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Dynamic Modeling of Energy Demand in Educational Institutions Affected by COVID-19 and Energy Crisis

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Abstract

This study explores the electricity consumption patterns in institutional buildings at a university campus in Greater Paris, employing time-series analysis to assess the effects of major disruptions like the COVID-19 pandemic and the subsequent energy crisis triggered by the war in Ukraine. Utilizing dynamic linear modeling, our research achieved a Mean Absolute Percentage Error of 6.2%, demonstrating the model's efficacy in capturing complex consumption patterns under fluctuating conditions. We observed a 13% reduction in electricity usage during the initial pandemic lockdowns, with varying responses in subsequent phases due to the energy crisis. These results underscore the critical role of adaptive energy policies and advanced modeling techniques in enhancing energy efficiency and resilience in educational institutions. By providing detailed insights into the factors influencing energy usage, our study assists policymakers and energy managers in devising robust strategies to improve energy management and meet sustainable development goals, particularly in response to external shocks.

Keywords: Electricity Consumption analysis, Institutional Buildings, Dynamic Linear Modeling, Sustainable energy management, Energy Resilience and Crisis Management

1. Introduction

Effective electricity consumption management is crucial for sustainable energy development today. Given that the building sector consumes approximately 40% of global primary energy and produces more than 30% of CO₂ emissions (Taylor, 2010), understanding building energy use at the city scale is a critical component of advancing urban sustainability, Greenhouse Gas (GHG) emissions reduction, and energy efficiency across the globe (Kontokosta and Tull, 2017). Moreover, understanding and

forecasting electricity consumption patterns are crucial for policymakers and consumers to make informed decisions regarding energy efficiency, capacity planning, and integrating renewable energy sources (Sun et al., 2021; Wang and Lu, 2021). Future energy use forecasts predict increased consumption in commercial buildings and decreased consumption in residential buildings. Commercial and institutional buildings are crucial in social, environmental, and economic sustainability (Morovat et al., 2024). However, despite their importance, these buildings are less frequently studied, and there is still a lack of models that can effectively capture and explain changes in consumption patterns over time, especially in response to external events that may occur in times of crises.

In this research, we analyze the electricity consumption data in two higher education and research buildings located on a University campus in Greater Paris, France, under external shocks such as a global health crisis (2020 COVID-19 pandemic) or energy crisis (2021-2022 energy crisis post-COVID-19 and war in Ukraine). The two buildings have been described and studied in two former works Allab et al. (2017); Bourdeau et al. (2021). The COVID-19 pandemic has caused a severe global crisis and has impacted every aspect of life. It has caused economic, social, technological, political, and health consequences. It has also brought about environmental and energy-related effects because of measures like lockdowns, shelter-in-place, and stay-at-home orders implemented to control the pandemic locally (Abu-Rayash and Dincer, 2020). The International Energy Agency (IEA) reported an average of 5% decrease in global electricity demand in 2020 due to the COVID-19 pandemic (IEA, 2020). However, this reduction can vary among different countries, regions, and building types. This point makes it crucial in this study to model the impact of lockdowns on electricity consumption in institutional and university buildings. Assessing these changes is particularly interesting given the restrictions placed on students attending physical classes and the consequent strong decrease in the building's occupancy.

In addition to the lockdown, the energy crisis that started in 2021 due to the rapid economic rebound following the pandemic reached its highest magnitude in 2022 after the beginning of the war in Ukraine induced great changes in energy consumption patterns from the winter of 2022. In France, for example, the authorities announced a decrease of 5% in electricity consumption in 2022 (sob, Year). It is also interesting to see how much this second crisis and the related governmental measures (energy sobriety plan in this case) have impacted the electricity consumption in university buildings in addition to the impact of permanent organizational changes (teleworking, for, e.g.) that has been partially maintained after the COVID-19 crisis. Time series models have found extensive application in various studies

focused on modeling and predicting electricity consumption and demand. Different methodologies have been employed to model electricity consumption data Bourdeau et al. (2019), with various degrees of success. Fortunately, during the last decade, advanced metering infrastructure and smart meters have enabled the collecting and storing of large-scale electricity consumption data (Bourdeau et al., 2020). The data provided by the advanced metering infrastructure can be used to develop and apply data-driven methodologies for modeling electricity consumption, providing insights into energy use patterns, and identifying energy-saving potential (Ahammed and Khan, 2022). Many studies have been completed in recent years to focus on issues related to automatically extracting information from these data using different approaches (Miller et al., 2018). These studies employ diverse techniques, including regression with seasonality, exponential smoothing, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and more (Sarkodie, 2017; Hussain et al., 2016; Clements et al., 2016). McLoughlin et al. (2013) evaluate various time series techniques to characterize domestic electricity demand patterns. The study assesses the suitability of different methods in accurately modeling and forecasting residential electricity consumption. These traditional statistical methods are valuable for electricity demand modeling but have limitations. They might struggle with complex consumption patterns, assumptions of data stationarity, and the need for high-quality data (data that is accurate, reliable, and free from significant errors or inconsistencies). Model selection can be challenging, and incorporating external factors can be problematic. These methods might excel in the short term but struggle in long-term forecasting.

In addition to these challenges, in their 2016 review on enhancing energy efficiency in commercial and institutional buildings, Ruparathna et al. emphasized the need for studies focused on behavior-specific improvements to improve building energy performance (Ruparathna et al., 2016; Heinrich et al., 2022).

The rapid development of machine learning and computational intelligence made it possible to develop new approaches that can effectively deal with randomness and non-linear factors (Qiu et al., 2017) and consider the users' behaviors. Chou and Tran (2018) reviews various machine-learning methods to model and predict the electricity consumption patterns in residential households. They show the potential of these methods in modeling the energy data.

In their study, Hong et al. (2013) show that annual weather variation greatly impacts the buildings' electricity demand, especially during peak hours. Li et al. (2019b), explain that ambient temperature is one of the important factors as it directly drives the operation of the cooling/heating system and influences the corresponding building cooling and heating energy consumption. Santamouris et al.

(2015) show that the building’s peak electricity load would increase up to 4.6% for one degree of temperature increase. They estimate the corresponding increase in total electricity consumption as high as 8.5%. In addition to the impact of weather, other exogenous variables can impact the level of consumption. The authors in Li et al. (2019a) investigate how calendar-related factors, such as holidays, weekends, and seasons, impact electricity prices and demand. Their analysis led to an understanding of the patterns and anomalies in electricity market behavior associated with different calendar effects.

In addition to these commonly used explanatory variables, recent years have witnessed unforeseen events that had a substantial impact on global energy consumption. One of the most important ones is the COVID-19 pandemic, which had a significant effect on the energy sector, resulting in notable changes in electricity consumption patterns across residential, commercial, and industrial sectors due to lockdown measures (Cerqueira and da Silva, 2023; Garcia-Rendon et al., 2023; Liu and Lin, 2021).

Additionally, the recent global energy crisis exacerbated by the war in Ukraine in 2022 has prompted the adoption of energy-saving measures, further influencing energy consumption dynamics (Brodny and Tutak, 2023). It also affected energy markets and, consequently, consumption behaviors. In this context, it is crucial to understand the impact of such events on energy consumption patterns and consider their long-term effects when forecasting future consumption patterns. It can also be useful to guide policymakers to develop more sustainable and resilient energy policies.

Hence, we need an improved method to analyze electricity consumption data. This method must detect complex patterns and account for external factors and unexpected events. Traditional models, while helpful, have shown limitations in their adaptability and ability to handle complexities. In this paper, we introduce Dynamic Linear Modeling (DLM) as a solution. DLM is chosen for its flexibility and accuracy in modeling complex data over time (Petris et al., 2009). We apply DLM to electricity data from 2017 to 2023, covering periods before and after significant events like the COVID-19 pandemic and the last energy crisis.

In this context, Dynamic Linear Modeling (DLM) emerges as an effective method to analyze the impact of these changes on electricity consumption patterns (Honjo et al., 2018). DLM is particularly well-suited for capturing the time-varying dynamics of energy consumption and understanding how external factors, such as the COVID-19 pandemic and energy crises, influence consumption behavior over time (Campagnoli et al., 2009; Durbin and Koopman, 2012). By incorporating time-series data and latent variables, DLM enables us to accurately model the evolving energy

consumption patterns and forecast future trends more reliably (Kitagawa and Gersch, 1984; Pedregal and Trapero, 2010). Although DLM has been previously utilized for country-level electricity data modeling (Honjo et al., 2018), this paper represents the first application of Dynamic Linear Modeling to analyze electricity consumption patterns, specifically in buildings. This novel approach allows for a more granular analysis of energy use dynamics within individual buildings or building types.

This study utilizes Dynamic Linear Modeling to analyze real electricity consumption data, aiming to identify and quantify various components contributing to consumption patterns. Dynamic Linear Modeling (DLM) is a flexible approach that has found applications in various fields, including energy demand analysis. It offers several advantages, making it a valuable tool for modeling and understanding complex time series data.

DLM is adept at capturing stochastic trends within time series data, making it particularly useful for uncovering hidden patterns in energy demand data (Dordonnat et al., 2008; Murthy and Kishore Kumar, 2021). Additionally, it excels in describing structural changes over time, which is essential for analyzing evolving phenomena (Harvey and Durbin, 1986). Díaz et al. (2019) highlights the effectiveness of DLM as a versatile tool for modeling and analyzing complex time series data in the context of electricity market research by using DLM in capturing the dynamics of uncertain electricity market prices and wind speed.

An additional benefit of utilizing DLM is the fact that we can assess the changing impact of an unexpected event over time without increasing the complexity of the model through an excessive number of parameters (Durbin and Koopman, 2012). This property aligns with the objectives of our study, which seeks to investigate the impact of unpredicted events, such as the COVID-19 pandemic, increasing teleworking trends, and energy crises, on electricity demand in institutional buildings.

Our analysis reveals the trend and different seasonality components, providing valuable insights into factors influencing electricity usage. Also, the model enables us to assess the impact of exogenous factors such as weather conditions, the building’s occupancy changes over the years, and calendar events.

In this study, we have gathered a dataset of sub-hourly electricity demand measurements from 2017 to the present, encompassing both the pre-pandemic period and the subsequent lockdown and energy crisis phases for two campus buildings. Analyzing these data can help us answer some of the critical questions related to electricity consumption patterns:

- How can we effectively capture and explain changes in electricity consumption patterns over time?

