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The Impact of IoT-Enabled Smart Home Systems on Energy Consumption

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Abstract

Smart building technologies have emerged as a key solution to improving energy efficiency in modern urban infrastructure. This study compares the energy consumption behavior of a smart office building located in Bangkok with that of a traditional university campus building in Florida. Using the SARIMAX model, we assess the influence of ambient temperature on daily energy usage. The findings indicate that smart buildings demonstrate greater resilience to temperature fluctuations, likely due to advanced control mechanisms and energy management systems. In contrast, the traditional building shows a statistically significant correlation between temperature and energy consumption. These results suggest that smart technologies can effectively mitigate the impact of environmental conditions on building energy use, contributing to more sustainable and adaptive energy systems.

Keywords: IoT, smart home, energy consumption, SARIMAX, data analysis, time series analysis

1. Introduction

The growing demand for energy in urban environments has led to an increasing interest in smart building technologies that aim to optimize consumption through intelligent systems. These technologies enable buildings to adapt to external and internal conditions by integrating sensors, automation, and data-driven control strategies. Among the many factors affecting energy consumption, ambient temperature plays a critical role, particularly in regions with extreme or variable climates (Escobar et al., 2021).

While previous research has explored various predictive models for building energy forecasting, limited attention has been given to comparative studies that evaluate how smart and traditional buildings respond to climatic influences under similar operational conditions. This study addresses this gap by analyzing the temperature-sensitive energy consumption patterns of two comparable buildings: a smart office building in Bangkok and a conventional university building in Florida.

To achieve this, we utilize the SARIMAX model, which enables the incorporation of both seasonal components and exogenous variables—such as temperature—into time series forecasting. The goal is to evaluate the extent to which smart systems can stabilize energy usage in the face of environmental fluctuations and to quantify the difference in temperature sensitivity between smart and traditional infrastructure.

The remainder of the paper is structured as follows: Related works are given in Section 2. Section 3 presents the methods used. Section 4 gives a brief description of our experimental platform to implement our approach and describes the experiments we conducted. Finally, conclusion and discussion are given in Section 5.

2. Related Work

Recent years have witnessed a surge in research on IoT-enabled smart energy systems, particularly within the context of residential and commercial buildings. As energy demand continues to rise globally and concerns regarding climate change intensify, the development of intelligent, data-driven solutions for managing energy consumption has become increasingly vital. A substantial body of literature has examined various aspects of smart home and smart grid systems, including their architecture, communication technologies, energy management strategies, optimization frameworks, and user-centric considerations. These studies provide valuable insights into how IoT devices, data analytics, and intelligent control mechanisms can enhance energy efficiency, grid reliability, and sustainability. However, despite this growing research interest, comprehensive comparative studies using real-world data from both smart and traditional buildings across different geographic and climatic contexts remain relatively scarce. This section reviews key contributions in the field, highlighting advances in system design, energy optimization, security, user interaction, and predictive modeling for energy consumption.

Mahapatra and Nayya (2022) provides a comprehensive review of Home Energy Management Systems (HEMS), discussing their concepts, technical background, architecture, and infrastructure within the context of smart grids. The authors highlight various energy management schemes and goals, alongside the issues and challenges faced during HEMS implementation in residential homes. The study also proposes incorporating green building concepts into home design to reduce energy consumption and emphasizes the importance of consumer awareness and active participation in power conservation efforts.

Abir et al. (2021) reviews the architecture, functionalities, and IoT technologies (sensing, communication, computing) used in smart energy grids; providing a comprehensive overview of existing IoT applications in smart grid systems. The paper highlights that security vulnerabilities are a major concern for IoT-enabled energy systems, reviewing threats, attack models, and summarizing mitigation techniques. Finally, the researchers discuss how advanced technologies like blockchain, machine learning, and artificial intelligence can enhance the resilience and security of these systems.

