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Analysis of the Best Neural Network Configuration for Predicting Household Customer Kwh Sales in Banda Aceh City

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Abstract

Energy consumption (kWh) is critical to the operation of electrical systems. Predictive modeling optimizes energy usage, increasing power system efficiency. This study created an artificial neural network (ANN) architecture to estimate energy consumption (kWh) for home users in Banda Aceh. The ANN topology consisted of 5 input layers, 5-25 hidden layers, and one output layer. This study used two scenarios: first, the ANN topology was trained using the logsig activation function, and then the tansig activation function was used for training. Based on training simulations, the ANN architecture with 5 input layers, 5 hidden layers, and 1 output layer has the lowest Mean Squared Error (MSE) of 0.00035. The next phase involved testing this ANN topology. The next stage is to analyze the ANN architecture with 5 input layers, 5 hidden layers, and 1 output layer using the testing technique. Based on the testing technique, the ANN architecture with 5 input layers, 5 hidden layers, and 1 output layer had a MAPE value of 3.34%.

Keywords*: Energy consumption prediction, Multilayer feedforward network, MSE, MAPE*

Abstrak

Konsumsi energi (kWh) sangat penting untuk operasi sistem kelistrikan. Pemodelan prediktif mengoptimalkan penggunaan energi, meningkatkan efisiensi sistem tenaga. Studi ini membuat arsitektur jaringan saraf tiruan (ANN) untuk memperkirakan konsumsi energi (kWh) bagi pengguna rumah tangga di Banda Aceh. Topologi ANN terdiri dari 5 lapisan input, 5-25 lapisan tersembunyi, dan satu lapisan output. Studi ini menggunakan dua skenario: pertama, topologi ANN dilatih menggunakan fungsi aktivasi logsig, kemudian fungsi aktivasi tansig digunakan untuk pelatihan. Berdasarkan simulasi pelatihan, arsitektur ANN dengan 5 lapisan input, 5 lapisan tersembunyi, dan 1 lapisan output memiliki Mean Squared Error (MSE) terendah yaitu 0.00035. Tahap selanjutnya melibatkan pengujian topologi ANN ini. Tahap berikutnya adalah menganalisis arsitektur ANN dengan 5 lapisan input, 5 lapisan tersembunyi, dan 1 lapisan output menggunakan teknik pengujian. Berdasarkan teknik pengujian, arsitektur ANN dengan 5 lapisan input, 5 lapisan tersembunyi, dan 1 lapisan output memiliki nilai Mean Absolute Percentage Error (MAPE) sebesar 3,34%.

Kata kunci: Prediksi kWh Rumah Tangga, Jaringan Syaraf Tiruan, MSE, MAPE

Introduction

In the previous two decades, electricity prediction has played a critical role in ensuring reliable and cost-effective power system operations [1]. Electricity projection allows power facilities to plan their production capacity more effectively. Electricity forecast contributes to the continuity of power supply to users [2]. Furthermore, electricity forecast can be used as a key reference when developing power system infrastructure, such as boosting generation capacity, expanding transmission and distribution networks, and deciding utility scheduling methods. To do all of this, the electricity prediction model must be correct [3]. Currently, research is being performed to develop accurate electricity prediction models.

Artificial neural network (ANN) is one way for developing electricity prediction models. In multiple investigations, the ANN technique has been shown to yield very accurate prediction models. Based on that research [4]. The ANN approach was used to generate a short-term load forecasting model. The study's load forecasting model was developed on the basis of variable and rapidly changing power demand [4]. The short-term load forecasting model had the minimum error value of 0.83% and the highest error value of 8.33% [4]. The error numbers obtained by the model show that the ANN approach is capable of producing very accurate models. The artificial neural network (ANN) method has been developed for both short-term and long-term load forecasting or prediction models. The ANN approach to create a long-term electrical load prediction model. Accurate long-term load forecast models lead to focused power system operation planning and measured utility infrastructure construction [5]. Based on this research, the created ANN technique has been shown to produce very accurate long-term load prediction models [5].

