

A scenic landscape photograph featuring three white wind turbines on a grassy hill. The sun is setting in the background, creating a warm orange and yellow glow that reflects on the water in the distance. The sky transitions from a deep blue at the top to a soft orange near the horizon. The foreground shows a dirt path leading towards the turbines and a small pond on the left.

# Energy prices in Spain

Timeseries forecasting and management summary

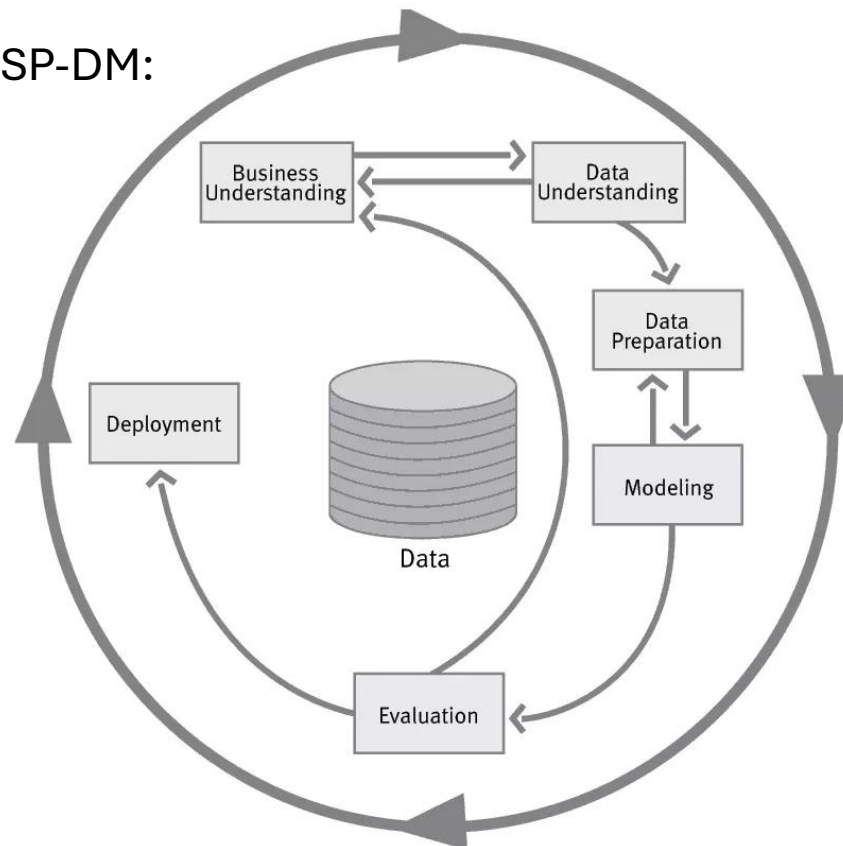
# 1. Workflow – CRISP-DM:

- Forecasts for the Spanish energy transition

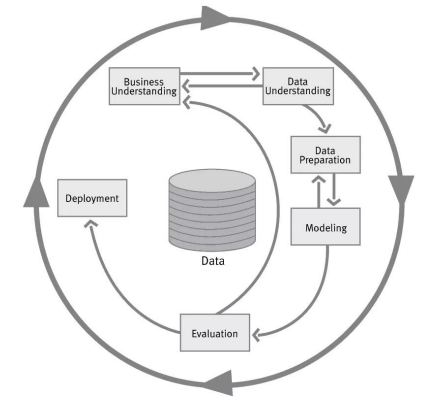
- **Data Preparation and Feature**

- Checking and removing outliers
- Checking and removing duplicates
- Check for missing values
- Fill in missing values with mean
- Create dataset per city for each year
- Restrict dataset to highly relevant features
- Create simple time features

CRISP-DM:



CRISP-DM:



