

PREDICTING ELECTRICITY POWER LOAD FOR SAUDI CENTRAL OPERATING AREA

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Ebrahim
Balgunaim



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Ibrahim
Hakami




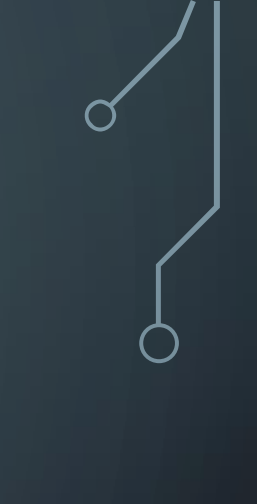
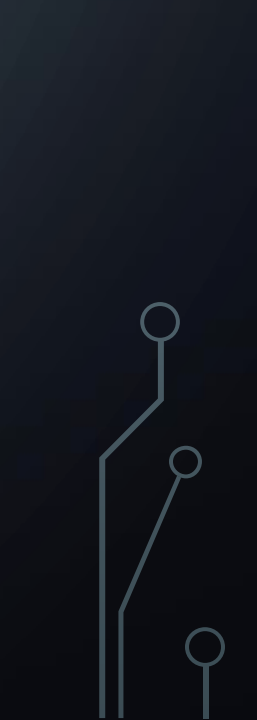
• 2019

Husain Al-
Amer





PROJECT STATEMENT



- Usage of electricity drains from a country's resources, specifically Saudi Arabia.
 - As such, forecasting it in the long, medium, and short terms is essential to better estimate how much resources will be used and to drive policy in expansion of the grid.
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OUR TARGET

- In this project, we aim to **forecast the usage of electricity** for Saudi Arabia's Central Operating Area (COA).



INTERESTED PARTIES

- We aim from this project to prove that we can predict electricity demand with a good accuracy and hopefully present our findings to interested stakeholders that either drive policy or are relevant to the electricity sector.
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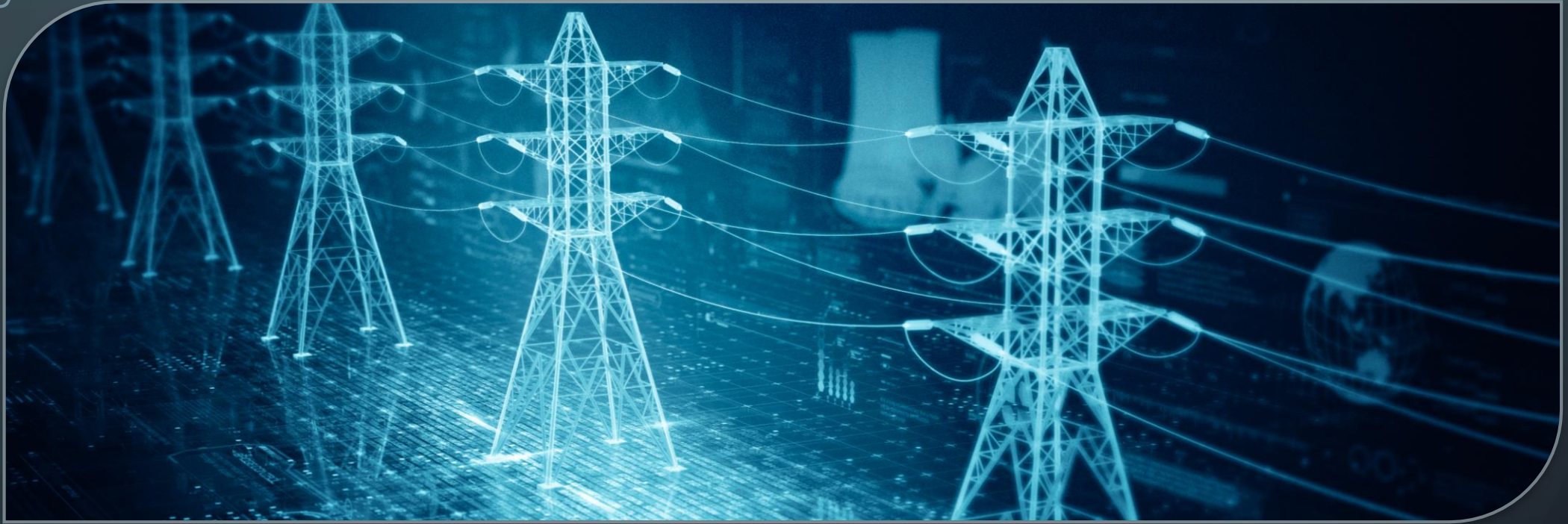
APPROACH

- Thanks to the latest advances in computing, and specifically in machine learning and data science, we can now get close to accurate predictions of how much electricity will be used in the long, medium, and short terms.



PROJECT DATA

- Hourly electricity demand for Saudi Central Operating Area
 - Covers year from 2012 to 2017
 - Total of 52,607 records
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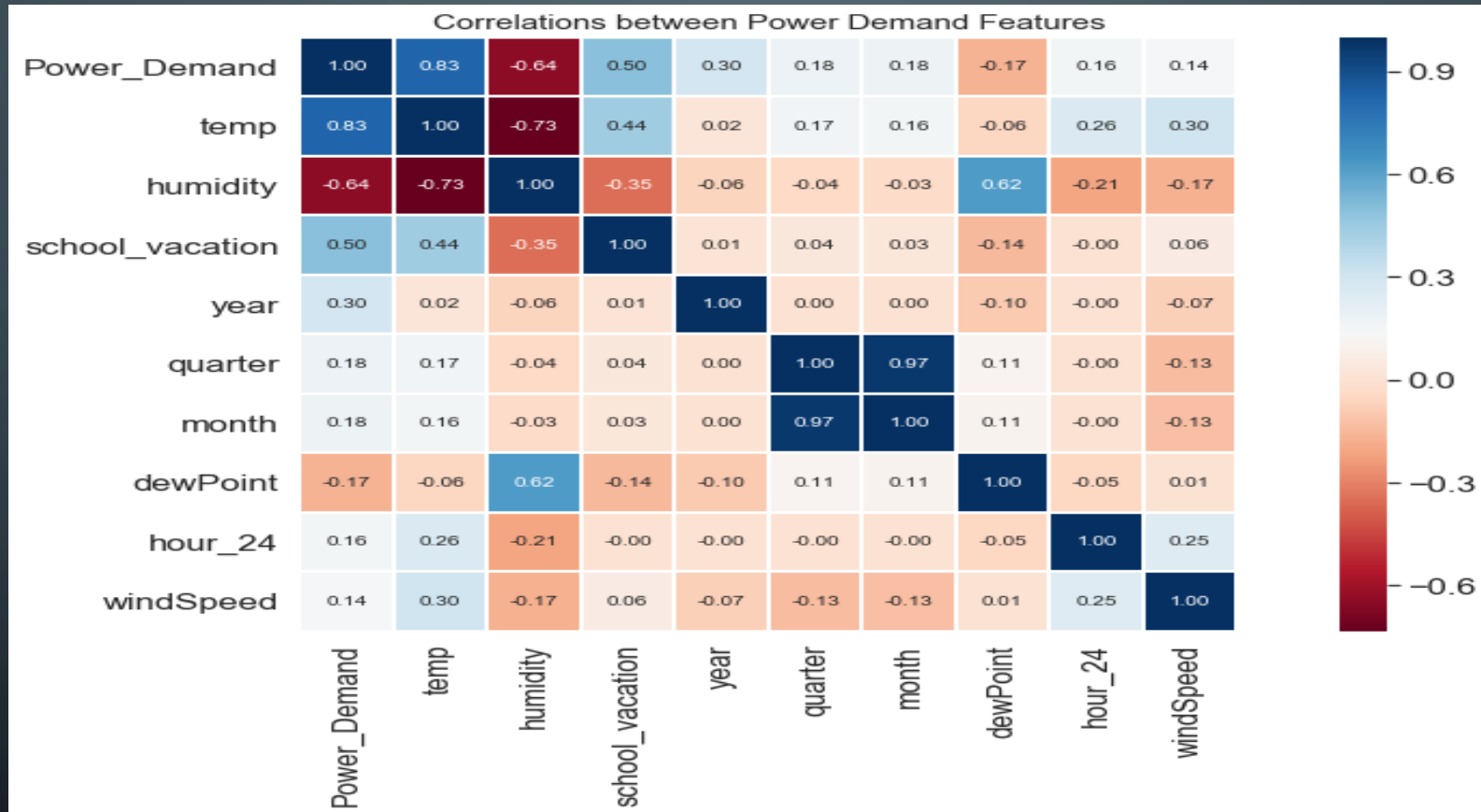


