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計　畫 名　稱：	以半監督式深度學習法建立風力發電機內部耗能之預測模型

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Abstract

Burning fossil fuels produce a lot of greenhouse gases, which will cause global warming and climate change. For sustainable development of the earth, many countries are actively conducting research on clean and low-pollution green energy. The wind power generation is one of them. Most of the previous works on wind power have focused on the impact of external environments on energy generation efficiency. However, they ignored the energy consumption of internal parts of the wind turbine. Reducing internal energy consumption can not only improve efficiency, but also reduce the maintenance cost of wind turbines. Therefore, this study adopts deep learning to predict the energy consumption inside the wind turbine through installing dozens of sensors inside it, and find the parts that have greater impact on energy consumption to reduce energy consumption and improve generating efficiency. Since most wind turbine data is collected by humans currently, it is inevitable that the data will have missing or wrong. Due to a large number of parts inside the wind turbine, the collected data belongs to multi-dimension data. In order to use these data effectively, this study proposes a semi-supervised deep learning method which can correct the data to solve this problem. Compared to traditional supervised deep learning methods, the proposed semi-supervised method can more effectively use the missing data, and can also reduce the time and labor costs required to manually correct the wrong data. After all the data are corrected and the model is completely trained, this study uses the Matthews correlation coefficient (MCC) method to judge the predicting results of the model. The results show that when the label data accounts for 15-20% of the total data, the trained model has the best predictive ability. Therefore, this study suggests that when establishing a prediction model of internal energy consumption of wind turbine in the future, the label data should account for 15-20% of the total data. In this way, the proposed method not only can train a model with considerable accuracy, but also provides an economical way to determine the amount of revision data.

Keywords: Renewable energy, wind power generation, deep learning, energy forecasting

1. Introduction

In recent years, renewable energy has become one of the focal points of today's research. Due to the gradually reduction of fossil fuel for power generation, the world is facing the problems of energy crisis and resource shortage. In order to find renewable energy for replacement of fossil fuels, many innovative research fields have emerged, including the studies that analyze and predict the energy consumption of power generation.

Wind power is one of the renewable energy. It is characterized by low cost of power generation and no exhaustion of raw materials. Therefore, many countries have begun to pay attention to the construction of wind turbines, hoping to fill the insufficiency caused by lack of traditional fossil fuel power generation. With the increasing use of wind turbines around the world, accurate and reliable energy consumption prediction has become difficult but must be solved. One of the main methods to solve these problems is the deep learning that can establish a related prediction model.

Many studies have proposed various models that use deep learning to predict energy consumption of wind turbines. For example, the work in [1] proposed a prediction model based on wind speed and power using a mixing method of physics, statistics, and different time ranges to improve the model accuracy and find the source of the error. In addition, solving the problems is related to wind energy prediction. The work in [2] analyzed two cases based on wind speed and wind power generation, and systematically and comprehensively studied the applicability of different methods for wind power forecasting. Its study results showed that the mixed method is one of the feasible options for predicting wind speed and wind power time series. In addition, the work in [3] used a variety of different prediction models to predict the energy consumption of wind power generation. Since all the prediction models have inherent errors, they discussed the error evaluation criteria in various wind energy predictions and studied the most common wrong measurement that makes the prediction of the wind energy model more accurate.

Most of the previous works above focused on the changes in the external environment of wind turbines, and used deep learning to analyze and predict energy consumption to improve generating efficiency. However, many works did not consider the impact of the internal energy consumption of wind turbines. The energy consumption of internal parts is not only related to the overall energy consumption of the wind turbine. When the internal energy consumption is abnormal, it may also be a precursor to the potential failure of the machine. Therefore, this study decides to analyze the data of various parts inside the wind turbine, and uses a semi-supervised deep learning method to train a prediction model of wind turbine internal energy consumption, hoping to improve the accuracy of wind turbine energy consumption prediction and reduce the wind power generation cost.

In this study, we install dozens of sensors inside the wind turbine to collect data of various parts inside the wind turbine, such as grid voltage, grid current, hydraulic oil temperature, hydraulic oil pressure, and gear oil temperature, etc. With the aid of deep learning to analyze the correlation between these parts data. Exploring the impact of each part on the internal energy consumption of wind turbine. Factors that affect the efficiency of power generation include wind speed, blade diameter, and number of blades, etc. The wind turbine internal parts are illustrated in Fig. 1.