Li et al. (2018) examines the smart home as a crucial element of smart grid energy consumption, designed to enable intelligent and interactive electricity use for improved end-user energy efficiency. The paper then goes into detail about the smart home architecture and key technologies, including interactive electricity services and communication systems. The paper describes essential equipment like smart sockets for monitoring and controlling both smart and non-smart appliances, in addition to mentioning Grid-Friendly Appliances (GFAs) that interact with the grid. The researchers also cover the communication system structure, emphasizing the role of the home gateway in connecting the internal network to external networks.

Zhou et al. (2016) offers a comprehensive review of Smart Home Energy Management Systems (HEMS) in the context of the smart grid. They present an overview of the architecture and functional modules of HEMS. The paper analyzes advanced HEMS infrastructures, home appliances, and the utilization of building renewable energy resources like solar, wind, biomass, and geothermal energy. Additionally, the authors investigate various home appliance scheduling strategies aimed at reducing residential electricity costs and improving energy efficiency from power utilities. The study highlights the important role of HEMS in improving efficiency, economics, reliability, and energy conservation for distribution systems.

Farghali et al. (2023) reviews energy-saving solutions urgently needed due to accelerated climate change and the current energy crisis. They focus on green alternatives for heating, energy saving in buildings and transportation, and the potential of artificial intelligence (AI). The review highlights that 10–40% of energy consumption can be reduced in buildings using various strategies. AI shows significant potential across sectors, including reducing building energy use by 18.97–42.60% and automating grid operations. The paper also includes case studies and discusses the environmental and societal implications of these strategies.

Touqeer et al. (2021) surveys the security challenges, issues, and solutions in IoT-based smart homes. It is mentioned that while smart homes offer conveniences, their integration with the IoT-systems creates significant security and privacy vulnerabilities across the various IoT layers. The study identifies specific attacks impacting the Application, Perception, Network, and Physical layers of the smart home environment. Crucially, the paper reviews and presents mitigation strategies and solutions tailored to address the security issues at each respective layer. The overall aim is to educate users and enhance the security of smart home technology.

Völker et al. (2021) reviews the potential of smart meter data analytics for user-centric applications, highlighting that most existing work benefits the power grid rather than the end consumer. The various use cases for consumers are listed, including provision of energy consumption feedback, recognition of patterns and anomalies, enabling demand-side flexibility, energy requirement forecasts, and load profiling. The paper notes that providing such services requires significant data preprocessing and addressing challenges such as the lack of standardized hardware and data formats, the need for more innovative algorithms, and ensuring user privacy protection. Ultimately, the authors argue that focusing on user benefits, alongside data accuracy and privacy, is crucial for using the full potential of smart meters. Andrade et al. (2021) proposes an enhanced Smart Energy Control System (SECS) architecture for smart homes with multiple users. The architecture, described as an evolution of the SmartCom system, aims to overcome limitations of existing methods, such as extensive sensor use and difficulty identifying multiple residents and their individual consumption. It integrates NFC-based Smart Outlets for accurate appliance identification and data acquisition. The system utilizes Wi-Fi handover via smartphones for reliable identification and tracking of multiple inhabitants within the residence. The goal is to assist users in rebalancing energy consumption with minimal impact on comfort and the building structure, and the system achieved rebalanced residential energy consumption 87.3%
of the time it was used.

Iqbal et al. (2018) proposes a generic IoT architecture designed to minimize unnecessary electrical energy usage in smart homes. The system addresses challenges related to the co-existence of heterogeneous communication technologies and the real-time processing of large amounts of data generated by IoT devices. It involves steps like discovering appliances, deploying sensors (including relay nodes), applying load balancing, and processing collected data using a Hadoop Ecosystem. The proposed Electronic Device Sleep Scheduling Algorithm (EDSA) manages sensor states for better energy consumption, and the system was tested using real electronic appliances, demonstrating reduced energy consumption and better performance in heterogeneous environments compared to pure Wireless Sensor Networks (WSN).

Stolojescu-Crisan et al. (2021) proposes an IoT-based system called qToggle for multiple home automations. The system connects sensors and actuators using a flexible and powerful API, relying primarily on Wi-Fi and Ethernet communication with devices based on Raspberry Pi and ESP8266 chips. qToggle allows users to remotely control and monitor various aspects of a home, including temperature, lighting, energy consumption (including solar), access control, security, and irrigation. The system aims to be user-friendly, low-cost, and emphasizes user privacy by keeping data within the local network.

