AI-IoT based Smart Energy System for Multi-Unit Residential Buildings

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ABSTRACT
The growing electricity demand, coupled with challenges such as energy wastage, biased billing in multi-unit buildings, and the absence of adequate predictive energy management, necessitates intelligent solutions. This paper presented the development of a smart energy system tailored for multi-unit residential buildings. By integrating IoT technology with a trained LSTM machine learning model, the system enabled real-time energy monitoring, control, and hourly prediction of energy consumption. Core components include dual PZEM004T sensors, an ESP32 microcontroller, a keypad, an LCD, and relays, all managed via the Blynk IoT platform. The system performed key functions such as threshold-based relay switching, overvoltage and overcurrent protection, and AI-powered forecasting. Results demonstrated high accuracy in monitoring, responsive control through local and remote interfaces, and effective prediction with a low Mean Squared Error (MSE) of 0.0229. The solution ensured fair energy billing, reduced waste, and supported sustainable energy practices.

General Terms
Artificial Intelligence, Internet of Things, Smart Energy Meter, Residential Buildings.

Keywords
ESP 32, Blynk, Machine Learning, Long Short-Term Memory, Energy Prediction, Energy Management.

1. INTRODUCTION
The steady rise in electricity demand has become a major challenge for the power systems sector in recent years. Increased energy use harms the environment and climate because it often involves burning large amounts of fossil fuels. As a result, saving and reducing energy use directly affect both the economy and the environment [1]. People often leave their appliances turned on when they are not being used, which leads to unnecessary energy waste. This common behavior can cause higher electricity bills and waste important energy resources. It can also shorten the lifespan of appliances [2]. It is also difficult to accurately measure the electrical energy usage of different sections in a multi-unit residential building comprising many households, which leads to a bias when purchasing electricity units from electricity distribution companies.

This study incorporates Artificial Intelligence (AI) into the Internet of Things (IoT) system to produce a smart system that is capable of monitoring, controlling, and forecasting energy consumption in a multi-unit residential building. In the development, a few hardware components, including the Blynk IoT platform, are utilized along with a suitable machine learning model. This marks a significant advancement in energy efficiency and informed decision-making by allowing users to remotely monitor and control their energy usage via Blynk, an integrated web server and mobile application with a user-friendly interface. View the next hour's energy usage predicted by a trained Long Short-Term Memory (LSTM) ML model wrapped in a Flask-based Representational State Transfer Application Programming Interface (RESTful API).

The rise of the Internet of Things (IoT) has greatly changed how people manage energy by making it possible to use smart meters widely. These meters are capable of monitoring real-time energy consumption, voltage levels, and power quality [3]. Adding Artificial Intelligence (AI) to energy system management is a big step forward, helping to make energy use more efficient, eco-friendly, and smarter for better decisions [4].

The importance of this research resides in its prospective impact to offer a solution to the problem of energy, funds, and revenue wastage, environmental repercussions due to the combustion of substantial quantities of fossil fuels, and bias amongst households living in the same residential building when purchasing electricity units. Aside from this, one of the interesting aspects of the project is the integration of an AI predictive energy consumption model, and energy use can be monitored from any location worldwide, using the internet.

1.1 Internet of Things
The Internet of Things (IoT) refers to a network of physical devices embedded with electronics, software, and sensors, enabling them to collect and exchange data. These objects can be monitored and controlled remotely through the internet, helping connect the physical world with digital systems. This connection improves how accurately and efficiently tasks are done [5].

1.2 Artificial Intelligence Forecasting
Artificial Intelligence (AI) is the capability of machines to mimic human reasoning and actions. One of the most powerful AI methods today is machine learning, especially deep learning, which allows systems to learn and make decisions from collected data without being manually programmed. Recent research has made great progress in using AI and statistical models for predicting energy use. Some of the commonly used models include Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Linear Regression (LR), Multi-Layer Perceptron (MLP), and ARIMA. Among these, LSTM has shown the best results, with a forecasting accuracy of 97% and strong performance in detecting unusual patterns [6].

1.3 Multi-Unit Residential Buildings
A single building or a complex of buildings may contain two or more separate living spaces, designed for multiple households, families, or tenants. Thus, inhabited by more than one household with unique livelihoods according to their income, a variety of electrical appliances with different power consumption may be possessed [7].

