Các mô hình mạng nơ ron hồi quy dùng cho dự báo điện gió

TÓM TẮT

Các giá trị lịch sử của công suất phát điện gió thường được sử dụng trong hầu hết các mô hình và phương pháp dự báo điện gió trong các tài liệu. Tuy nhiên, các thông số vận hành có thể ảnh hưởng đến kết quả dự báo chẳng hạn như tốc độ gió, góc pitch, nhiệt độ môi trường, vị trí nacelle, và hướng gió chưa được xem xét trong các phương pháp hiện tại. Do đó, mục tiêu cơ bản của bài báo này là đề xuất các mô hình mạng nơ ron hồi quy dùng cho dự báo công suất phát điện gió có xem xét các tham số vận hành này. Nghiên cứu này xem xét dữ liệu công suất phát điện gió và các tham số vận hành tương ứng từ máy phát tuabin gió số 5 của 1 trang trại gió. Dữ liệu từ ngày 01 tháng 07 năm 2024 đến 31 tháng 07 năm 2024 được thu thập từ hệ thống SCADA. Đầu tiên, mô hình mạng nơ ron tự hồi quy phi tuyến có các đầu vào được áp dụng để dự báo công suất phát điện gió. Thứ hai, mô hình mạng hồi quy lớp được sử dụng để dự báo công suất phát điện gió. Thứ ba, mô hình mạng nơ ron trễ phân tán được dùng để dự báo công suất phát điện gió. Thứ tư, mô hình mạng nơ ron trễ thời gian được huấn luyện để ước lượng điện gió. Cuối cùng, các mô hình mạng nơ ron hồi quy này được so sánh để xác định mô hình dự báo công suất phát điện gió tốt hơn khi xét theo các tiêu chí sai số tuyệt đối trung bình, sai số phần trăm tuyệt đối trung bình và sai số bình phương trung bình.

Từ khóa: *Dự báo điện gió, mạng nơ ron tự hồi quy phi tuyến có các đầu vào, mạng nơ ron hồi quy lớp, mạng nơ ron trễ phân tán, mạng nơ ron trễ thời gian*.

Recurrent neural network models for wind power forecasting

ABSTRACT

The historical values of wind power generation are generally utilized in most forecasting models and methods in the literature. Unfortunately, the operational parameters such as wind speed, pitch angle, ambient temperature, nacelle position, and wind direction may affect the forecasting results. Therefore, the primary objective of this paper is to propose recurrent neural network models for wind power generation forecasting considering these operational parameters. In this study, the wind power generation data and the associated operational parameters from the wind turbine generator 05 of a wind farm are investigated. The data from July 1st, 2024 to July 31st, 2024 is collected from the SCADA system. Firstly, the nonlinear autoregressive neural network with external input is applied to make the wind power generation prediction. Secondly, the layer recurrent neural network model is employed to forecast wind power generation. Thirdly, the distributed delay neural network model is implemented to predict wind power generation. Fourthly, the time delay neural network model is trained to estimate the wind power. Finally, these recurrent neural network models are compared to determine the better wind power generation forecasting model in terms of mean absolute error, mean absolute percent error, and root mean square error.

Keywords: *Wind power forecasting, nonlinear autoregressive neural network with external input, layer recurrent neural network, distributed delay neural network, time delay neural network.*

