Forecasting Hourly Electricity Demand: A Crash Course in Time Series Analysis

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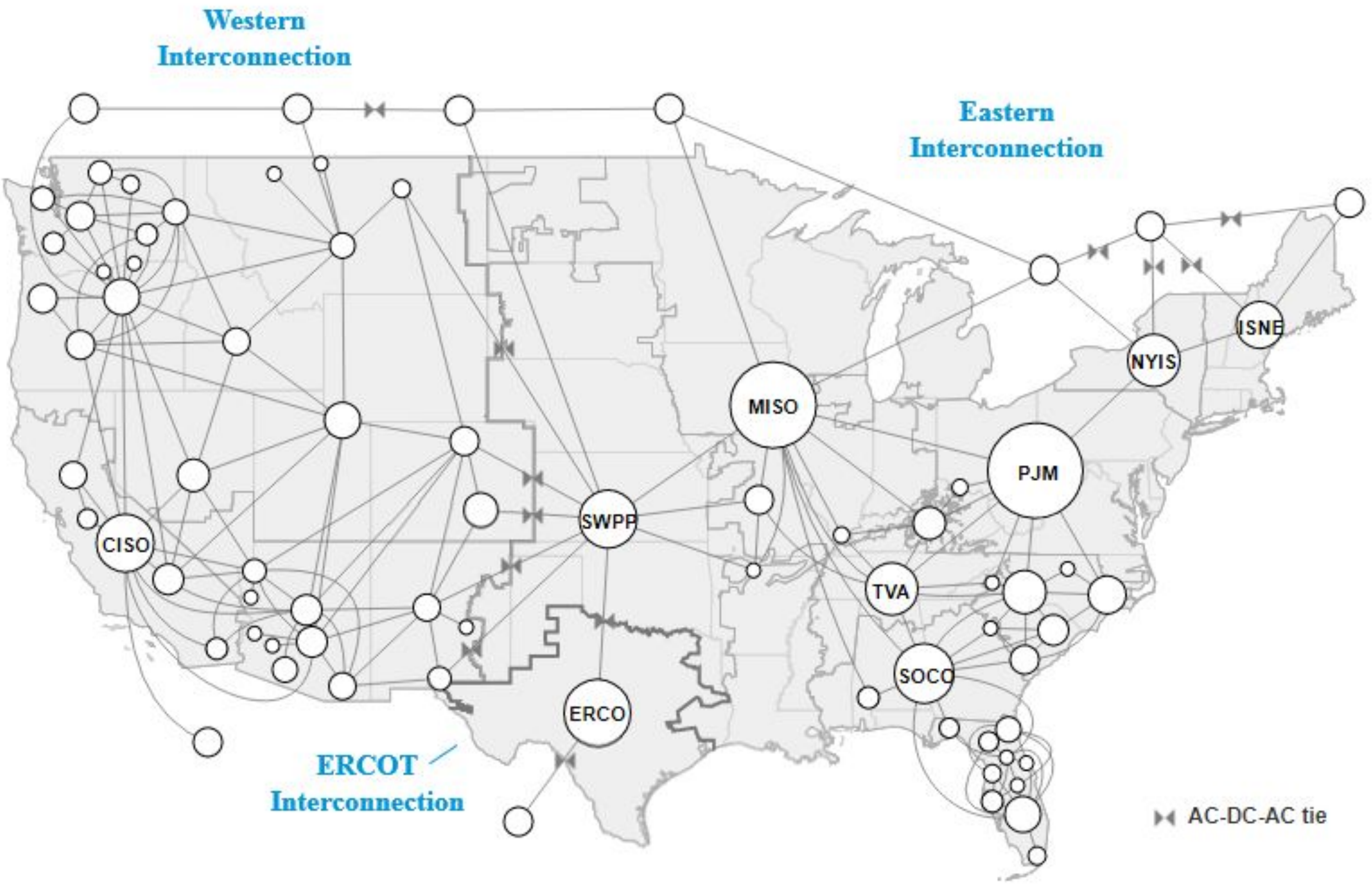
Why Estimate Electricity Demand?

Public electric utility companies estimate their customers' demand in order to determine:

- How much to produce
- Where to produce it
- Where to send and store it
- How much and for what price to buy or sell to other "balancing authorities"



Source: https://www.eia.gov/electricity/gridmonitor/about

What is the best way to predict electricity demand?

- What type of model should be used?
  - Exponential Smoothing, ARIMA, something else?
- What exogenous variables could help?
  - Temperature, weekends, residential solar production?
- How should models be evaluated?
  - Typical train/test split?

Data - Hourly Electricity Demand

- U.S. Energy Information Administration (EIA) API
- Portland General Electric (PGE) Balancing Authority
  - Serves 900,000 customers in most of Portland metro area, the Willamette River Valley down to Salem, and outlying areas east toward Mt. Hood, west toward Oregon coast.
- About half of Oregon's population, 75% of commercial, industrial activity

Data - PDX Daily Temperatures

- National Weather Service (weather.gov)
- Daily high, low, precipitation and snow data from the Portland airport, 1940-2022

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	Daily Temperature and Precipitation Data																						
2	Portland, Oregon Airport																						
3	Period of Record			October 1940 to April 2022																			
4																							
5				File last updated:				########			Reason:		Addition of 2021 and early 2022 data										
6																							
7		TX is Maximum Temperature (deg F), TN is Minimum Temperature (deg F), PR is Precipitation (inches), SN is Snowfall (inches)(Note: T/A of snow is Trace of Hail (A).																					
8		Example: High Temperature 23 October 1940 is 58 while low was 53 deg.																					
9																							
10	YR	MO		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
11	1940	10	TX	M	M	M	M	M	M	M	M	M	M	M	M	75	70	64	72	72	78	78	64
12	1940	10	TN	M	M	M	M	M	M	M	M	M	M	M	M	57	53	52	50	58	58	59	54
13	1940	10	PR	M	M	M	M	M	M	M	M	M	M	M	M	0.01	T	T	0	0.13	0	T	0.14
14	1940	10	SN	M	M	M	M	M	M	M	M	M	M	M	M	0	0	0	0	0	0	0	0
15	1940	11	TX	52	53	47	55	51	58	56	50	48	47	46	45	45	47	53	49	46	49	46	49
16	1940	11	TN	40	38	36	32	42	46	46	42	35	34	35	33	34	33	28	27	36	30	29	36
17	1940	11	PR	0.17	0.02	T	0	0.07	0.28	0.85	0.29	0.02	0.01	0.01	0	0	0	0	0	0.29	0.01	0	0.37
18	1940	11	SN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	1940	12	TX	51	53	52	51	56	54	50	51	48	50	46	45	43	40	39	39	41	41	45	46
20	1940	12	TN	42	40	42	42	44	37	34	35	32	26	34	28	27	25	29	33	35	34	35	41
21	1940	12	PR	0.06	0	0.2	0.01	0.49	0	0	0.13	0	0	0	0	0	0	0	T	0.1	0.46	0.88	1.12
22	1940	12	SN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	1941	1	TX	35	42	39	42	52	42	46	51	48	46	43	40	45	50	48	44	45	51	53	48
24	1941	1	TN	29	28	31	31	33	34	34	37	36	32	29	30	34	35	39	40	40	40	38	35
25	1941	1	PR	0	0	0.04	T	0.35	0.16	0.21	T	0	0	0	0.09	0.01	0.33	0.2	0.77	0.89	0.62	0	0

