UTILIZING OPEN ELECTRICITY CONSUMPTION DATA IN ASSESSING HOUSEHOLD CONSUMPTION FLEXIBILITY

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ABSTRACT

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Utilizing open electricity consumption data in assessing household consumption flexibility

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This thesis examines the consumption flexibility of three household electricity customer groups in Finland during the year 2024, using the most recent national data from Fingrid. The study focuses on how spot market price variations affect household electricity usage, aiming to quantify and forecast demand-side flexibility.

The primary objective of this study is to:

- Develop a statistical model that describes the mathematical relationship between hourly household electricity consumption and spot market prices.

- Uncover temporal patterns in consumption flexibility.

- Quantify the flexibility potential of households for comparison between groups.

- Forecast future household electricity consumption using machine learning techniques.

The research methodology involves data processing, regression modeling, flexibility estimation, and time-series forecasting using LSTM networks. The results reveal that BE02 (electrically heated households) exhibit the highest flexibility, both in relative and per-household terms. Flexibility varies significantly throughout the day and year, with the strongest responsiveness occurring during late-night hours. Surprisingly, in winter, no negative demand response was observed in the long-term analysis; however, shorter-term surge events did show some evidence of demand response. These findings underscore the value of time- and group-specific analysis in assessing household demand response.

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1 Introduction

In Finland, electricity is traded at the Nordic Power Exchange Nord Pool, and the wholesale price of electricity varies hourly based on the demand-supply relation (Annala, S. et al. 2023). As of the end of 2023, 31% of Finnish households have signed electricity contracts bound to the exchange price with suppliers (Energy Authority, 2024). Although real-time pricing is not without drawbacks, it is widely regarded as a more efficient alternative to flat-rate tariffs, which have been shown to damage market efficiency and hinder optimal capacity investment (Borenstein and Holland, 2003). As more households adopt spot-based pricing, it is increasingly likely that they will exhibit behavioral responses to price fluctuations, as demonstrated by international dynamic pricing experiments (Faruqui and Sergici, 2010). This thesis assesses the annual consumption flexibility of household electricity customers in Finland in 2024 by formulating the statistical correlation between hourly household electricity consumption and spot market prices. At this moment, this research is critical, as the year 2023 saw a significant increase in the proportion of exchange price-bound contracts, nearly doubling compared to previous years (Energy Authority, 2024). This rising trend is expected to continue, highlighting that an increasing number of customers are focusing on spot market prices. Consequently, there is an imminent need to conduct this study to address these emerging dynamics. What's more, this research holds profound long-term value, particularly for Fingrid, as it provides a deeper understanding of customer behavior under varying electricity prices. These insights can support the development of more effective pricing strategies and enhance frequency stability, ensuring reliable grid operations in the face of fluctuating demand. For households, the findings serve as a practical guideline for optimizing electricity expenses, empowering consumers to make informed decisions.

Previous research on this subject has produced valuable outcomes, offering a solid foundation that informs and motivates this study. A sophisticated mathematical model developed by Peter C. Reiss and Matthew W. White at Stanford University utilized data from California to evaluate the effects of alternative tariff designs on residential electricity use and addressed heterogeneity in consumer price sensitivity (Reiss and White, 2005). Similarly, research conducted in Norway focused on the Nord Pool spot price and derived a formula to calculate electricity consumption using the parameter "Heating Degree Days" (HDD), defined as the number of degrees the average weekly temperature falls below a critical threshold (Fuglerud et al., 2012). Additionally, a recent paper from Aalto University introduced a methodology to analyze changes in Finnish customer electricity use behavior and price sensitivity, using smart electricity meter data (Einolander et al., 2024). These prior studies provide essential background for this research on assessing household flexibility.

While these studies have established foundational models, none have provided an updated, hour-by-hour analysis using the latest Fingrid data. Peter's model directly explores the relationship between consumption and price, yet California employs tiered prices while Finland uses per-hour prices, so this study does not need to account for constraints such as marginal boundaries or tiered price thresholds, making the analysis more straightforward. The focus on the spot price of the Nord Pool of Fuglerud's study aligns with this study, but instead of relating price to consumption, his work introduced the HDD concept as the independent variable which is not the major condition considered in this research. Research of Aalto, though perfectly based on the Finnish context, did not provide an explicit formula to describe such a relationship. Therefore, the necessity of conducting this research is not overshadowed by the success of prior works.

In this study, the primary objective is to establish a model that quantifies the relationship between hourly household electricity consumption and spot market prices in Finland during 2024. This research seeks to answer four key questions: How does household electricity consumption respond to spot market price changes? How does demand response flexibility vary across different times of day and seasons? How can flexibility potential be quantified and compared between household groups? Can future electricity consumption be forecasted using machine learning models? This study does not account for external factors such as weather conditions or household income, limiting its potential to forecast future consumption. However, it can be regarded as a good starting point, laying a solid foundation for more advanced analysis. The structure of this thesis is as follows: Methods (Chapter 2), Results (Chapter 3), Discussion (Chapter 4), and Conclusion (Chapter 5).

2 Methods

This chapter describes the methodology used to analyze electricity consumption flexibility in response to spot price variations.

2.1 Data Collection and Preprocessing

This study utilizes electricity consumption data sourced from Fingrid Open Data Datasets, for the period from 1 January 2024 to 31 December 2024 (Fingrid, 2024). This dataset provides aggregate hourly metering data for electricity accounting points across Finland. All customers are classified into 14 groups based on the standard Statistics Finland classification. Each data entry includes electricity consumption (kWh) and the number of accounting points. Focusing on household consumers, this thesis examines BE01 (Apartments, apartment blocks), BE02 (Apartments, small buildings, electrically heated), and BE03 (Apartments, small buildings, not electrically heated), as they best represent residential demand response behaviors. BE02 households consume a large proportion of their electricity for space heating (Statistics Finland, 2012), so they are more likely to exhibit price-responsive behavior, as electric heating systems—particularly when combined with thermal mass storage—enable demand-side flexibility through load shifting (Arteconi et al., 2013). The hourly price data was obtained via LUT University's institutional access to Nord Pool spot market data.

The raw datasets were cleaned by extracting relevant columns and converting time columns from UTC to EET for consistency. Missing hourly consumption records at the end of 2024 were automatically excluded, as their absence had negligible impact. Electricity consumption and spot price datasets were merged by aligning EET timestamps using an inner join. This produced a unified dataset for regression modeling and demand response analysis.

2.2 Regression Models

This thesis adopts standard regression models. Although more advanced regression forms, such as semi-parametric additive models, have been employed in Australia to capture complex nonlinear dependencies (Fan and Hyndman, 2012), this thesis focuses on simpler models to ensure transparency and computational efficiency.

2.2.1 Linear Regression

This model assesses a proportional relationship between price and consumption. It assumes that changes in electricity prices lead to linear changes in consumption, represented as:

$$y = \beta_0 + \beta_1 x + \epsilon, \tag{1}$$

where y is Dependent Variable (Electricity Consumption); x is Independent Variable (Spot Price), β_0 is the intercept, β_1 is slope and ϵ is a random error component.

2.2.2 Polynomial Regression

To capture potential nonlinear behaviors, this thesis extended the linear model by introducing quadratic and cubic terms to model curvature in the relationship between price and consumption. The general polynomial regression model is expressed as:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \epsilon, \tag{2}$$

where β_2 represents the quadratic curvature and β_3 the cubic term. For purely quadratic model, $\beta_3 = 0$.

2.2.3 Log-log regression

Log-log regression was also conducted because the log-log specification is a widely adopted approach in electricity demand analysis. It allows for the direct interpretation of elasticity from regression coefficients and has been shown to outperform the linear model in terms of statistical fit (Xiao et al., 2007). This approach transforms both the dependent and independent variables using natural logarithms:

$$\ln(y) = \beta_0 + \beta_1 \ln(x) + \epsilon, \tag{3}$$

where: β_0 is the intercept, $\beta_1$is the elasticity coefficient, which represents the percentage change in consumption given a 1% change in price, and ϵ is again a random error term.

This model was chosen because it allows for interpretable elasticity estimation. If $\beta_1 < 0$, it confirms a negative demand elasticity (higher prices lead to lower consumption); yet if $\beta_1 > 0$, it can be concluded that consumption increases with price.

2.2.4 Exponential Regression

Exponential regression was employed to analyze how electricity consumption responds to price changes in an exponential manner. The model follows the form

$$y = \alpha e^{\beta x} + \epsilon, \tag{4}$$

where α represents baseline consumption, and β is the rate of change of consumption per unit price change.

