A Short-Term Wind Power Forecasting Tool for Vietnamese Wind Farms and Electricity Market*

Dinh Thanh Viet, Vo Van Phuong, Minh Quan Duong, Alexander Kies,
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Abstract - ***The Vietnamese government have plan to develop the wind farms with the expected capacity of 6 GW by 2030. With the high penetration of wind power into power system, wind power forecasting is essentially needed for a power generation balancing in power system operation and electricity market. However, such a tool is currently not available in Vietnamese wind farms as well as electricity market. Therefore, a short-term wind power forecasting tool for 24 hours has been created to fill in this gap, using artificial neural network technique. The neural network has been trained with past data recorded from 2015 to 2017 at Tuy Phong wind farm in Binh Thuan province of Viet Nam. It has been tested for wind power prediction with the input data from hourly weather forecast for the same wind farm. The tool can be used for short-term wind power forecasting in Vietnamese power system in a foreseeable future.***

Keywords: ***power system; wind farm; wind power forecasting; neural network; electricity market.***

I. NECESITY OF WIND POWER FORECASTING

Today, the integration of wind power into the existing grid is a big issue in power system operation. For the system operators, power generation curve of wind turbines is a necessary information in the power sources balancing. From the dispatchers' point of view, wind power forecast errors will impact the system net imbalances when the share of wind power increases, and more accurate forecasts mean less regulating capacity will be activated from the real time electricity market [1]. In the deregulated market, day-ahead electricity spot prices are also affected by day-ahead wind power forecasting [2]. Wind power forecasting is also essential in reducing the power curtailment, supporting the ancillary service. However, due to uncertainty of wind speed and weather factors, the wind power is not easy to predict.

In recent years, many wind power forecasting methods have been proposed. In [3], a review of different approaches for short-term wind power forecasting has been introduced, including statistical and physical methods with different models such as WPMS, WPPT, Prediktor, Zephyr, WPFS, ANEMOS, ARMINES, Ewind, Sipreolico. In [4], [5], the methods, models of wind power forecasting and its impact on the electricity market and power systems have been presented. The practice and experience of short-term wind power forecasting accuracy and uncertainty in Finland has also been investigated [1].

In general, the equation for wind power P (W) of each wind turbine is given by the formula (1):

$$P = (1/2)\rho \times A \times C_p \times N_g \times N_b \times V^3 \quad (1)$$

where ρ: air density (kg/m^3), A: rotor swept area (m^2), C_p: coefficient of performance, V: wind speed (m/s), N_g: generator efficiency, N_b: gear box bearing efficiency [6].

Unfortunately, many multiplication factors in the formula (1) are uncertain. It leads to uncertainty in relationship between wind speed and wind power of each wind turbine [7].

II. WIND POWER FORECASTING IN VIETNAM

A. Wind power in Vietnam

Vietnam is considered to have high potential for wind energy. The wind energy potential of Vietnam is shown in Table 1, Fig. 1 and Fig. 2 [8]:

TABLE 1. WIND ENERGY POTENTIAL OF VIET NAM AT 80 M ABOVE GROUND LEVEL

Average wind speed (m/s)	**<4**	**4-5**	**5-6**	**6-7**	**7-8**	**8-9**	**>9**
Area (km^2)	95,916	70,868	40,473	2,435	220	20	1
Area (%)	45.7	33.8	19.3	1.2	0.1	0.01	0
Potential (MW)	956,161	708,678	404,732	24,351	2,202	200	10

The development of wind power has been paid attention by both the Vietnamese government and investors. The national renewable energy development strategy by 2030, which was approved by the Vietnamese Prime Minister, emphasizes the role of wind power in particular. Expectations about installed wind power capacity are 800 MW in 2020; 2,000 MW in 2025 and around 6,000 MW by 2030 [9], [10].

