14.05.2025

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Software Project Distributed Systems

Consumption Data Forecast for HPC Systems

Sprint 1
Preprocessing

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Digital Twin

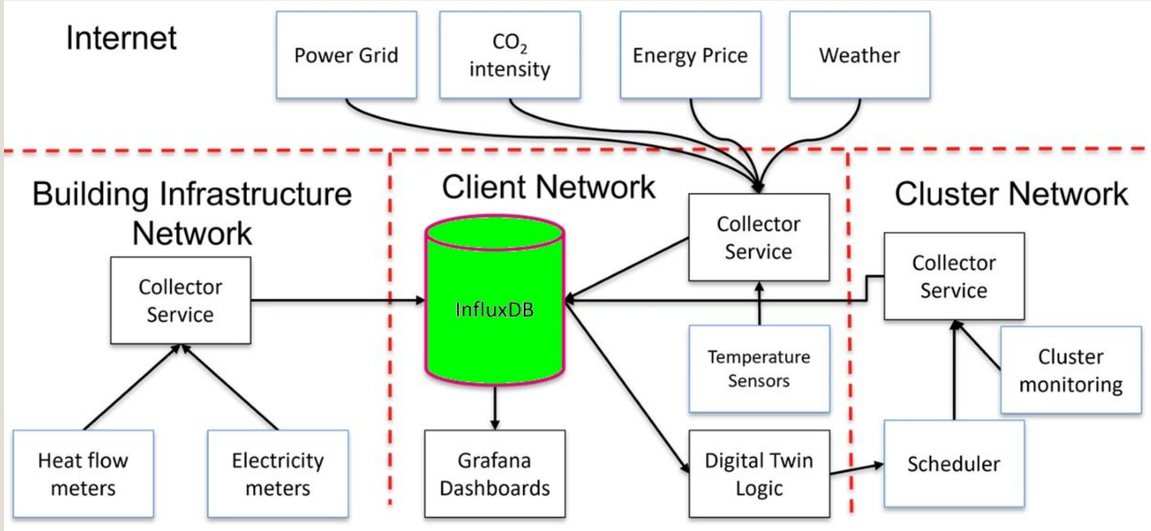
The Digital Twin is a virtual construct that represents a physical counterpart, integrates several data inputs with the aim of data handling and processing, and provides a bi-directional data linkage between the virtual world and the physical one.

- Physical counterpart : HPC cluster of PTB
- Data inputs : Cluster monitoring, Webservices
- Aim : Optimization of cluster usage, regarding e.g. more FLOPS per Watt, less energy per task, overall energy costs, CO2 emissions

Kammeyer et al.:

- 2023, Optimization of Energy Efficiency of an HPC Cluster, SMSI 2023, pp. 378-379
- 2023, Towards an HPC cluster digital twin and scheduling framework for improved energy efficiency, ACSIS 35:265-268
- 2024, HPC operation with time-dependent cluster-wide power capping, ACSIS 39:385-393
- 2024, Developing a digital twin to measure and optimise HPC efficiency, Measurement: Sensors, 2024.101481

Data Collection



[1]

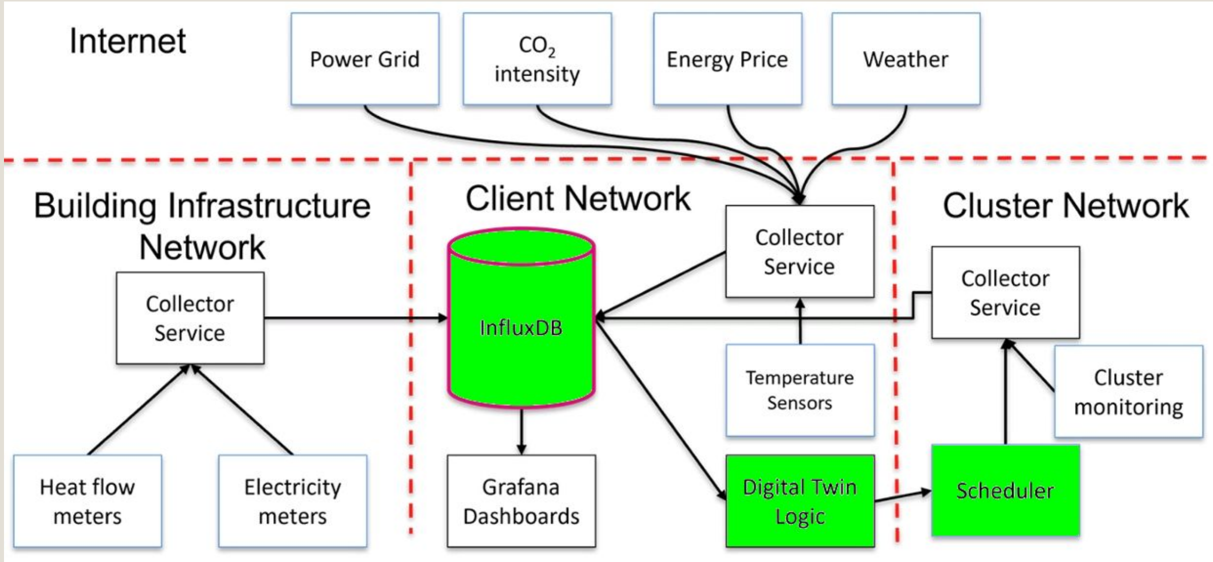
Data stored with InfluxDB, a time series database system

