PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION

PROJECT REPORT

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ABSTRACT

Wind energy play an increasing role in the supply of energy world wide. The energy output of a wind farm is highly dependent on the weather conditions present at its site. If the output can be predicted more accurately, energy suppliers can coordinative production of different energy sources more efficiently to avoid costly over production.

In this paper, we take a computer science perspective on predicting the energy output of wind turbine based on weather data and analyse the wind speed/power has received increasing attention around the earth due to its renewable nature as well as environmental friendliness. With the global installed, with power capacity rapidly increasing, the wind industry is growing into a large scale business. Reliable short term wind speed forecasts play a practical and crucial role in wind energy conversion systems, such as the dynamic control of wind turbines and power systems scheduling. A precise forecasts needs to overcome problems of variable energy production caused by fluctuating weather conditions. Power generated by wind is highly dependent on the wind speed. Thought it is highly non-linear, wind speed follows a certain pattern over a certain period of time. We exploit this time series pattern to gain useful information and use it for power prediction.

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1. INTRODUCTION

1.1PROJECT OVERVIEW

Over the wind power generation differs from conventional thermal generation due to the stochastic nature of wind. Thus wind power forecasting plays a key role in dealing with the challenges of balancing supply and demand in any electricity system, given the uncertainty associated with the wind farm power output. Accurate wind power forecasting reduces the need for additional balancing energy and reserve power to integrate wind power. For a wind farm that converts wind energy into electricity power, a real-time predicting system of the output power is significant. In this guided project, a prediction system is developed with a method of combining statistical models and physical models. In this system, the inlet condition of the farm forecasted by the regressive model. wind plant has lower cost of energy compared to other renewable energy source for large scale application. Due to the different geographical pattern , weather, and properties of the wind turbines, a wind turbine may have various performances given different situations. If the total output of a wind power plant can be predicted with high accuracy, more useful information can be provided to the power companies to help in scheduling the power generation. This information will allow a more flexible and intelligent control at a WPP. Methods for predicting wind power generation can be categorized into physical methods, statistical methods, methods based on neural networks, and hybrid methods. The physical methods rely heavily on numeric weather prediction, which is confined by the sensors and monitoring devices placed within the WPP, the quality of hardware chosen, the parameters settings, the computation time, the time delay, and the sampling rates influences the accuracy of data collected from the WPP .it is easier to predict a single wind turbines performances rather than a whole WPP power generation. Statistical and neural networks methods are based on the historical data and have a low prediction cost. The relationship between input data and output data based on the historical measured data is learned and then a non-linear relationship model between them is built. But when new data not previously including in the training data set is used as input into this kind of model, the prediction error might be large, which is a disadvantages. Different prediction methods mentioned above can be combined as hybrid methods to achieve better prediction results.

1.2 Purpose

Extracting electricity from renewable resources has been widely investigated in the past decades to decrease the worldwide crisis in the electrical energy and environmental pollution. For a wind farm which converts the wind power to electrical energy, a big challenge is to predict the wind power precisely in spite of the instabilities. The climatic conditions present in the site decides the power output of a wind farm. As the schedule of wind power availability is not known in advance, this causes problems for wind farm operators in terms of system and energy planning. A precise forecast is required to overcome the difficulties initiated by the fluctuating weather conditions. If the output is forecasted accurately, energy providers can keep away from costly overproduction. In this paper, an end-to-end web application has been developed to predict and forecast the wind turbine's power generation based on the weather conditions. The prediction model has been developed using Bidirectional Long Short-Term Memory which is a unique kind of RNN (Recurrent Neural Network). It performs admirably in terms of capturing long-term dependencies along with the time steps and is hence ideal for wind power forecasting.

2. LITERATURE SURVEY

2.1EXISTING PROBLEM

Research objectives are prepared after correlating the various works done by contemporary researchers. Most of the researchers have developed methods for wind speed based forecasting. Apart from wind speed forecasting, many other parameters required to assess the wind energy potential are studied. Meteorological information coupled with topographical data has to be utilized for wind power estimation at a particular place. After this, wind turbine power curves have to be mapped against the wind parameters. This is to establish the number of energy units that can be generated at wind plant level, for a month. In most of the wind plants in India, wind speed measurements taken from a single location for the whole plant which is an average indicator of wind power potential at plant level. Deviations from mean position of the wind measurement to the wind turbine are not considered. Hence, Average wind speed indicator continues to contribute for wind 38 power estimation at plant level. Wind speed and wind power generation along with changing values across time series in the present focus of work.

