Predicting Singapore's Electricity Peak Demand

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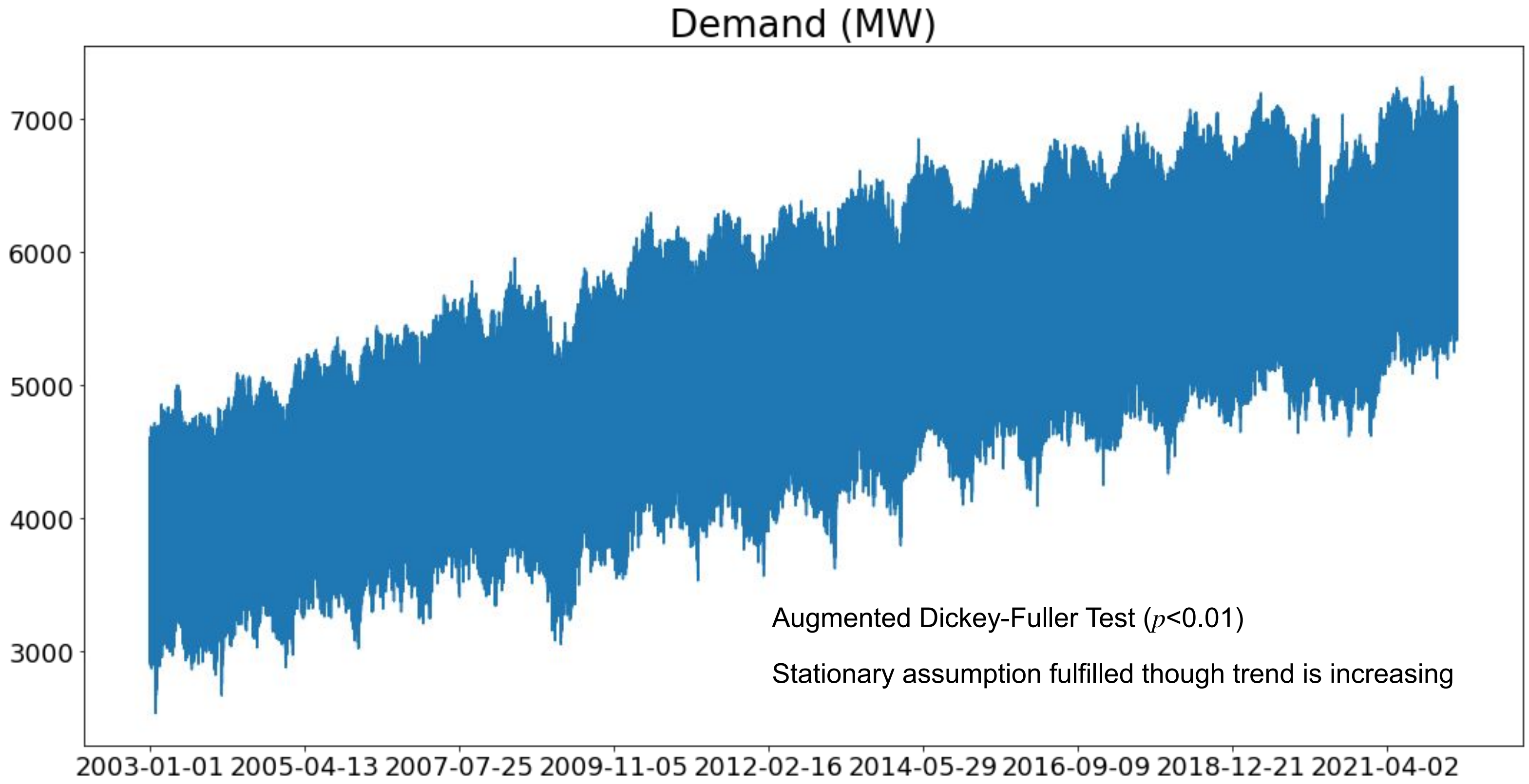
Problem Statement:
Predict Singapore's peak electricity demand for 2022

- Peak electricity demand = Highest instantaneous demand

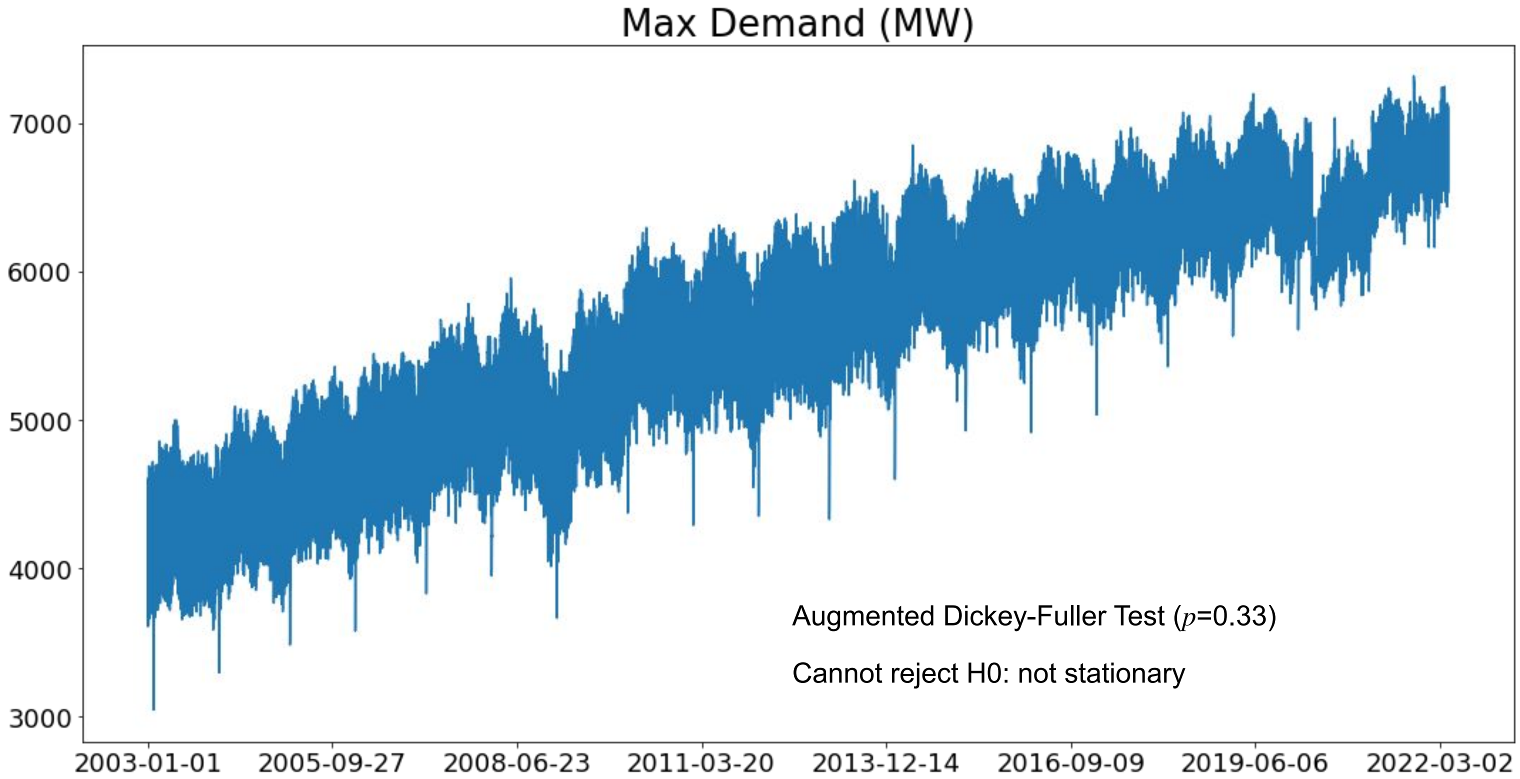
- Important because there needs to be sufficient electricity infrastructure in place to meet total system demand at any point in time

- Accurate prediction to advise decision makers on amount of infrastructure required
  - Over prediction -> waste resources
  - Under prediction -> black out (reserve margin of 27% to maintain system security)

Data: Half-hourly System Demand (MW)