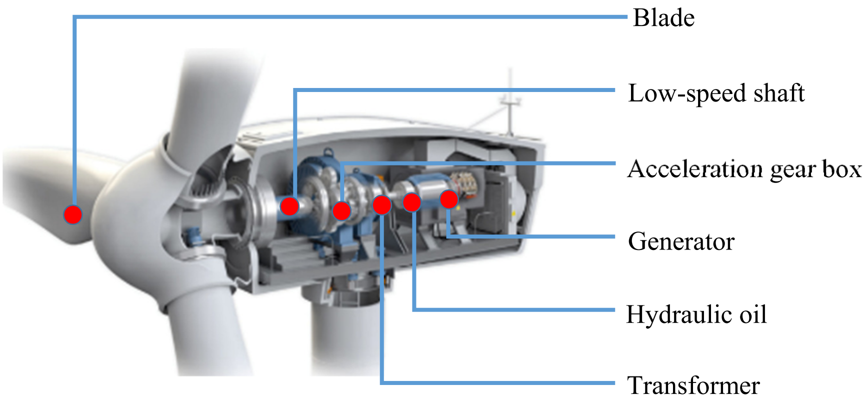


Fig. 1. Internal parts of a wind turbine.

At present, most of the data of wind turbines are manually recorded. However, in the process of manual recording, it is inevitable that there will be data missing or recording errors. To correct these errors, it will cost a lot of labor and time. In addition, since dozens of sensors are installed on the wind turbine, the collected data belongs to high-dimensional data, how to effectively use these data is also a problem that needs to be considered.

In order to solve the problem of time-consuming conversion data and high-dimension data, this study decides to use the semi-supervised deep learning method to deal with this problem. The reason why the semi-supervised deep learning method is used is because compared to traditional supervised deep learning methods, semi-supervised deep learning method requires only a small amount of label data and a large amount of unlabeled data to generate a predictive model. The semi-supervised deep learning method is between the supervised method and the unsupervised method which combines the advantages of the two. The characteristic of semi-supervised deep learning method is that it only needs a small amount of label data and a large amount of unlabeled data through label propagation and label compensation processing the data into a form that can be used to train the model. Then using deep learning to find the hidden layer between the part data and the internal energy consumption. Finally, it will generate a set of prediction models which can use wind turbine internal parts data to predict internal energy consumption.

2. Literature Review

Semi-supervised deep learning is a new method that combines supervised learning and unsupervised learning which was first proposed by [4]. At the beginning, it mainly hoped to use a small amount of label data and a large number of unlabeled data to solve the problem of training and classification. Then it has divided into several different aspects to be studied by other researchers. Table 1 shows various aspects used in semi-supervised deep learning. The works in [5], [6] used a co-training method to train two different learning machines based on different views, which improve the confidence of the training samples. The work in [6] adopted the co-training method to train a model that can recognize different kinds of medical pictures. The works in [7], [8] used the algorithm of label propagation, which finds unlabeled data with the most similar features to label data, so that the label of unlabeled data can be defined more accurately. The work in [8] used deep learning with label propagation plus label compensation to predict the energy consumed in the steelmaking process, further improving the efficiency of steelmaking. The works in [9], [10] used a self-training model to add unlabeled data to the model purpose to improve the accuracy of the model. The work in [10] used the self-training model to determine the sufficiency of labeled data. The work in [11] put forward a semi-supervised support vector regression method based on self-training, and applied it to virtual metrology in semiconductor manufacturing. The work in [12] used the method of generative model based on the gamma distribution. The label image in the category is used to construct a generative model for a category to update the parameters of the generated model. It can be seen from the application of the above mentioned semi-supervised deep learning method in various new technological fields that the semi-supervised deep learning method has gradually developed robustly and perfected.

Table 1. Classification of recent works.

Reference	Co-training	Label propagation	Self-training	Generative model
[5], [6]	V			
[7], [8]		V		
[9], [10], [11]			V	
[12]				V

As for the works on wind turbines, the work in [1] considered efficiency prediction at different time scales that studies different types of prediction models, and discusses the accuracy and sources of errors of the models. The work in [2] analyzed two cases based on different wind power generations, studied the applicability of different methods to wind power forecasting, and proposed that hybrid methods are feasible options for predicting wind speed and wind power time series. The work in [3] considered a variety of prediction models to predict wind power consumption. Since all prediction models have inherent errors, the error evaluation standard in various wind power energy predictions are discussed. The common error measures are studied and analyzed to make the prediction model of wind power energy can be more accurate.

The work in [13] studied the wind power capacity and average wind power density of different countries. Considering various aspects of wind power efficiency, environment, economy, and energy security, they found that several countries are most suitable for development of wind power as an object that various countries can refer to when considering the development of wind power. The work in [14] measured the wind turbine speed and efficiency in different latitudes, and found that the variability of wind power generation is mainly affected by the cumulative energy distribution index and the impact of wave motion factors. The work in [15] used high-resolution material inventory data to quantify the bottom-up material flow analysis model and efficiency index of materials, by analyzing the concrete and steel used in the construction of wind turbines to calculate the relationship between consumed materials and generating efficiency. Through the analysis, they hoped to reduce the gap between wind power production and demand, and reduce the construction cost of wind turbine. The work in [16] studied the efficiency of wind energy production, used regression models to explain the occurrence of losses caused by natural disasters, and pointed out the importance of anti-icing and de-icing systems for wind turbine, in order to reduce the losses caused by natural disasters.

