Introduction & Data Preparation

Dataset window: 2022-01-01 00:00 → 2024-06-12 23:00 (UTC)

The data are consolidated into a single **hourly** table. All timestamps use **UTC**. An hourly time grid defines the index.

Each source is reindexed to this grid: day-ahead price, load, generation by technology, cross-border flows, commodity drivers (natural gas, coal, CO_2), and installed wind/solar capacity.

Lower-frequency or irregular series are upsampled with (first) forward fill and (then) back fill. Then, the sources are combined with outer joins.

Column names are cleaned. Units are standardized to **EUR/MWh** (power and gas), **EUR/ton** (coal and CO_2), and **MWh per hour** (load, generation, flows).

For trade flows, a positive `trade_balance` means **net imports**. Exports are negative.

The final dataset is `clean_data.csv`. It is used in Tasks 1–4. The code lives in `original_data/preprocess.ipynb`.

Consistency note. In real systems the hourly energy balance $$\text{Generation}+\text{Imports}-\text{Exports}-\text{Load}\approx 0$$ should be near zero. In this dataset it does not close. The likely cause is that the load series is a **day-ahead forecast**, plus small reporting noise. This was taken into consideration for task 4 specifically.

Task 1 — Day ahead prices ~ commodities

> **Question:**
> Suppose that you want to understand the influence that key commodities, i.e., prices of natural-gas, coal, CO2 allowances have on day-ahead prices. Model and quantify these relationships, and suggest a potential trading strategy based on your findings.

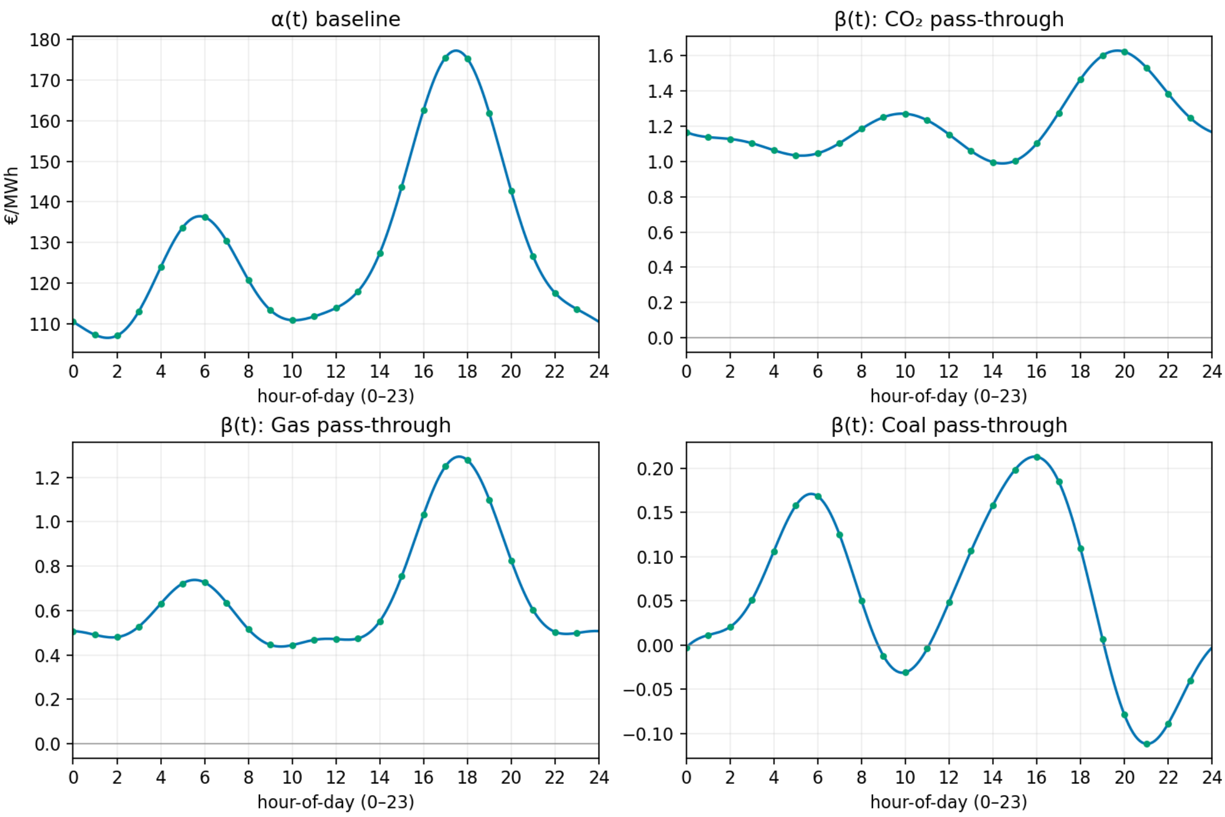
Model

A **concurrent functional linear regression** is fitted.
Each observation is a **curve** over a calendar axis (e.g., hour-of-day or month-of-year), not a

single row as in OLS. The model can be expressed as: $$y*t(u)=\alpha(u)+\sum*j \beta*j(u)\,x*{j,t}(u)+\varepsilon*t(u)$$ Here, u is the calendar position (daily, monthly, quarterly, etc). The coefficients $\beta*j(u)$ are **smooth curves**. Each $\beta*j(u)$ is the* ***pass-through*** *at the same u: if gas moves by 1 unit at $u*0$, price moves by about $\beta*{\text{Gas}}(u*0)$ units at u_0, all else equal.

This differs from OLS: OLS uses one fixed coefficient per driver. The functional model lets the coefficient vary smoothly with time-of-day or season, which is more interpretable for power markets.

Figure A — Hour-of-day coefficient curves



How to read the curves: - $\alpha(u)$ is the **baseline price** shape. It shows typical intraday levels without commodity shocks.

