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Potential Solar and Wind Energy Forecasting for Capital City Using Neural network

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Abstract

This study discusses the forecasting of the potential of solar power and wind power in the province of Central Java. The forecasting model is determined based on the parameter indicators of population growth and the demand for electrical energy in Central Java. The neural network is used to forecast the database with the best architecture on the number of hidden neuron networks 15, 10, 1. The results show that the neural network is capable of forecasting solar and wind power potentials. This is indicated by the value of MSE 3.7984e-08 for solar power and MSE 2.0889e-07 for wind power. The neural network model produces output in year of 2030, solar electricity of 1.146.45 KW or 0.02605% of energy consumption in Central Java and wind power of 114.28 KW or 0.002596 % of energy consumption in Central Java.

Keywords: *Solar & wind energy, Electrical Energy Consumption, Forecasting, Neural networks.*

1. Introduction

Population growth in province of central java Indonesia continues to increase, resulting in increased demand for electrical energy. The population of central java in 2020 is 36.52 million people, and increases by 1.17 percent per year[1] [2] [3]. This resulted in the consumption of electrical energy continues to increase every year. Another problem is that the use of fossil fuels in power plants leaves a carbon footprint in the air and has a negative impact on our lives on earth, causing climate change to accelerate[4]. This condition is the reason why G20 member countries are committed to reducing these impacts. The G20 set a Net Zero Emission (NZE) target to reduce its carbon footprint by 2050-2070[5]. Meanwhile, Indonesia targets to use clean energy power plants by 2060, and there will be no more construction of steam power plants in the 2021-2030 period[6][7][8]. As a result, the demand for electrical energy as a result of population growth will be insufficient. Development and investment strategies are needed to encourage the Indonesian economy to be greener, especially investment in power plants. Central Java is a power plant supporting province for the national electricity supply, so it is important that the development strategy is carried out by this province. The solution to these problems is how to meet the supply of electrical energy demands by utilizing the potential of renewable energy, solar power and wind power.

Several studies on forecasting electrical energy demands have been carried out, including: calculation of web-based solar electric potential using google maps satellite image[9], a decision support system for determining wind potential for wind power plants using the fuzzy method[10], the study of the selection of suitable neural networks and the determination of parameters related to the use of algorithms in engineering applications[11], simulation of energy potential using a neural network to predict the potential of wind energy and solar energy, research on the potential of a hybrid (solar-wind) power plant in Banda Aceh using the neural network method[12][13], forecasting using neural network in predicting India's energy in the future[14]. radial basis function (RBF) neural network model for short term load forecasting (STLF) energy applications [15][16]. This study takes an object in the province of central java Indonesia, focusing on the conditions and character of long-term electricity demand by estimating renewable solar energy and wind power using artificial intelligence neural network methods on a wider parameter scale.

2. Research Method

Data on population, number of customers, energy sold and electricity load in central java Indonesia are input data. This data is processed by using the regression function. Furthermore, training on solar electricity as a target is carried out using a neural network. The parameters used in forecasting the potential of solar energy and wind energy in central java use data on the number of residents, the number of energy electricity customers sold and the load factors associated with energy

development. Indicators of the development of solar energy and wind energy are used to measure how much potential there is in the conditions of several predetermined parameters. The research model is shown in Fig.1.