- Accessible via web API
- Queries can be formulated in SQL-alike InfluxQL or the functional script language Flux

Forecasting

Problem : Limited budget of money, energy, and CO_2 emission

Task : Forecast energy prices and CO_2 footprint for effective scheduling



What has been done

- Created the GitLab for our project
- Created the database connection on our local system
- Queried the database to get familiar with structure and shape
- Analyzing the data with python pandas library
- Creating Charts
- Analyzed results of SWP 2023/24 group

Database Scheme

General Bucket Columns

Column	Meaning
_start, _stop	Provided time interval within the requested one
_time	Field timestamp within the provided interval
_field	Field key, designating a category of measurement
_value	Field value
table	Field index. Can change with each query

Database Scheme

Bucket: co2

Column	Possible values
_measurement	co2
_field	carbonIntensity, fossilFuelPercentage
contryCode	DE, PL, FR, …
status	ok

Database Scheme

Bucket: co2

Column	Possible values
_measurement	co2_calculated (based on bucket “energy”)
_field	carbonIntensity, fossilFuelPercentage
contryCode	DE

Database Scheme

Bucket: energy

Column	Possible values
_measurement	energy_production
_field	“Kernenergie”, “Biomasse”, “Wind Onshore”, “Photovoltaik”, “Braunkohle”, “Steinkohle”, “Erdgas”, “Pumpspeicher”, “Wasserkraft”, “Sonstige Erneuerbare”, “Sonstige Konventionelle”, “Wind Offshore”
region	DE

Database Scheme

Bucket: price

Column	Possible values
_measurement	price
_field	“Deutchland/Luxembourg” (Sic! Typo from the web service)
region	DE

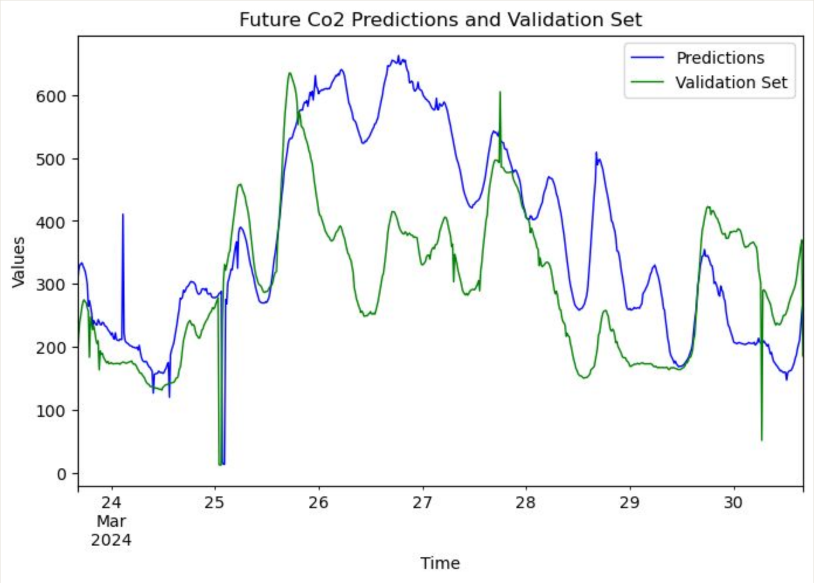
Database Scheme

Bucket: weather

Column	Possible values
_measurement	weather
_field	icon, pressure_msl, solar, source_id, sunshine, temperature, visibility, wind_direction, wind_gust_speed, wind_speed

