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.

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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.

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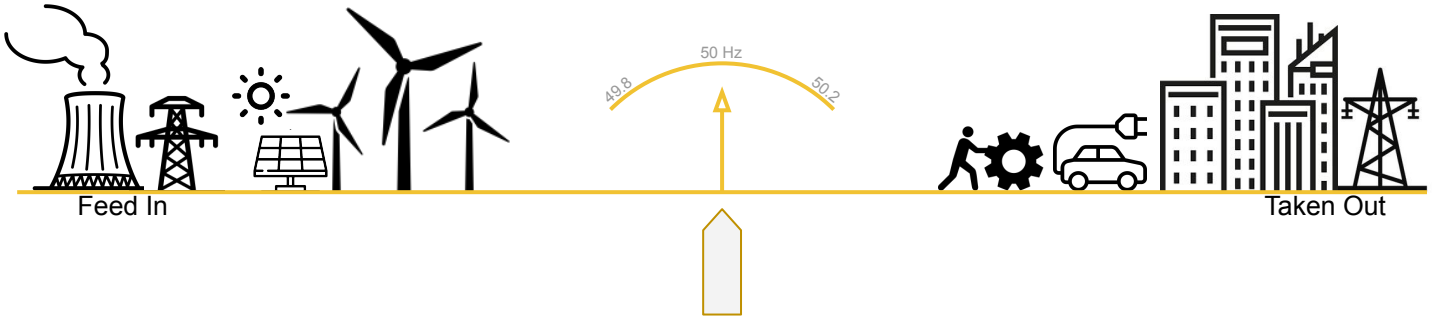
Energy fed into the system needs to equal energy taken out of the system at all times. This was already difficult with conventional electricity generation. It is even more difficult with a combination of volatile renewable energy sources. For example, on a windy and sunny day in June, there is potentially 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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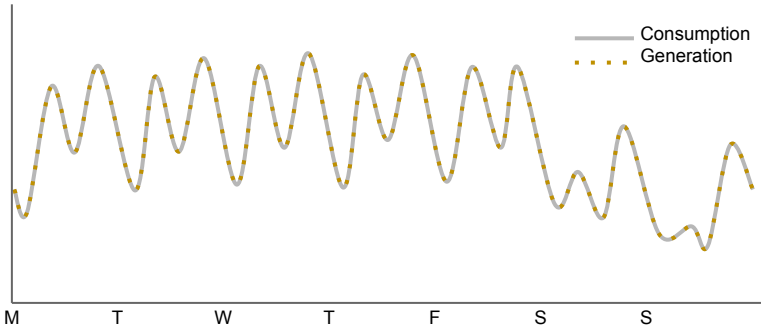
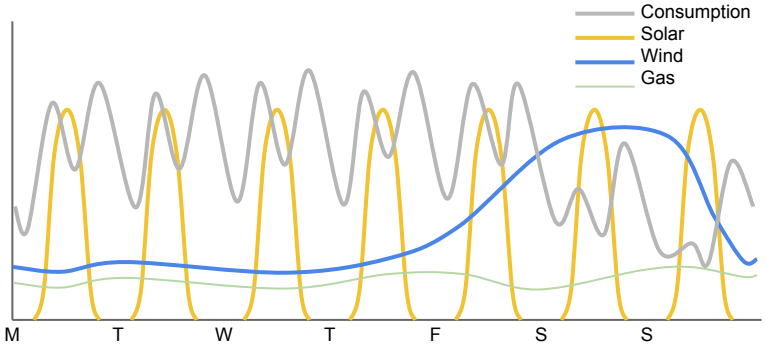
Conventional Electricity Grid



Renewable Electricity Grid



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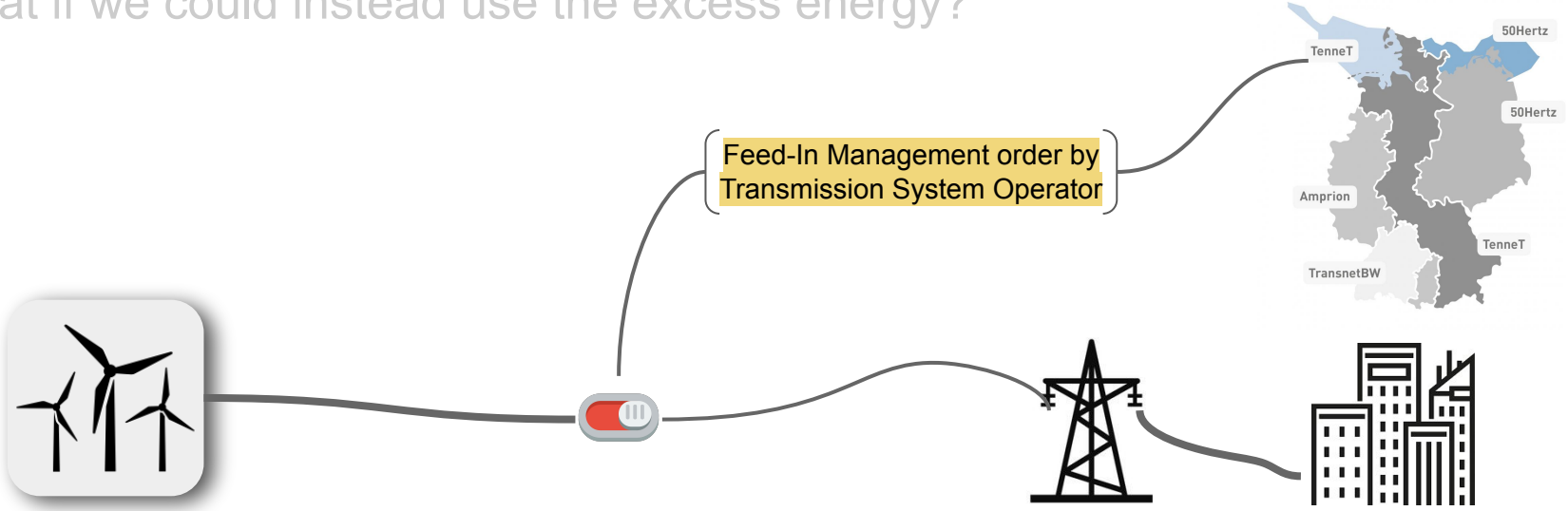

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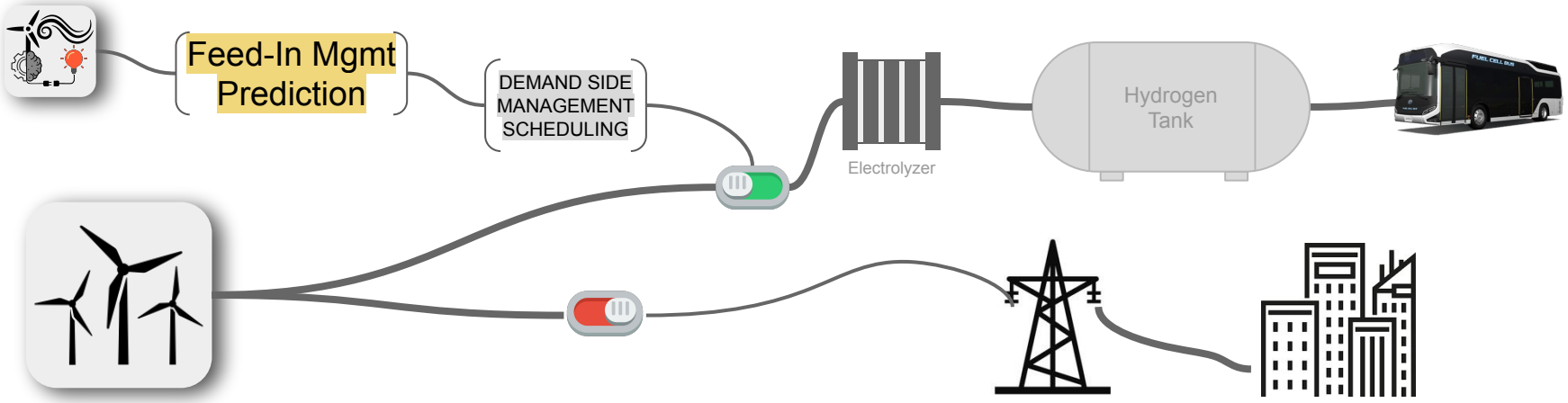


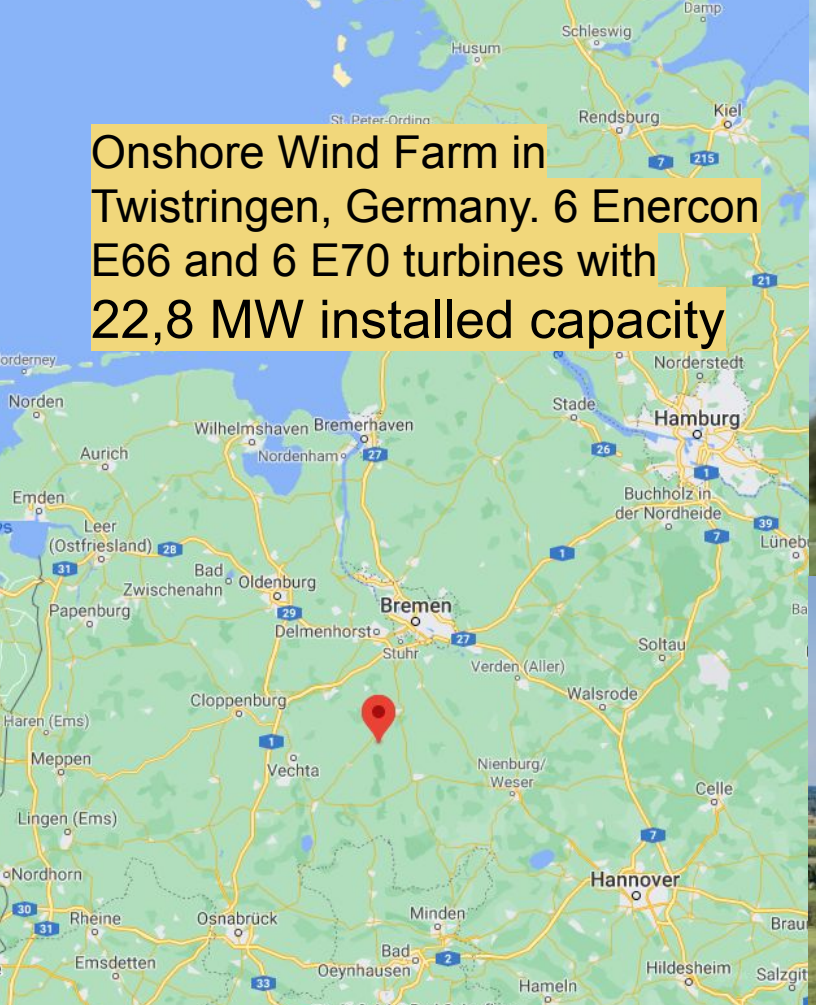
BACKGROUND

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

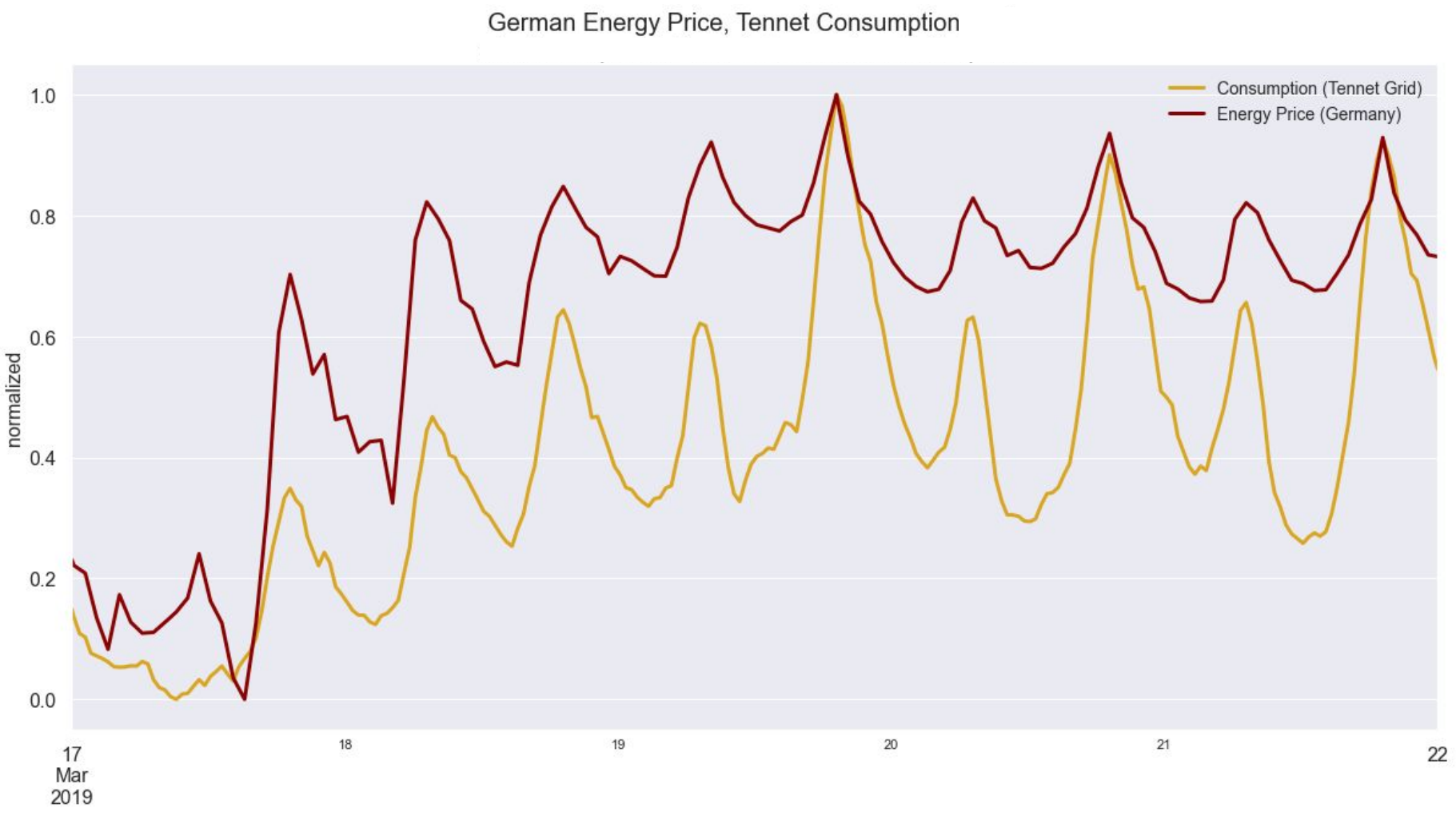
Started with 57 features,
used 25 features for
multivariate
predictive models

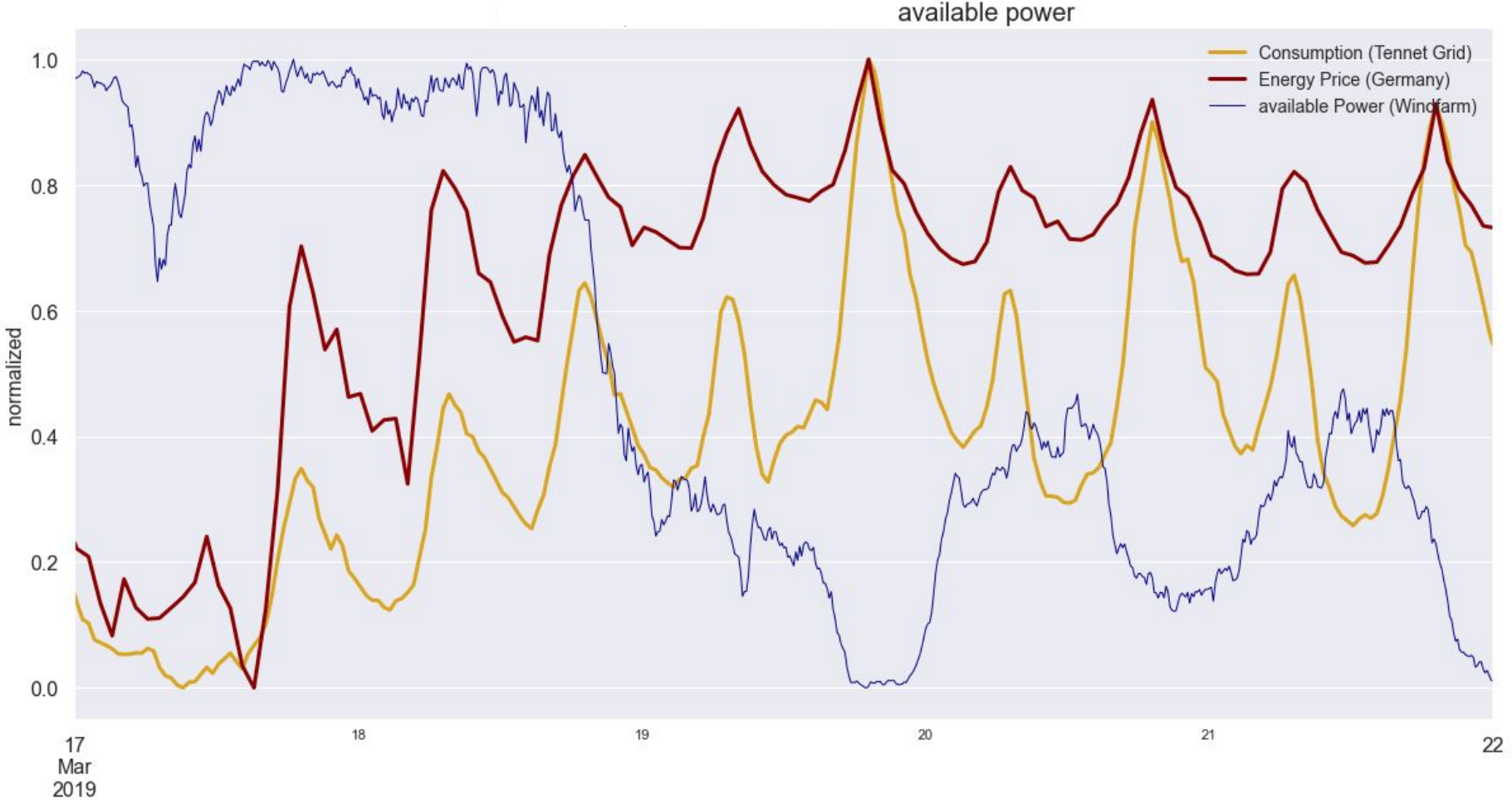
Feed-In Management Data

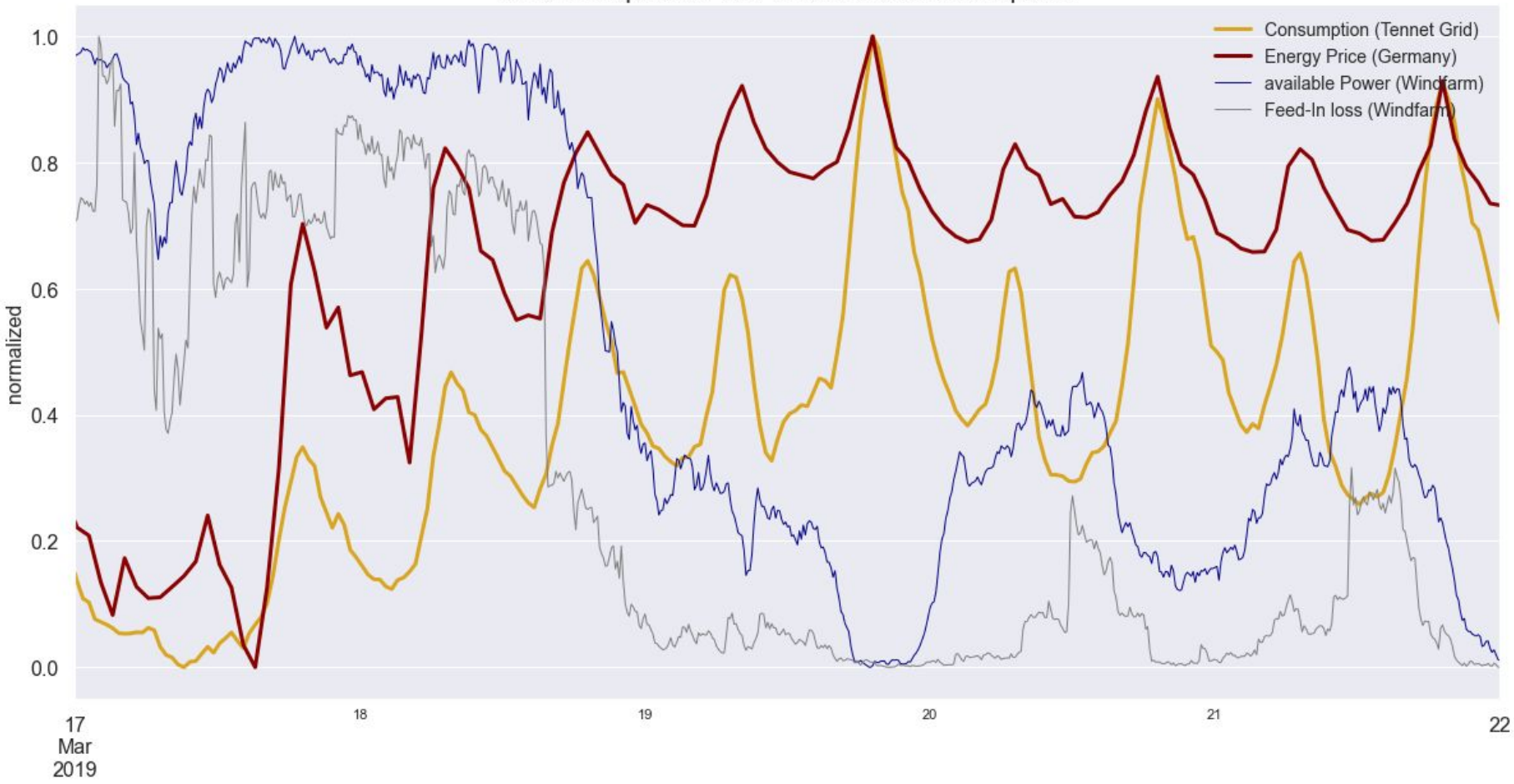
Consumption and Price Data

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

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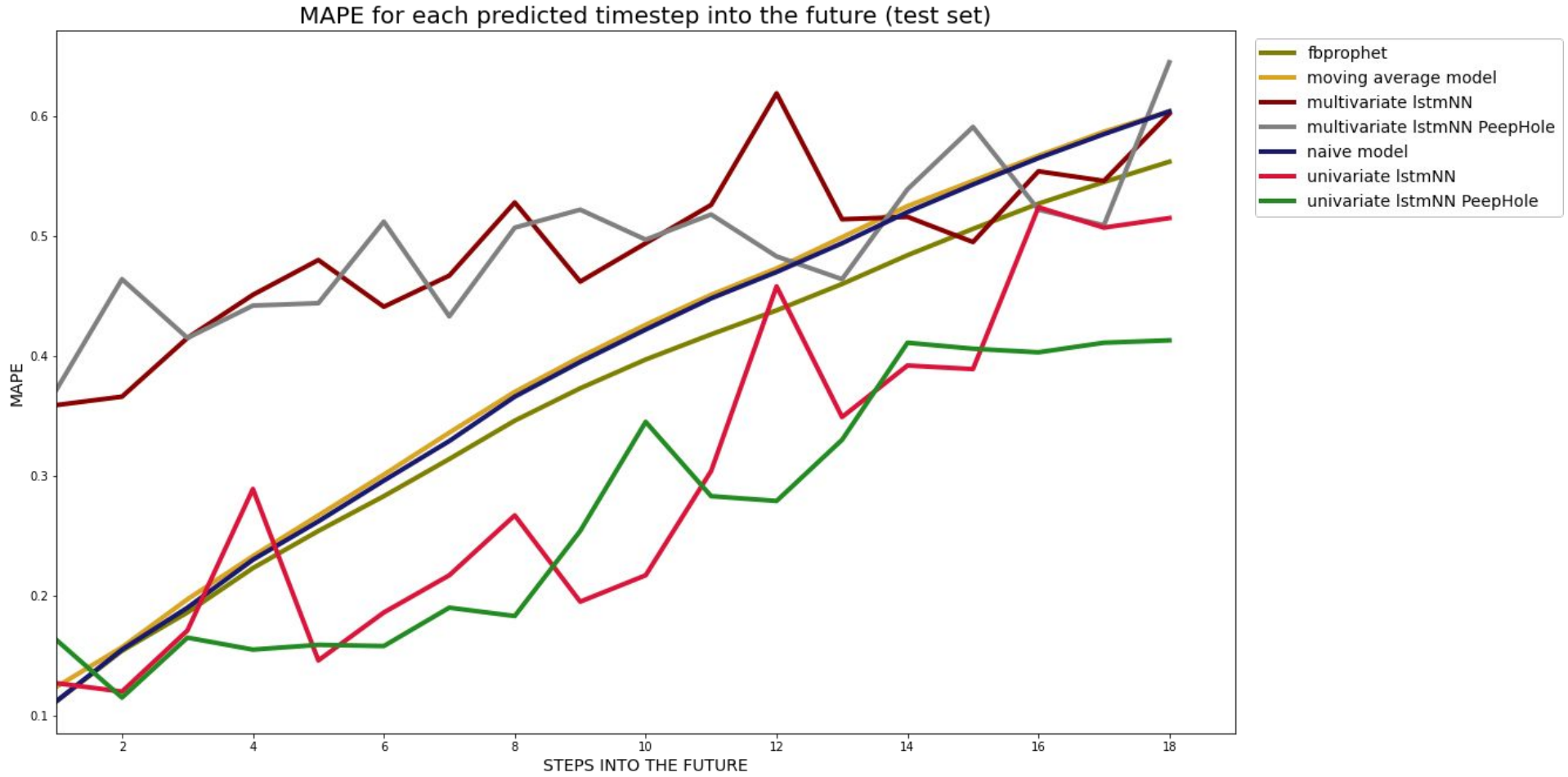
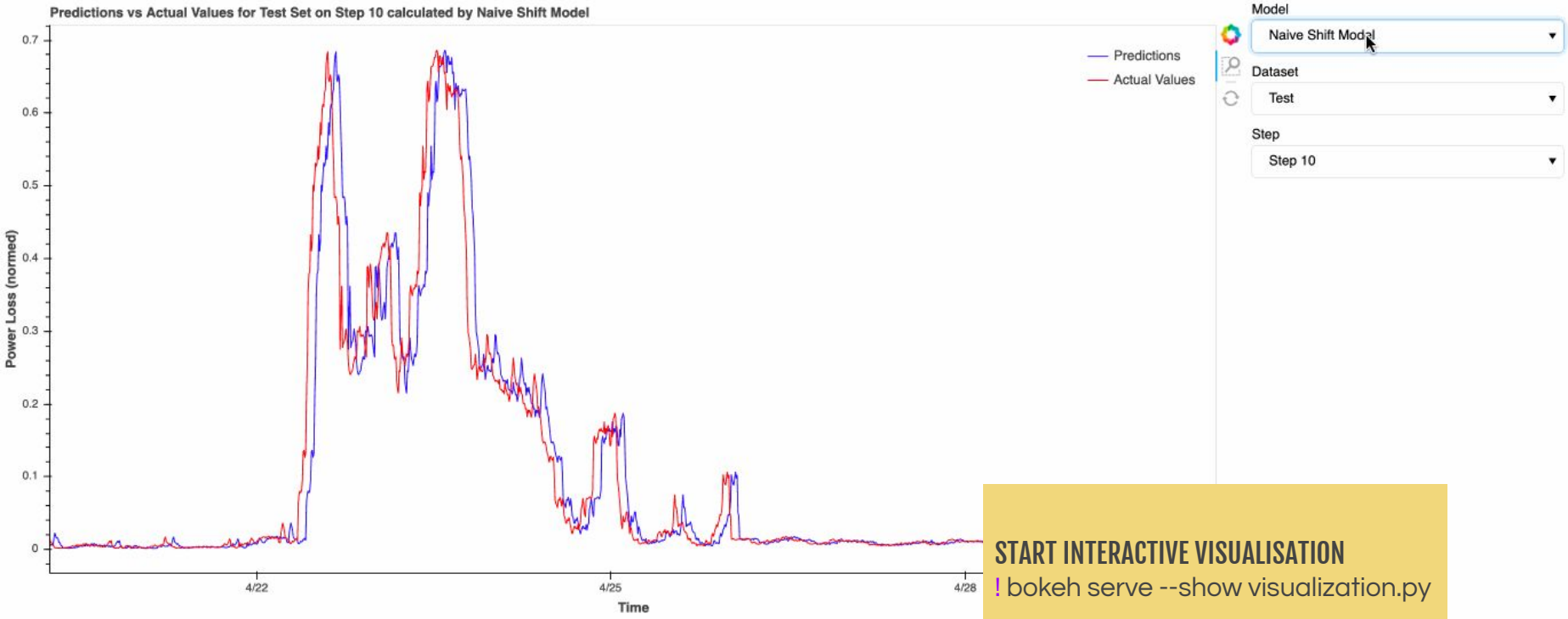
MODEL RESULTS

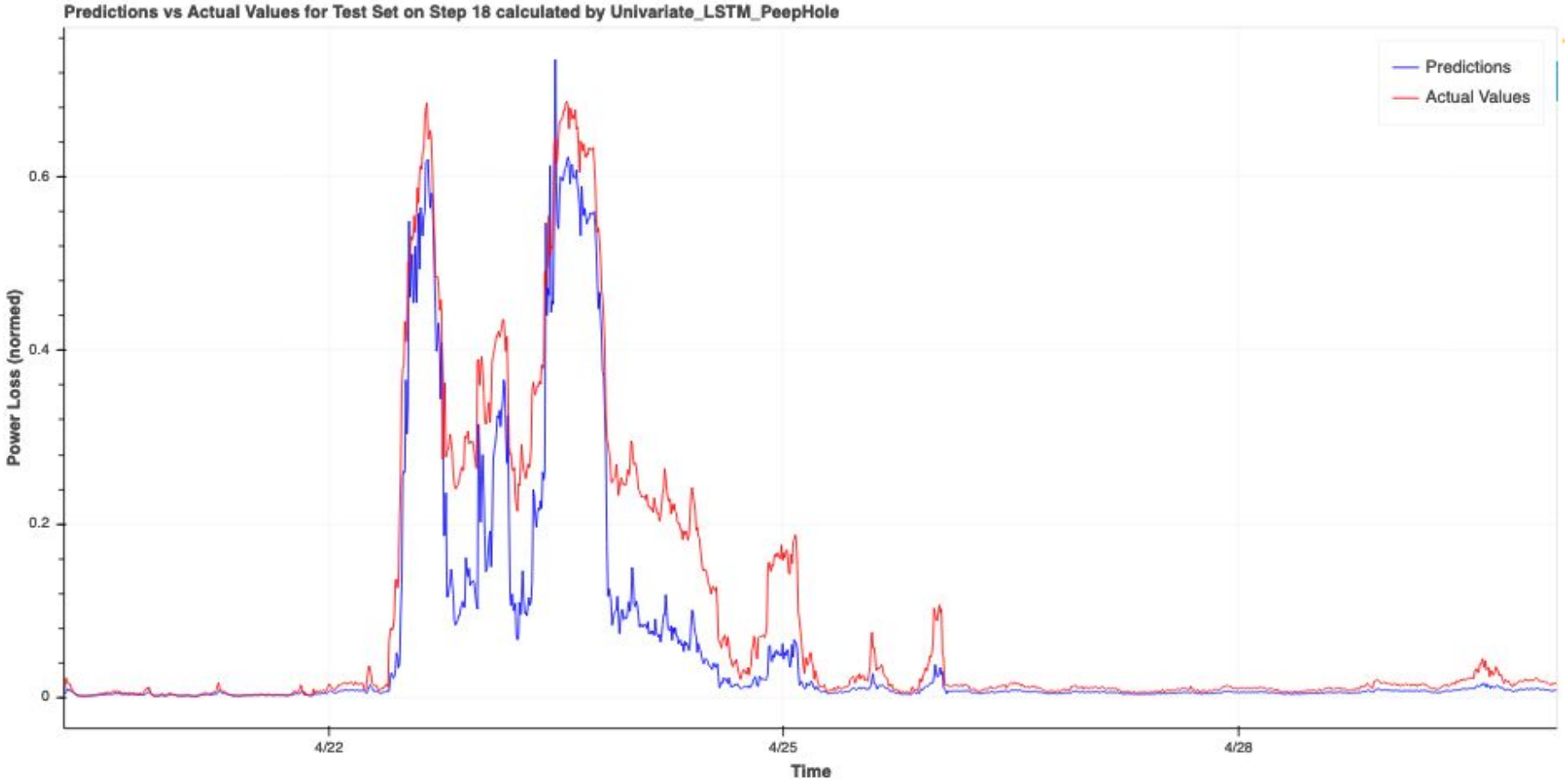
FUTURE WORK


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
fbprophet
moving average model
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
univariate lstmNN PeepHole



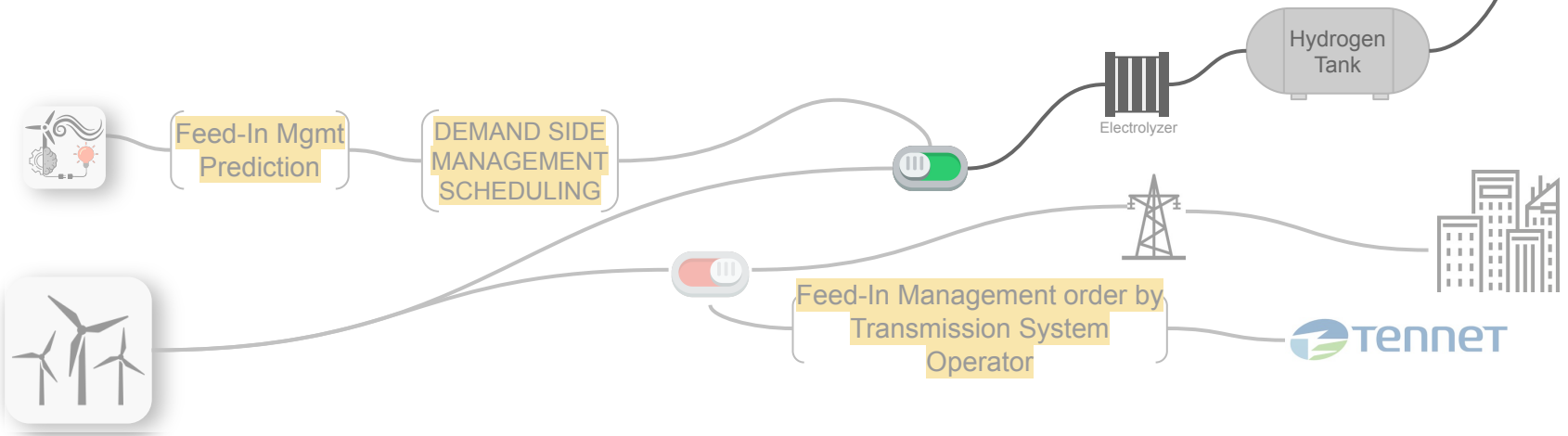
START INTERACTIVE VISUALISATION

! bokeh serve --show visualization.py


Predictions vs Actual Values for Test Set on Step 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



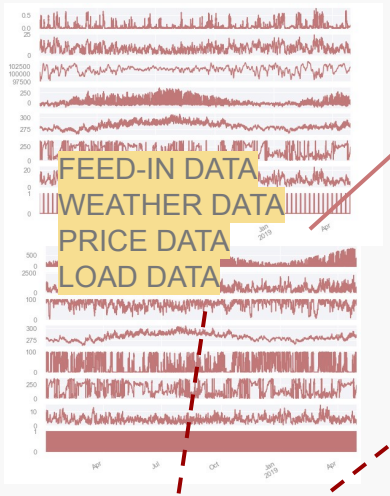
BACKGROUND

DATA ANALYSIS

MODEL RESULTS

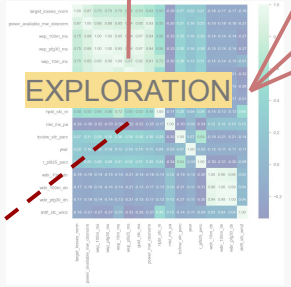
FUTURE WORK

[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

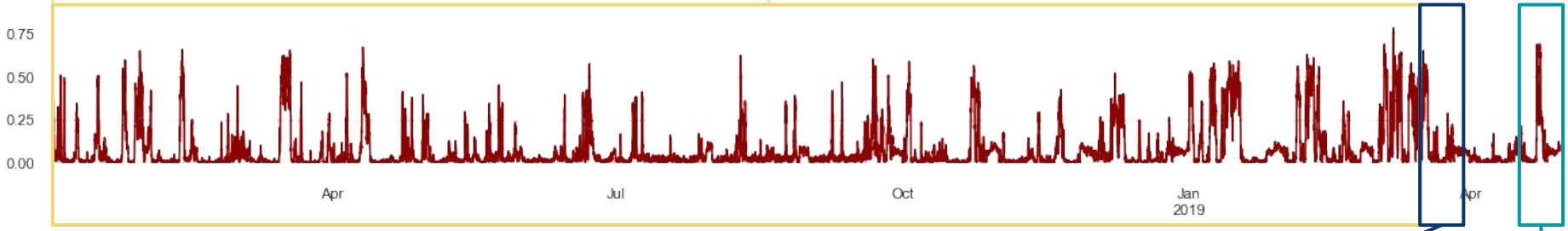
FEED-IN MANAGEMENT PREDICTIONS

DEMAND SIDE MANAGEMENT SCHEDULING

END.

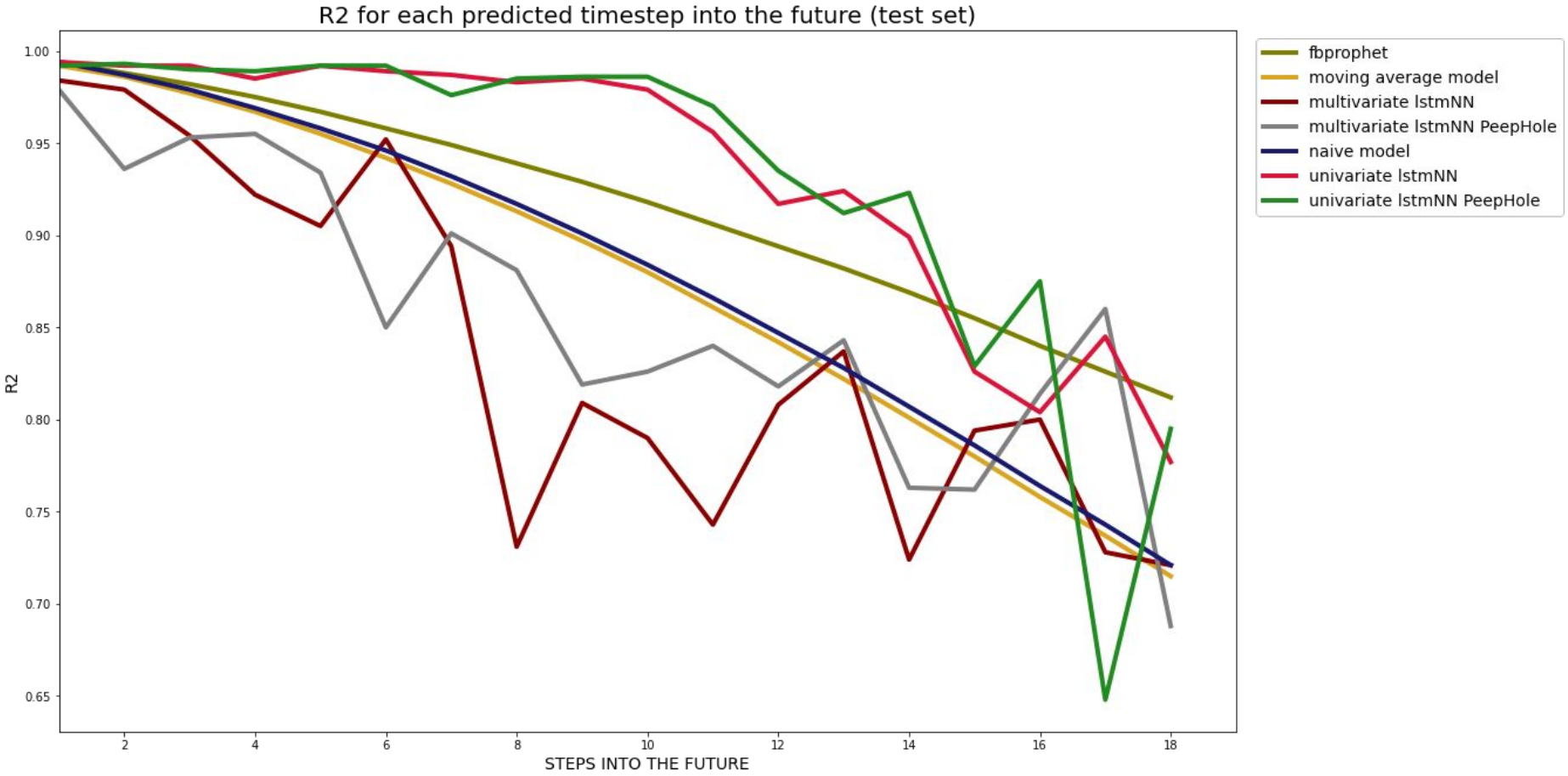
QUESTIONS?

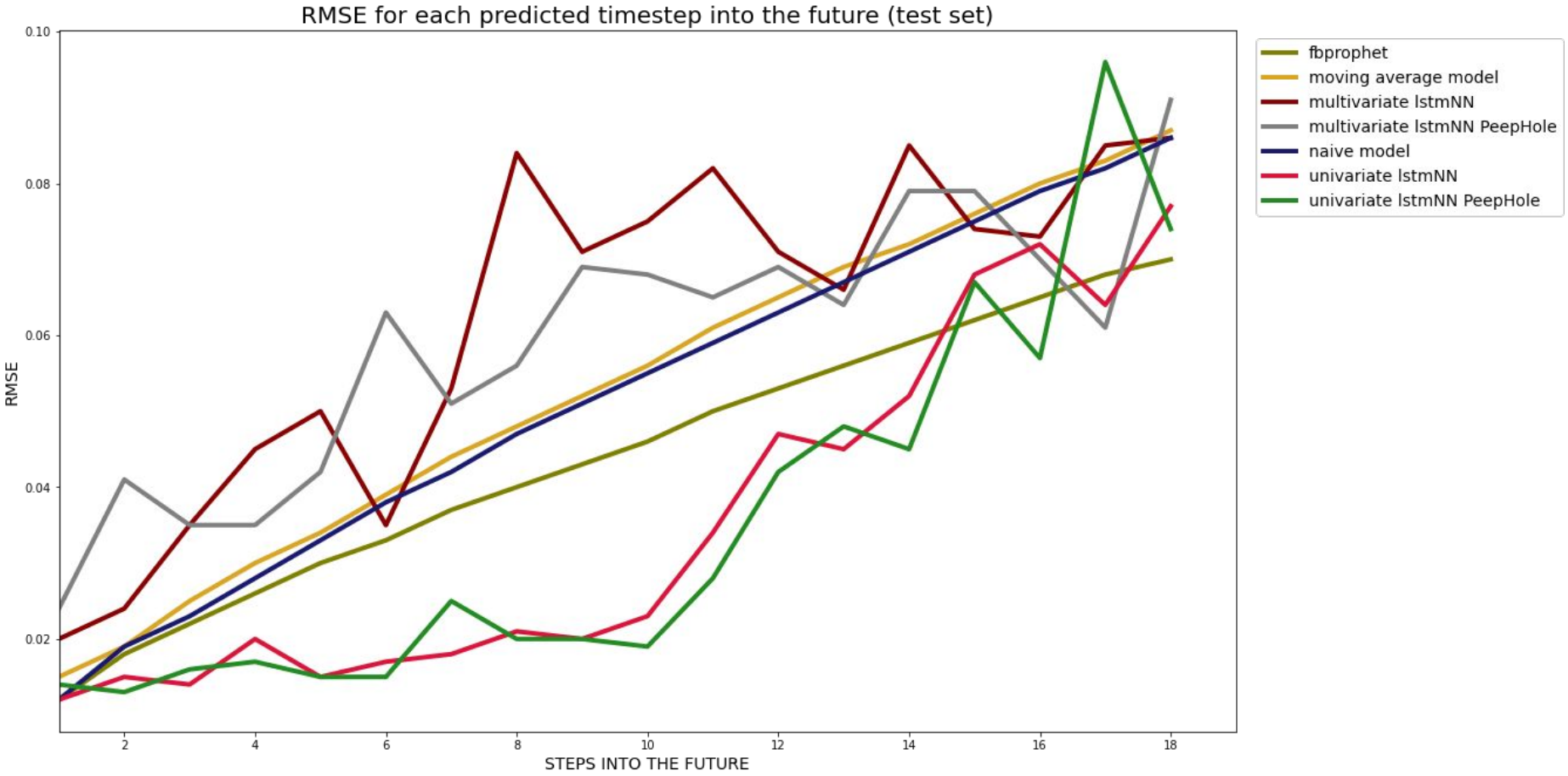
Training 440 Days (63.360 timesteps)
'01.01.2018 06:00:00' to '17.03.2019 05:50:00'



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

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


R2 for each predicted timestep into the future (test set)
R2
STEPS INTO THE FUTURE
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
2
4
6
8
10
12
14
16
18
fbprophet
moving average model
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
univariate lstmNN PeepHole


RMSE for each predicted timestep into the future (test set)
RMSE
STEPS INTO THE FUTURE
0.10
0.08
0.06
0.04
0.02
2
4
6
8
10
12
14
16
18
fbprophet
moving average model
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
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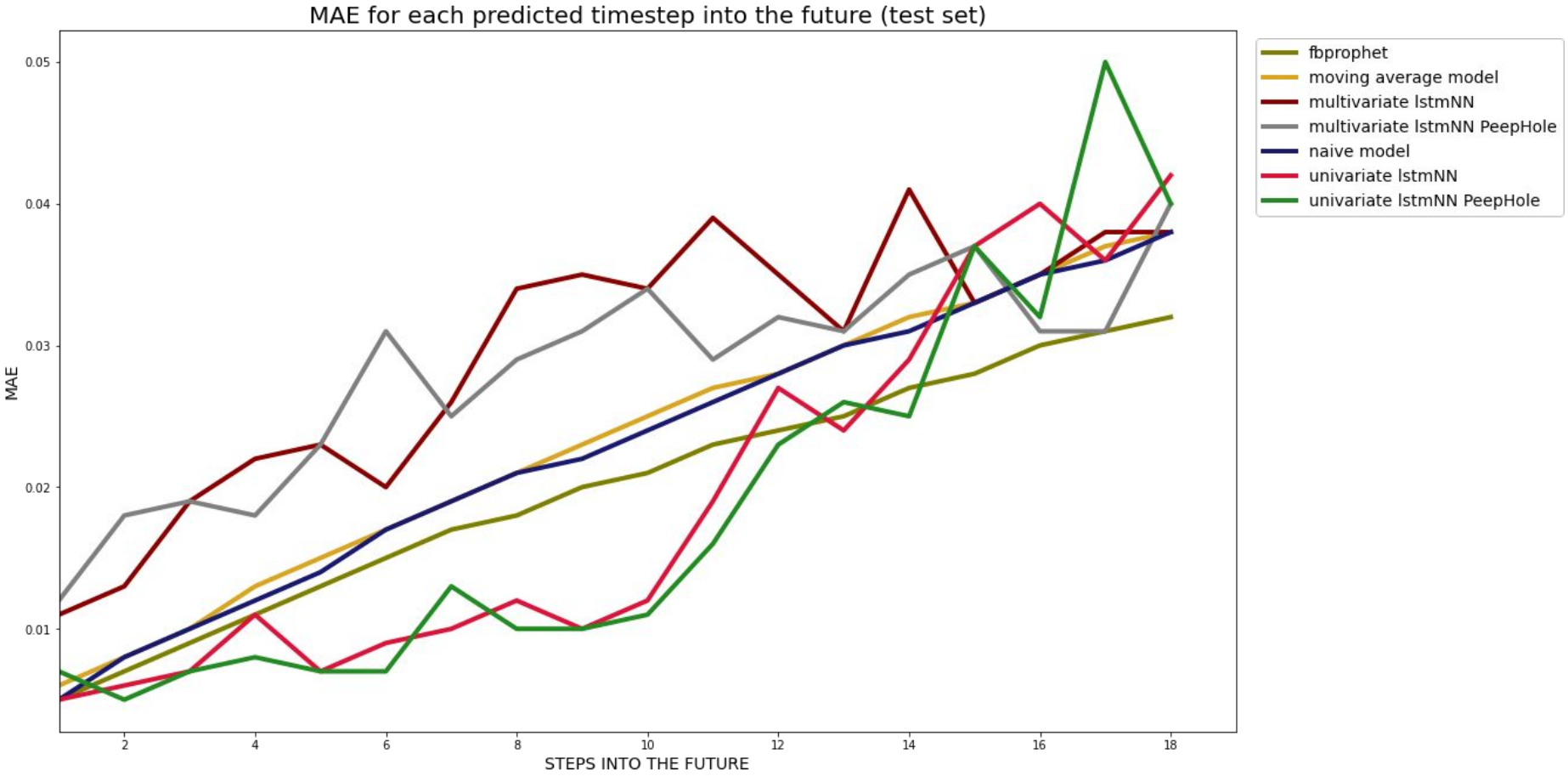
MAE for each predicted timestep into the future (test set)
MAE
STEPS INTO THE FUTURE
0.01
0.02
0.03
0.04
0.05
2
4
6
8
10
12
14
16
18
fbprophet
moving average model
multivariate lstmNN
multivariate lstmNN PeepHole
naive model