2. REVIEW OF PAST WORKS

Msimbe et al. (2022) [7] proposed an IoT-based smart energy monitoring system that tracks real-time power consumption of individual tenants in rental houses in Tanzania. It provides daily usage updates via a mobile application, even during power outages, thanks to a backup battery. Core features included voltage regulation, overload protection, remote operation, data logging, and real-time online monitoring. The system empowers tenants to manage energy use better, budget effectively, and reduce waste by identifying unused or inefficient appliances. However, this system does not feature an energy prediction system.

Ali et al. (2023) [8] developed an IoT-based intelligent energy monitoring system using the ESP32 module. The system measures key electrical parameters, which include current, voltage, power, power factor, energy, and unit consumption in real time and across various time intervals (hourly, weekly, monthly). Data is transmitted via Wi-Fi to the cloud and displayed through an Android application. Beyond real-time visualization, the app integrates machine learning models (ARIMA, Prophet, LSTM) for forecasting future energy consumption. Among these, the LSTM model proves to be the most accurate for time-series prediction of unit consumption. However, the machine learning models were trained with a small parameter dataset, which reduced prediction accuracy.

Hettiarachchi et al. (2021) [9] proposed an IoT-based energy management system integrated with the XGBoost machine learning model to accurately forecast electricity usage. The system includes a central dashboard that connects to a NodeMCU device and a cloud database for data collection and analysis. It monitors plug loads and air conditioners and provides real-time occupancy information to help building managers make informed decisions. The system gathers electricity consumption, weather, and time data every minute, and uses XGBoost for its superior forecasting accuracy compared to other models. However, the developed system does not include real-time energy control capabilities.

Essa et al. (2023) [10] designed a smart Building Management System (BMS) for an educational lab using IoT and AI to enhance energy efficiency. The system integrates Siemens PLC, Arduino Mega 2560, and NodeMCU ESP8266 to monitor and control temperature, humidity, motion, smoke, and air quality sensors via Wi-Fi, using ThingSpeak and Blynk for real-time visualization and remote access. An Artificial Neural Network (ANN) forecasts indoor temperature, helping manage HVAC, lighting, ventilation, and fire-fighting systems. However, the prototype demonstrated reliability in reducing energy use but does not incorporate voltage and current sensing.

Starace et al. (2022) [11] developed a low-cost, modular IoT-based system for monitoring energy and indoor air quality in public buildings. Using open-source tools, it collects real-time data via room-installed sensors and supports cloud-edge processing. LSTM was reported to outperform SARIMA for energy forecasting, and the system enables predictive analytics, integration with other modules, and improved occupant wellness. Though effective under the D-SySCOM project, the system lacks real-time energy control features.

3. METHODOLOGY

3.1 Overview of Developed System

The methodology adopted in this study involves both hardware and software approaches towards the design and development of the proposed smart energy monitoring and prediction system for residential buildings. The system comprises hardware components, embedded firmware development on the ESP32 microcontroller, cloud-based IoT integration via Blynk, a custom-trained LSTM machine learning model, and a Flask-based API for AI predictions. Figure 1 illustrates the developed system in blocks.

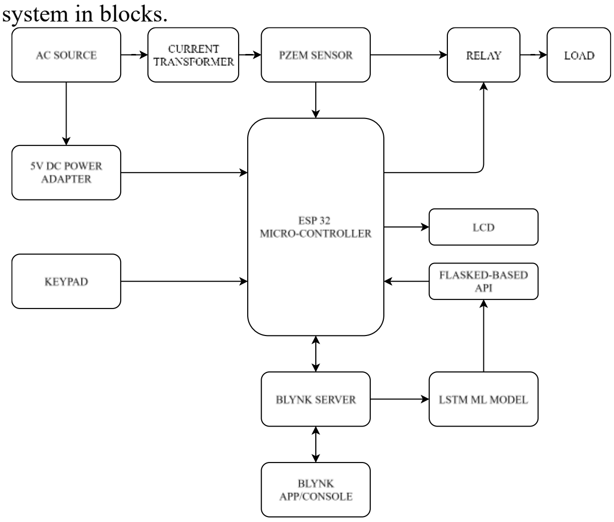


Figure 1: Block diagram of the developed system.

3.2 Hardware and Software Implementation

The architecture consists of sensors in individual building units, a central ESP32 controller, cloud communication using Wi-Fi, an AI-powered prediction API, and a web/mobile interface. Each unit was equipped with a PZEM-004T sensor to measure real-time electrical parameters: voltage (V), current (A), active power (W), and energy consumption (kWh). These readings were processed by the ESP32, which also controlled the power supply to each unit via relays.

