Bachelor's Project
Power Grid Load Forecasting using Machine Learning Approaches

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Abstract

The Swiss transmission system experiences frequent mismatches between electricity generation and consumption, which requires the use of balancing energy to maintain grid stability, as reported by Swissgrid [12]. This project focuses on developing time series forecasting models enhanced by machine learning techniques, including AR(1), ARIMA, SARIMA, and SARIMAX. The models are trained on historical Swissgrid data[13], incorporating information on energy consumption and weather information.

Comprehensive time series diagnostics using autocorrelation, stationarity tests, and spectral analysis revealed strong yearly seasonal patterns. Among all the models tested, the SARIMAX model incorporating exogenous variables such as weather data produced the most accurate forecasts, achieving a mean absolute percentage error of 4.83 percent. This performance represents a substantial improvement over the baseline AR(1) model, which had an error rate of 8.39 percent.

The results demonstrate the potential of SARIMAX for improving grid forecasting, reducing dependence on emergency balancing energy, and supporting more stable and cost-efficient energy system operations in Switzerland.

Acknowledgment

I would like to express my deepest gratitude to my supervisors, Clément Targe and Youssef Saïed, for their invaluable guidance and thoughtful feedback throughout the development of this research. Their mentorship played a crucial role in shaping the direction of this project.

I would also like to thank my family for their support. Their belief in me has been a constant source of motivation.

Contents

1 Introduction

The growing complexity of modern energy systems and the increasing reliance on renewable energy sources have made accurate electricity load forecasting a critical task for grid operators. In Switzerland, the national transmission system operator, Swissgrid, is tasked with maintaining grid stability in the face of frequent imbalances between energy production and consumption. To address this challenge, robust forecasting models are necessary to anticipate load patterns and reduce the need for costly emergency balancing measures.

This project investigates the use of machine learning and statistical time series models for medium-term energy load forecasting. Specifically, it evaluates autoregressive (AR), ARIMA, SARIMA, and SARIMAX models using historical Swissgrid data on energy consumption, production, and cross-border exchanges. Through a rigorous model development pipeline, including data preprocessing, statistical diagnostics, model training, and evaluation, the project aims to identify the most effective forecasting model to improve operational decision making and energy system stability.

2 Background

2.1 Data Source

SwissGrid Data

This study leverages open-source operational data from Swissgrid, the national transmission system operator of Switzerland, which publishes detailed records on energy production, consumption, and cross-border exchanges [13]. The dataset used spans from January 2021 to March 2025, with an original temporal resolution of 15 minutes. This high-frequency data was aggregated into weekly values to align with forecasting standards outlined by the European Network of Transmission System Operators for Electricity (ENTSO-E), which recommends forecasting on a Monday–Sunday basis [5].

Weather Data

In addition to grid data, the study incorporates exogenous weather data to improve forecasting accuracy. Specifically, it uses ensemble mean temperature forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) SEAS5 seasonal forecast product, available through the Copernicus Climate Data Store [4]. These forecasts, provided at a monthly resolution, were spatially averaged over Switzerland based on user-defined coordinates.

Each monthly temperature forecast was assigned to the corresponding weeks within that month, creating a weekly-aligned covariate series without interpolation.

2.2 Forecasting Type and Horizon

The forecasting objective was framed as a medium-range horizon, targeting the total weekly energy consumption in Switzerland for the upcoming 8 weeks. Medium-range forecasting, as defined in energy planning literature, typically refers to predictive horizons of 1 to 12 weeks, where seasonality begins to play a substantial role and predictive accuracy remains actionable for operational decisions [11].

2.3 Objectives

This project focuses on developing machine learning models for load forecasting in the Swiss energy grid, using historical data on energy consumption, production, and cross-border exchanges. The datasets include detailed information on total energy consumed and produced in the Swiss control block, grid feed-ins, net outflows, and energy trades with neighboring countries (Germany, France, Austria, and Italy).

The primary objectives are:

1. Visualize the Data
2. Develop a Medium Term Forecasting Model (Predicting Total Amount of Energy Consumed per day/week)
3. Setting a Baseline Model and model evaluation Metric
4. Evaluate the results
5. Discussing challenges and conclusions

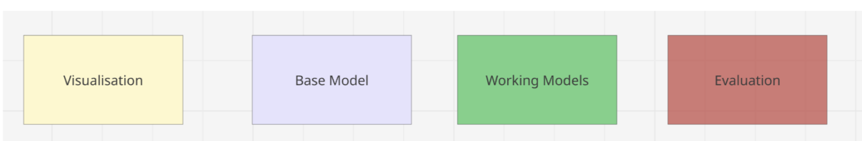

Figure 1: Objectives

3 Methodology

This section outlines the important steps followed throughout the project, including data preprocessing, time esries analysis, statistical testing, and model construction. The methodology is structured to ensure a rigorous approach to energy consumption forecasting using time series.

