



**IDENTIFYING ELECTRICITY CONSUMPTION FLEXIBILITY FROM ELECTRICITY MEASUREMENTS AND  
ELECTRICITY PRICE DATA - CASE DETACHED HOUSE**

Lappeenranta–Lahti University of Technology LUT

Bachelor's Programme in Electrical Engineering, HEBUT DD, Bachelor's thesis

2025

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## ABSTRACT

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41 pages, 11 figures, 8 tables

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Keywords: Electricity Distribution Networks, Electricity price, Flexible electricity use, Statistical analysis, Demand response

This thesis looks at the relationship between electricity consumption and electricity prices using actual measurement data from a detached house in Lappeenranta, Finland. The data includes readings from an electricity metre and a distribution board. The detached house is an example of a flexible electricity use location, in which electricity consumption responds to price changes. The study uses data and statistical analysis to investigate these relationships and sheds light on how pricing mechanisms can influence electricity consumption. the following questions are addressed:

1. How does household electricity consumption respond to fluctuations in electricity prices?
2. What methods can effectively measure and identify demand-side flexibility in residential electricity use?

While the overall relationship between electricity consumption and SPOT market prices is weak when analysed by Pearson, Spearman and Kendall coefficients. However, there is a significant response during extreme price events. This is particularly noted when SPOT prices fall below 0 €/MWh. On these occasions electricity consumption increased by up to 40%, indicating that households adjust their energy usage in response to large price fluctuations.

## TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUTin energijärjestelmien tiedekunta

Sähkötekniikka

Hebei University of Technology

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## **SÄHKÖNKULUTUKSEN JOUSTAVUUDEN TUNNISTAMINEN SÄHKÖMITTAUSTEN JA SÄHKÖNHINNAN TIETOJEN AVULLA - TAPAUSTUTKIMUS OMAKOTITALO**

Sähkötekniikan kandidaatintutkielma

2025

41 sivua, 11 kuvaa, 8 taulukkoa

Tarkastaja(t): Tutkijaopettaja Juha Haakana, Tutkijaopettaja Shanhu Li

Avainsanat: Sähkönjakeluverkot, Sähkön hinta, Joustava sähkökäyttö, Tilastoanalyysi, Kysyntävastaus

Tämä kandidaatin tutkielma tutkii sähkönkulutuksen ja sähkön hintojen välistä suhdetta käyttämällä todellisia mittaustietoja omakotitalosta Lappeenrannan alueella, Suomessa. Tutkimuksessa hyödynnetään sähkönkulutusmittarin ja jakokeskuksen mittaustietoja. Omakotitalo toimii esimerkkinä joustavasta sähkökäytöstä, jossa kulutus mukautuu hintavaihteluihin. Tutkimuksessa käytetään data-analyysiä ja tilastollisia menetelmiä näiden suhteiden tarkasteluun ja valaistaan, kuinka hinnoittelumekanismit voivat vaikuttaa sähkönkulutukseen. Tutkielmassa käsitellään seuraavia kysymyksiä:

1. Miten kotitalouksien sähkönkulutus reagoi sähkön hinnan vaihteluihin?
2. Mitä menetelmiä voidaan tehokkaasti käyttää kotitalouksien sähkönkulutuksen kysyntäjouaston mittaamiseen ja tunnistamiseen?

Vaikka sähkönkulutuksen ja SPOT-markkinahintojen välinen yleinen suhde on heikko Pearsonin, Spearmanin ja Kendallin korrelaatiokertoimilla analysoituna, merkittäviä reaktioita havaitaan ääritilanteissa. Erityisesti, kun SPOT-hinnat laskevat alle 0 €/MWh, sähkönkulutus kasvaa jopa 40%. Tämä osoittaa, että kotitaloudet mukauttavat energiankäyttöään merkittävien hintavaihteluiden aikana.

## SYMBOLS AND ABBREVIATIONS

### Roman characters

$r$	Pearson correlation coefficient
$r_s$	Spearman correlation coefficient
$\tau_n$	Kendall Tau Metric
$x_i, y_i$	Individual observations of variables X and Y
$\bar{x}, \bar{y}$	Mean values of variables X and Y
$d_i$	Difference between the ranks of paired observations
$S$	Net difference of concordant and discordant pairs ( $c - d$ )
$c, d$	Number of concordant and discordant pairs
$n$	Total number of paired observations

### Subscripts

$i$	Index of individual observations
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### Abbreviations

kWh	Kilowatt-hour
€/MWh	Euros per megawatt-hour
DSM	Demand-Side Management
SPOT	Short-term Power Market Price
IQR	Interquartile Range
€/MWh	Euros per megawatt-hour

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# 1 Introduction

Electricity price volatility has increased significantly over the last decade, this is driven by disruptions in energy infrastructure especially from the Russia-Ukraine war drastically reducing the import of natural gas from Russia. Another recent notable event was the sabotage of critical electrical cables in Northern Europe, specifically the Estlink-2 power cable, which connects Finland and Estonia across the Baltic Sea. On December 25, 2024, the Estlink-2 cable ruptured which disrupted energy flow between neighbouring countries. Although the immediate impact on services was minimal, this incident followed previous damage to two data cables and the Nord Stream gas pipelines, all of which were attributed to sabotage. These incidents have heightened concerns about the security and reliability of energy networks, exacerbating the already volatile electricity market here within Finland.

In addition to the security risks posed by infrastructure damage, Finland is also going through a major energy transition. Non-renewable fuel sources are being phased out in favour of renewable energy sources, quote “In Finland renewable energy sources represent about 40 per cent of energy end-consumption. The aim set in the National Energy and Climate Strategy to 2030 is to increase the use of renewable energy so that during the 2020s its share in energy end-consumption rises to more than 50 per cent.” By the Ministry of Economic Affairs and Employment of Finland (Renewable Energy in Finland, 2020). Furthermore, research towards this can be seen notably in LUT University as Olli Pyrhönen stated “Energy’s central role in international crises cannot be overstated either.” (LUT University new energy outlook, 2024). While these changes in energy production have long-term benefits, they also increase volatility in electricity prices, particularly during periods of high demand or network instability. As electricity prices fluctuate, households are increasingly adopting flexible consumption practices, so they are able to adjust their energy usage in response to price signals.

The relationship between electricity prices and consumption with a focus on how to make electricity use more flexible can assist households in adapting to price changes while also contributing to overall energy system stability. Real-time data will be collected from a detached house in the area of Lappeenranta, Finland, with a total heated area of 150 m<sup>2</sup> and

an 80 m<sup>2</sup> heated garage. The property uses a ground source heat pump to heat both the house and the garage, drives an electric vehicle and adheres to a SPOT price electricity contract to study how electricity pricing mechanisms influence household consumption patterns and whether demand-side flexibility can reduce distribution network stress.

The primary goal of this thesis is to investigate the relationship between household electricity consumption and fluctuations in electricity prices. Understanding this relationship between the two will give us insight in determining how households react to price signals and evaluating the potential for demand-side flexibility to stabilise energy systems. The second key goal is to investigate methods for accurately measuring and identifying demand-side flexibility in residential electricity consumption.

## 1.1 Electricity Prices

Electricity prices in Europe, particularly in countries such as Finland are closely tied to the wholesale market. The wholesale price of electricity is linked to the supply and demand curve which is formed by the sale bids and purchases done on the electricity exchange (Electricity Markets – Lecture Notes 2023). Finland, as a member of the Nordic electricity market does also benefit from a high proportion of renewable energy sources which typically help to keep prices more stable than countries that rely heavily on fossil fuels. However, Finland is still vulnerable to external influences such as fluctuations in natural gas prices or disruptions in energy imports which both have contributed to recent price increases.

Wholesale electricity prices are set in the market using a system known as the merit order, which ranks power plants from lowest to highest production cost. Renewable sources are dispatched first due to their low operating costs, which is then followed by nuclear and then fossil fuel plants. When demand is high, more expensive power sources need to be used which raises the overall cost. Finland has a strong commitment to expanding renewable energy and energy efficiency initiatives which is supervised by The Energy Authority in Finland (Energy Authority, 2014). The detriment to this is during periods of low renewable energy generation or increased demand, prices can rise particularly during the winter when electricity consumption peaks which is predictable due to the necessity of heating.

## 1.2 SPOT Price Electricity Contracts

For this thesis, A SPOT price electricity contract is used in the house. SPOT price electricity links a consumer's electricity rate to real-time market prices set by the Nord Pool electricity exchange. This means that prices can fluctuate hourly to reflect changes in supply and demand. SPOT prices allow consumers to take advantage of lower prices during off-peak hours, however they also carry a higher risk during periods of high demand when the price can increase and electricity is still required by the user. In Finland SPOT price contracts have grown in popularity as consumers look for ways to adapt to rising electricity costs while lowering their overall energy costs.

One of the primary advantages of a SPOT price contract is its transparency, which allows consumers to track wholesale prices in real time and adjust their energy consumption accordingly. Households with adaptable consumption patterns can optimise their usage to avoid costly periods. The negative to this is the unpredictable nature of SPOT prices. External factors such as extreme weather or geopolitical tensions can raise prices above what fixed-rate customers would normally pay.

