SMARTINTERNZ INTERNSHIP

PROJECT REPORT

Name :- R.RUCHITHA

Roll No:- 20R15A0230

Project Title : Predicting The Energy Output Of Wind Turbine Based On Weather Conditions using IBM cloud.

1. Introduction :

1.1 Overview

Category : Machine Learning

Skills Required : Python, Python for Data Analysis, Machine Learning, IBM Cloud, IBM Watson

1.2 Purpose

Predicting the energy output of wind turbine based on weather conditions Using IBM cloud.

2. Literature Survey :

2.1 Existing Problem

Wind energy plays 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 is predicted more accurately, the energy suppliers can coordinate the collaborative production of different energy sources more efficiently to avoid costly overproduction. In this paper, we do energy prediction based on weather data and analyse the important parameters as well as their correlation on the energy output.

2.2 Proposed Solution :

Our aim is to map weather data to energy production. We wish to show that even data that is publicly available for weather stations close to wind farms can be used to give a good prediction of the energy output. Furthermore, we examine the impact of different weather conditions on the energy output of the wind farms. We are building an IBM Watson Auto AI Machine Learning technique to predict the energy output of wind turbine. We deploy the model. on IBM cloud to get scoring end point. It can be used as API in mobile app or web app building. We are developing a web application which is built using node red service. We use the scoring end point to give user input values to the deployed model. The model prediction is then showcased on User Interface to predict the energy output of wind turbine.

3. Theoretical Analysis

Wind Power Forecasting (WPF) has applications in generation and transmission maintenance planning, energy optimization as well as energy trading. WPF models exists at different scales and they can be used to predict the production for a single WT to a whole Wind Farm (WF). WPF models are generally divided into two main groups physical and statistical, but hybrids state-of -the-art methods are also common. The physical approach physical aspects into the model l, such-as information about surrounding terrain and properties of the WT. These models try to get as good estimate of local wind speed as possible before finally reducing the remaining error with some form of MOS. Statistical approaches, relies more on the historical observations and their statistical relation to meteorological predictions as as well as measurements from Supervisory Control And Data Acquisition (SCADA).

SCADA is a control system that is used in industrial processes and is the main tool to evaluate the state of individual power plants. As the name indicates, it is not a full control system, but rather a system for supervision. In the case of wind turbines it allows remote access to online data that has been gathered by sensors inside and around the plant. Variables accessible through these systems are those directly related to the wind flow as well as the produced power generated by the plant. I.e. things like rotor wind speed, nacelle position, pitch angle, active power, etc.

Forecast models that use SCADA data as their primary input source usually have a god forecast accuracy at least for first few hours but they tend to be less useful for longer prediction horizons. . SCADA data can also be used to detect problem in WT something that can be helpful to improve the reliability of WT.