- How well does DLM quantify the impact of external events on electricity consumption patterns? What are the complex relationships within the data that DLM can help uncover?
- How did the COVID-19 pandemic influence electricity consumption in institutional buildings?
- How does the energy crisis impact energy consumption in university buildings?
- What is the explanatory power of the different considered variables?

The paper is organized as follows. We describe in section 2 the datasets and different data types we use in this study. We introduce in section 3 dynamic linear modeling for electricity consumption data. We present in section 4 the electricity data modeling results in two institutional buildings. Finally, section 5 concludes the study and outlines the prospects for future work.

2. Data description

In this section, we describe the use case and the data we used in our study. The goal is to analyze the electricity consumption patterns within institutional buildings and assess how different crises, such as COVID-19 (2020) and the last energy crisis in France (2022), impacted these patterns. We consider two buildings with different features (described in subsection 2.1), which can help in the analysis of the results. In addition to internal factors, the electricity consumption also depends on different exogenous factors such as weather conditions, occupancy patterns, calendar events, and non-planned events such as COVID-19 lockdowns and energy crises. In this section, we present a comprehensive foundation to clarify the context of the study.

2.1. Buildings description

We have accessed electricity consumption data from January 1st, 2017, to the end of December 2022 for two buildings (building 1 and building 2) located within the "Cité Descartes" campus in the Paris metropolitan area in France (Bourdeau et al., 2018).

A summary of the building characteristics and technical information for these two buildings is given in table 1. We have selected these two buildings as they were constructed in different years under different buildings' thermal regulation codes and, therefore, have different energy consumption patterns. More importantly, the size, the occupancy, and the level of electricity consumption in these two buildings have

major differences. This enables us to compare the electricity consumption pattern in institutional buildings with different characteristics.

Building 1, built in 1987, has a net floor area of 30,580 square meters and comprises a ground floor and four additional levels. Its heated volume amounts to 144,173 cubic meters. In contrast, Building 2 is a more recent construction from 1999, with a net floor area of 10,343 square meters. It has a ground floor and five upper levels, with a heated volume of 51,274 cubic meters.

Regarding their energy systems, Building 1 has an electricity contract power of 900 kW and relies on a gas furnace for heating and ventilation. It also employs refrigeration units for cooling purposes, predominantly in lecture halls and specific laboratories. Building 2, conversely, has a lower electric contract power of 250 kW, utilizing similar heating and ventilation systems and refrigeration units in lecture halls. It is worth mentioning that, in addition to its large surface area and early construction year, Building 1 exhibits a main difference from Building 2. It provides additional specific equipment which can significantly affect the overall energy consumption. Such equipment mainly includes a gym of significant surface area with a large mechanical air renewal rate, a canteen, several computer labs and server rooms with cooling needs, and a 600m² R&D clean-room facility with a huge air renewal rate and humidity control needs.

Occupancy figures reveal that Building 1 accommodates a larger community, with 2,250 students and 210 staff members, while Building 2 serves a smaller population of 700 students and 65 staff members in 2022.

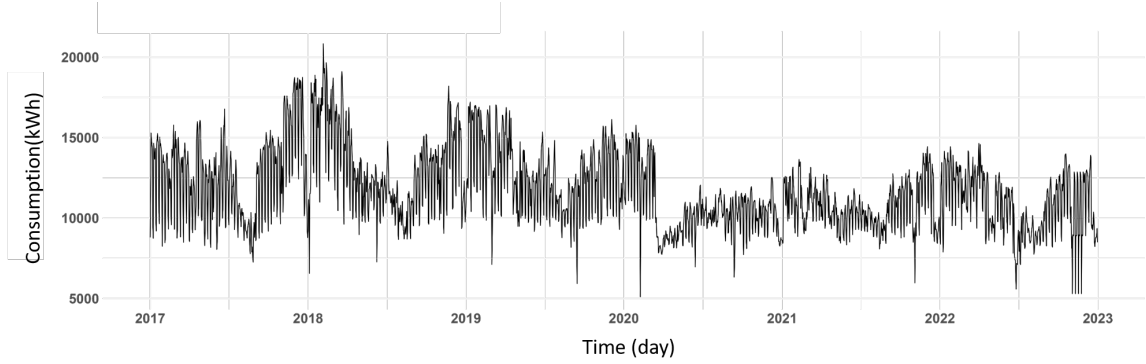
2.2. Electricity consumption data

The data is provided by the French distribution system operator (eco).

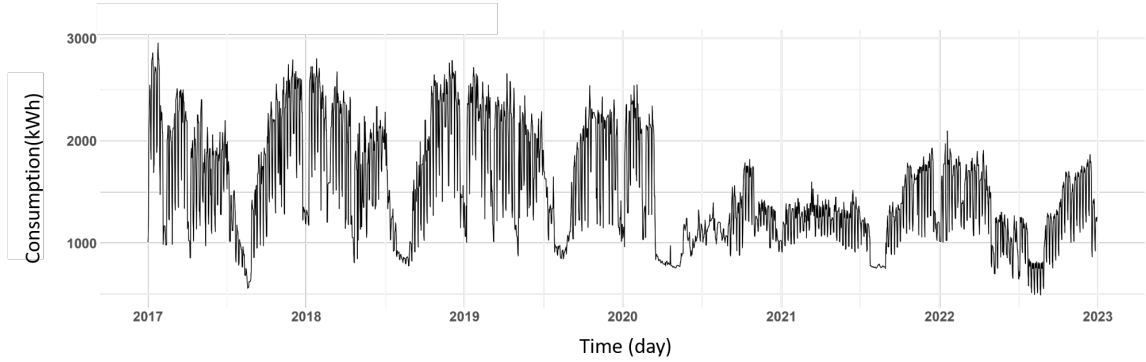
This comprehensive data set includes active power measurements recorded in kilowatts (kW) at 10-minute intervals. In this study, we consider the daily consumption. Figure 1 shows the data corresponding to this specific time frame for two buildings.

Table 1: Buildings Characteristics

Characteristics		Building 1	Building 2
Activity	Teaching and research activity	Science and Technology	Art and Humanities
Built	Construction year	1987	1999
	Net floor area (m^2)	30,580	10,343
	Floors	Ground floor + 4	Ground floor + 5
	Heated volume	144,173	51,274
Energy	Electricity (contract power)	900kW	250 kW
	Heating	Gas boiler	Gas boiler
	Cooling	Refrigeration units	Refrigeration units
	Ventilation	Central ventilation (gas boiler)	Central ventilation (gas boiler)
Occupancy	Number of students (in 2022)	2250	700
	Number of staff (in 2022)	210	65



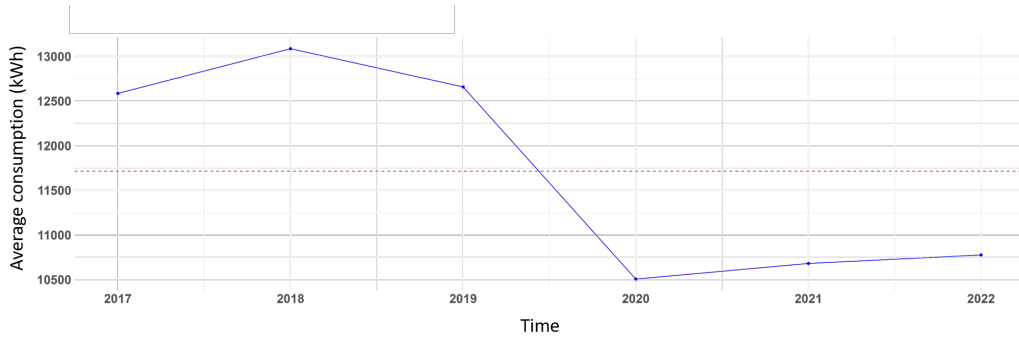
(a) Building 1



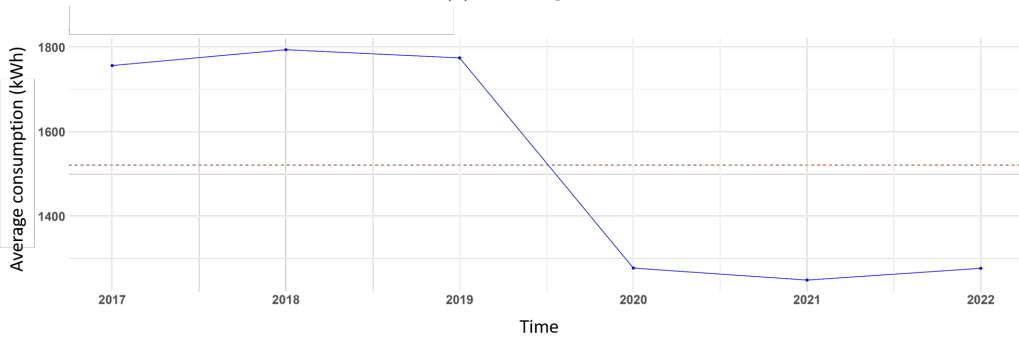
(b) Building 2

Figure 1: Raw data for daily electricity consumption from January 2017 to December 2022

Figure 2 shows the average yearly consumption (kWh) for the two buildings, revealing a similar trend for both buildings. There is an increasing trend from 2017 to 2018 for both buildings. However, a decrease of 3.3% for Building 1 and 1.2% for Building 2 is observable between 2018 and 2019. There is a substantial decreasing trend for both buildings in 2020, which can be attributed to the COVID-19 lockdowns that started in March 2020. Since then, there has been a gradual rise in consumption for Building 1; however, it remains below the 2017 consumption level. Also, building 2's decreasing trend has been continued but with a lower slope. This may be in response to increased awareness and adoption of energy-saving practices as a consequence of the energy crisis generated by the war in Ukraine.



(a) Building 1



(b) Building 2

Figure 2: Average daily electricity consumption per year from 2017 to 2022

We conducted an investigation to identify and analyze various seasonal components present in the electricity consumption data. We found two types of seasonality in these data: yearly seasonality and weekly seasonality.

Figures 3 and 4 display the yearly electricity consumption data in Building 1 and Building 2, respectively. The figures reveal a similar pattern for each year except

2020, where a decline was observed due to the COVID-19 lockdown. Electricity consumption decreases during the winter. Also, we observe less consumption during vacation times, including winter and summer vacations.