## 1.3 Lappeenranta, Finland

The location which will be used in the thesis is in the general area of Lappeenranta, located in southeastern Finland. The location of the detached house used to be studied on was chosen because Lappeenranta was named the National Earth Hour Capital of Finland in 2014 and has a Climate Programme and ten action plans which helped reduce greenhouse gas emissions by 21% in 2011 compared to 1990 levels therefore making it an excellent place for this thesis. Lappeenranta also has Finland's largest bioenergy plant, Kauvo, which uses renewable energy to generate 40% of the city's electricity and more than 50% of its district heating. Lappeenranta University of Technology (LUT University) also plays an important role in the city's green transformation, conducting research and development in renewable energy and sustainable technology. (Panda.org, 2014)

The city is very conscious with the use of electricity and has integrated green solutions into its infrastructure in recent years. A notable example is the introduction of hybrid buses in collaboration with LUT University which has made public transportation emissions reduced by 50%. Lappeenranta also has Finland's largest solar power plant, located on LUT's Green Campus which serves as a test bed for renewable energy technologies. The Green Campus has received international recognition for its sustainability efforts. (Panda.org. 2014)

## 2 Literature Review

As electricity prices are becoming progressively more complex and unpredictable to analyse and predict, this has led to significant research into understanding the relationship between electricity consumption and price fluctuations. This can be notably seen in household energy consumption, particularly in regions with volatile energy markets which are influenced by both external factors and pricing mechanisms such as SPOT price contracts, which can drive flexible usage behaviors. As more information into how to predict electricity prices become public the shift from fixed price contracts to flexible is becoming more and more relevant.

The EU is predominantly using fixed price contracts which on one hand shields the consumer from any market shifts however this does lock the consumer into an overall higher contract and slows down the adoption of any flexible energy practices and the overall energy transition (ACER & CEER, 2024). There has been a push towards having different contract types within the EU as the Agency for the Cooperation of Energy Regulators (ACER) and Council of European Energy Regulators (CEER) have been heavily promoting this change. This would allow for the consumers to be able to choose from stable and variable price options which would relate to their needs and wants more effectively. With the accessibility of being able to choose flexible energy prices some protection would be need as quote “ACER and CEER reiterate their recommendation from the 2023 Retail MMR that Member States adopt balanced and targeted protection measures for vulnerable consumers.” (ACER & CEER, 2024).

### 2.1 Electricity Consumption and Price Correlation

For electricity consumption and price correlation a recent review of energy models was made where energy demand can be modelled in terms of price signals, which helps to explain how different energy consumption patterns emerge in response to price fluctuations. Price signalling being the pricing changes that are designed to communicate information to the consumer while also influencing their behaviour (Jebaraj and Iniyar, 1976). To add to this a recent review discussed the evolution of energy forecasting models and the relevance of

price elasticity in understanding consumption patterns. They wrote about that energy demand responds more elastically to price changes in the long run, especially when consumers have access to price-responsive mechanisms such as real-time pricing (Suganthi, L. & Samuel, A., 2012).

In a research conducted examines demographic parameters impacting energy consumption across European countries, demonstrating that the elasticity of demand varies dramatically with income levels, household size, and climate. York emphasises that in European Union countries, including Finland, demographic trends such as ageing populations and urbanisation influence overall energy demand and price responsiveness (York, R., 2007). Also, highlighted in “Dynamic multilevel modelling of industrial energy demand in Europe” the complex relationship between energy pricing and consumption in the industrial and residential sectors of Europe. They argue that during times of high demand or market disruptions, consumers are more inclined to change their usage and that this reaction is more prominent in markets with flexible pricing structures. (Sharimakin, A., Glass, A.J., Saal, D.S. & Glass, K., 2018)

### 2.1.1 Demand-Side Management and Flexibility

Demand-side management (DSM) and flexibility mechanisms of the sort are being increasingly recognised as solutions for mitigating the effects of any price volatility and relieving pressure on energy systems. DSM refers to companies proactively trying to influence consumer behaviour in order to optimise electricity use. One notable example is by encouraging energy consumption during off-peak hours to even out the load. There have been investigations on how non-parametric models such as rolling regressions, which might aid in optimising energy consumption patterns for customers under flexible pricing schemes. These models allow for time-varying price elasticity and demand characteristics, which is important for customers wanting to control their energy expenses efficiently (Salisu, A.T. & Ayinde, O., 2016).

In the context of Finland, SPOT pricing electricity contracts enable families to actively participate in demand-side flexibility with the effects of DSM. In such systems, it has been

noted that there is a correlation in users modifying their consumption in response to real-time pricing signals. (Jebaraj and Iniyar, 1976). Additionally, with research in Modelling energy demand, by encouraging demand flexibility it is feasible to reduce the requirement for expensive peak-time power sources, lowering the danger of blackouts and energy prices in the process (Salisu, A.T. & Ayinde, O., 2016).

### 2.1.2 Price Elasticity in Residential Electricity Demand

Price elasticity is a measure of how responsive the quantity demanded is to price changes and is another factor that has to be taken into account when looking at electricity consumption and electricity pricing because households' consumption is frequently inelastic in the short term, which means they are less likely to reduce consumption immediately in response to price increases.

(Sharimakin, A., Glass, A.J., Saal, D.S. & Glass, K., 2018) provide important information about the long-term price elasticity of electricity demand. They demonstrate that, while households may initially maintain consistent consumption patterns despite price increases, as price signals become more integrated into consumers' decision-making processes, they may adjust their usage. The researchers propose that there is a negative elasticity in the long run, which means that as prices rise, consumption falls, particularly in regions with advanced DSM strategies. (Bhattacharyya, S.C. & Timilsina, G.R., 2010) investigate indirect aspects of price elasticity, observing that higher-income households may be able to absorb higher energy costs without adjusting consumption, whereas lower-income households may be more likely to reduce consumption when prices rise.

While in Finland the electricity price is very volatile during the electricity transition period, as renewable sources such as wind and solar become more integrated into the energy mix this will begin to level out. As a result, households may become more sensitive to price signals over time as the overall pricing structure becomes more stable and transparent.

## 2.2 Statistical Analysis Approach in Energy Consumption Analysis

To get a quantitative result in the correlation of electricity consumption and pricing statistical analysis methods need to be used. Correlation analysis is based on measures such as Pearson, Spearman, and Kendall correlation coefficients which directly quantify the strength and direction of relationships between two variables which is extremely useful in this case. Pearson correlation is the most popular and effective for linear relationships, whereas Spearman and Kendall correlations are for non-linear and monotonic relationships. These methods enable the analysis of how energy consumption behaves across time series data, taking into account variance and covariance to assess dispersion and dependency between variables.

In correlation studies Linear regression is used frequently and it captures the relationship between variables using a straight line and can be evaluated using metrics such as the R-squared value. R-squared value shows the proportion of variation in the dependent variable explained by the independent variable. Also, variance and covariance show how variables differ in relation to one another. (Flygare, C., Wallberg, A., Jonasson, E., Castellucci, V. and Waters, R., 2023)

## 2.3 Identified Research Gaps

While significant research has been conducted to better understand the relationship between electricity prices and consumption patterns, several critical gaps still remain. This transitional period is distinguished by an increased reliance on renewable energy as in 2023, renewable energy sources represented an estimated 24.1% of the European Union's final energy use (European Environment Agency, 2024) and also many other factors. So a deeper understanding on how different households, such as those in rural or low-income areas respond to flexible pricing systems need to be further explored and analysed. However, the longer we are in the transition period the more data will be available to analyse.

## 3 Methodology

### 3.1 Correlation analysis

Correlation analysis employs statistical methods to evaluate the relationship between variables.

#### 3.1.1 Pearson correlation coefficient ( $r$ )

The Pearson correlation coefficient is said to be the most direct method for correlation analysis since it directly measures the linear relationships between two variables, returning values ranging from  $-1$  to  $+1$  that indicate direction and strength. A positive score indicates positive linear correlation whereas a negative value indicates negative linear correlation. The linear correlation increases as the value approaches  $+1$  or  $-1$ . The Pearson's correlation coefficient is defined as:

$$r = \frac{\sum[(x_i - \bar{x}) \cdot (y_i - \bar{y})]}{\sqrt{\sum(x_i - \bar{x})^2} \cdot \sqrt{\sum(y_i - \bar{y})^2}} \quad (1)$$

In this context,  $x_i$  and  $y_i$  show the individual observations of the variables  $\bar{X}$  and  $\bar{Y}$ . While  $\bar{x}$  and  $\bar{y}$  represent the mean values of all observations of  $x$  and  $y$ . The terms  $x_i - \bar{x}$  and  $y_i - \bar{y}$  indicate the deviations of each observation from their respective means, which is quantifying how far each data point lies from the average of its variable.

#### 3.1.2 Spearman correlation coefficient ( $r_s$ )

With a little bit more enhancements the Spearman Correlation analyses the monotonic relationships with ranked data, which is appropriate for non-linear trends. The Spearman correlation is useful because it relies on nearly all of the same assumptions as the Pearson correlation, but it does not require normality and also the data can also be ordinal. Thus, it is a non-parametric test. The Spearman correlation coefficient is defined as:

$$r_s = 1 - \frac{6 \cdot \sum d_i^2}{n \cdot (n^2 - 1)} \quad (2)$$

$d_i$  represents the difference between the ranks of each pair of observations, calculated for each observation  $i$  as  $d_i = \text{rank}(x_i) - \text{rank}(y_i)$  while  $d_i^2$  denotes the square of this rank difference. The term  $\sum d_i^2$  is the sum of all squared rank differences across the dataset, and  $n$  refers to the total number of paired observations.

### 3.1.3 Kendall Tau Metric ( $\tau_n$ )

The final method that will be used for correlation analysis is the Kendall correlation coefficient known as Kendall's tau which compares concordant and discordant data pairs to evaluate relationships which is ideal for data with tied ranks or monotonic trends and just like the Spearman correlation it is nonparametric. It is a statistic for the dependence between two variables. The Kendall Tau Metric is defined as:

$$\tau_n = \frac{c - d}{c + d} = \frac{S}{\binom{n}{2}} = \frac{2S}{n(n-1)} \quad (3)$$

$c$  represents the number of concordant pairs which is where the ranks of both elements in a pair move in the same direction, and then  $d$  denotes the number of discordant pairs, where the ranks move in opposite directions. The difference between these,  $S = c - d$ , is the net number of concordant minus discordant pairs. The total number of possible observation pairs in a dataset of size  $n$  is given by  $\binom{n}{2} = \frac{n(n-1)}{2}$ .

