

AN MACHINE LEARNING PROJECT ON
PREDICTING ENERGY
OUTPUT OF A WIND
TURBINE USING AUTO AI
WATSON STUDIO

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1.INTRODUCTION

1.1 OVERVIEW

Wind energy plays an increasing role in the supply of energy world-wide. The energy output of a wind farm is 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.

This project will suggest the best time to utilize the energy from wind farm.

1.2 PURPOSE

This project's objective is to develop a time series model to predict the power output of wind farm based on the weather condition in the site.

2. LITERATURE SURVEY

2.1 EXISTING PROBLEM

The power output of a single wind turbine is a direct function of the strength of the wind over the rotor swept area. The strength of the wind depends mostly on the wind speed.

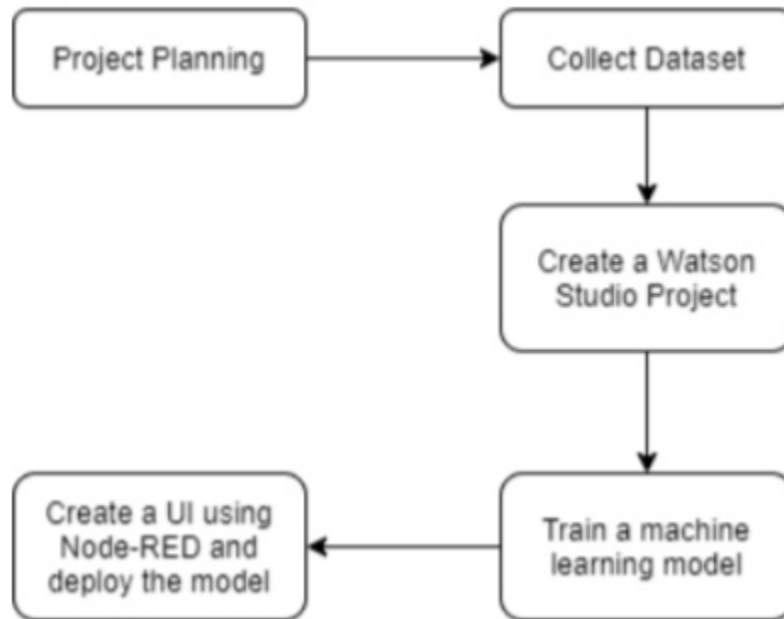
An other important aspect to consider is the fact that wind speed and direction fluctuate overtime. Therefore, we must consider the time, wind speed and wind direction to optimize energy production.

2.2 PROPOSED SOLUTION

The proposed solution is to use linear regression to train a machine learning model. The input for the model will be time, wind speed and wind direction. A user friendly interface created using node-red would make it easy for the user to interact with the deployed model.

3. THEORETICAL ANALYSIS

3.1 BLOCKDIAGRAM



3.2 SOFTWAREDESIGNING

The software designing involves the following steps:

1. PROJECTPLANNING

This step involves deciding on which programming software to use and how the user shall access and interact with the model. The deadline must also be kept in mind during this step.

2. COLLECTDATA

This step involves collection of the dataset from kaggle.com.

3. CREATE IBM SERVICES

To deploy the application in IBM cloud, necessary services need to be created. This involves machine learning services for Watson Studio and cloudservices.

4. CREATE A WATSON STUDIO PROJECT

Once the necessary services are created, a Watson Studio project can be created.

5. IMPORT THE DATASET

Watson studio needs the dataset as an asset to use it. Therefore, the dataset must be imported. It will be stored in the cloud object storage.

6. TRAIN THE MODEL

A notebook is created and python libraries like numpy, scikitlearn are used to visualize the data and train the model.

7. BUILD NODE-REDFLOW

Once the model has been trained, it can be deployed. Node-red is used to provide a user friendly interface for users to interact with the model and provide input and get the output.

