Patterns and Correlations in European Electricity Prices

Julius Trebbien, [1,2,a] Anton Tausendfreund, [3,2,a] Leonardo Rydin Gorjão, [4] and Dirk Witthaut [1,2,b]

[1] *Institute for Energy and Climate Research (IEK-10), Forschungszentrum Jülich, 52428 Jülich, Germany*

[2] *Institute for Theoretical Physics, University of Cologne, 50937 Köln, Germany*

[3] *Institute for Energy and Climate Research – Energy systems engineering (IEK-10), Forschungszentrum Jülich, 52428 Jülich, Germany*

[4] *Faculty of Science and Technology, Norwegian University of Life Sciences, 1432 Ås, Norway*

Electricity markets are central to the coordination of power generation and demand. The European power system is divided into several bidding zones, each having an individual electricity market price. While individual price time series have been intensively studied in recent years, spatio-temporal aspects have received little attention. This article provides a comprehensive data-centric analysis of the patterns and correlations of the European day-ahead electricity prices between 2019 and 2023, characteristically abnormal due to the energy crisis in Europe. We identify the dominant communities of bidding zones and show that spatial differences can be described with very few principal components. Most bidding zones in Continental Europe were brought together during the energy crisis: Correlations increased and the number of relevant principal components decreased. Opposite effects occur in the Nordic countries and the Iberian Peninsula where correlations decrease and communities fragment.

The European energy crisis, inextricably connected with the Russian invasion of Ukraine, resulted in electricity price levels never before seen. Europe's dependence on Russian gas led to soaring prices coupled with the uncertainty brought about by the war. Remarkably, the various electricity markets of each European country were affected in quite different, sometimes unexpected ways. As a consequence, topics in energy markets and energy security took center stage in the political discussion. Electricity markets have always been a central topic in energy economics, but the interactions and interdependencies of markets received rather little attention. This article provides a data-centric investigation of electricity prices in the various bidding zones in Europe and quantifies similarities and differences.

I. INTRODUCTION

A reliable supply of electric power is crucial for almost all aspects of our daily lives. Most economic activities as well as most technical infrastructures are dependent on the robust and stable operation of the electric power system, making it a uniquely critical infrastructure[1]. Since a power grid cannot easily store energy in itself, generation and demand must be balanced at all times[2]. A balanced system operates at a nominal frequency (commonly 50 Hz or 60 Hz). Small deviations are corrected by the load-frequency control system in real time[3,4], but most of the generation must be scheduled beforehand in order to match the forecasted demand of all consumers in the synchronous grid. In liberalized electricity markets, this is achieved by trading on various electricity markets[5], wherein electricity producers and consumers buy and sell generation capacity. Apart from long-term contracts, the day-ahead spot markets play a central role in fulfilling the power demands of the consumers in the synchronous grid[6,7].

The aggregation of generation and demand in an interconnected synchronous grid can improve the stability and efficiency of the grid for several reasons. First, long-distance transmission facilitates the balancing of variable renewable power sources[8]. Second, short-term power fluctuations average out, reducing the demand for real-time control and improving frequency stability[9,10]. Finally, the liberalization and integration of markets increases competition and thus leads to lower costs[5]. For example, the Continental European (CE) synchronous area included a generation capacity of more than 600 GW and served more than 400 million customers as of 2021[11].

Electricity trading in interconnected grids is limited by physical constraints. An overhead line can transmit only a certain amount of electric power before stability is at risk[2,12]. To reflect these limitations – and to create a financial incentive to supply power across countries – the European power system is divided into various bidding zones, often corresponding to the respective countries. Every bidding zone has its different electricity prices, reflecting the local supply and demand.

Electricity spot market prices across all European bidding zones have intricate statistical properties, featuring heavy tails and a strong persistence[6]. The complexity of the data reflects the inherent complexities of each bid-

[a] These authors contributed equally.
[b] Electronic mail: d.witthaut@fz-juelich.de

ding zone. These comprise the balance of renewable and non-renewable generation, the limitation of importing or exporting power, and naturally the daily human activity patterns. One element that highly influences the prices is the ability to sell or buy generation between adjacent bidding zones, be it between countries or even within a country.

In this article, we provide a statistical analysis of the *spatio-temporal properties* of electricity price time series in Europe between 2019 and 2023 and the impacts of the European energy crisis. Prices are coupled due to cross-border trading and common drivers, i.e. similar temporal patterns of the demand. This gives rise to strong correlations and intricate spatio-temporal patterns reflecting the specific power demands of each bidding zone. Moreover, the energy markets are inextricably coupled to the gas and oil markets in Europe. Price changes in one, driven either by market economics or political events inadvertently affect electricity prices[13]. In fact, the European energy crisis related to the Russian invasion of Ukraine strongly affected the electricity systems across Europe[13,14], but impacts differed from country to country. Hence, we observe not just an overall increase of electricity prices, but a comprehensive modification of their correlations and spatio-temporal patterns.

The article is structured as follows. We provide a short review of the structure and functioning of European electricity markets in Sec. II. We then give an overview of the price time series and their fundamental statistical properties in Sec. III, including a first glimpse on the effect of the European energy crisis. Section IV contains a detailed analysis of the spatial correlations of the electricity price time series. We then proceed to identify and investigate the main spatio-temporal patterns of day-ahead electricity prices in Sec. V. We conclude with a short discussion and outlook in Sec. VI.

II. BACKGROUND: ELECTRICITY MARKETS AND PRICES

A. European Electricity Markets

In liberalized electricity markets, the balancing of power systems is mainly achieved by trading of generation and consumption capacities. Each market participant must sell or buy the electricity that they are going to inject or withdraw from the grid in a certain time window[15]. For instance, an operator of a photovoltaic power plant, upon agreeing on a forward contract on the electricity spot market, must provide the exact amount of electricity that they produce in any given hourly time window.

Market participants may buy and sell electricity either via individual long-term contracts, commonly referred to as power purchase agreements (PPA), via over-the-counter (OTC) direct contracts or via trading on an electricity exchange. Given the variability in generation and consumption due to different factors, such as changing weather, most market participants are dependent on forecasts[16]. Since forecasts become increasingly uncertain as the time horizon extends from actual delivery, a variety of electricity markets including future, day-ahead and intraday markets exist within Europe. The spot markets are the main market for physical trading of electricity and consist of the day-ahead and intraday markets[7,17,18]. The European day-ahead markets generally trade in hourly blocks for the 24 hours of the following day and close at 12:00 CET. Different exchanges may adopt slightly different rules but mostly follow the mentioned structure[19].

Day-ahead trading is auction-based, i.e. the bids and offers of all market participants are collected inside the order book until market closure. Aggregating both offers and bids in volume for each hour creates the respective supply and demand curves. The Market Clearing Price (MCP) of the day-ahead market results from the intersection between supply and demand curves, which corresponds to the highest price that finds a buyer[20,21]. All bids and offers that are consistent with the price are realized at the market clearing price in the respective hour. Consequently, every offer below the market price and every bid above the market price gets executed exactly at the MCP, commonly referred to as “pay-as-cleared”. All bids above and all offers below the market clearing price are discarded.

The European electricity market is separated into bidding zones to reflect regional market conditions and limited transmission capacities. In principle, each bidding zone constitutes a separate electricity market with a separate market clearing price. Clearing the bidding zones individually ensures that generation and load are balanced regionally, given the limited capacities for long-distance transmission. Bidding zones are coupled to a limited extent as described below to enable exports and imports. In Europe, most bidding zones correspond to countries, with some countries sharing a bidding zone or being divided into several inter-country bidding zones[22]. For instance, the Norway, Sweden and Italy are divided into various smaller bidding zones within each country.

