Trends in Renewable Energy
OPEN ACCESS ISSN: 2376-2144
Peer-Reviewed Article futureenergysp.com/index.php/tre

Backpropagation Neural Network (BPNN) Algorithm for Predicting Wind Speed Patterns in East Nusa Tenggara

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Received March 8, 2022; Accepted April 4, 2022; Published April 10, 2022

The Paris agreement compels all countries to make major contributions to the zero-emission scheme, a legally binding international treaty on climate change. This fulfilment must be supported by technological developments towards Society 5.0, forcing every country to develop renewable energy (clean energy) on a large scale. One of the renewable energies with the highest efficiency is wind power generation. Its construction requires a large cost, and the best location must consider the high wind speed. East Nusa Tenggara Province is one of the locations in the border area with insufficient electricity. The choice of location was supported by military operations in guarding the border which required a lot of energy. Therefore, it is necessary to predict wind speed patterns based on historical data from the database so that wind power plants can be realized. One of the best methods for long-term prediction of wind speed is the backpropagation neural network (BPPN) method. Wind speed data was used from January 2003 to December 2020 with a total of 216 data sets obtained from NASA. It should be noted that January 2003 to December 2010 data is positioned as input data, while training target data is from January 2011-December 2015. Validation data is determined from January 2016-December 2020. The best predictive architecture model is 8-11-5- 5, learning rate is 0.4 and epoch is 20,000. Prediction accuracy is very good with a mean square error (MSE) value of 0.007634 and a mean absolute percentage error (MAPE) of 11.62783. The highest wind speed was shown in February 2018 as 10.75 m/s.

Keywords: *BPPN, Wind Speed, MSE, MAPE, East Nusa Tenggara*

Introduction

Adaptation of technological developments from digital 4.0 to society 5.0 forces humans to have three main abilities that need to be possessed (namely creativity, critical thinking, communication and collaboration) [1]. This is because society 5.0 was initiated by the Japanese state. This concept allows us to use modern science-based (AI, Robot, and Internet of Things) for human needs with the aim that humans can live comfortably [2]. Society 5.0 was inaugurated 2 years ago, on January 21, 2019, and was made as a resolution to the industrial 4.0 resolution [3].

The main problem faced by humans today is the transition of clean energy to a net-zero emission condition [4]. The condition of Net Zero Emission necessitates the massive development of renewable energy [5]. One of the renewable energies with the

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Tr Ren Energy, 2022, Vol.8, No.2, 107-118. doi: 110.17737/tre.2022.8.2.00143

greatest electrical efficiency is wind power generation [6]. A wind power plant is a generator that utilizes wind pressure at a high enough speed to drive a turbine to produce electrical energy. However, its development is limited due to its intermittent nature due to changes in wind direction and wind circulation, thus requiring accurate prediction of wind circulation patterns in an area, especially in borderline, remote and less developed areas of Indonesia [7].

Indonesia is a country traversed by the equator and surrounded by two oceans and two continents. This position makes Indonesia a region that has a tropical climate [8]. Climate is a natural habit driven by a combination of factors such as solar radiation, temperature, humidity, rainfall, air temperature, air pressure and wind pressure [9]. One of the border areas in Indonesia is the province of East Nusa Tenggara [10].

The development of infrastructure in border areas must be increased for the sake of sustainability and equal human rights [11]. Apart from that, the use of radar and military operations for guarding the border areas must be fully supported by the availability of energy [12]. Therefore, wind speed prediction is needed to drive turbines from windmills to produce electrical energy [13]. However, the changing wind speed causes the efficiency of the electrical energy produced to decrease [14]. Climate change in the world has many impacts on changes in wind speed patterns [15]. For that, we need a method that can predict wind speed based on wind speed patterns that occur after climate change. Renewable energy development is accelerating with accurate information about how much wind speed will occur in East Nusa Tenggara in a certain period.

