Asian Journal of Economics, Business and Accounting

Volume 23, Issue 21, Page 197-207, 2023; Article no.AJEBA.107826
ISSN: 2456-639X

Electricity Consumption (kW) Forecast for a Building of Interest Based on a Time Series Nonlinear Regression Model

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJEBA/2023/v23i211127

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/107826

Original Research Article

Received: 11/08/2023
Accepted: 17/10/2023
Published: 20/10/2023

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ABSTRACT

This paper investigates the relationship between a building's past energy consumption and the outdoor temperature and predicts the next day's energy consumption using a refined time series model. Maintaining optimal indoor temperatures relative to outdoor temperatures determines a building's HVAC demand and, thus, energy consumption. We want to determine how outdoor temperature and other factors determine this consumption. With increasing urbanization and energy demand, it is important to understand building energy consumption, especially in terms of its impact on the environment. Previous research has shown the link between electricity consumption and external environmental factors and highlighted energy optimization's importance in urban structures. As cities become large energy consumers, studies point to the need to understand energy use patterns on a regional and temporal scale.

For accurate energy forecasts, data becomes the linchpin. Time series—data points arranged in chronological intervals—are foundational in predictive modeling. Due to buildings' intricate electricity consumption patterns, traditional linear forecasting often falls short. Enter nonlinear regression models: These complex models are apt for mapping and predicting nonlinear data trends. Notwithstanding their advantages, they come with challenges, primarily the high-frequency data influx from smart meters and IoT devices. But their potential benefits - from cost savings to efficient energy management - are significant. In a world caught between urban expansion and ecological preservation, efficient energy management is crucial. Accurate energy forecasting, especially for buildings, combines technological advances, statistical acumen and environmental imperatives. Understanding building energy consumption using sophisticated nonlinear regression models is evolving from an academic goal to a global necessity.

Keywords: Building; energy; consumption; temperature; forecast; time series model; heating; ventilation; electricity; environmental implications; CO2 emissions.

1. INTRODUCTION

In this age of urban intensification and increasing energy demand, electricity consumption in buildings is at the center of academic and industrial discourse. According to Ahmed et al. [1], the interplay between electricity consumption and its impact on the environment is evident in Australia's efforts to reduce CO_2 emissions through the development of clean energy sources. This focus on energy consumption and its impact on the environment has sparked interest in how urban habitats, particularly buildings, consume energy and how they can optimize their use [1]. Modern cities are centers of human activity, technological innovation, and infrastructural marvels. In this landscape, buildings, whether commercial skyscrapers or residential complexes are significant energy consumers. Bakó et al. [2] have documented the electricity consumption patterns of urban households in Hungary, highlighting the importance of understanding regional and temporal variations in energy consumption [2]. Such studies highlight the complexity of electricity consumption in buildings and the importance of accurate forecasting models.

Forecasting, at its core, relies heavily on data. A time series, a collection of data points indexed in successive intervals, forms the foundation of many predictive models [3]; this could translate to minute-by-minute, hourly, or yearly energy use records within electricity consumption. Traditional linear forecasting methods often need to be revised when faced with buildings' complex, nonlinear patterns in their electricity consumption. Lin et al. [4] emphasized that factors such as seasonal changes, daily routines, machinery operations, and events like conferences or festivals can introduce spikes or drops in electricity consumption [4]. Hence, there is an evident need for more sophisticated models. Nonlinear regression models, equipped to map and predict intricate, nonlinear data relationships, are increasingly seen as the answer to the forecasting challenge. Ramos et al. [5] employed such models for short-time electricity consumption forecasts in industrial facilities, showcasing their effectiveness [5]. However, as with all sophisticated tools, nonlinear regression models have challenges. The proliferation of smart meters and IoT devices has led to a deluge of high-frequency data [6]. While this rich data tapestry promises better forecasts, it poses challenges regarding data handling, noise filtration, and ensuring computational efficiency. Moreover, missing or inaccurate data entries can skew predictions, necessitating robust data cleaning and validation techniques.

The potential benefits of adeptly harnessing these models, however, are manifold. Accurate forecasts can lead to cost savings, better grid management, and efficient energy procurement strategies. With reliable predictions, utility providers can optimize grid operations, reducing outages and ensuring consistent supply [7]. Beyond the immediate logistical advantages, accurate forecasting also holds broader societal implications. As cities globally aim to transition to smart, sustainable habitats, understanding and optimizing energy consumption emerges as a keystone objective. Szabó et al. [8] highlighted the role of electricity consumption forecasts in shaping energy transition strategies in Southeast Europe, emphasizing its broader societal and environmental impact [8].

