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Short-term active power forecasting for wind farms using artificial neural networks

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ABSTRACT

These days, wind energy plays an increasingly crucial role in the energy sector, posing challenges in its management and operation. Given the current upgrade of Vietnam's 500 kV grid infrastructure, wind farms are concentrated in specific regions. This concentration can lead to significant power influxes into the grid at certain times, causing grid overcurrent. Hence, the National Load Dispatch Center is currently regulating power generation based on forecasted data from generating units. Therefore, short-term power forecasting for wind farms is crucial to mitigate grid overcurrent. This article proposes a short-term forecast of active power in wind farm using a model based on Artificial Neural Network (ANN) on Matlab platform. In the process of building the ANN model, this article considers eliminating the impact of capacity regulation on the power grid. The model was tested using real data from the Ia Pết Đăk Đoa 1 wind farm in Gia Lai province. The time forecast is given in 15-minute intervals for the next 4 hours. The collected results show the superiority of the method in forecasting with low errors and saving calculation time.

1. INTRODUCTION

In recent years, due to the scarcity of fossil fuels and the urgency of the need to protect the environment, renewable energy has become an important choice and accounts for an increasingly high proportion in the power grid of the world. From Global Wind Report 2024 (GWEC, 2024), it is showed that the growth rate of the renewable energy industry in the recent 5 years has always exceeded that of other electric energy industries. As of November 1, 2021, Vietnam Electricity reported 84 wind power plants in commercial operation, totaling 3,980.27 MW of capacity. After the above period, there are still more than 62 projects that have signed electricity sales contracts but have not been completed and deployed while waiting for the new pricing mechanism for transitional projects. In addition, Power Development Plan 8, approved by the Vietnamese Government on May 15, 2023, also clearly mentioned the viewpoint of strongly developing renewable energy sources for electricity production reaching a rate of about 30.9 - 39.2% by 2020. 2030, with a vision to 2050, the proportion of renewable energy will reach 67.5 - 71.5%. With wind power, by 2030, onshore wind power capacity will reach 21,880 MW (Vietnam's total technical potential is about 221,000 MW). Offshore wind power serves domestic electricity demand of about 6,000 MW. Estimated offshore wind power capacity to produce new energy is about 15,000 MW by 2035 and about 240,000 MW by 2050 (Government of Viet Nam, 2023).

Accurate forecasting of the capacity of renewable power sources plays a very important role in ensuring efficiency and optimization in power system operation. Forecasting the capacity of renewable power sources is essential for planning, managing, and operating the power system. With the current situation when wind power plants are often concentrated in certain areas at certain times, a large amount of capacity flows to the power grid, causing an overcurrent of the power grid amid grid upgrades. The 500 kV power line is still under construction and has not been completed.

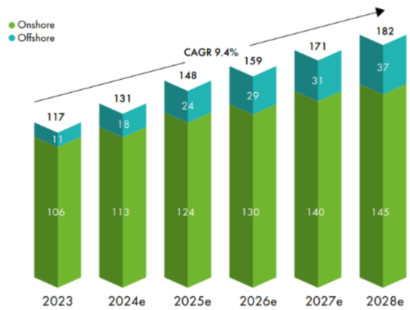

Figure 1. New installations outlook 2024–2028 (GW) (GWEC, 2024)

Currently, The National Load Dispatch Center is considering the capacity forecast factor in its capacity dispatching work for the power system. The need to perform short-term capacity forecasts with a forecast period of 15 minutes over the next 4-hour period for wind farm generating units is very important to help limit overcurrent on the grid as well as choosing higher generating capacities to help increase profits for wind farm (Electricity Regulatory Authority Of VietNam, 2021).

There have been many studies on wind power generation capacity forecasting with different methods proposed. In the article (Wang et al., 2021) the author divided the types of forecasting into 4 types as Figure 2: Time scale, Forecasting by objective, Type of forecast and Modeling theory. There are many forecasting methods that have been and being used for renewable energy power sources with forecast time frames ranging from a few weeks to just a few minutes such as Ultra-short term wind power forecasting based on LSTM neural network (Li et al., 2019), A Double-Stage Hierarchical Hybrid PSO-ANN Model for Short-Term Wind Power Prediction (Eseye et al., 2017), Wind Speed and Wind Power Forecasting using Statistical Models: AutoRegressive Moving Average (ARMA) and Artificial Neural Networks (ANN) (Gomes & Castro, 2012), Investigation and application of deep learning in wind power forecasting (Viet et al., 2021), Short-term forecasting wind power using feedforward neural network (An & Phuong, 2023), etc.

