Prediction of Renewable Power Loss caused by Feed-In Management

Capstone Presentation
26.November 2020
Tjade Appel &
Jonas Jaenicke

Using Advanced Linear Models and Recurrent Neural Networks for Time Series Predictions

Tjade Appel

- B.Eng. in Mechanical Engineering
- M.Sc. in Sustainable Energy Systems
- M. Thesis: Modelling Environmental Conditions for the Design of Offshore Wind Turbines
- 1 year internship experience in the energy industry
- If you want to talk sports, I'm your man!

Looking for a challenging position as a Jr. Data Scientist.

GitHub.com/tjade27
LinkedIn.com/in/Tjade-Appel

Jonas Jaenicke

- B.Eng. in Industrial Engineering
- M.Sc. in Computer Science
- M. Thesis: Modelling of Pumped Hydro Power Energy Storage
- 2 years internship experience in energy industry
- adventures Kitesurfer & Rock Climber

Let’s explore together! Data, Systems, Cultures, Models.

GitHub.com/JonJae
LinkedIn.com/in/JonasJaenicke

TABLE OF CONTENTS

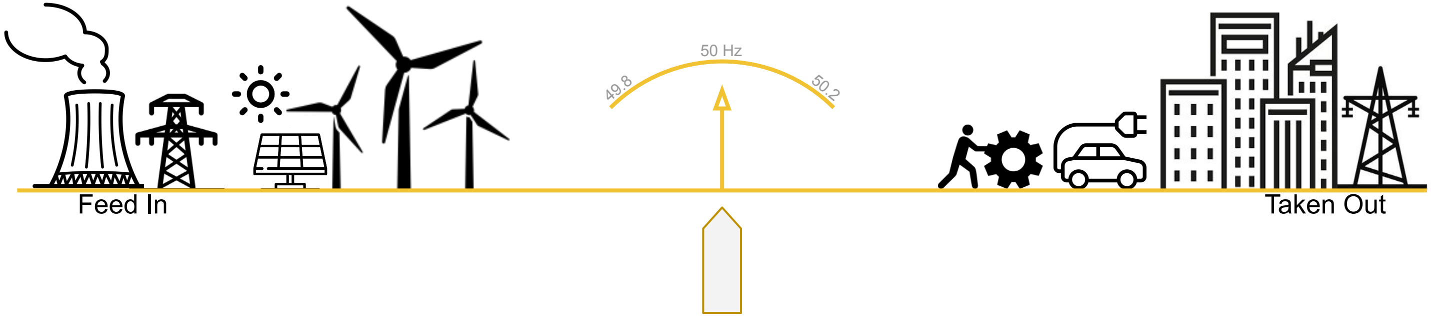
BACKGROUND

DATA ANALYSIS

MODEL RESULTS

FUTURE WORK

Energy fed into the system needs to equal energy taken out of the system at all times. This was already difficult with conventional electricity generation. It is even more difficult with a combination of volatile renewable energy sources. For example, on a windy and sunny day in June, there is potentially a lot of excess wind energy. Feed-In Management describes the curtailment of energy to protect grid infrastructure of overloads.
What if we could instead use the excess energy?



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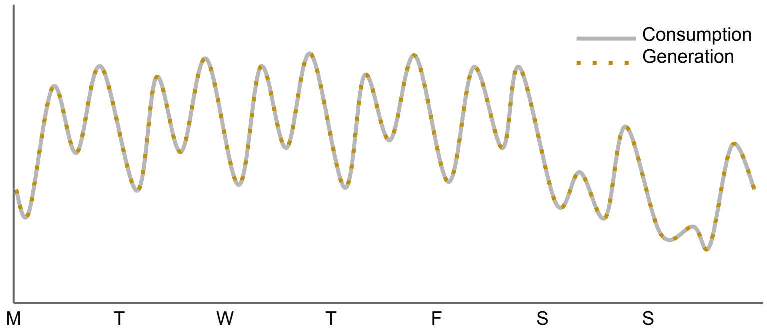
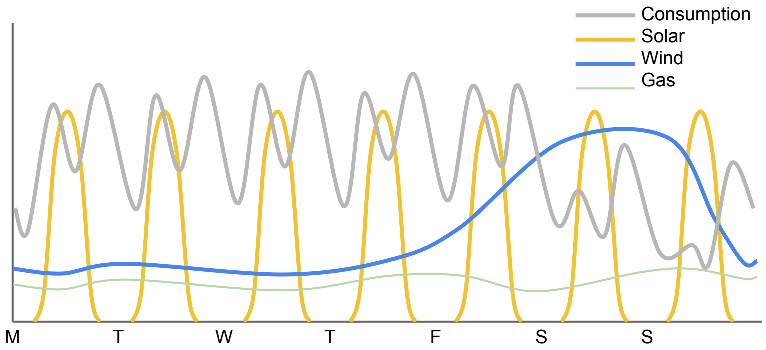
Conventional Electricity Grid



Renewable Electricity Grid



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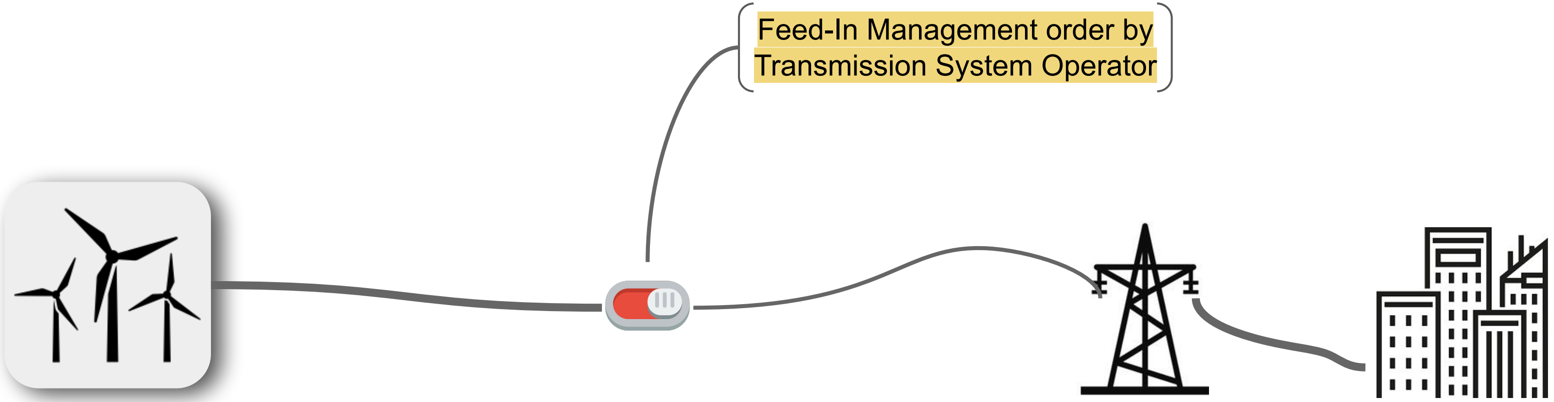

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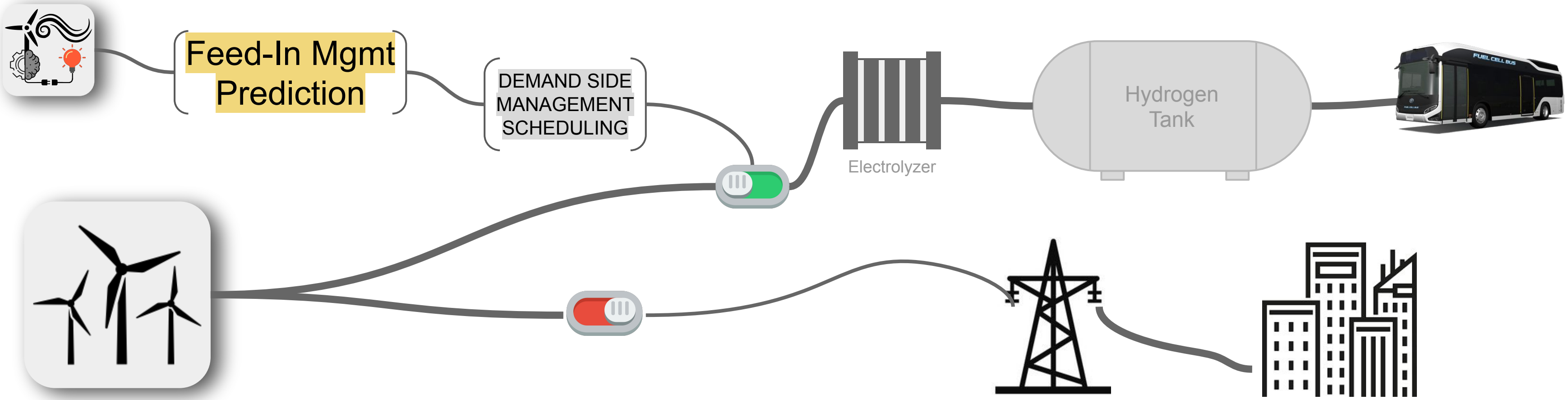


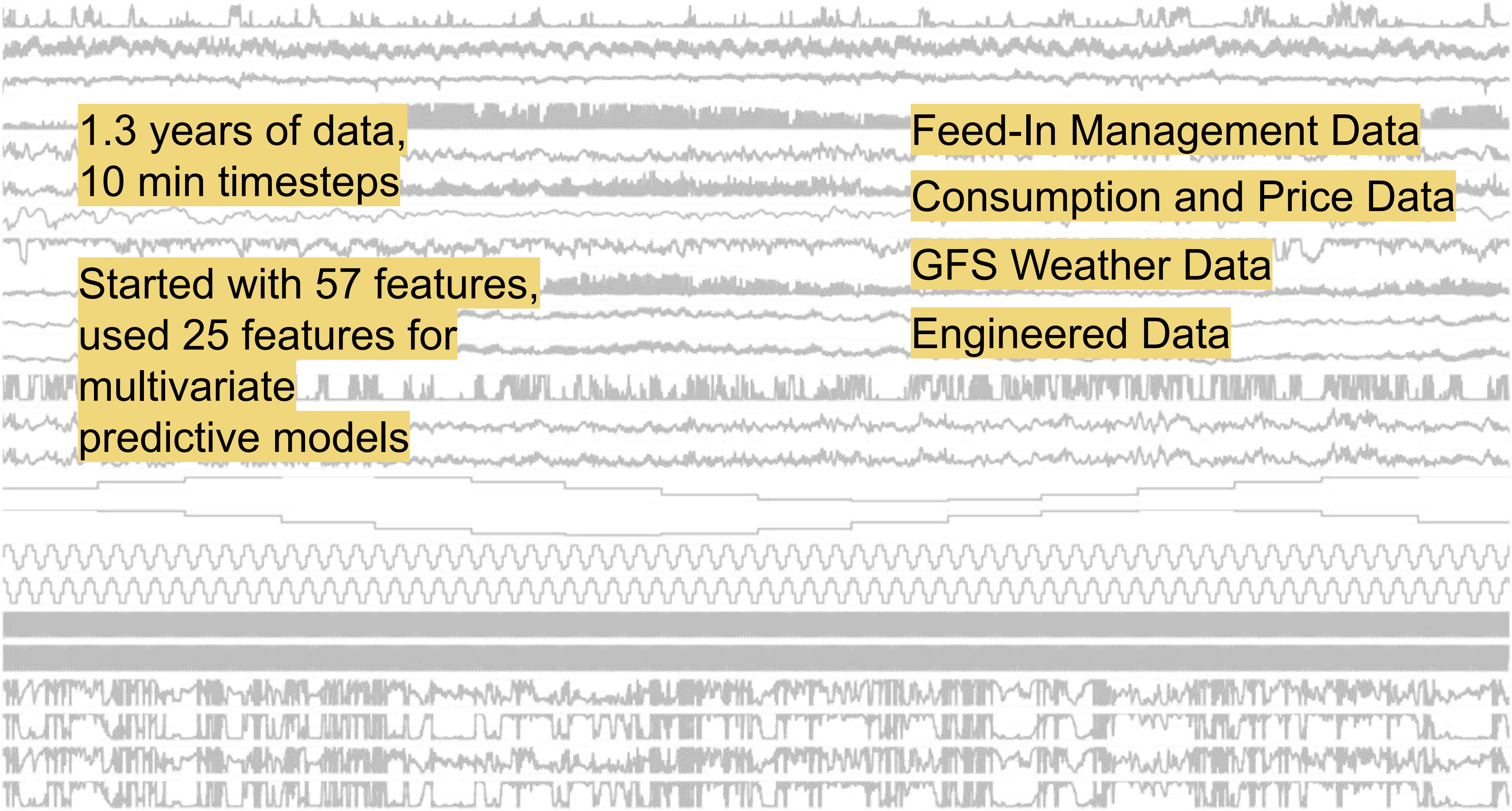
BACKGROUND

DATA ANALYSIS

MODEL RESULTS

FUTURE WORK

Onshore Wind Farm in Twistringen, Germany. 6 Enercon E66 and 6 E70 turbines with 22,8 MW installed capacity



1.3 years of data,
10 min timesteps

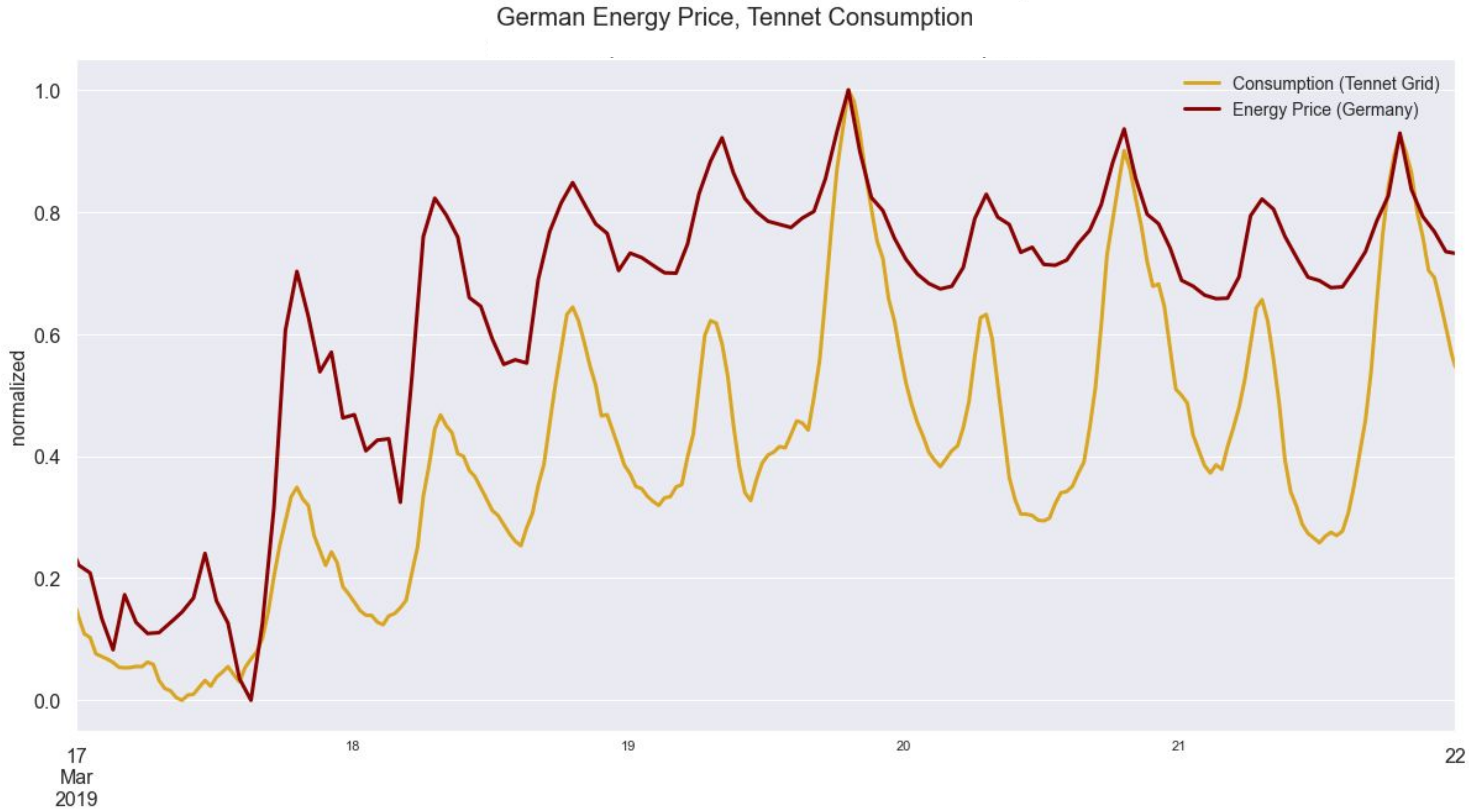
Started with 57 features, used 25 features for multivariate predictive models