One of the machine learning methods that make predictions based on patterns in the available data is the backpropagation neural network method [16-20]. The Backpropagation Neural Network Algorithm (BPNN) is a supervised learning algorithm consisting of a perceptron with several layers to change the weights associated with the neurons in the hidden layer [21]. The principle of the Backpropagation Neural Network Algorithm can be seen in Figure 1. The backpropagation algorithm utilizes the output error to change/improve the weight value in the backward direction. Attempts to get the initial error by skipping the previous forward propagation.

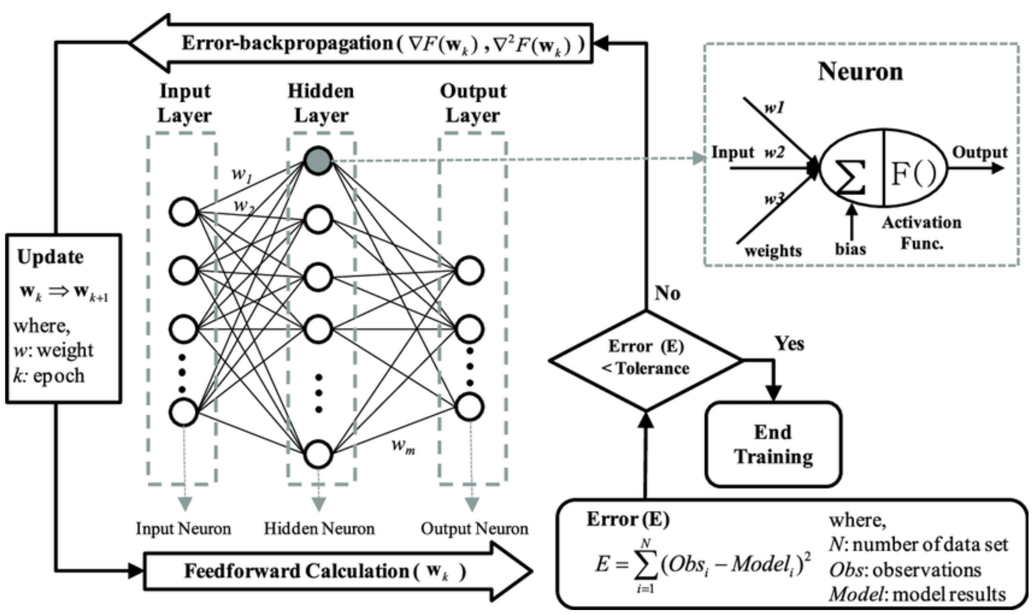


Figure 1. Diagram of Backpropagation Neural Network Algorithm [22]

Data Source and Methods

Overall wind speed range data from January 2003 to December 2020 is taken from "https://power. larc.nasa.gov/data-access-viewer/" (NASA Power Data) with a point location of Latitude -8.6048 and Longitude 121.1418 in East Nusa Tenggara, Republic of Indonesia. The training data used in this study is from January to December 2003-2015, while validation uses data from January-December 2016-2020.

Backpropagation Neural Network (BPNN) Method

The Backpropagation Neural Network (BPNN) method was originally introduced by Paul Werbos in 1974, then re-admitted by Rumelhart and McCelland in 1986 [23]. In the BPNN algorithm, network architecture uses a multilayer network. Basically, the BPNN architecture consists of three layers, namely the input layer, hidden layer and output layer. For the input layer, there is no computational process, but at the input layer, the input signal is sent to the hidden layer [24]. In the hidden and output layers, there is a computation process on the weights and biases and the magnitude of the output from the hidden and output layers is calculated based on certain activation functions. Meanwhile, the activation function usually uses binary sigmoid with the output value 0-1 [25-26]. The BPNN flowchart can be seen in Figure 2

