Real-Time Electric Load Forecasting

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Capstone Spring 2023

AGENDA

Mission: Our mission is to lower electricity prices and improve reliability of the electrical grid by giving operators real time forecasts to more accurately predict demands of their customers.

Goal: Build a model that can accurately predict electric load for New York City using real time weather conditions with up to 98% accuracy in 5 minute intervals for a length of 90 minutes.

01 INTRODUCTION
Problem Statement

02 DATA SETS
Data Description

03 EDA
Data Insights

04 MODEL RESULTS
Model Performance

05 OUR PRODUCT
Product Demonstration

06 CONCLUSIONS
Next Steps

BREAKING NEWS

TEXAS ELECTRICITY CRISIS

THE TV NEWS

LIVE

Severe winter storm leads to disruptive electricity generation failure in Texas. People are calling it the Great Texas Freeze.

FEB 2021

In February 2021, Texas suffered a major power crisis when three severe winter storms hit the United States, triggering the worst energy infrastructure failure in Texas state history.

45M

homes loss power

57

deaths

$195B

property damages

ERCOT's demand forecasts for severe winter storms were too low.

01. Why Should We Care?

Impact of Better Forecasts

Electric Load Forecasting

Predicting electrical power required to meet customer demand

1. **Reduce Liability**
   - Reduce major blackouts, saving billions in property damages
2. **Decrease Price of Electricity**
   - Prevent waste and optimize for more cost saving for consumers
3. **Increase Reliability**
   - Better planned capacity to ensure consumers are supplied with required energy

Target Audience

Independent System Operators

Transmission Owners

Existing solutions could be better

- ERCOT's underestimation of load for the Great Texas Freeze resulted in 57 deaths and billions in property damage
- NY ISO chains linear regression models together, which isn't the best model for this type of data

01. Project Overview

Our Goal

Build a model that can accurately predict electric load for New York City with up to 98% accuracy in 5 minute intervals for a length of 90 minutes

- Leverage historic electric load behavior and real time weather & solar data

How Are We Different

Existing programs primarily focus on forecasting hourly loads days in advance

Our focus is:

1. **More Real-Time Predictions**
   Give operators a better account for more sensitive real-time weather events, like sudden drops in wind or a large system of clouds rolling in

2. **Higher Accuracy**
   Achieve a 2% error rate

3. **Packaged into an Easy-to-Use Application**

02. Dataset Description

Electric Load

Description
New York electric load [in MWh] for 11 zones

Source: New York ISO

Data Granularity: 5 min

Data Size:
13 columns x 631K rows

Additional Notes:
Key fields to keep is the time stamp and electric load values for zone = N.Y.C.

Training on data from 2017-2021 and testing on 2022

Weather

Description
NYC weather data collected from JFK weather station

Source: National Oceanic & Atmospheric Administration (NOAA CDO)

Data Granularity: Hourly

Data Size:
125 columns x 80K rows

Additional Notes:
Used pandas interpolate function to get 5 minute increments for this data

Solar

Description
Provides forecast, live and historical solar irradiance data (GHI, DNI, Diffuse)

Source: Solcast

Data Granularity: 5 min

Data Size:
21 columns x 631K rows

Additional Notes:
While Solcast also contains temperature data, its values are not as accurate for NY as the weather dataset

* Full data join found in the Appendix

03. Key Data Insights

Key Insights

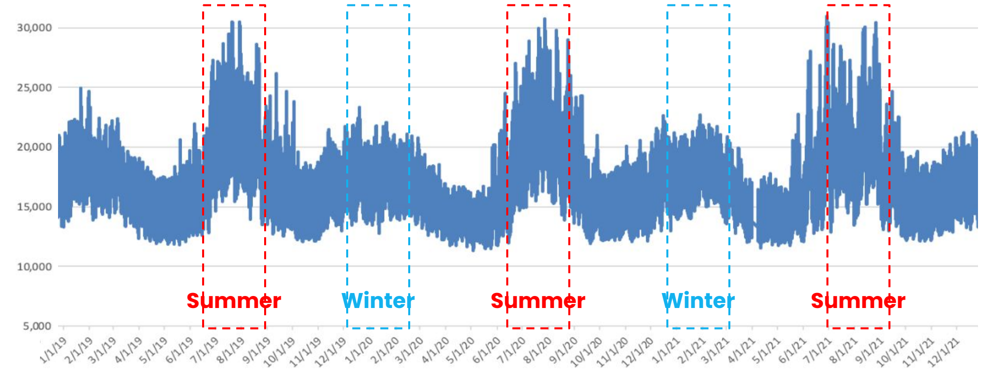
1. **Heavy seasonality** with peak consumption during summers (July - Sept) and slightly rises again during winters (Dec - Mar)
   - Load lowest during spring & fall

2. Electric load is higher during **weekdays**
   - Daily load spikes during morning pick-up (6:30AM), hitting its peak at 6PM and begins declining as consumers sleep

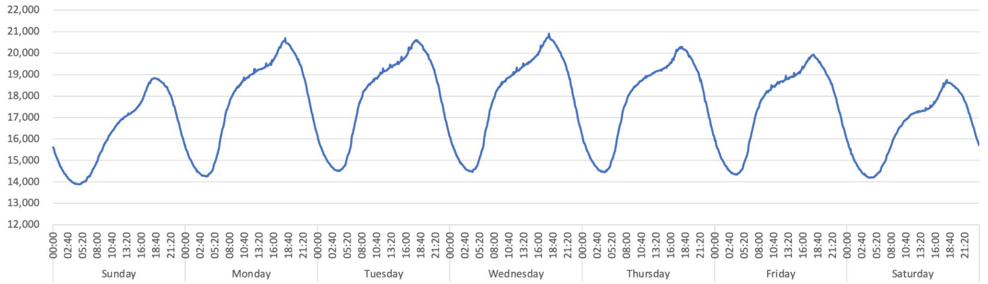
3. **Extreme temperature** (heat waves or cold snaps) encourages individuals to use more load to power A/C or heating

4. Days with **high solar irradiance** corresponds with less load
   - Consumers can use behind-the-meter solar devices to offset electric load consumption

New York State Electric Load [MWh] - 2019 to 2021



New York State Electric Load [MWh] - Average Weekly Load in 2021



* More EDA examples found in the Appendix

04. Modelling Framework | Overview

Prediction Aim: Forecasting electric load for the next 90 mins in 5 min intervals

Model Formation: A **time series** problem based on previous available loads & other indicators