Daily System Highest Demand trend is not stationary



Stationary assumption fulfilled for first-ordered differenced demand

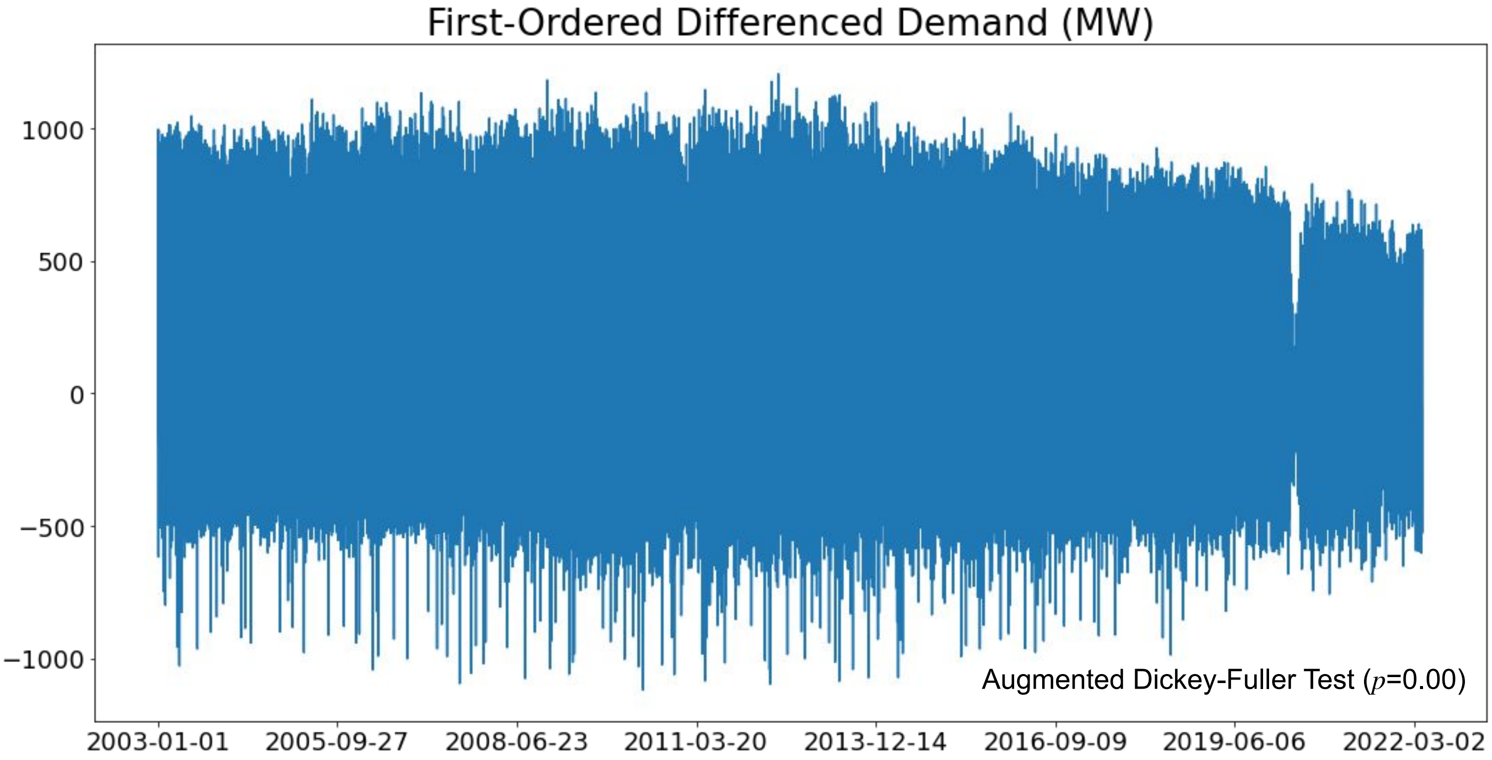
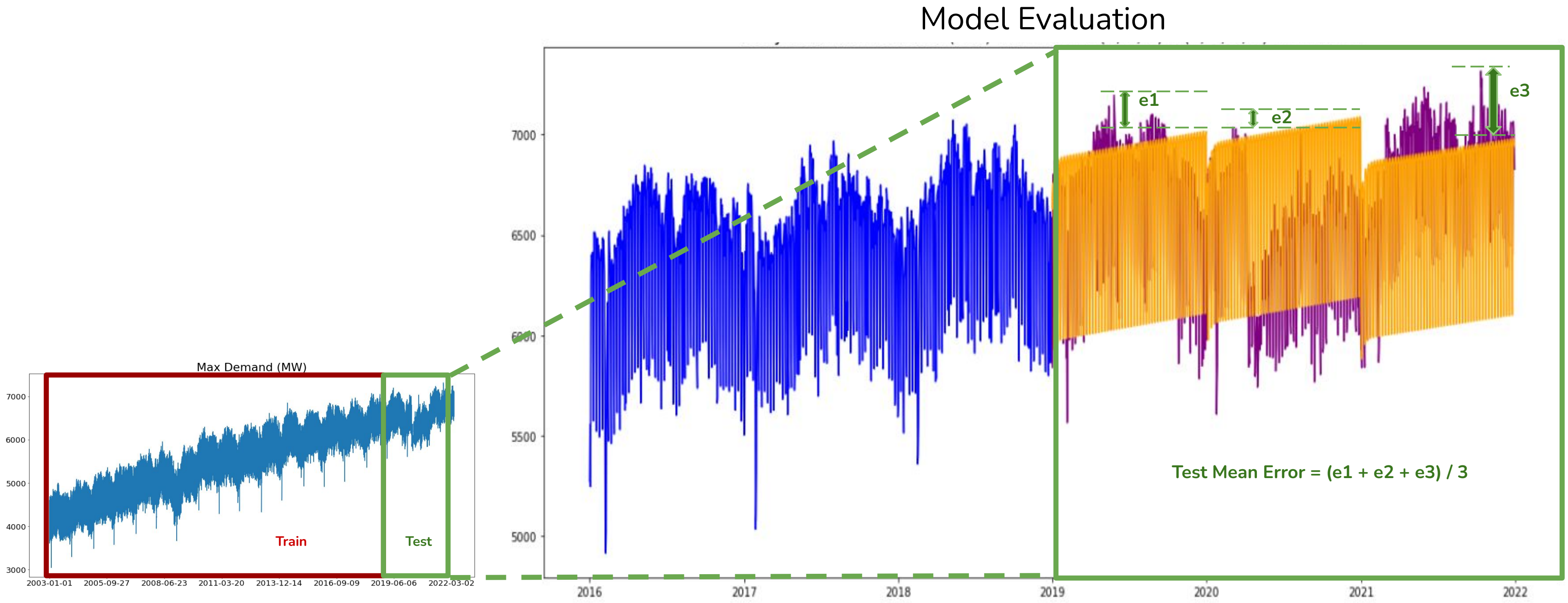
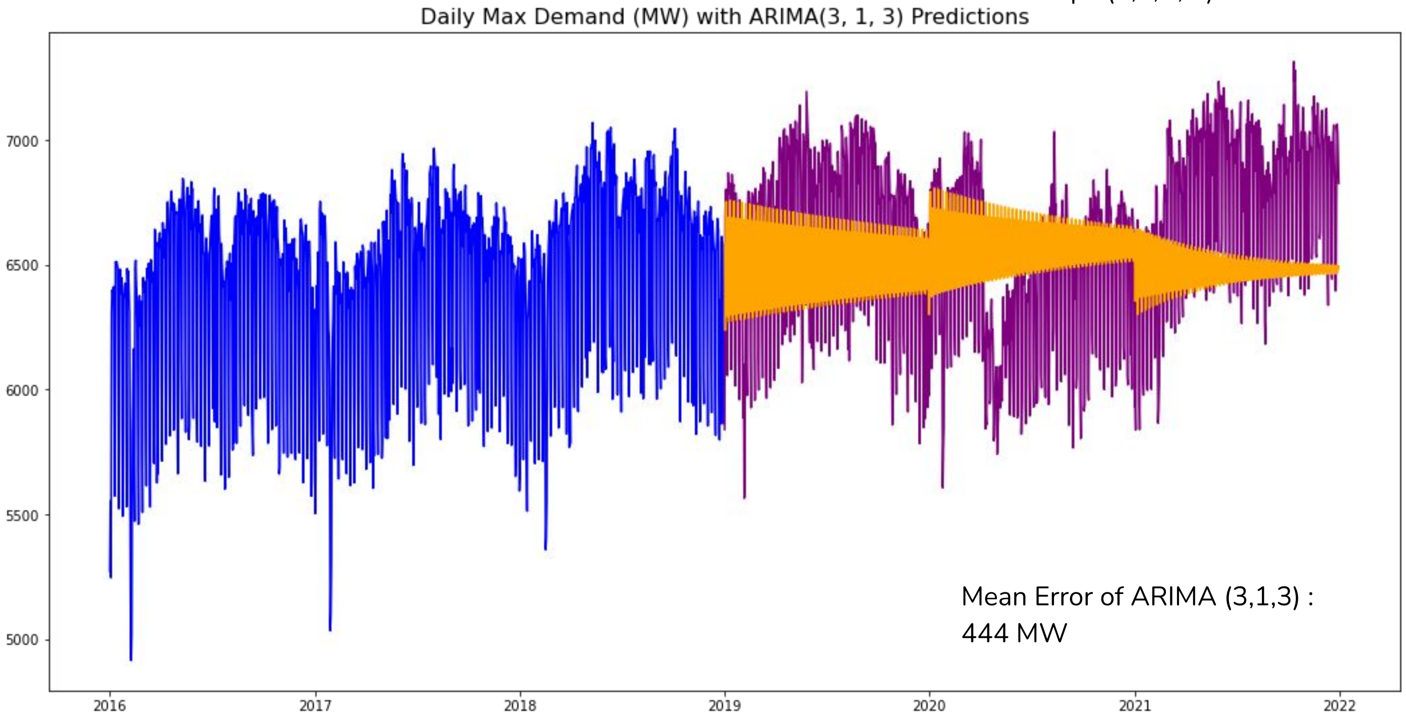