For the 12:00 day-ahead auction, the different bidding zones are coupled through the Single Day-Ahead Coupling (SDAC) mechanism. The SDAC, implemented in North-West Europe in 2014 and later expanded to most European bidding zones, integrates day-ahead electricity markets across Europe. The mechanism enhances market efficiency by pooling demand and supply across bidding zones, breaking the confines of local markets with respect to transmission capacity constraints between bidding zones[23].

The aim of market coupling is to increase the efficiency of trading through increased liquidity and efficient utilization of all generation resources in Europe[24]. In contrast, transmission capacities within a bidding zone are not resolved and must be dealt with afterwards[12].

The SDAC employs the *PCR EUPHEMIA* algorithm for price calculation and capacity allocation, complet-

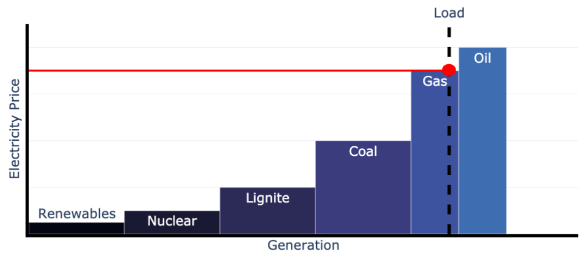

Figure 1. Visualization of the merit-order principle. Generation is sorted according to their estimated marginal cost. The load is approximated as independent of the price. The price is set by the power plant with the highest marginal cost needed to match the load. Typically, renewable generation has the lowest marginal cost such that it is always included in the merit order principle. Therefore, power plants using fossil fuels, like coal, gas or oil power plants determine the price.

ing these tasks for all zones and hourly intervals of the next day[25]. EUPHEMIA processes inputs from Nominated Electricity Market Operators (NEMOs) and Transmission System Operators (TSOs), encompassing order books and network constraints (e.g. interconnector restrictions, line losses, tariffs). The optimization algorithm maximizes social welfare by considering consumer and supplier surplus alongside congestion rent[26].

We note that the actual generation may differ from the amount that has been sold on an electricity market, for instance, due to forecasting errors. Various layers of control reserve are implemented to balance the generation in real-time but are limited to small imbalances[3]. Most countries or bidding zones have energy reserve markets to promote balancing schemes for small power imbalances, but this is beyond the scope of the present article.

B. The merit-order principle

The temporal evolution of the electricity market price $p(t)$ in one bdding zone can roughly be understood from the merit-order principle[27]. In the short run, the demand for electricity D is largely inelastic[28]. In perfect competition, the demand is satisfied by generating units according to their marginal costs. All units with marginal costs below the market price p can realize positive contribution margins and are thus “on”, all others are “off”. Hence one can obtain an approximate view of the market outcome by sorting all generating units according to their estimated marginal costs – the merit order. The marginal cost of the last power plant entering the market then corresponds to the market clearing price as illustrated in Fig. 1.

The merit-order principle can be formalized as follows. At each point in time, the demand must equal the sum of intermittent renewable generation (wind and solar) and dispatchable generation such that

$$G_{\mathrm{ren}}(t) + G_{\mathrm{d}}(p) = D(t). \tag{1}$$

Here, $G_{\mathrm{d}}(p)$ is the supply curve of the dispatchable generation according to the merit-order principle[27]. Renewable generation and demand are assumed to be independent of the market price p, but vary strongly in time. Solving Eq. (1) for the market price thus yields

$$p(t) \approx G_{\mathrm{d}}^{-1}[D(t) - G_{\mathrm{ren}}(t)], \tag{2}$$

where G_{d}^{-1} denotes the inverse function of the supply curve. Hence, wind and solar generation and demand are essential factors that determine the electricity market price[29].

We emphasize that Eq. (2) provides only a rough estimate of the actual market price as it neglects many other influencing factors[29]. Conventional power plants, especially nuclear and lignite plants, have limited flexibility such that any ramping or cycling induces additional costs[30]. Thus, in the short run, power plant operators may choose a bidding price below their marginal costs. In case of a decreasing demand, the operators may bid at a lower price to remain in the market. In the medium to long run, fuel prices evolve and the set of dispatchable power plants changes which also affects the function $G_{\mathrm{d}}(p)$.

III. ELECTRICITY PRICES AND THE EUROPEAN ENERGY CRISIS

In this section, we provide an overview of the spot market prices across Europe and the impact of European electricity prices. Our analysis is based on data from the European Network of Transmission System Operators for Electricity (ENTSO-E)[31]. Further details are given in Appendix A.

A. Electricity price time series

Before turning to spatio-temporal aspects, we review essential aspects of price time series, focusing on a single bidding zone.

Figure 2 shows the electricity price in the DE-LU bidding zone together with the load and renewable generation for one week. This figure highlights the main driving factors of electricity spot market prices as introduced in Sec. II B as well as typical recurring patterns. The load has a pronounced daily and weekly pattern, being substantially smaller during the night and on the weekend. The load typically peaks in the early morning and the evening, and so do the electricity prices. Solar power generation peaks at noon, such that the residual load $D(t) - G_{\mathrm{ren}}(t)$ and the price $p(t)$ assume a minimum. During the week displayed in the figure, wind power is decreasing, such that we observe an overall increase in

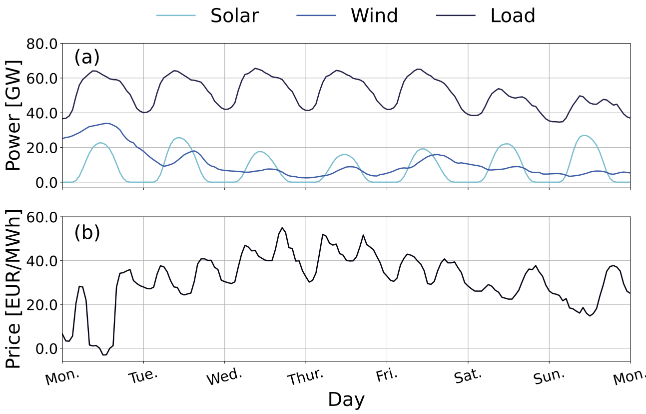

Figure 2. Electricity prices and major driving factors. We show the time series for (a) load, solar power and wind power generation and (b) the day-ahead spot market price in the DE-LU bidding zone for the week starting on 2020-07-06. Prices generally increase with the residual load, i.e. the load minus the variable renewable generation, cf. Sec. II B. Data sources and processing are summarized in Appendix A.

electricity prices until the weekend. The relation of electricity prices and the residual load for European bidding zones have been investigated in Ref.[32] while further influences have been discussed in Ref.[29]. Electricity price time series have intricate statistical properties including heavy tails and a pronounced persistence as discussed in detail in Ref.[6].

The European electricity markets were strongly affected by the European energy crisis of 2021 and 2022. Energy prices soared in many regions following the Russian invasion of Ukraine[14]. Europe was particularly strongly affected due to the dependence on Russian fossil fuels in many countries. Figure 3 shows the electricity prices in the DE-LU bidding zone over a time period of several years. We observe a strong increase in electricity prices starting at the end of 2021. While prices never exceeded 300 EUR/MWh before the crisis, they regularly do during the crisis with peaks above 800 EUR/MWh. Figure 3 also shows that it is generally not possible to pinpoint the exact start of the European energy crisis. However, to be able to compare the data for the period before and during the energy crisis, we have set the start of the crisis to 2021-09-13, the first week in which the weekly average price in Europe was significantly higher (≥ 50 EUR/MWh) than the average price for the previous six months. Further effects of the energy crisis have been discussed in the literature: The volatility of prices increases strongly[33], and the likeliness of negative prices decreased drastically[34].