By 2017, 160 MW of wind power capacity has been installed, some large wind farms with capacity and year of beginning operation are listed - Tuy Phong: 30 MW (2009); Bac Lieu: 16 MW (2013), and 99.2 MW (2016); Phu Lac: 24 MW (2016); Phu Quy: 6 MW (2013) [8].

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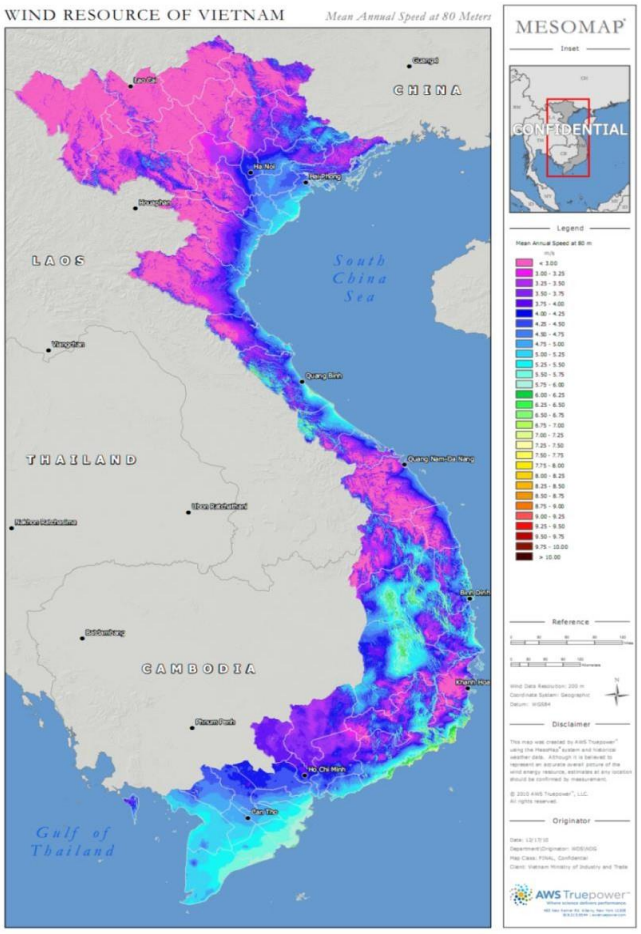


Figure 1. *Wind resource map of Vietnam at the height of 80 m*

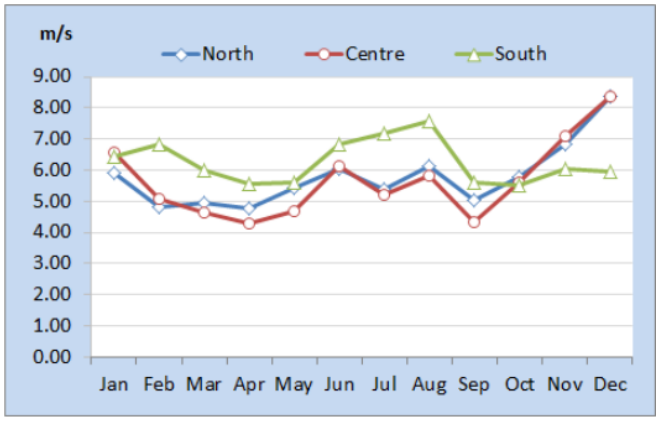


Figure 2. *Representative wind profile for the three regions in Vietnam*

B. *Wind power forecasting in Vietnam*

At present, there is no effective tool for predicting wind power in Vietnam. With the increasing integration of wind energy into the Vietnamese power system, the projected capacity of wind power plays an important role in supporting the optimal operation of wind power plants as well as the electricity market.

The forecast error of the whole wind farm will be much affected by the forecast errors from all wind turbines as a sum. For the electricity market operators, the predicted power of the whole wind farm at the point of coupling into the power grid is needed, rather than the sum of predicted powers of all turbines. In this paper, the approach of wind power forecasting for the whole wind farm will be investigated.