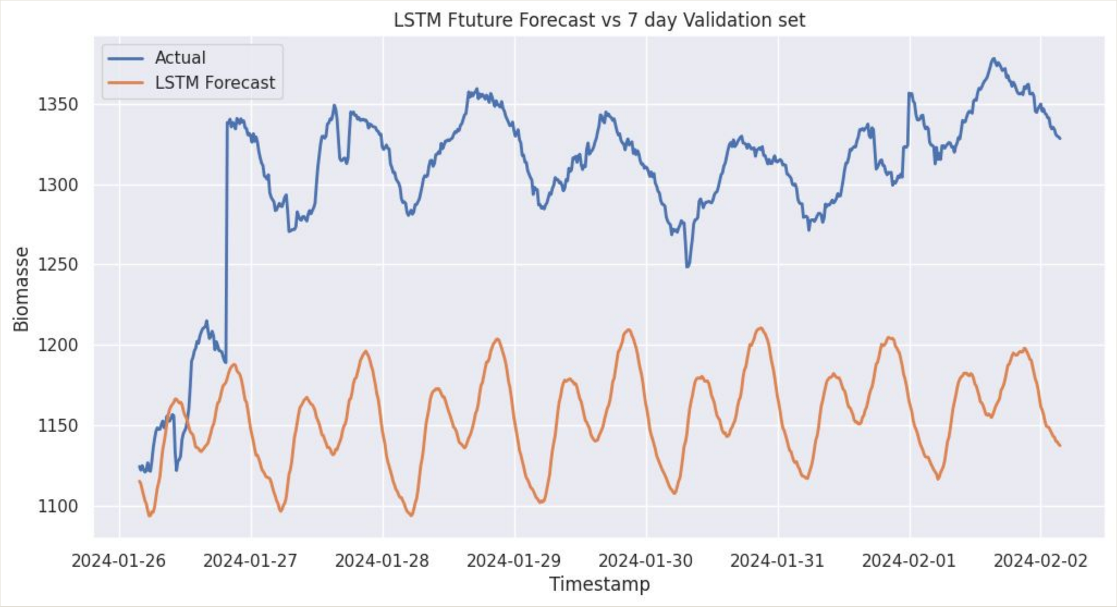
SWP WS 2023/24
Results

Forecast on the Carbon Intensity, calculated from the energy mix data, using a Random Forest Regressor trained on the Exponential Moving Average, with a Mean Absolute Error of 51%.



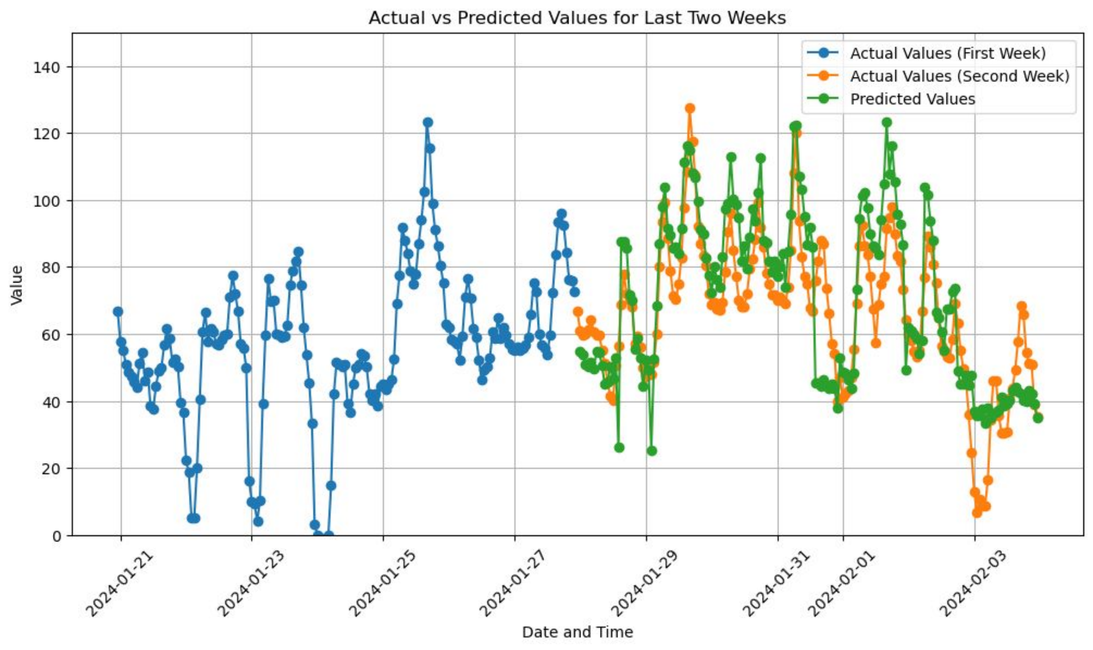
SWP WS 2023/24
Results

Forecast on the production of each energy carrier, using a Long Short-Term Memory Neural Network. Mean Absolute Error: 9-505%



SWP WS 2023/24
Results

Forecast on the energy price with two Random Forest Approaches.
Mean Absolute Error of best approach: 25%