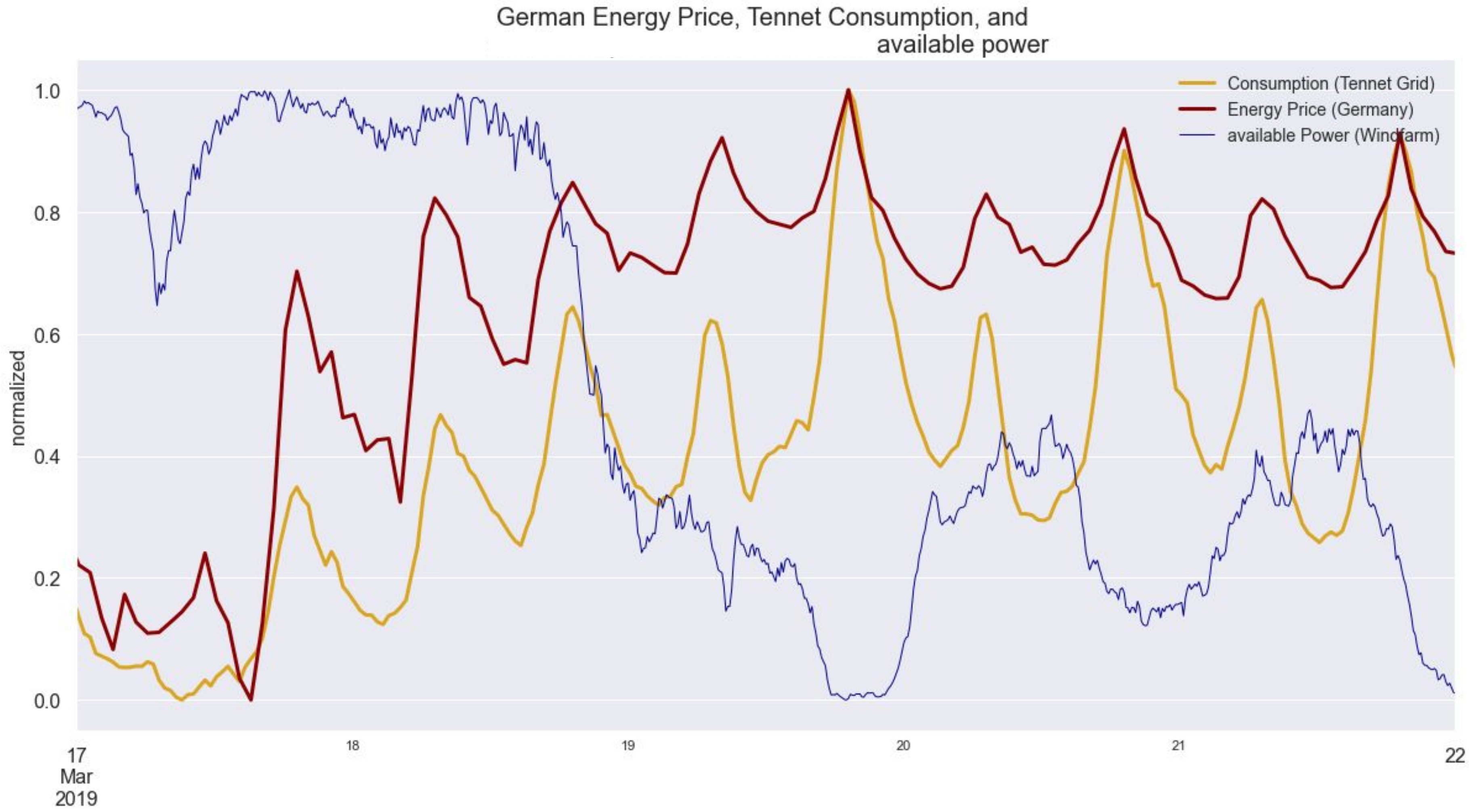
Feed-In Management Data

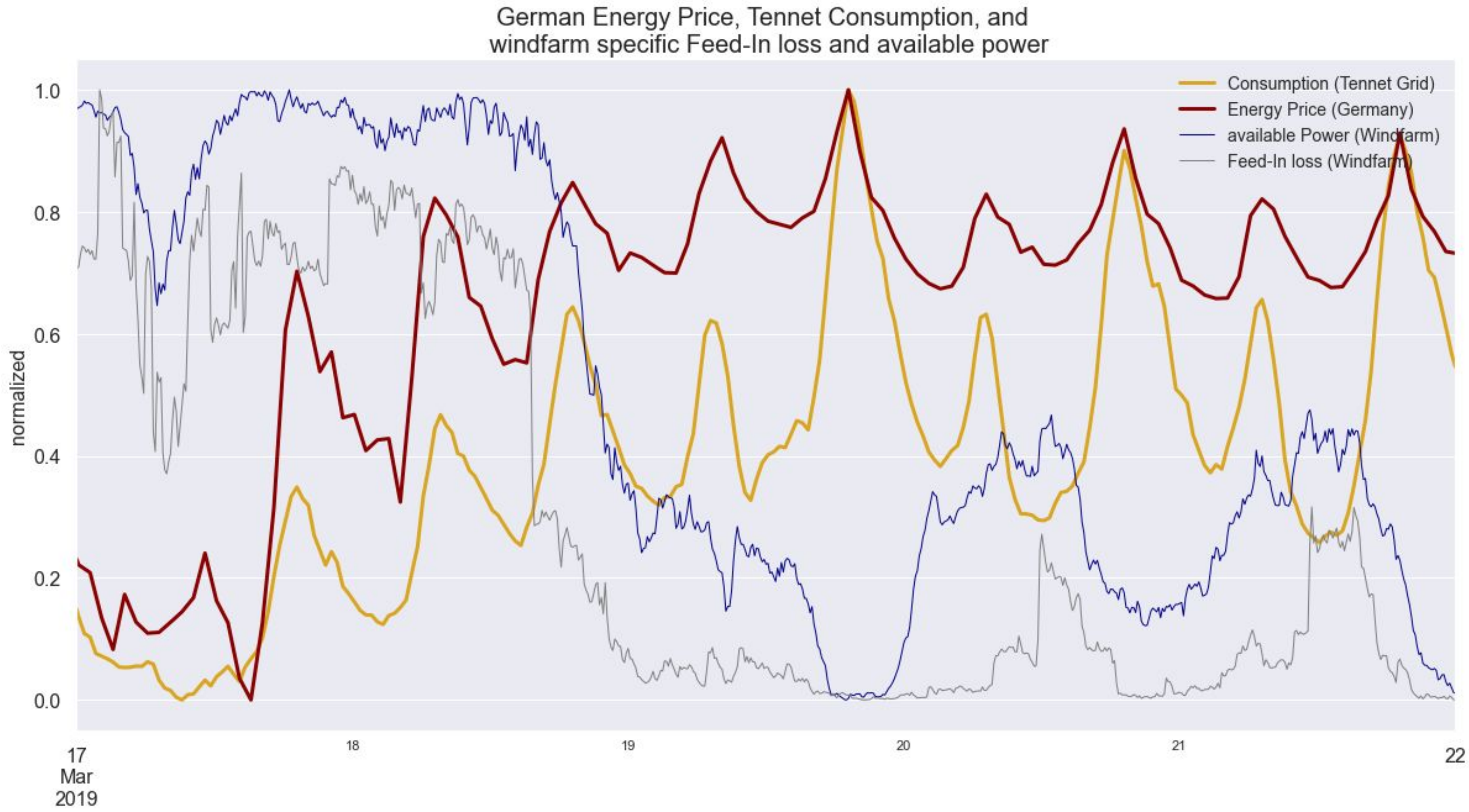
Consumption and Price Data

GFS Weather Data

Engineered Data

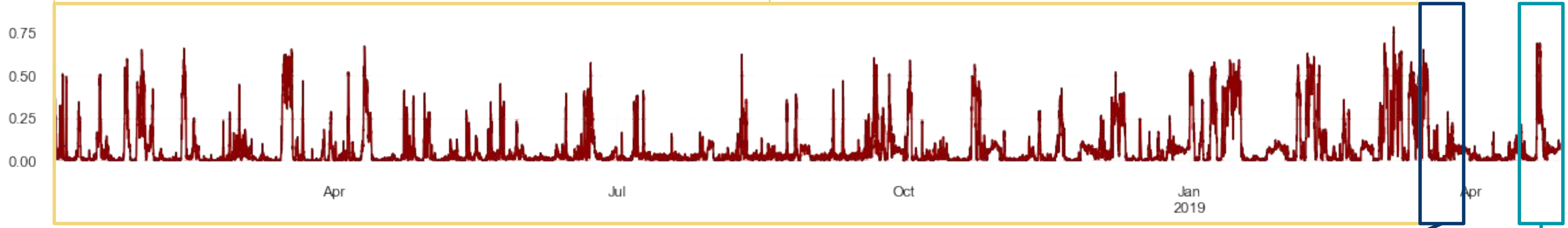

German Energy Price, Tennet Consumption
Consumption (Tennet Grid)
Energy Price (Germany)
normalized
1.0
0.8
0.6
0.4
0.2
0.0
17
Mar
2019
18
19
20
21
22


German Energy Price, Tennet Consumption, and available power
Consumption (Tennet Grid)
Energy Price (Germany)
available Power (Windfarm)
normalized
1.0
0.8
0.6
0.4
0.2
0.0
17 Mar 2019
18
19
20
21
22


German Energy Price, Tennet Consumption, and
windfarm specific Feed-In loss and available power
Consumption (Tennet Grid)
Energy Price (Germany)
available Power (Windfarm)
Feed-In loss (Windfarm)
normalized
1.0
0.8
0.6
0.4
0.2
0.0
17
Mar
2019
18
19
20
21
22

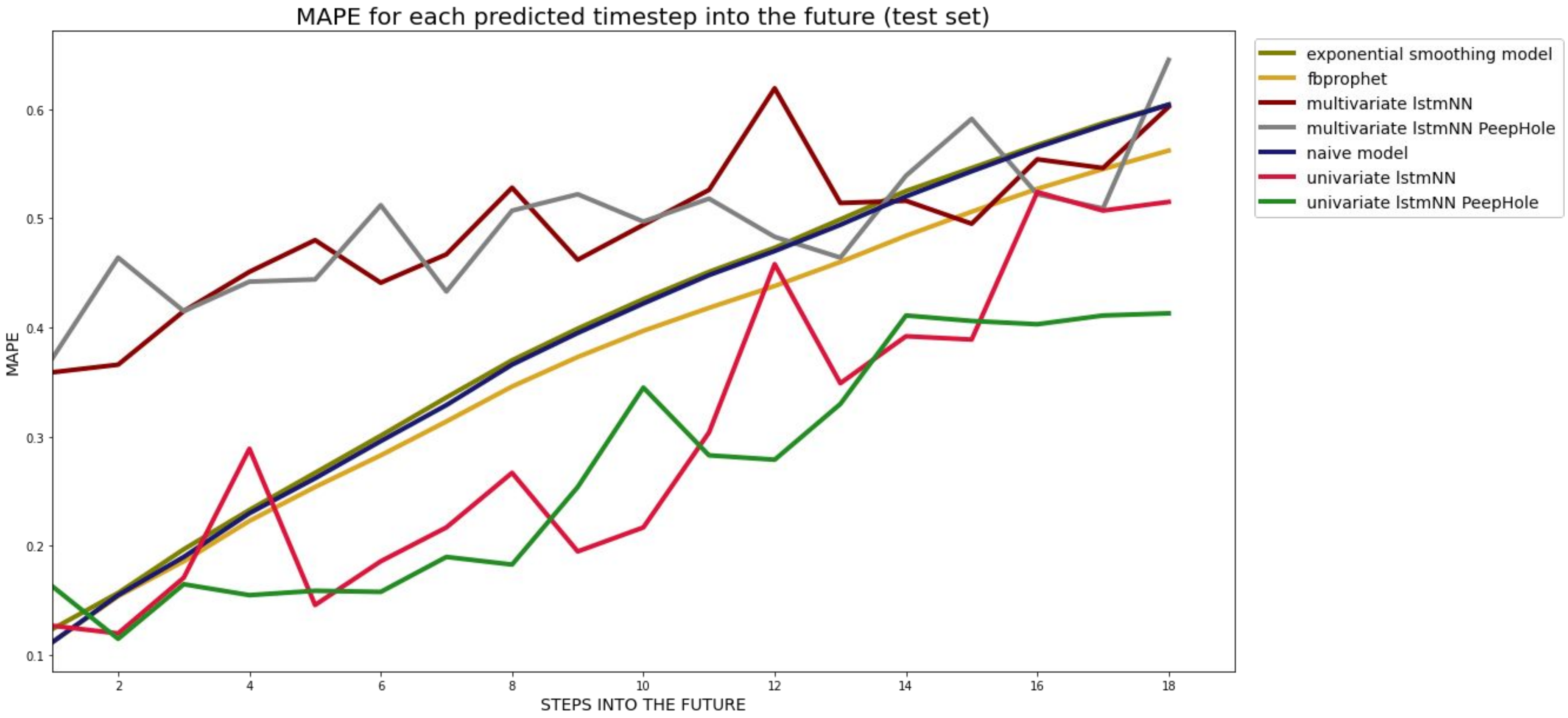
BACKGROUND
DATA ANALYSIS
MODEL RESULTS
FUTURE WORK

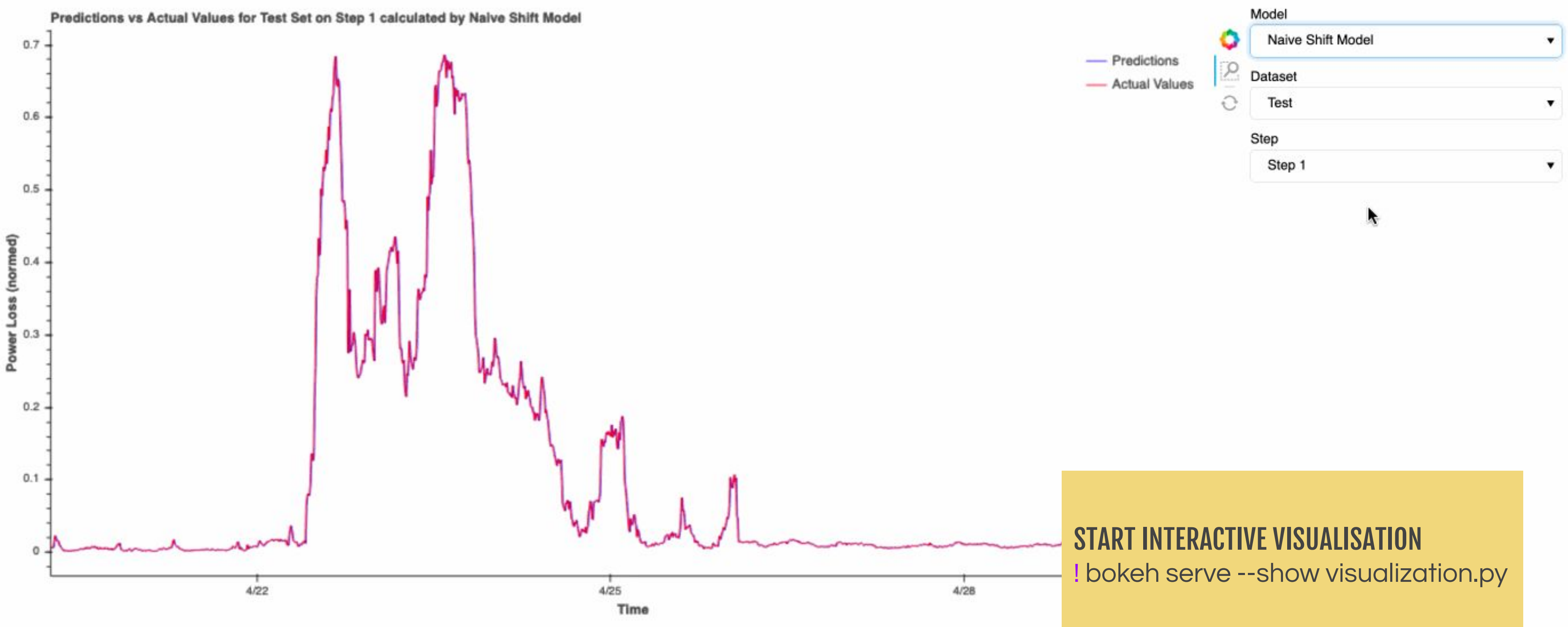
Training 1 year (63.360 timesteps)
'01.01.2018 06:00:00' to '17.03.2019 05:50:00'



Validation 10 Days (1440 time steps)
'17.03.2019 06:00:00' to '27.03.2019 06:00:00'

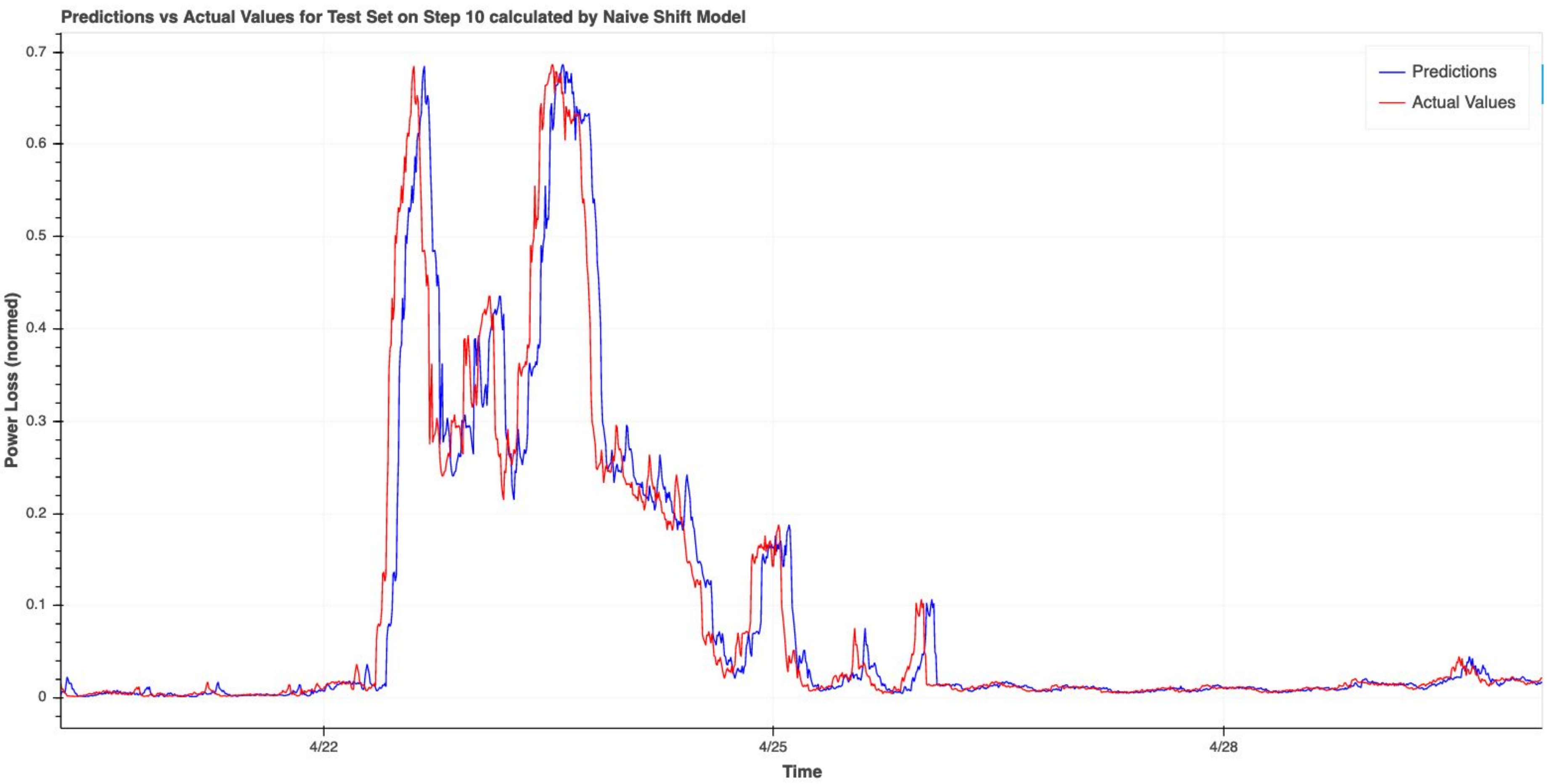
Test 10 Days (1440 time steps)
'20.04.2019 06:00:00' to '30.04.2019 06:00:00'

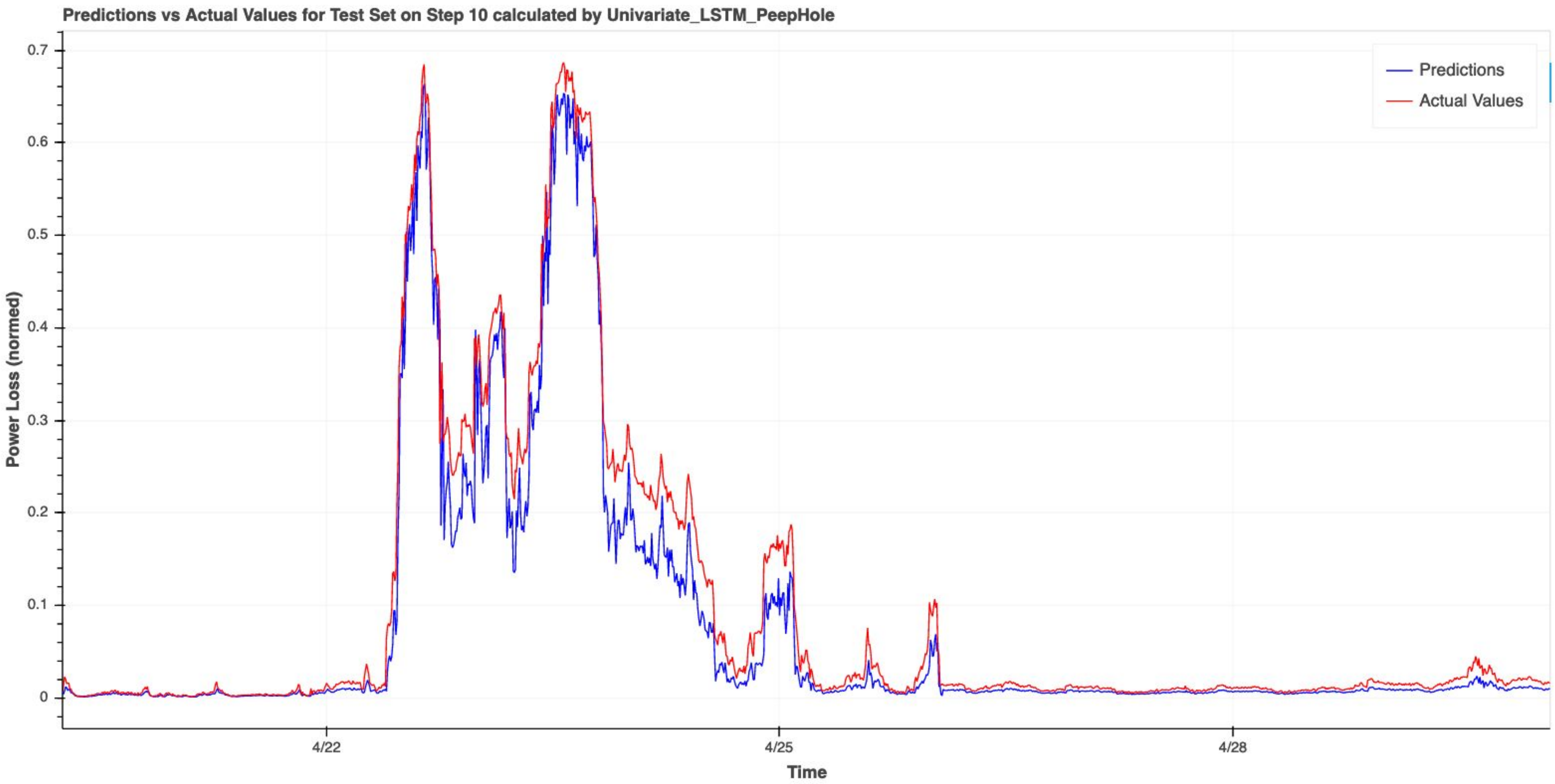

MAPE for each predicted timestep into the future (test set)
MAPE
STEPS INTO THE FUTURE
0.1
0.2
0.3
0.4
0.5
0.6
2
4
6
8
10
12
14
16
18
exponential smoothing model
fbprophet
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
univariate lstmNN PeepHole