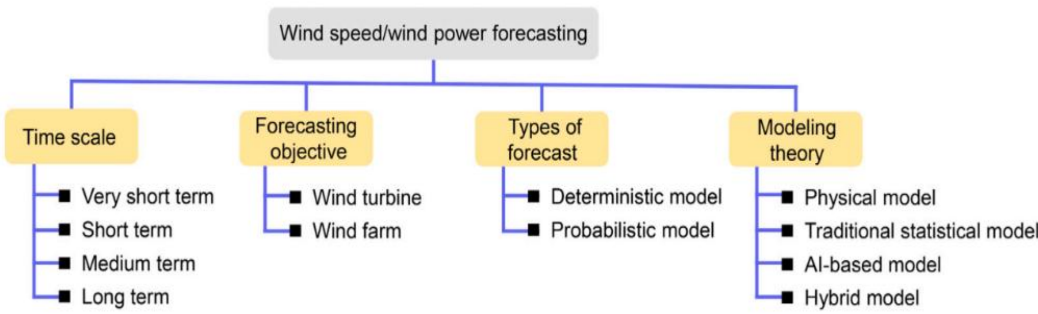

Figure 2. Classification of WS/WP forecasting (Wang et al., 2021)

Although there are many forecasting methods, there are still many limitations to apply in practice at wind power plant in Vietnam, depending on the unique characteristics of each wind power plant as well as the continuous participation in Automatic Generation Control (AGC) leads to success. The generation rate is greatly regulated, requiring research and application of appropriate wind power generation capacity forecasting methods (Ngoc, 2020). The proposed method is to apply the ANN model to forecast short-term generation capacity at the Ia Pet Dak Doa 1 wind farm with a capacity of 99 MW, including 22 turbines, considering the impact of power regulation on the grid. The data collected in the past of the wind farm including: Time, Actual Active Power, Active power setpoint from National Load Dispatch Center (NLDC), Possible Active Power. In particular, the model provides quick calculation results, meeting the needs of operating the ever-changing electricity market. Using artificial neural network to model and simulate complex electrical systems and predict turbine generation capacity in reality is a suitable choice.

2. MATERIALS AND METHOD

2.1. Artificial neural network algorithm

There are many types of artificial neural network. In the proposed prediction method, a single-layer, feed-forward artificial neural network is used. Artificial neural network are designed to be similar to biological neurons. The mathematical model for artificial neurons was first studied by McCulloch-Pitts in 1943 (McCulloch & Pitts, 1943). In a neural network, each neuron is a network node. To facilitate the construction of artificial neural network, it is stipulated that the neural network is divided into three layers: input layer, middle layer (hidden layer), and output layer. Information in each previous layer neuron must be transmitted to all subsequent layer neurons. The computation process is carried out in parallel and distributed across many neurons almost simultaneously. This calculation process is called the learning process. Specifically, when a signal x is input to the beginning of the neuron coupling channel, at the end of the channel we will have an amplified signal with weight w as Figure 3 (Rajendra et al., 2019).

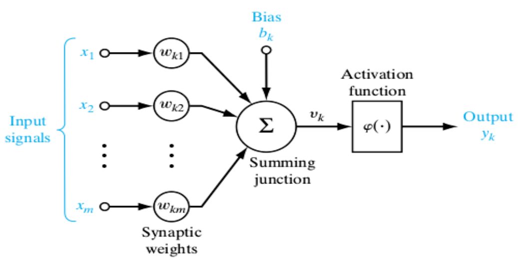

Figure 3. Nonlinear neuron model (Rajendra et al., 2019)

$$u = \sum_{i=1}^{m} x_i . w_{ki} + b_k \qquad (1)$$

In there:

- $\mathbf{x_i}$ is the inputs.

-$\mathbf{w_k}$ is the connection weights.

- $\mathbf{b_k}$ is the activation threshold.

- **φ** is the activation function.

- **u** is the total input response.