3.1 Visualisation

3.1.1 Variable to Predict

The target variable for prediction is the weekly energy load, specifically Total Energy Consumption. The original data is recorded at 15-minute intervals and is aggregated into weekly values using a 7-day window (Monday to Sunday), in accordance with EU forecasting standards. According to Swissgrid, this variable represents the total energy consumed within the Swiss control block, based on aggregated feed-in sequences reported by distribution network operators. It includes only production plants equipped with load profile meters.

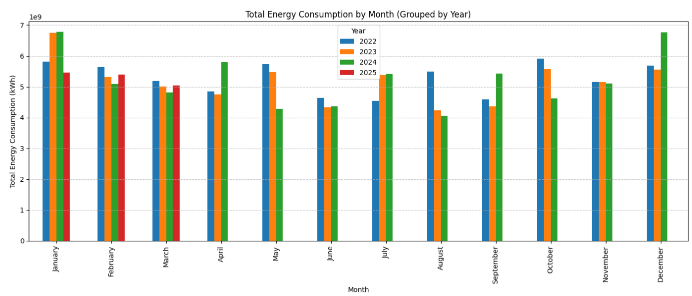

Figure 2: Total Energy Consumption by month, compared to each year

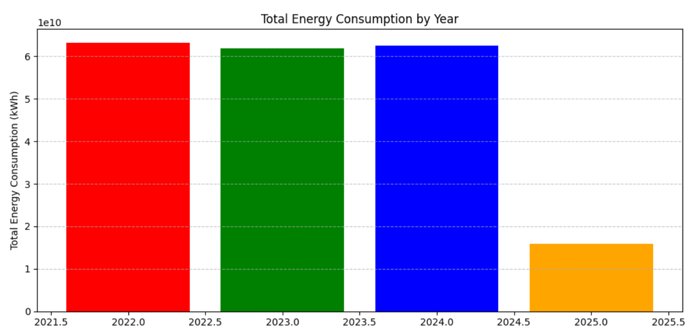

Figure 3: Total Energy Consumption by year

The dataset used spans from January 2021 to March 2025, aggregated into weekly values.

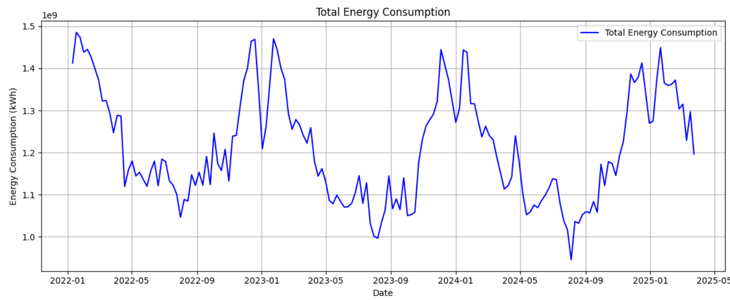

Figure 4: Total Swiss Energy Consumption

3.1.2 Weather Data

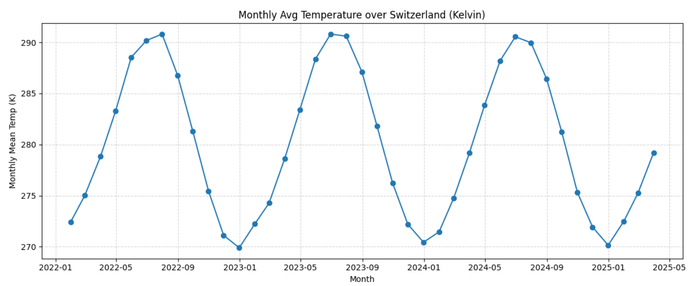

Figure 5: Monthly Weather Forecast (2 months ahead)[4]

The weather data chosen is the ensemble mean temperature forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) SEAS5 seasonal forecast product [4], provided at a monthly resolution.

3.2 Data Cleaning

All values were first converted to numeric types, with any errors replaced by NaN and removed. The dataset was found to be complete, with no missing values even before this step.

The uniqueness of timestamps was then verified to ensure proper alignment of time series data. All timestamps were confirmed to be unique, so no further adjustment was necessary.

Summary statistics,including the mean, minimum, maximum, and standard deviation, were examined for the energy consumption values. The results appeared consistent, indicating no significant outliers or anomalies.

3.3 Data Correlation

The Pearson correlation coefficient measures the linear relationship between two continuous variables. It is defined as:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where x_i and y_i are the individual sample points, and $\bar{x}$, $\bar{y}$ are the sample means of the variables x and y, respectively.

