

# PHOTOVOLTAIC POWER PREDICTION WITH SHORT TERM BOOST CONVERTER USING BACKPROPAGATION ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

Prediction (forecasting) of optimal photovoltaic power output is needed in power system planning and operation. Photovoltaic (PV) technology is used to generate electrical energy from direct sunlight. The irradiance of sunlight can affect how much electrical energy a solar module produces. This study discusses a simulation of the predicted output power of photovoltaic and boost converter systems with MPPT, in the next 1 hour with the approach of the backpropagation artificial neural network (ANN) method. In this study the learning rate used is 0.01 and the minimum target error is 0.001 with 5 predetermined network architectures. The results of this study are expected to be able to predict the photovoltaic output power with optimal accuracy.

**Keyword :** - Photovoltaic output power, Backpropagation artificial neural network and boost converter

## 1. INTRODUCTION

Natural weather conditions such as sunlight exposure, temperature and wind speed have a significant impact on the photovoltaic output power. The quantity of solar radiation that can be absorbed by a solar power plant is very dependent on the solar panel itself [1]. The quantity of electricity generated can vary depending on the intensity of the sun, with high intensity solar energy generating more power and low intensity solar energy producing less [2],[3]. Weather variations of the PV output which impact the stability and schedule of photovoltaic operation by causing intermittents, voltage spikes, reverse current etc. This uncertainty will be significantly reduced and stability will increase with a good PV output estimate [5],[6]. It is known that the output power of the photovoltaic (PV) is closely correlated with the solar radiation from the PV module. Other climatic factors such as ambient temperature, relative humidity, wind speed and dust deposition have been observed to impact PV efficiency [7]. For proper power planning, it is necessary to predict solar panel power [4].

The surface temperature of a solar cell has an impact on its ability to generate power [8]. The characteristics of the voltage and output power of solar panels (photovoltaic) can change at any time, along with the amount of radiation absorbed by the solar cells [9]. The output voltage of solar cells can be stabilized using boost converter technology [10]. To overcome this problem, a step-up converter and PV power forecasting are needed to increase the stability of the solar power generation system. Research [12] is also related to the prediction of PV output power using input data from the RET screen database. In research [13], regarding the prediction of PV generation power using machine learning and artificial neural networks. Data is sampled every ten minutes within 24 hours. Input data parameters for ANN are Irradiance, PV temperature, ambient temperature and time for 8 days based on the variables that affect PV production.

The backpropagation approach is often applied to problems involving identification, prediction, pattern recognition and other similar problems. Another benefit of ANN is its ability to learn (adaptive). In his research

[11], using the ANN approach with Decomposition Backpropagation Neural Network (D-BPNN) to anticipate solar power one hour earlier, from 14.05 WIB to 15.00 WIB. The equipment used is a solar module without a converter to obtain research data in the form of photovoltaic output power data and meteorological data obtained with measuring equipment.

### 1.1 PV output power prediction with boost converter

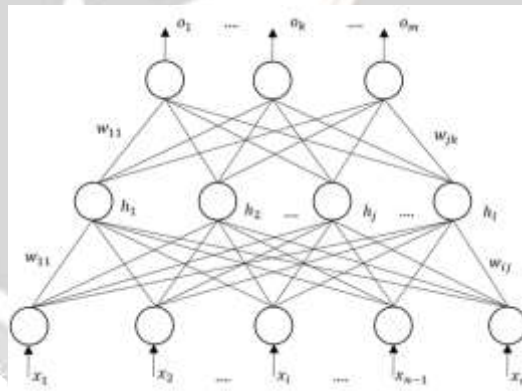
This proposed research presents an ANN simulation model predicting the output power of photovoltaic and boost converter systems with MPPT for the next 1 hour. The boost converter in this study is used to produce a more certain prediction of the power required by the load. Based on the explanation of previous studies, one of the main factors that influence the PV output power is irradiance, PV temperature, ambient temperature and time. In this study, the artificial neural network's input parameters are expanded to include meteorological input information like humidity and wind speed. To improve forecasting accuracy, the hidden layer's number of neurons will be adjusted.

### 1.2 Artificial neural network

Artificial neural network (ANN) is a connectionist system based on the biological neural network of the human brain, which has the ability to learn, remember and connect data. Neurons are the basic building blocks of ANNs that are connected to other neurons via weighting factors to determine the strength of the connection [14],[15].

### 1.3 Backpropagation architecture

ANN techniques, which are widely used in forecasting, can simulate complex and non-linear connections through non-linear units (neurons). The most common type of ANN model is the backpropagation neural network [16]. The ability to learn and store various input and output mapping connections without prior knowledge of the required mathematical expressions is known as nonlinear mapping capability. By computing the gradient of the loss function and attempting to reduce the sum of the squared network errors, the gradient descent optimization approach is frequently employed in learning situations to update the neuron weights [17].

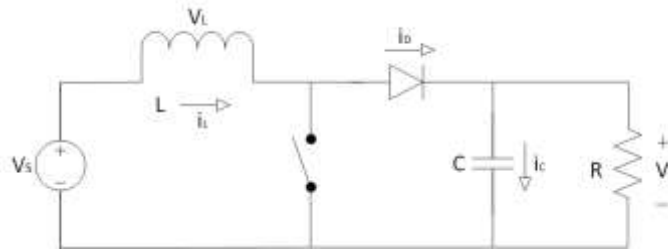


**Fig -1:** Structure of BP Neural Network [18]

Figure 1, shows input layer neurons  $x_1, x_2, \dots, x_n$ , hidden layer neurons  $h_1, h_2, \dots, h_n$  and output layer neurons  $o_1, o_2, \dots, o_n$ .  $w_{ij}$  is the weight of neuron  $i$  in the input layer to neuron  $j$  in the hidden layer.  $w_{jk}$  is the weight from neuron  $j$  in the hidden layer to neuron  $k$  in the output layer [17].