In a world struggling with the twin challenges of urbanization and environmental protection, the importance of efficient energy management cannot be overstated. Accurate prediction of electricity consumption, especially for buildings, is caught between technological innovation, statistical modeling, and the imperative of sustainability. In this academic terrain, we address the methods, opportunities, challenges, and wider societal implications of using nonlinear time series regression models to predict electricity consumption in buildings [9]. As the 21st century brings an unprecedented increase in urban population [10] and an increased focus on sustainability, predicting electricity consumption in buildings using advanced nonlinear regression models is not only of scientific interest but a global necessity.

This paper aims to estimate electricity consumption (kW) in a building given data measurement taken from January 1, 2010, 01:15 a.m. to February 17, 2010, 23:45. This measurement also includes the outdoor air temperature of the building for the same time frame. To aid predictions, the outdoor air temperature of the building is available for February 18, 2010. Two forecasts were made for power consumption on February 18, 2010, and this projected energy usage in the building is arrived at from the following viewpoints:

i. Taking the outdoor air temperature of the building into perspective and predicting the expected energy usage.
ii. Predicting the expected energy usage without taking into effect the outdoor air temperature of the building into perspective.

Our analysis explored approaches that considered univariate and covariates towards arriving at our optimal model.

2. LITERATURE REVIEW

Electricity consumption and its various influencing factors have garnered much attention in recent literature. The work by Ahmed et al. [1] offers an in-depth analysis of electricity consumption in Australia, emphasizing the role of clean energy in mitigating CO2 emissions. Their findings reveal a strong correlation between the uptake of clean energy sources and the reduction of CO2 emissions, indicating that clean energy adoption significantly aids Australia's environmental goals [1]. While Australia's efforts lean towards clean energy adoption, Ghana's electricity consumption shows a different dynamic. Ansu-Mensah and Kwakwa [11] delve into the association between electricity consumption in Ghana and financial development indicators. Their research suggests a nuanced relationship wherein economic and financial advancements play crucial roles in shaping the electricity consumption patterns in the country [11].

Electricity consumption and its various influencing factors have attracted much attention in the recent literature. The work of Ahmed et al. [1] provides an in-depth analysis of electricity consumption in Australia and highlights the role of clean energy in reducing CO2 emissions. Their results show a strong correlation between the use of clean energy sources and reductions in CO2 emissions, suggesting that the adoption of clean energy significantly supports Australia's environmental goals [1]. While Australia's efforts are focused on clean energy adoption, electricity consumption in Ghana shows a different dynamic. Ansu-Mensah and Kwakwa [11] examine the relationship between electricity consumption in Ghana and financial development indicators. Their research suggests a differentiated relationship where economic and financial progress plays a crucial role in the development of electricity consumption in the country [11].

Switching the lens to a micro-scale perspective, the consumption patterns within urban households and smart buildings also offer valuable insights. Bakó et al. [2] investigate electricity consumption habits within Hungarian urban households. Their study highlights the varying consumption patterns influenced by socioeconomic factors, urban infrastructure, and public policy measures [2]. Similarly, Arteconi and Arteconi [12] assess smart buildings' energy efficiency and flexibility attributes. They argue that with advancing technology and growing awareness of energy consumption, smart buildings are evolving to become more adaptive and energy efficient [12]. Behavioral patterns play a significant role in electricity consumption, especially within organizational settings. Charlier et al. [13] embarked on an intriguing field experiment to understand how nudges can influence electricity consumption behaviors within firms. Their findings indicate that when effectively applied, nudges can result in tangible reductions in electricity consumption, making behavioral interventions an essential tool for sustainability [13].

Prediction and risk assessment related to electricity peaks are also important aspects of the overarching narrative on electricity consumption. Jacob et al. [3] provide a comprehensive approach to predicting and assessing the risks associated with individual electricity peaks. Their methodology provides policymakers and utilities with valuable tools to effectively predict and manage consumption peaks [3]. Given the increasing urgency to adopt sustainable energy models, recent literature has addressed forecasting methodologies, technology deployment, data-driven decision-making for electricity consumption, and broader business applications. The Long Short-Term Memory (LSTM) method stands out among forecasting methods for electricity consumption. Lin et al. [4] conducted a comprehensive study to investigate the effectiveness of the LSTM method in predicting electricity consumption in high-rise office buildings. Their results highlight the potential of LSTM to provide accurate forecasts and thus contribute to efficient energy management in urban infrastructures [4].