3. System framework

This study considers a system of wind turbines which consists of an offshore wind turbine and a control room, as shown in Fig. 2. A number of sensors are installed in various parts of the main body of the wind turbine to collect continuous time data of internal parts of the wind turbines. Then, the collected data is transferred back to the computer located in the control room. In addition to accepting the data of the generator, the control room can also control the internal parts of the wind turbines, and use deep learning to analyze the data of various parts of the wind turbine.

This system is set as follows. Wind power generation is a power generation method that converts wind energy into electrical energy through mechanical energy. Assuming that the wind generator is set up in a region with stable wind and less natural disasters, it can continue to collect wind power under different climate conditions throughout the year. Because data is collected directly back to the computer in the control room through sensors, the collected data is continuously updated. Different from the previous works on the surrounding environment of wind turbines, this study focuses on analyzing the data of internal parts of an offshore wind turbine, and uses the data of internal parts to establish a prediction model of internal energy consumption of the wind turbine, to improve the power generating efficiency of the wind turbine through adjusting internal parts.

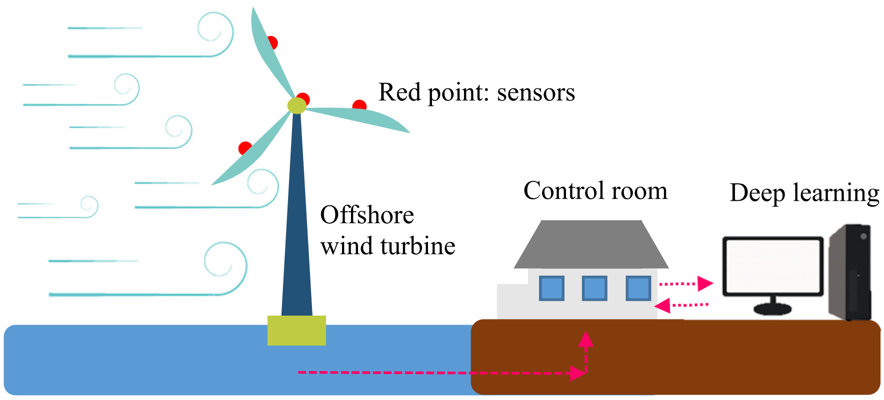


Fig. 2. Model of offshore wind turbine.

4. Methodology

This chapter first introduces the problem concerned in this study, and then proposes a semi-supervised deep learning method for solving this problem.

4.1 Problem description

This study continues collect data of different parts of the wind turbine under different conditions through installing sensors in each part of the wind turbine. Then, the collected data is modified into a format suitable for deep learning method through the help of label propagation and label compensation. Finally, deep learning is used to find the hidden layer between the data and the internal energy consumption. A prediction model to predict the internal energy consumption of the wind turbines is trained. The internal energy consumption of wind turbines is related to dozens of parts, which are grid voltage, grid current, grid rotor temperature, hydraulic oil temperature, hydraulic oil pressure, rotor speed, original wind speed and gear oil temperature, etc. Therefore, there are dozens of variables in this study. In this study, the frequency of the data collected by the internal sensors of the wind turbine is set every five minutes, so there are $24 \times 60 \times 12 = 17280$ data samples in a day.

As a result, the data collected in this study are huge and high-dimensional data.

4.2 Proposed algorithm

This study uses a semi-supervised deep learning method, which requires only a small amount of labeled data and a large amount of unlabeled data, so that the wind power data which may be missing or typographical errors in the process of collecting can be effectively used. The flowchart of this deep learning method is shown in Fig. 3. The notations used in the method are shown in Table 2.