[1] - <https://datasolut.com/crisp-dm-standard/>

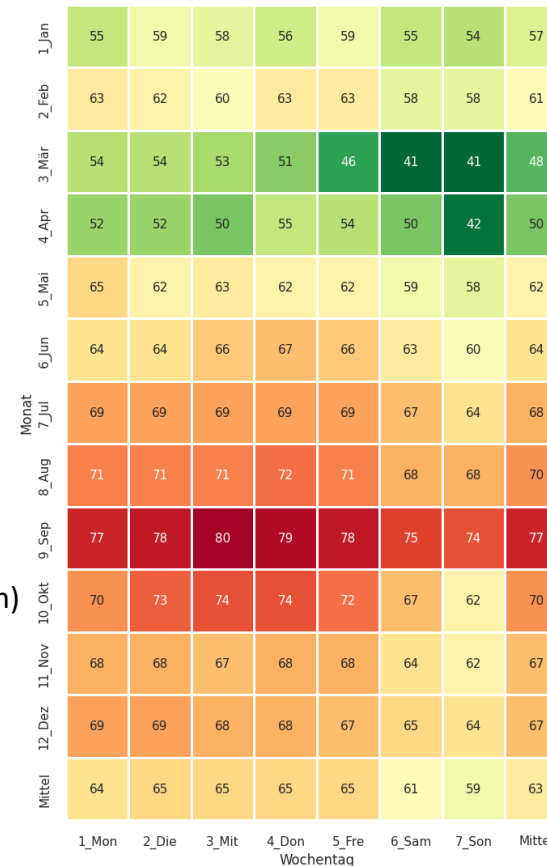
# 2. Factors influencing the electricity price

## • Trends and Seasonality

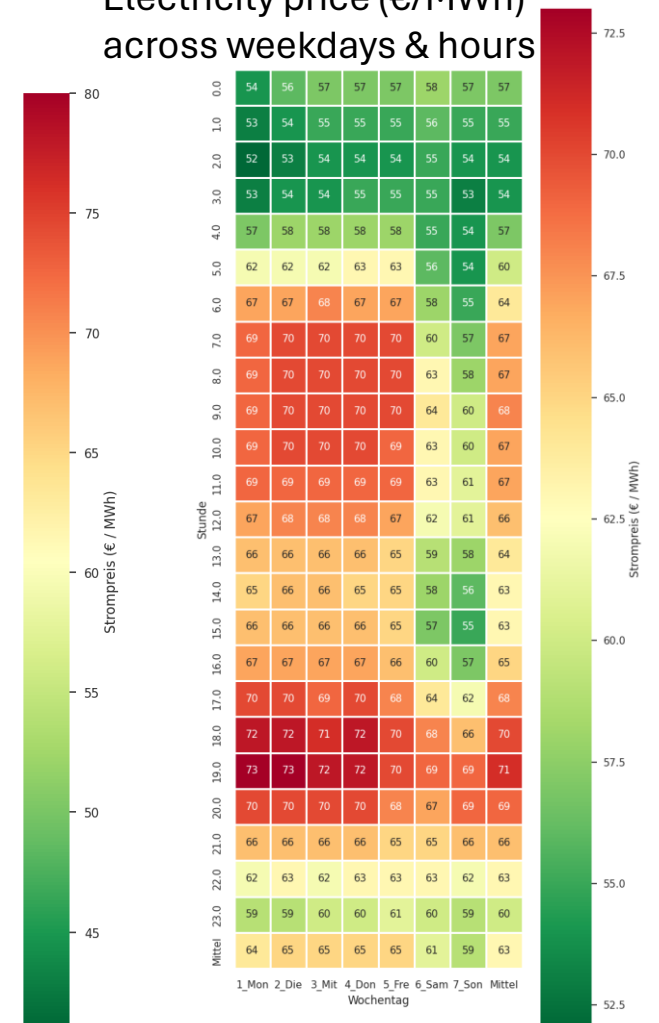
### Trends & Seasonality of electricity prices

- **Seasonality:** Monthly, daily and hourly
- **Monthly:**
  - Electricity prices tend to be lower in winter
  - Highest electricity prices in late summer (September maximum)
    - Possible reason: high demand (ac) and lower production (water)
  - Does not correlate 1:1 with electricity demand (highest in winter and summer)
- **Daily:**
  - Working days higher than weekends (possible reason: industry)
- **Hourly:**
  - Cheapest at night, most expensive in the evening (5-9 pm)
  - Striking: 13-16 h the electricity price is lower (possibly siesta time in Spain)