Before being sent to the next neurons or output, the synthesized signals will be passed through the activation function. Based on the activation function, neurons may or may not produce an output in the ANN

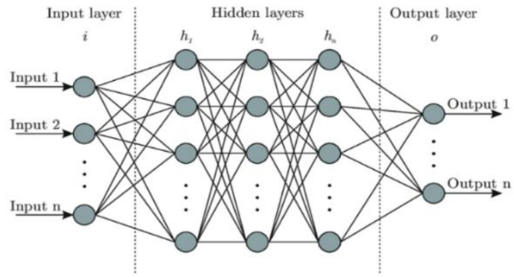

Figure 4. Neural Network (Sharma et al., 2020)

$$y = \begin{cases} 1 \text{ when } \varphi(u) \geq 0 \\ 0 \text{ when } \varphi(u) < 0 \end{cases} \qquad (2)$$

In there:

- **y** is the output response.

- **φ** is the activation function.

- **u** is the total input response.

With a data set consisting of m samples {**φ**(u_i) ,y_i} with i = 1,2,…, m. Input value **φ**(u), desired value y, we can use the objective function which is the sum of squared errors (Gupta & Raza, 2019).

$$E = \frac{1}{2}\sum_{i=1}^{m}(\varphi(u_i) - y_i)^2 \rightarrow \min \qquad (3)$$

In there:

φ(u) is the calculated output

E is the sum of squared errors

y is the actual output.

During the training process, ANN is performed through the error mechanism between the output layer and reality, which will be transmitted back to fine-tune the weights between connections. The model's weights are initialized from small random values and updated by the optimization algorithm during the backward process. The update is based on the prediction error (loss) during training. This will be done using a method called gradient descent. When the derivative is negative, the weight should be increased, when the derivative is positive, the weight should be decreased. The general architecture of the artificial neural network used for prediction is shown in Figure 4 (Sharma et al., 2020). In the figure, the neural network includes 3 layers: input layer, hidden layer, and output layer. Each hub in the input layer gets the esteem of a free variable and passes it into the network. Data from all nodes in the input layer are integrated (weighted) and the results are passed to the nodes in the hidden layer. In the covered up layer, the hubs will communicate between the hubs in the input and yield layers. Each hub in the yield layer compares to a subordinate variable.. Nodes in the same layer are not linked to each other. In the network, every node of the i^{th} layer (0<i<n) is connected to every node in the $(i+1)^{th}$ layer, and nodes in the same layer are not connected to each other. Each neuron receives input data (Inputs), processes them and produces a unique result (output). The processing results of one neuron can be input to other neurons.

2.2. Forecast data

In this study, data used for forecasting is collected from the SCADA system at the Ia Pet Dak Doa 1 wind farm - Gia Lai from January 01, 2022 to December 31, 2022. Samples were collected continuously at 10-minute intervals of the farm. Collected data includes: Time, Actual Active Power, Active power setpoint from NLDC, Possible Active Power. The data structure is in the form of a table:

Table 1. The structure of the data set is collected according to a 10-minute sampling period

Time	Actual Active Power	Active power setpoint from NLDC	Possible Active Power
Mar 08, 2022 0:10:00	54.32	99	53.99
Mar 08, 2022 0:20:00	54.23	99	53.76
…	…	…	…
Dec 31, 2022 23:40:00	4.74	99	4.83
Dec 31, 2022 23:50:00	5.04	99	5.10

In which:

– **Actual active power** is the actual power generation of the wind farm (MW).

– **Active power setpoint from NLDC** is the power command sent from the National Load Dispatch Center to ensure the grid is not overcurrent (MW).

– **Possible Active Power** is the theoretical generation capacity based on calculations by the SCADA system (MW).

Based on the provided data, this article used the Orange software for preprocessing the data by removing instances where the power was regulated (Active power setpoint from NLDC less than Possible Active Power) and outliers using the Local Outlier Factor algorithm. After preprocessing the data, the data structure is presented as the following table 2. This data will be used to construct an artificial neural network.