## 3.2 Data Description and Collection

This thesis relies on two major datasets. The first includes power usage statistics for a separate residence in the general area of Lappeenranta from 2024. This first dataset comprises of timestamped records of electricity use in kilowatt-hours (kWh) and temperature data in degrees Celsius ( $^{\circ}\text{C}$ ) for each recorded time that is taken.

Then for the second dataset that was provided contains SPOT market power prices of 2024 that relates to the Lappeenranta detached house case. It incorporates SPOT pricing that is calculated in euros per megawatt-hour (€/MWh).

### 3.3 Data Analysis

The intended reason for the data analysis is to find any correlations between electricity consumption, temperature, and market price trends for the detached house. Although simple methods, the Pearson, Spearman, and Kendall Tau correlation metrics are used because they are very effective at revealing relationships between variables in time series data.

#### 3.3.1 Outlier Detection and Filtering

To ensure consistency when performing correlation analysis, the data has to be processed beforehand. One important step is to identify and remove any outliers that may distort the results. The main outliers which were considered was with the SPOT pricing.

To address this, the interquartile range (IQR) filtering method is used. The IQR method is particularly effective because it is immune to the influence of extreme values and provides a dependable measure of data distribution.

$$\begin{aligned} \text{Upper limit} &= Q3 + (1.5) \cdot IQR \\ \text{Lower limit} &= Q1 - (1.5) \cdot IQR \end{aligned} \tag{4}$$

The first quartile (Q1) represents the value below which 25% of the data points fall and then the third quartile (Q3) represents the value below which 75% of the data points fall. The interquartile range which is ( $IQR = Q3 - Q1$ ) measures the spread of the middle 50% of the data. Which serves as a reliable indicator of variability that is less sensitive to extreme values. This then creates in producing a more representative dataset for statistical analysis.

### 3.3.2 Data Segmentation

To explore a broader and to gain a better understanding of the trends and correlations, the then processed data was divided into segments. This segmentation helps identify any patterns that are in electricity usage and pricing.

For example, a seasonal analysis can show how increased heating demands during the winter months would directly affect the electricity consumption. On the other hand, the monthly and daily breakdowns would aid in the identification of specific patterns of high or low usage in response to external factors such as temperature fluctuations or any sudden changes in SPOT pricing.

### 3.3.3 Human Behavioural Factors

While raw statistical relationships are important, the impact of human behaviour needs to also be considered when analysing. Specifically, it's necessary to determine how much variation in the electricity pricing is actually required to cause any behavioural shift in the homeowner's consumption patterns. If the price change is not perceived as significant or does not provide a clear economic incentive then there is a strong chance that the homeowner is unlikely to make significant changes to their normal electricity consumption.

### 3.3.4 Defining levels of correlation

Correlation coefficients are numerical values that range from -1 to 1 and represent the strength and direction of a linear relationship between two variables. According to widely accepted statistical standards (Hinkle, Wiersma, & Jurs, 2003), the definitions to the interpretation of the correlation that will be used in this is:

- Very High Correlation: 0.90 to 1.00 (or -0.90 to -1.00)
- High Correlation: 0.70 to 0.90 (or -0.70 to -0.90)
- Moderate Correlation: 0.50 to 0.70 (or -0.50 to -0.70)

- Low Correlation: 0.30 to 0.50 (or -0.30 to -0.50)
- Negligible Correlation: 0.00 to 0.30 (or -0.00 to -0.30)

This classification offers a framework for how to interpret correlation results and to determine the strength of relationships between variables when looking over the results.

## 4 Results

### 4.1 Overview of the Data Set

Firstly, to set the groundwork this is the raw data in graphical form to provide an initial visual of electricity consumption, temperature, and SPOT pricing patterns. As seen in figure 1 it visually shows that there was a significant spike in the SPOT price during the January period which exceeds 1500 €/MWh.

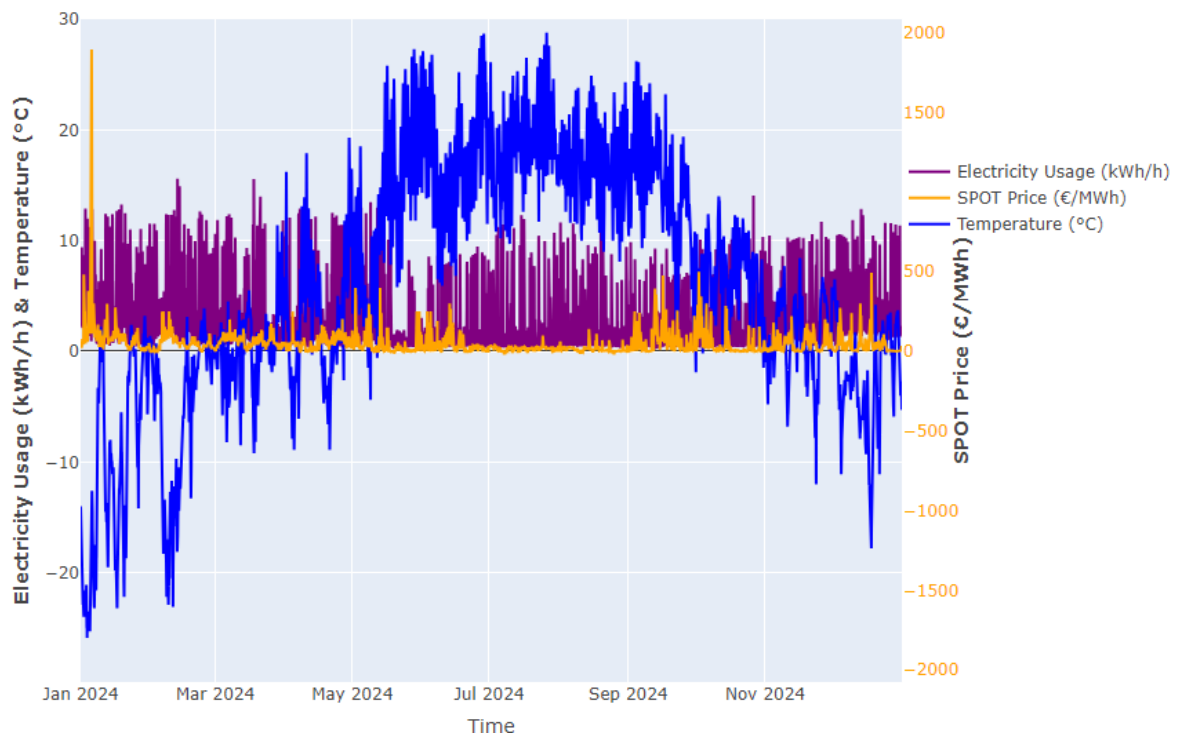


Figure 1: Electricity Consumption, Temperature, and SPOT Pricing

Without removing this outlier, later analyse became bound to this section therefore it will be removed using the interquartile range and also separately investigated since this will also show what correlations there are at extreme cases. Also, during the summer period there is

a noticeable decrease in the SPOT pricing as the electricity usage also slightly decreases and the temperature rises.

#### 4.1.1 SPOT Price outliers

For most of the results there was a set maximum and minimum boundary for the data set, outliers from the SPOT price were removed using interquartile range (IQR) filtering. The IQR method makes it, so the focus is on the centre observations in the data. By using this technique, a total of 397 outliers are removed from the data set.

#### 4.1.2 Analysis of main outlier removed

The SPOT price data for the year reveals a mean value of 45.57 €/MWh, which is the average price across the dataset. However as can be seen in Figure 2, there is a large increase in the SPOT price in early January 2024 with the value topping 1500 €/MWh.

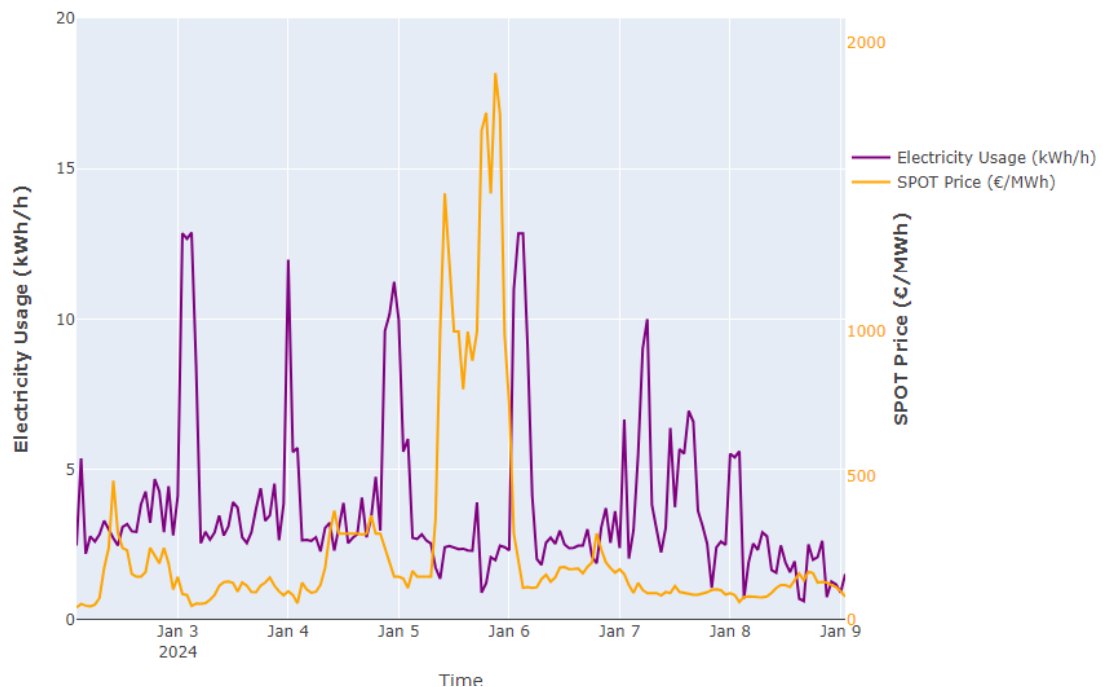


Figure 2: Electricity Usage and SPOT Price, SPOT Price Peak

The correlation analysis shows that the Pearson correlation for January 5, 2024 is -0.41. This represents a mild negative correlation between energy use and SPOT pricing on this particular day. While the correlation is not exceptionally strong, it does indicate a significant inverse relationship. Furthermore, it is worth noting that electricity usage shows a slight shift in its peak in relation to SPOT price trends. Prior to January 5, the electricity usage typically peaks around midnight (00:00) but after this date, it peaks slightly later. This adjustment indicates a deliberate effort to align electricity consumption with periods of lower pricing.