Current is denoted as I measured in Amperes (A), voltage is denoted by V measured in Volts (V), while the power factor is written as $cos\ \phi$ where ϕ is the phase difference between the voltage and current waveforms. Then the associated power P in Watt (W) is given by;

$$P = IV\ cos\ \phi \qquad (1)$$

while the corresponding energy (E) in kilowatt-hours (Kwh) is expressible as;

$$E = P \times t \qquad (2)$$

The hardware components used include: an ESP32 microcontroller, which serves as the central processing and communication hub. Two units of PZEM-004T sensor for dual-channel energy metering. 4x4 Matrix Keypad to enable user interaction for resetting energy readings, setting thresholds, and toggling power ON and OFF.

An I2C Liquid Crystal Display (LCD) to provide local visual feedback of readings. 5V 2-Channel Relay used for controlling the power supply to individual units based on user input. 5V DC Power Adapter for converting the AC supply voltage to 5V DC required for the ESP32 and other electronics components. Figure 2-7 depicts some of the important components employed in the development of the proposed smart energy metering system.

Figure 2: ESP32 Microcontroller [12].

Figure 3: PZEM-004T Sensor [13]

Figure 4: I2C Liquid Crystal Display [14].

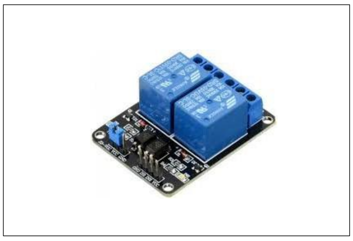


Figure 5: 5V Two-Channel Relay [15].

Figure 6: 4x4 Matrix Keypad [16].

Figure 7: 5V DC Power Adapter [17].

All these hardware components were connected by correctly joining the right terminals. For this project, signals were taken from two building units. Hence, 2 units of PZEM-004T sensors and a 5V Two-Channel Relay were used. Figure 8 depicts the schematic diagram of the developed system. The ESP32 firmware was developed using C++ on the Arduino Integrated Development Environment (IDE) framework. The developed system can work in three different modes: monitoring, control, and prediction. Figure 9 illustrates the flowcharts describing each of the three operating modes.

3.3 Machine Learning Model Development

A Long Short-Term Memory (LSTM) model was developed and trained using historical energy consumption data. The training data came from a public dataset on Mendeley Data titled “8 years of hourly heating and electricity consumption data - a residential building”. This dataset covers the period from December 2010 to November 2018, with readings taken every hour, totaling 70,160 data points [18].

The LSTM model training begins by setting a fixed random seed across Python, NumPy, and TensorFlow to ensure reproducibility. Essential libraries for data processing, visualization, and deep learning are imported. The dataset is loaded from a CSV file, and the datetime column is parsed to extract temporal features (hour, day of week, month), which are useful for modeling time-based energy patterns. Missing values were filled using column-wise means, and feature normalization is applied using MinMaxScaler to scale values between 0 and 1. A 24-hour sliding window is then used to generate input sequences, with each input predicting the energy usage of the next hour. The data is split into training (75%) and testing (25%) sets while preserving time order.

The LSTM architecture includes one LSTM layer (64 units), followed by dense layers with ReLU activation and dropout for regularization. The model uses MSE as the loss function and the Adam optimizer with a low learning rate. It is trained for 52 epochs with a batch size of 256 and uses early stopping to avoid over-fitting. Model performance is tracked using loss visualizations, and the final trained model is saved as model.h5 for deployment.

The trained LSTM model was wrapped in a Flask-based Representational State Transfer Application Programming Interface (RESTful API) hosted on Render. The API accepts a JavaScript Object Notation (JSON) payload containing 24-hour sequence data and returns a normalized prediction.

Mean Squared Error is denoted by MSE, Root Mean Squared Error by RMSE, Mean Absolute Error by MAE, and Coefficient of Determination by R^2.

$$MSE = \frac{\sum(y_i - \hat{y}_i)^2}{n} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \tag{4}$$

$$MAE = \frac{\sum|y_i - \hat{y}_i|}{n} \tag{5}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{6}$$

Where: n = number of samples, y_i = actual value, $\bar{y}$= mean of actual values, $\hat{y}_i$= predicted value.