Example: baseline is low at night (~€105/MWh around 02:00), has a morning shoulder (~€135/MWh around 06:00), and a strong evening peak (~€175–€180/MWh around 18–19). - $\beta*{\text{Gas}}(u)$ is the* ***gas pass-through*** *by hour.*

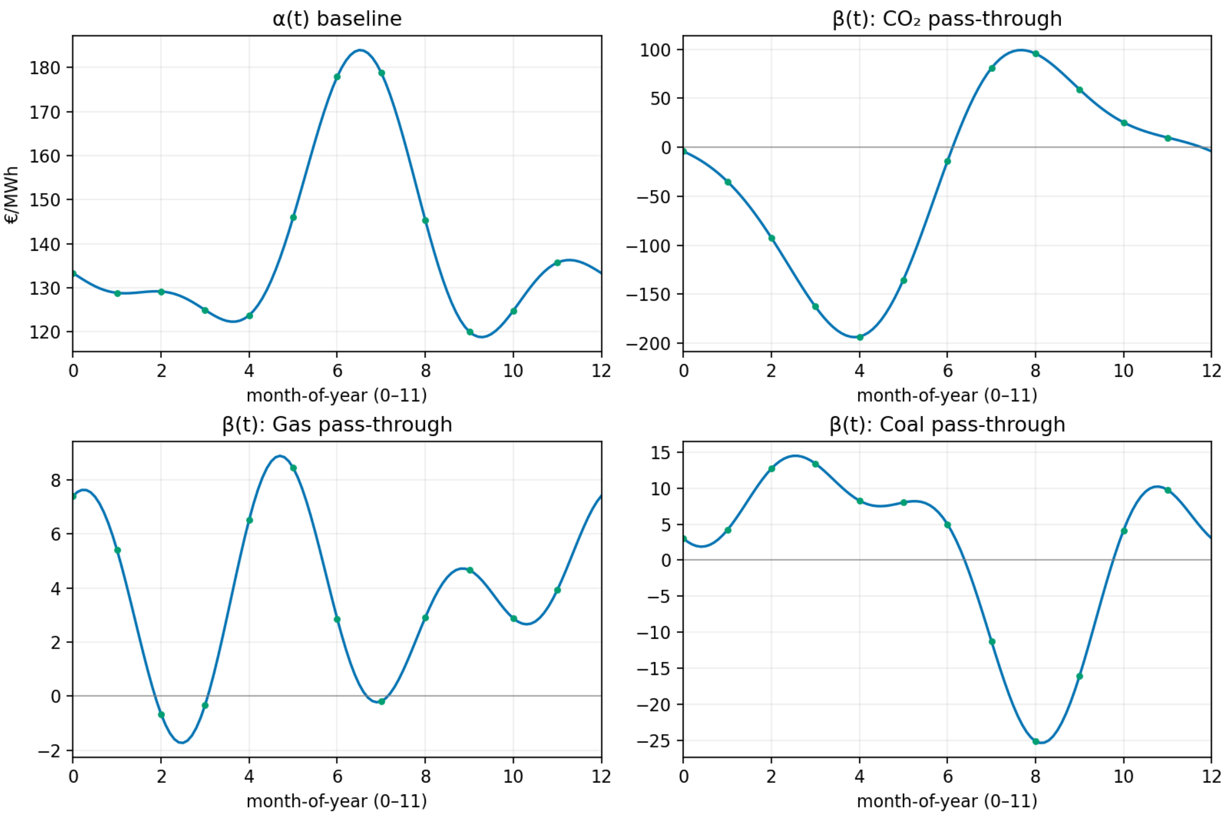
*Example: $\beta*{\text{Gas}}(18)\approx 1.25$. If gas rises by €1/MWh at 18:00, the day-ahead power price at 18:00 rises by ≈€1.25/MWh (ceteris paribus). Around 06:00 it is ≈0.7; around 23:00 ≈0.5. Gas matters **more** in the evening peak. - $\beta*{\text{CO2}}(u)$ is the* ***carbon pass-through*** *by hour.*

Example: around 20:00 it peaks near ≈1.6; before dawn it is closer to ≈1.0. A higher carbon price lifts peak-hour power more, which is consistent with carbon-intensive units setting the

*margin in peak. - $\beta*{\text{Coal}}(u)$ is the **coal pass-through** by hour.
It is small for most hours (near zero), slightly positive in late afternoon (~0.2), and near zero or slightly negative late evening. Coal is a **second-order** driver in this sample for intraday moves.

What positive/negative/zero mean at hour u: - **Positive** $\beta*j(u)>0$: an increase in driver j raises the day-ahead price* ***at the same hour****.*
*- **Negative** $\beta*j(u)<0$: an increase in driver j lowers the price at that hour (can happen if another correlated factor dominates).
- **Zero** $\beta_j(u)\approx 0$: the driver has **no material linear effect** at that hour after controlling for the others.

Figure B — Month-of-year coefficient curves



How to read the curves (simple): - $\alpha(u)$ is the **baseline seasonal level**. It peaks in summer in this sample and is lower in early autumn. - $\beta*{\text{CO2}}(u)$ changes* ***sign*** *across months.*
*Interpretation: when the curve is **positive**, higher EUA prices (Euro/ ton CO2) push up power more strongly that month; when **negative**, the month-level regression attributes an opposite association.*
*- $\beta*{\text{Gas}}(u)$ varies by season.
It is larger in parts of winter and late spring, smaller around midsummer. This matches higher

gas dependence in colder months and transitional periods. - $\beta_{\text{Coal}}(u)$ is modest and smoother.

Coal contributes less than gas/carbon in most months.

Strategy

Peak-hour pass-through.
The hour curves show the strongest pass-through in the evening (about 18–20).
Before the **day-ahead** auction, if gas or CO_2 are **up**, buy the evening hours. If they are **down**, sell the evening hours.
Size the expectation with the hour betas:
$$\widehat{\Delta \text{Power}}(u)=\beta_{\text{Gas}}(u)\,\Delta \text{Gas}+\beta_{\text{CO2}}(u)\,\Delta \text{CO2}.$$

Trade only when the expected move is clearly bigger than costs involved with the buy.

Note: The way the electricit market for those things works is quiet new to me so my strategy, although I hope it's correct, it might be a bit too simple.