### 1.4 Boost Converter

DC-DC converters are known as converters that can stabilize the voltage by increasing the voltage where the output voltage is greater than the input voltage without using a lot of power to compensate for the lack of voltage. When changing the form of electrical energy, the DC-DC converter only changes the DC output voltage level and current without changing the power. The boost converter circuit design consists of switches, diodes, capacitors, resistors and forming inductors. The boost converter circuit is as follows, as shown in Figure 2:



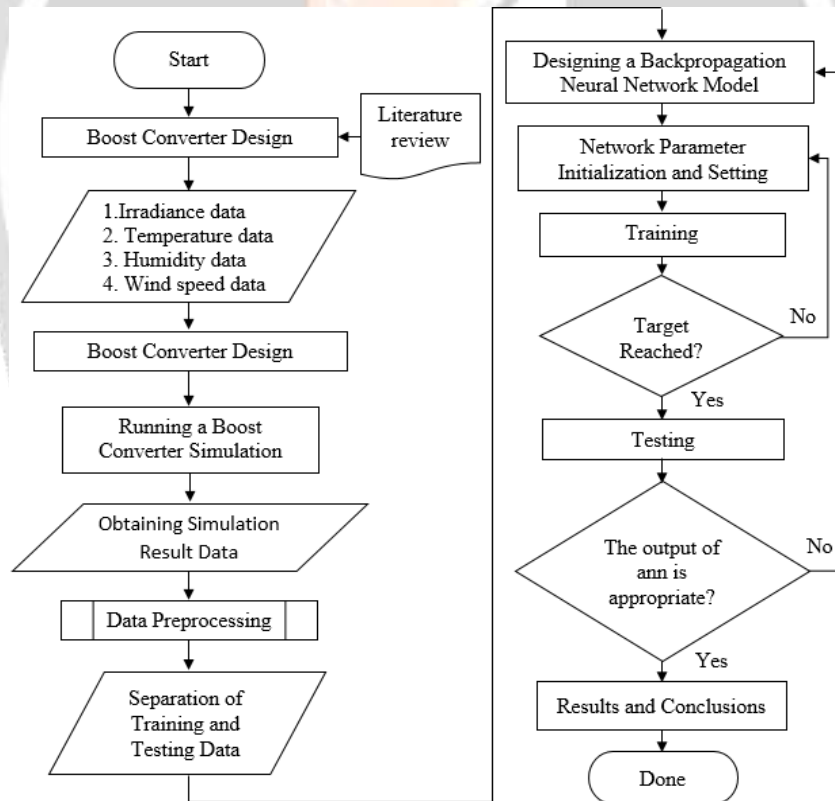
**Fig -2:** Boost Converter circuit

The energy stored in the inductor increases when the switch is closed, because current flows through it. The energy stored in the inductor will decrease when the switch is opened because the inductor current will flow to the load through the diode. The duty cycle, also known as the ratio between the switching period and the switch opening time, is inversely proportional to the ratio between the output voltage and the input voltage. If  $D$  = duty cycle, the relationship between the input voltage  $V_d$  and output voltage  $V_o$  is expressed by the following equation (1):

$$\frac{V_o}{V_d} = \frac{1}{1 - D} \tag{1}$$

## 2. METHODOLOGY

In *this* study, it was arranged through several stages shown in Figure 3.



**Fig -3:** Research Flowchart

The research process starts from conducting a literature study to study previous research related to current research. as well as the selection of titles, algorithms for forecasting and methods used from various sources, journals and books related to the discussion of photovoltaics, machine learning and backpropagation artificial neural

networks. Identification of the problem from this research plan is needed to determine the photovoltaic performance that depends on the irradiance of sunlight. The secondary data used in this study was taken from the Weather Underground website with the station name ISEMAR1, Semarang City on 1 January – 2 January 2022 every 5 minutes, starting at 07:00 – 17:00 WIB. The data to be used is the average data in 1 hour.

## 2.1 Research Data

The tools and materials needed in the research are as follows:

Hardware : Toshiba Laptops  
 Software : MATLAB R2018a, software PSIM and microsoft excel  
 Processor : Intel Pentium CPU B960 2.20 GHz  
 RAM : 4 GB  
 Harddisk : 500 GB

In short, the data search carried out includes:

### 2.1.1 Weather data

In this study secondary data was taken from the Weather Underground website with the station name ISEMAR1 Semarang City on January 1 - January 2 2022 every 5 minutes, starting at 07:00 - 17:00 WIB. The data to be used is the average data in 1 hour. The input data for this study consisted of sunlight irradiance ( $W/m^2$ ), temperature ( $^{\circ}C$ ), humidity (%) and wind speed (mph).

**Table -1:** Meteorological data from the Weather Underground website January 1, 2022

Input Data				
Time	Irradiance ( $W/m^2$ )	Temperature ( $^{\circ}C$ )	Humidity (%)	Wind speed (mph)
7:00	267.1	27.2	72	0.91
8:00	461.7	27.8	72	2.03
9:00	449.4	27.9	73	2.68
10:00	140.9	27.2	77	4.00
11:00	323.5	27.7	77	3.92
12:00	79.6	26.6	81	2.58
13:00	342.5	25.6	88	0.80
14:00	34.0	24.6	88	2.36
15:00	70.8	23.0	91	0.52
16:00	93.3	24.4	89	0.47
17:00	22.8	25.1	85	0.68

**Table -2:** Meteorological data from the Weather Underground website January 2, 2022

Input Data				
Time	Irradiance ( $W/m^2$ )	Temperature ( $^{\circ}C$ )	Humidity (%)	Wind speed (mph)
7:00	133.2	25.6	80	0.6
8:00	385.9	26.4	77	2.2
9:00	433.0	27.3	73	3.3
10:00	536.6	28.0	70	3.9
11:00	279.7	27.8	74	3.8
12:00	227.5	28.1	72	3.5
13:00	116.8	28.3	71	4.5

\*) continuation of table -2

Input Data				
Time	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Humidity (%)	Wind speed (mph)
14:00	87.1	25.8	84	3.4
15:00	273.1	25.5	86	2.0
16:00	101.3	27.3	80	1.3
17:00	22.8	26.7	82	1.8

The irradiance and temperature data obtained from the weather underground website will then be used as simulation input parameters to find the output power in the PSIM software.