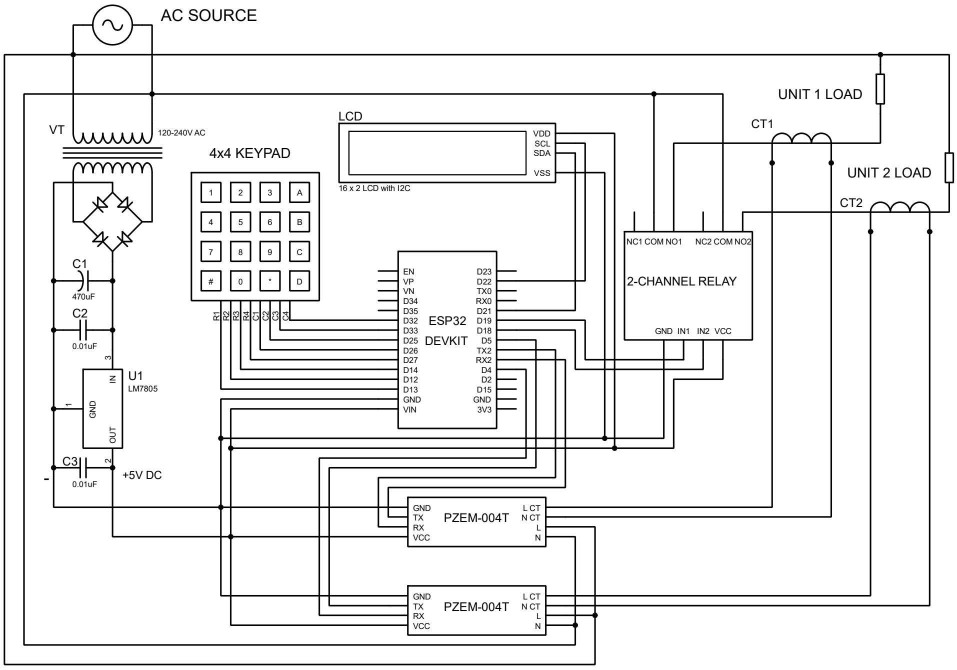


Figure 8: Schematic diagram of the developed system.

