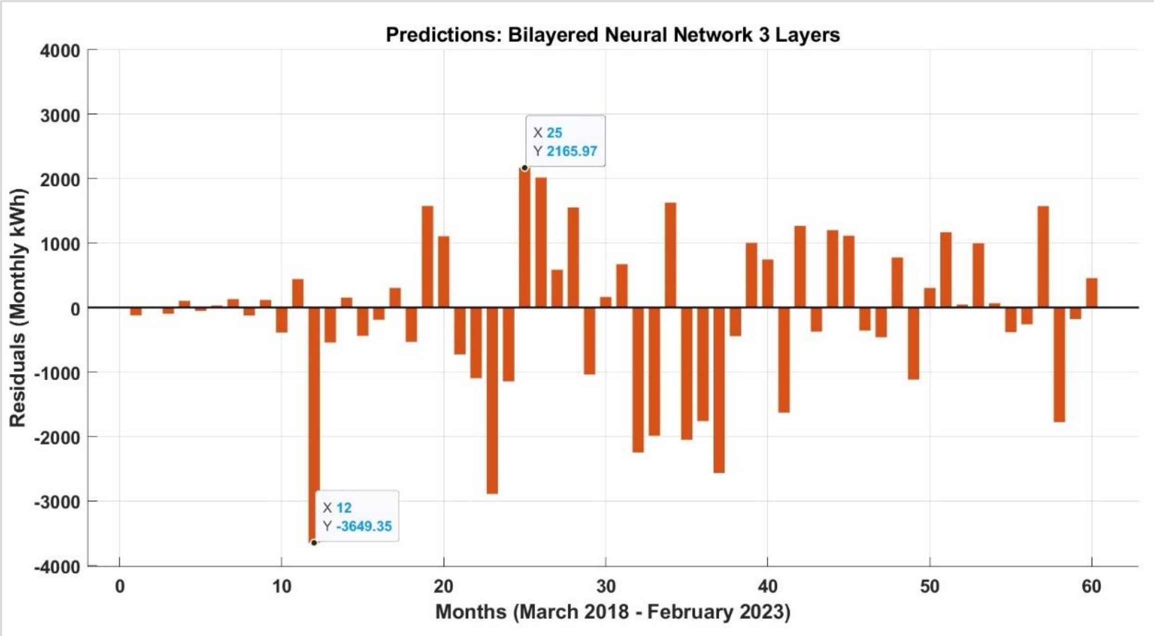

Figure 10. Residual between Actual Data and BNN 3 Layers Prediction

In figure 10 above, the residual between actual data and predictions is shown, with the largest reaching -3649.35 and 2165.97. The average difference is 1210.7 (RSME). Based on the residuals generated, it can be observed that the distance of the residual data is not too far, as seen in the residuals of the BNN 1 Layers training, and slightly better than BNN 2 Layers.

D. Selection of ANN Regression Model

Based on the previous training, the next step is to examine the training summary results of BNN 1 Layer, BNN 2 Layers, and BNN 3 Layers to be used as predictive models for data before and after the audit. As a general rule, the smaller the values of RMSE, MSE, and MAE produced, the better the model is at predicting data. An R-Squared value of 1 indicates that the regression model is capable of perfectly explaining all the variations in the data.

Table 11. Summary of BNN Model Training Results

Type Network	RSME	R-Squared	MSE	MAE	*Training Time* (s)
BNN 1 *Layers*	1511.3	0.99	2.28E+06	1040.7	7.2695
BNN 2 *Layers*	1237.5	1	1.53E+06	938.37	10.172
BNN 3 *Layers*	**1210.7**	**1**	**1.47E+06**	**901.19**	**4.819**

In Table 11 above, it can be observed that the testing of the BNN 3 Layers model yielded the best results, significantly better than the training of BNN 1 Layer and slightly superior to the training of BNN 2 Layers. Therefore, the BNN model with 3 Layers is chosen to predict monthly kWh data before and after the audit for the year 2024.

E. Results of Testing the BNN 3 Layers Neural Network Model

After the training and selection of the ANN regression model, the BNN 3 Layers model is the one that will be used to make predictions. Subsequently, testing is carried out by comparing the actual data with the predicted data from the selected BNN model, using the Export Model BNN 3 Layers command trained Model BNN. Predict Fcn (Test Data) in the Command Window of the MATLAB R2022a application.