2.2.5 Model Evaluation: R^2 Calculation

To assess the goodness-of-fit of each regression model mentioned above, the coefficient of determination (R^2) was calculated. R^2 quantifies the proportion of the variance in electricity consumption that can be explained by variations in electricity prices, defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}, \tag{5}$$

where y_i is actual electricity consumption values, $\hat{y}_i$ is predicted electricity consumption values from the regression model, and $\bar{y}$ is the mean of the actual electricity consumption values.

R^2 values range from 0 to 1. When $R^2 = 1$, it indicates that the model perfectly explains all variations in consumption; when $R^2 = 0$, it suggests that the model explains no variance, meaning price fluctuations do not affect consumption.

2.3 Full-Year and High-Price Events Analysis

The first step in this thesis examined the correlation between electricity consumption and spot prices across the entire year. All regression models were applied to determine how well electricity consumption responds to price variations over the full dataset. The R^2 values for each regression model were calculated and compared to determine which model best described the demand response. Two visualizations of the full dataset were also created for clarity.

As only a minority of the customers have signed spot price contracts, while the datasets cover all customers in Finland regardless of contract type, the full-year analysis might not reveal significant flexibility. Therefore, next step focuses on short-term high-price periods—specifically, three sudden price surges and one absolute peak price day—to better inspect potential demand response behavior among spot price customers.

In the first part, sudden surge events were selected based on the largest relative changes in spot prices between consecutive hourly data points, calculated as:

$$\Delta P_i = \frac{P_i - P_{i-1}}{P_{i-1}}, \tag{6}$$

where:P_i is the spot price at hour i, P_{i-1} is the spot price at the previous hour, and ΔP_i is the relative change in price.

To ensure event independence, a 24-hour minimum separation was enforced between selected points. For each event, a ±6-hour window was extracted for analysis and visualization.

In addition, the absolute peak price day was examined separately as an extreme case. This single-day event is assumed to demonstrate the most pronounced demand flexibility, providing a critical benchmark for model validation and comparative assessment.

2.4 Temporal Demand Response Patterns

Research in UK shown that household flexibility might not remain constant for the whole year; instead, they are subject to fluctuate throughout a year and a day (Torriti, J, 2022). To find temporal demand response patterns, two separate research was conducted: daily temporal patterns analysis and yearly temporal patterns analysis.

For the daily analysis, the 24-hour peak window was divided into three time slots based on typical household activity schedules: Daytime (06:00–17:59), Evening (18:00–23:59), and

Late Night (00:00–05:59). For the seasonal analysis, the dataset was divided into four seasons: winter (December–February), spring (March–May), summer (June–August), and autumn (September–November). Each time slot was then independently analyzed to evaluate potential differences in demand flexibility.

2.5 Time-Series Forecasting Using Long Short-Term Memory (LSTM)

Inspired by the successful use of LSTM networks for short-term electricity load forecasting in residential contexts (Marino et al., 2016), this thesis adopts an LSTM-based approach to predict future household electricity consumption in 2025. Unlike traditional regression models, LSTM networks are designed for sequential data and can retain information over time, making them well-suited for household load forecasting where consumption patterns reflect repetitive behavioral routines (Kong et al., 2019).

To enhance the predictive accuracy of the model, several seasonal and trend-related features were incorporated. One key feature was day-of-year encoding, which represents each day's position within the year (ranging from 1 to 365). To ensure that the model captures the periodic nature of electricity consumption, this feature was transformed using sine and cosine functions:

$$\text{sin\_DoY} = \sin\left(\frac{2\pi \cdot \text{day-of-year}}{365}\right), \quad \text{cos\_DoY} = \cos\left(\frac{2\pi \cdot \text{day-of-year}}{365}\right) \qquad (7)$$

This approach is consistent with Karatasou et al. (2006), who used sine and cosine encoding of calendar variables to enhance ANN-based load prediction accuracy.

In addition to seasonality (day-of-year encoding), a trend component was introduced to capture the long-term variations in electricity consumption over the year. This component is represented as a normalized index ranging from 0 to 1, where 0 corresponds to the start of the year and 1 to the end. The inclusion of this trend feature helps account for gradual shifts in electricity consumption patterns that may arise due to economic factors, policy changes, or variations in energy usage behaviors across different seasons.

A sliding window approach was adopted to construct input-output pairs, using the past 30 days of data to predict the next day's consumption, following established methods in LSTM-based forecasting (Karevan & Suykens, 2020).

In terms of architecture, the LSTM network consisted of an input layer that received time-series data with multiple features (electricity consumption, seasonal indicators, and trend), followed by a single LSTM layer with 50 units to capture sequential dependencies. This was connected to a fully connected layer that mapped the output to a single value, and finally a regression layer to compute the predicted electricity consumption. The network was trained using the Adam optimizer with a learning rate of 0.001. The dataset was split into 80% training and 20% testing, ensuring that past data was used exclusively for training while recent data was reserved for evaluation.

This thesis employs two forecasting approaches: one-step ahead prediction and multi-step ahead forecasting, each serving a distinct purpose. The one-step ahead prediction is used to evaluate the model's short-term accuracy by forecasting the next day's electricity consumption based on the previous 30 days. This approach helps assess how well the model captures recent consumption patterns and price fluctuations. The multi-step ahead forecast is used to analyze long-term electricity consumption trends by predicting daily consumption for an entire year. It helps identify seasonal variations and potential shifts in household electricity demand over time.

To evaluate the forecasting accuracy of the proposed LSTM model, this study adopts commonly used metrics such as R^2 and the Mean Absolute Percentage Error (MAPE). The selection of MAPE is consistent with prior works in the field (Zheng et al., 2017), which demonstrated that MAPE is particularly effective for quantifying forecasting errors in short-term electric load forecasting using LSTM networks. The MAPE is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \times 100\%, \tag{8}$$

where y_i represents actual electricity consumption, and $\hat{y}_i$ is the predicted consumption from the LSTM model. MAPE quantifies the relative forecasting error, providing a scale-independent measure of prediction accuracy. Lower MAPE values indicate more precise forecasts.

The model's one-step prediction performance was visualized by comparing the actual vs. predicted daily consumption over the test set. Additionally, the 365-day forecast was plotted to illustrate seasonal trends and long-term consumption patterns.

2.6 Flexibility Potential Calculation

Based on the above work, this study quantifies household electricity consumption flexibility by assessing two aspects: flexibility potential in proportion to the overall annual consumption, and flexibility potential per household based on the average number of households in each user group.

For each user group, the total annual electricity consumption was calculated as the sum of the hourly consumption values over the entire year. Simultaneously, the average household count was computed by averaging the number of accounting points (households) recorded hourly throughout the year. Consumption per capita is also calculated, with BE02 ranked first due to the existence of electrical heating. The extracted values for each group are summarized in Table 1.

Table 1. Background Table of Consumption and Household Counts.

User Group	Total Annual Consumption (GWh)	Average Household Count	Consumption per Household (kWh/a)
BE01 (Apartments, apartment blocks)	3,185.28	1,458,589	2,183.1
BE02 (Apartments, small buildings, electrically heated)	10,872.73	1,016,980	10,688.3
BE03 (Apartments, small buildings, not electrically heated)	2,181.38	325,436	6,700.3

This study quantified the flexibility potential based on linear slope values derived from previous analysis and spot price variations. This simplified approach was inspired by the regression modeling strategy proposed by Lawrence Berkeley National Laboratory, where linear and piecewise linear models were used to quantify DR potential under varying outdoor air temperatures (OAT) and operational contexts (Yin et al., 2016).

For each user group, a separate dataset containing regression results of events was imported. Only the four most significant events (Surge Events 1, 2, 3, and the Peak Price Day) were selected from each group, excluding long-term observations, as demand response is primarily evident over short durations. Additionally, three time slots from the Peak Price Day were excluded to avoid repetition in calculations within the peak event. Events with positive regression slopes were excluded from calculation, as they do not align with expected demand response behavior.

For each valid event where slope is negative, the spot price variation ΔP (in €/MWh) was calculated by taking the difference between the maximum and minimum spot prices observed during the event period. The absolute slope of the regression (in kWh/(€/MWh)) was then multiplied by ΔP to estimate the event-level flexibility potential (kWh), using the formula:

$$\text{Flexibility}_{\text{event}} = |\text{Slope}| \times \Delta P \tag{9}$$

The group-level total flexibility potential was calculated by summing the flexibility values of all qualifying events. This total value was then evaluated from two perspectives mentioned above.