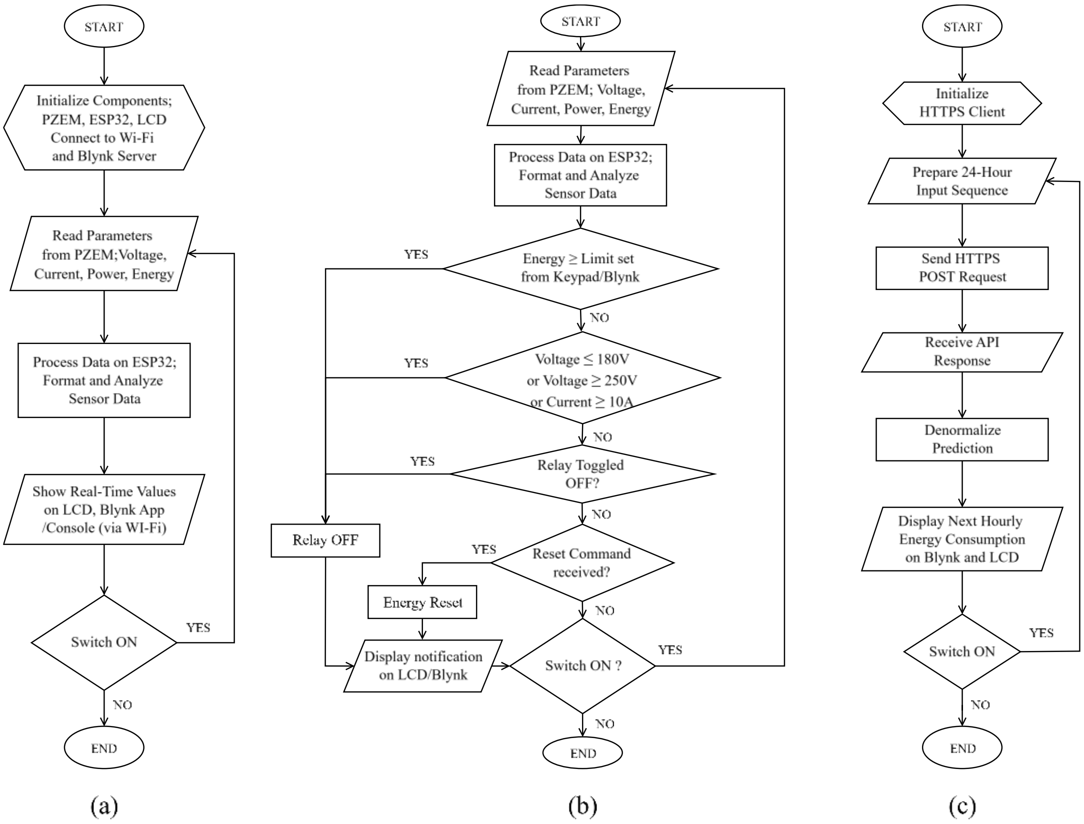


Figure 9: Flow charts of the system operating modes (a) monitoring, (b) control, (c) prediction

Figure 10 presents variations of both training and validation losses with epochs (number of iterations).

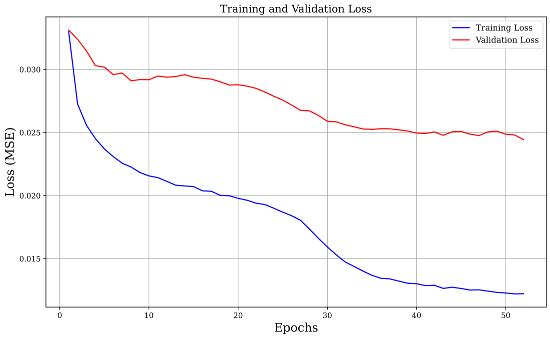


Figure 10: Graph of loss during training of the energy prediction model. The horizontal axis shows the number of training iterations, while the vertical axis represents the model loss

4. RESULTS AND DISCUSSION

4.1 Assembled Prototype of the Developed System

The assembled prototype of the developed AI-IoT smart energy system is depicted in Figure 11.

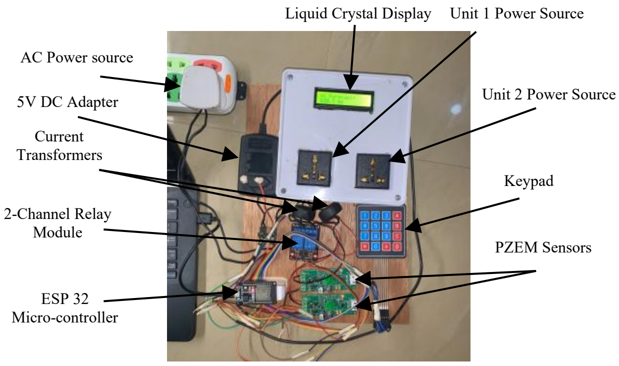


Figure 11: Prototype of the developed system.

4.2 Performance Evaluation

4.2.1 Metering Accuracy

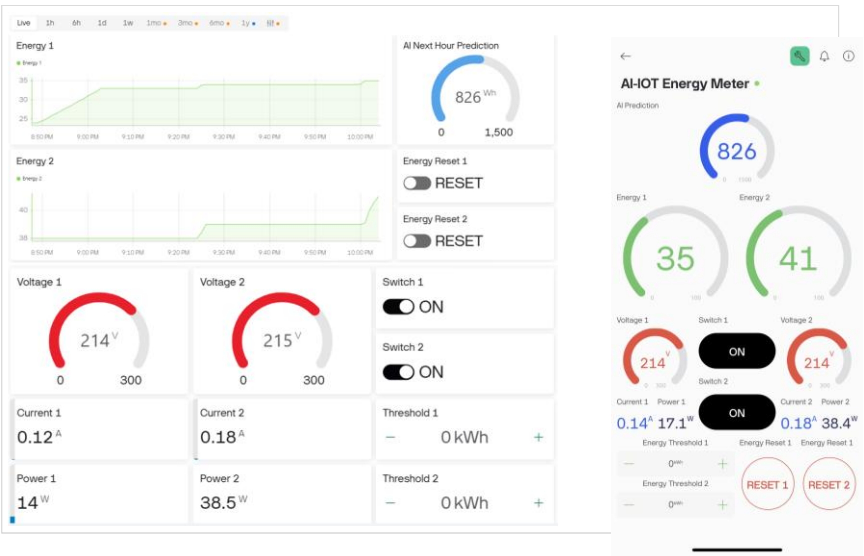
The monitoring operating mode of the developed system was tested by evaluating its real-time metering accuracy. It was validated with a multimeter. However, the multimeter used could only take voltage and current readings. Domestic loads such as a 10 W bulb, a laptop, and a soldering iron were used for evaluation. It was expected that the system would display current, voltage, power, and energy consumption of two building units each. Measurements were displayed on the LCD and Blynk mobile/web console at five-second intervals. The average percentage error across measurements was low. Unit 1 and Unit 2 produced an average absolute error of 2.84% and 3.69%, corresponding to reported accuracy of 97.16% and 96.31%, respectively. These results indicate that the prototype provides sufficiently accurate readings for residential monitoring applications. Shown in Figure 12 are snapshots of the Blynk webpage and application interface of the developed system, while Table 1 presents a summary of readings taken by the developed system and the multimeter.