1. INTRODUCTION

The rapid increase in energy demand forces people to seek alternative energy sources in addition to traditional ones that are depleting and causing pollution issues. Wind power is a clean and renewable source. From the Global Wind Report 2024 of GWEC (Global Wind Energy Council), it is shown that 2023 saw the highest number of new installations in history for onshore wind (over 100 GW) and the second highest for offshore wind (11 GW). Wind energy installations will increase from a level of 117 GW in 2023 to at least 320 GW of annual installations by 2030 [1]. Actually, wind power generation plays a significant role in electricity supply. Wind energy integration into power systems presents inherent unpredictability because of the intermittent nature of wind energy [2]. As wind energy makes significant penetration into the electricity grid, the need for accurate predictions of wind power generation becomes critical and urgent [3,4]. To solve these challenges, wind power forecasting can be a useful solution. Consequently, numerous WPF models and methods have been proposed and executed in the literature. According to the time horizon, wind power forecasting can be categorized as ultra short-term, short-term, medium-term, and long-term. Various types of forecasting models and methods are proposed for wind power generation time series. The traditional statistical models and methods are usually applied by using the previous historical data to perform a forecast. In WPF, the statistical models are applied as exponential smoothing approach [5,6], autoregressive [7], autoregressive moving average (ARMA) [8,9], autoregressive integrated moving average (ARIMA) [10,11]. Besides, artificial intelligence-based models are another research direction in wind power forecasting. Depending on the neural network (NN) structures, various models are proposed in wind power generation forecasting. Feed-forward NN models are used to make the wind power prediction such as multi-layer perceptron [12] and back-propagation NN [13]. Another kind of NN model with feedback namely the recurrent NN (RNN) model is also used in this research direction. The RNN model-based wind power forecasting methods are Elman NN [14], layer RNN [15], nonlinear autoregressive NN [16], long short-term memory (LSTM) [17], bidirectional LSTM [18], gated recurrent unit [19], and echo state network [20]. Support vector machine [21], gradient boosting regression tree algorithms [22], and ensemble model [23] belonging to machine learning are also implemented in wind power forecasting. Other attempts to combine different models or methods using different ways to improve the forecasting results such as autoregressive fractionally integrated moving average and least square support vector machine [24], boosting algorithm and ARMA model [25], hybrid CEEMDAN-EWT deep learning method [25], and neuro wavelet and LSTM models [26]. In these existing studies, most wind power forecasting models handle the wind power generation time series data issues without considering the operational parameters which might affect the forecasting results. Some significant operational parameters can be considered wind speed, pitch angle, ambient temperature, nacelle position, and wind direction. In this paper, one of the 6 turbines of a wind farm, located on the south-central coast, Vietnam with a 114-metre height and a 132-metre rotor is considered. These operational parameters and wind power generation time series data are collected at 10-minute intervals from the SCADA system. The data is collected from July 01st, 2024 to July 31st, 2024. This data is divided into three different case studies. Then, numerous RNN models including nonlinear autoregressive NN with external input (Narxnet), layer RNN (Layrecnet), distributed delay NN (Distdelaynet), and time delay neural network (Timedelaynet) investigating both operational parameters and wind power generation are proposed for wind power generation forecasting. To identify the efficiency of wind power forecasting models, evaluation criteria such as mean absolute error (MAE), mean absolute percent error (MAPE), and root mean square error (RMSE) are used. Based on the final results, a better forecasting model can be determined. An overview of wind power generation forecasting using RNN models can be represented in Figure 1.

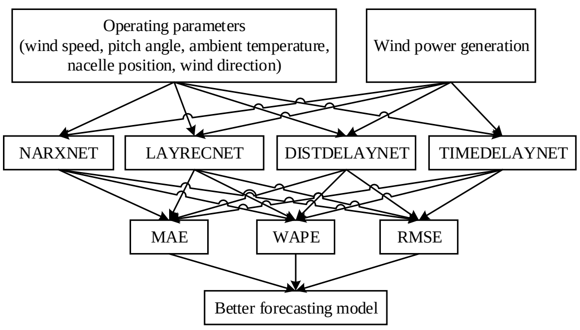

Figure 1. Overview of the wind power generation forecasting using RNN models.

2. METHODOLOGY

2.1. Nonlinear autoregressive neural network with external input

Narxnet is a nonlinear autoregressive model with exogenous inputs in time series modeling. In this model, the current value of a time series relates to both past values of the same series and current and past values of exogenous series. The Narxnet model, applied to time series forecasting, can be written as follows:

$$y_t = f(y_{t-1}, y_{t-2}, ..., x_t, x_{t-1}, x_{t-2}, ...) \qquad (1)$$

where f denotes an unknown nonlinear function (i.e., transfer function or activation function); y_t denotes the predicted value of the time series data of y at a discrete time t; and x_t denotes the externally determined variable. The Narxnet model can be shown in Figure 2.

