Wind Energy Analysis and Prediction

GA Capstone Project

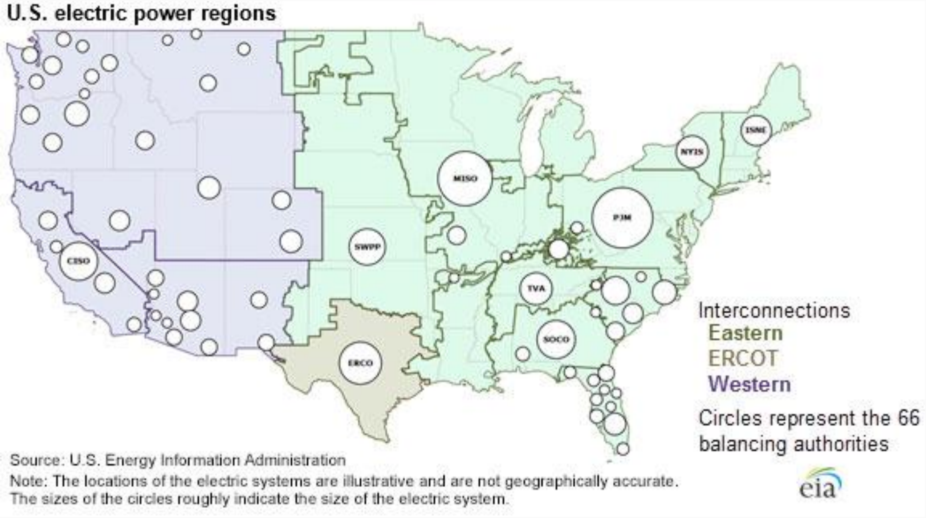
Presented by: Zaid Aziz

Problem Statement

I am an analyst at General Analytics, a consulting company with an expertise is in forecasting. Our audience is the forecasting department at (Electric Reliability Council of Texas) or ERCOT, the Texas power regulator. We want to sell them an application that predicts hourly wind power output for a month in advance.

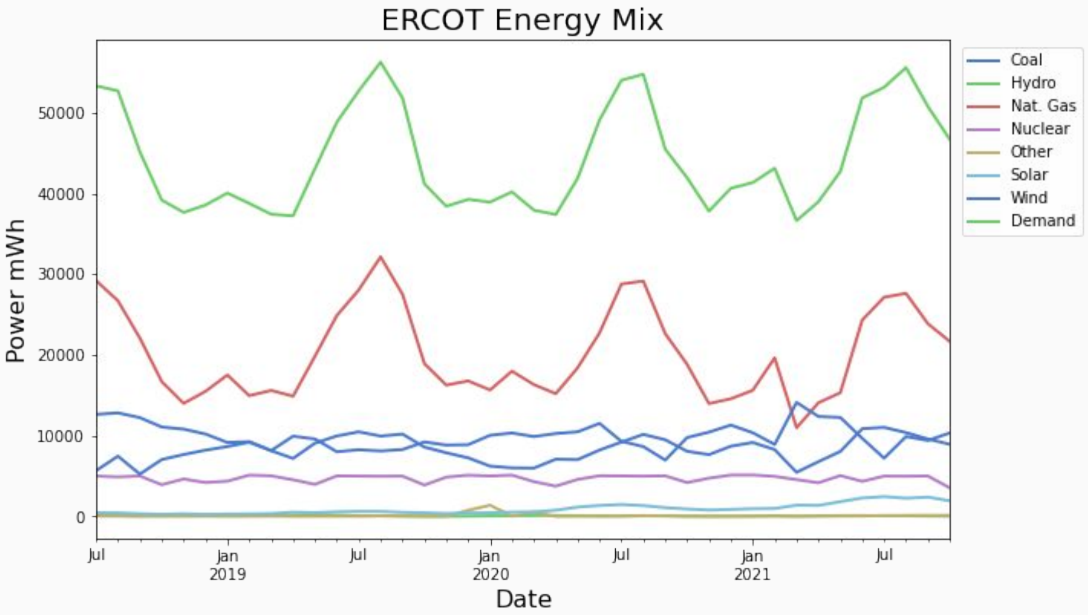
Background: ERCOT (Texas Power Grid)

- ERCOT Responsibilities
  - Interconnection
  - Regional Transmission
  - Balancing Authority



Background: ERCOT Balancing Authority

- ERCOT as balancing Authority
  - Ensure Supply meets Demand
  - Ensure that there is adequate supply
- ERCOT Energy Mix
  - Coal
  - Hydro
  - Nat. Gas
  - Nuclear
  - Other
  - Solar
  - Wind