- Train Test Split: Training on 2017 - 2021 and testing on 2022

Goal: Achieve 98% accuracy or 2% error rate

Baseline
ARIMA
Autoregressive Integrated Moving Average

LSTM
Long Short-Term Memory

XGBRegressor
Extreme Gradient Boosting

Neural Prophet

TFT
Temporal Fusion Transformer

04. Modelling Framework | Evaluation Metrics

Performance Measurement Plan

- Relative Root Mean Square Error (RRMSE)
- Forecasting Error Distribution
- Max Error = Largest error [MWh] between forecasted and actual value
  - NYISO procures 2620 MWs of Reserves for NYS (1000 MWs for NYC) each day [1]
    - Reserves are MWs NYISO buys on top of the forecasted load to cover contingencies, like generator tripping offline or lines unexpectedly coming out of service
  - Using reserves to accommodate forecasting error is something NYISO tries to avoid

Additional Considerations

- While we want our forecasts to be as accurate as possible, ramifications for under-predicting is worse than over-forecasting
  - Too much load = more expensive electric load
  - Too little load = **BLACKOUTS**

[1] *https://www.nyiso.com/documents/20142/3694424/Locational-Reserves-Requirements.pdf*

04. Modelling Approach | Feature Engineering

Initial Model Attempt
(for each model class)

Feature Selection & Engineering

Model Training
(including parameter tuning with cross validation)

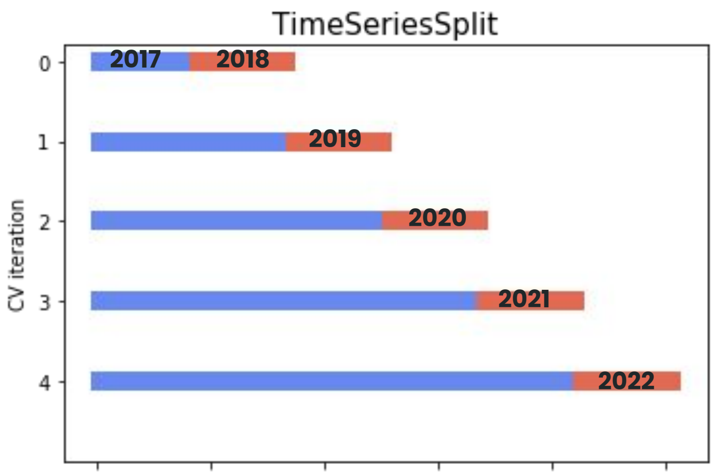
Error Analysis

Final Model

01	**Previous Load**	Store previous 90 minute vector of 5 minute increments of electric load
02	**Holiday**	Flag US observed holidays using holiday library (ex: MLK, Christmas, etc.)
03	**Weekday**	Flag to indicate weekday 1 = Mon - Fri; 0 = Sat & Sun
04	**Large Error Indicator**	Indicator for larger errors that occur during morning pick-up & evening drop-off
05	**Forecasted Weather & Solar**	Variation between historical and forecasted [yet to happen] weather

04. Model Fitting & Hyperparameter Tuning | LSTM

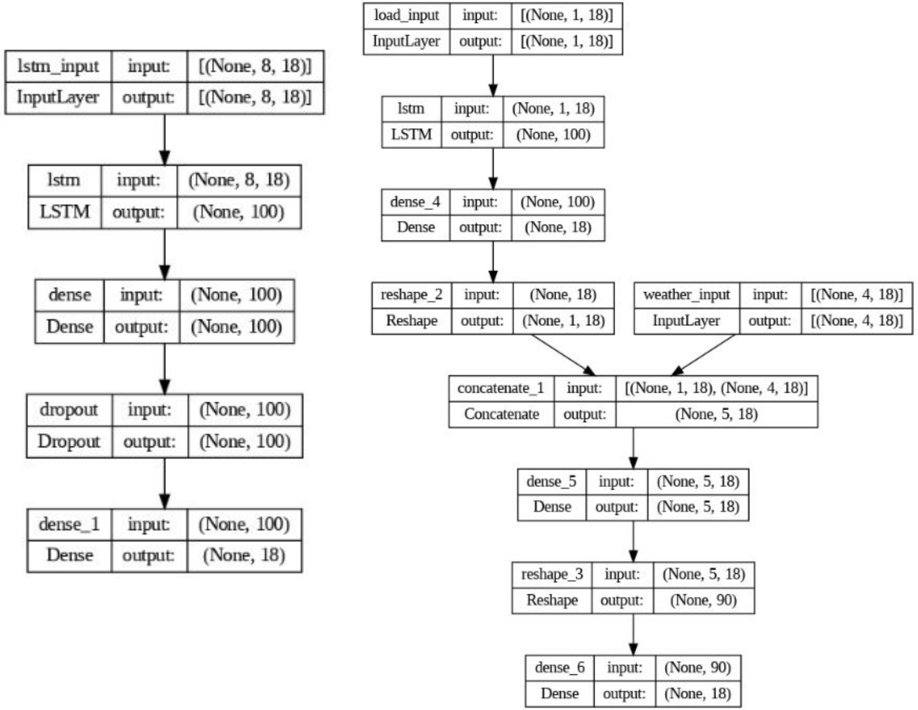
Illustration of Fold Splitting During Cross Validation



Best LSTM model:
Recurrent size of 500 with recurrent dropout 0.1 and drop out 0.05