Short answer (what was quantified)

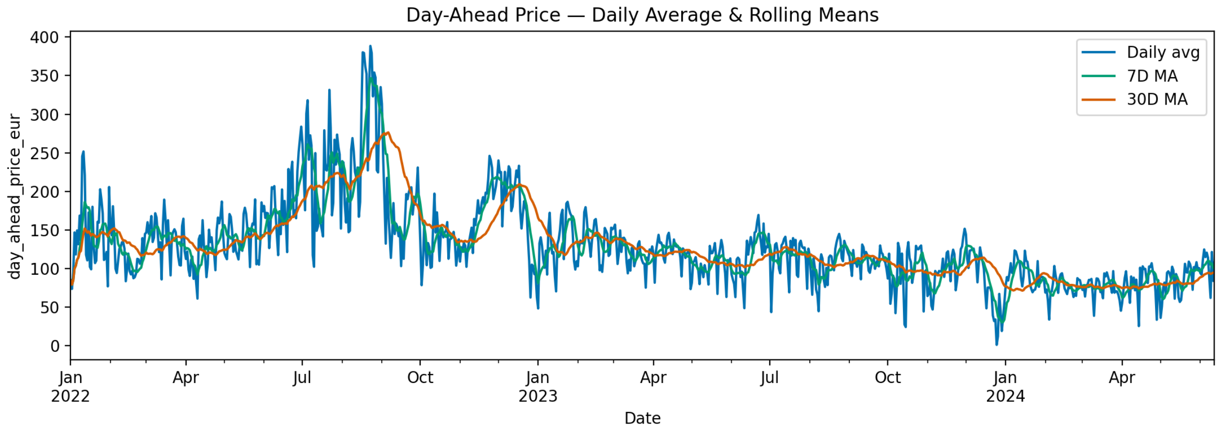
- Hour curves show **strong** gas and CO_2 pass-through in **peak hours**; coal is **small**.
- Month curves show **seasonal** pass-through, including sign changes for CO_2 at the month level.
- These shapes give **hour-specific** and **month-specific** hedge ratios and trade filters that standard OLS cannot provide cleanly.

Task 2 — Price Evolution, Trends, Seasonality

> **Question:**
> Visualize the evolution of day-ahead power prices over time. Quantify the most obvious trends and provide possible explanations, e.g., seasonality, geopolitical factors etc. If possible, derive some non-trivial observations, that could inform traders better.

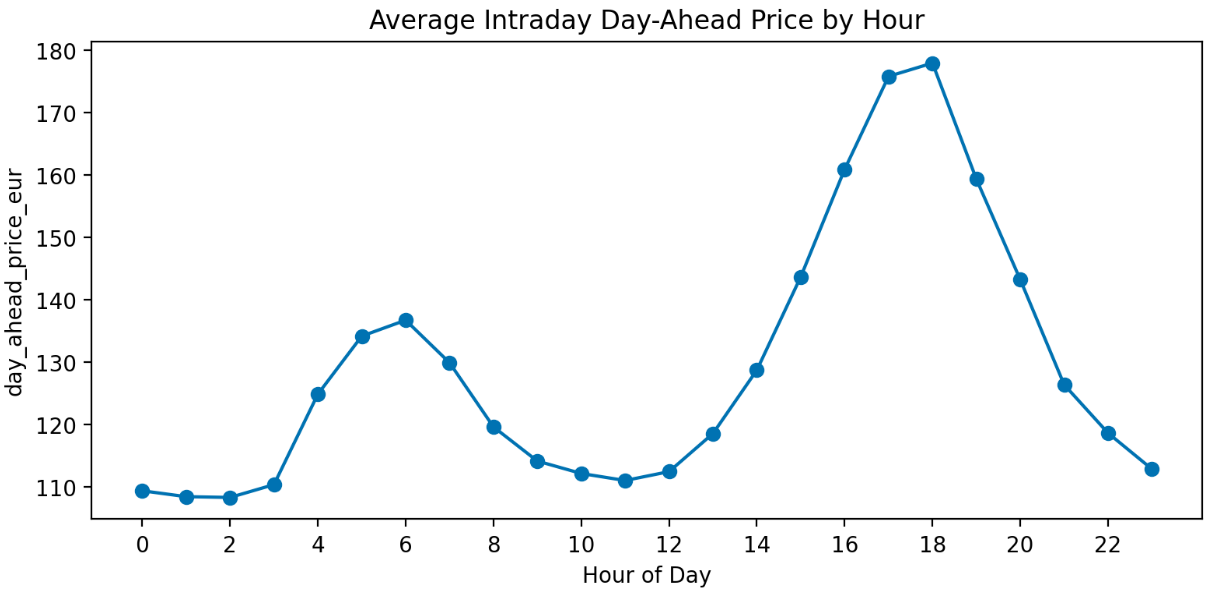
Plots

Daily averages with rolling means



What it shows.
Prices are high and volatile during 2022. They fall and stabilize through 2023–2024. The 7-day and 30-day lines make the regimes clear.
Why: This peaks shows the clear affect of the Russo-Ukrainian War had on electricity prices. Later in the analysis we discuver a downwards trend, showcasing that the market is still recovering from that spice.

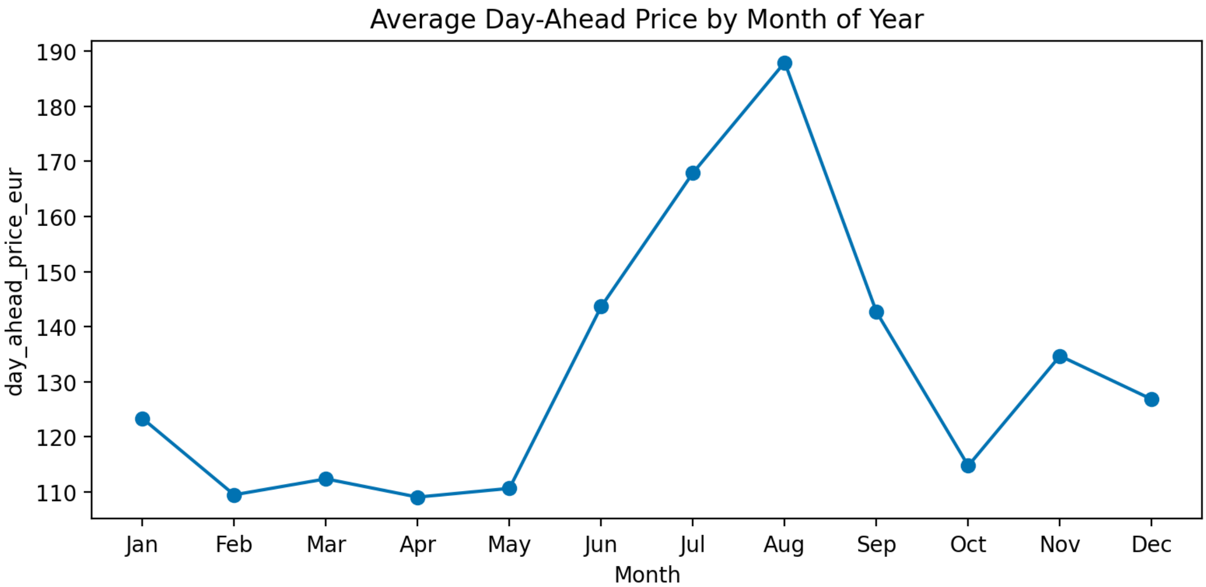
Intraday average by hour (0–23)