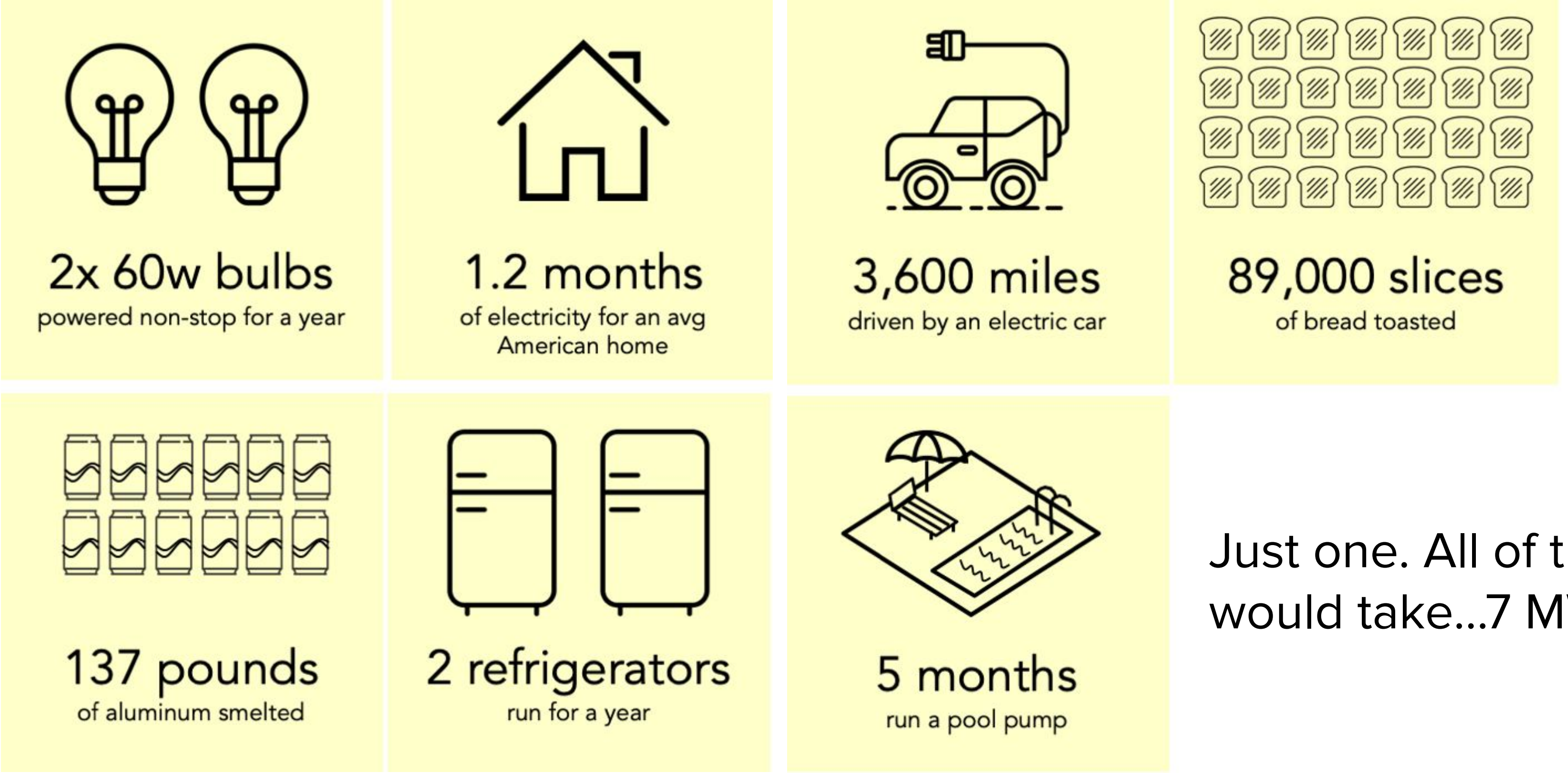
Two Goals of this Project:

1. To understand the advantages and disadvantages of various modeling and forecasting methodologies
2. To produce forecasts as good as PGE's own:
   a. MAE of PGE's day-ahead hourly forecasts (for hours with no missing data): **50.8 MWh**

So What’s a Megawatt-hour (MWh)?

- 1 MWh = 1 million watt-hours
- 1 Watt-hour = Using 1 joule per second for an hour
  - 3,600 Joules
- 1 Joule = 1 N*m
- 1 N*m = the amount of “work” done in displacing an object by 1 meter with a force of 1 Newton

Enough to do this stuff:

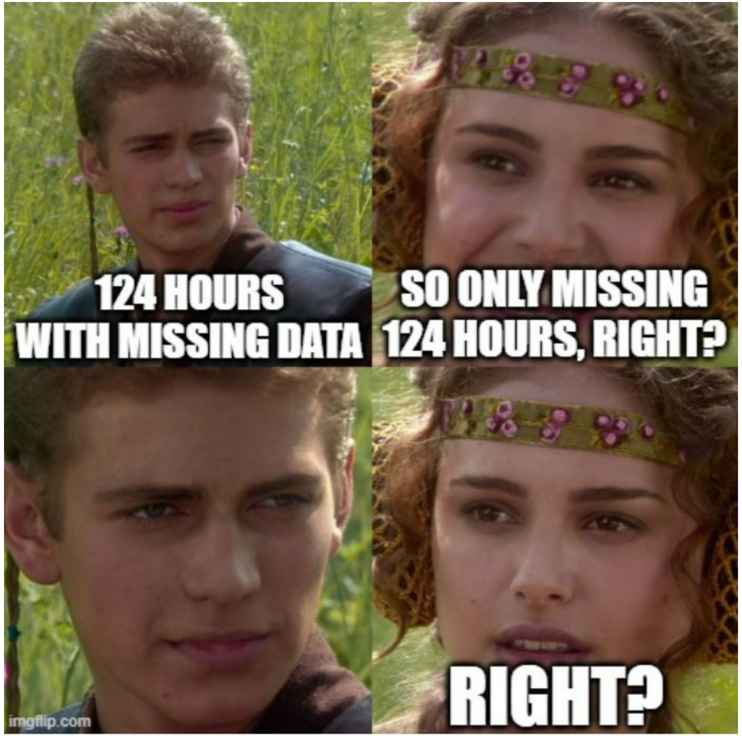


Just one. All of this would take…7 MWh.