Background: Renewable Energy

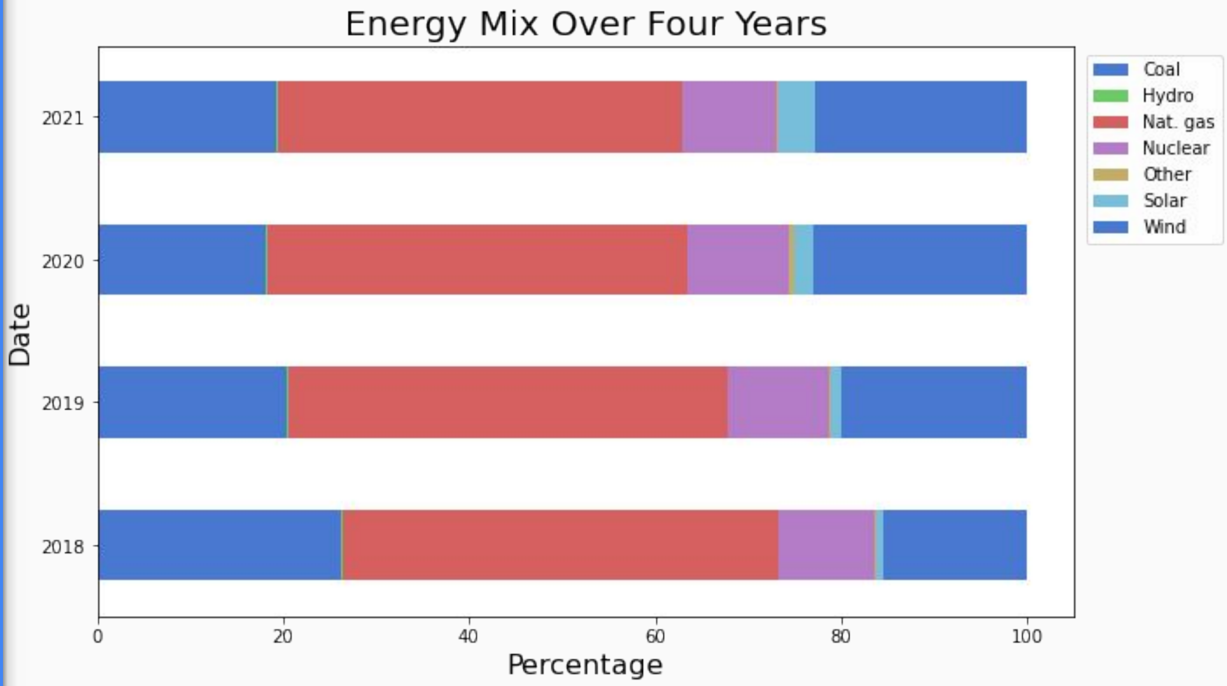
- Wind Turbines: No wind no power
- Solar Panels: No sun no power
- Our forecasting application will allow ERCOT to better plan for periods of intermittent wind.

Source: [Image by Ed White from Pixabay]