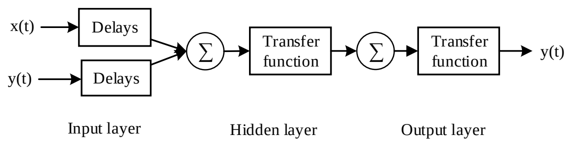

Figure 2. Narxnet model.

2.2. Layer recurrent neural network

Layrecnet is another type of RNN models. However, the output of the hidden layer is connected to the input layer with delays. Therefore, the network may have an infinite dynamic response to time series input data. The Layrecnet model can be shown in Figure 3.

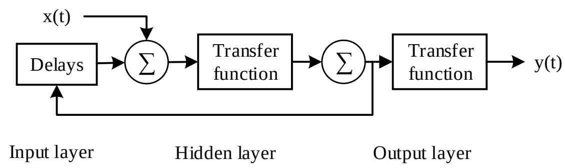

Figure 3. Layrecnet model.

2.3. Distributed delay neural network

Distdelaynet is another type of RNN models. The input layer and hidden layer have a tap delay line associated with them. Therefore, the network may have a finite dynamic response to time series input data. The Distdelaynet model can be shown in Figure 4.

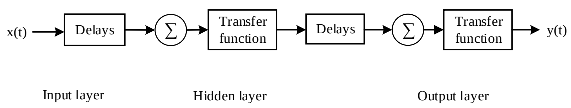

Figure 4. Distdelaynet model.

2.4. Time delay neural network

Timedelaynet is another type of RNN models. The input layer has a tap delay line associated with it. Therefore, the network may have a finite dynamic response to time series input data. The Timedelaynet model can be shown in Figure 5.

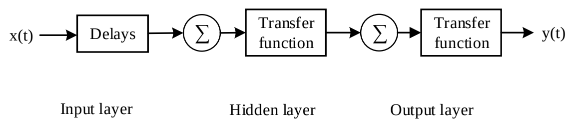

Figure 5. Timedelaynet model.

2.4. Transfer function

Normally, three transfer functions are used as follows:

Linear (i.e., purelin):

$$f = x. \tag{1}$$

Hyperbolic tangent sigmoid (i.e., tansig):

$$f = \frac{2}{1+e^{-2x}} - 1. \tag{2}$$

Log-sigmoid (i.e., logsig):

$$f = \frac{1}{1+e^{-x}}. \tag{3}$$

2.5. Training algorithm

The weights of the network are randomly initialized, and then repeatedly adjusted through the minimization of the cost function, which is calculated by measuring the difference between the actual output and the desired value [27]. Several training algorithms are used in NN training such as resilient back-propagation (i.e., trainrp), Bayesian regularization back-propagation (i.e., trainbr), BFGS quasi-Newton back-propagation (i.e., trainbfg), Levenberg-Marquardt back-propagation (i.e., trainlm), …

2.6. Evaluation criteria

MAE:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|A_t - F_t\right| \tag{4}$$

where A_t is the actual value, F_t is the forecasted value, and n is the number of observations.

WAPE:

$$WAPE = \frac{\sum_{t=1}^{n}\left|A_t - F_t\right|}{\sum_{t=1}^{n}\left|A_t\right|}. \tag{5}$$

RMSE:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(A_t - F_t\right)^2}. \tag{6}$$

3. CASE STUDIES

The time-series data from the wind turbine 05 (3.5 MW with a height of 114 meters, 132-meter rotor diameter) in a wind farm is collected from July 01st, 2024 to July 31st, 2024 (i.e., case study 3) with 10-minute intervals. Two investigated sub-periods in this period are from July 01st, 2024 to July 07th, 2024 (i.e., case study 1) and from July 25th, 2024 to July 31st, 2024 (i.e., case study 2). The total number of observations in three case studies is given in Table 1.

Table 1. Number of observations.