Source: https://www.freeingenergy.com/what-is-a-megawatt-hour-of-electricity-and-what-can-you-do-with-it/

Data Cleaning and Imputation

- Weather data messy but complete for duration of demand series
- Demand series had missing values for 124 out of 63,083 hours

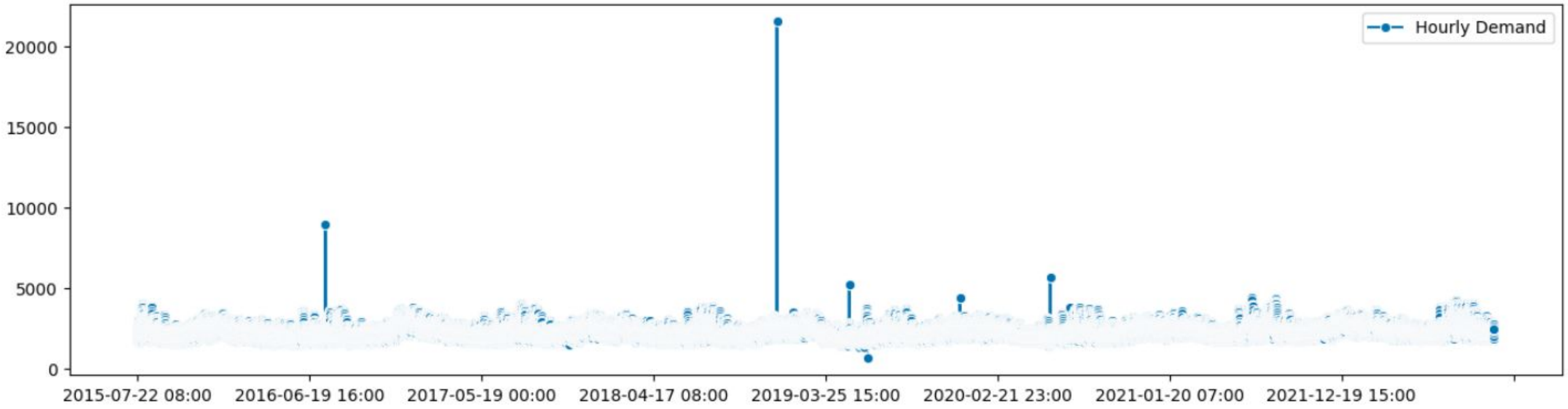


Imputation

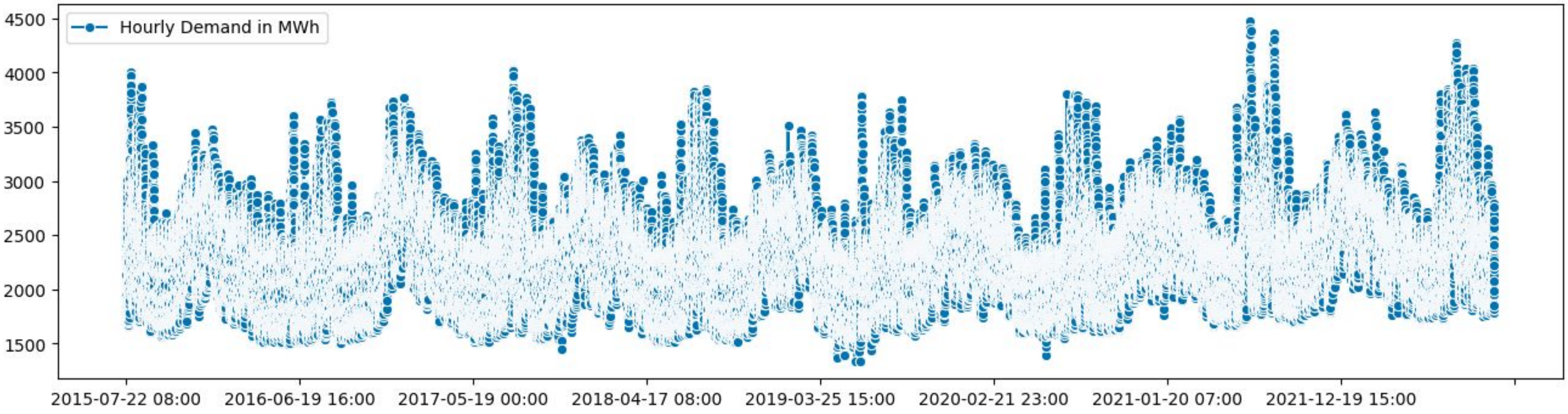
- Used mean of surrounding values (adjacent hours if available, else corresponding hours from adjacent days) to fill gaps in 124 missing hours
- Based method on idea that model evaluation would follow a typical temporal train/test split
    - More on this later...

Outliers

- Some values far higher than adjacent (hourly) values in series
- Same imputation strategy