Chafak Tarmanini and colleagues [6] compared the artificial neural network (ANN) approach to the autoregressive integrated moving average (ARIMA) method while creating short-term electrical load prediction models. The two approaches have extremely different properties [7]. The ARIMA approach generates short-term power load prediction models by using mathematical formulas to identify correlations between variables in a dataset [8]. This becomes difficult when there are nonlinear factors in the dataset. In contrast, the ANN technique does not rely on a mathematical model to connect the variables. The ANN approach, which uses a neural network topology similar to that of the human brain and nervous system, can comprehend data patterns or information inside a dataset without the requirement for a mathematical model equation [6]. In addition to the models and methodologies used to create prediction models, factors influencing electricity usage must be considered [9]. These factors include meteorological or weather variables, which have a major impact on power use [10].

This study used an artificial neural network (ANN) architecture to build a prediction model for residential kWh sales in Banda Aceh. According to PLN figures, residential consumers in Banda Aceh account for up to 86% of all customers in the city [11]. Five multilayer feedforward network topologies were used to create the residential customer kWh sales prediction model [12]. These five prediction models were trained under two situations. Initially, the five prediction models were trained with the sigmoid activation function [10]. Second, the five prediction models were trained with the Tansig activation function. The Gradient Descent algorithm with adjustable learning rate (TRAINGD-A) served as the training algorithm for these five prediction models [13]. The kWh sales forecast model with the lowest MSE value from the training simulations will be assessed during the model testing phase.

Method

The stages of this study are separated into four parts. First, create or compile the dataset. Second, create the neural network topology. Third, train the neural network architecture to generate a kWh sales prediction model. Fourth, the kWh sales model will be evaluated using the testing technique.

a. Dataset Construction

The dataset is required to construct the artificial neural network topology for a prediction model. The dataset construction used consists of input and target variables [14]. The input variables in the dataset construction used in this study consist of air pressure (kPa), air temperature (°C), wind speed (m/s), the total number of household customers, and installed load (MVA), whereas the goal variable in the dataset construction is the household customer energy usage (kWh). The kWh sales statistics of UP3 PLN Banda Aceh and the Banda Aceh coordinates obtained from NASA POWER provide the data required to build the dataset. The period of data collection for this was January 2012–December 2021. From this data period, 120 pairs of input and target variable data were formed.

After constructing the dataset, the next step is to normalize the data. Data normalization aims to standardize the attributes in the dataset construction. Consistent data attributes will impact the computational process performed by the neural network topology used to build the kWh sales prediction model. Equation (1) is the formulation used in the data normalization stage.

$$X = \frac{\alpha}{\alpha_{maks}} \quad \text{……………………..(1)}$$

Where X represents the normalized data value, α_{maks} is the maximum data value in the dataset construction, and α is the value in the dataset.

a. Topology of Replicated Nerve Tissue

After data normalization is performed, the next step is to form the artificial neural network topology [15]. The neural network topology is the architecture that builds the model, in addition to the dataset construction. A multilayer feedforward network topology is used as the architecture for building the kWh sales prediction model for household customers [16]. Generally, a multilayer feedforward network topology consists of an input layer, hidden layers, and an output layer.