In order to obtain flexibility as a proportion of total annual consumption, the total event-based flexibility (kWh) for each user group was divided by its total annual electricity consumption, as extracted earlier in Table 1.

This yielded a relative metric (in percentage) that quantifies the scale of flexibility compared to the overall demand level.

To reflect user-level responsiveness, the total flexibility was divided by the average number of households in each group. The resulting value (in kWh) represents the potential reduction in electricity usage per household during high-price events.

These values complement the regression and forecasting analysis by translating demand sensitivity into actionable and comparable quantities across user groups.

3 Results

This chapter presents the key findings, including full-year correlations, short-term price surge responses, daily and seasonal consumption patterns, an LSTM-based forecast and flexibility quantification. Taken together, these observations illuminate how each group's electricity usage varies with SPOT price changes, offering insights into the extent and nature of demand response.

3.1 Full Year Correlation

To establish an initial understanding of demand-price dynamics, Figure 1 illustrates the hourly electricity consumption and spot price variation for a representative dataset (BE01). All three datasets (BE01, BE02, and BE03) exhibit similar seasonal consumption patterns, peaking in winter and declining during warmer months. However, there is no clear visual evidence of price-responsive consumption behavior across any of the groups, which is further confirmed by the random dispersion of points in the scatter plot shown in Figure 2.

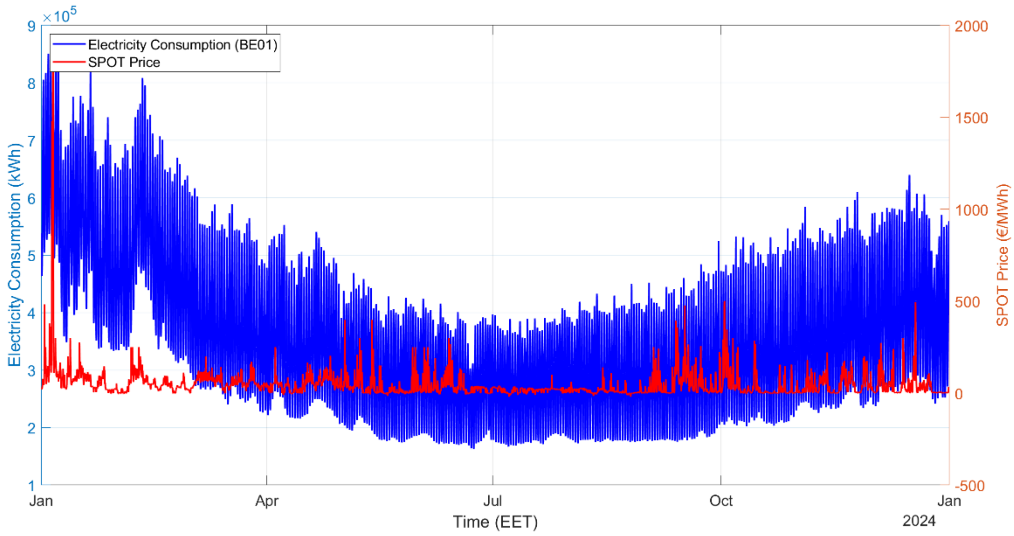

Figure 1. Electricity Consumption and Spot Price for BE01 in 2024.

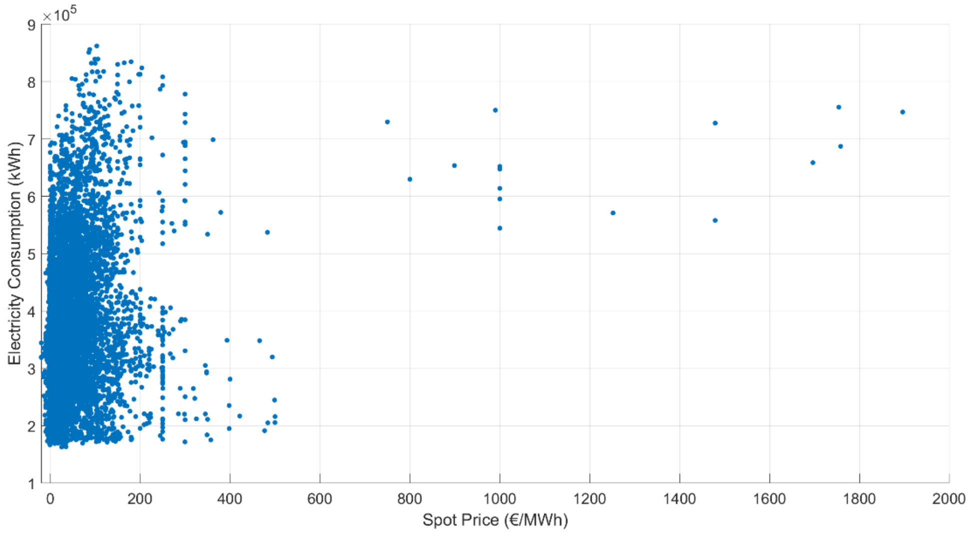

Figure 2. Scatter plot of hourly spot price versus electricity consumption for BE01 (2024)

Regression analysis confirms these visual findings. For all three groups, the highest R^2 values emerged from cubic regression models but remained extremely low (for example, for BE01, it is only 0.0564), suggesting that electricity prices have limited influence on household consumption behavior when assessed over the entire year. This suggests the need for more granular, short-term analyses to identify potential demand response behavior.

3.2 Sudden Price Surge Events Correlation

While full-year analysis showed weak correlations, demand response may be more evident during sudden price spikes. To examine this, three surge events with sharp SPOT price increases were identified for each customer group. As the results across events were similar, only the most representative case is presented, and it is set to be the same date February 29 – March 1, because this consistency enables comparison between groups. This selection might also provide some insights into the winter seasonal flexibility behavior of each group as it is a winter day.

3.2.1 BE01 (Apartments, apartment blocks)

For BE01, electricity consumption visibly decreased as prices rose. The corresponding regression equations are listed in Table 2.

Table 2. Regression Results for Price Surge Event (BE01), February 29 – March 1.

Model	Regression Equation	R^2 Value
Linear	$y = -4750.16\,x + 448667.05$	0.1406
Quadratic	$y = -1246.90x^2 + 24942.18x + 428427.84$	0.3121
Cubic	$y = 172.77x^3 - 7472.33x^2 + 74962.59x + 412762.48$	0.5555
Log-Log	$\ln(y) = -0.0076\ln(x) + 12.9293$	0.0038
Exponential	$y = 508615.70e^{-0.0192x}$	0.3610

The regression results confirmed that BE01 households reduced electricity use as prices increased. The linear regression showed a drop of about 4.75 MWh for every 1 €/MWh rise in price. The cubic model gave the best fit ($R^2 = 0.5555$), suggesting a non-linear relationship where consumption first rose slightly, then dropped sharply after a certain price point. This could mean that households tolerated mild price changes but reduced usage more clearly once prices went beyond a certain level. The exponential model also reflected this negative trend, with an R^2 of 0.3610. The negative exponent (β = -0.0192) indicated that as prices went up, consumption fell more quickly, matching the general idea that extreme price increases pushed people to cut back more noticeably. This response was stronger than what was seen in the full-year analysis, which showed that short-term price surges may encourage more immediate demand reductions.

3.2.2 BE02 (Apartments, small buildings, electrically heated)

BE02 households exhibited a clear negative demand response to the sharp increase in electricity prices, as demonstrated by the negative slope of the linear model. Unlike BE01, where demand reductions were moderate, BE02 consumers showed a more pronounced and immediate adjustment in consumption due to its higher R^2. Results and their visualization are provided in Table 3 and Figure 3 respectively.