### 2.1.2 Selection of Solar Panels

The solar panel used is from the Kyocera KC50T product. This panel contains 36 multicrystal cells where one solar panel can generate a total power of 54 Wp. The specifications of the module used can be seen in table 3:

**Table -3: KC50T Solar Panel Specifications**

Parameter	Value
Power (Pmax)	54 W
Open Circuit Voltage (Voc)	21,7 V
Short Circuit Current (Isc)	3,31 A
Voltage @Max Power (Vmp)	17,4 V
Current @Max Power (Imp)	3.17 A
Number of Cell in Series (Ns)	36

### 2.1.3 Photovoltaic output power data

To obtain photovoltaic output power data, a simulation of the MPPT system design with a boost converter circuit will be carried out using PSIM software.

#### a) Boost Converter Design

In designing a boost converter, what needs to be done is to calculate the required component sizes, expressed by the following equation:

The amount of duty cycle that is set in the boost converter switching process is obtained by equation (2) [19],

$$D = 1 - \frac{17,4}{36} = 0,52 \quad (2)$$

where  $D$  is the duty cycle,  $V_i$  is the input voltage (V) and  $V_o$  is the output voltage (V). The value of the resistor resistance used in the boost converter circuit can be determined by calculating in equation (3).

$$R = \frac{V_o}{I} = \frac{36}{3,17} = 11,36 \Omega \quad (3)$$

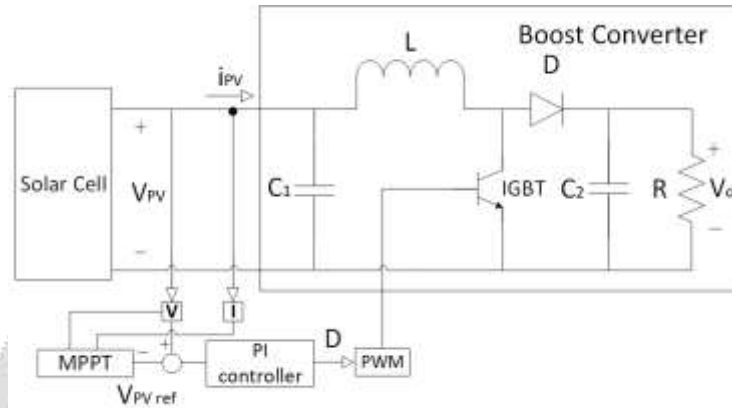
Determination of the value of the inductor in the boost converter, calculated by equation (4)

$$L_{min} = \frac{0,52(1 - 0,52)^2 11,36}{2 \times 20 \times 10^3} = 34,3 \mu H \quad (4)$$

where  $L_{min}$  is the minimum inductance ( $\mu H$ ),  $R$  is the resistor ( $\Omega$ ) and  $f$  is the switching frequency (Hz). Determination of the value of the capacitor to be used to reduce the output voltage ripple is calculated by equation (5)

$$C = \frac{0.52}{11.36 \times 0.03 \times 20000} = 2729.72 \mu F \tag{5}$$

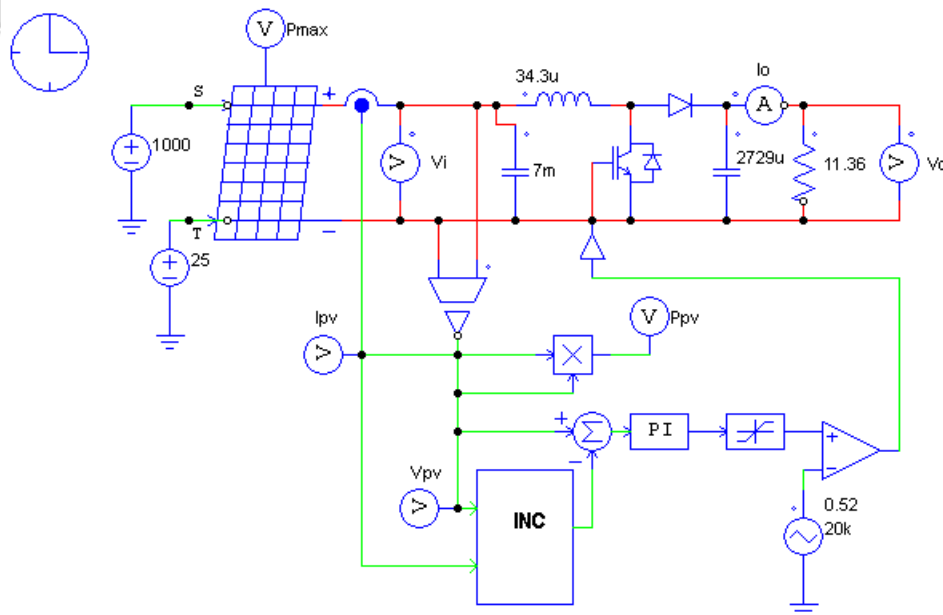
where  $\frac{\Delta V_o}{V_o}$  is the output voltage ripple and  $C$  is the capacitor.



**Fig -4:** Boost Converter System Design with MPPT

Figure 4 shows the design plan of the Boost Converter with MPPT. Figure 4 demonstrates how a solar cell is linked to the MPPT system. This MPPT system has 4 blocks that have their respective functions, namely the boost converter circuit block, the MPPT block and the PI controller block [20].

b) Boost Converter Simulation



**Fig -5:** The design of the PSIM software

The circuit is made in the PSIM software and executed, by changing the parameters of the sunlight irradiance value and temperature which will then be carried out the data retrieval process, namely the value of the output power (P). After getting the output power data from the simulation results, the data will be processed as input for artificial neural networks in the Matlab software.