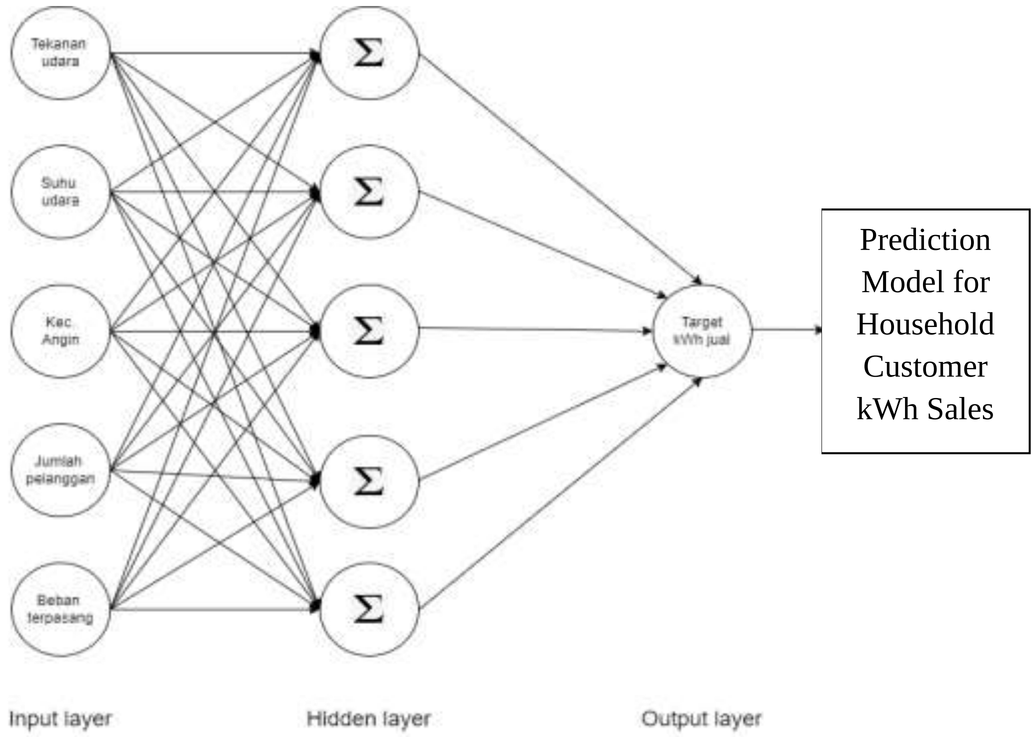

Figure 1. Neural Network Topology for the Household Customer kWh Sales Prediction Model

Figure 1 shows the deep neural network topology developed to build the household kWh sales prediction model. The neural network topology forming the household kWh sales prediction model in this study consists of 5 input layers, hidden layers, and 1 output layer. The five input layers and one output layer are derived from the number of input data variables and target variables in the dataset construction, while the hidden layer topology forming the model consists of 5 to 25 units (5, 10, 15, 20, 25). Based on this description, there are a total of 5 (five) neural network topologies that form the household kWh sales prediction model.

b. Training Simulation of the Prediction Model

After the neural network topology forming the household kWh sales prediction model is established, the next step is to perform model training simulations [17]. There are two scenarios applied in the training procedure for predicting household kWh sales. In the first scenario, the five models predicting household kWh sales are trained using the logsig activation function, while in the second scenario, the models are trained using the tansig activation function [5]. Both scenarios utilize the Gradient Descent with adaptive learning rate (TRAINGD-A) learning algorithm. Figure 2 shows the flow diagram of the simulation for the training stage of the household kWh sales prediction model.

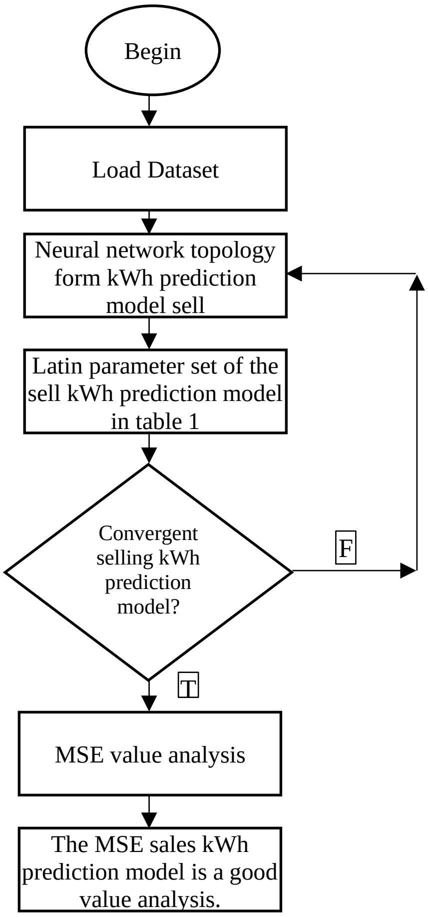

Figure 2. Flow Diagram of the Training Simulation for the kWh Sales Prediction Model

Table 1. Simulation Parameters for Training the Predictive Model

No	Simulation Parameter	Description
1	Network Topology	*5* input layer, 5-25 hidden layer and 1 output layer
2	Maximum epoch	500
3	Minimum goal error	1e-03
4	Learning rate incremental	0,01
5	Activation Function	Logsig, tansig
6	Training Algorithm	Backpropagation with mechanism *traingd-a*

The output of the training simulation for the kWh sales prediction model is the Mean Square Error (MSE) value. The MSE value represents the average squared error between the predicted kWh sales model output and the target data in the dataset. MSE is represented by the equation (2).

