Electricity consumption (kW) forecast for a building of interest based on a time series nonlinear regression model.

Abstract

This paper scrutinizes the relationship between a building's historic energy consumption and external temperature, forecasting the subsequent day's energy usage using a refined time series model. Maintaining optimal indoor temperatures relative to outdoor temperatures determines a building's HVAC needs and, consequently, its energy consumption pattern. We aim to discern how external temperature and other factors dictate this consumption. Given the urbanization surge and increasing energy demand, understanding building energy consumption becomes pivotal, especially considering its environmental implications. Prior research has highlighted the correlation between electricity usage and outside environmental factors, emphasizing the importance of energy optimization in urban structures. With cities evolving as major energy consumers, studies suggest the need to comprehend energy usage patterns regionally and temporally.

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.

Nevertheless, their potential benefits, from cost savings to efficient energy management, are significant. Proficient energy management becomes crucial in a world straddling urban expansion and ecological preservation. Accurate energy forecasts, especially for buildings, merge technological advancements, statistical acumen, and environmental necessities. As we progress, understanding building energy consumption via sophisticated nonlinear regression models morphs from academic pursuit to global necessity.

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

Introduction

In an age of urban intensification and soaring energy demands, electricity consumption within buildings takes center stage in academic and industry discourses. According to Ahmed et al. (2021), the interplay of electricity consumption and its environmental implications is evident in Australia's endeavors to reduce CO_2 emissions by tapping into clean energy sources; this focus on energy usage and its environmental implications has sparked interest in how urban habitats, especially buildings, consume and can optimize energy utilization (Ahmed et al., 2021).Modern cities are hubs of human activity, technological innovations, and infrastructural marvels. Within this landscape, buildings, whether commercial skyscrapers or residential complexes emerge as significant energy consumers. Bakó et al. (2021) documented the electricity consumption patterns in urban households in Hungary, underscoring the importance of understanding regional and temporal variations in energy use (Bakó et al., 2021). Such studies exemplify the multifaceted nature of electricity consumption in buildings and the necessity 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 (Jacob et al., 2020). 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. (2021) 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 (Lin et al., 2021).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. (2022) employed such models for short-time electricity consumption forecasts in industrial facilities, showcasing their effectiveness (Ramos et al., 2022).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 (Rausser et al., 2018). 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 (Solarin et al., 2021). 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. (2019) highlighted the role of electricity consumption forecasts in shaping energy transition strategies in Southeast Europe, emphasizing its broader societal and environmental impact (Szabó et al., 2019).

In a world grappling with the dual challenges of urbanization and environmental conservation, the importance of efficient energy management cannot be overstated. Accurate electricity consumption forecasting, particularly for buildings, sits at the confluence of technological innovation, statistical modeling, and sustainability imperatives. As we traverse this academic terrain, we will delve deeper into the methodologies, opportunities, challenges, and broader societal implications of using time series nonlinear regression models for building electricity consumption forecasting (Zhao et al., 2022). As the 21st century sees an unprecedented surge in urban populations (Olaniyi et al., 2023) and a heightened focus on sustainability, electricity consumption forecasting in buildings using advanced nonlinear regression models becomes not just an academic interest but a global imperative.

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 ofthe building for the same time frame. To aid predictions, the outdoor air temperature of the building is available for February 18, 2010.Two forecastswere made for power consumptionon February 18, 2010, and thisprojected 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 covariatestowards arriving at our optimal model.

Literature Review

Electricity consumption and its various influencing factors have garnered much attention in recent literature. The work by Ahmed et al. (2021) 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 (Ahmed et al., 2021).While Australia's efforts lean towards clean energy adoption, Ghana's electricity consumption shows a different dynamic. Ansu-Mensah and Kwakwa (2022) 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 (Ansu-Mensah &Kwakwa, 2022).

Switching the lens to a micro-scale perspective, the consumption patterns within urban households and smart buildings also offer valuable insights. Bakó et al. (2021) 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 (Bakó et al., 2021). Similarly, Arteconi and Arteconi (2021) 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 (Arteconi&Arteconi, 2021).Behavioral patterns play a significant role in electricity consumption, especially within organizational settings. Charlier et al. (2021) 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 (Charlier et al., 2021).

