House of Energy Markets & Finance

UNIVERSITÄT DUISBURG ESSEN
Open-Minded

Spatial Weather, Socio-Economic and Political Risks in Mid-Term Forecasting of Hourly Electricity Load

Monika Zimmermann[1], Florian Ziel

Chair of Data Science in Energy and Environment
University of Duisburg-Essen Germany

EFC25 - Wrocław, Poland
December 11th, 2025

[1] Monika.Zimmermann@uni-due.de

Hourly Load Forecasts: Who Relies on It and Why

Electricity is difficult to store:

- ⇒ delivered through an interconnected European grid
- requires constant balance between supply and demand for stability
- achieved by adjusting supply to fine-resolution anticipated demand through domestic power plant production, storage utilization, and imports or exports

power plant, **storage**, **grid** and **financial operators** need **hourly** load forecasts

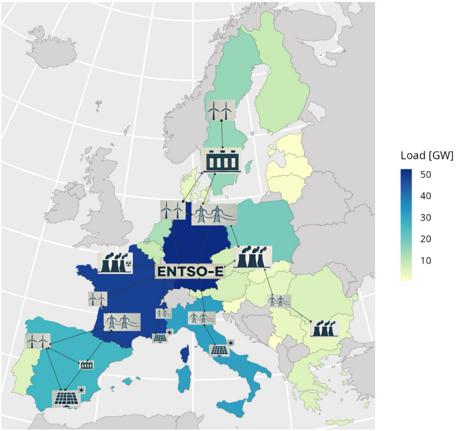
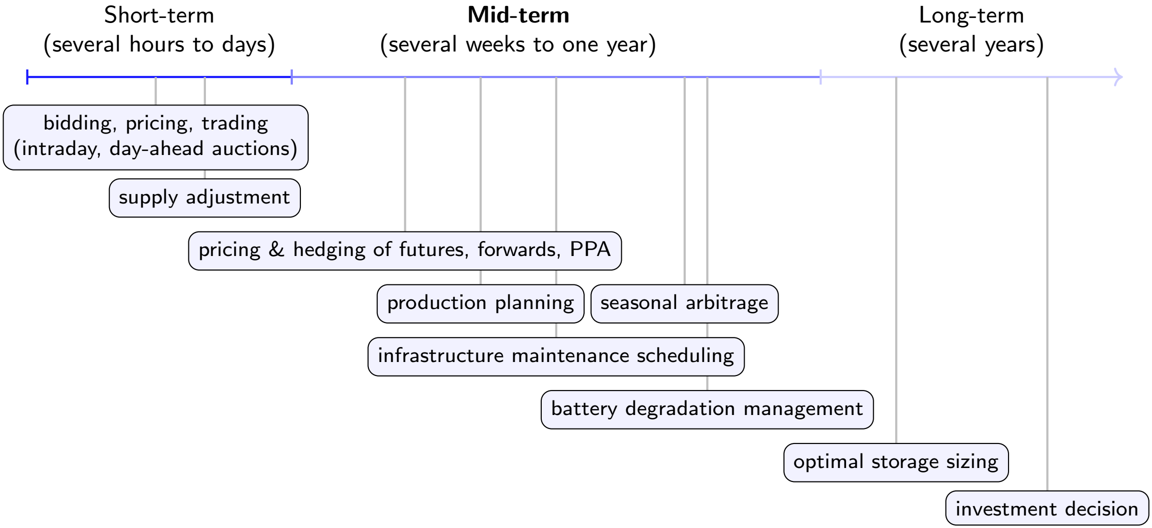


Figure 1: Schematic illustration of the ENTSO-E power grid with average load (2023) across 24 participating European countries.

Hourly Mid-Term Load Forecasts:

A **Research Gap** [4, 1] Crucial for Practitioners



Probabilistic and Multivariate Hourly Mid-Term Load Forecasts:

Accounting for Cross-Country Uncertainties in Load Characteristics

Characteristic	**Load Effect**	**Spatial Level**	**Type of Uncertainty**
Calendar	Daily, weekly, yearly, and holiday patterns due to calendar-based human behavior	National	Deterministic
Meteorological	*Temperature*, climate conditions, humidity, wind speed, cloud cover affecting electric heating, cooling, and lighting	**National**-(Transnational)	**Stochastic** (multiple seasonalities)
Socio-Economic & Political	E.g. Economic growth, population size, fossil fuel prices, political incentives for decarbonization impacting mid- to long-term load levels	(National)-**Transnational**	**Stochastic** (non-stationary with **unit root**)
Autoregressive	Remaining short to mid-term load deviations	**National**-(Transnational)	Stochastic

Table 1: Various facets, see [3], explaining load categorized in terms of spatial level and uncertainty type.