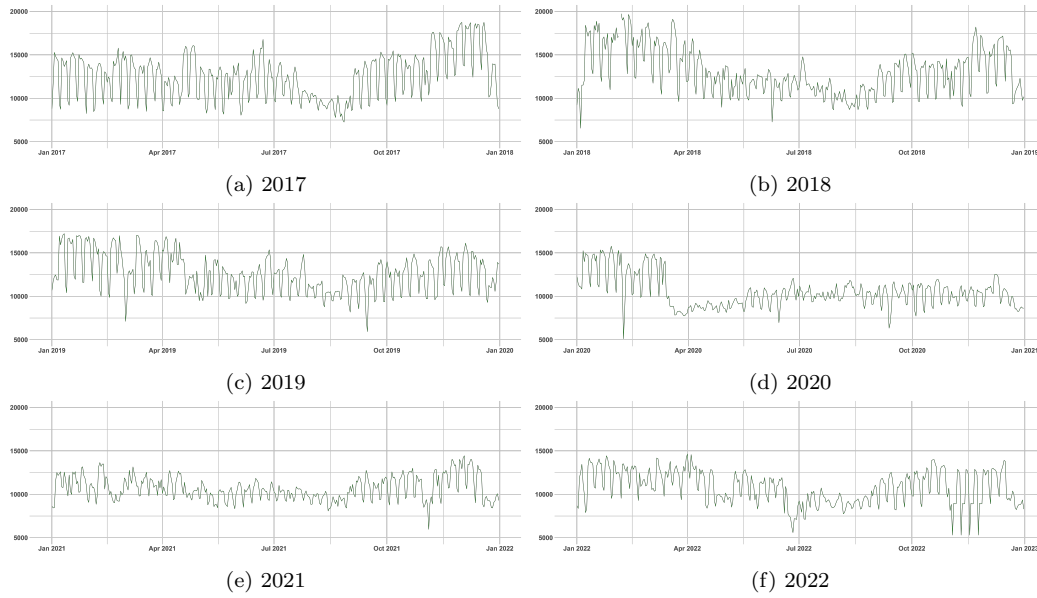


Figure 3: Daily electricity consumption (kWh) in Building 1 per year

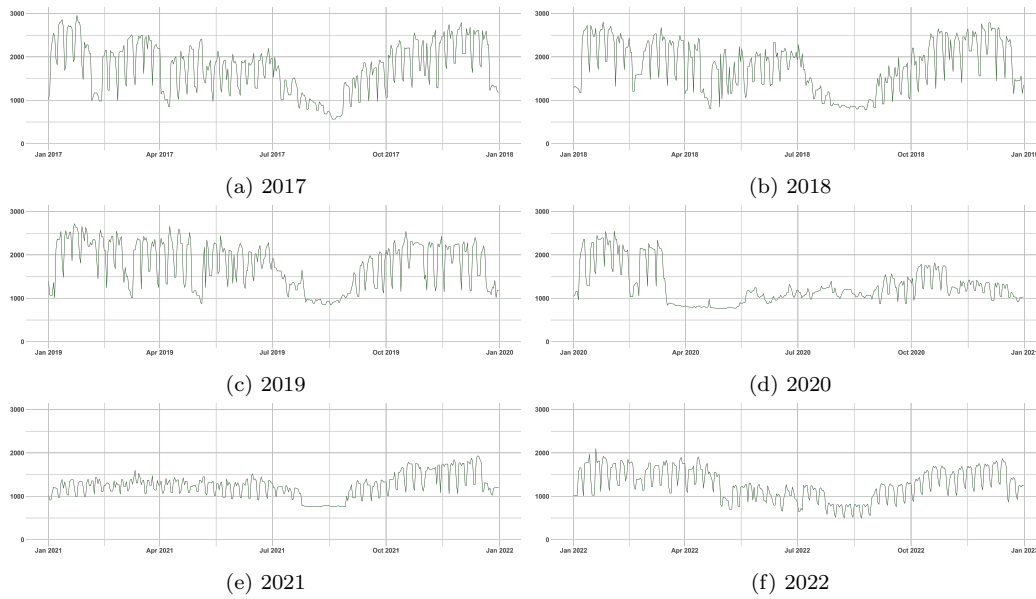


Figure 4: Daily electricity consumption (kWh) in Building 2 per year

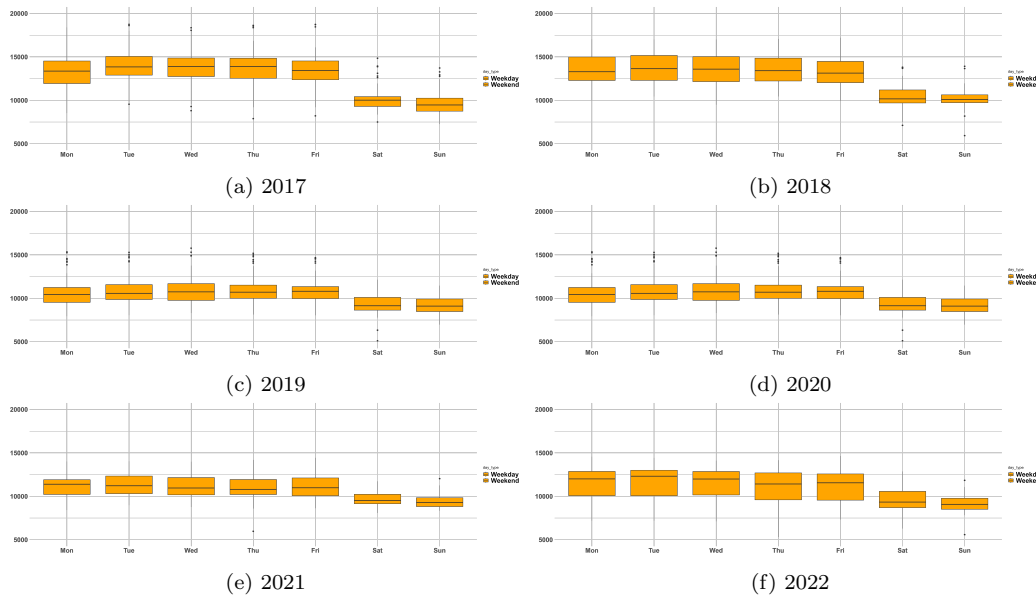


Figure 5: Average electricity consumption (kWh) in Building 1 per weekdays over one year from 2017 to 2022.

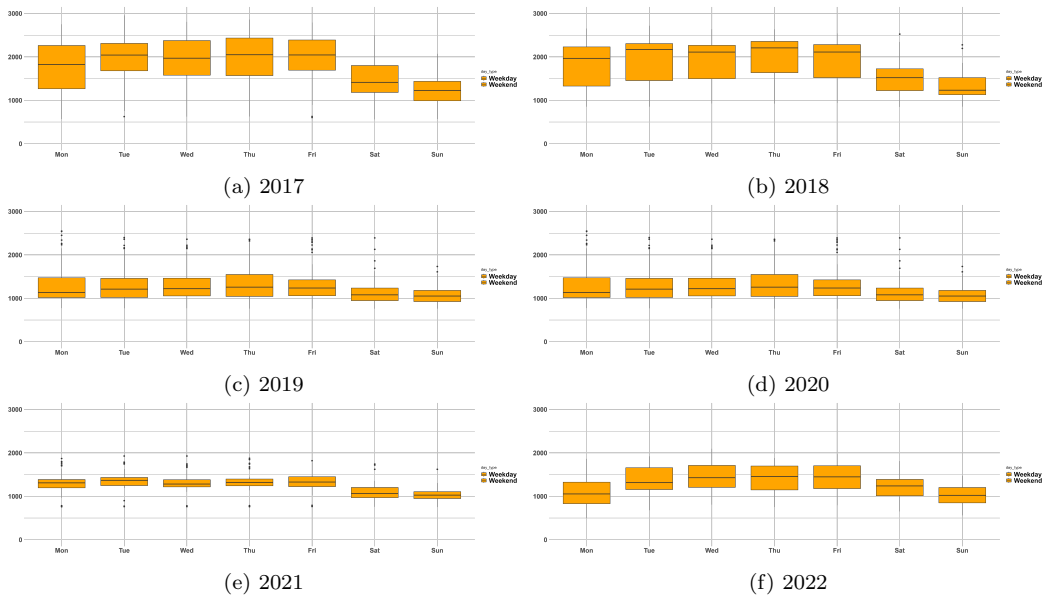


Figure 6: Average electricity consumption (kWh) in Building 2 per weekdays over one year from 2017 to 2022.

Furthermore, it can be observed that electricity consumption varies between weekdays and weekends. Figures 5 and 6 show boxplots of the average consumption for each day of the week per year. The data reveals that electricity usage tends to be lower during weekends, especially on Sundays. This decrease in consumption can be attributed to lower occupancy during weekends. This leads to a noticeable drop in overall electricity usage these days. This behavior is notably observed due to the institutional nature of the buildings, where usage patterns and occupancy directly influence electricity consumption.

2.3. Explanatory data

The seasonal effects alone cannot explain all the phenomena in the electricity consumption time series data. Multiple external factors impact consumption patterns. Significantly, the lockdowns that happened in 2020 and 2021 and the regulations in the energy consumption policies following the war in Ukraine had major impacts on the electricity consumption in these institutional buildings. We have identified five categories of exogenous variables listed in Table 2. Below, we provide explanations for the selection of each variable and the data sources used for their inclusion.

As shown in Figure 1, there is a significant decrease in electricity consumption data after 2019. This drop in consumption in institutional buildings is due to the lockdowns that had been set to mitigate the spread of the coronavirus.

Table 2: Explanatory variables in the model

Categories	Exogenous variables
COVID-19 period	Days of lockdown
Energy crisis	Days since the beginning of the war
Meteorological factors	Temperature Daylight duration
Calendar events	School vacations and National holidays
Occupancy data	Number of occupants

France experienced three major COVID-19 lockdowns during which universities and schools were closed (2023a,b):

- First lockdown: March 17, 2020 to May 10, 2020
- Second lockdown: October 30, 2020 to December 15, 2020
- Third lockdown: April 3, 2021 to May 3, 2021

As mentioned before, in addition to the lockdown, followed by the war in Ukraine, the French government, under the "Energy Sobriety Plan", asked people to curtail their gas and electricity usage starting in the winter of 2022. This initiative extended to both public and private institutions, with a requirement to maintain indoor temperatures not exceeding 19 degrees Celsius and strong recommendations to reduce consumption, cut unnecessary energy use, and shift non-urgent uses to low-demand hours. It is interesting to assess how this plan affected the electricity consumption in institutional buildings. We include the impact of this explanatory variable by considering an exogenous variable from October 2022.

We also consider local weather data as explanatory variables.