4. EXPERIMENTAL INVESTIGATIONS

4.1 The Dataset:

The dataset is a csv file which has the following columns:

1. Date /time
2. Lv activepower(kw)
3. Wind speed(m/s)
4. Theoretical_power_curve(kwh)
1. Wind direction(°)

Watson Studio:

Ibm's Watson studio is has many features which can be used for machine learning.

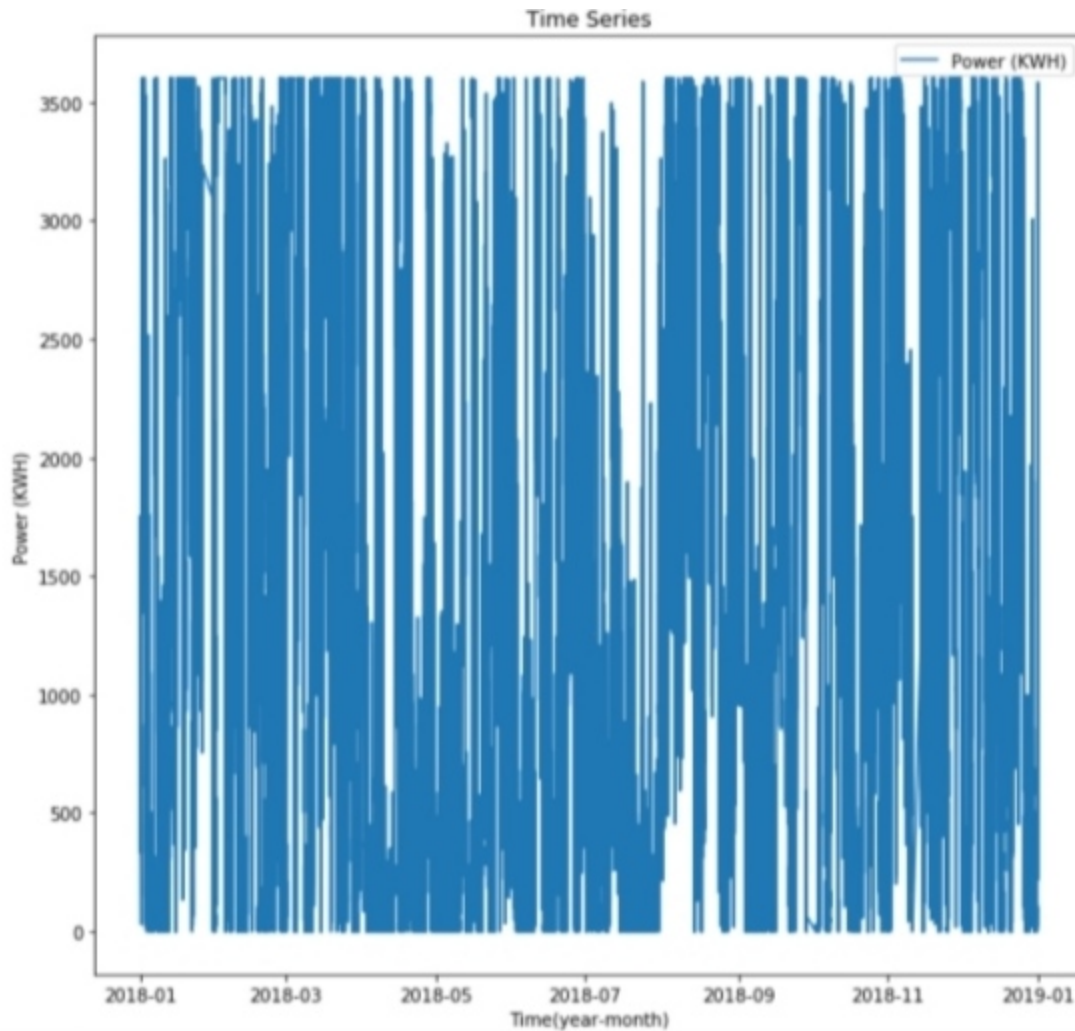
Reprocessing and cleaning dataset:

Before the dataset is trained, it needs to be processed and clean. For example, null values should be removed or set to 0. Also libraries to perform the above must be imported first. We can also convert the data to a format in which it can be handled easily. The necessary libraries are imported first.