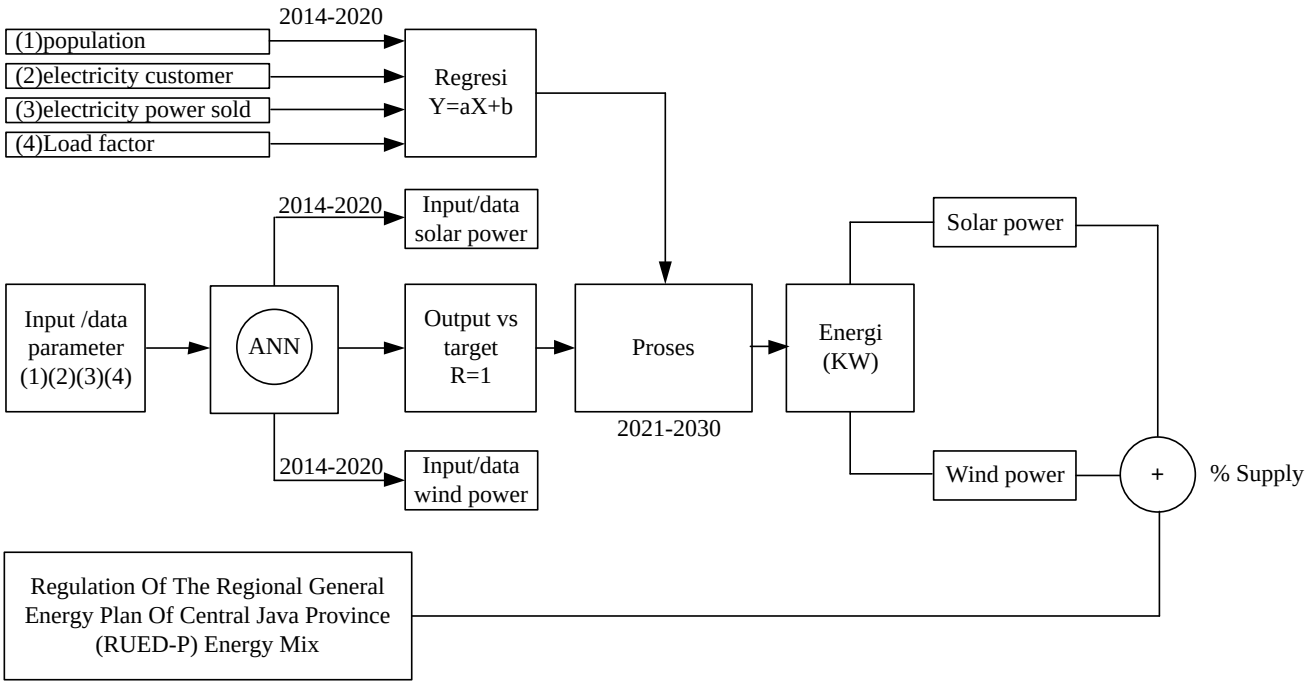

Figure 1. Research Model

Neural network is an information modeling system that seeks to create a model of an information computing system that can imitate a series of how biological neural networks work in humans that are integrated with simpler parts so that they can do structured things and produce a better and measurable success rate[17][18]. The same is done on the neural network approach which is applied to wind power as a target. The neural network will carry out a training process or training that is carried out many times until it finds a regression formulation equal to 1 (R=1) or close to 1. If R is close to 1 then the training process on the model is worth continuing because the model has worked well through training, like a human neural network[19][20]. One of the indicators used to measure the quality of the neural network is the correlation coefficient equation (R). The value of R will show the relationship between the target value and the output value generated by the neural network, correlation (R) can be calculated using equation (1)[21].

$$R = \frac{\sum_{m=1}^{N}(T_m - \mu_T)(O_m - \mu_o)}{\sqrt{\sum_{m=1}^{N}(T_m - \mu_T)^2}\sqrt{\sum_{m=1}^{N}(O_m - \mu_o)^2}} \quad \text{..... (1)}$$

Variable μT in equation (1) shows the average of the target and μo is the average value of the output issued by the neural network, whether or not the value of R is seen from the range between -1 and 1. If the prediction results are perfect, then the target value and the output value will have the exact same value (R=1). With this value, it means that the target value and the output have a perfect correlation. But this kind of correlation is very rare. On the other hand, if the R value in the prediction results is close to -1, it means that the target and output values are not correlated[20].

After obtaining a well-trained neural network model, data from the population, number of customers, energy sold and electricity load in Central Java in Fig. 1 is forecasting the next 10 years using the linear regression method[22]. The linear regression method can be chosen to process data with a linearly identical structure. The simple linear regression equation is mathematically expressed in equation (2)[23][24].

$$Y=aX+b \quad \text{..... (2)}$$

with :

Y = dependent variable (dependent variable)

X = Independent variable (independent variable)

a = Constant (value of Y if X = 0)
b = Regression coefficient (positive or negative effect)

The data resulting from linear regression data processing is used to apply a trained neural network model as input data so that the output is obtained as a target for solar power and wind power in the next 10 years. The results of these acquisitions have gone through a normalization and denormalization process, so that the potential values for solar power and wind power are obtained in the expected period. The calculation of the potential is obtained by taking the potential energy consumption in the same year with the indicator value of the percentage generated. These results will be represented by the regulations in central java province regions concerning regional energy plans that have been established[25], so that it can be compared as a further action plan by looking at the results of the forecasting model that has been carried out[26].
Neural networks are inspired by the biological processing of information by the nervous system, such as information processing in the human brain. The key element of this paradigm is the structure of the information processing system which consists of a large number of interconnected processing elements (neurons), working simultaneously to solve a particular problem. Neural networks work the same way humans work, namely learning by example[27]. Matlab is used for solving mathematical problems and is equipped with a very useful library to assist in solving various arithmetic problems[28][29]. To evaluate the forecasting approach, the mean squared error (MSE) presented in equation (3) is used[30][31].