Illustration of Evaluation Metrics: Mean error of peak demand for 3 one-year ahead testing periods



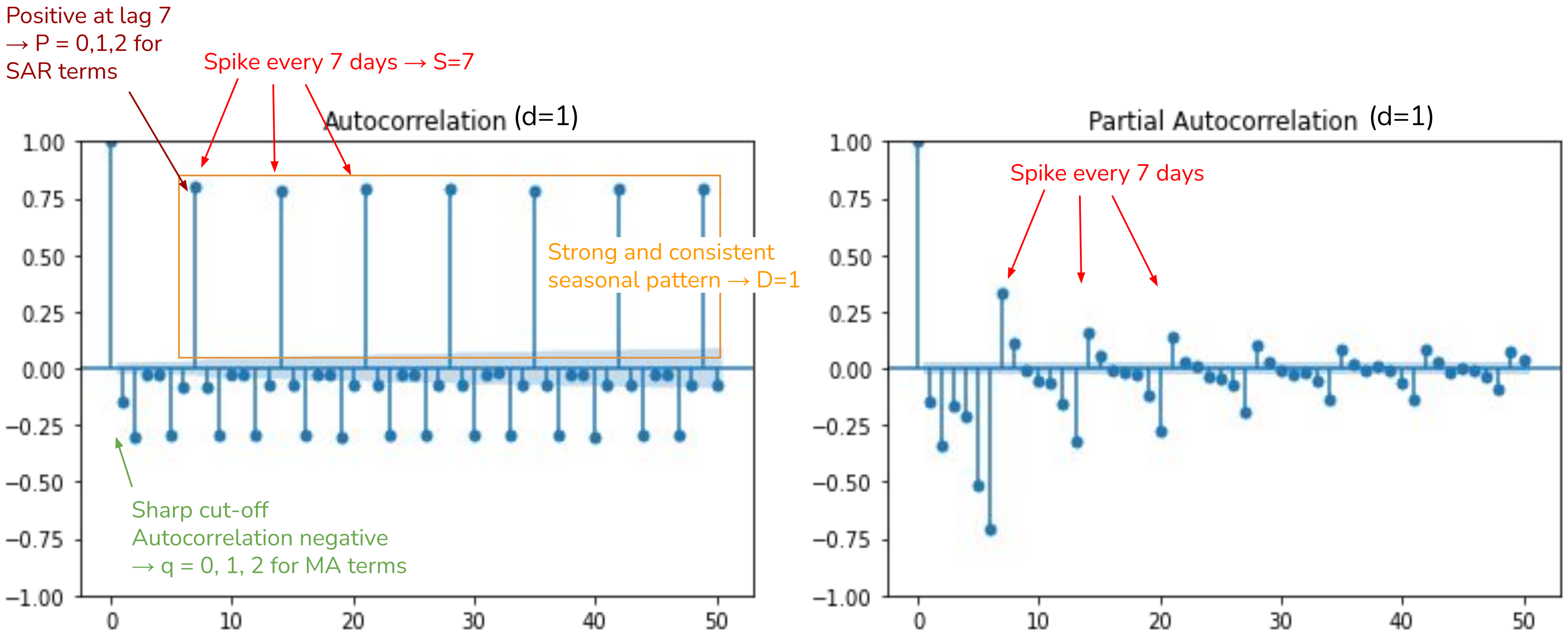
Model Exploration: Base Model ARIMA

Tuning parameters for ARIMA:
p = (0,1,..., 5)
d = 1
q = (0,1,..., 5)



Mean Error of ARIMA (3,1,3) :
444 MW

Model Exploration: ACF and PACF* shows strong and consistent seasonal pattern

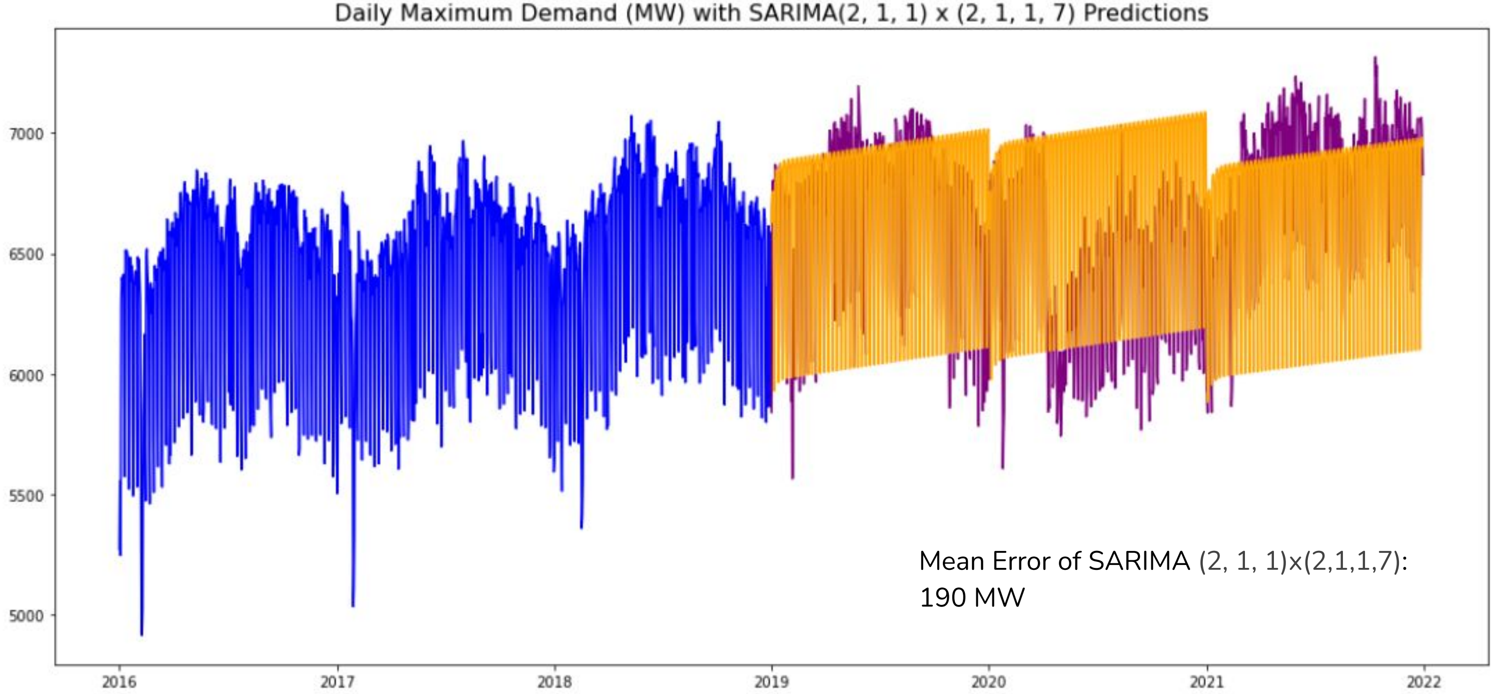


* Details of identifying AR, MA terms and seasonal components can be found in “Summary of rules for identifying ARIMA models” (https://people.duke.edu/~rnau/arimrule.htm)

