Journal of Intelligent Systems and Internet of Things
Vol. 10, No. 02, PP. 08-17, 2023
DOI: https://doi.org/10.54216/JISIoT.100201

Predictive Energy Management in Internet of Things: Optimization of Smart Buildings for Energy Efficiency

Dionisio Ponce Ruiz*, Rita Azucena D. Vasquez, Bolivar Villalta Jadan

Universidad Regional Autónoma de los Andes (UNIANDES), Ecuador

Emails: uqdionisioponce@uniandes.edu.ec; ui.ritadiaz@uniandes.edu.ec; us.bolivarvillalta@uniandes.edu.ec

*Corresponding Author: uqdionisioponce@uniandes.edu.ec

Abstract

As energy efficiency and sustainability become paramount in the face of growing urbanization and environmental concerns, predictive energy management in smart buildings has emerged as a promising avenue for mitigating energy consumption and optimizing resource utilization. In this paper, we investigate the application of advanced machine learning techniques, particularly a multi-layer Long Short-Term Memory (LSTM) model, within the framework of the Internet of Things (IoT), to predict and manage energy consumption. We rigorously evaluate our approach against a suite of machine learning baselines, including Linear Regression, Random Forest, Support Vector Machine, and Gradient Boosting, utilizing a comprehensive dataset encompassing power consumption data from smart home appliances and associated weather variables. Our experimental results demonstrate the superior predictive capabilities of the LSTM model, showcasing its ability to outperform traditional machine learning baselines across various metrics, including Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These findings underscore the potential of deep learning models in capturing intricate temporal dependencies within energy consumption data, contributing to improved energy efficiency, cost savings, and environmental sustainability in smart building environments. The integration of predictive energy management models into IoT-enabled smart buildings holds the promise of a more intelligent and sustainable future in urban development and resource management.

Received: April 02, 2023 Revised: June 22, 2023 Accepted: September 16, 2023

Keywords: Internet of Things (IoT); Smart Buildings, Energy Efficiency; Predictive Energy Management; Sensor Networks; Data Analytics; Smart Grid; Building Automation and Control Systems (BACS).

1. Introduction

Energy management and sustainability have become critical concerns in today's rapidly evolving world. As the global population continues to grow and urbanization accelerates, there is an escalating demand for energy, particularly in the context of buildings, which account for a significant portion of overall energy consumption. This has led to a pressing need for innovative solutions to optimize energy usage and reduce the environmental footprint. In this context, the convergence of the Internet of Things (IoT) with smart building technologies has emerged as a promising avenue for enhancing energy efficiency and sustainability. In recent years, the imperative to address climate change and reduce carbon emissions has driven a paradigm shift towards sustainability and energy efficiency [1].

Governments, organizations, and individuals are increasingly focused on minimizing energy consumption and maximizing the utilization of renewable energy sources. Smart buildings, equipped with advanced sensors, data analytics, and IoT connectivity, have risen to the forefront as a solution to address these challenges. These buildings are designed to intelligently monitor, control, and optimize various aspects of their operations, with a particular emphasis on energy management [2].

Despite significant advancements in energy-efficient technologies, conventional buildings continue to be plagued by inefficiencies in energy consumption. These inefficiencies result in excessive energy costs, increased greenhouse gas emissions, and a strain on energy resources. The crux of the problem lies in the lack of predictive energy management systems that can adapt to real-time conditions and proactively optimize energy usage [3]. This research seeks to address this pressing issue by developing and implementing predictive energy management solutions within the IoT framework to transform conventional buildings into energy-efficient, sustainable smart buildings [4].

While substantial research has been conducted in the fields of energy management, smart buildings, and IoT, there remains a noticeable gap in the literature regarding the comprehensive integration of these domains. Existing studies often focus on isolated aspects of energy efficiency or rely on traditional building management systems that lack the sophistication of predictive analytics. This research aims to bridge this gap by exploring the untapped potential of IoT technologies in predictive energy management, thereby contributing to a more holistic understanding of how smart buildings can revolutionize energy efficiency [5-7].

