Swiss Electricity Consumption Forecasting

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Contents

Abstract

This report explores four time series forecasting approaches—referred to as **Model 1**, **Model 2**, **Model 3**, and **Model 4**—applied to high-frequency Swiss electricity consumption data. Using data from 2021 through 2024 for training and 2025 for evaluation, each model is benchmarked using RMSE, MAE, and MAPE. The study identifies the best-performing approach suitable for deployment in grid planning and forecasting tasks.

1 Introduction

1.1 Context and Motivation

Electricity load forecasting plays a critical role in the stability and efficiency of national power grids. In Switzerland, the national transmission grid is managed by Swissgrid, which must ensure a continuous balance between electricity supply and demand in real time. Accurate forecasting allows for optimal scheduling of electricity generation, prevents supply shortages or overloads, and reduces reliance on expensive reserve power. It also supports market operations and helps minimize operational costs.

As the energy mix evolves with growing integration of intermittent renewable sources such as solar and wind, the importance of robust load forecasting has increased. These energy sources introduce variability and uncertainty into the grid, making traditional planning methods insufficient. Therefore, advanced forecasting methods are needed to support grid reliability, operational planning, and long-term infrastructure investment.

1.2 Objectives

This report focuses on developing and comparing four distinct electricity demand forecasting approaches (Model 1–4). The models are trained using 15-minute resolution electricity load data from 2021 to 2024 and evaluated on unseen data from 2025.

The main objectives of this work are as follows:

- To build forecasting models using diverse methodologies, including statistical, machine learning, and sequence-based approaches.
- To evaluate each model's performance using standard error metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).
- To compare the predictive accuracy of all models on the same test set and select the best-performing model for deployment.
- To prepare the selected model for production use through a reproducible and scalable framework.

The goal is to identify a reliable and scalable method for forecasting Swiss electricity load that can support operational decision-making and contribute to the resilience of the national power grid.

2 Data Description

2.1 Data Source

The dataset used in this project consists of high-resolution Swiss electricity consumption data obtained from the Swiss national grid operator, Swissgrid. The raw data captures total electricity load in kilowatt-hours (kWh) at 15-minute intervals, representing the aggregate demand across the country. This granularity allows for precise modeling of intraday variations, which are essential for operational forecasting.

2.2 Time Frame and Granularity

The dataset spans from January 1, 2021 to July 1, 2025, with each observation recorded at a 15-minute interval. This results in over 140,000 data points, offering both seasonal and trend information necessary for training and validating robust forecasting models. The data was split into two parts:

- **Training Set:** January 1, 2021 to December 31, 2024
- **Test Set:** January 1, 2025 to July 1, 2025

This temporal split simulates a realistic deployment scenario where models are trained on historical data and evaluated on future, unseen values.

2.3 Preprocessing and Feature Engineering

Several preprocessing steps were applied to ensure consistency and model readiness:

- **Missing Value Handling:** Linear interpolation was applied to fill occasional missing entries.
- **Datetime Indexing:** All timestamps were parsed as timezone-aware datetime objects and set as the DataFrame index.
- **Resampling:** For some experiments, the original 15-minute data was resampled to hourly totals using aggregation.

In addition, a separate feature engineering pipeline was used to create lag features, time-based cyclical encodings (hour of day, day of week), and holiday indicators. These engineered features were particularly important for models that do not natively handle time series seasonality.

2.4 Exploratory Analysis

Exploratory analysis revealed clear patterns of daily and weekly seasonality, along with long-term trends influenced by temperature and public holidays. Peak demand typically occurred during morning and evening hours on weekdays, with lower consumption on weekends. These patterns were consistent across all years in the training period.

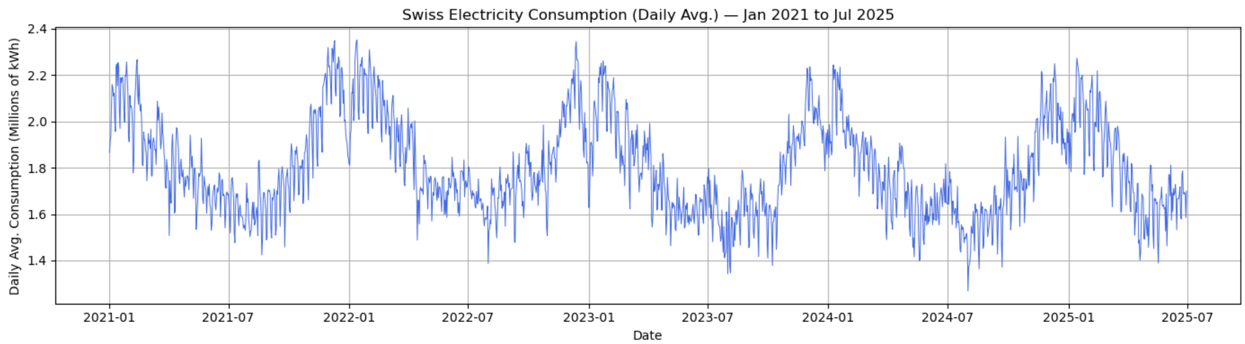

Figure 1: Swiss electricity consumption trend (daily average) from 2021 to July 2025 (in millions of kWh).