4.2.2 Control Performance and Protection

The control operating mode of the system, consisting of relays, a keypad, and Blynk virtual switches, was put to various switching and protection tests as follows:

(1) Manual Switching: The relay was manually controlled to switch a unit ON or OFF. Pressing the "A" button on the keypad toggles Unit 1, while the "B" button controls Unit 2.

(2) Automatic Switching: The system automatically disconnects the power supply when energy consumption exceeds a predefined kWh limit. This limit can be set using the Blynk console or initialized through the "C" and "D" keypad buttons. Testing confirmed that the system effectively cuts off power via the relay once the limit is reached.



(a) **(b)**

Figure 12: Testing of the developed smart energy meter, screenshot of (a) Blynk webpage, (b) Blynk application interface.

Table 1: AI-IoT Smart Energy Meter metering accuracy evaluation.

LOAD	DATA	UNIT 1			UNIT 2		
		AI-IOT	Multi-meter	|Error (%)|	AI-IOT	Multi-meter	|Error (%)|
10W Bulb	Voltage (V)	216	207	4.34	215	207	3.86
	Current (A)	0.02	0.02	0	0.02	0.02	0
Laptop	Voltage (V)	216	207	4.34	216	207	4.34
	Current (A)	0.26	0.25	4	0.23	0.21	9.52
Soldering Iron	Voltage (V)	215	206	4.37	215	206	4.43
	Current (A)	0.16	0.16	0	0.14	0.14	0
Accuracy (%)		Average |Error (%)| = 2.84 Accuracy = 100 – 2.84 = 97.16%			Average |Error (%)| = 3.69 Accuracy = 100 – 3.69 = 96.31%		

(3) Remote Switching: An LED bulb was used to test the Blynk app's relay control feature. As expected, tapping the switch icon toggled the unit's state, turning the bulb ON and OFF accordingly, confirming successful remote operation.

(4) Voltage and Current Protection: For overcurrent protection, simulated current values were fed into the ESP32, and power was successfully cut off when the current reached or exceeded 10A. Similarly, during the voltage protection test, the system disconnected the power when simulated voltages fell outside the safe range of 180–250V, confirming proper voltage and current protection functionality.

(5) Energy Reset: The energy count can be reset to 0 kWh using the Blynk console or the "#" and "*" keypad buttons. During testing, the reset function worked successfully.

Additionally, the system provides user notifications via both the LCD and Blynk whenever a control action is performed. Tables 2 and 3 present the manual and remote switching test of the system while operating in control mode.

Table 2: Results from manual switching control of the developed system.

UNIT	AI-IOT KEYPAD	LOAD
1	"A" pressed "A" pressed again	LED Bulb 1 ON LED Bulb 1 OFF
2	"B" pressed "B" pressed again	LED Bulb 2 ON LED Bulb 2 OFF

Table 3: Results from remote switching control of the developed system.

UNIT	BLYNK APP/WEB	LOAD
1	Switch 1 ON Switch 1 OFF	LED Bulb 1 ON LED Bulb 1 OFF
2	Switch 2 ON Switch 2 OFF	LED Bulb 2 ON LED Bulb 2 OFF

4.2.3 IoT Responsiveness and Remote Accessibility

The Internet of Things system was put to a remote accessibility and responsiveness test over both 3G and 4G networks. Blynk response times were measured for switch operations and averaged between approximately 0.32 and 2.29 seconds, depending on network conditions and the operation. It can be observed that the response time of Blynk is proportional to the internet speed. The device maintained stable HTTPS communication with the prediction API and the Blynk server. The system was also tested at a very close proximity and several kilometers away from the mobile device. Remote control and telemetry functions operated correctly regardless of the user's location. Table 4 presents the results.