$$\boldsymbol{MSE} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \sqrt{\left(\frac{\boldsymbol{targetted\ score - output\ model}}{\boldsymbol{target\ value}}\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

where *n* indicates the number of data pairs in the dataset construction.

c. Prediction model testing

The model testing phase involves the prediction of household electricity sales (kWh) using the model with the minimum MSE value [4]. The purpose of the model testing phase is to find the prediction value through the best kWh sales prediction model. In addition to the kWh sales model, the model testing phase uses a different dataset construction from the model training dataset. The testing dataset construction consists of input variables without a target. Table 2 shows the testing dataset construction used in the model testing phase.

Table 2. Construction of Predictive Model Test Datasets

No	Air Pressure (kPa)	Air Temp. (^{0}C)	Wind Speed (m/s)	Number of Household Customers	Load Installed (MVA)
1	87,82	18,65	0,94	148.921	152
2	87,89	19,33	0,61	152.709	161
3	87,85	19,55	0,70	159,771	168
4	87,86	19,40	0,69	160.350	169
5	87,85	19,17	0,83	181,264	201
6	87,89	19,51	0,83	182,177	202
7	87,87	19,51	0,91	183,196	204
8	87,87	18,69	1,16	190,457	214
9	87,89	18,64	1,22	191,253	216
10	87,87	19,79	0,86	199,858	228
11	87,88	19,80	0,71	201,020	230
12	87,91	19,18	0,98	201,956	231

The MAPE (Mean Absolute Percentage Error) instrument is used to measure the percentage of the average error rate between the predicted output value and the actual value. The actual value is the kWh data value of household sales in 2022. Unlike MSE instruments, MAPE contains an interpretative narration of the MAPe value produced. Describe the interpretation of the MAPE values, including:

1. If the MAPE value is less than 10%, then the built prediction model is very accurate,
2. If the mape value is between 10 % - 20 %, the built forecast model is accurate,
3. If the map value is in the range of 20 % - 50 %, then the formed forecasting model is valid,
4. If the value of the mAPE is in a range of more than 50 %, the builded predictive model has a very poor accuracy level.

In this study, the MAPE value determined should not be more than 10%. The equation (3) is used to find the mape value against the output of the predictive model with its actual value.

$$MAPE = \sum_{i=1}^{n} abs\left(\frac{actual\ value - output\ model}{aktual\ score}\right) x\ 100\% \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Where n is expressed as the number of data pairs on the construction of the test dataset. Figure 1 shows the entire stages of the research represented in the flow diagram.

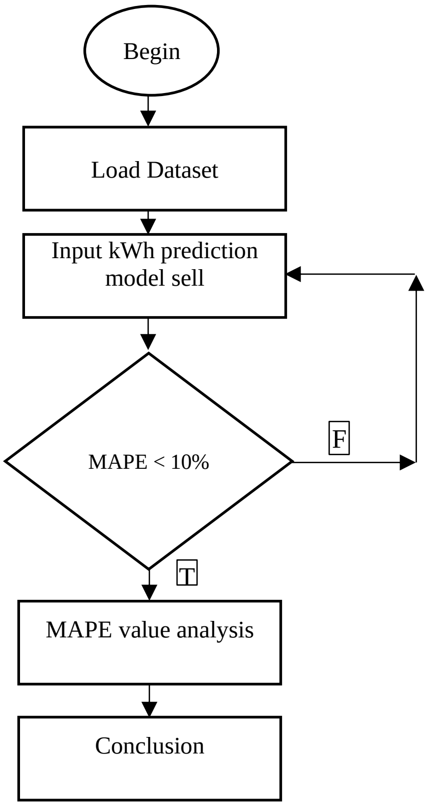

Figure 3. Model Test Flow Diagram

Results and Discussion

In this study, the MATLAB R2015a software was used to train network topology and test the kWh sales prediction model of household customers. There are two scenarios that are applied in training network topology to build a predictive model of kWh sales to household customers. The first scenario, the network topology is trained using the logsig activation function and the second scenario is the net topology trained with the tansig activation functions. Table 3 shows the results of a simulation of network topological training using the Logsig activating function.