Table 2. New dataset structure after preprocessing the data with a 10-minute sampling period

Time	Actual Active Power
Jan 01, 2022 0:02:40	71.46
Jan 01, 2022 0:02:50	79.07
…	…
Jan 31, 2022 23:40:00	4.74
Jan 31, 2022 23:50:00	5.04

2.2.1. Input data

The input layer is responsible for receiving input signals and transmitting them to neurons in the hidden layer for processing. Basically, the neurons in the input layer do not perform any calculations. From the above equation, it can be seen that the turbine generating capacity depends on many factors. Normally, the data input into the neural network for power forecasting is selected, such as wind speed, temperature, wind direction, past generation capacity. In reality, during operation, the generation capacity is affected by AGC, so the author uses a data set including time and actual generation capacity for forecasting, in which the input is the time.

2.2.2. Network output variable

The output variable of the network is selected based on the prediction purpose. For the problem of predicting active power of wind farm, the output variable is active power of wind farm.

2.2.3. Hidden layer and activation function

To determine the optimal number of units in the hidden layer, it is necessary to train the network with a set of units in the hidden layer and predict the generalization error of each choice (Viet et al., 2021). For the number of hidden layers, it is necessary to compare and select the smallest MAPE mean squared absolute error value that gives optimal prediction results with the forecast data set.

Regarding the current activation function, there are many activation functions that can be used for artificial neural network such as ReLu, Linear, sigmoid, tanh, etc. Depending on the data set and the construction of the prediction model as well as Consider advantages such as convergence speed, accuracy... to choose the appropriate activation function.

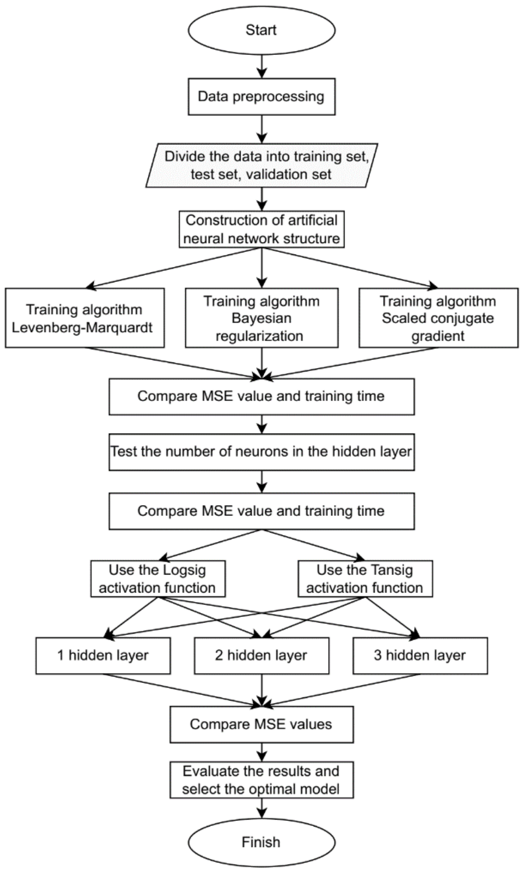

Figure 5. Flow chart for building an artificial neural network structure for the problem of forecasting for active power of wind farm

2.2.4. Neural network training algorithm

To train a neural network, it is necessary to consider an optimization algorithm to update the weights and biases of the network. During the network training process, the weights and biases of the network are adjusted repeatedly to optimize the objective function. The default performance for choosing a training algorithm can be decided by the mean squared error (MSE). In the article, the author chooses 1 of 3 basic algorithms in Matlab include: Levenberg-Marquardt algorithm, Bayesian Regularization algorithm, Scaled Conjugate Gradient algorithm.

2.2.5. Number of neurons in the hidden layer

The number of neurons in the hidden layer of a neural network depends on the specific problem and on the experience of the network designer. If the training data set is divided into groups with similar characteristics, the number of these groups can be used to select the number of hidden neurons. Using too few neurons can result in not being able to fully identify signals in a complex data set or underfitting. Using too many neurons will increase the network training time, and a large number of neurons can also lead to overfitting. Usually, the number of hidden layers is selected through the testing process with the criteria of MSE value and training time. The MSE value is data of special interest. Essentially, MSE shows the mean squared error between predicted and actual values. At the same time, MSE is a measure of the quality of the forecast model. With a lower MSE value, the model can have higher accuracy or better prediction.

2.3. Implementation steps

With the problem of forecasting the generating capacity of the wind power farm Ia Pet Dak Doa 1, the author builds the structure of an artificial neural network to serve the forecast as shown in the flow chart as Figure 5.