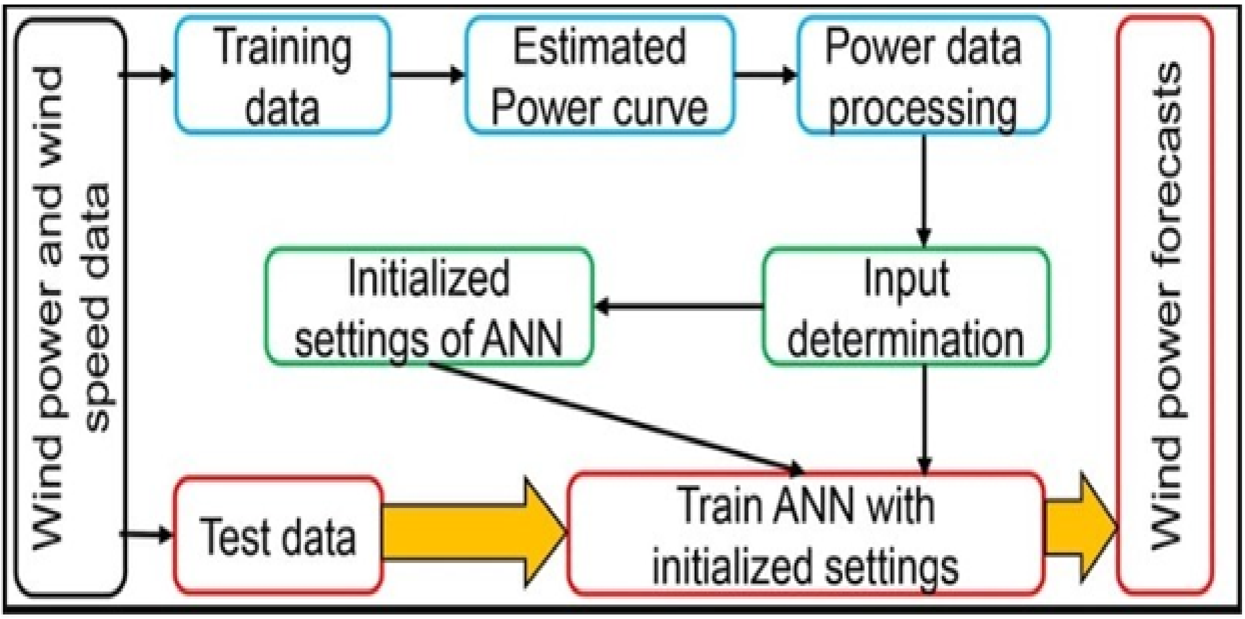
4. Experimental Investigations

Study shows that the accuracy of the current power curve method may depend on the distribution of wind speed, turbulence intensity, and shear at the test site, compared to the deployment site. If the test site conditions are similar to the deployment site, the power curve method may give good results. The greatest potential for error when using a power curve approach comes when the test site has high hub. height turbulence and high shear compared to the deployment site. In this study, the simulation data have been used to train a regression tree model of the WindPACT 1.5 MW baseline turbine. The regression tree method predicts wind turbine energy capture with two to three times more accuracy than

1. the industry-standard power curve method, and may be more

useful for predictions of energy capture at sites that experience different conditions than the test site. To use the regression tree modelling approach to predict the energy capture of turbine at a new site, several steps are required.

5. Flow Chart



6. Datasets

The dataset has been collected from Kaggle.

The data's in the file are:

1. **Date/Time** (for 10 minutes intervals)
2. **LV ActivePower (kW):** The power generated by the turbine for that moment

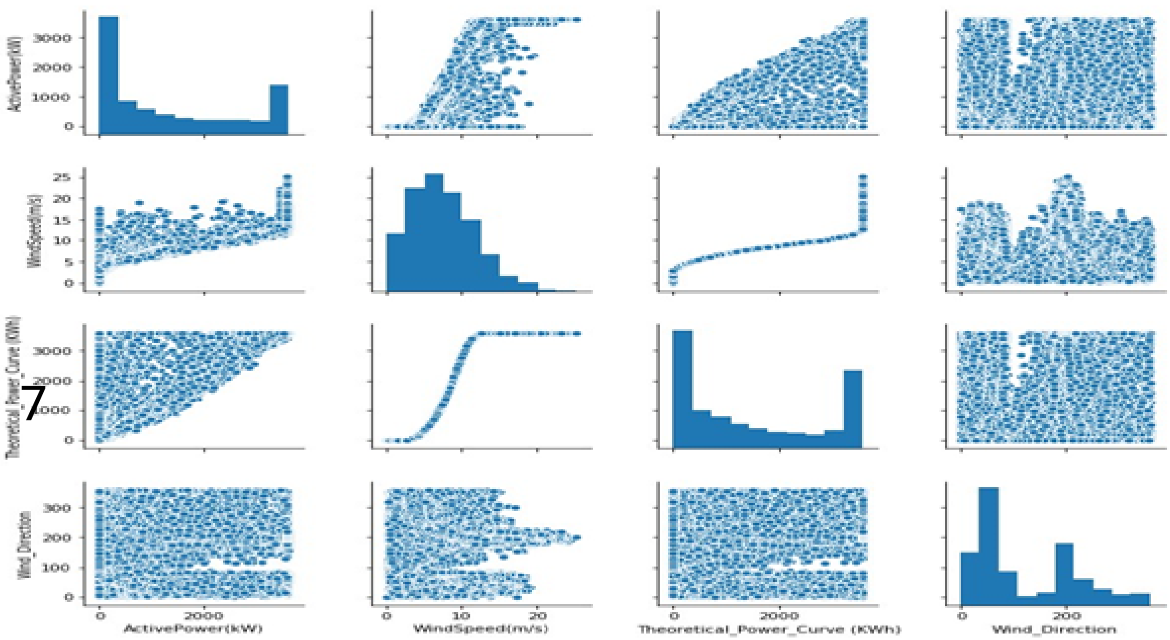
3. Wind Speed (m/s): The wind speed at the hub height of the turbine (the wind speed that turbine use for electricity generation)