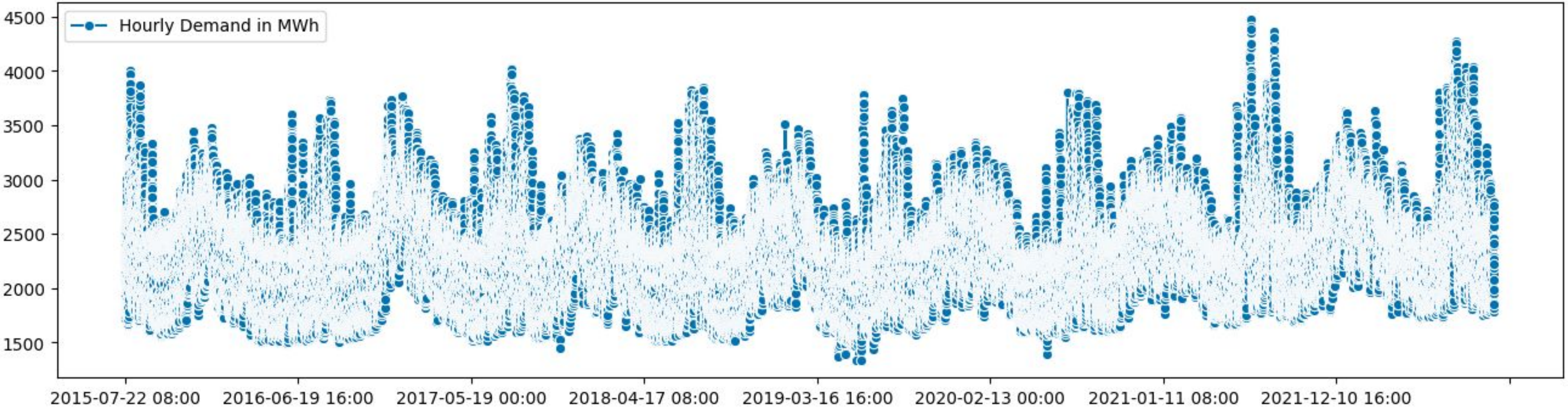
Initial Clean Series



Annual seasonality clearly visible:

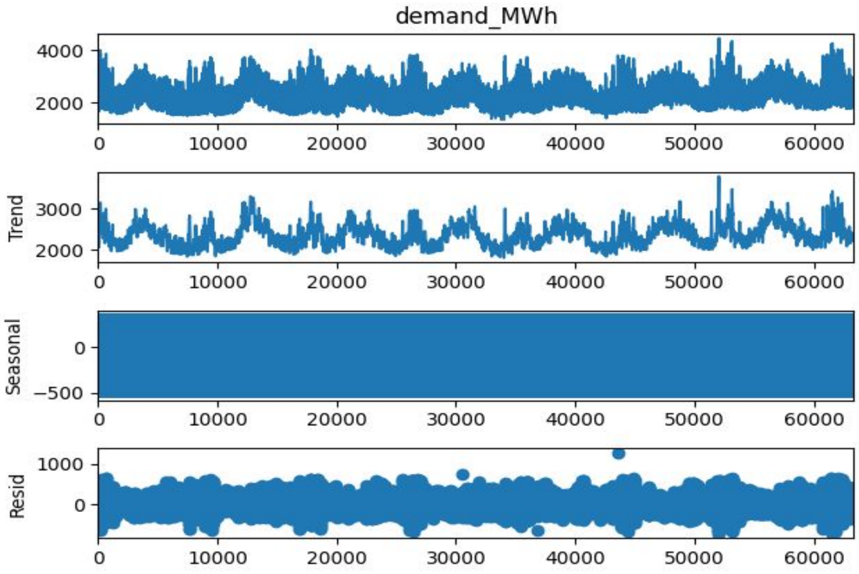
- Tallest peaks are summers, shorter peaks winters
- Troughs are springs and falls

Full Clean Series

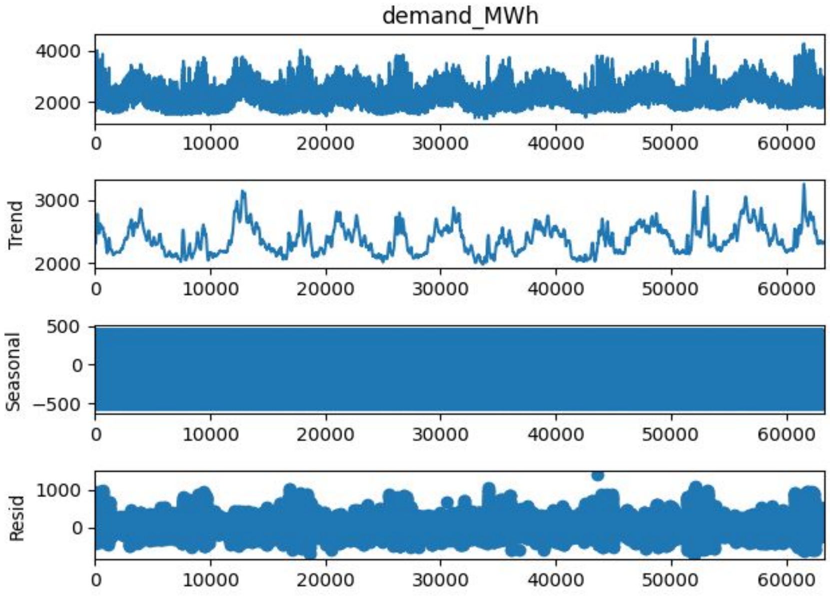


- 215 hours in March 2019 missing entirely from data set
- Imputed as mean of corresponding hours from previous three years: reason for different imputation still to come...