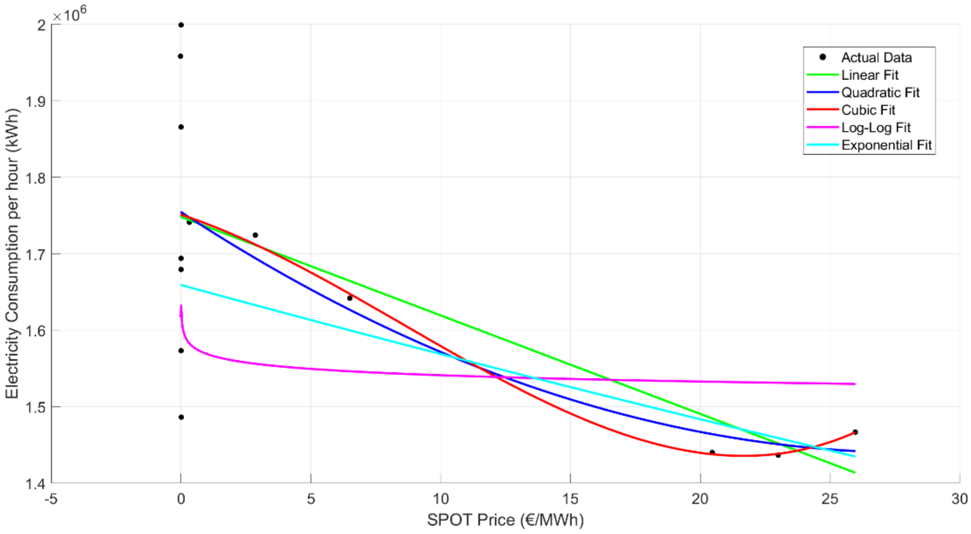

Figure 3. Price Surge Event Regression (BE02) February 29 – March 1.

Table 3. Regression Results for Price Surge Event (BE02), February 29 – March 1.

Model	Regression Equation	R^2 Value
Linear	$y = -12881.8131\,x + 1748131.7512$	0.4585
Quadratic	$y = 392.0254\,x^2 - 22217.0501\,x + 1754494.9356$	0.4661
Cubic	$y = 38.3093\,x^3 - 988.3405\,x^2 - 11126.0086\,x + 1751021.4506$	0.4714
Log-Log	$\ln(y) = -0.0077545\ \ln(x) + 14.2659$	0.0689
Exponential	$y = 1659068.5053 \cdot e^{-0.0055915\,x}$	0.5437

The exponential regression model performed best ($R^2 = 0.54$), capturing the sharp decline in electricity consumption as prices surged. The negative exponent indicated that as price increased, consumption declined exponentially, meaning that even small price increases could lead to significant demand reductions. The log-log regression model also supported this trend, revealing that households in BE02 exhibited elastic demand behavior, where consumption decreased more proportionally with price.

BE02 households showed a stronger demand response than BE01 during price surges, possibly due to their higher reliance on electricity for heating, proving the previous expectation that heating-intensive households were more reactive to short-term price fluctuations.

3.2.3 BE03 (Apartments, small buildings, not electrically heated)

For BE03, regression analysis indicates that electricity consumption decreased in response (Table 4).

Table 4. Regression Results for Price Surge Event (BE03), February 29 – March 1.

Model	Regression Equation	R^2 Value
Linear	$y = -2054.75x + 310502.30$	0.2289
Quadratic	$y = -294.94x^2 + 4968.64x + 305714.94$	0.3123
Cubic	$y = 53.10x^3 - 2208.40x^2 + 20343.02x + 300900.00$	0.5123
Log-Log	$\ln(y) = -0.0048\ln(x) + 12.5868$	0.0063
Exponential	$y = 324121.27e^{-0.0094x}$	0.3814

The linear regression model revealed a negative relationship between price and consumption. The exponential regression model also supported the negative demand response, reinforcing the idea that consumption declines exponentially as prices surge. The cubic regression model (R^2 =0.5123) provided the best explanatory power, suggesting that consumption initially increases with price increment but declines more sharply at higher price levels, resulting in an overall negative trend.

The results from Table 4 confirmed that BE03 households exhibit a moderate demand response to sudden price increases, stronger than BE01 but weaker than BE02. While cubic and exponential models captured the negative correlation, the response was not as sharp as in BE02, where heating loads played a key role.

3.3 Peak Events Correlation

The identified peak price event took place from January 5 to January 6, 2024, during which the SPOT price reached its highest levels in the observed dataset. This section investigated how different household groups responded to this price surge.

3.3.1 BE01 (Apartments, apartment blocks)

The results for BE01, as illustrated in Table 5, were counter-intuitive, indicating a moderate positive correlation between electricity price and consumption.

Table 5. Regression Results for Peak Price Event (BE01), January 5 to January 6.

Model	Regression Equation	R^2 Value
Linear	$y = 79.79x + 557857.09$	0.3418
Quadratic	$y = -0.0105x^2 + 98.56x + 553269.78$	0.3434
Cubic	$y = 0.00037x^3 - 1.08x^2 + 894.46x + 455539.02$	0.5183
Log-Log	$\ln(y) = 0.0772\ln(x) + 12.8492$	0.3766
Exponential	$y = 555482.82e^{(0.00013x)}$	0.3381

The linear regression suggested that for every 1 €/MWh increase in price, consumption increased by approximately 79.79 kWh, pointing to a weakly positive relationship rather than any demand reduction. The quadratic and cubic models provided further insight, revealing a nonlinear response where consumption increased with price. The log-log model also supported the notion that BE01 households did not exhibit any price elasticity because of its positive coefficient.

3.3.2 BE02 (Apartments, small buildings, electrically heated)

Unlike BE01, BE02 households exhibited a moderate negative correlation with price in Figure 4, indicating some level of demand response. This result was supported by most regression models (Table 6).

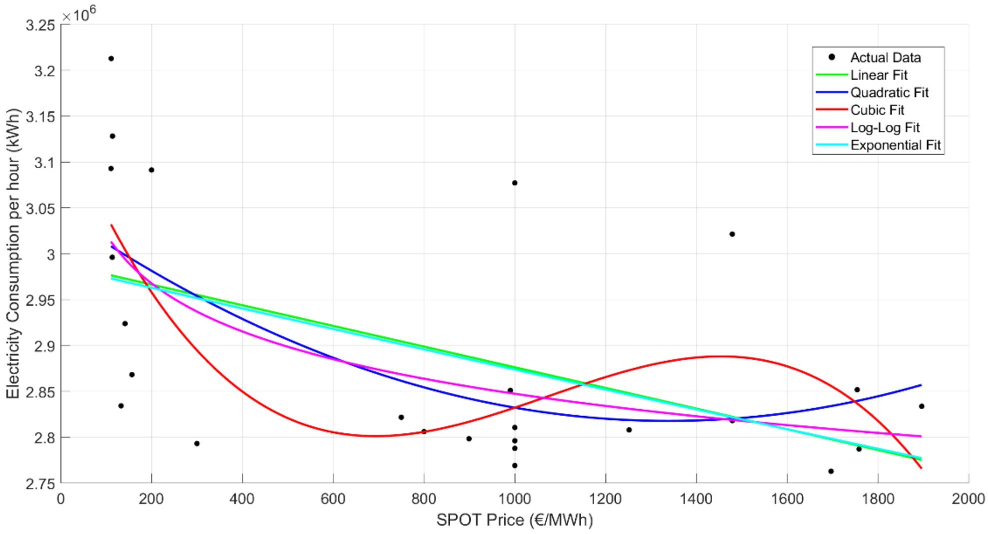

Figure 4. Price Peak Event Regression (BE02) January 5 to January 6.

Table 6. Regression Results for Peak Price Event (BE02), January 5 to January 6.

Model	Regression Equation	R^2 Value
Linear	$y = -112.66x + 2988914.93$	0.2674
Quadratic	$y = 0.1263x^2 - 338.04x + 3043980.01$	0.3549
Cubic	$y = -0.00039x^3 + 1.27x^2 - 1193.49x + 3149022.52$	0.4342
Log-Log	$\ln(y) = -0.0257\ln(x) + 15.0396$	0.3766
Exponential	$y = 2985582.48e^{-0.0000382x}$	0.2699

The negative linear slope suggested that BE02 consumers reduced their electricity usage in response to peak prices, though not drastically. The quadratic model showed an initial drop in consumption with increasing price but introduced a small inflection, suggesting that the response was not strictly linear but varied across different price levels. The cubic model, which provided the highest explanatory power (R^2 = 0.4342), indicated that consumption declined significantly at intermediate price levels but rebounded at extreme high prices, possibly due to essential energy needs that remained unchanged regardless of cost. The log-log regression model also reported a negative slope, implying that percentage changes in price led to proportional reductions in consumption, though the effect remained limited. The exponential model, while showing a small negative exponent, suggested that the rate of consumption decline diminished as prices increased. This finding indicated that while some reductions occurred initially, BE02 households may have reached a threshold where further price increases did not significantly impact consumption, corresponding to the conclusion given by cubic and quadratic models.

Overall, these results confirmed that BE02 households demonstrated a stronger demand response to peak prices compared to BE01. However, the moderate R^2 values suggested that factors beyond price, such as weather conditions and heating requirements, played a crucial role in shaping their electricity usage patterns.