Electricity price (€/MWh)  
across weekdays & months



Electricity price (€/MWh)  
across weekdays & hours

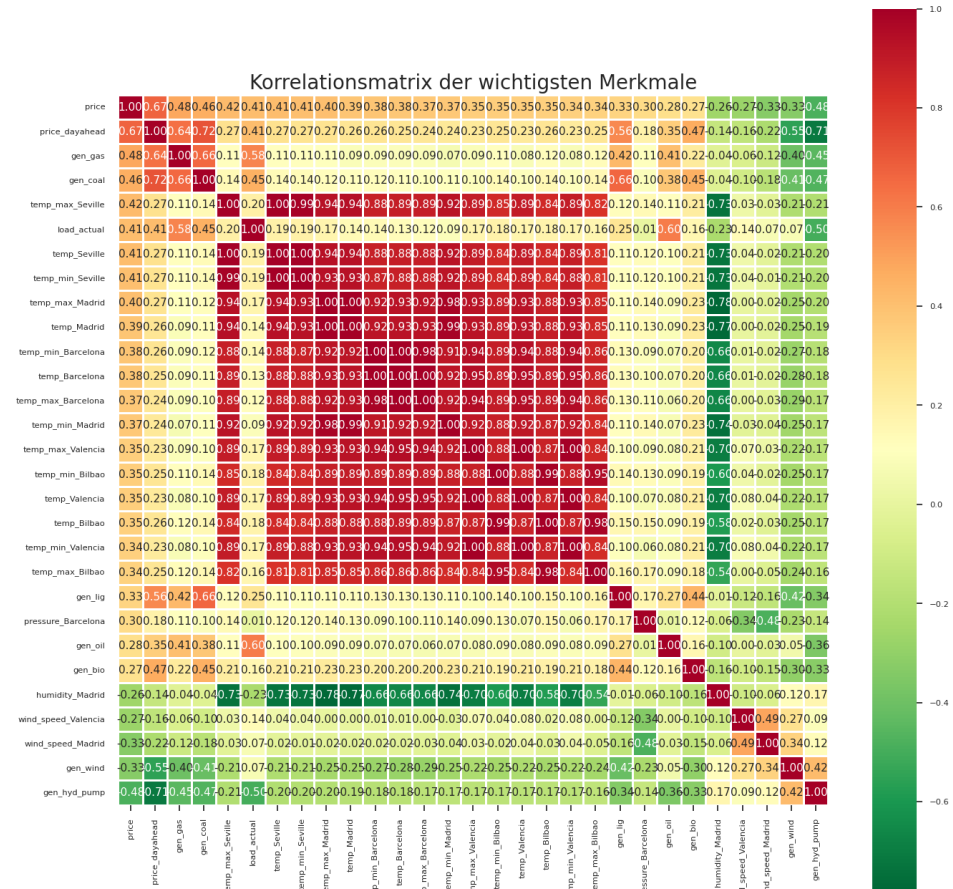


# 2. Factors influencing the electricity price

## • Results of correlationanalysis

Figure: Highest linear correlation to the target variable electricity price

- Positively correlated::
  - Day-Ahead-Preis (0.67)
  - Generation by natural gas (0.48)
  - Erzeugung durch Kohle (0.46)
- Negatively correlated:
  - Generation by hydro pump (-0.48)
  - Generation wind power (-0.33)
  - Wind speed Madrid (-0.33)
- Strong correlation of temperature data between the cities



## 2. Factors influencing the electricity price

- Results of correlationanalysis

Analysis of the high electricity prices in September compared to the year as a whole revealed

- Higher influencing factor due to consumption (possibly air conditioning systems with high consumption)
- Higher influencing factor Hydropower reservoir (water shortage due to drought → Generation more expensive)

Rank	September Merkmal	September Korrelation	Gesamtjahr Merkmal	Gesamtjahr Korrelation
1.	Electricity price	1.0	Electricity price	1.0
2.	Gaserzeugung	0.55	Day-Ahead-Price	0.67
3.	Generation by water reservoir	<b>0.52</b>	Generation by gas	0.49
4.	Electricity demand	<b>0.51</b>	Generation by coal	0.46
5.	Day-Ahead-Price	0.48	Temp_max_Sevilla	0.42