Table 3. Results of Simulation Training Topology of Nerve Tissue Using Logsig Activation Function

No	Network Topology	MSE Score	Coefisien R
1	5 input layer – 5 hidden layer – 1 output layer	0,00035	0,954
2	5 input layer – 10 hidden layer – 1 output layer	0,0024	0,949
3	5 input layer – 15 hidden layer – 1 output layer	0,0026	0,944
4	5 input layer – 20 hidden layer – 1 output layer	0,0011	0,954
5	5 input layer – 25 hidden layer – 1 output layer	0,0021	0,950

Based on Table 3, a prediction model with a hidden 5 layer configuration yields a minimum MSE value of 0,00035 compared to other configurations.

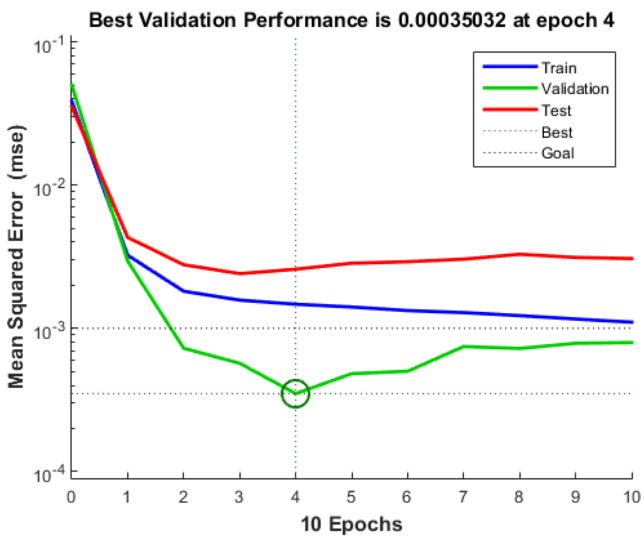

Figure 4. MSE Network Topology Graph 5 Input Layers – 5 Hidden Layers and 1 Output Layer Logsig Activation Function

Figure 2 shows a graph of simulation results of a predictive model with a hidden 5 layer configuration, logsig activation functions and traingd – a. As shown in the graph, the configuration prediction model completed computing with only 10 epochs of a maximum of 500 epoches. Moreover, the predictions model reached its convergence in the 4th epoch with the best MSE value of 0,00035.

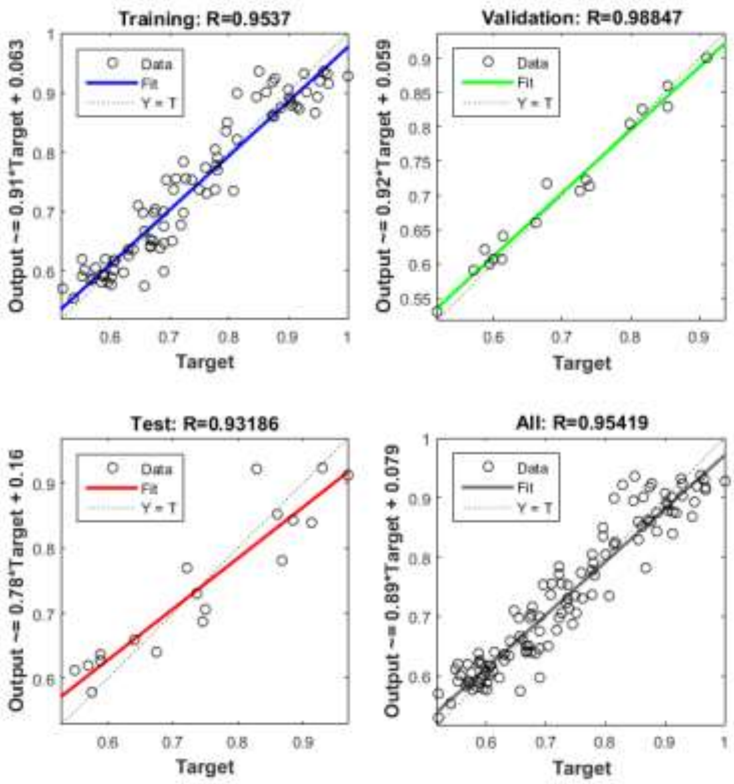

Figure 5. Network Topology Regression Plot Graph 5 Input Layers – 5 Hidden Layers and 1 Output Layer with Logsig Activation Function