Probabilistic and Multivariate Hourly Mid-Term Load Forecasts:

Accounting for Cross-Country Uncertainties in Load Characteristics

Characteristic	**Load Effect**	**Spatial Level**	**Type of Uncertainty**
Calendar	Daily, weekly, yearly, and holiday patterns due to calendar-based human behavior	National	Deterministic
Meteorological	*Temperature*, climate conditions, humidity, wind speed, cloud cover affecting electric heating, cooling, and lighting	**National**-(Transnational)	**Stochastic** (multiple seasonalities)
Socio-Economic & Political	E.g. Economic growth, population size, fossil fuel prices, political incentives for decarbonization impacting mid- to long-term load levels	(National)-**Transnational**	**Stochastic** (non-stationary with **unit root**)
Autoregressive	Remaining short to mid-term load deviations	**National**-(Transnational)	Stochastic

Table 1: Various facets, see [3], explaining load categorized in terms of spatial level and uncertainty type.

cross-country uncertainties in mid-term load ⇒ **probabilistic** and **multivariate** forecasting across Europe

Starting Point: A **Country-Specific Point Forecasting** Model

Generalized Additive Model (GAM) Specification [2, 5]

$$\text{Load}_t = o + \underbrace{\mu(\boldsymbol{X}_t)}_{\text{smooth effects in covariates}} + \underbrace{\mathcal{E}_t}_{\text{short-term autoregressive effects}}, \quad o \in \mathbb{R},$$

$$\mathcal{E}_t = \phi_1 \mathcal{E}_{t-1} + \ldots + \phi_p \mathcal{E}_{t-p} + \epsilon_t^{\mathrm{AR}},$$

Starting Point: A **Country-Specific Point Forecasting** Model

Generalized Additive Model (GAM) Specification [2, 5]

$$\text{Load}_t = o + \underbrace{\mu(\boldsymbol{X}_t)}_{\text{smooth effects in covariates}} + \underbrace{\mathcal{E}_t}_{\text{short-term autoregressive effects}}, \quad o \in \mathbb{R},$$

$$\mathcal{E}_t = \phi_1 \mathcal{E}_{t-1} + \ldots + \phi_p \mathcal{E}_{t-p} + \epsilon_t^{\mathrm{AR}},$$

$$\mu(\boldsymbol{X}_t) = \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{calendar effects}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{meteorological effects}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{socio-econ. \& political effects}}$$

Starting Point: A **Country-Specific Point Forecasting** Model

Generalized Additive Model (GAM) Specification [2, 5]

$$\text{Load}_t = o + \underbrace{\mu(\boldsymbol{X}_t)}_{\text{smooth effects in covariates}} + \underbrace{\mathcal{E}_t}_{\text{short-term autoregressive effects}}, \quad o \in \mathbb{R},$$

$$\mathcal{E}_t = \phi_1 \mathcal{E}_{t-1} + \ldots + \phi_p \mathcal{E}_{t-p} + \epsilon_t^{\text{AR}},$$

$$\mu(\boldsymbol{X}_t) = \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{calendar effects}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{meteorological effects}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{socio-econ. \& political effects}}$$

- Calendar variables $X_{t+h}^{Calendar}$ are known

Starting Point: A **Country-Specific Point Forecasting** Model

Generalized Additive Model (GAM) Specification [2, 5]

$$\text{Load}_t = o + \underbrace{\mu(\boldsymbol{X}_t)}_{\text{smooth effects in covariates}} + \underbrace{\mathcal{E}_t}_{\text{short-term autoregressive effects}}, \quad o \in \mathbb{R},$$

$$\mathcal{E}_t = \phi_1 \mathcal{E}_{t-1} + \ldots + \phi_p \mathcal{E}_{t-p} + \epsilon_t^{\mathrm{AR}},$$

$$\mu(\boldsymbol{X}_t) = \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{calendar effects}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{meteorological effects}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{socio-econ. \& political effects}}$$

- Calendar variables $X_{t+h}^{Calendar}$ are known
- Stochastic variables X_{t+h}^{Temp}, $X_{t+h}^{SocEconPol}$, $\mathcal{E}_{t+h}$ need to be forecasted