univariate lstmNN
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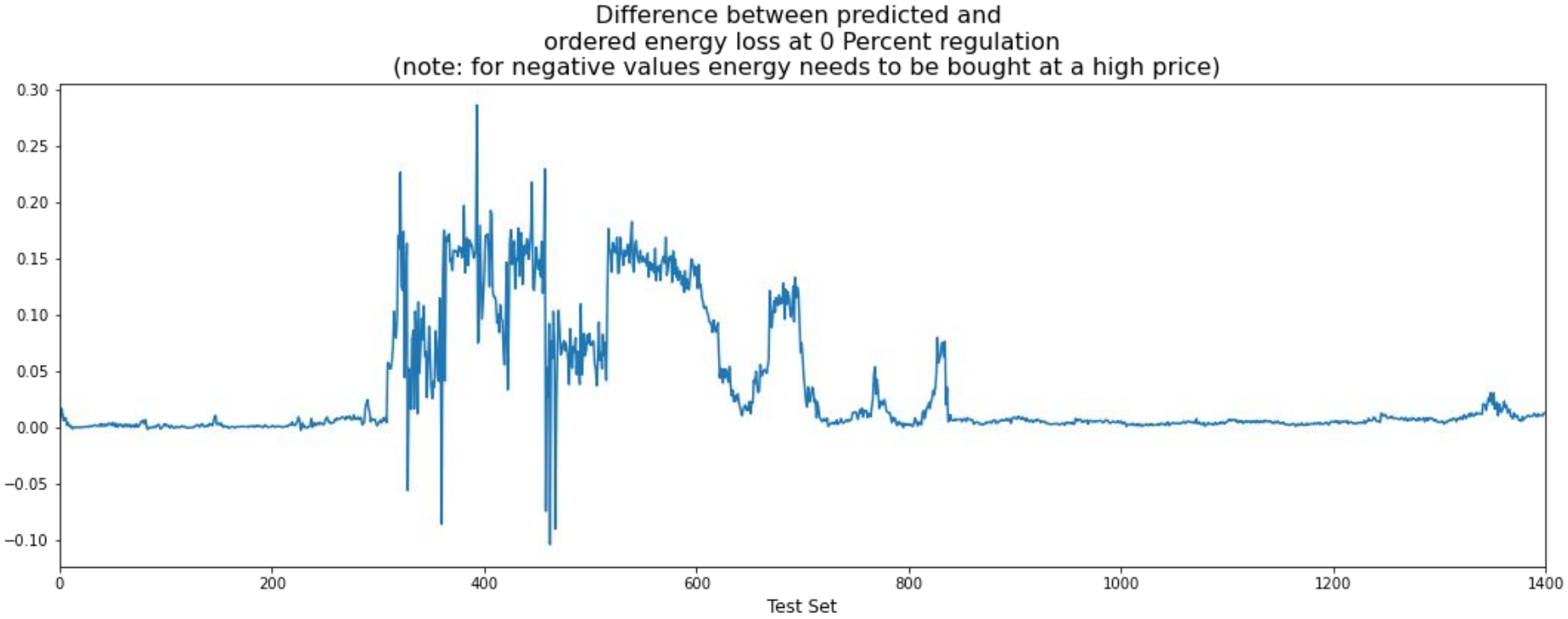
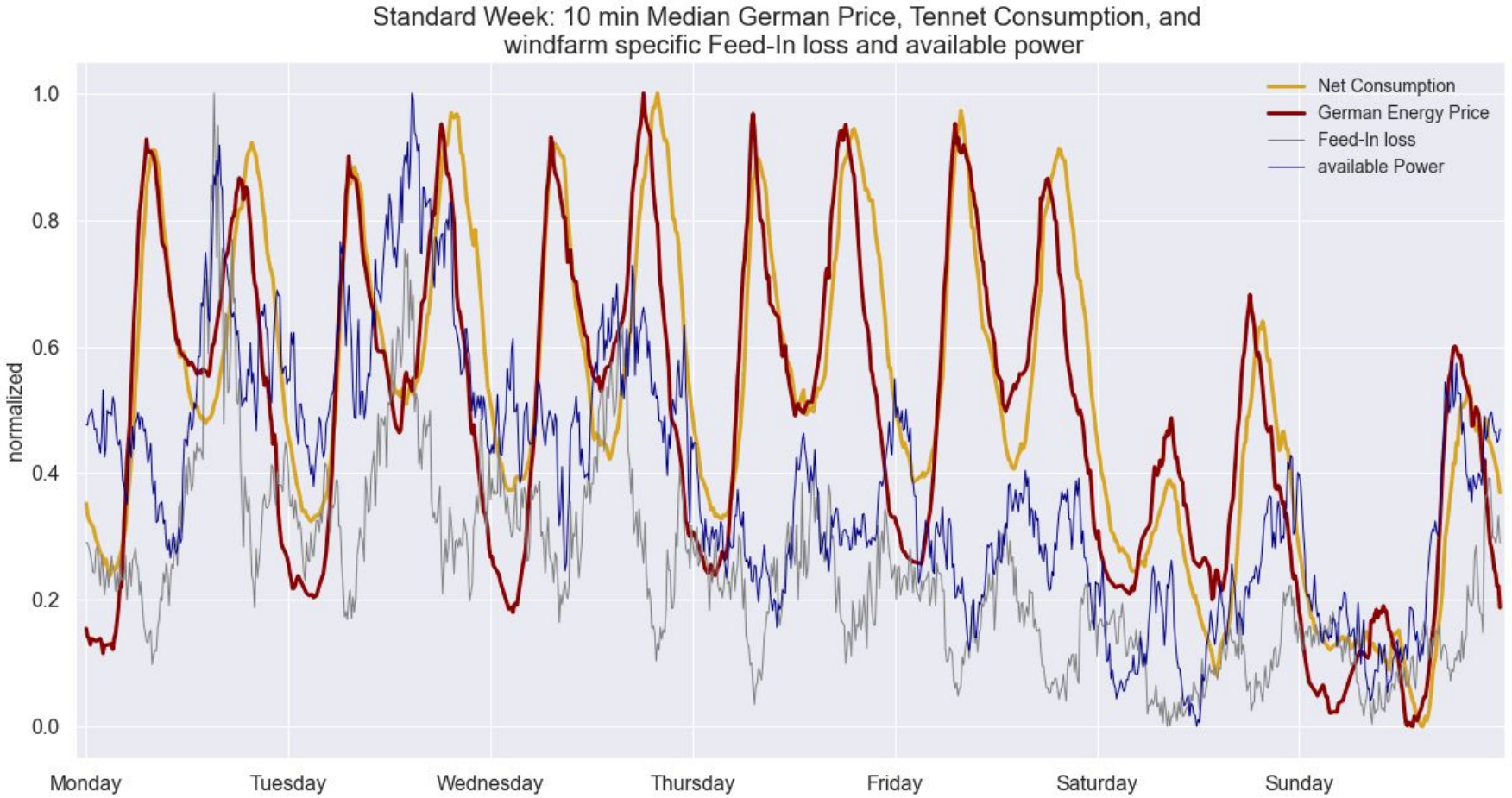
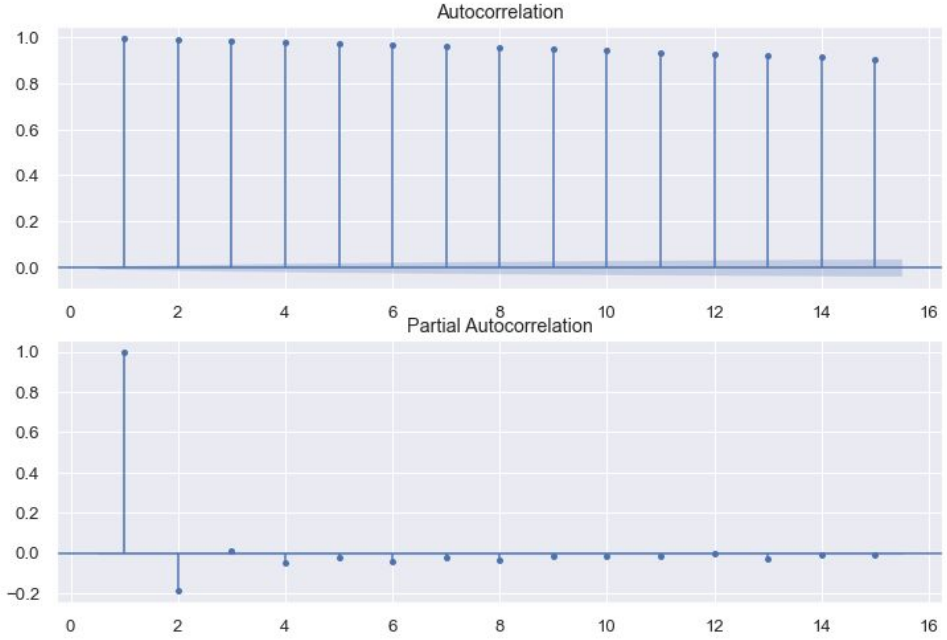
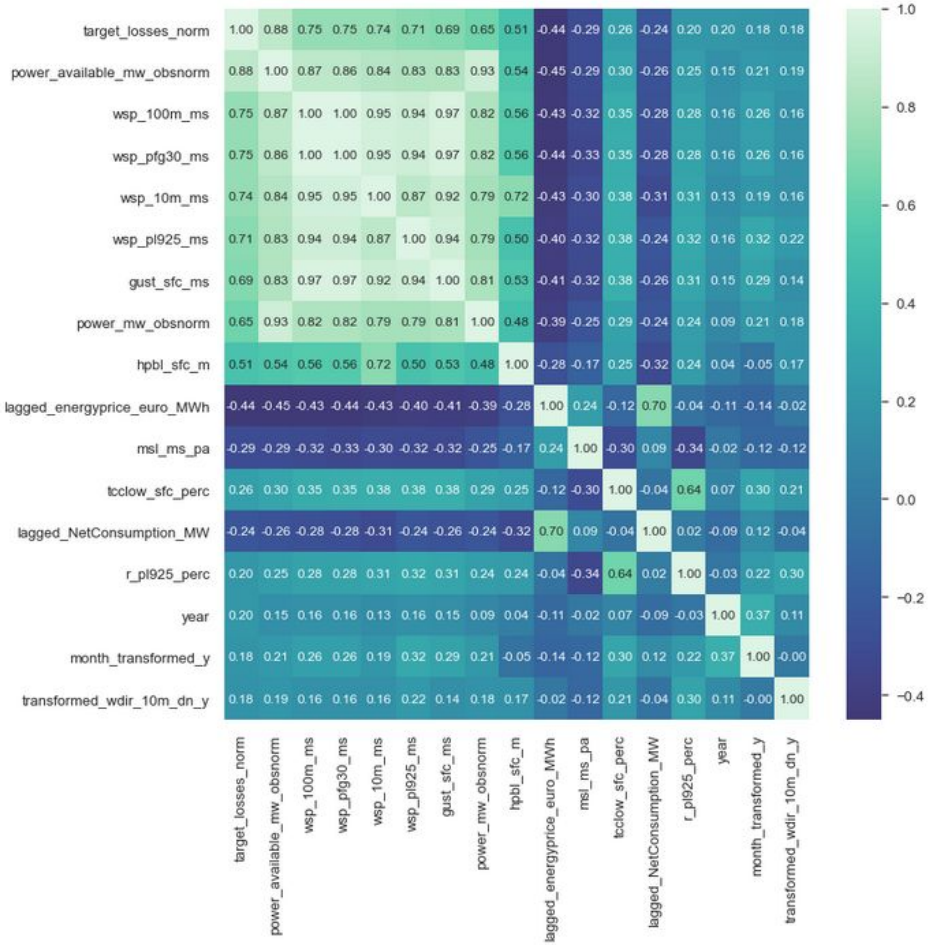

Difference between predicted and
ordered energy loss at 0 Percent regulation
(note: for negative values energy needs to be bought at a high price)
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
0
200
400
600
800
1000
1200
1400
Test Set


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