Modeling EDA: Seasonal Decomposition



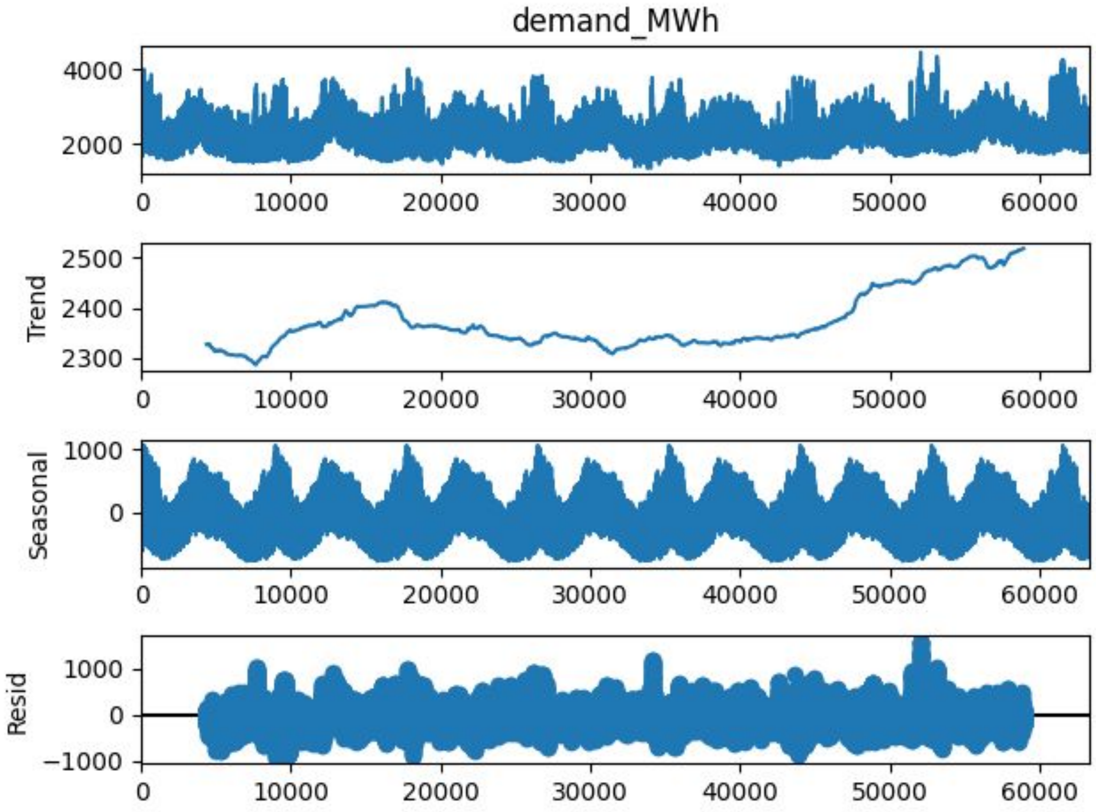
Daily



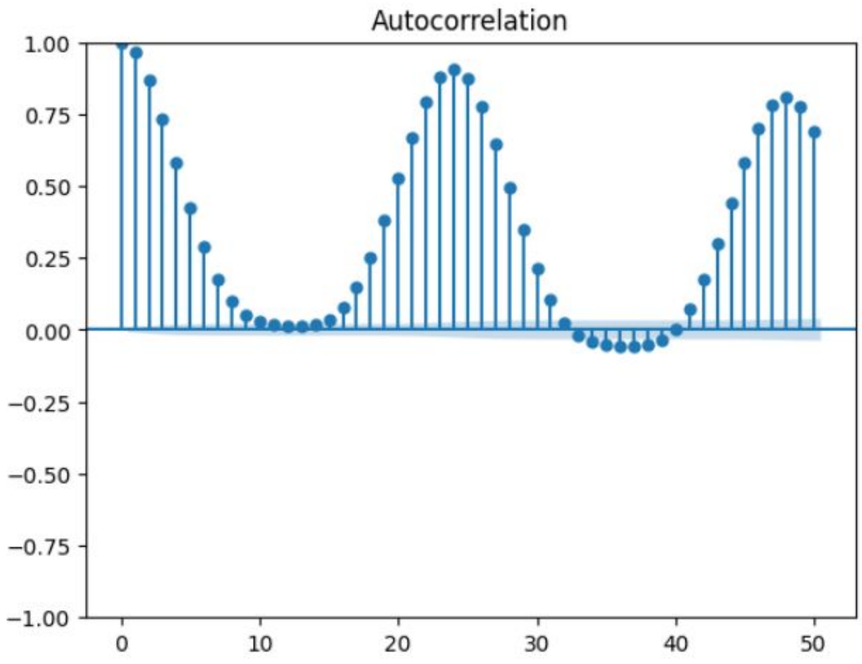
Weekly

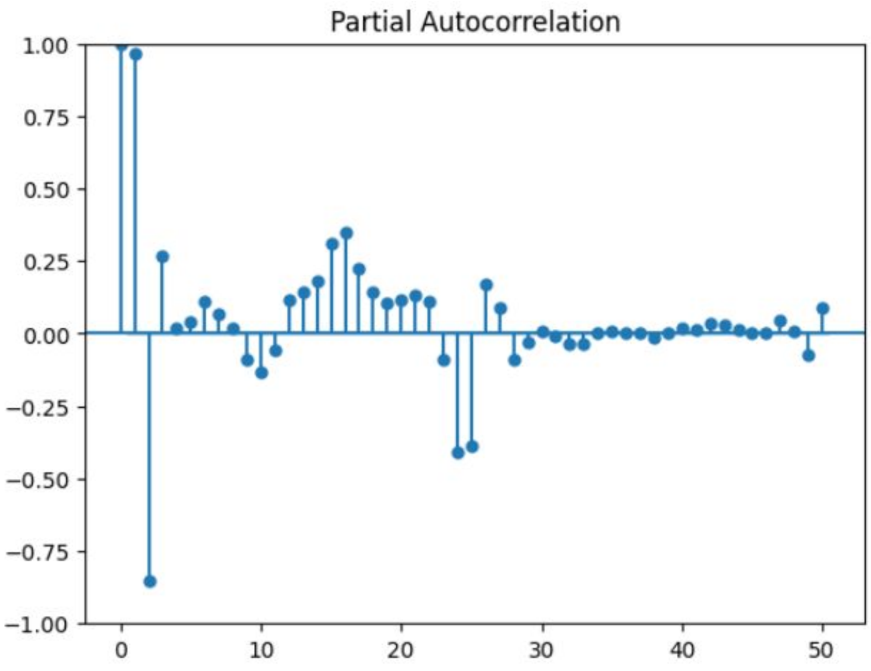
Modeling EDA: Seasonal Decomposition

- Only annual seasonality visible in whole series
- Apparent upward trend in demand 2015-2022



Modeling EDA: Correlation



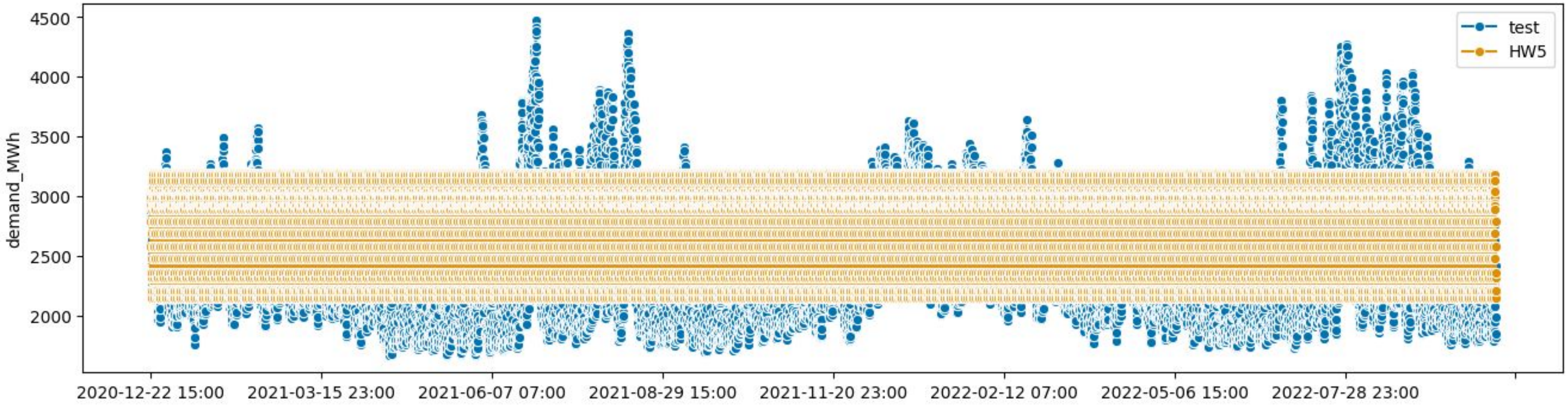


Modeling and Evaluation Methodology

Let’s see how that temporal train/test split works.