FEATURE ENGINEERING & EDA

FEATURE ENGINEERING

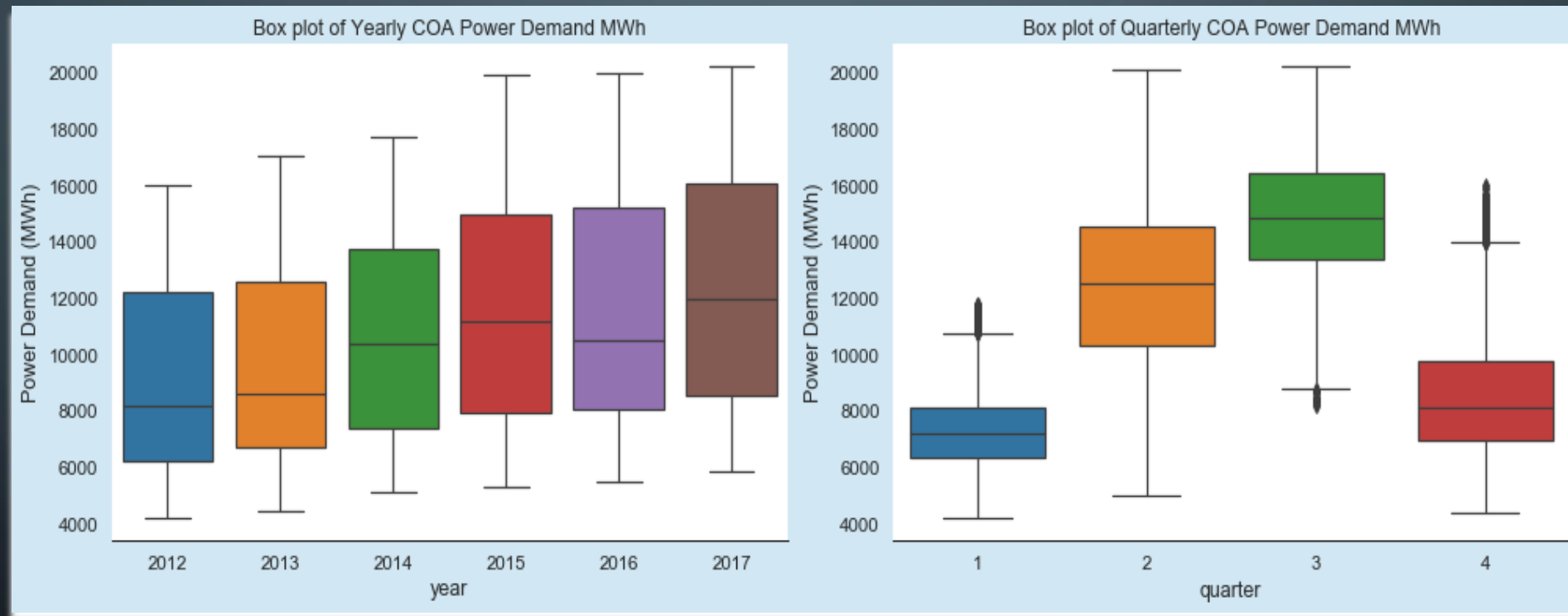
Feature	Description
COA Power Consumption	Central operating area demand (MWh)
Temperature	We have got this from Darksky API. Showing the hourly temperature of Riyadh City from 2012-2017
Humidity	Hourly humidity of Riyadh 2012-2017 (Dark sky API)
WindSpeed	Hourly wind speed of Riyadh (Dark sky API)
School_Vacation	Is it school vacation or not? (0,1)
Weekend_bool	Is it weekend or not? (0,1)
Year	Year of the observation
Quarter	Quarter of the year of the observation
Month	Month of the year of the observation
day	Day of the year of the observation
Hour_24	Hour of the day using 24-hour scheme

FEATURES CORRELATIONS



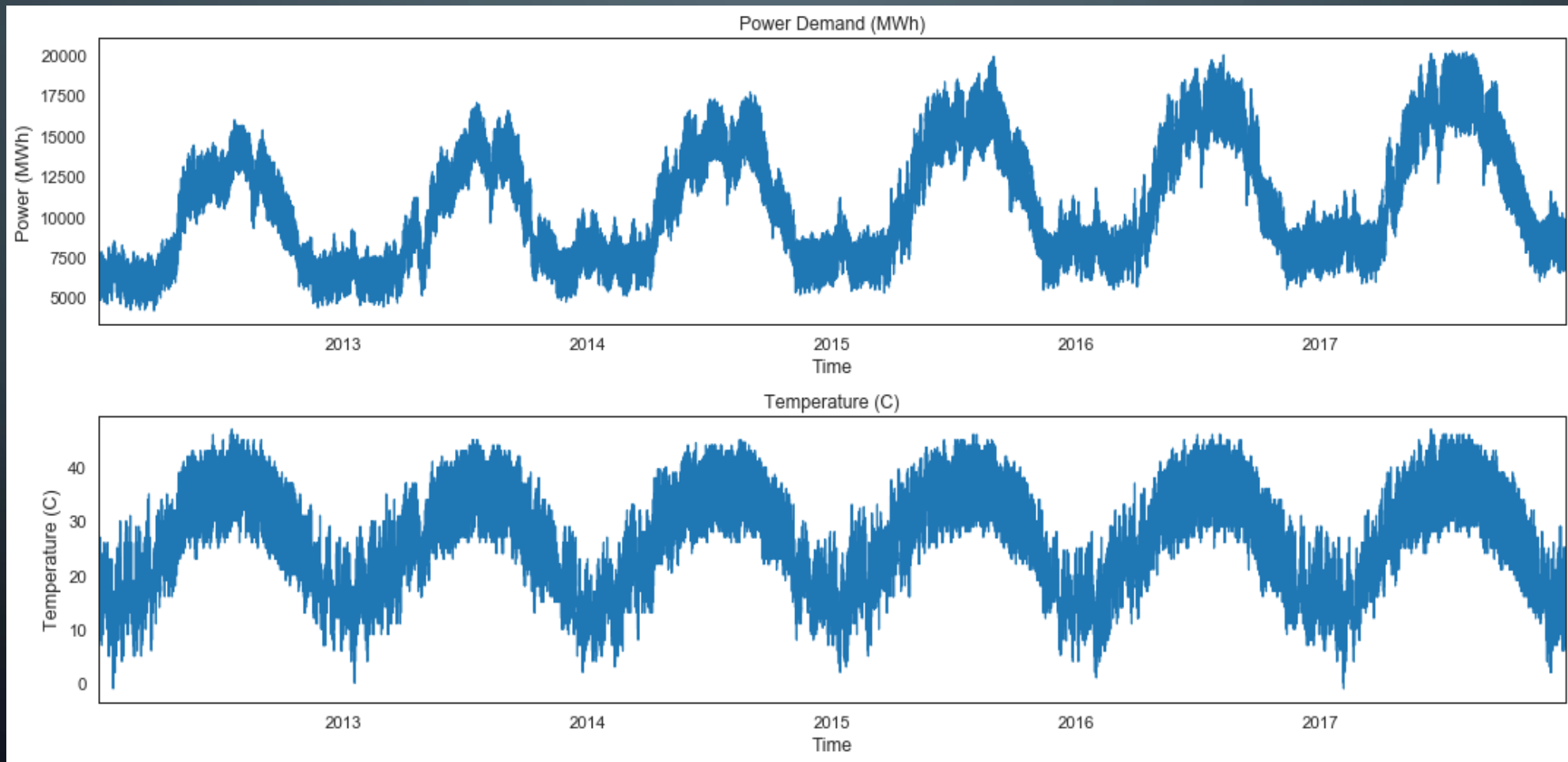
- Notice: High correlation with temperature and humidity. Noticeable correlation with school vacation