– Step 1: Preprocess data

As stated in the previous sections, capacity forecasting is done based on data from the plant Scada turbine. This method depends heavily on data, so data preprocessing is inevitable. This article used the Orange software for preprocessing the data by removing instances where the power was regulated (Active power setpoint from NLDC less than Possible Active Power) and outliers using the Local Outlier Factor algorithm.

– Step 2: Enter data after processing and dividing the data into training and testing data sets. In this step, the author divides the data into a training set, test set, and validation set with a ratio of 70/15/15.

– Step 3: Build the neural network structure

At this stage, the author constructs the model as shown in Figure 5 for each month. During the model building process, the author conducts experiments to select the number of network layers, the number of neurons in each hidden layer, the activation function, and the training algorithm. The model's requirements include low error values and short forecasting times (around 1 minute).

– Step 5: Train the artificial neural network model.

– Step 6: Calculate error values.

– Step 7: Compare and conclude.

2.4. Evaluation of the models

2.4.1. APE

To evaluate the effectiveness of forecasting models, in the article use the accuracy measurement standard absolute percentage error (APE).

$$\text{APE} = \frac{\left|P_i^{\text{predict}} - P_i^{\text{true}}\right|}{P_{\text{true}}} \times 100\% \qquad (4)$$

Moreover, in practical operation in Vietnam, the plant are applying the Electricity regulatory authority of VietNam equation for APE calculation as follows:

$$\text{APE} = \frac{\left|P_i^{\text{predict}} - P_i^{\text{true}}\right|}{P_{\text{max}}} \times 100\% \qquad (5)$$

Where:

– **APE:** absolute percentage error of the i^{th} forecast signal, %;

– $\mathbf{P_i^{predict}}$: predicted output power value of the ith forecast signal, MW;

– $\mathbf{P_i^{true}}$: actual measured value of the ith forecast signal, MW;

– $\mathbf{P_{max}}$: The maximum generation value of the wind farm, (at Ia Pet Dak Doa 1 wind farm, P_{max} = 99 MW).

In this article, the author uses equation number 4 during the testing process of building an artificial neural network. Equation 5 is employed for forecasting error calculation.

2.4.2. MAPE

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \text{APE}_i \qquad (6)$$

Where, is the absolute percentage error (APE) of the i forecast signal, n is the total number of data samples collected.

2.4.3. MSE

Mean square error is determined by:

$$\text{MSE} = \frac{\sum_{i=1}^{n}\left(P_i^{\text{predict}} - P_i^{\text{true}}\right)^2}{n} \qquad (7)$$

Where:

– $\mathbf{P_i^{predict}}$: predicted output power value of the ith forecast signal, MW;

– $\mathbf{P_i^{true}}$: actual measured value of the ith forecast signal, MW;

– **n**: Sample number.

MSE is always a non-negative number. The smaller the value, the more accurate the model.

2.4.4. Pearson correlation coefficient

The Pearson Correlation Coefficient is calculated mathematically thus (Ferreira et al., 2019):

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (8)$$

- R represents the linear correlation coefficient for a sample;

– **n** is number of paired values considered;

– $\mathbf{y_i}$ is prediction value;

– $\mathbf{\bar{y}}$ is mean of prediction value;

– $\mathbf{x_i}$ is observed value;

– $\mathbf{\bar{x}}$ is mean of observed value.

3. RESULTS AND DISCUSSION

3.1. Results of building artificial neural network structure for 2022

Criteria for model construction are outlined in section 2.4, where this article prioritizes building models for months with low Mean Squared Error (MSE) and a forecasting time of around 1 minute (due to practical operational time constraints).

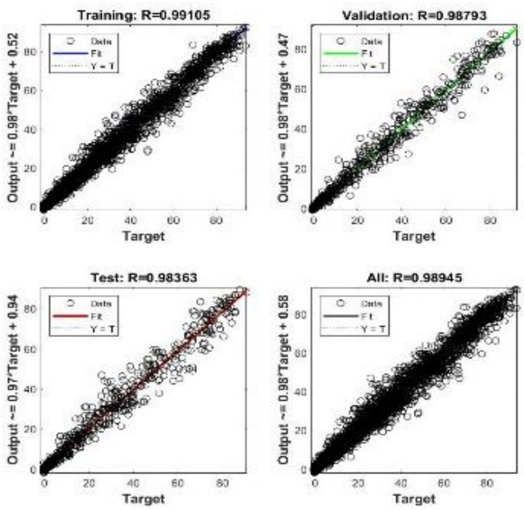

Figure 6. Regression graph for February 2022

Results from constructing models for the 12 months of 2022:

– ANN model with 1 hidden layer.

