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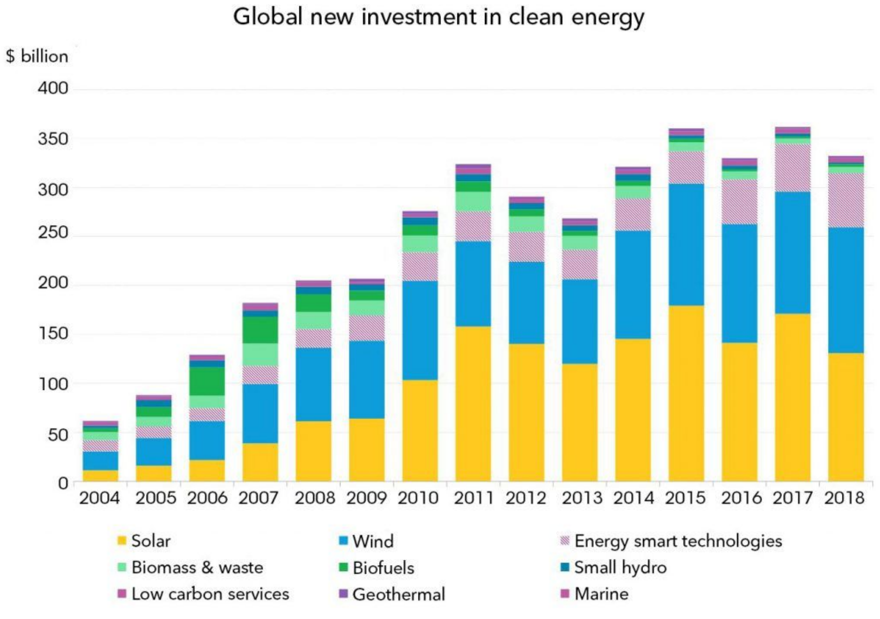
Wind Turbine Signal Analysis

An approach to predict and evaluate the quality of signals

Introduction

The energy world is changing at an exponential speed. Years ago, conventional sources of energy like thermal and generation and were the main sources in the industry, and project budgets were only possible for a few big companies. Currently, the birth of new energy sources like wind and solar power allow for the construction of smaller power plants, increasing their business. This allows smaller and more flexible energy companies to have a larger stake in the industry. [1]



Source: BloombergNEF

[1] https://about.bnef.com/blog/clean-energy-investment-exceeded-300-billion-2018/

In the past, only a few companies with enough experience handling and manipulating complex models had access to data. Currently, the continuous improvements in data science have created new methodologies that allow more people to gain access to data for analysis. If servers are required, there are many cloud suppliers that offer high speed computing at affordable costs[2].

Considering all of the above, energy projects with lower budgets now have access to affordable technology. Previously, within big energy projects, it was common to spend more than 100,000 USD implementing intelligent systems to predict signals. As of now, smaller energy projects have business models that cannot afford to spend that amount of money. Utilizing machine learning and cloud servers, it is now possible to accurately predict signals.

Through the use of predictive methodologies, there are 2 main impacts in the business model: maximizing availability and minimizing maintenance costs. If it is possible to predict when the machine is going to break, then measures can be taken in advance to avoid breakage. Income is lost every time a machine breaks due to a loss of functionality within the plant. In addition, prediction can allow optimization of preventive maintenance that is more efficient and cost effective than the current corrective maintenance.

What I propose is to create a model that maximizes the usage of the current data, employees experience, and machine learning tools, and to create a model for wind turbine signal analysis.

This analysis will identify signals whose qualities are wrong and predict a value for the signal and compare with the real value to detect if signals are out of the confidence interval. If the signal's qualities are wrong, systems technicians will be sent to analyze the issue. If signals are out of the confidence interval, operations and maintenance staff will solve the issue. This allows the model to easily direct work to systems technicians or to operations and maintenance staff. To do this, the user will have access to a Tableau that will display the graph with the trends of the signals and an indicator of the number of issues for both signal quality and measures for those out of range. This model will allow employees to focus more on using their experience to prevent breakdowns in more power plants.

Motivation

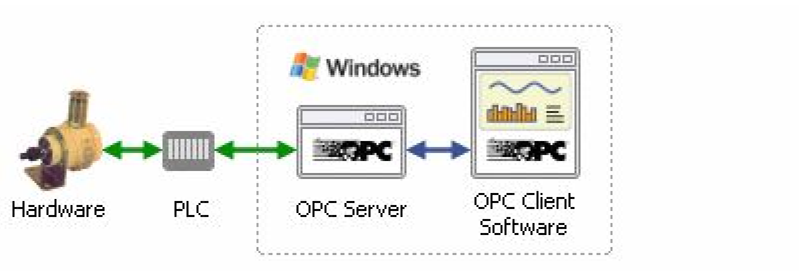
[2] Llorente, Ignacio M. "The Limits to Cloud Price Reduction". June 29, 2017

This project comes from the need to be more efficient at work. I have more than 7 years of experience in the energy sector and from a digital point of view, I see how companies are required to be more efficient if they want to stay relevant in the market[3].