Further, electricity consumption forecasting in industry facilities also gains attention, with Ramos et al. [5] focusing on short-time electricity consumption prediction. Their work, detailed in the IEEE Transactions on Industry Applications, mirrors the significance of precise forecasting in optimizing industrial operations and mitigating associated risks [5]. On a broader scale, Rausser et al. [6] approached the subject from the household perspective. The researchers scrutinized the impact of smart meters on household electricity consumption in Ireland, suggesting that introducing this technology has altered consumption patterns and instigated behavioral changes among consumers [6].

Within the Southeast European context, Szabó et al. [8] highlighted the energy transition in the electricity sectors, presenting a roadmap modeling this transition. Their study underlines the challenges and opportunities associated with this change, focusing on the balance between sustainable electricity generation and consumption [8]. However, outside the realm of pure electricity consumption, there is a growing emphasis on the role of data in modern business decisions. Olaniyi et al. [10] explored using big data analytics and business intelligence at a leading Fortune Company. Their insights underscore the transformative power of these tools in guiding strategic decision-making and fostering business growth [14].

Moreover, the trio has made significant contributions in other areas. For instance, they also shed light on the budding landscape of Decentralized Autonomous Organizations (DAOs), providing a comprehensive review of blockchain initiatives that underpin these organizations [15]. Furthermore, their exploration into smart cities, specifically data-driven decision-making within these urban hubs, further accentuates the role of big data analytics in shaping the future [16]. While the role of technology and data in advancing business operations cannot be understated, navigating the associated risks remains paramount. Olaniyi et al.'s work [17] on enterprise risk management implementation, offers a timely insight, providing strategies and insights to tackle the challenges of the modern business landscape [18]. The relationship between ICT, economic growth, and electricity consumption in Malaysia is eloquently discussed by Solarin et al. [7]. Their work draws a nexus between these domains, emphasizing the multifaceted impact of technological evolution on the nation's economy and energy landscape [7].

The multifaceted realm of electricity consumption behavior is characterized by the interplay of various factors, ranging from individual consumer habits to broad regional dynamics affected by climate change. Several studies have delved deep into these intricate relationships to decipher electricity consumption's overarching patterns and trajectories. Wang, Yang, Z., Wang, Y., & Gu, J. [19] investigated the behavior patterns of individual consumers, suggesting that consumption is not merely a byproduct of demand but also intricately linked to specific behavioral parameters. Their research, conducted within the purview of physics, offers an analytical insight into how customers react to the electricity consumption ecosystem, shedding light on patterns that could potentially optimize energy efficiency and distribution [19].

Wenz, Levermann, A., & Auffhammer [20] examined the impact of global warming on electricity consumption in a very different context. Their study shows a clear polarisation between northern and southern European regions. If global temperatures continue to rise, the demand for cooling in southern Europe could increase, while the demand for heating in northern European countries could decrease. Such regional differences underline the importance of understanding geographical differences in consumption patterns and preparing for future infrastructure needs [20].

Pivoting toward economic landscapes, Xu et al. [21] explored the nexus between financial development and electricity consumption in China. Their findings unravel the 'spatial spillover effects,' a phenomenon where regions with pronounced financial development indirectly influence neighboring regions, driving their electricity consumption patterns. The study underscores the importance of integrating financial models and policies with energy consumption planning, ensuring that rapid financial growth does not inadvertently lead to unsustainable energy consumption [21]. Zhang, Ai, Q., & Li [22] implemented an innovative approach to segment electricity consumers. Using an f-divergence-based hierarchical clustering model, they categorized dynamic electricity consumption behavior into distinct groups. Such categorization paves the way for customized energy distribution solutions, allowing utilities to provide services tailored to specific consumer clusters, thereby optimizing efficiency [22].