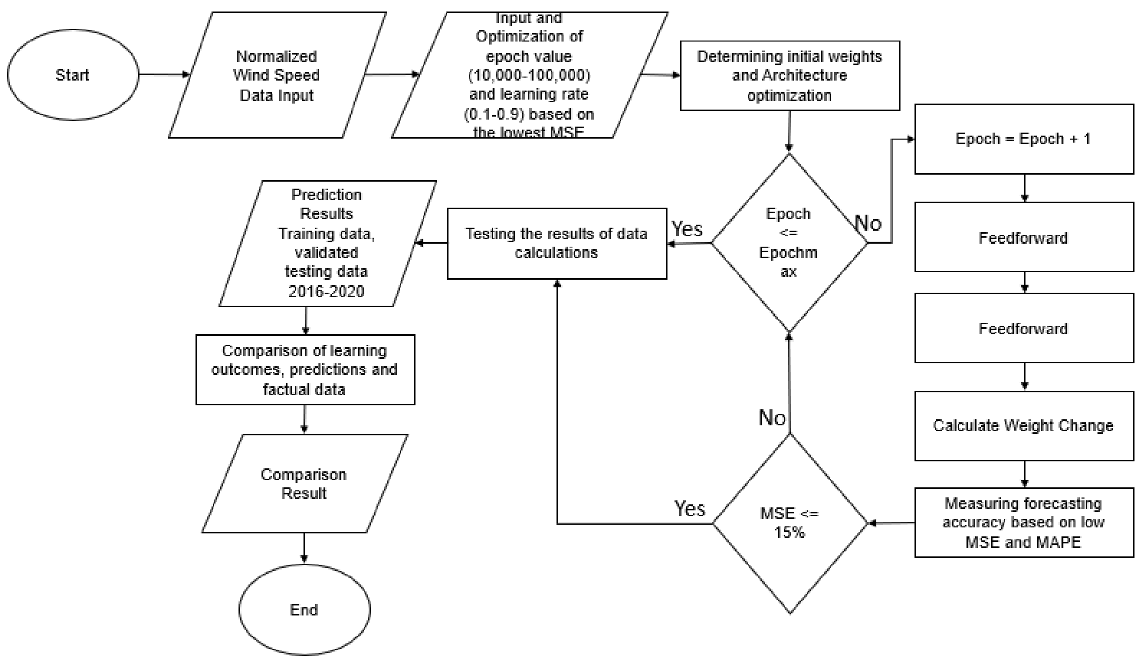


Figure 2. Flowchart Backpropagation Neural Network

The steps that need to be taken for BPNN training are:

1. Initialize weights with small random values.
2. As long as the stop condition is not met, do steps 3 – 8

Step 1: Feedforward

3. Each input unit (xi, =1,.....,n) receives the input signal xi and is forwarded to the hidden layer units.

4. Each hidden unit (zj, =1,.....,p) adds up the weight of the input signal by equation (1).

$$Z_{in_{jk}} = v_{0f} + \sum_{i=1}^{n} x_i v_{ij} \tag{1}$$

where Z are hidden neurons; v_{0f} is the bias weight neuron of the j; x_i input neuron for i; and v_{ij} input is the weight of the input neuron to the hidden neuron.
The application of the activation function is calculated by equation (2).

$$Z_j = f(Zin_j) \tag{2}$$

where Z_j is unit for -j in the hidden layer; and Z_{inj} is the output for Z_j unit. For example, the activation function used is sigmoid with equation (3).

$$Y = f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The sigmoid activation function sends this signal to all units on the output unit.
5. Each output unit (yk, = 1,.....,) adds a weighted input signal using equation (4).

$$Y_{in_k} = w_{0k} + \sum_{k=1}^{p} z_j w_{jk} \tag{4}$$

where Y_{in_k} is output for yk unit; w_{0k} is bias weight for hidden neurons for-k; Z_j is unit for-j in hidden layer; and w_{jk} is hidden neuron weights to output neurons.
By applying the activation function calculated by equation (5).

$$Y_k = f(Yin_k) \tag{5}$$

where Y_{in_k} is output fot Y_k unit.