What it shows.
A night trough (≈01–04). A morning shoulder (≈05–07). A strong evening peak (≈18–20).
Why:

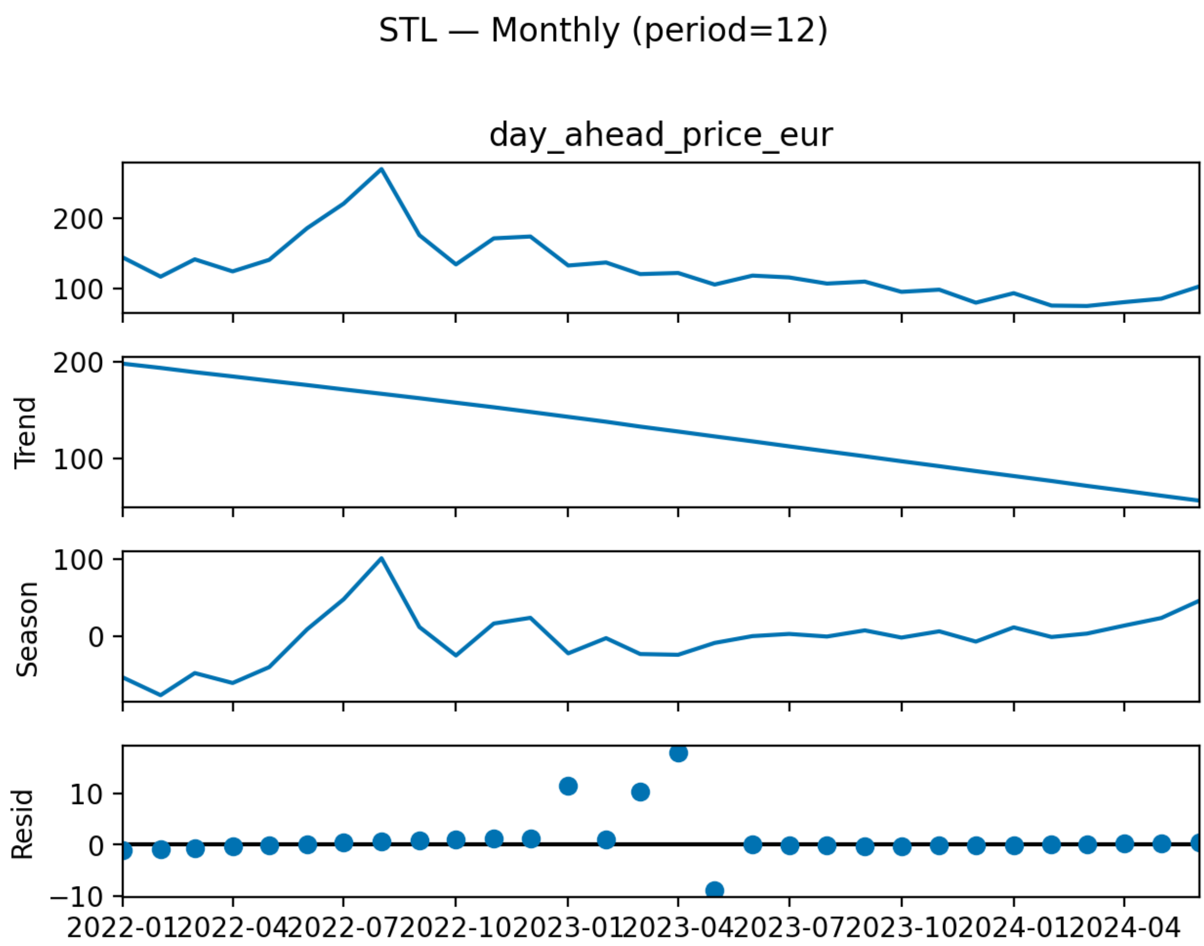
- **Demand shape.** Usage is low at night, rises in the morning, and peaks in the evening. Solar fades after sunset.
- **Marginal unit.** The last plant needed to meet demand sets the price. At night, cheaper units set it ⇒ lower prices and small pass-through. In the evening, gas often sets it ⇒ higher prices and larger $\beta{\text{Gas}}(u)$ and $\beta{\text{CO2}}(u)$.

Month-of-year averages



What it shows.
A seasonal cycle. Higher levels in summer in this sample. Lower levels in early autumn.
Why: temperature, renewables, and hydro/wind vary by season.