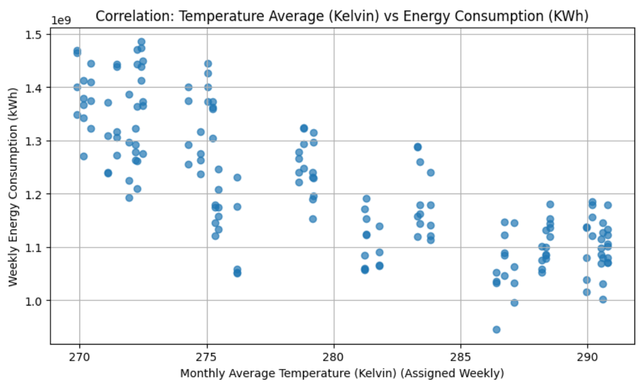

Figure 6: Weather Correlation to Energy Consumption Plot

This scatter plot displays values using Cartesian coordinates—here, with monthly average temperatures (Kelvin) on the x-axis and weekly energy consumption (kWh) on the y-axis—to reveal their statistical relationship.

Table 1: Strength of Correlation Analysis

Metric	**Value**
Correlation Coefficient (r)	-0.777
Absolute Correlation ($\|r\|$)	0.777
Threshold for Strong Correlation ($\|r\|$)	≥ 0.7
Result	Strong Correlation

In this study, the Pearson correlation coefficient was applied to the weekly-aggregated series of average temperature and total energy consumption.

The resulting correlation indicated a strong negative correlation between temperature and energy consumption. According to Cohen's statistical guidelines, a correlation is considered strong if $|r| \geq 0.7$ [2].

3.4 Time Series Analysis

A comprehensive time series analysis was conducted to understand the structure and dynamics of the energy consumption data. The following techniques were employed:

3.4.1 Autocorrelation of Initial Series

The covariance function for equally spaced data $y_1, \ldots, y_n$ is defined as:

$$c_h = \frac{1}{n-h-1} \sum_{i=1}^{n-h} (y_i - \bar{y})(y_{i+h} - \bar{y}), \quad h = 0, 1, \ldots, n-2,$$

where $\bar{y}$ is the sample mean. The correlogram (ACF) is a graph of $\hat{\rho}_h = \frac{c_h}{c_0}$ against lag h [3].

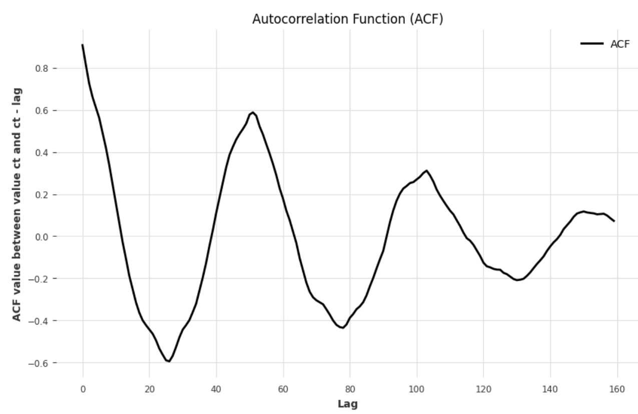

Figure 7: AutoCorrelation Function - Total Energy Consumption

According to the Time Series Analyis book, To summarise: for causal and invertible ARMA models the ACF and PACF have the following properties:

	AR(p)	**MA(q)**	**ARMA(p,q)**
ACF	Tails off	Cuts off after lag q	Tails off

This gives an approach to identifying AR and MA models based on the ACF and PACF, and suggests how to choose p or q. [3]

3.4.2 Testing for stationarity

To build reliable model, we need to check whether the data is stationary. One way to test this is to decompose the time series Y_t into three components:

$$Y_t = \xi_t + \eta_t + \varepsilon_t$$

[3]

Where:

- ξ_t is the deterministic trend, as in a fixed, predictable pattern over time
- η_t is a supposed random walk,
- ε_t is noise

Types of stationarity:

- **Level stationarity**: If $\sigma_u^2 = 0$ and $\xi_t = 0$, then Y_t is stationary around a constant mean.
- **Trend stationarity**: If $\sigma_u^2 = 0$ and $\xi_t = \beta t$, then Y_t becomes stationary after removing the trend.

KPSS Test: The KPSS test is used to test the null hypothesis that a time series is stationary. It does this by estimating the test statistic:

$$C(l) = \frac{1}{\sigma^2(l)} \sum_{t=1}^{n} S_t^2, \quad \text{where } S_t = \sum_{j=1}^{t} e_j$$

Here, $e_1, \ldots, e_n$ are the residuals from regressing Y_t on a constant or a linear trend (depending on whether testing for level or trend stationarity), and $\sigma^2(l)$ is a long-run variance estimate using a truncation lag l. [3] The test is interpreted as follows:

- If the test statistic is small (below the critical value), we **do not reject** the null hypothesis: the series is stationary.
- If the test statistic is large (above the critical value), we **reject** the null hypothesis: the series likely contains a unit root and is non-stationary.

KPSS Test Decision Summary

Metric	Value
p-value	0.1
Significance Level (α)	0.05
Decision	Do not reject H_0 (Stationary)

Figure 8: KPSS result (Probability and Decision)

We conclude that our time series is indeed stationary.

