Wind Power Forecasting

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Source: ("EDPR Wind Farm", 2022)

Introduction

In this project, our aim is to to answer the our central question:

> **Using machine learning, can we predict the power output of a wind farm using local point source metrics to better inform electric grid adjustments ?**

Utilities put a premium on steady power supply. Unfortunately, wind energy is only supplied when the wind blows. With improved power forecasts, electric grid operators can adjust grid patterns switching to other power sources or battery storage with more efficiency. As little as a 1% error in forecasted wind speeds could result in a loss of $12,000,000 during a wind facilities life cycle (Shouman, 2022). Better models can give the wind industry substantial savings, and make the wind energy resource more attractive for future development.

Current wind forecasting models are reliant on meteorological forecasts from other entities such as the National Weather Service in the United States as seen in the figure below. If forecasting could take better advantage of local production and meteorological metrics collected on site, errors in weather forecasting could be eliminated.

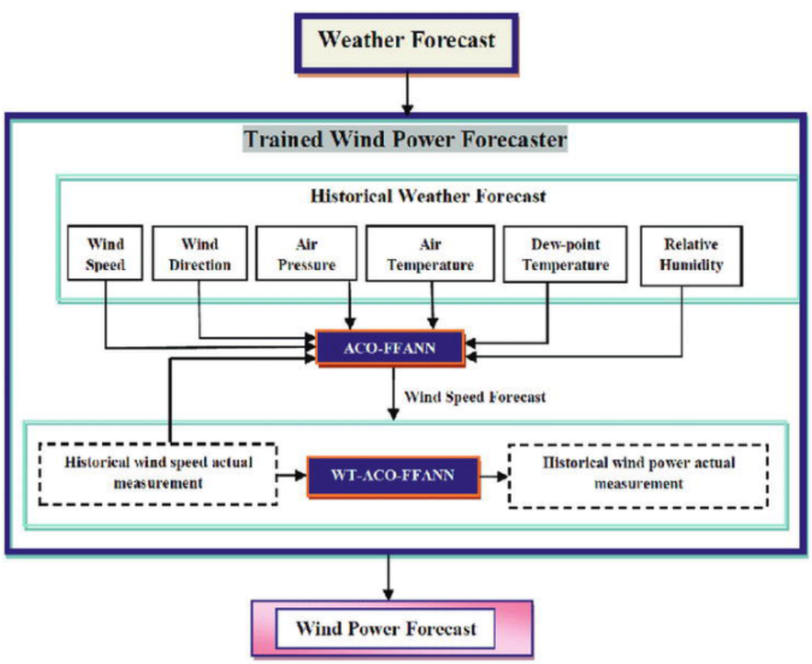

Figure 1 - Concept illustrates the intricacies of wind power forecasting.
Source: (Shouman, 2022)

According to Mark F. Bielecki and his thesis on wind forecasting, mean absolute error of forecasts can depend on many variables, such as ramp up and ramp down periods. Ramp up and down periods are where turbines are accelerating up to and from optimal rotational speed to match wind speeds. During non-ramping times, mean absolute error(mae) can range from five percent of capacity for one hour out to upwards of 20 percent of capacity for 72 hours out. During ramp up and ramp down times, mae can be as high as 40 percent of capacity. (Bielecki, Mark F., 2010)

We have gathered meteorological and power production data from EDP Renewables. Our data comes off four turbines from EDPR Wind Farm 1 located in the Atlantic Ocean as shown in the map on the last page.

The turbines that we analyze each have a maximum capacity of 2000 Kw and a mean power output of approximately 514 kW for the year of 2016. Taking into account Bielicki's findings on error of wind forecasting, we can set goals for our main error metric of mean absolute error(MAE). With expert models attaining MAE scores of 5 to 20 percent of capacity depending on forecast windows. On the high end using maximum power capacity, we will try to achieve MAE scores in that range which would be between 100 kW for one hour out and 400 kW for 72 hours out. Turbines don't run at maximum capacity all the time. So, comparing our results to mean power output is probably a better measuring stick. This would set our MAE goal to be 25 kW on one hour forecasts and 100 kW on 72 hour forecasts to compete with leading industry models.