Data	Case study 1	Case study 2	Case study 3
Number of observations	1008	1008	4464

The wind speed, pitch angle, ambient temperature, nacelle position, and wind direction from July 01st, 2024 to July 31st, 2024 are illustrated in Figures 6, 7, 8, 9, and 10, respectively.

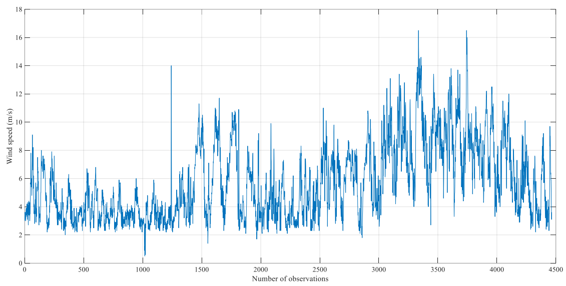

Figure 6. Wind speed.

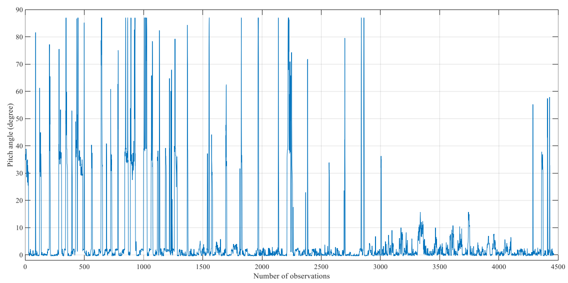

Figure 7. Pitch angle.

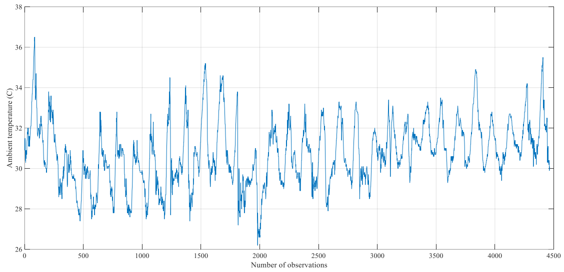

Figure 8. Ambient temperature.

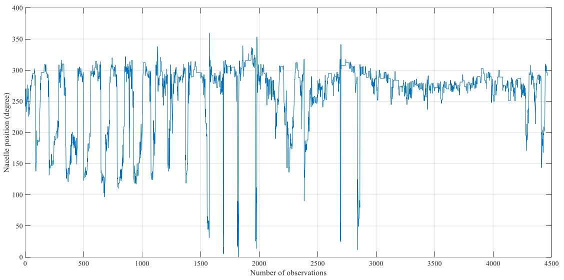

Figure 9. Nacelle position.

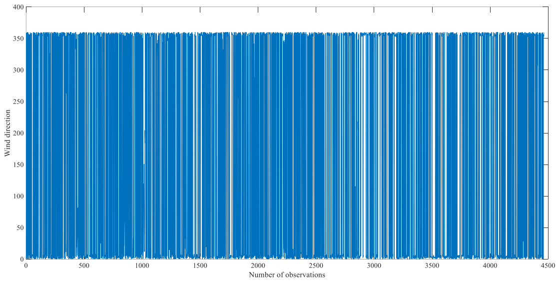

Figure 10. Wind direction.

All the recurrent NN models with one hidden layer are implemented. Moreover, all these recurrent NN models with 1 feedback delay in their corresponding structures are coded and trained in Matlab software. The transfer function, training function, and number of hidden neurons of all the trained Narxnet, Layrecnet, Distdelaynet, and Timedelaynet models in case studies 1, 2, and 3 are represented in Tables 2, 3, and 4, respectively.

Table 2. Information of the recurrent NN models in case study 1.

Model	Transfer function	Training function	Hidden neurons
Narxnet	Tansig	Trainbr	47
Layrecnet	Tansig	Trainbr	30
Distdelaynet	Tansig	Trainbr	143
Timedelaynet	Logsig	Trainbr	253

Table 3. Information of the recurrent NN models in case study 2.