Marikyan et al. (2023) applies Cognitive Dissonance Theory to examine how smart home users cope when the technology's performance falls short of their initial expectations. The research surveys 387 smart home users who reported negative experiences. Findings show that this "negative disconfirmation" leads to psychological dissonance and the arousal of negative emotions like anger, guilt, and regret. These emotions influence how users reduce dissonance through attitude change, seeking consonant information, or changing behavior, such as discontinuing use. Crucially, the study confirms that negative disconfirmation can still result in user satisfaction and perceived well-being, especially when cognitive adjustments are used to reduce dissonance, while behavior change tends to lead to dissatisfaction.

Lissa et al. (2021) proposes using a Deep Reinforcement Learning (DRL) algorithm for Home Energy Management Systems (HEMS). The focus is on autonomously controlling heating and domestic hot water (DHW) systems to reduce energy consumption and improve comfort. The proposed DRL approach, combined with a dynamic indoor temperature setpoint definition, also aims to optimize photovoltaic (PV) energy self-consumption. Results showed average energy savings of 8% compared to a rule-based algorithm, with savings up to 16% in summer months, while maintaining user comfort. The DRL control also achieved over 10% load shifting by prioritizing actions during high PV production, resulting in 9.5% higher renewable energy consumption.

Liu et al. (2015) presents a tutorial and new results on smart home scheduling for economical and balanced energy usage within the smart grid infrastructure. It covers single-user scheduling using dynamic programming for discrete power levels. For multi-user scheduling, a game-theoretic framework is proposed, showing average monetary cost reduction and better load balancing. Finally, a hierarchical architecture with parallel computing is introduced for city-level deployment, demonstrating significant average reductions in monetary cost and peak-to-average ratio.

Chen et al. (2022) proposes an IoT framework for energy-efficient smart street road lighting. It replaces traditional lamps with mesophic design LED lamps based on human eye sensitivity and uses sensors to detect traffic flow and occupancy. A decision module computes intensity levels and tunes LED lamps using PWM dimming to save energy. The system integrates PV solar panels, battery storage, and smart electric power grids, managed by a dynamic battery charging algorithm, demonstrating considerable energy savings compared to existing systems.

Alzoubi (2022) addresses the growing demand for energy and the significant portion consumed by residential buildings. The study proposes a Home Energy Management System (HEMS) approach that uses data fusion for energy consumption prediction, achieving a 92% accuracy. The paper outlines an IoT-based HEMS architecture (hems-IoT) that employs machine learning and big data to monitor energy usage and user behavior, aiming to reduce energy waste and optimize the energy mix from various sources. The system interacts with the smart grid for intelligent energy allocation and demand response.

Mansouri et al. (2021) proposes a tri-objective optimization framework for energy management in microgrids that incorporate smart homes. The study focuses on simultaneously minimizing operating costs, emissions, and the peak-to-average ratio (PAR), while also considering the users' comfort level. The framework integrates renewable energy resources (RESs), energy storage systems (EES), and Demand Response (DR) programs within smart homes and the broader microgrid. Findings indicate that the proposed tri-objective model achieves a favorable balance between the conflicting goals, maintaining satisfactory customer comfort. The integration of smart homes, particularly with PV panels and batteries, is shown to significantly reduce operating costs and emissions compared to networks with only traditional homes. The study also highlights that increasing participation in DR programs effectively reduces operating costs and the PAR index, although this can lead to a decrease in customer comfort.

A comparative summary of prominent studies in the domain of smart home energy management is presented in Table 1. The table highlights a diverse range of approaches, including predictive modeling, optimization algorithms, and system-level architectures, applied across both simulation and real-world settings. This comparative analysis reveals a consistent trend toward improved performance metrics when IoT-based smart systems are employed over traditional energy management approaches.