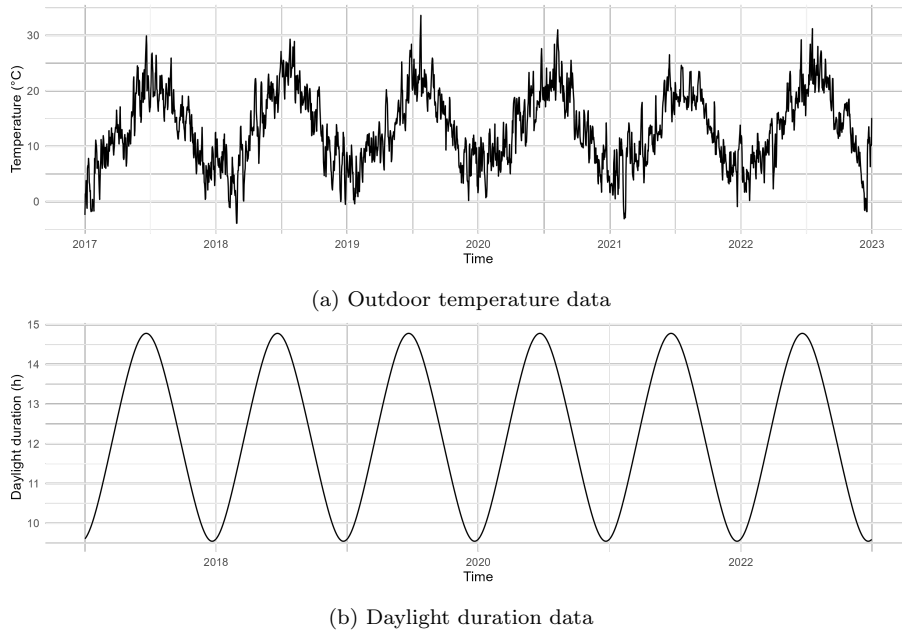


Figure 7: Weather metrics data

To identify the weather variables that impact the electricity consumption in these buildings, we conducted regression analyses between the common weather metrics (including temperature, dew point temperature, relative humidity, wind speed, wind direction, sea level pressure, incident solar radiation, and daylight duration) and the electricity consumption in both buildings. The weather data represents Paris’s daily averages (Data and API). Table 3 shows the results of these analyses. Each row in the table represents a different meteorological metric, and the ‘Coefficient’ columns show the estimated effect of that metric on electricity consumption in Building 1 and Building 2. The ‘p-value’ columns indicate the statistical significance of these effects. As shown, the temperature (indicating the outdoor temperature) and the daylight duration (indicating the amount of time during which natural daylight is available at a specific location on a given day) are the two metrics that significantly impact electricity consumption. The coefficients for both metrics are positive, suggesting that higher temperatures and longer daylight durations correspond to increased electricity consumption. The data for these two metrics is shown in figure 7.

Consistent with our findings, prior studies have also reported a significant positive correlation between temperature and electricity consumption by examining the effect of climate change on the electricity demand of New South Wales, Australia (Ahmed et al., 2012; Vu et al., 2015). As demonstrated in our analysis, daylight duration also

plays a crucial role in influencing electricity usage (Moral-Carcedo and Pérez-García, 2019).

It is important to note that in these two buildings, the heating system is powered by gas, and the electricity is used for refrigeration units, ventilation, electric devices, and lighting without excluding some residual electric heating. One should note that the ancillaries of the heating system, such as pumps, turbines, etc, consume electric energy. Scatter graphs of daily energy consumption as a function of average external temperature are plotted in figure 8 to analyze better the dependence between temperature and electricity consumption for each building. We observe a high-temperature sensitivity of the electric demand. Energy consumption significantly increases when outdoor temperature rises, especially for building 1 (Bourdeau et al., 2021). As shown in Figure 8, it is important to note that the relationships between temperature, daylight duration, and electricity consumption may exhibit non-linear patterns. While our linear regression analysis provides valuable insights into these relationships, we acknowledge the limitation that the true relationships might be more complex than what a linear model can capture.

Table 3: Regression analyses between different meteorological factors and electricity consumption

Variable	Building 1		Building 2	
	Coefficient	p-value	Coefficient	p-value
Temperature	49.280	0.006 **	4.134	0.019 *
Dew point	-165.700	0.119	-21.374	0.375
Humidity	34.390	0.187	9.836	0.09686
Wind speed	1.990	0.835	2.501	0.24997
Wind direction	-0.0378	0.940	-0.021	0.847
Sea level pressure	-2.386	0.704	-0.540	0.704
Solar radiation	-0.464	0.568	0.576	0.185
Daylight duration	18.110	0.004 **	98.734	0.016 *

* Significant ($0.01 \leq p - value < 0.05$)

** Very significant ($0.001 \leq p - value < 0.01$)

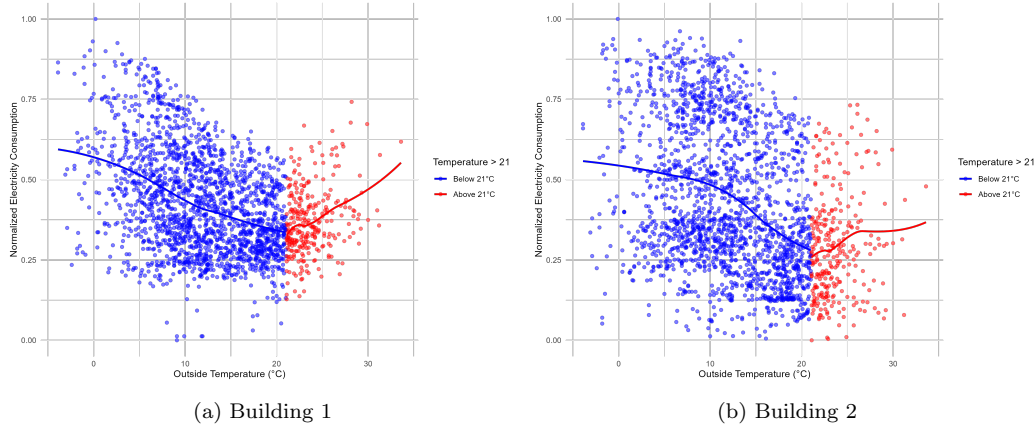


Figure 8: Scatter plot of normalized electricity consumption vs. outdoor temperature

In addition to the aforementioned explanatory variables, since we are analyzing a long period of electricity data, it is essential to account for variations in the number of occupants in the buildings, as they significantly impact the energy demand. In table 4 we show the evolution in the number of students and staff for both buildings.

Table 4: Number of occupants in the buildings

Academic Year	Building 1			Building 2		
	Students	Staff	Total	Students	Staff	Total
2017-2018	1700	200	1900	668	141	809
2018-2019	1800	200	2000	733	180	913
2019-2020	1950	200	2150	734	131	865
2020-2021	2100	210	2310	668	125	793
2021-2022	2250	210	2450	742	167	909

3. Model description

Dynamic Linear Modeling (DLM) is a powerful statistical framework used to analyze and forecast time series data. It allows us to represent time series data as a combination of unobservable states and observable measurements, making it well-suited for modeling complex temporal dependencies and capturing latent structures in the data (Campagnoli et al., 2009; Durbin and Koopman, 2012). This framework proves suitable for our study’s purpose, where we aim to gain insights into the factors influencing electricity consumption within buildings. In this section, we present how we model the time series data for electricity consumption.

In our model, we have considered various components to capture the trend and different existing seasonalities in electricity consumption. By considering these components, we aim to understand the factors that influence electricity consumption in buildings.

In addition to these components, we can access extra measurements specific to these buildings. These parameters provide us with valuable information on the building’s performance and environmental conditions, among other factors. In the next step of our analysis, we plan to include these explanatory variables in our model to assess if they can help enhance the accuracy of our predictions and provide a better understanding of the electricity consumption patterns.

3.1. Decomposition model structures description

In this section, the goal is to break down the complex patterns of electricity consumption into comprehensible components, each serving a unique purpose. We want to understand the underlying factors driving electricity consumption.

To achieve this, we employ a decomposition model that accounts for the trend, yearly pattern, and weekly pattern.

As we proceed, we will delve further into the analysis by introducing Dynamic Linear Model (DLM) along with additional explanatory variables. This step is crucial for refining our understanding of the electricity consumption patterns within the buildings.

The method we use is based on a decomposition model that includes the different components (de Nailly et al., 2022). The model can be represented as follows:

$$y_t = \theta_t + \alpha_t + \beta_t + v_t \tag{1}$$

Where $y_t(kW)(t = 1, \dots, n)$ is the electricity consumption at time interval t . v_t is a random error term that accounts for any residual variation in the data that is not explained by the other components of the model, and it follows a normal density:

$$v_t \sim N(0, \sigma_v^2)$$

Each component in the model represents a specific aspect of the electricity consumption patterns:

- θ_t : The trend component captures the underlying long-term direction or movement of the data. This component helps us understand how electricity consumption changes over time. The trend is a stochastic local-level model defined as follows:

$$\theta_t = \theta_{t-1} + \mu + \eta_t^1 \quad (2)$$

where μ is the drift parameter, and η_t^1 is white Gaussian noise, which follows a normal distribution with mean 0 and variance $\sigma_{\eta^1}^2$:

$$\eta_t^1 \sim N(0, \sigma_{\eta^1}^2)$$

- α_t : The yearly seasonality component captures the fluctuations in electricity consumption that recur annually. This component is particularly useful for identifying patterns that have a strong yearly cycle. We use Fourier series models to capture the periodicity of the yearly cycle.

$$\alpha_t = a_0 + \sum_{j=1}^J (a_j \cos(2\pi jt/365) + b_j \sin(2\pi jt/365)) + \eta_t^2 \quad (3)$$

where a_j and b_j are the Fourier coefficients for the j -th frequency, J is the number of frequencies included in the model, and η_t^2 is the white Gaussian noise, which follows a normal distribution with mean 0 and variance $\sigma_{\eta^2}^2$:

$$\eta_t^2 \sim N(0, \sigma_{\eta^2}^2)$$

- β_t : The weekly seasonality component captures the differences in electricity consumption between weekdays and weekends. This component is essential for understanding how electricity usage varies based on the typical weekly schedules at the institutional buildings, such as classes, events, and varying occupancy levels. We use the stochastic model for the weekly seasonality component. The model assumes that the current value of the weekly seasonality component β_t is a linear combination of the previous six weekly values of β_t plus a white Gaussian noise term η_t^3 :

$$\beta_t = - \sum_{j=1}^6 \beta_{t-j} + \eta_t^3 \quad (4)$$

Where,

$$\eta_t^3 \sim N(0, \sigma_{\eta^3}^2)$$

The initial values of all the components also follow the Gaussian distribution. The term Ω shows the set of unknown parameters of the model, and X_t is the state vector.

$$\begin{aligned}\Omega &= (\sigma_{\eta^4}^2, \sigma_{\eta^4}^2, \dots) \\ X_t &= (\theta_t, \theta_{t-1}, \dots)\end{aligned}$$

The decomposition model allows us to decompose the electricity consumption data into its underlying components: trend, yearly seasonality, weekly seasonality, and random error.