Different LSTM Model Architecture

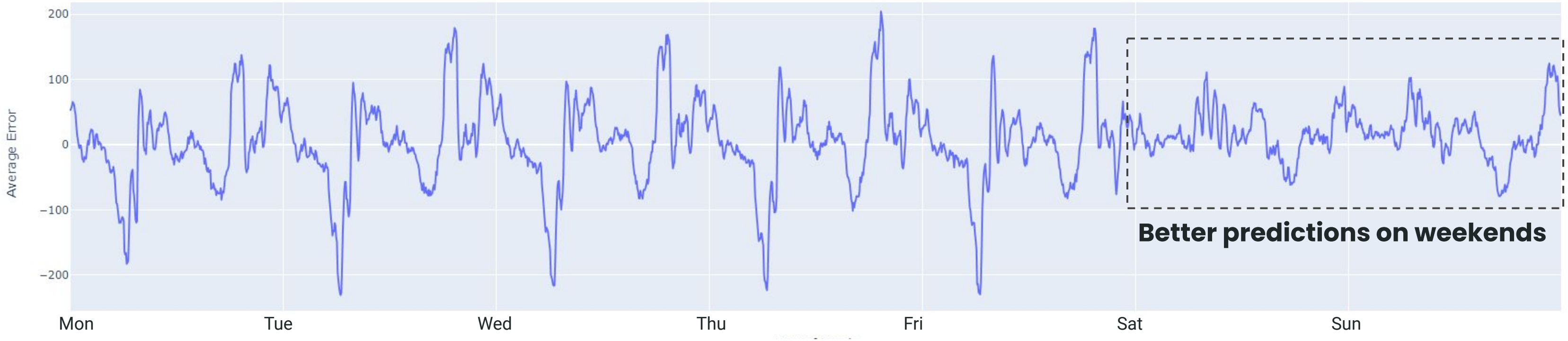
Experimenting w/ Different Iterations



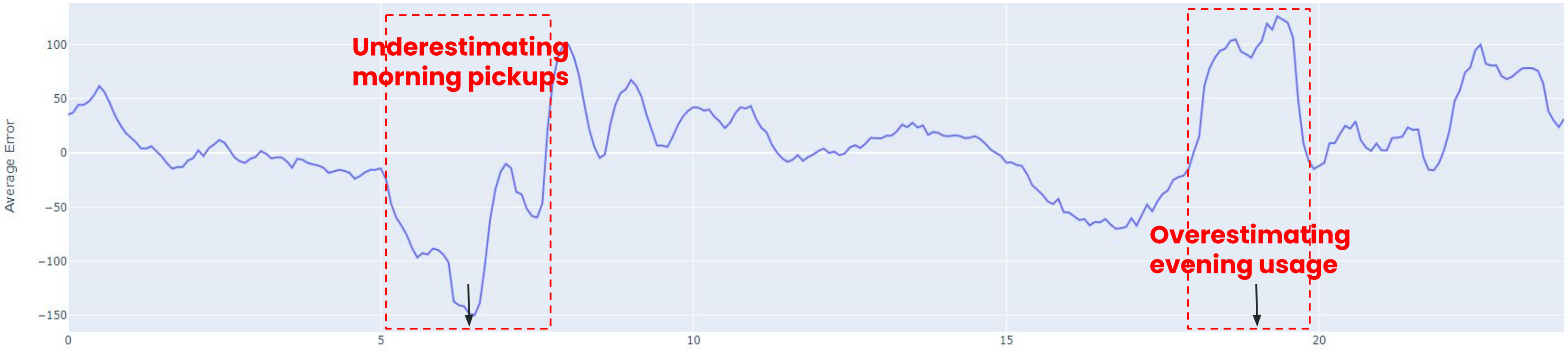
* More on Cross Validation found in Appendix

04. Error Analysis

Average Error Plot of a Week | LSTM



Average Error Plot of a Day | LSTM



Create additional feature indicators for large error timeframes

* Addition error plots found in the Appendix

04. Model Evaluation | Scorecard

Our team explored four classes of models. This was the best result for each model with its corresponding inputs.

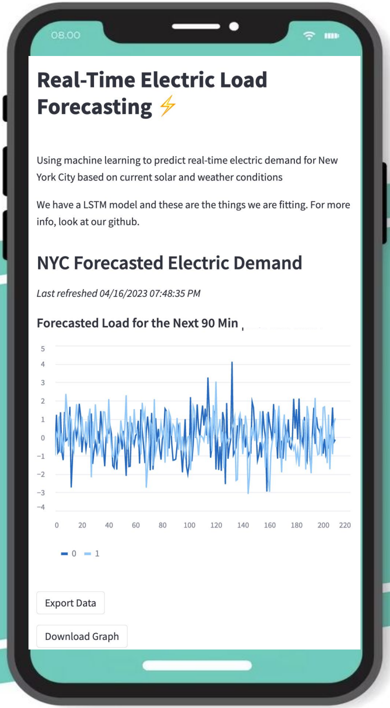
Benchmark	LSTM	XGBRegressor	Neural Prophet	TFT
2.87 RRMSE	**1.42** RRMSE 🎉 **48% improvement over baseline** 🎉	**1.87** RRMSE	**1.68** RRMSE	**3.61** RRMSE
Features Used: Previous Load	**Features Used:** Previous Load Holiday/Weekend Temperature & Solar Forecasted Weather Large Error Indicator	**Features Used:** Previous Load Temperature & Solar Forecasted Weather	**Features Used:** Previous Load Holiday/ Weekend Temperature & Solar Forecast Weather Large Error Indicator	**Features Used:** Previous Load Temperature & Solar
Largest Overestimation: 900 MW **Largest Underestimation**: -758 MW	**Time to Train**: 30 Min Normally distributed error centered at 2 +/- 97 MWs **Largest Overestimation**: 801 MW **Largest Underestimation**: -760 (Lower than reserve)	**Time to Train**: 2 Hour Normally distributed error centered at 12 +/- 108 MW	**Time to Train**: 20 Min Normally distributed error	**Time to Train**: 2.5+ Hour

05. Our Product

We used FastAPI & Streamlit to deploy our model and create an easy-to-use application.

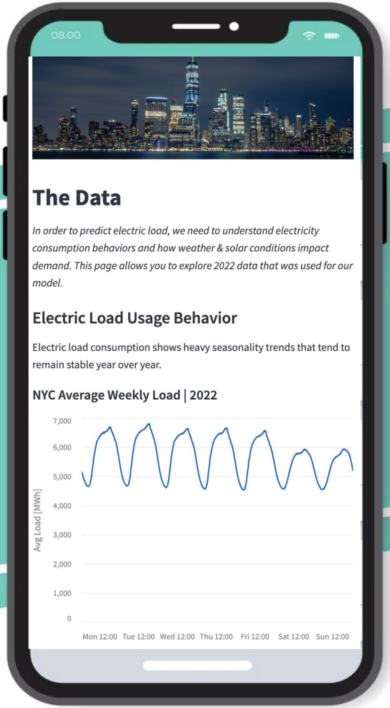
Home Page

Get real-time electric load forecasts for NYC



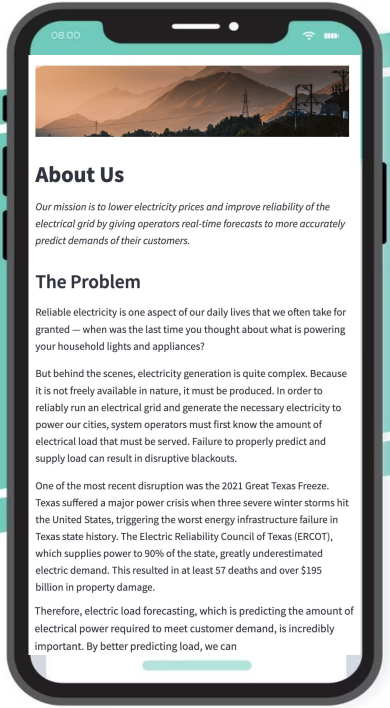
Data Page

Explore the data used to build our model



About Us Page

Learn more about the importance load forecasting



06. Conclusions & Next Steps

Highlights

- LSTM was our best performing model with the lowest RRMSE of 1.4%.
- While our model struggled with morning pickup and evening drop-off predictions, introducing a flag for those time frames improved its accuracy.
- Our model only used half of the reserved amount to accommodate underestimations for 4 days in an entire year.