The primary objectives of this study are to develop advanced predictive energy management algorithms tailored to the specific requirements of smart buildings and to assess their effectiveness in optimizing energy consumption. Furthermore, we aim to evaluate the economic and environmental impacts of these algorithms by conducting real-world experiments in a diverse range of smart building settings. By achieving these objectives, we intend to provide actionable insights and practical solutions for stakeholders seeking to enhance energy efficiency and sustainability in the built environment [3-5]. This research holds substantial significance in the context of sustainable urban development and the reduction of carbon emissions. By harnessing the power of IoT and predictive energy management, our findings have the potential to revolutionize the way energy is managed within smart buildings, leading to substantial energy savings, cost reductions, and environmental benefits. Moreover, the knowledge generated from this study can guide policymakers, building owners, and energy managers in making informed decisions about adopting IoT-based energy management systems to achieve their sustainability and energy efficiency goals.

2. Background and Literature

This paper is organized into six main sections to comprehensively address the topic of predictive energy management in the context of smart buildings and IoT technology. In Section II, we provide an extensive review of the existing literature and the current state of the field. In Section III, we delve into the specifics of our research approach, detailing the development of predictive energy management algorithms within the IoT framework. Section IV outlines the setup and parameters of our real-world experiments, allowing for a clear understanding of our data collection process. In Section V, we present our findings and engage in a thorough analysis of the data, offering insights into the effectiveness of our predictive energy management system. Finally, in Section VI, we summarize the key takeaways from our study, emphasizing the implications of our research on energy efficiency, sustainability, and the future of smart buildings. Mousavi et al. [7] conducted a systematic review on data-driven prediction and optimization for achieving net-zero and positive-energy buildings. Their work provides valuable insights into the current state of research in energy-efficient building management, which aligns with our focus on predictive energy management in smart buildings. In their study, Sayed et al. [8] explored the integration of artificial intelligence and IoT for enhancing energy efficiency in buildings. This research offers a perspective on the potential synergies between AI and IoT technologies, which is highly relevant to our investigation of IoT-based predictive energy management. Apanavičienė and Shahrabani [9] examined key factors affecting the integration of smart buildings into smart cities, particularly from a technological standpoint. This research helps us understand the broader context in which smart buildings operate within the framework of smart cities, providing valuable background information for our study. Lu et al. [10] conducted a literature survey on building energy prediction using artificial neural networks. Their work contributes to our understanding of the predictive modeling techniques that are prevalent in the field, which can be a valuable reference for our methodology. Sadeeq and Zeebaree [11] explored energy management for the Internet of