Starting Point: A **Country-Specific Point Forecasting** Model

Generalized Additive Model (GAM) Specification [2, 5]

$$\text{Load}_t = o + \underbrace{\mu(\boldsymbol{X}_t)}_{\text{smooth effects in covariates}} + \underbrace{\mathcal{E}_t}_{\text{short-term autoregressive effects}}, \quad o \in \mathbb{R},$$

$$\mathcal{E}_t = \phi_1 \mathcal{E}_{t-1} + \ldots + \phi_p \mathcal{E}_{t-p} + \epsilon_t^{\text{AR}},$$

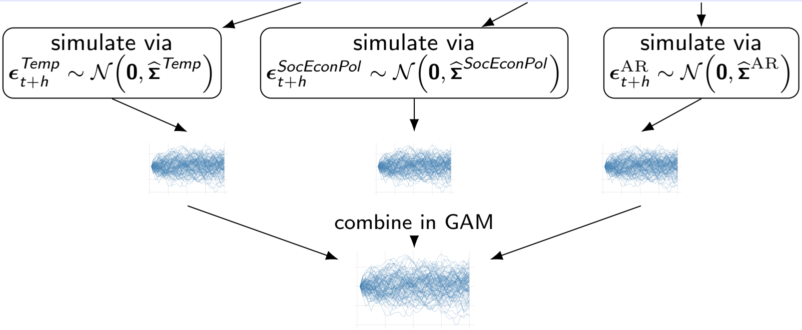
$$\mu(\boldsymbol{X}_t) = \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{calendar effects}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{meteorological effects}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{socio-econ. \& political effects}}$$

- Calendar variables $X_{t+h}^{Calendar}$ are known
- Stochastic variables X_{t+h}^{Temp}, $X_{t+h}^{SocEconPol}$, $\mathcal{E}_{t+h}$ need to be forecasted
- Separately estimated models

$\Rightarrow$ error processes $\boldsymbol{\epsilon}^{Temp}, \boldsymbol{\epsilon}^{SocEconPol}, \boldsymbol{\epsilon}^{\text{AR}}$ are treated as independent

From Country-Specific Point to and **Probabilistic Forecasts**

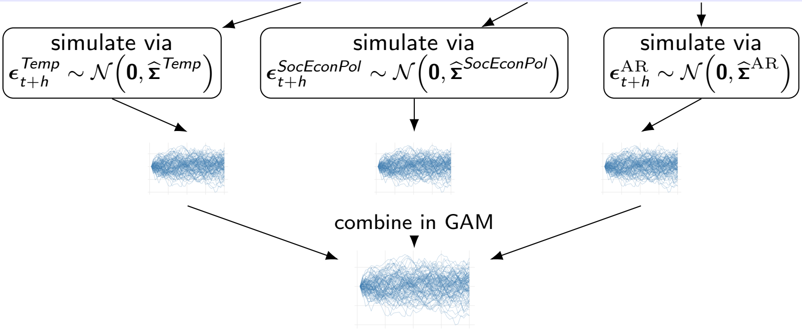
$$\text{Load}_t = o + \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{deterministic}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{stochastic}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{stochastic}} + \underbrace{\mathcal{E}_t}_{\text{stochastic}}$$



$\Rightarrow$ For each stochastic component, simulate trajectories via the model mean and error

From Country-Specific Point to and **Probabilistic Forecasts**

$$\text{Load}_t = o + \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{deterministic}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{stochastic}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{stochastic}} + \underbrace{\mathcal{E}_t}_{\text{stochastic}}$$

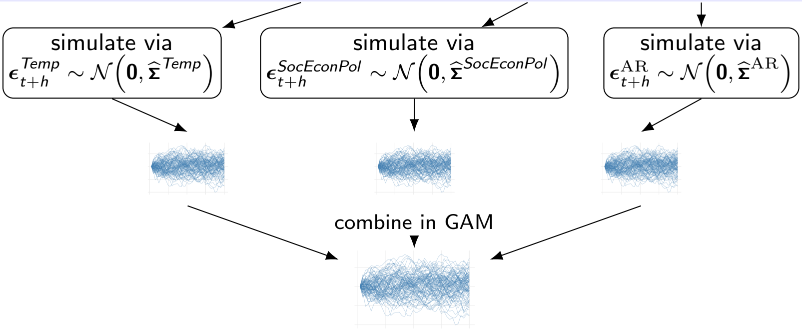


$\Rightarrow$ For each stochastic component, simulate trajectories via the model mean and error