Given More Time & Resources

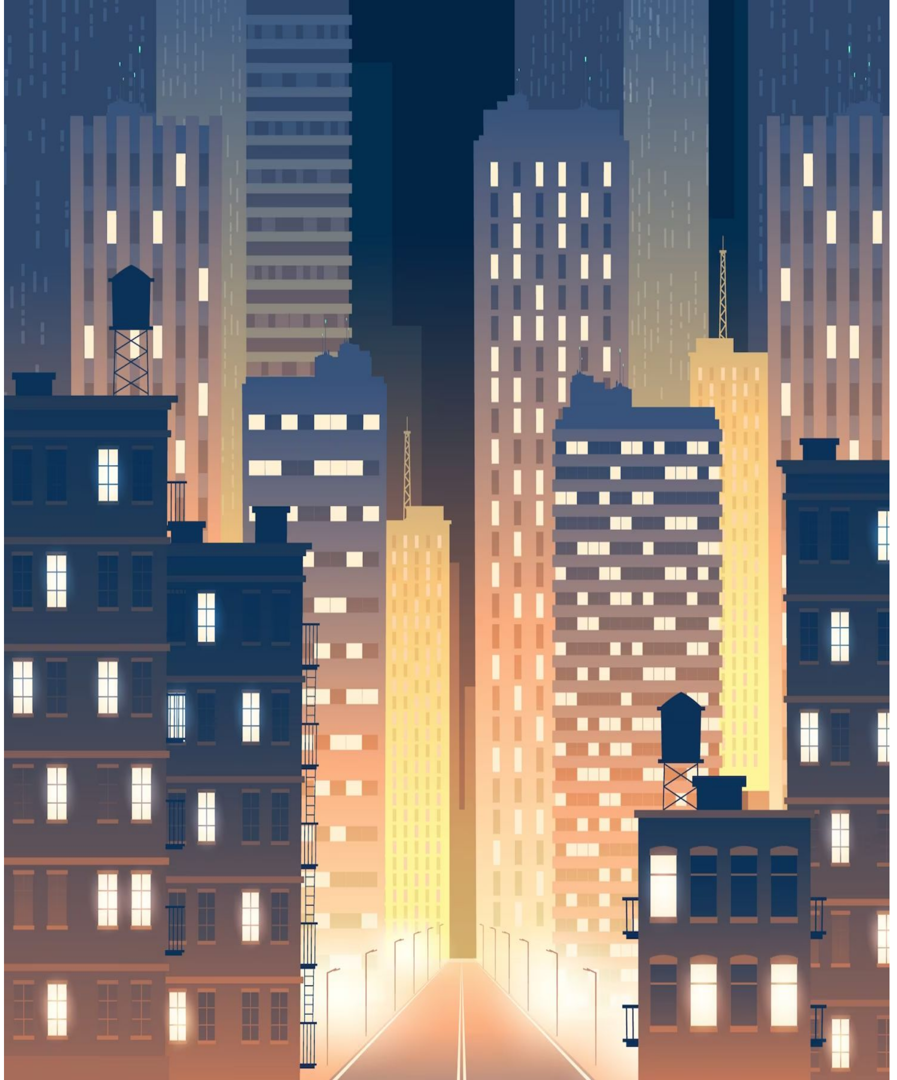
- Get access to more accurate forecasted weather data
  - Challenging to find, merge and clean these datasets
  - Would consider paying for a private dataset that has more accurate information
- Expand to all of New York State

Next Steps

Plan on deploying this model in NYISO’s control center

Questions?

Our mission is to lower electricity prices and improve reliability of the electrical grid by giving operators real time forecasts to more accurately predict demands of their customers.



Appendix

01. The Team and Acknowledgements

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Melinda Leung
Senior Data Analyst

Dunny Semwayo
Project Manager

Our team would like to thank the support from our professors (Puya Vahabi & Alberto Todeschini) in guiding the project. We also acknowledge the contributions to the W231 team that reviewed our project through the lens of several privacy frameworks and provided a model card on managing data privacy.

02. Data Join

Weather

Kept only 2 features
- Dry Bulb Temperature
- Hourly Relative Humidity

Utilized pandas **interpolate** function (linear method) to get 5 minute increments → Interpolation analysis showed that results are accurate & representative of true data

Electric Load

Remove data points not on 5 minute increment (:00, :05, :10, etc)