BOX PLOT

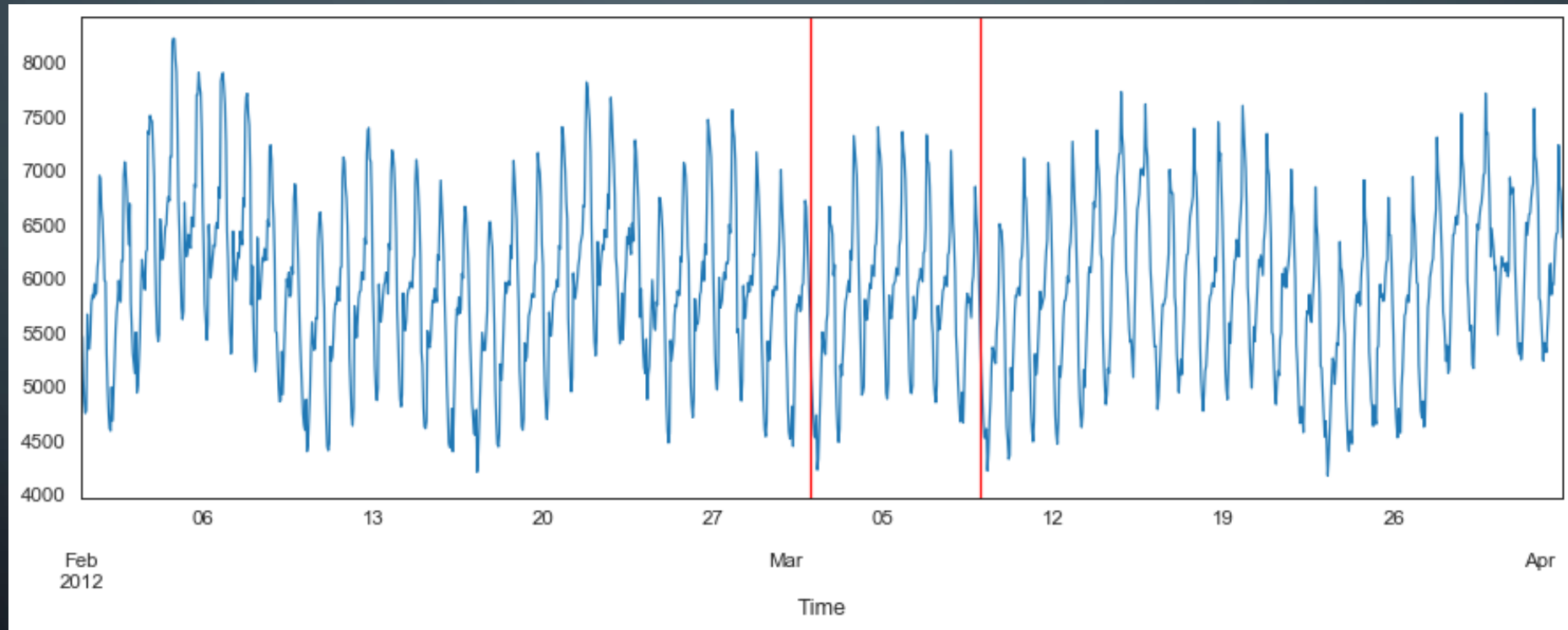


- Notice: An increase trend in power demand

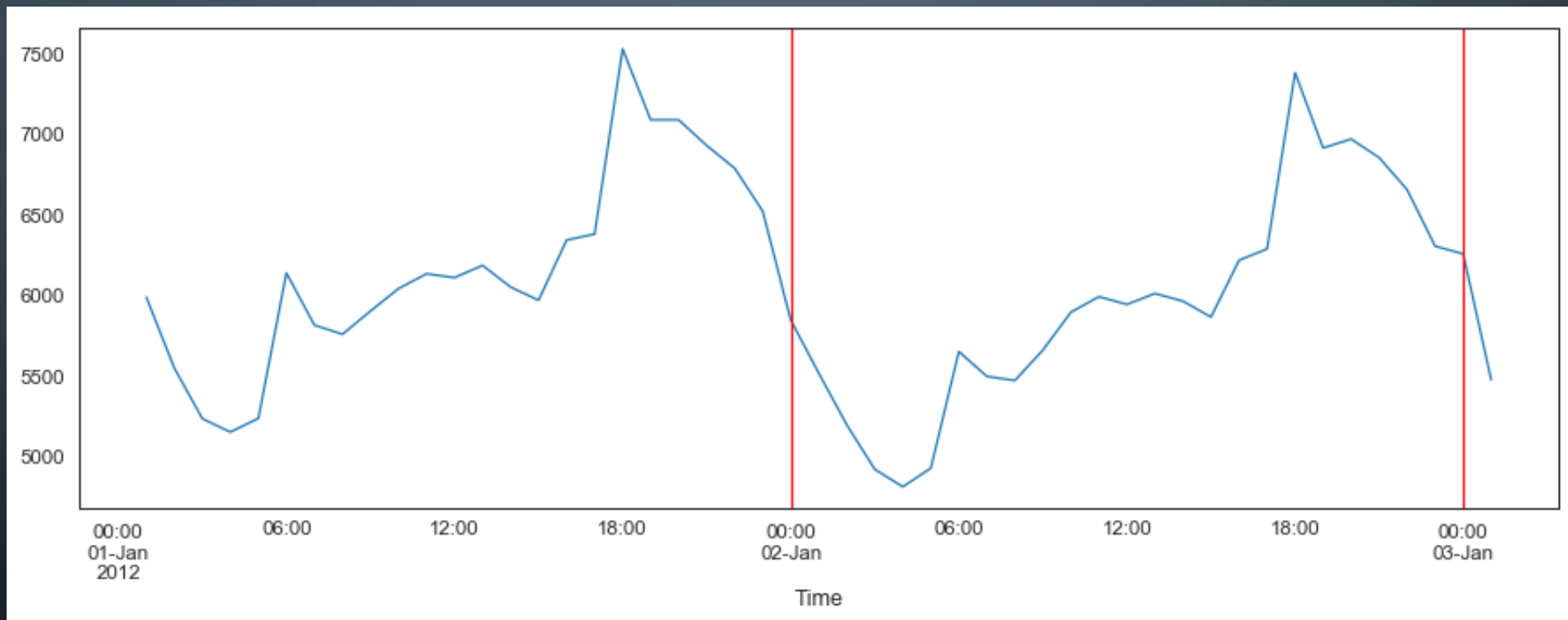
YEARLY SEASONALITY



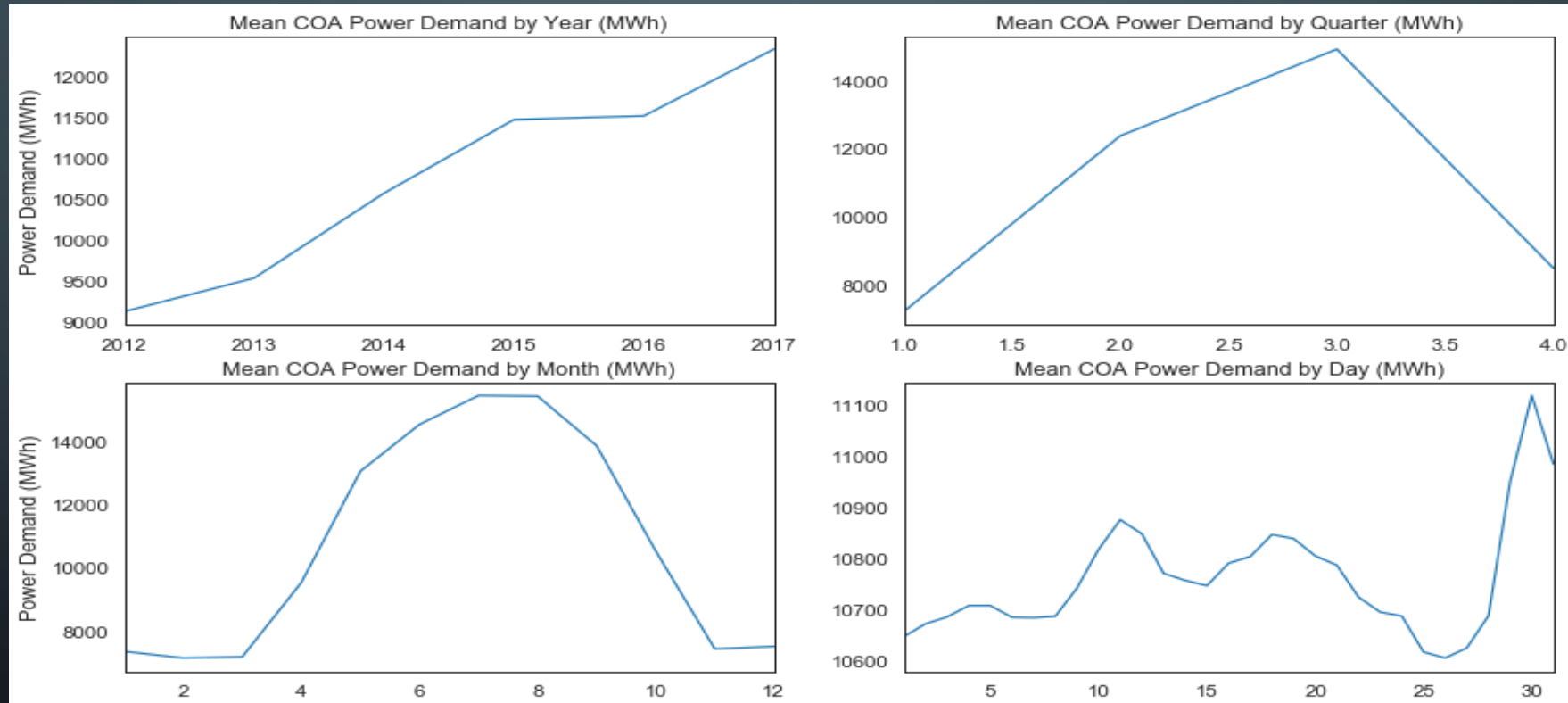
WEEKLY SEASONALITY



DAILY SEASONALITY



POWER DEMAND IN DIFFERENT TIME FRAME





MACHINE LEARNING

PREDICTION METHODOLOGY

- We tried different models with different time frames, we assumed that Saudi Electricity Company (SEC) would like short and long term predictions, so we grouped our data to make prediction as follow:
 - Hourly prediction for next year
 - Daily prediction
 - Monthly prediction
 - Next day hourly prediction

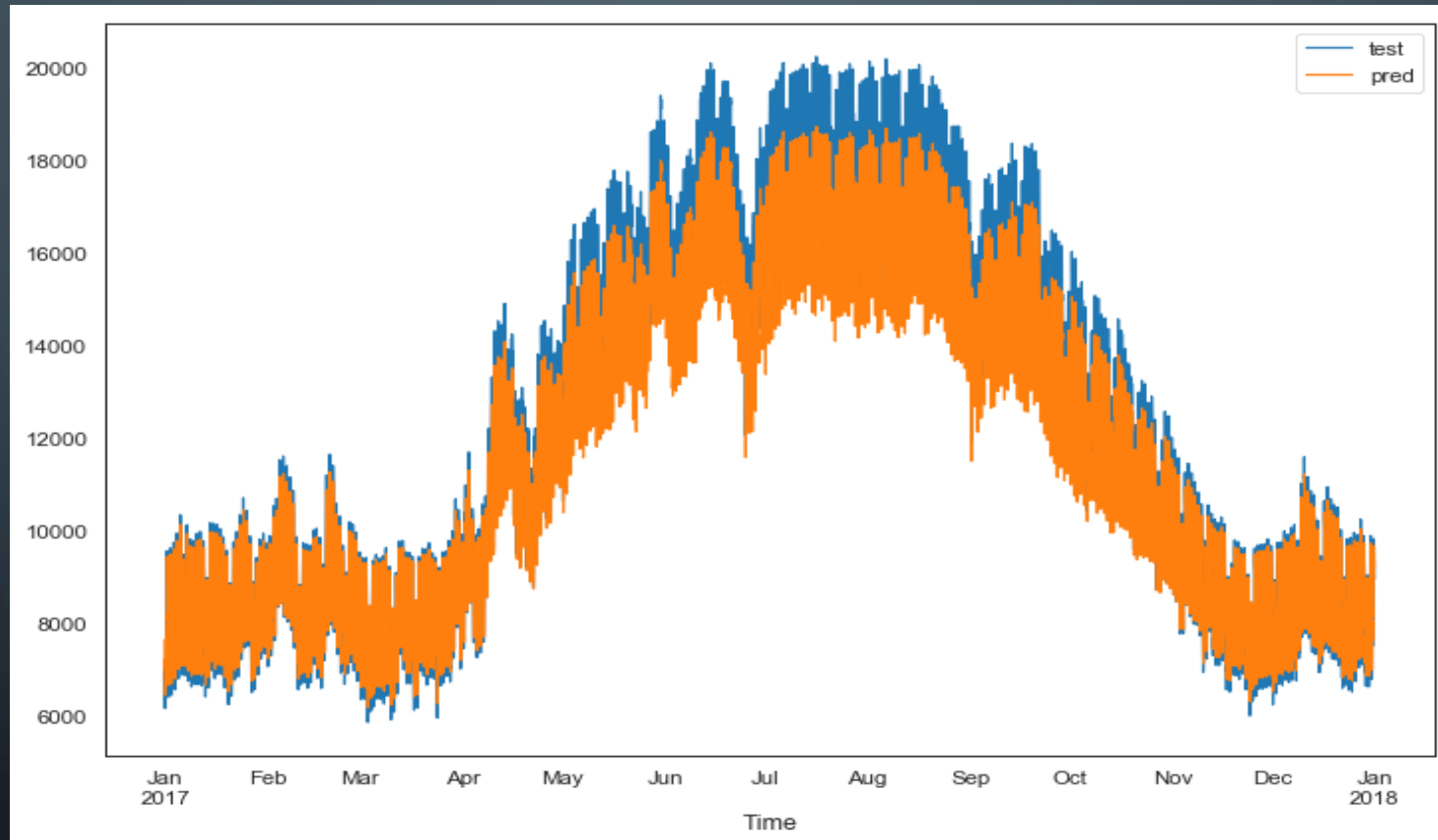
MODELS USED

The models we used are:

- SARIMAX (Seasonal AutoRegressive Integrated Moving Averages with eXogenous Regressors)
- RNN LSTM cells (Long Short-Term Memory)
- Prophet
- XGBoost (eXtreme Gradient Boosting)
- lightGBM (A Highly Efficient Gradient Boosting Decision Tree)

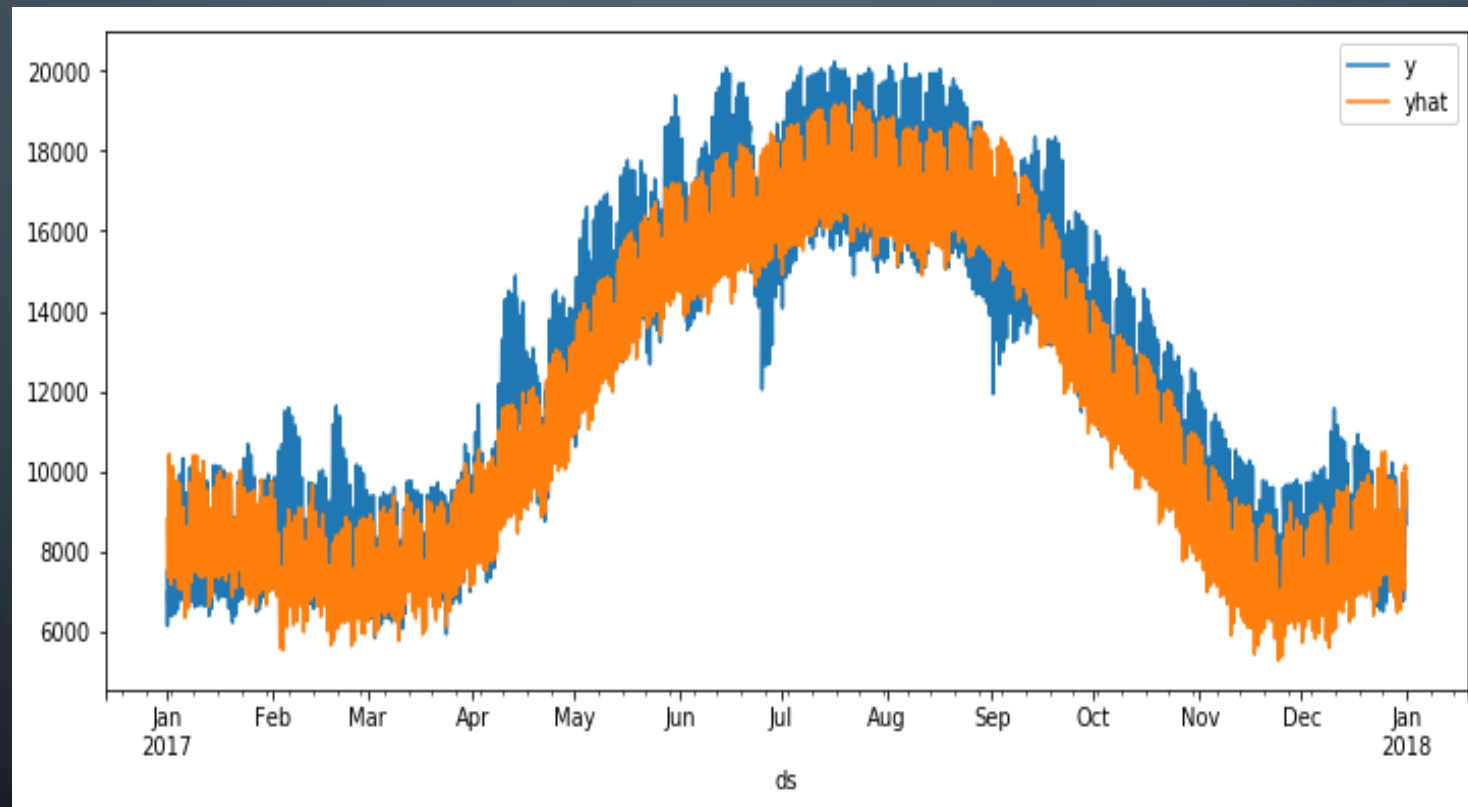
HOURLY DATA PREDICTION

LSTM hourly prediction vs actual (MWh)



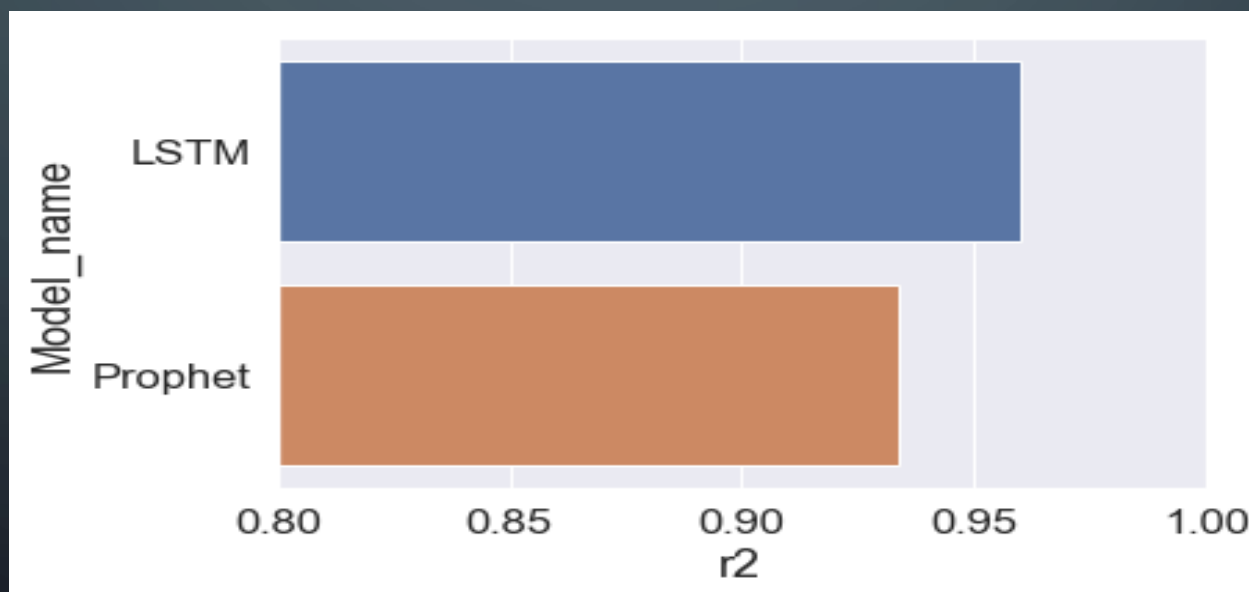
HOURLY DATA PREDICTION

Prophet hourly prediction vs actual (MWh)