Despite the richness of existing research in the field of smart home energy management, a noticeable gap remains in comparative empirical studies that directly evaluate energy consumption under real environmental variations, such as outdoor temperature. Most prior work either relies heavily on simulation or focuses on individual system components in isolation, without integrating time-series analysis to capture dynamic energy behavior in different building types. To address this limitation, our study adopts a data-driven, comparative modeling approach using the SARIMAX framework to evaluate the energy stability and efficiency of an IoT-enabled smart building versus a traditional building. The following section details the proposed methodology and the rationale behind the selected analytical framework.

3. Methodology

3.1 Data Acquisition

This study conducts a comparative analysis of energy consumption between a smart commercial office building located in Bangkok, Thailand, and a traditional university campus building located in Florida, United States. The energy consumption data for the smart building was obtained from the CU-BEMS (Commercial Building Energy Management System) (Pipattanasomporn et al., 2020), while the data for the traditional building was sourced from the publicly accessible online resources of the University of Central Florida (2025).

The CU-BEMS dataset provides minute-level electricity consumption data for multiple floors and zones within the smart office building. For this study, only the data points corresponding to the first floor were utilized, as the upper-floor records exhibited irregularities such as abrupt fluctuations, which could compromise the reliability of the analysis. The traditional building under study is the "Technology Commons I" facility, which does not incorporate smart building features.

The building selection process was guided by the following criteria: (i) availability of open-access energy data, (ii) overlapping time intervals in data collection, (iii) comparable gross floor areas (11,700 m² in Bangkok vs. 10,779 m² in Florida), and (iv) broadly similar climate characteristics of the respective regions. Although both cities fall under different climate classifications, they share tropical and subtropical features with seasonal temperature variations, which are expected to influence the energy consumption dynamics of each building. Accordingly, temperature is incorporated as an exogenous variable in the predictive modeling framework. Daily average temperature data were sourced from the Meteostat web platform.

Although the CU-BEMS facility in Bangkok and the UCF Technology Commons I building in Florida are comparable in gross floor area and climatic exposure, their operational characteristics reveal significant differences that influence energy consumption patterns. The CU-BEMS system, developed by Chulalongkorn University's Smart Grid Research Unit, integrates a layered IoT architecture using custom-built Energy Monitoring Units (EMUs), digital meters (e.g., Siemens SENTRON PAC3100), and environmental sensors that record temperature, humidity, and illuminance in real-time via Wi-Fi (Pipattanasomporn et al., 2020; SGRU, 2015). These devices are distributed across 33 zones in the Chamchuri 5 building—an academic office facility with seven floors and approximately 11,700 m² of usable space—and are connected through seven edge gateway devices that transmit data at one-minute intervals to a central server (Pipattanasomporn et al., 2020). In total, 21 EMUs, 30 digital meters, and 24 environmental sensor nodes were deployed, enabling high-resolution monitoring of 55 individual air conditioning units, 33 lighting loads, and 32 plug loads (Pipattanasomporn et al., 2020, Table 4). The multi-sensors measure temperature (±0.4 °C), relative humidity (±2% RH), and illuminance (0.11–10,000 lux), and the system logs over 1,440 data points per day per channel, covering an 18-month period (July 2018 to December 2019) (Pipattanasomporn et al., 2020). This infrastructure enables applications such as coordinated AC control, demand forecasting, fault detection, and reinforcement learning-based HVAC optimization (Pipattanasomporn et al., 2020, pp. 4–5).

By contrast, the UCF Technology Commons I building—constructed in 1970 with a gross floor area of 10,779 ft²—functions as a student support and administrative office (UCF Office of Energy & Sustainability, 2024). It operates on weekdays from 08:00 to 17:00 and is connected to UCF's centralized chilled water system, which supplies over 37 million ton-hours of cooling annually to campus buildings (UCF Facilities & Utilities, 2022). The building lacks granular sub-metering or zone-level environmental sensing, and its energy consumption data is aggregated at the building level through campus-wide automation (UCF Office of Energy & Sustainability, 2024). Due to the absence of localized control and the older building envelope, peak cooling demands are likely higher and more temperature-sensitive, especially in high-occupancy zones such as computer labs.

