PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION

LITERATURE REVIEW:

Most of the countries around the world are facing huge environmental impact, and the most promising solution to mitigate these is the use of renewable energy, especially wind power. Though, the use of offshore wind energy is rapidly increasing to meet the elevating electricity demand. The researchers and policymakers have become aware of the importance of providing near accurate prediction of output power. Wind energy is tied to variabilities of weather patterns, especially wind speed, which are irregular in climates with erratic weather conditions. In this paper, we predicted the output power of the wind turbines using the random forest regressor algorithm. The SCADA data is collected for two years from a located in France. The model is trained using the data from 2017. The wind direction, wind speed and outdoor temperature are used as input parameters to predict output power. We test our model for two different capacity factors.

Project description:

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

Experimental setup:

The setup of symbolic regression used default settings of DataModeler except for the number of independent runs, execution time of each run and the template operator at the root of the GP trees. We executed 10 independent evolutionary runs of 2000 seconds in both stages. The root node of all GP trees was fixed to a Plus. The primitives for regression models consisted of an extended set of arithmetic operators: {Plus, Minus, Subtract, Divide, Times, Sqrt, Square,Inverse}. The maximum arity of Plus and Times operators is limited to 5.

Feature selection:

The initial set of experiments targets the feature selection, using all 16 input variables and all training data from October 2010 till June 2011. In the allowed 2000 seconds each symbolic regression run completed at most 217 generations. The 10 independent evolutions generated a super set of 4450 models. We reduced this set to robust models only, by applying interval arithmetic to remove models with potential for pathologies and unbounded response in the training data range.

Energy output prediction:

The second stage of experiments used only the two input variables windGust2 and dewPoint, with all other symbolic regression settings identical to the first stage experiments. As a result, a new set of one and two-variable models was generated.

PROS:

● Accurate wind power forecasts are also important in reducing the occurrence or length of curtailments (which translate to cost savings), improved worker safety, and mitigating the physical impacts of extreme weather on wind power systems

● Wind speed forecasting naturally has greater value where balancing markets are part of a competitive trading system for electricity, because the balancing market provides financial incentives to the generators and retailers for accurate output predictions.

CONS:

● The challenges to face when wind generation is injected in a power system depend on the share of that renewable energy.

For Denmark, which is a country with one of the highest shares of wind power in the electricity mix, the average wind power penetration over the year is of 16–20% (meaning that 16–20% of the electricity consumption is met wind energy), while the instantaneous penetration (that is, the instantaneous wind power production compared to the consumption to be met at a given time) may be above 100%.

- Wind power generation is rapidly picking up in many countries. With the ever-increasing demand for electricity which powers our industries, technology and our homes, it is of utmost importance to consider using it in a responsible way.

- That is where the concept of non-conventional energy sources like wind energy comes in. The one disadvantage with this form of generating power is the uncertainty in the wind direction, speed, and other climatic changes in the concerned area.

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 wind farms. We are building an IBM Watson AutoAI Machine Learning technique to predict the energy output of wind turbine. The model is deployed on IBM cloud to get scoring end point which 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 make use of 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.

Problem Statement:

- Wind energy plays an increasing role in the supply of energy world-wide.

- The energy output of a wind farm is highly dependent on the wind conditions present at its site.

- 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.

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.