1. **Introduction**

The Austrian electricity system is characterized by a high share of renewable energy sources, seasonal variability, and close integration with neighboring European power markets. Hydropower, wind, and solar generation play a key role in shaping electricity prices, load patterns, and cross-border energy exchanges. As renewable penetration increases, understanding the interactions between generation, demand, market prices, and transmission flows becomes increasingly important for system operation and market efficiency.

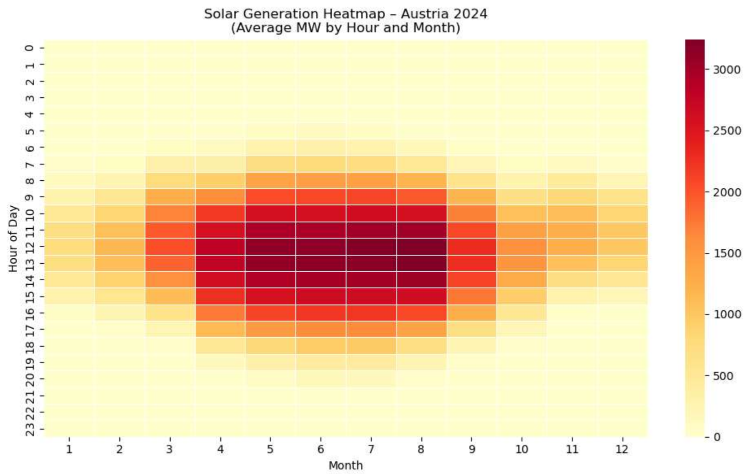
This project presents a comprehensive data-driven analysis of Austria's electricity system using hourly time-series data from 2024. By combining day-ahead market prices, electricity load, generation by production type, and cross-border physical flows, the study investigates how renewable generation affects market prices, how demand evolves over time, and how Austria exchanges electricity with neighboring countries. The analysis aims to provide quantitative insights into the balance and interdependence of the Austrian power system and to demonstrate the application of statistical and visualization techniques to real-world energy data.

2. Electricity Prices and Renewable Generation

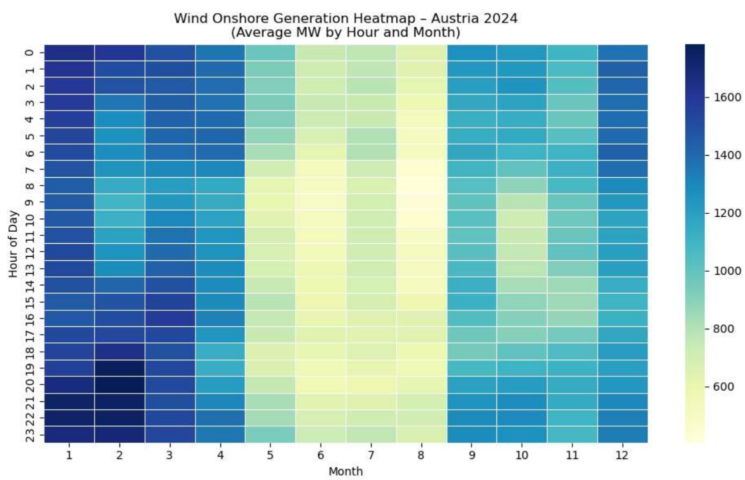
As shown in figure 1, the solar generation heatmap shows a seasonal pattern, as expected for photovoltaic production. Generation is zero during night hours and peaks between 10:00 and 15:00, with the highest values occurring from May to August. Summer midday production reaches its maximum levels, reflecting longer daylight hours and higher solar irradiance. In contrast, winter months (November–January) exhibit substantially lower output across all hours, indicating limited solar contribution during this period.

The wind generation heatmap displays a different behavior compared to solar. Wind production is less dependent on daytime hours and is present throughout the entire day. Seasonal variability is evident, with higher average wind generation during winter and early spring months (January–March and October–December) and lower output during summer months (June–August). Additionally, wind generation tends to be stronger during nighttime and early morning hours. The day-ahead electricity price heatmap reveals clear daily and seasonal price structures. Prices tend to be lowest during midday hours, particularly in spring and summer months, Conversely, evening peak hours (17:00–21:00) show significantly higher prices, especially during autumn and winter.

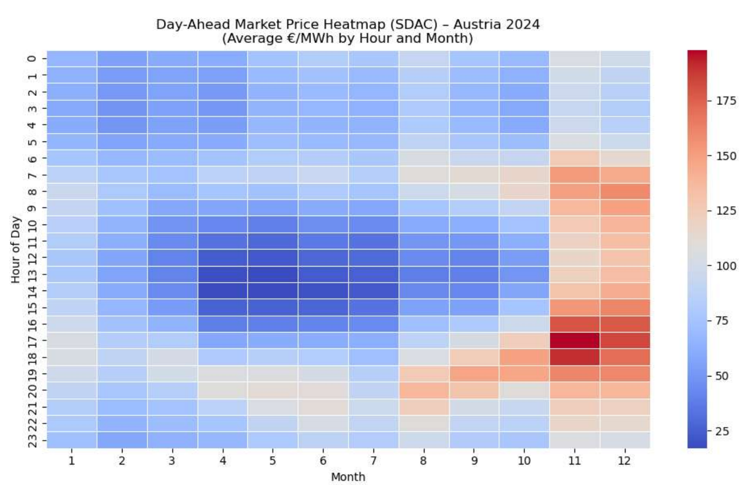
As illustrated in figure 2, the scatter plot shows a negative relationship between solar generation and the day-ahead market price (SDAC). As solar output increases, electricity prices decline, which is further emphasized by the downward-sloping regression line. At low or zero solar generation, prices exhibit high variability and can reach very high levels, indicating stronger reliance on dispatchable and often higher-cost generation. In contrast, high solar generation levels (above 3000 MW) are associated with significantly lower prices and occasional negative price events. The wind generation scatter plot also indicates a negative relationship with day-ahead prices, although the effect is weaker and more dispersed than for solar generation. Prices tend to decrease as wind output increases, but substantial price variability remains even at high generation levels.


Solar Generation Heatmap – Austria 2024
(Average MW by Hour and Month)
Hour of Day
Month
0
500
1000
1500
2000
2500
3000

(a)

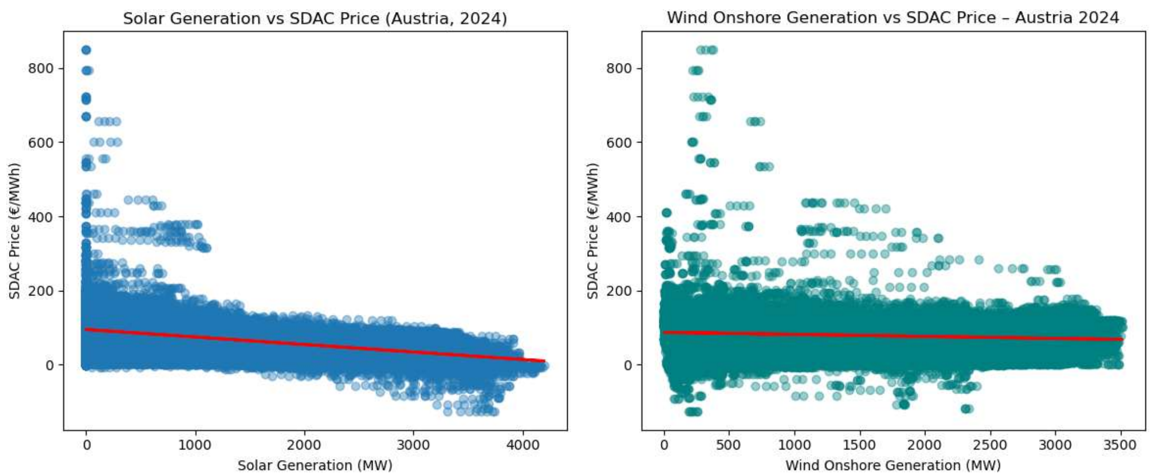

Wind Onshore Generation Heatmap – Austria 2024
(Average MW by Hour and Month)
Hour of Day
Month
600
800
1000
1200
1400
1600

(b)


Day-Ahead Market Price Heatmap (SDAC) – Austria 2024
(Average €/MWh by Hour and Month)
Hour of Day
Month
25
50
75
100
125
150
175

(c)

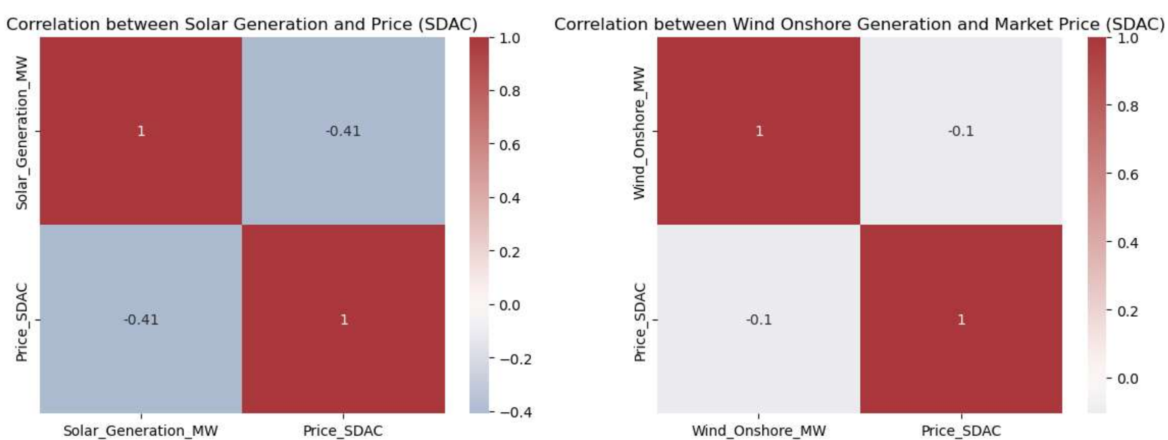
Figure 1: Heatmap of a) solar generation, b) wind generation and c) day-ahead market price



(a) (b)

Figure 2: The scatter plot of a) solar generation and b) wind generation with day-ahead market price

The correlation matrix indicates a moderate negative correlation between solar generation and the day-ahead market price (SDAC), with a Pearson correlation coefficient of −0.41 in figure 3. The magnitude of the correlation suggests that solar power has a meaningful effect. In contrast, the correlation between wind generation and the day-ahead market price is weakly negative, with a coefficient of −0.10. This low absolute value indicates that wind generation alone has a limited direct impact on market prices when considered in isolation. This outcome reflects the more irregular temporal distribution of wind generation and its weaker alignment with peak demand hours.



(a) (b)

Figure 3: Correlation between a) solar generation and b) wind generation with day-ahead market price

The histogram of day-ahead electricity prices in figure 4 shows a right-skewed distribution with most prices concentrated between approximately 50 and 150 €/MWh. A long right tail indicates the occurrence of price spikes exceeding 500 €/MWh. The distribution also extends into negative price territory, reflecting periods of excess generation.