#### 4.2 Electricity Consumption, SPOT Price Over Time and Temperature

After removing outliers, the correlation between electricity consumption and temperature was measured and it shows a relatively strong and consistent inverse relationship. Figure 3 shows a Pearson correlation coefficient of -0.31, which sits within the low correlation range which indicates a modest linear relationship. Then with a Spearman coefficient of -0.53 and the Kendall Tau coefficient of -0.37 being in the moderate correlation range, indicates a stronger and more consistent trend in ranked data.

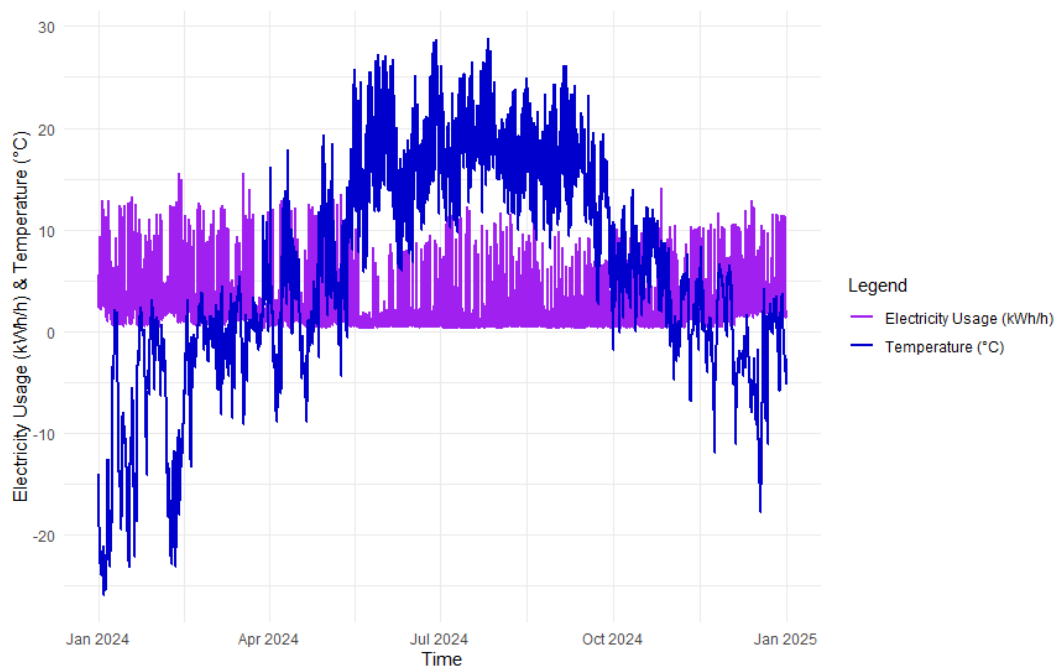


Figure 3: Electricity Usage and Temperature

From this it can be noted that there is some degree of relationship between electricity consumption decreasing as temperatures rise, which is consistent with expectations due to reduced heating needs during warmer months. Although not classified as "very high," the consistent negative direction and strength of all three correlation methods indicate that temperature is a significant factor influencing electricity consumption.

When considering the relationship between electricity consumption and SPOT market price appears to be relatively weak. Within Figure 4 there is a Pearson correlation coefficient of 0.016, which is well within the definition of negligible correlation which indicate that the two variables have almost no linear relationship between each other. Similarly, the Spearman (0.13) and Kendall Tau (0.09) correlation coefficients are both sitting in the negligible to low range and only indicate a very minor positive association in ranked data.

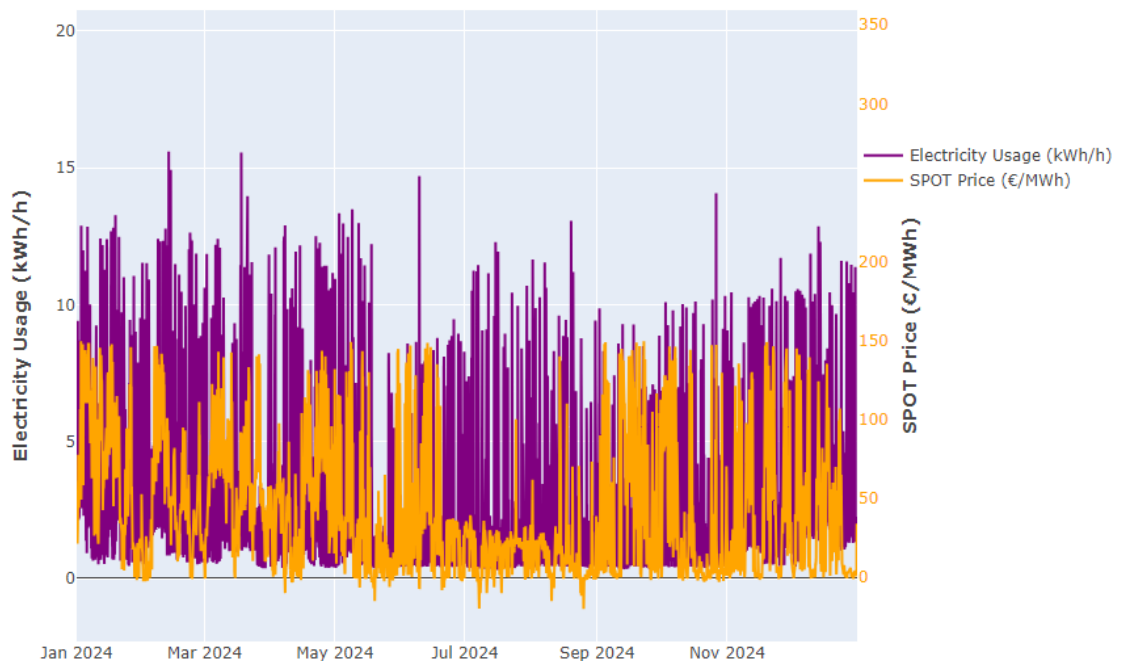


Figure 4: Electricity Usage and SPOT Price

This suggests that while looking at electricity usage and SPOT pricing, fluctuations in electricity consumption do not strongly correspond to variations in SPOT prices, or vice versa. However, this can be further explored when the data is segmented into smaller

timeframes mainly in or context-specific circumstances, clearer patterns emerge, implying that short-term or context-specific correlations may exist.

### 4.3 Highest Correlations between SPOT price and electricity usage

#### 4.3.1 Four Days with the Highest the Negative Pearson Correlation

Certain dates show pronounced correlations, these four specific dates July 9, August 11, December 19, and March 14, as shown in Table 1 indicate the most significant negative correlations between SPOT price and electricity consumption.

Table 1: Four Days with the Highest the Negative Pearson Correlation

Date	2024-07-09	2024-08-11	2024-12-19	2024-03-14
Pearson Correlation	-0.855	-0.689	-0.675	-0.662

With the most notable date being July 9, 2024, which demonstrates a high negative correlation between the two variables. It can be seen Figure 5 that on these days as electricity consumption rose, the SPOT price fell sharply, or vice versa. The consistency of these strong inverse relationships shows that there is a certain correlation with the electricity usage and SPOT pricing.

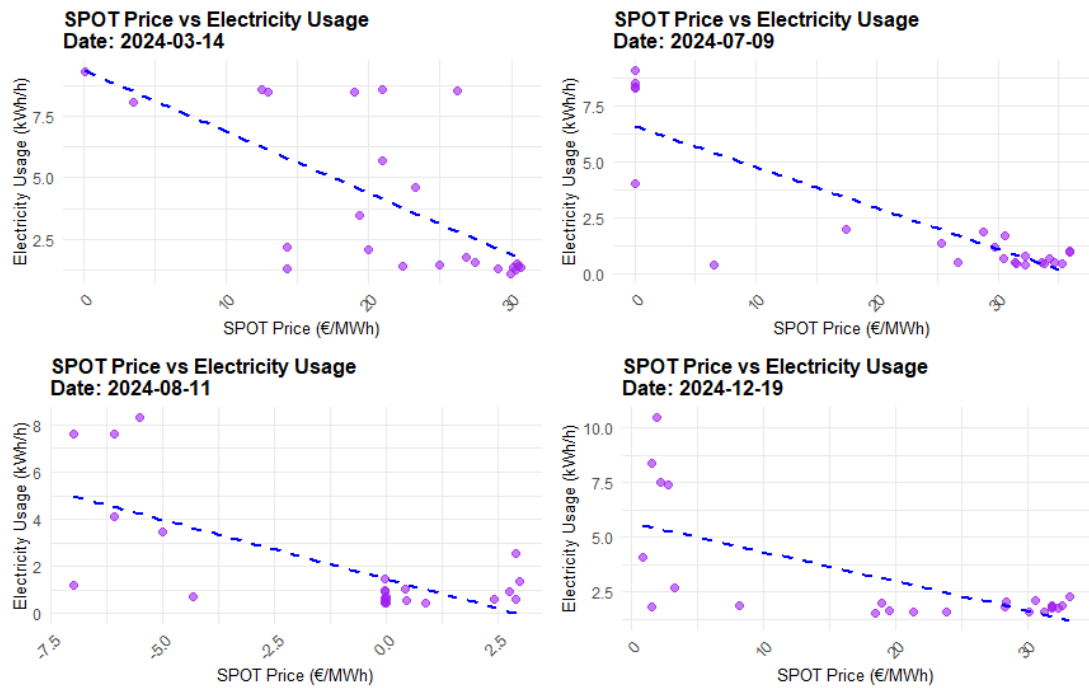


Figure 5: Four Days with the Highest the Negative Pearson Correlation

On December 19, 2024, during a winter day, the negative correlation shows that there was not much of a change in electricity usage since there was not any significant before the SPOT price peak and then the correlation on March 14, 2024, a late-winter or early-spring day can suggest that a shift in electricity demand caused this inverse relationship. It can be noted that during August 11, 2024, the SPOT pricing went below 0 €/MWh and this resulted in the electricity usage to suddenly increase which the results in the high negative correlation.

