Modeling Temporal Correlation for Prediction of Wind Power

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Abstract. The use of clean energy increase in the worldwide with an increasing number of people realizing the energy and environmental problems. Wind power is one of most likely to be widely used power, which can produce a huge amount of power by wind power stations. This paper used long short term memory (LSTM) to calculate the wind power curve. By analyzing the principle of the algorithms and establish the model to predict the real data, the feasibility of the model was proved. Furthermore, extensive comparison experiments are conducted to demonstrate the LSTM model has a highest accuracy and efficiency. In summary, the model can be used for the wind power curve forecast system.

Keywords: Deep Learning Models; Wind Power Forecast; LSTM.

1. Introduction

Wind power, one of the most ancient energies used by human, the establishment of windmills can be traced back hundreds of years. In the 13th century, the Dutch invented and began to use windmills to make their daily life much easier [1]. Today, since the fossil fuels are not inexhaustible and the use of it will destroy the global ecological environment, the development of clean energy become the concern of most countries in the world [2]. For the fact that wind power is clean and renewable, it has been used to be transformed into electrical energy for several years in the worldwide [3]. According to the Global Wind Energy Council (GWEC), in 2021, 837GW electrical energy was created by the worldwide wind power generator, the amount of CO2 being avoided to be discharged reached 1.2 billion tons [4].

For the fact that the amount wind energy created by specifically machine is not constant, it basically depends on strength and direction of the nature wind. The ability to predict the electrical energy created by the wind power is important, for the fact that the grid operators need to create a steady supply of electrical energy for the society [5]. Once the energy is lower than prediction, it would lead to a power failure crisis for the society, which would harm the societies' normal life. Once the power is more than the prediction, the redundant of energy would be wasted. By conventional physical and statistical methods, the calculation would be extremely complex and would not have a high accuracy. The data need to be used for prediction is a huge amount, which will waste time and energy of calculators.

Machine learning (ML) models covers several areas, such like energy engineering [6], medical science, and psychology [7]. The regression models can be used to predict the wind power by the data about wind speed and wind direction. For the fact that the wind speed has a strong indirect volatility and randomness, the relationship between wind power and these two variables is not simply linearly, the ML models have the ability to create complex curves to fit the data [8].

Deep learning (DL) algorithms play an important role when dealing with huge outbreak data patterns, the weight of different variables will be corrected after each training terms, which makes it can performance when the relationship between outcome and income are complex [9]. The wind power is a time series data, which can be processed by recurrent neural network (RNN), which has a good performance in dealing with sequential data, since it can mine time information in the data [10]. However, for the fact that wind speed and wind direction have a strong relationship with time and the cycle is long, RNN cannot memory the previous information [11]. Long short-term memory (LSTM) is a variety of RNN, which have a new memory unit can be used for linear circular information

transmission [12]. The LSTM model is more complex than RNN model, which satisfy the need to deal with the long-term time data. So, this paper will use the LSTM model to deal with the data.

The rest of this article is divided into three sections. In section Ⅱ, the data will be analyzed and the methods will be described. In sectionⅢ, the detailed result of all the methods will be compared and the last the section will provide the conclusion.

2. Data Analysis

The data consists of five parts: The time, active power produced by wind power generator, wind speed, wind direction and theoretical power curve. The data from a wind power station in 2018 is selected a s the train and test data, which was recorded every ten minutes.

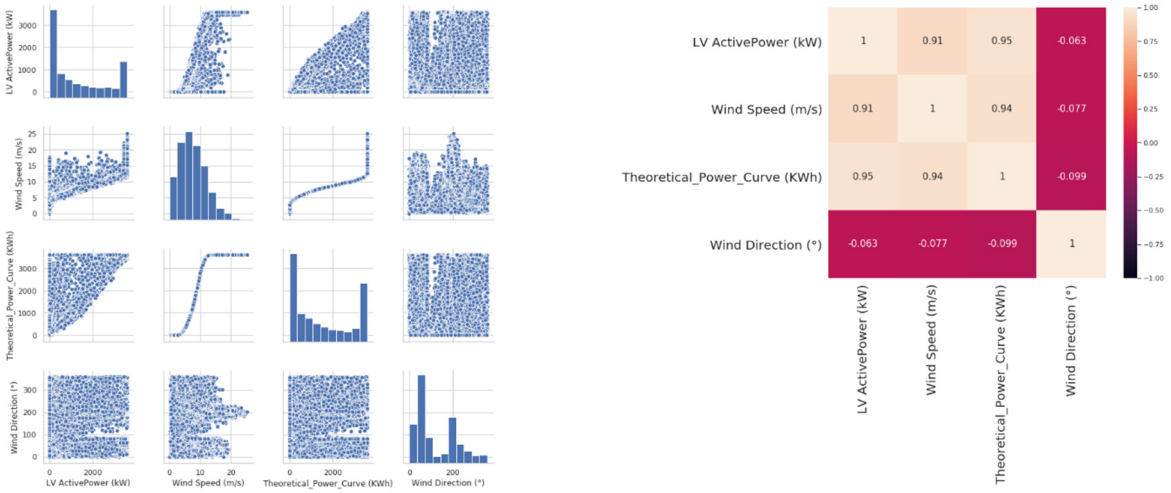


Fig 1. Relationship of variables

According to figure 1, the theoretical power curve is the prediction of wind power that would be created by traditional methods, which would cost a huge amount of effort. That would be the expect for the prediction of new model. The wind direction seems has a weak relationship with the active power and wind speed, however, only in some specific direction the wind speed will be high, which is showed in figure 2.

