臺灣能源期刊　第八卷　第三期　第235-254頁　中華民國110年9月
Journal of Taiwan Energy
Volume 8, No. 3, September 2021, pp. 235-254

Prediction and Analysis of Wind Power by Regression and Neural Network Method

Ming-Hong Chen[1*]

ABSTRACT

The purpose of this study is to conduct the wind power prediction by the regression and neural network methods. Results show that smaller errors are achieved with more deleted data set in the Nonlinear Autoregressive (NAR) model. However, the ratio of the deleted data and raw data should be considered simultaneously, especially for the small wind turbine. In the case using Nonlinear Autoregressive with External Input (NARX) model, additional decomposed data set is employed, and the improvement is still achieved without the alteration of raw data. The performance of the proposed prediction model on the MW scale wind farm is also investigated. Results show that better performance is obtained using the NARX model combined with the decomposed data sets, and the resulted mean absolute percentage error (MAPE) is less than 5%. There is no obvious improvement (< 1%) in the prediction by using the method of wavelet transformation.

Keywords: wind power, prediction, regression, neural network.

1. Introduction

Wind energy will play an important role on the energy source for Taiwan in the coming future. The variation of generated power by wind, however, will lead to impact and uncertainty on the management of electricity network, power regulation, planning and scheduling. To deal with this issue, a lot of efforts have been invested into the development of power prediction model with high precision.

The prediction of wind power is complicated since it is affected by a lots of factors including the feature of wind farm, height of wind turbine system, nearby building and trees. Unlike the sunlight for photovoltaic (PV) system, the fluctuation of coming wind for the wind turbine system is much stronger. The seasonal variation of wind in Taiwan is obvious. The Northeast Monsoon would be observed each year, and strong wind from consistent direction is expected. In other months, coming wind would be much weaker from every direction, leading to higher difficulties in prediction of wind power.

The renewable energy is expected to provide 20% of power for Taiwan in 2025. The installed capacity expected in 2025 is 20 GW for PV and 5.7+ GW for wind power. For the condition that wind power provides less than 1% of power to grid system, its fluctuation and impact could be neglected. However, as long as the wind power provides more than 10% of the power to the grid,

[1] Assistant Researcher, Mechanical and System Engineering Program, Institute of Nuclear Energy Research.
* Corresponding Author, Phone: +886-3-4711400#3351, E-mail: minghongchen@iner.gov.tw

Received Date: November 2, 2020
Revised Date: April 20, 2021
Accepted Date: May 6, 2021

its variation should be predicted preciously for regulation and management. The policy goal of wind power prediction is announced by the Bureau of Energy, Ministry of Economic Affairs in 2020 that the error of one-hour ahead prediction should be less than 6.5% in 2022, 5% in 2025, and 4% in 2030, respectively.

The commonly employed methods are physical, statistical and artificial intelligence (AI). For the physical model, geographic data will be introduced for the development of complicated model. Relatively large error was observed due to the required computational cost to implement the calculation (Safari *et al*., 2018). For the statistical method, the relationship model was built based on the surveyed weather data and wind power. This model is then employed to predict the wind power as the output with corresponding input data including the measured and forecasted weather information. The assumption was made for the commonly employed statistical model (autoregressive moving average (Erdem and Shi, 2011) and autoregressive integrated moving average model (Aasim and Mohapatra, 2019)) that normal distribution and linear relationships were applicable for wind power. By observing the actual site data of wind power, those assumptions might not be valid, leading to larger deviation in the prediction (Jiang *et al*., 2019). Recently, the AI-based algorithm was largely proposed for the short-term wind power prediction (Marugán *et al*., 2018). Among the proposed model, the artificial neural network (ANN) with the capability to capture the non-linear relationship of the training data was largely employed (Zhang *et al*., 2016; Guo *et al*., 2011).

1.1 Literature review

Yin *et al*. (2019) proposed a hybrid wind power prediction approach by the cascaded deep learning model. The empirical decomposition was introduced to decompose the time series data into a set of intrinsic mode functions (IMFs). Results showed that the improvement was observed in the prediction with the proposed model. The proposed hybrid model performed better than the surveyed studies in the short-term wind power prediction. Ouyang *et al*. (2017) proposed a combined multivariate model to improve the accuracy of wind power prediction. Integrated with four trained data mining algorithms, the performance of the proposed model in the industrial data was better than the traditional methods. Naik *et al*. (2019) proposed a hybrid multi-objective predictive method for the wind power. Results showed that the presented model was superior on the quality of wind power prediction than the other single and multi-objective methods.

Liu *et al*. (2018) combined the Gaussian process regression and multiple imputation approach to deal with the issue of missing data in the prediction of wind power. With the proposed method, a new data set was generated. With the introduction and comparison of experimental data, the effectiveness of the proposed model was observed in the prediction of wind power with missing data. Yuan *et al*. (2017) proposed a hybrid autoregressive fractionally integrated moving average and least square support vector machine model for the prediction of wind power. Comparison via two examples with other models showed that the proposed hybrid model led to better results in terms of 3 selected performance indexes. Qureshi *et al*. (2017) proposed a prediction model of wind power which integrated the deep neural network and transfer learning concept. The performance of the proposed model was evaluated by root mean square error (RMSE), mean absolute error (MAE), and standard deviation error (SDE) with other methods. Better results were observed via the introduced performance evaluation indexed. Harrou *et al*. (2019) developed a model based on the bagging ensembles of decision trees method for the prediction of wind power. The performance of the proposed method was compared with four existing methods. Results showed that the highest prediction performance with the coefficient of determination of 0.982 was obtained by the proposed model. The proposed model would also be a useful tool to identify the anomaly in wind turbines.

Taslimi Renani *et al*. (2016) compared the direct and indirect way in the wind power prediction. By combing the mutual information and neural network, the feature selection technique was proposed in this study. Results showed that the proposed method outperforms the 5 compared algorithms. Li *et al*. (2018) proposed the data mining based wind power prediction method with improved support vector machine. In this study, the data mining method was employed to survey the relationship between the wind speed and wind power. The modification of the invalid original data was made afterward. The high frequency parts were eliminated by the wavelet transform method. The prediction was improved by the cuckoo search algorithm and the penalty factor of support vector machine. In the investigation of a case study, the proposed method was the best based on the error evaluation indexes. Ouyang *et al*. (2019) proposed a new method to predict the ramp of wind power. A primary model was developed firstly by wind power curve. Then the residual predicted by the primary model was corrected by the proposed Markov-Switching-Auto-Regression method. The improved swinging door algorithm and ramp definition were integrated into the proposed model. The performance of the proposed model was evaluated by a wind farm data. Results showed that the performance has been improved by the proposed numerical model on the prediction of wind power and ramp.