B. Differences between bidding zones

Electricity prices may differ considerably between the different bidding zones. In this section, we compare and

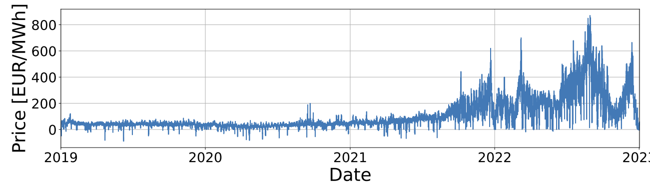

Figure 3. Electricity price time series from the German day-ahead market from January 2019 to 2023. Data sources and processing are summarized in Appendix A.

discuss global statistical features of respective price time series, before turning to the spatio-temporal correlations and patterns in the following.

Figure 4(a) shows the average day-ahead spot market price before the onset of the European electricity crisis. The lowest prices are observed in the Nordics, especially in the Northern bidding zones of Norway and Sweden, which is mostly due to the abundance of water power. The marginal costs of water power plants are typically very low, such that electricity is offered at comparably low prices. At the same time population density and thus load is rather small, resulting in low overall prices. The highest prices are observed in Italy, in particular Sicily. Italy has a limited a amount of generation facilities leading to a small supply and thus to higher prices. In fact, Italy imports a substantial amount of electricity from neighboring countries. For instance, in 2021 Italy imported 46.6 TWh of electricity while it exported only 3.8 TWh[35].

The impact of the European electricity crisis is illustrated in Fig. 4(b,c). We observe that the average price increases strongly in many bidding zones up to a factor of almost six. Almost no change is observed in the Northern bidding zones of Norway and Sweden, which can again be attributed to the dominant role of water power which was not affected by increasing fuel prices. Furthermore, the increase is rather modest in Finland, Southern Sweden, Poland and the Iberian Peninsula. The electricity system in these bidding zones does not rely strongly on natural gas imports from Russia for different reasons. Power generation in Sweden and Finland mainly relies on nuclear power, while domestic coal and lignite are dominant in Poland. Spain and Portugal import almost no natural gas from Russia, but rely on liquefied natural gas (LNG) from other sources instead[35].

The strongest increase of prices is observed in Southern Norway and France. This is surprising because power generation in these bidding zones does *not* rely strongly on Russian natural gas – but on water power in Norway and nuclear power in France[35].

These unexpected findings can be connected to two effects that occurred simultaneously but independently of the Russian invasion of Ukraine. First, a large number of French nuclear power plants had to go into revision. Figure 5(a) shows the reported unavailability of nuclear generation capacity. There is a strong seasonal pattern

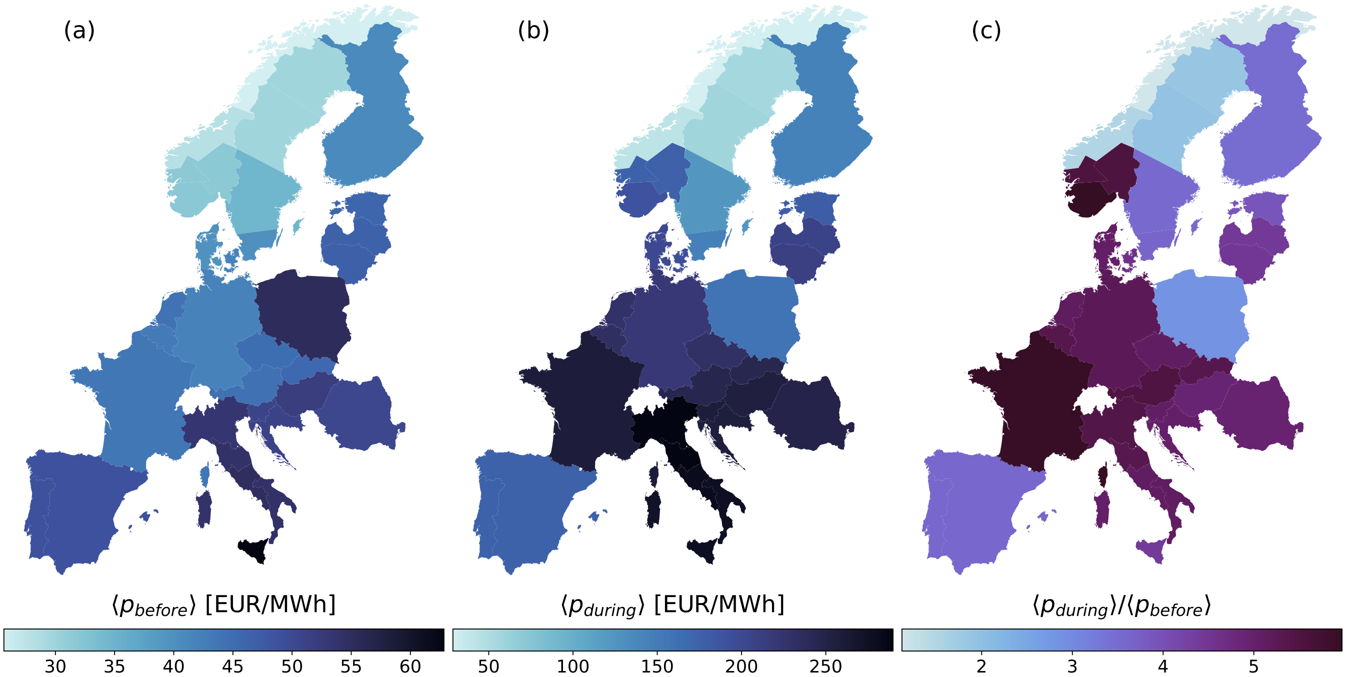

Figure 4. Average electricity price and the impact of the European electricity crisis. (a,b) The colormap shows the average spot market price for each bidding zone before and during the European electricity crisis. (c) The colormap shows the ratio of the average price during and before the crisis. In some bidding zones, the prices increase up to a factor of almost six. Data sources are summarized in Appendix A.

as revisions are preferably planned during the summer months. Comparing different years we find that the unavailability reached previously unknown values of more than 36 GW during the summer 2022. Similarly, the unavailability in the winter 2021/2022 was higher than in preceding winters by several GW. We conclude that the price increase in the French bidding zones can be attributed at least partially to this effect.

The strong increase in Southern Norway occurs at the time when the NordLink interconnection to Germany was put into commercial operation in 2021[36]. This high-voltage DC connection has a transmission capacity of 1.4 GW, the actual power exchange being shown in Fig. 5(b). NordLink enables direct electricity trading between the bidding zones in Germany (DE-LU) and Norway (NO2), which typically leads to an alignment of the respective day-ahead prices. Given the comparably small size of the NO2 bidding zone, we expect a much stronger effect than in the German bidding zone. Indeed, we see that the average price p_{during} shown in Fig. 4 is very similar.

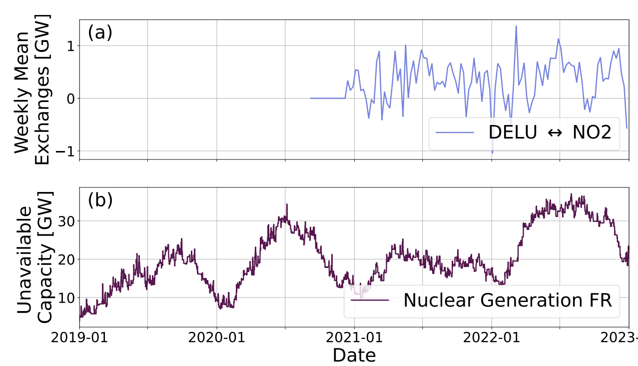

Figure 5. Features affecting electricity supply and trading in 2021/22. (a) The NordLink interconnector between Germany and Norway was put into commercial operation in 2021[36]. The figure shows the physical exchange between Norway (NO2) and Germany (DELU) as a function of time, averaged over one week. Positive values correspond to a flow from Norway to Germany. (b) The reported unavailability of nuclear power plants in France was larger than in previous years. Data sources are summarized in Appendix A.

