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.

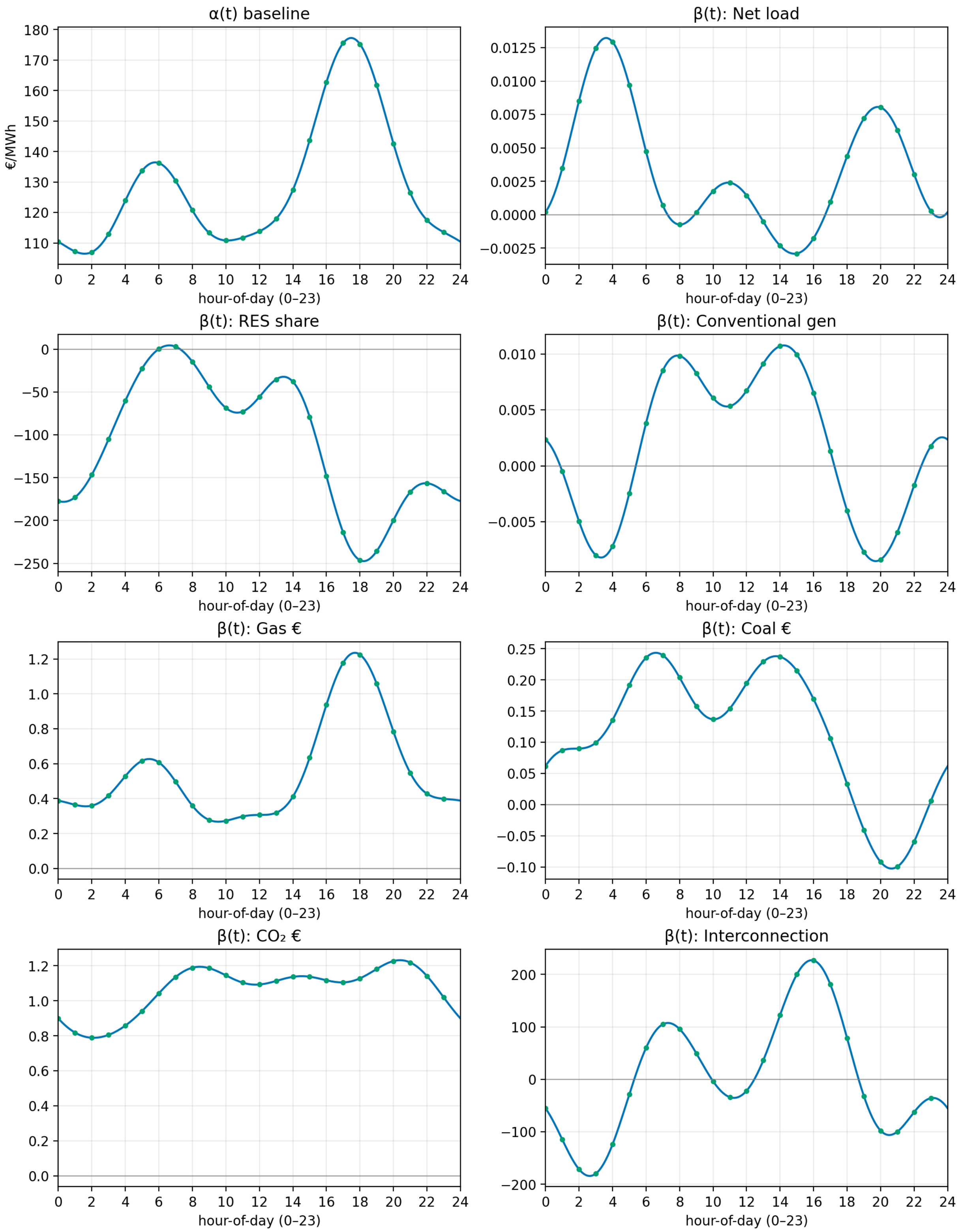
Why not “use everything”?
Many raw columns move **together** (load, conventional gen, imports/exports, wind, solar, etc.).

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

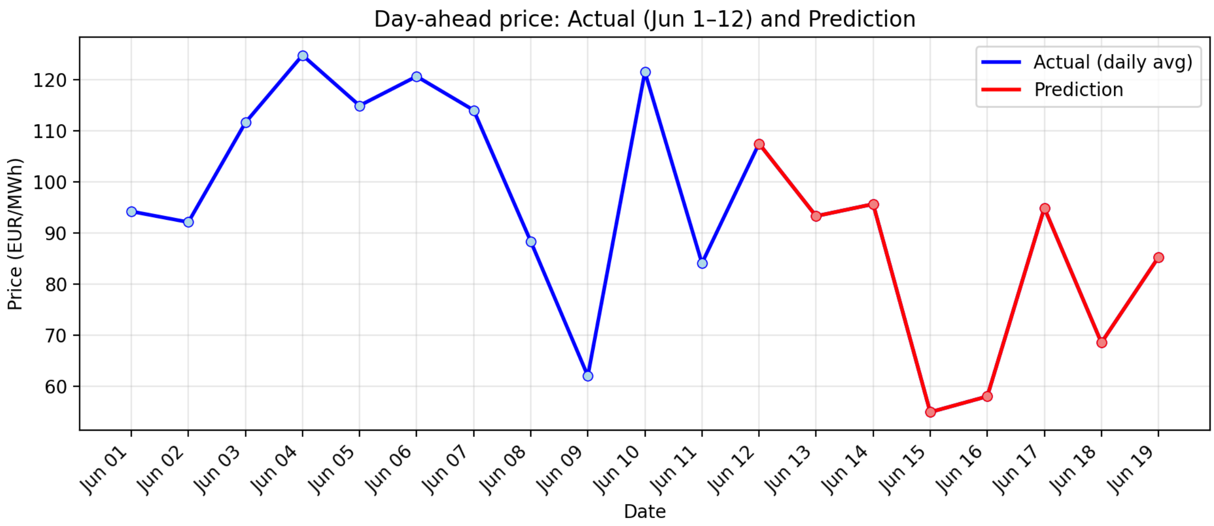
A **concurrent functional linear** model is fitted on **hour-of-day** curves.
For hour $t\in\{0,\dots,23\}$:
$P(t)=\alpha(t)+\sum_j \beta_j(t)\,X_j(t)+\varepsilon(t).$ - Rows are **days**; columns are **hours**.
- Predictors are **centered by hour**.
- Curves are smoothed with a **Fourier basis** (K=9).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