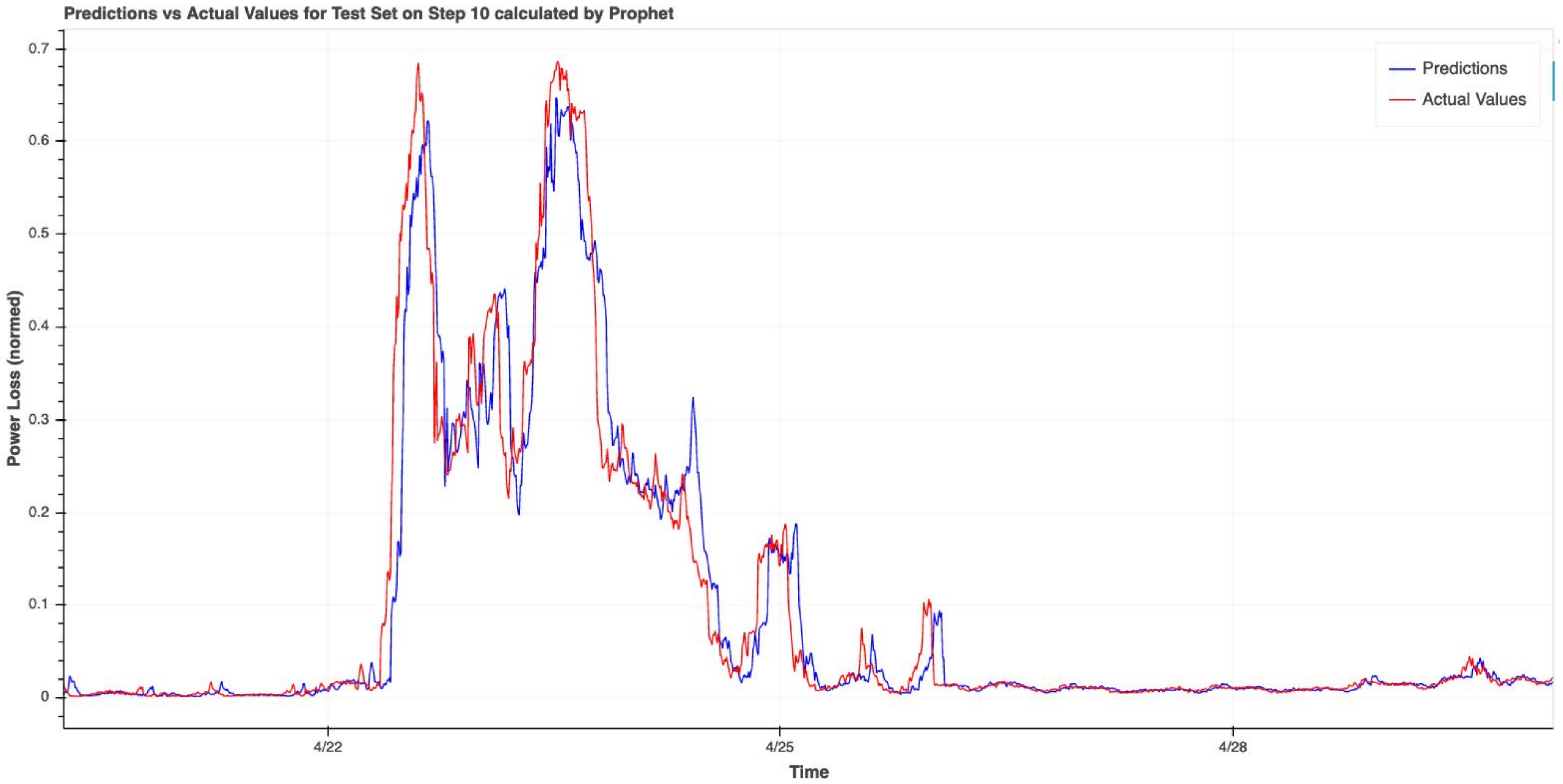
START INTERACTIVE VISUALISATION

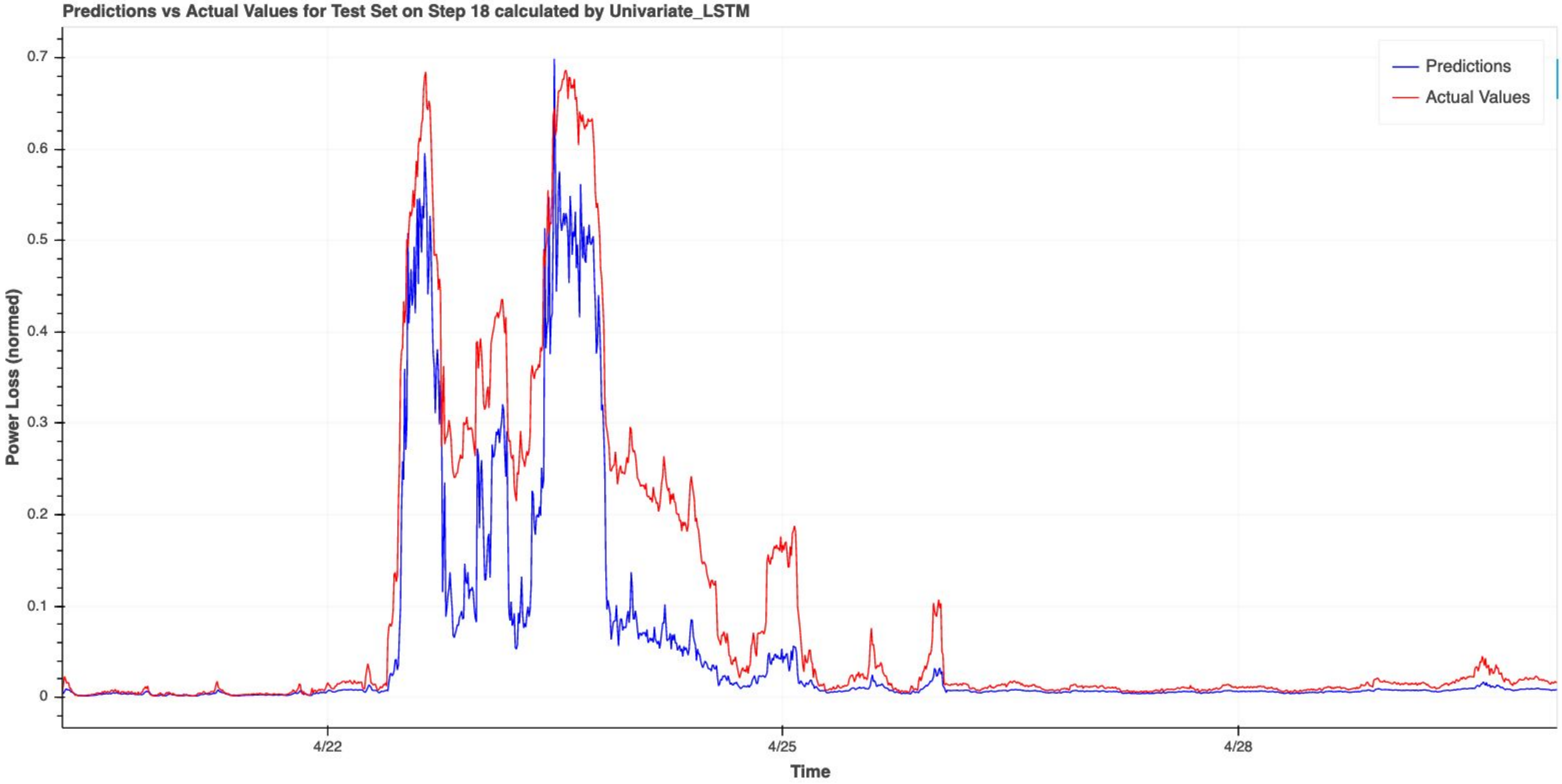
! bokeh serve --show visualization.py


Predictions vs Actual Values for Test Set on Step 10 calculated by Naive Shift Model
Predictions
Actual Values
Power Loss (normed)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
4/22
4/25
4/28
Time

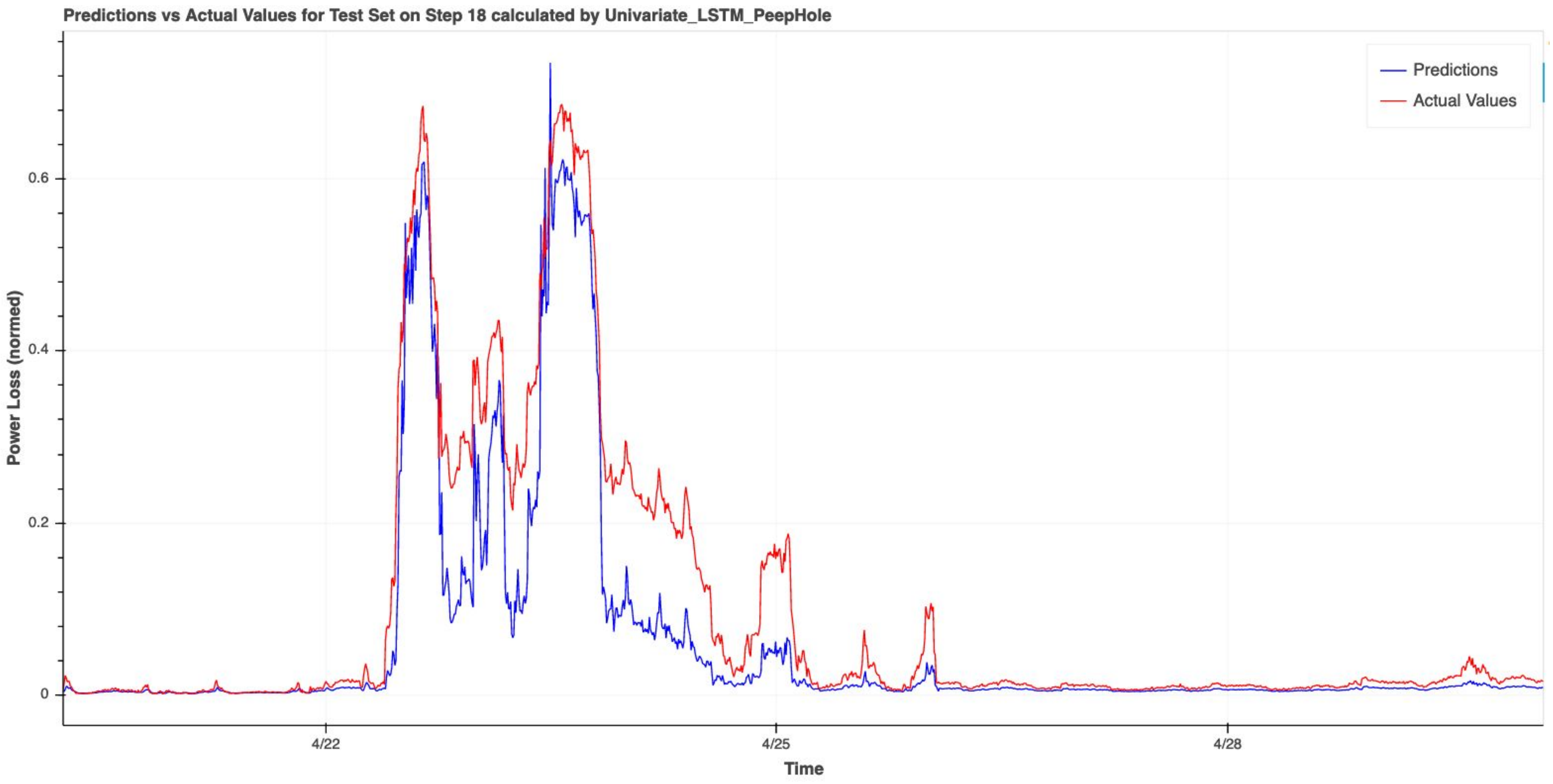


Predictions vs Actual Values for Test Set on Step 10 calculated by Univariate_LSTM_PeepHole
Predictions
Actual Values
Power Loss (normed)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
4/22
4/25
4/28
Time


Predictions vs Actual Values for Test Set on Step 10 calculated by Prophet
Predictions
Actual Values
Power Loss (normed)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
4/22
4/25
4/28
Time

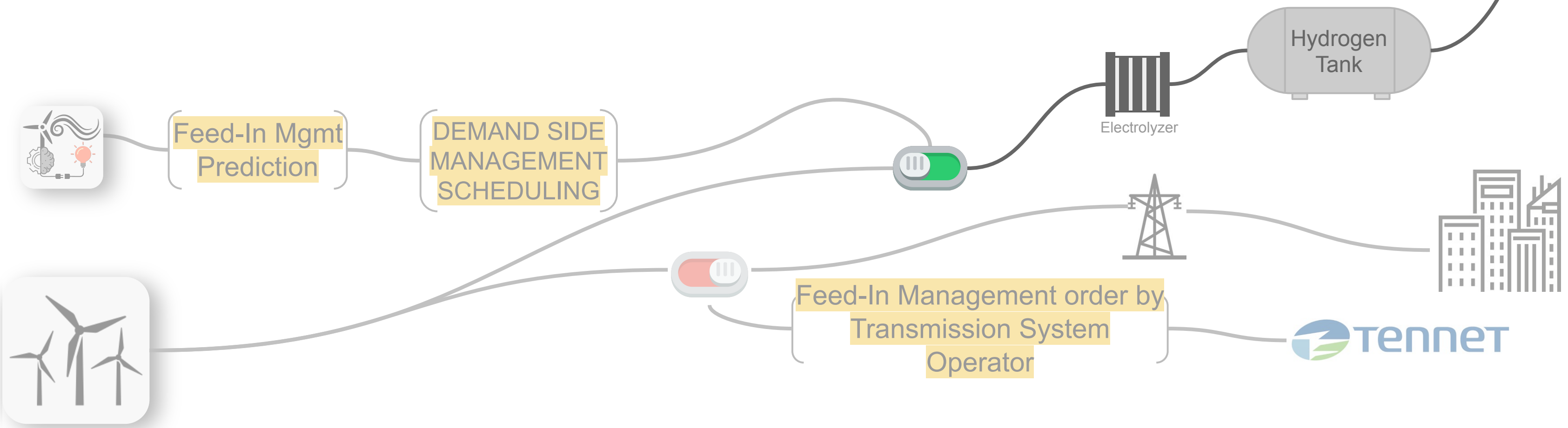


Predictions vs Actual Values for Test Set on Step 18 calculated by Univariate_LSTM
Predictions
Actual Values
Power Loss (normed)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
4/22
4/25
4/28
Time


Predictions vs Actual Values for Test Set on Step 18 calculated by Univariate_LSTM_PeepHole
Predictions
Actual Values
Power Loss (normed)
0.6
0.4
0.2
0
4/22
4/25
4/28
Time

Simplifications:
- energy to hydrogen conversion rate: 48 kWh/kg
- fuel cell passenger bus 13.3 kg H_2/ 100 km
- no ramp-up time, no extra logistics

	Lost Power in MWh	Lost Power (forecasted) in MWh	Percentage in %	Potential Mileage of Fuel Cell Bus in km
Prediction 10 minutes ahead	503	495.0	98.4	77343
Prediction 1.5 hours ahead	503	451.9	89.8	70609
Prediction 3 hours ahead	**503**	**322.3**	**64.1**	**50359**