Solar

Utilized pandas interpolate function to fill in missing 5 minute values

Join on **Timestamp**

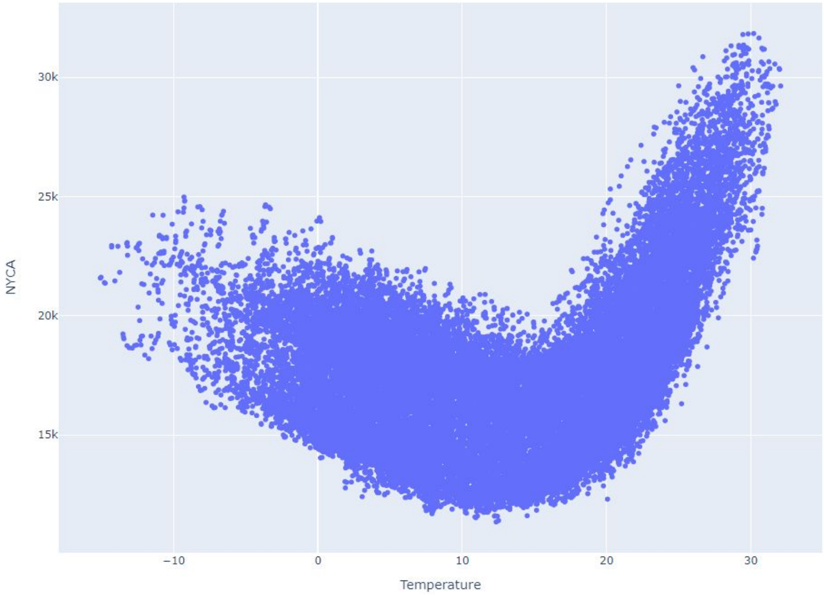
Merged Dataset

44 columns x 631,008 rows

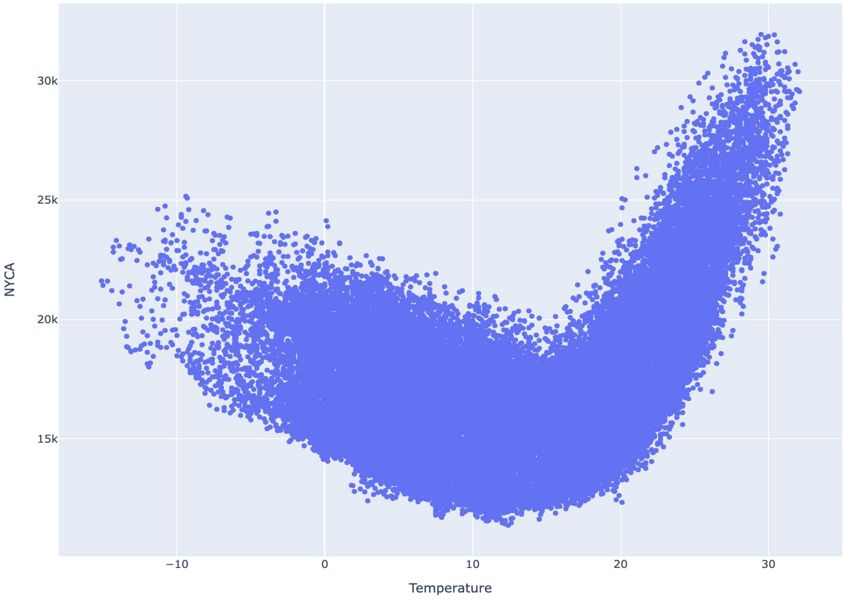
02. Interpolation Analysis

Because the weather dataset lacks 5 minute granularity, we used the pandas interpolate function to generate data. The interpolated data is accurate & representative of true data

Interpolated Temperature vs Load



Actual Temperature vs Load



02. Merged Dataset

Sample data in our 44 feature dataset

		Temperature				Solar Irradiance					Precipitation, Wind, Weather Conditions				
Time Stamp	NYC Electric Load	AirTemp	DewpointTemp	HourlyDryBulbTemp	HourlyRelativeHumidity	Zenith	DHI	DNI	EBH	GHI	CloudOpacity	PrecipitableW	SurfacePress	WindDirection	WindSpeed
1/1/17 8:05	4576.6	5.6	-1.4	43.7	49.83333333	84	30	450	47	76	0	7.4	1017.6	276	4.6
1/1/17 8:10	4588.3	5.6	-1.3	43.95	49.41666667	83	32	480	56	87	0	7.3	1017.7	277	4.6
1/1/17 8:15	4601	5.6	-1.2	44.2	49	83	34	513	67	101	0	7.3	1017.8	277	4.6
1/1/17 8:20	4624.7	5.6	-1.1	44.45	48.58333333	82	36	538	76	112	0	7.3	1017.9	278	4.6
1/1/17 8:25	4610.8	5.7	-1	44.7	48.16666667	81	39	566	88	126	0	7.2	1018	279	4.7
1/1/17 8:30	4648.1	5.7	-0.9	44.95	47.75	80	40	587	97	138	0	7.2	1018.1	279	4.7
1/1/17 8:35	4643.7	5.7	-0.8	45.2	47.33333333	80	42	611	109	152	0	7.2	1018.2	280	4.7
1/1/17 8:40	4649.1	5.8	-0.7	45.45	46.91666667	79	44	629	119	163	0	7.2	1018.3	280	4.7
1/1/17 8:45	4673.5	5.8	-0.6	45.7	46.5	78	45	650	132	177	0	7.1	1018.5	281	4.7
1/1/17 8:50	4699.6	5.8	-0.5	45.95	46.08333333	78	47	666	142	188	0	7.1	1018.6	281	4.8
1/1/17 8:55	4699.3	5.9	-0.4	46.13333333	45.33333333	77	48	684	154	202	0	7.1	1018.7	282	4.8
1/1/17 9:00	4700.1	5.9	-0.3	46.3	44.5	76	49	698	164	213	0	7.1	1018.8	282	4.8
1/1/17 9:05	4681.2	5.9	-0.2	46.46666667	43.66666667	76	50	714	176	226	0	7	1018.9	283	4.8
1/1/17 9:10	4746.5	5.9	-0.1	46.63333333	42.83333333	75	51	726	186	237	0	7	1019	283	4.9
1/1/17 9:15	4744.2	6	0	46.8	42	75	52	740	198	250	0	7	1019.1	284	4.9
1/1/17 9:20	4726.5	6	0	46.96666667	41.16666667	74	53	751	207	260	0	6.9	1019.2	284	4.9
1/1/17 9:25	4790.4	6	0.1	47.13333333	40.33333333	73	54	763	219	273	0	6.9	1019.4	285	4.9
1/1/17 9:30	4782	6.1	0.2	47.3	39.5	73	55	773	228	283	0	6.9	1019.5	285	4.9
1/1/17 9:35	4773	6.1	0.3	47.46666667	38.66666667	72	55	784	239	295	0	6.9	1019.6	286	5
1/1/17 9:40	4812.3	6.1	0.4	47.63333333	37.83333333	72	56	793	248	304	0	6.8	1019.7	286	5