III. SHORT-TERM WIND POWER FORECASTING USING NEURAL NETWORK

A. *Neural network*

A neural network is a multi-input, multi-output system, consisting of an input layer, one or two hidden layers and an output layer. Each class uses a number of neurons, and each neuron in a layer is connected to neurons in the adjacent layers with different weights. The architecture of the typical neural network is shown in Fig. 3 [11], [18].

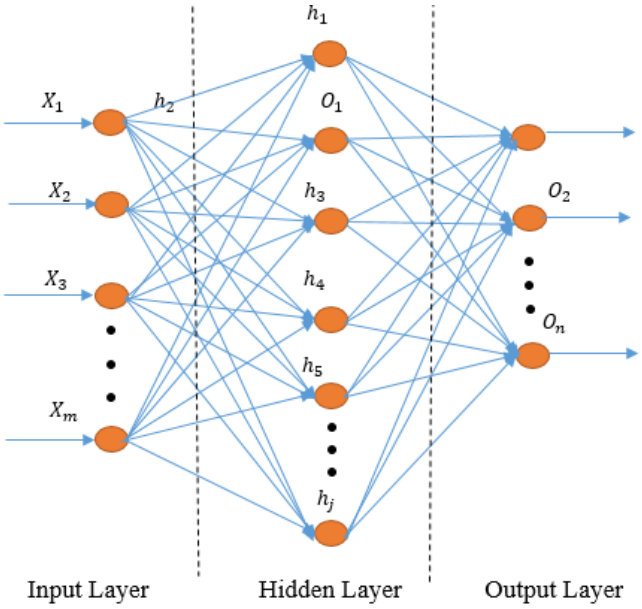


Figure 3. *Neural network structure*

where input $X = (x_1, x_2, ..., x_d)$, output $O = (o_1, o_2, ..., o_n)$. The signal is fed into the input layer, passing through the hidden layer and to the output layer. In a neural network, each neuron (except neuron at the input layer) receives and processes stimuli (inputs) from other neurons. Each input is first multiplied by the corresponding weight, then the resulting products are added to produce a weighted sum, which is passed through a neuron activation function to produce the output of the neuron [11], [12].

B. *Feedforward neural network*

A feedforward neural network usually has one or more hidden layers of sigmoid neurons followed by a linear neurons output layer. The paper uses the model of a feedforward neural network as described in Fig. 4. The input layer consists of 3 neurons of historical wind speed, temperature and wind power. The neural network has 20 neurons in the hidden layer and 01 neuron in the output layer.

The neural network may be used as a general function approximator. With enough neurons in the hidden layer, any function with a specific number of discontinuities arbitrarily can be approximated well. The algorithm for building the neural network - wind power forecasting model is shown in

Fig. 5. The historical data from wind farm, including wind power, wind speed and temperature, are loaded into the program and stored as a matrix of forecasting variable. Because of different operation scenarios, the historical data may not correctly reflect the relationship between wind power to wind speed and temperature. In few cases, historical data in practice may show negative values of wind power during generator starting time. Therefore, a data preprocessing is needed for reducing forecasting error. The historical data is used for training the forecasting neural network.