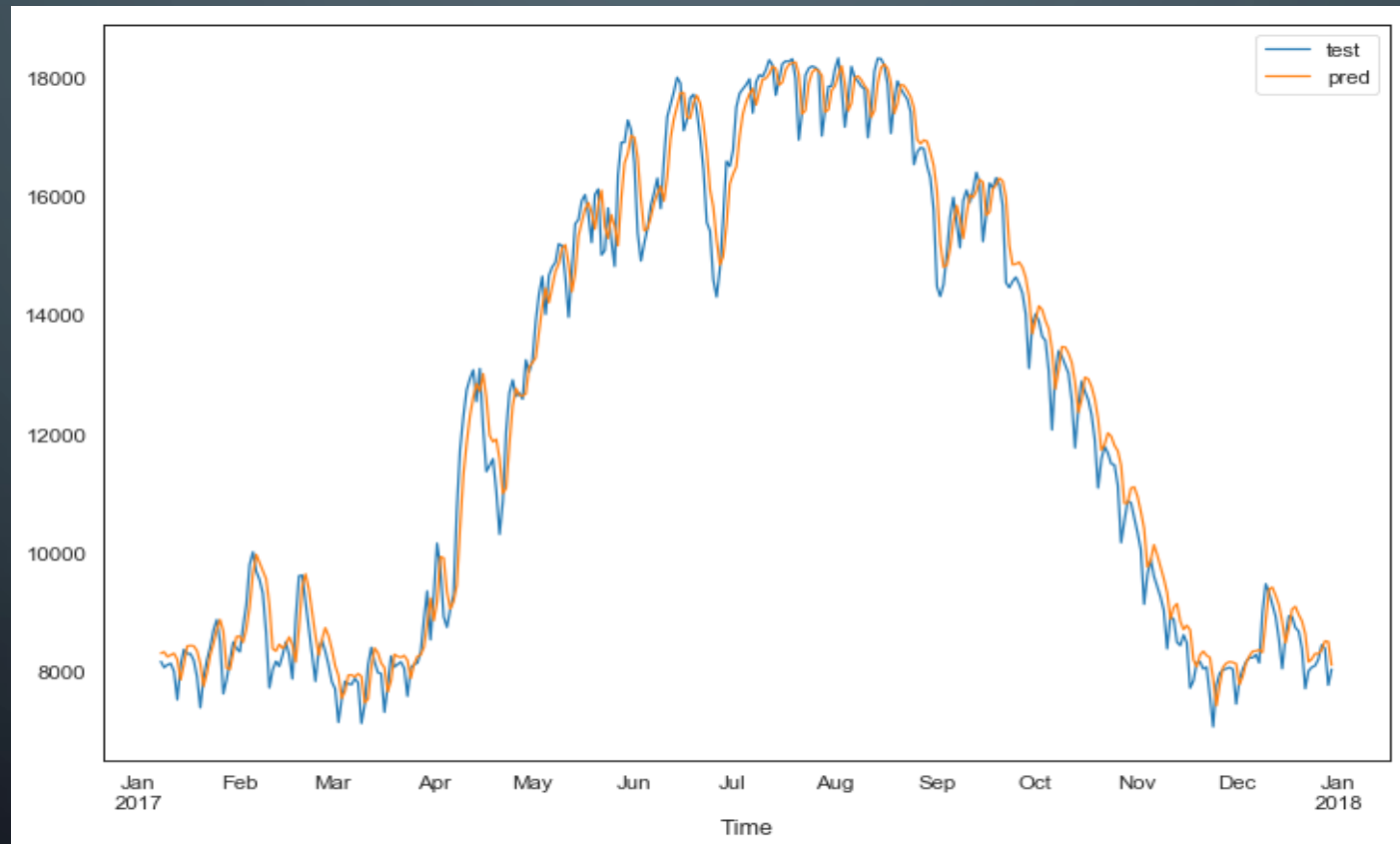
ML HOURLY PREDICTION SUMMARY

Model name	RMSE	r2
LSTM	821.53	0.96
Prophet	1034.6	0.93



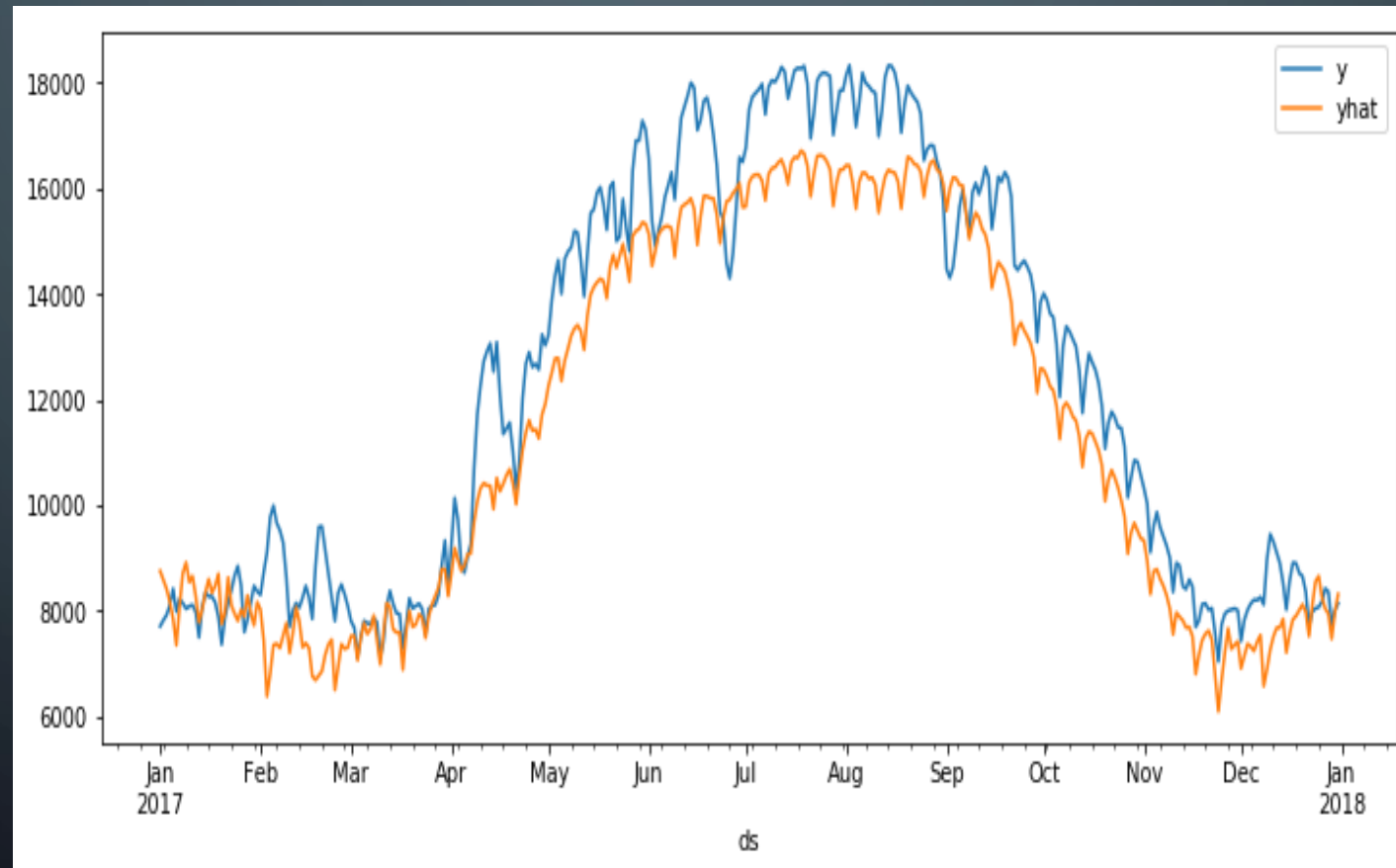
DAILY PREDICTION

LSTM daily prediction vs actual (MWh)



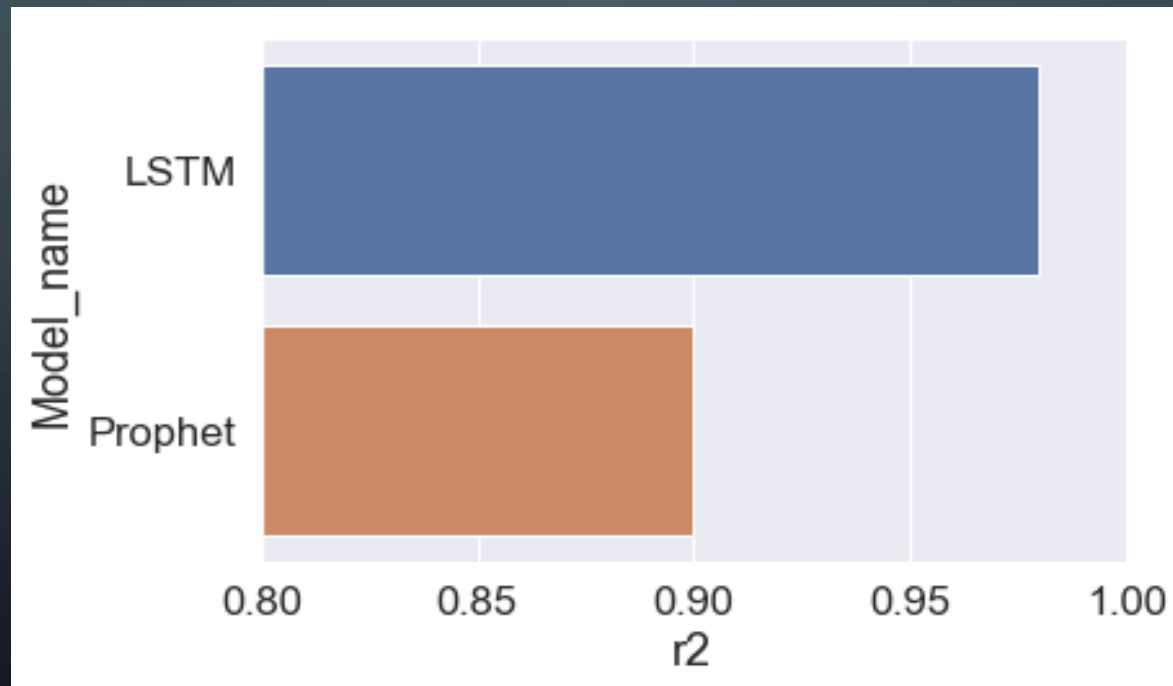
DAILY PREDICTION

Prophet daily prediction vs actual (MWh)