Data Structure and Data Processing

We downloaded four data sets from the open data page of EDP Renewables. Two data sets contained wind turbine production data and two data sets contained meteorological measurements from the wind farm. The data was collected at 10 minute increments from 2016 to 2017. The both years contained 124 features of different power, maintenance and weather metrics. The 2016 data set contained between 209,705 rows and 2017 contained 209,236 rows.

We made the decision to clean and process the 2016 data and leave the 2017 to use as a testing set once we established a solid model. The 2016 data had very few null values or duplicates. Although, when we separated the data by the four turbine IDs we found that there were between 264 and 2,135 missing time stamps depending on the turbine. These missing data entries or time stamps were imputed using interpolation. A final data frame was created combining the data frames for each turbine and the meteorological data frame.

Exploratory Data Analysis(EDA)

After cleaning and processing the 2016 data we carried out EDA visualizing our key features of average wind speed and average power production. The distribution of both features were both right skewed as seen in Figure 2.

We did a correlation analysis and saw strong positive correlations between wind speed, turbine rotational speed, and power output as one would expect. Some interesting notes to consider for future modeling are that temperature has a low positive correlation to power output, approximately 0.17. Humidity has a low negative correlation to power output of approximately -0.17. These relationships should be further researched and analyzed to contribute to our wind forecast modeling.

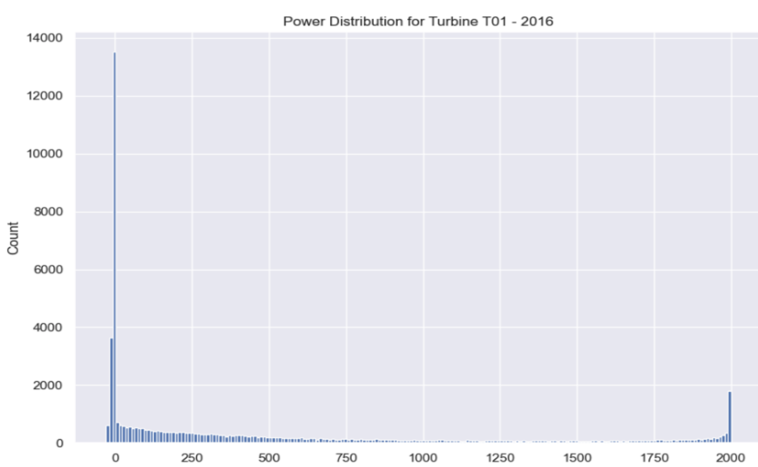

Figure 2 - Distribution of power for Turbine T01 for 2016

Initial Modeling

For our first models, we fit a SARIMAX and a Vector Autoregressive Model(VAR). Both models were developed exclusively for times series analysis. Both models showed little predictive value until we moved to only predicting an hour time frame from the training set. Results of our models are in Table 1 below. We can visualize the SARIMAX models performance in Figure 3.

Model	Train MAE	Test MAE	Baseline Train	Baseline MAE
SARIMAX with Wind Speed	0.5	2.81	3.05	2.81
SARIMAX with Power - 1 Day	80.94	541.39	525.08	560.23
SARIMAX with Power - 1 Hour	81.36	360.77	525.08	482.37
VAR with Wind & Power - 1 Hour	264.31	183.76	525.08	482.37

Table 1 - Results of initial modeling with univariate SARIMAX and multivariate VAR. The MAE scores show little predictive power. The VAR test MAE score is misleading as when visualized it does not track the train or test data.