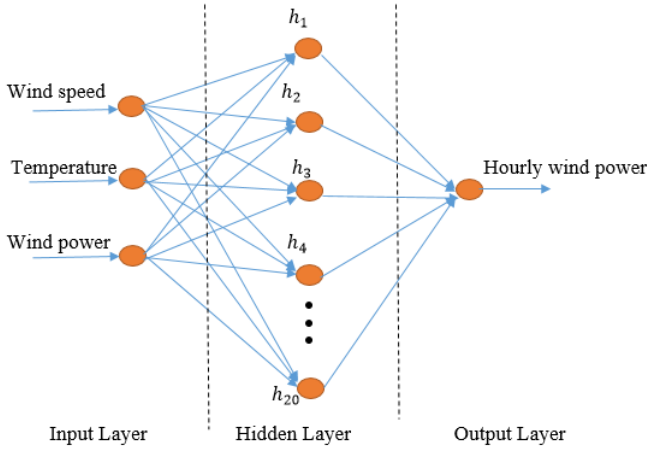


Figure 4. *Feedforward neural network.*

C. Wind power forecasting model

From the formula (1), it is obvious that generating power of each wind turbine depends largely on the wind speed. The temperature of environment is chosen as second input, affecting on the output power [13], [14], sum of output powers from the turbines serves as another input for neural network wind power forecasting model (Fig. 6). The input data is used to forecast the generating power of the wind farm. This model is designed for Vietnamese wind farms' power forecasting (short name: VWPF).

IV. CASE STUDY: WIND POWER FORECASTING FOR TUY PHONG WIND FARM

A. Simulation data

Tuy Phong is the first large-scale wind farm in Vietnam with a total capacity of 30MW, including 20 turbines of Fuhrländer, each turbine has a height of 85m, a blade diameter of 77m, and capacity of 1.5MW. The research is based on real data on wind speed and wind power production at Tuy Phong wind farm for 3 years. Collected data from January 1, 2015 to December 31, 2017 was used for wind power forecasting.

The data in the forecasting model VWPF includes wind speed, environmental temperature and wind power, which are collected every hour, represented by 24 lines per day. Example of data on October 7, 2017 for wind power forecasting is shown in Table 2.

The data set is divided into two data subsets:

- Data subset 1 from 01/01/2015 to 30/10/2017 is used to train the neural network. This is a database with data collected in 24,816 hours, almost 3 years, large enough for the neural network training purpose.
- Data subset 2 from 01/11/2017 to 31/12/2017 is used to compare the forecast results with the collected actual data for the error evaluation purpose.

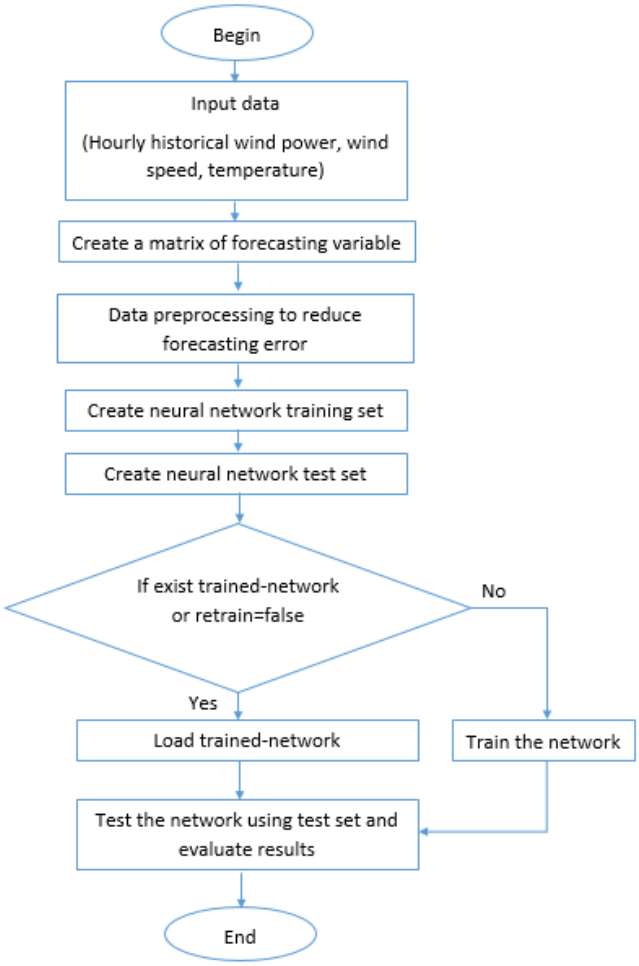


Figure 5. *Algorithm for building the neural network - wind power forecasting model VWPF.*