Forecasting and risk assessment associated with electricity peaks are also vital aspects of the overarching narrative of electricity consumption. Jacob et al. (2020) offer a comprehensive approach to forecasting and evaluating the risks tied to individual electricity peaks. Their methodologies provide valuable tools for policymakers and energy providers to effectively anticipate and manage high-consumption periods (Jacob et al., 2020).With the growing urgency to adopt sustainable energy models, recent literature has explored forecasting methods, technology adoption, and data-driven decision-making in electricity consumption and broader business applications. Among the methods highlighted in predicting electricity consumption, the Long Short-Term Memory (LSTM) technique emerges as a notable tool. Lin et al. (2021) conducted a comprehensive study emphasizing the effectiveness of the LSTM method in forecasting electricity consumption in high-rise office buildings. Their findings underscore the potential of LSTM to provide accurate forecasts, thus assisting in efficient energy management in urban infrastructures (Lin et al., 2021).

Further, electricity consumption forecasting in industry facilities also gains attention, with Ramos et al. (2022) 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 (Ramos et al., 2022).On a broader scale, Rausser et al. (2018) 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 (Rausser et al., 2018).

Within the Southeast European context, Szabó et al. (2019) 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 (Szabó et al., 2019). 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. (2023) 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 (Olaniyi et al., 2023).

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 (Olaniyi et al.; O. J., 2023). 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 (Olaniyi, Okunleye, O.J., &Olabanji, S.O., 2023).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 (2023) on enterprise risk management implementation, offers a timely insight, providing strategies and insights to tackle the challenges of the modern business landscape (Olaniyi et al.; A. I., 2023). The relationship between ICT, economic growth, and electricity consumption in Malaysia is eloquently discussed by Solarin et al. (2021). Their work draws a nexus between these domains, emphasizing the multifaceted impact of technological evolution on the nation's economy and energy landscape (Solarin et al., 2021).

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. (2022) 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 (Wang et al., 2022).

In a starkly contrasting environmental backdrop, Wenz, Levermann, A., &Auffhammer (2017) focused on the broader implications of global warming on electricity consumption. Their study revealed a distinct polarization between Northern and Southern European regions. As global temperatures continue to rise, the need for cooling in southern Europe may surge, while northern European nations might experience declining heating demands. Such regional disparities underline the importance of understanding geographical differentiation in consumption patterns and preparing for future infrastructural demands (Wenz et al., 2017).

Pivoting toward economic landscapes, Xu et al. (2022) 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 (Xu et al., 2022).Zhang, Ai, Q., & Li (2021) 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 (Zhang et al., 2021).

Lastly, Zhao, Zhang, C., Ujeed, T., & Ma (2022) enriched the discourse with a comprehensive analysis of electricity consumption characteristics in buildings. Their methodology integrated clustering algorithms and fuzzy matrices, providing a robust framework to both understand and predict electricity consumption behaviors. In an era where buildings are becoming increasingly sophisticated, understanding their energy footprints becomes pivotal for sustainable development (Zhao et al., 2022). Therefore, the evolving narrative on electricity consumption behavior presents a rich tapestry of individual, regional, economic, and technological threads. These studies, taken together, emphasize the importance of a holistic understanding of consumption patterns, essential for crafting effective energy policies and strategies.

Data Preparation andAnalysis

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. Itrequired 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 datatype into a datetime datatype to leverage the timestamp column as a time series index.

iii. The columns were renamedto remove white spaces and make them more amenable to automated processing, as shown below:

    a. Power (kW) to *power.kw*

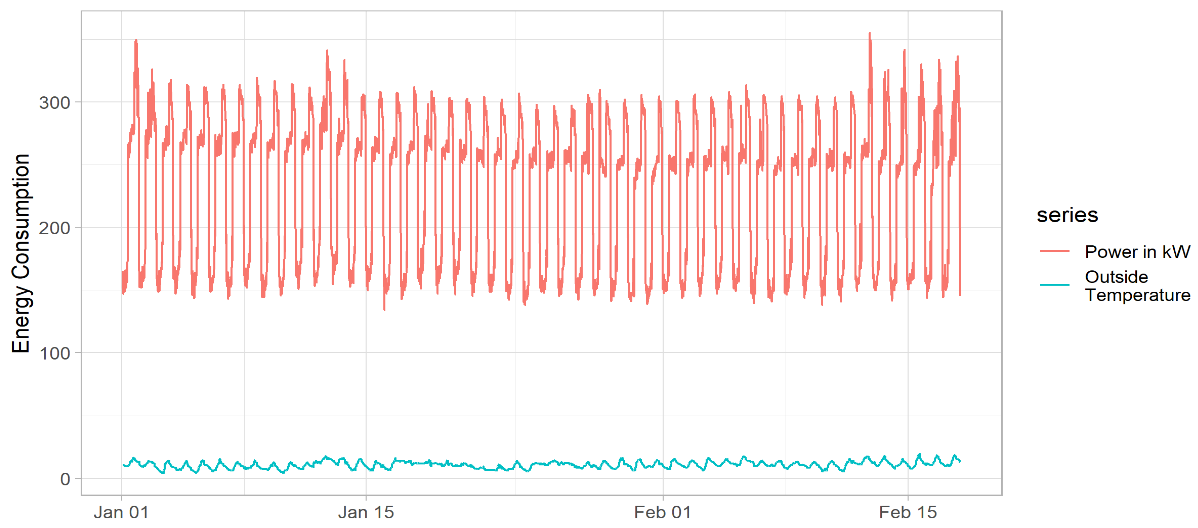
    b. Temp (C°) to *temp.c*

    c. Timestamp to *time.obs*

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

Figure 1

The time series plot.



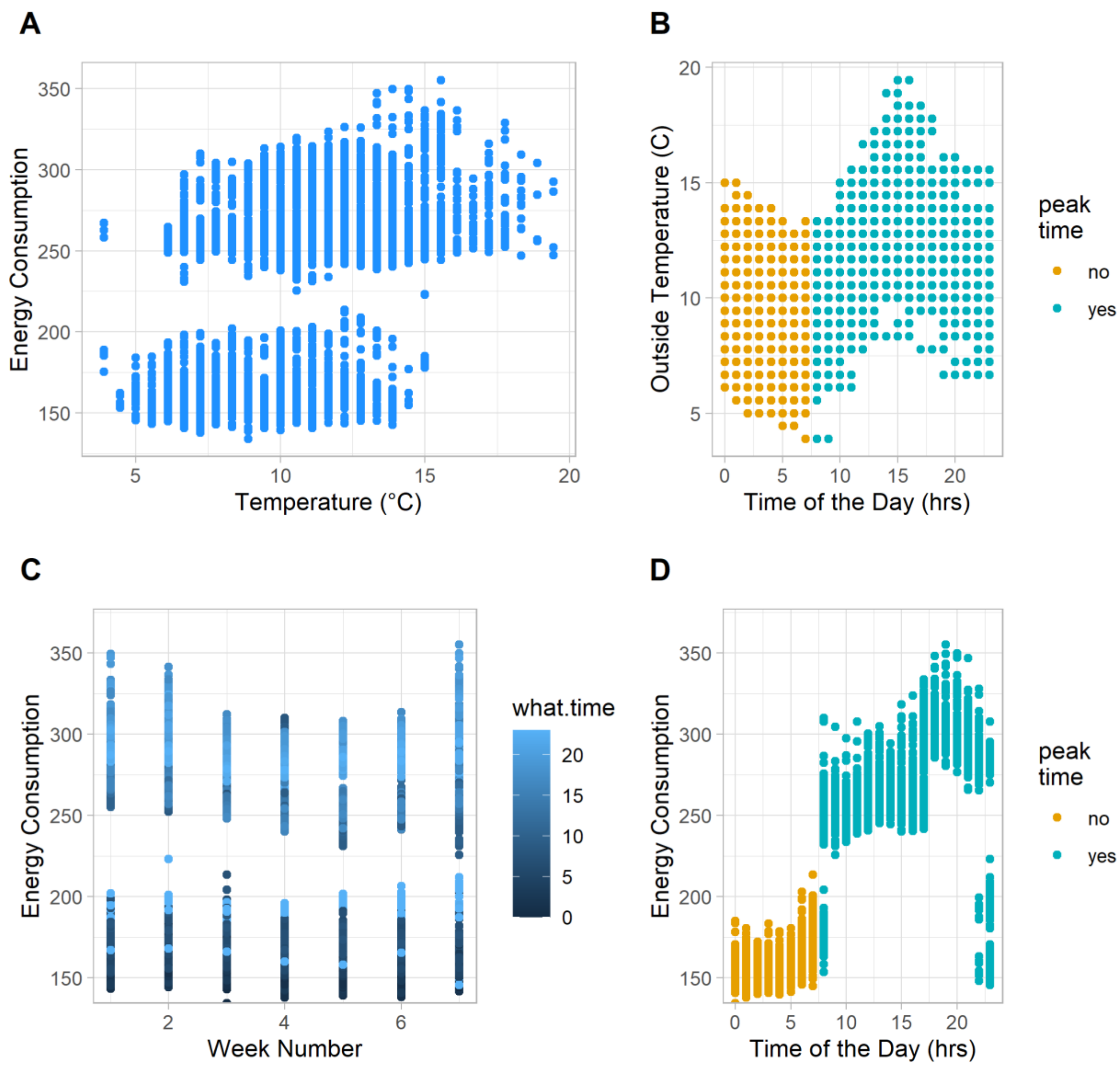
Exploratory data analysis showed that the relationship between *power.kw* (the response variable) and *temp.c* (outside air temperature) may include interaction terms. The additional time-based predictor variables identified to support modeling activities further are:

- 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 Figure 2:

Figure 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.

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 suitabilitytoward identifyingthe initialbasket of candidate models. These candidate models were further fine-tuned towards making an informedchoice. 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 thenonlinearmultivariate 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 wassignificantly 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-hourperiodicity.

Forecasting Results

From the model performance in table 1 below, and as expected, simpler models showed a poorfit 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 better a fit as obtained from ARIMA and Nonlinear Regression frameworks.

Hence, Dynamic Regression with ARIMA and Nonlinear Time Series Multivariate Regression provided the overall best performance values. Furthermore, in comparing these two top candidate frameworks, as shown in the performance table, the RMSE and MAPE values obtained from the ARIMA-based dynamic regression fit plateaued, maintaining approximatelythe same values despite varying the order of the ARIMA error model. However, incremental gains in model accuracy for Nonlinear Time Series Multivariate Regression were achieved when the nonlinear relationship was modeled iteratively with the inclusion of interaction terms. Consequently, Nonlinear Time Series Multivariate Regression implemented with polynomial splines and factoring in the interaction term between temperature and time of the day gave the best performance result.

An analysis of the residuals in Nonlinear Time Series Multivariate Regression indicated some deviation from white noise having aresidual autoregression pattern compared with ARIMA with dynamic regression, which gave a residual closer to white noise.While making the forecasts, a warning associated with rank deficiency was encountered. However, this was not considered a cause for prediction concern given the paucity of data variables inherent in the original dataset and how well the chosen model performed on test data. In addition, a plot of the residuals against the fitted values was satisfactory.

Findings

In the model for our building of interest, it wasobserved that notable days had greater than normal power consumption. Similarly, with constancy, during intra-day use, higher energy usage is associated with peak time that extends late into the night. We expect periods when a sustained increase in energy use is observed to be largely driven by the nature of activities occurring within that time frame. Hence, although the outside temperature is an important variable in predicting energy consumption, the activities carried out within the building impact energy consumption beyond that imposed by outside temperature. Commercial activities, for example, linked with a restaurant/café or a production facility with a defined production schedule, could be associated withthe analyzed energy use profile. Capturing additional data on the components of these activity variables and includingthese inan updated model will further increase performance accuracy and deliver better residuals.

Conclusion

In examining the energy consumption patterns within our focal building, certain key observations emerged that hold implications for future research and energy management practices. A striking discovery pertained to distinct days showcasing an unusually high power consumption (Ahmed et al., 2021). This observation resonates with a broader research trend that underscores variations in energy usage based on temporal patterns (Bakó et al., 2021; Lin et al., 2021). Specifically, intra-day analyses revealed a consistent pattern wherein energy consumption peaks were limited to conventional hours and extended considerably 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 (Jacob et al., 2020). This perspective is supported by Arteconi&Arteconi (2021), 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 brings us to a consequential consideration—what might these internal activities be? A careful analysis suggests that commercial operations, especially those associated with hospitality sectors like restaurants and cafes, or manufacturing entities adhering to strict production schedules, might contribute significantly to this energy use profile (Ansu-Mensah &Kwakwa, 2022). It is not just about the intensity but the timing of these operations that can lead to heightened energy demands. Consequently, a more holistic and nuanced approach to modeling energy consumption would necessitate incorporating data on these internal activities. Including variables related to the type, intensity, and timing of operations within the building would refine our understanding and lead to models with improved predictive accuracy (Ramos et al., 2022; Zhang et al., 2021). The value of such an integrative approach can be gauged from studies like those of Charlier et al. (2021), who highlight the intricate dynamics of electricity consumption within firms and how subtle nudges can influence consumption patterns.