EDA

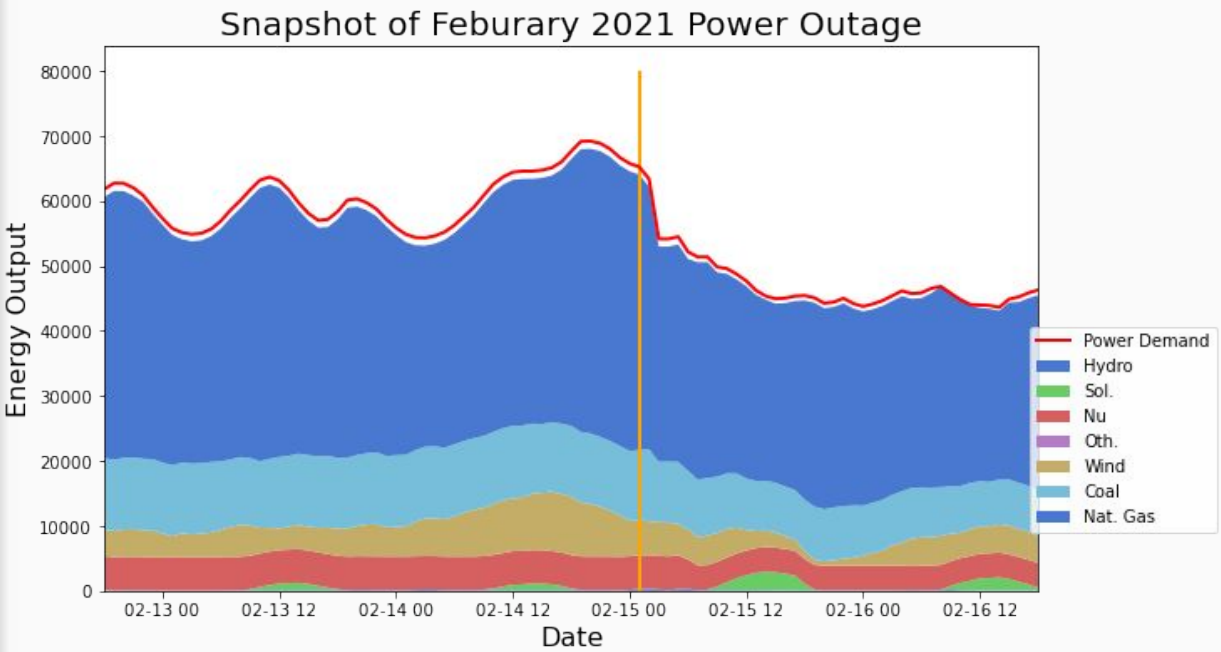
ERCOT Energy Mix

- Decrease In Coal power
- Increase In Wind power
- Large Increase in Solar Power
- Slight decrease In Natural Gas power
- Natural Gas main supplier to the ERCOT grid



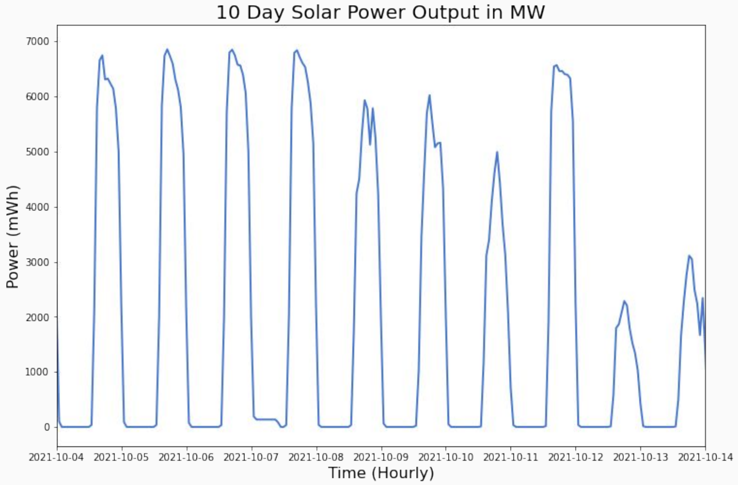
February 2021 Power Outage

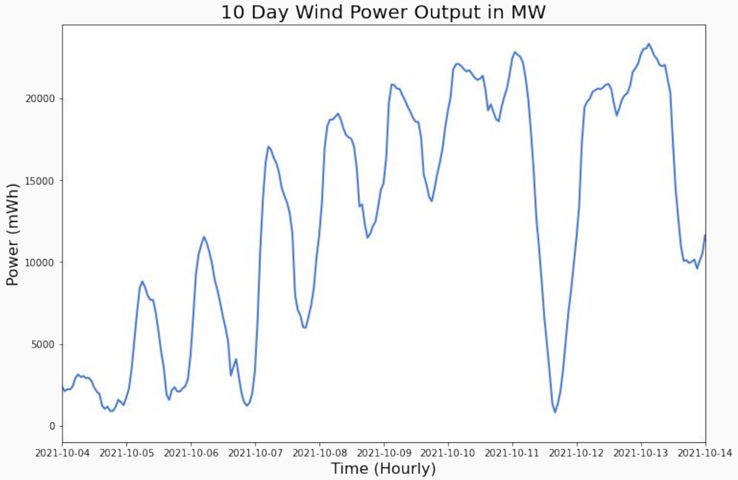
- Loss of supply to Natural Gas power stations.
- Sharp drop in natural gas generation.
- Supply could not meet demand.
- Power balance in this case means rolling blackouts.



Wind And Solar Generation

- Solar Power output peaks during the day, and is zero at night
- The Sun slightly Influences the wind Power as well, due to the heating of the earth.
- Movement of high/low air pressure creates the wind.