3.3.3 BE03 (Apartments, small buildings, not electrically heated)

For BE03, during the peak price event, the results indicated a weak to moderate positive correlation, as shown in Table 7.

Table 7**.** Regression Results for Peak Price Event (BE03), January 5 to January 6.

Model	Regression Equation	R^2 Value
Linear	$y = 20.22x + 515677.52$	0.3624
Quadratic	$y = -0.0117x^2 + 41.15x + 510564.04$	0.3942
Cubic	$y = 5.92 \times 10^{-5}x^3 - 0.18x^2 + 169.33x + 494824.07$	0.4691
Log-Log	$\ln(y) = 0.0237 \ln(x) + 13.0356$	0.4226
Exponential	$y = 515292.88e^{(3.86 \times 10^{-5}x)}$	0.3599

The regression models indicated a weakly positive relationship. The cubic model achieved highest R^2 while log-log and exponential models reinforced the absence of price elasticity. Despite slight variations across the models, the overall results suggested that price-based demand response mechanisms may have been less effective for BE03 households during high-price periods, similar to the observations for BE01.

3.4 Daily Temporal Patterns

This section examined the flexibility across different times of the peak price day. By evaluating the strength and direction of correlation in each period, this analysis provided insight into whether household consumption behaviors vary throughout the day.

3.4.1 BE01 (Apartments, apartment blocks)

Consumption for BE01 households exhibited a consistent positive correlation with price across all three time periods, as shown in Table 8**.** Results indicated that households did not actively reduce electricity usage in response to high prices, regardless of the time of day.

Table 8. Optimal Results (BE01) for 3 Time Periods, January 5 to January 6.

Time Period	Model	Regression Results	R^2 Value
Evening (18:00–23:59)	Linear	$y = 27.53x + 701327.28$	0.5859
	Cubic	$y = 6.34 \times 10^{-5}x^3 - 0.2362x^2 + 285.29x + 628113.54$	0.8362
Daytime (06:00–17:59)	Linear	$y = 86.53x + 512530.42$	0.4488
	Cubic	$y = 0.0005x^3 - 1.4959x^2 + 1254.29x + 343308.22$	0.8089
	Log-Log	$\ln(y) = 0.1012\ln(x) + 12.6203$	0.5727
Late Night (00:00–05:59)	Linear	$y = 978.51x + 441750.95$	0.3131
	Quadratic	$y = 56.64x^2 - 16550.31x + 1709041.86$	0.7247

During the evening period (18:00–23:59), the strongest yet positive correlation was observed, with the cubic model yielding the highest explanatory power (R^2=0.8362), suggesting a predictable but non-linear relationship between price and consumption. The daytime period (06:00–17:59) also displayed a moderate positive correlation, with the cubic model again providing the best fit. At late night (00:00–05:59), consumption patterns were less affected by price, as reflected by lower R^2 values in most models.

3.4.2 BE02 (Apartments, small buildings, electrically heated)

Electricity consumption for BE02 households displayed mixed responsiveness across different time periods, as shown in Table 9. Unlike BE01, BE02 demonstrated varying trends, with a limited response in daytime but a stronger negative correlation at late night.

Table 9. Optimal Regression Results for 3 Time Periods (BE02), January 5 to January 6.

Time Period	Model	Regression Results	R^2 Value
Evening (18:00–23:59)	Linear	$y = 22.71x + 2801129.97$	0.4007
	Cubic	$y = 5.22 \times 10^{-5}x^3 - 0.2035x^2 + 255.13x + 2732424.62$	0.6538
Daytime (06:00–17:59)	Linear	$y = -8.03x + 2848696.01$	0.0016
	Cubic	$y = -0.00056x^3 + 1.57x^2 - 1155.65x + 2987681.15$	0.1618
	Log-Log	$\ln(y) = -0.0018\ln(x) + 14.8712$	0.0019
Late Night (00:00–05:59)	Linear	$y = -495.63x + 3139505.60$	0.0300
	Cubic	$y = -5.32x^3 + 2518.81x^2 - 387428.16x + 22383555.90$	0.6170
	Log-Log	$\ln(y) = -0.0310\ln(x) + 15.0887$	0.0488
	Exponential	$y = 3137702.60e^{-0.00015864x}$	0.0301

During the evening period (18:00–23:59), regression models indicated a positive correlation between price and consumption, deviating from previous expectations. The cubic regression model provided the best fit, confirming that consumption tended to increase with price fluctuations.

In contrast, the daytime period (06:00–17:59) showed almost no correlation between price and consumption. The linear regression coefficient was close to zero, and all tested models yielded very low R^2 values. What's more, the log-log model showed a very weak elasticity, suggesting that consumers were relatively insensitive to price variations. This suggested that electricity consumption in BE02 households during the day is highly stable and less relevant to price change.

The late-night period (00:00–05:59) exhibited the strongest negative correlation, where higher prices led to decreased consumption (Figure 5**)**. The cubic regression model yielded the highest R^2 =0.6170, and both linear, exponential and log-log models also suggested negative relationships. This trend implies that BE02 households may be more willing to adjust electricity usage overnight instead in the evening in response to price signals, possibly due to automated heating control or shifting non-essential loads.

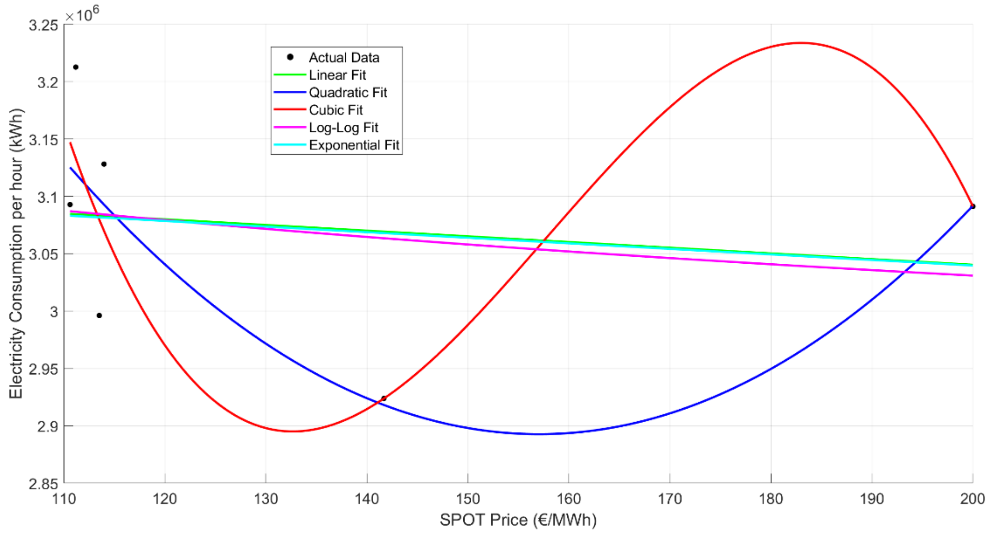

Figure 5. Late Night of Peak Day Regression (BE02) 00:00–05:59.

The contrasting results across different time periods highlighted that demand response potential varied significantly based on household routines. While evening consumption appeared inflexible, late-night usage showed more price sensitivity, indicating a possible opportunity for demand-side management strategies targeting night-time price fluctuations.

3.4.3 BE03 (Apartments, small buildings, not electrically heated)

Unlike BE02, BE03 showed a consistently positive correlation across all time slots. However, the strength of correlation and non-linearity varied, with the daytime period exhibiting the strongest relationship, as illustrated in Table 10.

Table 10. Optimal Regression Results for 3 Time Periods (BE03), January 5 to January 6.

Time Period	Model	Regression Results	R^2 Value
Evening (18:00–23:59)	Linear	$y = 12.93x + 537106.54$	0.5902
	Cubic	$y = 1.83 \times 10^{-5}x^3 - 0.0775x^2 + 108.37x + 507186.22$	0.8625
Daytime (06:00–17:59)	Linear	$y = 26.55x + 501647.80$	0.5543
	Cubic	$y = 7.57 \times 10^{-5}x^3 - 0.2487x^2 + 248.85x + 459823.54$	0.9546
Late Night (00:00–05:59)	Linear	$y = 337.98x + 477555.90$	0.2707
	Log-Log	$\ln(y) = 0.0855\ln(x) + 12.7495$	0.2124
	Exponential	$y = 480196.38e^{(0.00062873x)}$	0.2747

During the evening period, regression models indicated a moderate positive correlation. The cubic model performed best (R^2 = 0.8625), showing a trend where consumption increased with price but at a diminishing rate.