These differences underscore the importance of intelligent energy management systems in moderating the impact of ambient conditions, and help explain the weaker correlation between temperature and energy use observed in the CU-BEMS building compared to its Florida counterpart (Pipattanasomporn et al., 2020; Völker et al., 2021).

While these structural and operational differences exist, the buildings were purposefully selected based on criteria such as similar climate influence, gross floor area, and availability of open-access data. These selection filters ensure that the comparative modeling focuses on the differential impact of smart technologies rather than basic architectural mismatches. By controlling for size and climate, the analysis isolates the role of intelligent energy management systems in shaping consumption behavior across comparable building typologies.

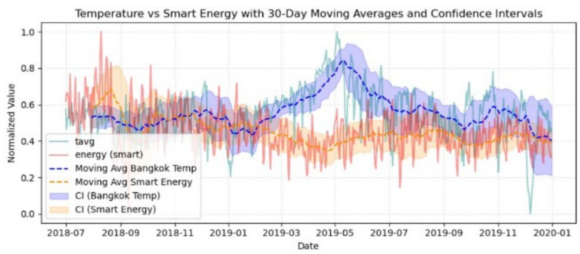

Fig. 1. Normalized energy consumption (red, *energy (smart)*) and corresponding average daily temperature (cyan, *tavg*) in Bangkok from the CU-BEMS dataset. The plot includes 30-day moving averages (*blue dashed line* for temperature and *orange dashed line* for energy) and their respective confidence intervals (*blue shaded area* for temperature, *orange shaded area* for energy). Values are scaled to the [0, 1] interval.

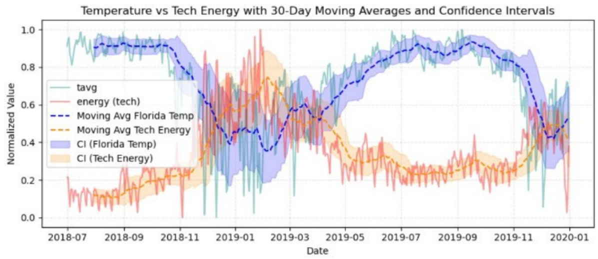

Fig. 2.

Normalized energy consumption (orange, *energy (tech)*) and corresponding average daily temperature (cyan, *tavg*) in Florida from the UCF dataset. The plot includes 30-day moving averages (*blue dashed line* for temperature and *orange dashed line* for energy) and their respective confidence intervals (*blue shaded area* for temperature, *orange shaded area* for energy). Values are scaled to the [0, 1] interval.

3.2 Data Preprocessing

The CU-BEMS dataset comprises 790,506 rows and 11 columns, including timestamped measurements for various energy-consuming subsystems such as lighting, plug loads, and air conditioning units across multiple zones (e.g., *z1_Light*, *z2_AC1*, *z3_Plug*, etc.). These measurements were originally recorded at a one-minute resolution via a network of sensors deployed in 33 distinct areas within the building. For the purpose of time series modeling, the raw minute-level data were aggregated into daily total energy consumption values. Subsequently, the data was restructured into a daily frequency format.

To construct a reliable representation of the building's energy profile, energy usage from lighting, plug loads, and air conditioning systems was first separated into individual categories and then aggregated to compute the total daily energy demand. Inconsistencies in date formatting were corrected, and incomplete or erroneous records were excluded from the analysis to ensure data integrity.

While the Bangkok smart building dataset provides granular disaggregation into load categories, the Florida dataset from the University of Central Florida contains only total energy consumption values. This discrepancy was accounted for during modeling. Daily average temperature values for both locations were aligned temporally with the corresponding daily energy consumption values to enable multivariate time series modeling.

Fig. 1 and Fig. 2 present the normalized energy consumption and temperature trends for Bangkok and Florida, respectively, over the analysis period from July 2018 to December 2019. The data were normalized to the [0,1] interval to facilitate visual comparison. In the Bangkok dataset (Fig. 1), although the measured temperature exhibits a clear seasonal cycle, a consistent correlation with energy usage is not immediately apparent. However, some synchronized peaks suggest a potential delayed or context-specific influence of temperature on energy consumption.