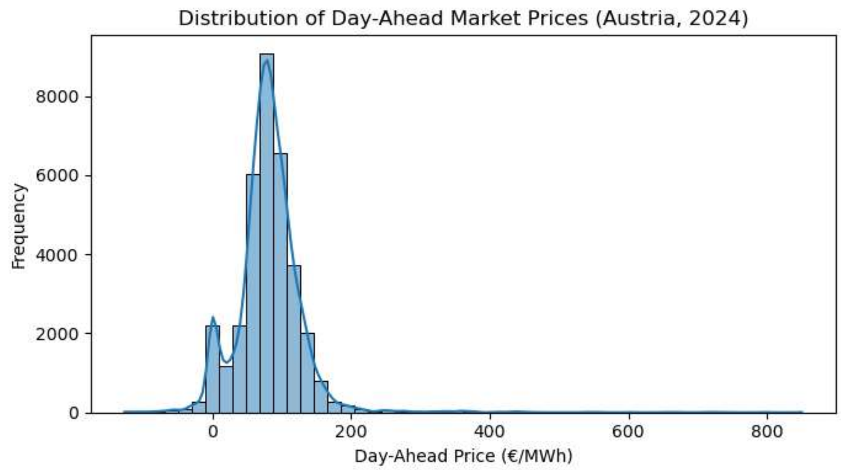


Figure 4: The histogram of day-ahead electricity prices

Figure 5 shows the monthly redispatching costs in Austria for 2024. Redispatching costs exhibit a seasonal pattern, with relatively low values during winter months and significantly higher costs in late spring and summer. Costs increase steadily from January to March, followed by a temporary decline in April. A rise is observed from May to September, with a peak in August, where redispatching costs reach their maximum level of approximately 13–14 million EUR. After September, costs decline sharply and remain low during October to December.

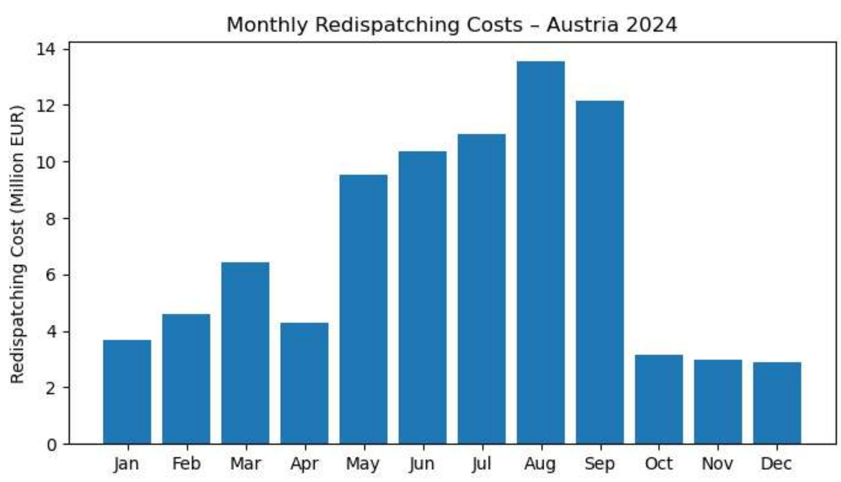


Figure 5: Monthly redispatching costs for 2024

In figure 6, the standardized (Z-score) time-series comparison between solar generation and market prices reveals an inverse co-movement over the year. During spring and summer months, positive deviations in solar generation consistently correspond to negative deviations in market prices. In contrast, during autumn and winter, when solar output is below average, price deviations become positive and more volatile.

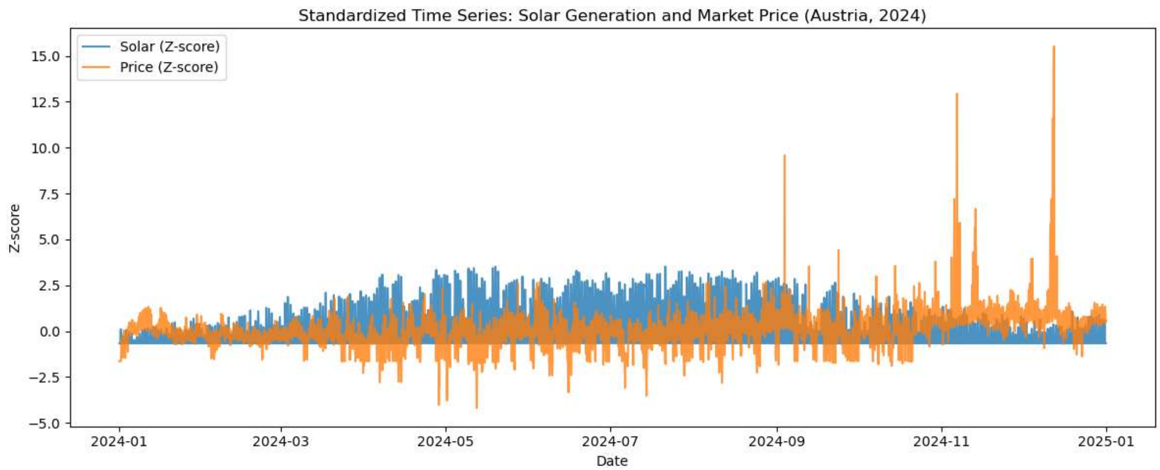


Figure 6: The z-score of market prices compared with solar generation

The figure 7 compares the raw hourly day-ahead electricity prices with the prices smoothed using a Savitzky–Golay filter**.** The raw price series exhibits frequent spikes, sharp drops, and occasional negative price events. The Savitzky–Golay filtered series reduces high-frequency noise while preserving the overall shape and local extrema of the original signal. Importantly, price spikes observed in the raw data remain visible, though attenuated, in the filtered series, indicating that these events are structurally meaningful rather than random noise. This confirms that the filter smooths short-term variability without eliminating relevant information.

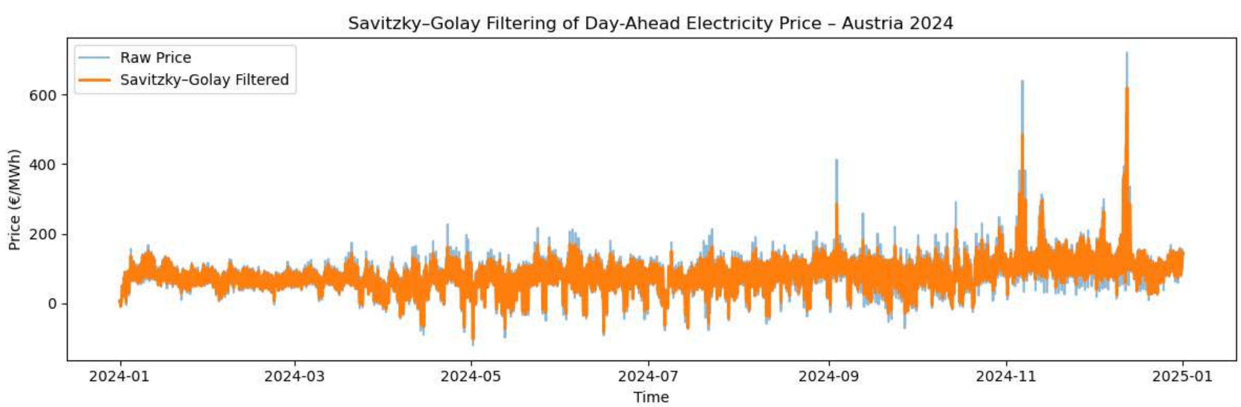


Figure 7: Savitzky–Golay filter of day-ahead electricity prices

Figure 8 presents the final outlier detection results for Austria's day-ahead electricity prices, combining spike detection and a rolling Z-score method. The raw price series exhibits volatility throughout the year, with price spikes and occasional negative price events. The identified outliers, highlighted in red, correspond to hours where price deviations significantly exceed local statistical norms. Outliers are sparsely distributed during the first half of the year. In contrast, a concentration of extreme price events appears in autumn and early winter, particularly during November and

December. Negative price outliers are also detected. Importantly, the applied detection approach distinguishes structural market events from random noise, ensuring that only significant deviations are flagged.

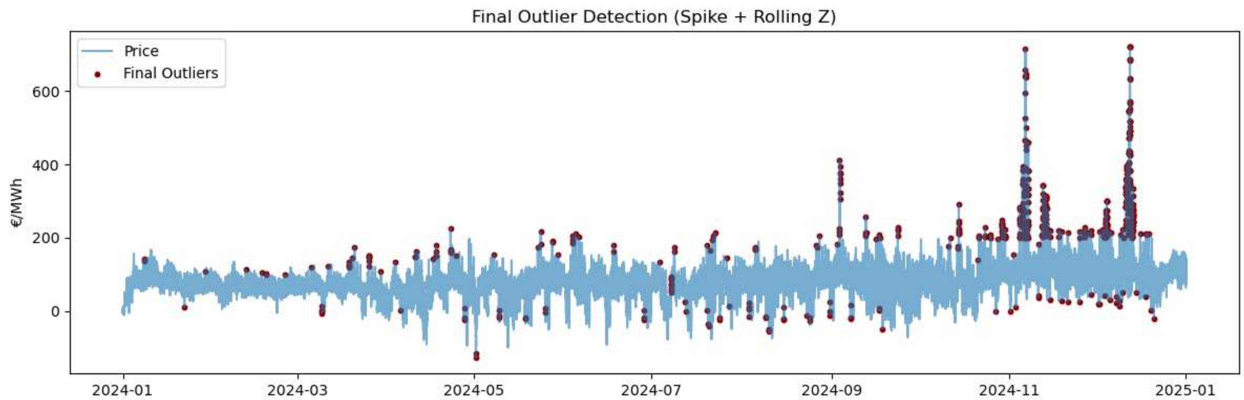
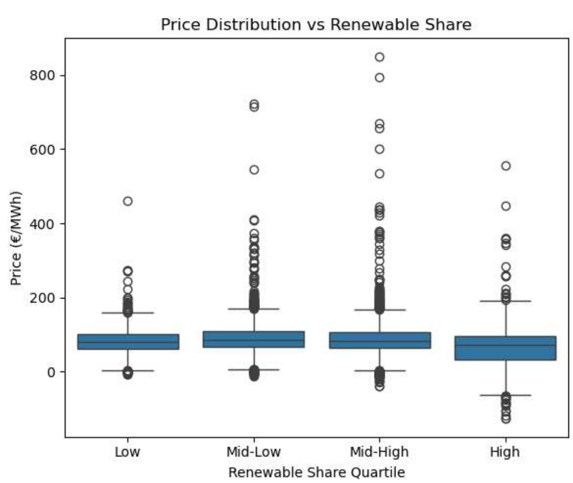
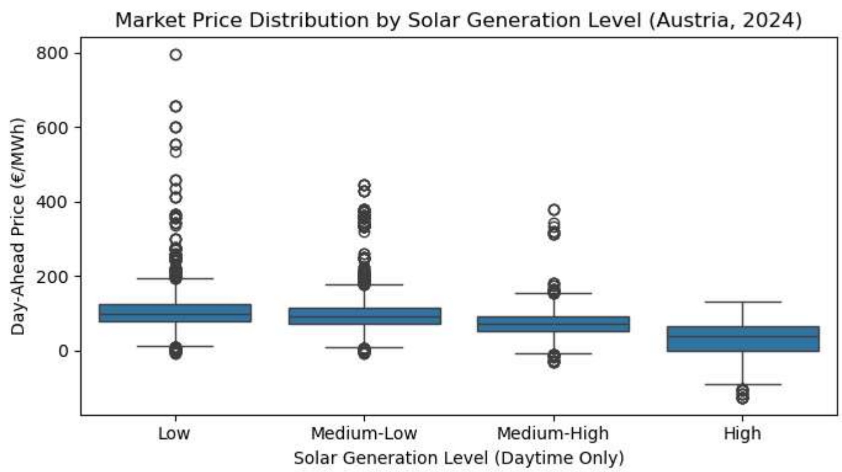


Figure 8: Outlier detection combining spike detection and a rolling Z-score

In figure 9, the boxplot shows day-ahead electricity price distributions grouped by renewable energy share (RES share) quartiles. As renewable penetration increases, prices become more predictable and stable. Even in High RES, there are some extreme price outliers (system stress). However, frequency and density of spikes are lower. Therefore, high renewable shares mitigate but do not eliminate scarcity events. The boxplot analysis further illustrates the relationship between solar generation and market prices. As solar generation increases from low to high levels, both the median price and the interquartile range decrease significantly.