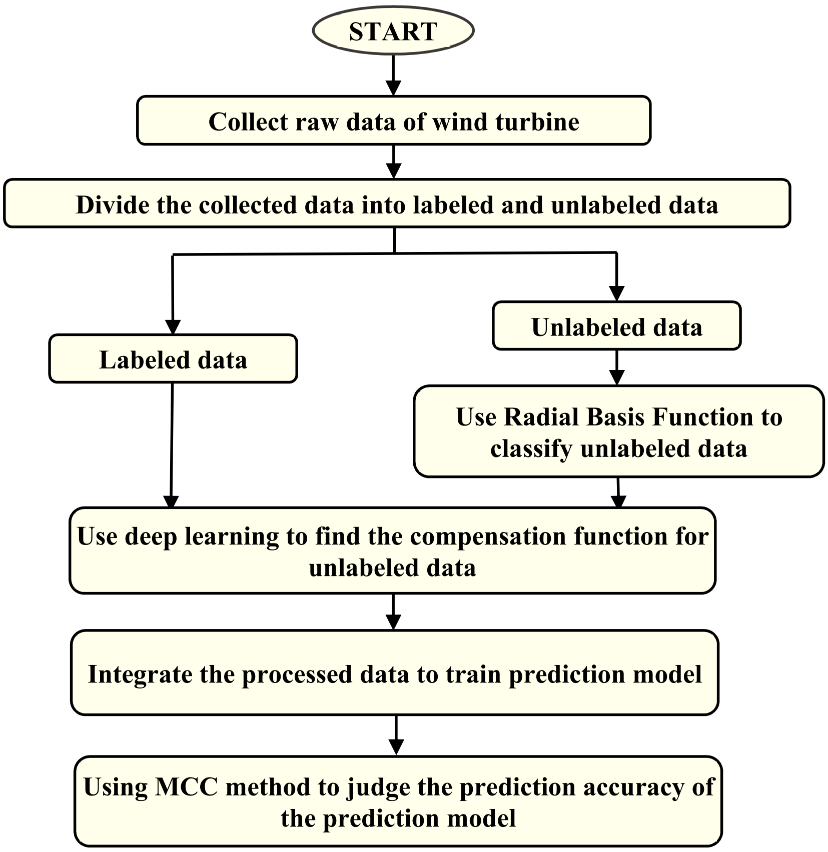


Fig. 3. Flowchart of the proposed semi-supervised deep learning algorithm.

This study installs dozens of sensors in the internal parts of the wind turbine to collect various continuous data of internal parts (e.g., hydraulic oil temperature and pressure, gear oil temperature, rotor speed, etc.). Therefore, there are dozens of variables in this study, and the collected data must include different time periods and different weather conditions. After collation, this group of data is used as the original data set. Since this study uses a semi-supervised deep learning method, the feature of this deep learning method is that it only requires a small amount of labeled data and a large amount of unlabeled data to train a predictive model with very high accuracy.

Table 2. Notations used in the proposed method.

Parameter	Definition
I	Total number of labeled wind turbine data.
J	Total number of unlabeled wind turbine data.
X_i	The i-th labeled wind turbine data.
Y_j	The j-th unlabeled wind turbine data.
L_i	The label of the i-th labeled wind turbine data.
$\hat{X}_i$	The most similar X_i to Y_j.
L_j	The initial label of Y_j.
$F(x)$	Hidden layers found through machine learning.
ΔX_i	The difference between any two X_i.
ΔL_i	The difference between any two L_i.
ΔY_j	The difference between X_i and Y_i.
ΔL_j	The compensation label of Y_j.
L'_j	The final label of Y_j.
S_{pa}	Covariance between predicted and actual values.
S_p	Variance of predicted value.
S_a	Variance of actual value.
p_i	The i-th predicted value.
$\overline{p}$	Average predicted value.
a_i	The i-th actual value.
$\overline{a}$	Average actual value.

When simulating real conditions, we randomly divide the original data set into two groups. The majority group is used as the original unlabeled data after removing the internal energy consumption of the wind turbine, and the minority group is kept as the original labeled data. There existed a lot of label propagation methods, and the Radial Basis Function (RBF) is one of them. The RBF algorithm uses the characteristics of the labeled data to make a preliminary grouping of unlabeled data. The detailed process of the RBF algorithm is as follows. First, each unlabeled data of wind turbine is compared with all label data once. This comparison is to calculate the Euclidean distance between unlabeled and labeled data parameters in (1) and find the minimum value. After all unlabeled data has found the labeled data with the smallest gap, copy the label of the labeled data to the unlabeled data as shown in (2). This step will be repeated until each unlabeled data is labeled. After this step, every unlabeled data of the wind turbine will have a basic label.

$$RBF(X_i, Y_j) = \exp\left(-\frac{\left\| X_i - Y_j \right\|^2}{2\sigma^2} \right) \tag{1}$$

$$(\hat{X}_i, L_i) \approx (Y_j) \rightarrow (\hat{X}_i, L_i) \approx (Y_j, L_j) \tag{2}$$

where X_i is the i-th labeled wind power data; Y_j is the j-th unlabeled wind power data; σ is the standard deviation between the labeled data; $\hat{X}_i$ is the most similar X_i to Y_j; L_i is the label of the i-th labeled wind power data; and L_j is the initial label of Y_j and equal to L_i.

Then, deep learning is used to find more accurate labels. First of all, we need to find out the relationship between the label data and the label of the label data, which is known as the hidden layer. Therefore, we use the difference of each variable in the original label data of wind power as the input layer, and the difference of each label data's label as the output layer. With the help of deep learning, we can find the hidden layer between the difference of each variable in the original label data and the difference of each label data's label in (3). After obtaining the hidden layer, we use the variable differences between the unlabeled data and the most similar labeled data found by the previous RBF algorithm as the input layer and couple with the hidden layer. As a result, we can obtain the compensation function of the unlabeled data in (4). Finally, we combine the results of label propagation and label compensation, and integrate them with the original wind power label data by the RBF algorithm to be the final label of the unlabeled data in (5), so that the labels the we attach to unlabeled data are more comprehensive and accurate.

$$\Delta L_i = f(\Delta X_i) \tag{3}$$

$$\Delta L_j = f(\Delta Y_j) \tag{4}$$

$$L'_j = L_j + \Delta L_j \tag{5}$$

where ΔL_i is the difference between any two L_i's; ΔX_i is the difference between any two X_i's; ΔL_j is the compensation label of Y_j; ΔY_j is the difference between any two X_i and Y_j; L'_j is the final label of Y_j; and L_j is the initial label of Y_j.