$$MSE = \sum \frac{(Y' - Y)^2}{n} \quad \text{..... (3)}$$

with :
Y ' = Predicted value
Y = True value
n = Number of data

Application design in Matlab requires a block diagram to explain the system's work process. The block diagram components consist of input parameter data on the neural network training process, the target system, and the relationship or process relations. This block diagram makes it easy to understand, helping research to identify problem points or focus of attention quickly so that understanding in the design flow becomes clear. The block diagram of this research neural network is described in Fig. 2.

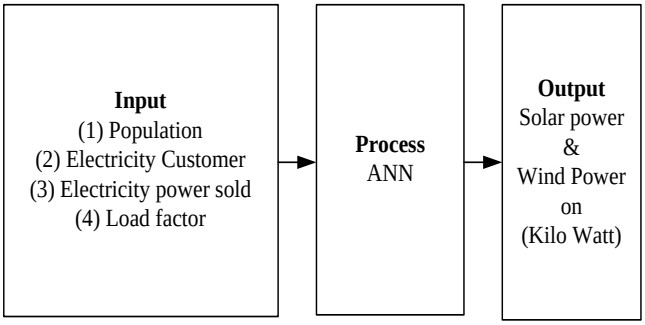

Figure 2. Block diagram of forecasting using a neural network.

Fig. 2 is a forecasting block diagram using a predictive neural network of 6 (six) input data. The training process uses a backpropagation neural network. The weights in the neural network are represented in a matrix by the system. The trained neural network will be tested using test data taken from input and output data. The result of the test is the percentage of forecasting, and then the network parameter analysis will be carried out on the accuracy of the forecasting results.
The data flow that occurs in training data, test data, the number of input and hidden neurons in the neural network, epochs, learning rates, momentum, and max mse will be entered by the user into the Matlab system. The number of neurons in the hidden layer is not determined because it is one of the variables that will be investigated for its effect on the output of the network by doing trial and error. After the data is processed by conducting training and testing on the system, the output of the system is in the form of prediction results and the final mse. Input layer 6 (six) neurons and the number of hidden layers used in this study are three hidden layers with the number of neurons in the hidden layer in the form of variables between 1 to 15 to test their effect on the accuracy of forecasting results. The output layer consists of one neuron, namely the potential for solar electricity development, the same network model will also be used to determine the potential for wind power. The arrangement of these layers can be seen in the neural network architecture shown in Fig. 3[32].

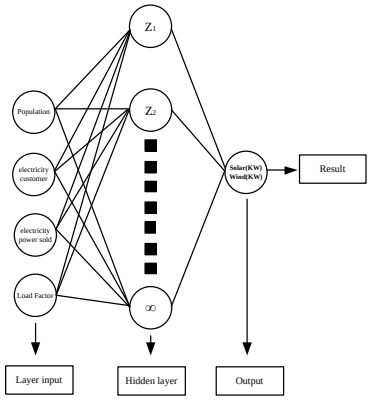

Figure 3. The architecture of the neural network for forecasting the potential of solar power and wind power.

Fig. 3 is an architecture for forecasting solar power and wind power with input layers of population, number of customers, energy sold and connected power loads as input neurons (input 7 years of previous data). The neurons in one layer are connected to the other layers. The information obtained on a neuron will be conveyed to all layers in the hidden layer (symbolized by the letter Z) and passed on to the output layer as a result. The flow chart for forecasting solar and wind energy in Central Java using a neural network is shown in Fig. 4.