(a)



(b)

Figure 9: The boxplot of day-ahead electricity price distributions a) by RES share and b) solar generation

Figure 10 illustrates the classification of Austria's daily electricity system states in 2024 based on average RES share and average day-ahead electricity price. Three system states are identified: Normal, High RES / Surplus, and High Price / Stress. Days classified as High RES / Surplus are concentrated at higher RES shares, typically above approximately 0.40–0.45, and are associated with lower average prices, often below 80 €/MWh. The Normal system state occupies an intermediate region, with moderate RES shares and prices generally between 50 and 120 €/MWh. In contrast, High Price / Stress days are characterized by low renewable shares, often below 0.35, combined with elevated prices, frequently exceeding 120 €/MWh and reaching extreme values above 300 €/MWh.

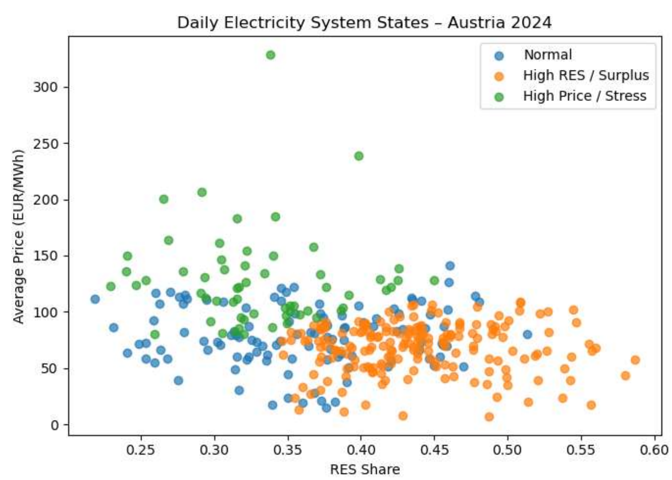
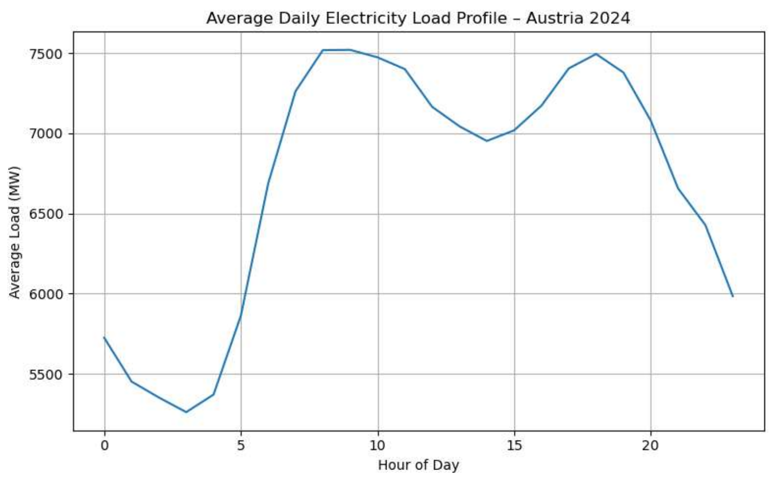


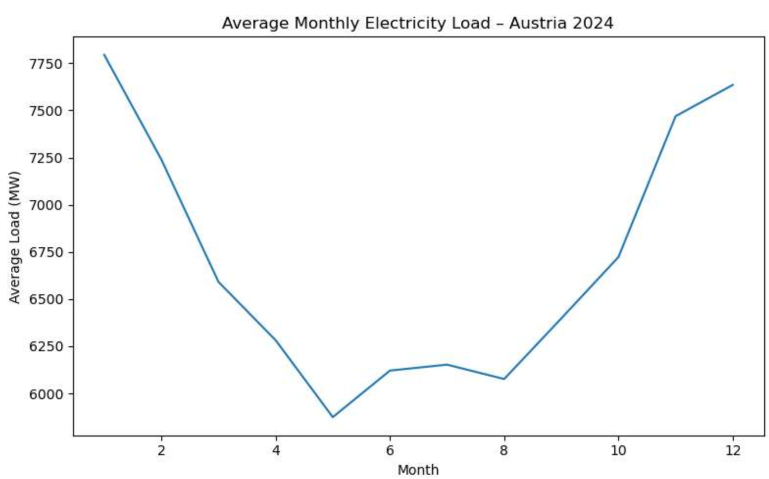
Figure 10: Clustering based on RES share and average day-ahead electricity price

3. Load Patterns and Electricity Price

As shown in figure 11, the average daily electricity load profile exhibits a diurnal pattern. Load levels are lowest during the night and early morning hours (approximately 02:00–04:00). Demand rises sharply from early morning, reaching a morning peak around 08:00–10:00. Following a slight midday dip, a second evening peak occurs between 17:00 and 19:00. After 20:00, electricity demand steadily declines toward nighttime levels. The monthly load profile shows a seasonal variation. Electricity demand is highest during winter months, with peaks in January, November, and December. In contrast, the lowest average load occurs during late spring and summer, particularly in May. A gradual increase in demand from late summer into autumn is evident, marking the transition toward the winter heating season.



(a)



(b)

Figure 11: a) Daily electricity load profile and b) monthly electricity load profile

In figure 12, the boxplot illustrates the distribution of weekly average electricity load for each month of 2024. Winter months (January**,** November**,** and December) exhibit the highest median load levels and the largest dispersion, indicating both elevated demand and strong week-to-week variability. The presence of high outliers during these months suggests occasional weeks of exceptional demand, likely driven by cold spells. Spring months (March and April) show a gradual decline in both median load and variability. The lowest weekly average loads occur during late spring and summer, particularly in May through August, where medians are minimal and interquartile ranges are narrow. From September onward, both the median load and variability increase steadily. October already shows higher dispersion, acting as a transitional month toward winter demand levels.

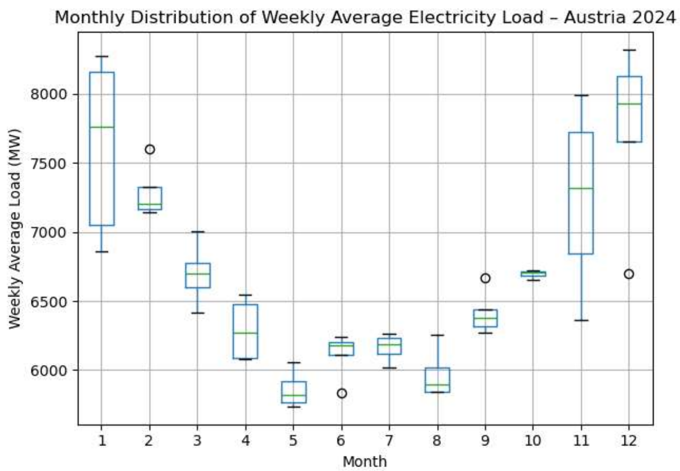


Figure 12: The boxplot of monthly distribution of weekly average electricity load for 2024

The time-series comparison of weekly average electricity load and day-ahead prices shows seasonal co-movement in figure 13. High load levels during winter weeks (January and November–December) coincide with elevated market prices, while summer weeks with lower demand are associated with lower prices. The scatter plot with regression line confirms a positive relationship between weekly average load and market price. As electricity demand increases, prices tend to rise, reflecting the activation of higher-cost generation units in the merit order. While the relationship is not perfectly linear, the upward slope demonstrates that demand is a key driver of price formation at the weekly timescale. The observed dispersion around the regression line suggests that load alone does not fully determine prices. The boxplot further illustrates how price levels vary across load regimes.

- Low-load weeks are characterized by lower median prices and limited variability.
- Medium-load weeks show higher median prices and increased dispersion.
- High-load weeks exhibit the highest median prices and the widest price spread, including extreme values.

This widening distribution at high load levels indicates heightened market sensitivity and increased exposure to price spikes during periods of system stress.