Modeling

Gathering the Data

- Data was gathered from the EIA website.
- Pulled in four years of hourly data for wind power.
- Most Power Utilities will publish their power generating data.
- Data for the application is from EIA API

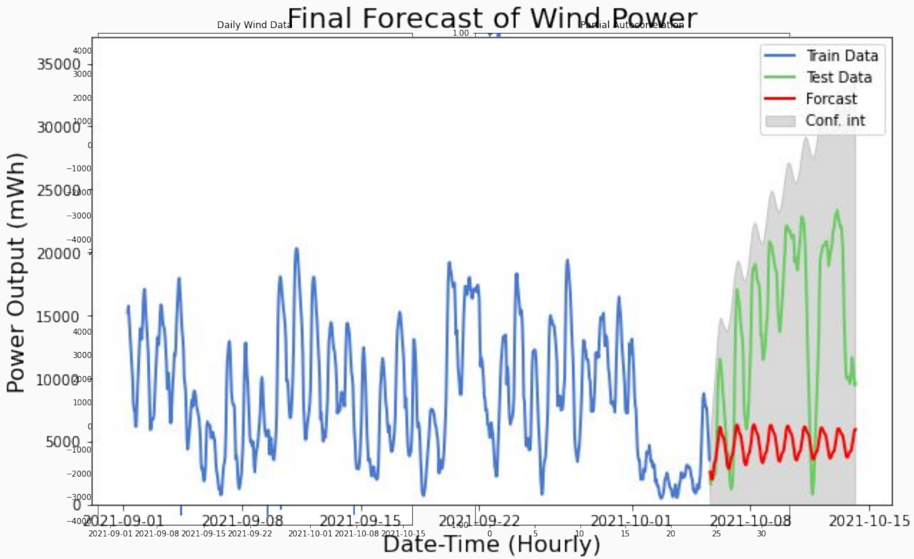
eia

Independent Statistics & Analysis

U.S. Energy Information Administration

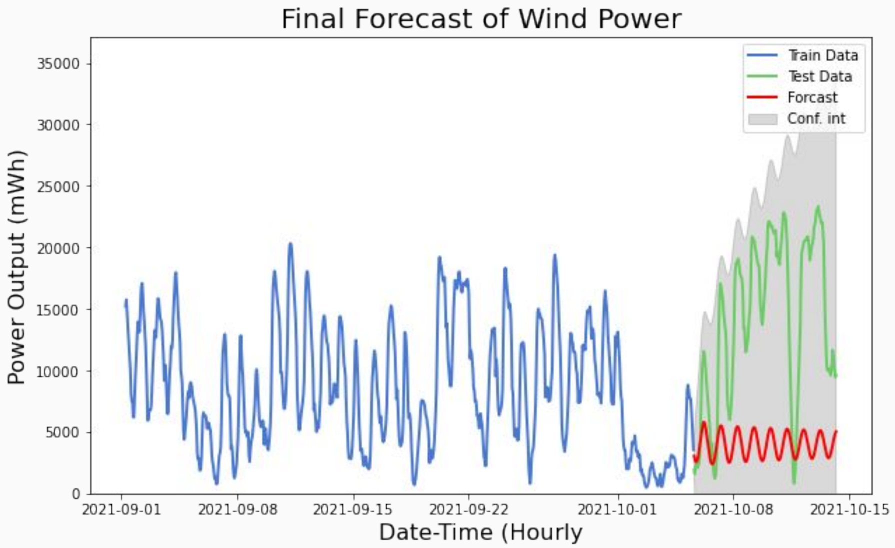
Model #1 ARIMA

- After several iterations Train/Test split on hourly data for 1.5 months
- Made Data Stationary : d=1
- Chose p,q terms based of the partial autocorrelation and autocorrelation plots.
- AR (p) = 26
- MA (q) = 23
- AIC = 13055
- Metrics:
  - Baseline RMSE: 6620 mWh
  - ARIMA RMSE: 11255 mWh