Ouyang *et al*. (2020) proposed a combined model of switching different data-driven chaotic time series models. The input data was reconstructed based on the chaotic characteristics of wind power. Secondly, the wind prediction model was constructed by three data mining algorithms. Results by the proposed model were compared with non-reconstructed method, traditional method and typical combined method. Results showed the improvement in the accuracy of power prediction for the proposed method. Mahmoud *et al*. (2018) proposed the wind power prediction method by incorporating the extreme learning machine (ELM) and self-adaptive evolutionary extreme learning machines (SAEELM). By conducting the comparison via the real wind farm in Australian, the proposed method was observed with better performance than other traditional method. Yan and Ouyang (2019) proposed a hybrid model for better precision and efficiency in the prediction of wind power. In the proposed method, the wind power was predicted by the physical model with low precision. Secondly, the correction model based on data-driven methods was developed. The correction and optimization for the second model was conducted. By comparing to the traditional methods, the proposed method improved the precision in the prediction of wind power by 40-80%. Ghadi *et al*. (2014) conducted a case study of wind power prediction by the proposed hybrid model of neural network and evolutionary algorithm. The prediction and comparison was made for the next 36 hours of short-term and very short-term interval. Results showed that the proposed method improved the accuracy in the prediction wind power for the investigated wind farm. Hao *et al*. (2019) predicted the wind power by the proposed dilation and erosion (DE) clustering algorithm. The proposed DE clustering algorithm was able to cluster the similar numerical weather prediction (NWP) information automatically without supervision. A case study conducted showed that the employed DE algorithm and new generalized regression neural network (GRNN) model led to better performance than other compared methods. Memarzadeh and Keynia (2020) proposed a hybrid wind speed forecasting model by including the modules of crow search algorithm (CSA), wavelet transform (WT), Feature selection (FS), mutual information (MI), and Long Short Term Memory (LSTM) neural networks for deep learning time series prediction. In the WT module, the original time series data was decomposed into 4 sub-layers for the training process. The proposed numerical model and included algorithm was validated via the 4 real site data in the Middle East. Better accuracy and lower error were demonstrated in this study by the proposed model. Ding and Meng (2020) proposed a hybrid model for wind speed forecasting. Linear and non-linear components were extracted, processed by individual sub-model, and integrated afterward. The effectiveness and uncertainty of the proposed model was verified by a case study. The decomposition method for the original data was introduced in some studies (Liu *et al*., 2020; Ding and Meng, 2020). In the study of Liu *et al*. (2020), the original data was decomposed into 9 layers, and the data of first layer was removed. The resulted mean absolute percentage error (MAPE) was about 5% in the prediction of wind speed among the investigated sites.

As mentioned in the reviewed literatures, the data pre-process treatments (i.e., decomposition and wavelet transformation, etc.) were integrated in the proposed hybrid model to improve the precision of wind power prediction. The effect of individual process on the prediction precision, however, was not discussed clearly in literature. The purpose of the present study is to conduct the case study of wind power prediction. The precision improvement methods are introduced separately. For the method of significant effect of improvement on prediction precision would be identified by comparing the calculated data with real values. The regression and neural network methods are introduced and compared. The first prediction is made by the raw data directly without the process of data treatment. Then, the methods of data process are introduced as the second prediction. The effect of data treatment process is also investigated by comparing the corresponding results. The combination of tested sub-model with better prediction precision is proposed for the experimental wind turbine system within the campus. A case study on a MW scale wind farm is then conducted to verify the performance of the proposed prediction model. The optimal procedure of the investigated wind turbines is proposed based on the calculated results of the present study.

2. Numerical Models and Investigated Wind Farms

In the present study, the regression and neural network models are employed for the prediction of wind power. The relationship between wind speed and generated power is developed by the training process. The performance of the produced prediction model is evaluated and compared with different wind turbine systems. By introducing the one-year-long wind data measured in the renewable energy campus of the Institute of Nuclear Energy Research (INER), the annual energy production (AEP) of the investigated wind turbine can be evaluated, especially via the regression model. The predicted AEP by the regression model is then compared with that by the linear prediction model evaluated in our previous works (Chen, 2018). Secondly, the method of neural network is introduced, especially for the short-term prediction of wind power. Different configurations of neural network algorithm are considered and the performances are evaluated and compared. Finally integrated algorithm for the prediction of wind power is proposed.

Among the available models of Machine Learning and Deep Learning, the Regression Learner model is employed in the present study. All of the available models are listed in Table 1.

Table 1. Available models of Machine Learning and Deep Learning (by author)

Model	Remark
Classification Learner	
Deep Network Designer	
Neural Network Clustering	
Neural Network Fitting	
Neural Network Pattern Recognition	
Neural Network Time Series	Preferred in short-term prediction
Regression Learner	Employed in the present study

Within the Regression Learner model, there are several sub-models available for the training process as listed in Table 2. All of the available sub-models are employed in the training process, and the one with minimum RMSE is exported for later prediction.

Table 2. Available sub-models of Regression Learner model (by author)

Prediction model	Sub-Model
Regression Learner	Linear
	Regression Trees
	Support Vector Machines (SVM)
	Gaussian Process Regression
	Ensembles of Trees

Comparing to the regression model, the neural network method is employed as the comparison on the precision of prediction. The type of time-series data is usually handled by the long-short-term-memory model. In the present study, the toolbox for time-series problem in MATLAB (Matrix Laboratory) is employed. There are 3 sub-models available. The first one is Nonlinear Autoregressive with External Input (NARX). In this sub-model, the generated power is predicted based on the historical value of power and corresponding wind speed and direction. The second sub-model is Nonlinear Autoregressive (NAR). In this sub-model, only the historical value of power generation is needed for model development and test. The last one is the Nonlinear Input-Output sub-model. As noted in the user menu of MATLAB code, the precision of NARX is much better than Nonlinear Input-Output sub-model. Thus, the last sub-model is not employed for the following investigation.

The employed NARX model is the recurrent dynamic network including the several layers of network and feedback connection. Several studies employed the NARX model for the time-series prediction in the past (Menezes and Barreto, 2008; Diaconescu, 2008; Guzman *et al.*, 2017). The mathematical formulation of NARX model is show in equation (1) as:

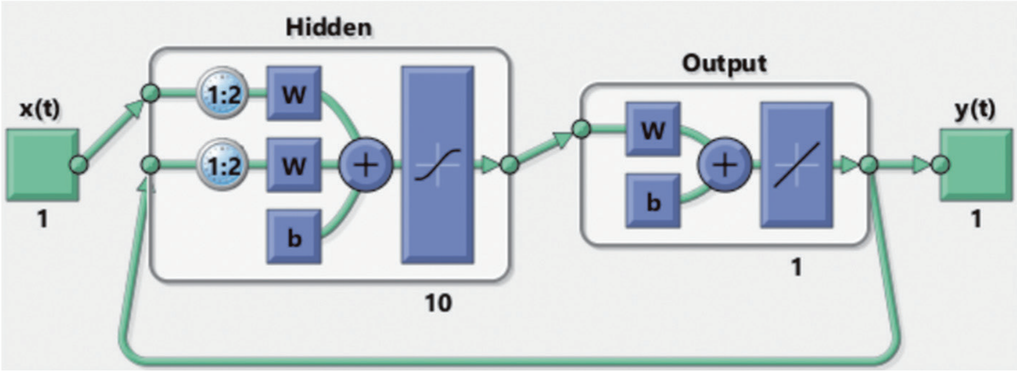

Fig. 1. Schematic diagram of NARX model (MathWorks, 2019).

$$y(t)=f(y(t-1), y(t-2), \ldots, y(t-n), x(t-1), x(t-2), \ldots, x(t-n)) \quad (1)$$

where x is the input data, y is the output data, and t represents the time-series data type. The schematic diagram of the NARX model in shown in Figure 1. By providing the historical input and output data, the prediction model will be obtained by the training process where the weighting parameters (w for weighting and b for bias) in the neural networks are determined.