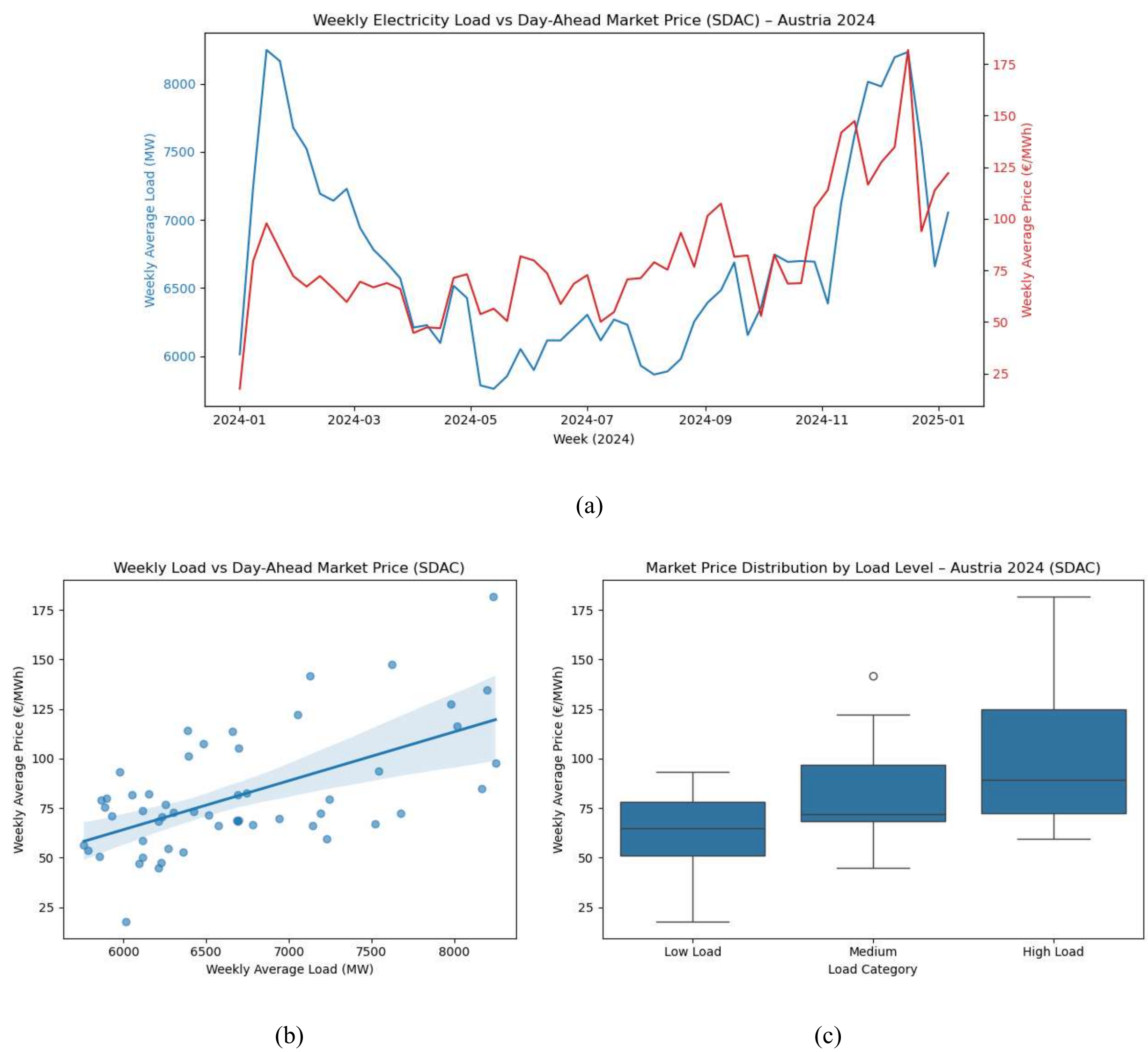
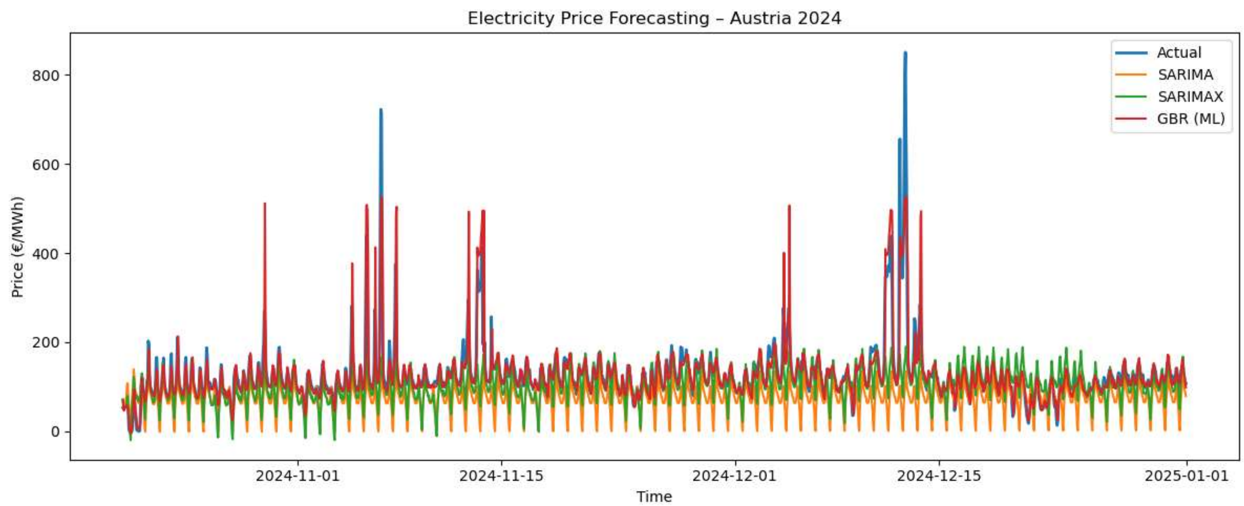


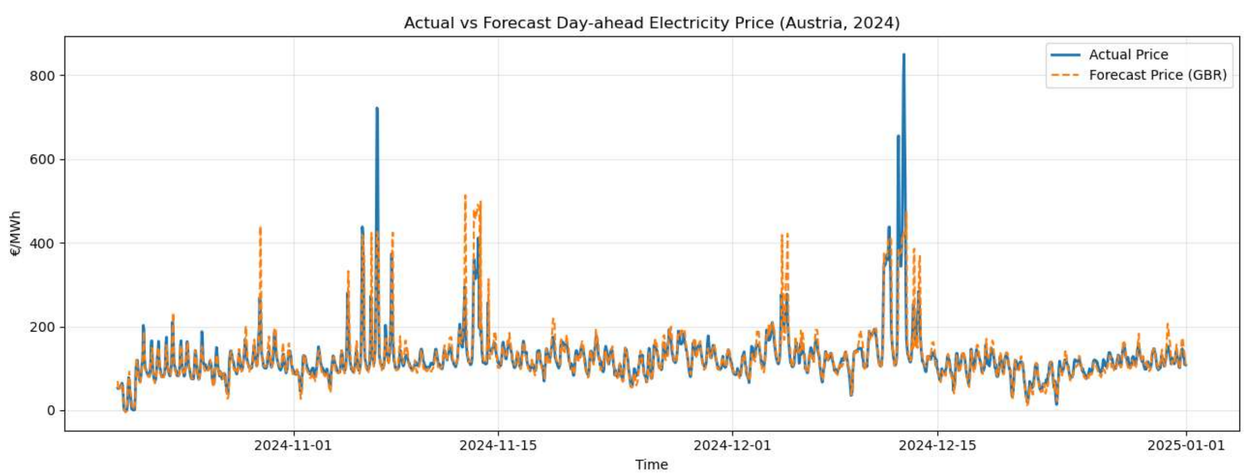
Figure 13: a) Time series, b) the scatter plot with regression and c) the boxplot of weekly electricity load and day-ahead market price

Figure 14 compares actual day-ahead electricity prices with forecasts produced by three different models: SARIMA, SARIMAX, and a Gradient Boosting Regressor (GBR) machine-learning model. The SARIMA model captures the regular temporal structure of electricity prices, such as daily and weekly seasonality. However, it systematically underestimates price volatility and fails to reproduce extreme price spikes. The forecasts appear overly smooth and occasionally dip into unrealistic negative values, indicating that purely autoregressive models struggle to represent sudden market shocks and non-linear behavior.

By including exogenous variables such as load, the SARIMAX model improves upon SARIMA by producing more responsive forecasts and better alignment with medium-term price movements. Nevertheless, extreme price spikes remain largely underpredicted. This suggests that while exogenous drivers improve average performance, linear time-series models still have limited ability to capture rare stress events. The GBR model shows the best overall performance, particularly in capturing price spikes and high-volatility periods. Its forecasts track the magnitude and timing of extreme price events more closely than the statistical models. Table 1 compares the forecasting accuracy of three models for day-ahead electricity prices using MAE and RMSE metrics.



(a)



(b)

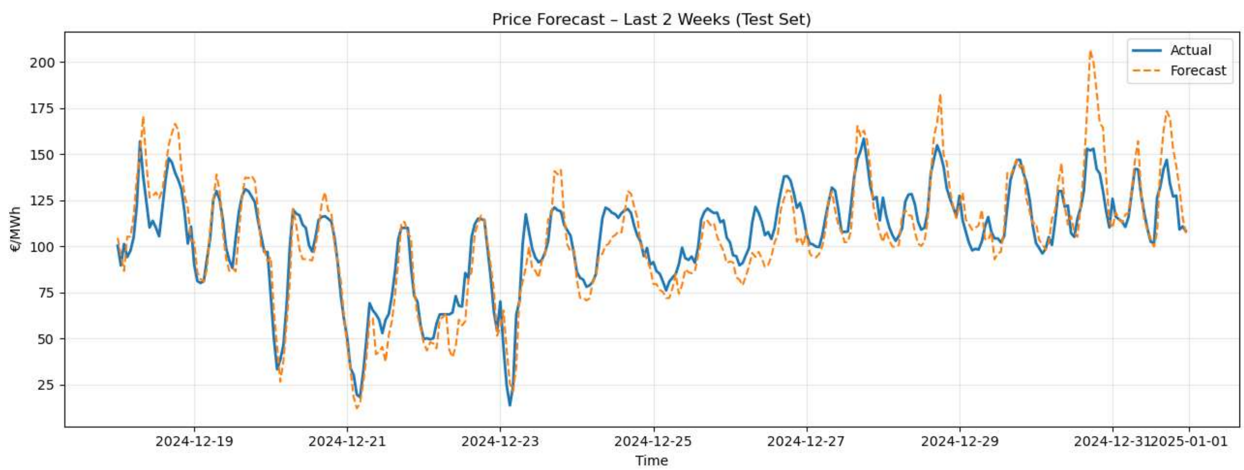
Figure 14: a) Day-ahead electricity prices with forecasts produced by three different models: SARIMA, SARIMAX, and GBR and b) GBR model specifically

Table 1: Forecast results of SARIMA, SARIMAX, and GBR

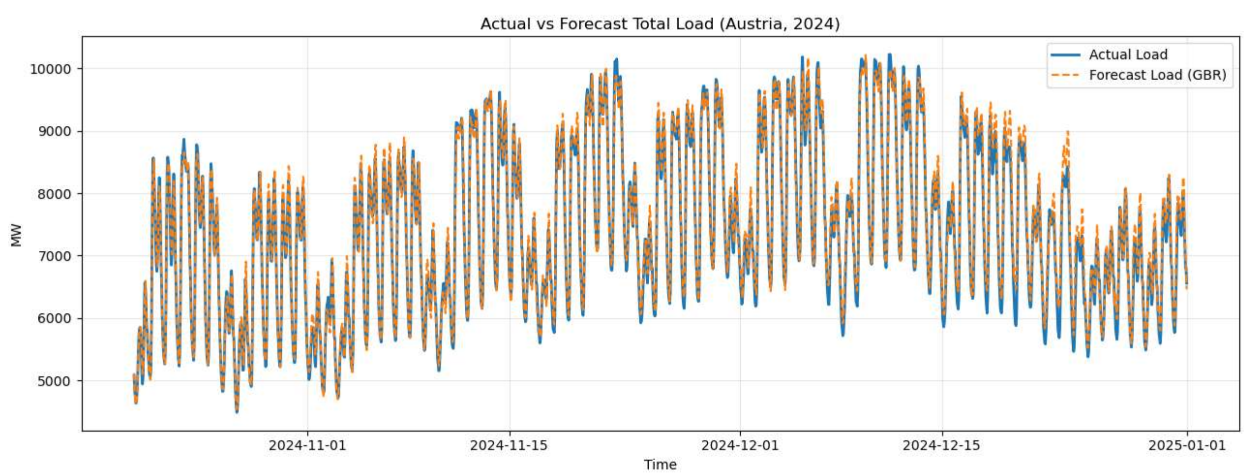
Model	MAE (€/MWh)	RMSE (€/MWh)
SARIMA	53.9	82.0

SARIMAX	33.5	62.3
GBR	13.4	34.4

Figure 15 compares actual day-ahead prices with GBR model forecasts over the final two weeks of the test period. The forecast closely follows the intra-day and daily price cycles, indicating that the model successfully captures short-term seasonality and baseline price dynamics. However, deviations are visible during sharp price movements, where the forecast tends to slightly overestimate peak prices and underestimate some rapid downward corrections. The second figure shows actual and forecast total electricity load over the same period. The forecasted load almost perfectly overlaps with the observed values, accurately reproducing daily demand cycles, weekday–weekend patterns, and seasonal trends. Deviations are minor and mainly occur during abrupt demand changes, but these errors remain small relative to the total load level. The model achieves a Mean Absolute Error (MAE) of 142 MW and a Root Mean Squared Error (RMSE) of 185 MW.