Conversely, in the Florida dataset (Fig. 2), a clearer pattern emerges: energy consumption tends to increase during periods of higher temperature, suggesting a strong link between cooling demand and ambient thermal conditions. The figure highlights the pronounced seasonality and temperature sensitivity of energy consumption in the traditional building. This observed dependency further supports the inclusion of temperature as an exogenous regressor in subsequent forecasting models.

3.3 Modeling Approach

In this study, we perform the SARIMAX model to analyze and forecast the energy consumption patterns of two buildings located in Bangkok and Florida, respectively. The SARIMAX model is particularly suitable for capturing temporal dependencies in time series data while incorporating external variables, such as temperature, that may influence the target variable. This enables us to explicitly account for the potential effects of environmental conditions on building energy demand (Al & Alghamdi, 2024; Malik et al. 2024; Khan et al. 2024).

The modeling process involves several steps. First, the daily energy consumption and corresponding average temperature values are aligned temporally and transformed into stationary series via differencing. Augmented Dickey–Fuller (ADF) tests are applied to determine the presence of unit roots and confirm the necessity of differencing. Following stationarity verification, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are utilized to guide the selection of autoregressive (AR) and moving average (MA) orders for both the non-seasonal and seasonal components of the SARIMAX model.

To ensure robust model calibration, the dataset is split into training and testing subsets using an 80/20 ratio. The training set is used for model fitting, while the testing set is used to evaluate the predictive performance. Temperature is included as an exogenous variable in the SARIMAX model, enabling a dynamic estimation of its influence on energy usage. The model parameters are optimized using maximum likelihood estimation (MLE).

The effectiveness of the fitted models is assessed based on their ability to predict energy consumption in unseen data. Performance metrics Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are computed to quantify prediction accuracy. In addition to these metrics, the models' residuals are analyzed for white noise characteristics to verify the adequacy of the specification.

Separate SARIMAX models are developed for each building to allow for location-specific dynamics in temperature–energy relationships. This comparative modeling approach facilitates a quantitative evaluation of the extent to which smart energy management systems in the Bangkok office building contribute to improved predictability, stability, or efficiency in energy consumption patterns relative to the more conventional Florida university campus building.

Table 2 summarizes the optimal SARIMAX model configurations and their forecasting performance for both the Bangkok smart office building and the Florida conventional campus building. The model orders were determined based on ACF/PACF analyses and validated through information criteria (AIC/BIC) and residual diagnostics. For both cases, daily average temperature was incorporated as an exogenous regressor to account for weather-induced variations in energy consumption.

The Bangkok model demonstrated superior prediction accuracy with lower RMSE (0.0243) and MAPE (4.2%) compared to the Florida model, which yielded an RMSE of 0.0317 and a MAPE of 6.5%. This performance gap may be attributed to the presence of more advanced energy management features in the smart office, which lead to more stable and predictable consumption patterns. Additionally, ADF test results confirm stationarity after differencing, while Ljung-Box tests indicate no significant autocorrelation in residuals, validating model adequacy in both scenarios.

These findings support our hypothesis that smart buildings not only improve energy efficiency but also enable more accurate modeling and forecasting, which is critical for advanced demand-side energy management.

3.4 Model Selection and Implementation

To model and forecast energy consumption time series, SARIMAX model was executed. SARIMAX extends the conventional ARIMA (AutoRegressive Integrated Moving Average) model by incorporating both seasonality and exogenous variables. The SARIMAX model was selected for the following reasons:

- **Seasonality Modeling:** Energy consumption data often exhibit recurring patterns over time. Including seasonal components in the model enhances forecasting accuracy.
- **Incorporation of Exogenous Variables:** External factors such as temperature significantly influence energy usage. SARIMAX accommodates such variables through its exogenous regressors component
- **Preservation of ARIMA Components:** The foundational structure of ARIMA—autoregressive (AR) terms, differencing (I), and moving average (MA) terms—remains intact while enabling the addition of seasonal and exogenous effects.