Step 2: Backward

6. Each output unit (yk, =1,.....,m) receives its input training pattern. Calculate the error (error) for each layer with equation (6).

$$\delta_k = (t_k - y_k) f'(y_{in_k}) \tag{6}$$

where δ_k is a correction factor of w_{jk}; t_k is target; y_k is output neuron for k; and y_{ink} is output fot y_k unit.
Calculate the weight and bias correction using equation (7).

$$\Delta w_{jk} = \alpha \delta_k x_j \tag{7}$$

$$\Delta w_{jk} = \alpha \delta_k$$

where Δw_{jk} = is the difference between w_{jk} (t) with $w(t+1)$; Δw_{0k} is the weight of bias for is hidden k; α is a learning rate; δ_k is the weight correction factor w_{jk}; and x is the input.
7. Each hidden unit (zj, =1,......,) adds up its input delta (from the units in its upper layer) with equation (8).

$$\delta_{in_j} = \sum_{k=1}^{p} \delta_k w_{jk} \tag{8}$$

where the δ_k is the correction factor of w_{jk}; and w_{jk} is the weight of neurons hidden to the output neuron. Calculate the error (error) for each layer with equation (9).

$$\delta_j = \delta_{in_j} f(x_{in_j}) \tag{9}$$

where δj is the correction factor of vij; δ_{inj} is the correction factor; x are inputting. Calculate the weight and bias correction with equation (10).

$$\Delta v_{ij} = \alpha \delta_j x_i \tag{10}$$

where Δv_{ij} is the weight of the input neuron to the hidden neuron; α is learning rate; δ_j is the weight correlation factor v_{ij}; and x_i is neuron input for i.

Step 3: Update Weight

8. Each output unit (yk, =1,.....) updates the weight, and bias (j = 0.1,..p) is calculated by equation (11).

$$w_{jk}(new) = w_{jk}(initial) + \Delta w_{jk} \tag{11}$$

where w_{jk} is the weight of hidden neurons to output neurons; and Δw_{jk} is the difference between the weights of the hidden neurons and the output neurons. Each hidden unit (zj, = 1,…) updates the weight, and its bias (i = 0.1,..n) is calculated by equation (12).

$$v_{ij}(new) = v_{ij}(initial) + \Delta v_{ij} \tag{12}$$

where v_{ij} is the weight of the input neuron to the hidden neuron; and Δv_{ij} is the difference in the weights of the input neurons to the hidden neurons.

9. Maximum input epoch will stop automatically

Forecast Accuracy

The Validation stage in BPNN serves to measure the accuracy of the resulting learning using the Mean Squared Error (MSE) method. Data Validation also aims to find forecasting errors in each period. The measurement of accuracy will later be divided by the number of forecasting periods that have been used [27]. The formula for calculating the MSE accuracy measurement can be seen in equation (13).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (r_i - \hat{r}\, i)^2 \tag{13}$$

where Υi is factual value, $\hat{r}_i$ is prediction value and n is number of periods or targets.

In particular, the determination of the best architectural optimization indicator is determined by the Mean Absolute Percentage Error (MAPE) value [28]. MAPE is a measure of predictive variation for forecasting methods in statistics, usually serveing to reveal the accuracy of the ratio determined by equation (14)

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \tag{14}$$

A. Data Sample

The wind speed data used were a total of 216 datasets obtained from NASA from January 2003 to December 2020. It should be noted that January 2003 to December 2010 data is positioned as input data and the data from January 2011-December 2015 is used as training target. Validation data is determined from January 2016-December 2020. Each data set is normalized within a range of 0.1-0.9 using the equation (15) [29] with the results of data normalization shown in Tables 1 and 2 and Figure 3.

$$X' = \frac{0.8(X-b)}{(a-b)} + 0.1 \tag{15}$$

The value of X' is the normalized data, a is the maximum value of factual data, b is the minimum value of factual data, and X is factual data. Next, the prediction calculation process is carried out using the BPNN algorithm. Prediction results are denormalized to get the predicted results to their original form. The formula for calculating the denormalization of the data is equation (16) [30].