SWP WS 2023/24

Issues

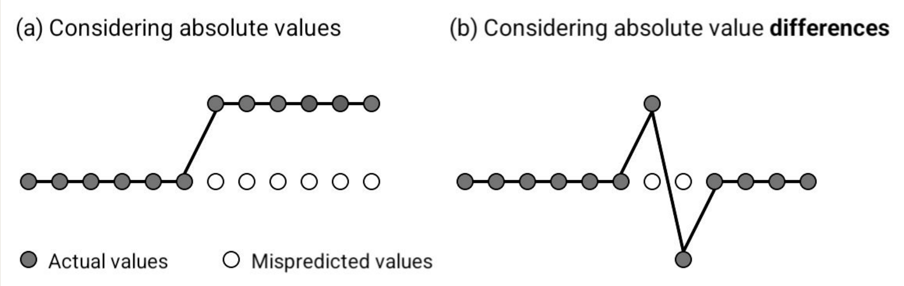
- Random Forest Tree produces more or less correct trends, but oftenly exaggerates
- Long Short-Term Memory NN is too static and reacts bad on any short- and mid-term deviation from long-term trends
- In general bad reaction on unexpected events, e.g. the shut-down of nuclear energy

- No use of correlations made
- Unreasonable to forecast each energy carrier for itself instead of grouping into fossiles and renewables

SWP WS 2023/24
Lessons for 2025

- Find and exploit meaningful **Correlations**, i.e. with causality

- **Predict Trends**
  - Abolute values can become easily obsolete, e.g. by political choices, but relative changes are usually more stable
  - Ruptures in absolute data with long-term impact are only outliers, when looking at differences



Data Visualization

Table for CO2 intensity and Fossil Fuel Percentage

CO_2-Daten (letzte 6 Monate)

CO_2-Intensität (gCO_2/kWh)	Fossiler Anteil (%)	Zeit
652.7663525109017	72.23472593426173	2024-11-12T04:15:00+00:00
652.6632070214545	72.78257639082382	2024-11-12T04:30:00+00:00
653.1047392932152	73.4248013880011	2024-11-12T04:45:00+00:00
652.3043517191977	73.36362822349571	2024-11-12T05:00:00+00:00
650.7329293461555	73.47516796206034	2024-11-12T05:15:00+00:00
646.0562019241071	73.23605665188232	2024-11-12T05:30:00+00:00
640.5154828862358	72.3294373471052	2024-11-12T05:45:00+00:00
635.5781599837167	71.11337268471402	2024-11-12T06:00:00+00:00
633.6506722438004	70.54277462404143	2024-11-12T06:15:00+00:00
630.9713368313885	70.15036416320777	2024-11-12T06:30:00+00:00
628.2613522085558	70.05492380289317	2024-11-12T06:45:00+00:00
621.603066633733	69.34506279569075	2024-11-12T07:00:00+00:00
618.8232682394552	69.03525604846295	2024-11-12T07:15:00+00:00
616.886651247626	69.04157499858971	2024-11-12T07:30:00+00:00
615.5335762721415	69.03845070157972	2024-11-12T07:45:00+00:00
607.5458911419423	67.81547860008097	2024-11-12T08:00:00+00:00
606.5950408659156	68.06199838008983	2024-11-12T08:15:00+00:00
605.394631167831	68.175733905422	2024-11-12T08:30:00+00:00
603.5312465637943	68.19814536524575	2024-11-12T08:45:00+00:00
606.2502120441052	68.51606003613969	2024-11-12T09:00:00+00:00
606.1563402052257	69.16587518855802	2024-11-12T09:15:00+00:00
604.2923329233292	69.13041857691304	2024-11-12T09:30:00+00:00
602.6317211816233	68.99450191035318	2024-11-12T09:45:00+00:00
600.9328917263267	68.41095283784782	2024-11-12T10:00:00+00:00