The effect of decomposition of the raw power generation data on the prediction performance is examined by using the Signal Multiresolution Analyzer of MATLAB. The treatment of decomposition of the raw data is also known as empirical mode decomposition (EMD). The raw data will be break down into several components. The decomposed component can be described as intrinsic mode function (IMF). By removing the component of high frequency part, a smoothed data will be obtained from a complicated raw data. The method of data decomposition is expected to improve the prediction precision as suggested in literature (Yin *et al*., 2019; Liu *et al*., 2020; Ding and Meng, 2020; Memarzadeh and Keynia, 2020). For the decomposition layers, a preliminary test showed that using more layers in decomposition leads to subtle improvement in the precision of prediction. Thus, the decomposition is made with default parameter.

2.1 Employed wind turbine systems

In this study, the 150 kW, 25 kW and 1 kW wind turbine systems are considered for the investigation. The 150 kW horizontal axis wind turbine (HAWT) system was developed by INER since 2009 with compliance of IEC 61400-1. Second generation with variable pitch was proposed in 2014. Detail specification of INER 150 kW-II is shown in Table 3. The turbine system of INER 25 kW is also included in the present study. The rated power is 25 kW at the wind speed of 12 m/s. Other specifications are listed in Table 3. The model of 3 and 5 blades of 1 kW wind turbine system are considered to investigate its effect on the performance of power generation. The 3 kW wind farm is developed with three 1 kW wind turbine systems. Its specification is shown in Table 3. The wind speed and power generation data for the system of 150 kW, 25 kW and 1 kW in the campus of INER are collected by the self-developed Supervisory Control and Data Acquisition (SCADA) system. Comparing the investigated wind turbine systems, the rated Revolutions per Minute (RPM) for the 1 kW system is much faster, and the active control

Table 3. Specification of three investigated wind turbine systems (by author)

Specification	150 kW	25 kW	1 kW
Standard	IEC 61400-1	IEC 61400-1	IEC 61400-1
IEC class	Class-IA	Class-IA	Class-IA
Blade number	3	3	3/5
Turbine type	Up-wind	Up-wind	Up-wind
Rated output power	150 kW	25 kW	1,000 W
Hub height	50 m	25 m	5 m
Tower type	Jacket	Monopile	Monopile
Cut-in speed	3 m/s	4 m/s	2.5 m/s
Rated speed	12 m/s	12 m/s	12 m/s
Cut-out speed	25 m/s	22 m/s	50 m/s
Rated RPM	45~50 RPM	55~65 RPM	750 RPM
Pitch angle control	Active control: 5° ~ 85°	Active control: 0° ~ 90°	N/A
Yaw angle control	Active control: ±180°	Active control: ±180°	N/A
Rotating diameter	22.8 m	12.46 m	2 m

systems for pitch and yaw angle are not available.

The MW scale commercialized wind farm is also considered in the present study. Three previously mentioned wind farms are developed as the experimental facilities for R&D. The long term operation data are available only for the 3 kW wind farm with the smallest scale among the investigated cases. The 25 and 150 kW wind turbine are operated only during the day time for experiment and test, without the long term continuous data. Thus, the commercial and MW scale wind farm is considered to examine the performance of the proposed prediction models.

The LuZhu wind farm was developed since December, 2013. The construction was completed and operation initiated since Feb-2015 with total cost of 480 million NTD. This wind farm belongs to Taiwan Power Company (TPC) and operated by Department of Renewable Energy of TPC. There were eight Enercon, E-44/90 wind turbines installed in this wind farm. The hub heights are 55 m with rotor diameter of 44 m. The wind speed of rated power is 16.5 m/s, and the total installed capacity is 7.2 MW.

The hourly power generation data of the LuZhu wind farm is collected from the website of Information Disclosure of Taiwan Power Company (TPC) (TPC, 2020). The corresponding wind speed and direction are collected from the website of Central Weather Bureau (CWB) (CWB, 2020). By observing the collected power generation and wind data, the duration with stronger wind and power is selected for the present study, i.e., from 10-15-2019 to 10-29-2019. The selected duration is also the season with strong Northeast Monsoon. Most of the wind power for Taiwan is mainly from the Northeast Monsoon in winter time. The collected power generation and corresponding wind speed are shown in Figure 2.

3. Results and Discussion

The performance of the trained model for wind power prediction is evaluated with the actual value for the investigated wind turbine systems. The performance of the developed model is

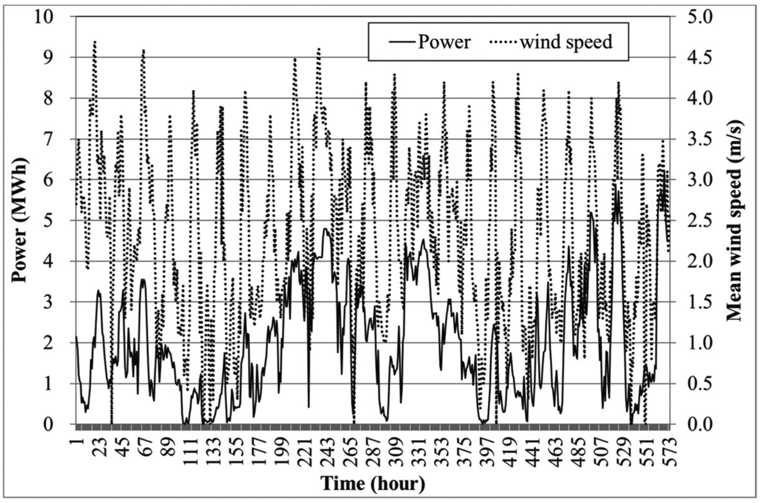

Fig. 2. Hourly power and wind speed of LuZhu wind farm (by author).

evaluated via the indexes of RMSE, MAE, and MAPE.

3.1 Regression model for wind power prediction

The relationship of wind speed and generated power via the 25 kW wind turbine system is shown in Figure 3. An obvious trend could be observed in this figure. With faster wind speed, larger wind power could be generated by the 25 kW wind turbine system.

The wind speed response plot of regression model in training process for 25 kW wind turbine is indicated in Figure 3. The predicted values are compared with the true value. Among the scattering variation, the predicted values are roughly in the middle of the true values. The optimized sub-model of this trained model is Quadratic SVM. The R-Squared value is 0.86 with RMSE of 94.34 and MAE of 66.637. It took 27.103 sec for training process.

The trained model is then employed to

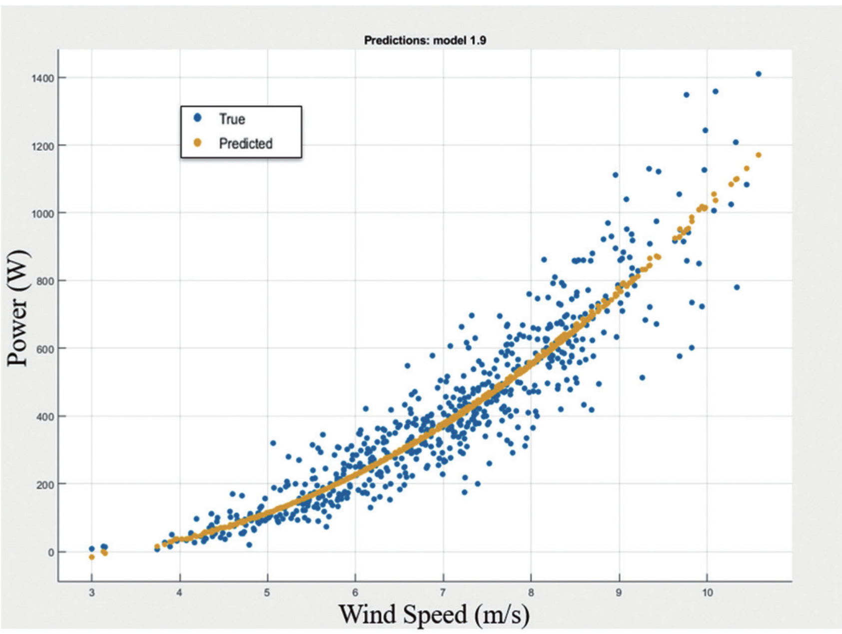

Fig. 3. Wind speed response plot of regression model training for 25 kW wind turbine (by author).

calculate the AEP with one-year-long wind data collected in the campus of INER. The predicted AEP by the regression model is 52 MWh, and it is 57 MWh by the Wind Atlas Analysis and Application Program (WAsP) model. As indicated in this comparison, the predicted AEP by the regression model is in the same order of that by WAsP in the case of 25 kW wind turbine system. Similar procedure for the model development by regression is conducted for the 150 kW and 3 kW wind turbines.