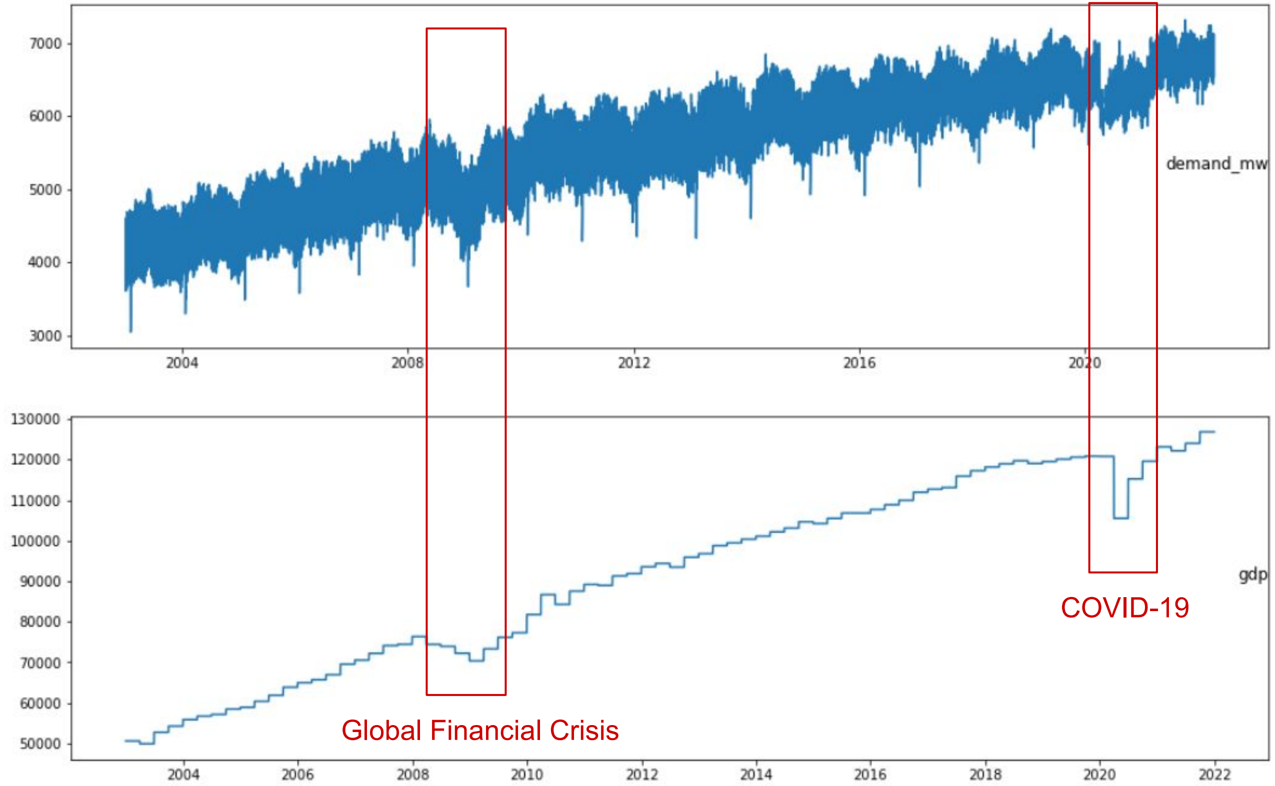
Model Exploration: SARIMA to account for seasonality over time

Tuning parameters for SARIMA:

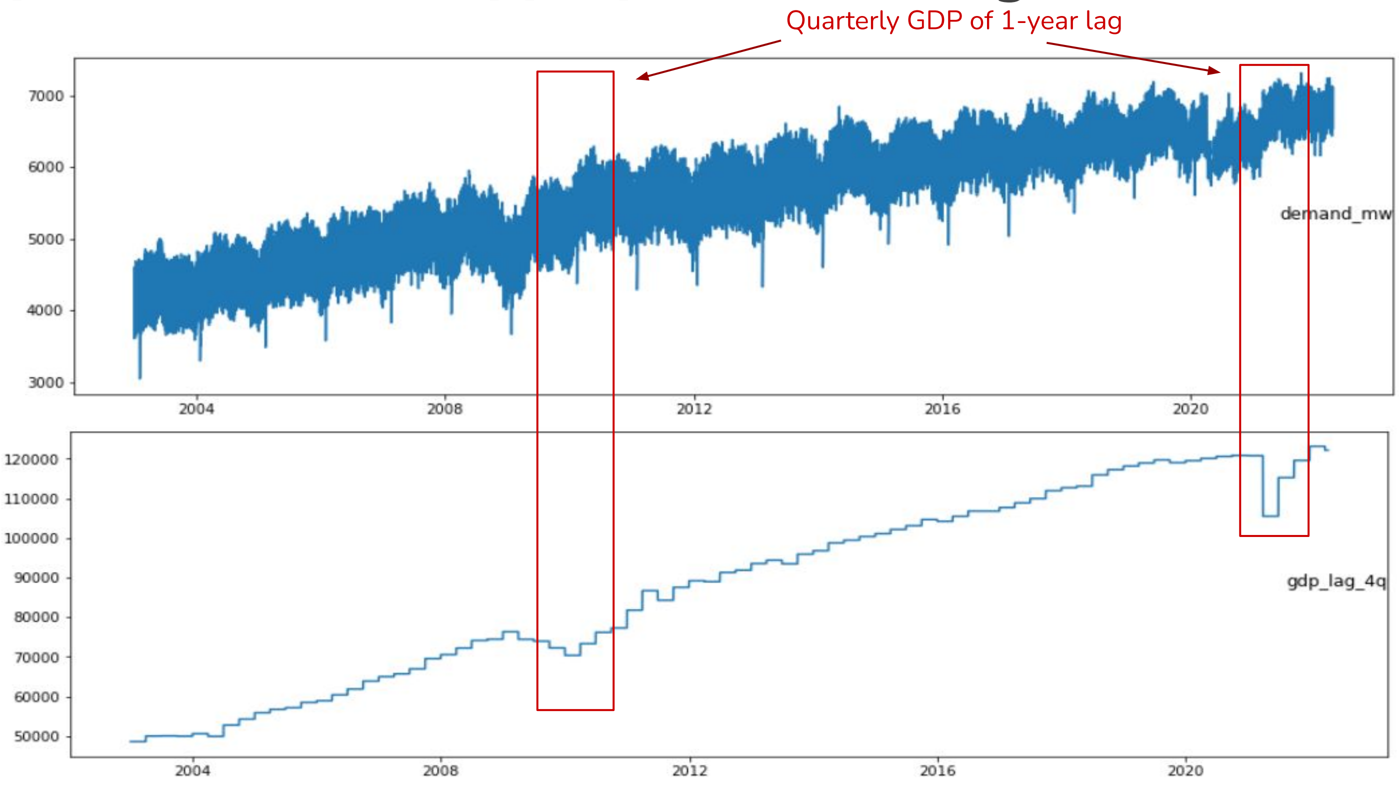
Non-seasonal	Seasonal
p = (0,1,2)	P = (0,1,2)
d = 1	D = 1
q = (0,1,2)	Q = (0,1,2)
	S = 7