The quest for accuracy and predictability in energy consumption modeling is more than just academic exercise. With the pressing challenges of climate change and the imperative for sustainable energy practices, there is an urgent need for models that depict current realities and guide actionable interventions (Wenz et al., 2017). To this end, refining our model by capturing granular data on internal activity components can lead to enhanced performance and better residuals, thus paving the way for more precise interventions and strategies for energy conservation (Szabó et al., 2019). Finally, the intersection of internal activities and external factors influencing building energy consumption patterns is a fertile ground for further exploration. By marrying these two dimensions, we can move towards building models that reflect ground realities and are instrumental in guiding sustainable energy practices in the future (Zhao et al., 2022). As we embark on this journey, we must remain cognizant of the evolving nature of energy consumption and continuously iterate and refine our models in line with emerging trends and insights.

References

Ahmed, A., N., B., M., &Paramati, S. R. (2021). Electricity consumption in Australia: the role of clean energy in reducing CO2 emissions. Applied Economics, 53(48), 5535–5548. https://doi.org/10.1080/00036846.2021.1925080

Ansu-Mensah, &Kwakwa, P. A. (2022). Modelling electricity consumption in Ghana: the role of financial development indicators. Green Finance, 4(1), 54–70.https://doi.org/10.3934/GF.2022003

Arteconi, &Arteconi, A. (2021). Evaluation of Energy Efficiency and Flexibility in Smart Buildings. MDPI - Multidisciplinary Digital Publishing Institute.

Bakó, Berkes, J., & Szigeti, C. (2021). Households' Electricity Consumption in Hungarian Urban Areas. Energies (Basel), 14(10), 2899–. https://doi.org/10.3390/en14102899

Charlier, Guerassimoff, G., Kirakozian, A., &Selosse, S. (2021). Under Pressure! Nudging Electricity Consumption within Firms. Feedback from a Field Experiment. The Energy Journal (Cambridge, Mass.), 42(1), 129–. https://doi.org/10.5547/01956574.42.1.ccha

Jacob, Neves, C., & Vukadinović Greetham, D. (2020). Forecasting and Assessing Risk of Individual Electricity Peaks (1st ed. 2020.). Springer Nature. https://doi.org/10.1007/978-3-030-28669-9

Lin, Yu, H., Wang, M., Li, C., Wang, Z., & Tang, Y. (2021). Electricity Consumption Forecast of High-Rise Office Buildings Based on the Long Short-Term Memory Method. Energies (Basel), 14(16), 4785–. https://doi.org/10.3390/en14164785

Olabanji, S. O. (2023). Advancing Cloud Technology Security: Leveraging High-Level

Coding Languages like Python and SQL for Strengthening Security Systems and Automating Top Control Processes. Journal of Scientific Research and Reports, 29(9), 42–54. https://doi.org/10.9734/jsrr/2023/v29i91783

Olagbaju, O. O., Babalola R.O., & Olaniyi, O. O. (2023). Code Alternation in English as a Second Language Classroom: A Communication and Learning Strategy. *Nova Science*. https://doi.org/10.52305/YLHJ5878

Olagbaju, O. O., & Olaniyi, O. O. (2023). Explicit and Differentiated Phonics Instruction on Pupils' Literacy Skills in Gambian Lower Basic Schools. Asian Journal of Education and Social Studies, 44(2), 20–30. https://doi.org/10.9734/ajess/2023/v44i2958

Olaniyi O. O. (2022, April 26). Best Practices to Encourage Girls' Education in Maiha Local Government Area of Adamawa State in Nigeria. The University of Arkansas Clinton School of Public Service (Research Gate). https://doi.org/10.13140/RG.2.2.26144.25606

Olaniyi, O. O., Olabanji, S. O., &Abalaka, A. I. (2023). Navigating Risk in the Modern Business Landscape: Strategies and Insights for Enterprise Risk Management Implementation. Journal of Scientific Research and Reports, 29(9), 103–109. https://doi.org/10.9734/jsrr/2023/v29i91789