4. TheoreticalPowerCurve (KWh): The theoretical power values that the turbine generates with that wind speed which is given by the turbine manufacturer.

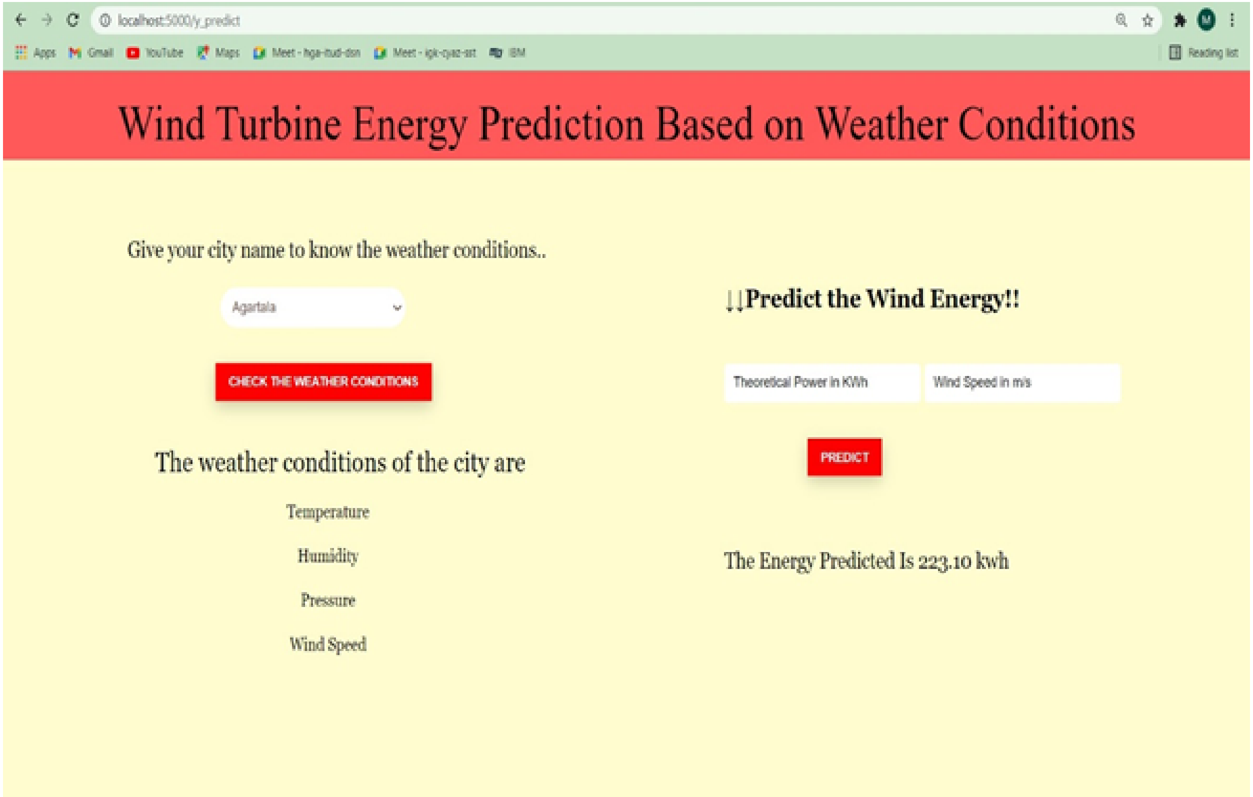
5. Wind Direction (°): The wind direction at the hub height of the turbine (wind turbines turn to this direction automaticaly).