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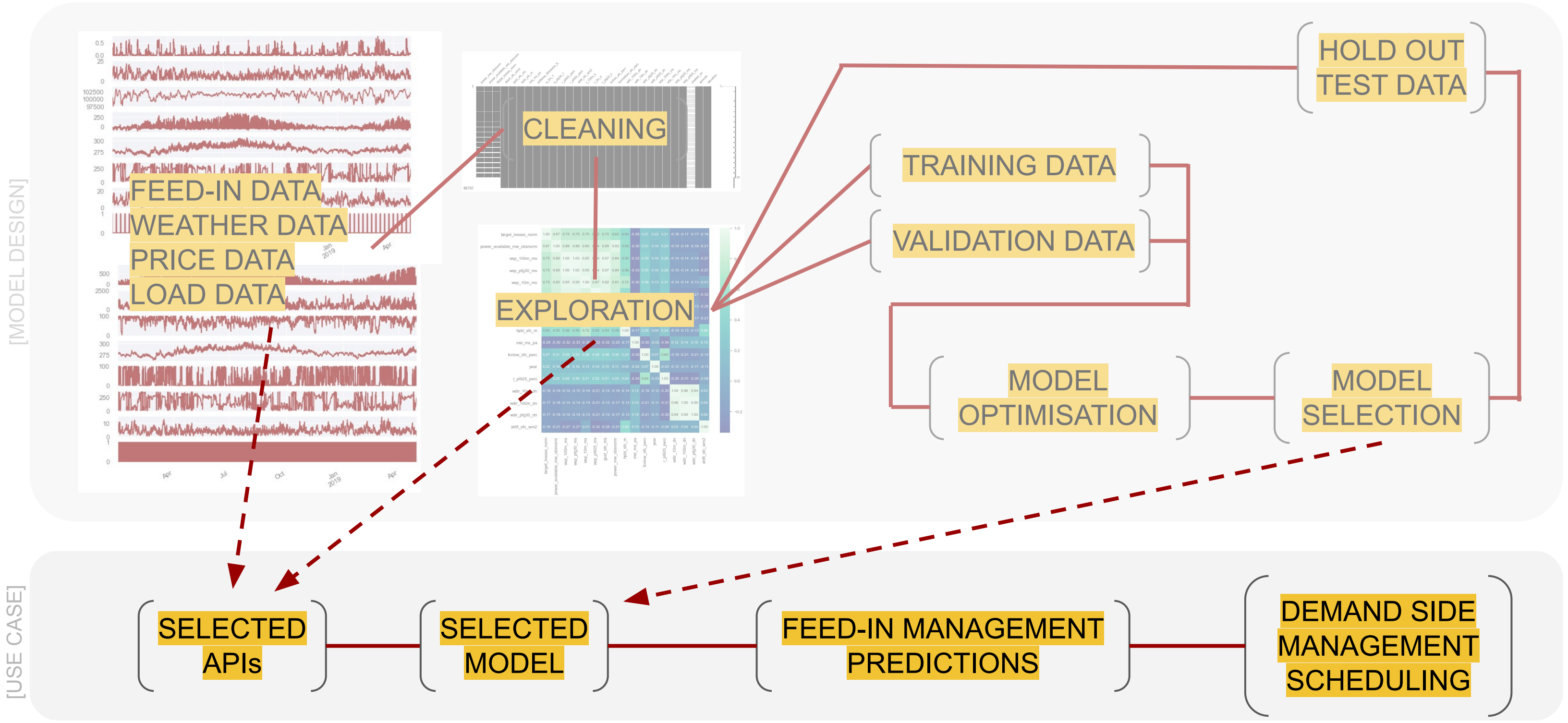
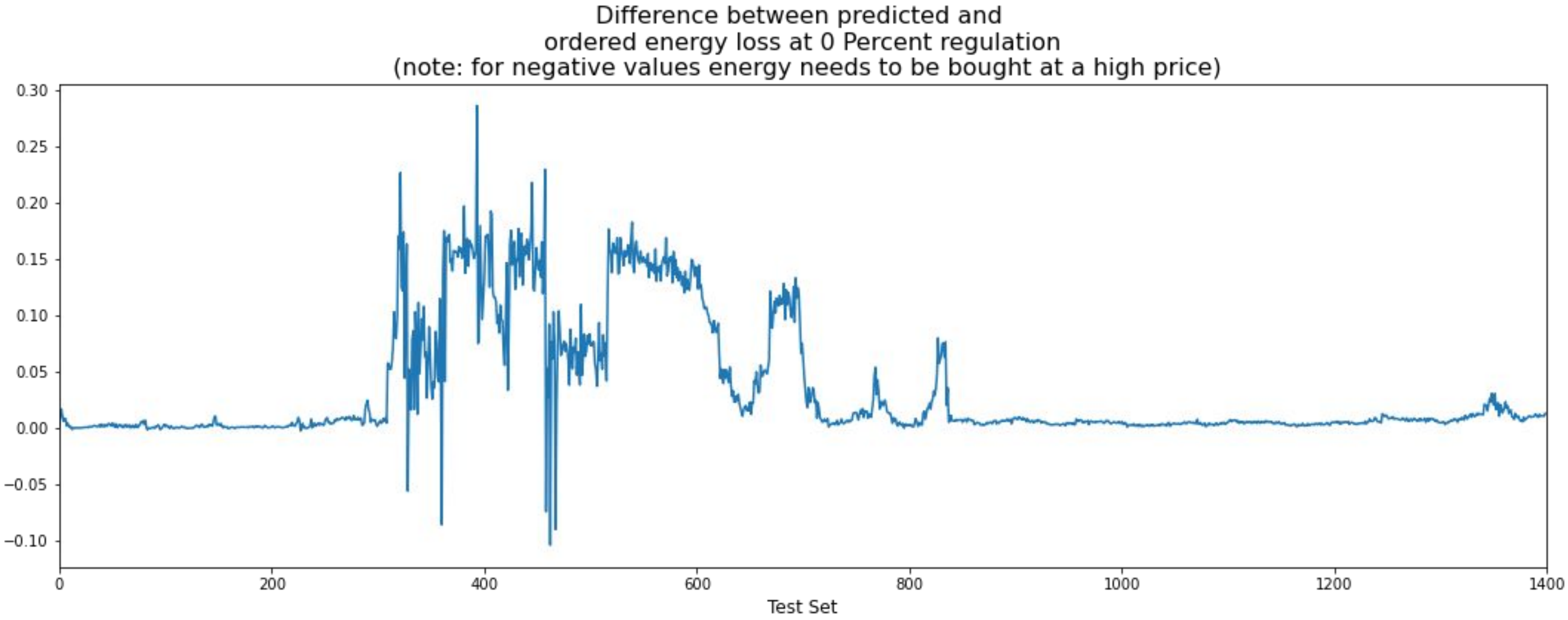
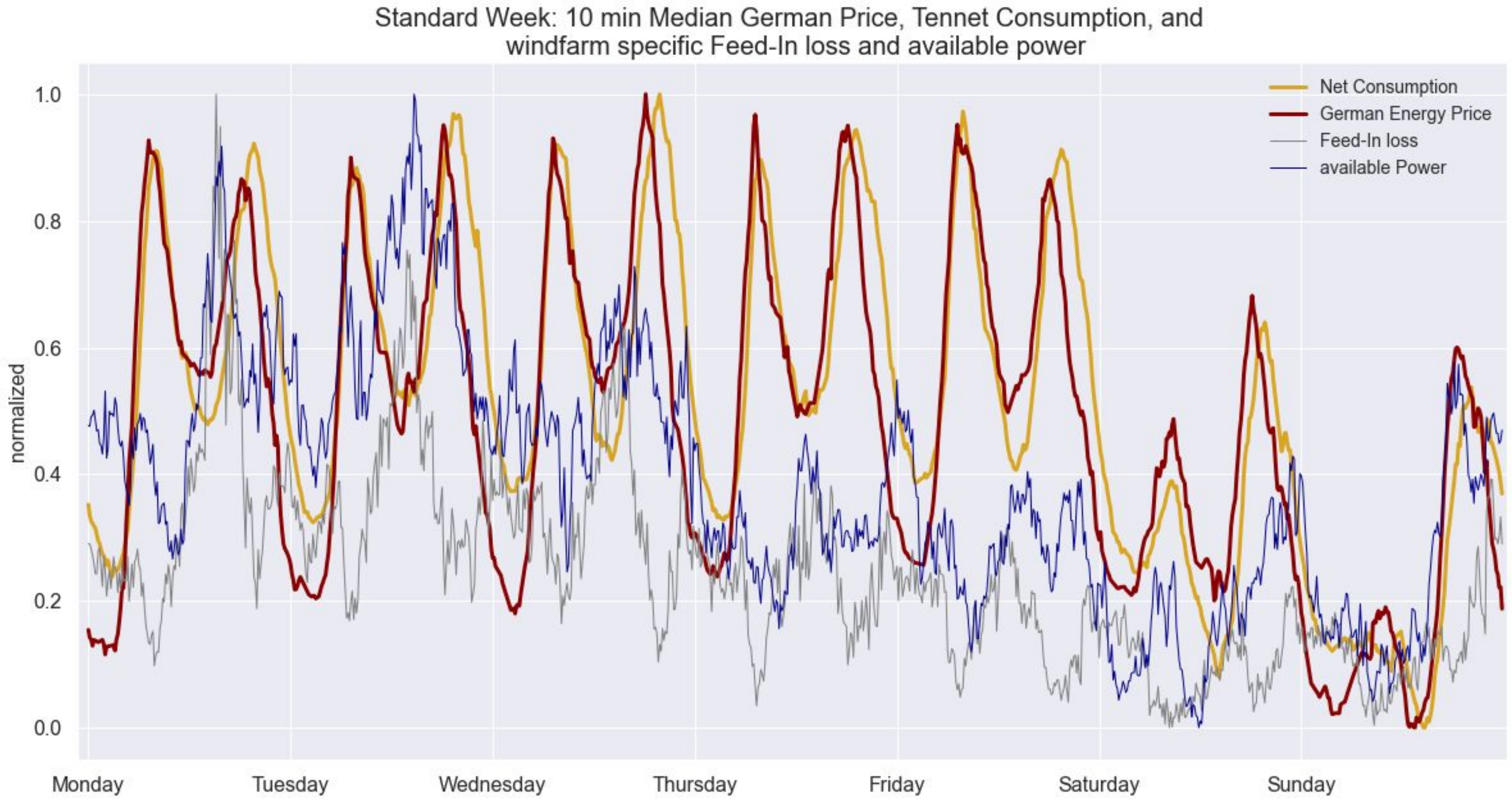
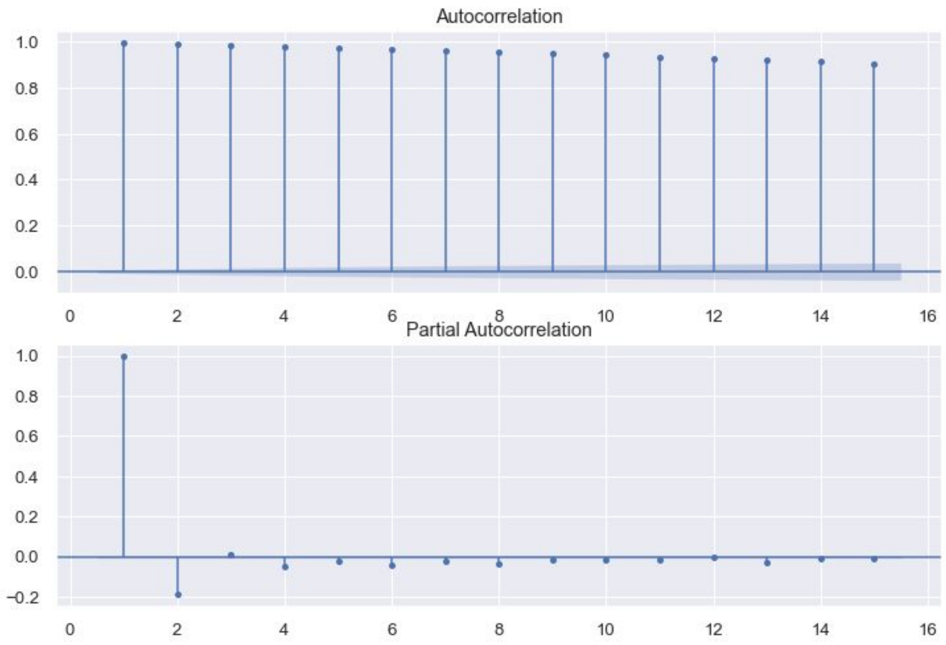
MODEL RESULTS
FUTURE WORK

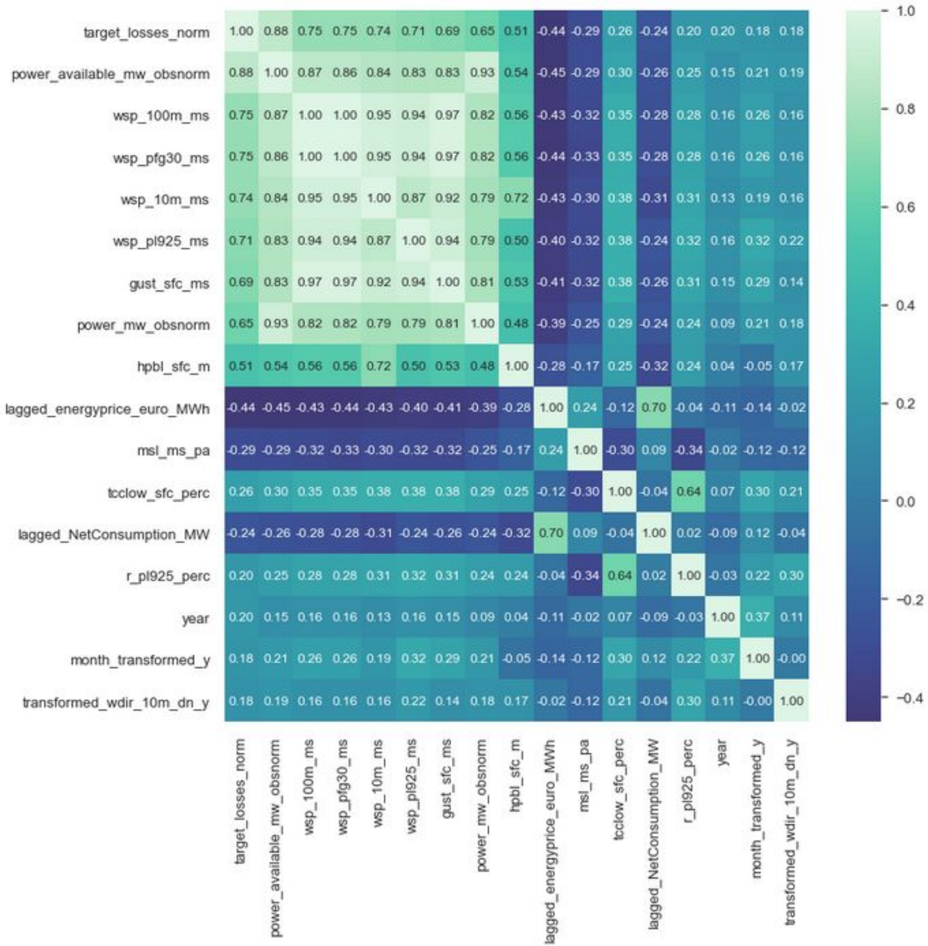

[MODEL DESIGN]
FEED-IN DATA
WEATHER DATA
PRICE DATA
LOAD DATA
CLEANING
EXPLORATION
HOLD OUT TEST DATA
TRAINING DATA
VALIDATION DATA
MODEL OPTIMISATION
MODEL SELECTION
[USE CASE]
SELECTED APIs
SELECTED MODEL
FEED-IN MANAGEMENT PREDICTIONS
DEMAND SIDE MANAGEMENT SCHEDULING

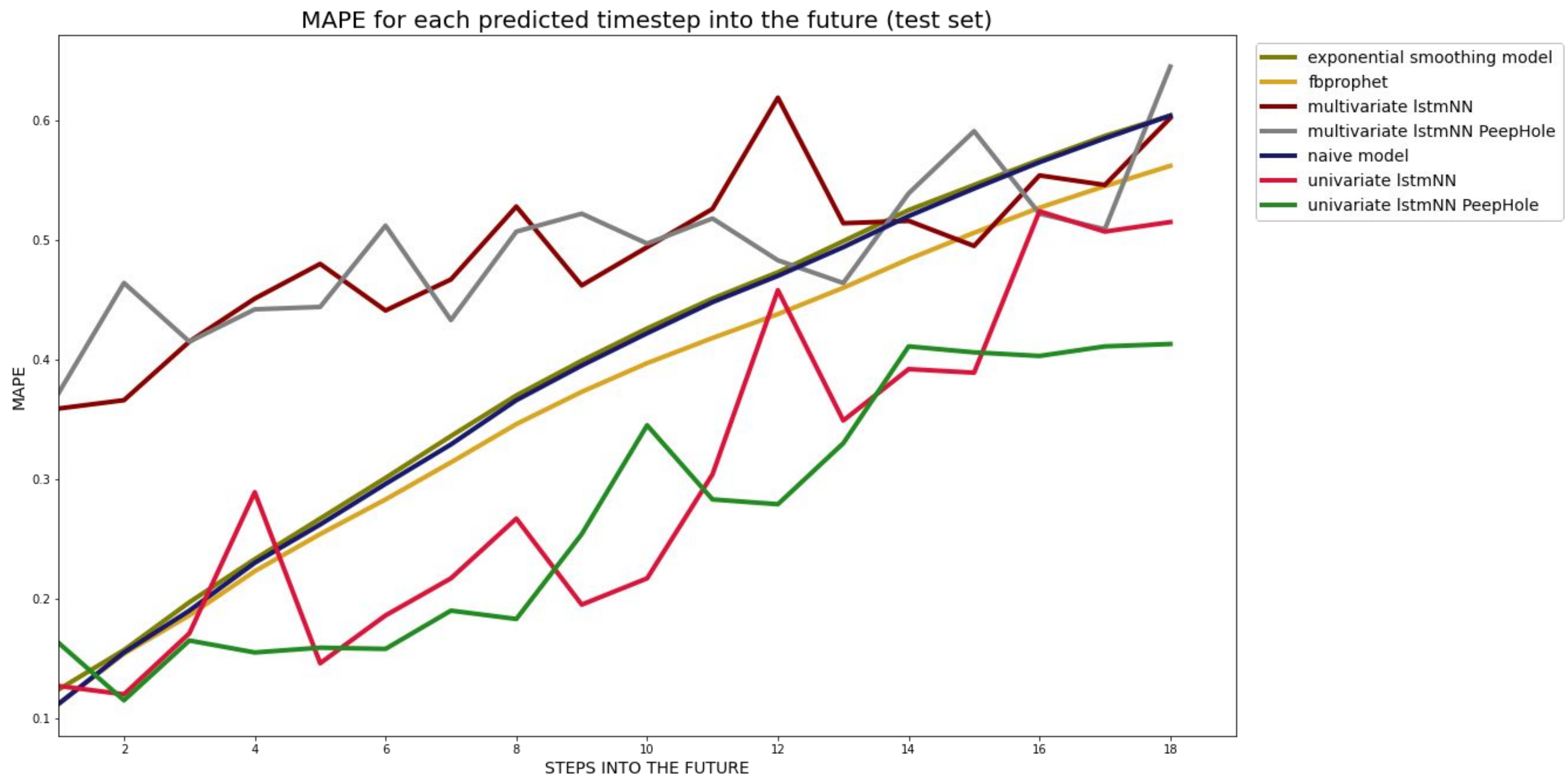
END.
QUESTIONS?

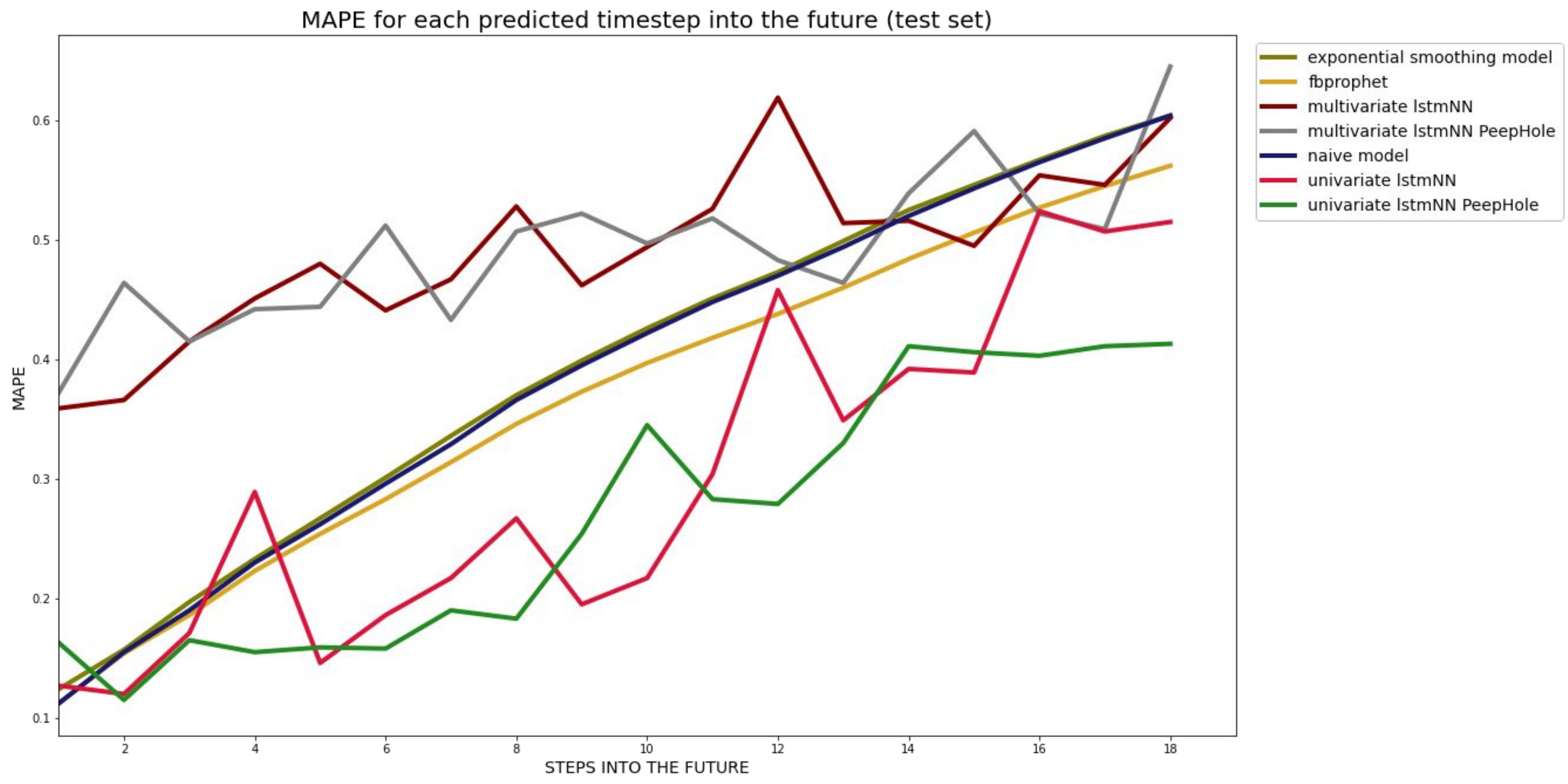

Difference between predicted and
ordered energy loss at 0 Percent regulation
(note: for negative values energy needs to be bought at a high price)
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
0
200
400
600
800
1000
1200
1400
Test Set