Figure 3 shows the regression plot graph produced by the network topology of 5 input layers – 5 hidden layers and 1 output layer. The R value produced for the network's overall topology is 0.95. This indicates that the input data variables organized on the datasets have a very strong influence on the value of kWh of sales. Figure 4 shows a graph comparing the output value of the network topology with the target value. As shown in the graph above, the output value of the network topology is close to the given target value. This indicates that the trained network topologies are able to understand the pattern of a given data set. From the graph also, the minimum network topology value produced was 19.85 MWh compared to the target data value of 19.42 MWh, while the maximum output value of the predicted model produced of 35.12 MWh versus the value of 37.49 MWh of target data.

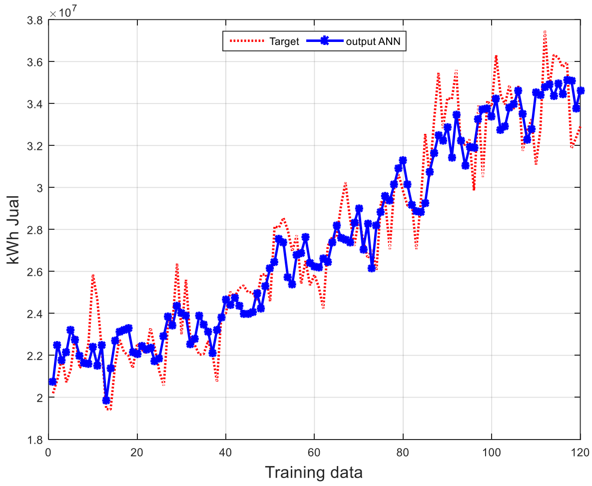

Figure 6. Graphic Comparison of Network Output Values with 5 Input Topology – 5 Hidden Layers and 1 Output Layer with Logsig Activation Function

Table 4. Results of Simulated Training of Neural Tissue Topology using the Activation Function of Tansig

No	Network Topology	MSE value	Coefisien R
1	5 input layer – 5 hidden layer – 1 output layer	0,00074	0,955
2	5 input layer – 10 hidden layer – 1 output layer	0,0022	0,957
3	5 input layer – 15 hidden layer – 1 output layer	0,0026	0,957
4	5 input layer – 20 hidden layer – 1 output layer	0,0045	0,942
5	5 input layer – 25 hidden layer – 1 output layer	0,00198	0,960

According to table 4, a neural network topology with 5 inputs layer-5 hidden layer-1 output layers yields the lowest MSE value compared to other network topologies. The MSE resulting value is 0,00074. In addition to the MSE, the R resulting from the entire networks topology has an excellent profile. Figure 8 shows a graph of MSE values generated by a network topology with 5 input layers – 5 hidden layer – 1 output layer. From the graph, such network topologies require 8 epochs out of a total of 500 maximum epoches specified. Network topology of 5 input layers – 5 hidden layers and 1 output layer yielded the best MSE value in the 4th epoch with a value of 0,00074. This indicates that the network topology of 5 input layers – 5 hidden layers and 1 output layer reaches its convergence with short computing.

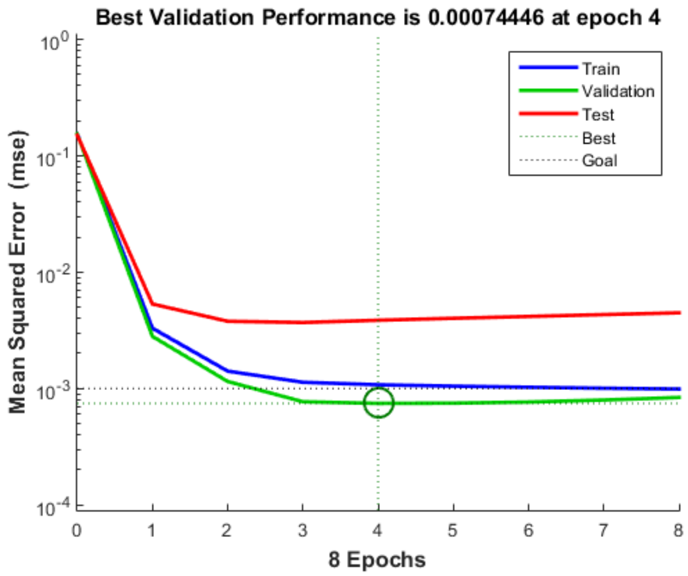

Figure 7. MSE Network Topology Graph 5 Input Layers – 5 Hidden Layers and 1 Output Layer Activation Function Tansig