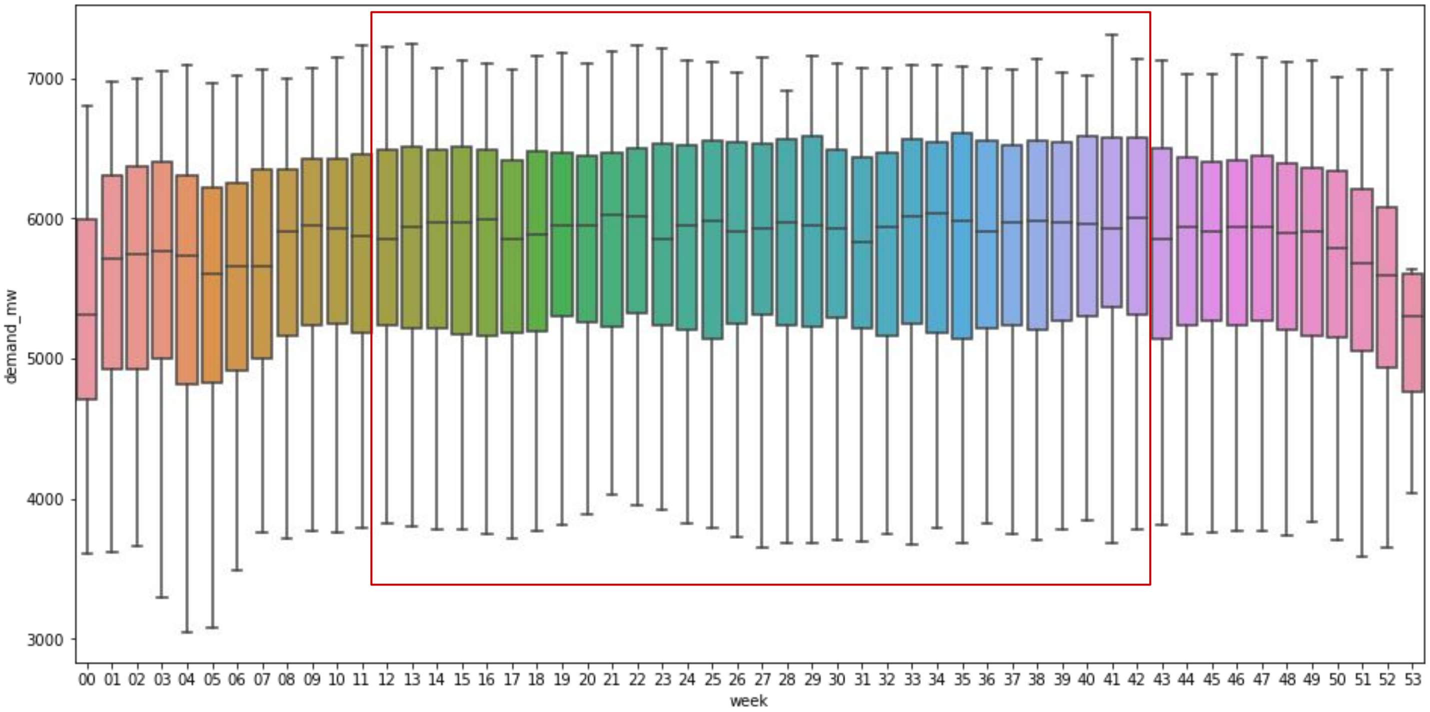
Demand is highly correlated with GDP as ~85% is contributed by Commercial & Industrial consumers



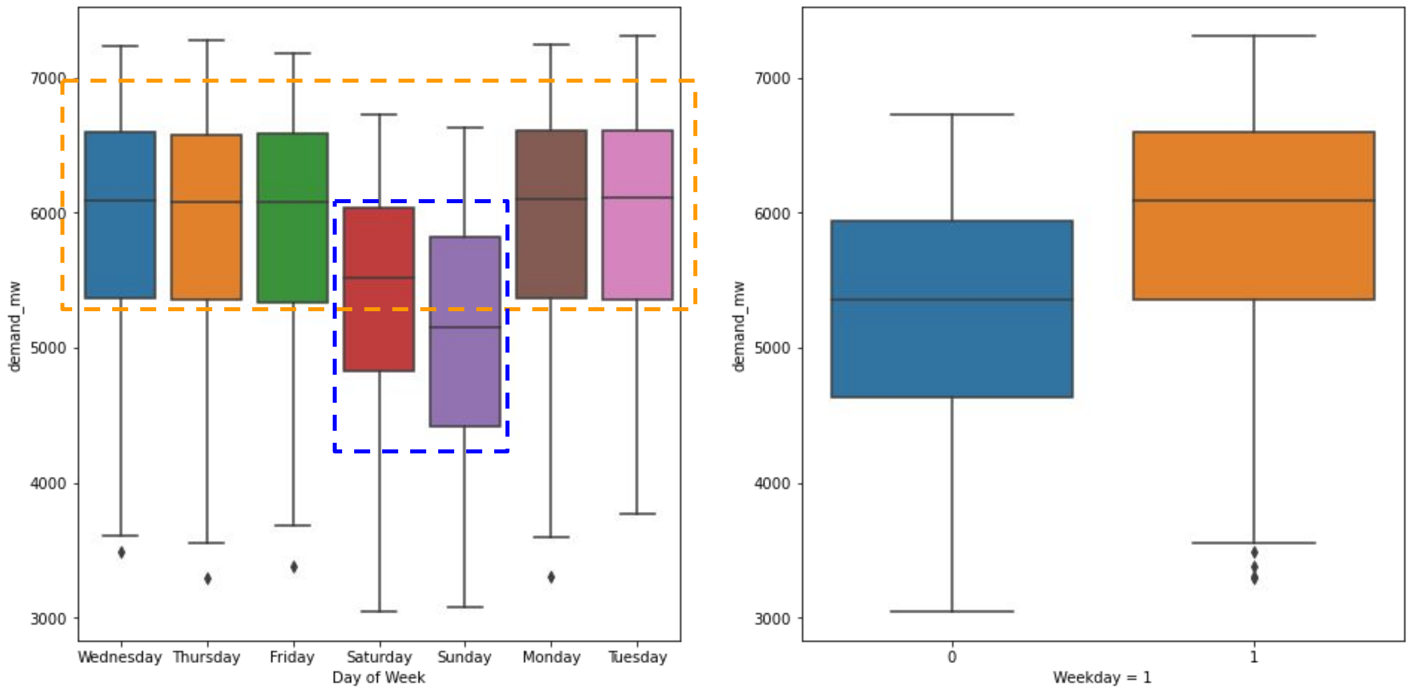
Based on least-error SARIMA, factor in exogenous predictors with appropriate time lag



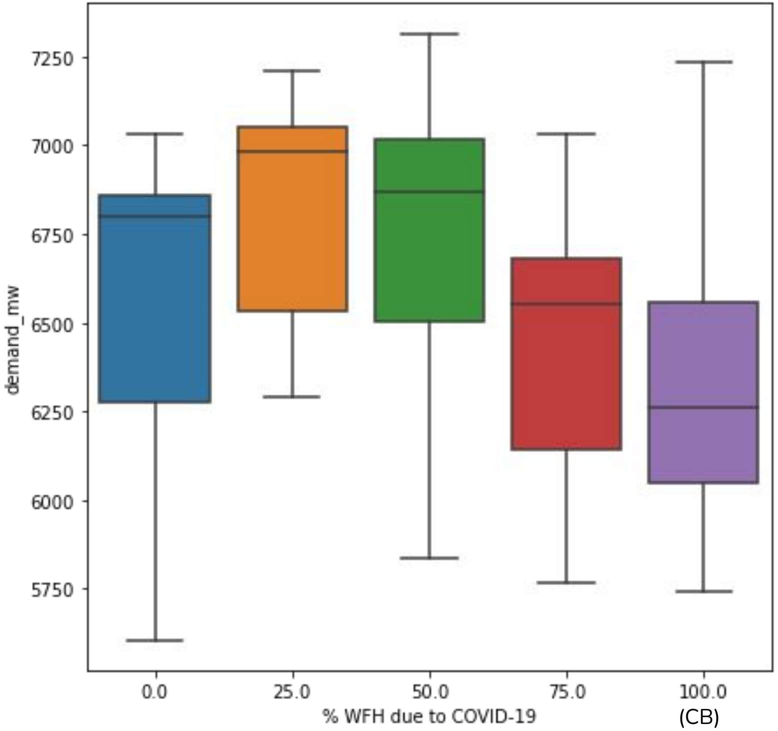
Demand is higher between week 12-42 (Mar - Oct)