3.4.3 Periodogram

Many series have cyclic structure (e.g. sunspots, CO2 data,...), but we may not know what the cycles are in advance of looking at the data. The periodogram is a summary description based on representing the observed series as a superposition of sine and cosine waves of various frequencies. [3]

If $y_1, \ldots, y_n$ is an equally-spaced time series, its periodogram ordinate for ω is defined as

$$I(\omega) = |d(\omega_j)|^2$$

this means that:

$$I(\omega) = \frac{1}{n}\left[\left(\sum_{t=1}^{n} y_t \cos(2\pi\omega t)\right)^2 + \left(\sum_{t=1}^{n} y_t \sin(2\pi\omega t)\right)^2\right], \quad 0 < \omega \leq \frac{1}{2}$$

Our plot for the linear periodogram:

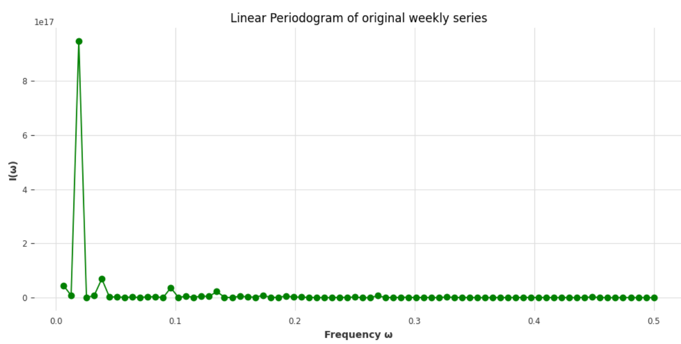

Figure 9: Linear Periodogram of original weekly series (Kwh / Hz)

We then plotted our most significant frequencies showing their frequency in weeks.

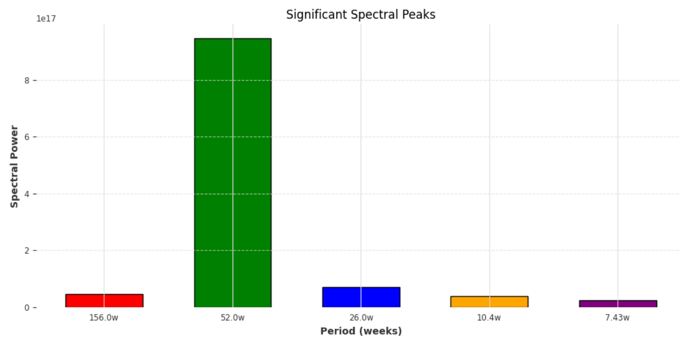

Figure 10: Plot of the most significant frequency powers (KWh)

The periodogram revealed a dominant spectral peak at a period of 52 weeks, indicating strong annual seasonality in the energy consumption data. This is supported by smaller secondary peaks at 26, 10.4, and 7.43 weeks. The overwhelming spectral power at 52 weeks confirms the presence of a yearly seasonal component.

3.4.4 Cumulative periodogram

The cumulative periodogram

$$C_r = \frac{\sum_{j=1}^{r} I(\omega_j)}{\sum_{l=1}^{m} I(\omega_l)}, \quad r = 1, \ldots, m$$

is a plot of $C_1, \ldots, C_m$ against the frequencies ω_j for $j = 1, \ldots, m$. [3]

According to Davidson, Gaussian and non-Gaussian white noise has a flat spectrum [3]

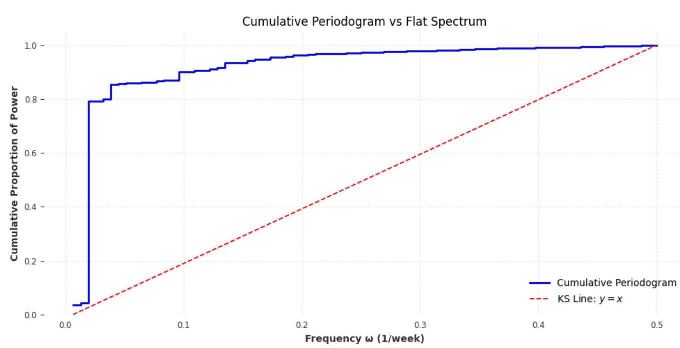

Figure 11: Cumulative Periodogram of Inital Series vs flat spectrum Line

3.4.5 Is this brownian noise?

To statistically test for white noise, the Kolmogorov–Smirnov (KS) test can be used. This test compares the empirical cumulative distribution of power to the expected uniform distribution. In this case, the maximum deviation from the uniform line was calculated to be around 76.85%, which is greater than the typical threshold of 15%. Thus, the null hypothesis of white noise is rejected.

Conclusion: Based on both the visual deviation in the cumulative periodogram and the result of the KS-type test, the time series does not resemble white noise. This confirms that further modeling is appropriate.