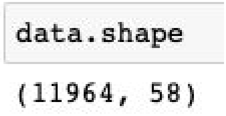
After a thorough analysis, I saw that energy companies have access to a lot of data, that if utilized properly, can add incredible value. Presently, many data files are stored in servers that are not used except in cases of a major breakdowns. Employees don't have the necessary tools able to see the status of the machines easily and if it is necessary to repair them, so they must manually mine through data and use their past experiences to make an analysis.

<u>Data used</u>

The data available is a time series for each wind turbine. All wind turbine signals are accessible through an OPC (OLE for Process Protocol)[4] with almost real time data. Every 10 minutes signals are refreshed, and each wind turbine has 57 signals (see "Dictionary of signals for further information")



For this project, signals for 3 months were analyzed from January 1, 2019 to March 25, 2019, and three wind turbines were analyzed. In the future, there will be larger date ranges and additional wind turbines.



```
data.shape
(11964, 58)
```

Although the data can be accessed in real time, this project is focused on batches, where the data will be imported to the model on demand by the employees. In the future, real time data analysis could be implemented.(screenshot of the current data)

[3] https://www.forbes.com/sites/louiscolumbus/2018/08/30/state-of-enterprise-cloud-computing-2018/#25d52760265e
[4] https://opcdatahub.com/WhatIsOPC.html

Methods

The model has been created using Python for data manipulation and prediction. The interface with the user has been developed using Tableau.
To perform the forecast in the time series I followed the 5 steps detailed in the book "Forecasting: principles and practice."[5]

1. Identify the problem
   a. The forecast is necessary for energy company employees that have large vats of data and need a summary that details the state of the power plant.
   b. The forecast then will be used to prevent major breakages by predicting signals that are out of confidence interval or of bad quality, and allowing for an analysis of the situation before any breakage.
   c. Signal forecast is defined by the convergence of the prediction model and the confidence interval.
   d. Signals are considered bad quality if:
      i. Flat: remains in the same value
      ii. Full scale: when signal measure goes to full scale value. This means that there is a failure in the instrument.
      iii. Gap: there are empty spaces with no value in the time series
      iv. Outliers: are observations that significantly differ from other observations of the same feature.

2. Gathering information
   a. Information can be either data or business know-how:

      i. Data: Gathering data is done from either accessing real time data through the use of OPC or on demand data import.

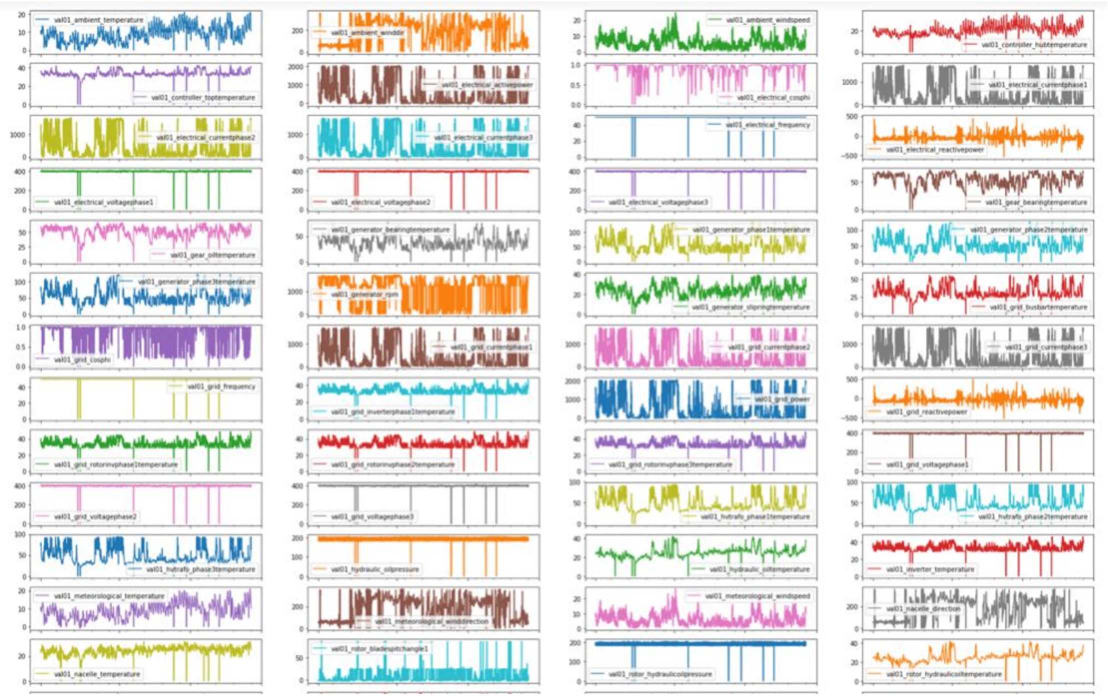
      ii. Business know-how: accessing domain experts that can accurately interpret the historical data, preventing future break downs, based on their experience.