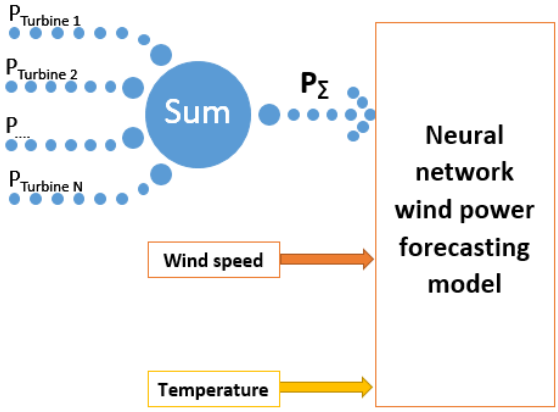


Figure 6. *Wind power forecasting model VWPF*

TABLE 2. EXAMPLE OF DATA ON OCTOBER 7, 2017

Date	Hour	Tempera-ture (℃)	Wind speed (m/s)	Wind power (W)
07/10/2017	1	24	3.56	272,299
07/10/2017	2	24	3.51	268,449
07/10/2017	3	24	3.52	266,840
07/10/2017	4	25	3.93	596,442
07/10/2017	5	25	3.9	572,175
07/10/2017	6	27	4.05	767,869
07/10/2017	7	27	3.96	772,839
07/10/2017	8	32	5.54	2,067,089
07/10/2017	9	32	5.47	2,137,362
07/10/2017	10	32	5.35	2,071,529
07/10/2017	11	32	5.4	2,044,341
07/10/2017	12	32	5.28	2,237,072
07/10/2017	13	32	5.25	2,105,929
07/10/2017	14	32	5.34	2,143,538
07/10/2017	15	30	4.68	1,683,934
07/10/2017	16	29	4.04	767,723
07/10/2017	17	24	4.53	1,632,532
07/10/2017	18	24	5.29	2,165,775
07/10/2017	19	24	5.77	2,943,629
07/10/2017	20	24	5.89	2,947,676
07/10/2017	21	24	6.13	3,200,192
07/10/2017	22	24	5.98	3,200,290
07/10/2017	23	25	5.75	3,084,564
08/10/2017	0	25	5.73	3,065,696

B. Error evaluation

The error measures - Mean Absolute Percent Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to evaluate the accuracy of the forecasting model [15], [16].

The MAPE represents the accuracy of the model as a percentage of the error, calculated according to formula (4):

$$\mathrm{MAPE} = \frac{100}{\mathrm{N}} \sum_{\mathrm{j}=1}^{\mathrm{N}} \left(\frac{|\,\mathrm{P_{real}} - \mathrm{P_{pred}}\,|}{\mathrm{P_{real}}} \right) \quad (4)$$

where:

P_{real}: actual power output of the wind power plant,

P_{pred}: generation power according to forecasting model,

N: number of forecasting data.

The MAE shows the accuracy of the model in the same unit of measure as the predicted data. This index is used to evaluate the margin of error and is calculated according to the formula (5):

$$\mathrm{MAE} = \sum_{1}^{\mathrm{N}} \left(|\mathrm{P_{real}} - \mathrm{P_{pred}}| \right) \quad (5)$$

In order to evaluate MAE in percentage for comparison between different models, we can use Normalized Mean Absolute Error (NMAE) (6):

$$\mathrm{NMAE}\ (\%) = \frac{\mathrm{MAE}}{\mathrm{P_{inst}}} \times 100\% \quad (6)$$

where P_{inst} is the wind farm installed capacity.