IV. CORRELATIONS AND COMMUNITIES

In this section, we turn to the spatio-temporal aspects of electricity prices in Europe. We first quantify correlations of price time series and identify communities in the European markets.

Correlations emerge via two different mechanisms: common driving forces and mutual interactions. Common driving factors affect both the demand and supply curves in the individual bidding zones. The demand

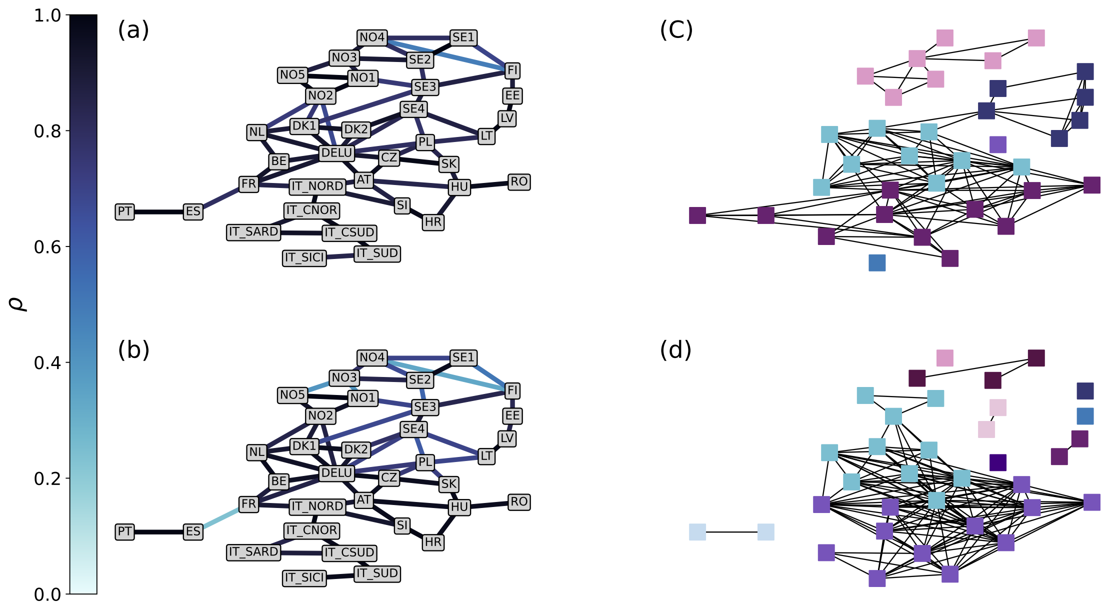

Figure 6. Correlations and communities of the European electricity price time series. (a,b) Pearson correlation ρ between neighboring bidding zones (a) before and (b) during the energy crisis. (c,d) Correlation networks and communities. Two bidding zones x, y are linked if the mutual Pearson correlations exceeds a threshold $\rho_{x,y} > h = 0.85$. Communities in these networks are marked by different colors. Communities are computed (c) before and (d) during the energy crisis. Data sources are summarized in Appendix A.

shows pronounced daily and weekly patterns, which are similar in most bidding zones[37,38]. The availability of renewable power also shows regular patterns, in particular seasonal patterns[39] and daily patterns for solar power. Furthermore, the actual weather is strongly correlated on the synoptic scale of around 1000 kilometers. As a consequence, electricity price time series in different bidding zones show similar recurring patterns and similar reactions to the weather, albeit at different magnitudes.

Cross-border electricity trading introduces an interaction between neighboring bidding zones. Consider the case that the price p_x in bidding zone x is lower than the price p_y in neighboring bidding zones y. In general, the EUPHEMIA algorithm will select further offers in bidding zone x and discard offers in bidding zone y to reduce the overall prices. As a consequence the prices in zone x increases, and the price in zone y decreases. Loosely speaking, cross-border trading leads to an averaging of prices in neighboring bidding zones.

We quantify the emerging correlations in terms of the Pearson coefficient $\rho_{x,y}$, which is illustrated for all neighboring bidding zones in Fig. 6(a,b). As before, we distinguish the periods *before* and *during* the European energy crisis. We observe a substantial decrease for some connections, in particular Spain and France, Norway (NO3, NO4 and NO5), and Finland and for several connections of Poland. Other correlations increase, for instance NO2 and DE-LU. The last finding may be attributed, at least partially, to the operation of NordLink as discussed above.

Further insights into the spatial aspects are obtained in terms of correlation networks, cf.[40,41]. Here, every bidding zone corresponds to a node of a network. Two bidding zones x and y are connected if the mutual Pearson correlation exceeds a threshold $\rho_{x,y} > h$. Note that we now take into account all pairs of biding zones in accordance with the literature[40,41]. We note that in many applications time-delayed correlations are used in the context of causal interactions. This is not appropriate in our case as all prices are set simultaneously.

The resulting correlation networks are shown in Fig. 6(c,d) for the threshold parameter $h = 0.85$, comparing the period before and during the energy crisis. We observe two general effects: The number of edges decreases in the Nordics and the Baltics, while they increase in Continental Europe. We recall that correlations emerge due to two reasons: common drivers and trading interactions. The observed changes in the number of links thus do not necessarily hint at less or more intense trading. Instead, it is also possible that the susceptibility to external drivers became less similar (the Nordics) or more similar (Continental Europe).

In a second step, we apply the Louvain algorithm[42] to identify communities in the respective network. For this, we use the implementation of the networkx python package with default parameters, i.e. resolution set to 1[43].

Before the crisis, the correlation network can be decomposed into six communities. First, we observe a Western Scandinavian and a Baltic community which are not connected at all for the given value of h. Notably, the Swedish bidding zones belong to different communities. Several high-voltage DC links enable electricity trading across the Baltic Sea, most notably NordBalt between Sweden and Lithuania and Estlink between Finland and Estonia[44]. We conclude that these links are essential for the formation of the Baltic community.

Continental Europe is divided into a Northern and a Southern community, the border roughly following the Alps and the Slovakian-Hungarian border. The community boundary may thus be at least partially explained in terms of the physical geography of Europe. Comparing to Fig. 4(a), we observe that average prices are higher throughout the Southern community. Unsurprisingly, Poland and Sicily form their own community as their electricity markets differ considerably from their neighbors. Poland has a distinct fuel mix, relying strongly on domestic coal and lignite[35].

The energy crisis has a stark effect on the correlation network in Northern Europe. The Nordic and Baltic communities fall apart into small fragments. This observation has to be interpreted in terms of the different fuel mix of each country and the dependency on Russian imports. On the one hand, Northern Norway and Northern Sweden rely strongly on water power such that prices were only weakly affected (cf. Fig. 4(c)). On the other hand, the Baltic countries are still part of the Russian synchronous area[45] and prices were affected to a much higher extent (cf. Fig. 4(c)). At the same time, the Southern Norwegian bidding zones join the Northern Continental community, which again may be attributed to the operation of the NordLink interconnector.

In Continental Europe, the number of edges generally increases during the energy crisis. A remarkable effect is observed for France, where correlations change considerably. These changes are not surprising given that France suffered a strong increase in nuclear unavailability (cf. Fig. 5(b)) and the strongest increase in average prices (cf. Fig. 4). In fact, one observes strong changes in the patterns of electricity trading between France and its neighbors. Comparing 2021 and 2022, France turned from a net exporter (43.4 TWh) to a net importer (16.5 TWh)[46]. The only exception is trading with Italy, which remained largely constant[46]. This manifests in changes of price correlations, which generally decreased for Northern Europe, but stayed high or even increased for Southern Europe. As a consequence, the French bidding zone left the Northern and joined the Southern community.

