PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION

LITERATURE REVIEW:

The utilisation of renewable energy, particularly wind power, is the most promising way to reduce the significant environmental impacts that the majority of countries throughout the world are currently experiencing. Although, to satisfy the rising need for electricity, the usage of offshore wind energy is fast expanding. Researchers and decision-makers are now aware of how crucial it is to anticipate output power with a high degree of accuracy. Wind energy is dependent on variations in weather patterns, particularly wind speed, which are unreliable in regions with unpredictable weather patterns. In this study, we used the random forest regressor algorithm to forecast the output power of the wind turbines. Two years' worth of SCADA data are gathered from a French location. 2017 data are used to train the model. To anticipate output power, the wind's direction, speed, and ambient temperature are used as input variables. We examine two alternative capacity factors in our model.

Project description:

Wind energy has an expanding role in the provision of electricity world-wide. The meteorological conditions at a wind farm's location have a significant impact on the amount of electricity it produces. Energy providers can more effectively coordinate the cooperative production of various energy sources if the output can be forecast more precisely. This will help them avoid expensive overproduction. In this study, we forecast energy output based on weather data and examine key variables and their relationships to energy output.

Experimental setup:

With the exception of the number of independent runs, the duration of each run, and the template operator at the root of the GP trees, symbolic regression setup used DataModeler's default parameters. In these stages, we carried out ten separate evolutionary runs lasting 2000 seconds. Every GP tree's root node was set to a Plus. An extensive set of arithmetic operators, including "Plus," "Minus," "Subtract," "Divide," "Times," "Sqrt," "Square," and "Inverse," made up the primitives for regression models. Five plus and times operators are the maximum number.

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:

• The Web Dashboard responds to non-manually completed weather condition analyses.

• By fitting our chosen parameters to the data, we can improve the outcomes.

• There is no need to look up weather analysis on various websites.

• It is simple to use and has a user-friendly interface.

• Businesses can use to increase the effectiveness of energy capturing.

Reduces the need for human labour and is applicable even in less connected places.

• Economically sound

• With a well managed database, businesses can easily keep track of users and access.

• Encourages the use of clean and green fuel and promotes alternative energy sources.

CONS:

• Demands all services that respond to queries and handle inquiries.

• Requires some difficult service integration.

Proposed system Solution:

We want to connect weather information to energy production. We want to demonstrate that accurate energy output predictions can be made using even publicly available data from weather stations around wind farms. We also look at how various weather conditions affect the amount of energy produced by wind farms. In order to forecast the energy output of wind turbines, we are developing an IBM Watson AutoAI Machine Learning approach. The model is set up on the IBM cloud to produce a scoring end point that can be utilised as an API for creating mobile or online applications. We are working on a web application that uses the node red service. We use the scoring end point to provide the deployed model with user input values. The user interface then uses the model prediction to forecast the wind turbine's energy output.

Conclusion:

We set out to improve wind energy estimates, and by employing the LSTM machine learning model and applying model optimization to it, we were able to do just that. Additionally, we have noted that the device produces no electricity at wind speeds below 4 m/s. Because this is not the part of the pattern that LSTM can comprehend in time series analysis, it is not able to learn it.

Therefore, if a hybrid new model is developed that combines LSTM, Random Forest, and Decision Trees, we can also enhance these outcomes.