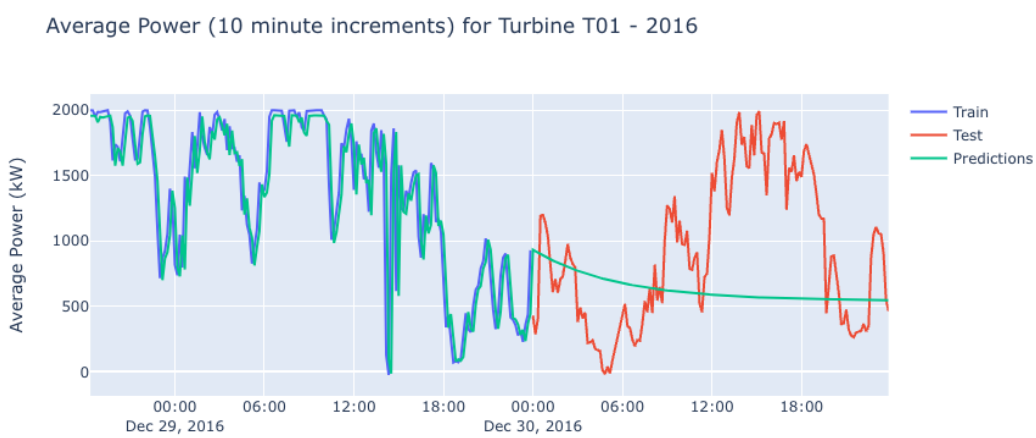

Figure 3 - We see the results of our SARIMAX below. The model tracks the training set but cannot track the test set.

Feature Engineering / Machine Learning

We created a new feature called `four_turbine_avg_power` that is the average power output of all four turbines in EDP's Wind Farm 1. This value will better average out the error from failures, ramp up times, and ramp down times that might influence power output on one turbine and not another. We also created a data frame of daily average power means and a data frame of hourly power means.

We then proceeded to fit a variety of Random Forest Regressors(RFR). The RFR has shown success in modeling time series data. Furthermore, if the model shows value then we can incorporate other features without being concerned with multicollinearity. We fit a number of RFR models using wind speed as our independent variable and average power as our dependent variable with different length test sets. We hoped that this could establish a baseline when paired with weather forecasts. Longer testing windows showed better error scores, and could be optimized for future use with weather forecasts. Unfortunately, these models used future wind data to predict future power not answering our central question, and so we moved on. Results are seen below in **Table 2**.

We then transformed our data set to create our independent variable as a series of time steps or time lags prior to our target to establish a window that can move over our dataframe and make one step predictions. We then evaluated this process with the Random Forest Regressor on daily data. These results marked some improvement on the SARIMAX and VAR as the model could track our test sets. Results are seen in **Table 2** below. (Brownlee, 2016 and 2020)

Model	MAE*	MAE Baseline	R-Square
RFR - X=Windspeed y=AvgPower	101 to 115	514	.78 to .89
2 to 14 Day Validation Sets			
RFR - X=Windspeed y=AvgPower	125 to 213	514	-540 to .63
2 to 48 Hour Validation Sets			
RFR - X=power(time lagged)	349 to 367	514	.16 to .27
14 Day Validation Sets			

Table 2 - Error metrics for RFR.

Deep Learning

We explored a number of LSTM models using our time lag window to make one step predictions. LSTM models have proven to be very effective in analyzing time series and predicting into the future. The drawback of LSTM models is that they have little interpretability, but that is not a problem in our use case. As we are trying to build a predictive model; we are less concerned about the "why" of our results.

Model	MAE*	MAE Baseline	R-Square
Vanilla LSTM - 1 Day Pred	310 to 423	514	-.99 to.33
6 and 14 Day Validation Sets			
Bidirectional LSTM -1 Day Pred	616	514	No Score
24 Day Validation Set			
Vanilla LSTM - 1 Hour Prediction	156 to 267	514	.54 to .83
6 and 12 Day Validation Sets			
LSTM/CNN - 1 Hour Predictions	194 to 288	514	.57 to .77
6 and 24 Day Validation Set			
Vanilla LSTM Optimization-Hourly	118 to 232	514	.66 to .89
11 to 24 Day Validation Set			

We trained a One hidden Layer LSTM or Vanilla LSTM on daily average power data to make one day predictions (Brownlee, 2018). A Bidirectional LSTM was also evaluated on making predictions one day out (D#DataScience, 2020).