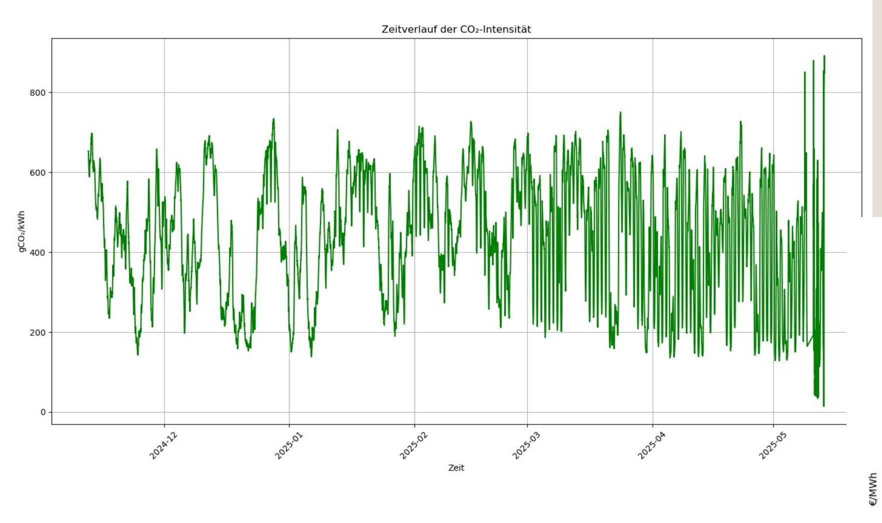
Data Visualization

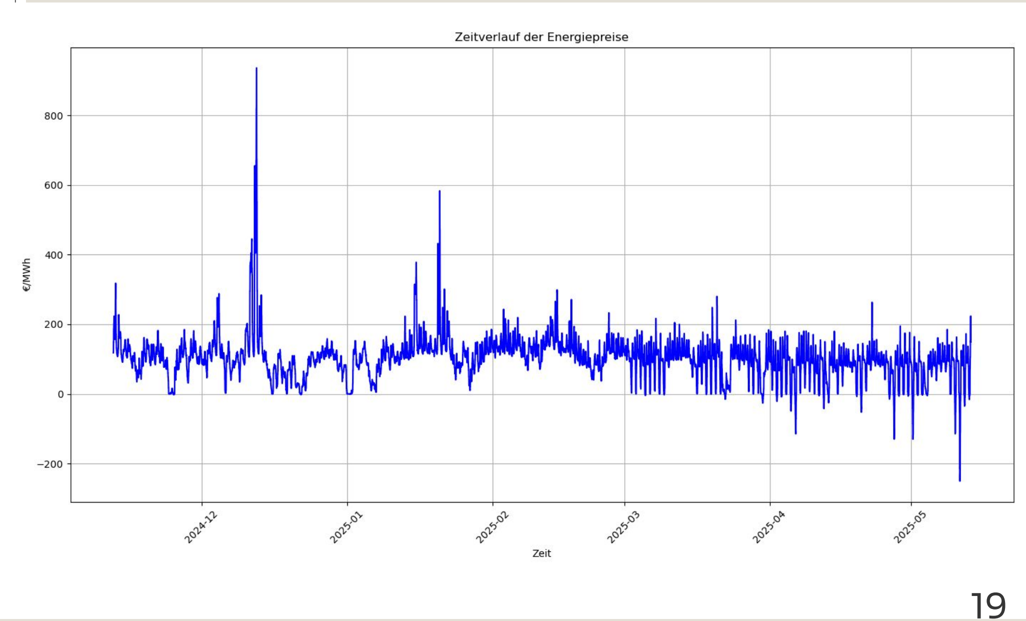
Table for energy types and price

Energieproduktion & Energiepreis (letzte 6 Monate)

time	Biomasse	Braunkohle	Erdgas	Photovoltaik	Sonstige Erneuerbare	Sonstige Konventionelle	Steinkohle	Wasserkraft	Wind Offshore	Wind Onshore	tchland/Luxembo
.1-12T04:15:00-	1008.25	2891.25	2813.75	1.75	32.5	270.75	1727	333.75	409.25	1165	118.01
.1-12T04:30:00-	1010	2890.75	2949.75	1.75	32.5	271	1725	337	387.25	1159.5	118.01
.1-12T04:45:00-	1018.75	2933.5	3128.5	2	32.5	270.75	1708	334	371.25	1151.25	118.01
.1-12T05:00:00-	1043.5	2989.75	3216.25	1.5	32.5	284.75	1702.5	343.25	348.25	1171.75	147.67
.1-12T05:15:00-	1058.25	3016.75	3353.75	1.5	32.25	280.5	1715.25	367	331	1178.75	147.67
.1-12T05:30:00-	1071.25	3018.5	3517.25	1.5	32	269.5	1739.75	411.75	312.5	1202.25	147.67
.1-12T05:45:00-	1088.75	3019.25	3610.5	1.75	32	269.75	1748.75	448.75	304	1216	147.67
.1-12T06:00:00-	1116.75	3047.25	3689.5	2	32	275	1722.75	474	286.75	1210.5	185.52
.1-12T06:15:00-	1131	3088.75	3750.5	2.5	32	289	1725.75	484.75	279.25	1226	185.52
.1-12T06:30:00-	1135.75	3101.25	3828.5	12	32	304.25	1723.5	494	268.25	1242	185.52
.1-12T06:45:00-	1142	3095	3916.5	49.25	32	325	1719.5	486	265.75	1241.5	185.52
.1-12T07:00:00-	1153.75	3098.25	3994.75	113	32	340.75	1690.5	520	250.5	1249.75	201.64
.1-12T07:15:00-	1151.25	3102	4038	205.25	32	339	1694.75	499.25	238.25	1249.75	201.64
.1-12T07:30:00-	1152	3103.5	4040.75	318.25	32	332	1703	495.5	225.25	1226.75	201.64
.1-12T07:45:00-	1150.5	3104.25	4051.25	443.5	32	327.75	1705.25	460.25	227	1183.25	201.64
.1-12T08:00:00-	1139	3104.75	4092.5	573.5	32	333.5	1683	524.75	212.5	1143.25	223.33
.1-12T08:15:00-	1139.5	3103.25	4102	700	31.75	354	1684.25	513.5	200	1092.75	223.33
.1-12T08:30:00-	1138	3104	4127.5	830.25	32	374	1689.75	492.5	190.25	1045.5	223.33
.1-12T08:45:00-	1135	3106	4129.25	947.5	32	374.75	1693.25	480	187	1017.5	223.33
.1-12T09:00:00-	1098.75	3110.75	4099.25	1058.75	32	373.5	1706.25	438	156.75	972.75	190.24
.1-12T09:15:00-	1091.75	3103	4096.75	1164	32	375.25	1710	444.5	128.25	945.5	190.24
.1-12T09:30:00-	1083.25	3112.75	4072	1260	31.75	375	1713.75	465.75	116.5	928	190.24
.1-12T09:45:00-	1078.75	3113.25	4047.75	1360	32	377	1716.75	445.25	113.75	912.75	190.24
.1-12T10:00:00-	1057.25	3117.5	4003	1435.75	32.25	378.5	1770	450.75	115	928.25	171.08