Standard Week: 10 min Median German Price, Tennet Consumption, and windfarm specific Feed-In loss and available power
Net Consumption
German Energy Price
Feed-In loss
available Power
normalized
1.0
0.8
0.6
0.4
0.2
0.0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday


Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
12
14
16
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
2
4
6
8
10
12
14
16


target_losses_norm 1.00 0.88 0.75 0.75 0.74 0.71 0.69 0.65 0.51 -0.44 -0.29 0.26 -0.24 0.20 0.20 0.18 0.18
power_available_mw_obsnorm 0.88 1.00 0.87 0.86 0.84 0.83 0.83 0.93 0.54 -0.45 -0.29 0.30 -0.26 0.25 0.15 0.21 0.19
wsp_100m_ms 0.75 0.87 1.00 1.00 0.95 0.94 0.97 0.82 0.56 -0.43 -0.32 0.35 -0.28 0.28 0.16 0.26 0.16
wsp_pfg30_ms 0.75 0.86 1.00 1.00 0.95 0.94 0.97 0.82 0.56 -0.44 -0.33 0.35 -0.28 0.28 0.16 0.26 0.16
wsp_10m_ms 0.74 0.84 0.95 0.95 1.00 0.87 0.92 0.79 0.72 -0.43 -0.30 0.38 -0.31 0.31 0.13 0.19 0.16
wsp_pl925_ms 0.71 0.83 0.94 0.94 0.87 1.00 0.94 0.79 0.50 -0.40 -0.32 0.38 -0.24 0.32 0.16 0.32 0.22
gust_sfc_ms 0.69 0.83 0.97 0.97 0.92 0.94 1.00 0.81 0.53 -0.41 -0.32 0.38 -0.26 0.31 0.15 0.29 0.14
power_mw_obsnorm 0.65 0.93 0.82 0.82 0.79 0.79 0.81 1.00 0.48 -0.39 -0.25 0.29 -0.24 0.24 0.09 0.21 0.18
hpbl_sfc_m 0.51 0.54 0.56 0.56 0.72 0.50 0.53 0.48 1.00 -0.28 -0.17 0.25 -0.32 0.24 0.04 -0.05 0.17
lagged_energyprice_euro_MWh -0.44 -0.45 -0.43 -0.44 -0.43 -0.40 -0.41 -0.39 -0.28 1.00 0.24 -0.12 0.70 -0.04 -0.11 -0.14 -0.02
msl_ms_pa -0.29 -0.29 -0.32 -0.33 -0.30 -0.32 -0.32 -0.25 -0.17 0.24 1.00 -0.30 0.09 -0.34 -0.02 -0.12 -0.12
tcclow_sfc_perc 0.26 0.30 0.35 0.35 0.38 0.38 0.38 0.29 0.25 -0.12 -0.30 1.00 -0.04 0.64 0.07 0.30 0.21
lagged_NetConsumption_MW -0.24 -0.26 -0.28 -0.28 -0.31 -0.24 -0.26 -0.24 -0.32 0.70 0.09 -0.04 1.00 0.02 -0.09 0.12 -0.04
r_pl925_perc 0.20 0.25 0.28 0.28 0.31 0.32 0.31 0.24 0.24 -0.04 -0.34 0.64 0.02 1.00 -0.03 0.22 0.30
year 0.20 0.15 0.16 0.16 0.13 0.16 0.15 0.09 0.04 -0.11 -0.02 0.07 -0.09 -0.03 1.00 0.37 0.11
month_transformed_y 0.18 0.21 0.26 0.26 0.19 0.32 0.29 0.21 -0.05 -0.14 -0.12 0.30 0.12 0.22 0.37 1.00 -0.00
transformed_wdir_10m_dn_y 0.18 0.19 0.16 0.16 0.16 0.22 0.14 0.18 0.17 -0.02 -0.12 0.21 -0.04 0.30 0.11 -0.00 1.00
target_losses_norm
power_available_mw_obsnorm
wsp_100m_ms
wsp_pfg30_ms
wsp_10m_ms
wsp_pl925_ms
gust_sfc_ms
power_mw_obsnorm
hpbl_sfc_m
lagged_energyprice_euro_MWh
msl_ms_pa
tcclow_sfc_perc
lagged_NetConsumption_MW
r_pl925_perc
year
month_transformed_y
transformed_wdir_10m_dn_y
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4


MAPE for each predicted timestep into the future (test set)
exponential smoothing model
fbprophet
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
univariate lstmNN PeepHole
MAPE
0.1
0.2
0.3
0.4
0.5
0.6
2
4
6
8
10
12
14
16
18
STEPS INTO THE FUTURE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MAPE
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0.4
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4
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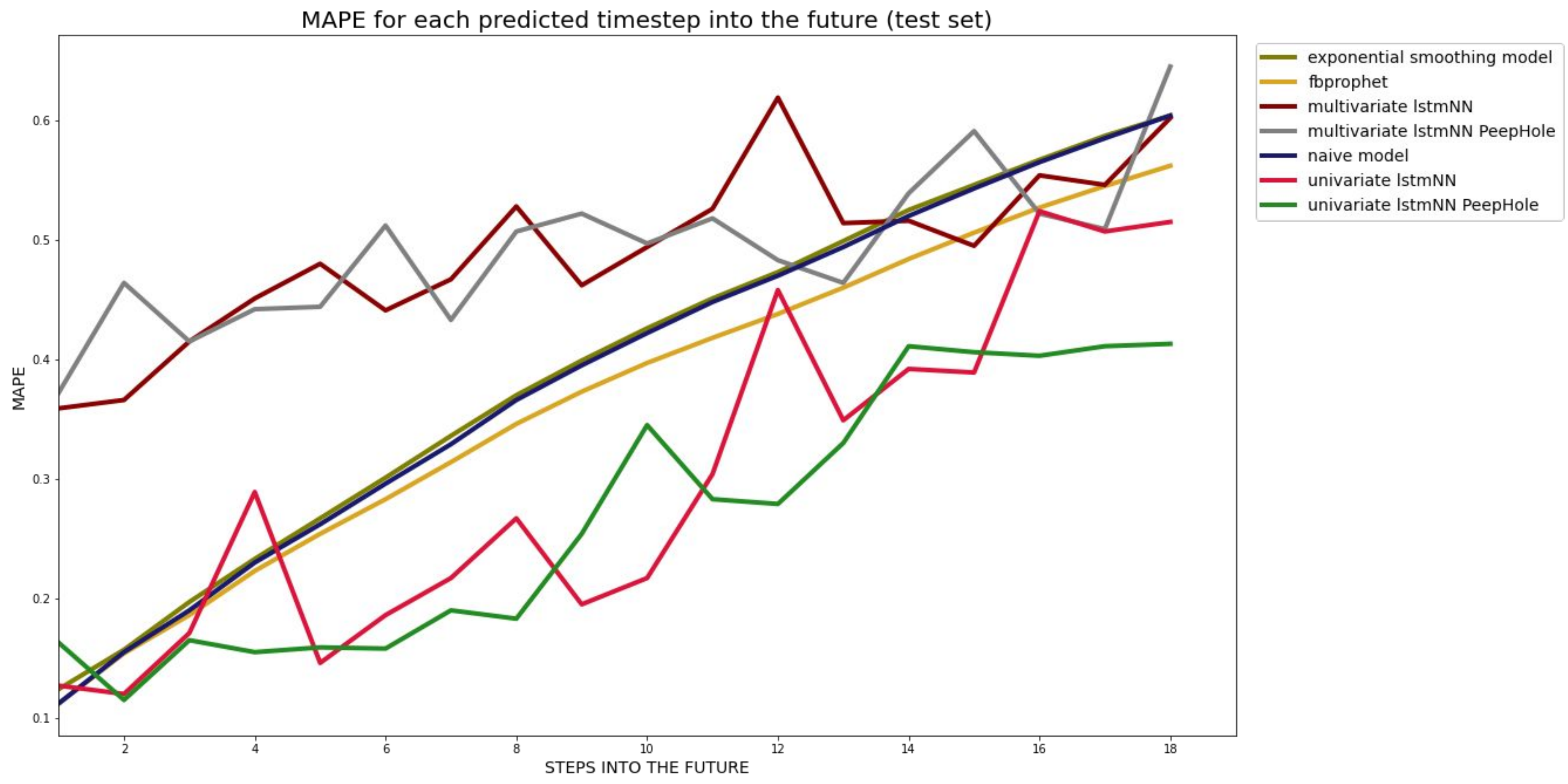
18
STEPS INTO THE FUTURE


MAPE for each predicted timestep into the future (test set)
MAPE
0.1
0.2
0.3
0.4
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0.6
2
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6
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14
16
18
STEPS INTO THE FUTURE
exponential smoothing model
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multivariate lstmNN
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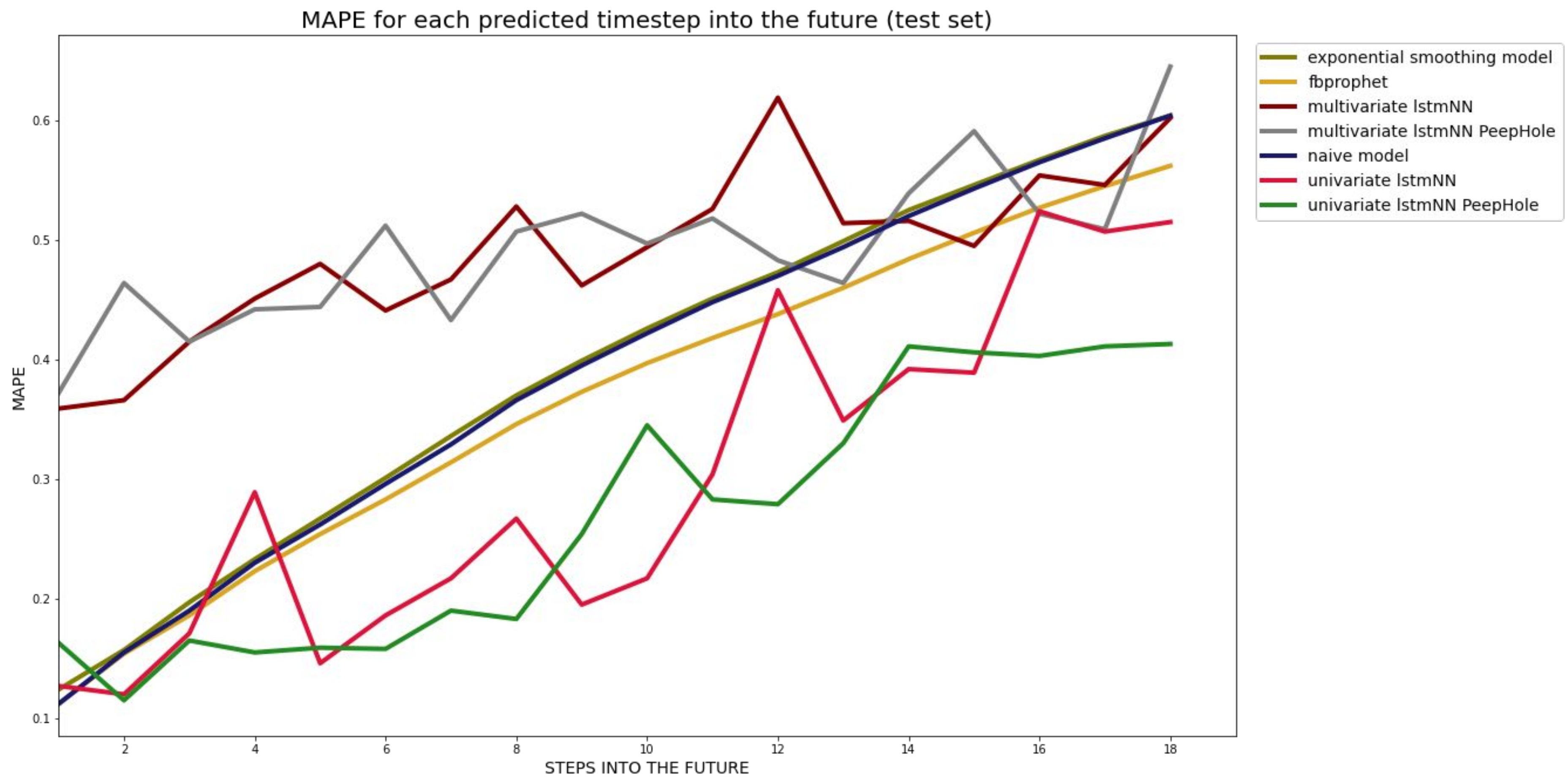
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exponential smoothing model
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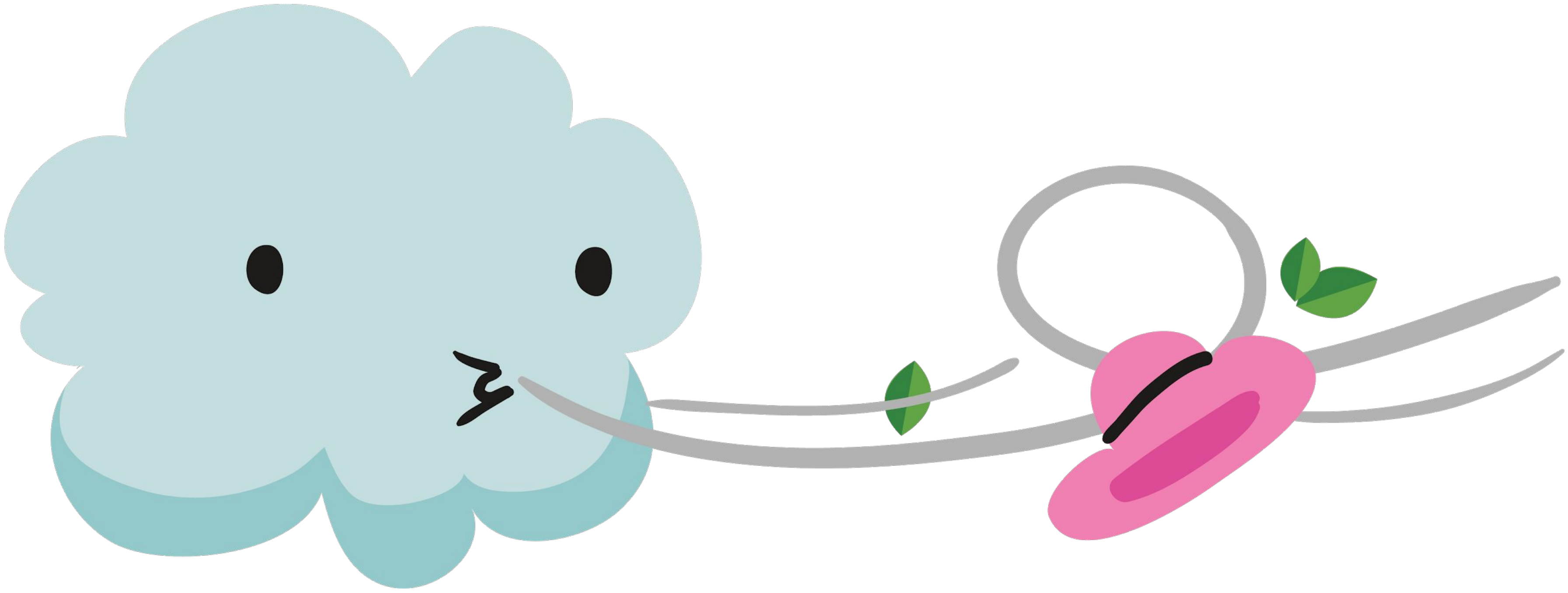
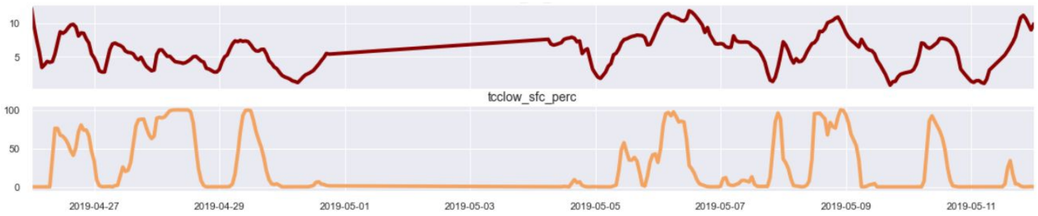
univariate lstmNN PeepHole
MAPE
0.1
0.2
0.3
0.4
0.5
0.6
STEPS INTO THE FUTURE
2
4
6
8
10
12
14
16
18





TensorBoard

SELECTED APIs — SELECTED MODEL — FEED-IN MANAGEMENT PREDICTIONS

Low Hanging

Extensiv Data Fixing: data after 1. May 2019 contained errors, could be fixed via its own seasonal model

LSTM Tuning via TensorBoard

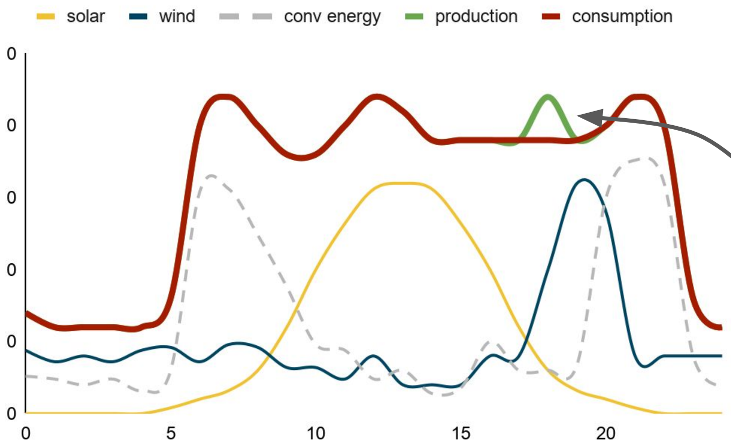
Forecast of GFS Data for Feed-In Mgmt predictions >1 timestep

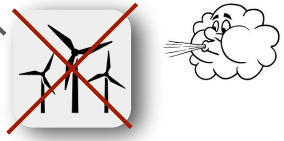
High Hanging

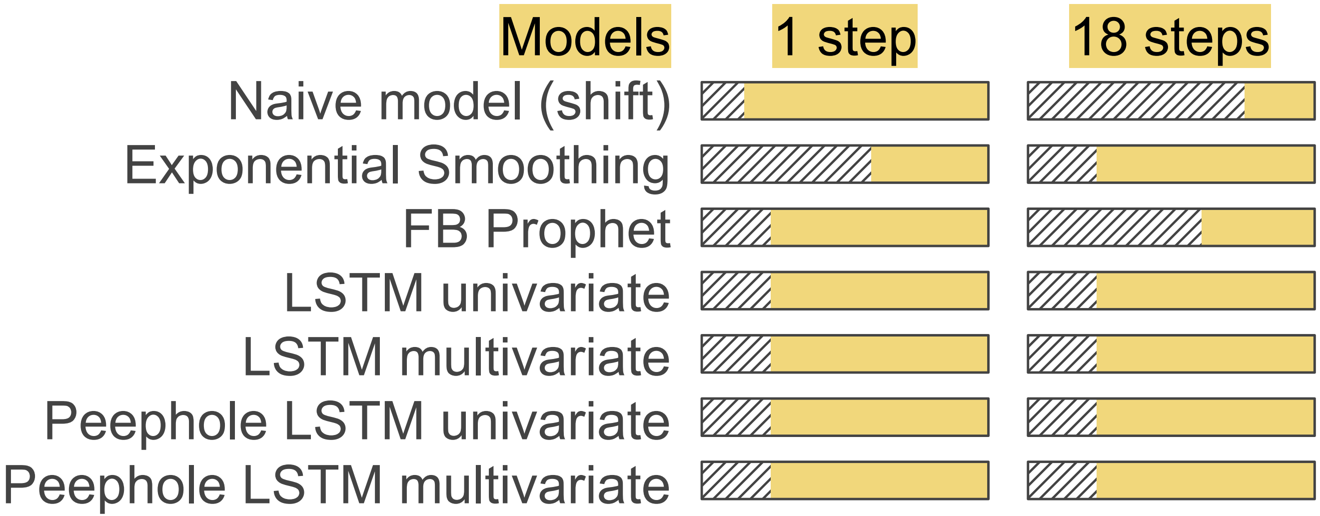
API: receiving data via an API for live predictions

Energy feet into the system needs to meet energy taken out of the system at all times. This was already difficult with conventional electricity generation. It is even more difficult with a combination of volatility renewable energy sources. For example, on a windy and sunny day in June, there is potentially a lot of excess wind energy. Feed-In Management describes the curtailment of energy to protect grid infrastructure of overloads.