Demand is higher on weekdays

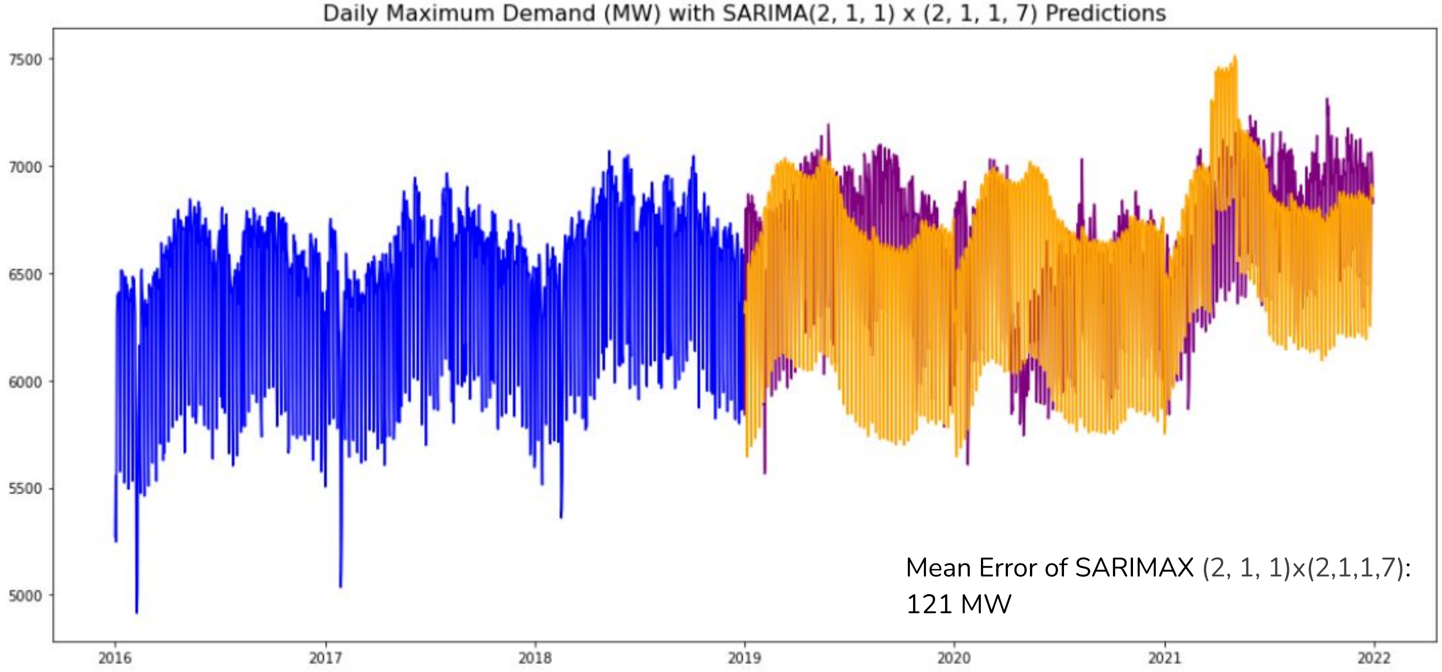


Demand is lowest during Circuit Breaker (CB) with severe disruption to economic activities



Use % WFH as a proxy of economy recovery

Model Exploration: SARIMAX with exogenous predictors 1-year lag GDP, Week, Day of Week, % WFH



Mean Error of SARIMAX (2, 1, 1)x(2,1,1,7): 121 MW

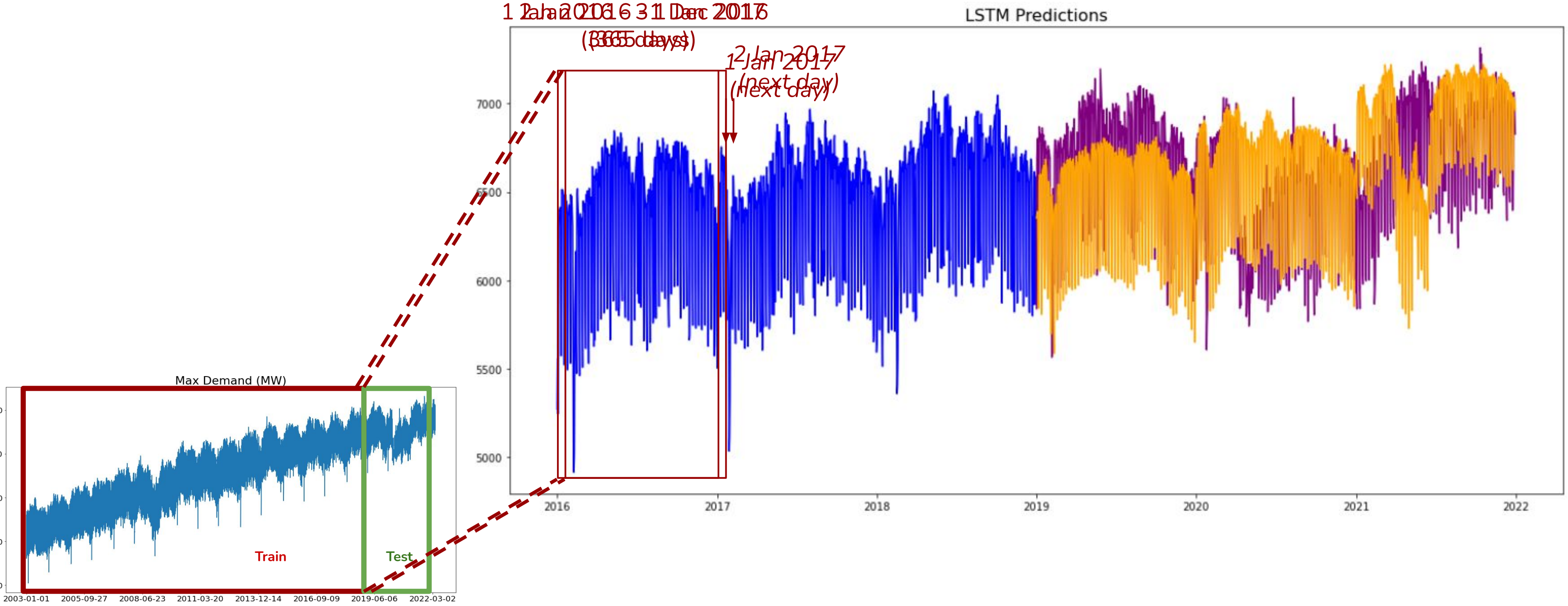
Tuning parameters for SARIMAX:

- Quarterly GDP of 1-year lag
- Week
- Day of week/ is_weekday
- % WFH due to COVID-19