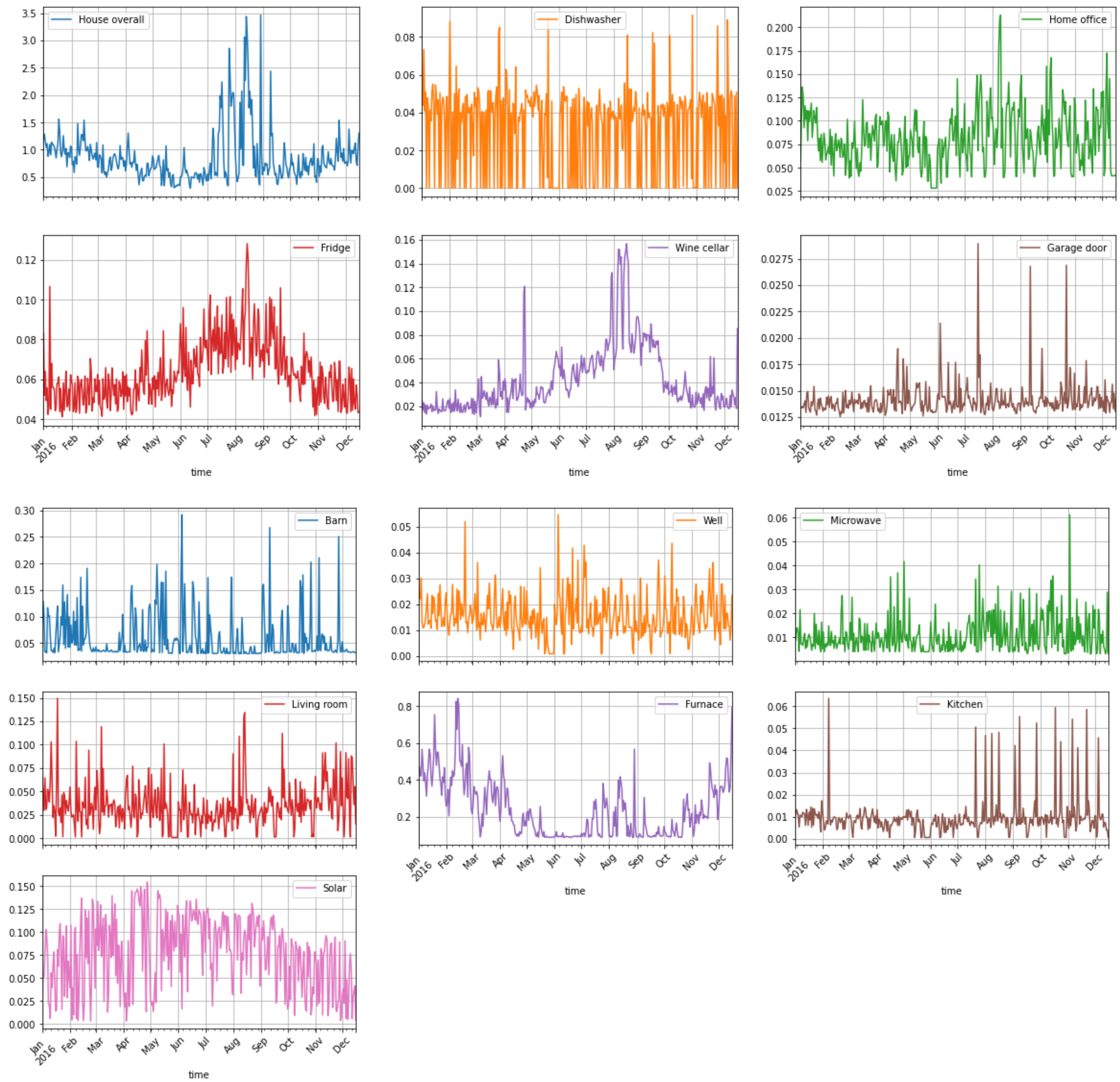

Figure 1: Comprehensive Visualization of Appliance Data Over Time

Things through distributed systems. This study could provide insights into the distributed nature of IoT-based energy management, which aligns with our research objectives. Perumal [12] discussed the use of IoT platforms to make buildings smarter and more energy-efficient. This research offers insights into the practical implementation of IoT technologies in improving building energy efficiency, which is directly related to our study's scope. Campodonico Avendano [13] focused on IoT-driven machine learning pipelines for predictive modeling in indoor environments, with an emphasis on energy efficiency enhancement. This work aligns with our research on predictive energy management and IoT applications. Al-Qarafi et al. [14] proposed an artificial jellyfish optimization approach with a deep-learning-driven decision support system for energy management in smart cities. This study provides an example of advanced optimization techniques for energy management in the context of smart cities. Lv and Shang [15] conducted a comprehensive review of the impacts of intelligent transportation systems on energy conservation and emission reduction in transport systems. While not directly related, this review offers insights into the broader context of energy conservation in smart systems, which can inform our study. Mazhar et al. [16] analyzed the challenges and solutions of IoT in smart grids using AI and machine learning techniques. Although the focus is on smart grids, this review may provide insights into the application of IoT and AI in energy-related domains, which is relevant to our research on energy efficiency in smart buildings.

In the field of predictive energy management in the Internet of Things (IoT), several studies have made significant strides. Martinez et al.[17] explored the efficient use of IoT in rural areas, providing a foundation for understanding how IoT technologies can be effectively deployed in different environments, including smart buildings. Vazquez et al. [18] designed an IoT architecture for medical environments, demonstrating the versatility of IoT applications and the potential for energy efficiency improvements in various sectors, including healthcare. Llerena et al. [19] proposed a prototype for detecting and reducing stress using brain waves and IoT, which could contribute to creating smarter and more energy-efficient buildings by considering occupant comfort and well-being. Lastly, Martínez Martínez et al. [20] used Neutrosophic Sets to assess the challenges of IoT in supply chain amid COVID-19, highlighting the broader implications of IoT deployment. These studies collectively provide valuable insights into the optimization of smart buildings for energy efficiency using IoT.