The RMSE is the standard deviation of the prediction errors (residuals). This is also a frequently used measure of the differences between values forecasted by a model and the values actually observed. The RMSE is calculated by the formula (7):

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}} \sum_{1}^{\mathrm{N}} \left(\mathrm{P_{real}} - \mathrm{P_{pred}} \right)^2} \quad (7)$$

Similarly, we can use Normalized Root Mean Square Error (NRMSE) in percentage (8):

$$\mathrm{NRMSE}(\%) = \frac{\mathrm{RMSE}}{\mathrm{P_{inst}}} \times 100\% \quad (8)$$

C. Result

By putting Tuy Phong wind farm data into the model and implementing neural network training, the forecasted model has been received and shown in Fig. 7, where the blue line represents the predicted wind power, the red line represents the actual generated wind power from the data subset 1. Fig. 7 shows a part of the snapshots for series of predicted time, the total number of snapshots is 23,856 hours (from 1/1/2015 to 20/9/2017).

The forecasting model VWPF is validated with data from any date in the data subset 2 for 92 days during period from 01/10/2017 to 31/12/2017. The real data of previous day is updated and included into the training database for the next day wind power forecast. As an example, the forecast on November 26, 2017 (the lowest wind speed was 8.39 m/s and the highest was 15.44 m/s with the steady change of wind speed throughout the day) is shown in Fig. 8. The error in the graph represents difference between real wind power and predicted wind power. The measures for the accuracy of the forecast result on November 26, 2017 are: MAPE=4.72%; NMAE=4.66%; NRMSE=5.66%.

Forecast results for December 17, 2017 with the speed changes from 6.15 m/s to 14.47 m/s are shown in Fig. 9. The measures for the accuracy of the forecast result on 17/12/2017 are: MAPE=5.44%; NMAE=4.74%; NRMSE=6.24%.

The wind power day-ahead forecast results in one week from 25/12/2017 to 31/12/2017 and relevant forecast error are shown in Fig.10. The forecast error or difference between the observed and the forecast wind power for one week from 25/12/2017 to 31/12/2017 is evaluated by the following values: MAPE=8.78%; NMAE=4.14%; NRMSE=4.58%

Based on the results of the forecasted wind power from VWPF, we have a practical range of errors as in Table 3:

TABLE 3. RANGE OF ERRORS FROM PRACTICAL TESTING WITH THE MODEL VWPF

No	MAPE (%)	NMAE (%)	NRMSE (%)
1	8.05	5.52	7.28
2	4.72	4.66	5.66
3	5.13	5.13	6.20
4	10.06	5.98	7.32
5	7.03	5.59	7.70
6	6.07	4.07	4.09
7	5.44	4.74	6.24
8	9.64	5.95	8.00
9	5.54	5.94	7.70
Average	6.85	5.29	6.69