3.4.6 Time Series Interpretation

3.4.7 Model Selection Justification

- **Autoregressive order ($p = 1$)**: To determine the autoregressive order p of a time series, we examine the behavior of the sample autocorrelation function (ACF). The ACF plot showed a slow decay and significant autocorrelation at lag 1, which is characteristic of an autoregressive process. Mathematically, for an AR(1) process, the autocorrelations decay geometrically according to:

$$\rho_k = \phi^k$$

  where ϕ is the autoregressive coefficient.

  In the observed series, the sample ACF values are as follows, along with the theoretical values computed using $\phi = 0.9028$ and their absolute errors:

  Table 2: Comparison of Sample ACF and Theoretical ϕ^k for $\phi = 0.9028$

Lag (k)	Sample ACF (ρ_k)	Theoretical ϕ^k	Absolute Error $\lvert\rho_k - \phi^k\rvert$
1	0.9028	0.9028	0.0000
2	0.8092	0.8151	0.0059
3	0.7166	0.7362	0.0196
4	0.6537	0.6647	0.0110

  The close agreement between the sample ACF values and the geometric decay of ϕ^k supports the conclusion that the process follows an autoregressive model of order p = 1.

- **Differencing order ($d = 0$)**: The KPSS test for level stationarity returned a statistic below the critical value, indicating that the original time series was stationary. So, no non-seasonal differencing was needed.

- **Moving average order ($q = 0$)**: The ACF did not display a sharp cut-off,, suggesting that a moving average component was not necessary.

- **Seasonal autoregressive order ($P = 1$)**: The seasonal lags in the ACF (especially at lag 52) showed strong, gradually declining correlation, indicating the presence of a seasonal autoregressive component with a period of 52 weeks. This observation was further supported by the dominant seasonal frequency observed in the cumulative periodogram.

  Since the ACF value at lag 52 exceeds the threshold of 0.5 and shows a gradual decline at subsequent seasonal lags (104 and 156), it indicates a persistent seasonal correlation structure. Therefore, a seasonal autoregressive order of $P = 1$ was selected to capture this pattern.

Table 3: ACF Values at Seasonal Lags

Lag (k)	ACF Value (ρ_k)
52	0.6
104	0.35
156	0.12

- **Seasonal differencing ($D = 0$):** The seasonal component of the original series was already stationary, as the ACF showed significant but decaying seasonal spikes at lags 52, 104, and 156. This confirmed that seasonal differencing was not necessary to achieve stationarity.
- **Seasonal moving average ($Q = 0$):** There was no clear seasonal pattern remaining in the ACF after confirming seasonal stationarity, suggesting that a seasonal MA term was not required.

Therefore, the SARIMA$(1, 0, 0)(1, 0, 0, 52)$ model effectively captures both short-term and annual dependencies in the energy consumption data with minimal complexity.

3.5 Models

3.5.1 Forecasting Method

A **rolling forecast** is a time series evaluation technique where the model is retrained iteratively on an expanding or fixed-size window of historical data, and forecasts are made for a defined horizon ahead. After each forecast, the training window is advanced forward in time, and the process is repeated.

This approach closely simulates real-world forecasting scenarios, where new observations become available sequentially, and models must update continuously to reflect recent trends.

In our study, a rolling forecast with a fixed training window (104 weeks) and an 8-week forecast horizon was used, with the model being retrained at each step. This setup ensures consistent, out-of-sample performance evaluation across all models.

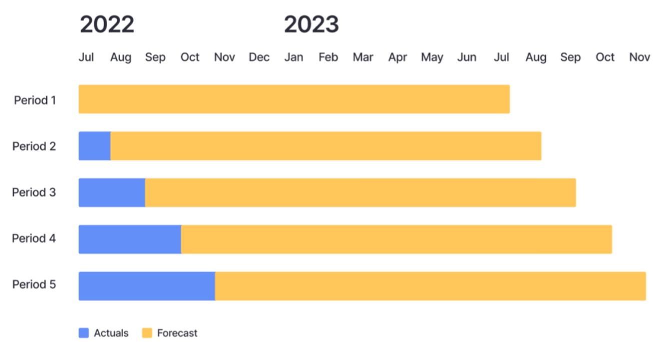

Figure 12: Rolling Forecast example from finmark's website [9]

3.5.2 AR

The first-order autoregressive, AR(1), process with mean is a stationary process satisfying

$$Y_t - \mu = \alpha(Y_{t-1} - \mu) + \varepsilon_t, \quad t \in \mathbb{Z}. \tag{1}$$

[3]

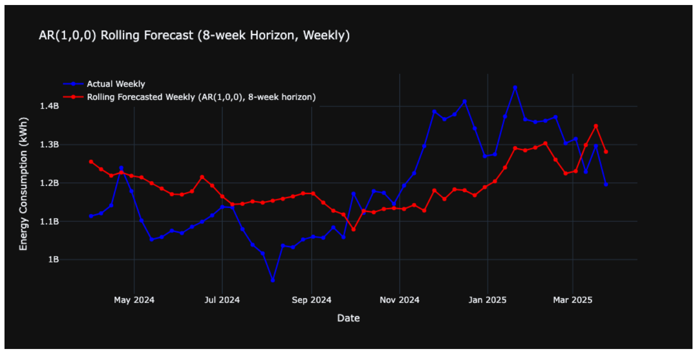

Figure 13: AR(1,0,0) model, 8 week daily forecast

3.5.3 ARMA

The AutoRegressive Moving Average (ARMA) model is a classical linear time series model used to capture autocorrelation structures without differencing or seasonality. It is suitable for stationary time series data that exhibit short-term dependencies.