After completing the above two steps, we obtain a new data set to train the model. Then we put the new data set into the model for training, in which various parameters of the wind turbine are used as the input layer and the internal energy consumption is used as the target layer, through deep learning to find the hidden layer. Finally, we can get a model that can use the data of internal parts of a wind turbine to predict internal energy consumption. After the model training is completed, we remove the internal energy consumption value from the collected data, and then put it into the model to obtain the predicted value. Then, we compare it with the actual value, calculate the variance and covariance between actual and predicted value in (6), and judge the correlation coefficient between actual and predicted values in (7) and (8). According to the definition of the MCC method in (9), the closer the calculated correlation coefficient to one, the better the predictive ability of this model.

$$S_{pa} = \frac{\sum i\left(p_i - \overline{p}\right)\left(a_i - \overline{a}\right)}{n-1} \tag{6}$$

$$S_p = \frac{\sum i\left(p_i - \overline{p}\right)^2}{n-1} \tag{7}$$

$$S_a = \frac{\sum i\left(a_i - \overline{a}\right)^2}{n-1} \tag{8}$$

$$MCC = \frac{S_{pa}}{S_p \cdot S_a} \tag{9}$$

where S_{pa} is the covariance between the predicted value and the actual value; S_p is the variance of the predicted value; S_a is the variance of the actual value; p_i is the i-th predicted value; $\overline{p}$ is the average predicted value; a_i is the i-th actual value; and $\overline{a}$ is the average of actual value.

5. Experimental Results

This chapter first introduces the case of this study, and adopts the proposed semi-supervised deep learning method to predict the energy consumption of internal parts of the wind turbine in this case. A comprehensive experimental analysis is conducted under various settings of parameters and conditions.

5.1 Case overview

This study considers mainstream offshore wind turbines in the market today. According to statistics of the American Wind Energy Association (AWEA) in 2019, there are nearly 46.5 GW offshore wind fields in the United States under construction. Among them, the newly built capacity reaches 22.651 GW, and the rest is in the preliminary test. In addition, offshore wind fields with a capacity of nearly 6 GW are under development. As this technology belongs to a new energy which is under development, there have been many related studies discussing the generating efficiency of offshore wind turbines in recent years. However, there is a lack of research on internal parts of the generator in these studies which is the research goal of this study. Therefore, this chapter will explain the process of analyzing and predicting the internal energy consumption of the wind power generator using the semi-supervised deep learning method.

5.2 Preliminary classification of unlabeled data

This study discusses an offshore wind turbine system. This system is set up in an area where the wind speed is stable and not prone to natural disasters to ensure the integrity of the data that we collect. A lot of sensors are installed on internal parts of the system, and the sensors are set to record once every five minutes, so that we can get a large number of experimental data sets. After the data collection is completed, we classify the data and take out the most representative twenty-five types of data for analysis. Since we use a semi-supervised deep learning method, we use a part of the data as labeled data that contains the internal energy consumption of the wind turbine, and the other part after removing the internal energy consumption of the wind turbine is the original unlabeled data. After deciding the ratio of labeled and unlabeled data, we use the RBF algorithm to find similar labels for each unlabeled data. The comparison between the initial label data generated by the BBF algorithm and the actual data is shown in Fig. 4. It can be seen that there is still a considerable gap between the label generated by the BRF algorithm and the actual value. In what follows, this study will gradually make the label data close to the actual data.

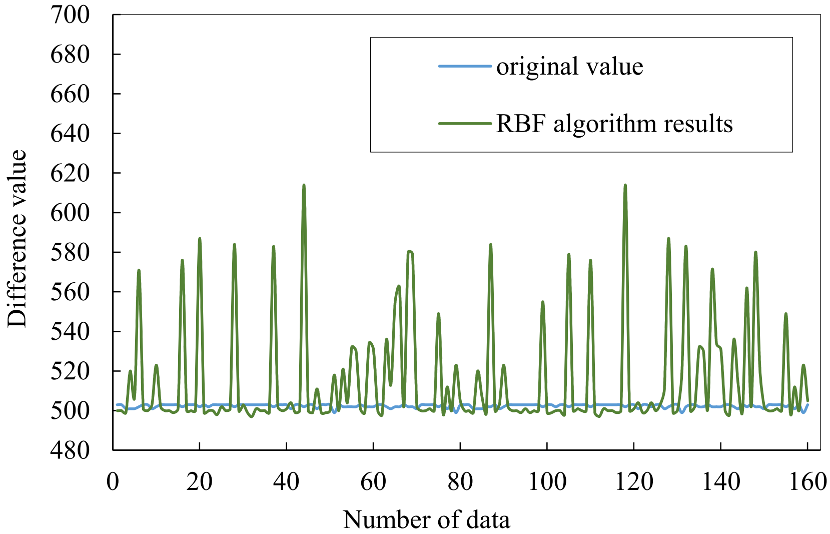


Fig. 4. Difference between the BRF and the original values.