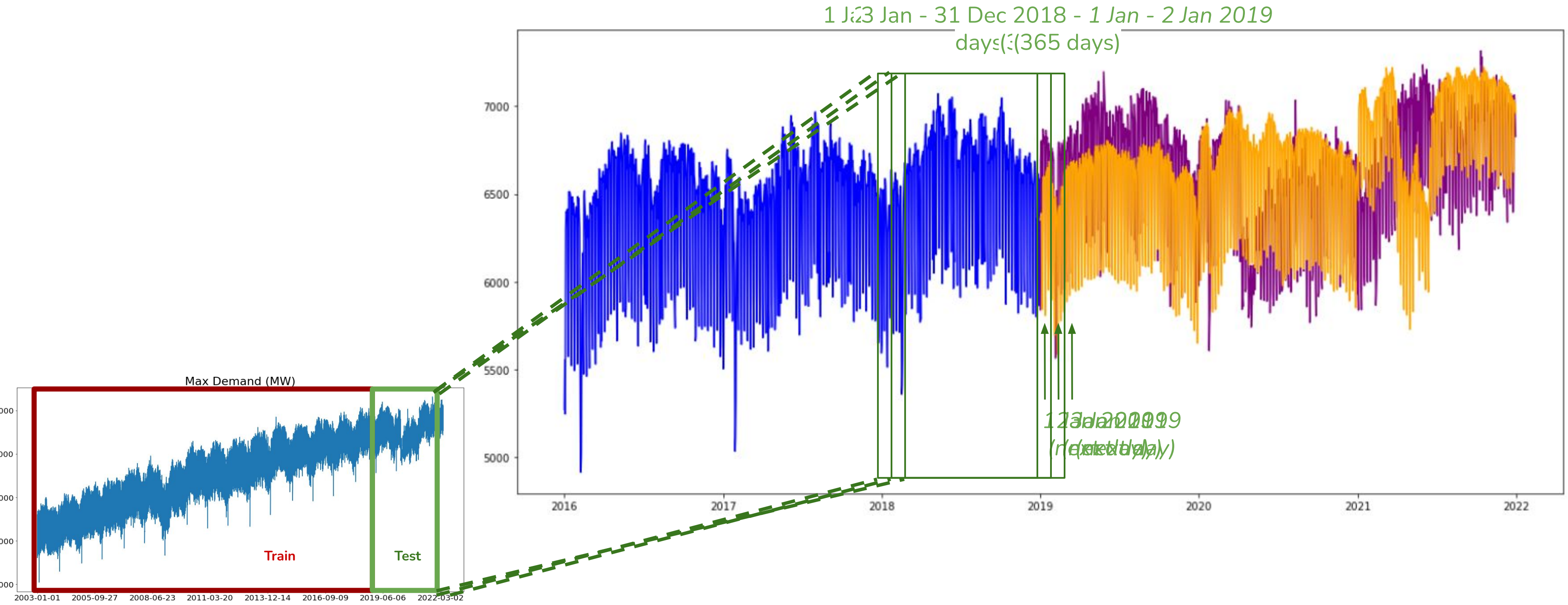
Summary of Performance of SARIMAX models

Model	Tuning parameters	Selected Model	MSE
ARIMA	p = (0,1,..., 5) d = 1 q = (0,1,..., 5)	ARIMA (3,1,3)	444 MW
SARIMA	p = (0,1,2) d = 1 q = (0,1,2) P = (0,1,2) D = 1 Q = (0,1,2) S = 7	SARIMA (2, 1, 1)x(2,1,1,7)	190 MW
SARIMAX	Individual and combination of following: ● Quarterly GDP of 1-year lag ● Week ● Day of week/ is_weekday ● % WFH due to COVID-19	SARIMAX (2, 1, 1)x(2,1,1,7) using all exogenous predictors (except is_weekday)	121 MW

Model Exporation:LSTM RNN with recursive strategy (many-to-one model)



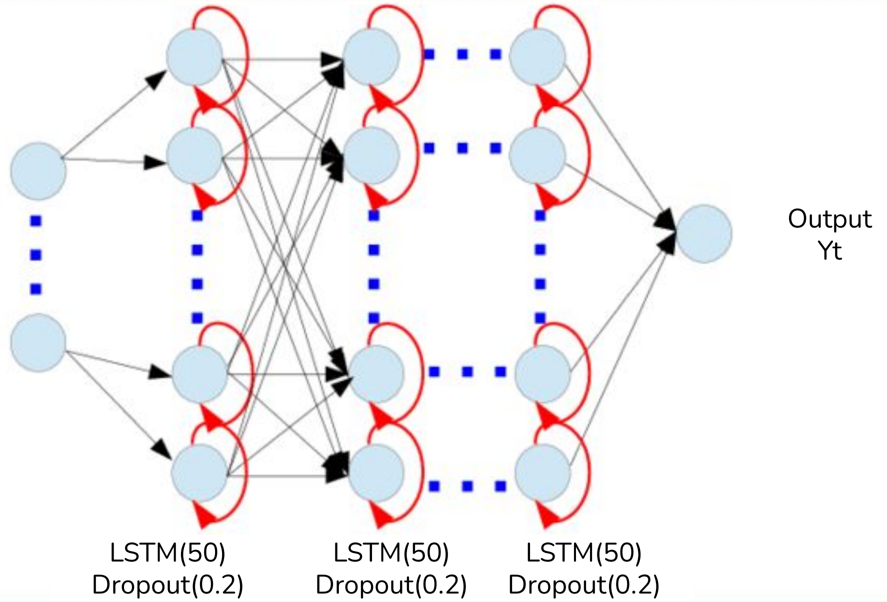
Model Exporation: LSTM RNN with recursive strategy (many-to-one model)



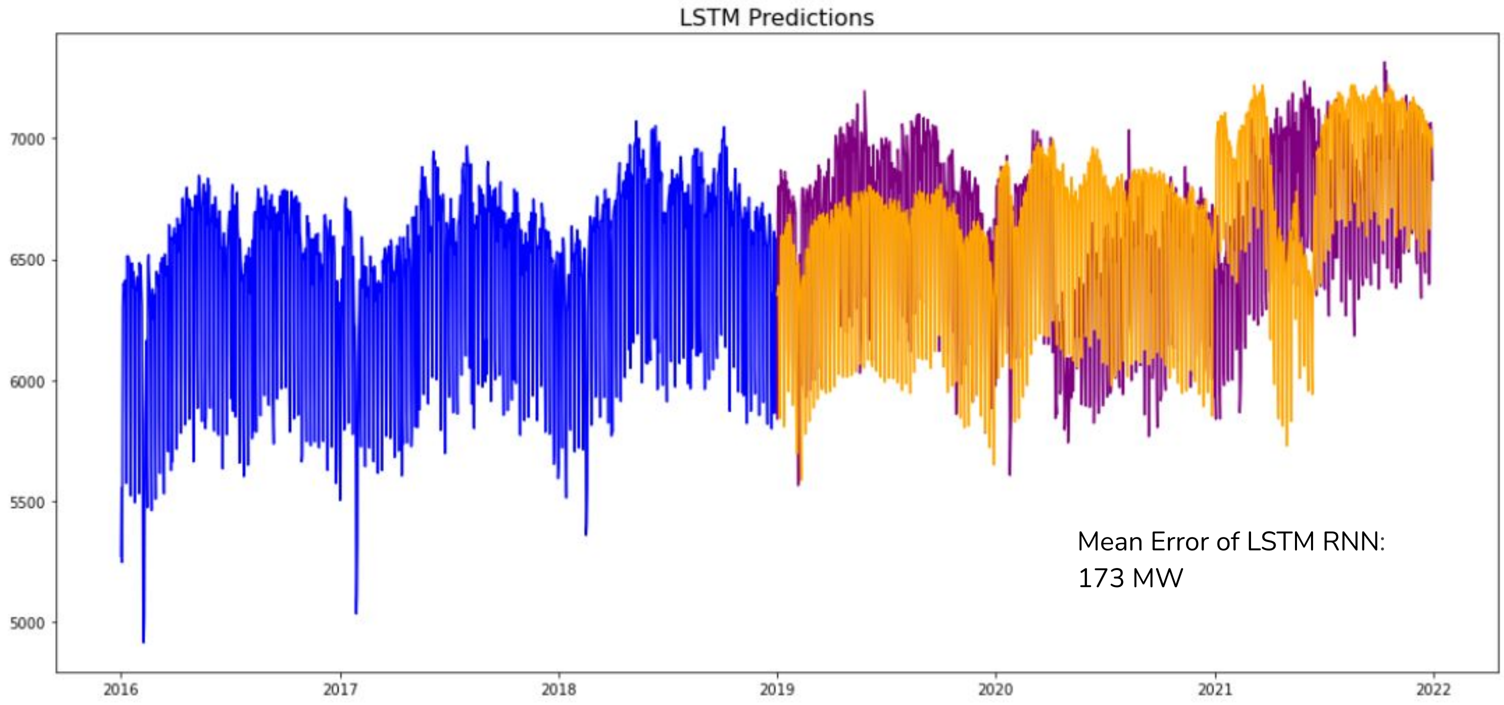
LSTM RNN with recursive strategy (many-to-one model)