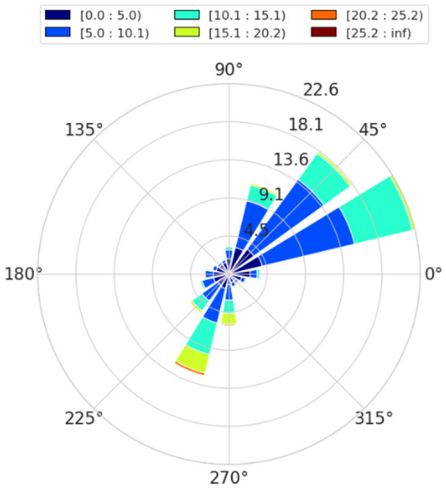


Fig 2. Wind speed and direction

According to the figure 2, only in specific direction the wind would have high speed, which is caused by the geographical location. For the fact that wind direction has timeliness, so the time should

be used as a variable to improve the performance of the forecast model. According to the figure 3, the linear correlation is high. Though the wind direction affects this relationship, the real power produced just near to the prediction. The new model would increase the accuracy of the forecast system by using more variables as input data.

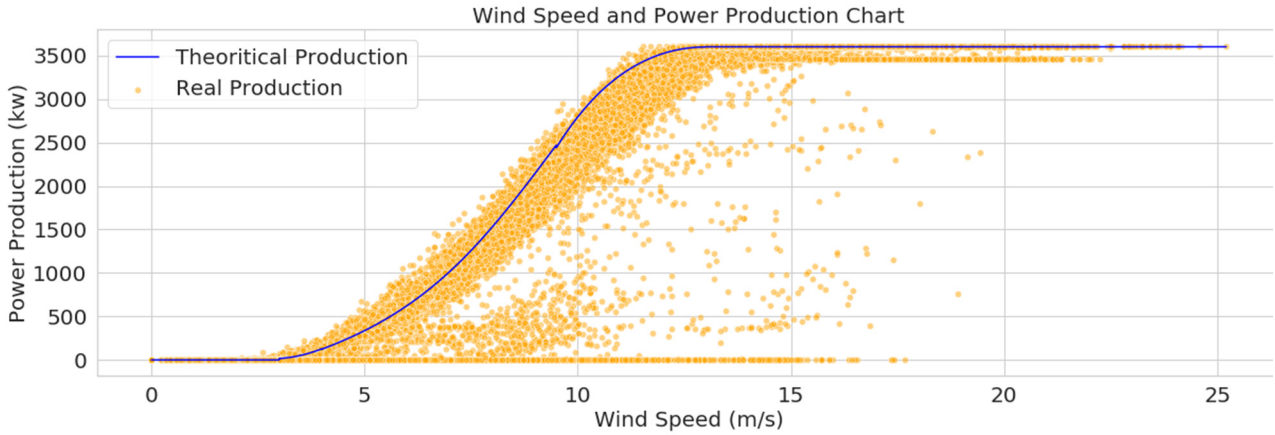


Fig 3. Wind speed and power

3. LSTM

RNN [13] has the capability to use previous information to process the latest data, which makes it always being used to deal with sequential time series data. However, RNN cannot use the previous data which is far away when the data sequence is long enough. Since the weight of the early data would continue descending in the process of back propagation, the model would not learn when the gradient is extremely small. and this problem is also called Long-Term Dependencies [14]. In order to deal with the problem, LSTM was invented [15]. The cells, which is the specific function of LSTM to calculate the hidden layer, have the capability to memory the long-term information. All the RNN have a chain type structure of repetitive neural network module, in normal RNN, the module is simple. For example, a layer of Tanh, which limit the value in the area from -1 to 1. The module of LSTM is complex, it consists of four interactive layers, three Sigmoid layers and a Tanh layer, in a specific interactive way. These layers constitute three gates: forget gate, input gate and output gate. The first step is to decide which information should be dropped from the cell. The decision is made by the forget gate. The forget gate will read the last output and the current input, then make a nonlinear mapping by Sigmoid and get a vector, the vector will multiply by the state of last cell. The input gate decide what information should be saved in the cell. The Sigmoid layer decide what value should be updated. The Tanh layer will create a new vector, which would be multiplied by the data that should be updated. Then, the latest state of cell will be the sum of the output of these two gates. The output gate decide what value should be the outcome. A Sigmoid layer will be used to decide which part of the latest state of cells need to be output, the vector from Sigmoid layer will be multiplied by the vector from a Tanh layer, whose input is the state of the latest cell, then we get the final output.