STL decomposition (monthly seasonality)



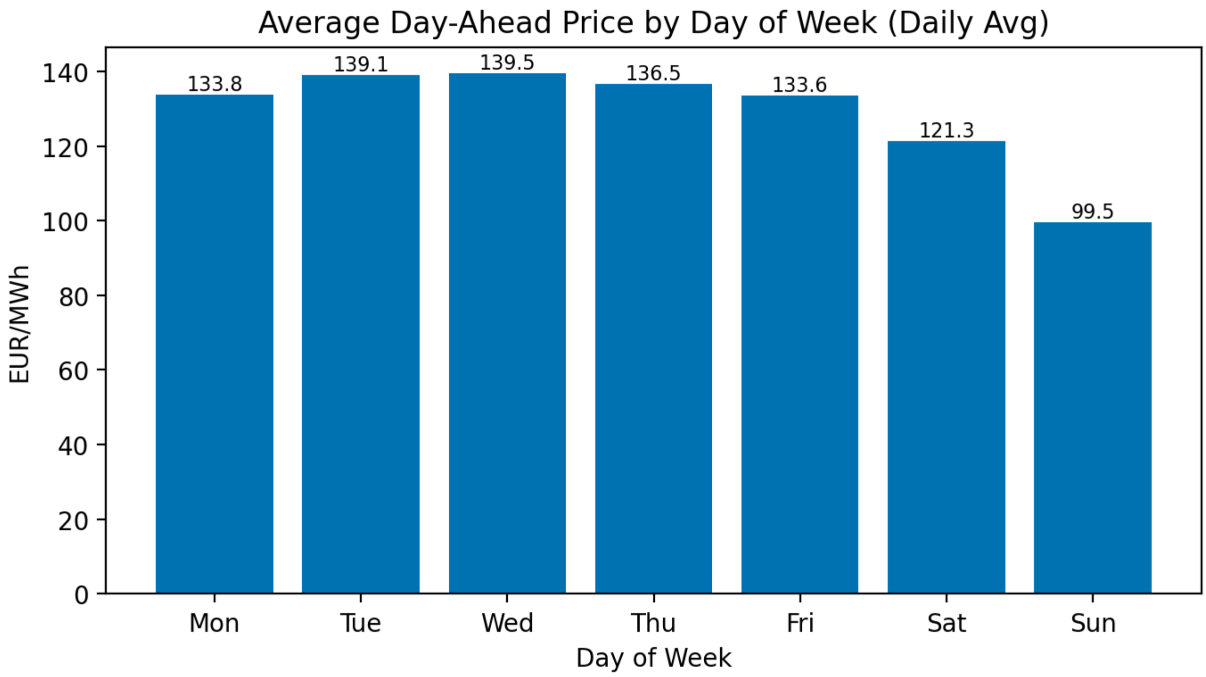
What it shows.
- **Top panel:** monthly averages of day-ahead prices.
- **Trend:** a smooth decline from 2022 into 2024.
- **Season:** a clear annual cycle; stronger in 2022, more modest later.
- **Resid:** short bursts that trend/season do not explain (notably early 2023).

Quantification (short)

- **Regimes:** rolling means and the STL trend both show the 2022 → 2024 shift (high → lower/stable).
- **Seasonality:** the **annual** cycle is visible and persistent.
- **Intraday:** the evening peak (≈18–20) remains the highest window in the intraday profile.

Non-trivial observations

- **Evening peak dominance.** Fuel and scarcity shocks bite most in the evening hours.
- **Weekend discount.** Weekends price is lower than weekdays (see `plot_dow_daily_avg.png`) due to possibly weaker industrial demand.



Files referenced

- `task2/plot_daily_avg_with_rollings.png`
- `task2/plot_intraday_by_hour.png`
- `task2/plot_month_of_year_avg.png`
- `task2/stl_monthly_period12.png`

Task 3 — Load Profiles and an Industrial Proxy

> **Question:**
> Develop a detailed analysis of the Polish electricity load profile by identifying distinct patterns and how they have changed throughout time. Visualize the typical weekday and weekend load profile. Moreover, given the aggregate hourly load data, isolate the power load profile of the Polish industrial sector.

What was done (short)

- The hourly load series from `clean_data.csv` is split into **weekdays** and **weekends**.
- Typical profiles are shown with medians and IQR (25–75%).
- **Load velocity** is computed as the hour-to-hour change and plotted for weekdays and weekends.

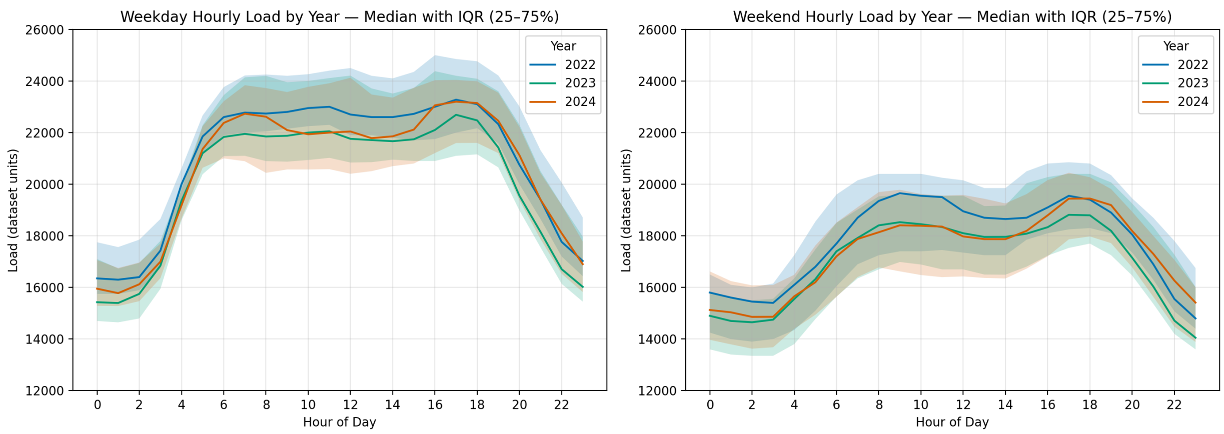
- An **industrial proxy** is built as weekday load **above** a weekend baseline at the same month and hour.