$\Rightarrow$ Capture **transnational dependence** by sampling **multivariate** $\epsilon_t \sim \mathcal{N}(\mathbf{0}, \widehat{\boldsymbol{\Sigma}})$

From Country-Specific Point to and **Probabilistic Forecasts**

$$\text{Load}_t = o + \underbrace{\mu^{Calendar}\left(X_t^{Calendar}\right)}_{\text{deterministic}} + \underbrace{\mu^{Temp}\left(X_t^{Temp}\right)}_{\text{stochastic}} + \underbrace{\mu^{SocEconPol}\left(X_t^{SocEconPol}\right)}_{\text{stochastic}} + \underbrace{\mathcal{E}_t}_{\text{stochastic}}$$



- $\Rightarrow$ For each stochastic component, simulate trajectories via the model mean and error
- $\Rightarrow$ Capture **transnational dependence** by sampling **multivariate** $\epsilon_t \sim \mathcal{N}(\mathbf{0}, \widehat{\boldsymbol{\Sigma}})$
- $\Rightarrow$ Ensemble these trajectories within the country-specific GAMs
- $\Rightarrow$ **probabilistic load forecasts**

Modelling of X^{Temp}: **Smoothing ▶ GAM ▶ AR**

Thermal inertia and delayed human reactivity

∇

Exponentially smoothed temperatures

$$\widetilde{X}_t^{\text{Temp}} = \alpha X_{t-1}^{\text{Temp}} + \alpha(1-\alpha) X_{t-2}^{\text{Temp}} + \cdots + \alpha(1-\alpha)^{t-2} X_1^{\text{Temp}}$$

where $\alpha^{-1} = 6,24$ governs the memory on past temperatures

Modelling of X^{Temp}: Smoothing ▶ GAM ▶ AR

Thermal inertia and delayed human reactivity

∇

Exponentially smoothed temperatures

$$\widetilde{X}_t^{\text{Temp}} = \alpha X_{t-1}^{\text{Temp}} + \alpha(1-\alpha) X_{t-2}^{\text{Temp}} + \cdots + \alpha(1-\alpha)^{t-2} X_1^{\text{Temp}}$$

where $\alpha^{-1} = 6,24$ governs the memory on past temperatures

To capture **extreme meteorological events**

∇

Extend in-sample data for **GAM** estimation to **20 years**, include monotonous smooth trend for **climate change effects**

$$\widetilde{X}_t^{\text{i, Temp}} = o^{\text{i, Temp}} + \mu^{\text{i, Season}}(X_t^{\text{Season}}) + \mu^{\text{i, Trend}}(X_t^{\text{Trend}}) + \varepsilon_t^{\text{i,Temp}}$$

$$\varepsilon_t^{\text{i,Temp}} = \sum_{k \in \mathcal{S}} \phi_k \varepsilon_{t-k}^{i,\text{Temp}} + \epsilon_t^i, \quad \text{for i} = 1, \ldots, \text{n countries}$$

$$\epsilon_{t+h}^{i,(m)} \sim \mathcal{N}\left(\mathbf{0}, \widehat{\mathbf{\Sigma}}^{Temp}\right), \quad \text{for hours h and simulation m}$$

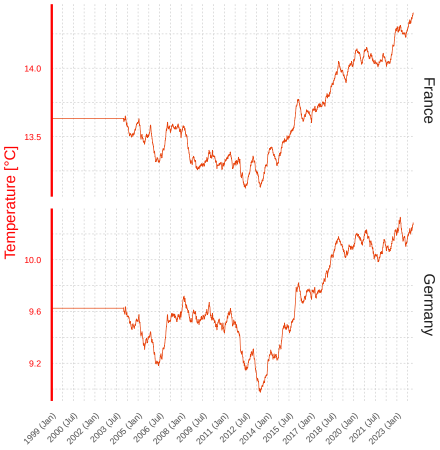


Figure 2: Five-year moving average temperature 1999–2024.