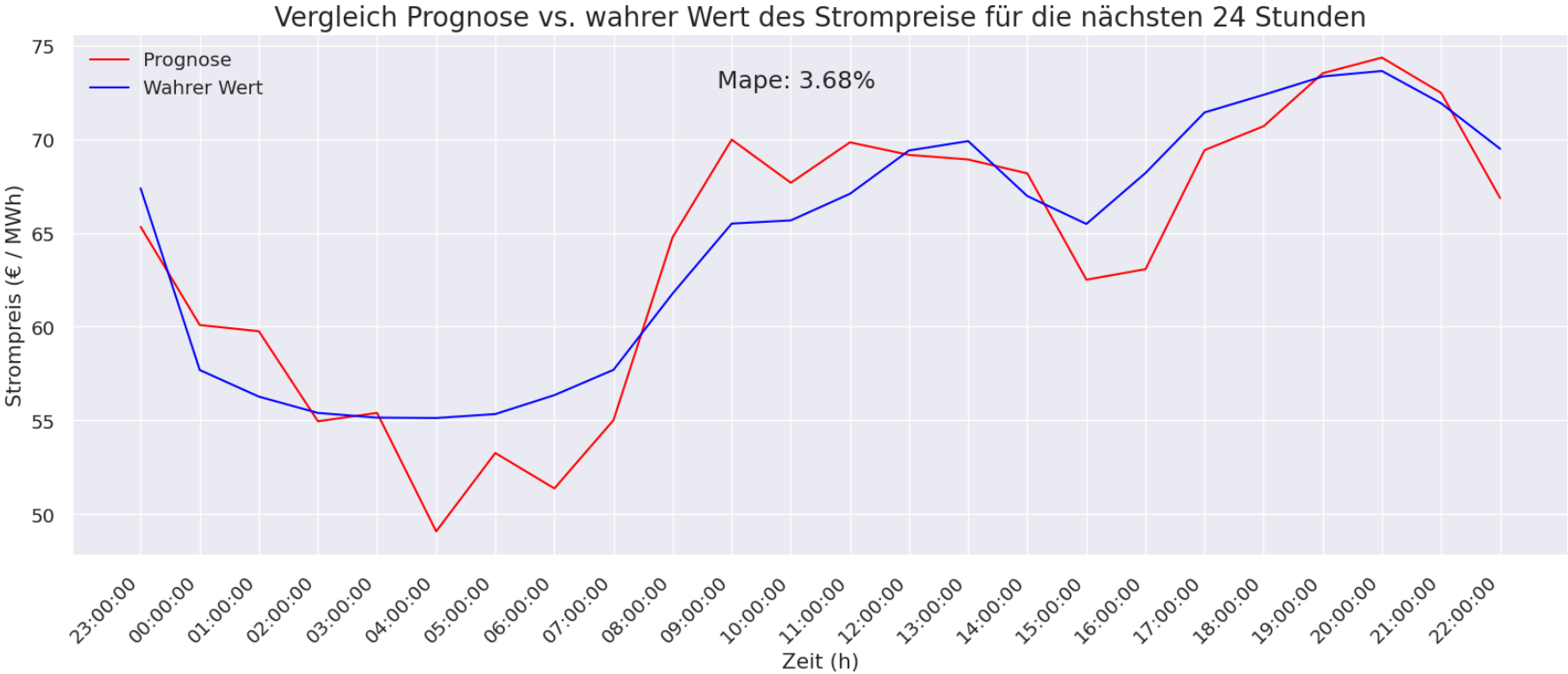


# 3. Time series forecast

- Comparison of different ML models with cross-validation and AutoML (criteria: **MAPE**)
- Choose EBM (ML-Model) – Explainable Boosting Machine (Regressor)  
[2] - <https://interpret.ml/docs/ebm.html>