3. Preliminary exploratory analysis
   a. This includes importing the data and manipulating it. During this step plots and reviewed and summarized and obvious temporal structures are noted. These

[5] Hyndman, Rob J and Athanasopoulos, George. "Forecasting: principles and practice". October 17, 2013

would include trend seasonality, anomalies like missing data, corruption, and outliers, and any other structures that may impact forecasting. This step is divided in two, cleaning and exploration:

i. Cleaning: select the right column and headers
ii. Exploration: prepare the data for the time series.
    1. Selecting Time index
    2. Type float all the values
    3. Including ploting:



    4. Check for outliers
    5. Missing values
    6. Seasonality

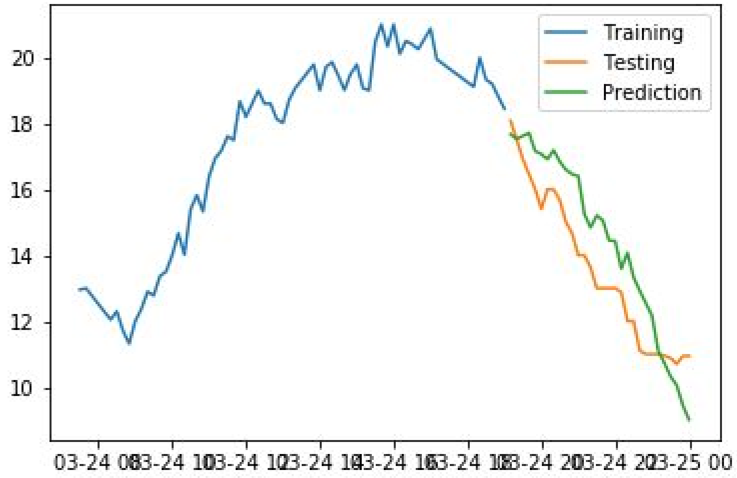
4. Choosing and Fitting Models

In order to choose the correct model, it is necessary to compare several forecasting models and select the one with the better prediction.

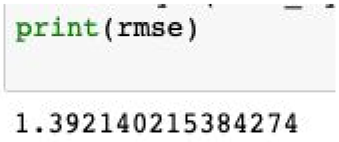
For this purpose the data is split in train and test. The model is created using all data. Then it is trained with the train data. Once the model is trained, it’s time to create a prediction for the time range of the test data. The prediction will be compared with the test data, analyzing the error with the RMSE (frequently used to measure difference between value and prediction). In this project it is used the most commonly used method to model Time Series: Auto Arima (for python from pyramid arima (pmdarima [6]).

To Model Time Series like the one presented, with many variables, it is recommendable to create clusters using K-means and create the model to the cluster, reducing the number of models to create. However that will be considered in future development.
Therefore it was pursued to model all variables one by one, however the computing time was too high, that that option was discarded.
An additional alternative was to use the web servers with higher computing power (like google research colab), however some of the packages were constantly failing, so this was also discarded.
The final choice was to create the model for an amount of signals that could be managable for the computer. Three signals were selected.

Fitting the Model: Auto Arima



Calculate the accuracy of the model with RMSE



```
print(rmse)

1.392140215384274
```

Once checked the accuracy it is time to forecast future values

[6] (https://www.alkaline-ml.com/pmdarima/about.html)

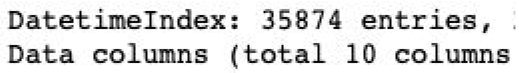
5. Using and Evaluating a Forecasting Model

With the model selected based on the accuracy, it is time to roll-out to future values and additional values. To do that it is necessary to define a period of time for the forecast, in this case 6 periods of time = 1hour is selected. The function predict() by auto arima provides 2 values:

- Prediction
- Confidence interval

These values are used to stored in the dataframe. To move along the variables it is used a for loop.

Since the output from the predictions is used as input in Tableau, it is used a long-shape (instead of wide-shape) dataFrame, resulting in:



```
DatetimeIndex: 35874 entries,
Data columns (total 10 columns
```

These values then are transported to Tableau for the analysis of the technical department that will easily identified if there is any issue that needs to be solved, and the matter of the issue.

In addition to all the previous, this machine learning algorithm will be updated with additional data, creating therefore new predictions and learning from the historical data.

Conclusion

This project creates a model to forecast time series values through the use of machine learning algorithm like Auto Arima. It is a non-expensive methodology unlike traditional forecasting software that can potentially help energy companies to reduce their OPEX (operational expenditures) budget.

It is possible to improve the forecast using K-means for clustering the variables creating a model for each cluster, however for the time being this model proves with an accurate result for the variables predicted.