What if we could instead use the excess energy?

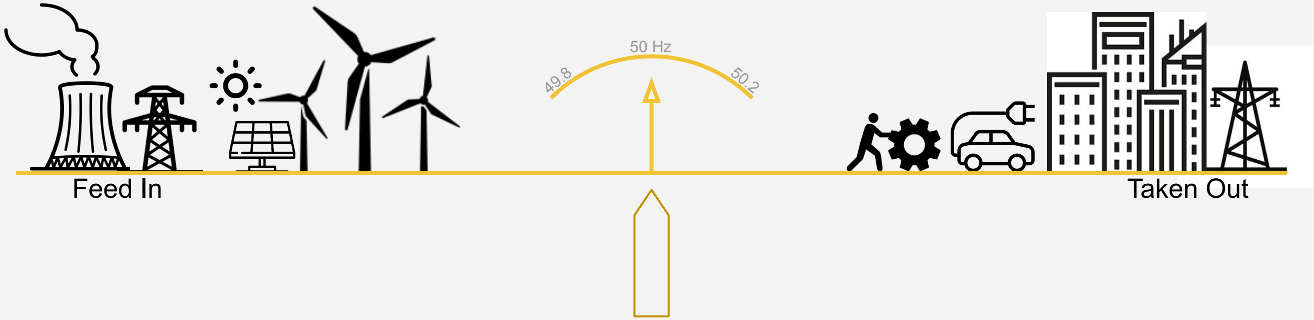





Models
1 step
18 steps
Naive model (shift)
Exponential Smoothing
FB Prophet
LSTM univariate
LSTM multivariate
Peephole LSTM univariate
Peephole LSTM multivariate

BACKGROUND

Energy feet into the system needs to meet energy taken out of the system at all times. This was already difficult with conventional electricity generation such as Nuclear Power. It is even more difficult with a combination of volatility renewable energy sources. For example, on a windy and sunny day in June, there is potentially a lot of excess wind energy. Feed-In Management describes the curtailment of energy production to protect grid infrastructure of overloads.



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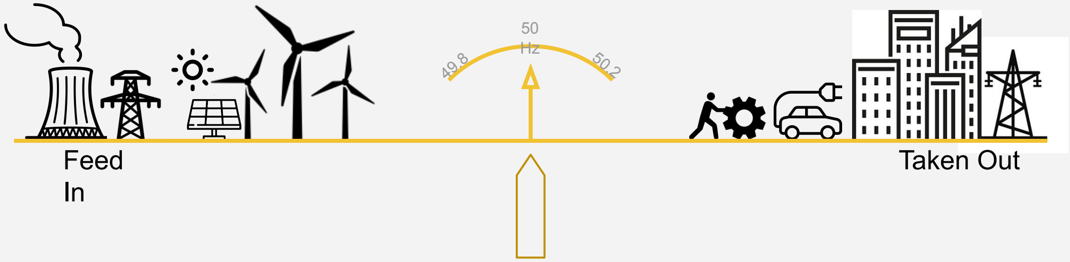
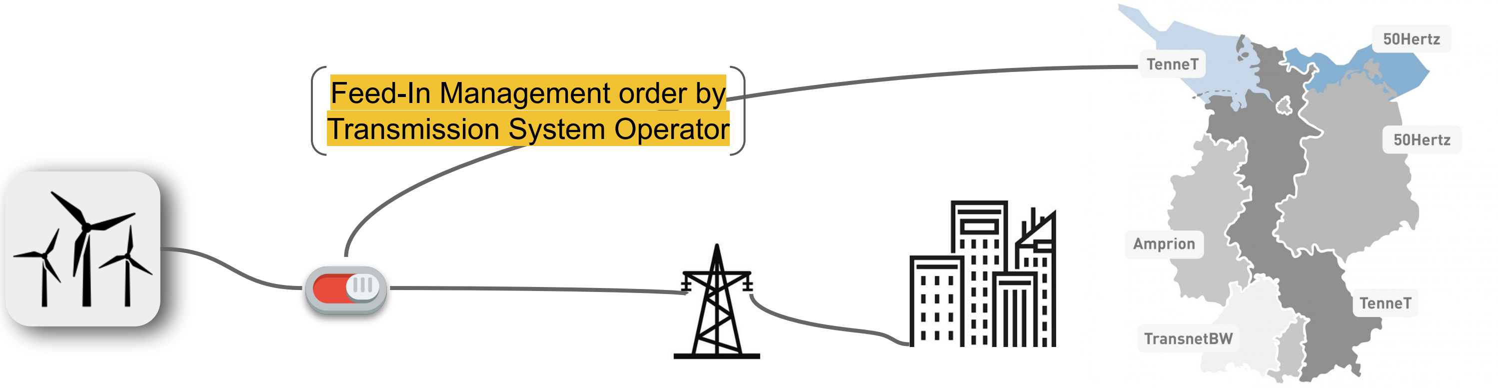


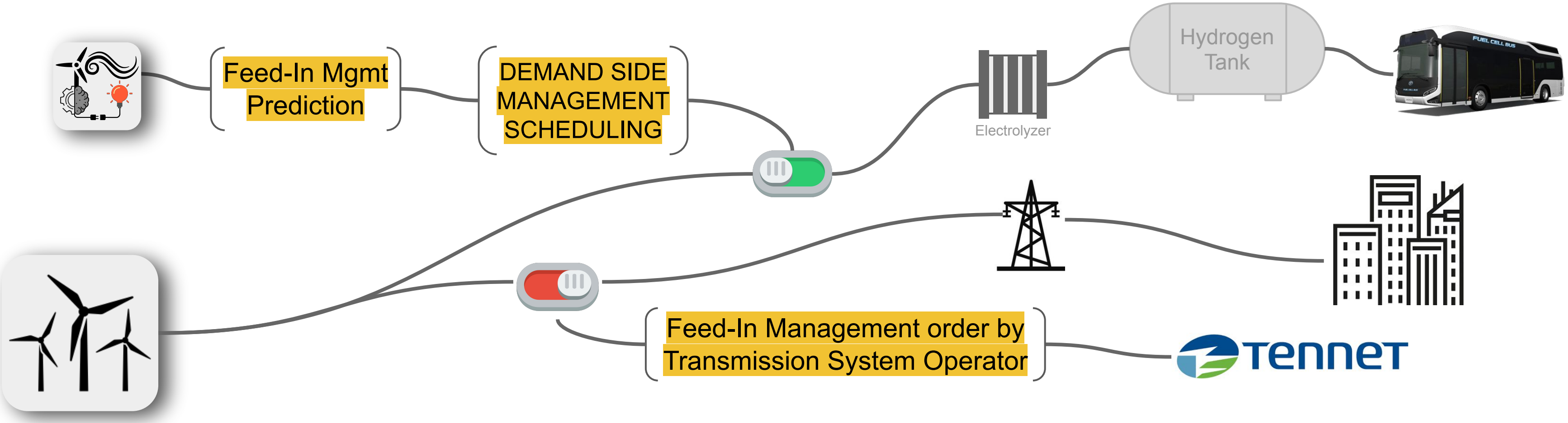
Capstone Presentation
8.October 2020

Tjade Apel
Jonas Jaenicke

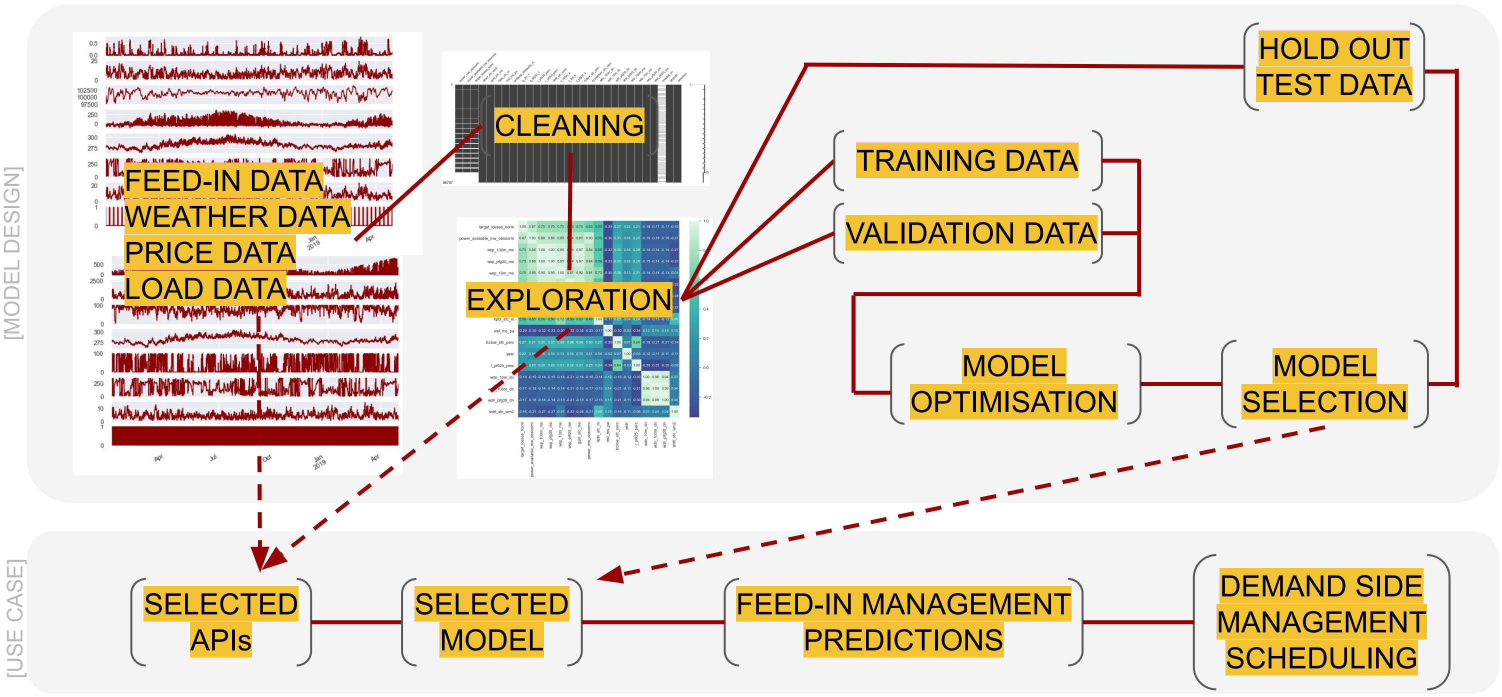
Feed-In Management Prediction

Feed In Management Event Prediction for Quadra Energy Onshore Windfarm


Feed-In Management order by
Transmission System Operator
TenneT
50Hertz
50Hertz
Amprion
TenneT
TransnetBW

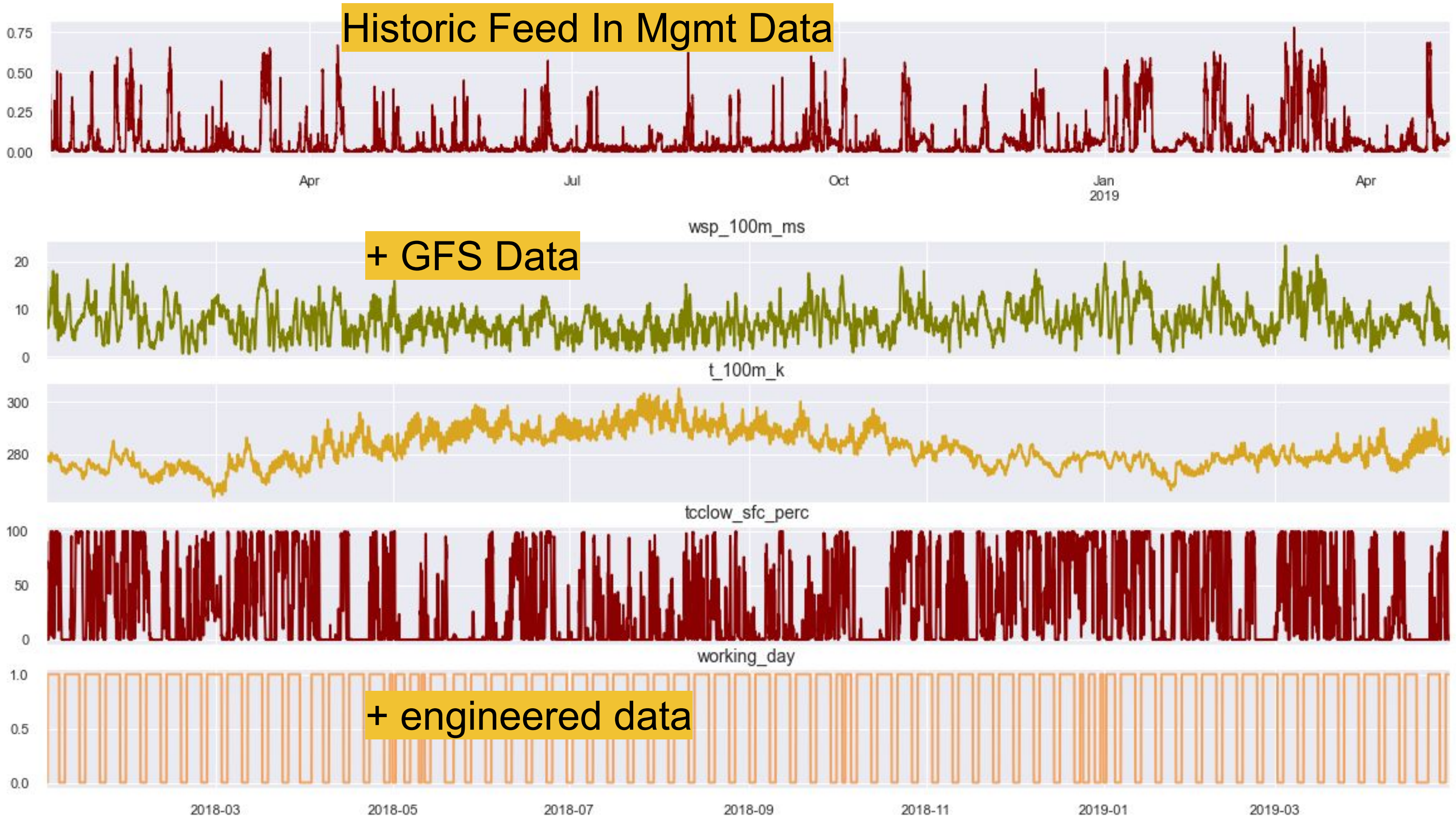


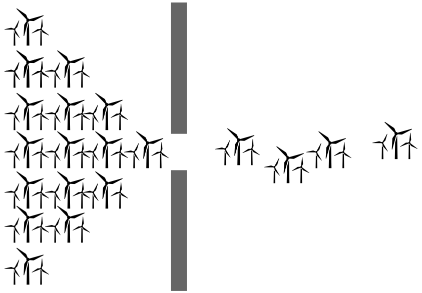
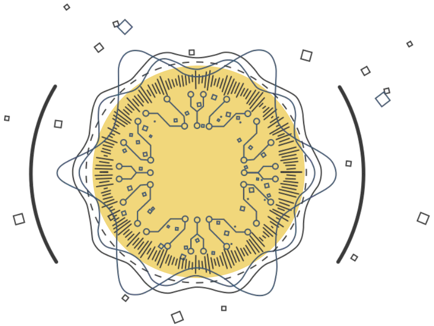
Feed-In Mgmt Prediction
DEMAND SIDE MANAGEMENT SCHEDULING
Electrolyzer
Hydrogen Tank
FUEL CELL BUS
Feed-In Management order by Transmission System Operator
TenneT

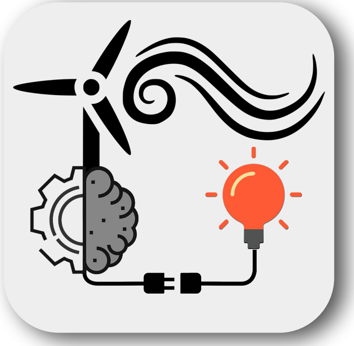


[MODEL DESIGN]
FEED-IN DATA
WEATHER DATA
PRICE DATA
LOAD DATA
CLEANING
EXPLORATION
HOLD OUT TEST DATA
TRAINING DATA
VALIDATION DATA
MODEL OPTIMISATION
MODEL SELECTION
[USE CASE]
SELECTED APIs
SELECTED MODEL
FEED-IN MANAGEMENT PREDICTIONS
DEMAND SIDE MANAGEMENT SCHEDULING

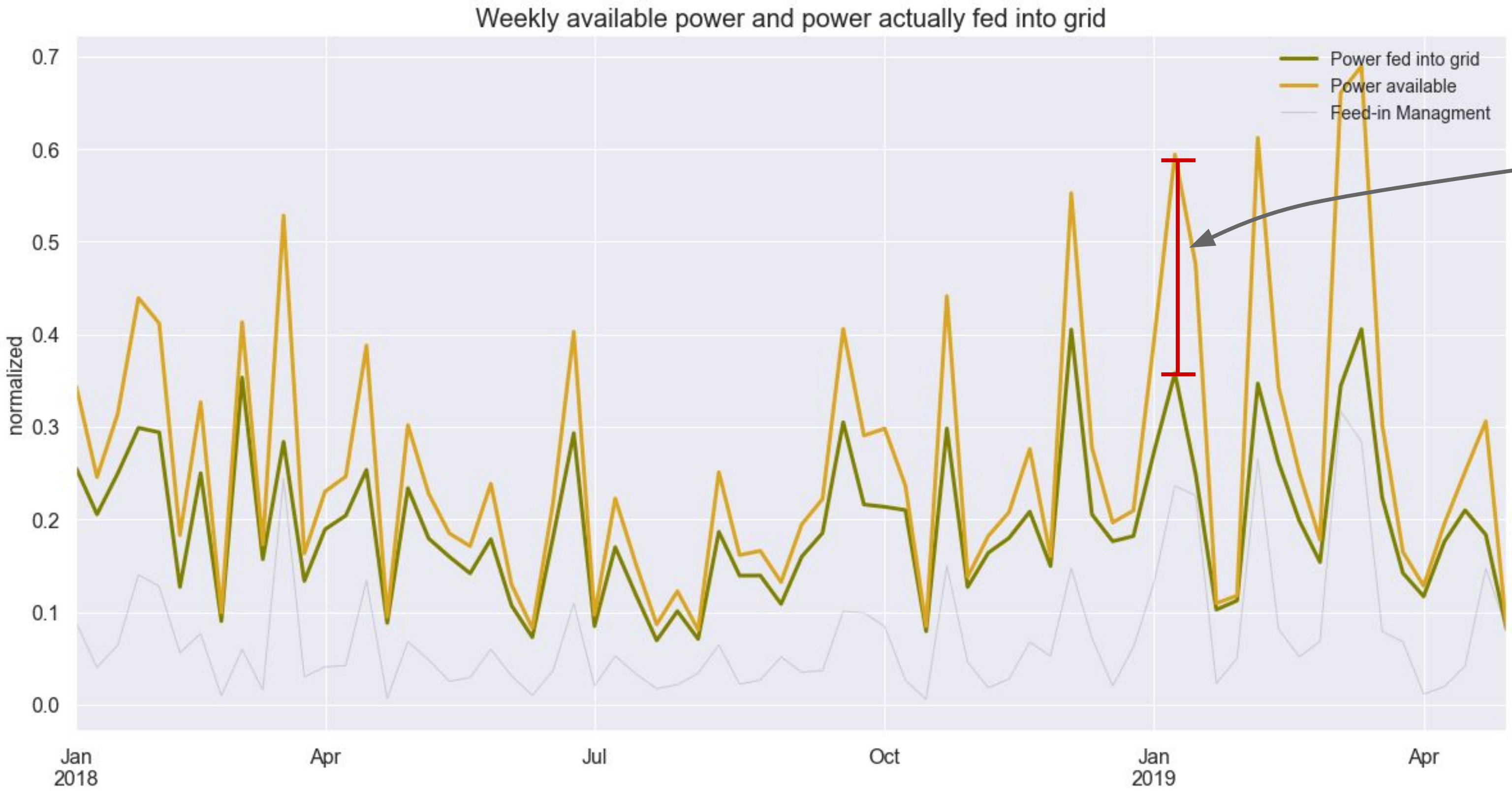
Our Data:


Historic Feed In Mgmt Data
0.75
0.50
0.25
0.00
Apr
Jul
Oct
Jan
2019
Apr
wsp_100m_ms
+ GFS Data
20
10
0
t_100m_k
300
280
tcclow_sfc_perc
100
50
0
working_day
1.0
0.5
0.0
+ engineered data
2018-03
2018-05
2018-07
2018-09
2018-11
2019-01
2019-03

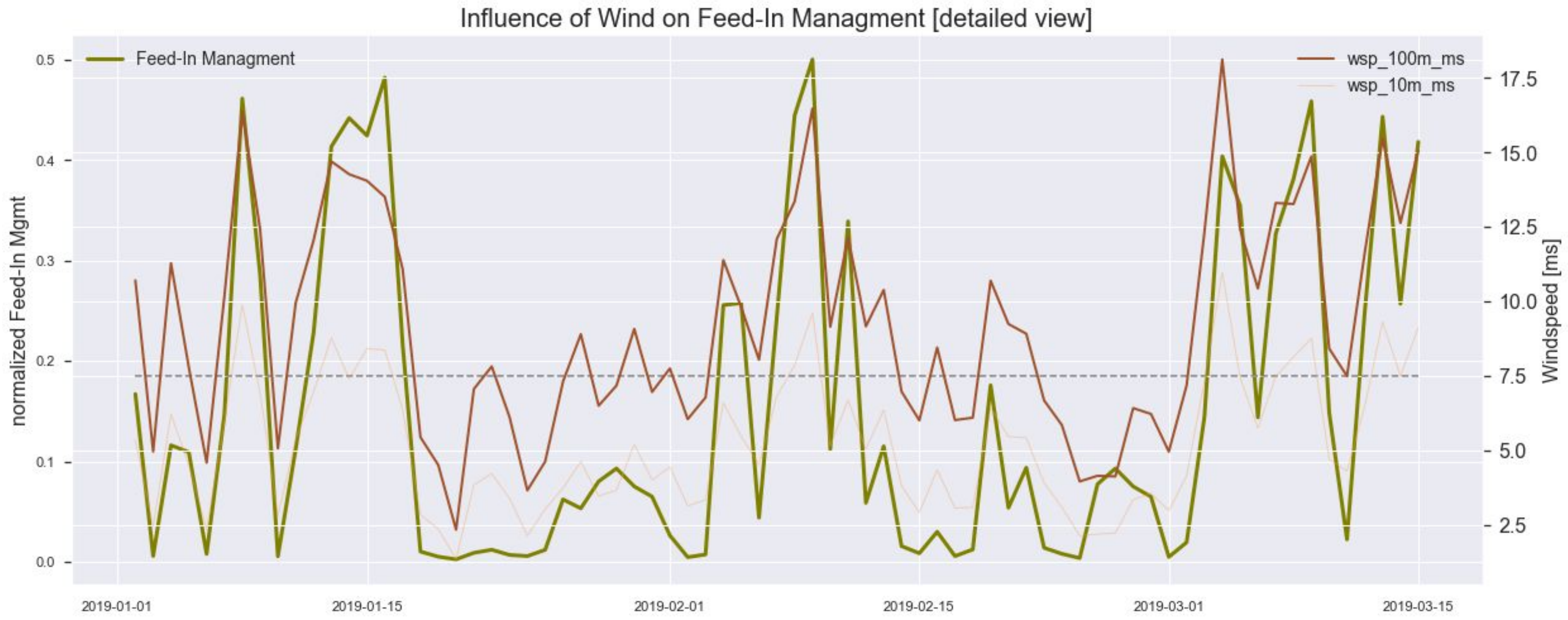


Feed In Mgmt Events in our Data



At any given week in our observation period, there is a Feed In Mgmt Event

Feed-In Mgmt Events connected to Wind



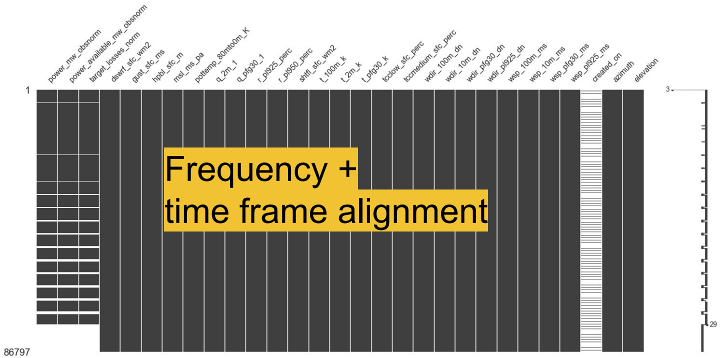
Data Cleaning

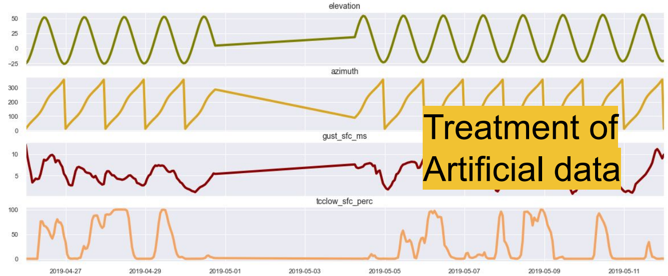
Feature Engineering

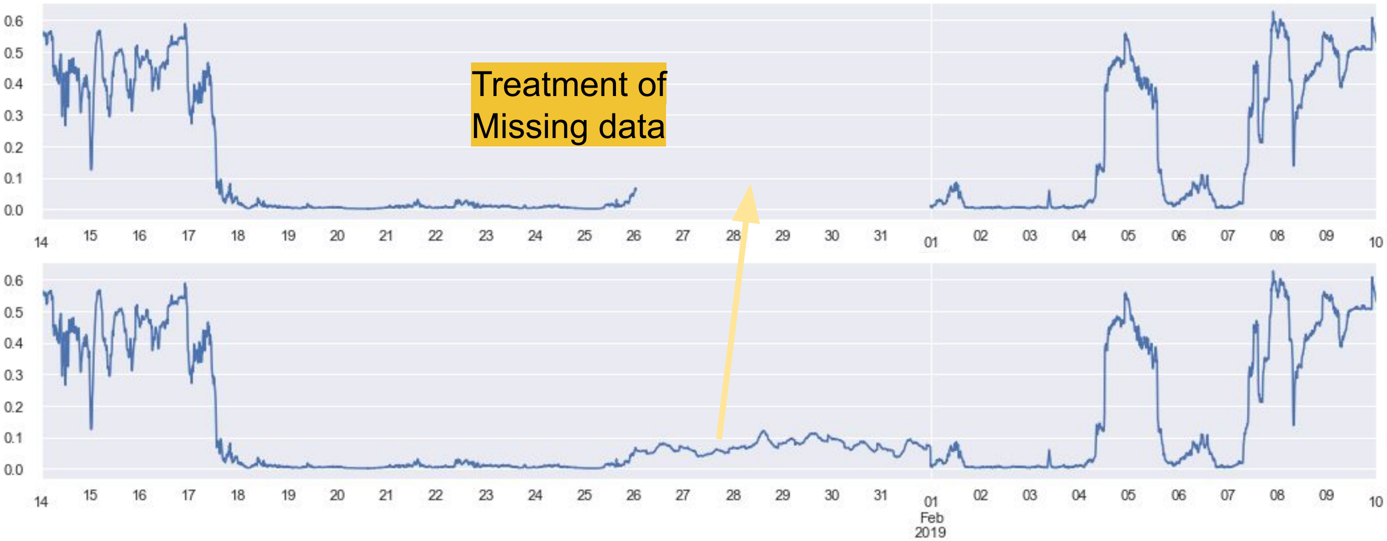
Feature Selection

Seasonality Analysis

ML Models







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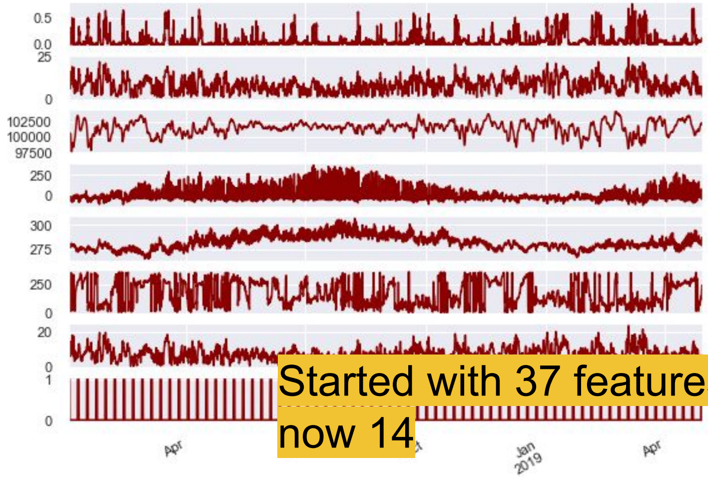
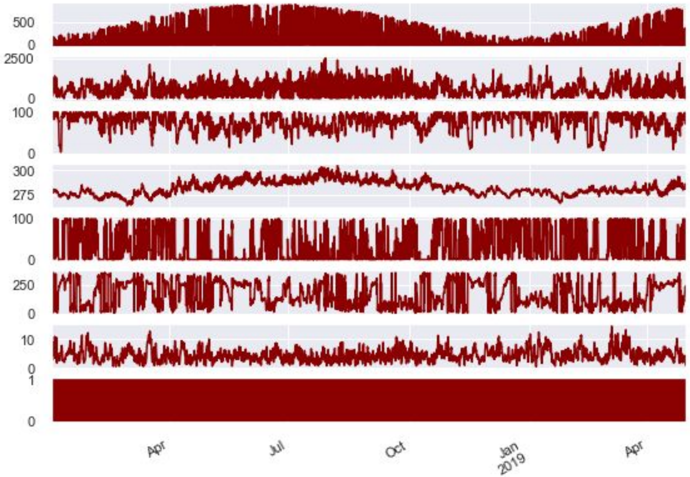
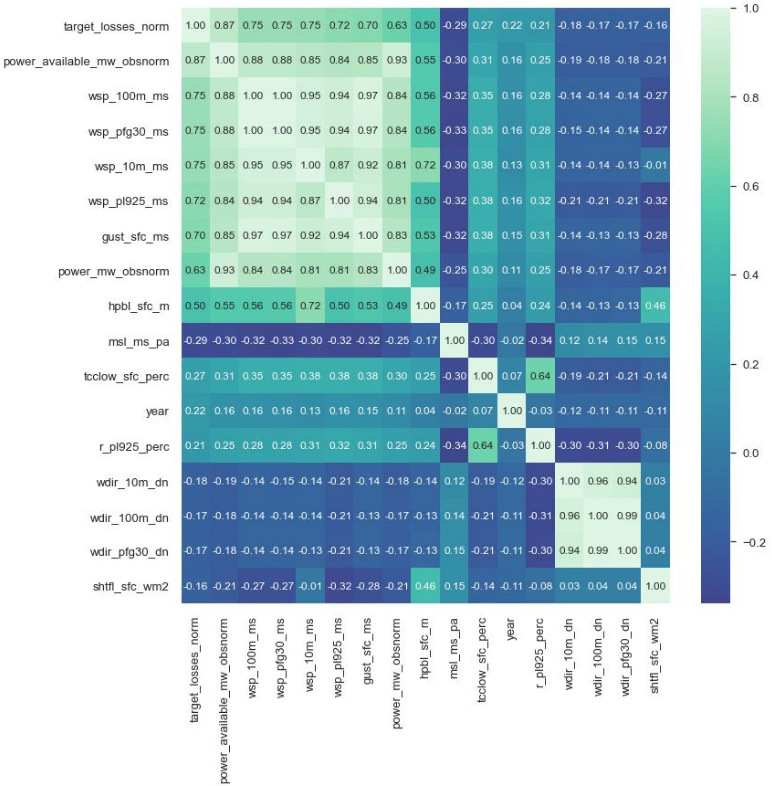


Started with 37 features, now 14





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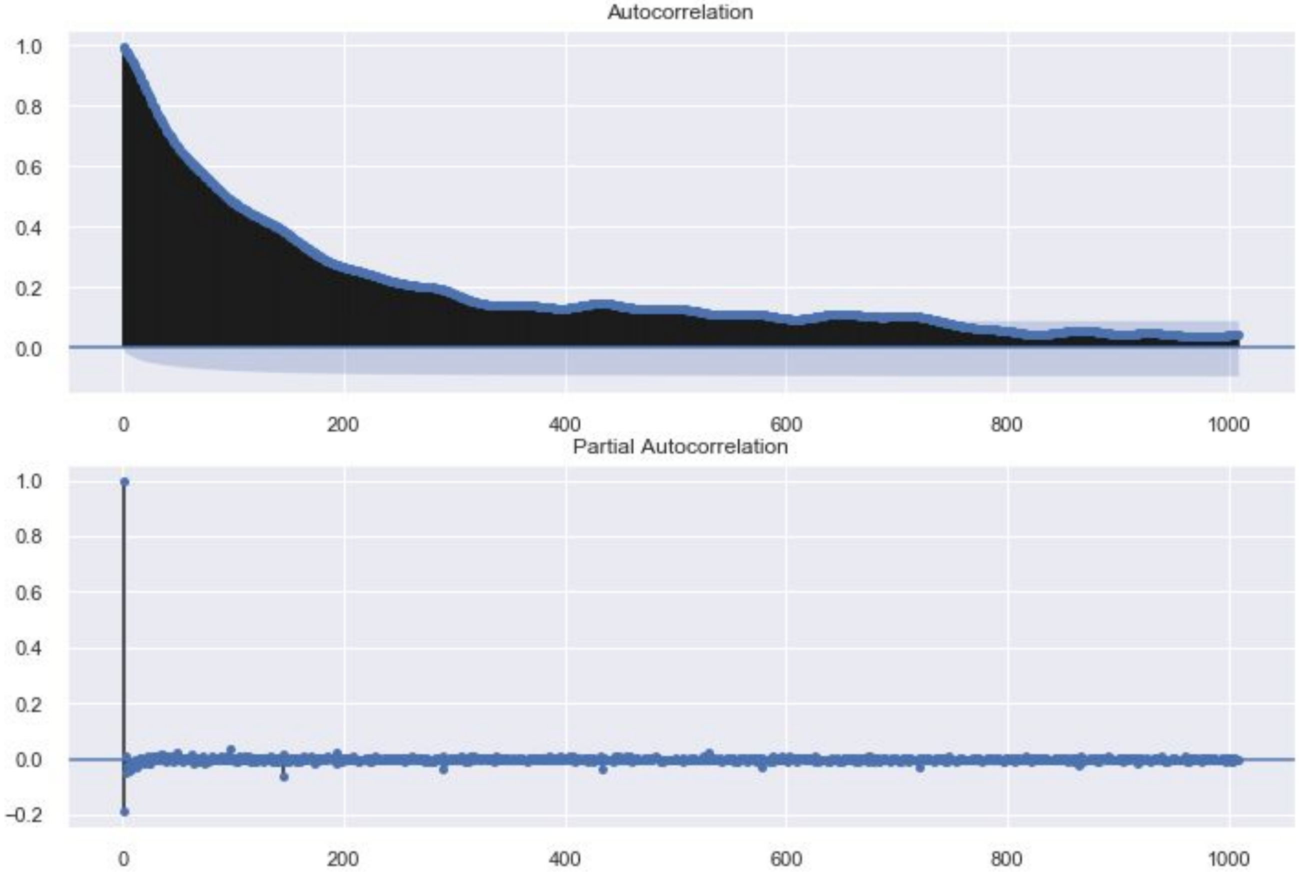


Data Cleaning

Feature Engineering

Feature Selection

Seasonality Analysis

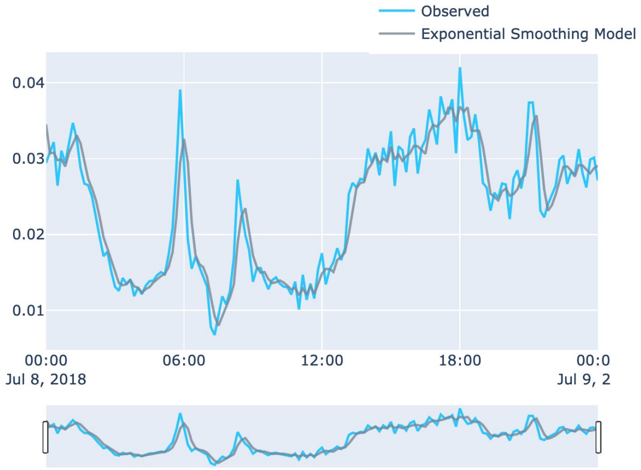
ML Models

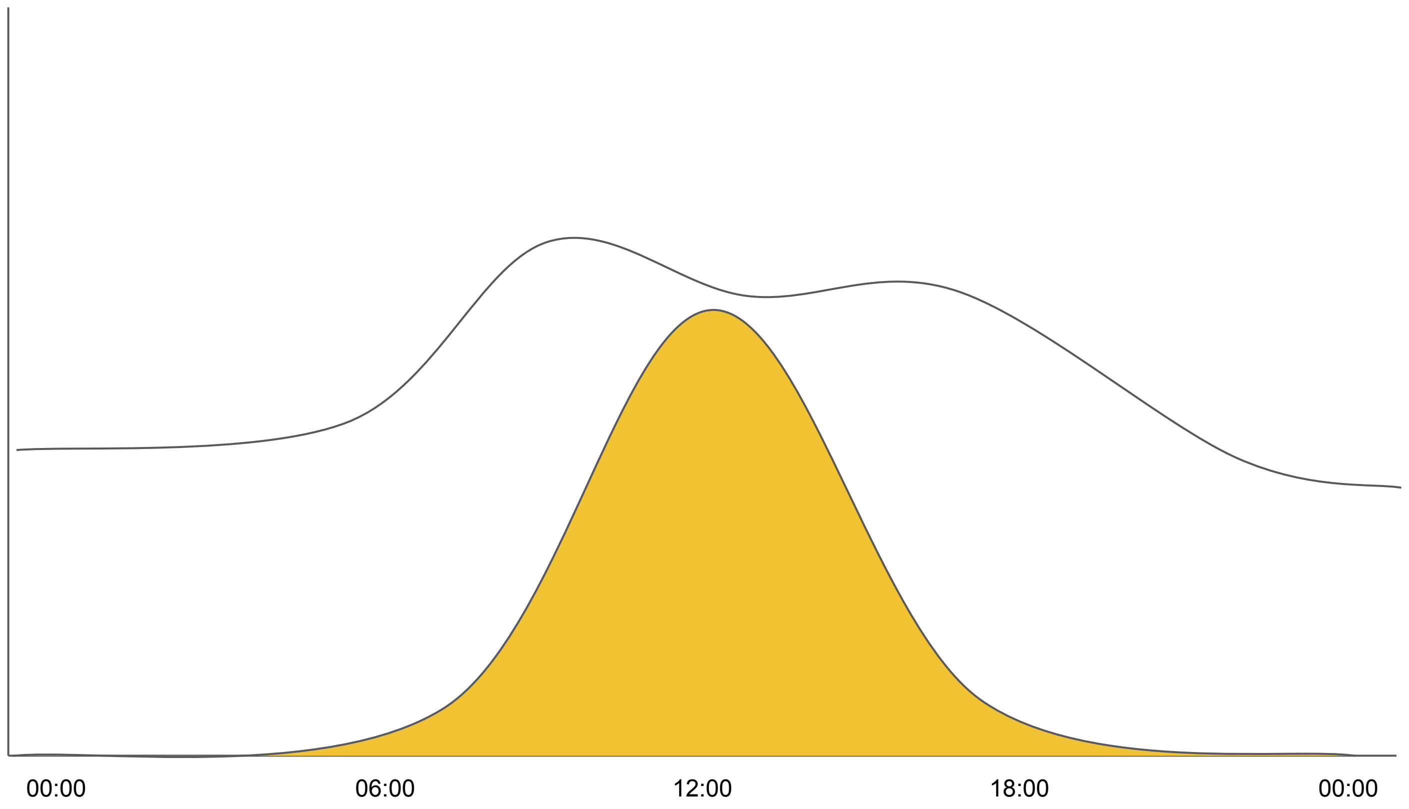
Shift + Exponential Smoothing	- Used for 1 timestep prediction - Worked great - best performing models so far
ARIMA + ARIMAX	- Computational expensive -
FB Prophet	-
LSTM	- Problems regarding Keras 3D Input Interface - Problems regarding multiple timestep prediction