Industrial method (concise math).
Weekend baseline by month and hour:
$B{m,h}=\operatorname{median}{\text{Load}}t:\ t\ \text{is weekend},\ \text{month}(t)=m,\ \text{hour}(t)=h}.$

Weekday “excess” at time t (month m, hour h):
$Et=\text{Load}t - B_{m,h}$

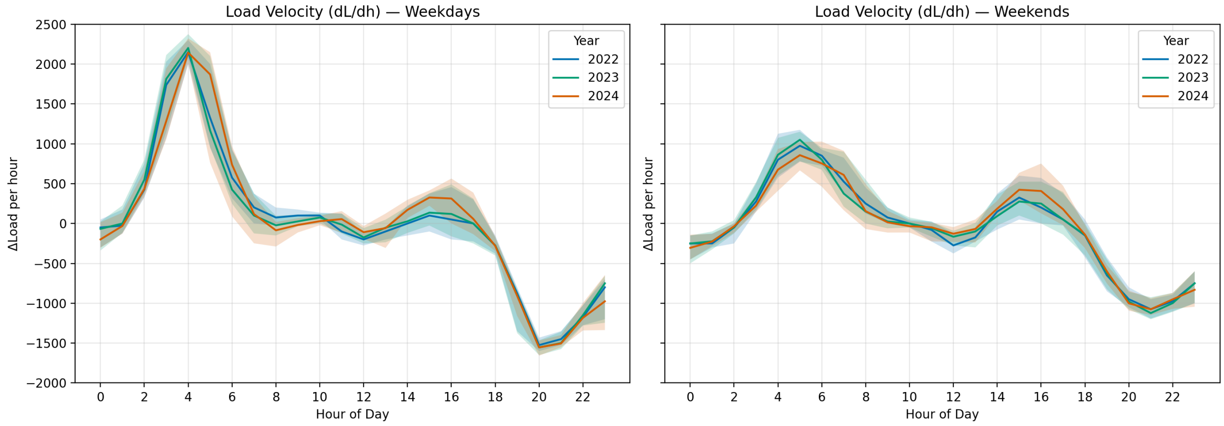
Plots

Weekday vs Weekend profiles by year



What it shows.
Weekdays sit **above** weekends and have a stronger **morning ramp** and **evening plateau**. Weekends are **lower** and **flatter**. The shaded IQR shows that profiles shift across years very little.

Load velocity (Δ per hour) — weekdays vs weekends

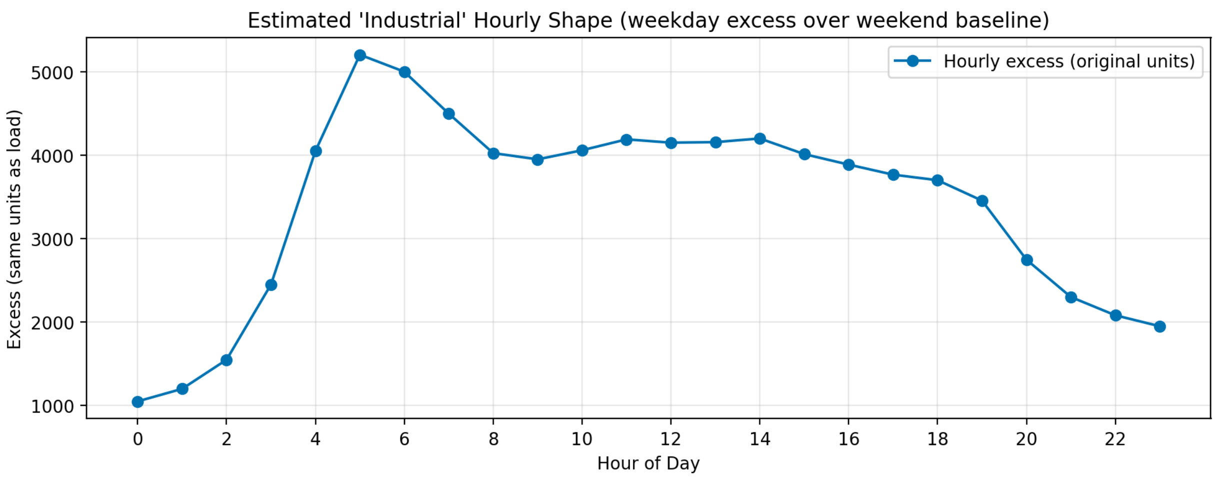


How it is computed.
Velocity is the hour-to-hour change: $\Delta L_t = L_t - L_{t-1}.$
For each hour of day, the medians (and IQR) of ΔL_t are taken by **year** and **weekday/weekend**.

What it shows.
- **Weekdays:** a sharp positive spike around **05–06** (morning ramp), near-zero around **midday**, and a large **negative** spike around **19–20** (evening drop).
- **Weekends:** the same pattern but **smaller** ramps.
- Year lines show that ramp **sizes** shift across **2022–2024**.

Why it helps.
Level plots show *how high* load is. Velocity shows *how fast* it moves.
This adds information on **ramping risk**, **flexibility needs**, and when the system is most sensitive to shocks.

"Industrial" hourly shape (weekday excess over weekend baseline)