We proceeded to then train and validate a Vanilla LSTM and LSTM/CNN model predicting just one hour out. We moved forward with optimizing our best LTSM model to achieve improved outcomes. Results of our models are in **Table 3** to the left. We saw a marked improvement in model performance when we started predicting one hour out instead of a day out.

Table 3 - Error metrics for LSTM.

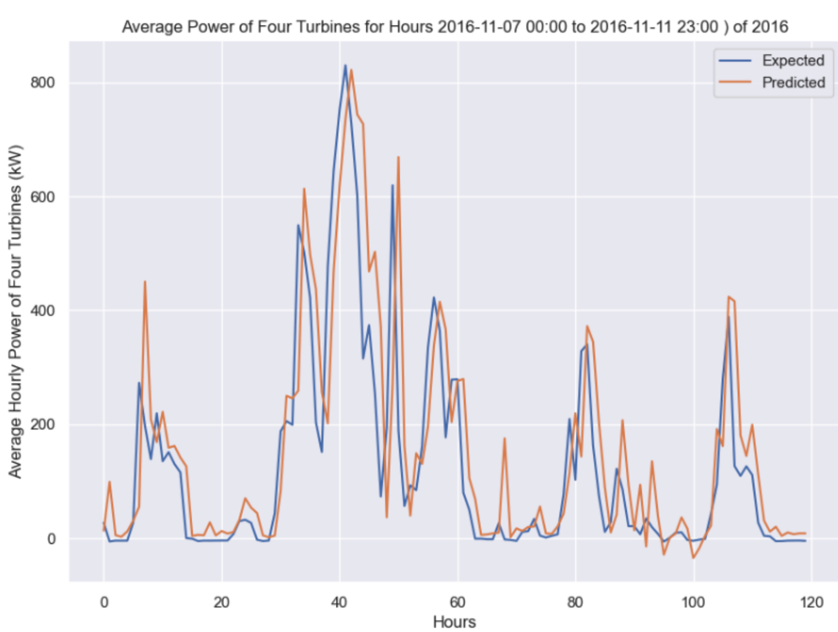

Figure 4 - One hour predictions for 120 hours by the Vanilla LSTM.

Conclusion

The results of our highest performing Vanilla LSTM fell into the range of targeted error metrics. The model could compete with more comprehensive models currently being used in industry as discussed in the Introduction. In addition to a good MAE, we also saw nice percent errors on the last unforeseen data points in the validation sets. These percent errors fell below 1 percent on some LSTM runs.

There is still a great deal of analysis that can still be completed on this project. We would like to return the Random Forest Regressor making hourly predictions as we saw a dramatic model improvement when we moved to hourly data rather than daily data on the LSTM. We will also look to try other machine learning models that have proven successful with time series such as the XGBoost Regressor. A grid search with cross validation could be conducted to optimize a model and then test it on a variety of time frames.

We would like to move forward, as well, with the Vanilla LSTM and see how it predicts 2 and 3 hours out. Altering the walk forward validation algorithm, we can look more days into the future. Furthermore, we would like to conduct a multivariate analysis that could strengthen the predictive power of our machine learning and deep learning models. We will also complete the cleaning and processing of the 2017 data to create more robust training, validation, and test sets.

When reflecting on this investigation, we are feeling good about predicting one hour out at EDP's Wind Farm. This model with further testing could be used to inform the decisions by local electric grid and wind farm operators to more efficiently switch to and from alternative power sources. Less error in forecasting translates to cost saving for the wind producers and utilities delivering power to the consumer.

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