* **Highlighted** columns of interest based on correlation matrix

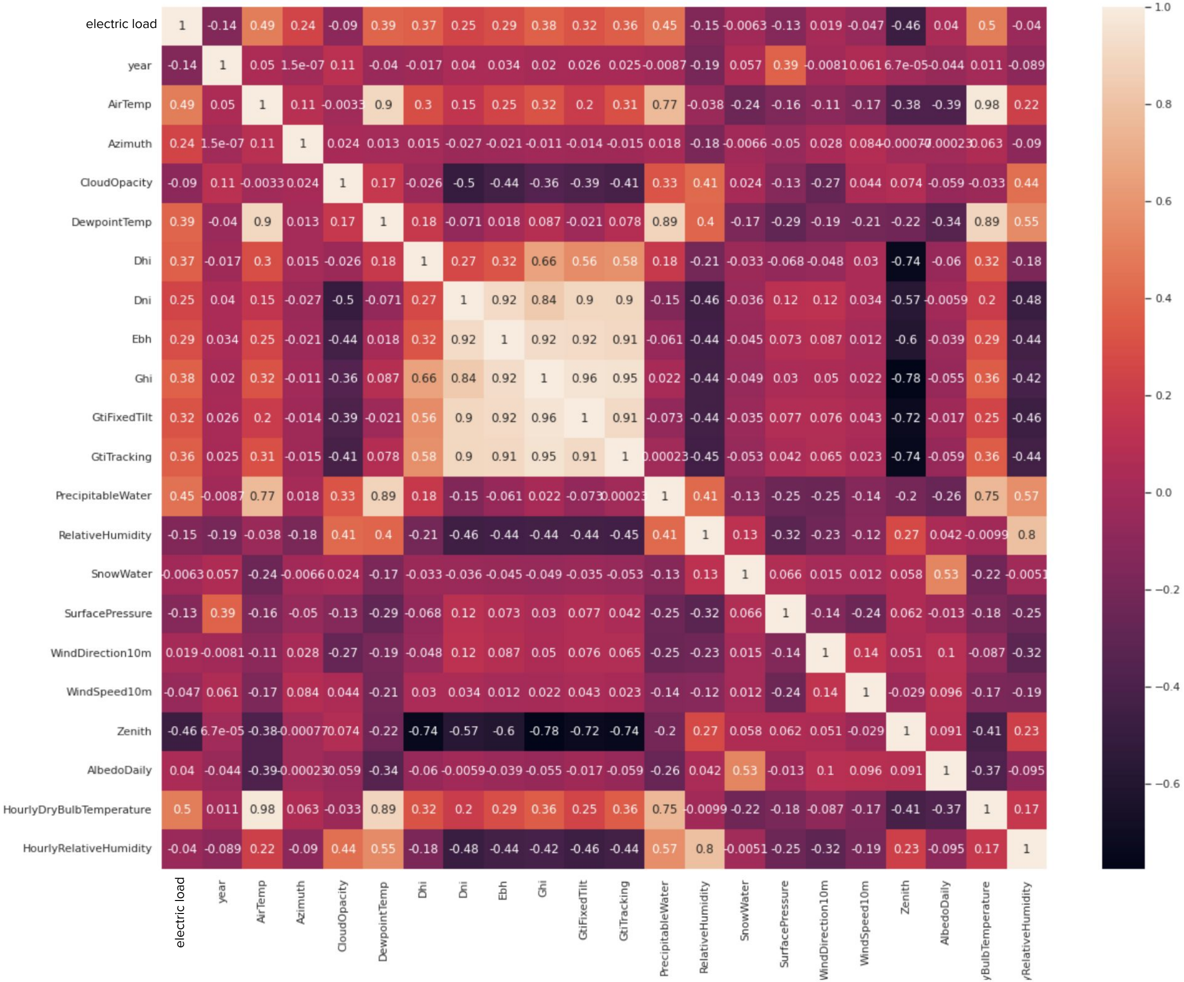
03. Correlation Matrix

Electric load

- Shows correlation to temperature & solar
- Weakly correlated to wind, precipitation, humidity and other weather conditions

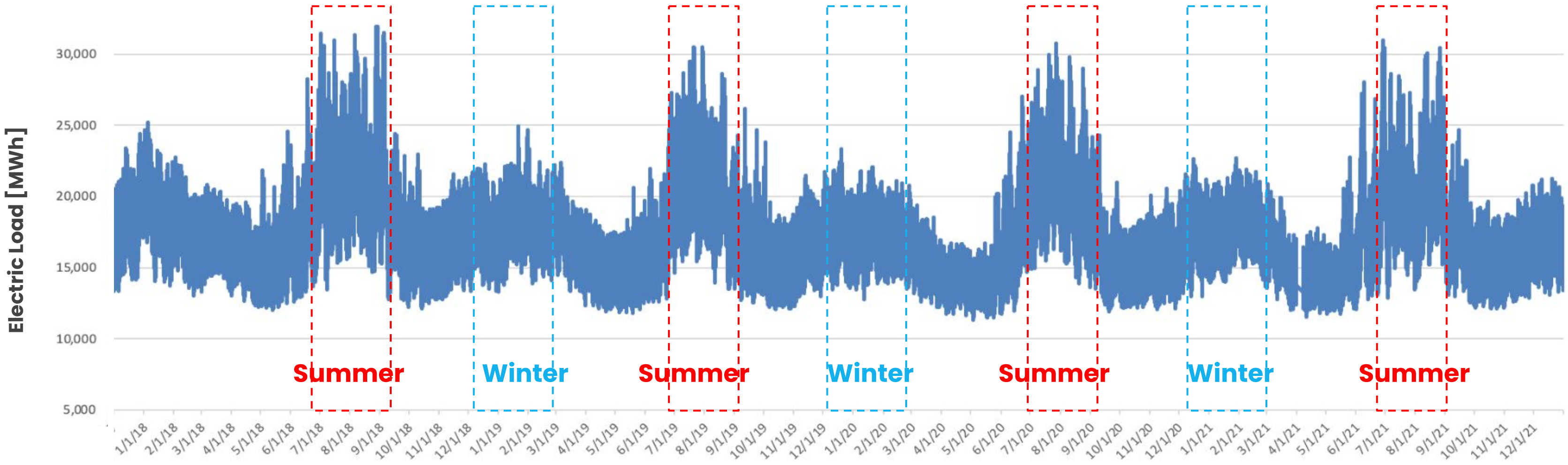
Solar metrics have strong correlation to each other

- DHI, DNI, EBH, GHI, GTI, Zenith
- Choosing one will be sufficient



03. Annual New York State Load

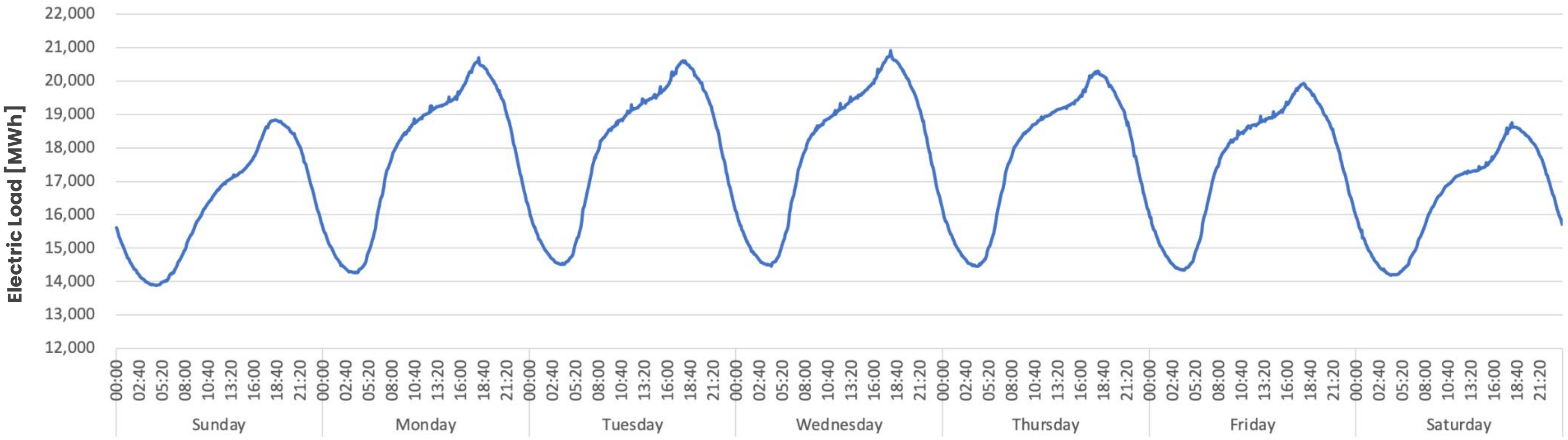
New York State Electric Load [MWh] between 2018 - 2021



- Heavy seasonality with peak load during summer (July - Sept)
    - Load lowest during spring & fall, but slightly rises again during winter (Dec - Mar)
- Trend relatively stable YoY