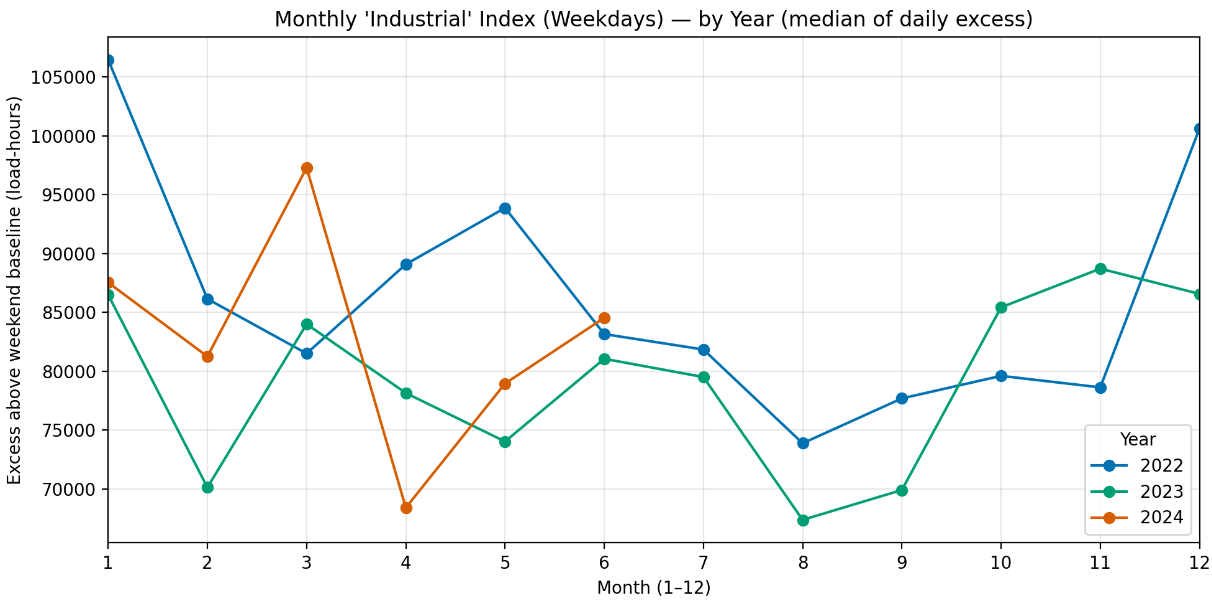


What it shows.
Excess load is near **zero at night** and concentrated in **working hours**.

This gives a simple, transparent **industrial profile** from aggregate data.

Limitations and a cleaner option.
This proxy is **crude**. It assumes weekends are "non-industrial" baselines.
A more precise approach would use **"hard holidays"** (e.g., **1 Jan**, **Christmas**, **Easter Sunday**, **Labour Day**).
On those days almost everything is closed, so what remains should be the **24/7 industrial** load plus a small set of other always-on uses.
That holiday baseline could replace (or calibrate) the weekend baseline.
This refinement was **not implemented due to time**.

Monthly "industrial" index by year (median of daily excess)



What it shows.
The index varies by **season** and **year**. It highlights months when industrial demand stands **well above** the weekend baseline.

Takeaways

- Weekdays are **higher and more peaked**; weekends are **lower and flatter**.
- **Velocity** reveals **when** ramps occur and how **large** they are (stronger on weekdays).
- The **industrial proxy** isolates working-hour excess; a **holiday-based** baseline would make it cleaner.

Files referenced (task folder)

- `task3/hourly_load_by_year_wd_we.png`
- `task3/load_velocity_wd_we.png`
- `task3/industrial_hourly_shape.png`
- `task3/industrial_index_monthly_by_year.png`
- (Tables: `weekday_daily_excess_matrix.csv`, `industrial_index_daily.csv`, `industrial_index_monthly_median.csv`)

Task 4 — Scenario Week & Price Prediction

> **Question:**
> Build a simple forecasting setup. Apply scenario tweaks to the drivers and forecast day-ahead prices for a target week. Explain the setup and show the results.

Window and scenarios

- **Target week:** 2024-06-13 → 2024-06-19 (UTC).
- **Base for scenarios:** the **previous week** shifted forward by 7 days.
- **Tweaks applied to the base week:** 1) **Solar +10%** (`solar *= 1.10`).
  2) **Wind +210 MW** from 2024-06-13 onward (flat add to `wind`).
  Note: 210 ≈ 300 MW × 70% utilization.
  3) **Cold surge at night:** add **+15% total** load across hours **00–06** each night.

Explanatory variables and rationale

The model uses a **small, engineered set** to avoid multicollinearity (see Task 1 discussion):

- **`net_load`** = total load minus wind/solar.
  Why: proxies the demand that must be met by thermal/expensive units. Reduces overlap with renewables.
- **`renewable_share`** = renewable generation / total generation.
  Why: A share is scale-free and less collinear with level variables.
- **`conventional_gen`** = aggregated thermal output.
  Why: availability/commitment of thermal fleet without splitting into many highly correlated series.
- **`ngas_price_eur_mwh`**, **`coal_price_eur_ton`**, **`co2_price_eur_ton`**.
  Why: core exogenous drivers of marginal cost (fuel and carbon).
- **`interconnection_share`** = net imports / load.

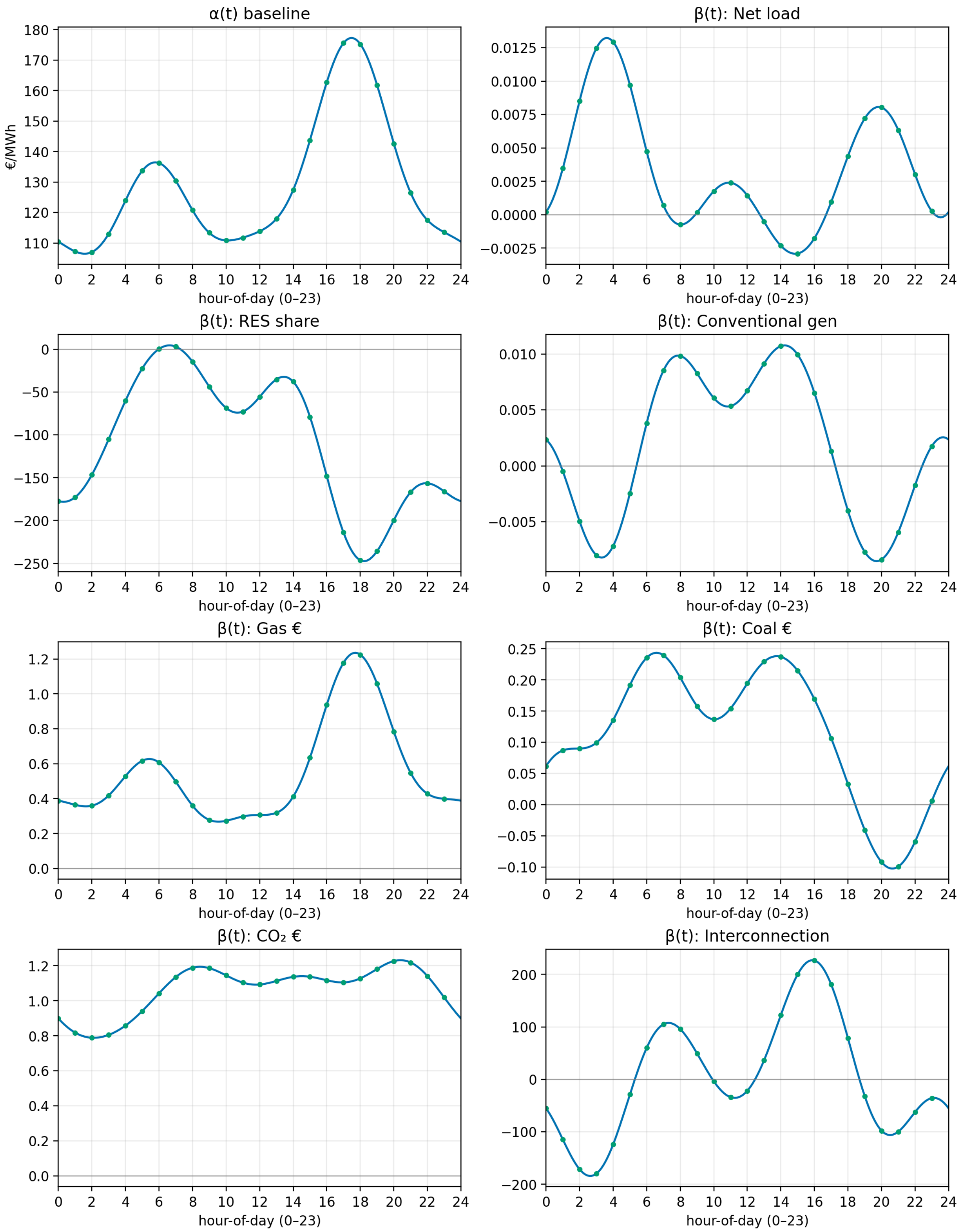
Why: scarcity relief or stress from cross-border flows, normalized by system size.