Modelling of $X^{SocEconPol}$: **Retrieved Endogenously**

- **Hourly mid-term forecasts** for **external** economic and policy indicators are **scarce**
  $\Rightarrow$ retrieve *SocEconPol* **trend from load data**

Modelling of $X^{SocEconPol}$: **Retrieved Endogenously**

- **Hourly mid-term forecasts** for **external** economic and policy indicators are **scarce**
  $\Rightarrow$ retrieve *SocEconPol* **trend from load data**
- Temperature, holidays and policy shocks act on **similar time scales**
  $\Rightarrow$ **simple detrending** of Load_t would **mix effects** (see figure)

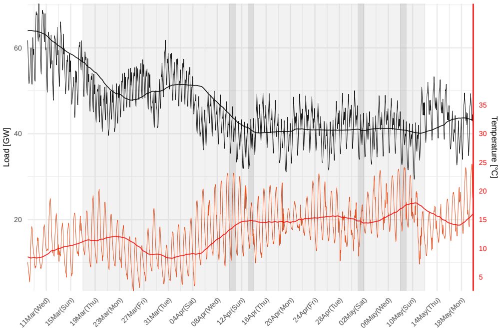


Figure 3: Hourly Load (black) and temperature (red) with their weekly moving average during first COVID-19 lockdown in France.

Modelling of $X^{SocEconPol}$: **Retrieved Endogenously**

- **Hourly mid-term forecasts** for **external** economic and policy indicators are **scarce**
  $\Rightarrow$ retrieve *SocEconPol* **trend from load data**
- Temperature, holidays and policy shocks act on **similar time scales**
  $\Rightarrow$ **simple detrending** of Load_t would **mix effects** (see figure)

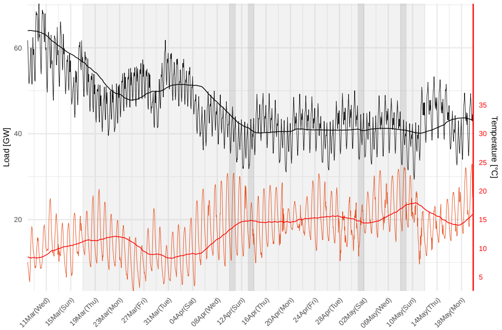


Figure 3: Hourly Load (black) and temperature (red) with their weekly moving average during first COVID-19 lockdown in France.

Two-stage retrieval:

(1) Remove calendar & weather effects: $\text{Load}_t = \mu^{Calendar}(X_t^{Calendar}) + \mu^{Temp}(X_t^{Temp}) + r_t$

(2) **Aggregate residuals**: $X_\tau^{SocEconPol} = \text{weekly aggregate}(r_t)$

Modelling of $X^{SocEconPol}$: Cross-Country Patterns

- $X_\tau^{i,SocEconPol}$ shows **geographically coherent clusters** of countries
- Dynamics align with **economic expansion, holidays, COVID-19, and the energy crisis**

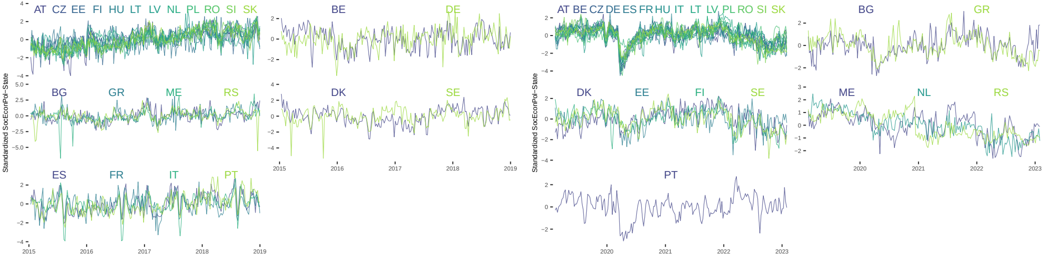


Figure 4: Standardized $X_\tau^{SocEconPol}$ by cluster for data 2015–2019 (left) and 2019–2023 (right).

Modelling of $X^{SocEconPol}$: **Correlations** with **External Indicators**

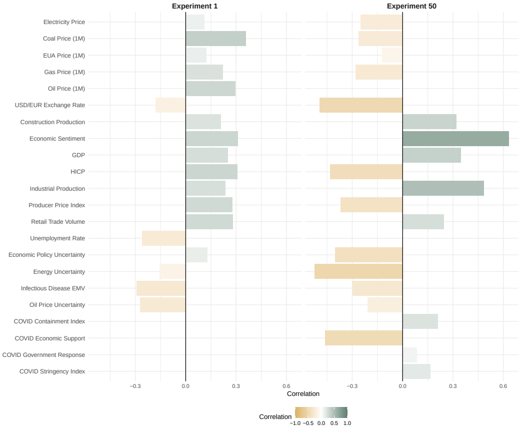


Figure 5: Correlations between $X_T^{SocEconPol}$ and energy prices, macroeconomic, energy and uncertainty indicators, for Germany 2015–2019 (left) and 2019–2023 (right).