3.2. Dynamic linear modeling description

In the previous section, a decomposition analysis was conducted on the electricity consumption data, whereby various components were identified. However, it should be noted that electricity consumption can be influenced by different variables, including but not limited to weather conditions, occupancy levels, and calendar events. Moreover, recent years have seen the emergence of extraordinary events like the COVID-19 pandemic and energy crises, causing substantial disruptions in consumption patterns. Therefore, in this section, we introduce and define the relevant explanatory variables to the model to better understand the underlying dynamics and trends of electricity consumption. The new model is as follows:

$$y_t = \theta_t + \alpha_t + \beta_t + \sum_{i=1}^p \lambda_t^i X_t + v_t \quad (5)$$

$\sum_{i=1}^p \lambda_t^i X_t$: This term represents the sum of the products of coefficients λ_t^i and their corresponding explanatory variables X_t ($i = 1, \dots, p$). It accounts for the contribution of various variables that can influence electricity consumption.

Our research examines various factors that could influence electricity consumption patterns, which have been discussed in section 2.3.

These factors determine how much electricity is used in the buildings under consideration.

3.3. Parameter estimation and model calibration

The term $u = (\sigma_{\eta^1}^2, \sigma_{\eta^2}^2, \dots)$ denotes the set of unknown parameters of the model and, X_t is the vector of latent components of the model, also known as the state vector:

$$\mathbf{X}_t = (\theta_t, \alpha_t, \beta_t, \theta_{t-1}, \eta_t^1, a_0, a_1, \dots, a_J, b_1, \dots, b_J, \eta_t^2, \beta_{t-1}, \eta_t^3, \dots)$$

Maximum Likelihood Estimation (MLE) is employed to estimate the unknown parameters of the DLM (Dempster et al., 1977). Likelihood estimation, also known as maximum likelihood estimation (MLE), is a method used to estimate the parameters of a statistical model based on observed data. The goal is to find the values of the model parameters that maximize the likelihood function, which measures the probability of obtaining the observed data given by the model. By maximizing this quantity, we find the set of parameters that best explains the observed data.

Then, the Kalman filter allows us to estimate the state vector X_t , given the parameters u (Shumway and Stoffer, 1982).

To implement the DLM approach, we used the DLM package in R, which offers a convenient and efficient way to specify the model components and estimate the parameters. The package also provides tools for model selection and diagnostics, allowing us to choose the best model and assess its goodness of fit. Appendix A shows the steps of the modeling process. The source code for the analysis with the dlm package is available here: <https://github.com/NeginAlisoltani/DLM>.

To evaluate and compare different models in order to select the most suitable one, we rely on two key criteria:

1- Akaike Information Criterion (AIC): AIC is an information criterion designed to strike a balance between the goodness of fit of a statistical model and its complexity (Akaike (1974)). It is formulated as:

$$AIC = 2k - 2L \tag{6}$$

Where k represents the number of estimated model parameters, and L is the likelihood of the model.

A lower AIC value indicates a better trade-off between model accuracy and simplicity, making it a valuable criterion for model selection.

2- Root Mean Square Error (RMSE): RMSE measures the average magnitude of errors between the model's predictions and the observed values in the dataset (Chai and Draxler (2014)). It is calculated as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \tag{7}$$

Where n is the number of data points, y_i represents the observed values and \hat{y}_i is the prediction of y_i .

Model calibration is important in crafting an accurate and reliable Dynamic Linear Model (DLM) for electricity data analysis. This process involves adjusting the

model’s hyperparameters to capture the underlying patterns and variations within the data. Our DLM framework has specific parameters embedded within the trend and seasonality components, which we can utilize for calibration.

Within the trend component of the DLM, we have the hyperparameter `order`, which corresponds to the degree of the polynomial model. For example, using (`order` = 1) implies a linear trend. Higher values for `order` capture more complex trends in the data. However, the risk of overfitting also increases with higher `order` values.

In the yearly seasonality component, the hyperparameter represents the number of harmonics used in the Fourier series model (α_t). This parameter influences how well the model captures recurring patterns in the data. Adjusting this parameter allows us to balance the granularity of seasonality representation with the complexity of the model.

To ensure that our DLM aligns with the distinct characteristics of the electricity data, hyperparameter tuning becomes imperative. It involves systematically experimenting with different values of the aforementioned parameters and observing their impact on model performance. By adjusting these hyperparameters, we can assess whether the model fit improves and if the chosen values effectively capture the data’s intrinsic features.

After the process of model calibration, it becomes essential to evaluate the performance of the calibrated model systematically. AIC is employed as a quantitative measure to assess the goodness of fit of our DLM. Lower values of AIC suggest a better trade-off between model accuracy and simplicity, indicating a preferable model choice. RMSE is also calculated to gauge the differences between the model’s predictions and actual observed values. Smaller RMSE values indicate a closer alignment between the model’s projections and the actual data.

The results of the model calibration are presented in Appendix B.

4. Results and discussion

In this section, we present and discuss the results obtained in our study on daily electricity consumption data in two institutional buildings from the beginning of 2017 to the end of 2022. Our investigation covers various aspects, including the decomposition of consumption data, the impact of external factors, and the response of electricity consumption to crisis.

4.1. Trends and seasonalities in electricity data

This section evaluates the performance of the decomposition model in capturing historical electricity consumption patterns for Building 1 and Building 2.

Figures 9 and 10 show the outcomes of the decomposition model applied to electricity data for Building 1 and Building 2, respectively. In Figure 9a1 and 10a1, a visual comparison is presented between the model’s estimated data (in blue) and the actual data (in red). A second comparison between the model’s estimates and the observed electricity consumption data is presented in the adjacent plot. Notably, the data points on this plot align closely along the 45-degree line. These comparisons assess how well the decomposition model’s estimated data aligns with the actual data. In addition to these comparisons, the Mean Absolute Percentage Error (MAPE) (De Myttenaere et al., 2016) is also used to quantify the accuracy of the model’s estimates. It measures the percentage difference between the model’s estimated values and the actual data. The MAPE for Building 1 stands at 4.7%, while for Building 2, it shows at 7.8%. This indicates that the model proficiently captures both buildings’ historical electricity consumption patterns. Furthermore, the model exhibits higher precision for Building 1.

The next plots show the different components of the model. The solid line in each plot represents the estimated value of the electricity consumption over time. The shaded area represents the 95% confidence interval for different components.

The plots in Figure 9b and 10b illustrate the trend of electricity consumption changes over the years. We can discern a slight decrease in consumption for both buildings during these seven years. For Building 1, we observe a positive slope after 2017 and a declining trend starting from 2018, resulting in a total decrease of 0.3% over the years. In contrast, Building 2 continuously experiences a decrease in consumption, amounting to a notable 4.8% reduction over this period.

The yearly component plots in Figure 9(c1) and 10(c1) show the recurring patterns in electricity consumption that occur on an annual basis. These patterns exhibit similarities between both buildings, attributed to their nearly identical business schedules and location. The plots in Figure 9(c2) and 10(c2) show this pattern for the year 2021. We observe drops in consumption during vacations, especially during the summer vacation, which is the longest. The yearly seasonality increases the electricity consumption by 3483 kWh (29.7% compared to the average consumption) after the New Year’s holiday at the end of January in Building 1 and by 1072 kWh (71.9%) in Building 2. We also notice a significant drop of 3322 kWh (28.3%) in mid-August for Building 1 and a drop of 1058 kWh (71.0%) at the beginning of August every year for Building 2, which is due to differences in the starting of the summer holiday season for the students in the two buildings. The yearly seasonality here captures the impact of vacation times and the seasonal changes over time. As the meteorological factors change over the year for different seasons, the yearly seasonality gets impacted.

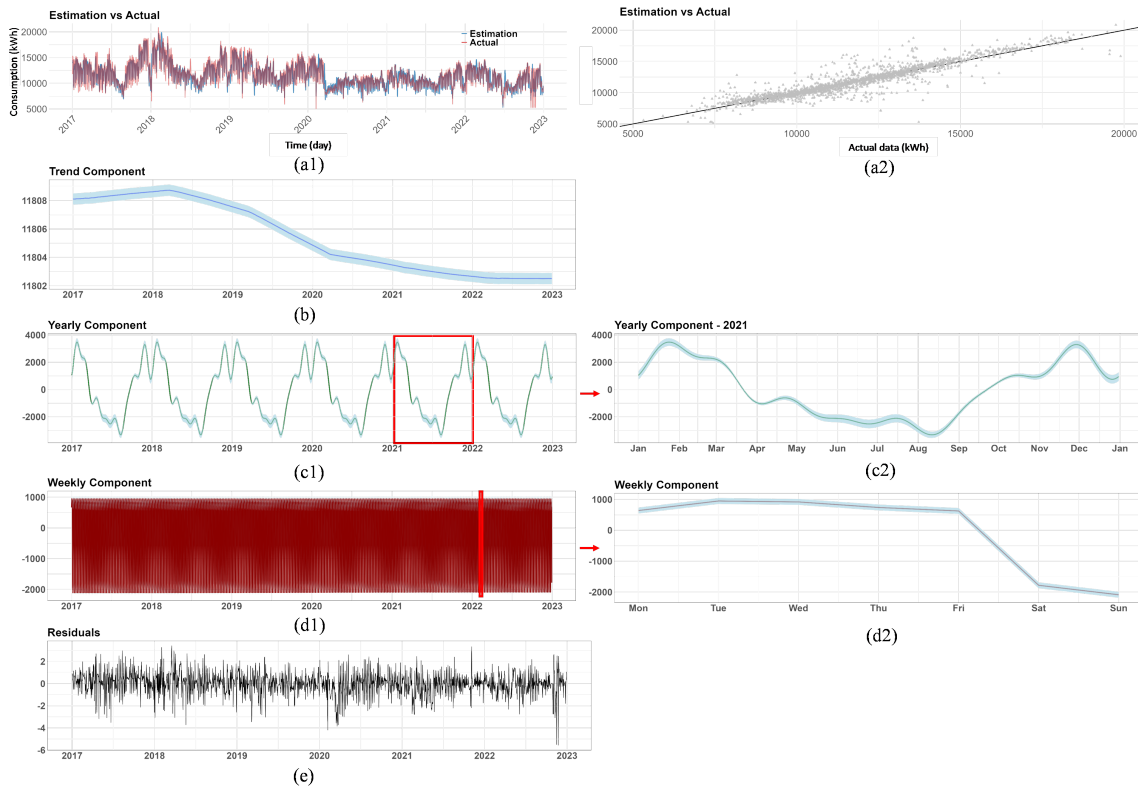


Figure 9: Decomposition of the time series of electricity consumption data in Building 1

To illustrate the impact of vacations on yearly seasonality, figure 11 visually depicts the periods of vacation overlaid on the yearly seasonality plots for one year for both buildings. In this figure, the periods when vacations occur are marked in red. The key observation from the figure is that the yearly decreases in both buildings are synchronized with the periods of vacation. In other words, the annual electricity consumption reductions align with official vacation dates. This pattern of energy usage reduction during vacation periods is particularly notable in the case of small vacations and major summer vacations. Small vacations generally induce local minima in electricity consumption, reflecting short-term decreases. However, the major summer vacation causes a global minimum, which is the most pronounced decrease in energy usage observed throughout the year. This effect is further exacerbated by the naturally lower demand for heating or cooling due to warmer weather, emphasizing the significant impact of seasonal and vacation-based variations on overall electricity consumption.