#### 4.3.2 Four Days with the Highest Negative Kendall Correlation

Another four notable dates are October 29, March 14, July 6, and December 20, 2024, which show moderate to strong negative correlations between SPOT price and electricity consumption, with Spearman and Kendall coefficients supporting the trends seen in the Pearson's correlation as seen in Table 2.

Table 2: Four Days with the Highest Negative Kendall Correlation

Date	Pearson Correlation	Spearman Correlation	Kendall Correlation
2024-10-29	-0.487	-0.826	-0.672
2024-03-14	-0.662	-0.681	-0.509
2024-07-06	-0.449	-0.667	-0.473
2024-12-20	-0.425	-0.549	-0.451

To start on October 29, the Pearson correlation indicates a moderate negative correlation, whereas the much stronger Spearman and Kendall correlations indicate a strong inverse relationship in ranked data, despite this being a slightly weaker linear relationship. For March 14, this shows a strong Pearson negative correlation and is also confirmed by Spearman and Kendall coefficients which show a moderate to strong inverse relationship even though it is hard to visually identify this from Figure 6.

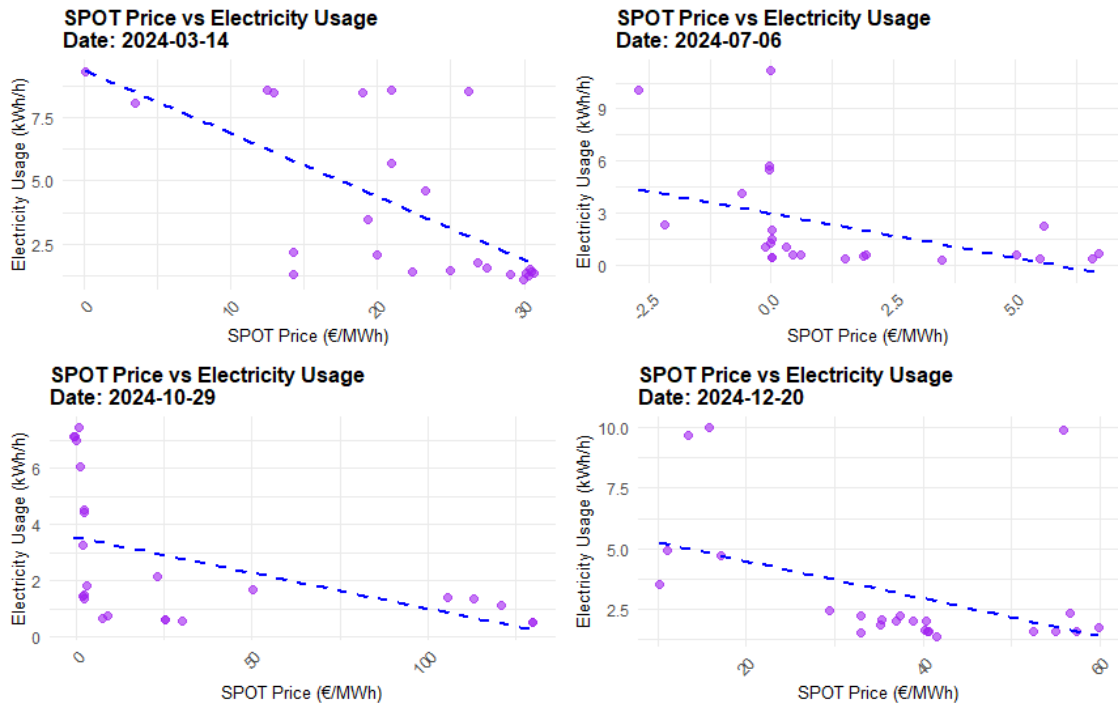


Figure 6: Four Days with the Highest Negative Kendall Correlation

The correlations that were measured on July 6 and December 20 are indeed slightly weaker, but they still do show consistent negative trends. The stronger rank-based correlations (Spearman and Kendall) indicate that, while using the linear relationship to measure correlation is not always perfect, the overall trend of higher electricity usage aligning with lower SPOT prices has remained relatively consistent allowing us to conclude that significant market dynamics is at work.

#### 4.3.3 Four Weeks with Highest Pearson Negative Correlation

The top four weeks largest negative Pearson correlations between SPOT price and electricity usage in the dataset were identified to be November 17, November 3, February 18, and March 10, 2024, as shown in Table 3.

Table 3: Four Weeks with Highest Pearson Negative Correlation

Date	2024-11-17	2024-11-03	2024-02-18	2024-03-10
Pearson Correlation	-0.431	-0.357	-0.295	-0.292

While the correlations are not as strong as those observed on individual days, they do show a consistent inverse relationship over longer time periods. In Figure 7 week 46 has the strongest negative correlation which is the first sign that increases in electricity usage were more frequently associated with any decreases in SPOT price. Week 44 has a moderately negative trend and a similar but slightly weaker inverse relationship.

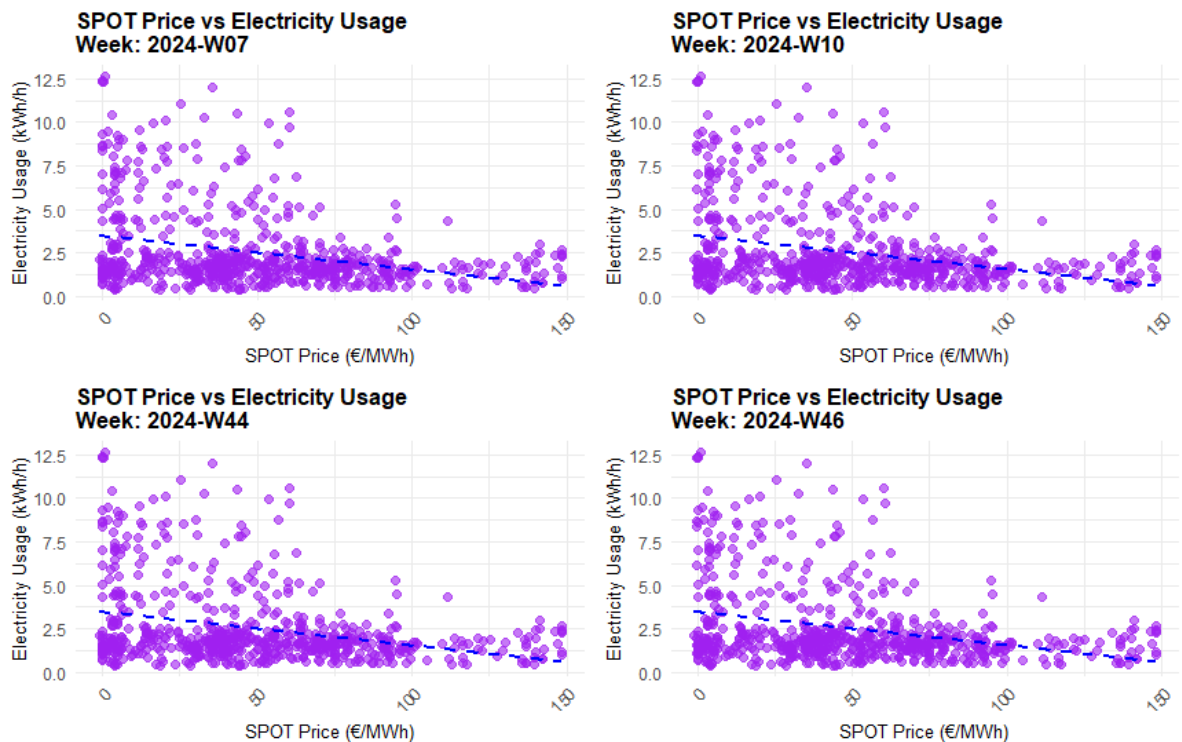


Figure 7: Four Weeks with Highest Pearson Negative Correlation

Week 7 and week 10 have weaker, but still significant negative correlations found from the correlations. While the negative correlation persists, its moderate strength suggests that SPOT prices were not solely driven by electricity consumption.

#### 4.3.4 Ten Days with the Highest Pearson Correlation

The top ten days that were calculated to have the strongest Pearson correlations between SPOT price and electricity usage are shown in Table 4. These days show a strong inverse relationship, with Pearson correlation coefficients ranging from -0.855 to -0.619 which is on the high correlation side.

Table 4: Ten days with the Highest Pearson correlation

Date	2024-07-09	2024-08-11	2024-12-19	2024-03-14	2024-07-16	2024-02-03	2024-11-11	2024-11-18	2024-09-16	2024-01-18
Pearson Correlation	-0.855	-0.689	-0.675	-0.662	-0.649	0.649	-0.640	-0.638	-0.631	-0.619

On these days, higher electricity usage was generally associated with lower SPOT prices, and vice versa. The most extreme case from the ten day was July 9, 2024, which had a Pearson correlation of -0.855, indicating a strong inverse relationship. Other notable days from the ten include August 11, December 19, and March 14, which all show significant negative correlations ranging from -0.731 to -0.619. The consistency of these strong negative correlations across different months suggests an inverse relationship between electricity usage and SPOT pricing from across the board and not just specifically one certain season, month or time period.