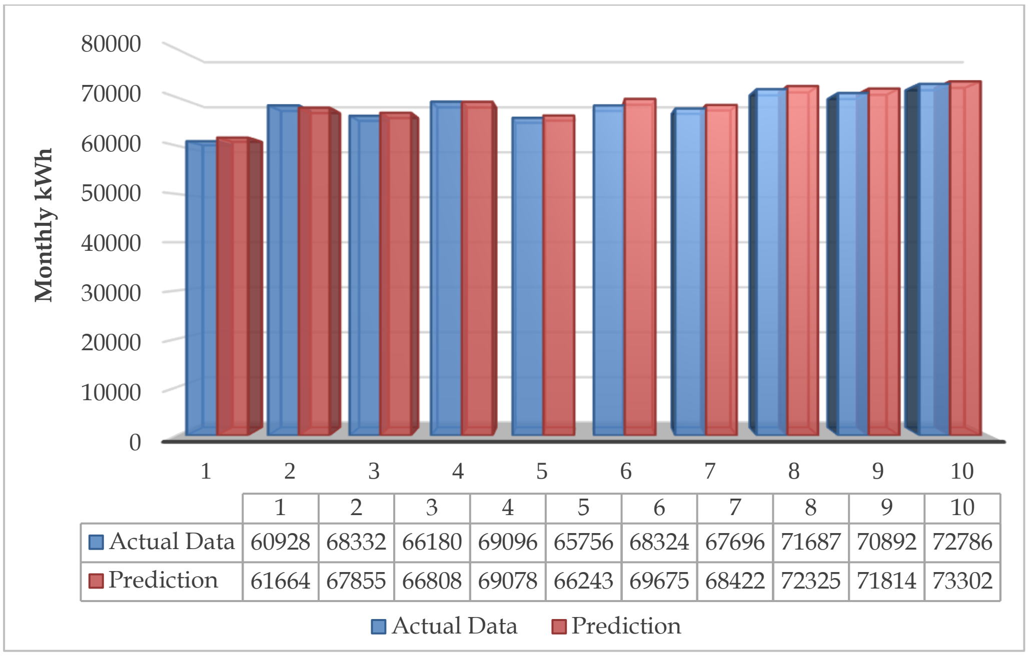

Figure 11. Comparison between Actual Data and Prediction Results

In Figure 11 above, a comparison between actual data and prediction results for the months (March 2023 - December 2023) can be observed. The figure shows that the prediction results successfully follow the pattern of actual data very well. It can be concluded that the BNN 3 Layers model can predict data very effectively.

F. Results of Electricity Load Prediction Before and After Audit

After testing the BNN 3 Layers model, the next step is to predict the monthly kWh before the energy audit using the existing (AC) devices and predict the monthly kWh after the energy audit using the new (AC) devices. Predictions are made for the months (January 2024 to December 2024), and then the prediction results will be compared to assess the potential savings that can be achieved. Below are the prediction results obtained using the previously exported BNN 3 Layers model.