Model	Transfer function	Training function	Hidden neurons
Narxnet	Logsig	Trainbr	21
Layrecnet	Tansig	Trainbr	79
Distdelaynet	Tansig	Trainlm	232
Timedelaynet	Tansig	Trainbr	301

Table 4. Information of the recurrent NN models in case study 3.

Model	Transfer function	Training function	Hidden neurons
Narxnet	Tansig	Trainlm	32
Layrecnet	Tansig	Trainbr	48
Distdelaynet	Logsig	Trainlm	372
Timedelaynet	Tansig	Trainbr	180

The evaluation values of all the forecasting recurrent NN models in all case studies are illustrated in Tables 5, 6, and 7, respectively.

Table 5. Evaluation criteria of the proposed forecasting models in case study 1.

Model	MAE	WAPE(%)	RMSE
Narxnet	56.0914	22.3584	87.4324
Layrecnet	18.6198	7.4220	24.9867
Distdelaynet	65.9784	26.2994	130.9846
Timedelaynet	49.9778	19.9215	98.3547

Table 6. Evaluation criteria of the proposed forecasting models in case study 2.

Model	MAE	WAPE(%)	RMSE
Narxnet	269.7987	17.0885	382.9613
Layrecnet	80.9957	5.1301	104.7831
Distdelaynet	341.8460	21.6519	490.9236

Timedelaynet	207.4276	13.1381	289.5628

Table 7. Evaluation criteria of the proposed forecasting models in case study 3.

Model	MAE	WAPE(%)	RMSE
Narxnet	168.6443	18.3242	263.3885
Layrecnet	41.3159	4.4892	58.1676
Distdelaynet	248.0907	26.9565	388.8692
Timedelaynet	164.6041	17.8852	256.3703

Based on the results in Table 5, the Narxnet model can provide better forecasting results (with MAE = 56.0914, WAPE = 22.3584%, and RMSE = 87.4324) compared to the Distdelaynet model (with MAE = 65.9784, WAPE = 26.2994%, and RMSE = 130.9846). In addition, the Timedelaynet model with MAE = 49.9778, WAPE = 19.9215%, and RMSE = 98.3547 can provide better prediction results compared to the Narxnet model. Finally, the Layrecnet model with MAE = 18.6198, WAPE = 7.4220%, and RMSE = 24.9867 can provide better prediction results compared to the Timedelaynet model. Obviously, the Layrecnet model is the best wind power forecasting method in this case study. Similarly, as shown in Table 6, the Layrecnet model (with MAE = 80.9957, WAPE = 5.1301%, and RMSE = 104.7831) can provide better wind power forecasting results compared to the Timedelaynet model (with MAE = 207.4276, WAPE = 13.1381%, and RMSE = 289.5628), the Narxnet model (with MAE = 269.7987, WAPE = 17.0885%, and RMSE = 382.9613), and the Distdelaynet model (with MAE = 341.8460, WAPE = 21.6519%, and RMSE = 490.9236). As shown in Table 7, the Layrecnet model (with MAE = 41.3159, WAPE = 4.4892%, and RMSE = 58.1676) also can provide better wind power forecasting results compared to the Timedelaynet model (with MAE = 164.6041, WAPE = 17.8852%, and RMSE = 256.3703), the Narxnet model (with MAE = 168.6443, WAPE = 18.3242%, and RMSE = 263.3885), and the Distdelaynet model (with MAE = 248.0907, WAPE = 26.9565%, and RMSE = 388.8692). The four forecasting results from Narxnet, Layrecnet, Distdelaynet, and Timedelaynet models with the actual wind power generation data in case studies 1, 2, and 3 are shown in Figures 11, 12, and 13, respectively. The actual wind power values are represented by the solid line (blue color). The forecasted values using the Narxnet, Layrecnet, Distdelaynet, and Timedelaynet models are demonstrated by the dash lines with red color, blue color, purple color, and light blue color, respectively.