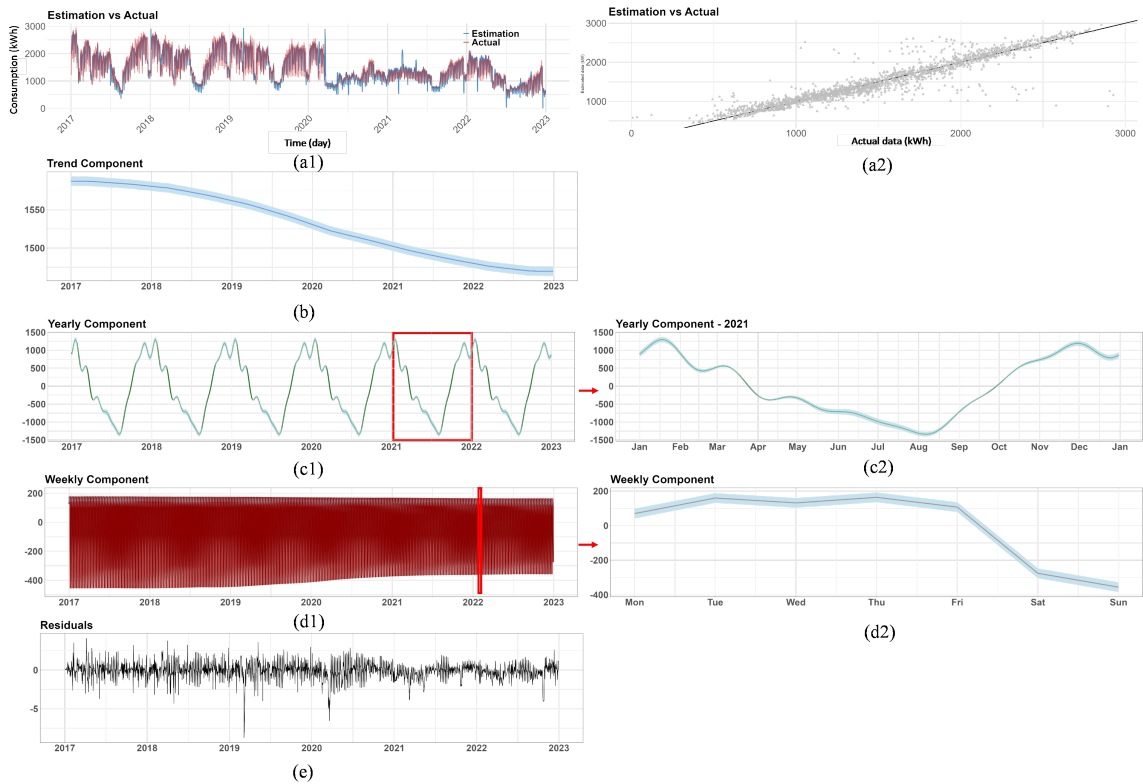


Figure 10: Decomposition of the time series of electricity consumption data in Building 2

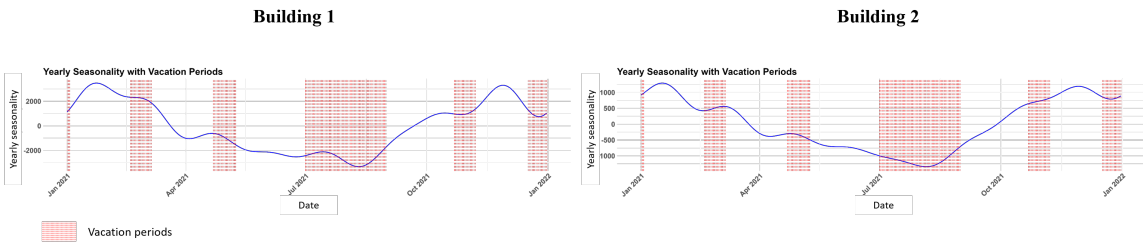


Figure 11: Coordinated decreases in electricity data yearly seasonality during vacation periods

Figure 12 illustrates the relation between the yearly component and the seasonal temperature variations throughout 2021. It is evident that peaks in energy usage are closely associated with temperature extremes. During the colder months of the year, there is a notable increase in consumption, with building 1 experiencing a rise of 2055 kWh (a 17.5% increase compared to the seven-year average consumption) and building 2 showing a substantial increase of 730 kWh (a 49.0% increase compared

to the average consumption). Conversely, during the warmer months, there are modest reductions in consumption, with building 1 decreasing by 2023 kWh (a 17.3% decrease) and building 2 reducing by 723 kWh (a 48.5% decrease) compared to their respective averages. These patterns confirm the influence of outdoor temperature changes on electricity consumption.

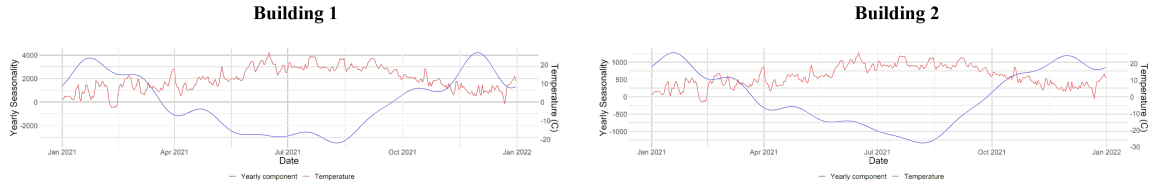


Figure 12: coordination between outdoor temperature changes over the year with yearly seasonality in electricity consumption data

In our analysis, we explored the weekly seasonality component in electricity consumption for both Building 1 and Building 2 (Figures 9(d1) and 10(d1)). It reveals patterns that exhibit variations across the days of the week. This component represents the recurring, seven-day cycle in electricity consumption, starting on Monday and ending on Sunday. To clarify, the plot on the right (Figure 9(d2) and Figure 10(d2)) shows this component for one week in winter 2022 (after the New Year vacation). The negative values on Saturday and Sunday indicate a significant reduction in electricity consumption over the weekend due to reduced occupancy and operational changes during this period. For Building 1 on Monday, we observe a substantial increase in electricity consumption of 952 kWh (8.1% increase), suggesting heightened demand during the early weekdays. The trend continues on Tuesday, with a consumption of 921 kWh (7.8%). By Wednesday, consumption remains relatively high, with an increase of 737 kWh (6.3%). However, on Saturday, and especially on Sunday, there is a remarkable reduction in electricity consumption, with drops of -2090 kWh (17.8% decrease) and -1785 kWh (15.2%), respectively. These negative values indicate a significant reduction in consumption over the weekend, attributed to decreased occupancy and operational changes during this period.

In contrast, Building 2 exhibits a different weekly seasonality pattern. While Building 2 experiences some fluctuations in consumption over the weekdays, these changes are generally smaller in magnitude compared to Building 1, suggesting a more consistent electricity usage pattern throughout the week. Notably, there is still a reduction in electricity consumption during the weekend, albeit with smaller negative values. On Saturday and Sunday, the consumption values for Building 2 drop for -357 kWh (23.9%) and -276 kWh (18.5%), respectively.

These detailed observations underscore the varying electricity consumption patterns between the two buildings, with Building 2 demonstrating more pronounced fluctuations over the weekend consumption compared to Building 1.

Residual analysis (in Figures 9(e) and 10(e)) indicates that our model generally captures the underlying trends well, with minor deviations, highlighting its overall effectiveness in modeling electricity consumption.

The findings in this section provide valuable insights into the underlying trends, seasonal patterns, and the dynamic nature of electricity consumption.

4.2. Impact of weather conditions

In this section, we analyze the impact of temperature and daylight duration on electricity consumption in both buildings. Understanding these relationships can be crucial for optimizing energy usage and implementing energy-saving strategies in institutional buildings. Figure 13 shows the results of these impacts for both buildings.

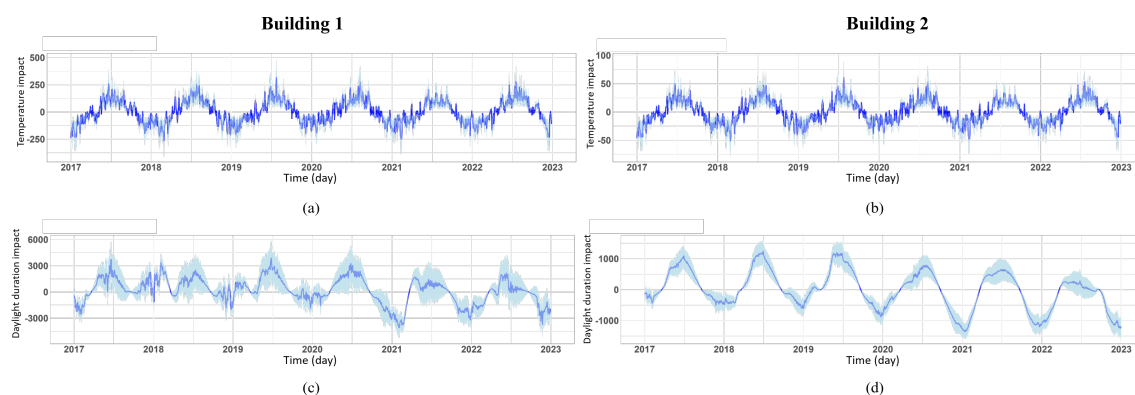


Figure 13: Impact of weather conditions (outdoor temperature and daylight duration) on electricity consumption data

It is important to note that our previous analysis, as demonstrated in Figure 12, has effectively captured the correlations between the yearly component and the seasonal temperature variations throughout the year. This yearly component accounts for the changes in electricity consumption over the course of the year. However, to gain a more comprehensive understanding of the influences of outdoor temperature on electricity consumption, we introduced exogenous variables into our model. These exogenous factors are specifically designed to capture aspects that may not be fully accounted for by the yearly seasonality. Figures 13(a) and (b) present the results of these additional impacts for both buildings.