## 2.2 Solar panel simulation using MPPT

The simulation results using MPPT on January 1, 2022 can be observed in Table 4. When there is a change in sunlight irradiance and temperature, the average power value is 8.07 W with an average voltage and current of 7.63 V and 0.68 A. the power obtained at 07.00 was 8.78 W with a voltage and current value of 9.93 V and 0.88 A. The highest increase in power occurred at 08.00 with a power value of 24.25 W, a voltage of 16.57 V and a current of 1.46 A. Then it experienced a decrease in power reaching 0.06 W at 17.00 with a voltage and current value of 0.85 V and 0.08 A.

**Table -4:** Simulation Results with MPPT January 1, 2022

Time	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Voltage V <sub>pv</sub> (V)	Current I <sub>pv</sub> (A)	Power P <sub>pv</sub> (W)
7:00	267.1	27.2	9.93	0.88	8.78
8:00	461.7	27.8	16.57	1.46	24.25
9:00	449.4	27.9	16.26	1.44	23.39
10:00	140.9	27.2	5.24	0.47	2.44
11:00	323.5	27.7	12.02	1.07	12.86
12:00	79.6	26.6	2.96	0.26	0.78
13:00	342.5	25.6	12.72	1.13	14.40
14:00	34	24.6	1.27	0.11	0.14
15:00	70.8	23	2.63	0.23	0.62
16:00	93.3	24.4	3.47	0.31	1.07
17:00	22.8	25.1	0.85	0.08	0.06
Mean	207.8	26.1	7.63	0.68	8.07

The results of the solar panel simulation with MPPT on January 2, 2022 can be seen in Table V. When there is a change in sunlight irradiance and temperature, the average power value is 9.10 W with a voltage and current of 8.49 V and 0.77 A. The power value at 07.00 is 2.18 W with a voltage and current value of 4.95 V and 0.44 A. The highest power increase occurred at 10.00 with a power of 28.45 W, a voltage of 17.11 V and a current of 1.66 A. Then it experienced a decrease in power reaching 0.06 W at 17.00 with a value of voltage and current of 0.85 V and 0.08 A.

**Table -5:** Simulation Results with MPPT January 2, 2022

Time	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Voltage V <sub>pv</sub> (V)	Current I <sub>pv</sub> (A)	Power P <sub>pv</sub> (W)
7:00	133.2	25.6	4.95	0.44	2.18
8:00	385.9	26.4	14.29	1.27	18.14
9:00	433.0	27.3	15.82	1.40	22.18
10:00	536.6	28.0	17.11	1.66	28.45
11:00	279.7	27.8	10.40	0.93	9.62
12:00	227.5	28.1	8.46	0.75	6.37
13:00	116.8	28.3	4.34	0.39	1.68
14:00	87.1	25.8	3.24	0.29	0.93
15:00	273.1	25.5	10.15	0.90	9.17
16:00	101.3	27.3	3.77	0.34	1.26
17:00	22.8	26.7	0.85	0.08	0.06
Mean	236.1	27.0	8.49	0.77	9.10

The boost converter in this thesis research is used as a model to obtain photovoltaic output power, simulated using PSIM software. The data generated from this boost converter in the form of photovoltaic power is then used as input data for artificial neural networks in the Matlab software.

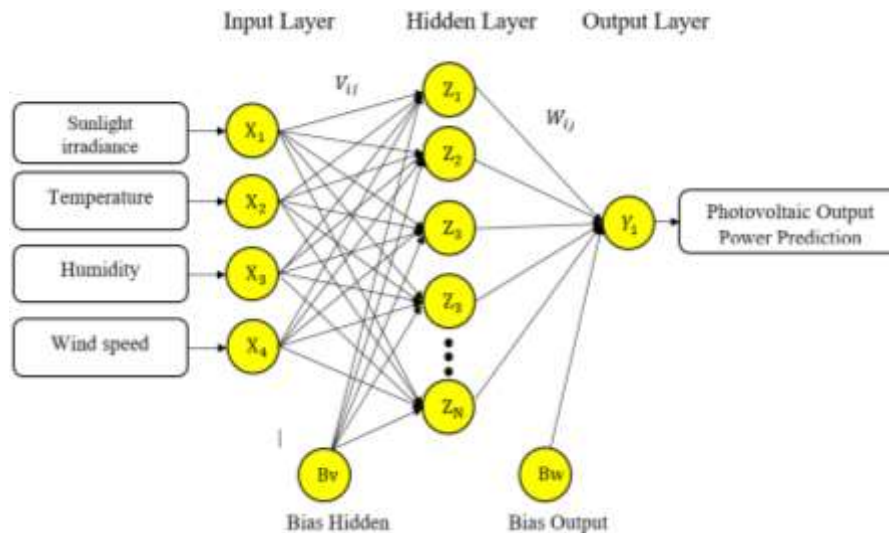


Fig -6: ANN architecture to be built

Where:

- $X_1$  to  $X_4$  = Input layer
- $Z_1$  to  $Z_N$  = Hidden layer
- $V_{ij}$  = The weight from the input layer to the hidden layer
- $W_{ij}$  = Weight from hidden layer to output layer
- $B_v$  = Bias weight from input layer to hidden layer
- $B_w$  = Bias weight from hidden layer to output layer
- $Y_1$  = Output result (output)

In Figure 6 is the architecture of the artificial neural network that will be built using the Matlab R2018a software. To create a network using the Levenberg-Marquardt algorithm to forecast the output power of a photovoltaic system, use the following command in Matlab:

```
net = newff(minmax(training_data),[10 1],{'tansig', 'purelin'}, 'trainlm');
```

In this command, there is a model architecture which consists of a hidden layer, there are 10 neurons and an output layer, there is 1. Before training is carried out, initialize and set network parameters to find out the MSE for changes in predetermined parameters and in order to obtain optimal results, as shown in table 6.