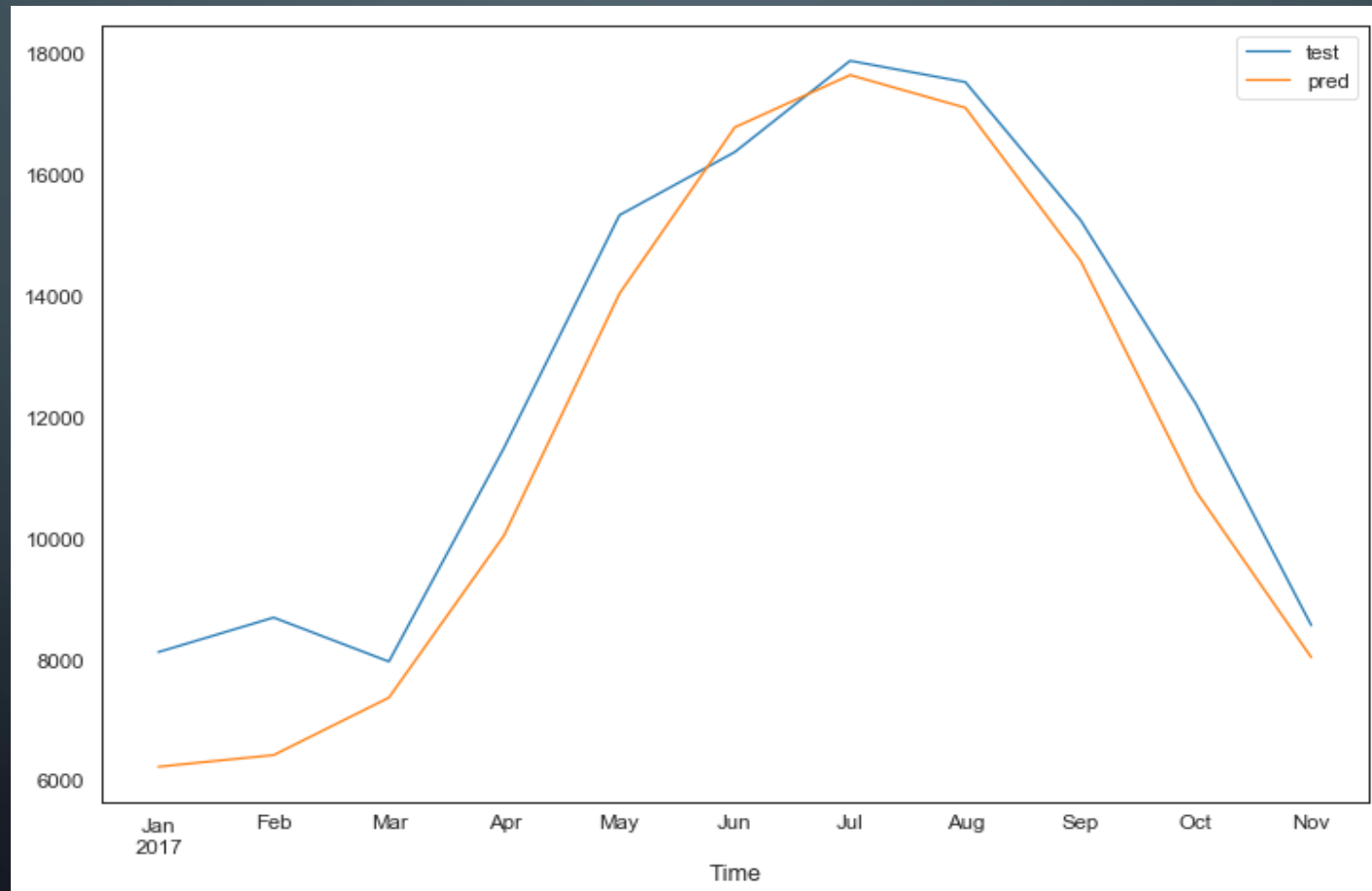
ML DAILY PREDICTION SUMMARY

Model name	RMSE	r2
LSTM	528.323	0.98
Prophet	1232.268	0.9



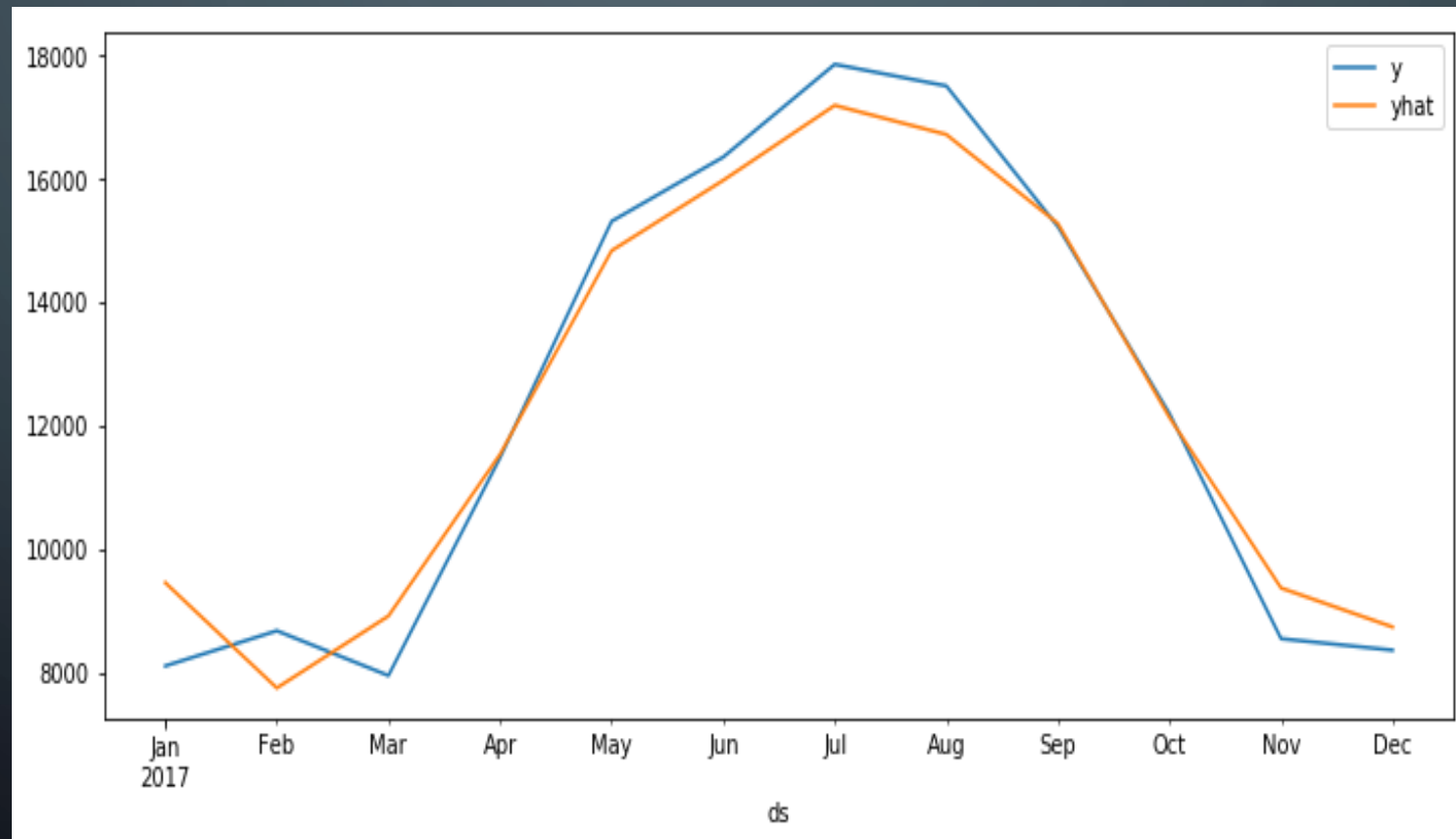
MONTHLY PREDICTION

LSTM monthly prediction vs actual (MWh)



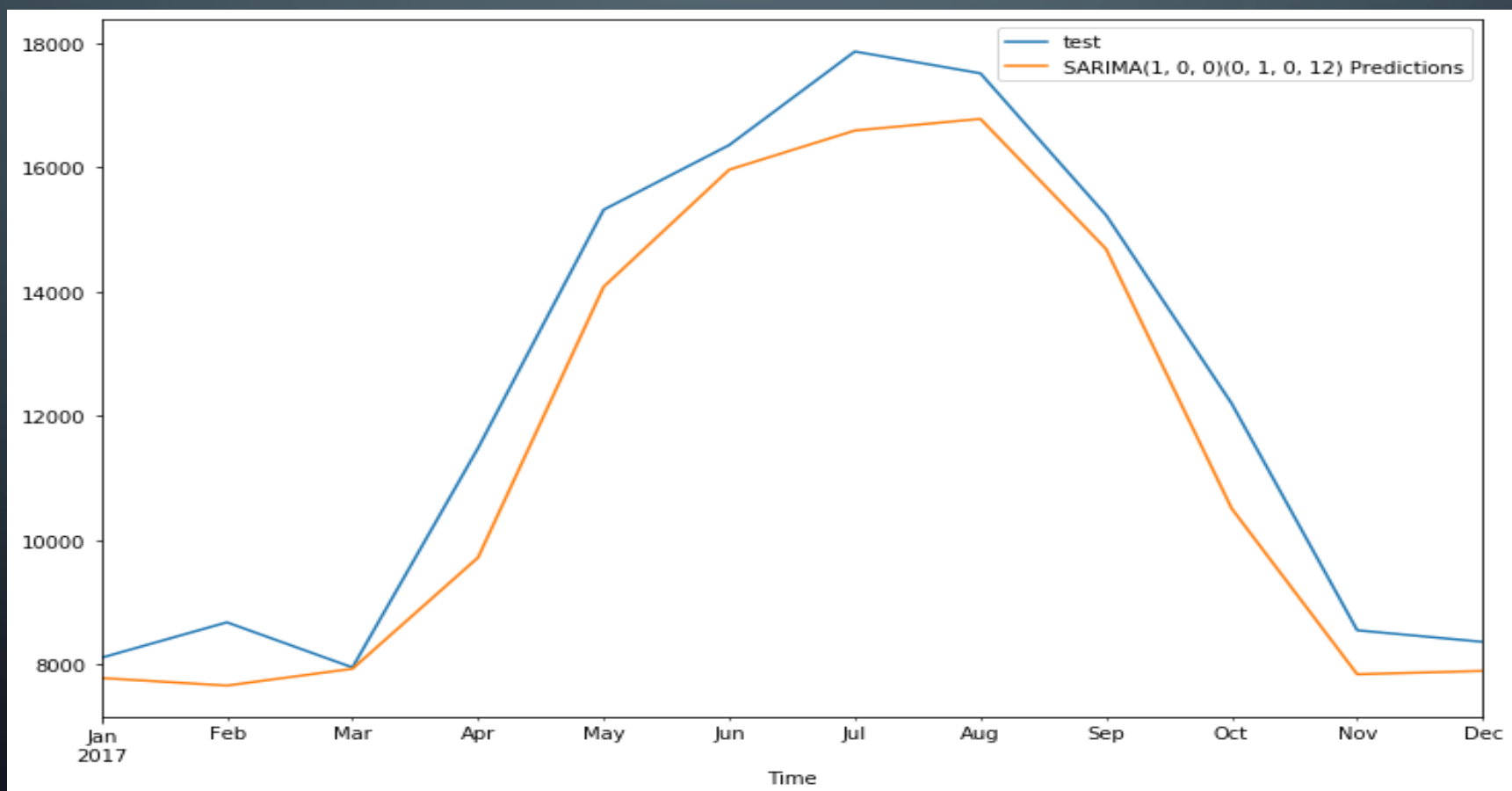
MONTHLY PREDICTION

Prophet monthly prediction vs actual (MWh)