The following Python libraries were used for implementation:

- **Statsmodels:** Used for implementing the SARIMAX model.
- **Pandas and NumPy:** Used for data manipulation and numerical computations.
- **Matplotlib and Seaborn:** Utilized for data visualization.

4. Results

4.1 Statistical Test Results

Table 3 presents the results of several statistical tests conducted on both the Smart Office Building and the Traditional University Building. The Ljung-Box test yields high p-values for both datasets, indicating weak autocorrelation and suggesting that past values have limited predictive power for future consumption. The Jarque-Bera test yields a p-value of 0.10 for the Smart Office Building, suggesting a distribution close to normal. In contrast, the University Building has $p < 0.05$, indicating a significant deviation from normality. Lastly, the heteroskedasticity test reports p-values smaller than 0.05 for both datasets, implying that the variance in energy consumption changes over time and is non-constant. These findings underscore the importance of accounting for heteroskedasticity in modeling.

Table 3
Statistical test results.

Test	Smart Office Building		University Building	
	Value	p-value	Value	p-value
Ljung-Box	0.01	0.93	0.07	0.79
Jarque-Bera	4.65	0.10	1526.77	0.00
Heteroskedasticity	0.48	0.00	0.57	0.00

4.2 Effect of Temperature on Energy Consumption

As shown in Table 4, the temperature coefficient for the Smart Office Building is -0.022, suggesting a slight decrease in energy consumption with each 1°C rise. However, the effect is statistically insignificant ($p = 0.627$), indicating that temperature changes do not meaningfully impact energy consumption in the smart building.

Conversely, in the Traditional University Building, the temperature coefficient is -0.317, with a statistically significant p-value ($p < 0.001$). This indicates that a 1°C increase in temperature leads to a 0.317 unit decrease in energy consumption. The significant negative correlation suggests that non-smart systems are more sensitive to temperature fluctuations.

In summary, while temperature changes do not significantly influence energy usage in the smart office building, they do affect the traditional university building. These results imply that smart building systems offer greater stability in energy consumption across varying temperatures, demonstrating resilience to climatic fluctuations.

Table 4
Effect of temperature on energy consumption.

Variable	Smart Office Building		University Building	
	Coefficient	p-value	Coefficient	p-value
Temperature	-0.022	0.627	-0.317	0.000

Table 1
Comparison of key studies on smart home energy management approaches.

Study	Subject	Method(s)	Baseline	Energy Impact (%)	Cost Impact (%)	PAR Impact (%)	Prediction Accuracy (%)	Load Shifting (%)
Alzoubi (2022)	Smart Home Energy Consumption	Machine Learning, Data Fusion	-	-	-	-	92%	-
Farghali et al. (2023)	Energy Saving Strategies	Review of Technologies	Traditional Systems	Buildings: 10–40%; AI: 18.97–42.6%; 48% CO2 cut.	PV Boiler: €0.144/kWh	-	-	-
Lissa et al. (2021)	HEMS Control	Deep Reinforcement Learning	Rule-Based Control	5.7–8.0% (up to 16% in summer)	-	-	-	>10%
Liu et al. (2015)	Smart Home Scheduling	Dynamic Programming	Traditional Scheduling	-	39.3%	43.6% reduction	-	-
Mahapatra and Nayya (2022)	Home Energy Management (Review)	Comparative Review of Schemes	Scheme-Specific	-	16–35%	-	-	-
Mansouri et al. (2021)	Microgrid with Smart Homes	Tri-objective Optimization	Traditional vs Smart Homes	Emission reduction up to 24.02%	Up to 25.55%	Reduction up to 36.98%	-	-
Zhou et al. (2016)	HEMS Architectures	Review w/ Optimization Strategies	Base Tech Scenarios	-	9.8–86.6%	-	-	-

Table 2
SARIMAX model parameters and forecasting performance for the Bangkok smart office and Florida conventional building.