Furthermore, February 3, 2024, was identified as having a medium positive Pearson correlation of 0.649, which is the only day that has a positive correlation out of the other top

9 that were found when calculating the top ten Pearson correlation days. Further analysis of this revealed that the Kendall correlation for this day was 0.201, and the graph as seen in Figure 8 showed that SPOT pricing had a minimal impact on electricity usage.

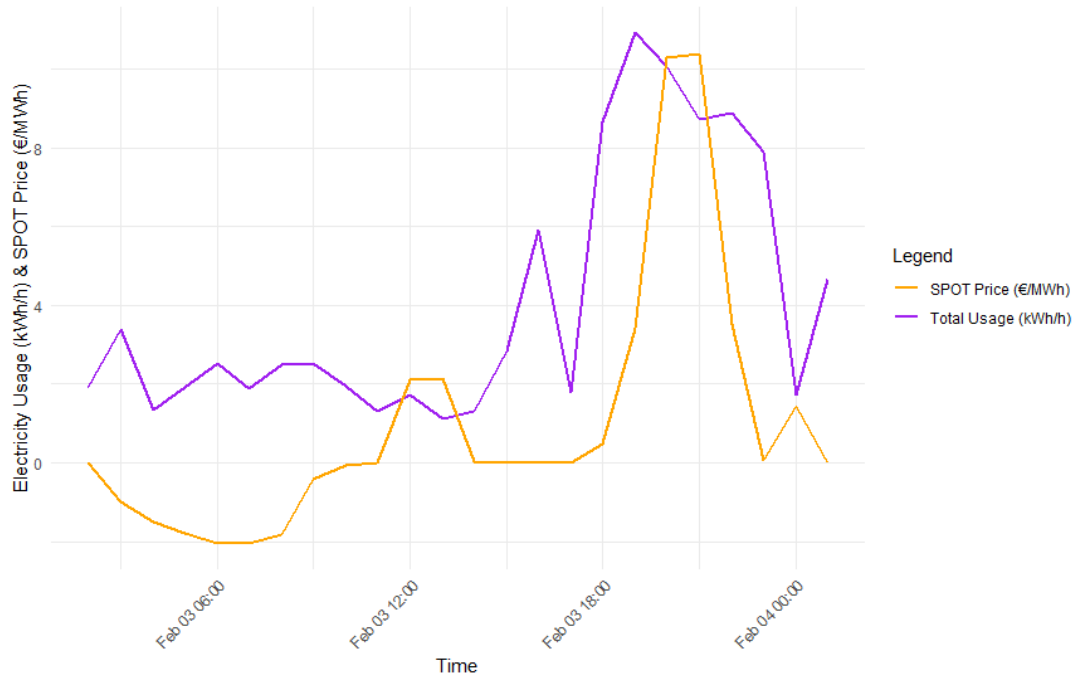


Figure 8: Electricity Usage and SPOT Price, February 3, 2024

With only one out of ten being negative correlations, adding to the observation that, on most days with significant correlations, electricity usage and SPOT prices tend to move in opposite directions.

#### 4.4 Looking at Extremes: Highest/Lowest SPOT Prices, Highest/Lowest Electricity Usage days, weeks, months and seasons

After looking at the average SPOT pricing and electricity usage cases the next step is to investigate the extreme cases. The correlation coefficients for the days with the highest and lowest average SPOT prices and electricity usage vary significantly.

On the day of the peak SPOT price in Table 5 (January 6, 2024), there is a moderate negative correlation between SPOT price and electricity consumption, implying that higher electricity consumption was associated with lower SPOT prices. This could be due to market conditions like excess electricity or regulatory interventions. On the highest usage day (January 20, 2024), however, the correlation is nearly zero.

Table 5: Correlation Coefficients for Highest and Lowest Average SPOT Price and Usage Days

Day	Pearson Correlation	Spearman Correlation	Kendall Correlation
Highest SPOT Price (2024.01.06)	-0.5640	-0.4963	-0.4075
Highest Usage (2024.01.20)	0.0273	0.0742	0.0438
Lowest Usage (2024.05.25)	0.2256	-0.1028	-0.0607
Lowest SPOT Price (2024.08.24)	0.1986	0.0044	-0.0148

May 25, 2024, which is the lowest usage day has a weak positive Pearson correlation but negative rank-based correlations, which then indicates that it has a slight incongruent relationship. For the lowest SPOT price day (August 24, 2024) this exhibits a weak correlation across all measurable metrics. Extreme pricing or usage days do not always follow the same correlation patterns as regular days.

The correlation analysis for electricity consumption and SPOT price over a one-week period reveals similarly weak relationships as seen in Table 6. The correlations for the week with the highest SPOT price (December 31, 2023 - January 6, 2024) are almost negligible in all account, with Pearson, Spearman and Kendall indicating little to no significant relationship between SPOT price and electricity usage.

Table 6: Electricity Consumption and SPOT Price correlation within One Week

Week	Pearson Correlation	Spearman Correlation	Kendall Correlation
Highest SPOT Price (2023.12.31 – 2024.01.06)	-0.0575	-0.0670	-0.0487
Highest Usage (2024.01.14 – 2024.01.20)	-0.2499	-0.1492	-0.0997
Lowest Usage (2024.05.19 – 2024.05.25)	0.0839	-0.0109	-0.0100
Lowest SPOT Price (2024.12.29 – 2025.01.04)	-0.1988	-0.1819	-0.1248

There is a mild negative correlation during the peak usage week (January 14 - January 20, 2024) The week with the lowest usage (May 19-25, 2024) has even weaker correlations compared to all the rest and finally, the week with the lowest SPOT price (December 29, 2024 - January 4, 2025) has weak negative correlations. When looking into one-week periods of extreme prices or usage, the relationship between SPOT price and electricity consumption is weak and inconsistent. Electricity consumption and SPOT price have a weak monthly correlation shown in Table 7.

Table 7: Electricity Consumption and SPOT Price correlation within One Month

Month	Pearson Correlation	Spearman Correlation	Kendall Correlation
Highest SPOT Price (January)	0.0165	0.1209	0.0800
Lowest SPOT Price (August)	-0.0867	-0.0171	-0.0113
Highest Usage (January)	0.0165	0.1209	0.0800
Lowest Usage (June)	-0.1276	-0.0585	-0.0381

For January (the month with the highest SPOT price), the correlations are extremely low, there is almost no significant relationship. Similarly, the month of August (with the lowest SPOT price) exhibits a weak negative correlation. The highest usage in January and the lowest usage in June both have near-zero correlations, indicating that even on a monthly

basis there is no correlation to be found. Table 8 examines the seasonal correlations (defined using the equinoxes and solstices as seasonal boundaries for the Northern Hemisphere) we find that the relationships between electricity consumption and SPOT price also remains weak across all four seasons.

Table 8: Electricity Consumption and SPOT Price correlation within Seasons

Season	Pearson Correlation	Spearman Correlation	Kendall Correlation
Winter	-0.0076	0.0093	0.0096
Spring	-0.0190	0.1291	0.0852
Summer	-0.0568	-0.0636	-0.0432
Fall	-0.1242	-0.0526	-0.0361

In winter, the correlations are negligible across all methods. Spring shows slightly stronger correlations for rank-based methods, but the linear relationship remains weak. Summer and autumn follow a similar pattern with consistently low correlations regardless of the statistical method used to try to find anything.

#### 4.5 Monthly Correlations

The correlation between electricity consumption and SPOT price varies by month, but overall, the relationships appear weak or negligible with no visible pattern shown in Figure 9. The Pearson correlation is highest in January and lowest in November and only showing overall a weak negative correlation. Spearman and Kendall correlations show a similar pattern to this, with November having the strongest negative association out of all the months.

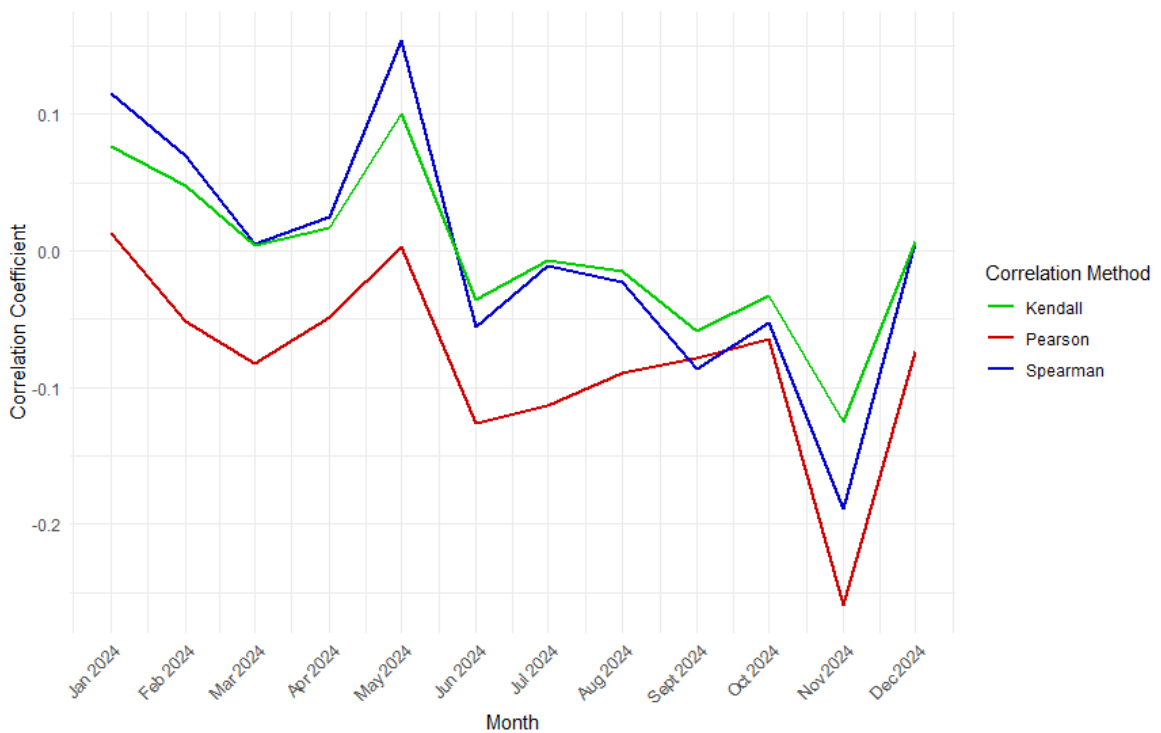


Figure 9: Monthly Correlation between SPOT Price and Electricity Usage

Despite minor variations, the correlations show no clear seasonal trend either from this. While some months, such as June and November, show more pronounced negative correlations, others such as May and January remain close to zero. One thing to be noted is during the time periods such as March and April Pearson correlation coefficient are negative, but Spearman and Kendall are both positive. With this, while the link may not be linear there is still a monotonic tendency in which higher SPOT prices consistently coincide with higher or lower electricity usage. In the end viewing the data in monthly aggregates may obscure any potential short-term patterns that exist on a daily or weekly basis.