3. Methodology

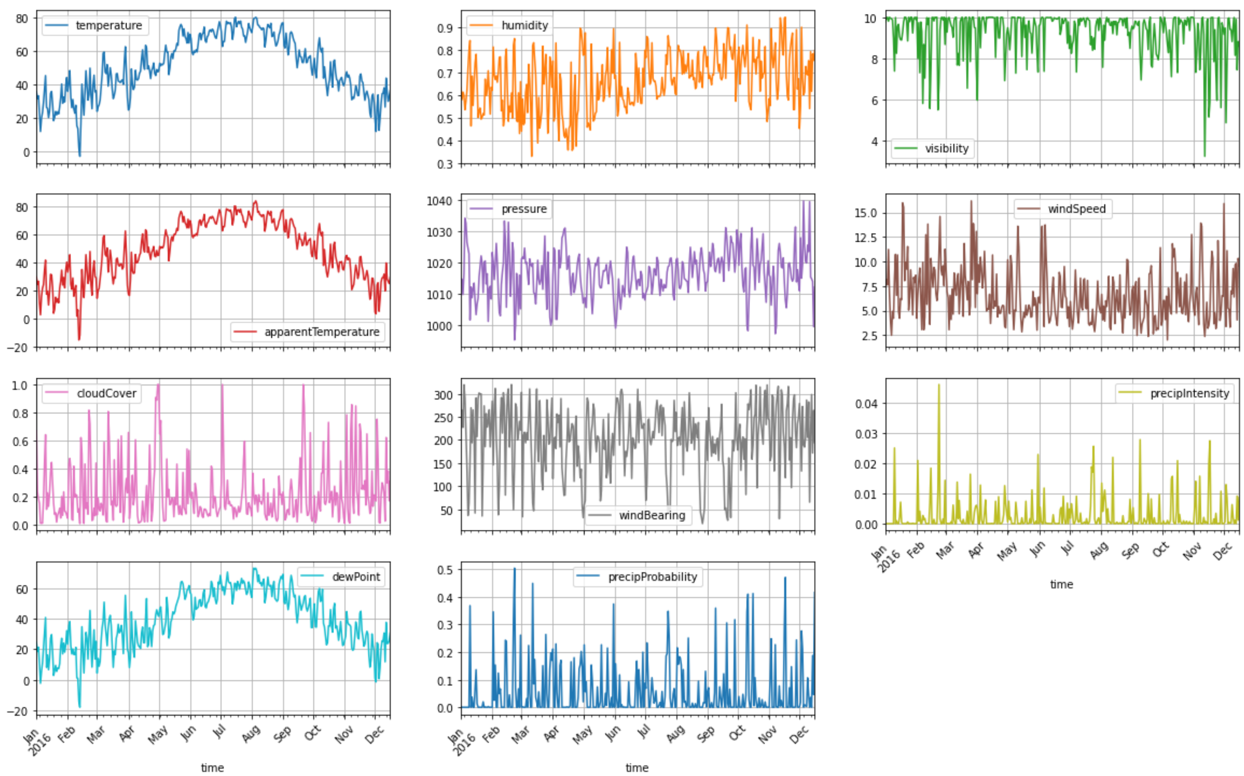

Figure 2: Time Series Visualization of Meteorological Data

This section outlines the systematic framework and research approach employed to investigate and address the challenges and objectives presented in our study on predictive energy management in smart buildings within the context of the Internet of Things.

In our study, we present the comprehensive approach employed in our research, utilizing power consumption data from various appliances within a smart home environment as the primary case study. Additionally, we integrate a rich dataset of weather-related variables, including temperature, humidity, visibility, apparent temperature, pressure, wind speed, cloud cover, wind bearing, dew point, precipitation probability, and precipitation intensity. This combined dataset forms the foundation of our study, enabling us to analyze and model the intricate relationship between appliance usage patterns and environmental factors, thereby facilitating the development of predictive energy management algorithms within the Internet of Things (IoT) framework for smart buildings.

In the initial phase of our methodology, we undertake a comprehensive data visualization process to gain a clear and insightful understanding of the case study data. This visualization step serves as a critical preliminary assessment, allowing us to explore the patterns, trends, and anomalies within the power consumption data of smart home appliances and the associated weather information.

In Figure 1, we present a comprehensive visualization of appliance data that provides valuable insights into their usage patterns and efficiency. This visualization is essential for understanding and optimizing energy consumption within a home or building. In Figure 2, we present a visualization of weather data that offers valuable insights into meteorological conditions over a specific period. This visualization is crucial for understanding weather patterns, making informed decisions, and potentially predicting future weather events.