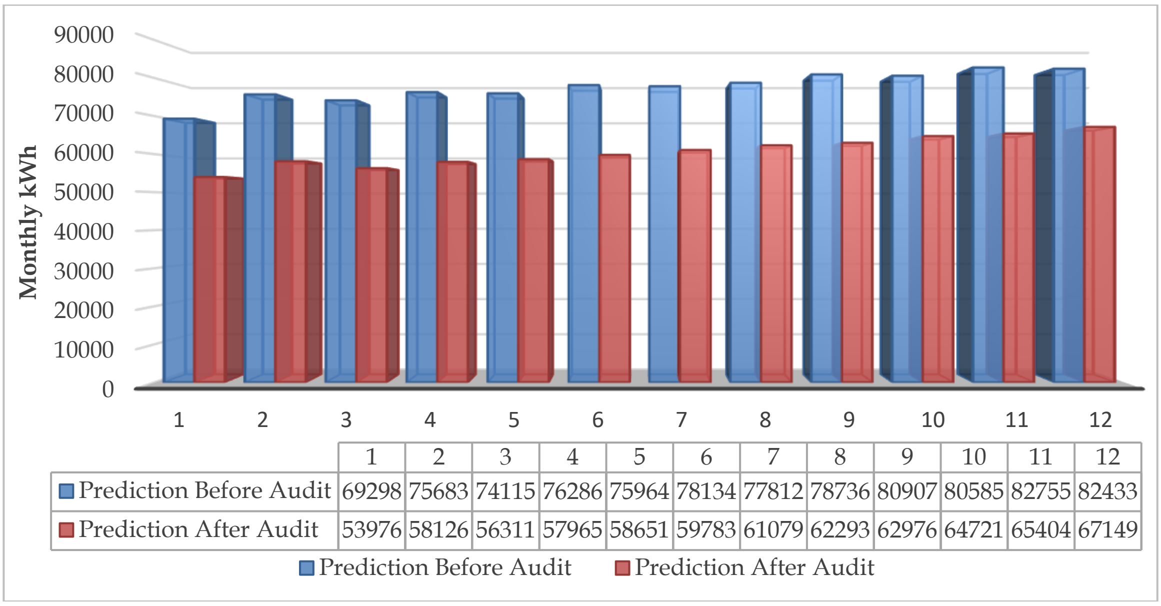

Figure 12. Results of Electricity Load Prediction Before and After Audit

In Figure 12 above, the predicted results of electricity consumption for the months (January 2024 to December 2024) at the PT. Telkom Indonesia Area Lhokseumawe building before and after the energy audit are shown. The average reduction in electricity consumption (kWh/month) before and after the audit is 17,023 kWh/month or 163327 kWh/year. The average electricity bill savings that can be achieved is IDR 19,406,209/month in 2024.

G. Payback Period Calculation

After predicting the results after the audit recommendation, the payback period is calculated for the capital spent on the audit recommendation. Below, the total investment required to implement the proposed device replacement can be seen.

Table 12. Proposed for New Air Conditioning (AC) Devices

Brand	Total Unit	Cost Per Unit	Total Cost
AC Inverter ½PK	3	IDR 6,229,000	IDR 18,687,000
AC Inverter ¾ PK	1	IDR 6,339,000	IDR 6,339,000
AC Inverter 1PK	2	IDR 7,769,000	IDR 15,538,000
AC Inverter 1½PK	3	IDR 13,058,000	IDR 39,174,000
AC Inverter 2PK	10	IDR 15,059,000	IDR 150,590,000
AC Inverter 2½PK	1	IDR 21,559,000	IDR 21,559,000
Total Investment			**IDR 251,887,000**

Table 12 above shows the proposal for new air conditioning (AC) devices with a recommendation for the lowest power usage. The total investment required for the predetermined audit recommendations is IDR 251,887,000, with additional assumed costs bringing the total investment to IDR 260,000,000. The payback period calculation is performed using the formula:

$$Payback\ Periode = \frac{Investment\ Cost}{Savings}$$

$$Payback\ Periode = \frac{IDR\ 260{,}000{,}000}{IDR\ 19{,}406{,}209} = 13{,}40\ Months$$

In the calculation above, the payback period to recover the investment for the replacement of the new air conditioning (AC) devices is approximately 14 months from the first month of installation of the new AC devices.

Conclusions

The air conditioning (AC) load is the highest burden in the PT. Telkom Indonesia Building in Lhokseumawe, reaching 61% of the overall building load. After conducting an audit on the AC devices, it was found that the existing AC units in some rooms of the building exceed the intended capacity. Therefore, there is a need for new AC devices to replace the existing ones with units that are suitable for the specific requirements of each room.

The Bilayered Neural Network (BNN) regression model with 3 Layers is deemed the most suitable for the provided dataset. With the obtained values: RMSE of 1210.7, R-Squared of 1.00, MSE of 1.4658e+06, MAE of 901.19, Prediction Speed ~1500obs/Sec, and Training Time of 4.8719 Sec. Therefore, it can be concluded that this model is the best for predicting electricity load data (monthly kWh) before and after the audit action.

The potential savings in electricity consumption in the PT. Telkom Indonesia Area Lhokseumawe are an average of 17023 kWh/month or 163327 kWh/year. The average electricity bill savings amount to IDR 19,406,209 per month in the year 2024. The Payback Period required to recover the investment made is 14 months.

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