– Number of neurons ranging from 325 to 525.

– Training algorithm: Levenberg - Marquardt backpropagation.

– Activation function in the hidden layer: Hyperbolic tangent sigmoid (Tansig).

The training results are presented as Figure 6 Regression graph shows good network performance. The regression graph shows the output of the network in relation to the training, testing, and validation goals. With data located along the 45^0 line, the network output is closer to the target, R value = 0.989.

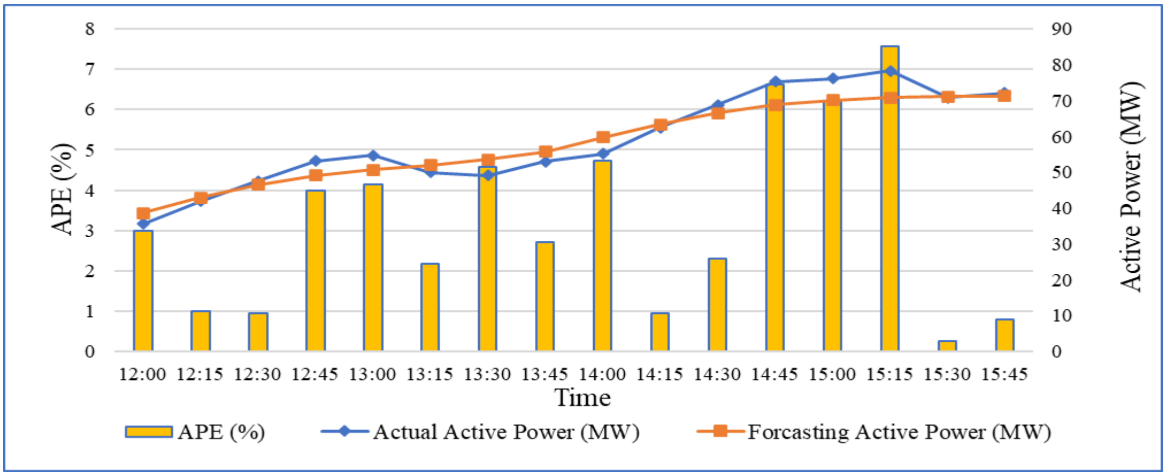

Figure 7. Correlation graph between actual and forecast generation capacity with absolute error percentage APE from cycle 49 to cycle 64 on September 27, 2022

3.2. Forecast results

After constructing the forecasting model using artificial neural network, this article proceeded with simulating power forecasts. The forecasted power results are presented in the tables below, where the Absolute Percentage Error (APE) is calculated using equation number 5.

Table 3. Forecast results from cycle 49 to cycle 64 on September 27, 2022

Cycle	Time	Actual Active Power (MW)	Forcasting Active Power (MW)	APE (%)
49	Sep 27, 2022 12:00	35.64	38.59	2.98
50	Sep 27, 2022 12:15	41.94	42.94	1.01
51	Sep 27, 2022 12:30	47.51	46.58	0.95
52	Sep 27, 2022 12:45	53.11	49.15	4.00
53	Sep 27, 2022 13:00	54.74	50.65	4.14
54	Sep 27, 2022 13:15	49.91	52.06	2.17
55	Sep 27, 2022 13:30	49.07	53.61	4.58
56	Sep 27, 2022 13:45	53.03	55.73	2.72
57	Sep 27, 2022 14:00	55.08	59.77	4.73
58	Sep 27, 2022 14:15	62.45	63.4	0.96
59	Sep 27, 2022 14:30	68.84	66.56	2.31
60	Sep 27, 2022 14:45	75.30	68.76	6.61
61	Sep 27, 2022 15:00	76.21	70.07	6.21
62	Sep 27, 2022 15:15	78.26	70.77	7.57
63	Sep 27, 2022 15:30	70.86	71.13	0.26
64	Sep 27, 2022 15:45	72.10	71.32	0.79
MAPE				**3.25**

Comparison between the plant actual generation capacity data and the generation capacity from the forecast model in 16 cycles (from cycle 49 to cycle 64) of September 27, 2022 shows that the estimated results The quality is quite good, the output power data curve and the predicted power data have little difference, the MAPE error parameter is only 3.25%.