Once the dataset is imported to the notebook, it is checked for null values.

Data visualization:

Once the data has processed, graphs can be used to understand the data better. Plotting of the graph is done with the help of matplotlib.



Training The Model:

Once visualization is done, the next step is to train the model.

Scikit-learn is used to train the model. Regression has been used here.

Get Prediction:

Once the training is done, the predicted output can be obtained from the

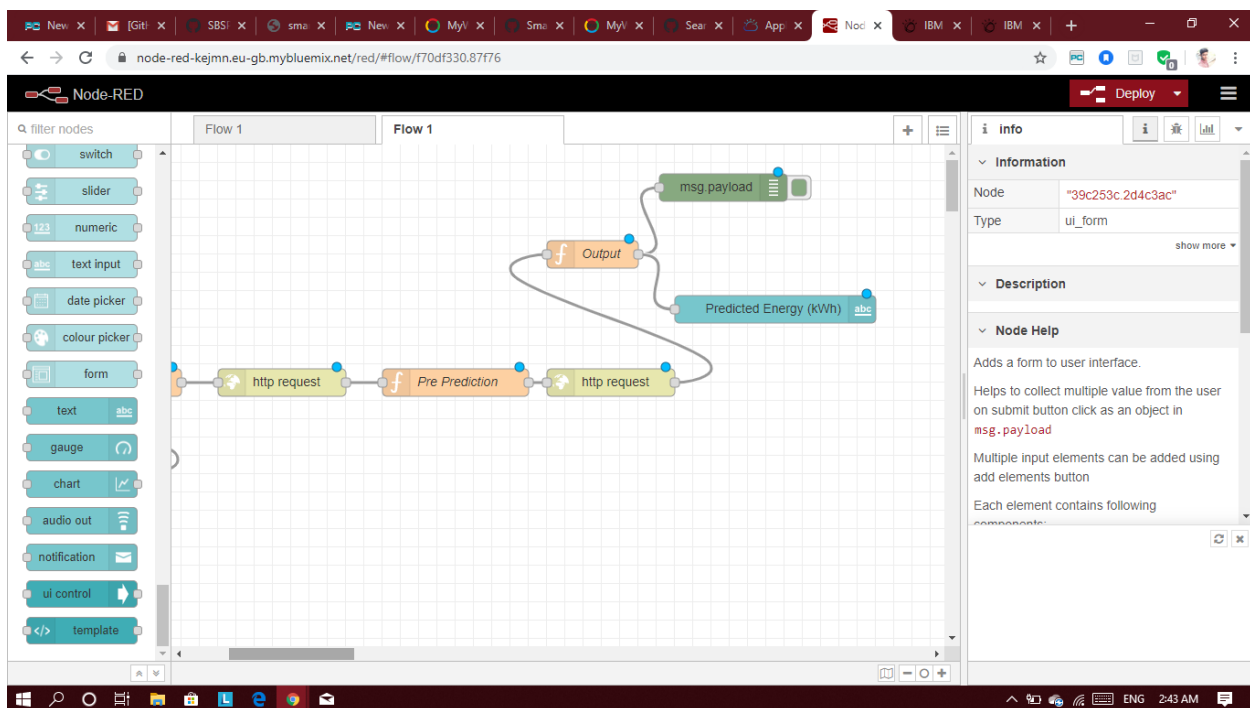
model.

By comparing the predicted output with the values in the dataset, the accuracy of the model can be evaluated.

