Capstone Presentation
8.October 2020

Tjade Apel
Jonas Jaenicke

Feed-In Management Prediction

Prediction of Renewable Power Loss caused by Feed-In Management

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

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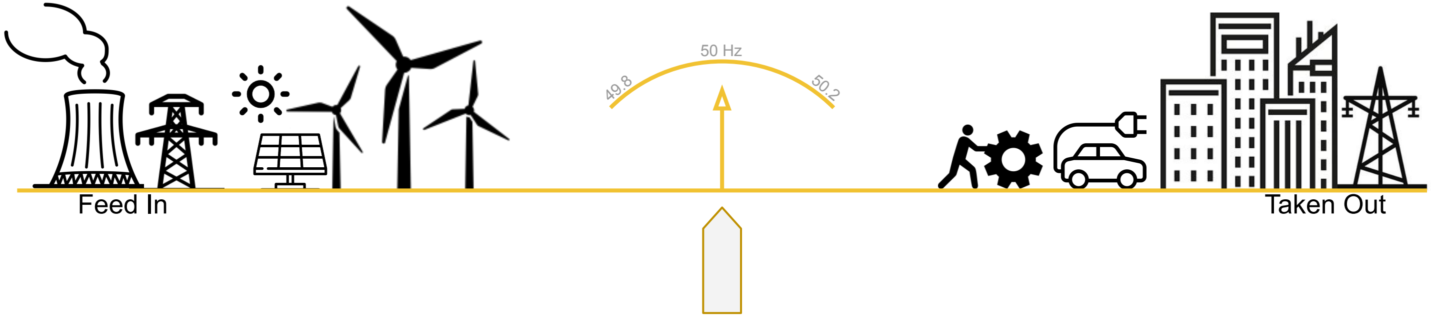
Energy feet into the system needs to meet energy taken out of the system at all times. This was already difficult with conventional electricity generation. It is even more difficult with a combination of volatility renewable energy sources. For example, on a windy and sunny day in June, there is potentially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



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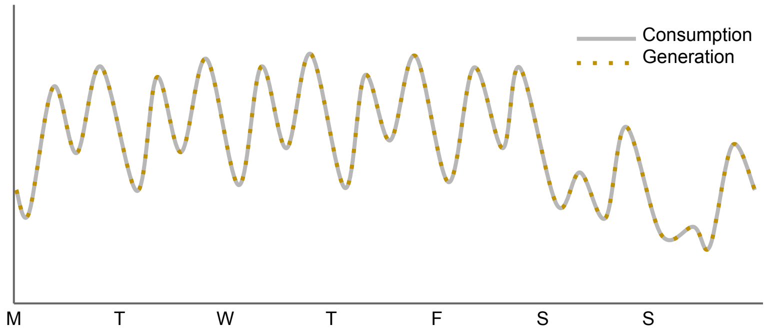
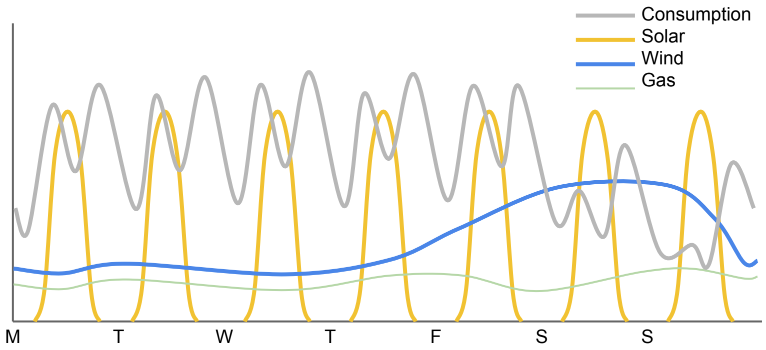
Conventional Electricity Grid



Renewable Electricity Grid



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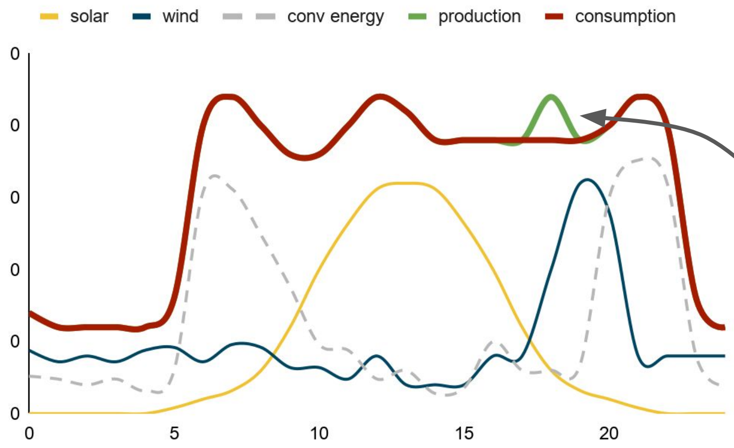

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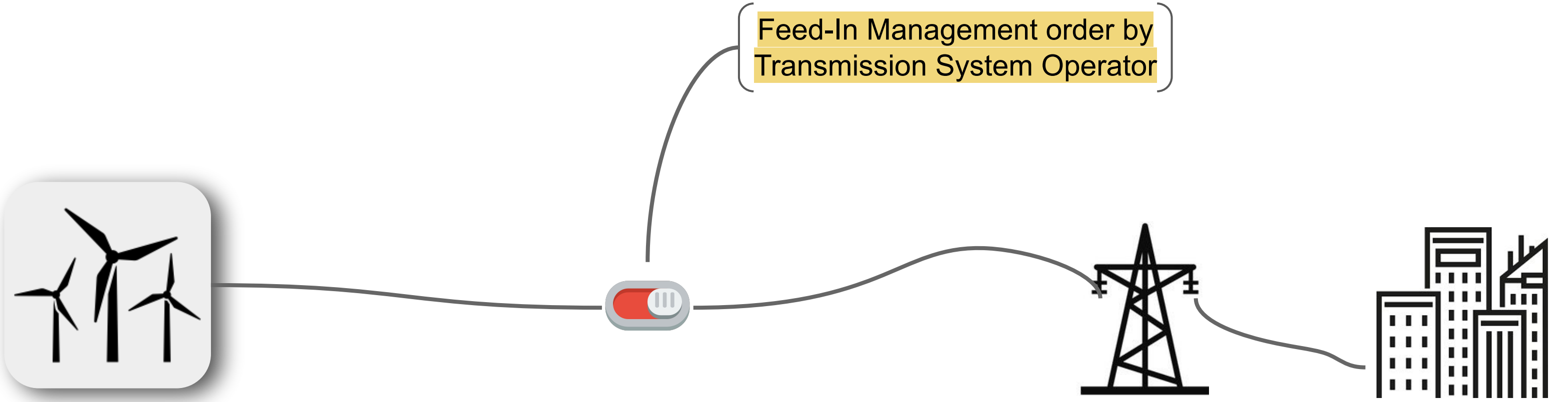

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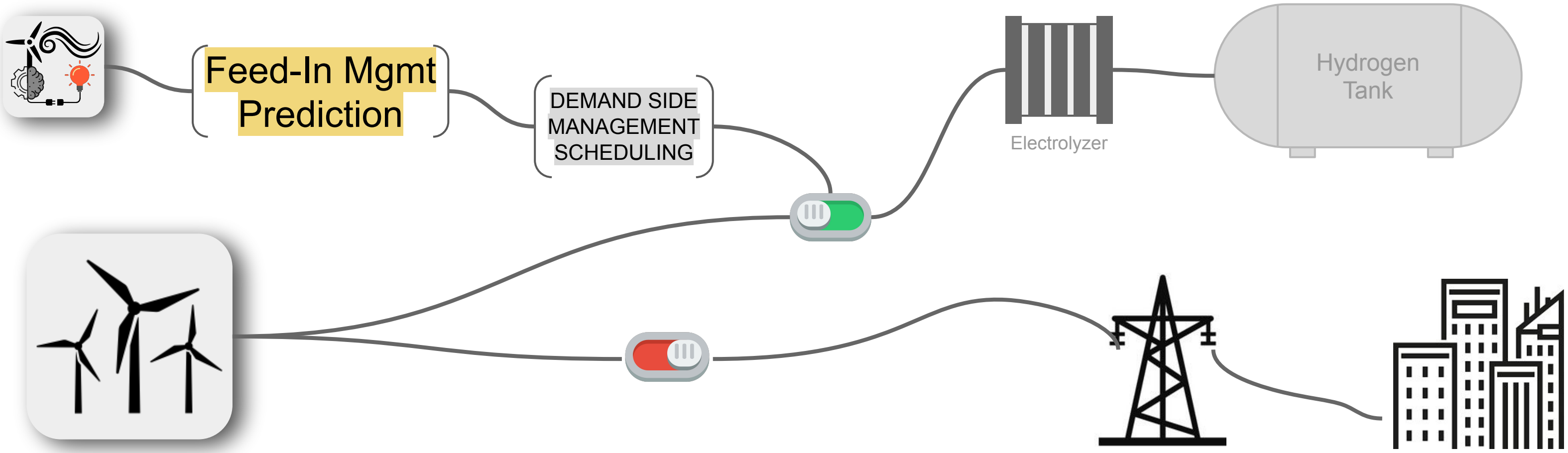
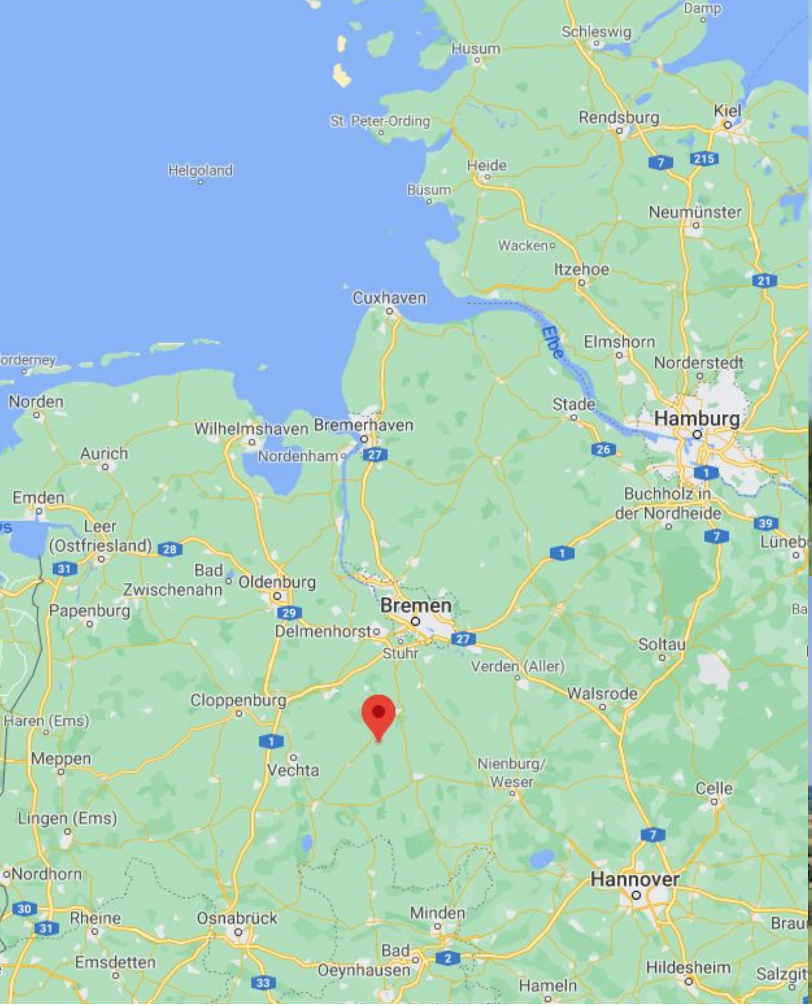


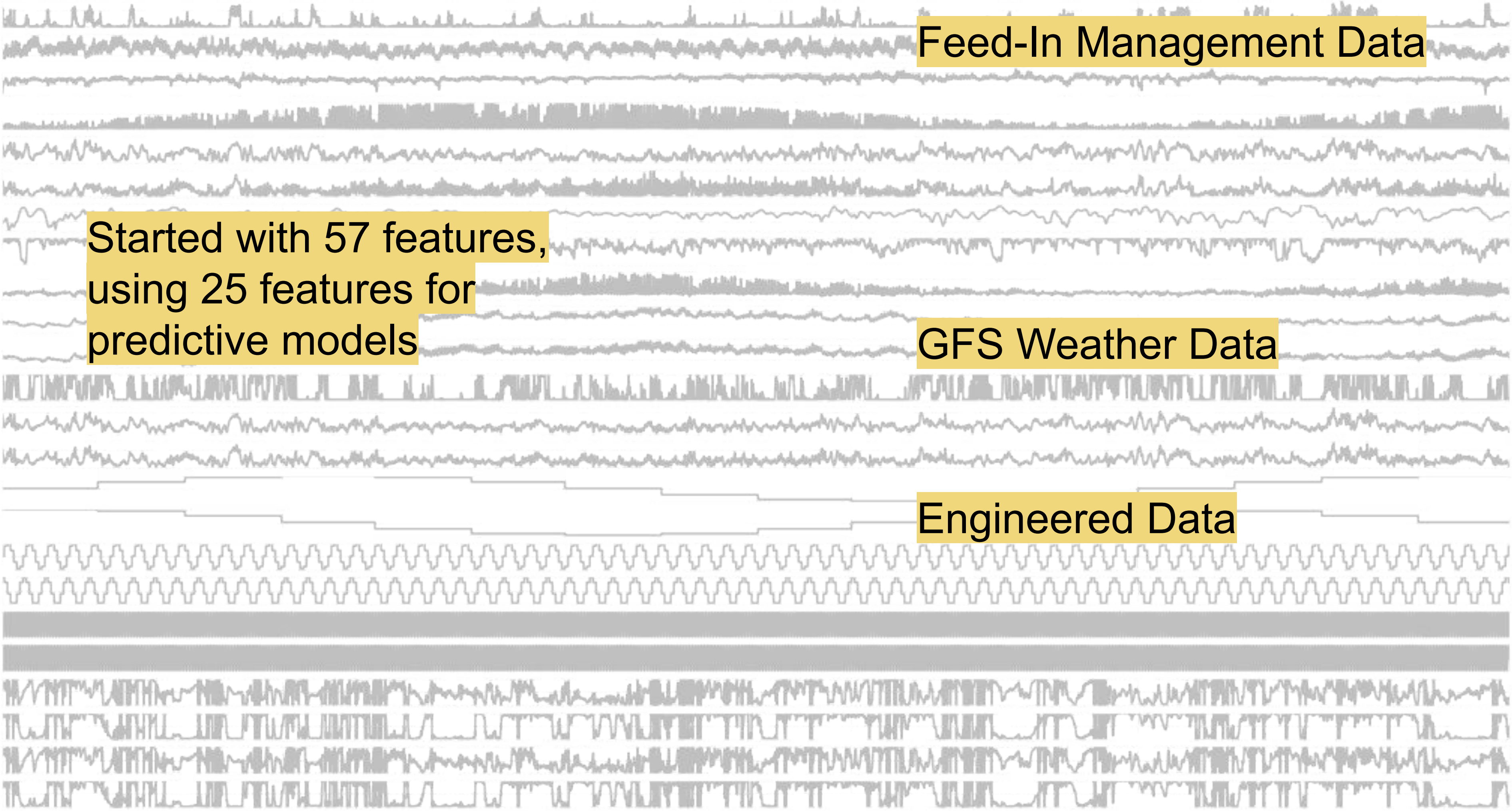
BACKGROUND

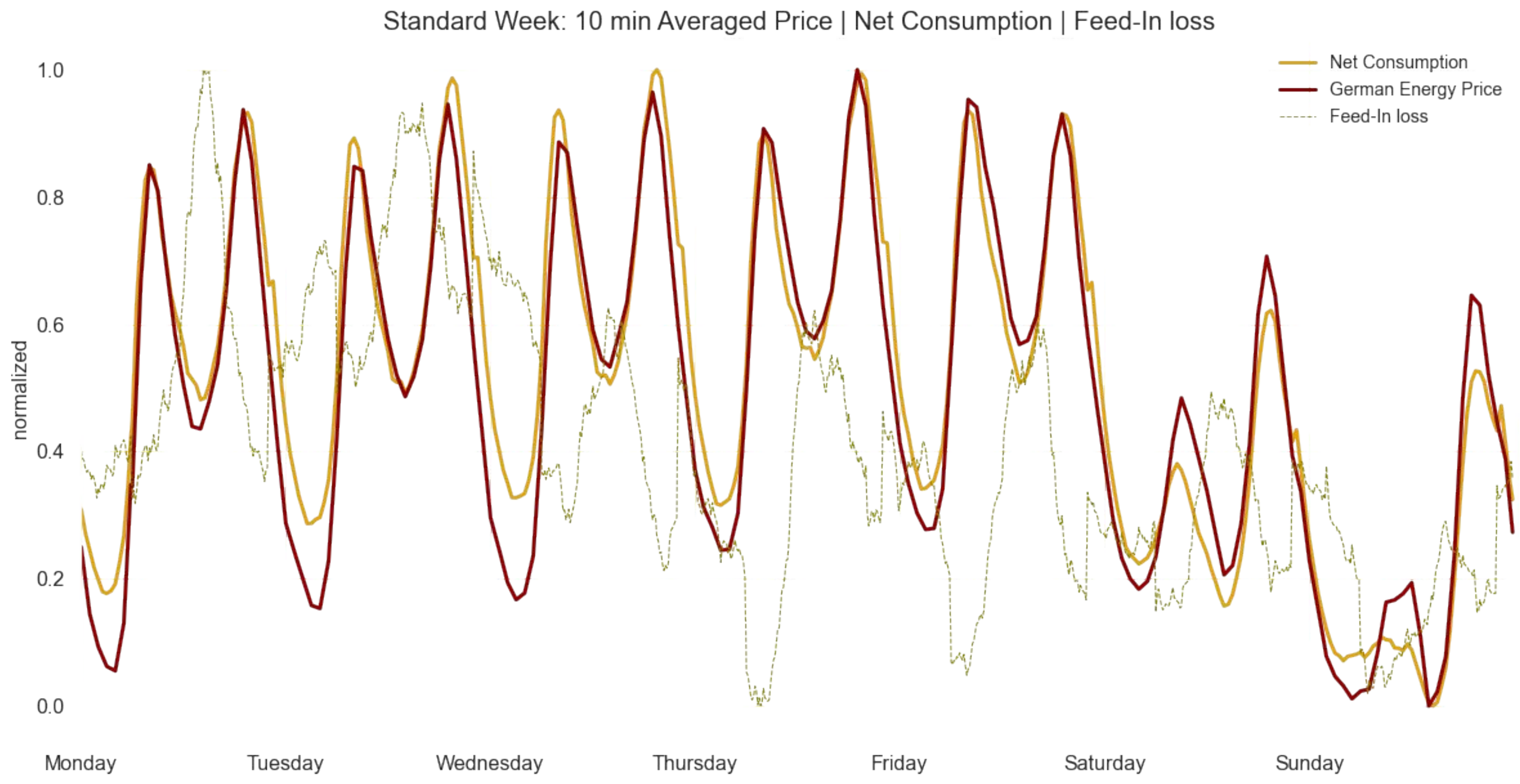
DATA ANALYSIS

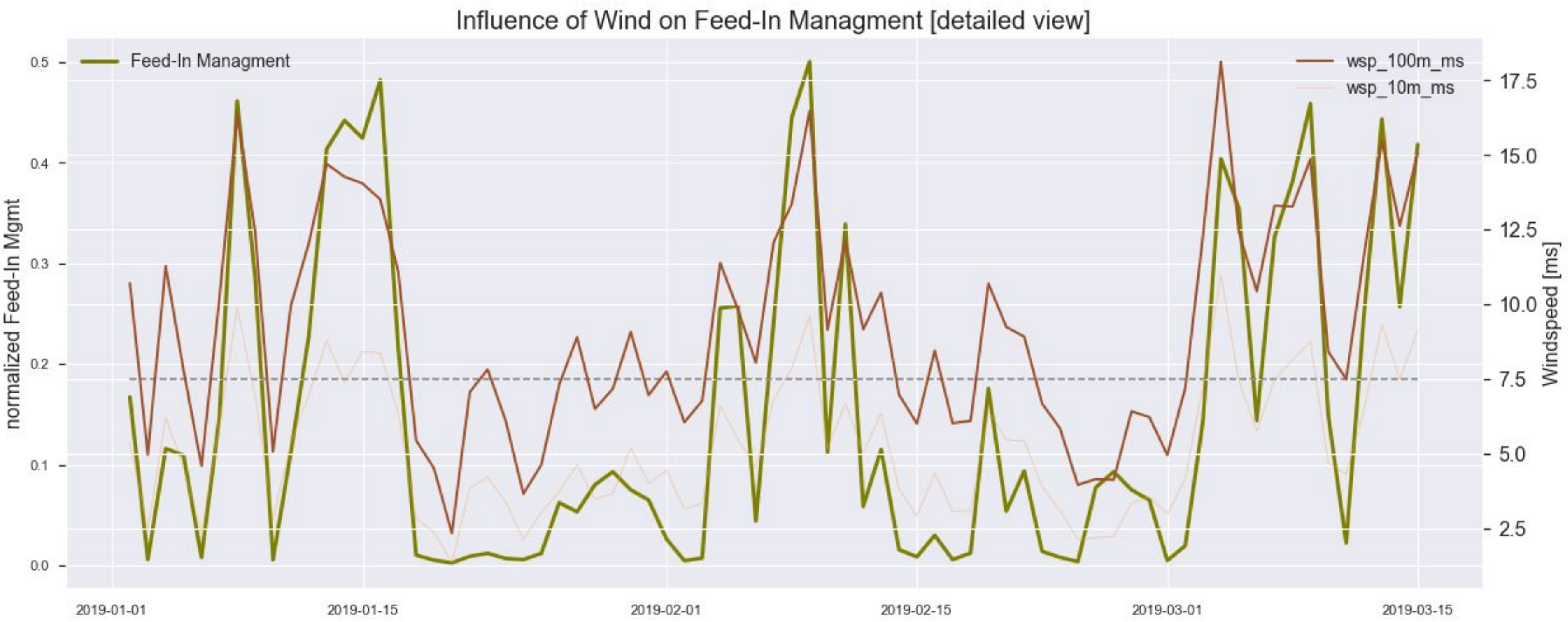
MODEL RESULTS

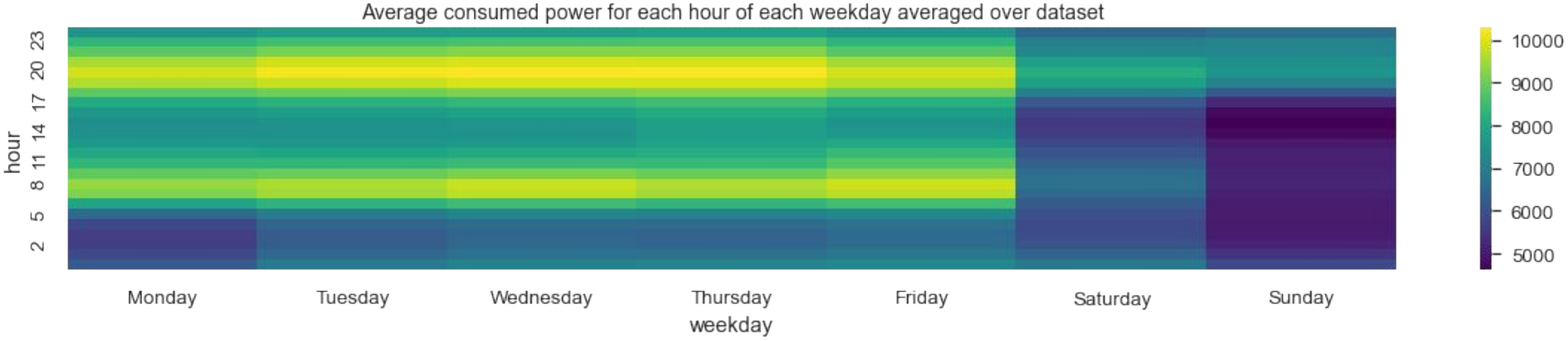
FUTURE WORK

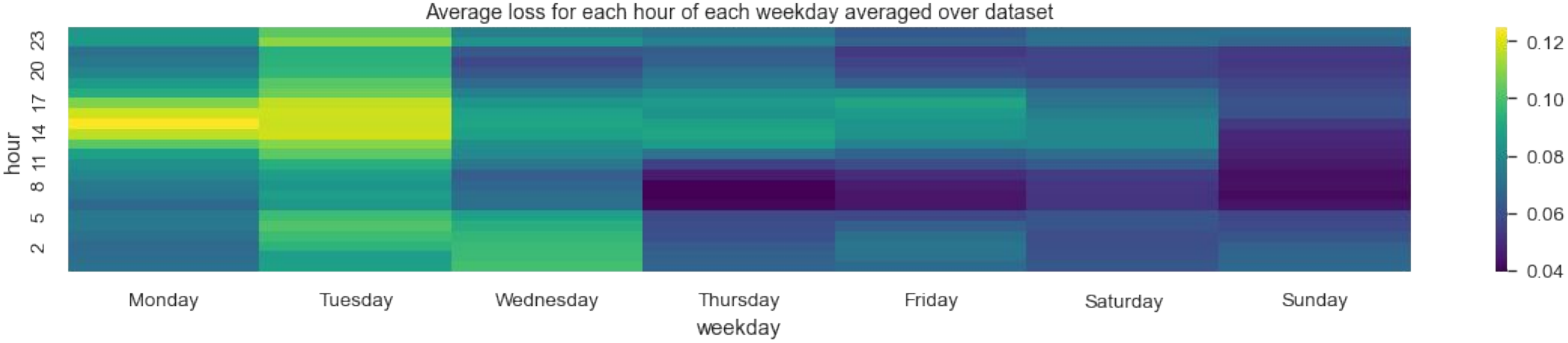

Damp
Schleswig
Husum
St. Peter-Ording
Rendsburg
Kiel
Helgoland
Heide
Büsum
Neumünster
Wacken
Itzehoe
Cuxhaven
Elbe
Elmshorn
Norderstedt
Norden
Wilhelmshaven
Bremerhaven
Nordenham
Stade
Hamburg
Aurich
Emden
Leer (Ostfriesland)
Buchholz in der Nordheide
Bad Zwischenahn
Oldenburg
Papenburg
Bremen
Delmenhorst
Stuhr
Verden (Aller)
Soltau
Walsrode
Cloppenburg
Haren (Ems)
Meppen
Vechta
Nienburg/Weser
Celle
Lingen (Ems)
Nordhorn
Hannover
Rheine
Osnabrück
Minden
Emsdetten
Bad Oeynhausen
Hildesheim
Hameln
7
215
21
27
26
1
39
28
31
29
2
30
33

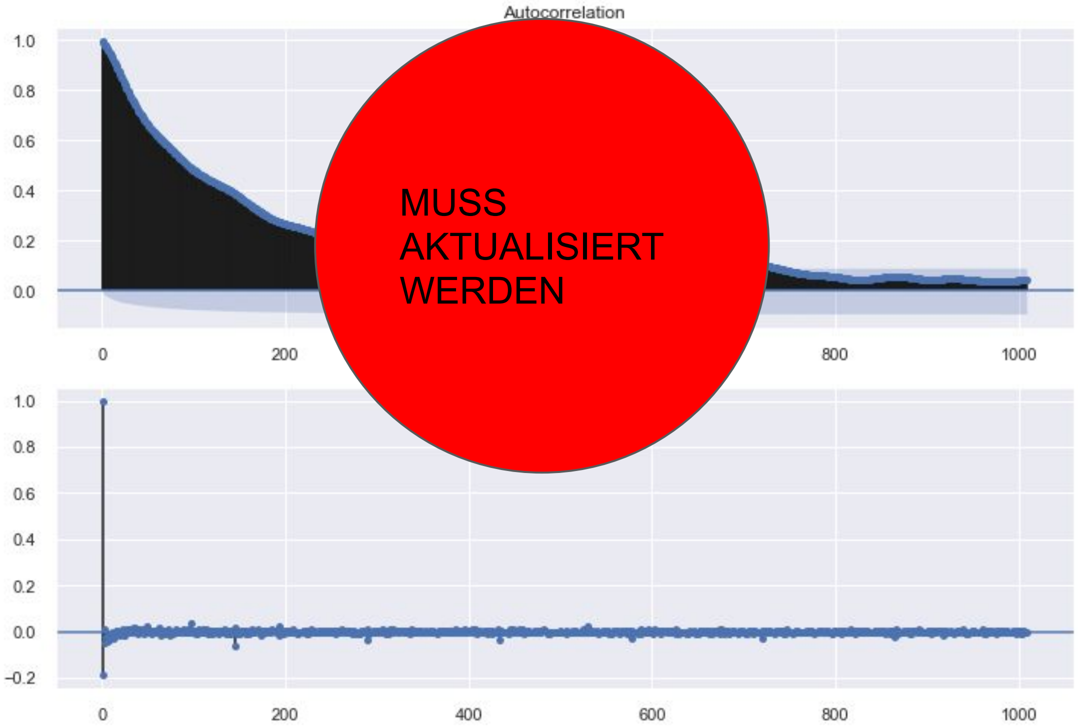

Feed-In Management Data
Started with 57 features, using 25 features for predictive models
GFS Weather Data
Engineered Data

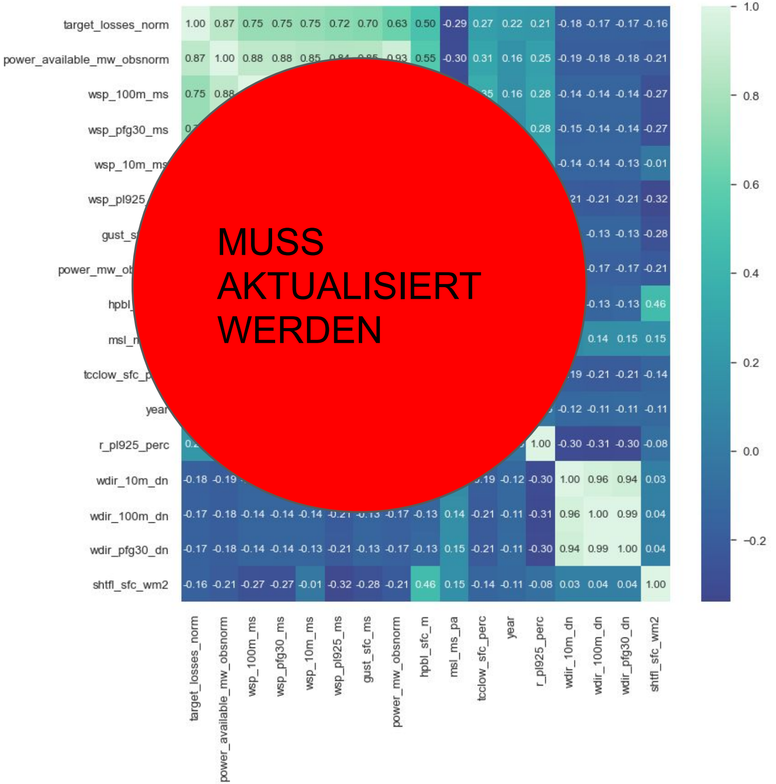

Standard Week: 10 min Averaged Price | Net Consumption | Feed-In loss
Net Consumption
German Energy Price
Feed-In loss
normalized
1.0
0.8
0.6
0.4
0.2
0.0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday


Influence of Wind on Feed-In Managment [detailed view]
Feed-In Managment
wsp_100m_ms
wsp_10m_ms
normalized Feed-In Mgmt
Windspeed [ms]
0.0
0.1
0.2
0.3
0.4
0.5
2.5
5.0
7.5
10.0
12.5
15.0
17.5
2019-01-01
2019-01-15
2019-02-01
2019-02-15
2019-03-01
2019-03-15


Average consumed power for each hour of each weekday averaged over dataset
hour
23
20
17
14
11
8
5
2
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
weekday
10000
9000
8000
7000
6000
5000


Average loss for each hour of each weekday averaged over dataset
hour
23
20
17
14
11
8
5
2
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
weekday
0.12
0.10
0.08
0.06
0.04


Autocorrelation
MUSS
AKTUALISIERT
WERDEN
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
200
400
600
800
1000


MUSS
AKTUALISIERT
WERDEN
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
msl_ms_pa
tcclow_sfc_perc
year
r_pl925_perc
wdir_10m_dn
wdir_100m_dn
wdir_pfg30_dn
shtfl_sfc_wm2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2

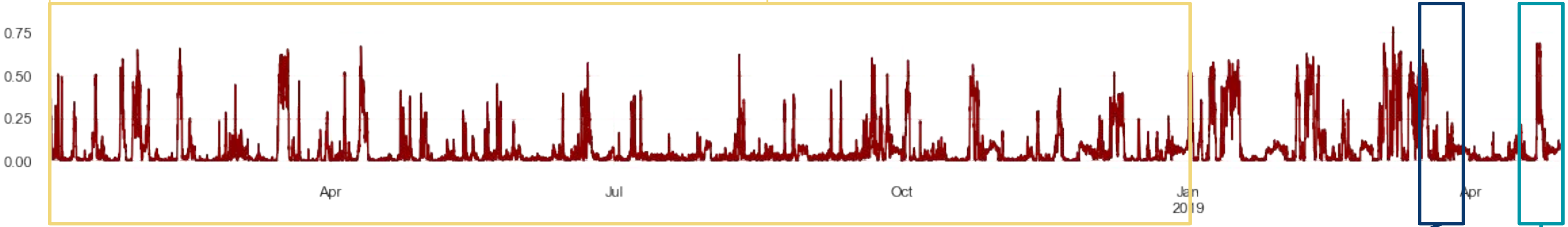
BACKGROUND

DATA ANALYSIS

TIME SERIES PREDICTION

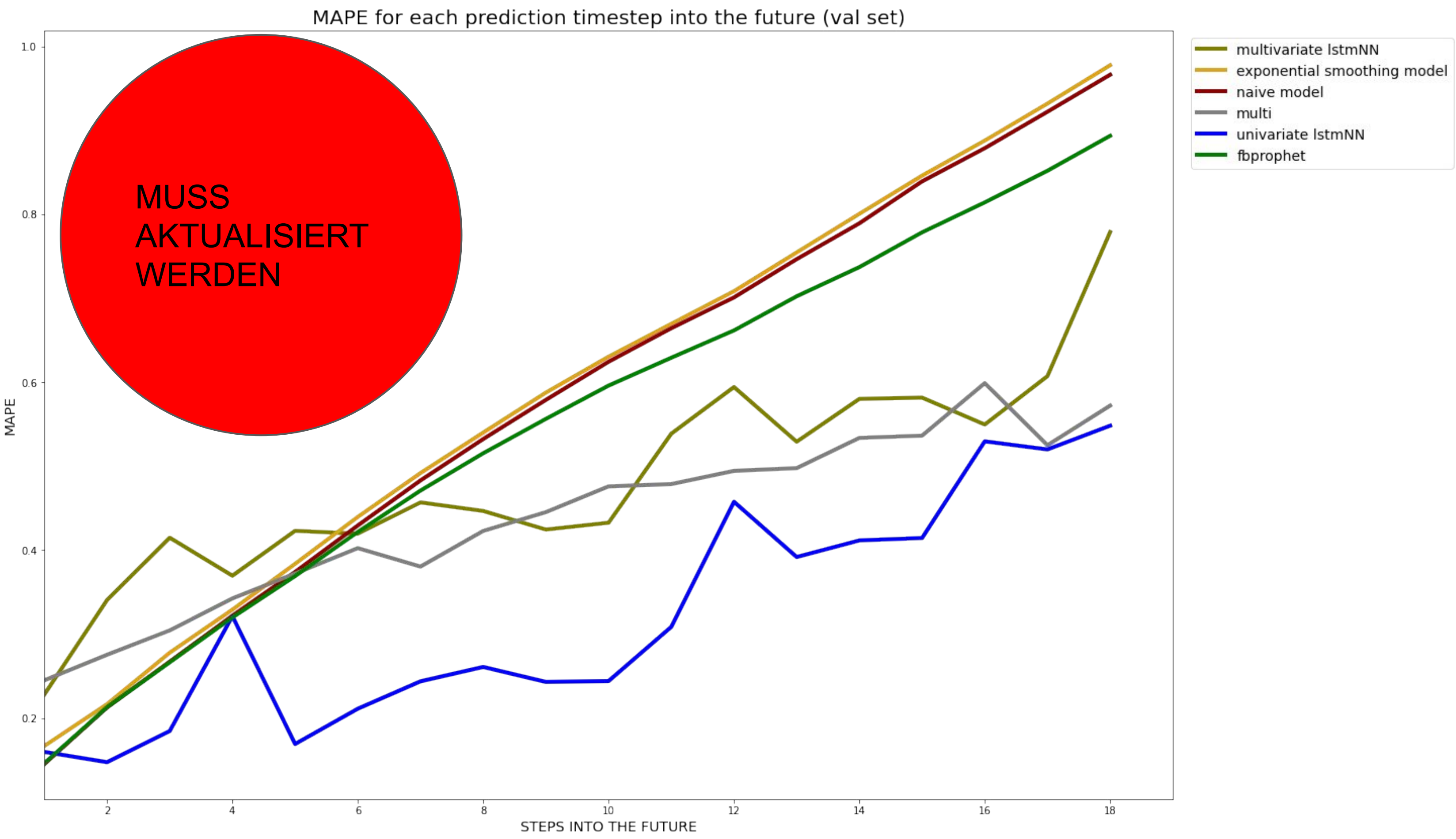
FUTURE WORK

Training
'01.01.2018 06:00:00' to '01.01.2019 06:00:00'

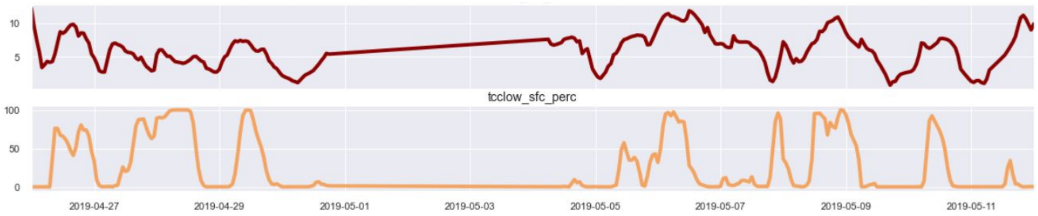


Validation
'17.03.2019 06:00:00' to '27.03.2019 06:00:00'

Test
'20.04.2019 06:00:00' to '30.04.2019 06:00:00'


MAPE for each prediction timestep into the future (val set)
MUSS AKTUALISIERT WERDEN
MAPE
STEPS INTO THE FUTURE
multivariate lstmNN
exponential smoothing model
naive model
multi
univariate lstmNN
fbprophet

BACKGROUND
DATA ANALYSIS
MODEL RESULTS
FUTURE WORK



TensorBoard

SELECTED APIs — SELECTED MODEL — FEED-IN MANAGEMENT PREDICTIONS

Low Hanging

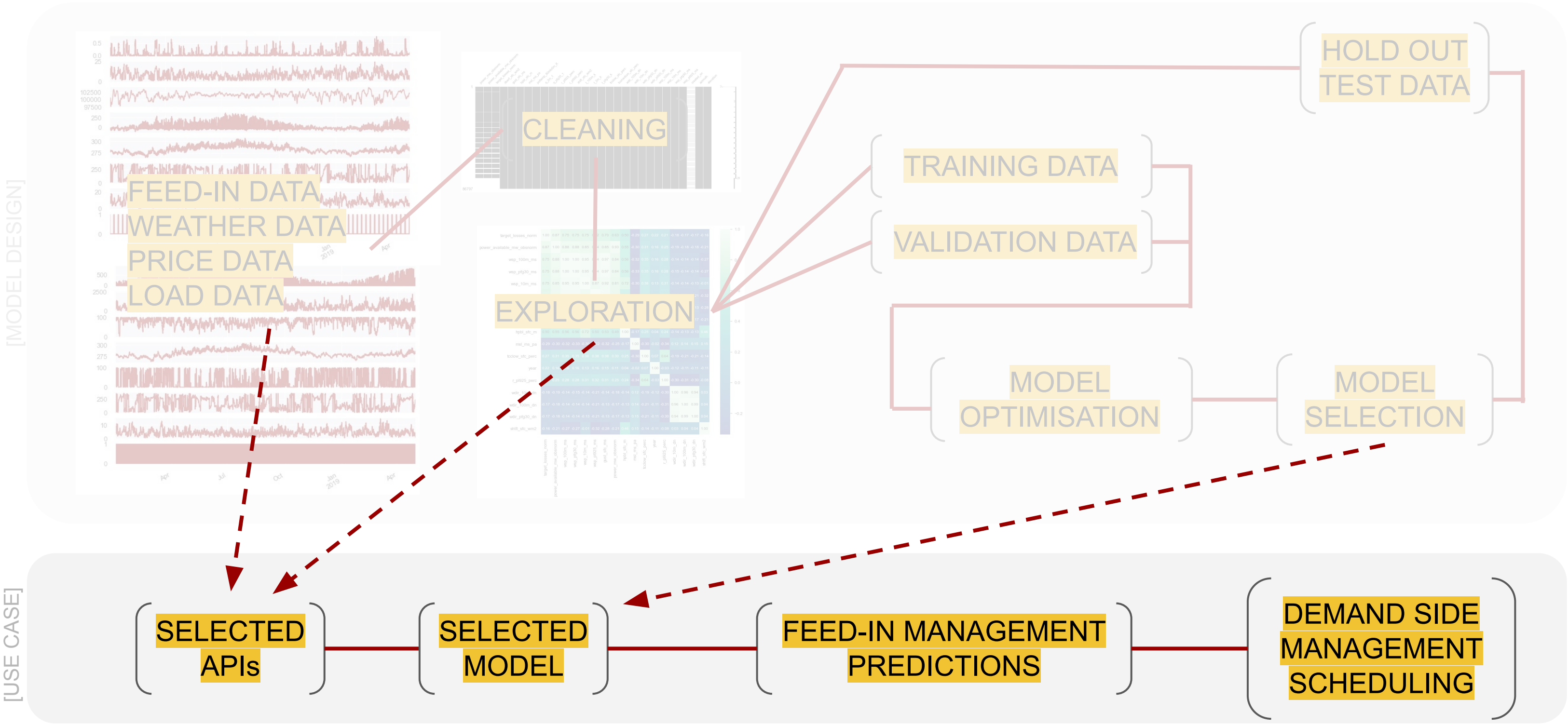
Extensiv Data Fixing: data after 1. May 2019 contained errors, could be fixed via its own seasonal model

LSTM Tuning via TensorBoard

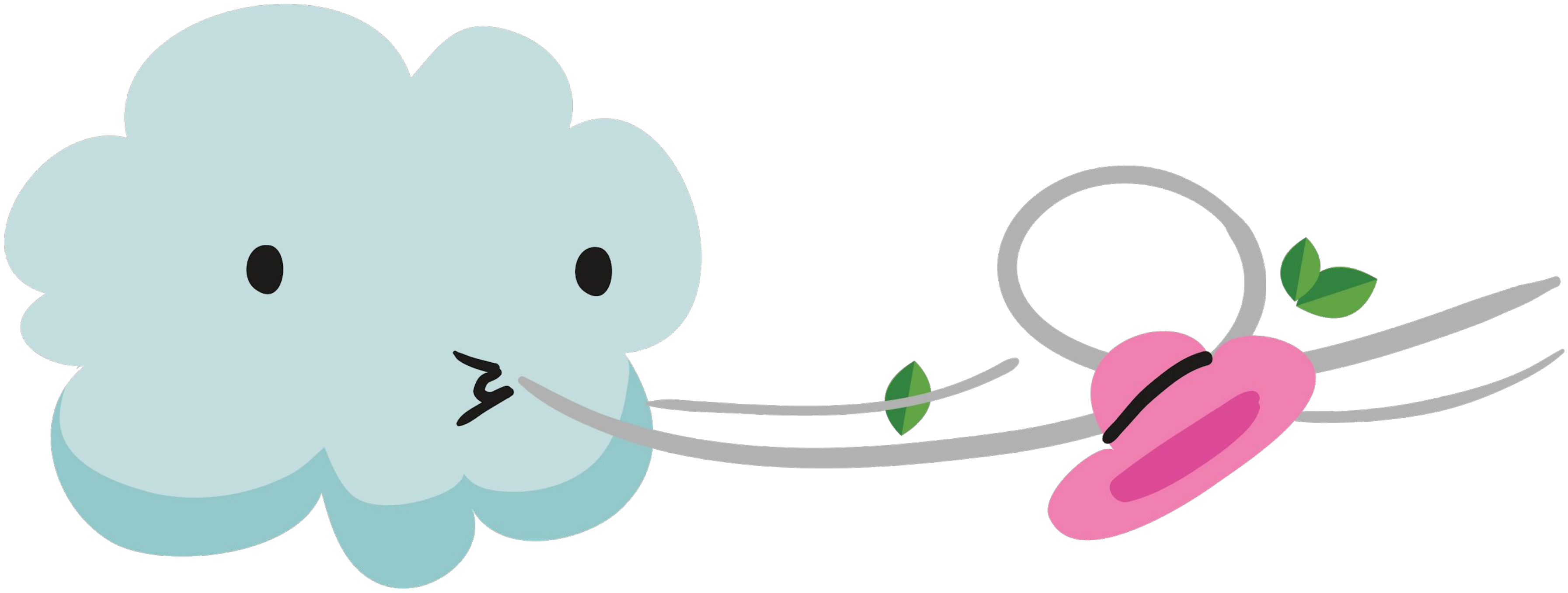
Forecast of GFS Data for Feed-In Mgmt predictions >1 timestep

High Hanging

API: receiving data via an API for live predictions


[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



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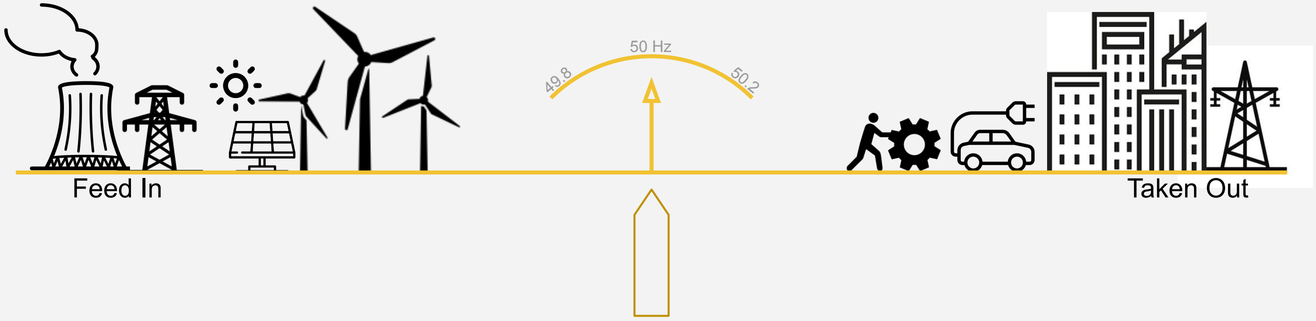

BACKGROUND

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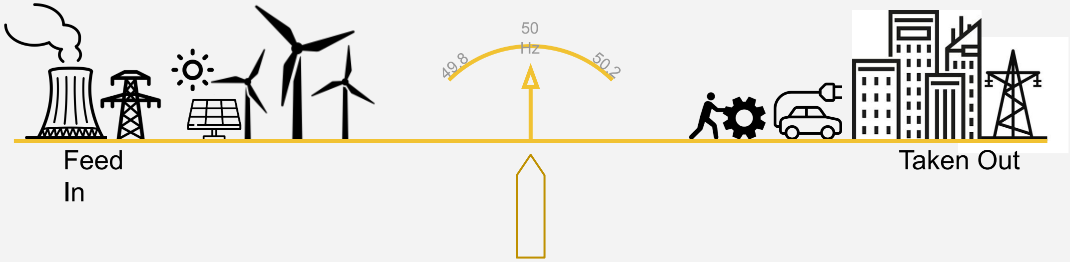
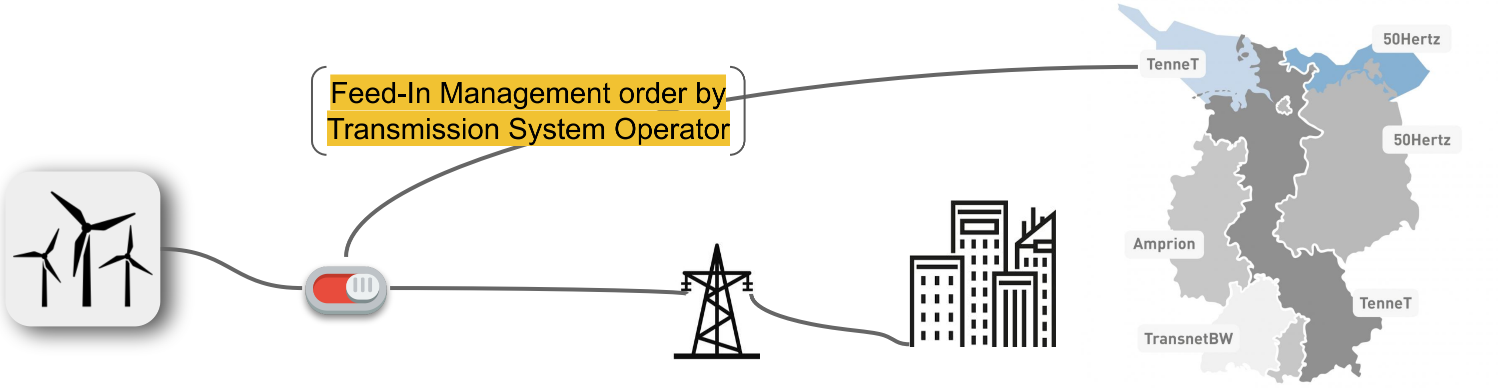
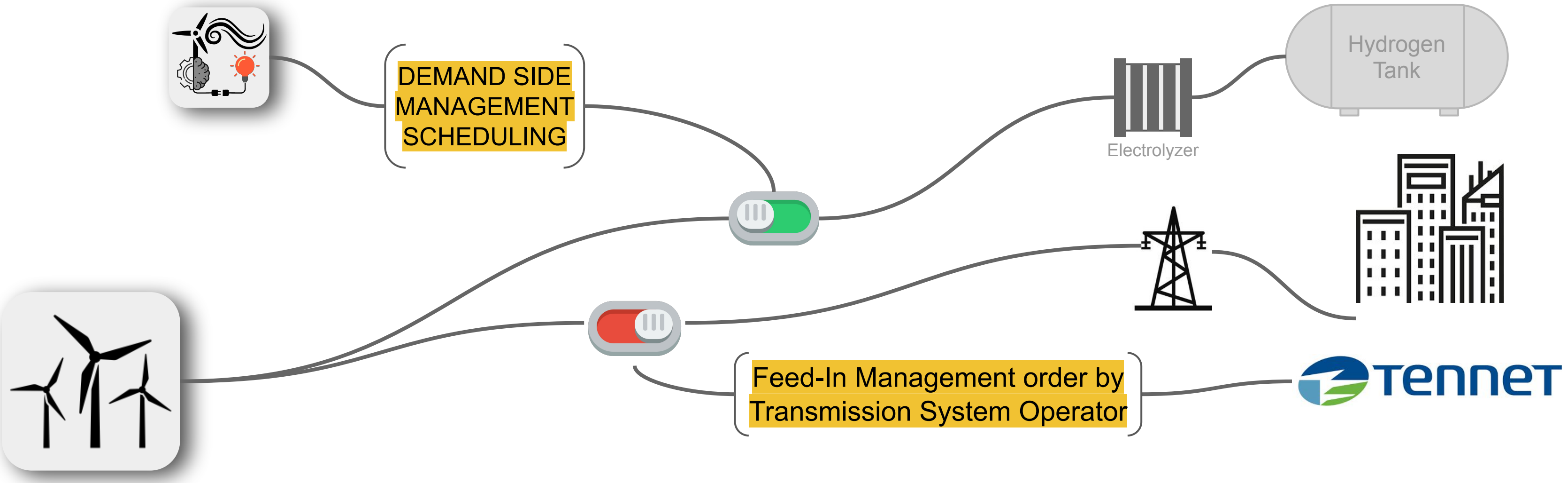
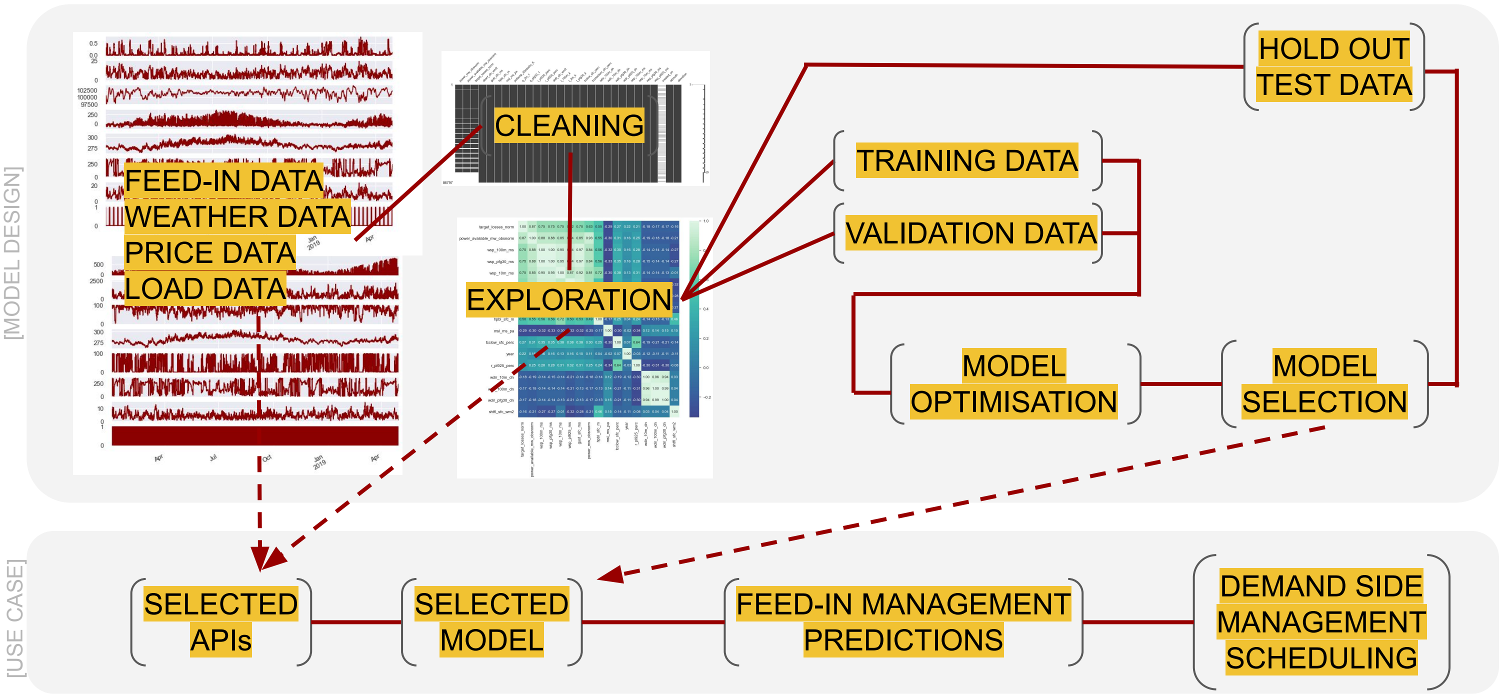


Feed In Management Event Prediction for Quadra Energy Onshore Windfarm


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


DEMAND SIDE MANAGEMENT SCHEDULING
Hydrogen Tank
Electrolyzer
Feed-In Management order by Transmission System Operator
TenneT


[MODEL DESIGN]
FEED-IN DATA
WEATHER DATA
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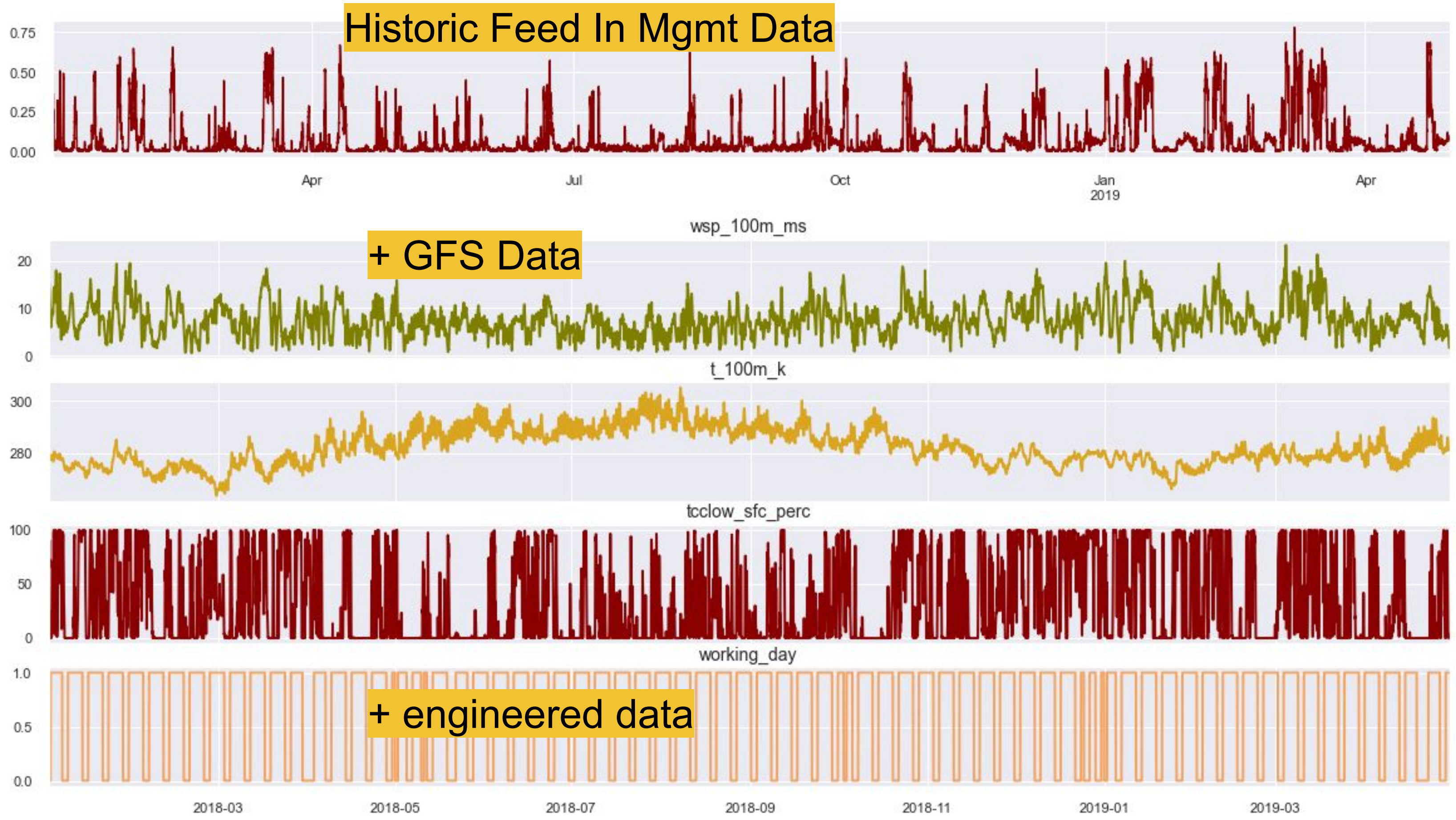
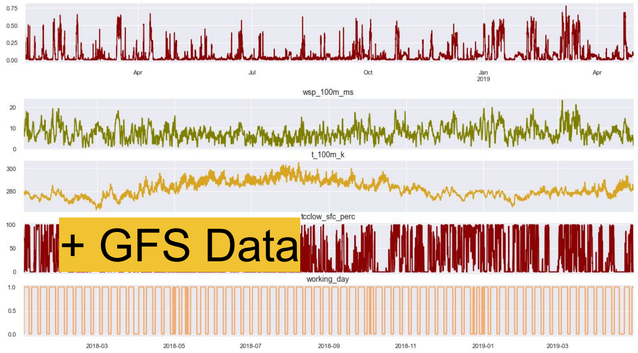
MODEL
SELECTION
[USE CASE]
SELECTED
APIs
SELECTED
MODEL
FEED-IN MANAGEMENT
PREDICTIONS
DEMAND SIDE
MANAGEMENT
SCHEDULING

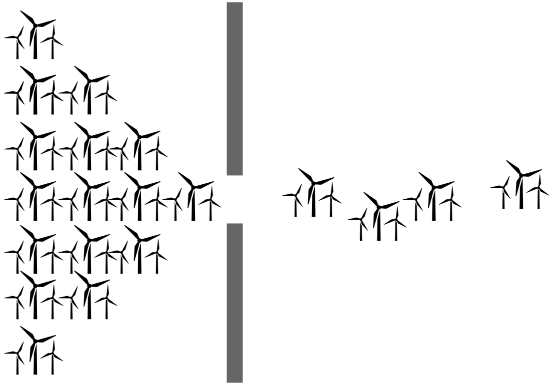
Our Data:



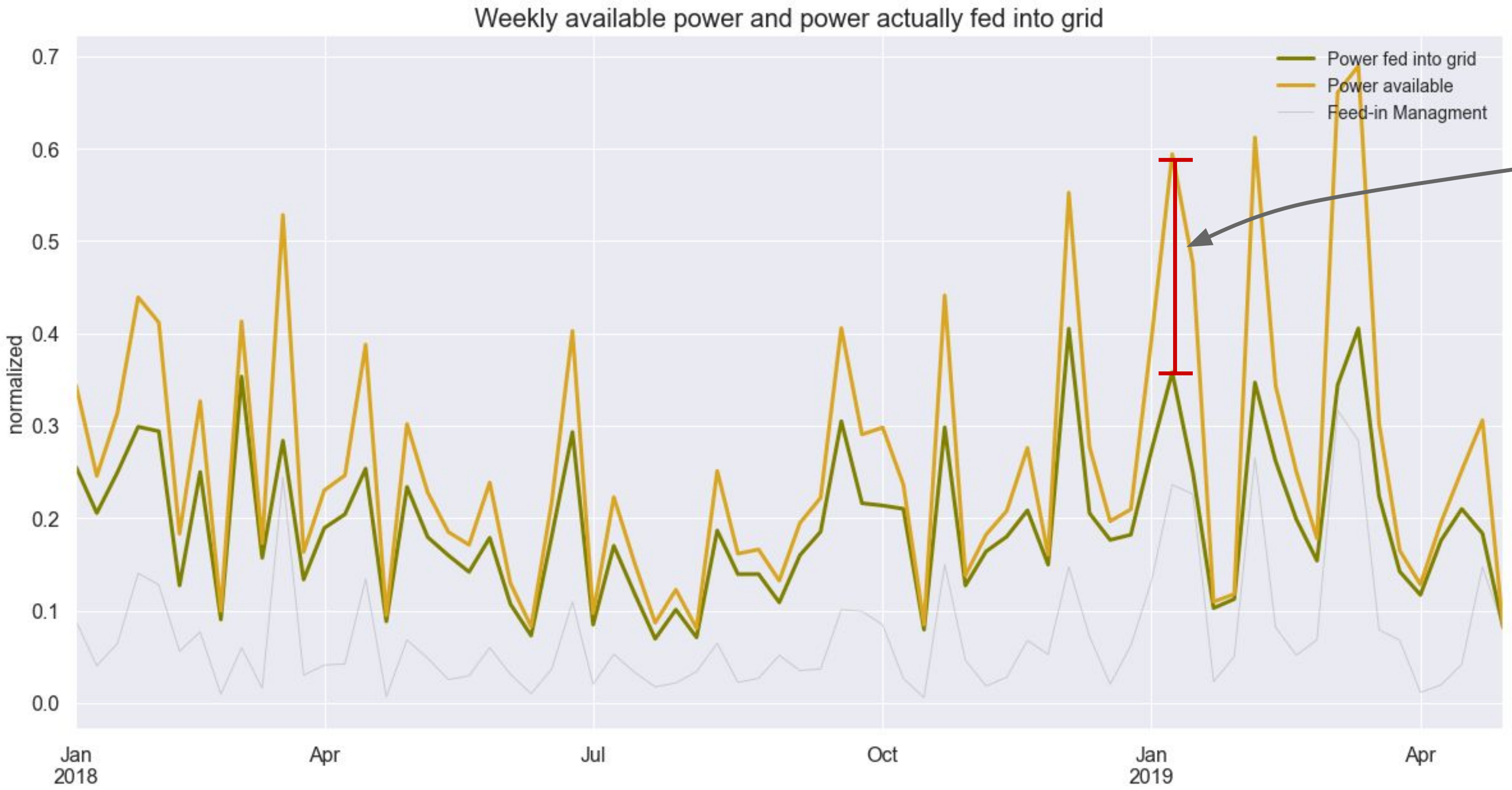
Historic Feed In Mgmt Data
0.75
0.50
0.25
0.00
Apr
Jul
Oct
Jan
2019
Apr
wsp_100m_ms
+ GFS Data
20
10
0
t_100m_k
300
280
tcclow_sfc_perc
100
50
0
working_day
1.0
0.5
0.0
+ engineered data
2018-03
2018-05
2018-07
2018-09
2018-11
2019-01
2019-03