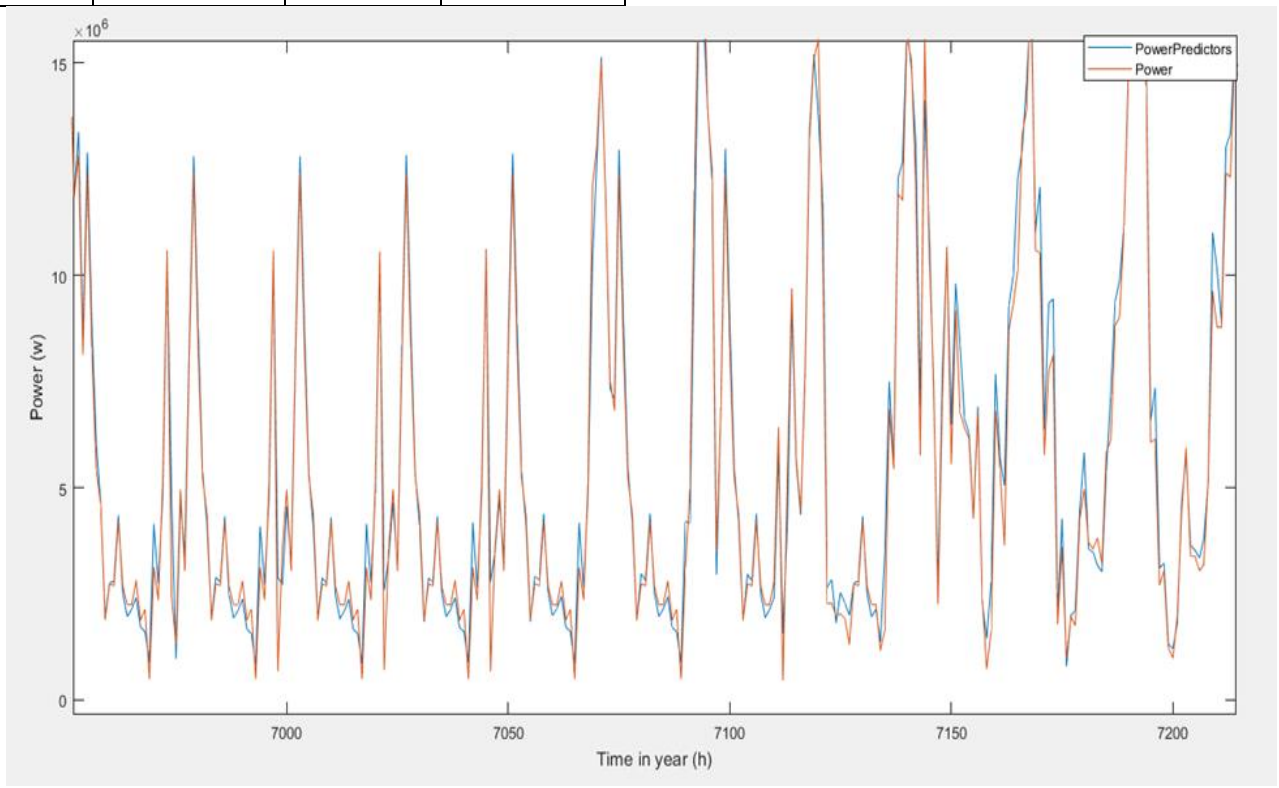


Figure 7. *Wind power forecasting result after neural network training.*

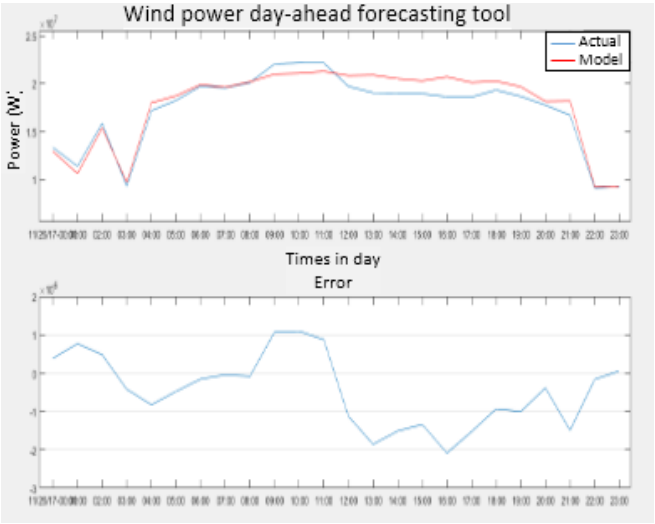


Figure 8. *Forecasted versus actual wind power on 26/11/2017*

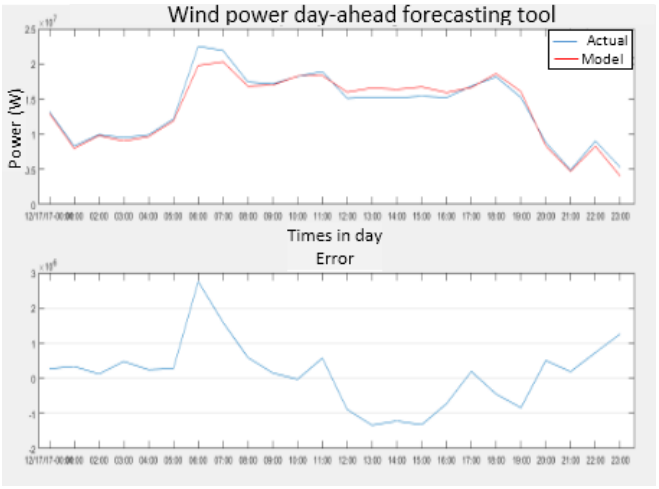


Figure 9. *Forecasted versus actual wind power on 17/12/2017*

Summary of error range from Table 3: MAPE = 4.72-10.06%, NMAE = 4.07-5.98%, NRMSE = 4.09-8.00%.

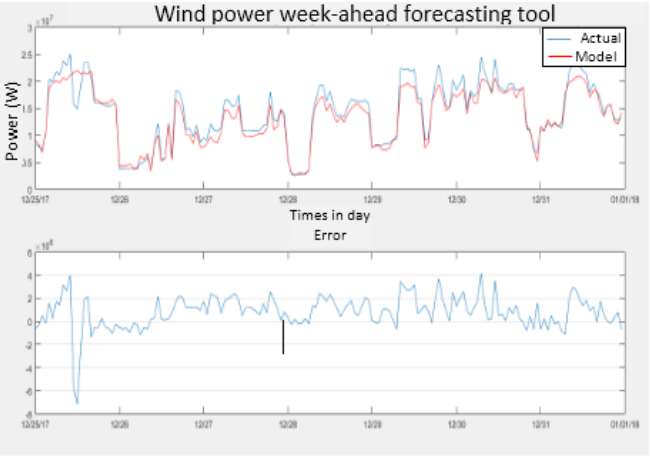


Figure 10. *Forecasted versus actual wind power during one week from 25/12/2017 to 31/12/2017*

TABLE 4. COMPARISON THE FORECAST ERROR INDICES OF THE PROPOSED MODEL (VWPF) WITH SOME OTHER MODELS

Forecasting Model	Error indices		
	MAPE (%)	NMAE (%)	NRMSE (%)
Persistence	14.43	6.18	7.99
BPNN	14.35	5.98	7.53
RBFNN	12.73	5.94	7.40
ANFIS	14.92	6.24	8.03
NNPSO	11.51	5.35	6.59
WT+BPNN	12.19	5.77	7.18
WT+RBFNN	11.18	5.62	6.95
WT+ANFIS	12.58	5.86	7.67
WT+NNPSO	8.19	4.86	6.28
VWPF	6.85	5.29	6.69

Table 4 showed comparison between the forecast errors of the proposed model with some other published models [17]. The error indices in different seasons [17] were recalculated as the average values. From Table 4, we find that the error indices between of the VWPF model is relatively smaller in comparison with most of the published wind power forecasting models. It proves that the VWPF model provides reliable forecasting results.

V. CONCLUSION

In the paper, a model of the wind power forecasting (VWPF) is developed for this need in Vietnam. The power system operators are usually interested in the forecasting of the whole wind farm's power, which is generated into the power system, rather than forecast power of each wind turbine. It shows advantage and effectiveness of the developed model in power prediction for the whole wind farm, which is well appropriate for dispatcher working as well as electricity market operator. The neural network prediction model can be used for short-time wind power forecasting (hour-ahead, day-ahead, and week-ahead). The forecasting model has been applied for estimating the wind power output of the Tuy Phong wind power plant in Binh Thuan province, Vietnam. The predicted results were evaluated with the average forecast error indices MAPE=6.85%, NMAE=5.29%, NRMSE=6.69%. The forecast error indices, showing the high accuracy of the model, are relatively smaller in comparison with most of similar research models (Table 4). Application of artificial intelligence technique at the connected point of the wind farm to the power grid proved effectiveness of this approach. This wind power forecasting tool can be applied not only for Tuy Phong wind farm, but also for the others in Vietnam.

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