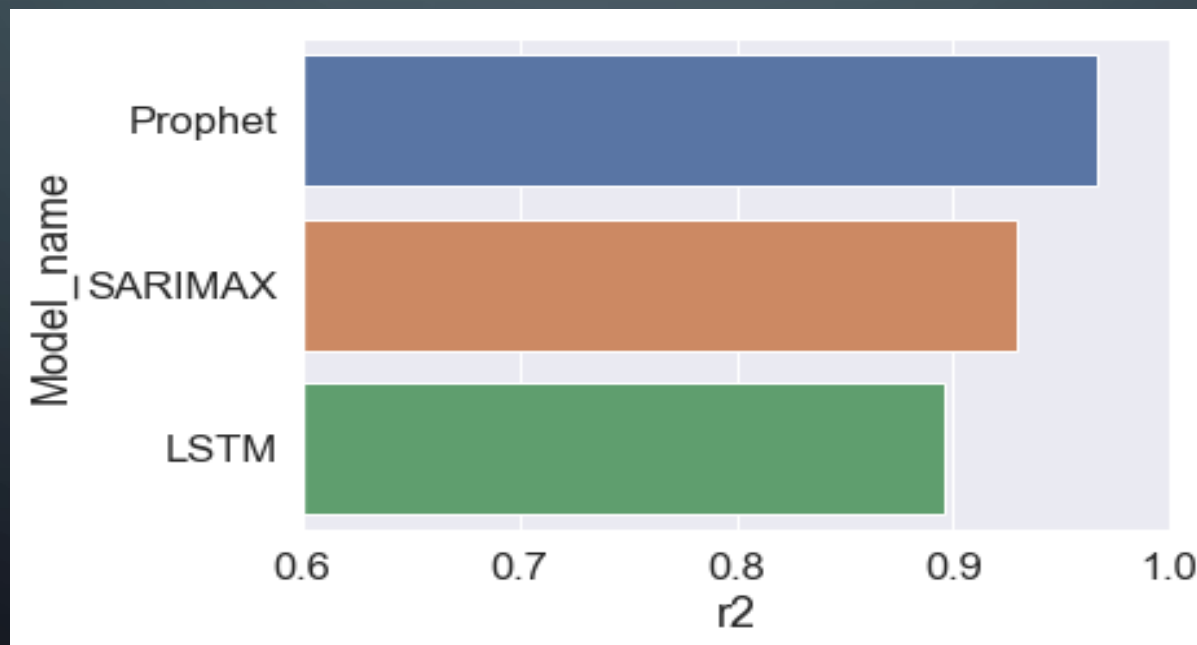
MONTHLY PREDICTION

SARIMAX monthly prediction vs actual (MWh)