- **Pre-COVID (left panel):**
  - positive with GDP, production, prices
  - negative with unemployment and some uncertainty measures
  - ⇒ endogenous trend reflects economic expansion
- **COVID / energy crisis (right panel):**
  - energy prices and several price indices turn negative
  - links to uncertainty indicators strengthen
  - ⇒ endogenous trend reflects contraction and heightened uncertainty

Modelling of $X^{SocEconPol}$: VAR, VECM, VETS

Incorporated through **Vector** models recognizing **transnational dependence**

Model	Unit-Root Assumption
Vectorautoregressive (VAR) Model	stationarity
Vector Error Correction Model (VECM)	one joint underlying unit root (single pan-European socio-economic and political non-stationary trend)
Vector Error-Trend-Seasonal (VETS) Model	country-specific unit root with common smoothing parameter (common memory of past observations)

varying assumptions on **persistence of socio-economic and political trend** in the forecasting horizon

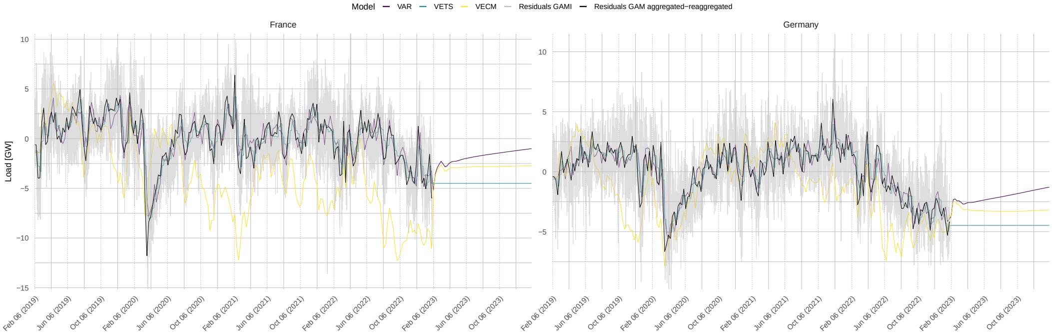


Figure 6: Fitted and forecasted $X_t^{\text{SocEconPol-Stat}}$ for in-sample data 2019–2023.

Results: **Forecasting Performance** in Terms of CRPS

	SRWA	FNN	VAR	VECM	VETS
Austria	0.333	0.277	0.252	**0.252**	0.257
Belgium	0.404	0.372	0.340	0.340	**0.334**
Bulgaria	0.253	0.210	0.205	**0.205**	0.228
Czech Rep.	0.343	0.260	**0.247**	0.248	0.253
Denmark	0.181	0.172	0.163	**0.154**	0.165
Estonia	0.049	0.040	0.040	**0.039**	0.043
Finland	0.541	0.427	0.422	**0.408**	0.421
France	5.052	2.834	**2.708**	2.748	2.834
Germany	2.422	2.043	1.789	1.814	**1.695**
Greece	0.419	0.335	0.326	**0.317**	0.362
Hungary	0.237	0.201	0.199	**0.192**	0.202
Italy	1.856	1.600	1.519	**1.470**	1.789
Latvia	0.036	0.034	0.031	**0.029**	0.031
Lithuania	0.063	0.054	**0.054**	0.058	0.060
Montenegro	0.030	0.028	**0.027**	0.029	0.027
Netherlands	**0.633**	0.751	0.734	0.723	0.669
Poland	0.802	0.590	0.590	**0.538**	0.575
Portugal	0.242	0.210	0.191	**0.187**	0.214
Romania	0.340	0.294	0.288	**0.269**	0.270
Serbia	0.256	0.287	0.258	**0.246**	0.252
Slovakia	0.186	0.152	0.146	**0.130**	0.143
Slovenia	0.086	0.078	**0.072**	0.079	0.086
Spain	1.249	1.185	1.091	**1.052**	1.091
Sweden	0.865	0.679	**0.674**	0.683	0.678
Sum	16.877	13.113	12.365	**12.208**	12.679

- **Design:**
  - forecast horizon $H = 24 \times 7 \times 52$
  - 24 European countries
  - 50 forecasting experiments in 2015–2024
  - 4 years of in-sample data per experiment
- **Key findings:**
  - superior forecasting accuracy compared to benchmarks
  - single pan-European socio-economic & political non-stationary trend