(a)



(b)

Figure 15: Forecasts produced by GBR model: a) day-ahead electricity prices in last two weeks b) actual and total load

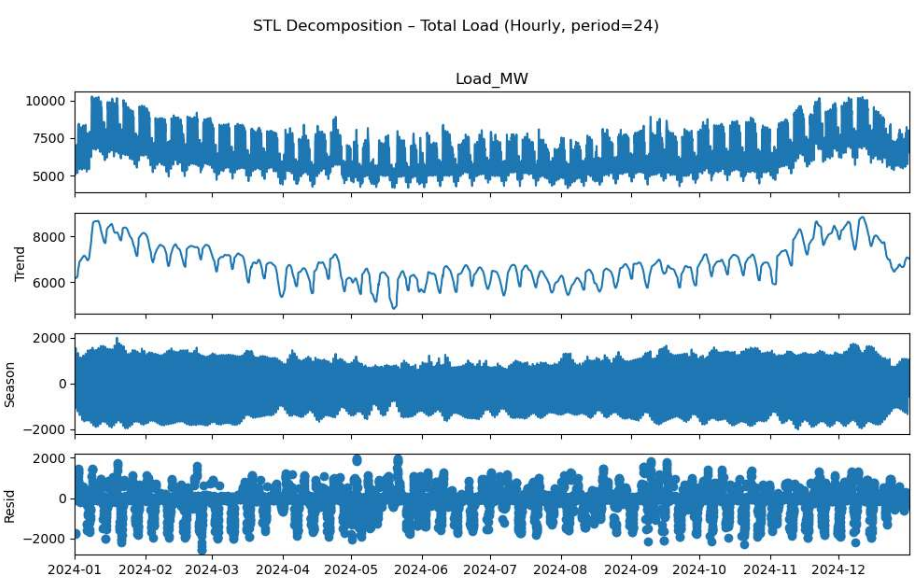
As illustrated in figure 16, the STL decomposition of hourly total load separates the series into trend, seasonal, and residual components. The trend component reveals a clear annual pattern. The seasonal component captures a daily cycle, with systematic deviations of up to ±2000 MW around the mean. The residual component remains relatively centered around zero, with larger deviations occurring during system stress periods. The STL decomposition of day-ahead prices shows a markedly different structure. While a medium-term trend is visible, the seasonal component is weaker, and more irregular compared to load. Price seasonality still exhibits a daily pattern, but its amplitude varies substantially over time. The residual component contains large spikes, especially in late autumn and winter. This confirms that electricity prices are more volatile and less predictable than load.

As shown in figure 16(c-f), the comparison of daily seasonal components between winter and summer reveals structural differences.

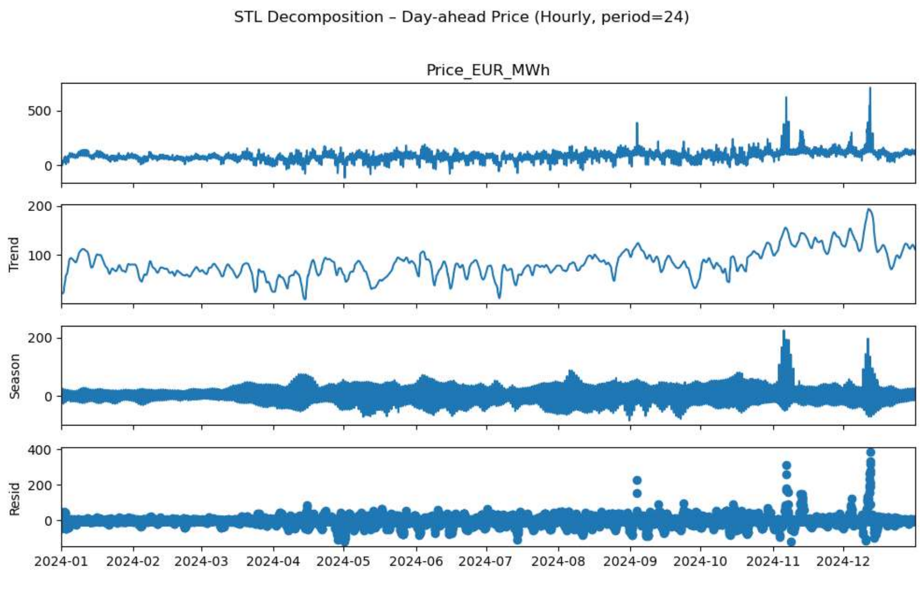
- Load seasonality: Winter exhibits deeper nighttime troughs and higher morning and evening peaks. Summer load profiles are flatter, with reduced peak amplitudes.
- Price seasonality: Summer prices show a midday price depression followed by higher evening prices. In winter, this midday dip is largely absent, and price peaks shift toward morning and evening hours.

The weekday–weekend comparison highlights behavioral effects.

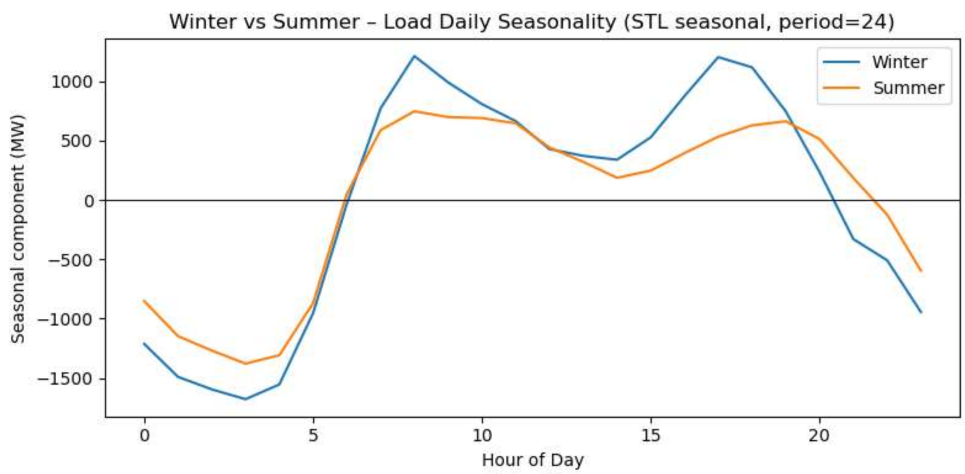
- Load profiles: Weekdays exhibit significantly higher demand throughout the day, especially during working hours, with morning and evening peaks. Weekend load is consistently lower and smoother.
- Price profiles: Day-ahead prices closely follow load behavior: weekday prices are higher and more volatile, while weekend prices are lower, particularly during midday hours.



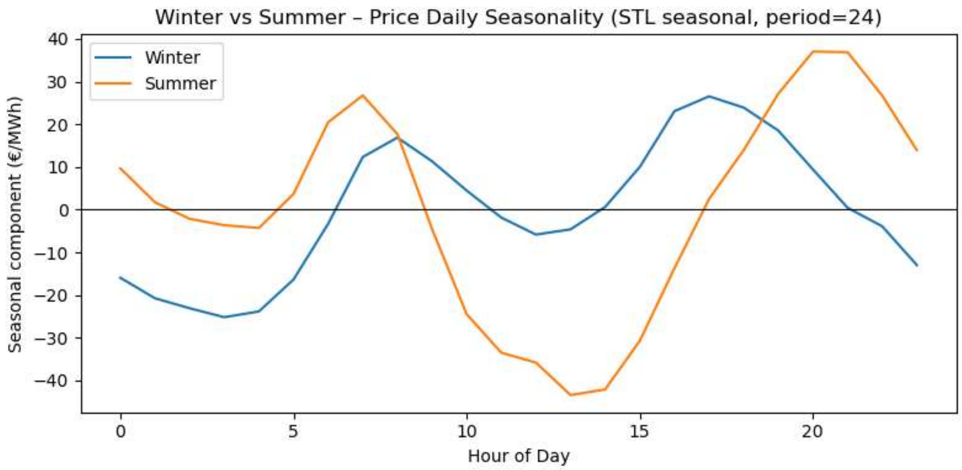
(a)


STL Decomposition – Day-ahead Price (Hourly, period=24)
Price_EUR_MWh
500
0
Trend
200
100
Season
200
0
Resid
400
200
0
2024-01
2024-02
2024-03
2024-04
2024-05
2024-06
2024-07
2024-08
2024-09
2024-10
2024-11
2024-12

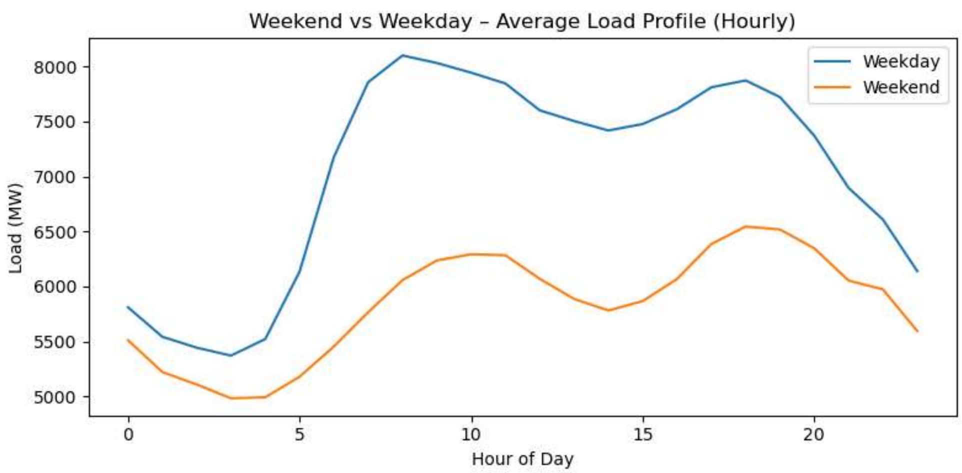
(b)


Winter vs Summer – Load Daily Seasonality (STL seasonal, period=24)
Winter
Summer
Seasonal component (MW)
1000
500
0
−500
−1000
−1500
0
5
10
15
20
Hour of Day