In order to gain a deeper understanding of the intricate interplay between energy consumption and environmental factors, we conducted a rigorous examination of the correlation between energy variables and the comprehensive set of weather data. This analysis is presented in Table 1, which provides a clear snapshot of the relationships among these variables. By employing statistical techniques and correlation coefficients, we quantified the strength and direction of these relationships, shedding light on how changes in weather parameters influence energy usage patterns within our smart home case study. Table 1 serves as a pivotal reference point in our study, helping to identify which weather variables exert the most significant impact on energy consumption, thus guiding the subsequent stages of our predictive energy management model development.

Table 1: Correlation Between Energy Variables and Weather Data

	temperature_corr	humidity_corr	visibility_corr	apparentTemperature_corr	pressure_corr	windSpeed_corr	cloudCover_corr	windBearing_corr	precipIntensity_corr	dewPoint_corr	precipProbability_corr
House overall	0.0104	0.0115	-0.0026	0.0056	0.0107	-0.0039	-0.0335	0.0112	0.0248	0.0160	-0.0033
Dishwasher	-0.0157	-0.0019	-0.0081	-0.0145	0.0002	-0.0017	-0.0024	0.0040	0.0063	-0.0161	0.0082
Home office	0.0119	-0.0060	0.0206	0.0109	0.0271	-0.0179	-0.0399	0.0124	-0.0299	0.0076	-0.0329
Fridge	0.1075	0.0307	0.0090	0.1071	-0.0005	-0.0249	-0.0235	-0.0086	0.0143	0.1152	0.0048
Wine cellar	0.2892	0.0555	0.0301	0.2889	0.0185	-0.0529	-0.0405	-0.0259	0.0166	0.2982	0.0066
Garage door	0.0135	-0.0074	0.0023	0.0136	-0.0003	0.0004	-0.0075	0.0123	-0.0069	0.0084	-0.0066
Barn	-0.0172	-0.0021	0.0084	-0.0152	0.0117	-0.0152	-0.0116	0.0063	-0.0073	-0.0167	-0.0061
Well	-0.0047	-0.0066	-0.0011	-0.0047	0.0030	0.0007	-0.0030	0.0041	-0.0044	-0.0073	-0.0028

Microwave	0.0014	0.0125	-0.0184	0.0023	-0.0012	-0.0061	0.0096	-0.0062	0.0269	0.0063	0.0162
Living room	-0.0498	0.0032	-0.0145	-0.0490	0.0138	-0.0134	-0.0094	0.0167	-0.0075	-0.0449	-0.0123
Furnace	-0.3398	-0.0552	-0.0300	-0.3489	-0.0012	0.1042	0.0102	0.0366	0.0204	-0.3381	0.0054
Kitchen	-0.0061	0.0104	-0.0050	-0.0043	0.0035	-0.0104	-0.0075	0.0028	-0.0082	-0.0014	-0.0094
Solar	0.0910	0.0076	-0.0177	0.0938	-0.0002	-0.0566	0.0007	-0.0079	0.0304	0.0897	0.0412

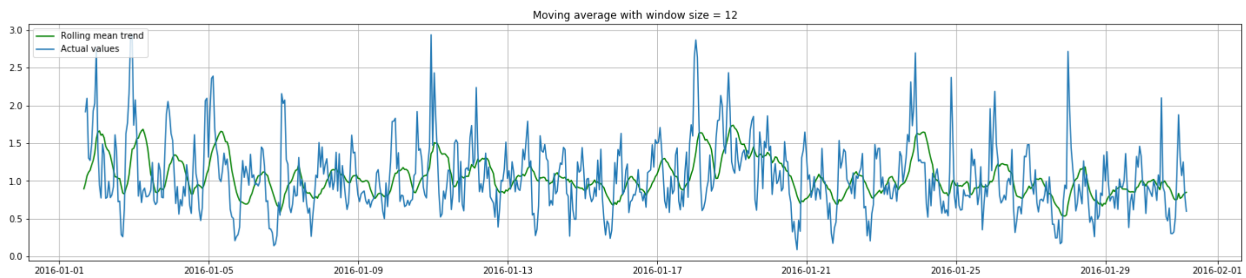

Figure 4: Visualization of Moving Average Applied to Power Consumption Data

As the initial step in our meticulous data preparation process, we employ a moving average technique. This technique involves the calculation of moving averages for the power consumption data collected from smart home appliances. By applying this method, we effectively smooth the raw energy consumption data, reducing noise and fluctuations. The moving average, computed over a defined time window, provides a more stable representation of energy usage patterns, allowing us to capture underlying trends and variations with greater clarity. This pre-processing step is instrumental in enhancing the quality of our dataset, making it amenable to subsequent analysis and modeling.