Comprehensive comparison of the prediction performance using raw data for different wind turbine systems is shown in Table 4. For the case of 25 kW wind turbine system, the main pattern is captured properly with high R-Square value comparing to other cases. In general, the regression model for the 25 kW wind turbine system should be applicable for the short-term prediction for wind power but not suitable for the prediction of AEP in this wind farm. For the case of 150 kW and three 1 kW wind turbine system, there is no obvious trend could be obtained due to the scattered distribution of the original data. The R-square values are 0.11 and 0.01, respectively, indicating almost no relationship could be obtained between the regression model and original data. Although the predicted AEPs are comparable with that by WAsP model, the regression models for the 150 kW and three 1 kW wind turbine system won't be applicable for the short-term prediction of wind power.

3.2 Effect of average interval

The effect of average interval of raw data for the 1 kW wind turbine system is conducted by processing the raw data with different time interval for average, namely 1 min., 10 min., 30 min., and 60 min. The regression models are re-built based on the processed data set. The performances of the regression model with two selected time series data are compared as indicated in Figure 4.

As shown in Figure 4, the RMSE for the case of 1 min. is very large with MAPE larger than 100%, indicating the developed regression model is unable to find reasonable trend from input data for prediction. In the case of 10 min., the reduction of RMSE is very obvious, and it is furtherly reduced in the case of 30 min. and 60 min. The optimal case is 60 min. of set 2 data with RMSE of 14 W and MAPE of 22%.

It can be deduced that the regression model is unable to predict reasonably with the data of 1 min. average interval. With larger average interval, namely 60 min., the performance of the proposed regression model is much better with smaller error. However, comparing to the referred studies, the resulted MAPE was generally smaller than 10%.

Table 4. Summary for the performance of regression prediction (by author)

Item	25 kW	150 kW	1 kW X 3
Optimized sub-model	Quadratic SVM	Linear	Linear
R-Square	0.86	0.11	0.01
RMSE (kW)	94.34	4.2	87.75
MAE (kW)	66.637	3.43	61.703
Training time (sec)	27.10	4.52	1.33
AEP prediction (MWh)	52	89.63	0.393
AEP by WAsP (MWh)	57	89.4	0.57

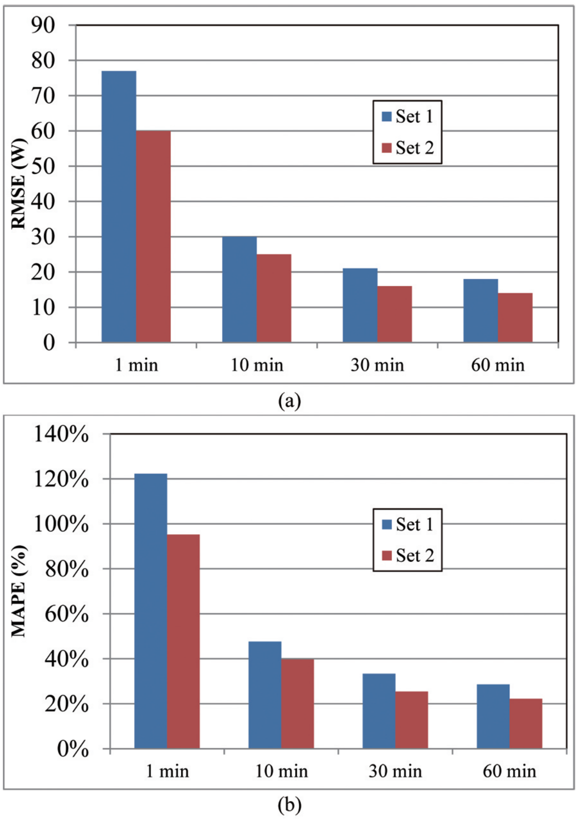

Fig. 4. Comparison of (a) RMSE and (b) MAPE for the effect of average time interval (by author).

Thus, other advanced data pre-process method and prediction algorithm should be introduced to improve the precision of the prediction model.

3.3 Neural network method with decomposition

The neural network model is developed by the NARX and NAR model. The data decomposition of raw data is made by the Signal Multiresolution Analyzer with default parameters. The relative energy of the decomposed data is shown in Figure 5. Original data is decomposed based on different range of frequencies. Higher frequency is classified into Level 1 (0.25 to 0.499). In Level 2, the frequency is from 0.121 to 0.259. In Level 3, the frequency is from 0.0603 to 0.129, and it is 0.0301 to 0.0647 for Level 4. The approximated results is obtained by extracted the data of Level 1 to 4 from the raw data.

Among the investigated wind turbines, it can be observed that the portion belonging to higher frequencies is higher for 3 kW wind turbine system. The remained approximation is less than half comparing to the raw data. For the system of 25 kW and 150 kW, however, high frequencies portion are much less (below 5%), and more than 80% data remained in the approximated data.

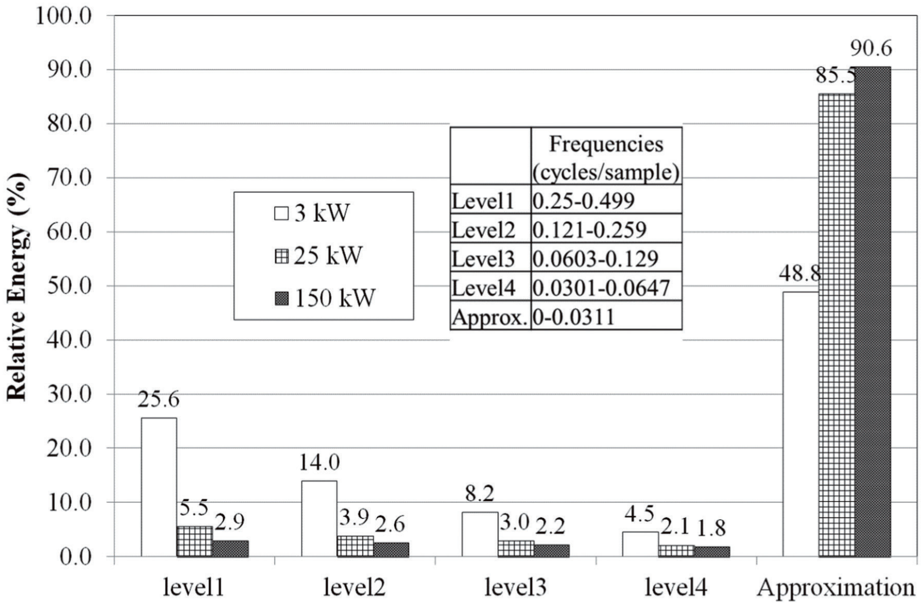

Fig. 5. Relative energy of decomposed data (by author).