In this study, the ARMA model is configured with the following parameters:

- **Non-seasonal order:** $(p, d, q) = (1, 0, 1)$, indicating one autoregressive term and one moving average term without differencing

The model is mathematically defined as:

$$y_t = c + \phi_1 y_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

Where:

- c: constant
- ϕ_1: Autoregressive coefficient (lag 1)
- θ_1: Moving average coefficient (lag 1)
- ε_t: White noise error term

This formulation follows the conventional ARMA structure as described in Box et al.'s foundational work on time series analysis [1].

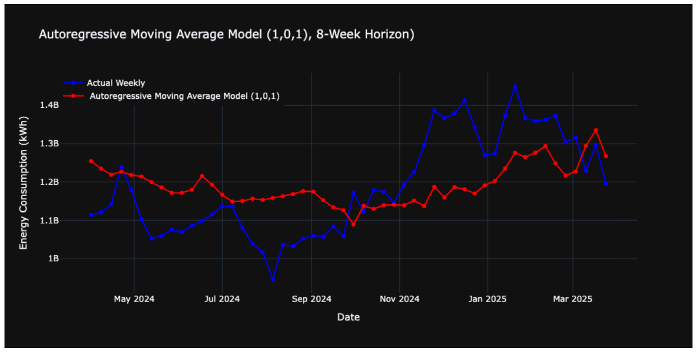

Figure 14: ARMA(1,0,1) over 8-week horizon

3.5.4 ARIMA

The AutoRegressive Integrated Moving Average (ARIMA) model generalizes the ARMA framework by incorporating differencing to handle non-stationarity in the data. It is particularly useful when the time series exhibits trends but lacks clear seasonal patterns.

In this study, the ARIMA model is configured with the following parameters:

- **Non-seasonal order:** $(p, d, q) = (1, 1, 0)$, where one differencing step is used to achieve stationarity and one autoregressive term models the remaining dependence

The model is mathematically defined as:

$$\Delta y_t = c + \phi_1 \Delta y_{t-1} + \varepsilon_t$$

Where:

- y_t: Target variable at time t (weekly energy consumption)
- $\Delta y_t = y_t - y_{t-1}$: First-order differenced series
- c: Intercept term
- ϕ_1: Autoregressive coefficient on the differenced series
- ε_t: Error term assumed to be white noise

This ARIMA specification follows standard practices for modeling non-stationary series with low-order autoregression and no moving average component, as formalized by Box and Jenkins [1].

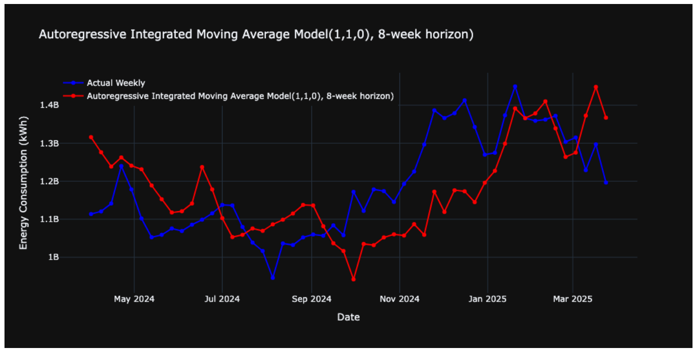

Figure 15: ARIMA(1,1,0) - 8 week horizon

3.5.5 SARIMA

The Seasonal AutoRegressive Integrated Moving Average (SARIMA) model extends the classical ARIMA framework by incorporating seasonal autoregressive and moving average terms. It is particularly effective for time series data exhibiting both short-term dependencies and strong seasonal patterns.

In this study, the SARIMA model is configured with the following parameters:

- **Non-seasonal order:** $(p, d, q) = (1, 0, 0)$
- **Seasonal order:** $(P, D, Q, s) = (1, 0, 0, 52)$, corresponding to a yearly seasonality over weekly data

The model is mathematically defined as:

$$y_t = c + \phi_1 y_{t-1} + \Phi_1 y_{t-52} + \varepsilon_t$$

Where:

- y_t: Target variable at time t (weekly energy consumption)
- c: Intercept term
- ϕ_1: Non-seasonal autoregressive coefficient (lag 1)
- Φ_1: Seasonal autoregressive coefficient (lag 52)
- ε_t: Residual error term, assumed to be white noise

This formulation follows the standard notation for SARIMA models as presented by Box et al. in their foundational work on time series modeling [1].