Illustration of the relations





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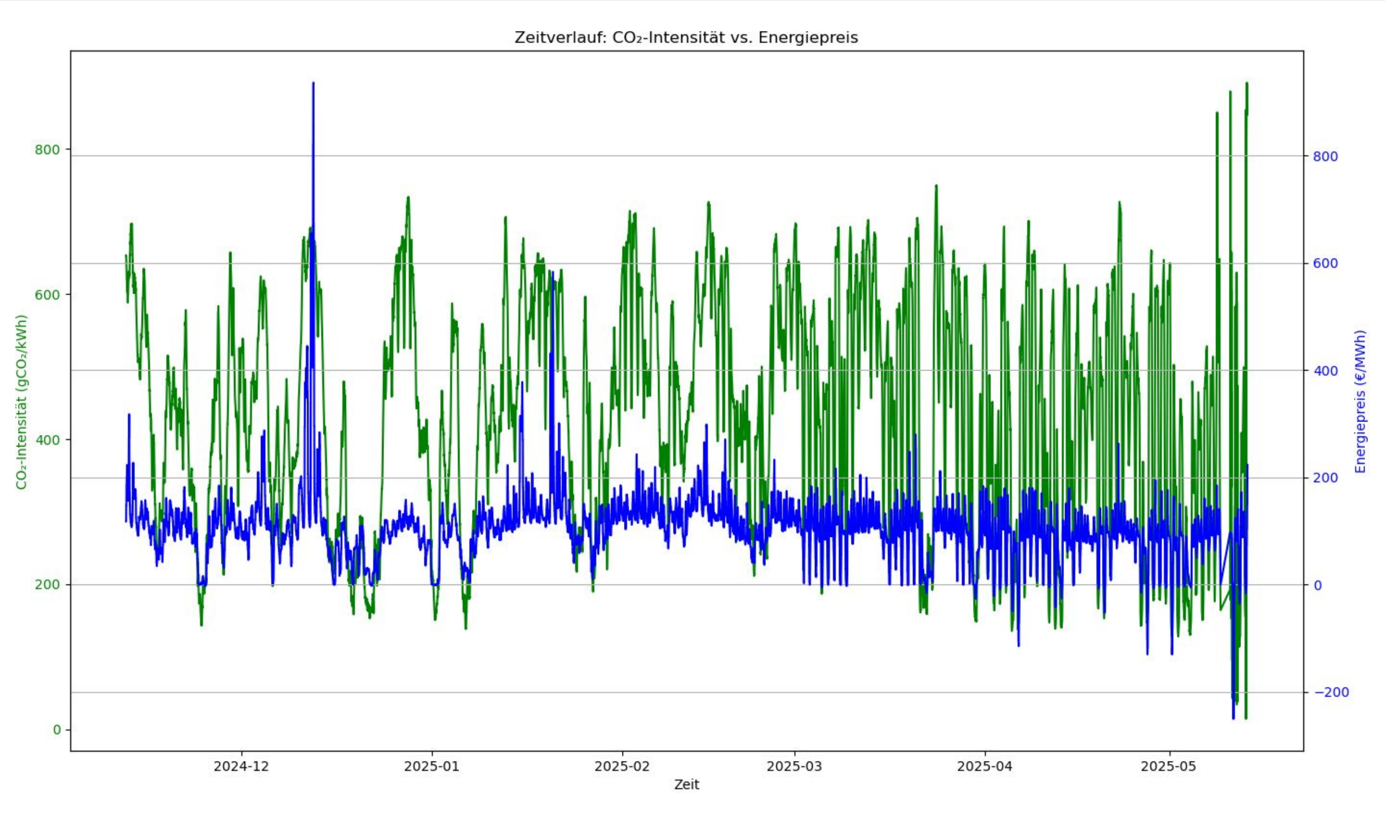