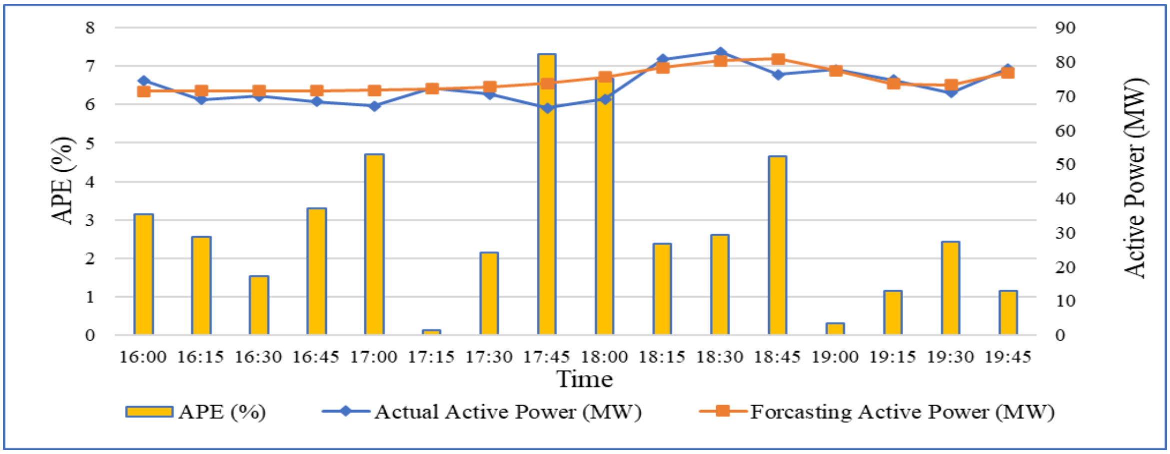

Figure 8. Correlation graph between actual and forecast generation capacity with absolute error percentage APE from cycle 65 to cycle 80 on September 27, 2022

Table 4. Forecast results from cycle 65 to cycle 80 on September 27, 2022

Cycle	Time	Actual Active Power (MW)	Forecasting Active Power (MW)	APE (%)
65	Sep 27, 2022 16:00	74.52	71.41	3.15
66	Sep 27, 2022 16:15	68.94	71.47	2.55
67	Sep 27, 2022 16:30	69.99	71.52	1.54
68	Sep 27, 2022 16:45	68.33	71.61	3.31
69	Sep 27, 2022 17:00	67.09	71.75	4.71
70	Sep 27, 2022 17:15	72.19	72.05	0.14
71	Sep 27, 2022 17:30	70.50	72.63	2.15
72	Sep 27, 2022 17:45	66.50	73.73	7.30
73	Sep 27, 2022 18:00	69.03	75.63	6.66
74	Sep 27, 2022 18:15	80.69	78.34	2.38
75	Sep 27, 2022 18:30	82.93	80.35	2.61
76	Sep 27, 2022 18:45	76.30	80.91	4.65
77	Sep 27, 2022 19:00	77.79	77.49	0.31
78	Sep 27, 2022 19:15	74.74	73.59	1.16
79	Sep 27, 2022 19:30	70.91	73.32	2.43
80	Sep 27, 2022 19:45	78.08	76.93	1.16
		MAPE		**2.89**

Comparison between the plant actual generation capacity data and the generation capacity from the forecast model in 16 cycles (from cycle 65 to cycle 80) of September 27, 2022, shows that the forecast results. The forecast is good, the output power data curve and the forecast power data have little difference, the highest APE error is 7.30% and the lowest APE error is 0.14%.

4. CONCLUSION

From the above research results, it can be seen that using a basic artificial neural network has solved the problem of forecasting the power generation capacity of a wind farm with a forecast cycle of 15 minutes for the next 4 hours during the day. The average MAPE error reaches 3.07%. This error completely meets the requirements of National Load Dispatch Center (A0) in updating capacity forecasts to serve dispatching generation capacity on the A0 power grid (less than 18%). Especially during the period when Vietnam's 500 kV power grid is under construction and the renewable energy industry is increasingly developing.

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