For the system of 150 kW, the remained portion is more than 90%. It can be concluded from this analysis that more high frequency relative energy is observed for smaller wind turbine, while it would be small portion for larger wind turbine among the present investigated systems.

The results are compared when introducing the method of decomposition with the NARX model as shown in Figure 6. As mentioned in the previous section, the prediction is made by the NARX model using the data of power, wind speed and direction as the case of Raw in Figure 6. Two additional models are proposed with approximated power data (Appro.) and raw data combined with 4 sets of decomposed data (L1234). For the case of Appro., the precision of 99% is achieved where the decomposed 4 sets of data are removed from the raw data.

It is obviously observed that the cases simply using raw data leads to larger MAPE. For the case of 3 kW, the resulting MAPE is larger than 100%. This is mainly due to the lower height of the 3 kW wind farm, and its coming wind and power production would be significantly affected by the nearby buildings and trees. For higher wind turbine system, such as 25 kW and 150 kW, their hub height are 25 m and 150 m, respectively. The effect of nearby obstacles on the wind farm and power production is relatively insignificant, leading to smaller MAPE in the prediction test as shown in Figure 6.

Considering the large alteration for the case of Appro. (more than 50% of decomposed data removed for the case of 3 kW), the results of this case might not be pragmatic, but as a reference for comparison. For the case of L1234, pretty good results are obtained. This configuration should be more pragmatic since the original data is still employed with 4 additional sets of decomposed data. With the extracted feature from the decomposed data, there is no need to modify the original power data to reach better prediction performance. For the case of 25 and 150 kW, the MAPE are below 10% (6.6% and 7.9%), but it is still relatively large for the case of 3 kW (17.7%). Among the investigated wind turbines, smaller wind turbine leads to larger error, and larger wind turbine leads to better prediction performance.

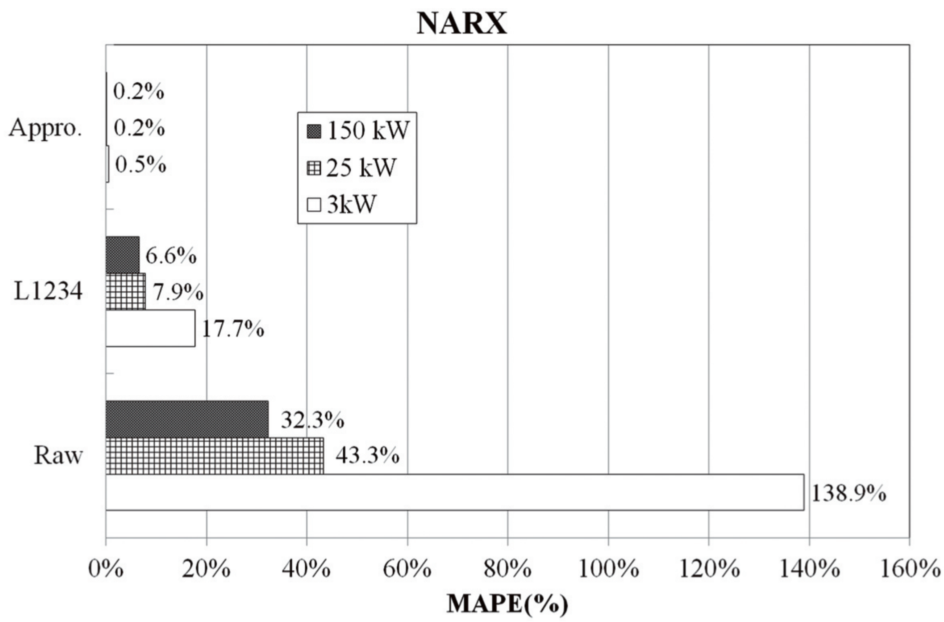

Fig. 6. Performance by different method with NARX model (by author).

The validity of this trend should be verified for the larger coastal wind turbines.

The results with decomposed process using NAR model are compared in Figure 7. When using the NAR model, only the data of power generation is needed without the information of wind speed and direction. It is shown that the MAPE for the case using raw data and NAR model is generally larger than 100%. This is mainly due to the weather data (wind speed and direction) is excluded in the NAR model comparing to NARX model. When directly introduce the highly non-linear power production data for the training and testing process for the NAR model, larger error is expected comparing to NARX model. Thus, the data decomposition and other pre-process methods should be included to improve the prediction precision.

Besides the case of raw and Appro., three additional tests are conducted with different level of extraction from the raw data. In the case of L234, the data of Level 1 is removed, and the removal is Level 1 and 2 for L34. In the case of L4, the data of Level 1, 2, and 3 are removed. In the case of Appro., all four sets of decomposed data are removed. It should be noted that the MAPE for the case of 25 kW-raw is divided by 100 for better presentation. Results show that smaller errors are achieved with more deleted data set. But the process of removing the decomposed data also makes the employed value far away from the original distribution. Besides the case of raw, larger MAPEs are obtained for the 3 kW wind turbine in other cases, and it is much smaller for 25 and 150 kW wind turbines. By deleting a layer of data, the MAPE lower than 20% can be achieved for 25 and 150 kW, and it is large improvement comparing the case of raw (258% and 7193% respectively). By deleting two layers of data, the MAPE lower than 5% is achieved for 25 and 150 kW, but it is still larger than 10% for 3 kW. Further deletion makes the MAPE smaller than 3%, and it is less than 1% for the case of Appro. Therefore, with more layers of data deleted, smaller error could be obtained by the proposed method. However, the ratio of the deleted data and raw data should be considered simultaneously, especially for the case of small wind turbine.

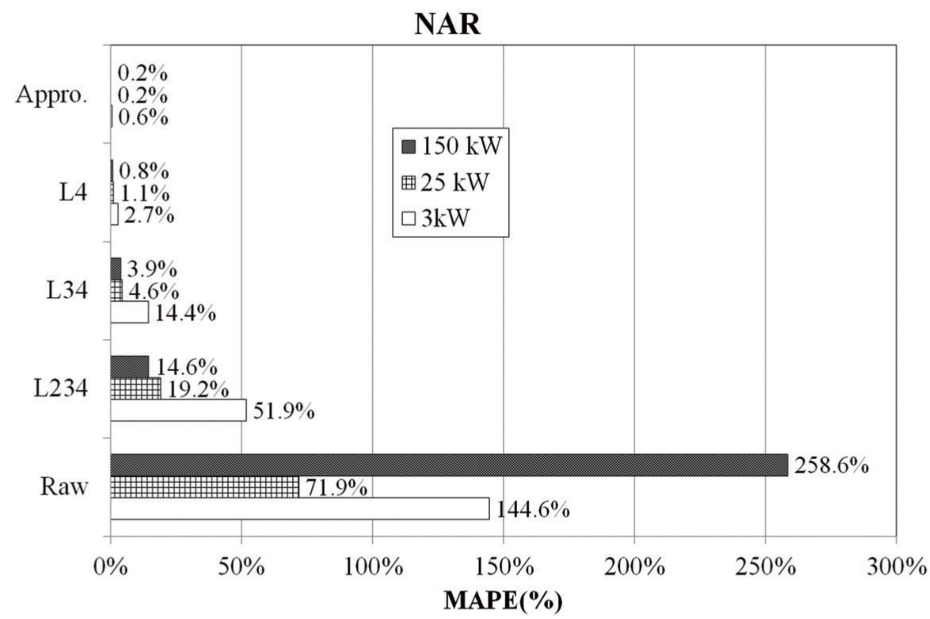

Fig. 7. Performance by different method with NAR model (by author).