3 Feature Engineering

3.1 Time Features

We derived several time-based features to capture the temporal patterns inherent in electricity consumption. These include:

- **Hour of day**: Captures diurnal patterns.
- **Day of week**: Captures weekly patterns (e.g., higher consumption on weekdays).
- **Weekend**: A binary feature distinguishing workdays from non-workdays.
- **Holidays**: Typically important for demand shifts; reserved for future iterations.

3.2 Cyclical Encoding

Time-based features like hours and months have inherent periodicity. We used **cyclical encoding** to represent them:

- **Hour of day (sin/cos)** to map hours on a circular scale.
- **Month of year (sin/cos)** to capture annual seasonality.

3.3 Rolling Means

To capture smoothed structure and long-term trends:

- **24-hour rolling mean** for daily cycles.
- **7-day rolling mean** for weekly cycles.

3.4 Seasonal Decomposition

We applied additive seasonal decomposition into trend, seasonal, and residual components.

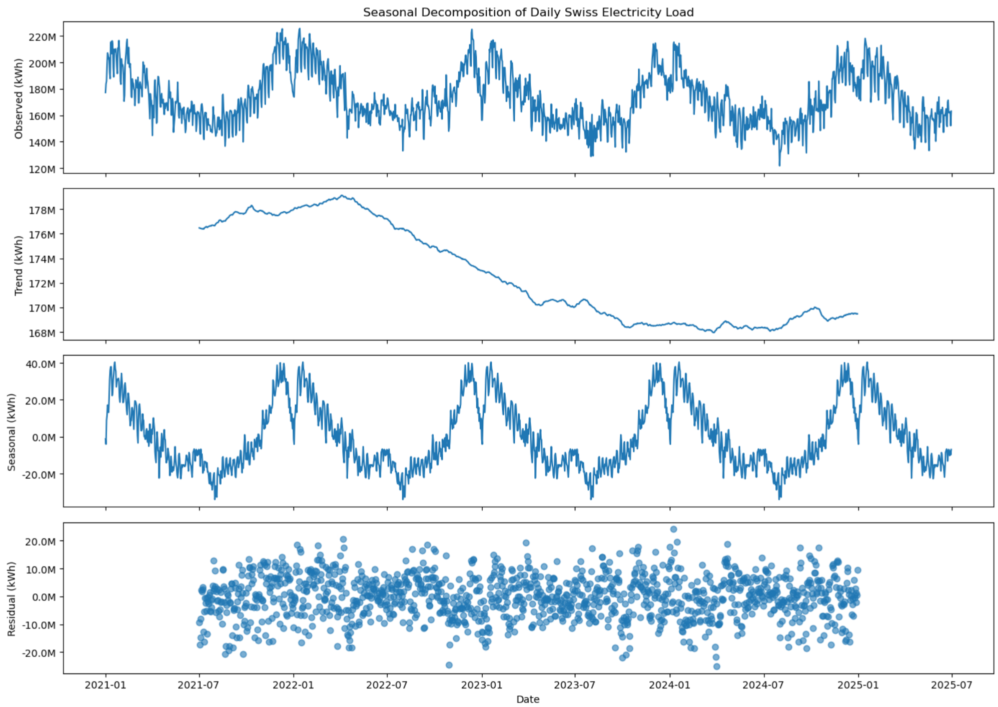

Figure 2: Daily seasonal pattern in electricity demand.

4 Forecasting Methodology

In this phase, four different forecasting methods were applied to predict Swiss electricity consumption. For confidentiality and business presentation, we anonymize them as **Model 1**, **Model 2**, **Model 3**, and **Model 4**. Each model was trained using electricity load data from January 2021 to December 2024 and evaluated on out-of-sample data covering January to July 2025.

4.1 Model 1

Overview. A decomposition-oriented approach capable of handling multiple seasonalities and trend changes.

Configuration. Included daily/weekly/yearly seasonal components and automated changepoint detection. Data were aggregated to daily frequency for stability, with interpolation for continuity.

Table 1: Model 1: Selected Configuration Elements

Component	Baseline	Tuned
Seasonality mode	additive	multiplicative
Daily/Weekly/Yearly	on	on
Changepoint prior	default	higher flexibility
Forecast frequency	15-minute	15-minute

4.2 Model 2

Overview. A seasonal autoregressive model with differencing and moving-average components.

Configuration. Trained on hourly aggregates with one seasonal cycle per day.

Table 2: Model 2: Selected Parameters

Parameter	**Value**
Non-seasonal order	(1, 1, 1)
Seasonal order	(1, 1, 1, 24)
Stationarity / Invertibility	relaxed
Max iterations	50

4.3 Model 3

Overview. A sequence model designed to capture nonlinear temporal dependencies over multiple 15-minute steps.

Configuration. Input windows of 96 steps (one day), scaled inputs, and a compact hidden representation.

Table 3: Model 3: Selected Configuration

Parameter	**Value**
Sequence length	96 (15-min steps)
Hidden units	64
Dropout	0.2
Loss / Optimizer	MSE / Adam
Batch size / Epochs	64 / 10
Validation split	10%

4.4 Model 4

Overview. A gradient-boosted decision-tree regressor leveraging lagged targets and calendar features.

Configuration. Trained on 15-minute data with engineered lags, cyclical encodings, and moderate regularization.

Table 4: Model 4: Selected Hyperparameters

Parameter	**Value**
Estimators	1000
Learning rate	0.01
Max depth	6
Subsample / Colsample	0.8 / 0.8
Random seed	69

5 Evaluation and Model Selection

5.1 Evaluation Metrics

We compare models on MAE, RMSE, and MAPE on the January–July 2025 test set:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \quad \text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \quad \text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|.$$

5.2 Performance Comparison

Table 5: Forecasting performance on the 2025 test set

Model	**MAE (kWh)**	**RMSE (kWh)**	**MAPE (%)**
Model 1	$\approx$ 168,800	$\approx$ 134,300	7.29
Model 2	$\approx$ 443,600	$\approx$ 339,900	5.29
Model 3	$\approx$ **30,200**	$\approx$ **20,600**	**1.18**
Model 4	$\approx$ 104,700	$\approx$ 80,300	4.64

5.3 Model Selection

The average electricity load during the 2025 test period was approximately 1.74 million kWh per 15-minute interval. This contextualizes the forecasting errors: for example, Model 3's RMSE of ∼30,200 kWh represents less than 2% of the typical load, while Model 2's RMSE exceeds 25% of the average interval demand.

Among the evaluated approaches, **Model 3** significantly outperformed all others in terms of RMSE, MAE, and MAPE, indicating highly accurate short-term predictions. **Model 4** performed well with a strong accuracy–speed trade-off. **Model 2**, while a useful statistical baseline, exhibited the highest absolute errors.

Based on these results, **Model 3** was selected as the final model for deployment.

6 Forecast Visualization

To visually assess predictive capability, we plotted actual vs. forecasted electricity demand on a sample week from the test set (2025). Figure 3 illustrates **Model 3**'s predictions against ground truth values.

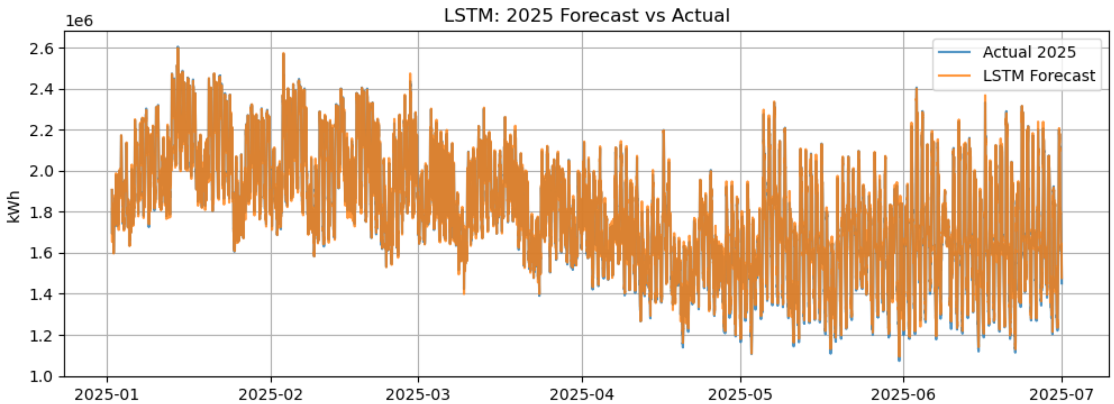

Figure 3: Model 3 forecast vs. actual values on a sample week in 2025.

Similar visualizations were generated for Models 1, 2, and 4, revealing varying degrees of underfitting or lag during rapid demand fluctuations.

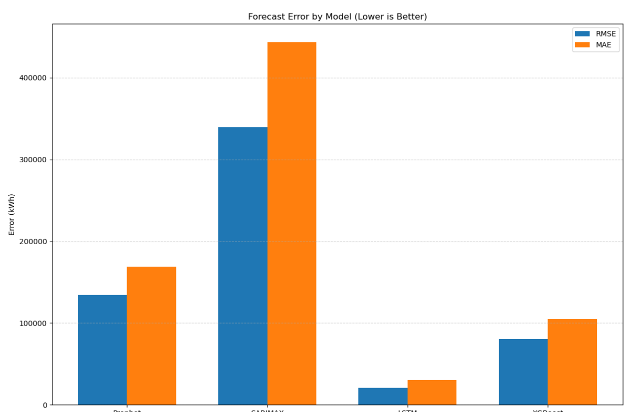

Figure 4: Comparison of RMSE and MAE across Models 1–4.