Finally, the correlation between Spain and France decreased strongly, such that the Iberian Peninsula left the Southern Continental community. As discussed before, the Iberian Peninsula was only weakly affected by the European energy crisis as it barely imports natural gas from Russia[35].

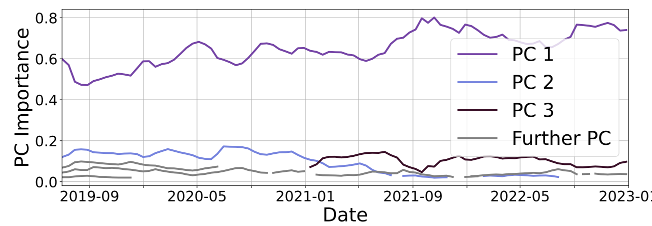

Figure 7. Importance of the Principal components (PCs) for the price vector $\boldsymbol{p}(t)$ as a function of the reference time t_r. The PCs were computed for a sliding window of 180 days and tracked according to their overlap. The importance is quantified by the fraction of the total variance explained by a given PC. Only PCs with an explained variance of at least 5% are shown to increase visibility. PC1 refers to the most important PC, explaining up to 80% of the variance, and is further analyzed in Fig. 8. PC2 refers to the second most important PC at the beginning of the analysis, explaining up to almost 20% of the variance. PC2 decreases in importance and becomes less substantial during the energy crisis. PC3 refers to the second most important PC at the end of the analysis. Both PC2 and PC3 have describe a North-South pattern as shown in Fig. 9.

V. ELECTRICITY PRICE PATTERNS

We now consider the spatio-temporal patterns of the European electricity price time series. We aim to identify and interpret the dominant pattern and discuss how they were affected during the energy crisis.

To this end, we aggregate all time series in a vector $\boldsymbol{p}(t)$, where the nth component corresponds to the electricity price time in a specific bidding zone n at time t. Our goal is to decompose this vector as

$$\boldsymbol{p}(t) = \langle \boldsymbol{p} \rangle + \sum_m a_m(t)\, \boldsymbol{c}_m, \tag{3}$$

such that $\boldsymbol{c}_m$ describes a spatial pattern and $a_m(t)$ the amplitude of the respective pattern at time t. The desired decomposition is provided by Principal Component Analysis (PCA), a standard technique for dimensionality reduction[47]. This decomposition is optimal in the following way. PCA selects the vectors $\boldsymbol{c}_m$, called principal components (PCs), in a way that they capture as much of the variance of the original time series as possible. Technically, the PCs $\boldsymbol{c}_m$ are given by the eigenvectors of the covariance matrix. The associated eigenvalue λ_m measures how much of the overall variance of the multivariate time series $\boldsymbol{p}(t)$ is explained by the mth PC[47]. The ratio of λ_m and the total variance will serve as a measure of the importance of a PC in the following.

We remark that PCA is a *linear* method in the following sense. Restricting the sum in Eq. 3 to M PCs corresponds to a projection of the original data onto an M-dimensional *linear* subspace. PCA thus efficiently identifies all linear correlations but fails to account for nonlinear relations in the data. Advanced methods of nonlinear data reduction thus aim to replace the linear subspaces by low-dimensional manifolds of arbitrary shape[48]. In this initial analysis, we restrict ourselves to common linear PCA because of its high interpretability. Furthermore, we remark that the leading PC already covers up to 80% of the variance, such that nonlinear effects can be assumed to be small.

In this context, we must take into account that the electricity markets can change strongly over time as grids, regulations, or the fuel markets evolve. Hence, we utilize an adaptive decomposition. We compute PCA for separate intervals $[t_r - T, t_r]$, then shift the reference date as $t_r \to t'_r = t_r + \tau$. In the following, we choose $T = 180$ days and $\tau = 14$ days. The individual PCs are then tracked to analyze their evolution. Two PCs $\boldsymbol{c}_m$ and $\boldsymbol{c}'_n$ at subsequent intervals are identified if their overlap exceeds a threshold:

$$|\langle \boldsymbol{c}'_n, \boldsymbol{c}_m \rangle| \geq 0.8. \tag{4}$$

We have tested other values of the parameters T and τ to assess the stability of the results. Choosing T substantially smaller than 180 days impedes the tracking of PCs and thus spoils interpretability. Choosing $T = 365$ yields very similar results, but reduces the temporal resolution of the analysis.

Figure 7 shows the variance explained by individual PCs as a function of time. We restrict the analysis to the most important PCs that explain at least 5% of the variance for a given interval $[t_r - T, t_r]$. Curves may stop or start if a PC cannot be tracked according to condition (4). We observe that only few PCs are important to capture the spatio-temporal patterns of European electricity prices. The leading PC can be tracked over the entire time period and explains more than half of the variance for the vast majority of intervals $[t_r - T, t_r]$. The next-to-leading PC explains between 5% and 20% of the variance, but cannot be tracked over the entire period. In particular, we observe a change for a reference time t_r in early 2021. The importance of PC2 drops while another PC3 emerges and gains importance, replacing PC2 as the next-to-leading PC.

A detailed analysis of the most important PC and its temporal evolution is provided in Fig. 8. We display their spatial shapes $\boldsymbol{c}_m$ at selected reference times t_r. Furthermore, we show their daily profile, i.e. the associated amplitude $a_m(t)$ for all hours of the day, averaged over all days in the respective interval $[t_r - T, t_r]$.

We find that the leading PC $\boldsymbol{c}_1$ mostly describes the response of the prices to the supply and demand illustrated in Fig. 2. The daily profile has a characteristic shape related to the daily profile of demand and solar generation. It peaks in the morning and early evening and has its minimum during the night. The components of $\boldsymbol{c}_1$ quantify how strongly the bidding zones participate in this temporal evolution. Before the energy crisis, bidding zones on the Balkan and Sicily show the strongest participation. The set of strongly participating countries strongly extends during the Energy crisis, covering most of Continental Europe. The participation is weak in the Nordics, the Iberian Peninsula, and, to a lesser degree, Poland and Estonia.

Notably, the Iberian Peninsula suffers a short period of participation in the early stage of the energy crisis and then reverts to levels from before the energy crisis (Fig. 8(c)). This may be related to the independence of Portugal and Spain from Russian gas. In the emergence of the energy crisis, prior to the Russian invasion, prices in European bidding zones may be mainly driven by the uncertainty of a gas shortage in Europe. This results in high volatility of the daily price patterns and therefore a strong participation of gas-dependent bidding zones. Once the actual impact of the energy crisis becomes evident, only the prices of countries with a high dependency on Russian gas stay highly volatile, reducing the participation of Portugal and Spain.

The observed spatial pattern largely coincides with the increase of the average prices during the energy crisis shown in Fig. 4(c). That is, the energy crisis did not just lead to an overall increase in the price level in certain countries. Instead, prices in these countries became much more susceptible to changes in the residual load and thus more volatile (cf. Ref.[33]). This effect was very similar in most of Continental Europe, boosting correlations and the importance of the respective PC.

The next-to-leading PCs are analyzed in Fig. 9. We observe that both PC2 and PC3 can be interpreted as North-South modes during the respective periods. Before the energy crisis, PC2 describes price differences between the Nordics and Southern Europe, in particular Sicily. We recall that average prices were higher in Southern Europe than in the Nordics, cf. Fig. 4. The analysis of the amplitude $a_2(t)$ of PC2 shows that this trend is strongly amplified in the early evening, while it is attenuated at noon and during the night when either solar generation is high or demand is low.