In the present study, the decomposition is made with 4 layers. More layers of decomposition was made in other studies (Liu *et al*., 2020; Ding and Meng, 2020). In the study of Liu (Liu *et al*., 2020), the original data was decomposed into 9 layers, and the data of first layer was removed. The resulted MAPE was about 5% in the prediction of wind speed among the investigated sites. In the present study, the proposed model is employed to predict generated power. By removing 1 layer of 4 decomposed data, the resulting MAPE are 19% and 14% for 25 kW and 150 kW wind turbine, respectively. The effect of decomposition layers on the precision of prediction can be conducted in the future. Better improvement is also observed for larger wind turbine in the present study. Further larger commercial wind turbine and its data are applied to examine the performance of the proposed model for power prediction in the next section.

3.4 Case study for the MW scale wind farm

The method of wavelet transformation is introduced in this section. It is also expected to improve the prediction precision by removing the data of high frequency as mentioned in relevant study (Li *et al*., 2018). The comparison of the raw data of the investigated MW scale wind farm and the processed data via decomposition and wavelet method is presented in Figure 8. As compared in Figure 8, the large scale fluctuations for the approximated curve via decomposition method are almost vanished, leading to pretty smooth variation. For the curve via the wavelet method, the denoise process only vanish small amount of peak fluctuations. In overall, the wavelet denoise data is almost the same with that of raw data. It is expected the performance of prediction via the approximated data will be very good since the processed curve is pretty smooth. However, the processed values are much far away from the original data, making it a not practical approach among the investigated methods. The data via the wavelet method are almost the same with that of raw data. It would be applicable if its prediction performance is good enough.

The time series data via the decomposition

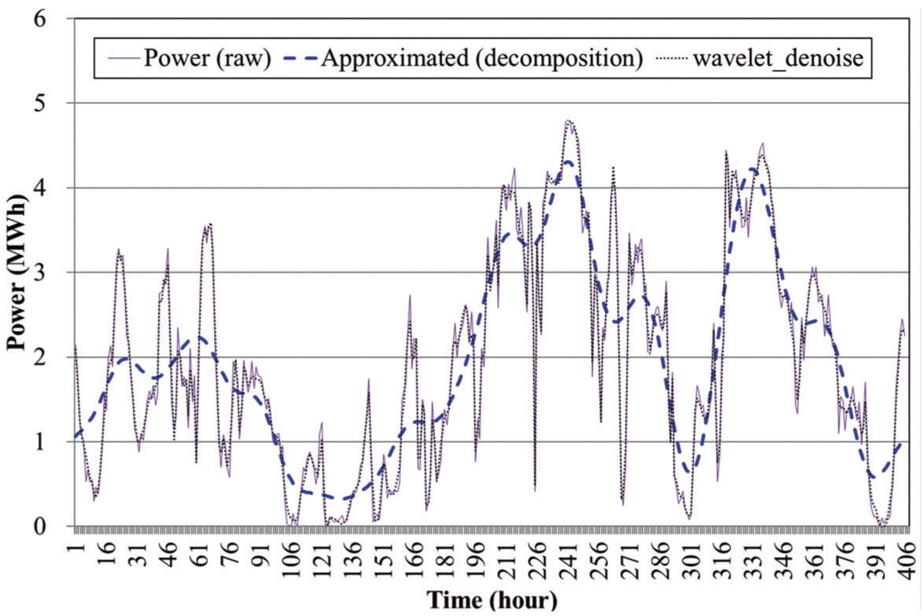

Fig. 8. Comparison of power data via different process method (by author).

method are presented in Figure 9, Figure 10, Figure 11, and Figure 12. Four additional sets of data are generated by the decomposition method, namely L1, L2, L3, and L4. Much more fluctuations are

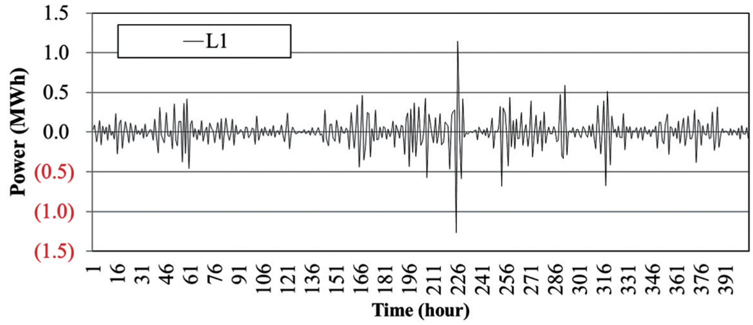

Fig. 9. Decomposition curve of level 1 (by author).

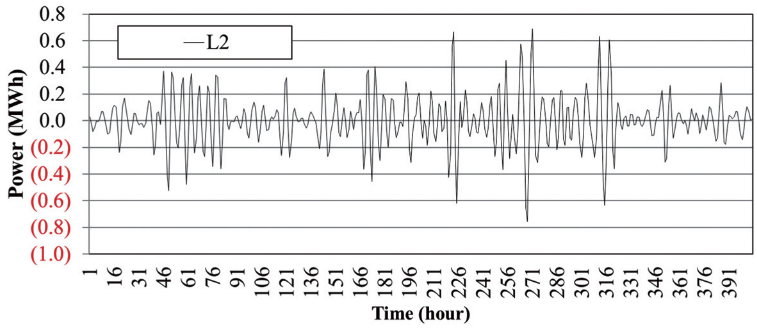

Fig. 10. Decomposition curve of level 2 (by author).

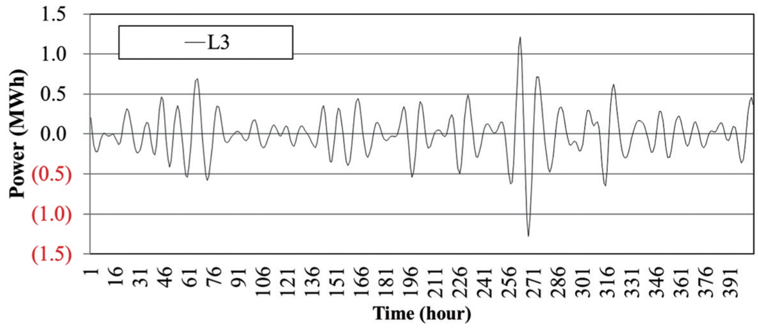

Fig. 11. Decomposition curve of level 3 (by author).

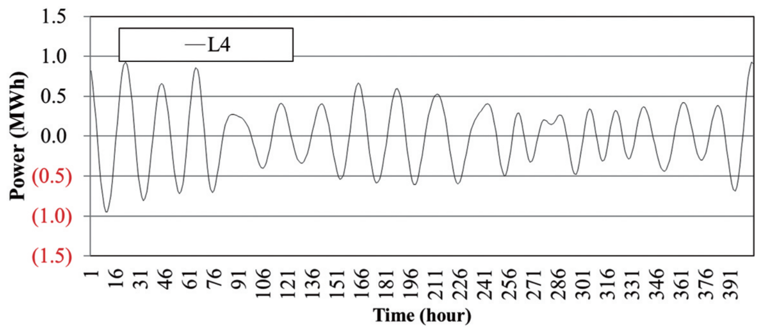

Fig. 12. Decomposition curve of level 4 (by author).

observed in the curve of L1, and it alleviates in the following curve. In the curve of L4, it is much smooth and only small amount of variations are observed.