The daytime period exhibited the strongest correlation, with the cubic model achieving an R^2 of 0.9546, the highest among all time periods. This suggested that daytime electricity usage in BE03 households follows a highly predictable pattern, where higher prices coincided with increased consumption.

At late night, electricity consumption showed a weaker correlation with price, as indicated by lower R^2 values in all models. However, the linear, log-log and exponential models still identified a positive trend.

3.5 Yearly Temporal Patterns

This section examined how electricity consumption patterns in the three household groups varied across the four seasons, aiming to identify potential differences in demand elasticity and to explore whether weather-dependent factors (such as heating needs during winter) shaped consumption patterns more strongly than price signals. The subsequent subsections detailed each group's seasonal behavior, highlighting both expected and counter-intuitive trends in electricity usage.

3.5.1 BE01 (Apartments, apartment blocks)

Electricity consumption in BE01 households exhibited distinct seasonal variations in response to price fluctuations, as shown in Table 11. Winter showed the strongest correlation, with a positive relationship between price and consumption. In contrast, spring, summer, and autumn exhibited weak or negligible demand responses, with correlations close to zero. Since most apartments in this group rely on district heating, the increase in winter electricity consumption is likely driven by other factors, such as lighting, ventilation, or shared facility usage.

Table 11. Optimal Regression Results for 4 Seasons (BE01).

Season	Model	Regression Results	R^2 Value
Winter (Dec–Feb)	Linear	$y = 278.99x + 471752.19$	0.0687
	Quadratic	$y = -0.40x^2 + 766.46x + 447189.83$	0.1256
	Cubic	$y = 0.00060x^3 - 1.63x^2 + 1161.39x + 432917.76$	0.1560
	Log-Log	$\ln(y) = 0.0635\ln(x) + 12.8573$	0.1419
Spring (Mar–May)	Linear	$y = 233.68x + 332185.44$	0.0113
	Quadratic	$y = -4.00x^2 + 939.15x + 314542.95$	0.0516
	Cubic	$y = 0.0150x^3 - 10.24x^2 + 1455.71x + 307425.95$	0.0593
	Log-Log	$\ln(y) = 0.0370\ln(x) + 12.5870$	0.0352
Summer (Jun–Aug)	Linear	$y = -175.55x + 285495.96$	0.0055
	Cubic	$y = 0.0012x^3 + 0.55x^2 - 286.28x + 286940.82$	0.0065
	Log-Log	$\ln(y) = -0.0126\ln(x) + 12.5473$	0.0043
Autumn (Sep–Nov)	Linear	$y = -126.65x + 342830.20$	0.0071
	Cubic	$y = 0.0017x^3 - 1.63x^2 + 151.17x + 337861.80$	0.0117
	Log-Log	$\ln(y) = -0.0059\ln(x) + 12.7037$	0.0014

During the winter months, regression models showed a moderate positive correlation between electricity price and consumption. The cubic model, which performed best, indicated that consumption generally increased with price, though with some fluctuations at higher levels. The quadratic model suggested a potential turning point at extreme prices, where consumption slightly declined. Other models also indicated a positive correlation.

However, extreme price fluctuations may introduce minor reductions in consumption, suggesting some level of price responsiveness in extreme cases.

In spring, all models produced low R^2 values, indicating weak correlation. While polynomial models hinted at minor declines in consumption at higher prices, the trend was inconsistent. The log-log model showed a slightly positive but statistically insignificant relationship, suggesting that other factors outweighed price in shaping electricity use.

In summer, electricity consumption was largely insensitive to price changes. Although the linear model suggested a weak negative correlation, all models—including the cubic and log-log—had very low R^2 values, confirming the absence of meaningful price sensitivity.

Autumn displayed similarly weak correlation. Although most models showed a slight negative trend, their explanatory power remained low ($R^2 < 0.012$). However, among all seasons, autumn still presented the most noticeable negative demand response, even if its magnitude remains small.

3.5.2 BE02 (Apartments, small buildings, electrically heated)

Electricity consumption in BE02 households exhibited stronger seasonal variations compared to BE01. Table 12 suggests that winter and spring displayed a moderate positive correlation with price, while summer and autumn showed weaker, yet negative responsiveness. This indicates that BE02 consumers may have some degree of demand elasticity, adjusting their usage slightly in response to price signals, particularly in the warmer months.

Table 12. Optimal Regression Results for 4 Seasons (BE02).

Season	Model	Regression Results	R^2 Value
Winter (Dec–Feb)	Linear	$y = 1405.39x + 1874360.74$	0.1292
	Quadratic	$y = -2.03x^2 + 3867.15x + 1750317.78$	0.2368
	Cubic	$y = 0.00205x^3 - 6.20x^2 + 5207.07x + 1701895.25$	0.2628
	Log-Log	$\ln(y) = 0.0605\ln(x) + 14.2612$	0.1731
Spring (Mar–May)	Linear	$y = 2134.43x + 1146592.26$	0.0481
	Quadratic	$y = -27.81x^2 + 7036.99x + 1023988.24$	0.1468
	Cubic	$y = 0.1866x^3 - 105.23x^2 + 13450.28x + 935628.49$	0.2076
	Log-Log	$\ln(y) = 0.0912\ln(x) + 13.6755$	0.1194
Summer (Jun–Aug)	Linear	$y = -1046.33x + 662237.96$	0.0435
	Quadratic	$y = 8.87x^2 - 2327.86x + 677810.60$	0.0635
	Cubic	$y = -0.0459x^3 + 22.40x^2 - 3110.93x + 683575.17$	0.0678
	Log-Log	$\ln(y) = -0.0309\ln(x) + 13.4102$	0.0387
Autumn (Sep–Nov)	Linear	$y = -1047.57x + 1154228.38$	0.0357
	Quadratic	$y = 0.25x^2 - 1108.91x + 1155552.11$	0.0358
	Cubic	$y = 0.0167x^3 - 9.08x^2 - 57.05x + 1143071.87$	0.0392

Winter demonstrated a modest positive price-consumption relationship, likely reflecting heating-driven demand, as shown in Figure 6. Although variation at extreme prices exists, the low R^2 highlights the dominant influence of non-price factors such as temperature.

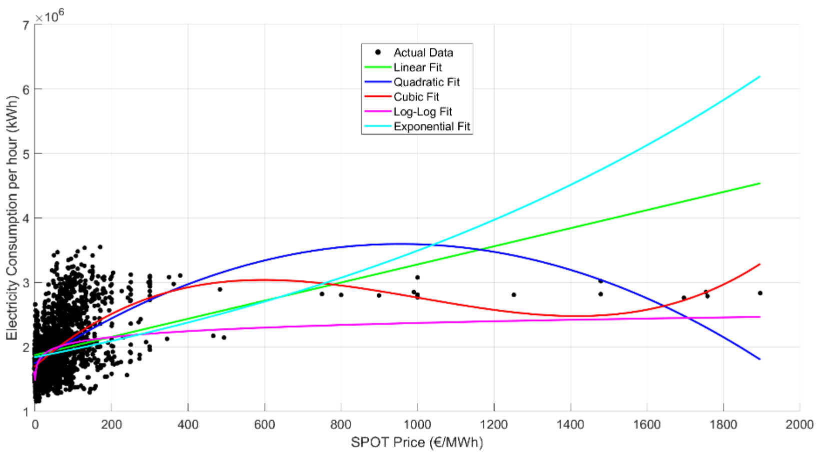

Figure 6. Regression Model Fits for Winter (BE02) December – February.

Electricity consumption in spring exhibited a weaker positive correlation with price, with all models producing low-to-moderate R^2 values. Both the linear and log-log models produced positive coefficients, suggesting that higher prices were generally associated with slightly higher electricity consumption. Polynomial models, particularly the quadratic model, showed an initial increase in consumption with price but declined after reaching a higher price. The cubic model followed a more complex pattern, but overall, it still suggested a general rising trend with some fluctuations. This reinforces the observation that during spring, households did not reduce consumption as prices rose, although extreme price levels may have led to slight adjustments.