5.3 Modified unlabeled data

Because the data generated in the previous step is not accurate enough. Therefore, this study will use deep learning to correct and compensate them. Deep learning methods can effectively use this multi-dimensional data. In the process of training the neural network, we obtained the input layer by subtracting each variable in all the label data, and the labels of the label data are also subtracted in pairs as the output layer. The purpose is to find the hidden layer. This study uses the Keras sequential model in deep learning. The input parameter is set to 25 and the output parameter is set to 1 to meet the study goal. The loss function uses the Mean Absolute Error (MAE) and the Adam optimization function. The MAE is used to avoid errors caused by abnormal values. After many tests, we found that the number of iterations is 1500 to get least error. The test results are shown in Fig. 5.

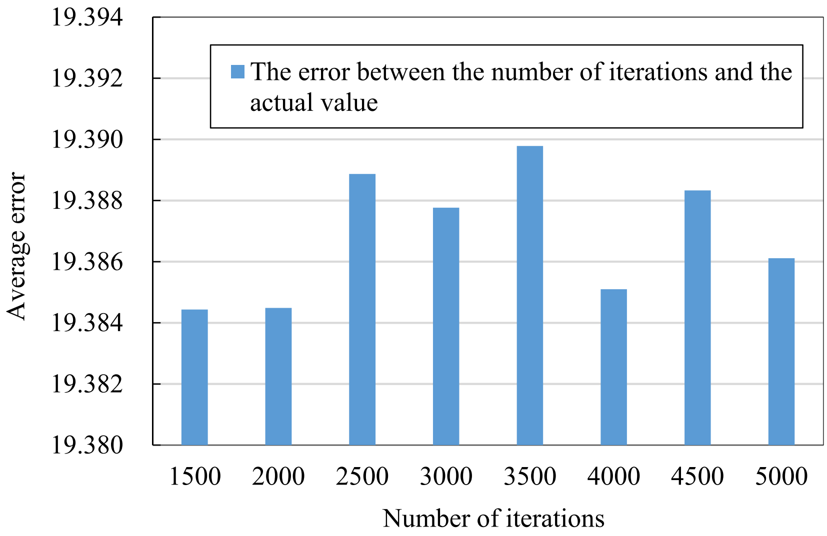


Fig. 5. The number of iterations of the modified unlabeled data model.

5.4 Training prediction model

After the model training is completed, we input the data into the model by subtracting all the unlabeled data variable and the labeled data variable obtained by the RBF algorithm. Then we can get the compensation label data for every unlabeled data. Finally, the label data of the RBF algorithm is combined with the compensation label data, and then we combine all of them with the original label data set. A set of fairly representative data sets that can be used to train models are obtained. After obtaining the complete data set, we can start training the model that predicts the internal energy consumption of offshore wind turbines that this study is expected to obtain. Also, we use the Keras sequential model in deep learning, in which the input parameter is set to 25, and the output parameter is set to 1. The difference from the previous model is that this time the loss function uses the Mean Square Error (MSE), while we still use the Adam optimization function. The number of iterations by experience is 500. The reason why using the MSE is because the data set has been corrected. There is no need to worry about the error caused by enlarging the outliers, and the MSE is better for model training. The number of iterations is obtained after testing, and the result is shown in Fig. 6.

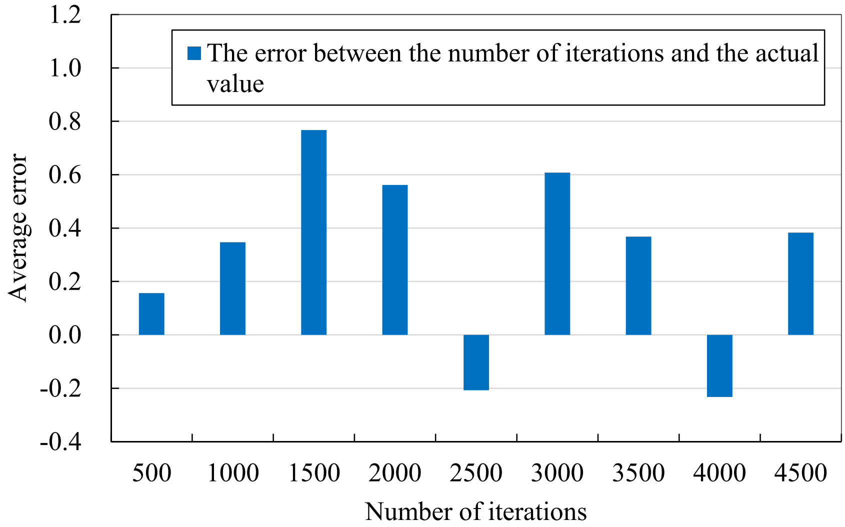


Fig. 6. Number of iterations of wind power internal energy consumption model.