2.2 PROPOSED SOLUTION

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable x is associated with a value of the dependent variable y.

The population regression line for p explanatory variables x1, x2,..., xp is defined to be y = 0 + 1x1 + 2x2 + ... + pxp. This line describes how the mean response y changes with the explanatory variables. The observed values for y vary about their means y and are assumed to have the same standard deviation .

The fitted values b0, b1, ..., bp estimate the parameters 0, 1, ..., p of the population regression line. Since the observed values for y vary about their means y, the multiple regression model includes a term for this variation.

In words, the model is expressed as DATA = FIT + RESIDUAL, where the "FIT" term represents the expression 0 + 1x1 + 2x2 + ... pxp. The "RESIDUAL" term represents the deviations of the observed values y from their means y, which are normally distributed with mean 0 and variance .

The notation for the model deviations is . Formally, the model for multiple linear regression, given n observations, is yi = 0 + 1xi1 + 2xi2 + ... pxip + i for i = 1,2,

... n. In the least-squares model, the best-fitting line for the observed data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the line (if a point lies on the fitted line exactly, then its vertical deviation is 0). Because the deviations are first squared, then summed, there are no cancellations between positive and negative values. The least-squares estimates b0, b1, ... bp are usually computed by statistical software.

3.THEORETICAL ANALYSIS

Wind energy plays an increasing role in the supply of energy world wide. [5] The energy output of a wind farm is highly dependent on the weather conditions present at its site. [5] If the output can be predicted more accurately, energy suppliers can coordinate the collaborative production of different energy sources more efficiently to avoid costly overproduction. In this paper, we take a computer science perspective on energy prediction based on weather data and analyze the important parameters as well as their correlation on the energy output. [6] To deal with the interaction of the different parameters, we use symbolic regression based on the genetic programming tool Data Modeller. Our studies are carried out on publicly available weather and energy data for a wind farm in Australia. [6] We report on the correlation of the different variables for the energy output. The model obtained for energy prediction gives a very reliable prediction of the energy output for newly supplied weather data.

4.EXPERIMENTAL INVESTIGATIONS

The photograph of wind turbines used for the present study is shown in Figure 1. These three WEG each of 250 kW rating are located among approximately 3370 machines in the Muppandal wind park in south India. The machines are located in high wind area spread over 40 km length with total installed capacity of 1670 MW. The machines where the readings were taken almost have logged in 15 years of operation in the past. All the 3 are located in same region, one nearby other. Due to this, the terrain constants are almost same.

25 m diameter at 30 m height

(a)

25 m diameter at 40 m height

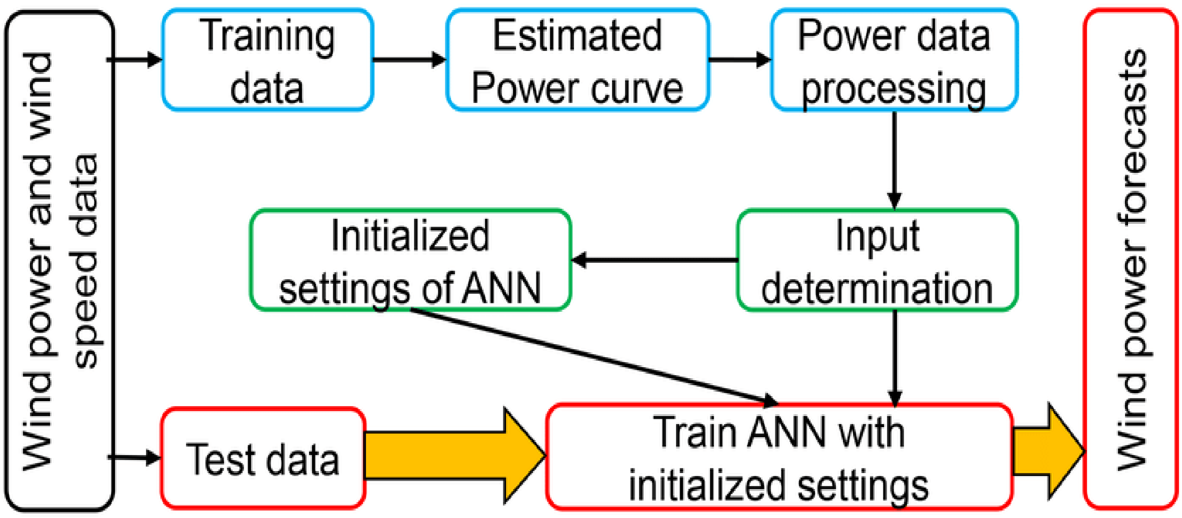
(b)

25 m diameter at 50 m height

(c)

The brief description of experimental setup test machines used for the present study is as follows. The 30 m and 40 m high towers are of tubular type and 50 m tower is of lattice type. All the turbines have the same rotor diameter of 25 m. The machines are fitted with same blades. The above towers are embedded into steel-reinforced cement concrete raft. The type of tower does not have any effect on the power output. The generated power is passed to the control room at the bottom of tower. The parameters like wind speed, net power output produced in ±kW and other variables namely, temperature, rotor rpm and turbine rpm are displayed in a LCD panel.