Why not "use everything"?
Many raw columns move **together** (load, conventional gen, imports/exports, wind, solar, etc.).
Feeding all of them into least squares makes the **betas unstable** and hard to read; tiny data changes flip signs.
Using **shares**, **net** quantities, and **aggregates** keeps the model **parsimonious** and the hour-by-hour coefficient curves **interpretable**.

Model

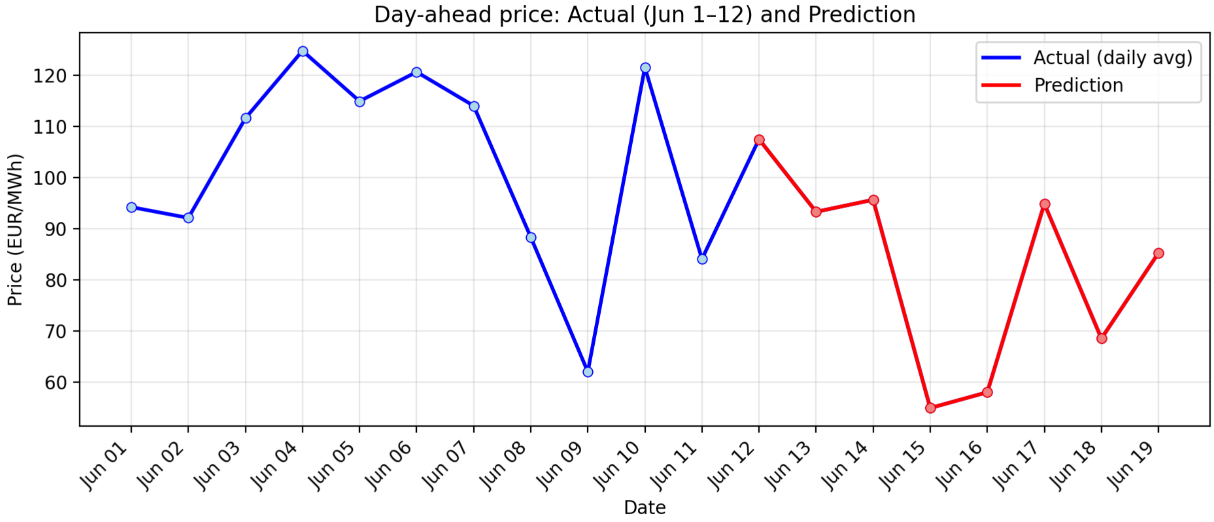
A **concurrent functional linear** model is fitted on **hour-of-day** curves.
For hour $t\in\{0,\dots,23\}$:
$P(t)=\alpha(t)+\sum_j \beta_j(t)\,X_j(t)+\varepsilon(t).$ - Rows are **days**; columns are **hours**.
- Predictors are **centered by hour**.
- Curves are smoothed with a **Fourier basis** (K=9).
- Train on **all data** except the target week.
- Predict the target week using the **scenario** drivers.

Coefficient shapes (hour-of-day)



Reading: $\alpha(t)$ is the baseline profile. $\beta_j(t)$ are hour-specific pass-throughs for the engineered drivers. Larger $\beta_j(t)$ ⇒ stronger effect **at that hour**.

Result — actual vs prediction (daily averages)



What it shows.
- **Blue line:** realized daily averages **before** the scenario week (2024-06-01 → 2024-06-12).
- **Red line: predicted** daily averages **for** 2024-06-13 → 2024-06-19 under the scenario.
- The vertical split marks the move from actuals to predictions.

Prediction table (daily averages)

Values from `task4/predictions_daily.csv` for the scenario week.

Metric	Thu 13 Jun	Fri 14 Jun	Sat 15 Jun	Sun 16 Jun	Mon 17 Jun	Tue 18 Jun	Wed 19 Jun
Predicted day-ahead avg (€/MWh)	93.25	95.60	54.88	57.96	94.83	68.47	85.20

Files referenced

- Tables: `task4/train_set.csv` , `task4/test_set.csv` , `task4/predictions_daily.csv` , `task4/model_basis_weights.csv` , `task4/combined_actual_and_prediction.csv` , `task4/actual_daily.csv`
- Plots: `task4/coefficients_alpha_beta.png` , `task4/actual_vs_prediction.png`

Notes and limits

- Effects are **concurrent** (no lag/lead). Cross-hour dynamics are not modeled.
- The night **+15%** load uplift is a **distributed** uplift (00–06). A fuller approach could build **seven** scenario datasets (each night chosen in turn), score each, and **average** the results to reflect timing uncertainty.
- A **single** model is shown here for clarity. For production, an **ensemble** with weights tuned by cross-validation would be more robust.