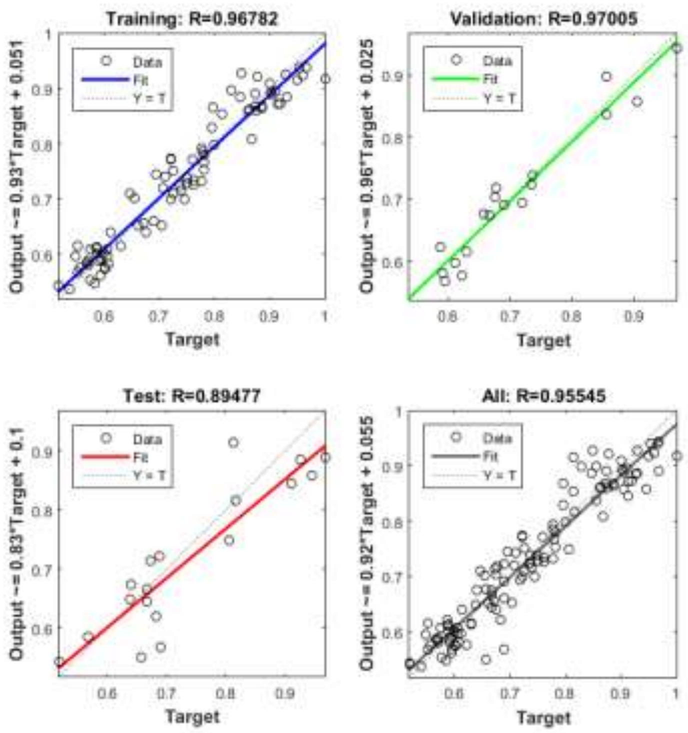

Figure 8. Graphic R Values Network Topology 5 Input Layers – 5 Hidden Layers and 1 Output Layer Activation Function Tansig

Figure 8 shows a graph of R values generated by a network topology with 5 input layers- 5 hidden layers and 1 output layer. From the graph, the R value produced by network topologies 5 inputs layers-5 hidden Layers and one output Layer is 0.955. From these values it can be concluded that the input variable has a strong influence on the kWh value of household sales. Based on a training simulation of the network topology that was formed, network topologies with 5 input layers – 5 hidden layers and 1 output layer became the construction of a predictive model of kWh sales to household customers. The next step is to test the predictive model. Model testing involves arranging datasets in table 2.

Table 5. Test Results of the kWh Prediction Model of Household Customers

No	Actual Data (MWh)	Output Model JST (MWh)	Error (%)
1	21,40	21,41	0,04
2	22,32	21,57	3,35
3	22,06	22,96	4,06
4	22,69	22,68	0,03
5	28,57	27,16	4,93
6	27,22	27,71	1,79
7	28,47	28,32	0,52
8	30,62	30,96	1,11
9	29,82	31,57	5,88
10	34,25	32,67	4,63
11	34,21	32,14	6,06
12	35,60	32,89	7,63
MAPE (%)			3,34

Table 5 shows the test results of the kWh prediction model of household customers. Based on table 5, the error value (%) generated by the model is less than 10%. The smallest error value generated of the model was 0.03% and the largest error rate (%) produced by a model was 7.63%. The MAPE value generate by a kWh forecast model for households based on the model testing is 3.34% Based upon the MAPe value and interpretation of the mape value, then the model for kWh sales of a household customer generated is able to generate a very accurate kWh value for sales.

Conclusion

Based on training and testing simulations, the neural network topology formed is able to produce a predictive model of kWh sales for household customers with great accuracy. Of the 5 neural networks topologies formed, the neural network topological with 5 input layers – 5 hidden layers and 1 output layer produces the best MSE values through network training simulations with logsig activation function schemes and traingd-a algorithms. Furthermore, through testing procedures, the kWh sales prediction model of the household customers produced a MAPE value of 3.34%. From the results, it can be concluded that the topology of the nerve network is able to produce a model of kWh sale of household insects in Banda Aceh city very accurately.

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