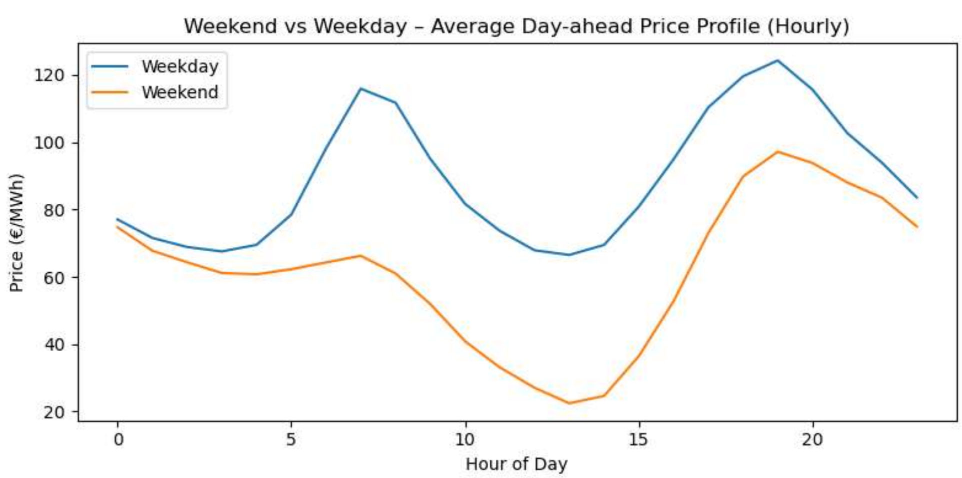
(c)


Winter vs Summer – Price Daily Seasonality (STL seasonal, period=24)
Winter
Summer
Seasonal component (€/MWh)
Hour of Day

(d)


Weekend vs Weekday – Average Load Profile (Hourly)
Weekday
Weekend
Load (MW)
Hour of Day

(e)


Weekend vs Weekday – Average Day-ahead Price Profile (Hourly)
Weekday
Weekend
Price (€/MWh)
Hour of Day

(f)

Figure 16: a) STL decomposition of total electricity load, b) STL decomposition of day-ahead electricity prices, c) winter and summer daily load seasonality, d) winter and summer daily price seasonality, e) weekday and weekend effects in load profiles, and f) weekday and weekend effects in price profiles

4. Generation Mix

Figure 17 illustrates the daily average electricity generation mix in Austria throughout 2024, highlighting the contributions of renewable and conventional generation technologies. The generation portfolio is dominated by renewable energy sources, particularly hydro, wind, and solar, with fossil generation playing a secondary and highly variable role.

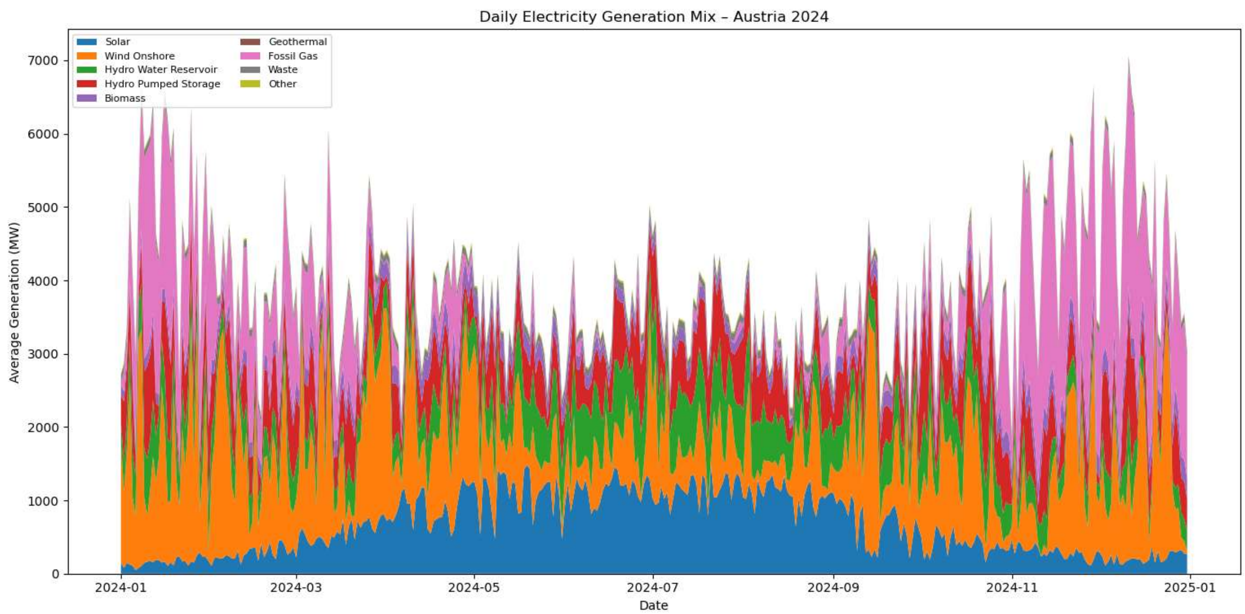
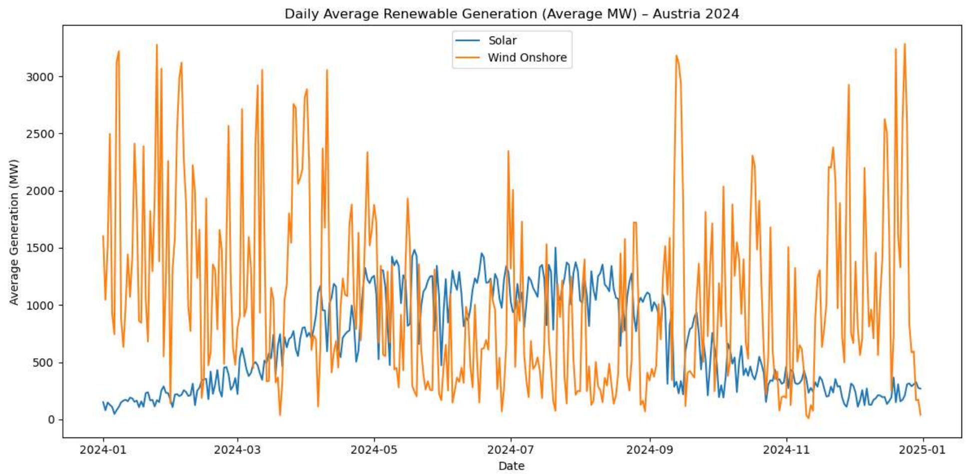
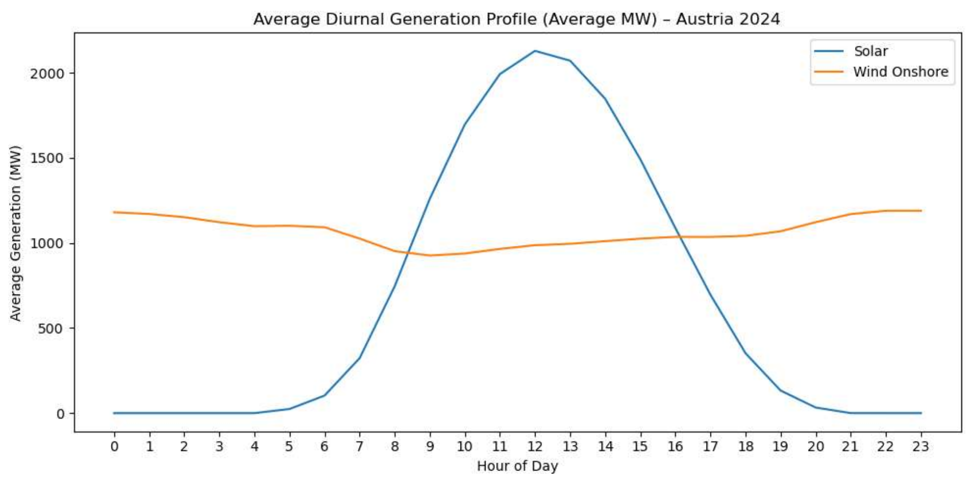


Figure 17: Daily electricity generation mix in Austria (2024)

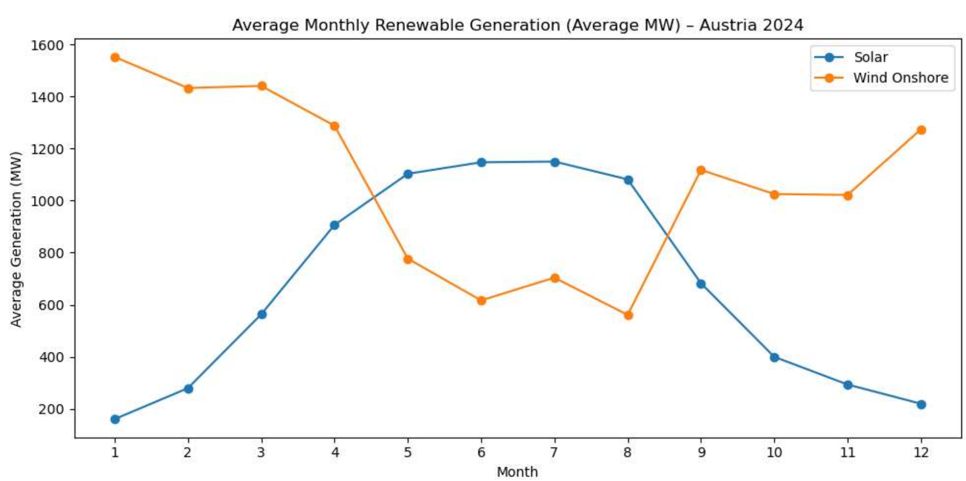
As shown in figure 18, the daily average renewable generation time series highlights the complementary nature of solar and wind energy in Austria. Solar generation follows a smooth seasonal trajectory, increasing steadily from winter toward summer and peaking during late spring and summer months. In contrast, onshore wind generation exhibits strong day-to-day variability throughout the year, with frequent spikes and drops driven by changing weather conditions. The average diurnal profiles reveal distinct intraday behaviors for the two renewable sources. Solar generation displays a bell-shaped curve, with output beginning after sunrise, peaking around midday to early afternoon, and declining to near zero during nighttime hours. Wind generation, by contrast, remains relatively flat across the day, with only minor diurnal variation. The monthly averages further emphasize the seasonal contrast between solar and wind. Solar output increases from approximately 150–300 MW in winter to over 1100 MW during summer, before declining again in autumn. Wind generation shows the opposite tendency, with higher average output in winter and early spring, a minimum in summer, and a resurgence in autumn and early winter.


Daily Average Renewable Generation (Average MW) – Austria 2024
Solar
Wind Onshore
Average Generation (MW)
Date
0
500
1000
1500
2000
2500
3000
2024-01
2024-03
2024-05
2024-07
2024-09
2024-11
2025-01

(a)


Average Diurnal Generation Profile (Average MW) – Austria 2024
Solar
Wind Onshore
Average Generation (MW)
Hour of Day
0
500
1000
1500
2000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

(b)


Average Monthly Renewable Generation (Average MW) – Austria 2024
Solar
Wind Onshore
Average Generation (MW)
Month
200
400
600
800
1000
1200
1400
1600
1 2 3 4 5 6 7 8 9 10 11 12

(c)

Figure 18: a) Daily evolution of solar and wind generation, b) average diurnal solar and wind generation profiles, and c) monthly average solar and wind generation

As illustrated in figure 19, the density plot compares the distributions of daily average solar and onshore wind generation in Austria for 2024, highlighting structural differences between the two renewable sources. Solar generation exhibits a bimodal distribution. The first peak at low generation levels corresponds to winter and low-irradiance periods, while the second peak at higher values reflects summer months with strong solar availability. In contrast, wind generation shows a broader, right-skewed distribution with a long tail extending toward high generation values. This shape reflects the high variability and intermittency of wind, with frequent moderate outputs and occasional extreme high-generation days. Unlike solar, wind generation does not cluster around distinct seasonal peaks but instead spans a wide range of values throughout the year.