Building 1 shows a clear relationship where electricity consumption increases during the hottest summer days and decreases during milder weather. On the hottest summer days, electricity consumption increases, averaging 317 kWh, corresponding to an approximately 2.5% increase compared to the average consumption. This rise in electricity consumption can be explained by the increased demand for cooling services in response to higher temperatures. Conversely, during periods characterized by favorable weather conditions (the times when outdoor temperatures are moderate), electricity consumption decreases by an average of 266 kWh, which represents a 2.1% reduction compared to the average consumption. This decrease indicates that occupants rely less on cooling and ventilation services when the weather is mild.

In Building 2, while the impact of temperature is less pronounced than in Building 1, it still follows a similar pattern. On the hottest summer days during this period, electricity consumption increases by up to 61 kWh, a 3.5% increase compared to the average consumption in 2019. During periods with more favorable weather conditions, such as in February and March, electricity consumption decreases by up to 51 kWh, which represents a 2.9% reduction compared to the average consumption in 2019. These variations suggest that Building 2 also experiences an increase in cooling and ventilation usage during hot weather and decreases during milder weather conditions.

Our analysis underscores the complementary nature of the exogenous temperature variable to the yearly seasonality in explaining electricity consumption patterns. While the yearly seasonality effectively captures significant temperature-related fluctuations in consumption, as highlighted in Figure 12, it primarily reflects the larger-scale impacts associated with seasonal temperature variations. In contrast, the exogenous temperature variable provides a finer-grained perspective, capturing more marginal and nuanced impacts that the yearly seasonality may not fully encompass. It enables us to discern smaller variations in electricity consumption associated with daily temperature fluctuations. This is particularly evident in the detailed quantifications we presented earlier, where we observed more subtle changes in consumption during specific temperature conditions. While the yearly seasonality paints the broader picture, the exogenous temperature variable offers a closer look at the day-to-day variations.

The impact of daylight duration on electricity consumption in both buildings varies from month to month (Figure 13(c) and (d)), but it follows almost the same pattern over the years for both buildings. However, Building 2 demonstrates more stable electricity consumption throughout the year. To clarify the differences, figure 14 shows the impact of daylight duration for different months of the year in 2019.

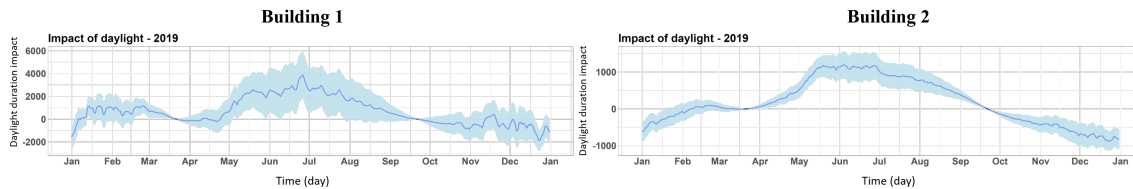


Figure 14: Impact of daylight duration on electricity consumption in 1 year (2019).

It is a well-established fact that daylight has a significant role in determining lighting needs in buildings, especially in institutional settings where minimum lighting levels are required for different activities and tasks.

The electricity consumption in both buildings indicates a slight uptick as the daylight hours increase from January to March. This rise can be attributed to the lengthening days after the winter solstice, resulting in more active hours during which occupants remain in the buildings. Despite the increase in daylight duration, there remains a dependence on artificial lighting in the mornings and evenings, which can lead to a net increase in electricity consumption. The data reveal a gentle decrease in electricity consumption even as daylight hours increase in the transition months of March and April. This trend suggests that the amount of natural light entering the buildings during these months is adequate enough to offset the need for artificial lighting to a certain degree. Moreover, this period marks the shift from winter to spring, where the intensity and angle of sunlight can have a more pronounced effect on interior illumination, reducing the demand for electrical lighting. Despite the prolonged daylight hours, electricity consumption rises from May to July. This can be explained by the increased activity in the buildings, as well as the potential use of shading devices like blinds or curtains to mitigate heat and glare from the sun. While these devices aid in temperature control, they can also obscure natural light, thereby necessitating the use of artificial lights. As daylight hours start to decrease post-summer solstice from the end of July to the end of the year, the data showcases a declining pattern in electricity consumption. A combination of factors may influence this drop: the reduction in daylight requiring more artificial lighting as the year progresses and potential changes in building occupancy and usage as the academic and work year winds down.

It's also crucial to note that while daylight duration undeniably impacts electricity consumption, other factors, such as cloud cover, building orientation, window design, and the use of daylighting controls, can influence the actual lighting needs and resultant electricity usage.

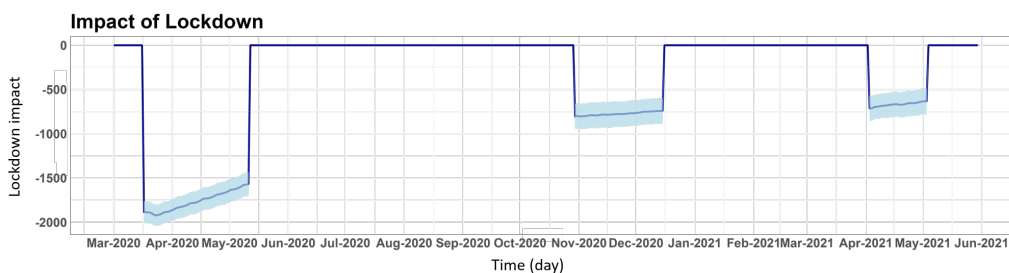
4.3. Response to a public health crisis: Impact of Covid-19 lockdowns on electricity consumption

The COVID-19 pandemic, which started in early 2020, presented unparalleled challenges that impacted daily life and operations worldwide. One significant aspect affected by the pandemic was energy consumption patterns, including electricity consumption in commercial and educational buildings. As countries imposed varying degrees of lockdown measures to curb the spread of the virus, a shift in energy use was observed. In France, where multiple lockdown phases were introduced in response to the pandemic's progression, the changes in electricity consumption provide an interesting case study. In this section, we delve into the influence of these lockdown measures on both buildings, examining how their electricity consumption patterns evolved during three distinct lockdown periods and what these shifts reveal about broader societal and operational changes during the pandemic.

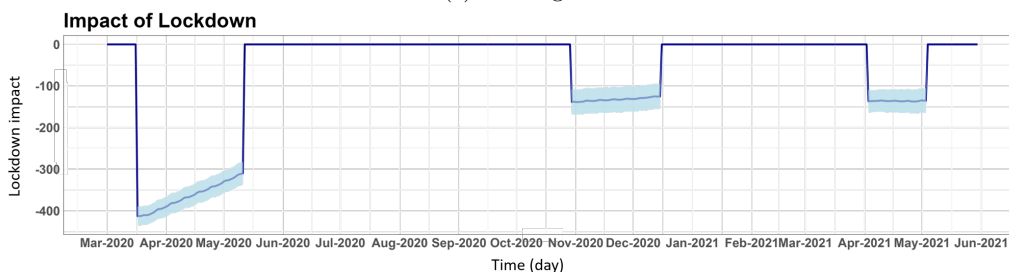
Our study investigated the influence of COVID-19 lockdown measures on electricity consumption in two buildings. We conducted a detailed analysis of three distinct lockdown periods to examine their effects on electricity usage patterns in each building. The results are shown in figures 15a and 15b for Building 1 and 2, respectively. In Building 1, during the initial lockdown period, we observed a substantial reduction in electricity consumption. The daily values, presented as reductions in kilowatt-hours (kWh) from the baseline, showed consistent and significant decreases of 1764 kWh on a daily average, equal to a 13.9% decrease compared to the average consumption in 2019. In Building 2, similar to Building 1, the first lockdown resulted in a significant reduction in electricity consumption equal to 213 kWh per day, which is a 12.1% decrease compared to the average consumption in 2019. This effect was particularly pronounced on weekends for both buildings, when consumption reached its lowest points, showing a sharp decline in energy demand. In the second lockdown phase, we again noted a noticeable reduction in electricity consumption, which is a 6.1% decrease for Building 1 and a 3.7% decrease for Building 2, compared to the average consumption in 2019. Similar to the first lockdown, weekends exhibited the most significant decreases, indicating a recurring pattern in response to lockdown measures. The third lockdown period demonstrated a trend similar to the previous lockdowns, with a decrease of 5.3% in Building 1 and 3.4% in Building 2 compared to average consumption in 2019. As observed in the other lockdowns, weekends displayed the most substantial declines.

We observe that the impact of the second and third lockdowns was less significant when compared to the initial lockdown. This variation is attributed to differences in the severity and nature of the lockdown measures imposed during each phase in France. The first lockdown, which started with stringent measures, represented the

initial and most comprehensive response to the COVID-19 pandemic. During this phase, restrictions encompassed various aspects of daily life, including the closure of schools and strict limitations on non-essential services. In contrast, the second and third lockdowns exhibited differences in terms of severity. In particular, primary- and secondary schools were not closed during these later phases, reflecting a more nuanced approach to education continuity and societal functioning. It is also very important to note that the evolving nature of lockdown measures led to varying public responses. The severity of the first lockdown has prompted a more immediate and drastic reduction in electricity consumption. In contrast, the subsequent lockdowns, with their comparatively milder restrictions, have resulted in different patterns of energy usage.