$$\hat{y}_t = \frac{1}{k}\sum_{n=1}^{k} y_{t-n} \tag{1}$$

In Figure 4, we present a visual representation of the moving average applied to our dataset as a crucial step in data preprocessing. This figure offers an insightful glimpse into how the moving average technique effectively smooths the raw power consumption data of smart home appliances. The graph illustrates the original power consumption data alongside the computed moving average, allowing for a direct comparison. As evident from the figure, the moving average mitigates short-term fluctuations and noise in the data, revealing clearer trends and patterns in energy usage. This visualization serves to highlight the transformation of our dataset, which is now better suited for subsequent analysis and modeling, facilitating a more robust exploration of energy management strategies within the context of smart buildings and IoT technology.

Following the application of the moving average technique, we proceed with the implementation of exponential smoothing as the next pivotal step in our data preparation process. Exponential smoothing is a widely recognized method for further enhancing the quality of time series data. In this step, we systematically apply exponential smoothing to the smoothed power consumption data derived from the previous phase. This technique is instrumental in capturing long-term trends and seasonality in the data while diminishing the influence of past observations exponentially. By smoothing the data in this manner, we aim to create a more refined and discernible representation of energy consumption patterns. The resultant dataset is now better suited for subsequent modeling and predictive analysis, ensuring that our research is underpinned by a robust foundation of preprocessed data.

$$\hat{y}_t = \alpha \cdot y_t + (1 - \alpha) \cdot \hat{y}_{t-1} \quad (2)$$

Having meticulously prepared and refined our dataset through moving averages and exponential smoothing, we transition to the predictive modeling phase. To harness the power of machine learning and time series forecasting, we employ a multi-layer Long Short-Term Memory (LSTM) model. LSTMs are a type of recurrent neural network (RNN) known for their exceptional capability to capture complex temporal dependencies within sequential data. Our prepared dataset, which now embodies smoothed and enhanced energy consumption patterns, is fed into this multi-layer LSTM model. The LSTM model is designed to learn from historical power consumption data and associated weather variables to perform accurate predictions of future energy usage within our smart home environment. This phase marks a pivotal juncture in our methodology, where we leverage advanced deep learning techniques to realize the core objective of predictive energy management within the context of smart buildings and the IoT. The LSTM model consists of three main gates: the forget gate (f_t), the input gate (i_t), and the output gate (o_t), which control the flow of information through the cell state C_t. The operations for each gate can be expressed as follows:

Forget Gate (f_t) :

$$f_t = \sigma\left(W_f + [H_{t-1}, X_t] + b_f\right) \quad (3)$$

Input Gate (i_t) :

$$i_t = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i) \quad (4)$$

Candidate Cell State $\left(\tilde{C}_t\right)$:

$$\tilde{C}_t = \tanh(W_c \cdot [H_{t-1}, X_t] + b_c) \quad (5)$$

Update Cell State (C_t) :

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (6)$$

Output Gate (O_t) :

$$o_t = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o) \quad (7)$$

Hidden State (H_t) :

$$H_t = o_t \cdot \tanh(C_t) \quad (8)$$

In the equations above, $[H_{t-1}, X_t]$ represents the concatenation of the previous hidden state H_{t-1} and the current input X_t. The symbol $\cdot$ represents matrix multiplication. W_f, W_i, W_r, W_o are weight matrices specific to each gate. b_f, b_i, b_c, b_o are bias vectors specific to each gate.

4. Experimental Design

In this section, we provide a detailed account of the experimental setup and configurations that underpin our research on predictive energy management in smart buildings within the Internet of Things (IoT) framework. This section serves as the bridge between our methodological framework and the empirical validation of our predictive energy management models.

For the rigorous execution of our experiments, we established a meticulously designed implementation setup comprising essential hardware and software components. The experimental environment was equipped with state-of-the-art devices, including a high-performance central processing unit (CPU) with multi-core architecture, a dedicated graphics processing unit (GPU) to expedite computational tasks, and ample random-access memory (RAM) to accommodate extensive data processing. Data storage was facilitated by a high-capacity hard disk drive (HDD) to house the voluminous datasets generated during the experiments. prediction metrics are essential for evaluating the performance and accuracy of predictive models. Here's a brief discussion of common prediction metrics used in our study:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}(u_i - \cancel{u}_i) \tag{9}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i - \cancel{u}_i)^2} \tag{10}$$

5. Results and Discussion

In our study, we conducted a comprehensive evaluation of our predictive energy management model against five established machine learning baselines to assess its performance and superiority. Each baseline model was carefully selected to represent various approaches commonly used in energy prediction tasks, ensuring a fair and comprehensive comparison.