Comprehensive comparisons for the wind farm of MW scale using different sub-models are presented in Table 5, Table 6 and Table 7. For the case using regression method, three additional sub-models are considered for comparison. In case 1, only the raw data are employed for training and test. In case 2, the 4 sets of decomposed data are included. In case 3, the target data are replaced by the approximated data. In case 4, the wavelet denoise data are employed as the target of training and test.

Table 5. Comparison of prediction results of regression method (by author)

Case Number	Sub-model	MAPE by Regression (%)
1	Raw	36.65
2	Raw + L1234	30.41
3	Raw + L1234, App. Target	31.44
4	wavelet denoise Target	37.63

Table 6. Comparison of prediction results of NARX method (by author)

Case Number	Sub-model	MAPE by NARX (%)
1	Raw	24.72
2	**Raw + L1234**	**4.19**
3	wavelet denoise Target	19.29

Table 7. Comparison of prediction results of NAR method (by author)

Case Number	Sub-model	MAPE by NAR (%)
1	Raw	20.62%
2	Decom. App	0.31%
3	wavelet denoise Target	20.62%

As compared in Table 5, the performance of the prediction model using the regression method is not good, with MAPE about 30% to 37%. For the case including the decomposed additional data set, the precisions are slightly improved, and there is no obvious variation when using the method of wavelet transformation. It is deduced that the non-linear behavior and pattern of the raw data for the MW scale wind farm cannot be effectively identified by the regression method.

Secondly, the prediction model using the neural network is proposed by the NARX and NAR method, respectively. Similar to previously mentioned procedure, three cases are considered. In case 1, only the raw data are included. Additional decomposed data sets are considered as case 2, and wavelet denoise data is designated as the target as case 3.

Results are compared in Table 6. Improvement of 33% (from 36.65% to 24.72%) is observed in case 1 when comparing to the case of regression model. In case 2 of NARX model, the MAPE significantly reduces to 4.19%, making it the most appropriate option among the considered models. Comparing to the relevant study (Liu *et al*., 2020) where the raw data was decomposed into 9 layers and the data of first layer was removes, the resulted MAPE was about 5%. Further investigation and parametric study could be conducted based on this case. In case 3, improvement of 49% (from 37.63% to 19.29%) is observed.

Finally, the prediction model using the NAR sub-model is proposed. In case 1, only raw data is employed. In case 2, the target is replaced to the approximated data since only the target data set is needed for the NAR sub-model. In case 3, the target is replace by the wavelet denoise data.

Results are compared in Table 7. Slightly improvement is observed in case 1 and case 3. The reduction of MAPE is about 5% comparing to that of NARX. In case 2, the MAPE reduces to only 0.31%, indicating the precision of prediction is higher than 99%. As mention in the previous section, the employed approximated data set of case 2 is significantly different from the original raw data. It is not practical when deploying to further prediction. In case 3, the effect of using the wavelet method is not significant on the improvement of precision as observed in the previous discussion.

4. Conclusion

The purpose of this study is to conduct the wind power prediction by the regression and neural network methods for the experimental and commercial wind turbine systems. The first prediction is made by the raw data without the process of data treatment. Then, the methods of data process are introduced for the second prediction. The method of dada process with significant effect on the performance of wind power prediction is identified for the case study of MW scale wind farm.

The effect of decomposition of the raw power generation data on prediction is examined. Results show that the relative energy of high frequency is observed for small wind turbine, while it is small portion for larger wind turbine. Among the investigated conditions, smaller wind turbine leads to larger error, and larger wind turbine results in better prediction performance. The proposed prediction model is then applied to the MW scale wind farm. Following points are drawn based on the calculated results:

(1) The performance of regression model is not good in the MW scale wind farm, and the resulting MAPE is generally larger than 30%.

(2) Better performance is obtained using the NARX model combined with the decomposed data sets, and the resulted MAPE is comparable (< 5%) with the relevant study in literature. The NARX model is also a practical method since the employed raw data is not altered.

(3) The precision of 99% can be obtained using the NAR model. Such high precision is reached by removing about 50% of the decomposed data. However, it is not pragmatic due to its significant alteration of the employed data.

(4) There is not obvious improvement (ΔMAPE < 1%) in the prediction by using the method of wavelet transformation due to its insignificant modification from raw data.

(5) By using the proposed NARX model with data decomposition method, the wind power prediction model can be employed to achieve the policy goal made by the Bureau of Energy, Ministry of Economic Affairs in 2020 (error of one-hour ahead prediction should be less than 6.5% in 2022, 5% in 2025, and 4% in 2030).

References

Aasim, S. N. Singh and Abheejeet Mohapatra, 2019. “Repeated Wavelet Transform Based ARIMA Model for Very Short-Term Wind Speed Forecasting.” *Renewable Energy* 136: 758-68. https://doi.org/https://doi.org/10.1016/j.renene.2019.01.031.

Chen, Ming-hong, 2018. “Wind Resources Assessment and Micro-Siting in Institute of Nuclear Energy Research.” *Journal of Taiwan Energy* 5 (3): 217.

CWB, 2020. “Observation Data Inquire System.” https://e-service.cwb.gov.tw/HistoryData

Query/index.jsp.

Diaconescu, Eugen, 2008. "The Use of NARX Neural Networks to Predict Chaotic Time Series." *WSEAS Transactions on Computer Research* 3(3): 182-91.

Ding, Wen and Fanyong Meng, 2020. "Point and Interval Forecasting for Wind Speed Based on Linear Component Extraction." *Applied Soft Computing 93* (August 2020): 106350. https://doi.org/10.1016/j.asoc.2020.106350.

Erdem, Ergin and Jing Shi, 2011. "ARMA Based Approaches for Forecasting the Tuple of Wind Speed and Direction." *Applied Energy* 88(4): 1405-14. https://doi.org/https://doi.org/10.1016/j.apenergy.2010.10.031.

Ghadi, M. Jabbari, S. Hakimi Gilani, H. Afrakhte and A. Baghramian, 2014. "A Novel Heuristic Method for Wind Farm Power Prediction: A Case Study." *International Journal of Electrical Power and Energy Systems* 63: 962-70. https://doi.org/10.1016/j.ijepes.2014.07.008.

Guo, Zhen-hai, Jie Wu, Hai-yan Lu and Jian-zhou Wang, 2011. "A Case Study on a Hybrid Wind Speed Forecasting Method Using BP Neural Network." *Knowledge-Based Systems* 24(7): 1048-56. https://doi.org/https://doi.org/10.1016/j.knosys.2011.04.019.

Guzman, Sandra M., Joel O. Paz and Mary Love M. Tagert, 2017. "The Use of NARX Neural Networks to Forecast Daily Groundwater Levels." *Water Resources Management* 31(5): 1591-1603. https://doi.org/10.1007/s11269-017-1598-5.

Hao, Ying, Lei Dong, Xiaozhong Liao, Jun Liang, Lijie Wang and Bo Wang, 2019. "A Novel Clustering Algorithm Based on Mathematical Morphology for Wind Power Generation Prediction." *Renewable Energy* 136: 572-85. https://doi.org/10.1016/j.renene.2019.01.018.