Table -6: Parameters in Backpropagation ANN Training

Characteristics	Specification
Neuron input	4
Network Type	Feed-Forward Backprop
Training Function	TRAINLM
Learning Function	LEARNGD
Performance Function	MSE (Mean Square Error)
Number of Hidden Layers	1
Neuron Hidden	2, 4, 6, 7, 8
Activation function	tansig and purelin
Target Error	0,001
Maksimum Epoch	1000
Learning Rate	0,01



### 2.3 Defining Inputs and Targets

Meteorological data and photovoltaic power data are processed by an Artificial Neural Network using the backpropagation method. The training data for this research input consisted of sunlight irradiance ( $\text{W}/\text{m}^2$ ), temperature ( $^{\circ}\text{C}$ ), humidity (%) and wind speed (mph). The output target data is the photovoltaic output power on January 1, 2022.

Testing data for this research input consists of sunlight irradiance ( $\text{W}/\text{m}^2$ ), temperature ( $^{\circ}\text{C}$ ), humidity (%) and wind speed (mph). The output target data is photovoltaic output power on January 2, 2022. This training and testing data will later be carried out using rotary rotation, meaning that each data set has the same opportunity to reach the target.

**Table -7: Training Data**

Time	Input Data				Target
	Irradiance ( $\text{W}/\text{m}^2$ )	Temperature ( $^{\circ}\text{C}$ )	Humidity (%)	Wind speed (mph)	
7:00	267.1	27.2	72	0.91	8.777
8:00	461.7	27.8	72	2.03	24.246
9:00	449.4	27.9	73	2.68	23.387
10:00	140.9	27.2	77	4.00	2.444
11:00	323.5	27.7	77	3.92	12.857
12:00	79.6	26.6	81	2.58	0.780
13:00	342.5	25.6	88	0.80	14.398
14:00	34.0	24.6	88	2.36	0.143
15:00	70.8	23.0	91	0.52	0.617
16:00	93.3	24.4	89	0.47	1.071
17:00	22.8	25.1	85	0.68	0.064

**Table -8: Testing Data**

Time	Input Data				Target
	Irradiance ( $\text{W}/\text{m}^2$ )	Temperature ( $^{\circ}\text{C}$ )	Humidity (%)	Wind speed (mph)	
7:00	133.2	25.6	80	0.6	2.183
8:00	385.9	26.4	77	2.2	18.145
9:00	433.0	27.3	73	3.3	22.178
10:00	536.6	28.0	70	3.9	28.451
11:00	279.7	27.8	74	3.8	9.624
12:00	227.5	28.1	72	3.5	6.369
13:00	116.8	28.3	71	4.5	1.680
14:00	87.1	25.8	84	3.4	0.934
15:00	273.1	25.5	86	2.0	9.174
16:00	101.3	27.3	80	1.3	1.263
17:00	22.8	26.7	82	1.8	0.064

### 2.4 Data Normalization

Before being processed into ANN, the data is normalized first by using the Sigmoid function. As in the equation (6) [21],[22].

$$x^1 = \frac{0.8(x - a)}{b - a} + 0.1 \tag{6}$$

Where:

- $x^1$  = Normalization results where the value is from 0 - 1
- x = The value to normalize
- a = The lowest value of a data
- b = The highest value of a data

Based on table 7, data on January 1, 2022 is used as training data, while data in table 8 on January 2, 2022 is used for testing data. On the training data, the maximum value (b) of the training is 461.7. The minimum value (a) is 0.1. Normalized data using the sigmoid function as follows:

$$x^1 = \frac{0.8(267,1 - 0,1)}{461,7 - 0,1} + 0,1 \tag{7}$$

Then the results of normalizing the training data at 07.00 WIB will be 0.5628617 and so on. As for the test data, the maximum value (b) of the test is 536.6. While the minimum value (a) is 0.1. By using the same formula, the test data will be obtained at 07.00 WIB, namely 0.2985177, and so on until normalization is complete.

**Table -9:** Train Data After Normalization

Time	Input Data				Target
	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Humidity (%)	Wind speed (mph)	
7:00	0.5628617	0.1470344	0.2248136	0.1014629	0.1150998
8:00	0.9000000	0.1480935	0.2246692	0.1034126	0.1419083
9:00	0.8787122	0.1482781	0.2271244	0.1045391	0.1404198
10:00	0.3441493	0.1470344	0.2330456	0.1068210	0.1041236
11:00	0.6605198	0.1478929	0.2326124	0.1066766	0.1221715
12:00	0.2379127	0.1459994	0.2409888	0.1043514	0.1012405
13:00	0.6934624	0.1443065	0.2528314	0.1012752	0.1248418
14:00	0.1587406	0.1424932	0.2529759	0.1039759	0.1001360
15:00	0.2225029	0.1397492	0.2577418	0.1007842	0.1009573
16:00	0.2616123	0.1421642	0.2538424	0.1006975	0.1017445
17:00	0.1393881	0.1433116	0.2474878	0.1010586	0.1000000

**Table -10:** Test Data After Normalization

Time	Input Data				Target
	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Humidity (%)	Wind speed (mph)	
7:00	0.2985177	0.1381479	0.2186945	0.1007366	0.1031594
8:00	0.6753046	0.1392248	0.2152153	0.1031348	0.1269595
9:00	0.7456097	0.1406537	0.2088782	0.1047999	0.1329728
10:00	0.9000000	0.1415926	0.2045292	0.1056448	0.1423274
11:00	0.5168884	0.1413165	0.2103693	0.1055330	0.1142537
12:00	0.4391403	0.1418618	0.2075113	0.1051478	0.1094016
13:00	0.2741011	0.1420965	0.2062688	0.1066389	0.1024087
14:00	0.2297535	0.1383619	0.2245347	0.1049490	0.1012962

\*) continuation of table -10

Time	Input Data				Target
	Irradiance (W/m <sup>2</sup> )	Temperature (°C)	Humidity (%)	Wind speed (mph)	
15:00	0.5071839	0.1379477	0.2283866	0.1029111	0.1135836
16:00	0.2509767	0.1405571	0.2184460	0.1017804	0.1017878
17:00	0.1338886	0.1397356	0.2219252	0.1025881	0.1000000

## 2.5 Training

At the training stage, the model is trained to minimize the error value so that the network model is suitable and can be used for predictions. If network performance falls short of expectations, the weights and biases are reset, and the network is retrained until satisfactory results are achieved.