Best Holt-Winters

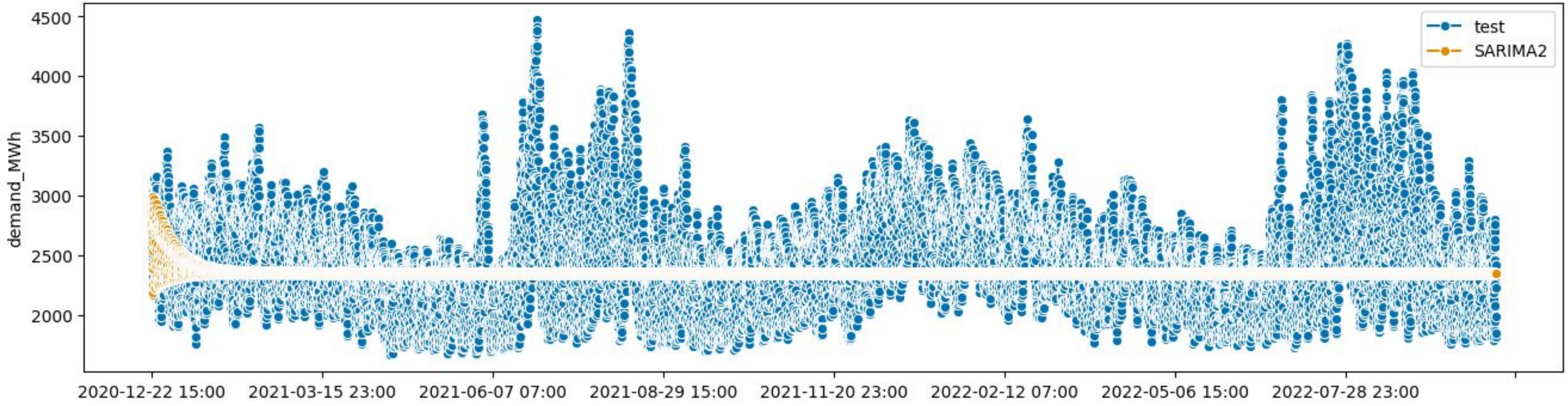
ETS Exponential Smoothing



MAE: 384.5 MWh

Best SARIMA

ARIMA(1,0,0)(1,0,0)[24]



MAE: 339.1 MWh

State-Space Models

- Basically, a set of equations that models a process as evolving through a series of “states”
- Each state is defined by its variables’ values and the relationships between these variables
- The result is that forecasting with a state-space model means taking steps forward from one state to the next
- Exponential Smoothing repeats the same pattern forever
- ARIMA regresses to the mean
- These models are designed for short-term forecasting!

Modeling and Evaluation Methodology

This one actually works.

Iterative Modeling and Forecasting

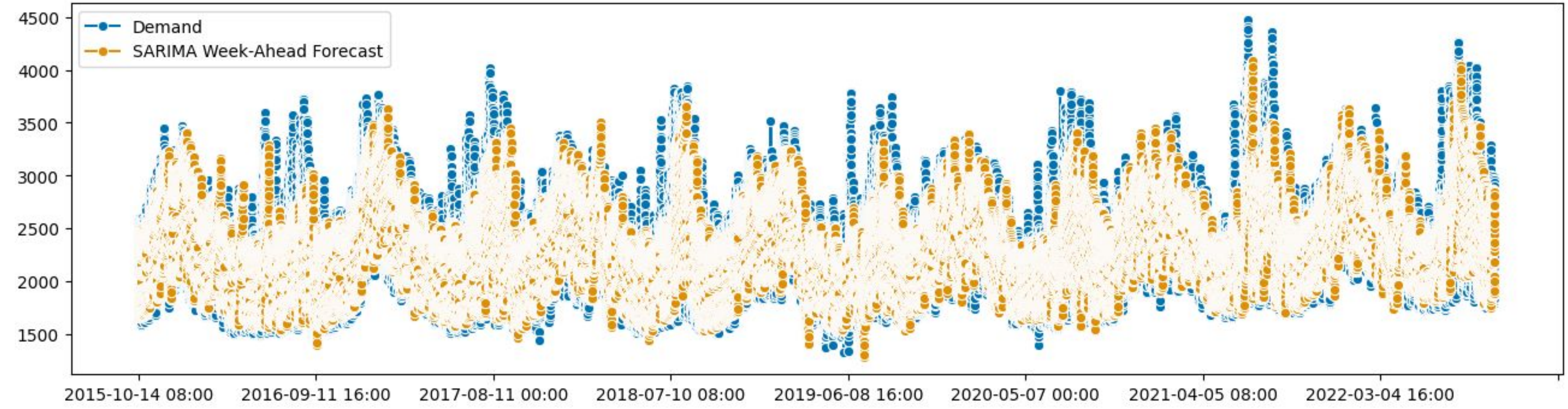
- Week-Ahead: Iterate fitting through 12-week training periods (overlapping in 11 weeks) to make week-ahead forecasts for 13th through 376th week of demand series
- Day-Ahead: Iterate fitting through 12-week training periods (overlapping in 12 weeks minus one day) to make day-ahead forecasts for 85th through 2637th day of demand series
  - PGE's own forecasts are day-ahead