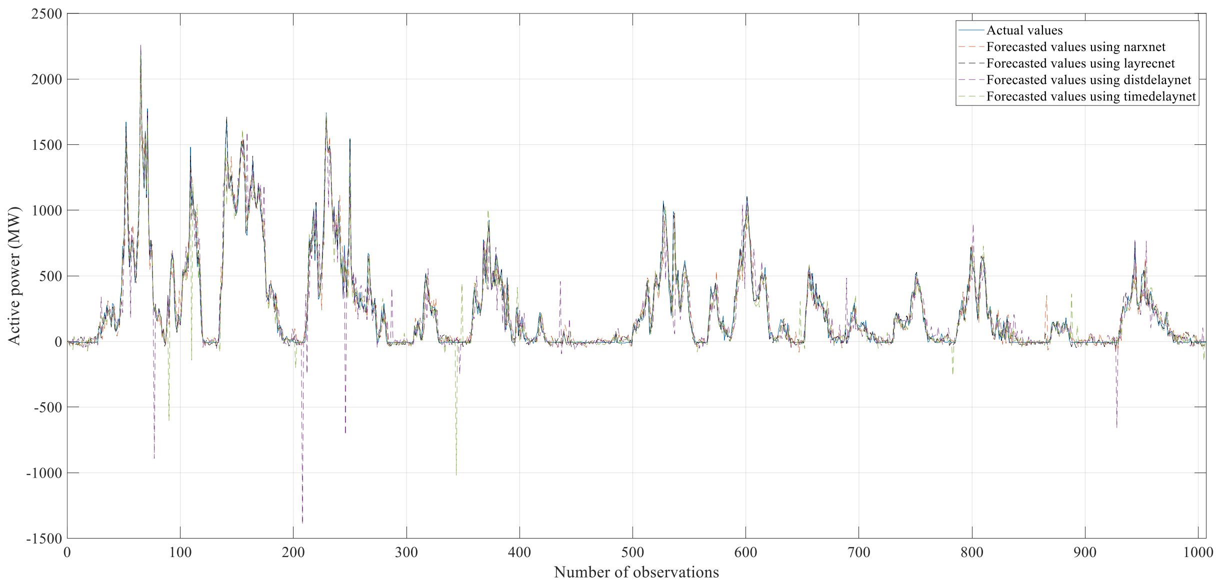

Figure 11. The forecasted results of wind power generation in case study 1.