#### 4.6 Electricity Usage rarely coincides with periods of peak SPOT Pricing

To see if a certain amount of change in the SPOT pricing or electricity usage was needed to make any noticeable electricity usage change, coinciding peaks were measured. Peaks were calculated by comparing real-time values to their corresponding moving averages, ensuring that only significant deviations from normal trends were considered. The low frequency of

coinciding peaks lends credence to the notion that electricity consumption is either relatively stable or managed in response to price fluctuations.

It occurred that SPOT price peaks coincided mostly around the summer period as seen from Figure 10, which is known to be the lower SPOT pricing periods as seen in Figure 4. Each bar in Figure 10 represents a month and the height represents the amount of coinciding peaks.

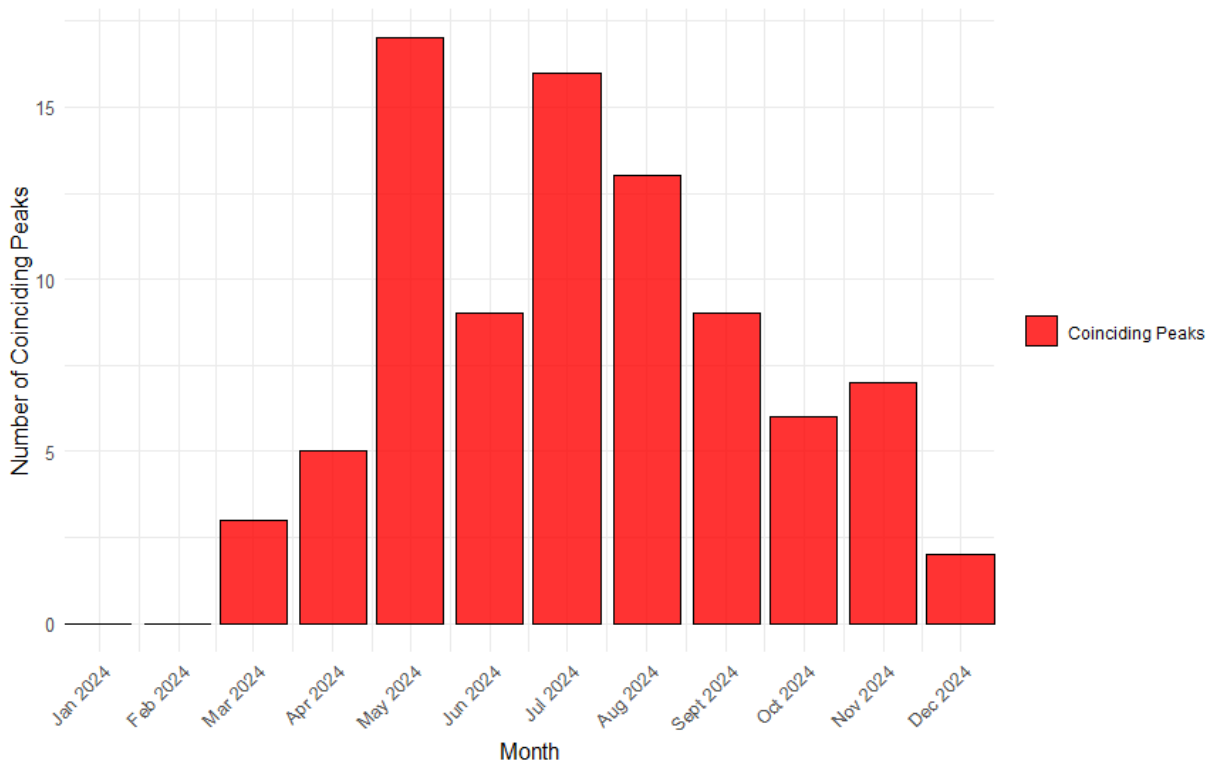


Figure 10: Number of Coinciding Peaks

The analysis of peak electricity usage and SPOT prices reveals a significant difference between the two. During the observational period there were 1,634 instances in which the SPOT price exceeded 1.5 times its 24-hour moving average which indicate that there was a price peak. Under the same threshold conditions, electricity usage peaked 497 times. More importantly, only 87 of these peaks coincided which then can be determined that in only 17.5% of cases where electricity usage peaked. This finding shows that the consumers actively reduce their consumption when prices are unusually high during that moment and it supports the broader trend observed in correlation analyses, which show that electricity usage and SPOT prices have medium relationships.

#### 4.7 Electricity Usage increase when SPOT price below 0 €/MWh

To see if there was any change in electricity usage behaviour when the SPOT price fell below 0 €/MWh, every time the SPOT price fell below 0 €/MWh and the electricity usage increased by at least 10% this was recorded. The relationship between electricity consumption and negative SPOT price events reveals a significant behavioural response to price decreases. During the analysis period, the SPOT price fell below zero 631 times. In 256 of these cases electricity usage increased by at least 10% after the price drop, accounting for 40% of all negative SPOT price events seen in Figure 11, with each bar representing the number of times the slight usage increased in each month and height being the amount of times the slight usage increased. When the electricity prices fell there is a measurable increase in consumption, most likely due to incentives for large-scale consumers or potentially automated systems designed to take advantage of cheap electricity and it can be most notably seen during the summer period especially when in August that the electricity usage increased slightly more than 60 times when SPOT price fell below 0 €/MWh.

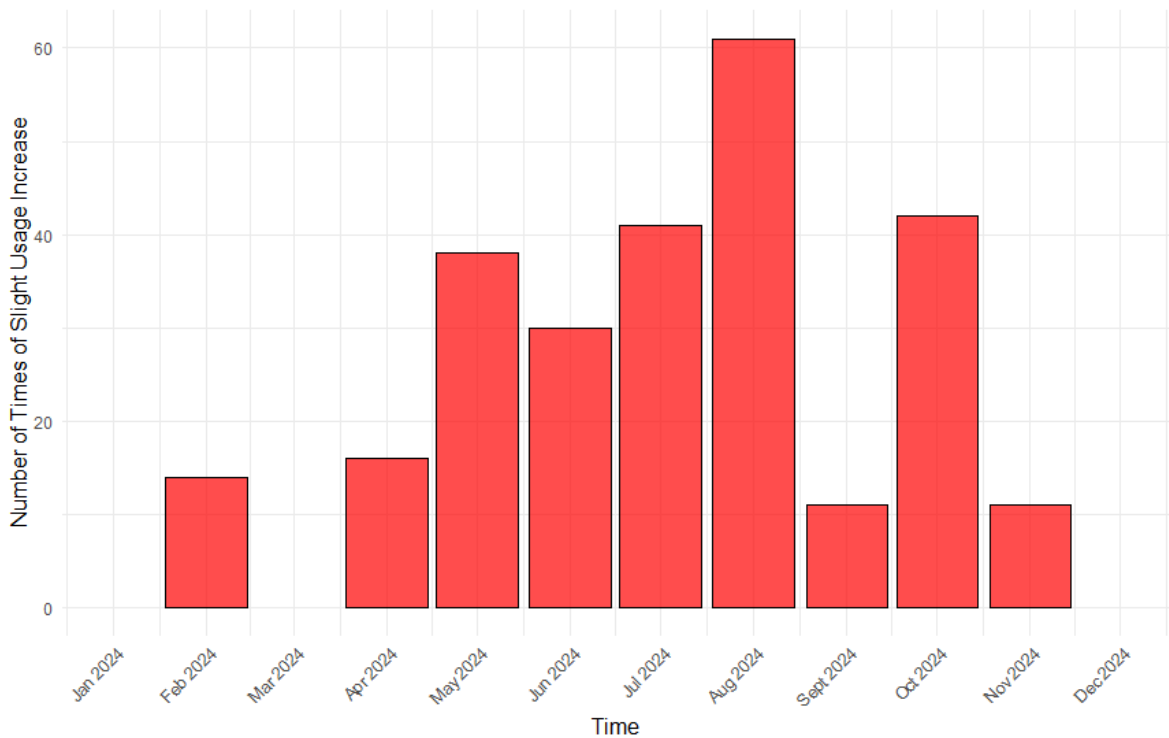


Figure 11: Slight Electricity Usage Increase After Price Drop

The 10% threshold for increased usage ensures that only significant consumption changes are considered, rather than minor fluctuations. The fact that nearly half of the negative price events resulted in an increase in consumption suggests that the consumer responded to the price signals by increasing usage when electricity is essentially free or when they are paid to consume.