Illustration of the relations

Fossile energy

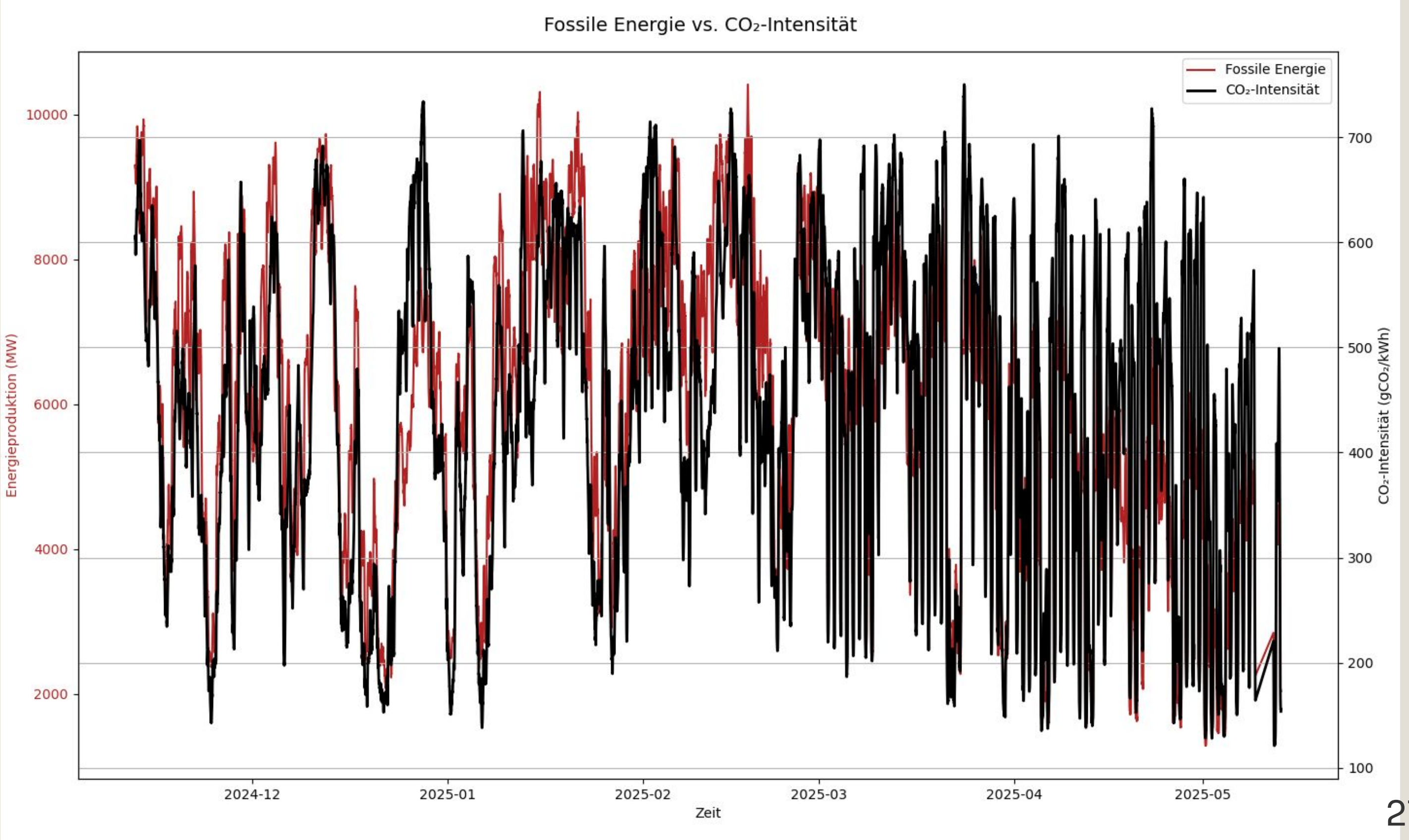
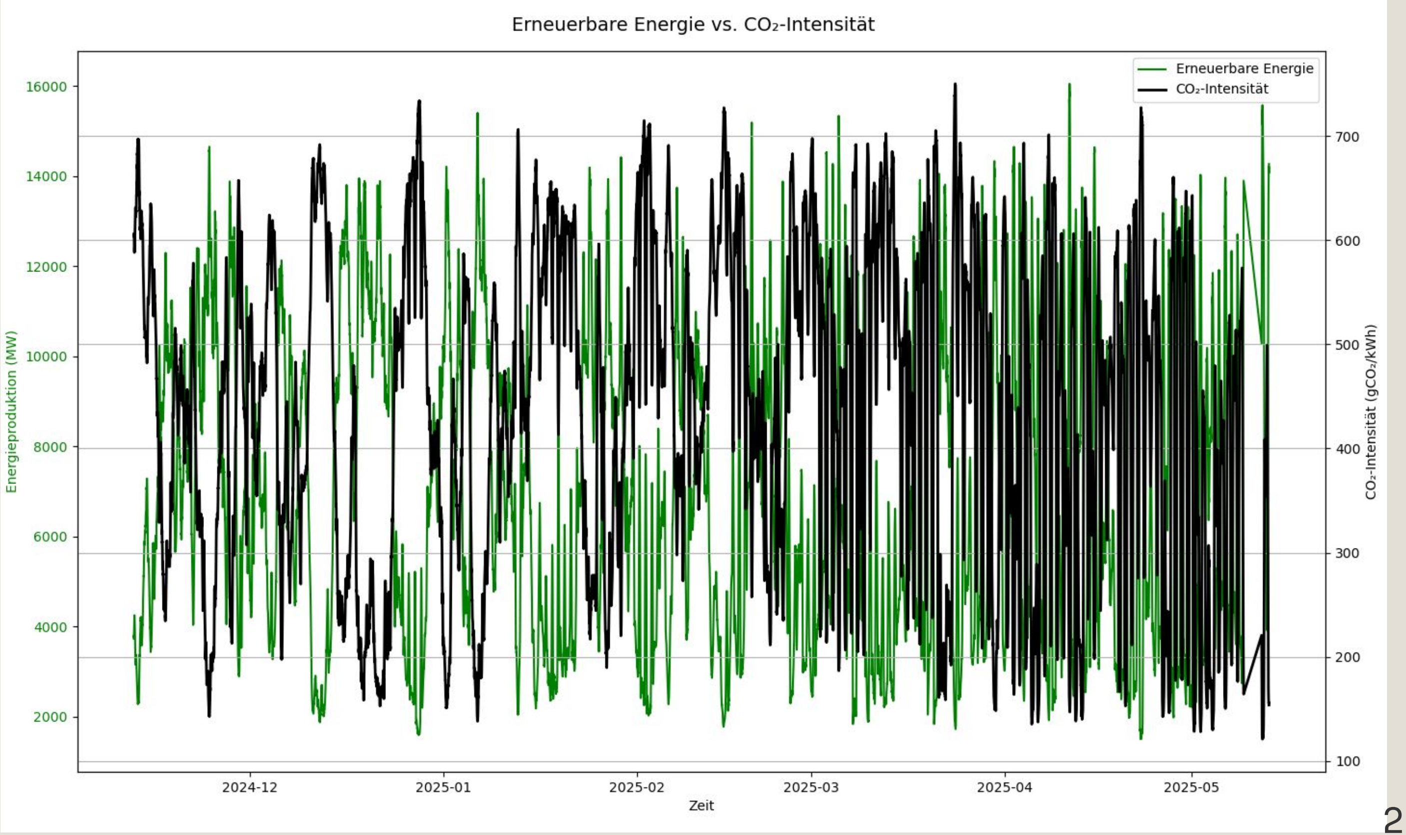


Illustration of the relations

Renewable energy



Did unexpected problems occur?

- Communication in the group
- Handling of gaps in the data

Previous Timeline

	Energy Price Group	CO2 Group	Dates
Sprint 1	Data prep & EDA; benchmark ARIMA	Data prep & EDA; energy-mix analysis	30 April – 14 May
Sprint 2	Train ML models (TimesFM, XGB); feature engineering	Train ML models; incorporate external regressors	14 May – 28 May
Sprint 3	Develop LSTM; hyperparameter tuning	Time-series cross-validation; tune ML and simple RNN models	28 May – 11 June

Outlook

- Meaningful correlations

- Data handling
  - Dealing with data gaps
  - Cleaning outliers

- Making decisions about models
  - Continue with Random Forests? Exclude LSTMs?
  - Other models?

Thank You

References

[1] A. Kammeyer et al. (2024), *Developing a digital twin to measure and optimise HPC efficiency, Measurement: Sensors*, 2024. 101481