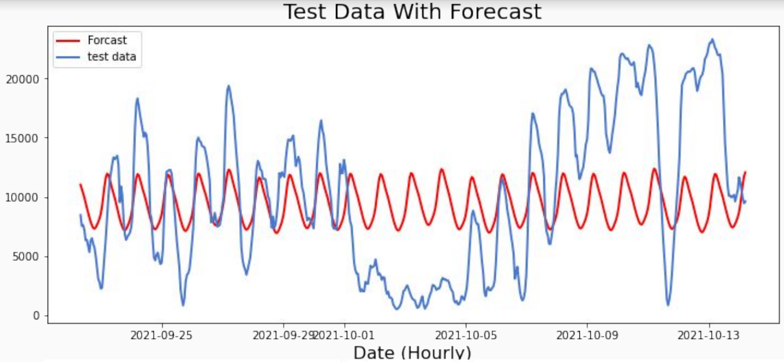
Model #2 Auto - ARIMA

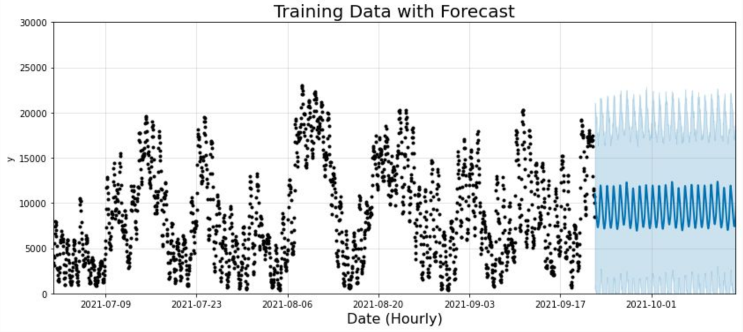
- Train/Test Split on data for 1.5 months.
- Selected : d=1
- M=28
- Solution: SARIMA (3,1,5)x(0,0,1[28])
- Metrics:
    - Baseline RMSE: 6620 mWh
    - SARIMA RMSE: 11977 mWh



Model #3 Facebook Prophet

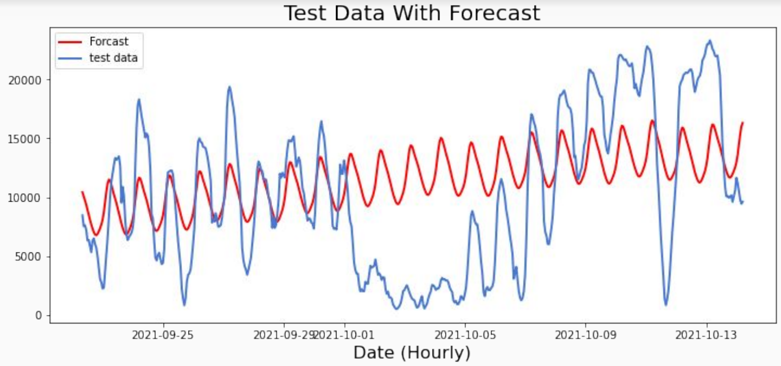
- Train Test Split on 1.5 years of data.
- Ran with default parameters
- Wanted this to be a baseline
- Metrics
    - Baseline: RMSE 6504
    - Model RMSE: 6132

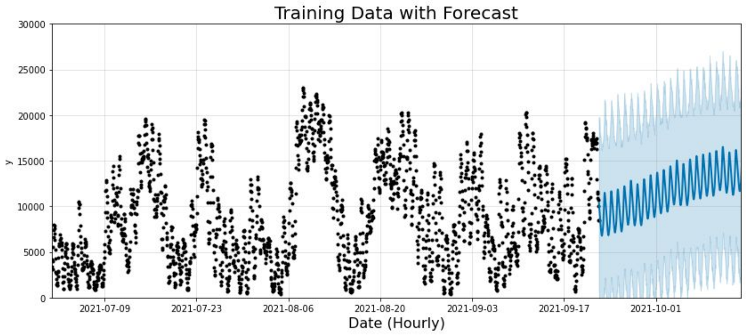




Model #4 Facebook Prophet (Tuning)

- Train/test split on 1.5 years of data.
- Modeled with some Tuning
- Yearly Seasonality = True
- Daily Seasonality = True
- Metrics
    - Baseline: RMSE 6504
    - Model RMSE: 5902





Model Selection

- Chose FB Prophet w/ tuning
- This is the Model that is incorporated in the App
- Prophet models the trend and the seasonality the best.

MODEL	Arima	Auto-Arima	FB Prophet	FB Prophet (Tuning)
Baseline Score	6620	6620	6504	6504
Model Score	11.2k	11.9k	6132	5902

Conclusion & Recommendations

Conclusion and Recommendations

Conclusion

- Final Model RMSE is quite high 5902mWh is 25% of Conf. Interval
- With our final model it is better that the user infers from the 95% confidence interval.
- Modeling Time Series can be difficult at times, modeling the weather adds a to that challenge

Recommendations

- Hyperparameter grid search with FB prophet
- Look into why ARIMA models predicted poorly
- Research weather patterns and their seasonal differences.

Thank you!

Any questions or comments would be greatly appreciated!