(a) Building 1



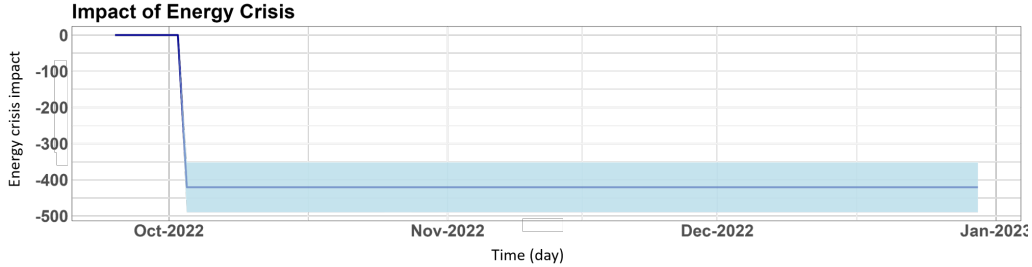
(b) Building 2

Figure 15: Impact of COVID-19 on electricity data (three lockdown periods)

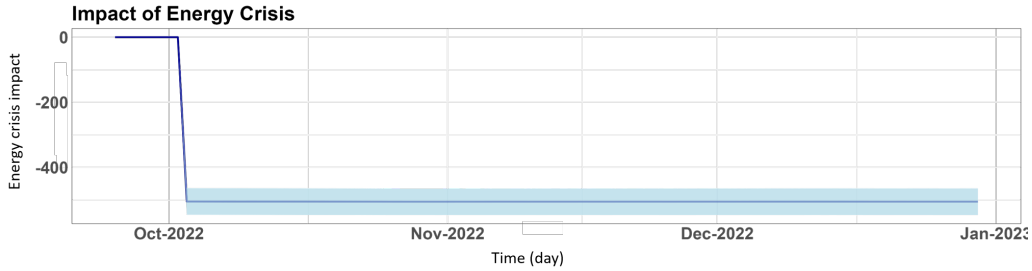
4.4. Response to an energy crisis: Impact of 2022 global energy crisis on electricity consumption

In our study, we extended our analysis beyond the impact of COVID-19 lockdowns to examine the influence of an additional explanatory variable known as the "Energy Sobriety Plan" introduced by the French government in response to the energy crisis followed by the geopolitical issues that started with the war in Ukraine in winter 2022. This plan called for a reduction in gas and electricity consumption, aiming

to promote energy conservation and sustainability. Our findings reveal insights into the effectiveness of this governmental initiative on electricity consumption patterns in institutional buildings.



(a) Building 1



(b) Building 2

Figure 16: Impact of the energy crisis on electricity data

As shown in Figure 16, we observe an average daily decrease of 421 kWh and 362 kWh in electricity consumption in Building 1 and Building 2 following the energy crisis generated by the war in Ukraine that started in early 2022.

These results highlight the significant impact of the Energy Crisis on electricity consumption and provide valuable insights into how individuals and institutions respond to energy supply constraints and related energy-saving recommendations in France. The reductions observed in both buildings, particularly Building 2, suggest a high level of awareness and willingness to contribute to energy conservation efforts. However, it is important to consider that while the energy crisis affected electricity consumption, the changes it caused were not as big as the significant shifts during the COVID-19 lockdowns. Additionally, during the period in which we evaluated the effects of the energy crisis, many individuals and organizations had already adapted to new operational modes due to the pandemic. Specifically, some people continued teleworking, either full-time or in hybrid formats. This behavioral modification, which persisted even after the official lockdowns, would naturally result in decreased

electricity consumption in institutional buildings. Thus, while the energy crisis undeniably prompted conservation efforts, it's essential to acknowledge the residual influence of pandemic-induced teleworking habits that weren't entirely eliminated.

5. Conclusion

This research has provided valuable insights into the complex dynamics of daily electricity demand in institutional buildings over several years, with a focus on the impact of external factors, external unpredicted shocks, and government initiatives. Several key findings emerge from this study.

First and foremost, Dynamic Linear Modeling (DLM) proves to be a robust method for capturing and explaining changes in electricity consumption patterns over time. It provides a reliable framework for understanding the evolving dynamics of energy use in institutional buildings. The Mean Absolute Percentage Error (MAPE) values, 4.7% for Building 1 and 7.8% for Building 2, underscore the model's efficacy in aligning with actual consumption data. DLM's ability to distinguish the impact of different periods of lockdowns from other factors has allowed us to uncover essential details about electricity consumption behavior. A slight decrease in consumption over the years was observed, with Building 1 and Building 2 showing a total decrease of 0.3% and 4.8%, respectively. The study further explored the impact of yearly and weekly seasonality on consumption patterns, revealing significant fluctuations linked to vacations, temperature variations, and weekly operational rhythms. Notably, the electricity consumption increased by 3483 kWh in Building 1 and 1072 kWh in Building 2 post-New Year's holiday, with substantial drops during summer vacations, indicating a strong correlation between vacation periods and consumption patterns. The temperature analysis highlighted a marked increase in consumption during colder months and a decrease during warmer months, affirming the influence of temperature on consumption patterns.

As expected, the COVID-19 pandemic had a significant impact on electricity consumption in these institutional buildings, particularly during lockdown periods. With DLM, we discerned and quantified the distinct impact of various lockdown phases. The study unveiled substantial reductions in electricity consumption during these lockdowns, with the most pronounced decrease occurring during the initial lockdown. On average, both buildings experienced a remarkable reduction of 13% during the first lockdown, followed by 4.9% and 4.4% reductions during the subsequent lockdowns though to a lesser extent, reflecting the varying severity and public response to the measures. These findings underscore the adaptability of energy consumption in times of crisis, its response to external shocks and emphasize the importance of flexible energy management strategies in institutional settings.

Furthermore, the global energy crisis resulting from the war in Ukraine starting in the winter of 2022 resulted in noteworthy reductions in electricity consumption in both buildings. Energy consumption reduction is probably a consequence of the general crisis effects (reduced fuels supply, prices run-up) and governmental initiatives to mitigate the crisis such as the 'Energy Sobriety Plan' implemented in France. This governmental initiative not only showcases institutions' willingness to contribute to energy conservation efforts but also highlights the potential impact of policy measures on consumption behaviors. In addition to the 'Energy Sobriety Plan' reducing electricity use in the buildings, the adoption of teleworking, especially among university researchers, also played a significant role in these reductions. This combination of government policy and flexible work arrangements that has been continued after COVID-19, demonstrates how both top-down initiatives and individual choices can contribute to energy consumption reduction. In conclusion, this research not only encapsulates the dynamic nature of electricity consumption in response to external factors but also provides valuable insights for energy management and policy-making in the face of crises and environmental changes.

5.1. Actionable insights and future directions

The findings of this research have broader implications. Policymakers can draw valuable lessons from this study to have more effective energy conservation policies. Recommendations can be tailored to promote flexible energy management during crises and sustainable practices during regular times.

In practical terms, the outcomes of this research can serve as a decision-support tool for authorities and policymakers. They can utilize these insights to develop real-time monitoring systems that incorporate dynamic linear models, allowing for the immediate detection of consumption pattern changes due to policy implementations or external events. Such systems could enable a proactive response to unforeseen events, such as public health emergencies, by adjusting energy strategies accordingly. Policymakers can use these findings to create energy policies that adapt and prescribe specific measures for reducing consumption, such as the 'Energy Sobriety Plan'. Furthermore, this study highlights the effectiveness of flexible work policies, which could inform future urban and transportation planning to reduce peak energy demand. By integrating predictive analytics with policy-making, authorities can foster an environment of continuous improvement in energy efficiency, contributing to the broader goals of GHG emission reductions and sustainability. This study, therefore, not only provides a framework for understanding energy consumption dynamics but also offers a guide for making practical, data-driven policies.

Future research can delve deeper into the precise mechanisms and efficacy of

energy-related policies in shaping consumption behaviors. A focused examination of residuals from DLM can uncover outlier events or system inefficiencies, aiding in the identification of areas for improvement. Additionally, the fusion of DLM’s robustness with the predictive power of machine learning models holds promise for accurate forecasting of electricity consumption, which is crucial for informed decision-making in the face of evolving energy landscapes Yusupova et al. (2023). Additional developments can also enable the applications of such models to hourly and sub-hourly data, which can be useful for energy system flexibility and demand response solutions.

In a broader context, these findings contribute to the global effort to address climate change and energy conservation challenges. Understanding and effectively managing electricity consumption in institutional buildings are critical steps toward a more sustainable future.

6. Acknowledgment

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Appendix A. DLM steps for electricity data modeling

Algorithm 1 Electricity consumption modeling using DLM

Input: Time series of electricity demand y

Output: Smoothed time series and components of electricity demand

1. Define the model components:
 - Trend component: `d1mModPoly`
 - Yearly seasonality component: `d1mModTrig`
 - Weekly seasonality component: `d1mModSeas`
 2. Define the regressors `d1mModReg`:
 - Calendar events: vacations
 - Covid-19 lockdowns
 - Start of energy crisis
 - Weather condition: outside temperature and daylight duration
 - Evolution of population in the building
 3. Combine the model components and regressors to build the initial model
 4. Maximum likelihood estimation to estimate the parameters of the initial model
 5. Save the estimated parameters for the initial model
 6. Start the next optimization using new initialization
 7. Repeat steps 4-6 for a predefined number of iterations
 8. Calculate the log-likelihood of each estimated model
 9. Select the best model with the highest log-likelihood
 10. Use the estimated parameters from the best model to build the final model
 11. Smooth the time series using the final model
 12. Calculate the error variance of the smoothed time series
 13. Define the components of the smoothed time series
 14. Calculate the error variance of each component using the smoothed error variance and the corresponding factor loading vector
 15. **Return:** Smoothed time series and components of electricity demand
-

Appendix B. Model calibration

Table B.5: AIC and RMSE criteria for different configurations of the model: Order (trend component) and Number of Harmonics (yearly component)

Order	Harmonics	Building 1		Building 2	
		AIC	RMSE	AIC	RMSE
1	2	-33136.93	2443.19	-25973.06	552.19
2	2	-33130.61	2443.22	-25954.55	552.87
3	2	Not converged	-	Not converged	-
1	3	-33137.94	2443.29	-25963.34	552.47
1	4	-33147.15	2443.30	-25980.23	552.60
1	5	-33153.95	2443.26	-25992.55	552.32
1	6	-33163.16	2443.17	-26002.26	549.35
1	7	-33173.65	2443.05	-26006.97	549.15
1	8	-33178.26	2444.82	-26014.64	549.04
1	9	-33186.89	2444.96	-26028.28	549.36
1	10	-33198.14	2445.34	-26046.58	549.27
1	11	-33211.11	2445.51	-26062.86	549.28
1	12	-33224.30	2445.63	-26078.35	549.04
1	13	-33233.61	2447.93	-26095.21	549.65
1	14	-33244.34	2447.78	-26114.66	549.61