Olaniyi, O. O., Olabanji, S. O., &Okunleye, O. J. (2023). Exploring the Landscape of Decentralized Autonomous Organizations: A Comprehensive Review of Blockchain Initiatives. Journal of Scientific Research and Reports, 29(9), 73–81. https://doi.org/10.9734/jsrr/2023/v29i91786

Olaniyi, O. O., Abalaka, A. I., &Olabanji, S. O. (2023). Utilizing Big Data Analytics and Business Intelligence for Improved Decision-Making at Leading Fortune Company. Journal of Scientific Research and Reports, 29(9), 64–72. https://doi.org/10.9734/jsrr/2023/v29i91785

Olaniyi, O.O., Okunleye, O.J., &Olabanji, S.O. (2023). Advancing Data-Driven Decision-Making in Smart Cities through Big Data Analytics: A Comprehensive Review of Existing Literature. *Current Journal of Applied Science and Technology*, 42(25), 10–18. https://doi.org/10.9734/cjast/2023/v42i254181

Olaniyi, O.O., Olaoye O.O., &Okunleye, O.J. (2023). Effects of Information Governance (IG) on profitability in the Nigerian banking sector. *Asian Journal of Economics, Business and Accounting*. 2023;23(18):22–35. https://doi.org/10.9734/ajeba/2023/v23i181055

Olaniyi, O.O. &Omubo, D.S. (2023). The Importance of COSO Framework Compliance in Information Technology Auditing and Enterprise Resource Management. *The International Journal of Innovative Research & Development*. https://doi.org/10.24940/ijird/2023/v12/i5/MAY23001

Olaniyi, O.O. &Omubo, D.S. (2023). WhatsApp Data Policy, Data Security, And Users' Vulnerability. *The International Journal of Innovative Research & Development*. https://doi.org/10.24940/ijird/2023/v12/i4/APR23021

Ramos, Faria, P., Vale, Z., & Correia, R. (2022). Short Time Electricity Consumption Forecast in an Industry Facility. IEEE Transactions on Industry Applications, 58(1), 123–130. https://doi.org/10.1109/TIA.2021.3123103

Rausser, Strielkowski, W., &Štreimikienė, D. (2018). Smart meters and household electricity consumption: A case study in Ireland. Energy & Environment (Essex, England), 29(1), 131–146. https://doi.org/10.1177/0958305X17741385

Solarin, Shahbaz, M., Khan, H. N., & Razali, R. B. (2021). ICT, Financial Development, Economic Growth and Electricity Consumption: New Evidence from Malaysia. Global Business Review, 22(4), 941–962. https://doi.org/10.1177/0972150918816899

Szabó, Kelemen, Á., Mezősi, A., Pató, Z., Kácsor, E., Resch, G., & Liebmann, L. (2019). South East Europe electricity roadmap - modelling energy transition in the electricity sectors. Climate Policy, 19(4), 495–510. https://doi.org/10.1080/14693062.2018.1532390

Wang, Yang, Z., Wang, Y., & Gu, J. (2022). Research on customer's electricity consumption behavior pattern. Journal of Physics. Conference Series, 2290(1), 12042–. https://doi.org/10.1088/1742-6596/2290/1/012042

Wenz, Levermann, A., &Auffhammer, M. (2017). North-south polarization of European electricity consumption under future warming. Proceedings of the National Academy of Sciences - PNAS, 114(38), E7910–E7918. https://doi.org/10.1073/pnas.1704339114

Xu, Ma, X., & Xu, X. (2022). Spatial spillover effects and action paths of electricity consumption driven by China's financial development based on global co-integration. Environmental Science and Pollution Research International, 29(35), 53137–53157. https://doi.org/10.1007/s11356-022-19386-6

Zhang, Ai, Q., & Li, Z. (2021). Grouping of dynamic electricity consumption behaviour: An f- divergence based hierarchical clustering model. IET Generation, Transmission & Distribution, 15(22), 3164–3175. https://doi.org/10.1049/gtd2.12248

Zhao, Zhang, C., Ujeed, T., & Ma, L. (2022). Methods of reflecting electricity consumption change characteristics and electricity consumption forecasting based on clustering algorithms and fuzzy matrices in buildings. Building Services Engineering Research & Technology, 43(6), 703–724. https://doi.org/10.1177/01436244221122851