5.FLOW CHART



6. DATASETS

Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)	
0	01 01 2018 00:00	380.047791	5.311336	416.328908	259.994904
1	01 01 2018 00:10	453.769196	5.672167	519.917511	268.641113
2	01 01 2018 00:20	306.376587	5.216037	390.900016	272.564789
3	01 01 2018 00:30	419.645905	5.659674	516.127569	271.258087
4	01 01 2018 00:40	380.650696	5.577941	491.702972	265.674286

LV Active Power(kW):

A very simple and effective means to eliminate leading or lagging power factor errors, reduce voltage fluctuations, enhance equipment operating life and improve system power capacity. The range offers consolidated features in one package without the risk of resonance, while stabilizing electrical networks by providing harmonic mitigation, power factor correction and load balancing.

In a simple alternating current (AC) circuit consisting of a source and a linear load, both the current and voltage are sinusoidal If the load is purely resistive, the two quantities reverse their polarity at the same time. At every instant the product of voltage and current is positive or zero, the result being that the direction of energy flow does not reverse. In this case, only active power is transferred.

Wind speed (m/s):

Wind speed is affected by a number of factors and situations, operating on varying scales (from micro to macro scales). These include the pressure gradient, Rossby waves and jet streams and local weather conditions. There are also links to be found between wind speed and wind direction, notably with the pressure gradient and terrain conditions.

Theoretical power curve(KWh):

The power of a binary hypothesis test is the probability that the test rejects the null hypothesis (H0) when a specific alternative hypothesis (H1) is true. The statistical power ranges from 0 to 1, and as statistical power increases, the probability of making a type II error (wrongly failing to reject the null hypothesis) decreases. For a type II error probability of β, the corresponding statistical power is 1-β. For example, if experiment 1 has a statistical power of 0.7, and experiment 2 has a statistical power of 0.95, then there is a stronger probability that experiment 1 had a type II error than experiment 2, and experiment 2 is more reliable than experiment 1 due to the reduction in probability of a type II error. It can be equivalently thought of as the probability of accepting the alternative hypothesis (H1) when it is true that is, the ability of a test to detect a specific effect, if that specific effect actually exists.

Wind direction:

Wind direction is reported by the direction from which it originates. For example, a northerly wind blows from the north to the south. [1] Wind direction is usually reported in cardinal directions or in azimuth degrees. Wind direction is measured in degrees clockwise from due north. Consequently, a wind blowing from the north has a wind direction of 0° (360°); a wind blowing from the east has a wind direction of 90°; a wind blowing from the south has a wind direction of 180°; and a wind blowing from the west has a wind direction of 270°. In general, wind directions are measured in units from 0° to 360°, but can alternatively be expressed from -180° to 180°.

CONCLUSION AND FUTURE SCOPE:

In this study, we showed that wind energy output can be predicted from publicly available weather data with accuracy up to 80% R2 on the training range and up to 85, 5% on the unseen test data. We identified the smallest space of input variables where reported accuracy can be achieved, and provided clear trade-offs in prediction accuracy when decreasing the input space to the wind speed variable.

We are pleased that the presented framework is so simple that it can be used by literally everybody for predicting Theoretical power based on wind energy production —for individual wind turbines on private farms or urban buildings, or for small wind farms. For future work, we are planning further study of the possibilities for longer-term wind energy forecasting.

Several forecasting models were discussed and a lot of researches on the models, which have their own characteristics, were presented. The major focus was on emphasizing the diversity of various forecasting methods available and also on providing a comparison of present mechanisms to determine the best available.

REFERENCES

[1] O. Kramer and F. Gieseke. Short-term wind energy forecasting using support vector regression. In International Conference on Soft Computing Models in Industrial and Environmental Applications, pages 271–280. Springer, 2011.

[2] A. Kusiak, H. Zheng, and Z. Song. Short-term prediction of wind farm Power: A data mining approach. IEEE Transactions on Energy Conversion, 24(1):125 – 136, 2009.