5.5 Model accuracy evaluation

Finally, this study uses the MCC method to analyze the correlation coefficient between the predicted value and the actual value to judge the accuracy of the prediction model. The result of the judgment is shown in Fig. 7. It can be seen from the experimental results that the value of the MCC method has risen sharply in the range of the number of labeled data between 400 and 500. Because the total number of data used in this study is 2500, it means that this model has better prediction accuracy when the label data accounts for 15-20% of the total data. Therefore, this study suggests that when predicting the internal energy consumption of wind power generation in the future, 15-20% of the label data ratio should be used to make predictions to obtain better prediction results.

5.6 Innovation and practicality

The objective of this study is to predict the internal energy consumption of offshore wind turbines, which is less discussed. The semi-supervised deep learning method used in the study has the feature that only a small amount of labeled data and a large amount of unlabeled data can be used to train a predictive analysis model with considerable accuracy. This feature can also solve the actual situation that most of the wind turbine data is incorrectly planted and missing due to manual records. Therefore, there is no need to modify too many unlabeled data and is more economical.

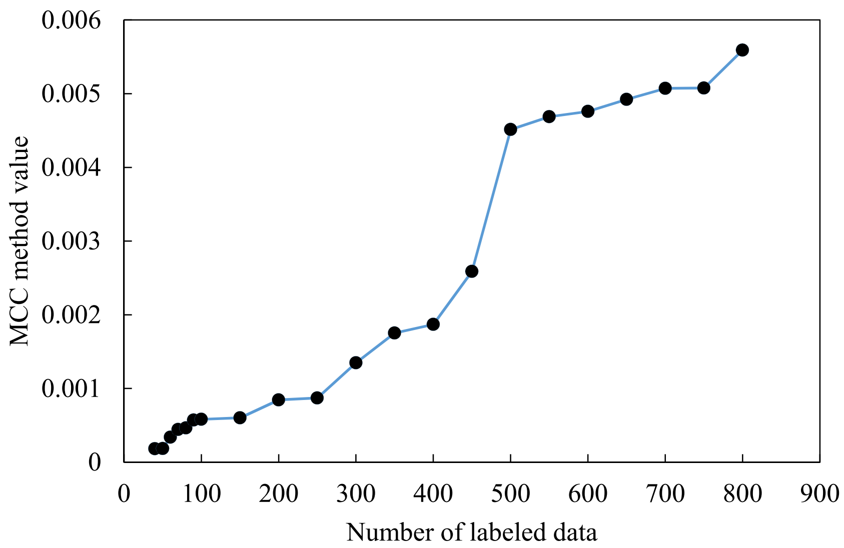


Fig. 7. Number of label data and MCC method value.

6. Conclusion

In this study, we collected a set of data from various parts inside the wind turbine. With the assistance of the semi-supervised deep learning method, we proposed a model that can predict the internal energy consumption of the wind turbine. This model is used to deal with the goal of reducing the internal energy consumption of wind turbines. The semi-supervised deep learning method that we use only requires a small amount of label data and a large amount of unlabeled data to train a predictive model with considerable accuracy. This feature can also solve the fact that most wind turbine data is mistakenly planted or missing due to manual records. In the experimental results, it is found that the label data accounts for about 15 to 20% of the total data. The effect of the training model is the best. Since there is no need to manually convert too many unlabeled data into label data, it is also more economical. In addition, according to the research results of this study, if there are problems in the future that need to predict the energy consumption of wind power generation, the proposed semi-supervised deep learning method which uses about 15 to 20% of the label data as a benchmark for training can be applied. In this way, we can generate a set of prediction models that can predict the internal energy consumption of wind turbines.

References

[1] X. Wang, P. Guo, and X. Huang, "A review of wind power forecasting models," *Energy Procedia*, vol. 12, pp. 770-778, 2011.

[2] J. Shi, J. Guo, and S. Zheng, "Evaluation of hybrid forecasting approaches for wind speed and power generation time series," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 3471-3480, 2012.

[3] H. Shaker, H. Zareipour, and D. Wood, "On error measures in wind forecasting evaluations," in *Proc. of IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2013.

[4] C. J. Merz, D. C. St. Clair, and W. E. Bond, "Semi-supervised adaptive resonance theory (SMART2)," in *Proc. of the 1992 International Joint Conference on Neural Networks*, pp. 851-856, 1992.