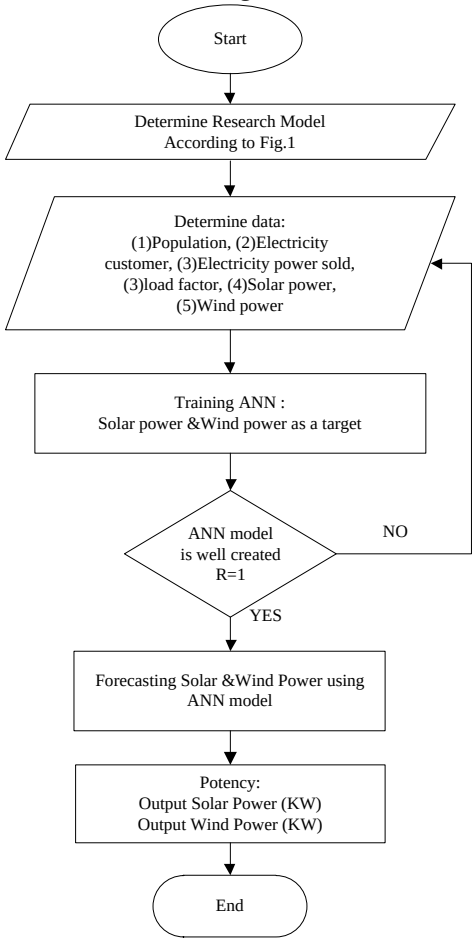

Figure 4. Research Flowchart Model

This research begins by determining the research model, then proceeds with determining the input data: . Data processing is carried out after all data is determined by the neural network method. Neural network learning is like a human neural network, it takes training on the network and evaluation to find the right formulation on the neural network model to

get accurate results. The training process on a very complex neural network will be carried out by the Matlab application, and evaluated to show the smallest errors.

Determination of the data in this study using population data in Central Java, the number of customers in Central Java, electrical power sold in Central Java, load factor, data on solar power in Central Java and wind power in Central Java. All data is converted into Microsoft Excel for easy management. The data are presented in tabular form as shown in Table 1.

Table 1. Input Data Parameters of population and energy development in Central Java[1], [33]

Year	Population	Number of Customers	Energy Sold (MWh)	Load Factor (%)	Solar electricity	Wind power
2014	33,522,663	8,456,230	19631475,000	78.26	126.35	1
2015	33,774,141	8,866.323	20407997,000	80.02	137.18	2.6
2016	34,019.095	9,191,764	21674848,090	62.62	260.08	26.5
2017	34,257,865	9,603,887	22402452,910	74.93	293.6	30
2018	34,490,835	10,011,388	23558014,300	78.64	613.14	40
2019	34,718,204	10,393,738	27786773,981	76.41	1027.48	100
2020	36,516,035	10,727,635	25279077,626	78.32	1227	100

3. Results and Analysis

3.1 Research Results

Neural network with reference to the selected network according to Fig. 3, data processing is carried out by identifying it as training data. The total data used for this study amounted to 4 indicator parameter data in Central Java. The training data in this study was taken from data on the development of energy indicators from 2014 to 2020, a total of 28 data. Parameter data used are shown in Table 2.

Table 2 : Data set of neural network input and target.

Year	**Input(x)**				**Target/ Output(y)**	**Target/ Output(y)**
	Population	Customer	Energy sold	Load factor	Solar electricity	Wind power
2014	33,522,663	8,456,230	19631475,000	78.26	126.35	1
2015	33,774,141	8,866.323	20407997,000	80.02	137.18	2.6
2016	34,019.095	9,191,764	21674848,090	62.62	260.08	26.5
2017	34,257,865	9,603,887	22402452,910	74.93	293.6	30
2018	34,490,835	10,011,388	23558014,300	78.64	613.14	40
2019	34,718,204	10,393,738	27786773,981	76.41	1027,48	100
2020	36,516,035	10,727,635	25279077,626	78.32	1227	100
--Forecasting data/output--						

Backpropagation is used to proceed data processing of neural network in Matlab with Lavenberg-Marquardt algorithm (trainlm) and using MSE performance reference. Data training was carried out several times by trial and error to get the best network by determining the number of neurons. After training and testing several times, the best settings are obtained with 3 hidden layers and the number of neurons 15-10-1, Learning rate (lr) 0.01, Epoch (iteration) 2000 and Goal to determine the limit of the MSE value so that the iteration stops at 1e -6. In this setting, it shows the Regression value or R=1, which means that the actual variables and the neural network in the test have a good or even perfect correlation for modeling with the network.

The neural network modeling is done on solar power with Regression value is R = 1, which means the network already used in data processing. The result of Regression plot as shown in Fig. 5.

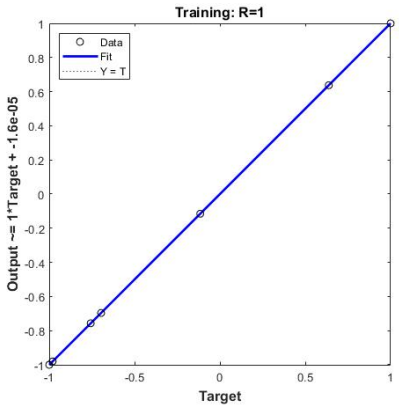

Figure 5. Regression graph of neural network architecture model results in Matlab for solar power forecasting.