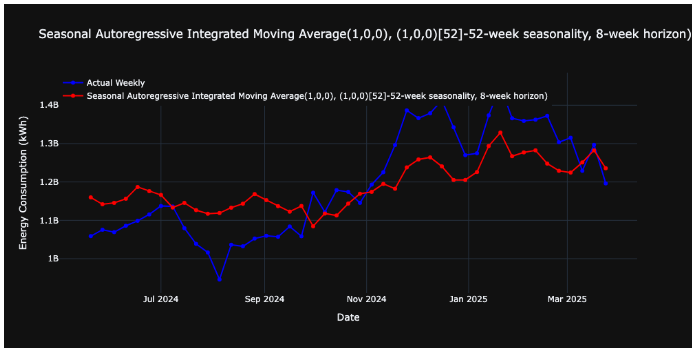

Figure 16: SARIMA(1,0,0(1,0,0,[52])), 8 week horizon

3.5.6 SARIMAX

The Seasonal AutoRegressive Integrated Moving Average with eXogenous variables (SARIMAX) is a linear time series model designed to capture non-seasonal and seasonal patterns, while also accounting for the influence of external variables.

In our configuration, the model is defined as follows:

- **Non-seasonal order:** $(p, d, q) = (1, 0, 0)$
- **Seasonal order:** $(P, D, Q, s) = (1, 0, 0, 52)$
- **Exogenous variable:** Monthly average temperature matched to the weekly indexes

The general form of the SARIMAX model is given by:

$$y_t = c + \phi_1 y_{t-1} + \Phi_1 y_{t-52} + \beta X_t + \varepsilon_t$$

Where:

- y_t: Target variable (weekly energy consumption)
- c: Constant
- ϕ_1: Non-seasonal autoregressive coefficient
- Φ_1: Seasonal autoregressive coefficient (with seasonal lag $s = 52$)
- X_t: Exogenous input (weekly temperature values)
- β: Coefficient for the exogenous variable
- ε_t: Error term

To enrich the SARIMAX model, we have incorporated weather data from European Centre for Medium-Range Weather Forecasts (ECMWF)[4]. Specifically, the forecasted average monthy temperature across the Swiss federation as an exogenous variable.

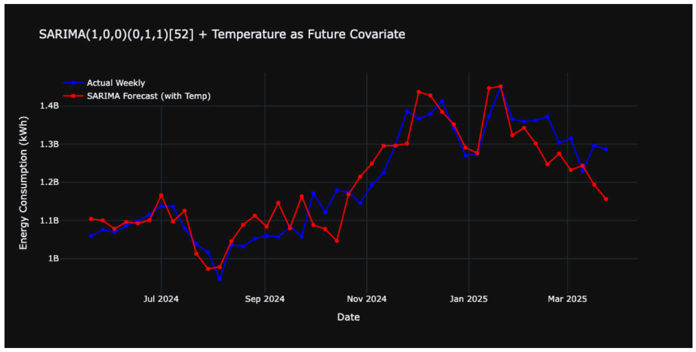

Figure 17: SARIMAX(1,0,0(1,0,0,[52]) + Temp) - 8 Week Horizon

3.6 Inspecting residuals

Standardized residuals are defined as

$$\tilde{e}_t = \frac{(y_t - \mu_t) - \alpha(y_{t-1} - \mu_{t-1})}{\sigma}, \quad t = 2, \ldots, n,$$

where $\mu_t = \mu + \delta I(t > 38)$.

The residuals should be approximately (Gaussian) white noise.

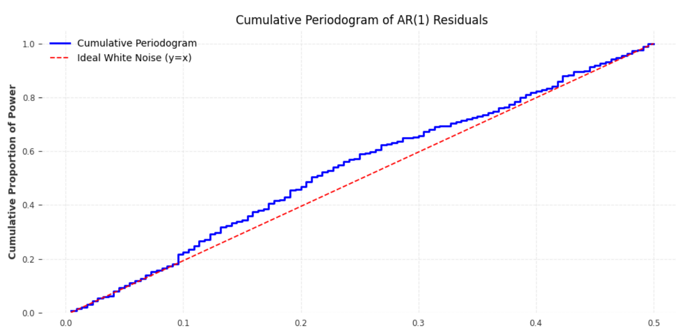

Figure 18: Cumulative periodogram and RS result for AR(1)

The Kolmogorov–Smirnov (K-S) test is a non-parametric statistical test used to compare the empirical distribution of a sample with a reference distribution.

In the context of time series analysis, it can be used to test whether the cumulative distribution of the periodogram matches that of a uniform (white noise) distribution.

The K-S test statistic is defined as:

$$D_n = \sup_x |F_n(x) - F(x)|$$

where:

- $F_n(x)$ is the empirical cumulative distribution function (ECDF) of the observed values,
- $F(x)$ is the cumulative distribution function of the reference distribution (here, uniform),
- D_n measures the maximum absolute difference between the two.