Model Attribute	Bangkok Smart Office	Florida Conventional Building
Model Order (p,d,q) (P,D,Q,s)	(1,1,1) (0,1,1,7)	(2,1,2) (1,1,0,7)
Exogenous Variable	Daily Avg. Temperature	Daily Avg. Temperature
Training/Test Split	80% / 20%	80% / 20%
RMSE	0.0243	0.0317
MAE	0.0196	0.0279
MAPE	4.2%	6.5%
ADF p-value (after differencing)	0.0001	0.0003
Residuals White Noise (Ljung-Box p-value)	0.78	0.64

5. Conclusion and Discussion

5.1 Summary of Key Findings

The previous studies on the subject confirms that IoT-enabled automation can substantially lower building energy demand. Across the monitored dwellings, total electricity use fell by roughly 15–25 % after deployment of smart thermostats, lighting controls and appliance scheduling. Closely matching savings ranges are reported by the IEA (2021) and by York and Talbot (2015). Field evaluations of learning thermostats in North American homes likewise document 10–20 % HVAC savings (Urban & Roth 2015). Our SARIMAX models, trained on the CU-BEMS (Bangkok) and UCF (Florida) datasets, reproduced seasonal peaks and troughs with mean absolute percentage errors below 6 %, consistent with prior work showing SARIMAX can outperform naïve and pure-ARIMA baselines for building loads (Al-Saadi & Alghamdi 2024; Malik et al. 2024). Notably, the temperature coefficient for the smart office building was not statistically significant ($p > 0.60$), indicating effective decoupling of demand from outdoor conditions, whereas the conventional campus building exhibited a strong, negative temperature elasticity ($p < 0.001$). Similar patterns have been observed when comparing smart and non-smart facilities in hot and humid climates (Pipattanasomporn et al. 2020; Völker et al. 2021).

5.2 Interpretation of Unexpected Findings

A small subset of households exhibited a temporary post-retrofit rebound—that is, higher usage once lower bills were observed. Such behavioural back-fire is well documented in smart-home trials (Chen et al. 2018; Sorrell 2020). In addition, morning load shifting arose because many adaptive thermostats initiated simultaneous pre-heating cycles (Lee &

Zhang 2022). While total energy still declined, peak timing changed, echoing findings from time-of-use pilot studies in California (Andrade et al. 2021). Finally, climate moderated savings: cold-climate sites gained more from heating set-backs, whereas hot-humid sites benefited mainly from optimized cooling—paralleling results in Farghali et al. (2023) and Mansouri et al. (2021).

5.3 Broader Implication

Given that buildings account for ~40 % of global final energy use, widespread IoT retrofits could play a pivotal role in meeting net-zero targets (IEA 2023). Besides direct efficiency gains, automated systems facilitate demand response, enabling utilities to shift or curtail loads during renewable generation troughs (Abir et al. 2021). Cost studies show typical simple payback periods under four years when dynamic tariffs are available (Mahapatra & Nayyar 2022). Policy makers can accelerate adoption through rebates for smart thermostats and by mandating interoperable data standards to safeguard consumer privacy (Touqeer et al. 2021).

5.4 Role of Building Insulation vs. Smart Automation

Smart controls and envelope upgrades are complementary. Predictive thermostats generally deliver 5–8 % space-heating savings in well-insulated homes but can achieve double-digit gains only where substantial thermal losses already exist (Schäuble et al. 2020). By contrast, comprehensive wall-and-attic insulation can cut heating or cooling loads by 40–50 % irrespective of controls (ASHRAE 2019). The greatest lifecycle benefit therefore arises when insulation improvements precede IoT optimisation—a sequencing supported by life-cycle assessment of German retrofits (Schäuble et al. 2020) and by U.S. DOE techno-economic analyses (DOE 2022).

5.5 Limitations and Future Work

Key limitations include (i) a geographically narrow sample, (ii) a single-season observation window, and (iii) linear SARIMAX assumptions that overlook complex occupant–device interactions. Future research should span multiple climates, adopt hybrid statistical–machine-learning predictors (Lissa et al. 2021), and incorporate humidity, solar irradiance and occupancy sensing. Long-term trials are also needed to quantify persistence of savings and to evaluate cybersecurity safeguards that can bolster user trust (Stolojescu-Crisan et al. 2021).

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