Finally, Zhao, Zhang, C., Ujeed, T., & Ma [9] enriched the discourse with a comprehensive analysis of electricity consumption characteristics in buildings. Their methodology integrates clustering algorithms and fuzzy matrices and provides a robust framework to understand and predict electricity consumption behavior. At a time when buildings are becoming increasingly sophisticated, understanding their energy performance is central to sustainable development [9]. The evolution of electricity consumption behavior is therefore, a rich web of individual, regional, economic, and technological aspects. These studies show the importance of a holistic understanding of consumption patterns, which is essential for the development of effective energy policies and strategies.

3. DATA PREPARATION AND ANALYSIS

The dataset is a detailed high-frequency time series collection, capturing data at regular 15-minute intervals. Each observation focuses on a specific building, meticulously recording its energy consumption in kilowatts. The dataset also documents the corresponding outdoor temperature, measured in degrees centigrade, for the exact moment of observation. A noteworthy aspect of this dataset is its pristine quality, devoid of common problems such as missing data points or any discernible anomalies. Three data-processing steps were taken to customize the dataset for use, and these are:

i. The first timestamp row was in Microsoft Excel time format. It required pre-processing, taking cognizance of Excel's date peculiarities for conversion to a character datatype with the format "*%m/%d/%Y %H:%M"* and a time zone of "*UTC*."
ii. Formatting the timestamp column from a character data type into a datetime data type to leverage the timestamp column as a time series index.
iii. The columns were renamed to remove white spaces and make them more amenable to automated processing, as shown below:

    a. Power (kW) to *power.kw*
    b. Temp (C°) to *temp.c*
    c. Timestamp to *time.obs*

Below is the time series plot, as shown in Fig. 1.

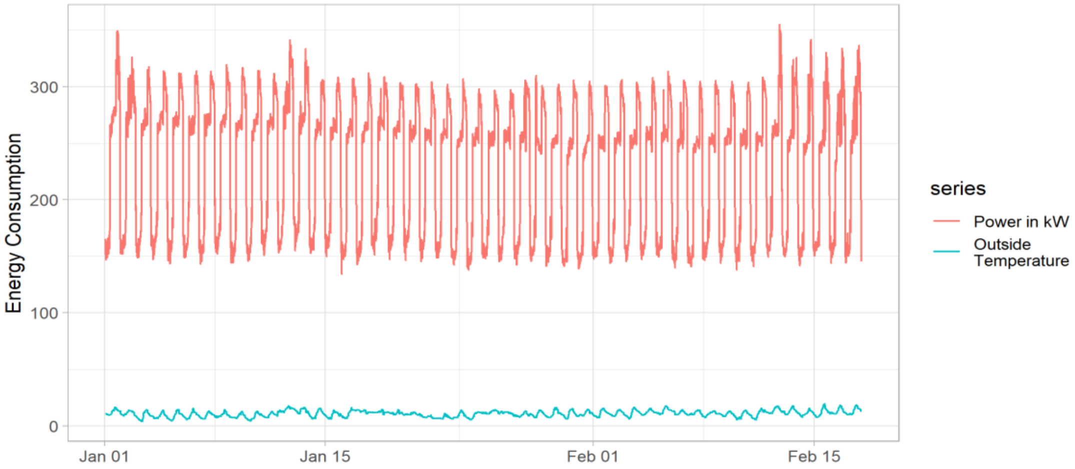

Fig. 1. The time series plot

Exploratory data analysis showed that the relationship between *power.kw* (the response variable) and *temp.c* (outside air temperature) may include interaction terms. The additional time-based predictor variables identified to support modeling activities further are:

- Time of the day (in hour-time) the recorded data was made (*what.time*)
- Periods of higher than average energy use observed (*peak.time*) as factors
- Numeric day of the week (*dofw*)
- Weekend or not (*weekend*) as factors
- Week number (*week.number*)
- Notable day or a holiday (*notable*)

Further analysis of the time series gave the following relationships, as shown in Fig. 2:

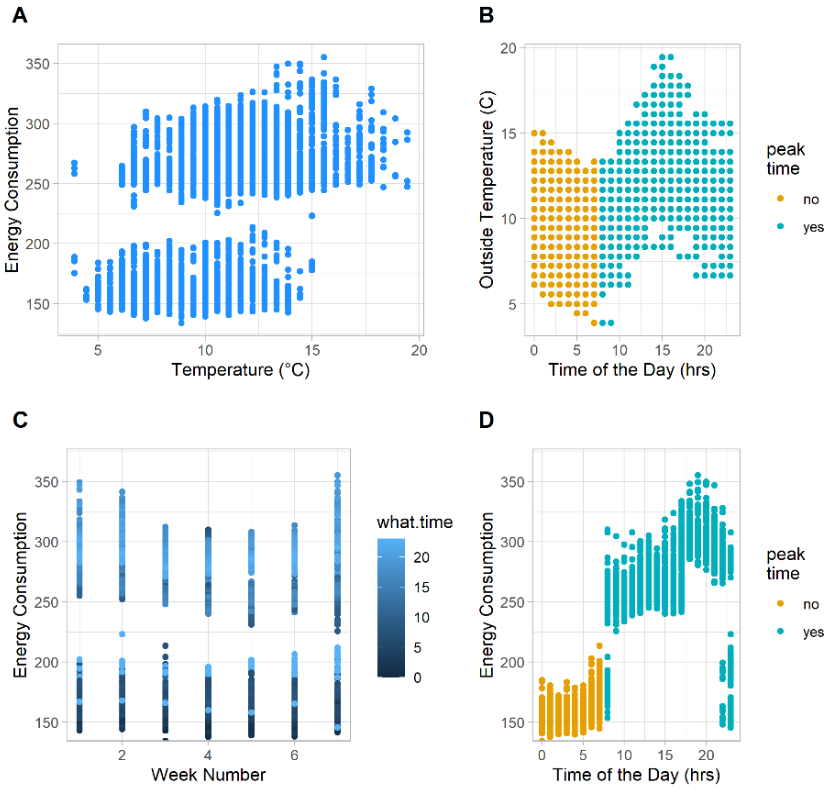

Fig. 2. The time series relationships

- Daily seasonality with a marked increase in energy consumption between 08:00 and 23:45 and recurs with constancy. The energy difference is substantial in comparison to the preceding or succeeding period.
- Outside temperature within this same period shows a nonlinear relationship with the hours of the day for the building.
- Mild weekly seasonality in energy consumption.
- A biweekly (two weeks) trend in the series pattern. Since the time span of the dataset does not extend for a long period, this trend was regarded as a short-term trend.

4. METHODOLOGY AND MODELLING

Both univariate and covariate approaches were considered in evaluating candidate models, which also informed our choice of frameworks. We streamlined these initial models based on their suitability toward identifying the initial basket of candidate models. These candidate models were further fine-tuned towards making an informed choice. The frameworks evaluated were:

- Seasonal Naïve Model
- Holt-Winters Model (Additive and Multiplicative
- ARIMA Models
- Time Series Regression (Linear and Nonlinear)
- Dynamic Regression Models
- Prophet Model

Variable selection for the nonlinear multivariate regression model category was made using Random Forest. A Variance Inflation Factor (VIF) of above 3.0 was associated with *a peak.time*, which was excluded from the model as it was significantly correlated with *what.time*. Specific features of the models are summarized below:

- Effects related to activities occurring at specific hours of the day are modeled using regression splines.
- Temperature effects are modeled using regression splines.
- Effects related to the week number are modeled using step functions.
- daily seasonality was modeled in the TLSM season function with a 24-hour periodicity.

5. FORECASTING RESULTS

From the model performance in table 1 below, and as expected, simpler models showed a poor fit in forecasting high-frequency data.

Table 1. Model performance table

The models are grouped by sub-families

Model	RMSE	MAPE
Pure Nonlinear Regression		
mlr5.fit	15.75506	4.647959
mlr2.fit	16.80271	5.143486
mlr1.fit	16.92725	5.160634
mlr3.fit	16.92725	5.160634
mlr4.fit	18.79134	5.583007
Dynamic Regression		
arima.202.001	17.07860	5.095754
arima101.002	17.08013	5.095794
arima.202.002	17.08146	5.096082
Advanced methods with covariate		
nl.mlr	16.92725	5.160634
arima500.001	17.08159	5.098284
prophet.mlr	22.58851	8.008237
n_net.fit	44.02737	14.619202
simple methods - temp covariate		
SLR	48.59009	20.937513
arima.slr	54.62253	22.432483
simple methods - no covariate		
arima.single	55.59971	23.315455
naive	78.12554	28.472753
holtw.add	131.67654	45.383436
holtw.mul	136.76011	47.673488

Root Mean Square Error (RMSE); Mean Absolute Percentage Error; Akaike information criterion Corrected (AICc)

Although a univariate approach using more capable frameworks to determine projected power consumption with temperature as a predictor variable improved the obtained forecast, it nevertheless fell short. A marked difference between the model performance estimates obtained with temperature as the variate and those derived using additional covariates could be observed. In evaluating more advanced frameworks for the covariate case, the Prophet and the Neural Network models could have given a better fit as obtained from ARIMA and Nonlinear Regression frameworks.