Results: **Interpretable GAM** with Trajectory Inputs

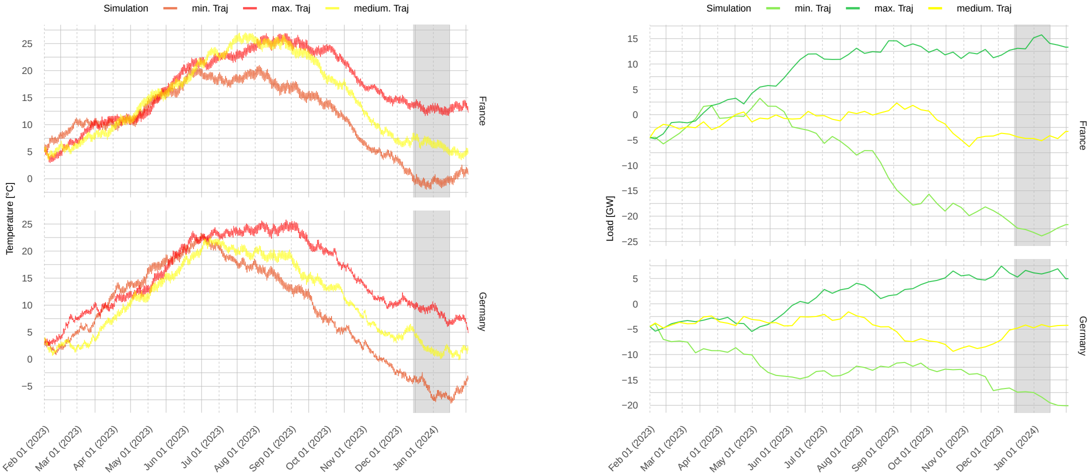


Figure 7: Temperature (left) and VETS SocEconPol (right) trajectories (min, median, max) based on the area under the curve in the Christmas holiday time.

Results: **Interpretable GAM** with Trajectory Inputs

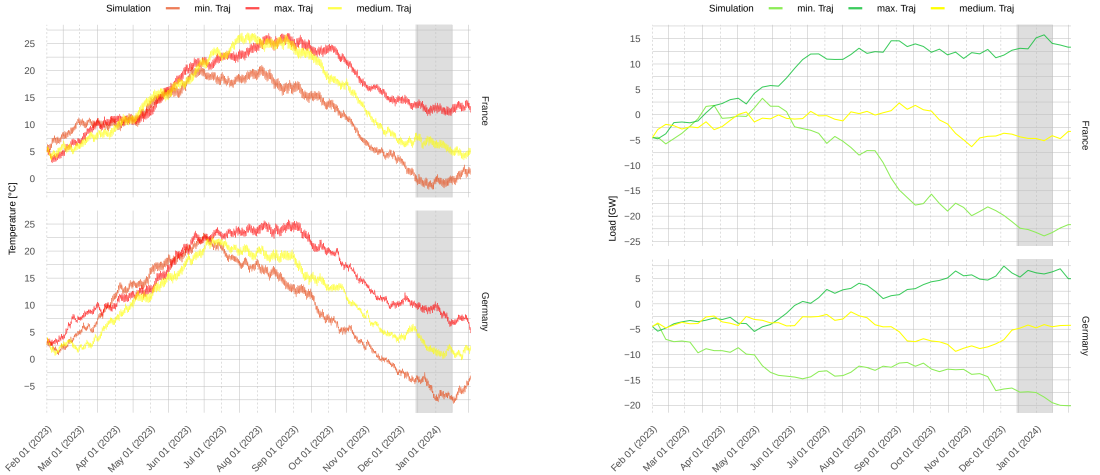
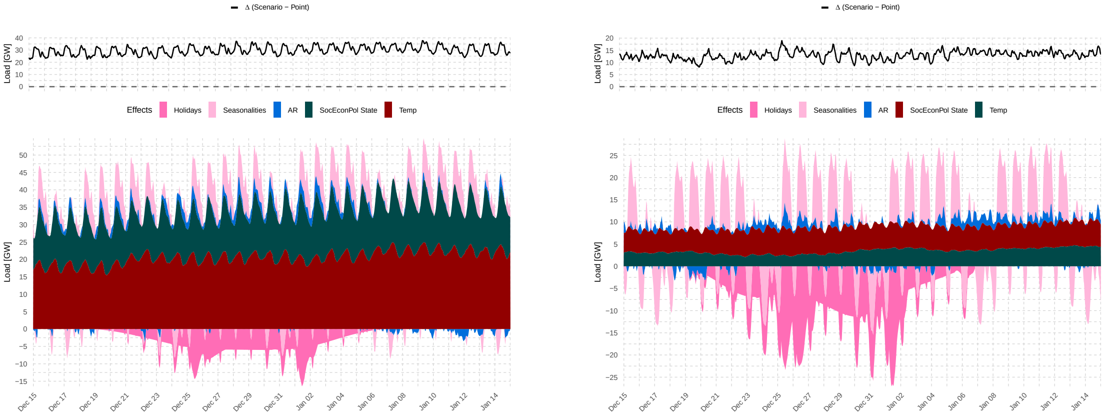