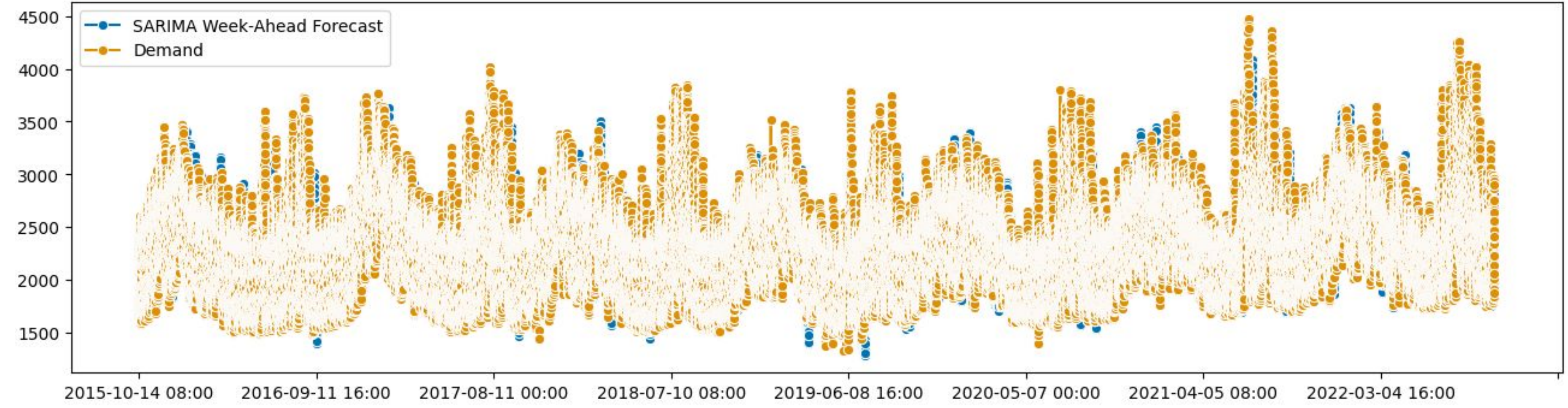
This is where my first imputation strategy becomes technically inappropriate. Information about the future has bled into the information on which the model is fit. This motivated my second imputation strategy, in which I used only data before a value to impute it. I will fix this when I revise this project for my portfolio.

Models Evaluated on Entire Series

Model	Holt-Winters	“SAR”: ARIMA(1,0,0)(1,0,0)	“SARIMA”: ARIMA(2,1,2)(1,0,1)
Week-Ahead MAE (MWh)	189.6	203.4	**178.8**
Day-Ahead MAE (MWh)	142.1	**116.8**	134.7

“Front and Backs”


Demand
SARIMA Week-Ahead Forecast
4500
4000
3500
3000
2500
2000
1500
2015-10-14 08:00
2016-09-11 16:00
2017-08-11 00:00
2018-07-10 08:00
2019-06-08 16:00
2020-05-07 00:00
2021-04-05 08:00
2022-03-04 16:00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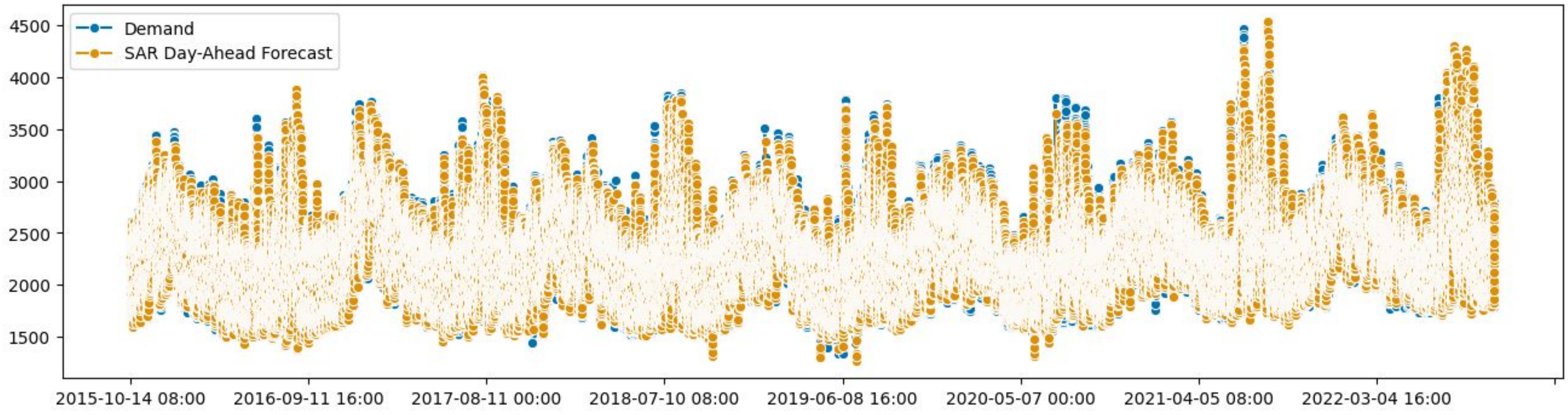
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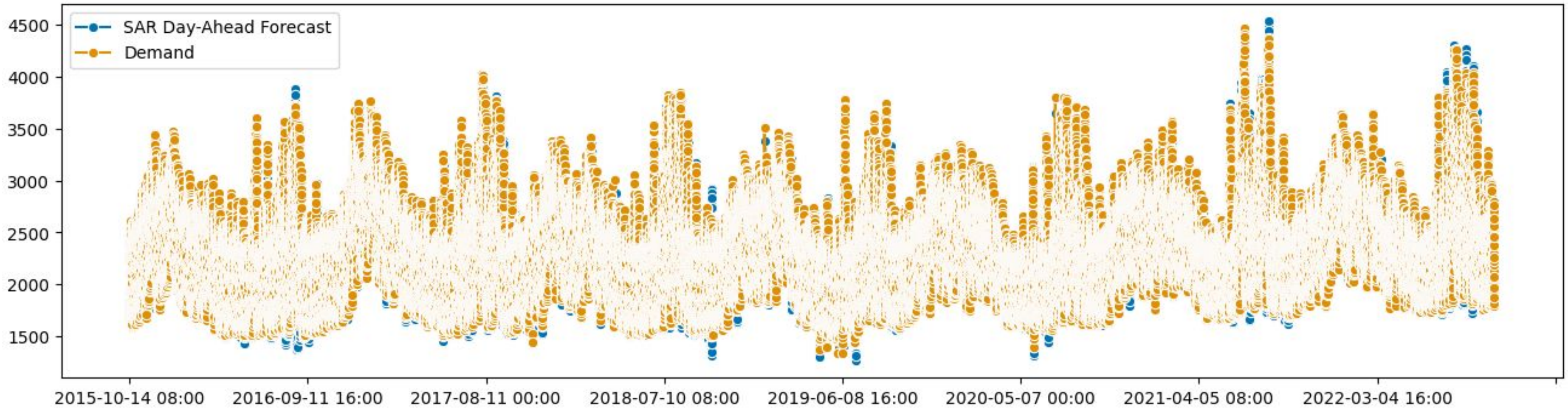
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Incorporating Exogenous Variables: SARIMAX