03. Weekly Consumer Behavior of New York Electric Load

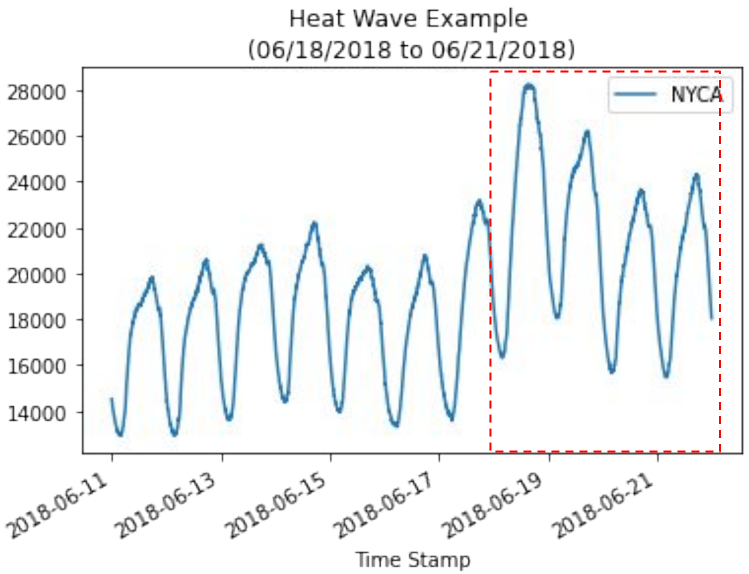
New York State Electric Load [MWh] - Average Weekly Load in 2021

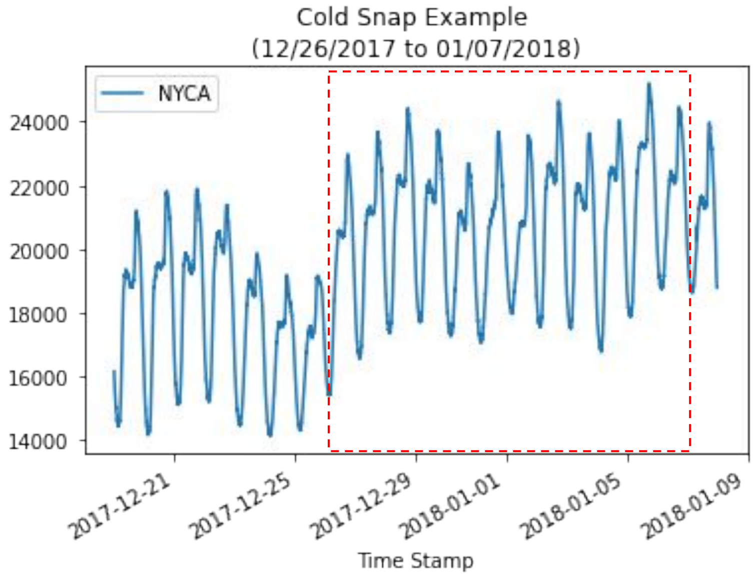


- Load is higher during the weekday vs. weekend
- Daily load begins to quickly rise around 6:30AM (morning pick-up), hitting its peak at 6PM and begins declining as consumers sleep

03. Weather Impacts on Electric Load

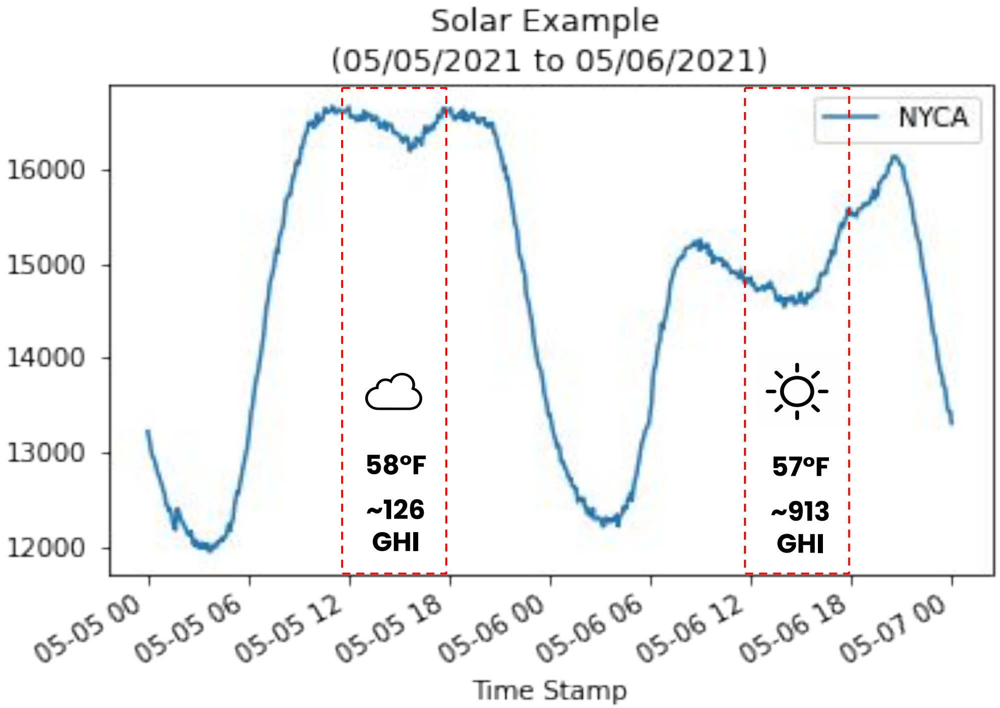
Extreme weather, like heat waves or cold snaps, encourages individuals to use more load to power A/C or heating. If there's just 1 hot day, people might hold out and not turn on the A/C yet. However, if there's consecutive hot days, individuals may cave and turn on the A/C on day 2 or 3. [same with heating]



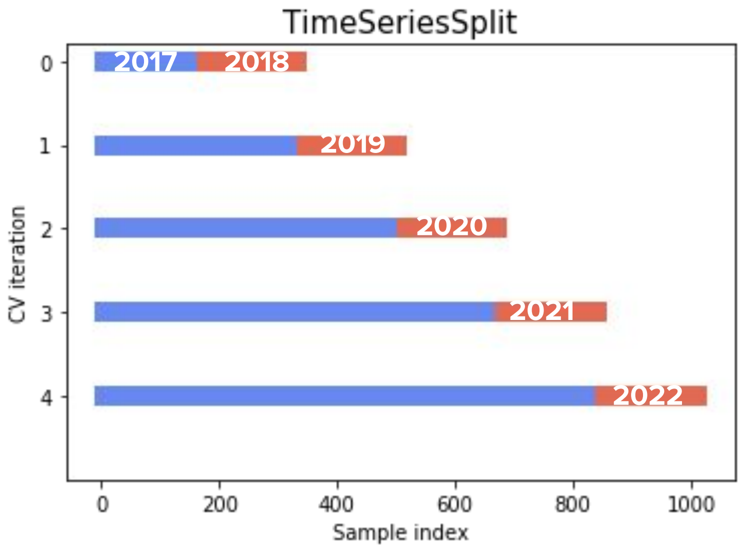


03. Solar Impacts on Electric Load

Days with high solar radiation (GHI) corresponds with less load. Consumes are able to use behind the meter solar devices, which reduces need for electric load.