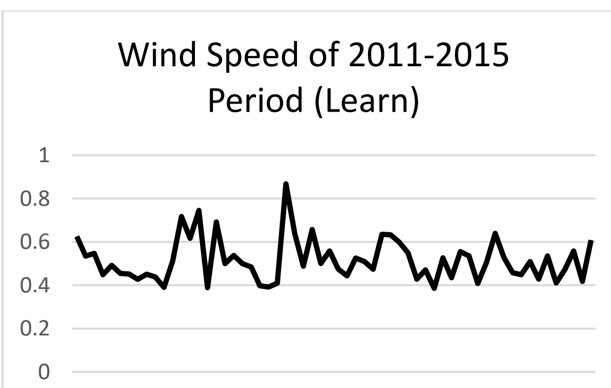
$$X = \frac{(X'-0.1)(b-a)+0.8a}{0.8} \tag{16}$$

Table 1. Wind speed of 2011-2015 period actual (Learning)

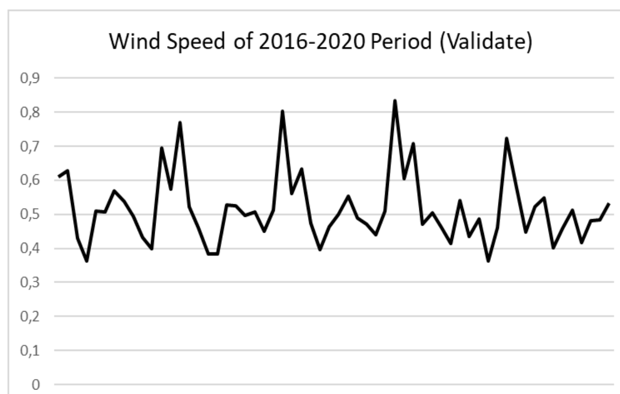
Month	Year (m/s in normalization scale)				
	2011	2012	2013	2014	2015
January	0.625444	0.716737	0.868216399	0.632883	0.639645
February	0.53415	0.616653	0.638968724	0.597718	0.52874
March	0.546999	0.745139	0.487489434	0.549028	0.457735
April	0.448267	0.388757	0.657227388	0.42798	0.448267
May	0.491547	0.691716	0.500338123	0.470583	0.509129
June	0.454353	0.499662	0.557819104	0.385376	0.42798
July	0.451648	0.537532	0.474640744	0.526036	0.534827
August	0.427303	0.499662	0.44353339	0.434742	0.410397
September	0.450972	0.484108	0.525359256	0.555114	0.473288
October	0.438123	0.397549	0.509129332	0.534827	0.557819
November	0.39011	0.391462	0.473964497	0.407692	0.417836
December	0.511158	0.409045	0.634911243	0.503719	0.608538

Table 2. Wind speed of 2016-2020 period actual (Validate)

Month	Year (m/s in normalization scale)				
	2016	2017	2018	2019	2020
January	0.60989	0.574725	0.80262	0.834404	0.722147
February	0.628825	0.769484	0.561877	0.605156	0.590279
March	0.430685	0.522654	0.632883	0.70727	0.448267
April	0.362384	0.461116	0.473288	0.470583	0.521302
May	0.509806	0.384024	0.397549	0.504396	0.549028
June	0.507101	0.384024	0.464497	0.461792	0.40093
July	0.569315	0.527388	0.498309	0.415131	0.457058
August	0.537532	0.526036	0.553085	0.540237	0.511158
September	0.493576	0.496957	0.490194	0.436095	0.416484
October	0.43339	0.507777	0.469907	0.487489	0.480727
November	0.398901	0.451648	0.439476	0.362384	0.484784
December	0.695773	0.511834	0.509129	0.461116	0.533474



(a)



(b)

Figure 3. (a) Graph of wind speed for the period 2011-2015 Factual (Learn) (b) Graph of wind speed for the period 2016-2020 Factual (Validate)

Results and Discussion

Wind speed predictions have been made from 2016-2020, and the data is generated from the optimization process to get the best learning rate and epoch. Learning rate and epoch are said to have the most ideal values when the resulting MSE parameter is very small. Therefore, optimization is carried out utilizing an input learning rate from 0.1-0.9. The number of epochs further optimized from 100 to 1000 with a step of 100. If the resulting accuracy is still low, the optimization is increased by the number of epochs from 1000 to 10,000 with a step of 1000. If the MSE accuracy still does not meet, then re-optimize the epoch value from 10,000 to 100,000 with Steps 10,000 (to get the best MSE score). The graph of the relationship between epoch optimization and learning rate on the MSE value is shown in Figure 4.