Input (365, 65)

- Yt-1, ... Yt-365
- GDP of 1-year lag
- Week
- Day of week
- % WFH due to COVID-19



Model Exploration: Multivariate time series forecasting using LSTM RNN



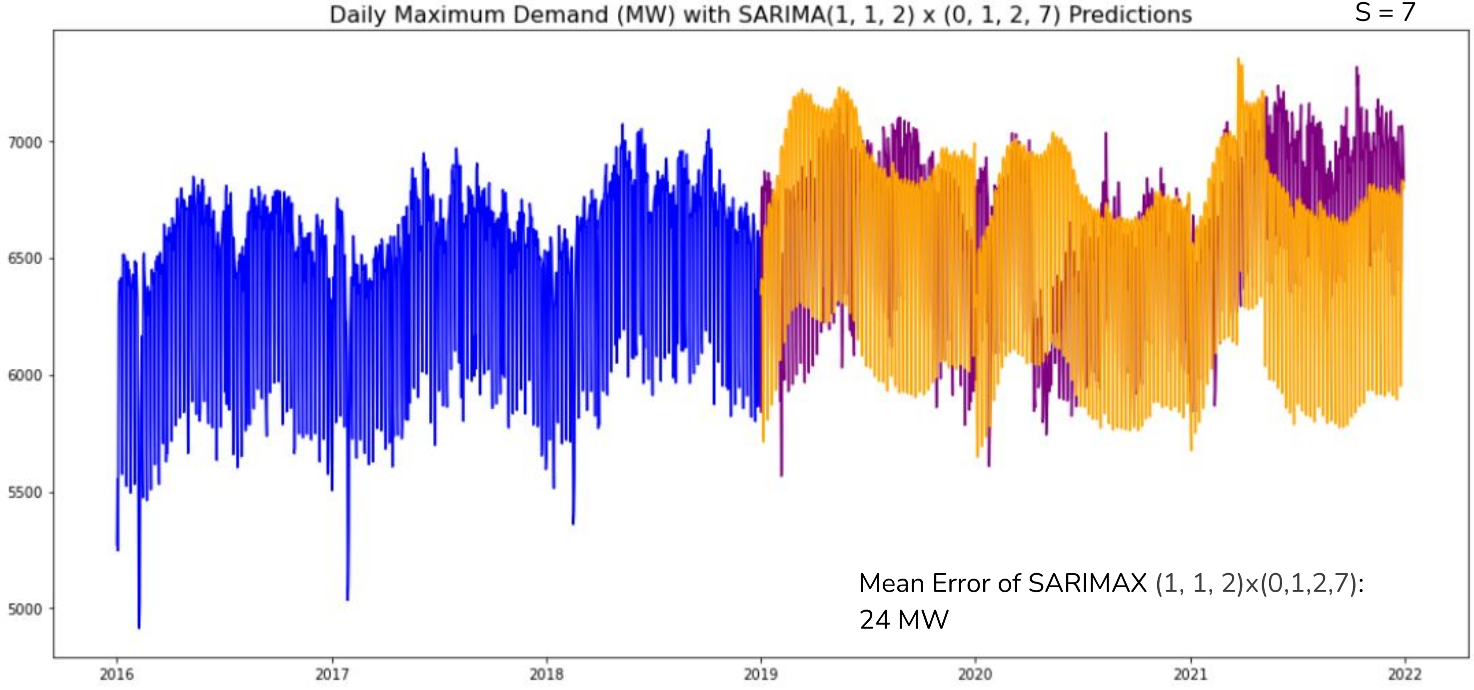
Features:

- Yt-1, … Yt-365
- GDP of 1-year lag
- Week
- Day of week
- % WFH due to COVID-19

Final Model: Choose SARIMAX considering its explanatory power

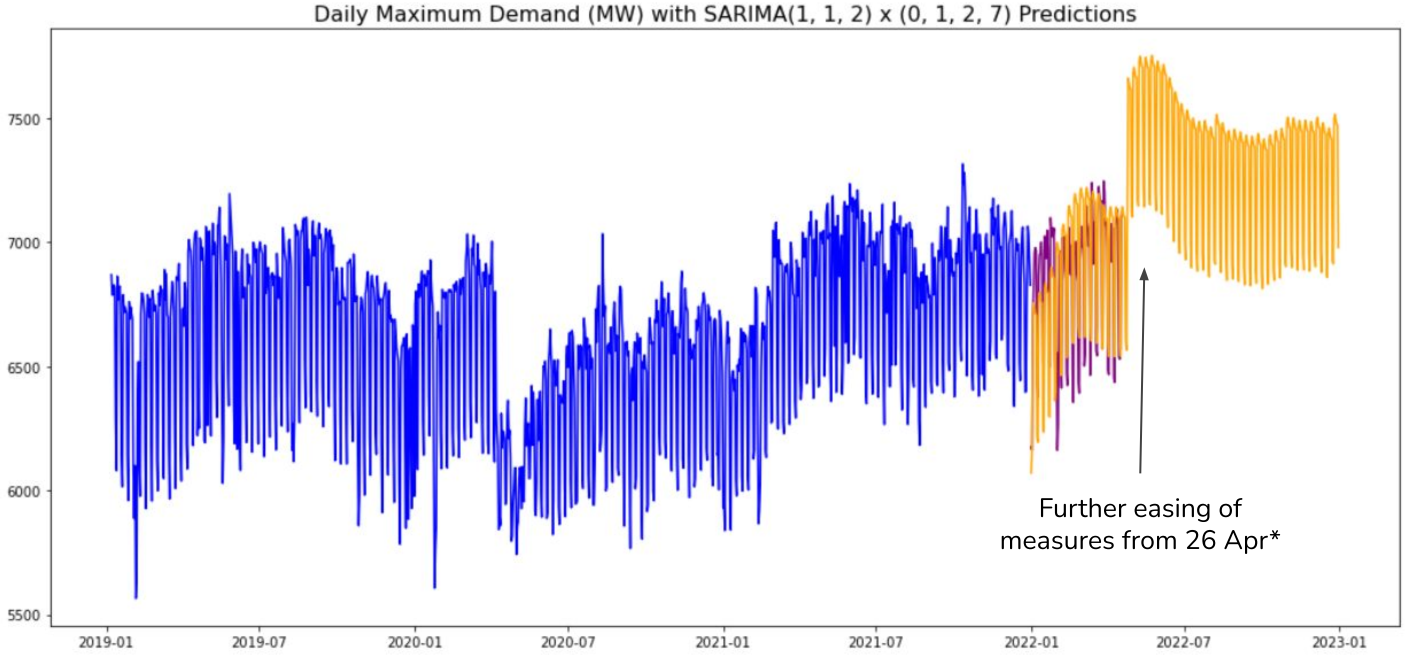
Tuning parameters for SARIMA:

Non-seasonal	Seasonal
p = (0,1,2)	P = (0,1,2)
d = 1	D = 1
q = (0,1,2)	Q = (0,1,2)
	S = 7



Mean Error of SARIMAX (1, 1, 2)x(0,1,2,7):
24 MW

Prediction:
Predicted peak demand for 2022 is 7750 MW



* Further easing of measures from 26 Apr which have no restrictions to the number of people returning to workplaces

Next Steps

- Feature Engineering
  - Incorporate public holidays
  - Transform day and week to sin and cos functions to better model their cyclical patterns*
- Model
  - Increasing testing period to 5 years (instead of 3)
  - Exploration:
    - Further tune the LSTM RNN model
    - Multiple output strategy (one ‘many-to-many’ architecture) for RNN (instead of sliding windows)^
    - GRU, CNN, etc.
- Application
  - Predict total annual demand -> useful for computing electricity tariff
  - Predict peak demand/total annual demand for a longer forecast period

* Reference source: Single and Multi-Step Temperature Time Series Forecasting for Vilnius Using LSTM Deep Learning Model (https://towardsdatascience.com/single-and-multi-step-temperature-time-series-forecasting-for-vilnius-using-lstm-deep-learning-b9719a0009de)
^ Reference source: How to make LSTM predict multiple time steps ahead (https://stats.stackexchange.com/questions/265426/how-to-make-lstm-predict-multiple-time-steps-ahead)