04. LSTM Cross Validation



- Tuning of recurrent layer size, recurrent drop out, drop out with additional alpine layer
- Mean and standard deviation inflated due to validation year 2019 where electricity load behaviour changed drastically

Cross Validation Result

LSTM_i	recurrent_dropout	dropout	mean	std	mean	std
100.0	0.00	0.00	108.909841	28.931939	1.863950	0.550840
		0.05	118.850023	44.453929	2.036579	0.826832
		0.10	111.134692	31.992846	1.902812	0.605616
	0.05	0.00	103.519922	24.161997	1.770703	0.464975
		0.05	109.029203	31.972625	1.864958	0.595833
		0.10	106.616379	26.656179	1.824024	0.507374
	0.10	0.00	108.443490	30.125519	1.855541	0.567753
		0.05	109.920792	35.192905	1.883692	0.665459
		0.10	113.599537	36.996335	1.949296	0.703961
250.0	0.00	0.00	109.974130	31.033092	1.884800	0.594352
		0.05	109.931454	30.332834	1.881732	0.574647
		0.10	109.029021	32.268934	1.868004	0.612887
	0.05	0.00	111.004959	35.774830	1.903864	0.680766
		0.05	109.938817	25.616306	1.877971	0.486175
		0.10	106.947182	30.114758	1.829450	0.563298
	0.10	0.00	109.996780	33.305872	1.879099	0.605609
		0.05	106.106126	28.353923	1.817280	0.544732
		0.10	113.466632	36.140353	1.941554	0.667348
500.0	0.00	0.00	109.741320	38.305240	1.883501	0.724677

Further table omitted

04. LSTM Cross Validation

- Recurrent size of 500 with recurrent dropout 0.1 and drop out 0.05 shows best performance but is not statistically significant

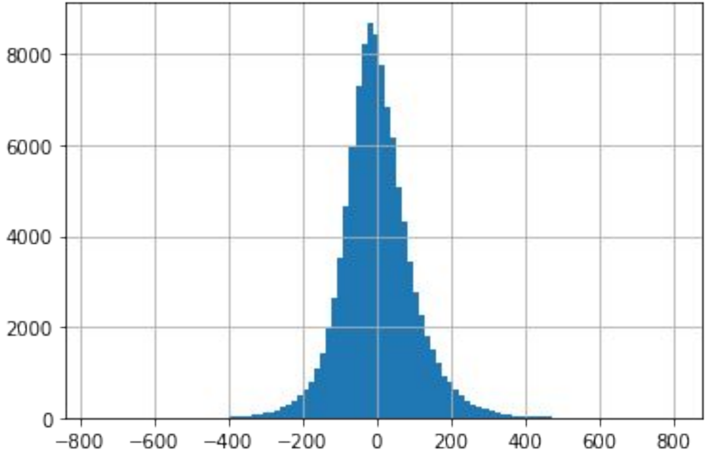
Cross Validation Result

Filtering out validation year 2019

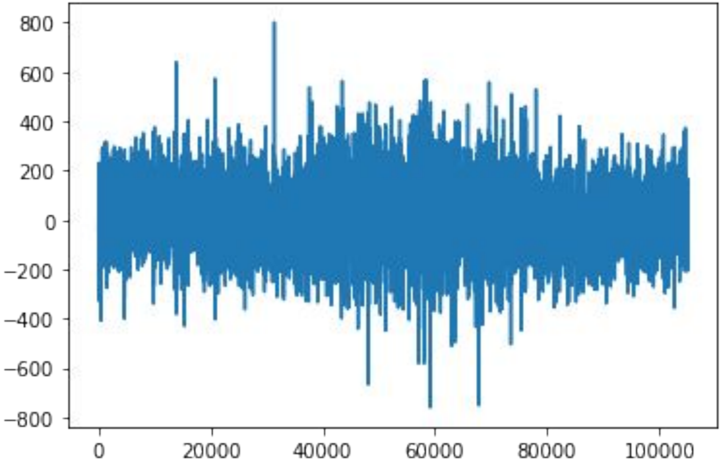
			rmse		rrmse	
			mean	std	mean	std
LSTM_i	recurrent_dropout	dropout				
100.0	0.00	0.00	96.661546	10.767448	1.624186	0.146017
		0.05	99.889926	15.436983	1.675550	0.206373
		0.10	97.563655	11.700537	1.639171	0.160161
	0.05	0.00	93.205354	8.314689	1.566289	0.098498
		0.05	95.886747	14.543183	1.608926	0.190637
		0.10	95.477606	10.966046	1.604366	0.146874
	0.10	0.00	95.813321	12.107359	1.608932	0.156049
		0.05	94.563610	8.893841	1.588764	0.102783
		0.10	97.576498	10.648315	1.642423	0.181493
250.0	0.00	0.00	96.695899	10.424057	1.627079	0.167937
		0.05	97.177162	11.928732	1.632802	0.164872
		0.10	95.121693	9.947546	1.599060	0.136516
	0.05	0.00	95.244268	7.103196	1.601920	0.100604
		0.05	98.499422	12.287663	1.648449	0.163646
		0.10	94.584090	13.792194	1.587780	0.183612
	0.10	0.00	97.459042	20.762362	1.633089	0.292480
		0.05	93.811659	8.014598	1.577555	0.111905
		0.10	99.108592	19.161020	1.663107	0.277338
500.0	0.00	0.00	92.980175	9.136848	1.564227	0.143661
		0.05	96.855403	16.714906	1.626216	0.242592
		0.10	96.316669	11.753922	1.620376	0.190949
	0.05	0.00	95.026492	8.112630	1.598284	0.122429
		0.05	93.644997	10.132130	1.574777	0.153575
		0.10	96.994972	6.474523	1.632330	0.105238
	0.10	0.00	93.696526	7.287568	1.576800	0.119272
		0.05	89.504302	6.859846	1.505716	0.104191
		0.10	93.190466	11.368623	1.565900	0.158134

04. Model Evaluation | Error Plots

Histogram for the Error Plot | LSTM



Error Plot | LSTM



- Errors are normally distributed without noticeable bias
- Largest Overestimation: `801.2 MW`
- Largest Underestimation: `-760.4 MW`
  - Lower than capacity reserve

- Largest underestimation occurred between June and September
- Underestimated half of the reserve for only 4 days