## 2.6 Testing

Testing (testing) on the built model will be simulated to find out the results of the accuracy, accuracy and output values by comparing the original data with actual data. If the network output value is far from the target, then the process will be repeated again from the neural network architecture design and reinitialized, then the network is trained again until the Mean Square Error value is small [11],[12]. So that it is hoped that the predicted value can approach the actual value.

## 3. RESULT AND DISCUSSION

### 3.1 Analysis

In this study, 5 architectural models are used, including: 4-2-1, 4-4-1, 4-6-1, 4-7-1 and 4-8-1. This network architecture model uses 1 hidden layer, input neurons = 4, minimum target error 0.001. While the training function used is trainlm. The hidden layer uses the sigmoid bipolar activation function (tansig) and the output layer uses the purelin activation function. The backpropagation training formula used with the Matlab software is as follows [23], [24], [25]:

```
>> filename = 'data_3.xlsx';
>> sheet = 1;
>> xlRange = 'K7:O17';
>> Data = xlsread(filename, sheet, xlRange);
>> training_data = Data(1:11,1:4);
>> training_data = training_data;
>> training_target = Data(1:11,5);
>> training_target = train_target;
>> [m,n] = size(training_data);
>> rng('default')
>> net = newff(minmax(training_data),[Hidden,Target],{'tansig','purelin'},'trainlm');
>> net.trainParam.epochs = 1000;
>> net.trainParam.goal = 0.001;
>> net.trainParam.lr = 0.01;
>> net.trainParam.show = 20;
>> [net_output] = train(net,training_data, training_target);
>> result_train = sim(net_output, training_data);
```

### 3.2 Results

The results of the training and testing data processing of the network architecture model using the bipolar sigmoid function and the linear identity function are shown in the figure below.

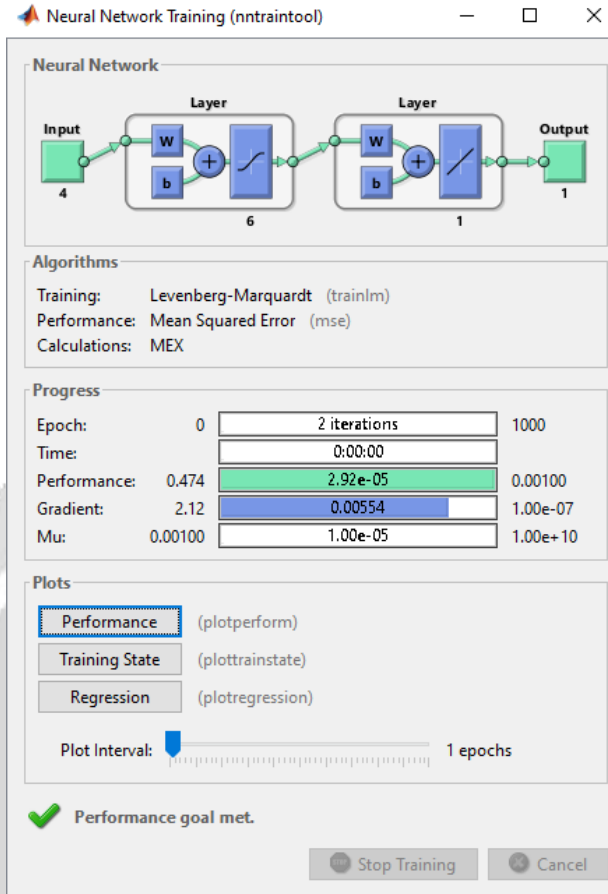


Fig -7: Training Results Model 4-6-1

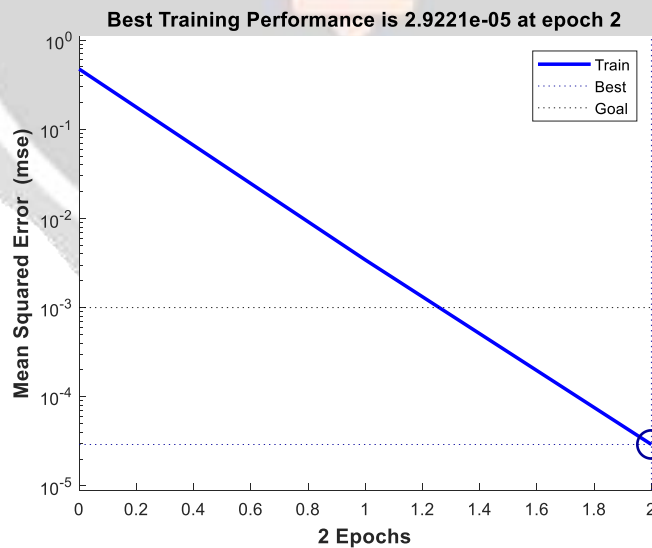
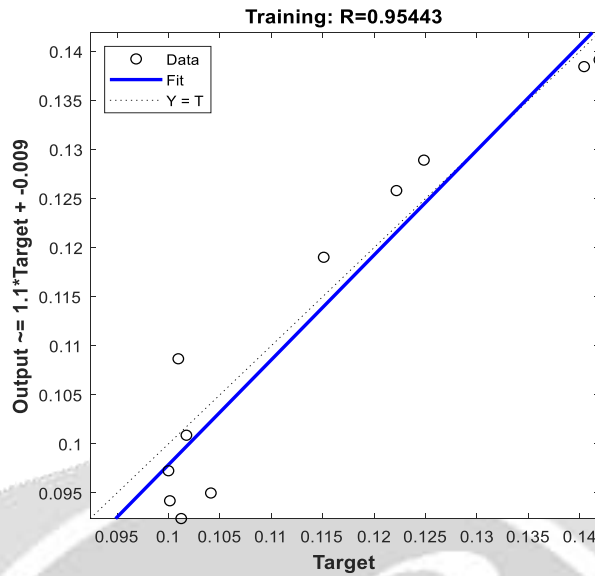


Fig -8: Model 4-6-1 Training Performance Results

Figure 8 shows that the training curve has achieved the best training performance during the training process. On the best training performance curve, the mean squared error (MSE) value is 2.9221e-05 and the training process stops at the 2nd iteration. Table 11 displays the findings of the training and testing accuracy of the five preset network architecture models.