[5] A. Blum and T. Mitchell, "Combining labeled and unlabeled data with co-training," in *Proc. of 11th Annual Conference on Computational Learning Theory*, pp. 92-100, 1998.

[6] J. Peng, G. Estrada, M. Pedersoli, and C. Desrosiers, "Deep co-training for semi-supervised image segmentation," *Pattern Recognition*, in press, 2020.

[7] X. Zhu and Z. Ghahramani, *Learning from Labeled and Unlabeled Data with Label Propagation*, CMU CALD Technical Report, CMU-CALD-02-107, 2002.

[8] C. Chen, Y. Liu, M. Kumar, J. Qin, and Y. Ren, "Energy consumption modelling using deep learning embedded semi-supervised learning," *Computers & Industrial Engineering*, vol. 135, pp.757-765, 2019.

[9] C. Rosenberg, M. Hebert, and H. Schneiderman, "Semi-supervised self-training of object detection models," in *Proc. of 2005 7th IEEE Workshops on Applications of Computer Vision*, 2005.

[10] N. Piroonsup and S. Sinthupinyo, "Analysis of training data using clustering to improve semi-supervised self-training," *Knowledge-Based Systems*, vol. 143, pp. 65-80, 2018

[11] P. Kang, D. Kim, and S. Cho, "Semi-supervised support vector regression based on self-training

with label uncertainty: An application to virtual metrology in semiconductor manufacturing," *Expert Systems with Applications*, vol. 51, pp. 85-106, 2016.

[12] S. Hamid Amiri and M. Jamzad, "Automatic image annotation using semi-supervised generative modeling," *Pattern Recognition*, vol. 48, no. 1, pp. 174-188, 2015.

[13] M. Papież, S. Śmiech, and K. Frodyma, "Factors affecting the efficiency of wind power in the European Union countries," *Energy Policy*, vol. 132, pp. 965-977, 2019.

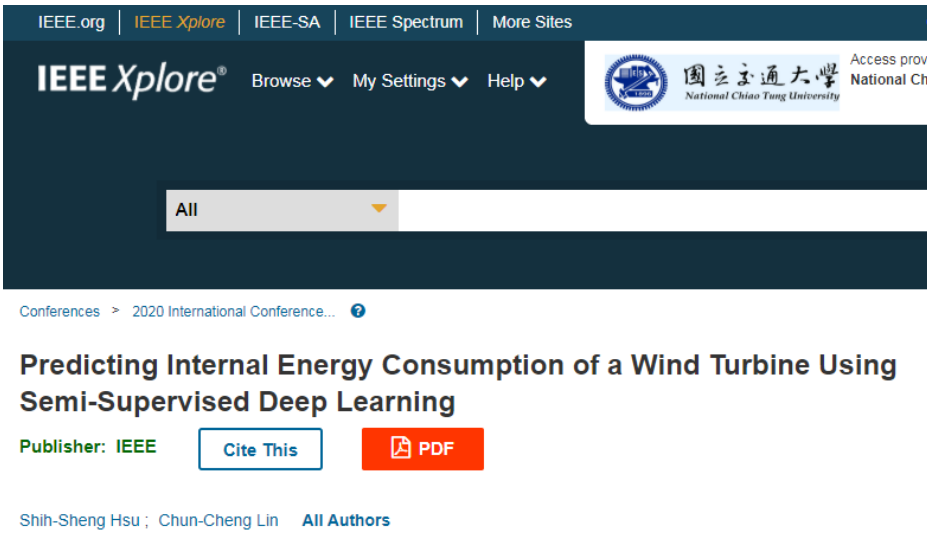
[14] Q. Yuan, K. Zhou, and J. Yao, "A new measure of wind power variability with implications for the optimal sizing of standalone wind power systems.," *Renewable Energy*, vol. 150, pp. 538-549, 2019

[15] J. Yang, L. Zhang, Y. Chang, Y. Hao, G. Liu, Q. Yan, and Y. Zhao, "Understanding the material efficiency of the wind power sector in China: A spatial-temporal assessment," *Resources, Conservation & Recycling*, vol. 155, article no. 104668, 2020.

[16] S. Pieralli, M. Ritter, and M. Odening, "Efficiency of wind power production and its determinants," *Energy*, vol. 90, pp. 429-438, 2015.

Appendix (現場用英文口頭報告發表論文於 IEEE 國際會議)

Shih-Sheng Hsu (徐士陞) and Chun-Cheng Lin (林春成) (2020) "Predicting internal energy consumption of a wind turbine using semi-supervised deep learning," in ***Proc. of International Conference on Pervasive Artificial Intelligence (ICPAI 2020)*, IEEE Press**, pp. 223-228, Taipei, Taiwan, Dec. 3-5, 2020.



Appendix (中文版發表獲得 TANET 2020 臺灣網際網路研討會「優良論文獎」)

- 本計畫成果發表於 TANET 2020 臺灣網際網路研討會，並獲得「優良論文獎」: