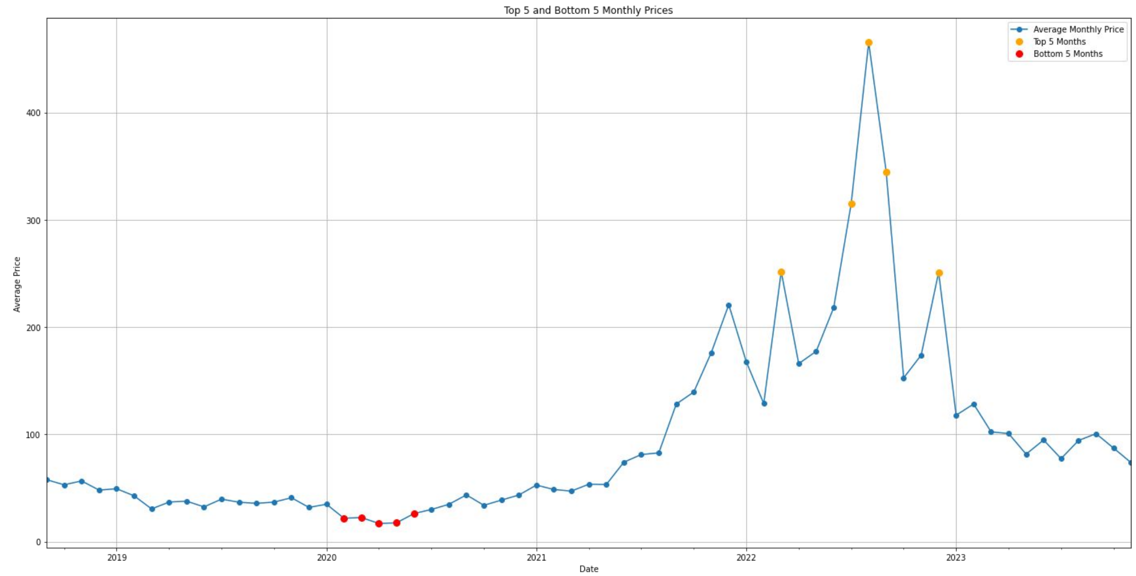
Prediction Team

Part 3: Energy Price Forecasting

Freie Universität Berlin

Price Prediction:



Observations:

- Data in hourly rate

- 2022 has abnormally high values

- 2020 records the lowest values

- Price seems dependent on demand, fuel prices for coal/ natural gas

- Negative Prices observed for days with excess energy stored

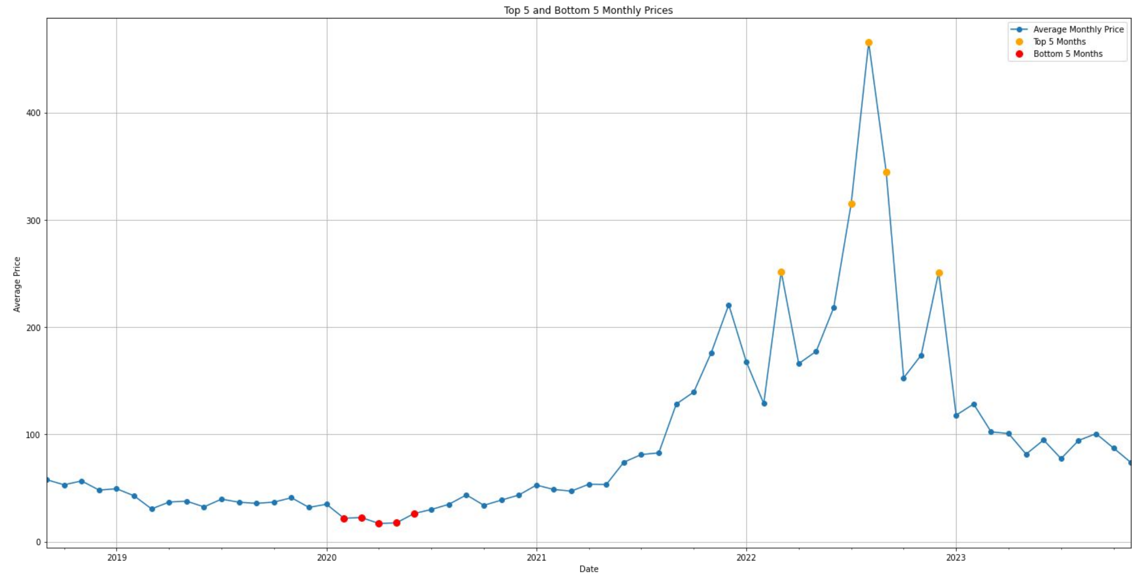
- No monthly or weekly patterns.

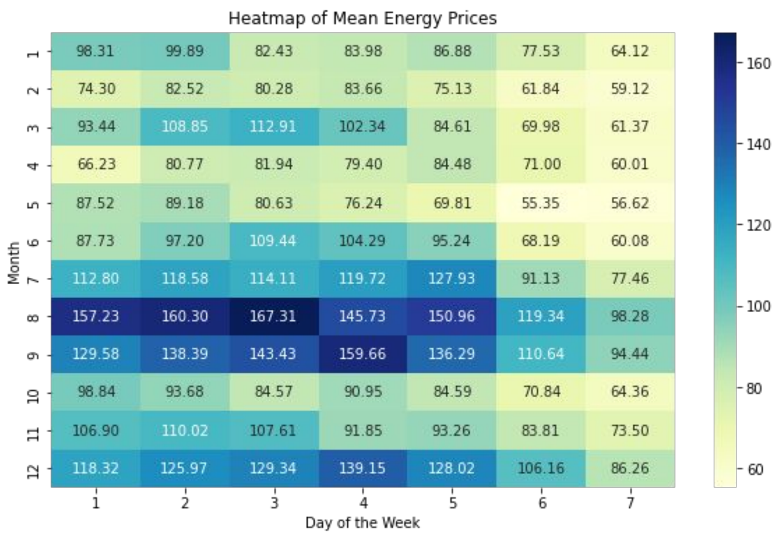
Price Prediction (Cont.):

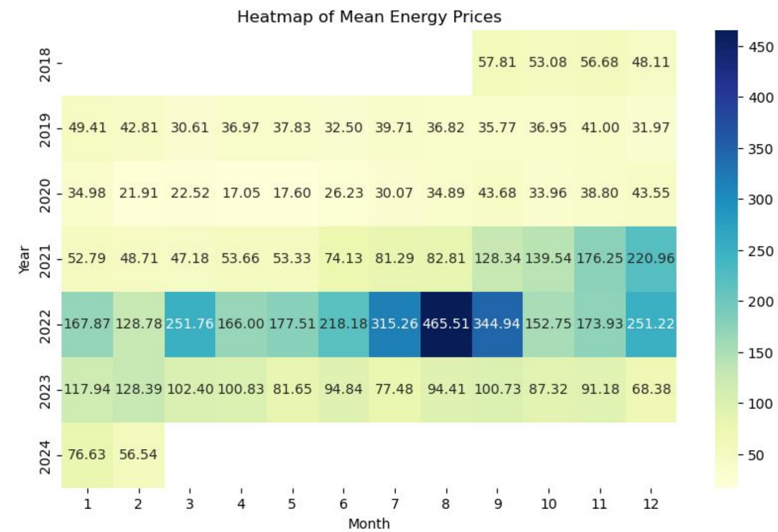
Challenges:

- No Yearly Trends
- No Seasonality

~ Classical Time Series Models do not work well







Price Prediction (Cont.):

Solutions

- Optimal model: Random Forest Regressor.

- Smaller range of data: Models trained on the past few months outperform those using 4-5 years of data.

- Feature enhancement: Including weather, energy, day-ahead electricity generation, control energy export/import, electricity consumption, and balancing energy improves results.

- Holidays, Cultural/ Political Events do not seem to have a major influence on price.

Random Forest Feature Importance

feature	
System_Stability_Balancing_Energy_Nettoerlöse [€]	0.462
System_Stability_Costs_Netzsicherheit [€]	0.143
Steinkohle	0.103
Braunkohle	0.079
Pumpspeicher	0.031
Erdgas	0.025
System_Stability_Secondary_control_reserve_Arbeitspreis (-) [€/MWh]	0.024
System_Stability_Secondary_control_reserve_Arbeitspreis (+) [€/MWh]	0.019
System_Stability_Costs_Regelreserve [€]	0.011

Price Prediction (Cont.):

Challenge:

- The forecasting of price depends on the predictions of other factors like weather, energy, etc.

Solution:

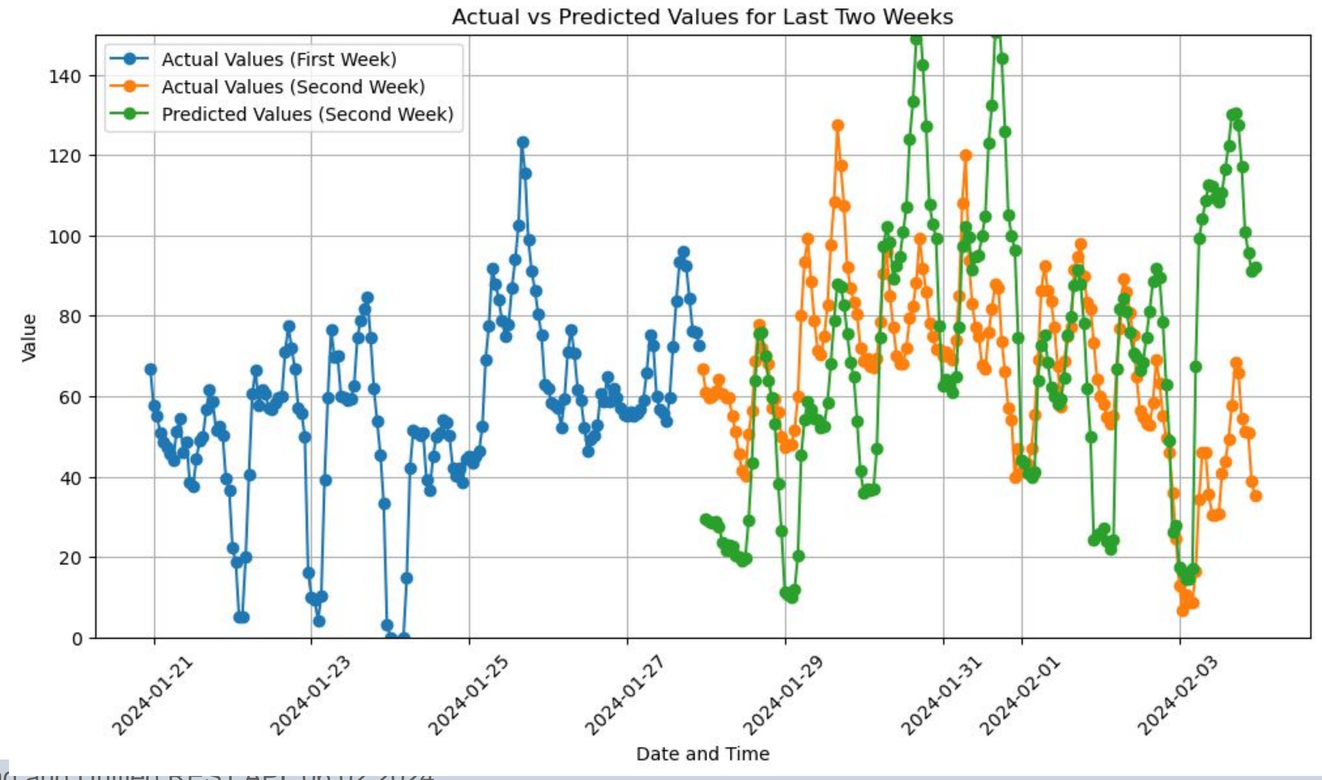
- Introduce Temporal Features: Year, Month, Day, Hour, Rolling Mean (24 hr)
- Random Forest with Grid Search CV for hyper-parameter tuning.
- Recursively predicting the price values for each day in the next week.

Price Prediction (Cont.):

Final Models:

Model 1:

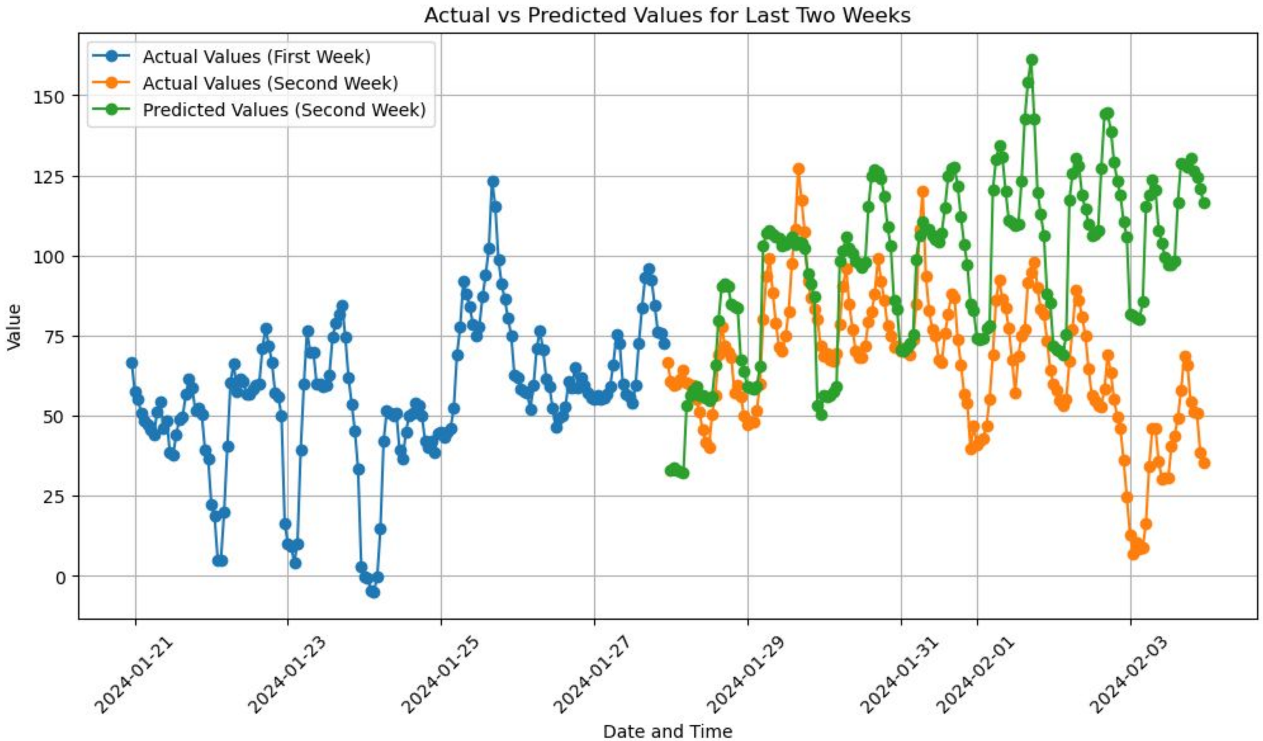
- Trained on last 3 months data
- Only used temporal features (e.g. year, month, hour, day of week) and rolling mean



Price Prediction (Cont.):

Final Models:
Model 2:

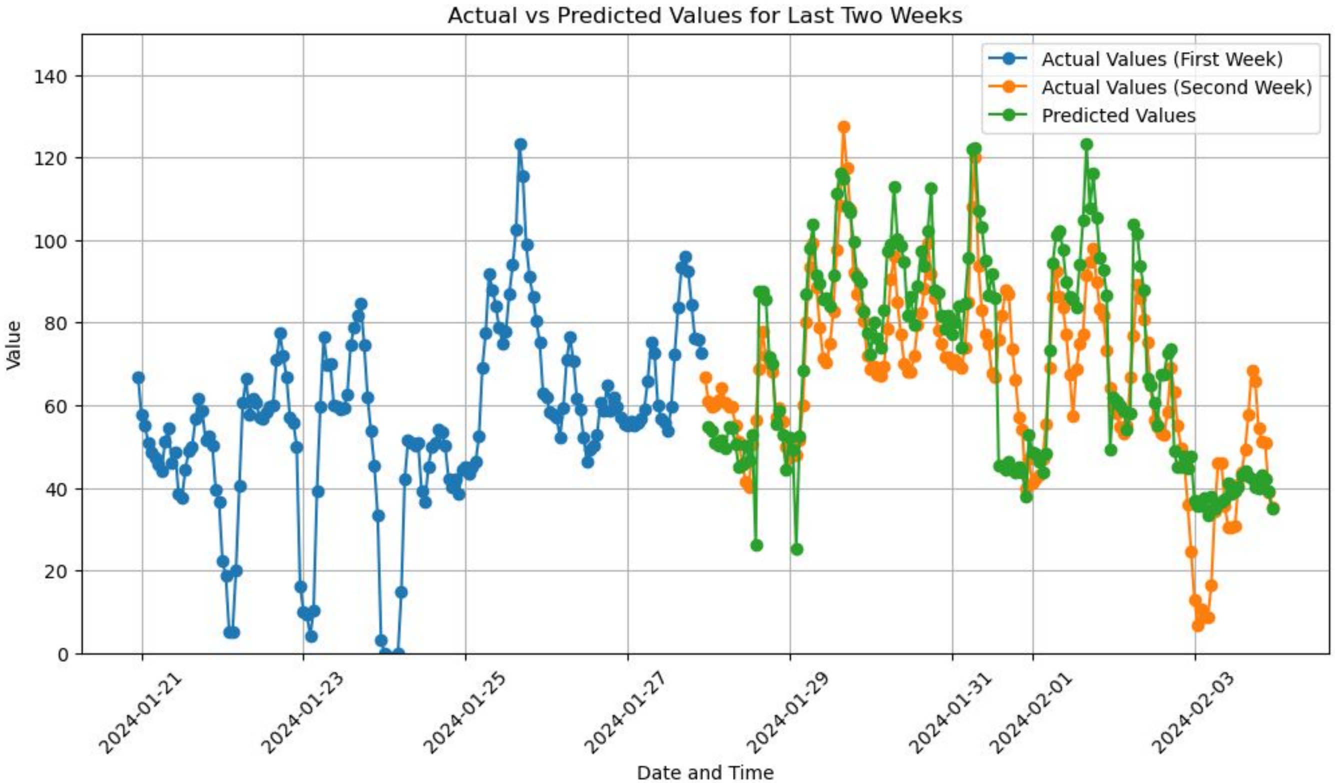
- Trained on last 3 months data + 3 Months data from around the same time last year.
- Only used temporal features (e.g. year, month, hour, day of week) and rolling mean.



Price Prediction (Cont.):

Final Models:
Model 3:

- Trained on last 3 months data
- Temporal Features + Rolling Mean + Other factors (e.g. weather, generated energy)



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Price Prediction (Cont.):

Final Models:
Model 4:

- Trained on last 3 months data + 3 Months data from around the same time last year.
- Temporal Features + Rolling Mean + Other factors (weather, generated energy)