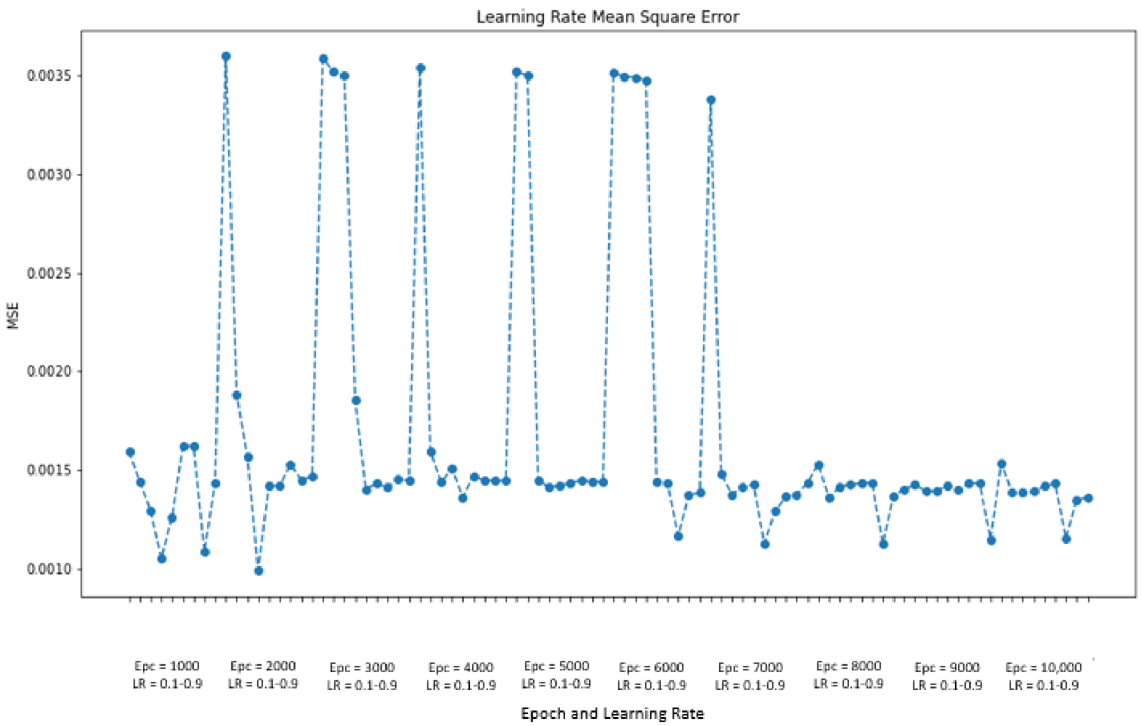


Figure 4. Graph of the relationship between epoch value and learning rate on MSE

Based on Figure 4, it can be seen that the distribution of the best epoch values and learning rate is based on the lowest MSE value. Figure 4 shows that the lowest MSE value is only 0.0001% (below 0.0010%) with the best learning rate parameter of 0.4 and the best epoch value is 20,000. This is the same as the parameter reported by Rozycki *et al.* [31]. However, the epoch and learning rate parameter values are not necessarily universally applicable to all data, but only applies to certain datasets. Therefore, before making predictions, it is better to optimize learning rate and epoch, which is the same as reported by Wanto *et al.* [32]. If all the best optimization parameters are obtained, then predictions are made using the BPNN method to produce the values in Table 3.

It can be seen that BPNN learning-prediction predicts the information/parameters from Layer, Epoch, Learning rate, MSE and MAPE as a whole during the learning process and validation process.The results of the optimization of the architectural model at the learning stage are 8-7-5, the learning rate is 0.4, and the epoch is 20,000. The model has obtained very good accuracy with MSE = 0.000552 and MAPE = 2.942524. These parameters can also predict validation data from 2016-2020 with fairly good accuracy with MSE Validate values = 0.00903 and MAPE Validate = 14.3468. This result is an ideal value, because the MAPE value is below 15%. This is following what was reported by Okumus *et al.* [33]. So, the learning process has met the requirements for use in the prediction process. But further optimization is needed for the prediction process, because the prediction stage is the most important stage for predicting wind speed patterns that may occur in East Nusa Tenggara.

Table 3. Best parameters of prediction wind speed with BPNN

Variable Result	Type	Value		
		Hidden Layer	**Neuron Hidden Layer**	**Architectures**
Layer	Learning	1	7	8-7-5
	Prediction	2	11 5	8-11-5-5
Epoch and Learning Rate	Learning	20,000 and 0.4		
	Prediction	20,000 and 0.4		
MSE (%)	Learning	0.000552		
	Prediction	0.001416		
MAPE (%)	Learning	2.942524		
	Prediction	5.982144		
Validate MSE (%)	Learning	0.00903		
	Prediction	0.007634		
Validate MAPE (%)	Learning	14.3468		
	Prediction	11.62783		

Based on Table 3, the data prediction process produces the best parameters with an 8-11-5-5 architectural model, a learning rate of 0.4 and 20,000 epochs. The best parameter is calculated based on the lowest value of MSE = 0.001416% and MAPE = 5.982144%. This value is quite large when compared to the results of the learning process. The learning architecture model (8-7-5) and predictions (8-11-5-5) have very low MSE and MAPE values, but these values are not absolute for data validation cases. This is indicated by the value of each MSE and MAPE which increases in the validation case. The Prediction Architecture Model has a relatively small accuracy of Validate MSE and Validate MAPE values of 0.007634 and 11.62783, respectively. When compared to the learning model, the predictive architectural model (8-11-5-5) is much more predictable than learning architecture (8-7-5). The accuracy is acceptable. this is relevant to the validated MSE and MAPE values reported by Saputra *et al.* [34]. The comparison graph between the best architecture for the learning process and the best architectural model for the prediction process against the actual/target value is shown in Figure 5.

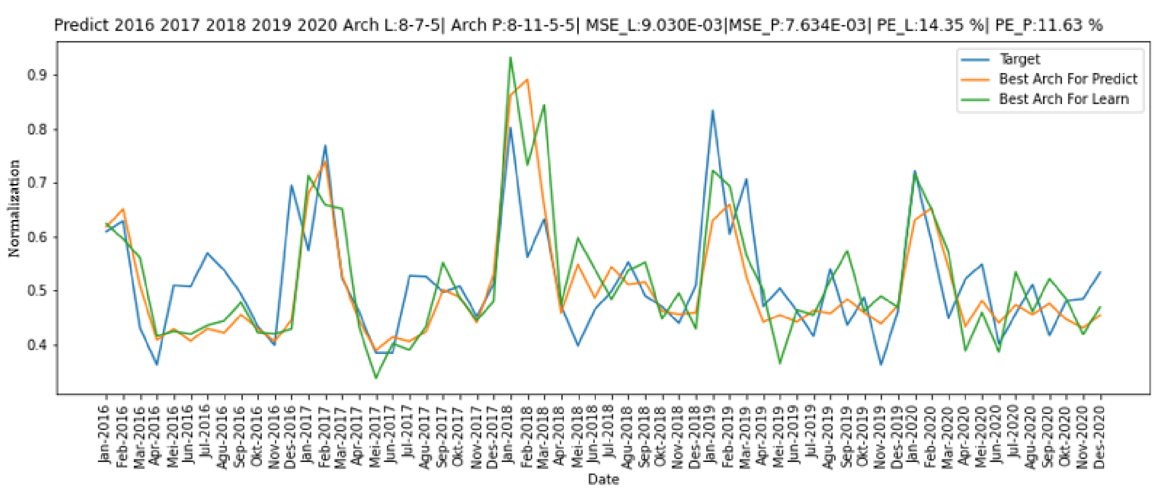


Figure 5. Graph of All Predict Process 2016-2020 (-- = Actual data/Target), (-- = 8-7-5/Best Architecture for learn), and (-- = 8-11-5-5/Best Architecture for predict)