## 5 Discussion

The purpose was to investigate the relationship between electricity consumption and electricity prices in a detached house in Lappeenranta, Finland, using statistical analysis of real-world measurement data. The key findings show that while the overall correlation between electricity consumption and prices is weak on a macro scale, significant correlations were found in specific timeframes particularly when looking at shorter periods or extreme price events. The findings highlight the potential for demand-side flexibility in residential electricity consumption especially when prices fluctuate significantly. It should be noted that more research with a larger dataset and additional external factors, such as household behavioural analysis is needed to fully confirm these findings.

### 5.1 Overall Relationship Between Electricity Consumption and Prices

The initial analysis revealed a weak overall correlation between electricity consumption and electricity prices. Also, when looking at longer timeframes such as monthly or seasonal data, the Pearson, Spearman, and Kendall correlation coefficients revealed only a modest association. This weak correlation can be attributed to a variety of factors, including habitual consumption patterns, external variables such as temperature, and the complexities of electricity pricing mechanisms. Furthermore, household energy consumption frequently follows patterns that are not immediately responsive to daily price fluctuations, particularly when prices remain in a narrow range.

Despite these conclusions when looking at the broad data, the data also showed that when examined over shorter time periods a much clearer and stronger relationship between consumption and prices emerged. While the overall relationship may be weak, there is significant responsiveness to price changes in specific situations.

## 5.2 Short-Term Responses to Price Fluctuations

A deeper look at shorter timeframes (daily or hourly data) revealed significant inverse relationships between electricity consumption and prices. On these days, the electricity consumption rose as prices fell, and vice versa when the situation warranted the need for this. Households definitely respond to price signals and adjust their consumption accordingly. This exemplifies the usefulness of demand-side flexibility in individual households.

## 5.3 Impact of Negative Electricity Prices

One of the most striking patterns that emerged was during periods when SPOT prices fell below zero. It was discovered that on nearly half of these occasions when this happened electricity consumption increased by more than 10%. The household was highly price sensitive, especially when prices dropped significantly. Such behaviour suggests that when prices are extremely low (or even negative), the consumer had an opportunity to increase consumption due to the availability of cheaper electricity or the activation of automated appliances designed to capitalise on these price drops.

## 5.4 Demand-Side Flexibility and Its Implications

The findings suggest that there is significant demand-side flexibility in residential energy use, albeit only under certain conditions. While price signals didn't always have a direct impact on daily consumption and human behaviour, certain market dynamics such as any extreme price drops or supply-demand imbalances did elicit a response. In terms of demand-side flexibility, it demonstrated that dynamic pricing mechanisms can effectively manage household energy use by giving consumers the option to shift consumption based on price incentives.

## 5.5 Answering the Research Questions

1. How does household electricity consumption respond to fluctuations in electricity prices?

While household electricity consumption is somewhat responsive to fluctuations in electricity prices, the correlation coefficient between the two is relatively weak when considering the total picture at the same time. The overall relationship between electricity consumption and SPOT prices as measured by Pearson, Spearman, and Kendall Tau correlations indicates that the linear connection is not particularly strong. When segmented by extreme price events or timeframes a more visible pattern emerges. For example, on days when SPOT prices fell significantly below 0 €/MWh, electricity consumption increased by 40%, indicating that the consumer is indeed taking advantage of lower prices by increasing their usage.

2. What methods can effectively measure and identify demand-side flexibility in residential electricity use?

To measure and identify demand-side flexibility, a combination of Pearson, Spearman, and Kendall Tau correlation methods were used which were effective at capturing the varying strengths of the relationship between electricity consumption and SPOT prices. These methods were useful for detecting more significant correlations during specific periods, particularly during extreme price events or fluctuations. Although the overall correlations were weak, the segmented analysis revealed more pronounced responsiveness, particularly on days with significant price fluctuations. While demand-side flexibility exists to a degree and its impact may be more visible in specific circumstances, such as during extreme price events or over shorter time periods, rather than as a consistent, long-term pattern.

## 6 Conclusion

This thesis sought to investigate the relationship between household electricity consumption and electricity prices, with the main focus being on determining how price fluctuations affect household energy behaviour and evaluate methods for measuring demand-side flexibility by analysing actual electricity consumption data from a detached house in Lappeenranta, Finland, and comparing it to SPOT market prices.

Key findings from the analysis show that there is a clear link between electricity consumption and price fluctuations in the SPOT pricing, particularly during extreme price periods. Also, when SPOT market prices fell significantly (e.g., below 0 €/MWh), there was a clear increase in electricity consumption, indicating some flexibility in household energy use in response to lower prices showing ultimately that price signals influence residential electricity consumption, especially when price changes are significant.

However, the overall correlation was not as strong as initially expected, especially when considering the entire range of price fluctuations. The Pearson, Spearman, and Kendall Tau correlation coefficients revealed a generally weak relationship from the given dataset. While price influences household electricity behaviour, other factors—such as time of day, weather conditions, and household preferences—are likely more influential in determining energy consumption if there is no notable difference in the SPOT pricing. Despite the weaker correlations, the analysis did confirm the existence of demand-side flexibility benefits which is critical for the optimisation of residential electricity consumption. The methods used to analyse the data, such as correlation analysis, were effective in capturing the subtle dynamics between price changes and consumption patterns. Also while the dynamic pricing mechanisms may have an impact on consumption at the extremes, their ability to drive significant changes in household energy usage on a day to day basis is limited unless other factors are addressed. To make these pricing mechanisms more effective, more research is needed to investigate more tailored strategies that consider such as behavioural factors and emerging technologies such as the use of advanced metering systems.

## References

ACER & CEER (2024). Annual Report on the Retail Market for Electricity and Gas. Available at: [https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER-CEER\\_2024\\_MMR\\_Retail.pdf](https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER-CEER_2024_MMR_Retail.pdf) [Accessed 1 Mar. 2025].

Bhattacharyya, S.C. and Timilsina, G.R. (2010). Modelling energy demand of developing countries: are the specific features adequately captured? *Energy Policy*, 38(4), pp. 1853–1867.

Electricity Markets – Lecture Notes (2023). Partanen, J., Viljainen, S., Lassila, J., Honkapuro, S., Salovaara, K., Niemelä, H., Annala, S., Makkonen, M., Belonogova, N., Sihvonen, V., and Jaanto, J. (2023). Electricity Markets – Lecture Notes. LUT School of Energy Systems, Electrical Engineering. Lappeenranta, Finland.

Energy Authority, (2014). Energiavirasto. Energiatohokkuuden ja uusiutuvan energian edistämistehtäviä ministeriöstä uuteen Energiavirastoon. [31.8.2017] [Tasks of promoting energy efficiency and renewable energy from the Ministry to the new Energy Authority. Energy Authority. In Finnish] <https://www.energiavirasto.fi/-/energiatohokkuuden-jauusiutuvan-energian-edistamistehtavia-ministeriostauuteen-energiavirastoon>

European Environment Agency (2024). Renewable energy. European Environment Agency. Available at: <https://www.eea.europa.eu/en/topics/in-depth/renewable-energy> [Accessed 9 Mar. 2025].

Flygare, C., Wallberg, A., Jonasson, E., Castellucci, V. and Waters, R. (2023). Correlation as a method to assess electricity users' contributions to grid peak loads: A case study. Uppsala University, Ångströmlaboratoriet, Lagerhyddsvägen 1, Uppsala, 752 37, Sweden. Available online 30 Nov. 2023.

Fu, T., Tang, X., Cai, Z., Zuo, Y., Tang, Y. and Zhao, X. (2020). Correlation research of phase angle variation and coating performance by means of Pearson's correlation coefficient. *Progress in Organic Coatings*, 139, p. 105461.

Hinkle, Wiersma, and Jurs (2003). In: Markossian, S., Grossman, A., Arkin, M., et al. (eds.) (2004–). *Assay Guidance Manual* [Internet]. Bethesda, MD: Eli Lilly & Company and the National Center for Advancing Translational Sciences. Available at: [https://www.ncbi.nlm.nih.gov/books/NBK550206/table/datareporting.T.meanings\\_for\\_pearson\\_s\\_c/](https://www.ncbi.nlm.nih.gov/books/NBK550206/table/datareporting.T.meanings_for_pearson_s_c/) [Accessed 5 Mar. 2025].

Jebaraj, S. and Iniyan, S. (2006). A review of energy models. *Renewable and Sustainable Energy Reviews*, 10(4), pp. 281–311.

LUT University (2024). How to produce sustainable energy in the future? – LUT University published a new energy outlook 2024. Available at: <https://www.lut.fi/en/news/how-produce-sustainable-energy-future-lut-university-published-new-energy-outlook> [Accessed 9 Mar. 2025].

Panda.org (2014). Lappeenranta green city. Available at: <https://wwf.panda.org/es/?229192/Lappeenranta-green-city> [Accessed 9 Feb. 2025].

Renewable Energy in Finland (2020). *Renewable Energy in Finland 2020*. Available at: <https://tem.fi/en/renewable-energy> [Accessed 5 Mar. 2025].

Sharimakin, A., Glass, A.J., Saal, D.S. and Glass, K. (2018a). Dynamic multilevel modelling of industrial energy demand in Europe. *Energy Economics*, 74, pp. 748–758.

Sharimakin, A., Glass, A.J., Saal, D.S. and Glass, K. (2018b). Dynamic multilevel modelling of industrial energy demand in Europe. *Energy Economics*, 74, pp. 120–130.

Salisu, A.T. and Ayinde, O. (2016). Modeling energy demand: some emerging issues. *Renewable and Sustainable Energy Reviews*, 54, pp. 1470–1480.

Suganthi, L. and Samuel, A. (2012). Energy models for demand forecasting—a review. *Renewable and Sustainable Energy Reviews*, 16(2), pp. 1223–1240.

York, R. (2007). Demographic trends and energy consumption in European Union Nations 1960–2025. *Social Science Research*, 36(3), pp. 855–887