Figure 7: Temperature (left) and VETS SocEconPol (right) trajectories (min, median, max) based on the area under the curve in the Christmas holiday time.

⇒ **High-demand scenario** by combining **coldest temperature** with **most positive SocEconPol**

Results: **Interpretable GAM** with Trajectory Inputs

Tracking the Hourly Impact of High-Demand Scenario Inputs Across Mid-Term Forecasts



(a) France (b) Germany

Figure 8: Difference between the scenario and point forecast (top) and stacked component contributions (bottom) during the Christmas holiday time (15 Dec 2023–14 Jan 2024).

Results: **Interpretable GAM** with Trajectory Inputs

Tracking the Hourly Impact of High-Demand Scenario Inputs Across Mid-Term Forecasts

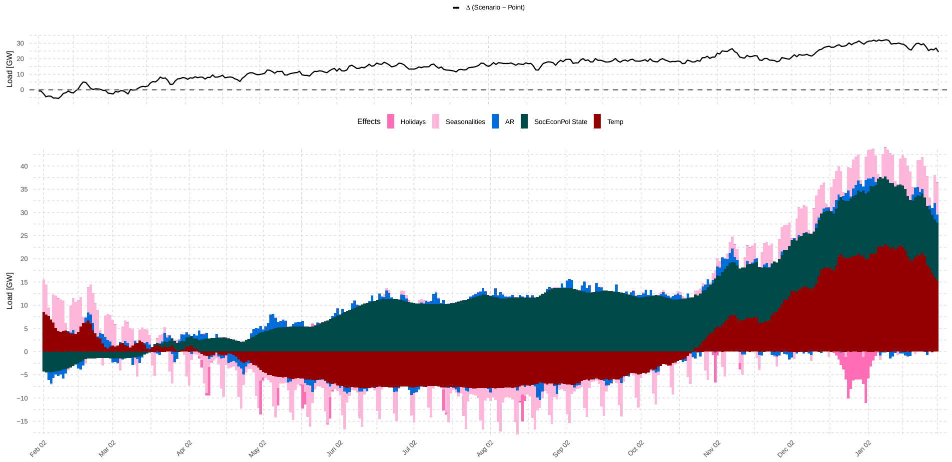


Figure 9: Daily averaged difference between the scenario and point forecast (top) and stacked component contributions (bottom) in France for the entire one-year forecasting horizon (Feb 2023–Jan 2024).

References I

UNIVERSITÄT DUISBURG ESSEN
Open-Minded

Thank you for your attention! Questions?

[1] Davis, K. O., Hong, T., & Fan, S. (2016). Probabilistic electric load forecasting: A tutorial review. *International Journal of Forecasting*, *32*, 914–938. doi:10.1016/j.ijforecast.2015.11.011. MAG ID: 2275088575 S2ID: 154102a5a5e3a96fcd37bd5e672137126f323490.

[2] Hastie, T., & Tibshirani, R. (1999). *Generalized additive models*. Boca Raton, Fla: Chapman & Hall/CRC.

[3] Pierrot, A., & Goude, Y. (2011). Short-Term Electricity Load Forecasting With Generalized Additive Models. *Proceedings of ISAP power Cordoba, Spain*, (pp. 593 – 600). doi:https://doi.org/10.1109/ISDA18915.2011.

[4] Verwiebe, P. A., Seim, S., Burges, S., Schulz, L., & Müller-Kirchenbauer, J. (2021). Modeling Energy Demand—A Systematic Literature Review. *Energies*, *14*, 7859. doi:10.3390/en14237859.

[5] Wood, S. N. (2017). *Generalized Additive Models: An Introduction with R*. (2nd ed.). Chapman and Hall/CRC. URL: https://www.taylorfrancis.com/books/9781498728348. doi:10.1201/9781315370279.