Harrou, Fouzi, Ahmed Saidi and Ying Sun, 2019. "Wind Power Prediction Using Bootstrap Aggregating Trees Approach to Enabling Sustainable Wind Power Integration in a Smart Grid." *Energy Conversion and Management* 201 (May): 112077. https://doi.org/10.1016/j.enconman.2019.112077.

Jiang, Ping, Biao Wang, Hongmin Li and Haiyan Lu, 2019. "Modeling for Chaotic Time Series Based on Linear and Nonlinear Framework: Application to Wind Speed Forecasting." *Energy* 173: 468-82. https://doi.org/https://doi.org/10.1016/j.energy.2019.02.080.

Li, Cunbin, Shuaishuai Lin, Fangqiu Xu, Ding Liu and Jicheng Liu, 2018. "Short-Term Wind Power Prediction Based on Data Mining Technology and Improved Support Vector Machine Method: A Case Study in Northwest China." *Journal of Cleaner Production* 205: 909-22. https://doi.org/10.1016/j.jclepro.2018.09.143.

Liu, Tianhong, Haikun Wei and Kanjian Zhang, 2018. "Wind Power Prediction with Missing Data Using Gaussian Process Regression and Multiple Imputation." *Applied Soft Computing Journal* 71: 905-16. https://doi.org/10.1016/j.asoc.2018.07.027.

Liu, Zhenkun, Ping Jiang, Lifang Zhang and Xinsong Niu, 2020. "A Combined Forecasting Model for Time Series: Application to Short-Term Wind Speed Forecasting." *Applied Energy* 259 (October 2019): 114137. https://doi.org/10.1016/j.apenergy.2019.114137.

Mahmoud, Tawfek, Z. Y. Dong and Jin Ma, 2018. "An Advanced Approach for Optimal Wind Power Generation Prediction Intervals by Using Self-Adaptive Evolutionary Extreme Learning Machine." *Renewable Energy* 126:

254-69. https://doi.org/10.1016/j.renene.2018.03.035.

Marugán, Alberto Pliego, Fausto Pedro García Márquez, Jesus María PinarPerez andD iego Ruiz-Hernández, 2018. "A Survey of Artificial Neural Network in Wind Energy Systems." *Applied Energy* 228: 1822-36. https://doi.org/https://doi.org/10.1016/j.apenergy.2018.07.084.

MathWorks, 2019. "Matlab 2019 User Guide."

Memarzadeh, Gholamreza and Farshid Keynia, 2020. "A New Short-Term Wind Speed Forecasting Method Based on Fine-Tuned LSTM Neural Network and Optimal Input Sets." *Energy Conversion and Management* 213 (December 2019): 112824. https://doi.org/10.1016/j.enconman.2020.112824.

Menezes, José Maria P. and Guilherme A.Barreto, 2008. "Long-Term Time Series Prediction with the NARX Network: An Empirical Evaluation." *Neurocomputing* 71 (16-18): 3335-43. https://doi.org/10.1016/j.neucom.2008.01.030.

Naik, Jyotirmayee, Pradipta Kishore Dash and Snehamoy Dha, 2019. "A Multi-Objective Wind Speed and Wind Power Prediction Interval Forecasting Using Variational Modes Decomposition Based Multi-Kernel Robust Ridge Regression." *Renewable Energy* 136: 701-31. https://doi.org/10.1016/j.renene.2019.01.006.

Ouyang, Tinghui, Heming Huang, Yusen He and Zhenhao Tang, 2020. "Chaotic Wind Power Time Series Prediction via Switching Data-Driven Modes." *Renewable Energy* 145: 270-81. https://doi.org/10.1016/j.renene.2019.06.047.

Ouyang, Tinghui, Xiaoming Zha and Liang Qin, 2017. "A Combined Multivariate Model for Wind Power Prediction." *Energy Conversion and Management* 144: 361-73. https://doi.org/10.1016/j.enconman.2017.04.077.

Ouyang, Tinghui, Xiaoming Zha, Liang Qin, Yusen He and Zhenhao Tang, 2019. "Prediction of Wind Power Ramp Events Based on Residual Correction." *Renewable Energy* 136: 781-92. https://doi.org/10.1016/j.renene.2019.01.049.

Qureshi, Aqsa Saeed, Asifullah Khan, Aneela Zameer and Anila Usman, 2017. "Wind Power Prediction Using Deep Neural Network Based Meta Regression and Transfer Learning." *Applied Soft Computing Journal* 58: 742-55. https://doi.org/10.1016/j.asoc.2017.05.031.

Safari, N, C. Y. Chung and G. C. D. Price, 2018. "Novel Multi-Step Short-Term Wind Power Prediction Framework Based on Chaotic Time Series Analysis and Singular Spectrum Analysis." *IEEE Transactions on Power Systems* 33(1): 590-601. https://doi.org/10.1109/TPWRS.2017.2694705.

Taslimi Renani, Ehsan, Mohamad Fathi Mohamad Elias and Nasrudin Abd Rahim 2016. "Using Data-Driven Approach for Wind Power Prediction: A Comparative Study." *Energy Conversion and Management* 118: 193-203. https://doi.org/10.1016/j.enconman.2016.03.078.

TPC, 2020. "Information Disclosure." https://www.taipower.com.tw/en/pageList.aspx.

Yan, Jing and Tinghui Ouyang, 2019. "Advanced Wind Power Prediction Based on Data-Driven Error Correction." *Energy Conversion and Management* 180 (October 2018): 302-11. https://doi.org/10.1016/j.enconman.2018.10.108.

Yin, Hao, Zuhong Ou, Shengquan Huang and Anbo Meng, 2019. "A Cascaded Deep Learning Wind Power Prediction Approach Based on a Two-Layer of Mode Decomposition." *Energy* 189: 116316. https://doi.org/10.1016/j.energy.2019.116316.

Yuan, Xiaohui, Qingxiong Tan, Xiaohui Lei, Yanbin Yuan and Xiaotao Wu, 2017. "Wind Power Prediction Using Hybrid Autoregressive Fractionally Integrated Moving Average and Least Square Support Vector Machine." *Energy* 129: 122-37. https://doi.org/10.1016/j.energy.2017.04.094.

Zhang, Chi, Haikun Wei, Junsheng Zhao, Tianhong Liu, Tingting Zhu and Kanjian Zhang, 2016. "Short-Term Wind Speed Forecasting Using Empirical Mode Decomposition and Feature Selection." *Renewable Energy* 96: 727-37. https://doi.org/https://doi.org/10.1016/j.renene.2016.05.023.

使用迴歸與類神經網路法進行風力發電量預測分析

陳銘宏[1*]

摘 要

本研究之目的在於使用迴歸與類神經網路法進行風力發電預測。在NAR (Nonlinear Autoregressive)模式下，將原始資料拆解並去除部分之後，可有較佳之預測結果，但須同時考慮去除之資料與原始數據之比例，尤其是小型風機；在NARX (Nonlinear Autoregressive with External Input)模式下，則無需刪除資料亦可改善預測之結果。本研究接著應用所提出之預報系統至MW等級之風場進行案例分析。計算之結果顯示，使用NARX模式結合數據拆解前處理程序時，可獲得較佳之結果，而採用小波轉換法處理數據後，對於預測準確度沒有明顯的影響。

關鍵詞：風能，預報，迴歸，類神經網路

[1] 核能研究所機械及系統工程專案計畫 助理研究員
*通訊作者電話: 03-4711400 #3351, E-mail: minghongchen@iner.gov.tw

收到日期: 2020年11月02日
修正日期: 2021年04月20日
接受日期: 2021年05月06日