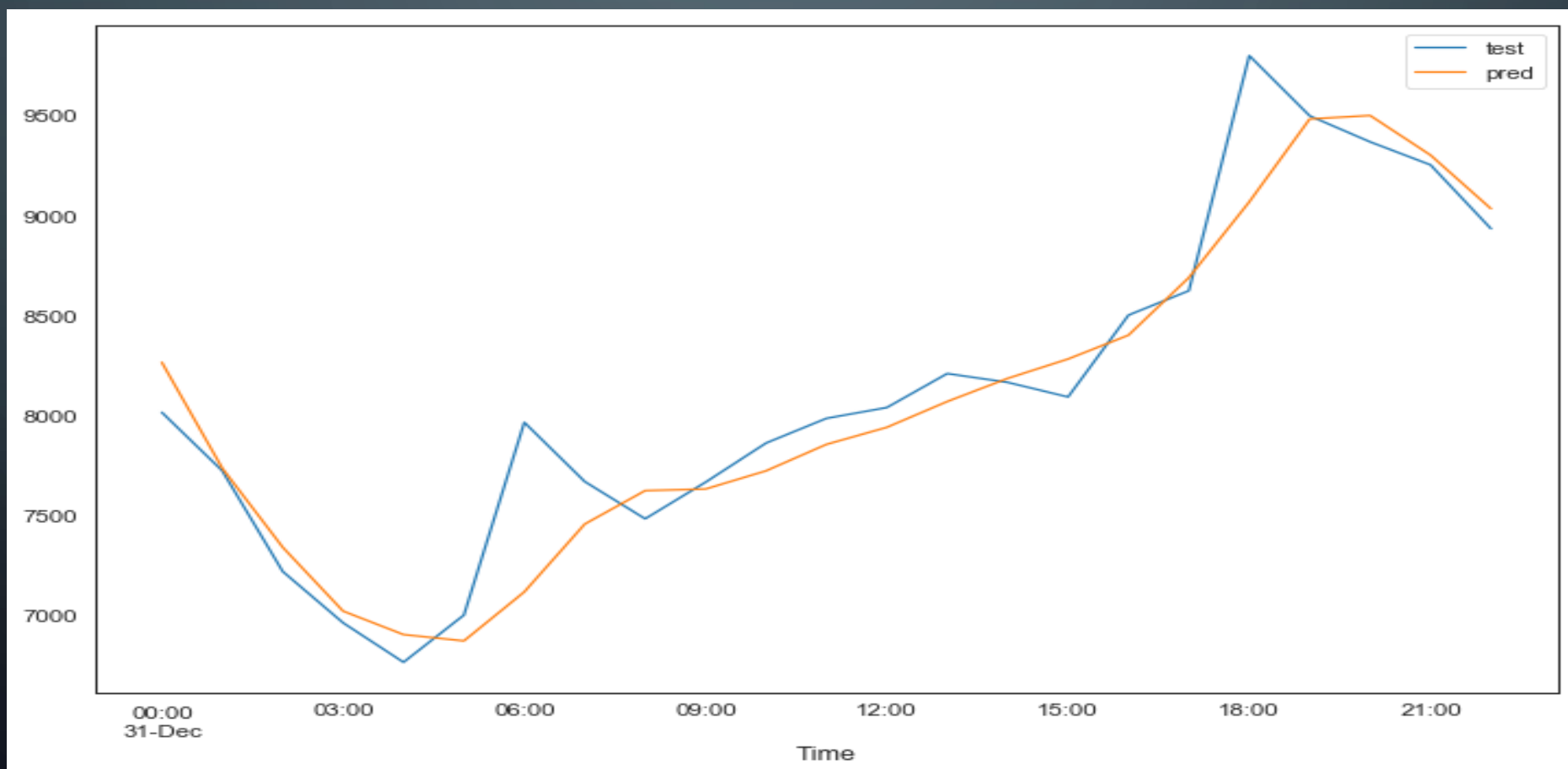
ML MONTHLY PREDICTION SUMMARY

Model name	RMSE	r2
LSTM	1208.16	0.9
Prophet	699.8	0.97
SARIMAX	998.6	0.93



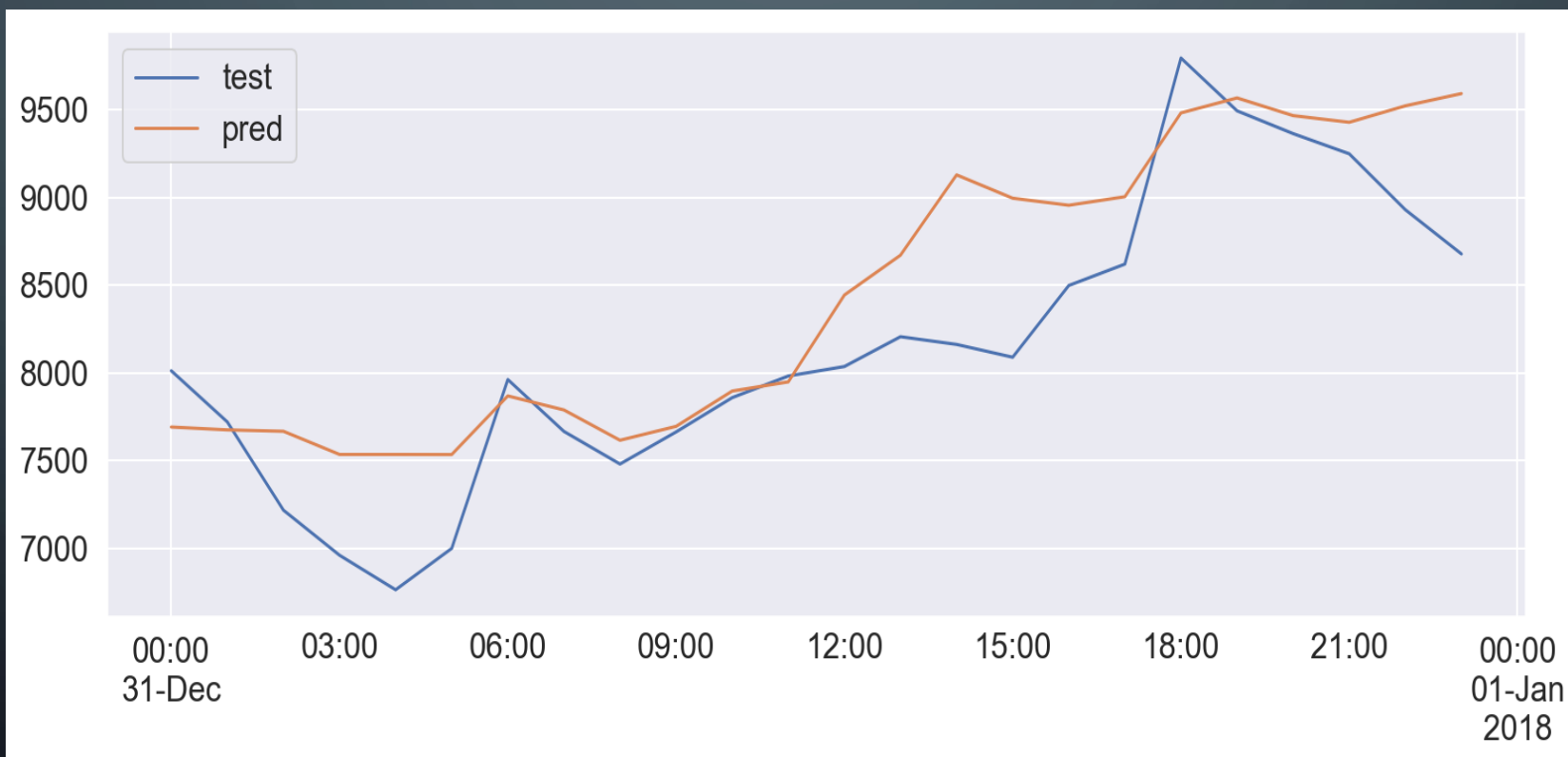
NEXT DAY HOURLY PREDICTION

LSTM Next day hourly prediction vs actual (MWh)



NEXT DAY HOURLY PREDICTION

Xgboost Next day hourly prediction vs actual (MWh)



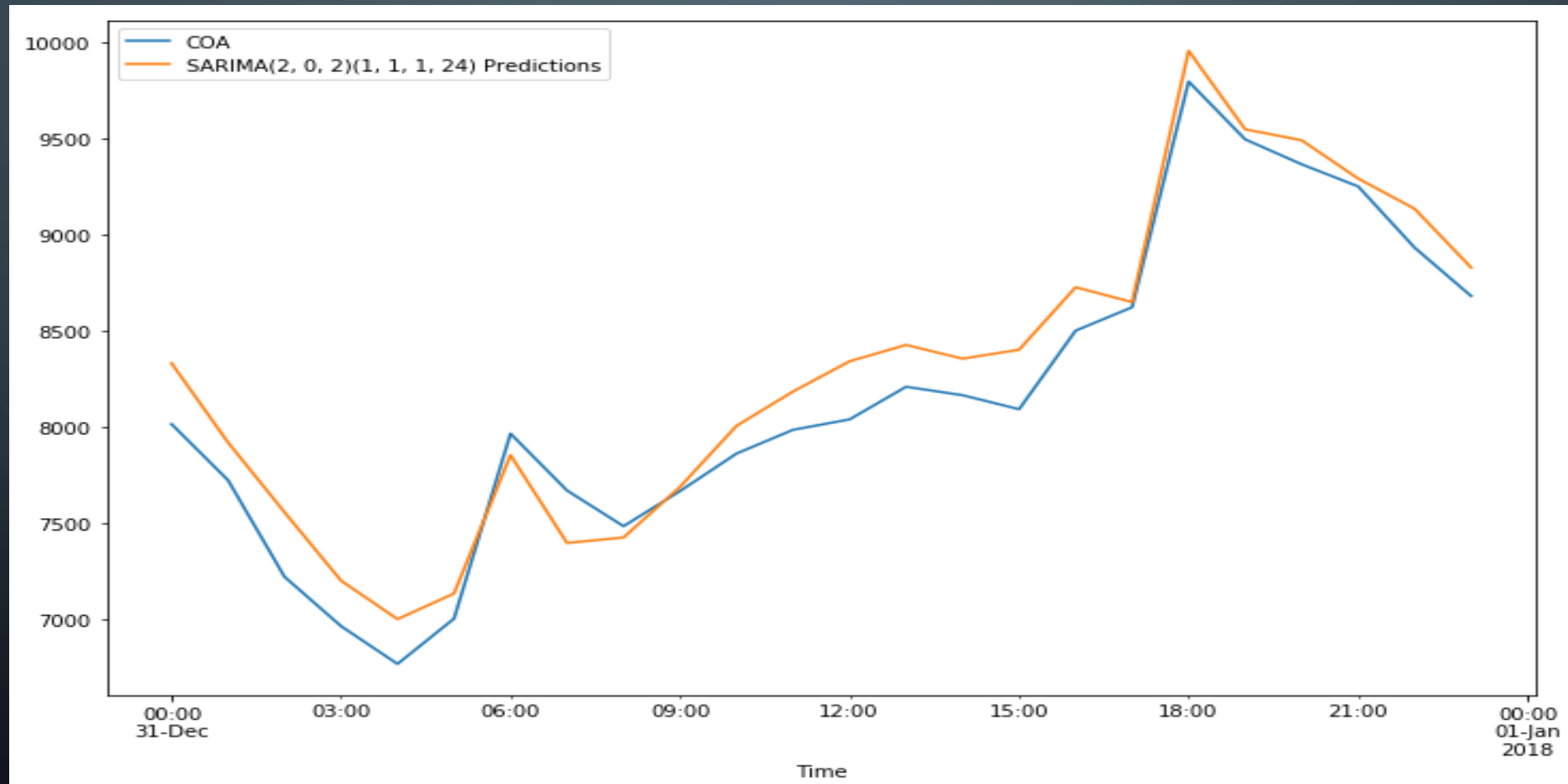
NEXT DAY HOURLY PREDICTION

lightGBM Next day hourly prediction vs actual (MWh)



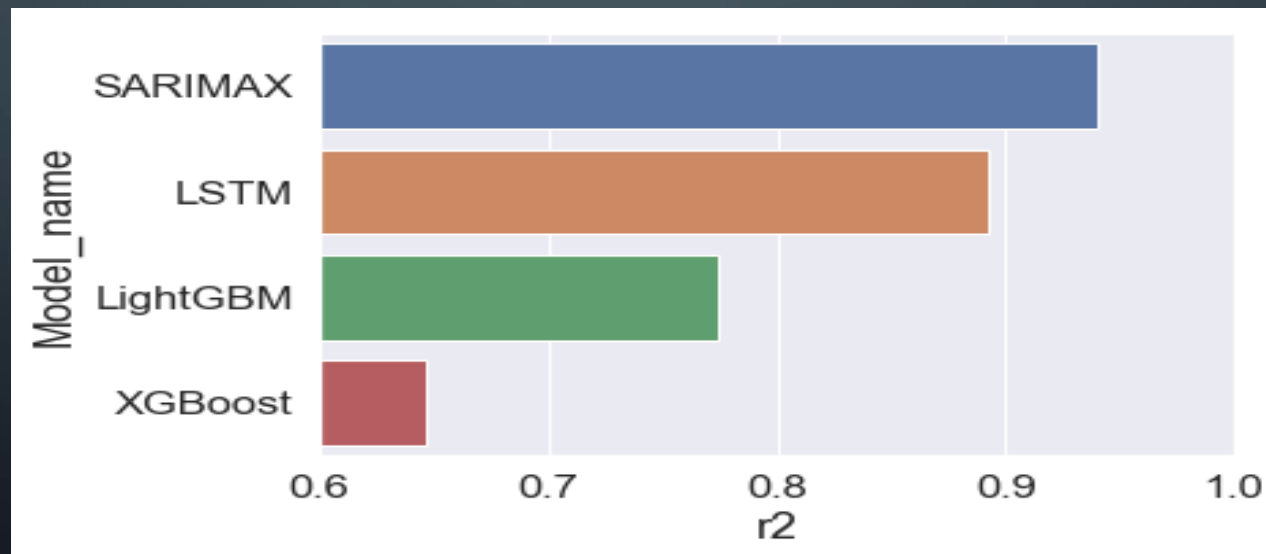
NEXT DAY HOURLY PREDICTION

SARIMAX Next day hourly prediction vs actual (MWh)



ML HOURLY NEXT DAY PREDICTION SUMMARY

Model name	RMSE	r2
LSTM	262.14	0.89
XGBoost	474.13	0.65
lightGBM	378.9	0.77
SARIMAX	200.5	0.94





FINAL WORDS

WHAT IS NEXT

- Getting the power load for individual cities can lead to an increase in the predicting result as each city has different temperature which affect the prediction.
- Predicting the daily power load peak.
- Implement a web interface that take an input and get the prediction from the model and present it.
- Exploring R programming language as it has powerful models for statistics and time series predictions.

CONCLUSION

- Machine learning can be used to predict power load with high accuracy rate.
- Electricity companies can use such a model to predict short/mid/long term power load and plan their power generation accordingly.
- This can save resources, money, and gives better services to their customers.

ACKNOWLEDGMENT

- Thanks to our instructors and IAs : **Junaid Qazi, Amine Mehabilia, Fatimah Aloqayli, and Fahad Alsharekh** for all their support they provide during the course and for this project, it was a wonderful experience.



QUESTIONS