During the energy crisis, we still observe a strong North-South mode given by PC3, but with different characteristics. Sicily no longer stands out, but France now shows a similar pattern as Southern Europe. On the other side, Finland now stands out on the opposite side. The amplitude now assumes its minimum at noon and remains positive most of the night.

VI. CONCLUSION AND OUTLOOK

Electricity trading is essential for the coordination of generation and demand in liberalized electricity markets. The European electricity system is separated into several bidding zones, that are coupled to enable cross-border

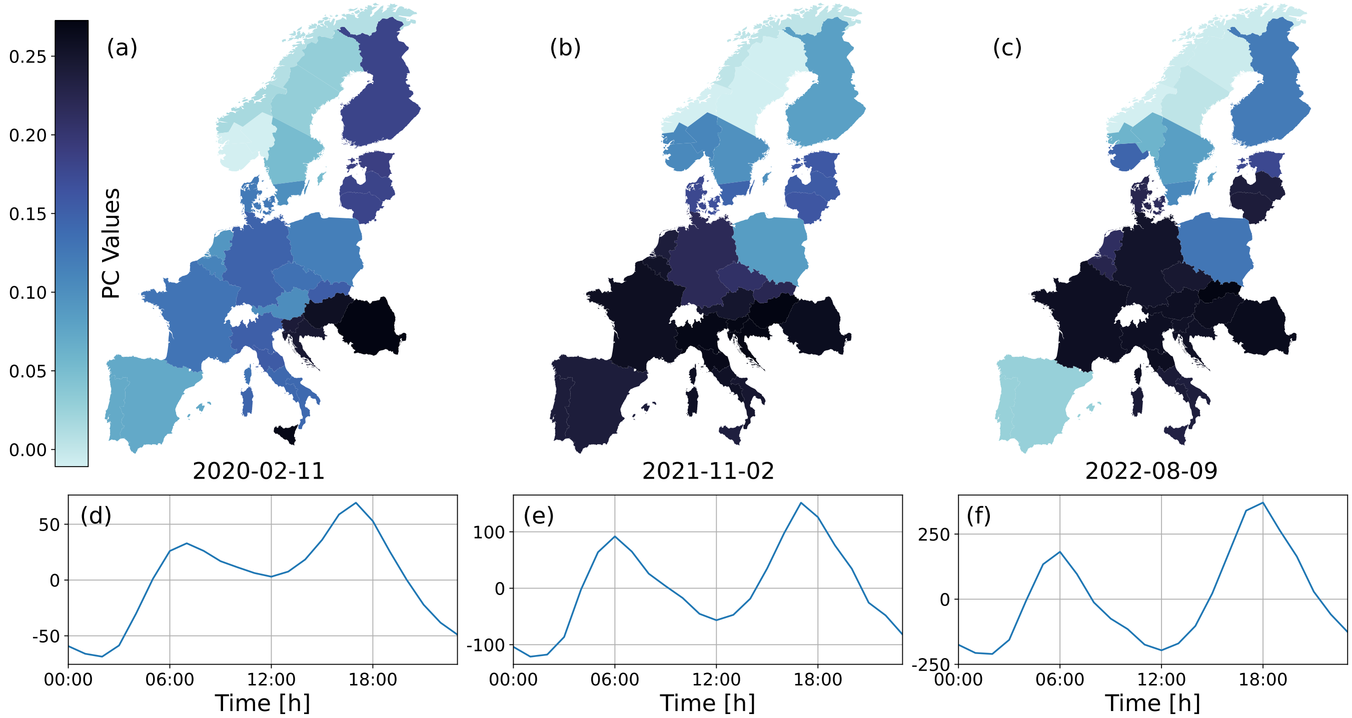

Figure 8. The leading principal component PC1 of the price vector $\boldsymbol{p}(t)$ and its temporal evolution. (a-c) The spatial pattern given by the components of the PC $\boldsymbol{c}_1$ is shown as a colormap. (d-f) For further interpretation, we compute the daily profile of the PC. For all hours of the day, we average the amplitude $a_1(t)$ over all days of the reference interval $[t_r - T, t_r]$. The PC is shown for three intervals: (a,d) before, (b,e) at the beginning and (c,f) during the energy crisis. The reference date t_r is given in the figure. This PC can be interpreted as the main response to changes in the residual load, leading to a characteristic daily pattern. The area of heavy participation in this pattern grows from the Balkan and Sicily before the crisis to most of Continental Europe during the crisis.

electricity trading. In this work, we have conducted an analysis of European electricity price time series with a focus on the emerging correlations and spatio-temporal patterns.

Prices in different bidding zones are typically strongly correlated for two reasons. First, all markets are subject to similar driving factors including daily patterns of the demand or similar changes in the availability of renewable power. Second, cross-border trading typically induces an averaging effect such that prices in two neighboring bidding zones become more similar. The emerging correlations between bidding zones show distinct spatial patterns, which become most obvious in the associated correlation network. Before 2021, six regional communities could be observed in this network: Western Scandinavia, the Baltic Sea, Poland, Sicily and two communities in Northern and Southern Continental Europe.

The European energy crisis starting in 2021 brought about significant changes both in the average electricity prices and in the spatio-temporal correlations and patterns, in particular the community structure. While correlations in Continental Europe increased, the communities in the Nordics fragmented. Stark changes were observed for France, Norway and the Iberian Peninsula. The southern Norwegian bidding zones became strongly coupled with German-Luxembourg and thus joined the Northern Continental community. France saw a strong increase in daily prices and turned from the Northern to the Southern European community, with increased correlations to Italy. In contrast, correlations to Spain diminished such that Portugal and Spain left the Southern Continental community.

While the European energy crisis is essentially connected to the Russian invasion of Ukraine and the soaring gas prices, not all observations can be linked to this reason. In particular, we conclude that the stark changes in Norway and France are strongly related to two simultaneous but independent events: The high unavailability of French nuclear power plants and the opening of the NordLink interconnector between Norway and Germany.

Typical spatio-temporal patterns were identified using Principal Component Analysis in a sliding window. We have shown that regional differences in electricity prices can be largely described with just a very few important principal components. The most important principal component describes the different susceptibility of prices to changes in supply and demand. Some bidding zones are heavily affected and thus have a much higher variability

