# ADAML 2025 Project Work - Predicting House Energy - Intermediary Submission Week 3

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# 1 Introduction

In this work, the aim is to forecast daily electric power consumption for a house with previous energy consumption data.

# 2 Materials and methods

## 2.1 Data description

The original time-series dataset contains approximately 2,000,000 measurements from a household between December 2006 and November 2010, with one measurement recorded per minute. Thus, all the variables are synchronized. In addition to date and timestamp, it includes 6 variables as follows:

- Global active power - minute-averaged active power (the target variable)

- Global reactive power - minute-averaged reactive power

- Voltage - minute-averaged voltage

- Global intensity - minute-averaged current intensity

- Sub-metering 1 - energy sub-metering corresponding to kitchen appliances

- Sub-metering 2 - energy sub-metering corresponding to the laundry room

- Sub-metering 3 - energy sub-metering corresponding to an electric water heater and an air-conditioner.

The dataset contains individual timestamps with missing values. Also, there are a few time periods when the measurements are missing for several straight days.

## 2.2 Time-series decomposition

Time-series decomposition refers to breaking down a time series into its different components in order to understand what causes variation of a specific variable. The components are trend, seasonality, and residual. The trend indicates long-term variation, seasonality indicates repeating seasonal variation, and residual indicates random variation that cannot be explained by trend or seasonality. Time-series decomposition can be represented as follows

$$y_t = S_t + T_t + R_t, \tag{1}$$

where $y_t$ is the observed data, $S_t$ is the component describing seasonality, $T_t$ is the trend component, and $R_t$ is the residual component, all at the time $t$ (Hyndman and Athanasopoulos, 2018).

## 2.3 Dividing a long time-series into sub-samplings

In time-series analysis, dividing a long series into shorter sub-samplings is a common strategy to capture local patterns, improve model performance, and handle non-stationarity. According to Hyndman and Athanasopoulos (2018), many real-world time series exhibit evolving dynamics where model parameters, trends, or seasonal effects change over time. Sub-sampling allows models to adapt to these local structures rather than forcing a single global fit.

Fixed-length rolling windows are a common method for dividing a long time-series into shorter, overlapping segments that capture local patterns. In this approach, the series is split into consecutive windows of equal length, and the window is then shifted forward one time step at a time. Rolling windows are particularly useful when the goal is to model short-term dependencies or extract features that describe recent trends. (Institute (2023))

The time series can also be divided into sub-samplings based on seasonal characteristics or other detected sources of variation. According to Sharma (2022), season-based segmentation divides a time series into segments that correspond to different seasonal periods, such as weekdays, weekends, or distinct seasonal cycles. Another segmentation strategy is change-point detection, which identifies points where the statistical properties of the series change, allowing the data to be split into segments with different behaviours (Aminikhanghahi and Cook (2017)).

Seasonality is an important factor in deciding how a time series should be split into sub-samplings. When seasonal patterns are strong and repeat regularly, each sub-sampling should include a whole number of seasonal cycles so that the periodic structure is preserved. (Hyndman and Athanasopoulos (2018))

When seasonality changes over time, sub-sampling can help by separating the series into periods where the seasonal pattern is more stable. If seasonality is weak or inconsistent, it may be better to use flexible windowing or change-point detection instead of strict season-based segmentation Cleveland et al. (1990).

## 2.4 Seasonal naïve predictor

The model considered as the baseline for predicting future consumption is seasonal naïve predictor. With this model, the predictions for future values are calculated using the previous observation of the same season. The predictions can be calculated using

$$\hat{y}_{t+T} = y_{t+T-h}, \tag{2}$$

where T is the prediction horizon and h is the length of the season. As the electricity consumption has seasonality in daily and weekly values this model can be considered as good model for benchmarking.

## 2.5 LSTM

Long short-term memory (LSTM) model is a recurrent neural network (RNN) model trying to overcome the vanishing gradient problem. LSTM includes memory cells consisting of gates deciding which input values effect the memory states and the model output.

Even though LSTM models have multiple strengths in powerful learning, nonlinear mapping and sequence modeling, they often struggle at finding trends and seasonality in time-series data. One way to overcome this is using hybrid models compounding a machine learning model, data pre-processing methods and an optimization algorithm. Some approaches do the pre-processing to learn seasonality and trends before using LSTM-models with the data while others include it to the model. (Wu et al. (2024))

Multiple different standardization methods can be used with LSTMs, but min-max normalization and z-score normalization seem to be the most used techniques. In their study, Tawakuli et al. (2025) compared different standardization methods for LSTM's by predicting carbon monoxide concentration using air quality data. Best results were achieved using z-score standardization and robust standardization, but also other methods such as min-max normalization and Box-Cox led to promising results, highlighting the possibility of using different methods.

In another study, Pranolo et al. (2024) compared min-max and z-score normalization techniques with LSTM models predicting energy load with different energy generation attributes. The results state that min-max normalization outperformed z-score in multiple scenarios.

These examples show that for different problems, different normalization methods can be the optimal ones with LSTMs.

## 2.6 Data partition plan for cross-validation

The data will be divided into several folds for cross-validation. We will start with a basic approach doing cross-validation on a rolling basis with expanding window. We will use 5 folds, and the

size of each test set will be a fifth of one year (73 days). In practice, it means that we first use all data but the last year (meaning last 365 days of the dataset) as a training set, and the first fifth of the last year of the data is the first test set. During the second fold, we add the previous test set into our training data, and try to predict the second fifth of the last year. This process is repeated so that across five folds, the test periods together span the entire last year of the data.

With this approach, the validation process includes the full seasonality of one year. Of course, we can try to change the number of folds and the size of test sets later. After cross-validation is done, we can also try to predict values for the entire last year to see if the model performs well for a longer period. One option is to leave some data as fully unseen for our model so we can test it. These details will be decided later when the model type is known.

## 3 Results

### 3.1 Data preprocessing and visualization

If the missing values were individual measurements or occurred over a short gap, maximum of 12 hours, they were approximated by simple linear interpolation. If the values were missing for a longer period, we used the value from one week before, as it correlates most with the missing value based on autocorrelation, which will be shown later.

As the goal of the work is to predict daily consumption, we decided to modify the original minute-level data into hourly measured values. Thus, the mean value of each variable during each hour is used.

The dataset after these modifications can be seen in Figure 1. Based only on these visualizations, we can see some kind of seasonality in almost each variable.
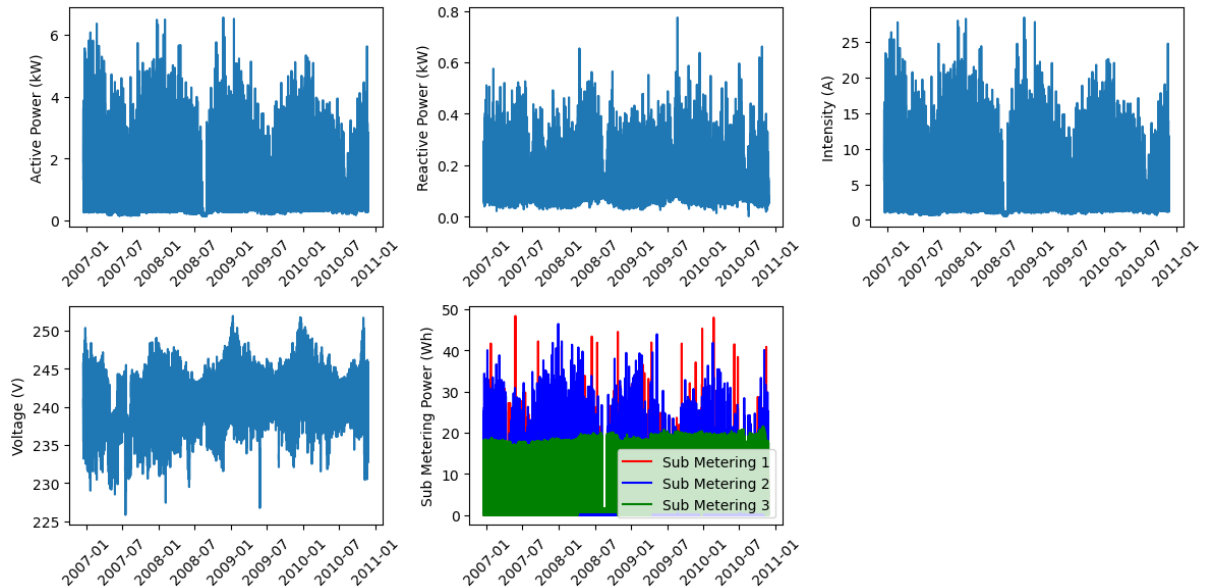


Figure 1: Variables after handling missing values and modifying data into hourly averages.

### 3.2 Time-series decomposition

The time-series data of the target variable is used to analyze and understand its temporal behavior. Time-series decomposition was first applied on data containing hourly averages of target variable, using a season length of one day (24 hours). The result of this is shown in the Figure 2. The figure shows that the trend still includes seasonal variability, which could be interpreted as annual, because at the same time of year, the trend behaves repeatedly in the same way. For this reason, time-series decomposition is not satisfactory, and we must try to define the length of the season so that the trend does not include seasonal variation.
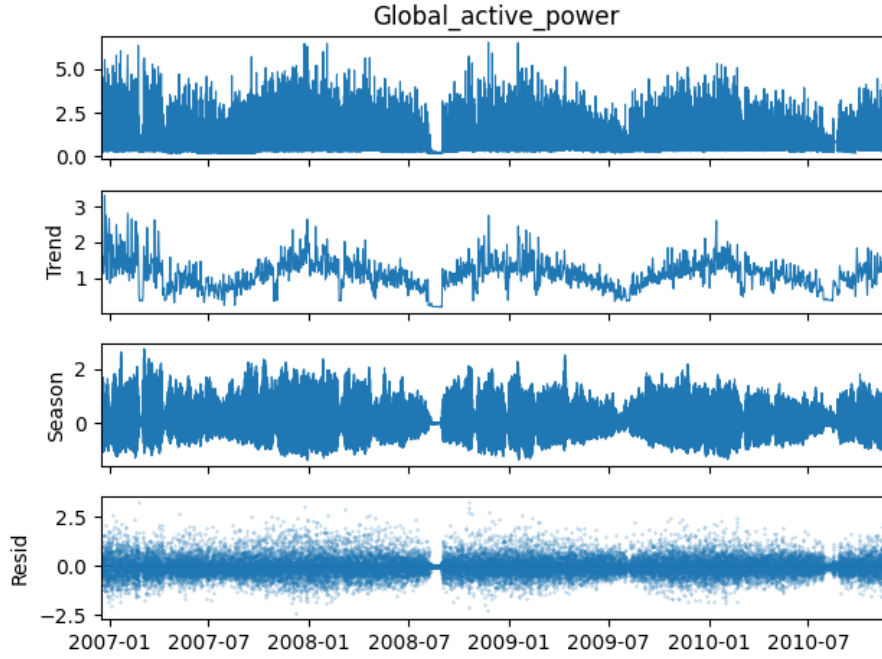
Figure 2: Time-series decomposition of the Global Active Power variable using hourly average values, and a day as a season length.

In the Figure 3, time-series decomposition is created for hourly average data, with the season length being one year (24 hours * 365). In Figure 4, daily averages have been taken from the data for the explained variable and a time-series decomposition has been performed using as a season length a year (365 days). Both annual season length distributions show a similar, slightly decreasing trend. Seasonality shows annual variation, with values of the target variable falling in summer and peaking in winter.

In the figure, the residuals appear to be quite evenly distributed around zero, although in the middle of the time series the residuals clearly show greater variance compared to the beginning and end. If the figure showed a single large residual that did not repeat itself seasonally, that sample could be considered a possible outlier. Trend and seasonal components should appear smooth without any distinct outliers, as such outliers are expected to appear in the residuals. At this moment, there are no clear potential outliers visible in the figure, but they may still appear in later analysis.
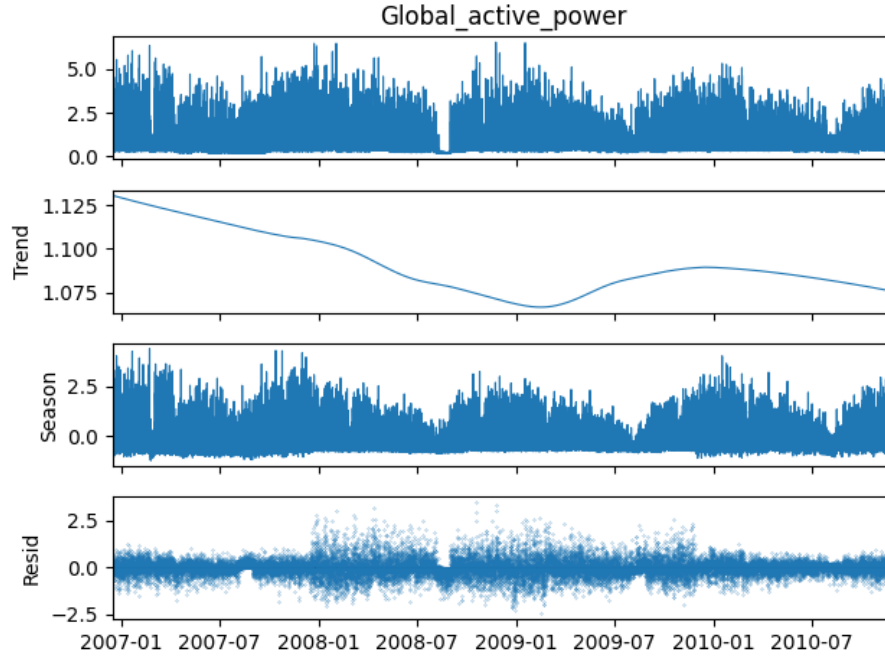
Figure 3: Time-series decomposition of the Global Active Power variable using hourly average values, and a year as a season length.
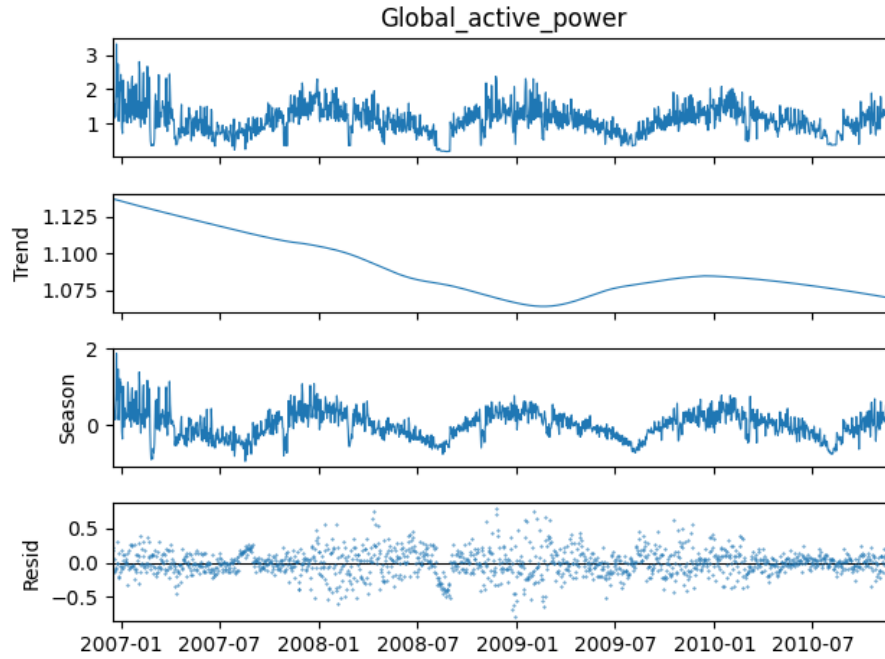


Figure 4: Time-series decomposition of the Global Active Power variable using daily average values, and a year as a season length.

## 3.3 Autocorrelation analysis

Autocorrelation function can be used to evaluate relationships between past and present observations. Significant correlation between these indicate that the time series is not a random walk.

Before using autocorrelation function, the stationarity of the observations was evaluated using

Augmented Dickey-Fuller (ADF) test. For Global active power, the ADF Statistic of -11.12 and p-value of $3 \cdot 10^{-20}$ indicated stationary observations, so no time series transformations were needed before applying the autocorrelation function.

The autocorrelation function plots for Global active power, using 48 and 168 lags are shown in Figure 5. Each lag represents delay of 1 hour, which means that 24 lags correspond to a one-day delay and 168 lags a one-week delay.
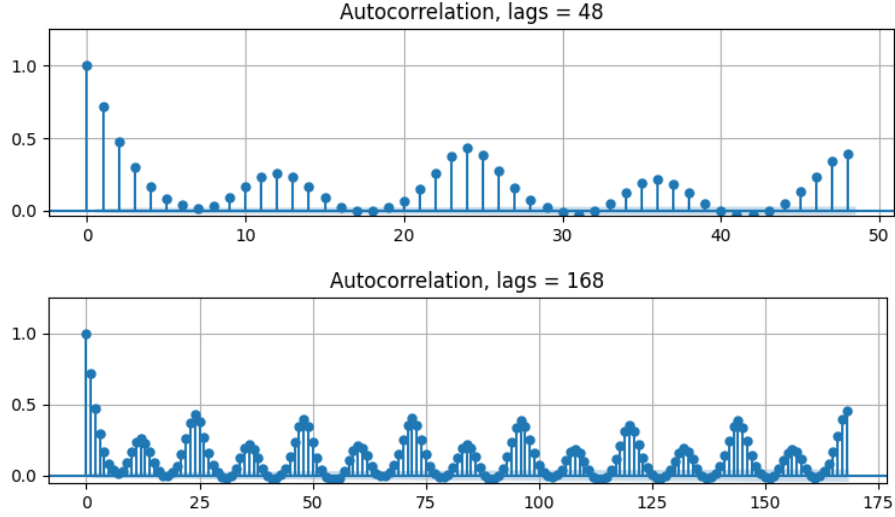


Figure 5: Autocorrelation function plots for Global active power, using 48 and 168 lags.

From the figure we could see that there were significant relationship between the past and the present observations, especially in daily and weekly periods. These significant relationships occurred also in explanatory variables.

## 3.4 Baseline model

For the seasonal naïve predictor we used one week as the length of the season which in the used dataset corresponds $h = 168$ hours. This means that, for predictions the previous value from same weekday and hour was used.

The predictions were calculated for a time horizon of one week with a resolution of one hour. An example of the model's predictions is shown in Figure 6.
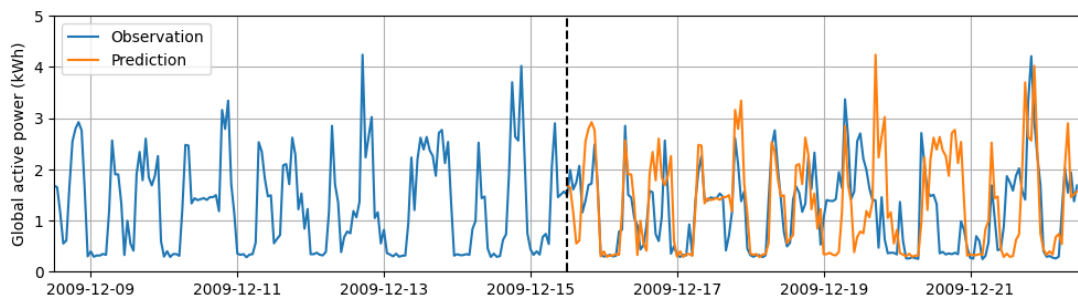


Figure 6: Observations and predictions using seasonal naïve predictor. The beginning of the predictions has been marked using a dashed line.

In addition to predictions, the root-mean-squared errors (RMSE) and mean arctangent absolute percentage errors (MAAPE) were calculated for each prediction horizon. The mean value for RMSE-values was 0.81 kWh and for MAAPE-values 0.44 %.

# References

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