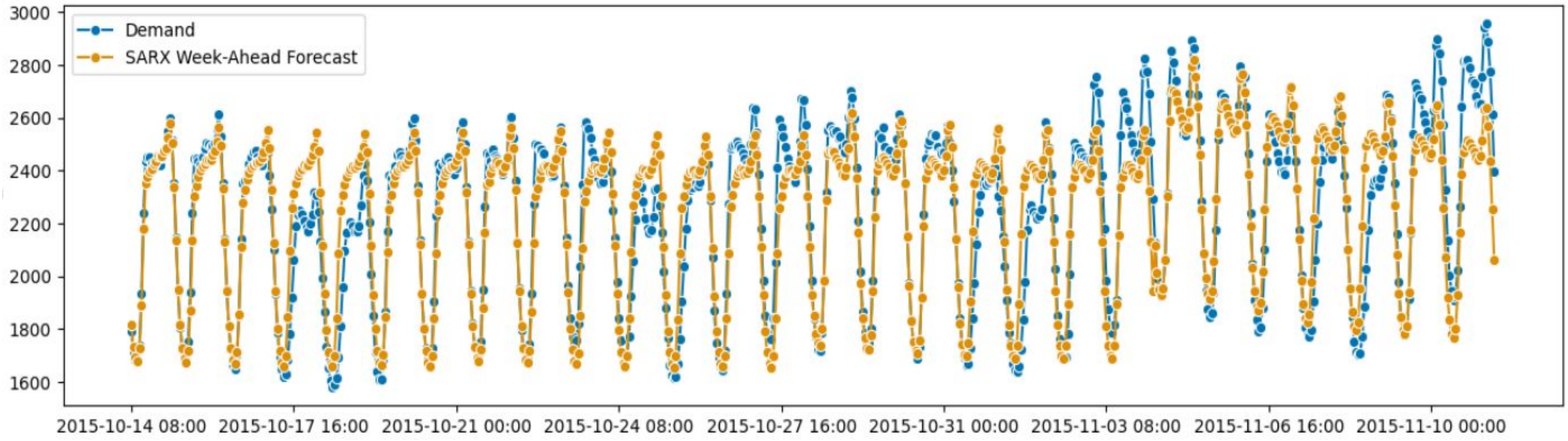
SARIMAX Modeling and Evaluation

- ARIMA hyper-parameter specification changed from (1,0,0)(1,0,0) to (1,0,0)(1,1,1) because the former caused a downward trend in forecasts
- Fitting took much longer, so forecasts only cover 4 weeks and are therefore only good for comparison to each other
- Analysis focuses on identifying best way to incorporate exogenous variables

Models Evaluated on First Four Weeks

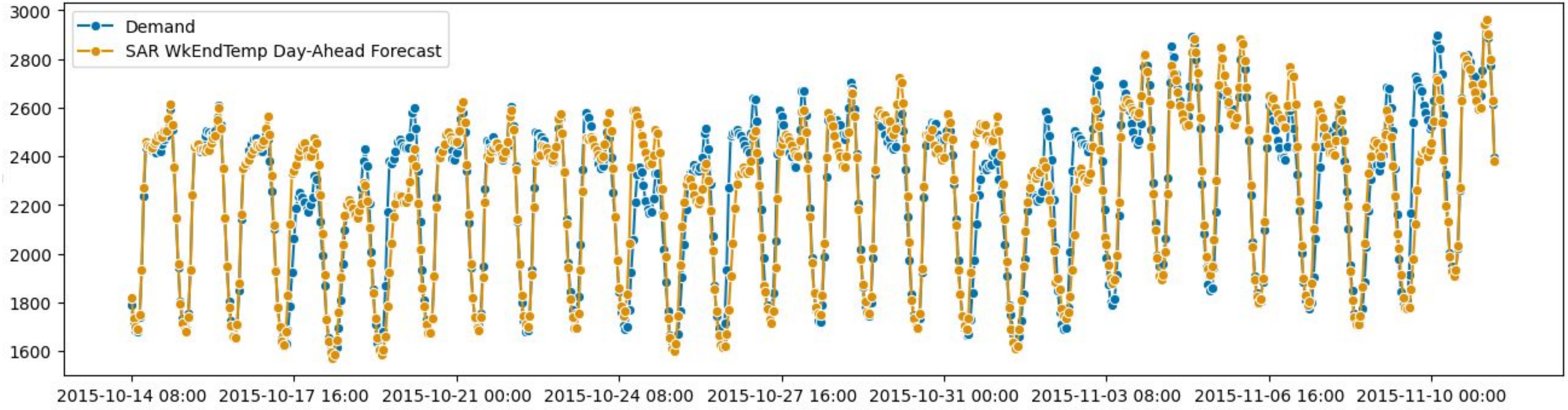
Model	Weekend	Day-of-Week	Weekend and Daily High, Low Temps
Week-Ahead MAE (MWh)	**92.9**	104.9	112.0
Day-Ahead MAE (MWh)	82.6	85.4	**82.0**

SARIMAX Weekend Dummy: Week-Ahead



- Good transitions between night and day
- During the day inherently harder, but not bad
- Weekend dummy works reasonably well

SARIMAX Weekend Dummy, Daily High and Low Temps: Day-Ahead



- Over-estimates Saturday
- Under-estimates Monday

Conclusions

- Time series analysis is a rabbit hole. I made many methodological decisions that could have drastically affected my results, including:
    - 12-week training periods
    - Week-ahead and day-ahead forecasts
    - Not splitting demand into residential/commercial/industrial
    - Using only state-space models
    - SARIMAX forecasts at beginning of demand series

Conclusions

- Time series math is advanced. I understand the models I used in a general way, but not well enough to fine-tune them. I also did not even get to dynamic harmonic regression, which appears to be a strong tool for series with multiple seasonalities, such as electricity demand.
- Iterative, short-term forecasting with Holt-Winters and ARIMA models worked well, providing a way to compare my models to each other and to PGE's own predictions. It is, however, quite slow for ARIMA.
- Exogenous variables can be helpful, but there is already a lot of information in the past values of the series itself.

Extensions

- Plot MAE vs. training period length to better understand optimal training period
- Dynamic harmonic regression to model multiple seasonalities
- Evaluate models on RMSE
- Produce daily forecasts going forward to test my best models on new data
- Further explore usefulness of exogenous variables