Therefore, Dynamic Regression with ARIMA and Nonlinear Multivariate Time Series Regression provided the best overall performance scores. As the performance table shows, although the order of the ARIMA error model was varied, the RMSE and MAPE values of the ARIMA-based dynamic regression stagnated and remained approximately the same. However, the model accuracy of the nonlinear multivariate time series regression increased when the nonlinear relationship was iteratively modeled with the inclusion of interaction terms. Consequently, the nonlinear multivariate time series regression performed with polynomial splines and the inclusion of the interaction term between temperature and time of day gave the best results.

An analysis of the residuals in the nonlinear multivariate time series regression showed some deviation from white noise with an autoregression pattern of residuals compared to ARIMA with dynamic regression, where the residuals were closer to white noise. There was a warning of a rank deficit in the predictions. However, this was not considered a concern as the original dataset contained few variables, and the chosen model performed well on the test data. In addition, the plot of the residuals against the fitted values was satisfactory [23-27].

6. DISCUSSION

In the model for the building we are interested in, it was observed that electricity consumption was higher than normal on conspicuous days. Similarly, the consistency is that the higher energy consumption during the day is associated with peak periods that extend late into the night. We hypothesize that the times when a sustained increase in energy consumption is observed are largely due to the nature of the activities during that time frame. Although outdoor temperature is an important variable in predicting energy consumption, the activities carried out in the building do not only affect the outdoor temperature. Commercial activities, such as in a restaurant/café or a production facility with a fixed production schedule, could be associated with the energy consumption profile analyzed. Collecting additional data on the components of these activity variables and incorporating them into an updated model will further increase the accuracy of the performance and provide better residual values.

7. CONCLUSION

The investigation of energy consumption patterns in our focal building revealed some important observations that are relevant for future research and energy management. One striking discovery concerned certain days with unusually high electricity consumption [1]. This observation is consistent with a broader research trend highlighting variations in energy consumption due to temporal patterns [2,4]. In particular, the time-of-day analyses revealed a consistent pattern in which peaks in energy consumption were limited to the usual hours and extended late into the night.

Such a revelation underscores the importance of understanding the activities taking place within the building during these periods. It is plausible that the high-energy demand is not solely a consequence of external factors, such as ambient temperature, but is heavily influenced by the nature and type of activities conducted within the building during these times [3]. This perspective is supported by Arteconi & Arteconi [12], who emphasize that while external variables, such as outside temperature, undeniably play a role in energy consumption patterns, internal activities can often be the more dominant drivers.

This leads us to another consideration: What could these internal activities be? Careful analysis suggests that commercial activities, particularly in the hospitality sector such as restaurants and cafés, or manufacturing operations that adhere to strict production schedules, could contribute significantly to this energy consumption profile [11]. Not only the intensity but also the timing of these operations can lead to increased energy demand. A more holistic and sophisticated approach to modelling energy consumption would, therefore require the inclusion of data on these internal activities. The inclusion of variables related to the nature, intensity, and timing of building operations would refine our understanding and lead to models with higher predictive accuracy [5,22]. The value of such an integrative approach is demonstrated by studies such as that of Charlier et al. [13], which show the complex dynamics of electricity consumption in companies and how subtle interventions can influence consumption patterns.

The quest for accuracy and predictability in energy consumption modeling is more than an academic exercise. Given the pressing challenges of climate change and the need for sustainable energy practices, there is an urgent need for models that reflect current conditions and lead to actionable measures [20]. To this end, refining our model by collecting detailed data on internal activity components can lead to improved performance and better residuals, paving the way for more precise energy-saving measures and strategies [8]. Finally, the intersection of internal activities and external factors affecting building energy consumption is fertile ground for further research. By combining these two dimensions, we can develop models that reflect reality on the ground and help us develop sustainable energy practices for the future [9]. Along the way, we need to keep an eye on the development of energy consumption and continuously develop our models according to new trends and insights.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/107826