Based on Figure 5, it can be seen that the blue line is the actual/target data, the green line is the learning data (the best Learning Architecture Model) and the yellow line is the predictive data (the best Prediction Architecture Model). The figure shows that the predicted wind speed pattern and learning have followed the actual/target data pattern that occurred in the field. The biggest deviation occurred in April 2016-August 2016. The large deviation in the learning model and predictions has the potential to be caused during the learning data process in 2011-2015 as shown in Figure 3(a). It can be seen that there is no peak or increase in wind speed data at the beginning of the graph pattern. So during validation, just comparing the data (where there is no learning process) leads to a sufficiently large deviation, but still tolerable. Therefore, it can be seen that an unusual natural phenomenon occurred because it disrupted the wind speed pattern from the year before and after.

Based on a report from the Kupang Meteorology, Climatology and Geophysics Agency stating the potential for natural phenomena that may occur in the East Nusa Tenggara region, every season transition is always interspersed with strong winds reaching 55 km/hour and rain with light to moderate intensity. In the Australian monsoon, there is movement the east-southeast wind to pass through East Nusa Tenggara once every two weeks, especially in June and July, even until August of the current year. However, this year, due to high climate deviations, the impact began to be felt in May and generally the Australian monsoon brings dry winds or heat from southern Australia to East Nusa Tenggara [35]. The results of the 2016-2020 wind speed prediction using the 8-11-5-5 architectural model are shown in Table 4.

Table 4. Wind Speed of 2016-2020 Prediction Denormalization Data (Validate)

Month	Year				
	2016 (m/s)	2017 (m/s)	2018 (m/s)	2019 (m/s)	2020 (m/s)
January	7.03725877	7.880751271	10.3559324	7.201820081	7.213083189
February	7.483151795	8.678004264	10.75178206	7.598292216	7.504696284
March	5.55199223	5.790933574	7.541137783	5.771525779	5.996668358
April	4.185202364	4.678376886	4.863762873	4.635143496	4.516272922
May	4.463298459	3.921113849	6.092103254	4.812364779	5.175955238
June	4.159088526	4.259921358	5.242626127	4.636795741	4.614035022
July	4.473087999	4.146567424	6.027708108	4.928017121	5.066550994
August	4.36522963	4.401729795	5.583364054	4.854122467	4.827021693
September	4.822082341	5.448518907	5.647863928	5.210321353	5.101519002
October	4.466720284	5.264611714	4.912645469	4.875180557	4.699240739
November	4.15191332	4.624395073	4.831298121	4.596285319	4.494179964
December	4.684534993	5.832190394	4.871558433	5.047697892	4.805826726

CONCLUSIONS

Wind speed prediction analysis in East Nusa Tenggara Province using the Backpropagation Neural Network (BPNN) method has been implemented. Based on the results of the approach, the BPNN method divides the Learning Phase from the January 2011-December 2015 data and the Validation Phase on the January 2016-December 2020 data. The best predictive architecture model is 8-11-5-5, the learning rate is 0.4 and the epoch is 20,000. The prediction accuracy is very good with MSE Validate value of 0.007634 and MAPE Validate of 11.62783. The highest wind speed was shown in February 2018 as 10.75 m/s. Therefore, the BPNN method can be an alternative in predicting wind speed in East Nusa Tenggara Province, so that it can be taken into consideration in building wind power plants. Future work can use other prediction methods to increase the confidence of the current predictive value.

ACKNOWLEDGMENTS

This research was supported and funded by Indonesia Defense University, Faculty of Defense Management, Department of Energy Security.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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