In contrast to winter and spring, summer displayed a weak but negative correlation between electricity price and consumption in Figure 7**.** The linear regression model indicated that for every 1 €/MWh increase in price, consumption decreased by approximately 1046.33 kWh, despite small R^2 value. The log-log model also suggested a weak negative elasticity, meaning that households may slightly reduce consumption when prices rise. However, all polynomial models had very low R^2 values, with the quadratic model first decreasing and then increasing and the cubic model exhibiting a more complex trend with an overall downward tendency. This reinforces that price is not the dominant driver of electricity consumption in summer.

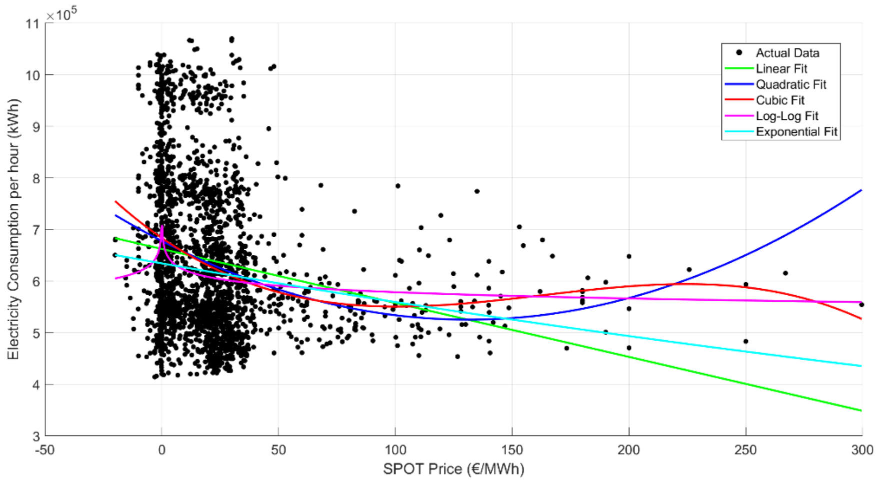

Figure 7. Regression Model Fits for Summer (BE02) June – August.

Like summer, Autumn displayed minimal negative correlation between electricity consumption and price in autumn. The quadratic model showed a general downward trend, while the cubic model initially declined before rising slightly. Despite the low explanatory power of all models, the overall tendency leans toward a weak negative response.

3.5.3 BE03 (Apartments, small buildings, not electrically heated)

Electricity consumption patterns in BE03 households followed similar seasonal trends as BE02, with winter and spring showing moderate positive correlations with price, and summer and autumn exhibiting weak negative responsiveness. Given this similarity, only a summary is provided here.

During winter, the cubic model performed best ($R^2 = 0.3463$), indicating that consumption generally increased with price, though some decline was observed at extreme price levels. Spring displayed weaker positive correlations, with polynomial models suggesting a turning point at higher prices. In summer and autumn, all models showed minimal and mostly negative relationships with price, with low R^2 values indicating weak demand elasticity, suggesting that BE03 households tend to maintain stable consumption regardless of price changes during the warmer seasons.

3.6 LSTM Forecast

In this chapter, an LSTM model was developed to forecast electricity consumption. First, daily (short-term) forecasts were assessed to gauge predictive accuracy, and then analysis was extended to full-year forecasts, highlighting seasonal patterns and long-term trends.

3.6.1 Forecasting Performance and Short-Term Accuracy

Short-term (daily) forecasts serve as a benchmark for model accuracy, ensuring that the LSTM effectively captures the underlying consumption patterns. The model exhibited varying levels of predictive performance across the three customer groups.

BE02 and BE03 demonstrated strong predictability, as confirmed by Figure 8, with R^2 at around 0.75 for both, and BE02 and BE03 yielded MAPE values of 6.72% and 5.56%, respectively.

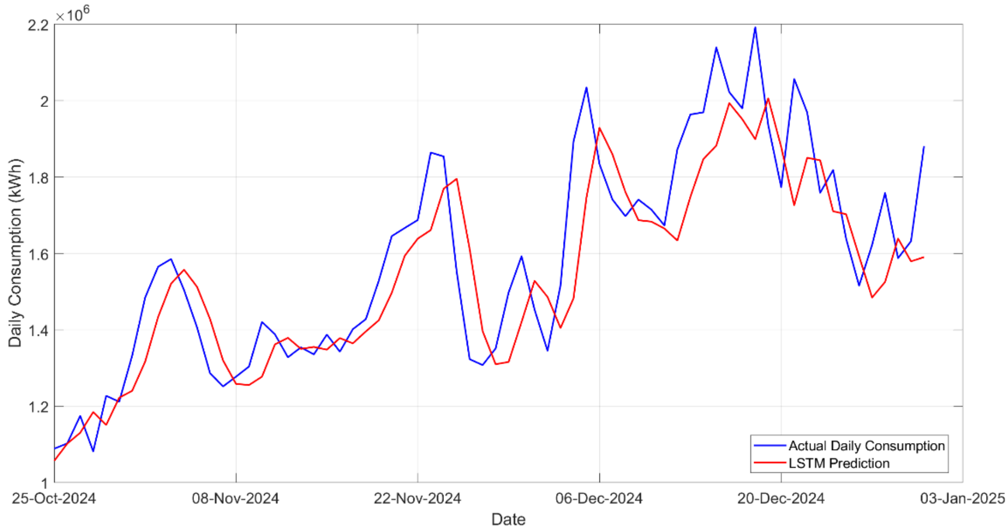

Figure 8. Short-Term Forecast Plot for BE02.

BE01 had the lowest forecast accuracy (R^2 = 0.36), but the smallest error (MAPE = 4.83%), suggesting that while the predictions are less precise, the overall deviation from actual consumption remains moderate. This could indicate a more stochastic or less structured consumption pattern.

3.6.2 Full-Year Forecast and Seasonal Patterns

While all groups exhibit similar seasonal cycles in forecast, differences in short-term variability and predictability highlight structural variations in household electricity usage.

All consumption forecasts follow a seasonal cycle, peaking in winter and declining in summer. However, the smoothness of these patterns varies across customer groups. BE02 and BE03 exhibit well-structured, gradual fluctuations, suggesting that their electricity usage is highly seasonal and predictable (Figure 9**)**.

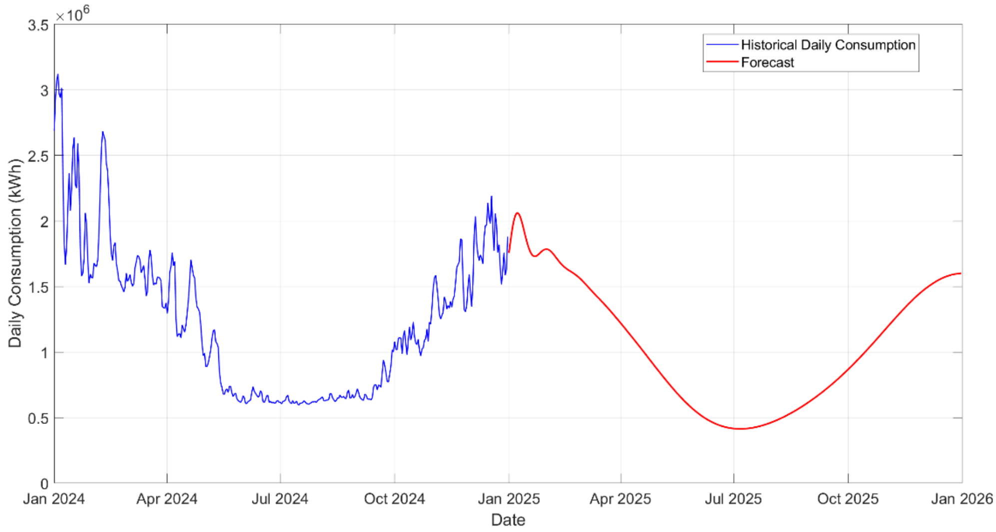

Figure 9. Long-Term Forecast Plot for BE02.

In contrast, BE01, while following the same general trend, shows greater short-term variability and less smoothness, indicating the influence of non-seasonal factors. This makes BE01 less predictable despite sharing the same overall seasonal structure.

3.7 Flexibility Potential Quantification and Comparison

Building on the regression analysis, this section presents the estimated flexibility potential across three household groups. As shown in Figure 10, BE02 households demonstrated the highest relative flexibility (0.0066%), followed by BE01 (0.0039%) and BE03 (0.0024%). These percentages were calculated by summing the flexibility potential from all valid demand response events (estimated as the product of the event-level regression slope and the corresponding spot price variation by Equation (9)) and dividing the total by the group's annual electricity consumption, as detailed in Table 1. This trend aligns with prior expectations, as BE02 users—more reliant on electric heating—are more likely to adjust their usage in response to spot price fluctuations.