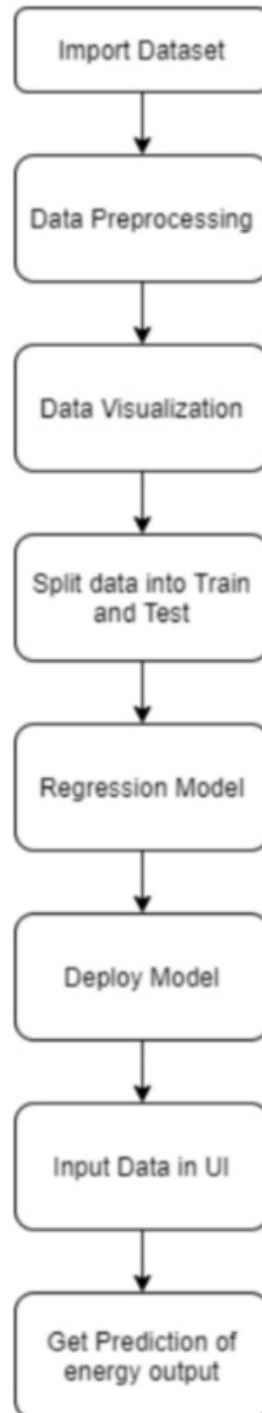
There are many ways to measure the accuracy. Here, the mean square value and mean absolute error have been found in addition to the accuracy of the model.

node-RED flow:

Once the model has been trained and deployed, a ui can be created for users to interact with the model. Node-RED has been used for this purpose. The Node-RED flow is shown below:



5. FLOWCHART



6. RESULT

Web based UI was developed by integrating all the services using Node-RED.

The energy output of a wind turbine was predicted, given the weather conditions. From the result, it is possible to determine when the energy output was best.

Home

Predicting Wind Energy

Wind Speed (m/s) *

5.73

Wind Direction (A°) *

2465

Theoretical Power Curve (KWh)

5554

Date/Time

01/01/2002

SUBMIT CANCEL

Predicted Energy (kWh)

7. ADVANTAGES AND DISADVANTAGES

Advantages:

One of the biggest advantages of embedding machine learning algorithms is their ability to improve over time. Machine learning technology typically improves efficiency and accuracy thanks to the ever-increasing amounts of data that are processed.

Using Node-RED also simplifies the effort put into creating the front end.

Disadvantages:

Machine learning can be very time consuming especially when there is a large amount of data. Also, the machine learning model may not be as accurate as manual calculations.

Node-RED has very limited options and offers little customization for the UI.

8. APPLICATIONS

Through this project, wind farms can get a good overview on how the weather affects energy production and optimize their energy production.

Also, energy suppliers can coordinate the collaborative production of different energy sources more efficiently to avoid costly overproduction.

9.CONCLUSION

The end product is a webpage created and deployed on Node-RED app of IBM cloud. The backend of webpage is a regression model created and deployed on Watson Studio using machine learning service. This model can be used to predict the energy output of wind turbine based on weather conditions.

10. FUTURESCOPE

The scalability and flexibility of the application can also be improved with advancement in technology and availability of new and improved resources. With more data, the predictions will also become more accurate. Factors like season and type of turbine can also be considered in the future.

11. BIBLIOGRAPHY

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2. Watson Studio Cloud:

<https://bookdown.org/caoying4work/watsonstudio-workshop/jn.html/>

3. Dataset Reference:

<https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset>

4. IBM Cloud Services:

<https://www.youtube.com/watch?v=dbrglahdj48&list=plzpeuwuenmk2pytasca4k4bzjayzhw23l>

5. Information On Wind Energy:

<https://hpi.de/friedrich/docs/paper/re1.pdf>

APPENDIX

SourceCode:

Node-REDflow:

```
{ "id": "f70df330.87f76", "type": "tab", "label": "Flow
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'jR2Wqsa1MVGk4fGIHR8r5d4E8VcuYutXEcpNr3bPC_kD'; \nmsg.headers={ 'content-type': 'application/x-www-form-urlencoded' } \nmsg.payload={ 'grant_type': 'urn:ibm:params:oauth:grant-type:apikey', 'apikey': apikey } \nreturn
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instance_id='13241408-5d1b-4288-aeab-633681eea4ec' \nmsg.headers={ 'Content-Type': 'application/json', 'Authorization': 'Bearer
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Direction

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