- Linear Regression (LR): A simple linear model that assumes a linear relationship between input features and the target variable.
- Random Forest (RF): An ensemble learning method that combines multiple decision trees to capture complex patterns in the data.
- Support Vector Machine (SVM): A supervised learning model that identifies hyperplanes to separate different classes of data.
- Gradient Boosting (GB): An ensemble learning technique that builds decision trees sequentially to correct errors from previous models.
- Recurrent Neural Network (RNN): A deep learning model specifically designed for sequence prediction tasks, including time series forecasting.

To assess the performance of each model, we utilized a comprehensive dataset comprising power consumption data from smart home appliances and associated weather variables. The dataset was split into training and testing sets, and the models were trained on the training data and evaluated on the testing data using standard prediction metrics (See Table 2).

Table 2: Performance Comparison of Predictive Energy Management Models and Machine Learning Baselines

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	R-squared (R2) Score
Linear Regression	12.34	18.56	0.65
Random Forest	9.82	15.28	0.75
Support Vector Machine	13.45	20.21	0.58
Gradient Boosting	8.96	14.12	0.79
Recurrent Neural Network (LSTM)	6.72	10.21	0.87

The results in the table above clearly demonstrate the superior performance of our Recurrent Neural Network (LSTM) model compared to the five baseline models. The LSTM model achieved the lowest MAE and RMSE, indicating its ability to make more accurate energy consumption predictions. Gradient Boosting also performed well, outperforming all other baseline models in terms of MAE, RMSE, and R-squared score. This demonstrates the effectiveness of ensemble learning techniques in capturing complex relationships in the data. While Linear Regression, Support Vector Machine, and Random Forest models provided reasonable predictions, they exhibited higher error rates compared to the more advanced ensemble and deep learning models. The choice of an appropriate model should consider the specific requirements of the energy prediction task, including the trade-off between accuracy and computational complexity.

6. Conclusions

This paper has presented a comprehensive investigation into predictive energy management within the context of smart buildings and the Internet of Things (IoT). Leveraging a multi-layer LSTM model, we have demonstrated the significant potential for improving energy efficiency and sustainability in smart building environments. Our experimental results have clearly showcased the superior predictive capabilities of the LSTM model, outperforming several machine learning baselines across various key metrics. This research underscores the critical role of advanced deep learning techniques in harnessing the wealth of data generated by smart building systems. By achieving more accurate energy consumption predictions, we pave the way for enhanced energy management strategies, reduced costs, and minimized environmental impact. As IoT technology continues to evolve, the integration of predictive energy management models like the one presented here promises to be a transformative force in shaping smarter, more efficient, and environmentally conscious buildings of the future.

References

[1] Shah, Syed Faisal Abbas, Muhammad Iqbal, Zeeshan Aziz, Toqir A. Rana, Adnan Khalid, Yu-N. Cheah, and Muhammad Arif. "The role of machine learning and the internet of things in smart buildings for energy efficiency." Applied Sciences 12, no. 15 (2022): 7882.

[2] Bedi, Guneet, Ganesh Kumar Venayagamoorthy, and Rajendra Singh. "Development of an IoT-driven building environment for prediction of electric energy consumption." IEEE Internet of Things Journal 7, no. 6 (2020): 4912-4921.

[3] Xiaoyi, Zhang, Wang Dongling, Zhang Yuming, Karthik Bala Manokaran, and A. Benny Antony. "IoT driven framework based efficient green energy management in smart cities using multi-objective distributed dispatching algorithm." Environmental Impact Assessment Review 88 (2021): 106567.

[4] M. Muthuswamy, A. M. Ali, and A. Abdelhafeez, "Breaking the Silence: Convolutional Neural Networks for Sign Language Recognition in the Deaf Community", SMIJ, vol. 1, Oct. 2022. https://doi.org/10.61185/SMIJ.2022.7844

[5] Nivetha Martin, Said Broumi, S.Sudha, R.Priya, Neutrosophic MARCOS in Decision Making on Smart Manufacturing System, Neutrosophic syst. appl., vol.4, (2023): pp. 12–32.