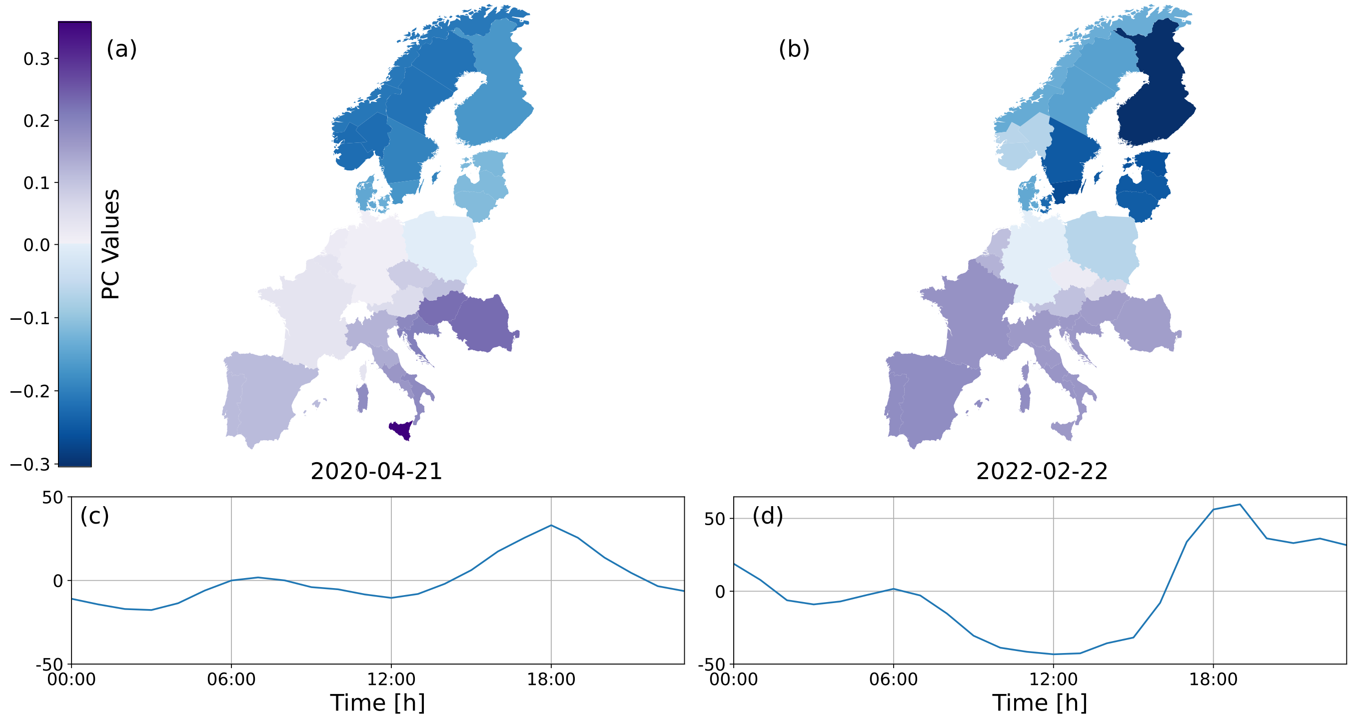

Figure 9. The next-to-leading principal components PC2 and PC3 of the price vector $\boldsymbol{p}(t)$ for two intervals (a,c) before and (b,d) during the energy crisis. The reference dates t_r are given in the figure. We show (a,b) the spatial pattern given by the components of the PC $\boldsymbol{c}_m$ and (c,d) the daily profile of the amplitudes $a_m(t)$. The second most important PC corresponds to a North-South mode, with Sicily being the driver before the energy crisis. During the energy crisis, the mode shifts to the Baltics.

of prices and a stronger daily profile. The next-to-leading principle component describes a North-South mode.

Both principal components underwent substantial changes during the energy crisis. As the dependency on Russian gas imports differs substantially between countries, so does the impact of the crisis. The leading principle component associated with the overall variability of prices changed its spatial shape during the crisis. The set of heavily affected countries grew from Italy and the Balkan to include large parts of Central Europe. Remarkably, Spain and Portugal were heavily affected only for a short period at the beginning of the crisis.

Our results shed light on the spatio-temporal interactions and dependencies of national electricity systems and markets. Cross-border trading is an important measure to balance the fluctuations of renewable power sources[8]. A strong development of cross-border interconnection capacities is foreseen in the next decade[49] such trading will become increasingly important.

Furthermore, our results may contribute to the growing field of electricity price forecasting[50]. Many current models focus on a single bidding zone. The observed strong correlations and patterns suggest that integrated modeling of all bidding zones is feasible and promising.

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AUTHOR DECLARATIONS

The authors have no conflicts to disclose.

DATA AVAILABILITY

The raw data that support the findings of this study are openly available at the ENTSO-E Transparency Platform[31] and Eurostat[35]. Data processing is described in detail in Appendix A.

Appendix A: Data sources and processing

The raw data analyzed in this article is openly available. Time series of day-ahead load and renewable generation forecasts, day-ahead electricity prices and cross-border exchanges, and unavailable nuclear generation have been obtained from the ENTSO-E transparency platform[31]. Notably, the ENTSO-E transparency platform includes both planned and unplanned unavailabilities of power plants. We consider only the planned unavailabilities because contingencies occurring on short notice should not affect trading one day ahead. Data is retrieved via the ENTSO-E restful API using the open source python package `entsoe-py`[51]. Data on aggregated imports and exports and natural gas dependency on Russia are available at Eurostat[35].

The raw data was processed at several points. Missing data for day-ahead forecasts of load, solar and wind generation was replaced by actual load, solar and wind generation. During a certain time period, the day-ahead prices for the bidding zones PL and RO were not denominated in EUR and were converted to EUR using a fixed exchange rate. The bidding zones of Italy changed on 2021-01-01. The region of Umbria was moved from IT-Centre-North to IT-Centre-South, the four production hubs IT-Brindisi, IT-Foggia, IT-Priolo and IT-Rossano were eliminated and IT-Calabria was added as a new bidding zone[52]. To account for this, data of the four hubs was aggregated with the bidding zone IT-South before 2021-01-01 and data from the bidding zones IT-Calabria and IT-South was aggregated after this date. Data of the bidding zones IT-Centre-North and IT-Centre-South remained unchanged.

REFERENCES

[1] E. Van der Vleuten and V. Lagendijk, "Transnational infrastructure vulnerability: The historical shaping of the 2006 european "blackout"," Energy Policy **38**, 2042–2052 (2010).

[2] D. Witthaut, F. Hellmann, J. Kurths, S. Kettemann, H. Meyer-Ortmanns, and M. Timme, "Collective nonlinear dynamics and self-organization in decentralized power grids," Reviews of Modern Physics **94**, 015005 (2022).

[3] J. Kruse, E. Cramer, B. Schäfer, and D. Witthaut, "Physics-informed machine learning for power grid frequency modeling," PRX Energy **2**, 043003 (2023).

[4] P. Kundur, "Power system stability," Power system stability and control **10**, 7–1 (2007).

[5] T. Jamasb and M. Pollitt, "Electricity market reform in the european union: review of progress toward liberalization & integration," The Energy Journal **26** (2005).

[6] C. Han, H. Hilger, E. Mix, P. C. Böttcher, M. Reyers, C. Beck, D. Witthaut, and L. Rydin Gorjão, "Complexity and persistence of price time series of the european electricity spot market," PRX Energy **1**, 013002 (2022).

[7] R. Huisman, C. Huurman, and R. Mahieu, "Hourly electricity prices in day-ahead markets," Energy Economics **29**, 240–248 (2007).

[8] D. P. Schlachtberger, T. Brown, S. Schramm, and M. Greiner, "The benefits of cooperation in a highly renewable European electricity network," Energy **134**, 469–481 (2017).

[9] B. Schäfer, C. Beck, K. Aihara, D. Witthaut, and M. Timme, "Non-gaussian power grid frequency fluctuations characterized by lévy-stable laws and superstatistics," Nature Energy **3**, 119–126 (2018).

[10] L. Rydin Gorjão, R. Jumar, H. Maass, V. Hagenmeyer, G. C. Yalcin, J. Kruse, M. Timme, C. Beck, D. Witthaut, and B. Schäfer, "Open database analysis of scaling and spatio-temporal properties of power grid frequencies," Nature Communications **11**, 6362 (2020).

[11] P. C. Böttcher, L. Rydin Gorjão, C. Beck, R. Jumar, H. Maass, V. Hagenmeyer, D. Witthaut, and B. Schäfer, "Initial analysis of the impact of the ukrainian power grid synchronization with continental europe," Energy Advances **2**, 91–97 (2023).

[12] M. Titz, S. Pütz, and D. Witthaut, "Identifying drivers and mitigators for congestion and redispatch in the german electric power system with explainable ai," Applied Energy **356**, 122351 (2024).

[13] M. Yagi and S. Managi, "The spillover effects of rising energy prices following 2022 Russian invasion of Ukraine," Economic Analysis and Policy **77**, 680–695 (2023).

[14] A. Goldthau and S. Tagliapietra, "Energy crisis: five questions that must be answered in 2023," Nature **612**, 627–630 (2022).