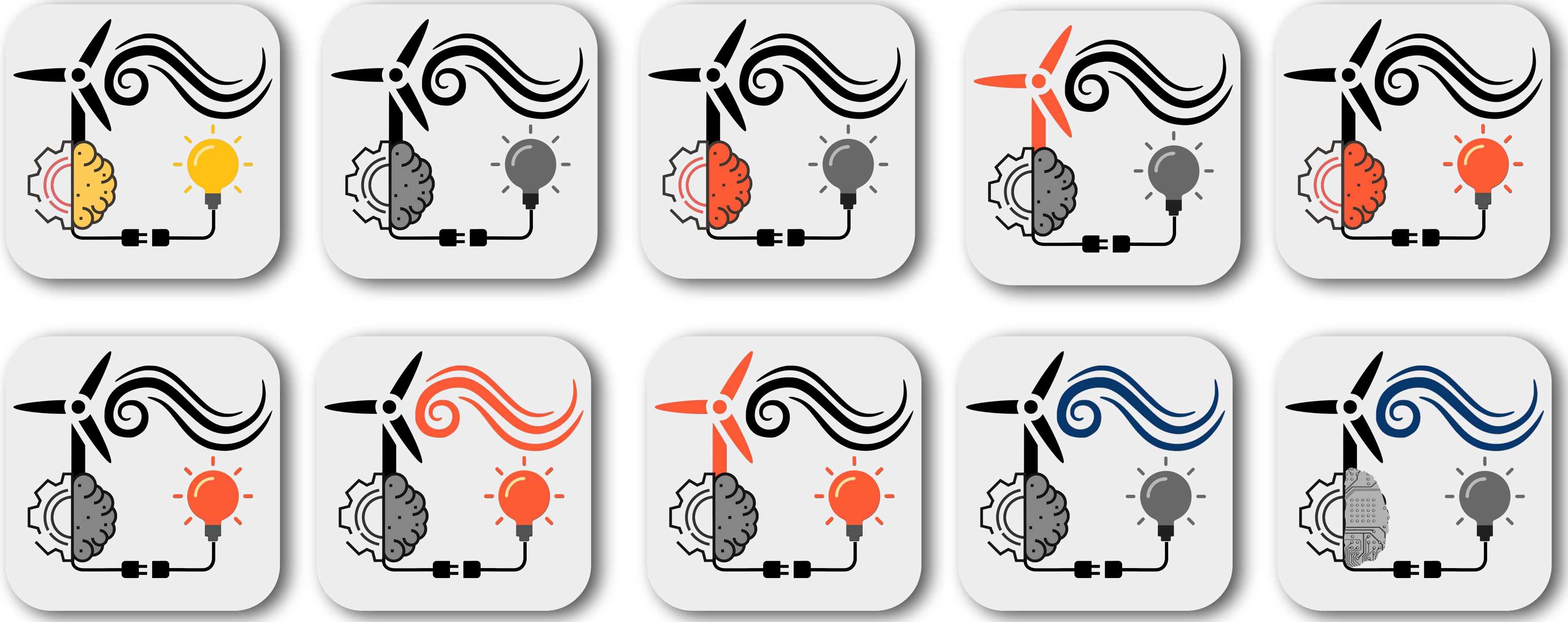
	Naive Base Model	Exponential Smoothing
RMSE	0.017165	0.014404
R2	0.987427	0.991147
MAE	0.008938	0.007483
MAPE	0.111866	0.091309

	FB Prophet Model
RMSE	0.016962
R2	0.988448
MAE	0.008184
MAPE	0.148100

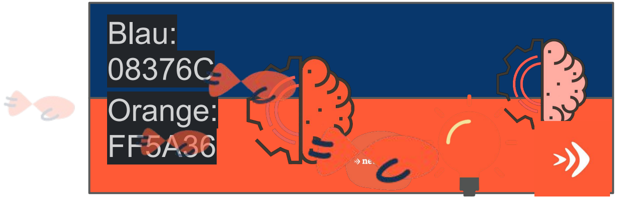
	LSTM - look_back: 1d, batch:1d
RMSE	0.024607
R2	0.975330
MAE	0.012663
MAPE	4.401784



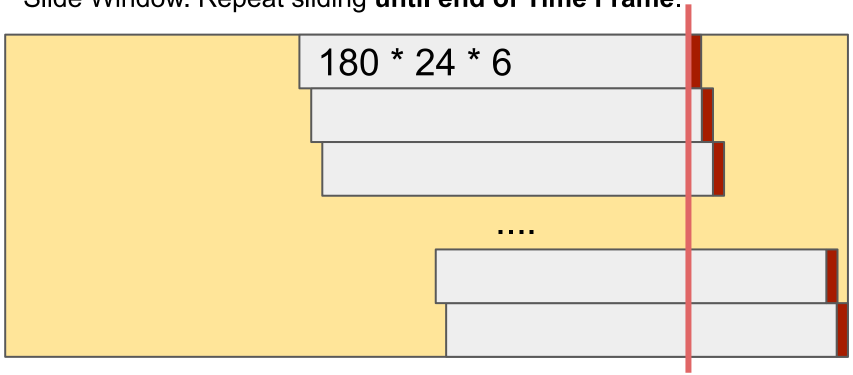

00:00
06:00
12:00
18:00
00:00



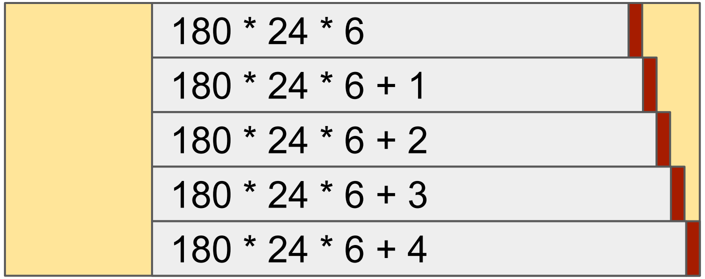
Icons at: [Renewable Energy PNG Images, Transparent Renewable Energy Image Download]()



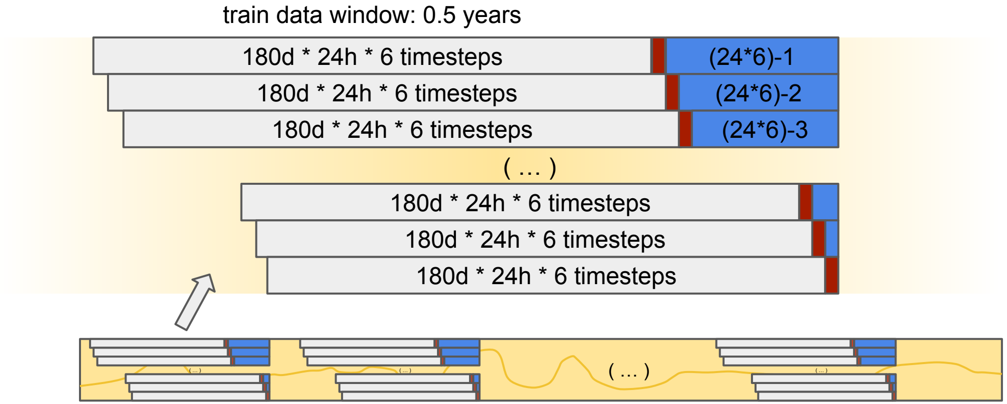
1) Cut at point X. Train with 0.5 years. Predict 1 time step ahead.
Slide Window. Repeat sliding **until end of Time Frame**.



2) Expanding Training Window.

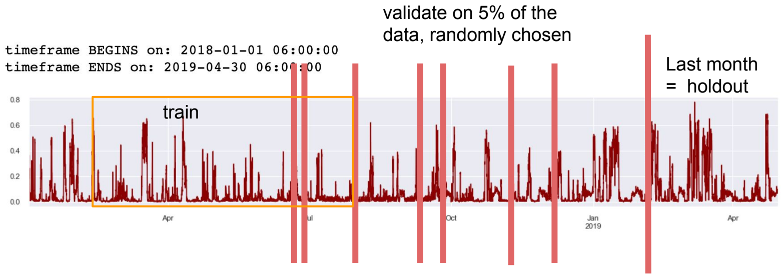


3) Sliding Window at 10 different timestamps. Training on 0.5 yea5rs.
Predicting 1 step ahead, at 10 different days for 24*6 steps each day.

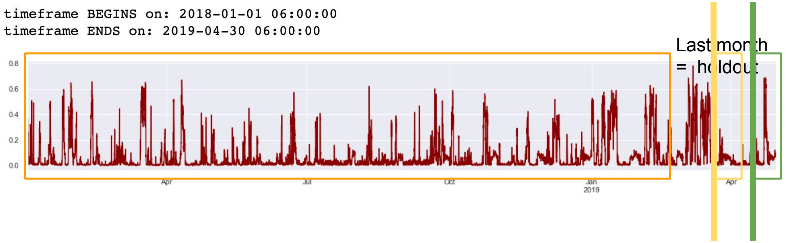


FUTURE

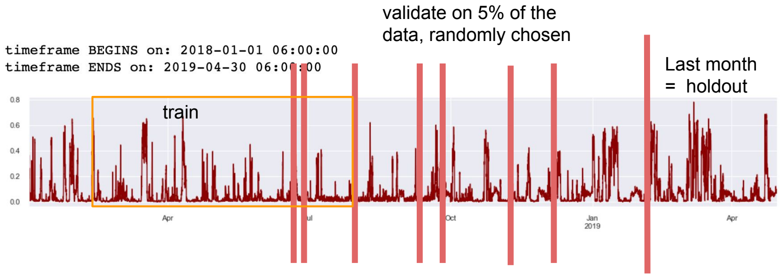
4) Predicting more than one time step ahead.



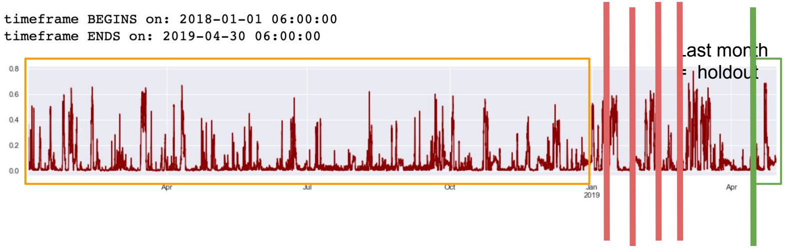
9. Nov 2020



Val: 17.3.2019 6 Uhr bis
27.03.2019 6 Uhr
test: 20.4. 6 Uhr bis 30.04. 6 Uhr



```
timeframe BEGINS on: 2018-01-01 06:00:00
timeframe ENDS on: 2019-04-30 06:00:00
```

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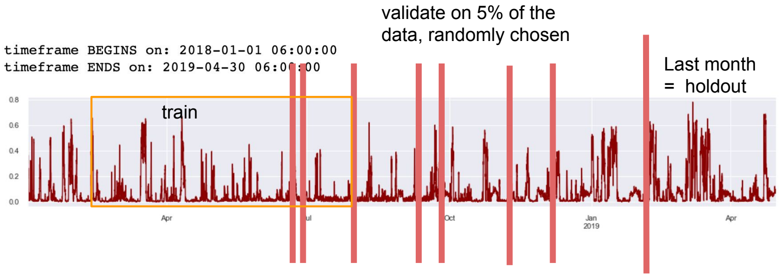
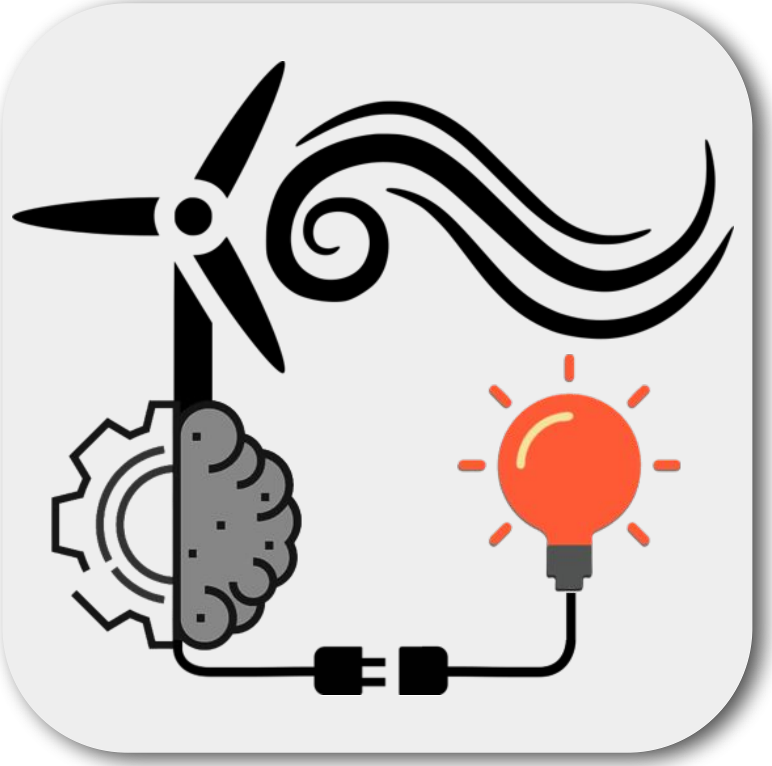
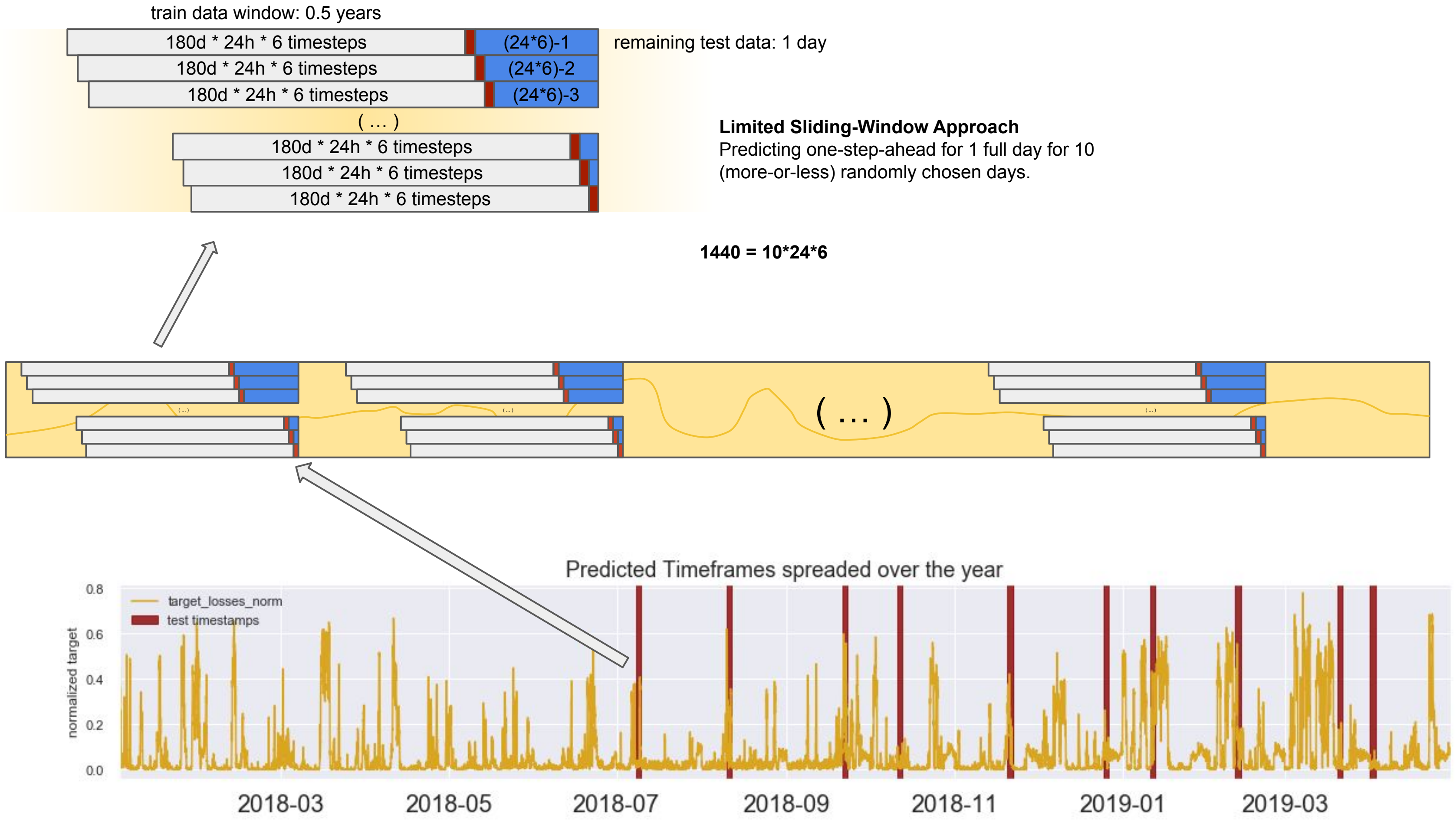
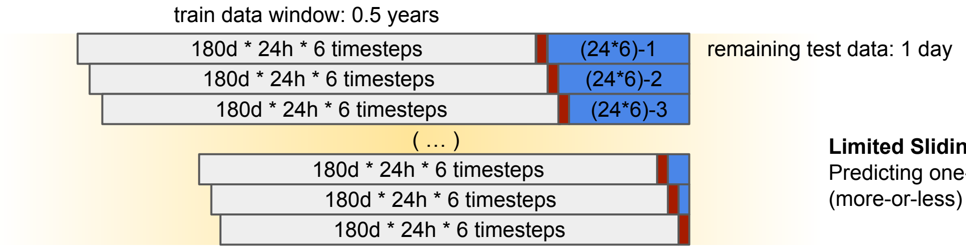
timeframe ENDS on: 2019-04-30 06:00:00
```




train data window: 0.5 years
180d * 24h * 6 timesteps
(24*6)-1
(24*6)-2
(24*6)-3
(…)
remaining test data: 1 day
Limited Sliding-Window Approach
Predicting one-step-ahead for 1 full day for 10 (more-or-less) randomly chosen days.
1440 = 10*24*6
(…)
Predicted Timeframes spreaded over the year
target_losses_norm
test timestamps
normalized target
0.0
0.2
0.4
0.6
0.8
2018-03
2018-05
2018-07
2018-09
2018-11
2019-01
2019-03



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