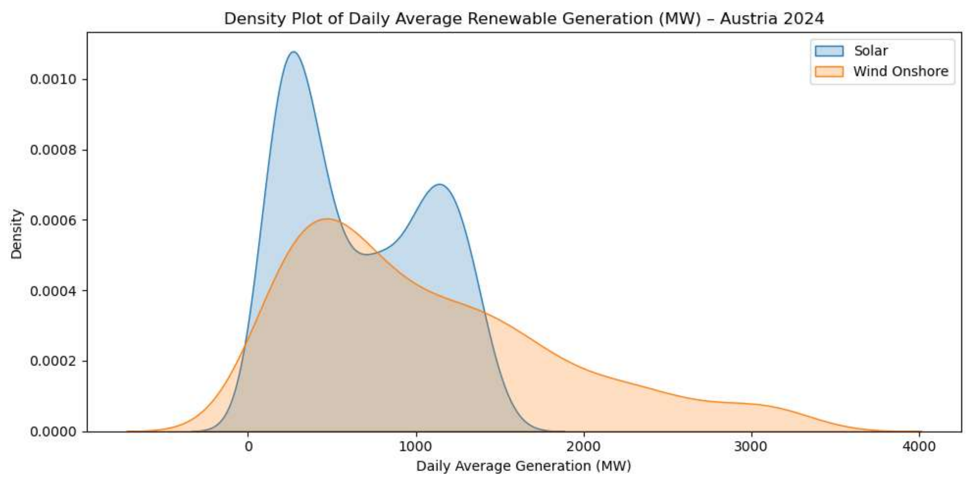


Figure 19: Distributions of daily average solar and wind generation

As shown in figure 20, the installed capacity mix highlights Austria's commitment to renewable energy: Solar, Hydro run-of-river and pondage, Wind onshore and hydro pumped storage. Fossil gas, while significant in capacity, is not the dominant technology.

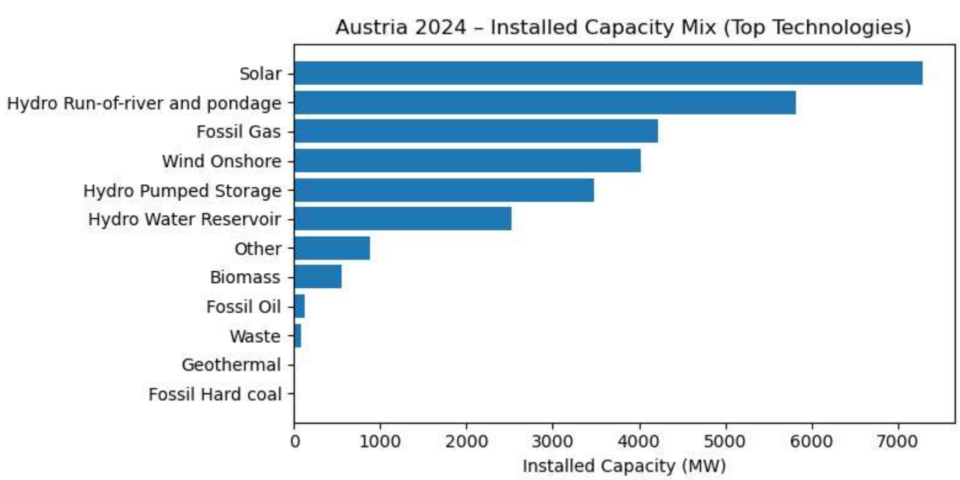


Figure 20: a) Installed capacity mix in Austria for 2024

This Principal Component Analysis (PCA) summarizes the main structural patterns in the generation mix by reducing production types into a few dominant modes of variation. In table 2, first three PCs explain 84% of total variability, meaning the generation mix dynamics can be well described by three underlying system factors. In table 3, PC1 contrasts dispatchable hydro flexibility against solar-driven generation. PC2 represents thermal support versus renewable availability. PC3 isolates wind replacing gas. Run-of-river hydro is near-zero loadings across all PCs, Indicating stable, baseload-like behavior.

Table 2: Explained variance ratio

Principal Component	Explained Variance
PC1	0.3880
PC2	0.2747
PC3	0.1797
Cumulative (PC1–PC3)	0.8425

Table 3: PCA loadings by production type

Production Type	PC1	PC2	PC3
Solar	−0.3513	−0.5522	−0.1647
Wind Onshore	−0.1849	0.5349	0.6776
Hydro Run-of-river and pondage	0.0000	0.0000	0.0000
Hydro Water Reservoir	0.6087	−0.2961	0.2404
Hydro Pumped Storage	0.6640	−0.0218	0.0593
Fossil Gas	0.1759	0.5664	−0.6726

5. Cross-Border Electricity Flows

Figure 21 illustrates Austria's net cross-border electricity flows with its main trading partners, Germany, the Czech Republic, Slovenia, Hungary, and Switzerland, over the course of 2024. Positive values indicate net imports into Austria, while negative values represent net exports. A strong and persistent exchange with Germany is evident, characterized by the largest absolute flow magnitudes among all partners. Flows with the Czech Republic are predominantly positive, indicating that Austria acts as a net importer from this region during most of the year. In contrast, exchanges with Slovenia and Hungary are mostly negative, showing that Austria is generally a net exporter toward these neighboring systems. The interaction with Switzerland exhibits bidirectional flows with moderate variability.

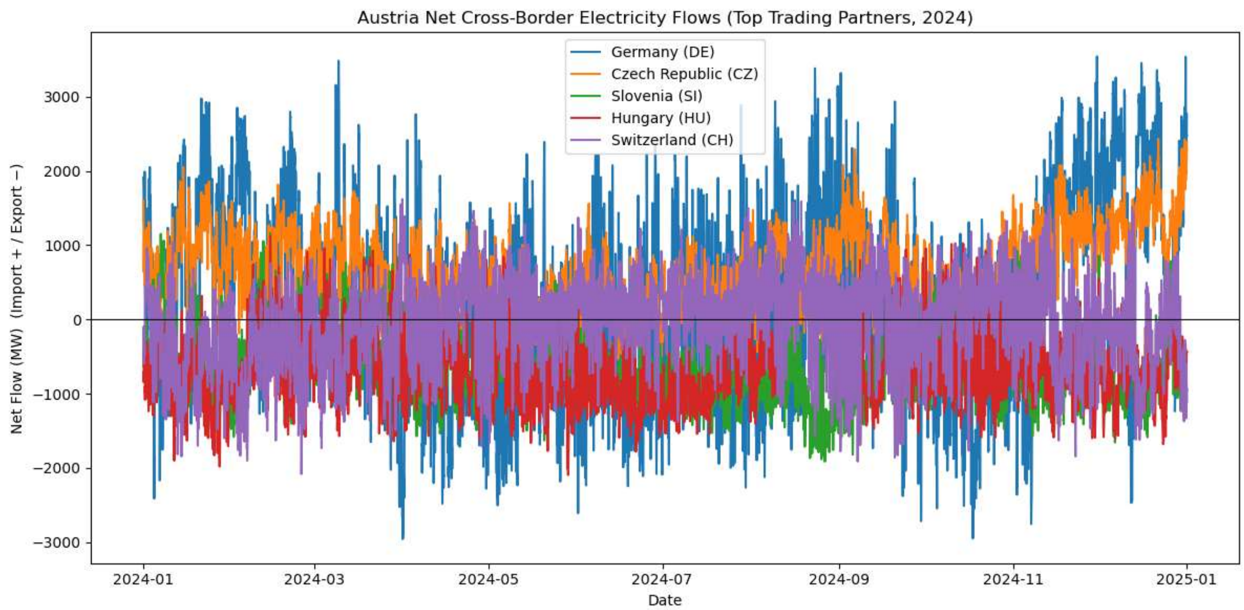


Figure 21: Hourly net cross-border electricity flows in Austria for 2024

The heatmap, in figure 22, shows average net cross-border electricity flows (MW) by hour day and month. Winter months (Nov–Feb) are dominated by positive values, Late Spring–summer (May–July) shows negative values, Night / early morning (0–6 h), strongest exports in summer (deep blue). Midday (9–15 h), reduced exports or even net imports, particularly outside summer. Evening peak (17–21 h), imports increase again, especially in autumn and winter.

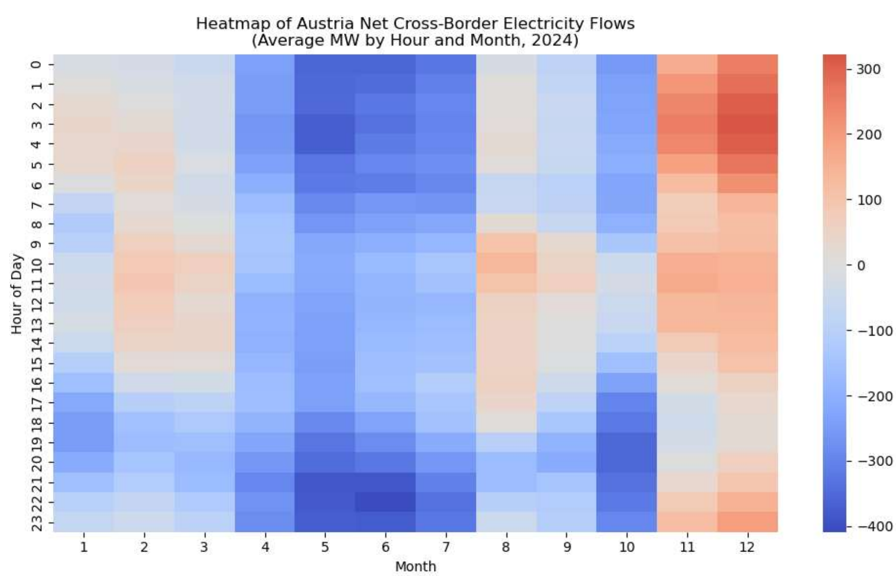
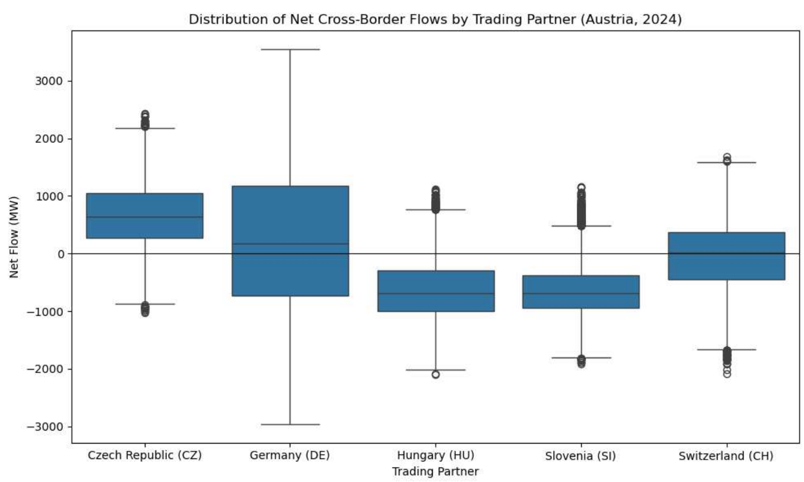