Based on the cumulative periodogram and the KS test, the resiudals of the AR(1) were white noise (12.89% , non-white noise threshhold is set to 15%)

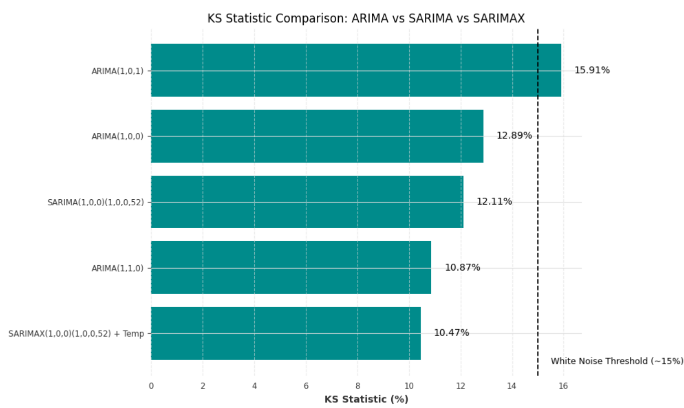

Figure 19: KS Statistic Comparison

Based on the Kolmogorov–Smirnov (KS) test applied to the model residuals, we find that AR(1), ARIMA(1,1,0), SARIMA(1,0,0)(1,0,0,52), and SARIMAX(1,0,0)(1,0,0,52) with temperature as a future covariate all yield residuals that are statistically indistinguishable from white noise. This indicates that these models sufficiently captured the temporal dependencies in the training data, leaving behind no significant structure.

3.7 Evaluation Metric

The mean absolute percentage error (MAPE) is a metric used to evaluate the accuracy of a forecasting model. It calculates the average of the absolute percentage errors between the predicted values and the actual values. Lower MAPE values indicate more accurate forecasts.

The formula is:
$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$
where y_t is the true value and $\hat{y}_t$ is the predicted value at time t. [14]

4 Results and discussion

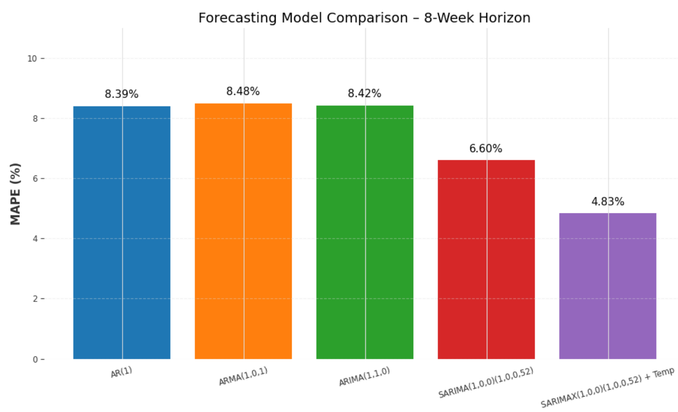

Figure 20: MAPE scores graph

The evaluation was based on the MAPE score. The baseline model selected was the AR(1) model. The results showed that the SARIMAX(1,0,0,[52]) with Temperature as future covariates was the best performer, outperforming all of the AR, ARMA, and ARIMAs.

5 Conclusion

The baseline AR(1) model yielded a modest prediction accuracy with a MAPE of 8.39%, providing a simple yet interpretable benchmark. Among all evaluated models, the SARIMAX$(1,0,0)(1,0,0,52)$ model incorporating temperature as a future covariate demonstrated the best forecasting performance, achieving a significantly lower MAPE of 4.83%. This represents a relative improvement of approximately 42.4% over the AR(1) benchmark.

The SARIMA$(1,0,0)(1,0,0,52)$ model also provided a substantial improvement, reducing MAPE to 6.60%, and highlighting the benefit of explicitly modeling seasonal patterns. However, SARIMAX outperformed SARIMA by additionally accounting for temperature effects, which led to both better predictive accuracy and more white-noise-like residuals, as confirmed by the lowest KS statistic (10.47%) in the residual diagnostic comparison.

While the AR(1) model exhibited relatively clean residuals, it lacked forecasting power. SARIMA still improved over ARIMA models, and SARIMAX achieved the best MAPE score of all the models, while also having clean residuals.

5.1 Future Work

Several avenues remain open for improving forecasting accuracy and model robustness:

- **Enhanced Residual Modeling:** Despite the improvements with SARIMAX, residuals still exhibit minor periodic structure. Incorporating post-model residual filtering could further refine forecasts.
- **Additional Exogenous Variables:** Integrating more contextual data (e.g., humidity, calendar effects) may improve performance under variable conditions.
- **Real-Time Forecasting:** Deploying models capable of online updates can enhance responsiveness and accuracy in dynamic grid environments.

In conclusion, SARIMAX with temperature covariates offers a robust, interpretable, and high-performing solution for mid-term energy load forecasting. Its extension of SARIMA through exogenous integration marks a promising direction for developing adaptive and operationally viable forecasting systems.

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