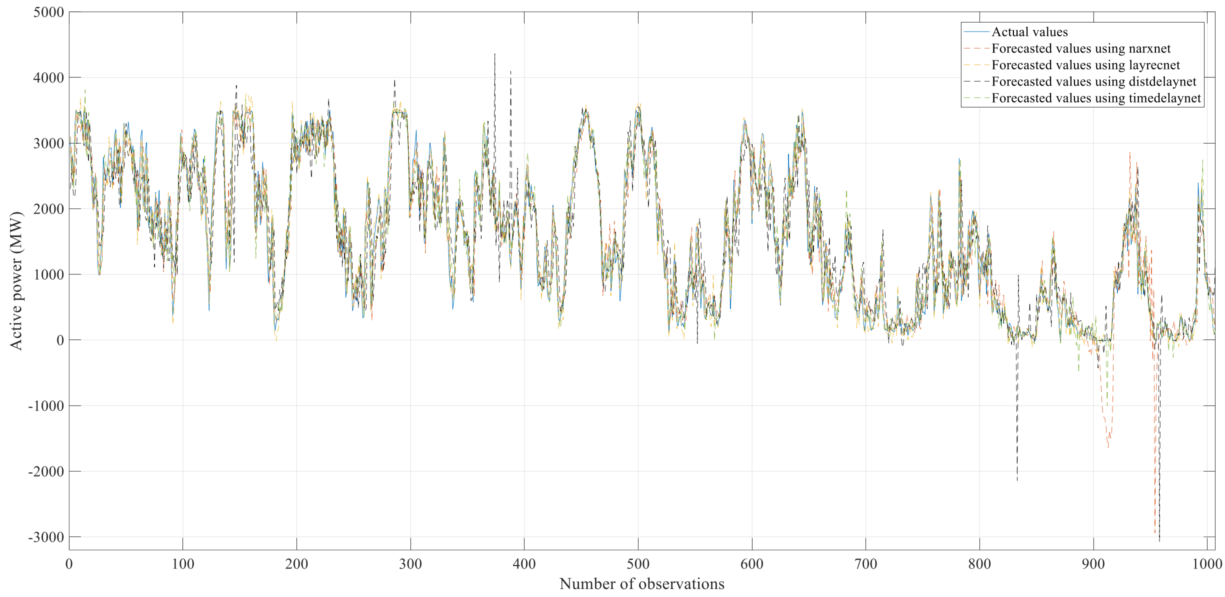

Figure 12. The forecasted results of wind power generation in case study 2.

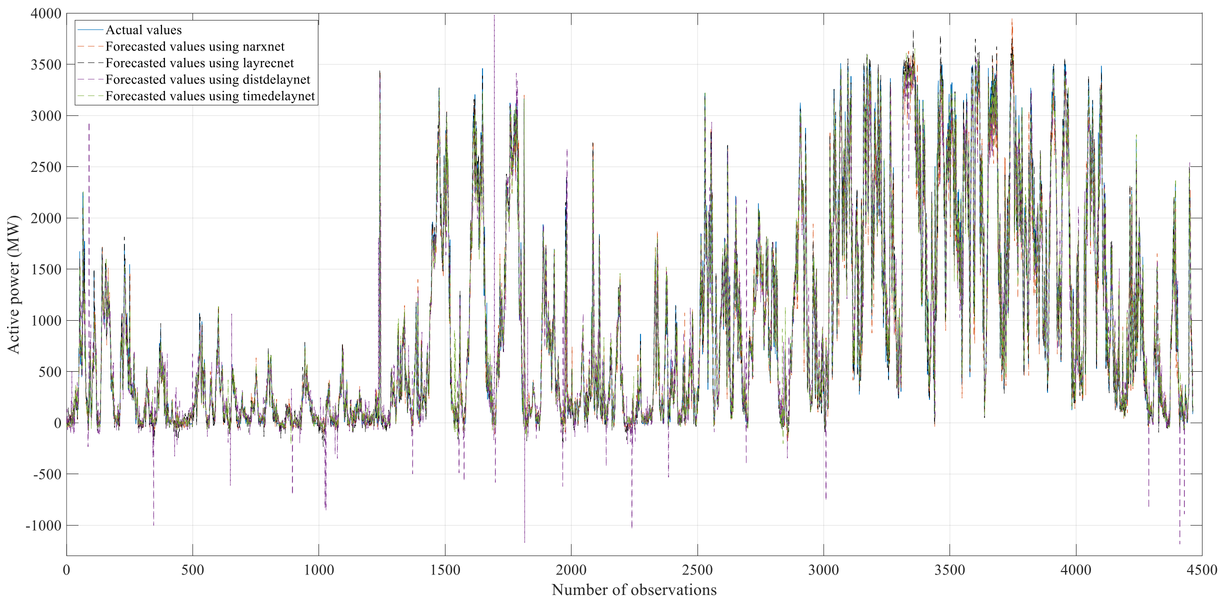

Figure 13. The forecasted results of wind power generation in case study 3.

4. CONCLUSION

In this paper, the operational parameters such as wind speed, pitch angle, ambient temperature, nacelle position, and wind direction are considered in wind power generation forecasting. A wind farm including 6 turbines (capacity of 3.5 MW per turbine) with a height of 114 meters and 132-meter rotor diameter is considered. The time series data of turbine 05 from July 01st, 2024 to July 31st, 2024 is collected. Several recurrent neural network models consisting of Narxnet, Layrecnet, Distdelaynet, and Timedelaynet are proposed as alternative wind power generation forecasting methods. The Layrecnet model can provide better wind power forecasting results compared to these other models in terms of MAE, WAPE, and RMSE. For further study, the optimal structures of these models can be identified to provide better solutions.

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