+ GFS Data
wsp_100m_ms
t_100m_k
tcclow_sfc_perc
working_day

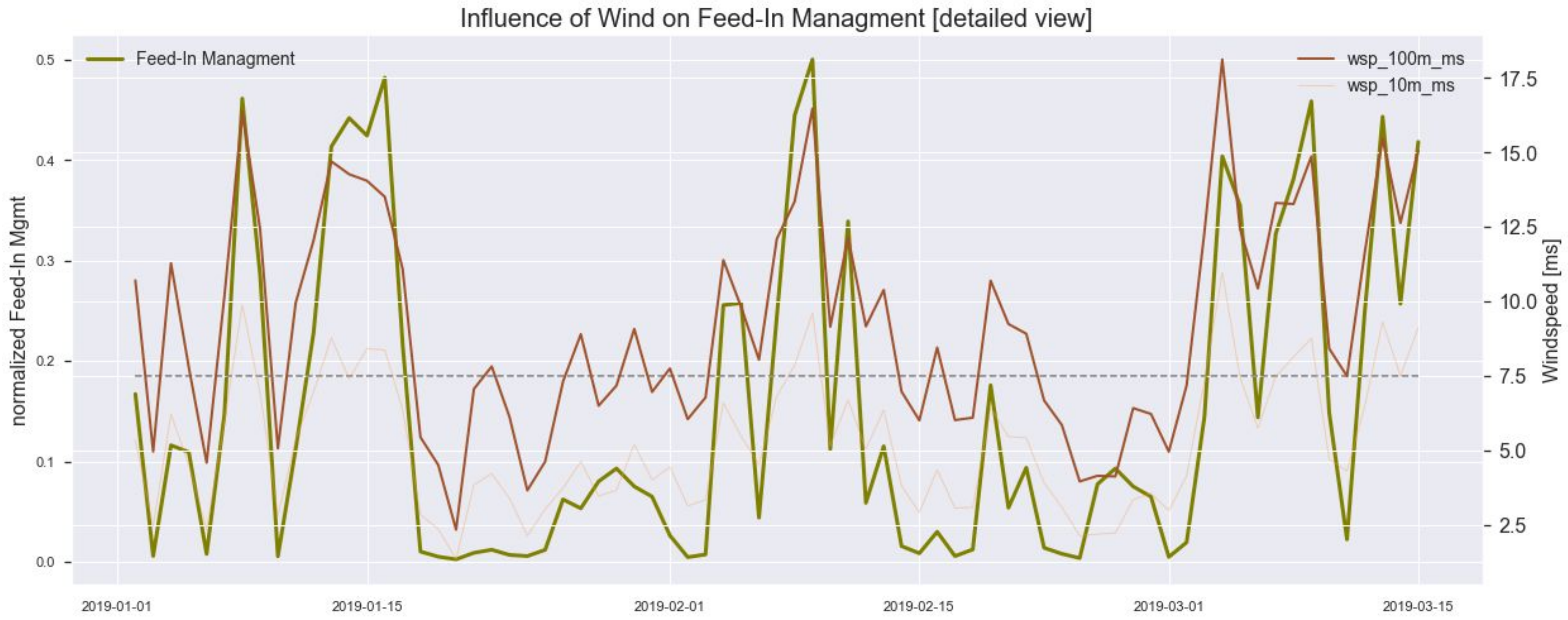


Feed In Mgmt Events in our Data



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

Feed-In Mgmt Events connected to Wind



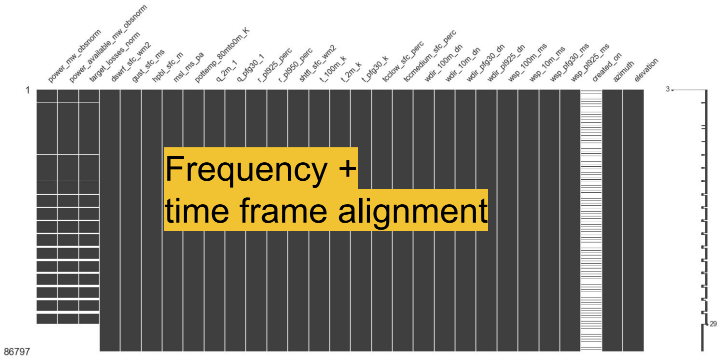
Data Cleaning

Feature Engineering

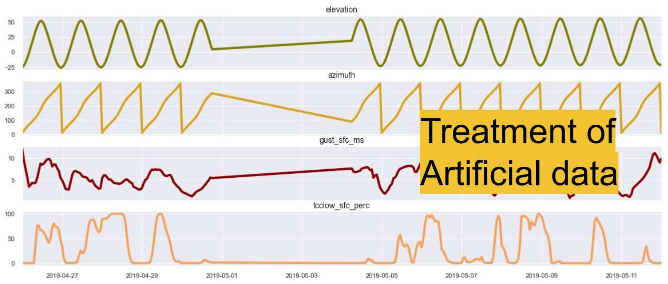
Feature Selection

Seasonality Analysis

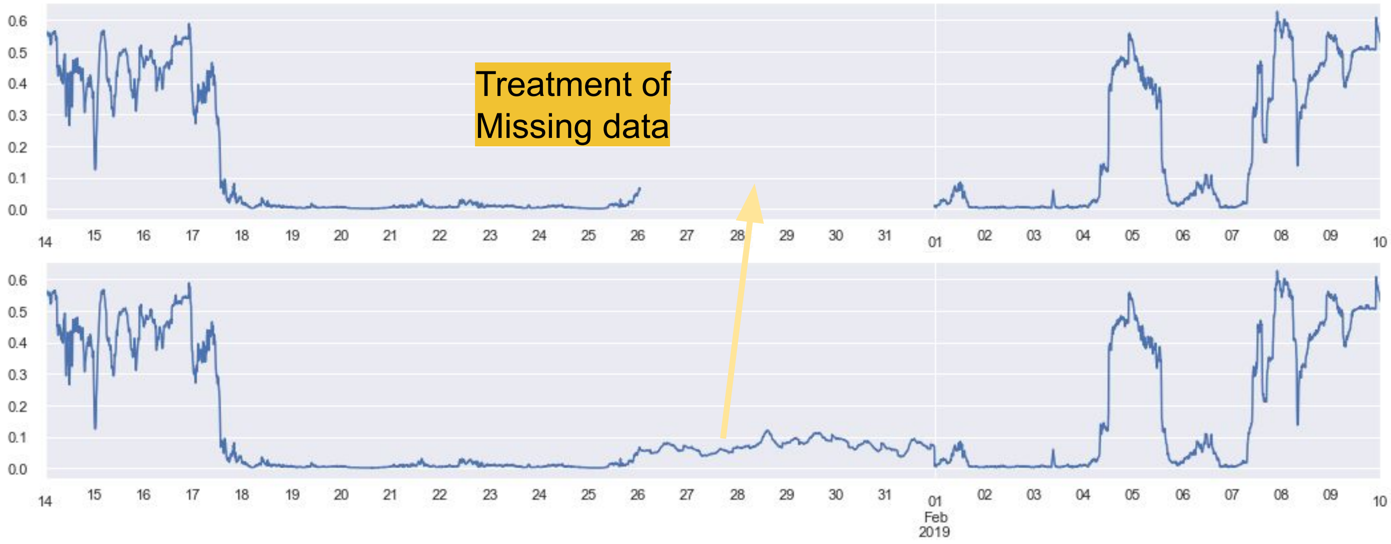
ML Models



Frequency + time frame alignment



Treatment of Artificial data



Treatment of Missing data

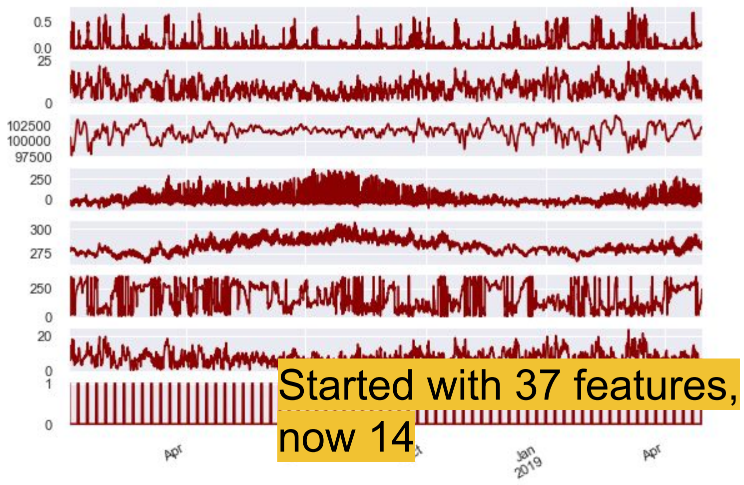
Data Cleaning

Feature Engineering

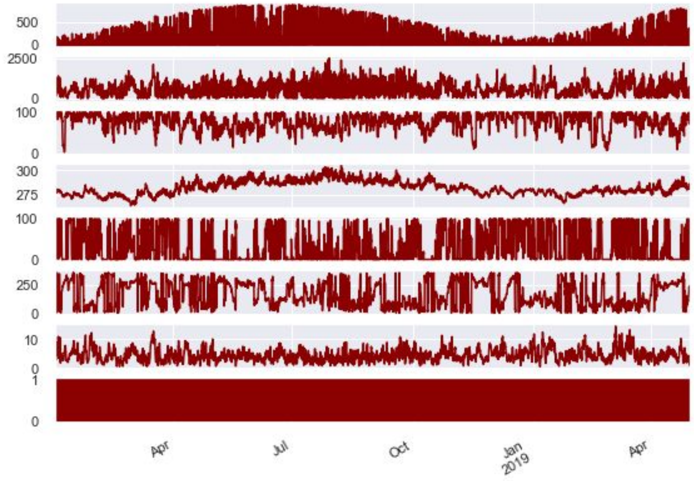
Feature Selection

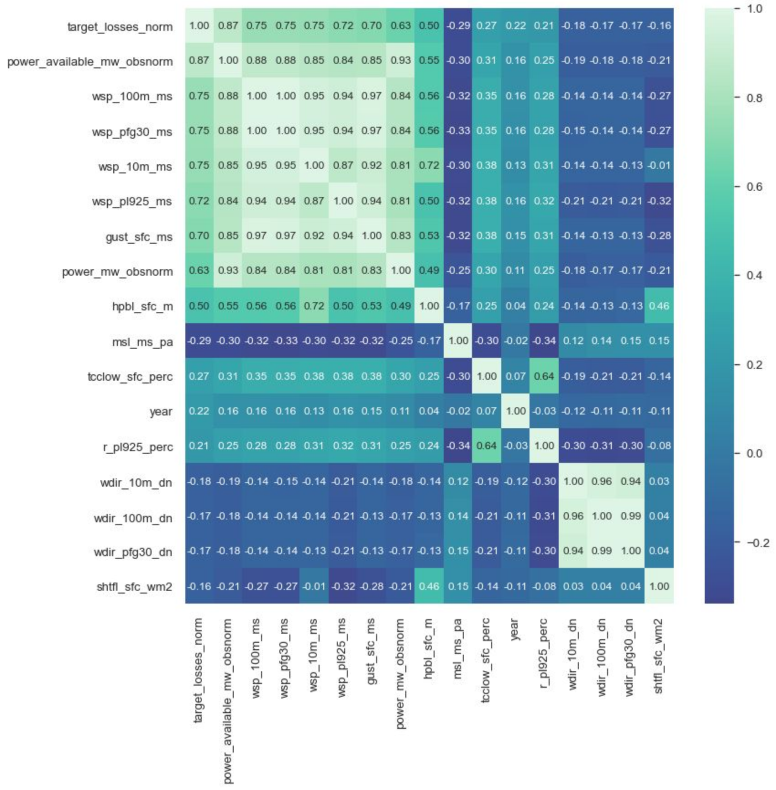
Seasonality Analysis

ML Models



Started with 37 features, now 14





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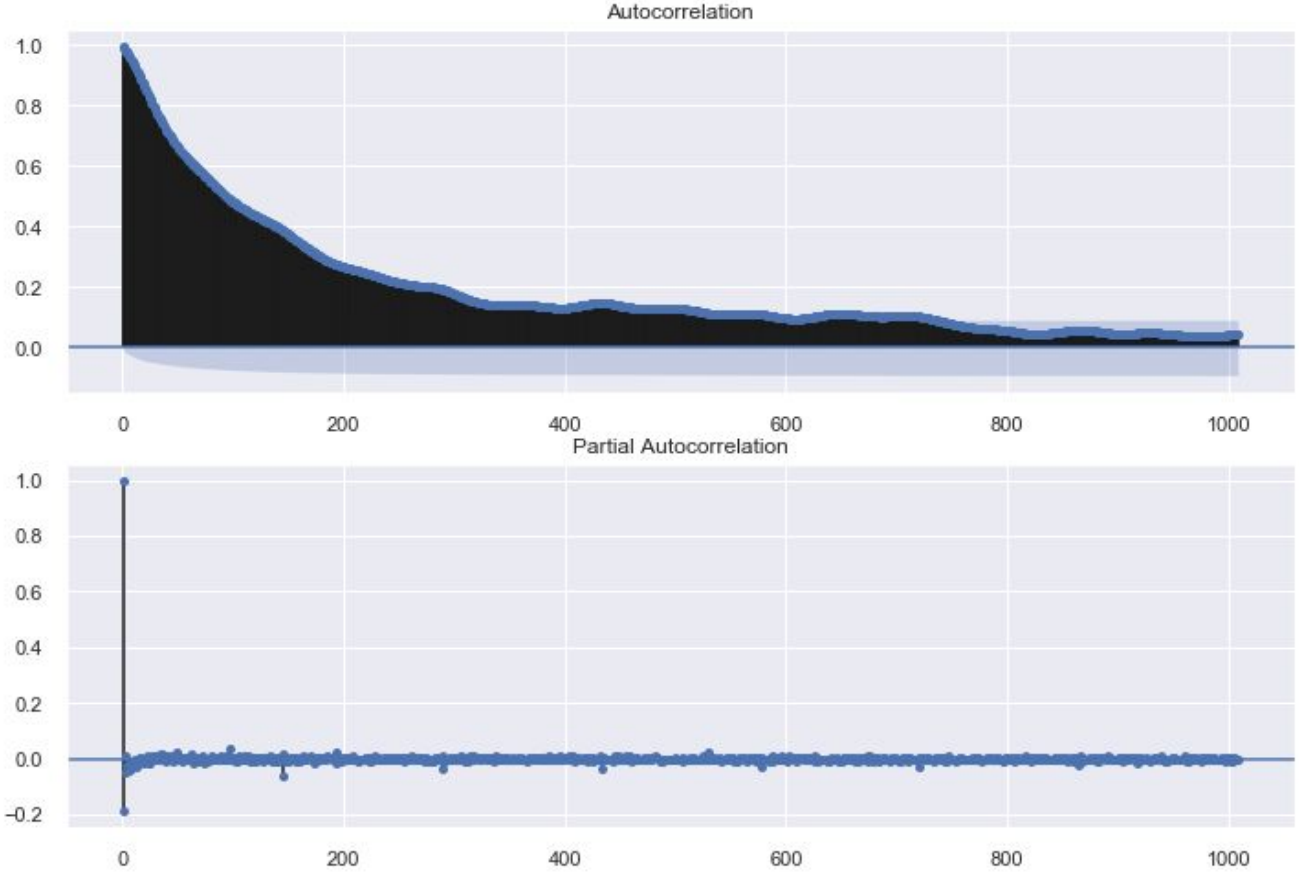

Data Cleaning

Feature Engineering

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Seasonality Analysis

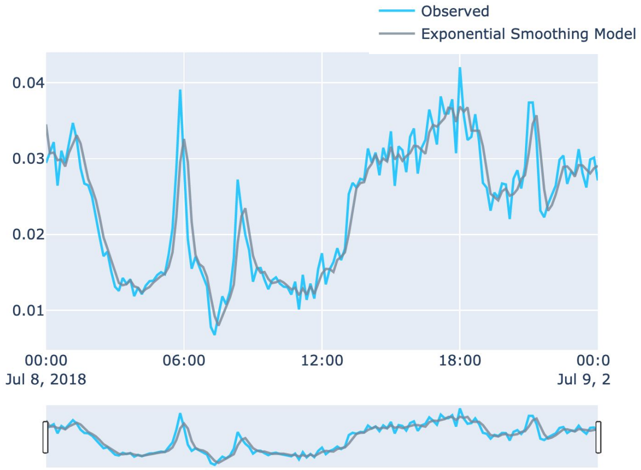
ML Models

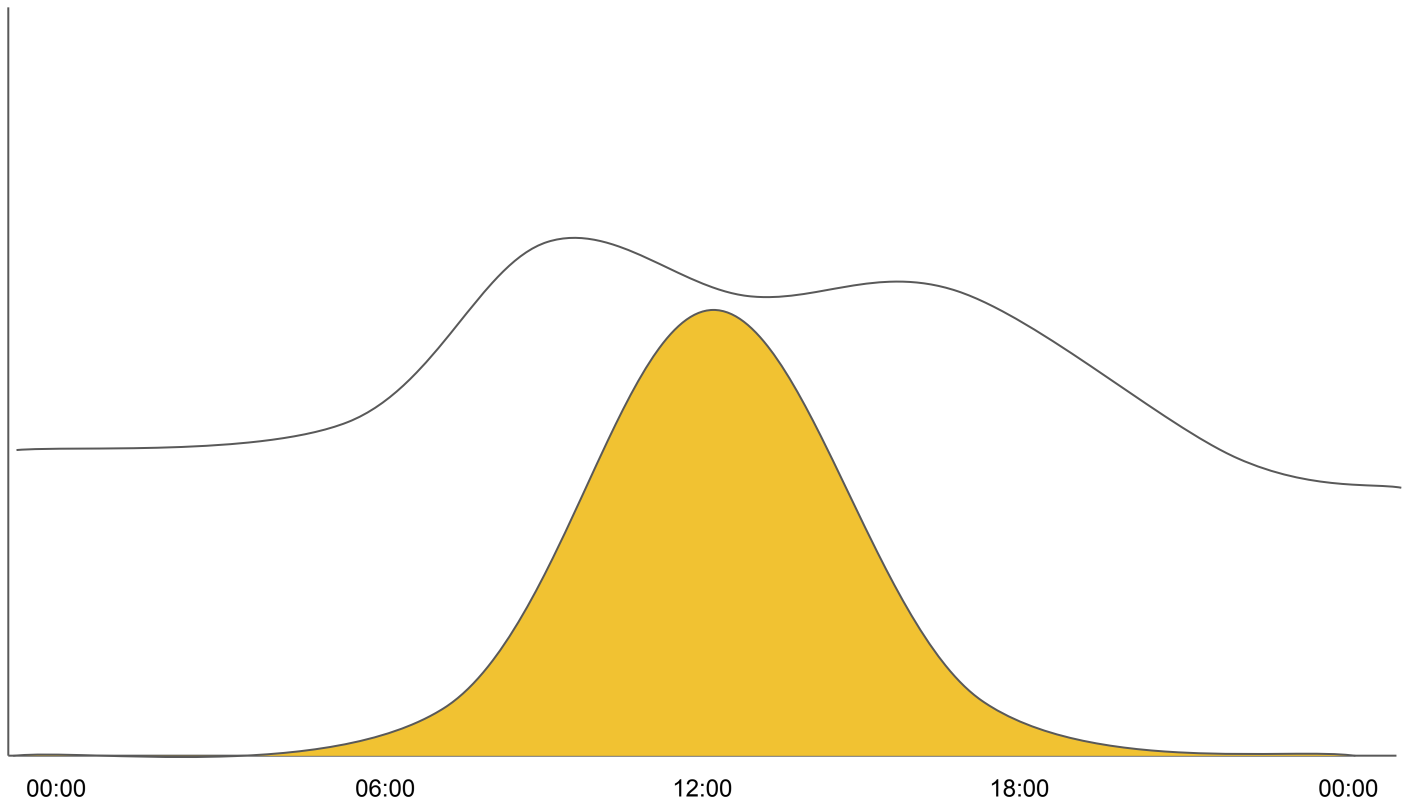
Shift + Exponential Smoothing	- Used for 1 timestep prediction - Worked great - best performing models so far
ARIMA + ARIMAX	- Computational expensive -
FB Prophet	-
LSTM	- Problems regarding Keras 3D Input Interface - Problems regarding multiple timestep prediction

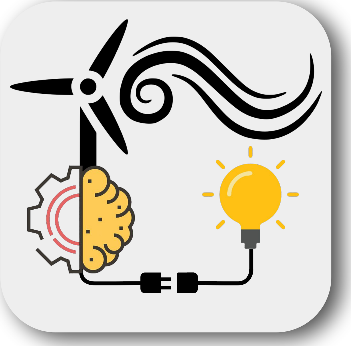
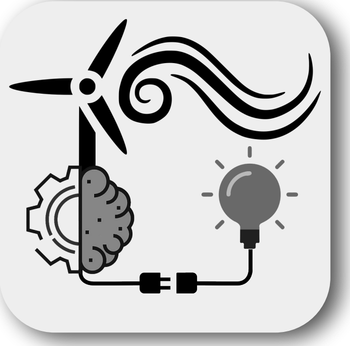
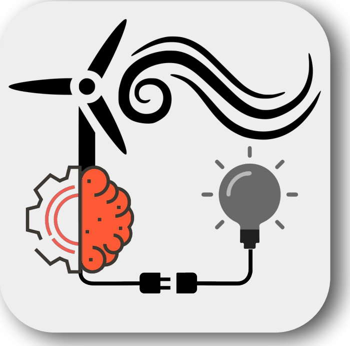
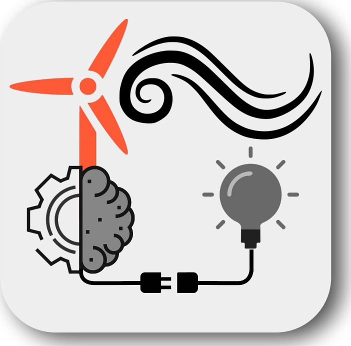
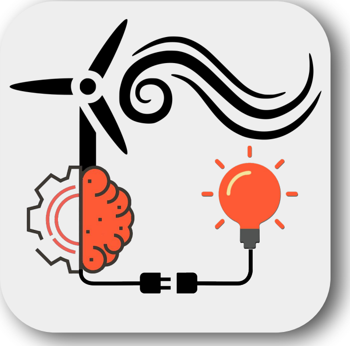
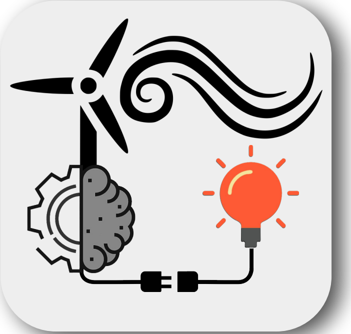
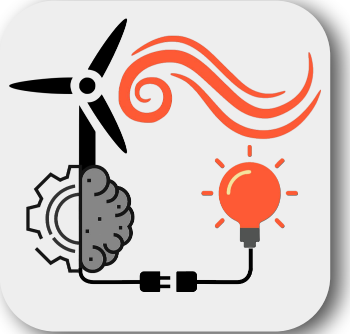
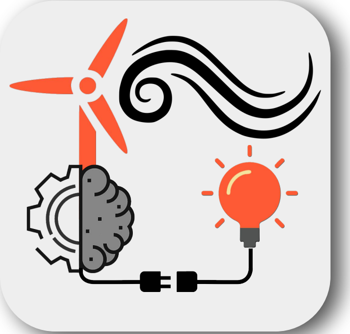
	Naive Base Model	Exponential Smoothing
RMSE	0.017165	0.014404
R2	0.987427	0.991147
MAE	0.008938	0.007483
MAPE	0.111866	0.091309

	FB Prophet Model
RMSE	0.016962
R2	0.988448
MAE	0.008184
MAPE	0.148100

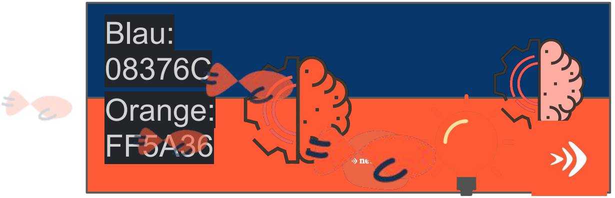
	LSTM - look_back: 1d, batch:1d
RMSE	0.024607
R2	0.975330
MAE	0.012663
MAPE	4.401784




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

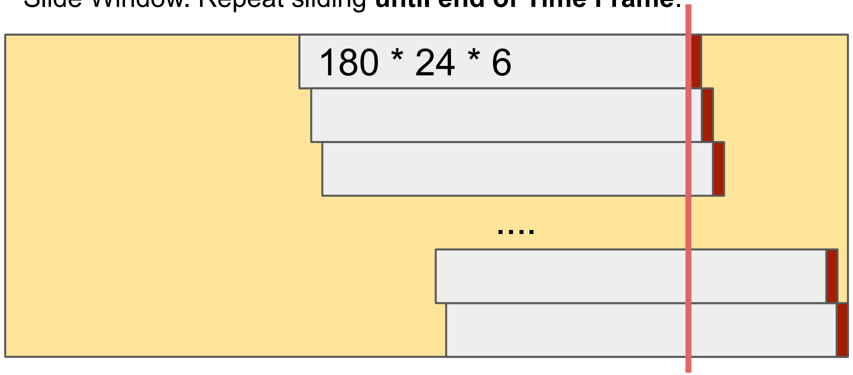











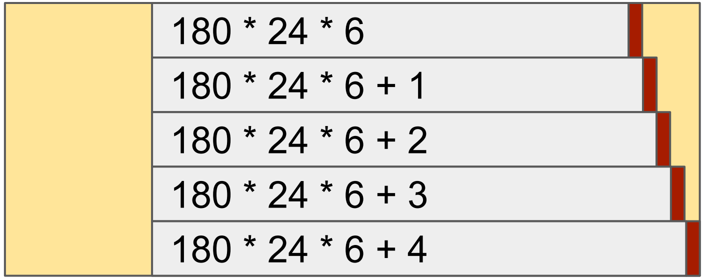


Icons at: [Renewable Energy PNG Images, Transparent Renewable Energy Image Download]

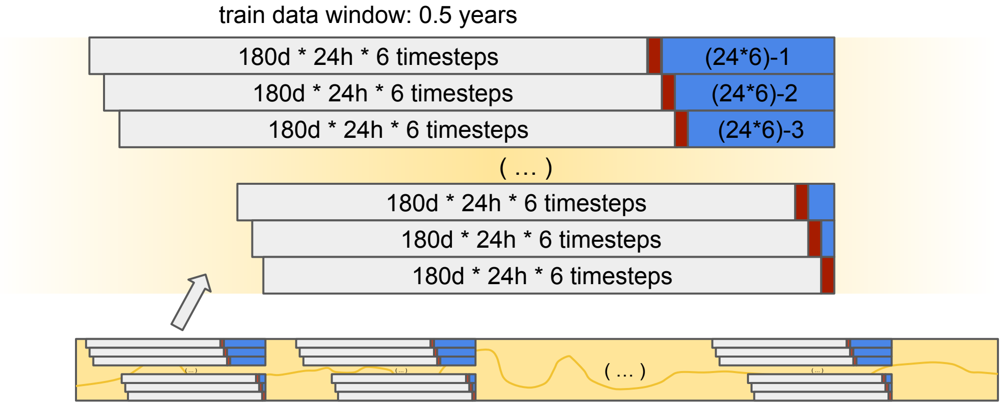
1) Cut at point X. Train with 0.5 years. Predict 1 time step ahead.
Slide Window. Repeat sliding **until end of Time Frame**.



2) Expanding Training Window.

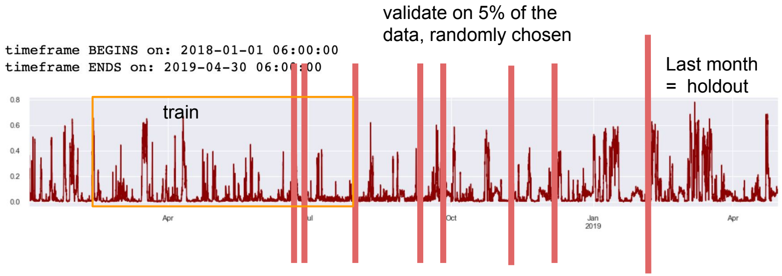


3) Sliding Window at 10 different timestamps. Training on 0.5 yea5rs.
Predicting 1 step ahead, at 10 different days for 24*6 steps each day.

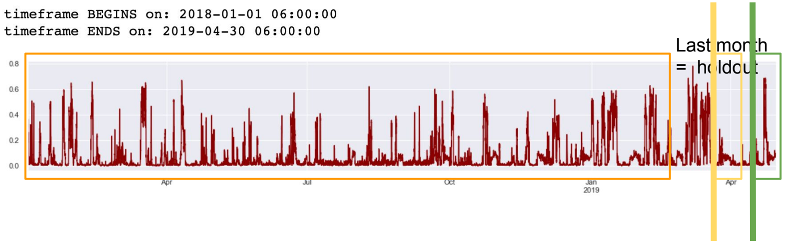


FUTURE

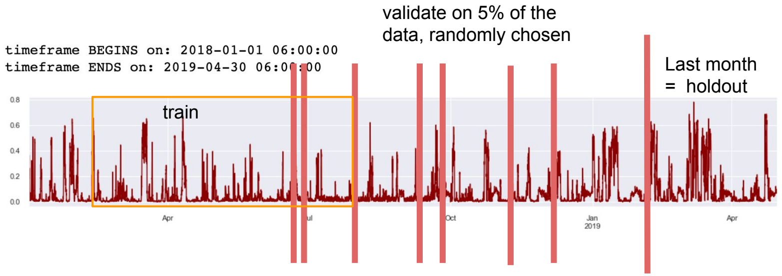
4) Predicting more than one time step ahead.

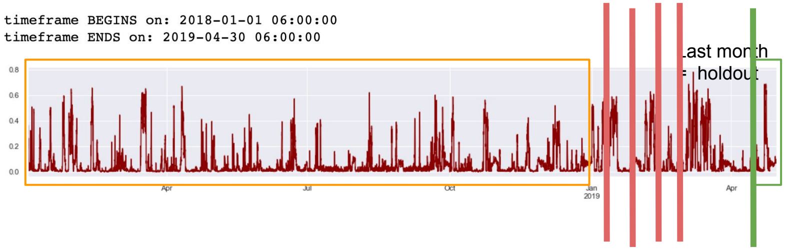


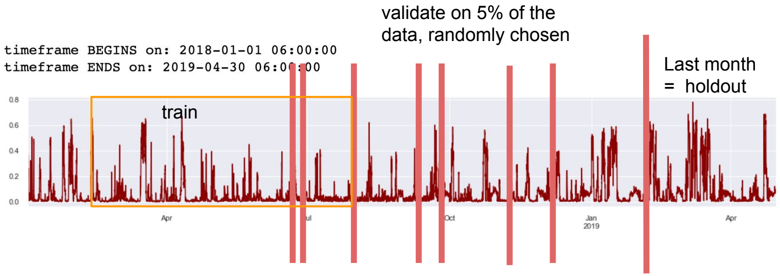
9. Nov 2020

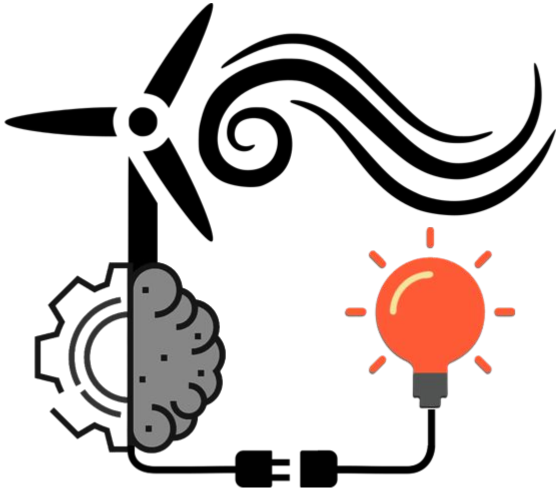


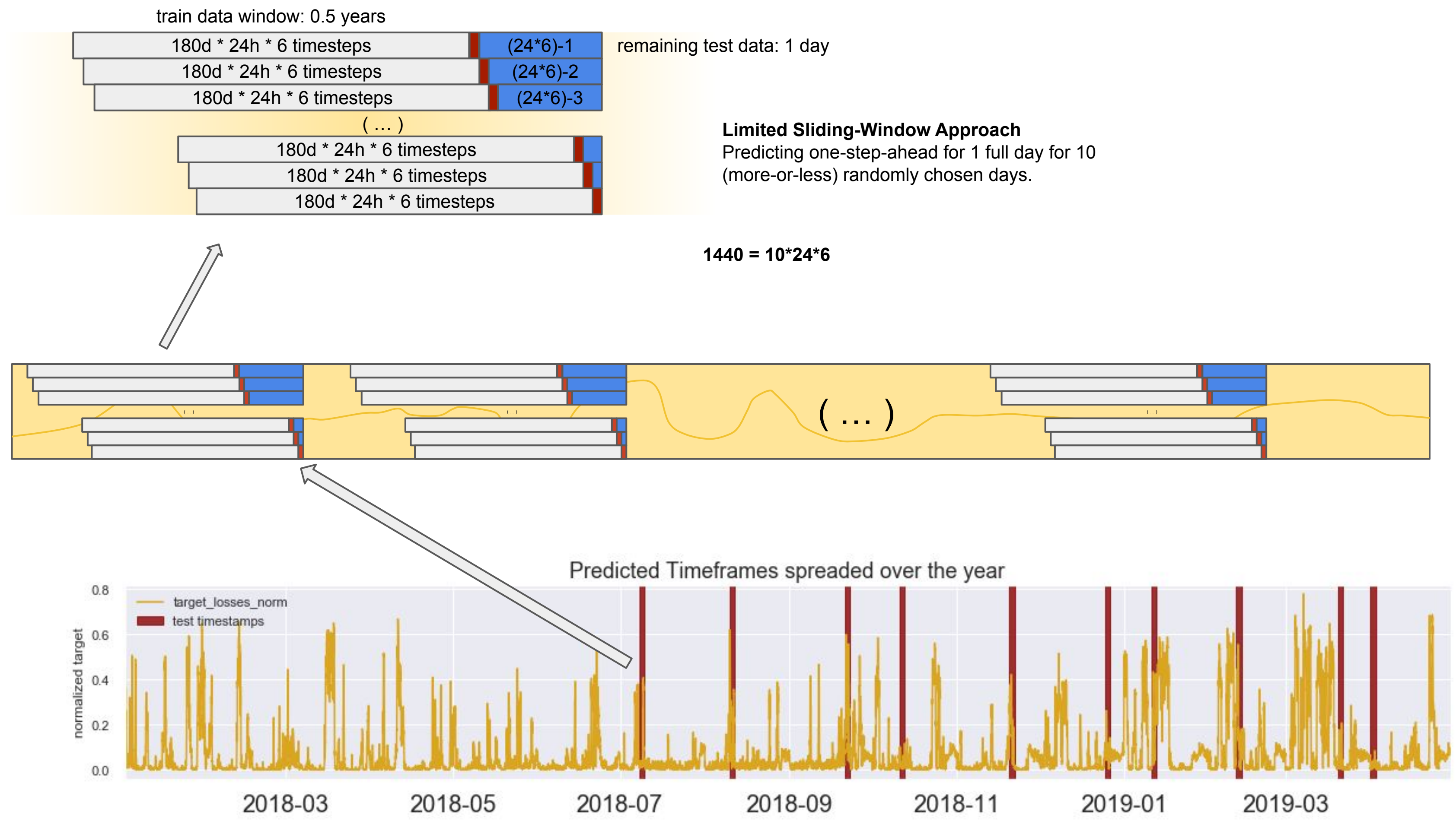
Val: 17.3.2019 6 Uhr bis
27.03.2019 6 Uhr
test: 20.4. 6 Uhr bis 30.04. 6 Uhr

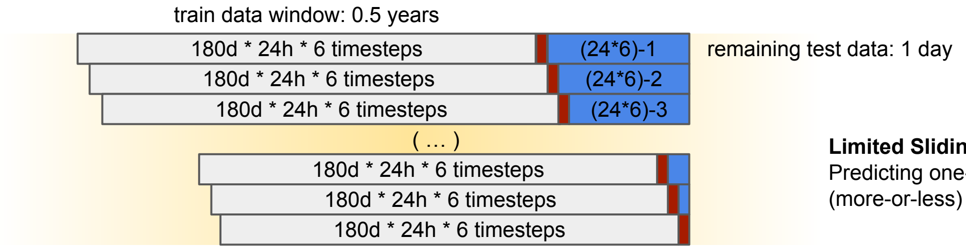



timeframe BEGINS on: 2018-01-01 06:00:00
timeframe ENDS on: 2019-04-30 06:00:00
Last month
= holdout
0.8
0.6
0.4
0.2
0.0
Apr
Jul
Oct
Jan
2019
Apr


validate on 5% of the
data, randomly chosen
timeframe BEGINS on: 2018-01-01 06:00:00
timeframe ENDS on: 2019-04-30 06:00:00
Last month
= holdout
train
0.8
0.6
0.4
0.2
0.0
Apr
Oct
Jan
2019
Apr




train data window: 0.5 years
180d * 24h * 6 timesteps
(24*6)-1
remaining test data: 1 day
180d * 24h * 6 timesteps
(24*6)-2
180d * 24h * 6 timesteps
(24*6)-3
(…)
180d * 24h * 6 timesteps
180d * 24h * 6 timesteps
180d * 24h * 6 timesteps
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
0.8
0.6
0.4
0.2
0.0
2018-03
2018-05
2018-07
2018-09
2018-11
2019-01
2019-03



Limited Sliding-Window Approach
Predicting one-step-ahead for 1 full day for 10 (more-or-less) randomly chosen days.

1440 = 10*24*6