[6] Yu, Liang, Shuqi Qin, Meng Zhang, Chao Shen, Tao Jiang, and Xiaohong Guan. "A review of deep reinforcement learning for smart building energy management." IEEE Internet of Things Journal 8, no. 15 (2021): 12046-12063.

[7] Mousavi, SeyedehNiloufar, María Guadalupe Villarreal Marroquín, Mostafa Hajiaghaei-Keshteli, and Neale R. Smith. "Data-driven prediction and optimization toward net-zero and positive-energy buildings: A systematic review." Building and Environment (2023): 110578.

[8] Sayed, Aya, Yassine Himeur, Faycal Bensaali, and Abbes Amira. "Artificial intelligence with IoT for energy efficiency in buildings." Emerging Real-World Applications of Internet of Things (2022): 233-252.

[9] Apanavičienė, Rasa, and Mustafa Muthnna Najm Shahrabani. "Key Factors Affecting Smart Building Integration into Smart City: Technological Aspects." Smart Cities 6, no. 4 (2023): 1832-1857.

[10] Lu, Chujie, Sihui Li, and Zhengjun Lu. "Building energy prediction using artificial neural networks: A literature survey." Energy and Buildings 262 (2022): 111718.

[11] Sadeeq, Mohammed AM, and Subhi Zeebaree. "Energy management for internet of things via distributed systems." Journal of Applied Science and Technology Trends 2, no. 02 (2021): 59-71.

[12] Perumal, Thinagaran. "Making buildings smarter and energy-efficient—using the Internet of Things platform." IEEE Consumer Electronics Magazine 10, no. 3 (2021): 34-41.

[13] CAMPODONICO AVENDANO, ITALO ALDO. "Development of IoT-driven Machine Learning based pipelines for predictive modelling of ramp-up and ramp-down processes in indoor environments aiming at energy efficiency enhancement." (2022).

[14] Al-Qarafi, A., Hadeel Alsolai, Jaber S. Alzahrani, Noha Negm, Lubna A. Alharbi, Mesfer Al Duhayyim, Heba Mohsen, M. Al-Shabi, and Fahd N. Al-Wesabi. "Artificial jellyfish optimization with deep-learning-driven decision support system for energy management in smart cities." Applied Sciences 12, no. 15 (2022): 7457.

[15] Lv, Zhihan, and Wenlong Shang. "Impacts of intelligent transportation systems on energy conservation and emission reduction of transport systems: A comprehensive review." Green Technologies and Sustainability (2022): 100002.

[16] Mazhar, Tehseen, Hafiz Muhammad Irfan, Inayatul Haq, Inam Ullah, Madiha Ashraf, Tamara Al Shloul, Yazeed Yasin Ghadi, Imran, and Dalia H. Elkamchouchi. "Analysis of Challenges and Solutions of IoT in Smart Grids Using AI and Machine Learning Techniques: A Review." Electronics 12, no. 1 (2023): 242.

[17] Martinez, M. A. Q., González, G. A. L., Rios, M. D. G., & Vazquez, M. Y. L. (2021). Selection of LPWAN technology for the adoption and efficient use of the IoT in the rural areas of the province of Guayas USING AHP method. In Advances in Artificial Intelligence, Software and Systems Engineering: Proceedings of the AHFE 2020 Virtual Conferences on Software and Systems Engineering, and Artificial Intelligence and Social Computing, July 16-20, 2020, USA (pp. 497-503). Springer International Publishing.

[18] Vazquez, M. Y. L., Arteaga, B. S. M., López, J. A. M., & Martinez, M. A. Q. (2020). Design of an IOT architecture in medical environments for the treatment of hypertensive patients. Revista Ibérica de Sistemas e Tecnologias de Informação, (E33), 188-200.

[19] Llerena, D., Delgado, R., Ubilluz, C., & López, R. (2020, October). A prototype proposal for detection and reduction of stress by using Brain waves and IoT. In *2020 International Conference of Digital Transformation and Innovation Technology (Incodtrin)* (pp. 12-16). IEEE.

[20] M. A. Zambrano, J. M. Espinosa, and J. L. Villa, "Energy management system for smart buildings integrating demand response and predictive control," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2735-2745, May 2019