Figure 22: Heatmap of net cross-border electricity flows (MW)

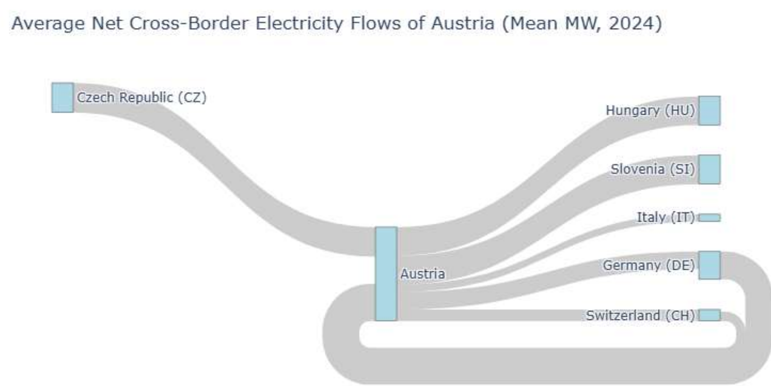
The boxplot in figure 23 illustrates the statistical distribution of Austria's net cross-border electricity flows with its main trading partners in 2024. Clear asymmetries are observed across trading partners:

- Germany (DE) shows by far the largest variability in net flows. The wide interquartile range and extreme outliers on both import and export sides indicate that Austria alternates frequently between importing from and exporting to Germany.
- Czech Republic (CZ) displays a consistently positive median, indicating that Austria is typically a net importer from the Czech system. While some export events occur, the distribution is skewed toward imports.
- Hungary (HU) and Slovenia (SI) both exhibit negative medians with relatively tight distributions, indicating that Austria is generally a net exporter to these countries. The narrower spread compared to Germany implies more stable and predictable export behavior.
- Switzerland (CH) shows a median close to zero but with wide tails on both sides. This reflects bidirectional and flexible exchanges.

The Sankey diagram highlights these dynamics visually. Italy appears as a minor net export destination.



(a)



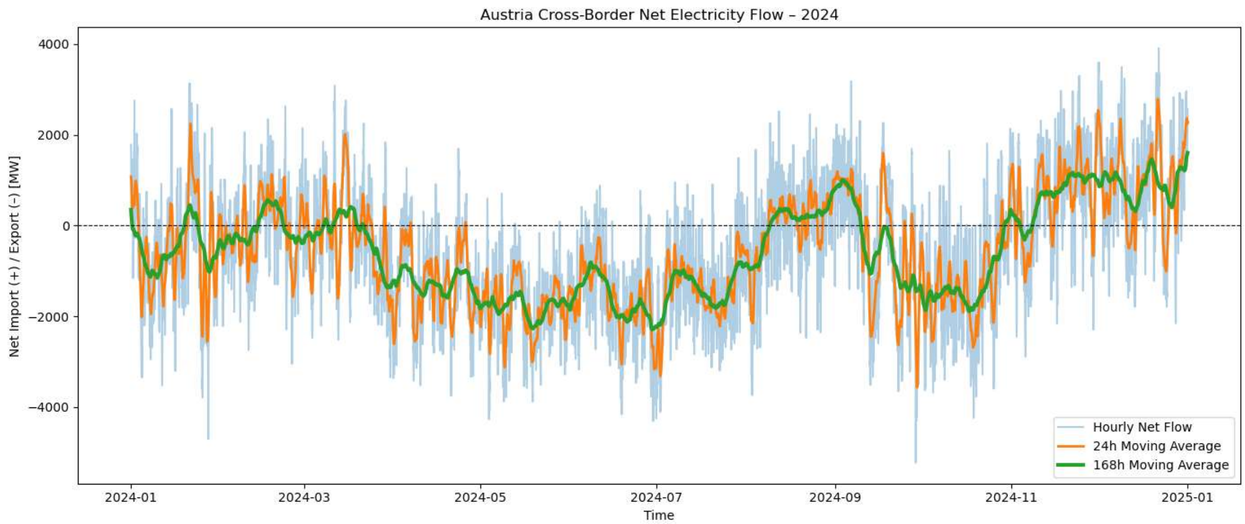
(b)

Figure 23: a) The boxplot and b) Sankey diagram of net cross-border electricity flows in 2024

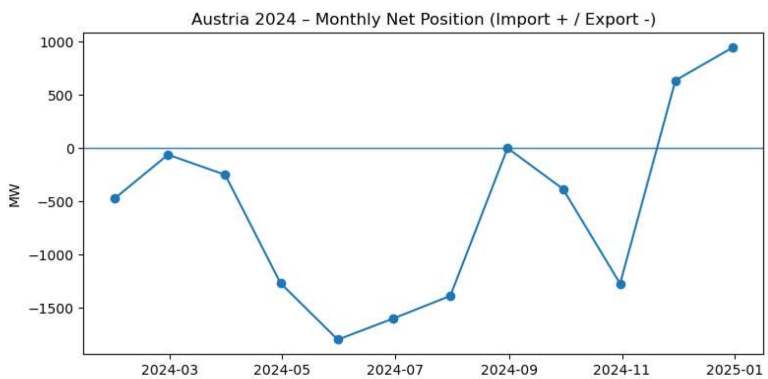
Figure 24 shows Austria’s hourly net cross-border electricity flows in 2024, together with a 24-hour moving average and a 168-hour (weekly) moving average. Positive values indicate net imports, while negative values indicate net exports. Hourly net flows exhibit very high volatility, frequently exceeding ±3000 MW. This reflects Austria’s participation in the coupled European electricity market. The 24-hour moving average smooths intraday noise but still shows oscillations, confirming that daily system conditions can shift Austria from net importer to net exporter within short time spans. The 168-hour moving average reveals seasonal regimes:

- Winter (Jan–Feb, Nov–Dec): The system tends toward net imports, reflecting high demand and limited solar availability. Imports increased markedly toward the end of the year, coinciding with higher prices and stressed system conditions.
- Spring and Summer (Mar–Aug): Austria becomes predominantly a net exporter, driven by hydro inflows and peak solar generation. The most sustained export phase occurs between May and August, where the weekly average remains clearly negative.
- Autumn transition (Sep–Oct): Flows fluctuate around zero, indicating a balanced system state where exports and imports alternate depending on short-term conditions.

Figure 24(b) summarizes Austria’s average monthly net electricity position. The numbers are different because the charts use different time scales and aggregation methods: the first chart shows hourly net electricity flows with short-term moving averages, while the second chart shows monthly aggregated net positions. Short-term fluctuations visible in hourly data often cancel out when averaged over an entire month, so the values do not match exactly.



(a)



(b)

Figure 24: a) Hourly net cross-border electricity flows with a 24-hour moving average and a 168-hour (weekly) moving average and b) monthly net position

In figure 25, the correlation matrix reveals how prices, load, RES share, cross-border flow, and load forecast interact within Austria's electricity system. Electricity prices are primarily driven by demand. Cross-border flows act as a balancing mechanism rather than a direct price driver.

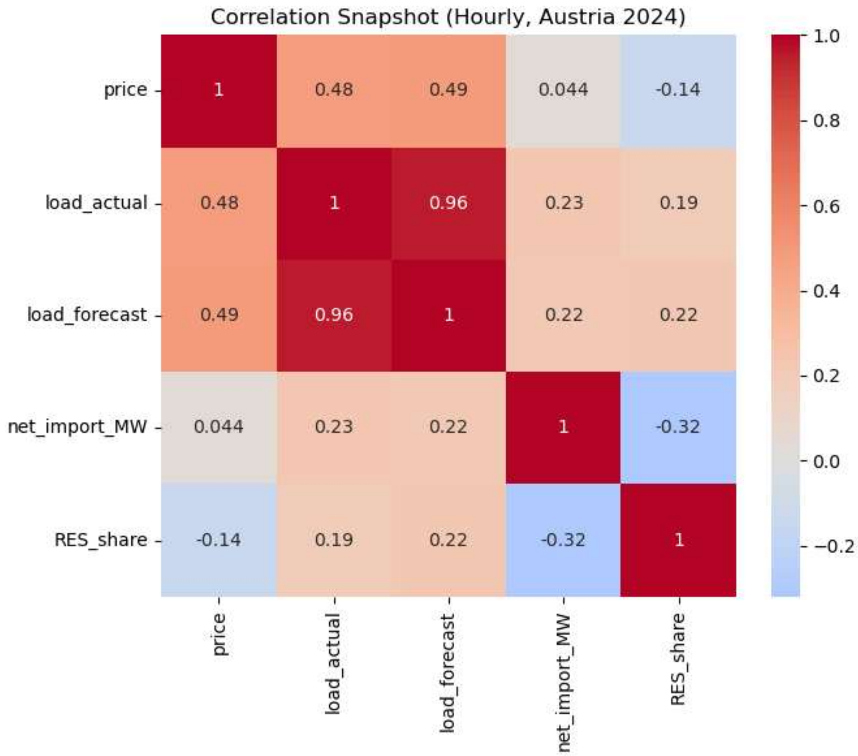


Figure 25: The correlation matrix of prices, load, RES share, cross-border flow, and load forecast

6. Conclusion

This project provided a comprehensive, data-driven assessment of the Austrian electricity system in 2024 by jointly analyzing electricity prices, load patterns, generation mix, forecasting performance, and cross-border electricity flows. The results clearly demonstrate that Austria's power system is shaped by a high penetration of renewable energy sources, seasonal variability, and tight integration with neighboring European markets .

The analysis confirms a robust inverse relationship between renewable generation, particularly solar power and day-ahead electricity prices. High solar output during spring and summer leads to lower and more stable prices, including occasional negative price events, while periods of low renewable availability, especially in winter, coincide with higher prices and increased volatility. Wind generation contributes to price mitigation as well, though its impact is weaker and more dispersed due to its intermittent and less demand-aligned nature. Load analysis further shows that demand remains a dominant price driver: high-load winter weeks are associated with elevated prices and a higher frequency of extreme price events, highlighting the persistent importance of demand-side pressures even in a renewable-rich system.

Advanced time-series analysis and forecasting results underline structural differences between load and price dynamics. Electricity load exhibits strong and predictable daily and seasonal patterns, whereas prices are substantially more volatile and sensitive to system stress. Among the forecasting approaches, the Gradient Boosting Regressor clearly outperformed SARIMA and SARIMAX models, particularly in capturing price spikes and high-volatility periods. This emphasizes the value of machine-learning methods for short-term electricity price forecasting in complex, non-linear energy systems.

The generation mix analysis illustrates Austria's reliance on renewable flexibility, especially hydropower and pumped storage, to balance variable solar and wind generation. Principal Component Analysis reveals that most variability in the generation portfolio can be explained by a small number of structural factors related to renewable availability and dispatchable flexibility. Cross-border flow analysis shows that Austria acts alternately as a net importer and exporter depending on season and system conditions, with Germany playing a central balancing role. Imports dominate during winter stress periods, while exports prevail in spring and summer when renewable generation is abundant.

Overall, the findings highlight that high renewable penetration improves price stability and reduces average price levels but does not eliminate system stress or extreme price events. Cross-border exchanges and flexible generation remain essential for maintaining system balance.