[15] Bundesnetzagentur, "Definitionen der marktakteuere und deren daten," `https://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Sachgebiete/Energie/Unternehmen_Institutionen/DatenaustauschUndMonitoring/MaStR/DefinitionenMarktakteuere.pdf`, accessed on 2024-01-29.

[16] I. Staffell and S. Pfenninger, "The increasing impact of weather on electricity supply and demand," Energy **145**, 65–78 (2018).

[17] P. Shinde and M. Amelin, "A literature review of intraday electricity markets and prices," in *2019 IEEE Milan PowerTech* (2019) pp. 1–6.

[18] G. Wolff and S. Feuerriegel, "Short-term dynamics of day-ahead and intraday electricity prices," International Journal of Energy Sector Management **11**, 557–573 (2017).

[19] J. Kühling, P. Knapp, D. Kollmann, T. Nöcker, and A. Wamback, "8th energy sector report of the monopolies commission," Tech. Rep. (Monopolkommission, 2021) `https://www.monopolkommission.de/images/PDF/SG/chapter-3-competition-between-electricity-exchanges.pdf`.

[20] EPEX SPOT, "Basics of the Power Market," `https://www.epexspot.com/en/basicspowermarket`, accessed on 2024-01-07.

[21] Nord Pool, "Day-ahead market," `https://www.nordpoolgroup.com/en/the-power-market/Day-ahead-market/`, accessed on 2024-01-07.

[22] European Union Agency for the Cooperation of

Energy Regulators (ACER), “Bidding Zone Review,” https://www.acer.europa.eu/electricity/market-rules/capacity-allocation-and-congestion-management/bidding-zone-review, accessed on 2024-01-07.

[23] Nominated Electricity Market Operators Committee, “Euphemia public description,” https://www.nemo-committee.eu/assets/files/euphemia-public-description.pdf, accessed on 2024-01-29.

[24] European Network of Transmission System Operators for Electricity (ENTSO-E), “Single Day-ahead Coupling (SDAC),” https://www.entsoe.eu/network_codes/cacm/implementation/sdac/, accessed on 2024-01-07.

[25] N-SIDE, “N-SIDE makes pan-European, single-day-ahead coupling possible with EUPHEMIA,” https://energy.n-side.com/resources/case-studies/euphemia, accessed on 2023-02-09.

[26] ALL NEMO COMMITTEE, “Euphemia Public Describtion,” Tech. Rep. (2020) https://www.nemo-committee.eu/assets/files/euphemia-public-description.pdf.

[27] F. Sensfuß, M. Ragwitz, and M. Genoese, “The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in germany,” Energy policy **36**, 3086–3094 (2008).

[28] M. G. Lijesen, “The real-time price elasticity of electricity,” Energy Economics **29**, 249–258 (2007).

[29] J. Trebbien, L. Rydin Gorjão, A. Praktiknjo, B. Schäfer, and D. Witthaut, “Understanding electricity prices beyond the merit order principle using explainable AI,” Energy and AI **13**, 100250 (2023).

[30] K. Van den Bergh and E. Delarue, “Cycling of conventional power plants: Technical limits and actual costs,” Energy Conversion and Management **97**, 70–77 (2015).

[31] European Network of Transmission System Operators for Electricity (ENTSO-E), “Entso-e transparency plattform,” https://transparency.entsoe.eu/dashboard/show, accessed on 2024-01-24.

[32] L. Pagnier and P. Jacquod, “How fast can one overcome the paradox of the energy transition? A physico-economic model for the European power grid,” Energy **157**, 550–560 (2018).

[33] J. Trebbien, S. Pütz, B. Schäfer, H. S. Nygård, L. Rydin Gorjão, and D. Witthaut, “Probabilistic forecasting of day-ahead electricity prices and their volatility with LSTMs,” arXiv preprint arXiv:2310.03339 (2023).

[34] H. Hilger, D. Witthaut, M. Dahmen, L. Rydin Gorjão, J. Trebbien, and E. Cramer, “Multivariate scenario generation of day-ahead electricity prices using normalizing flows,” arXiv preprint arXiv:2311.14033 (2023).

[35] Eurostat, “Energy statistics – quantities, annual data,” https://ec.europa.eu/eurostat/databrowser/explore/all/envir?lang=en&subtheme=nrg.nrg_quant.nrg_quanta&display=list&sort=category, accessed on 2024-01-18.

[36] Statnett, “Nordlink – new subsea interconnector between norway and germany,” https://www.statnett.no/en/our-projects/interconnectors/nordlink/, accessed on 2024-01-24.

[37] M. Anvari, E. Proedrou, B. Schäfer, C. Beck, H. Kantz, and M. Timme, “Data-driven load profiles and the dynamics of residential electricity consumption,” Nature Communications **13**, 4593 (2022).

[38] J. Többen and T. Schröder, “A maximum entropy approach to the estimation of spatially and sectorally disaggregated electricity load curves,” Applied Energy **225**, 797–813 (2018).

[39] D. Heide, L. Von Bremen, M. Greiner, C. Hoffmann, M. Speckmann, and S. Bofinger, “Seasonal optimal mix of wind and solar power in a future, highly renewable europe,” Renewable Energy **35**, 2483–2489 (2010).

[40] A. A. Tsonis and P. J. Roebber, “The architecture of the climate network,” Physica A: Statistical Mechanics and its Applications **333**, 497–504 (2004).

[41] T. Mizuno, H. Takayasu, and M. Takayasu, “Correlation networks among currencies,” Physica A: Statistical Mechanics and its Applications **364**, 336–342 (2006).

[42] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, “Fast unfolding of communities in large networks,” Journal of statistical mechanics: theory and experiment **2008**, P10008 (2008).

[43] A. A. Hagberg, D. A. Schult, and P. J. Swart, “Exploring network structure, dynamics, and function using networkx,” in *Proceedings of the 7th Python in Science Conference*, edited by G. Varoquaux, T. Vaught, and J. Millman (Pasadena, CA USA, 2008) pp. 11 – 15.

[44] S. Pütz, B. Schäfer, D. Witthaut, and J. Kruse, “Revealing interactions between hvdc cross-area flows and frequency stability with explainable ai,” Energy Informatics **5**, 46 (2022).

[45] European Commision, “Estonia, Latvia & Lithuania agree to synchronise their electricity grids with the European grid by early 2025,” https://energy.ec.europa.eu/news/estonia-latvia-lithuania-agree-synchronise-their-electricity-grids-european-grid-early-2025-2023-08-03_en, accessed on 2024-01-29.

[46] Réseau de Transport d’Electricité (RTE), “Annual electricity review 2022,” https://analysesetdonnees.rte-france.com/en/electricity-review-keyfindings, accessed on 2024-01-29.

[47] C. M. Bishop, *Pattern recognition and machine learning* (Springer, New York, NY, 2006).

[48] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The elements of statistical learning: data mining, inference, and prediction* (Springer, New York, 2009).

[49] ENTSO-E, “Ten-Year Network Development Plan 2020 (TYNDP 2020),” https://eepublicdownloads.blob.core.windows.net/public-cdn-container/tyndp-documents/TYNDP2020/Forconsultation/

TYNDP2020_Report_forconsultation.pdf (2020), accessed on 2024-01-31.
[50] A. Jędrzejewski, J. Lago, G. Marcjasz, and R. Weron, "Electricity price forecasting: The dawn of machine learning," IEEE Power and Energy Magazine **20**, 24–31 (2022).
[51] J. Pecinovsky, F. Boerman, "entsoe-py," https://github.com/EnergieID/entsoe-py, accessed on 2024-01-29.
[52] Trasmissione Elettricità Rete Nazionale (Terna), "The new electricity market zones: what you need to know," https://lightbox.terna.it/en/insight/new-electricity-market-zones, accessed on 2024-01-24.