Data Set Flow:

1	Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)
2	01 01 2018 00:00	380.0477905	5.31133604	416.3289078	259.9949036
3	01 01 2018 00:10	453.7691956	5.672166824	519.9175111	268.6411133
4	01 01 2018 00:20	306.3765869	5.216036797	390.9000158	272.5647888
5	01 01 2018 00:30	419.6459045	5.659674168	516.127569	271.2580872
6	01 01 2018 00:40	380.6506958	5.577940941	491.702972	265.6742859
7	01 01 2018 00:50	402.3919983	5.604052067	499.436385	264.5786133
8	01 01 2018 01:00	447.6057129	5.793007851	557.3723633	266.1636047
9	01 01 2018 01:10	387.2421875	5.306049824	414.8981788	257.9494934
10	01 01 2018 01:20	463.6512146	5.584629059	493.6776521	253.4806976



7.Result and Demo



7. Advantages:-

- Accuarate values
- Reliability
- Quick response
- On giving location permission,any one can predict power output at your live location
- it is more convenient to use in worldwide

9.Disadvantages:-

- Limited API requestes per day
- Android app can't be deployed on IBM cloud
- No free Server available on IBM Cloud for deploying Backend
- known people can operate

10. Applications:-

- Air Traffic
- Marine
- Agriculture
- Utility companies
- Private sectors
- Military application

11. Conclusion

We started with the aim of improving the predictions of power generated using wind energy and we have achieved that using LSTM as machine learning model and performing model optimization on it. We have also observed that if the wind speed is less than 4 m/s the power generated by the system is zero. LSTM is not able to learn this pattern as this is not the part which it can understand in time series analysis. So, if a hybrid new model is created which can work as the combination of Decision. Tree/Random Forest and LSTM we can improve upon these results as well.

12. Future Work

Most wind power forecasting models study ‘regular’ wind conditions. The EU funded project called ‘Safewind’ aims to improve wind power prediction over challenging and extreme weather periods and at different temporal and spatial scales. Development activities are on-going to reduce error in the wind power prediction, to improve regionalized wind power forecasting for on - shore wind farms and to derive methods for wind power prediction for offshore wind farms It is possible that use of ensemble and combined weather prediction methods together may enhance forecasting.

If the error in wind power forecasting and prediction is reduced then electricity markets can trade with more certainty. Contract errors as a function of time in electricity markets can be as high as 39% for a forecasting lead time of 4 h.

Gubina et al. present a new tool called the WILMAR and ANEMOS scheduling Methodology (WALT) to reduce the number of thermal generators on stand-by or in reserve using the probability of generation outages and load shedding are system reliability criteria instead of generation adequacy based solely on generation outage. The wind and load forecast errors are modelled using a Gaussian stochastic variable approach. However, in another study it was found that the prediction errors do not satisfy the KolmogoroveSmirnov test for normal distribution. In Ramìrez and Carta , it was shown that, the use of autocorrelated (and thus not independent) successive hourly mean wind speeds, though invalidating all of the usual statistical tests,has no appreciable effect on the shape of the pdf estimated.

13.Bibilography

1. Long-term wind speed and power forecasting using local recurrent neural network models IEEE Trans. Energy Convers.
2. https://smartinternz.com/Student/guided_project_info/2244#.