$$f_t = \sigma\left(W_f[h_{t--1}, x_t] + b_f\right) \ . \quad (1)$$

$$i_t = \sigma(W_i[h_{t--1}, x_t] + b_i) \ . \quad (2)$$

$$\tilde{C}_t = tanh(W_{ch}h_{t-1} + W_{cx}x_t + b_c) \ . \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \ . \quad (4)$$

$$O_t = \sigma(W_o[h_{t--1}, x_t] + b_o) \ . \quad (5)$$

$$h_t = O_t * tanh(C_t) \ . \quad (6)$$

4. Experiment

This paper intends to design a stable model which can forecast the wind power. By using eight months' data as the training data, and four months' data to test the predictions of the model, which is showed in figure 4.

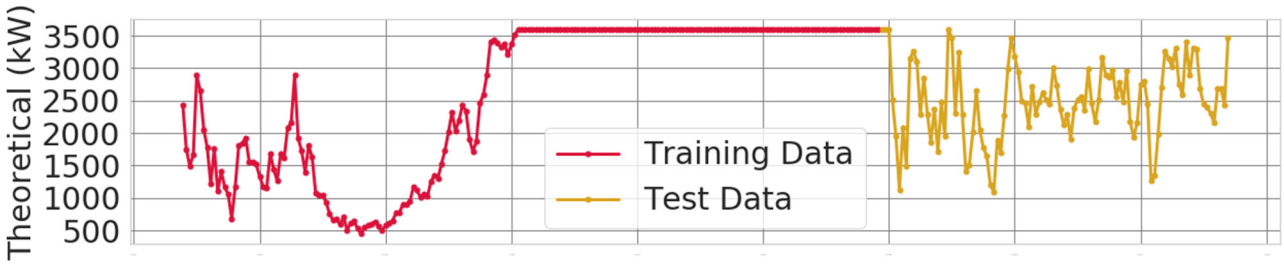


Fig 4. Data division

According to the Theoretical power curve, there are four months' data is stable, which is not suitable for the prediction. The last four months' data curve of the year is more tortuous, which is appropriate to test the robustness of the model.

The wind speed, wind direction and the active power are three variables, the time is the index.

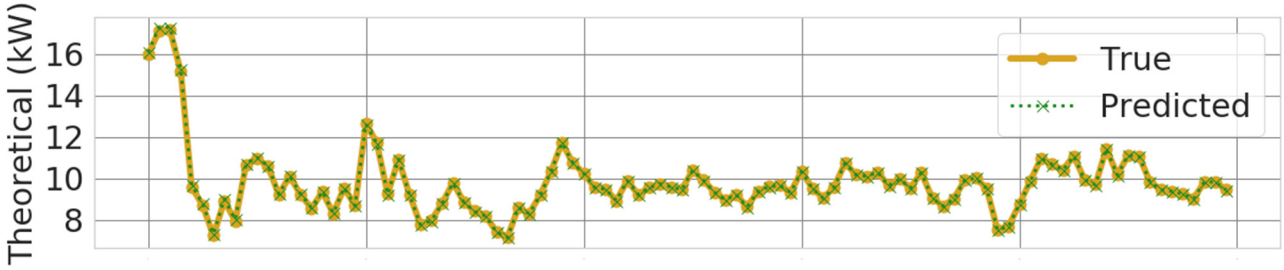


Fig 5. Prediction of the model

After several times of training and comparing, the final model consists of five LSTM layers and five Dense layers, whose accuracy is 99.22%. According to the figure 5, it's apparently that the prediction of the model can fit the true data well, which makes the later prediction of wind power easier. For the fact that the model would not cost much time to forecast the wind power curve and has high accuracy, it's more appropriate to be used to do the prediction.

For the fact that the accuracy is still not 100%, the forecast model could add another model to increase the accuracy. However, after testing, the performance didn't increase much when a Bi-LSTM model was being used, it's only 99.45%. While the time of training and testing increase much, which need a great amount of computational force. So, the original algorithm is used as the forecast model.

5. Conclusion

Deep learning algorithms have been used for several areas, the outstanding performance of which increase the efficiency of operators. For the wind power forecast system, the calculation of power that would be created will be simplified by deep learning models. For the fact that the LSTM model can predict the power curve quickly and exactly, most wind power stations can use it since the wind direction and wind speed are periodic in a specifical location. Though more complicated model can also be designed to increase the accuracy, the improvement of which is limited, while it would cost more time to calculate. For the economic and efficiency consider, the LSTM model is more appropriate for those wind power stations.

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