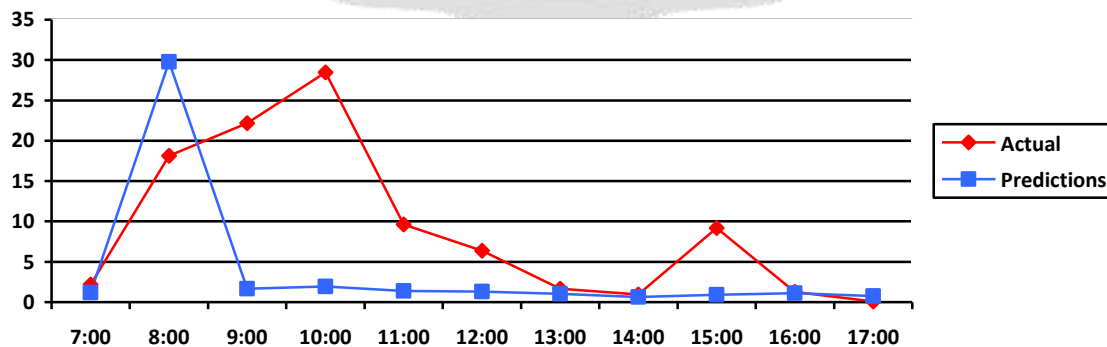
**Fig -9:** Output Compatibility Curve with Target

Figure 9 shows the relationship between the target and the network output that almost matches. From the network output that is close to the target, this can be seen from the diagonal fit line which is almost the same as the data point. Another indication is shown by the correlation between input and target which is symbolized by the regression coefficient R of 0.95443.

**Table -11:** Comparison of network architecture models

No	Architecture	Training	Testing	
		MSE	MSE	Accuracy
1	4-2-1	0.00087181	0.001196965	73%
2	4-4-1	0.00078063	0.004301739	27%
3	4-6-1	2.9221E-05	0.000461352	100%
4	4-7-1	7.1187E-05	0.000508604	82%
5	4-8-1	0.00017875	0.000158609	100%

Of the 5 best network architecture models, namely 4-6-1, the accuracy rate reaches 100% with an MSE iteration of 0.000461352 and the epoch obtained is 2 iterations. This model uses a sigmoid bipolar function and a linear identity function. The results of the training and testing accuracy of the 5 predetermined network architecture models can be seen in table 11.



**Chart -1:** Comparison of prediction results

From the training and testing processes that have been carried out using the backpropagation algorithm with trainlm optimization, the results of the comparison of actual power and predictive power are obtained as shown in chart 1. The results of the data comparison show that the model can be used to predict. Where it is useful to know the photovoltaic output power with a boost converter to predict how much average photovoltaic power will be obtained every hour.

#### 4. CONCLUSIONS

In this study, the backpropagation method of artificial neural networks (ANN) is used to predict the photovoltaic output power with a boost converter in the next one hour. The forecast results are close to the actual values based on experiments conducted with artificial neural networks that utilize the backpropagation approach, but further studies are still needed. This is evidenced by the results obtained by the average mean square error (MSE) for the first model is 0.001196965, for the second model is 0.004301739, for the third model is 0.000461352, for the fourth model is 0.000508604, and for the fifth is 0.000158609. The level of accuracy of this prediction is strongly influenced by the parameters used such as variations in solar irradiation which can affect the value of the photovoltaic output power and the selected network architecture model. Future studies may focus on improving predictions by incorporating more significantly correlated information by correlating more robust data and factors affecting other PV power forecasts in inputs such as rainfall, ambient temperature, etc.

#### 5. REFERENCES

- [1] T. NurHidayat, R. Subodro, and Sutrisno, "Analysis of Power Output in Solar Power Plants with a Capacity of 10Wp, 20Wp and 30Wp," *J. CRANKSHAFT*, vol. 4, no. 2, pp. 9–18, 2021, doi: <https://doi.org/10.24176/crankshaft.v4i2.6013>.
- [2] S. Yuliananda, G. Sarya, and R. R. Hastijanti, "The Effect of Changes in Solar Intensity on the Output Power of Solar Panels," *J. Pengabd. LPPM Untag Surabaya*, vol. 01, no. 02, pp. 193–202, 2015, doi: <https://doi.org/10.30996/jpm17.v1i02.545>.
- [3] M. Usman, "Analysis of Light Intensity on the Electrical Energy Generated by Solar Panels," *Power Elektron.*, vol. 9, no. 2, pp. 52–57, 2020, doi: 10.30591/polektr.v9i2.2047.
- [4] A. Saberian, H. Hizam, M. A. M. Radzi, M. Z. A. Ab Kadir, and M. Mirzaei, "Modelling and prediction of photovoltaic power output using artificial neural networks," *Int. J. Photoenergy*, vol. 2014, pp. 1–10, 2014, doi: <https://doi.org/10.1155/2014/469701>.
- [5] R. Ahmed, V. Sreeram, Y. Mishra, and M. D. Arif, "A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization," *Renew. Sustain. Energy Rev.*, vol. 124, no. June 2019, 2020, doi: <https://doi.org/10.1016/j.rser.2020.109792>.
- [6] L. Liu, D. Liu, Q. Sun, H. Li, and R. Wennersten, "Forecasting Power Output of Photovoltaic System Using A BP Network Method," *Energy Procedia*, vol. 142, pp. 780–786, 2017, doi: <https://doi.org/10.1016/j.egypro.2017.12.126>.
- [7] A. Khandakar *et al.*, "Machine Learning Based Photovoltaics (Pv) Power Prediction Using Different Environmental Parameters Of Qatar," *Energies*, vol. 12, no. 14, 2019, doi: <https://doi.org/10.3390/en12142782>.
- [8] F. Rahman, M. Rokhmat, and I. W. Fathonah, "Analysis of Effect of Solar Cell Surface Temperature on Output Power Capacity," 2020. [Online]. Available: <https://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/view/12906>
- [9] H. K. Putra, S. Handoko, and I. Setiawan, "Design of Voltage Level Up System in Stand – Alone Photovoltaic System Using Quadratic Boost Converter with Proportional – Integral Method Based on Dspic Microcontroller," *Transient J. Ilm. Tek. Elektro*, vol. 9, no. 3, pp. 327–333, 2020, doi: 10.14710/transient.v9i3.327-333.
- [10] Suwitno, Y. Rahayu, R. Amri, and E. Hamdani, "Design of a DC to DC Converter to Stabilize the Output Voltage of a Solar Cell Panel Using Boost Converter Technology," *J. Electr. Technol.*, vol. 2, no. 3, pp. 61–66, 2017, [Online]. Available: <https://jurnal.uisu.ac.id/index.php/jet/article/view/240>
- [11] U. N. Choirah and U. T. Kartini, "Forecasting Very Short Term Photovoltaic Power Using the Decomposition Backpropagation Neural Network (D-BPNN) Method," *J. Tek. Elektro*, vol. 09, no. 03, pp. 549–559, 2020, doi: <https://doi.org/10.26740/jte.v9n3.p%25p>.
- [12] S. Amely Jumaat, F. Crocker, M. Helmy Abd Wahab, N. Hanis Mohammad Radzi, and M. Fakri Othman,