The regression graph on the network architecture uses the parameter data in Table 2, and the solar power data as the output target is R = 1, this means that the network has good data accuracy. Network performance as a network evaluation to ensure network error errors in Matlab mathematical calculations is shown in Fig. 6.

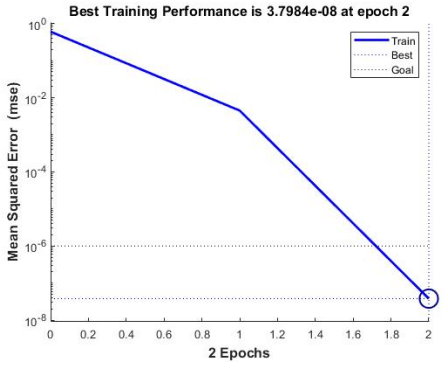

Figure 6. Graph of MSE Output Vs Solar Power Forecasting Target.

The best training process stops at epoch 2 with an MSE value of 3.7984e-08. Very small error indicator, as shown in Fig. 6, then the use of the neural network model can be used to perform further data processing.
Processing test data using parameter data from input for the next 10 years 2021-2030 which has gone through linear regression predictions, the neural network model is able to produce forecasts that are close to the desired target. The results of forecasting solar power using a neural network model are shown in Fig. 7.

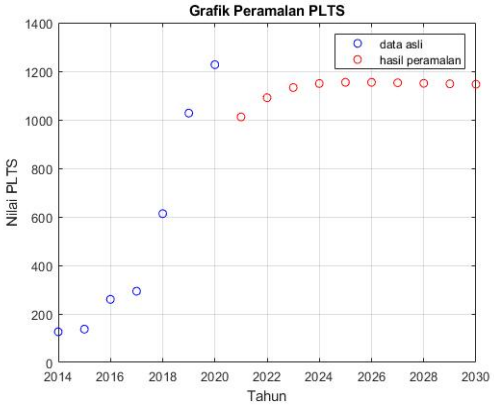

Figure 7. Graph of solar power forecast.

Solar electricity forecasting graph shown in the graph Fig. 7 Forecasting data / Output is displayed by the red node, and the original data is displayed by the blue node. Forecasting results increase, but not too high. Detailed forecasting results / output data are represented in numbers using certain coding commands in Matlab as shown in Table 3.

Table 3. Results of forecasting solar power 2021-2030

Year	Solar electricity
2021	1011,718734
2022	1091.06941
2023	1132.828491
2024	1149,49423
2025	1154,388427
2026	1154,365493
2027	1152.509633
2028	1150,198758
2029	1148,07297
2030	1146,450465

The backpropagation neural network is formed and trained with the neural network toolbox in Matlab. During the training process the weights and biases will continue to be corrected until the error value is small enough. The training will be stopped when the existing training parameters are met (epoch or goal). The neural network modeling that has been done on solar power as a target, will do the same thing with wind power as a target by setting 3 layers hidden layer and the number of neurons 15-10-1, Learning rate (lr) 0.01, Epoch (iteration) 2000 and Goal to determine the MSE value limit so that the iteration stops at 1e-6. Neural network modeling that has been done on wind power gets a Regression value or R = 1, so that the network model can be used. These values can be seen in the Regression plot, as shown in Fig. 8.

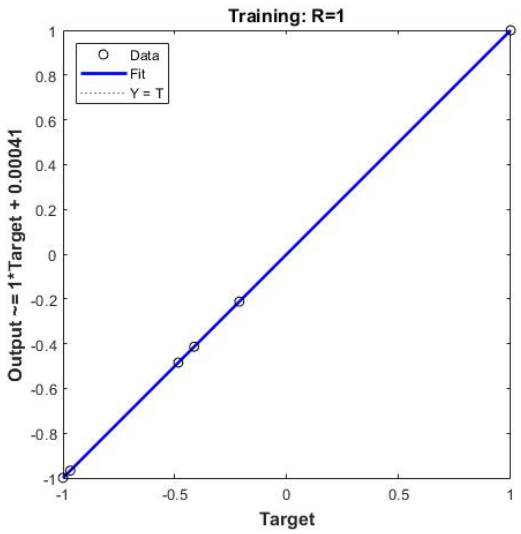

Figure 8. Regression graph of neural network architecture model in Matlab for wind power forecasting

The regression graph on the network architecture uses the parameter data in Table 2, and the wind power data as the output target is R=1, this means that the network has good data accuracy. Network performance as an evaluation to ensure network error errors in Matlab mathematical calculations is shown in Fig. 9.

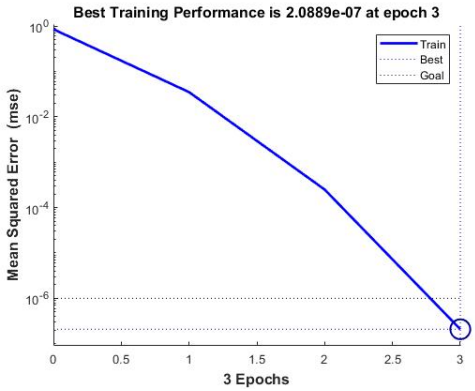

Figure 9. Graph of MSE Output Vs Wind Power Forecasting Target

The best training process stops at epoch 2 with an MSE value of 2.0889e-07. Very small error indicator, as shown in Fig. 9, then the use of the neural network model can be used to perform further data processing.
Processing test data using parameter data from input for the next 10 years 2021-2030 which has gone through linear regression predictions, the neural network model is able to produce forecasts that are close to the desired target. The results of wind power forecasting with a neural network model are shown in Fig. 10.

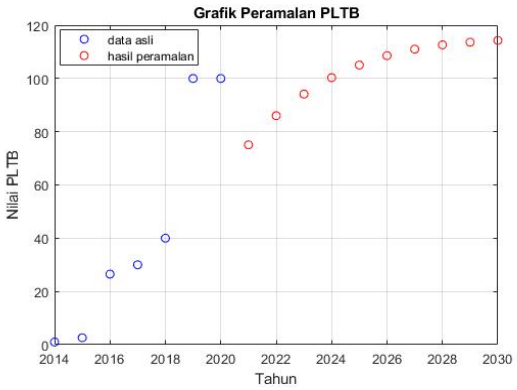

Figure 10. Wind Power Forecasting Graph

The solar power forecast graph is shown in the graph of Fig 10. Forecasting data / Output is displayed by the red nodes, and the original data is displayed by the blue nodes. Forecasting results tend to increase starting in 2024 and above. Detailed forecasting data / output is represented in numbers using certain coding commands in Matlab as shown in Table 4.

Table 4. Wind power forecasting results 2021-2030.

Year	Wind Power (KW)
2021	75.06084225
2022	86.01575202
2023	94.13155526
2024	100.311756
2025	105.0497842
2026	108.5667701
2027	111.0183427
2028	112.6185103
2029	113.62607
2030	114.2787751

3.2 Research Analysis

A. Analysis of solar electric potential

Forecasting analysis of solar power potential in 2030 is 1146,450465 KW. If it is calculated from the amount of power used at the same time (2030), it can be calculated the potential percentage of solar electricity to the electrical load sold as follows:

Solar electricity potential = (Σ kW solar electricity production x 8,760 hours)/
(Σ kWh of load sold per year) x100%
= (1146,450465 x 8760) / (38555300,72x103) x 100%
= 0,00026048 x 100 %
= 0.026048 %

B. Analysis of wind power potential

Forecasting analysis of wind power potential in 2030 is 114,2787751 KW. If it is calculated from the amount of power used at the same time (2030), it can be calculated the potential percentage of solar electricity to the electrical load sold as follows:

Wind power potential = (Σ kW wind power production x 8,760 hours)/
(Σ kWh of load sold per year) x100%
= (114,2787751 x 8760) / (38555300,72x103) x 100%
= 0.0000259648 x 100%
= 0.00259648 %

The proportion of renewable energy in regulations in central java province regions concerning regional energy plans in 2030 is 22.55%[34], so solar power and wind power are not more than 1 percent of the target of the Central Java province development plan. But if you look at the fluctuations in 2020 due to the COVID-19 pandemic, it is very possible that this energy will have little potential in 2030.

4. Conclusions

The neural network has proven to be able to be used to predict the potential of solar and wind power in Central Java. Based on the results of experiments that have been carried out in predicting solar and wind power forecasting. Forecasting models using neural networks on solar power have a small error rate with MSE of 3.7984e-08 and wind power of 2.0889e-07. Energy mix renewable energy in regulations in central java province regions in 2025 is 21.32% and in 2030 it is 22.55%, then as a forecast for that year, policy makers should be able to pursue or optimize strategic projects in the field of renewable energy.

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