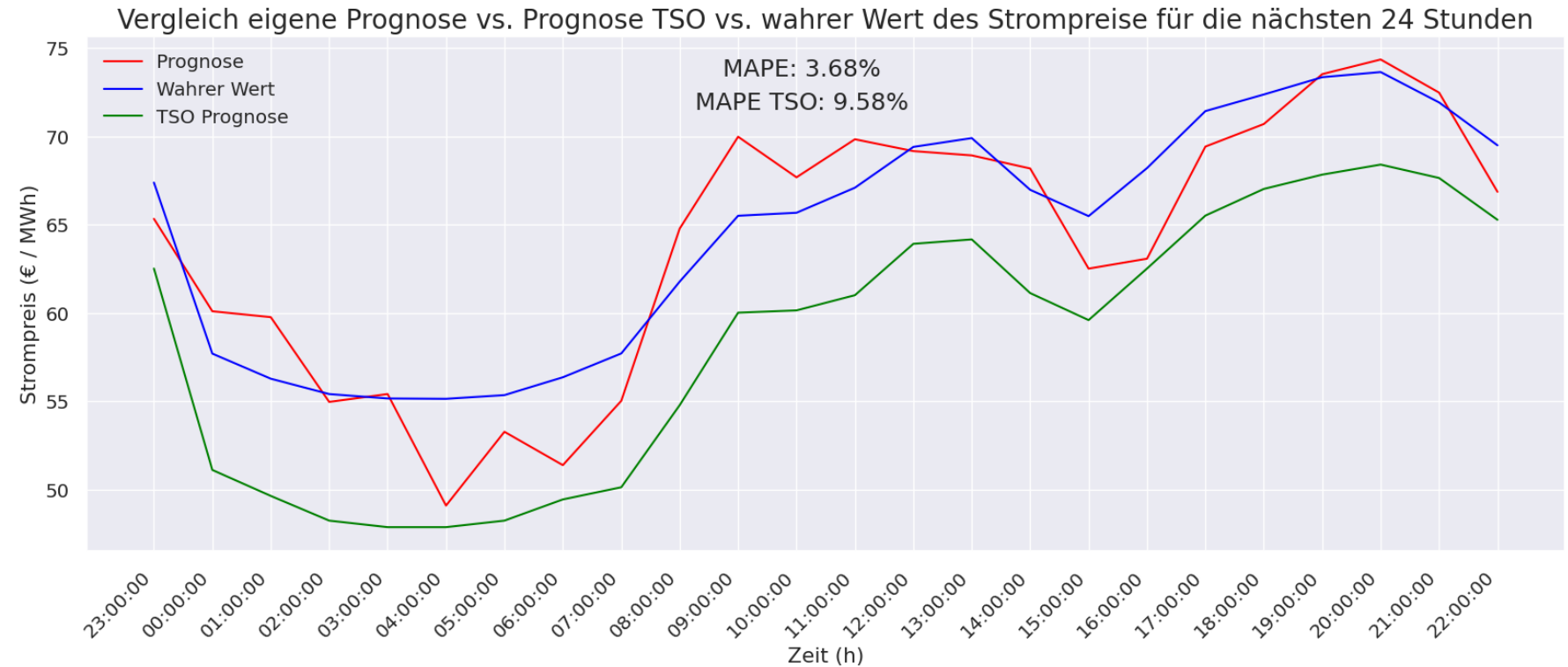
Mean absolute percentage error

Time	Preis	Preis Prognose	Abs(Preis – Prog.)	Abs / Preis
23:00:00	67	65	2	2 / 67 = 0,029
00:00:00	58	60	2	2 / 58 = 0,0345
				<b>MAPE = (0,029 + 0,0345) / 2 = 0,032 → 3,2 %</b>



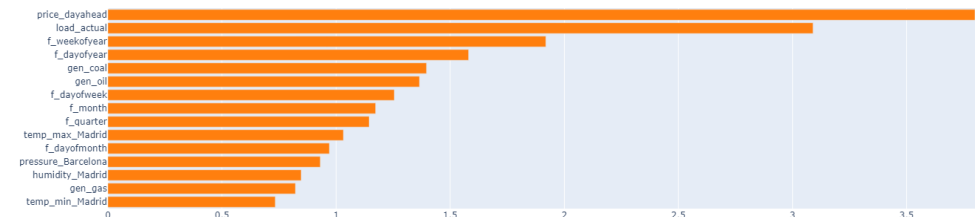
# 4. Evaluation & Explainability

- Evaluation with TSO:



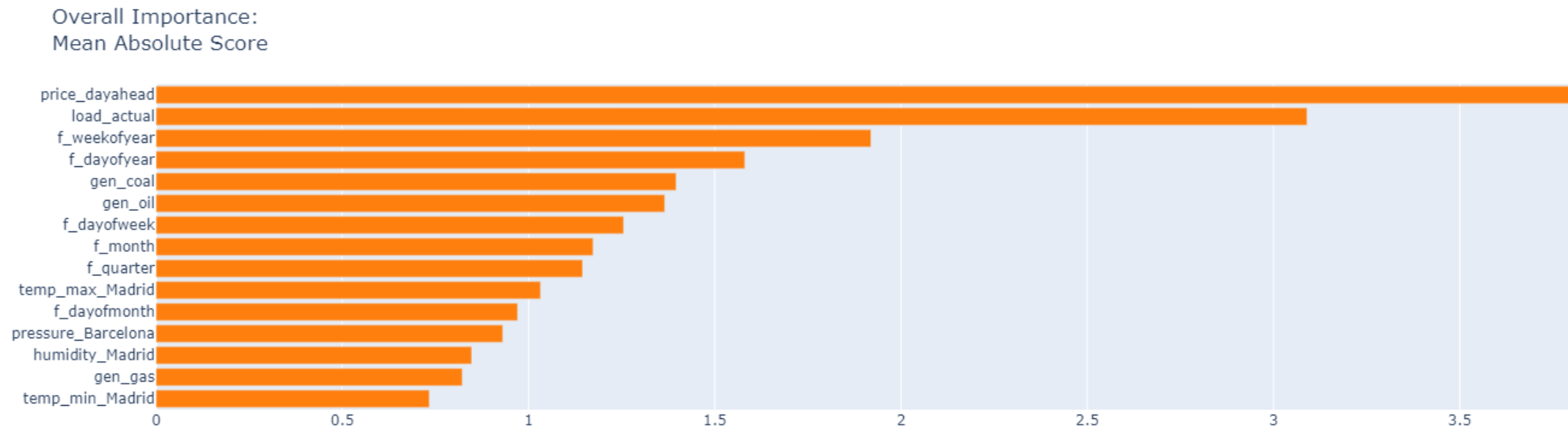
- Interpret Model:

- Global: <http://127.0.0.1:7777/140231638982464/>
- Lokal: <http://127.0.0.1:7777/140231638978864/>



# 4. Global Explainability

- Feature Importance from the EBM model





# 5. Conclusion and outlook

- **Conclusion:**

- Influencing factors identified and explained (see chapter 2)
- Forecast created with very low error (3.5%) for the next 24 hours
- Recommendation for transmission system operators → Own forecast is significantly more accurate

- **Next steps:**

- Forecast various weather data and producers for more accurate forecasts and out-of-sample forecasts
- Detailed analysis of additional features in order to identify further trends and derive new features from them
- Data set sufficiently large for an approach with artificial neural networks
  - But training computationally and time consuming

# 6. Additional Slides

# Additional slide: Explainable Boosting Machines

- Explainable Boosting Machine (EBM) is a tree-based, cyclic gradient boosting Generalized Additive Model with automatic interaction detection. EBMs are often as accurate as state-of-the-art blackbox models while remaining completely interpretable. Although EBMs are often slower to train than other modern algorithms, EBMs are extremely compact and fast at prediction time.
- [Explainable Boosting Machine \(interpret.ml\)](https://interpret.ml)
- [Exploring explainable boosting machines](#)

# Additional slide: Explain calculation MAPE

Time	Price	Price_Prediction	Abs(price -pred)	(M)APE
23:00:00	67	65	2	$2 / 67 = 0,029$
00:00:00	58	60	2	$2 / 58 = 0,035$
				$(0,029 + 0,035) / 2$ <b>= 0,032 → 3,2 %</b>