- “Prediction of Photovoltaic (PV) Output Using Artificial Neural Network (ANN) Based on Ambient Factors,” *J. Phys. Conf. Ser.*, vol. 1049, no. 1, 2018, doi: 10.1088/1742-6596/1049/1/012088.
- [13] L. Mahendra, J. Maknunah, B. Herwono, Y. Angraini, and K. Nisa, “Prediction of Pv Output Power Based on Neural Networks in Tangerang Shopping Centers,” in *Conference on Innovation and Application of Science and Technology (CIASTECH 2021)*, 2021, no. Ciastech, pp. 335–342. [Online]. Available: <https://publishing-widyagama.ac.id/ejournal-v2/index.php/ciastech/article/view/3327/1784>
- [14] M. B. A. Shuvho, M. A. Chowdhury, S. Ahmed, and M. A. Kashem, “Prediction of solar irradiation and performance evaluation of grid connected solar 80KWp PV plant in Bangladesh,” *Energy Reports*, vol. 5, pp. 714–722, 2019, doi: <https://doi.org/10.1016/j.egy.2019.06.011>.
- [15] C. R. Chen and U. T. Kartini, “K-Nearest Neighbor Neural Network Models for Very Short-Term Global Solar Irradiance Forecasting Based on Meteorological Data,” *Energies*, vol. 10, no. 2, 2017, doi: 10.3390/en10020186.
- [16] D. Huang and Z. Wu, “Forecasting outpatient visits using empirical mode decomposition coupled with backpropagation artificial neural networks optimized by particle swarm optimization,” *PLoS One*, vol. 12, no. 2, pp. 1–17, 2017, doi: 10.1371/journal.pone.0172539.
- [17] L. Gu, Y. Han, C. Wang, G. Shu, J. Feng, and C. Wang, “Inventory prediction based on backpropagation neural network,” *NeuroQuantology*, vol. 16, no. 6, pp. 664–673, 2018, doi: 10.14704/nq.2018.16.6.1608.
- [18] S. Hao, “Using multifactor inputs BP neural network to make power consumption prediction,” Binghamton University, 2018. [Online]. Available: <https://www.proquest.com/openview/88b031c5a6060e8e6a06a1aabc56b1ad/1?pq-origsite=gscholar&cbl=18750>
- [19] A. Fathurachman and A. Najmurokhman, “Design of a Boost Converter for a Solar Power Generation System,” 2015. [Online]. Available: [http://repository.unjani.ac.id/index.php?p=show\\_detail&id=486&keywords](http://repository.unjani.ac.id/index.php?p=show_detail&id=486&keywords)
- [20] R. Ayop and C. W. Tan, “Design of boost converter based on maximum power point resistance for photovoltaic applications,” *Sol. Energy*, vol. 160, pp. 322–335, 2018, doi: <https://doi.org/10.1016/j.solener.2017.12.016>.
- [21] I. L. Sirait, J. M. Gultom, J. Tindaon, R. J. Tampubolon, and W. J. Mawaddah, “Forecasting Soybean Productivity Levels in Indonesia Using the Backpropagation Algorithm,” *semanTIK*, vol. 4, no. 2, pp. 183–192, 2018, doi: 10.5281/zenodo.2528152.
- [22] A. Wanto, “Analysis of backpropagation neural networks using conjugate gradient fletcher reeves in the predicting process,” Universitas Sumatera Utara, 2017.
- [23] S. Setti and A. Wanto, “Analysis of Backpropagation Algorithm in Predicting the Most Number of Internet Users in the World,” *J. Online Inform.*, vol. 3, no. 2, p. 110, 2019, doi: 10.15575/join.v3i2.205.
- [24] A. Wanto, “Optimization of Prediction With Backpropagation Algorithm and Conjugate Gradient Beale-Powell Restarts,” *J. Nas. Teknol. dan Sist. Inf.*, vol. 3, no. 3, pp. 370–380, 2018, doi: 10.25077/teknosi.v3i3.2017.370-380.
- [25] D. Sinaga, S. Solikhun, and I. Parlina, “Artificial Neural Network to Predict Palm Oil Sales Using Backpropagation Algorithm,” in *Prosiding Seminar Nasional Riset Information Science (SENARIS)*, 2019, vol. 1, pp. 418–426. doi: 10.30645/senaris.v1i1.047.