When examining flexibility on a per-household basis, BE02 again exhibits the highest value at 0.7048 kWh, followed by BE03 at 0.1641 kWh and BE01 at just 0.0846 kWh. These values were computed by dividing the total demand response potential calculated above by the average number of households in each group (see Table 1).

Interestingly, although BE01 shows slightly higher relative flexibility than BE03, its per-household flexibility is the lowest. This confirms that while BE03 may have limited aggregate flexibility, individual households within this group still demonstrate modest responsiveness. In contrast, BE02 users show both high total and individual flexibility. These results suggest that flexibility cannot be fully understood from group-level data alone. Per-capita flexibility indicators are essential to reveal hidden demand response potential in smaller or less energy-intensive groups.

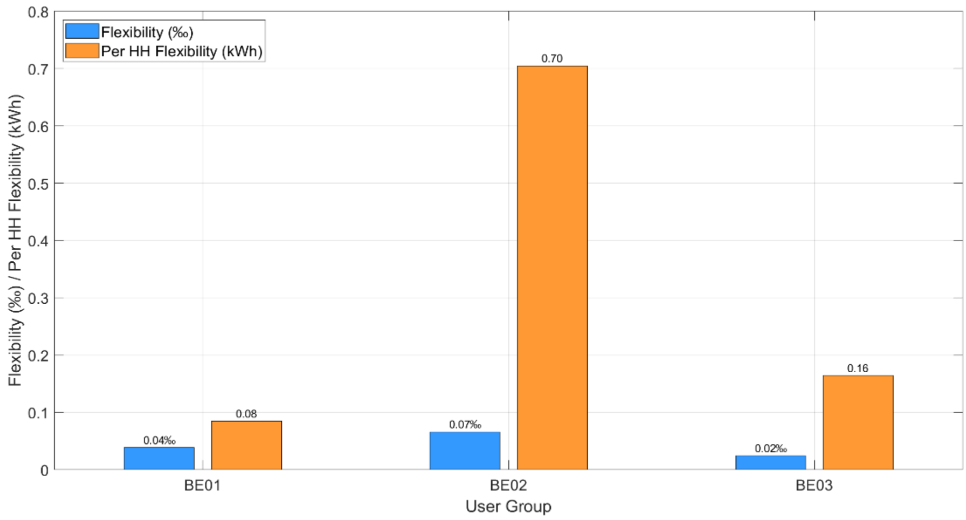

Figure 10. Demand Response Flexibility: Relative and Per-Capita Metrics by User Group.

These findings reinforce the earlier analysis. BE02 households consistently display stronger and more structured demand response behavior. Their responsiveness is observed not only during short-term price surges and peak events but also in quantified flexibility potential. On the other hand, BE01 and BE03 remain less flexible, both in total and per-household terms, likely due to the nature of their energy use—either being less sensitive to price (e.g., district heating in BE01) or reflecting more stable consumption routines (as in BE03). From a policy perspective, the results indicate that targeted demand response programs could achieve greater impact by focusing on electrically heated households (BE02).

4 Discussion

This chapter discusses the key findings, evaluates the effectiveness of the applied regression models, and examines the performance characteristics of the LSTM prediction model.

4.1 Interpretation of Main Findings

The results indicated that BE02 households consistently demonstrated the highest demand response flexibility. This is likely due to their reliance on electric heating, which provides more controllable and price-sensitive loads. In contrast, BE01 households showed the weakest responsiveness, possibly because of district heating and less discretionary electricity use, and BE03 exhibited moderate flexibility. These findings confirm that heating method plays a crucial role in determining demand-side flexibility potential.

In addition to group-level differences, this study also revealed important temporal patterns. While flexibility is conventionally expected to be higher during winter months and evening hours due to increased load variability (Bartusch et al. ,2011), this study finds that demand response was strongest during late-night hours and relatively weak during winter.

This late-night flexibility may reflect the use of thermal mass in residential buildings, enabling occupants to pre-heat their homes during the evening to maintain thermal comfort overnight while reducing heating loads in the late-night period (Le Dréau & Heiselberg, 2016). Moreover, winter months showed relatively limited demand response in seasonal regression results across all user groups. Yet, shorter price surge events happened in late winter revealed that some level of demand response still occurred. These findings highlight that other factors like daily routines and seasonal heating needs may override price signals, limiting flexibility during critical periods.

4.2 Value of the Regression Models in Flexibility Assessment

The use of multiple regression models in this thesis provided a comprehensive analytical framework, enabling the exploration of both linear and nonlinear dynamics in this big data–

based study. Among the tested models, the cubic regression consistently achieved the highest R^2 values (up to 0.9546) across most scenarios, making it the best-performing model overall.

The strength of the cubic model lies in its ability to capture nonlinear behavioral responses. The cubic model can reflect threshold effects, such as the point at which price increases become substantial enough to trigger abrupt reductions in consumption. For instance, in BE02 households, electricity uses initially showed a mild increase as prices rose but then declined sharply beyond a certain price level. While this may suggest some level of price responsiveness at extreme prices, such patterns could also be influenced by other contextual factors, such as outdoor temperature or heating needs. However, it is worth mentioning that while the cubic regression yielded high R^2 values in several scenarios, this merely reflects statistical fit and does not necessarily imply a causal or economically rational relationship between price and consumption.

While the linear regression model is more simplistic in structure, it plays an indispensable role in flexibility quantification. The slope coefficient in linear regression directly reflects the rate of consumption change per unit price variation, making it particularly suitable for estimating event-based flexibility in physical terms. Its interpretability and straightforward implementation make the linear model a practical and robust tool for engineering applications, especially when used in slope $\times$ ΔP–based estimations to quantify demand response potential in this thesis.

4.3 LSTM Prediction Lag and Model Behavior

Overall, the performance of LSTM is satisfactory, however, it can be seen in Figure 8 that the prediction is few days later than the real-world data.

The slight delay is likely due to the model's one-step-ahead training setup, where each forecast relies solely on the preceding 30-day sequence. As a result, the model tends to follow existing trends with some temporal inertia, causing predicted peaks and troughs to lag behind actual consumption patterns.

5 Conclusions

This thesis set out to assess the demand-side flexibility of Finnish households by quantifying the statistical relationship between electricity consumption and spot market prices in 2024. All four key objectives were achieved: (1) regression models were developed to describe the price–consumption relationship, (2) temporal patterns were uncovered on daily and seasonal scales, (3) group-level flexibility was quantified and ranked, and (4) future consumption was forecasted using LSTM.

The results suggest that flexibility may vary significantly between household groups and over time. Electrically heated households (BE02) tended to exhibit the highest responsiveness to price, while district-heated apartments (BE01) appeared to show the weakest. Temporally, the most observable demand response was found during late-night hours, whereas winter months were associated with lower reductions in consumption. This pattern may indicate that external seasonal and behavioral factors could partially overshadow price signals, limiting measurable flexibility during certain periods.

While flexibility is often expected to be higher during winter months and evening hours due to increased load variability, this study observed that demand response was more pronounced during late-night hours and less evident during the winter. However, it is important to note that demand response is inherently difficult to quantify, especially in aggregated data where many confounding variables exist. This deviation from expectation does not necessarily imply contradictory behavior but rather highlights the need to re-express or cautiously revisit certain assumptions in flexibility modeling, particularly within the Finnish residential context.

The findings of this thesis carry practical value for grid operators like Fingrid, demand response planners, and Finnish households. By improving understanding of household-level flexibility, the results can inform the design of spot-based pricing strategies and support real-time grid balancing, particularly as renewable integration increases. On a societal level, this research helps identify when and where flexibility exists, offering a foundation for more efficient electricity consumption and empowering consumers to participate in the energy transition.

Yet, this study also has several limitations. First, the analysis does not differentiate between contract types, meaning that households with fixed-rate and spot-based pricing are treated the same, which may dilute observable demand response effects—especially since only 31% of Finnish households follow real-time pricing. Second, the model does not include important explanatory factors such as weather conditions, socioeconomic status, or behavioral patterns (e.g., weekday vs. weekend), all of which may influence electricity use. Third, the flexibility estimation relies on a simplified slope-based approach, which, while intuitive and practical, may not capture underlying baseline consumption as accurately as machine learning–based methods. Future work could address these gaps by integrating more detailed contract-specific datasets, taking into account other external factors and combining statistical and neural network models to produce more detailed and robust assessments of consumption flexibility.

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