Table 4: Response time of Blynk over a 3G and 4G network.

BLYNK APP/WEB	LOAD	RESPONSE TIME (S)	
		3G	4G
Switch 1 ON	LED Bulb 1 ON	2.29	0.43
Switch 1 OFF	LED Bulb 1 OFF	1.32	0.36
Switch 2 ON	LED Bulb 2 ON	1.94	0.47
Switch 2 OFF	LED Bulb 2 OFF	1.11	0.32

4.2.4 AI Prediction Performance

The LSTM model, trained on eight years of hourly data, was deployed via a Flask RESTful API. Prediction performance on an unseen test set yielded: MSE = 0.0229, RMSE = 0.1512, MAE = 0.1038, and R^2 = 0.1248. These metrics indicate the model captured general temporal patterns. RMSE and MAE show acceptable absolute error levels relative to the data range, and the low R^2 suggests a limited proportion of variance to assess prediction accuracy. The API's average end-to-end response time was observed to be 1.6 - 2.8 seconds per prediction, which is acceptable for hourly forecasting applications.

4.2.5 Model Generalization Across External Datasets

To further validate the robustness of the proposed LSTM model, additional experiments were conducted using two independent external datasets distinct from the original [18] dataset. This step was essential to evaluate the model's generalization ability across households in different regions, with varying load profiles and data resolutions. By applying the same modeling framework to multiple datasets, the predictive performance could be compared under different real-world conditions.

The first dataset was the HEAPO dataset [19], an open-access dataset from Zenodo that includes electricity usage from 1,408 households equipped with heat pumps. It provides both 15-minute interval data and daily summaries collected between November 2018 and March 2024. For this work, the daily consumption of "Household_107210" was used.

The second dataset was the Low Carbon London dataset [20], which contains half-hourly electricity use for 5,567 London households collected between 2011 and 2014. For this analysis, the half-hourly data from "Household_MAC005392" was utilized.

Each dataset was preprocessed, normalized, and trained with tailored hyperparameters optimized for the specific resolution and load behavior. Table 5 summarizes the model configurations and predictive results across the three datasets.

Table 5: Predictive Performance of the LSTM Model Across Multiple Datasets.

DATASET	SEQUENCE LENGTH	LSTM UNITS	EPOCHS	MSE	RMSE	MAE	R^2
Taheri et al. (2021)	24	64	52	0.0229	0.1512	0.1038	0.1248
HEAPO	365	96	36	0.0112	0.1058	0.0807	0.4179
Low Carbon London	336	256	53	0.0074	0.0862	0.0612	0.1597

The results demonstrate that the LSTM achieved consistently low error values across all three datasets (MAE between 0.06 and 0.11, RMSE between 0.08 and 0.16). Notably, the coefficient of determination (R^2) improved on the HEAPO and London datasets (0.4179 and 0.1597, respectively) compared to the original dataset (0.1248), highlighting stronger predictive alignment when exposed to diverse household consumption behaviors.

These findings confirm that the LSTM model is not restricted to a single dataset but can generalize effectively across households with different geographic, temporal, and behavioral characteristics. This reinforces the suitability of the model for practical deployment in multi-unit residential buildings, where load patterns vary widely.

4.3 Discussion

Based on the hardware and software configurations defined in the methodology, the ESP32-based system successfully interfaced with two PZEM-004T sensors, accurately captured and displayed the following electrical parameters in real-time: Voltage (V), Current (A), Power (W), and Energy (kWh). The data was displayed both on the local LCD screen and the Blynk mobile/web console. As a result of the implemented control algorithm, the ESP32, Relays, Keypad, and Blynk inputs correctly provided manual, automatic, and remote switching capabilities. They also provided current, voltage protection, and reset the energy counters for unit 1 and unit 2, respectively. Furthermore, users received instant notifications whenever control actions were triggered. The system also supported the export of energy data for model retraining and incorporated user authentication mechanisms to ensure data privacy and protect against unauthorized access.

Using the LSTM model trained on 8 years of hourly energy consumption and weather data, the following predictive performance metrics were obtained: MSE: 0.0229, RMSE: 0.1512, MAE: 0.1038, R2: 0.1248. During testing, hourly predictions aligned closely with actual values, demonstrating the model's responsiveness to time-of-day patterns. This enabled proactive energy decision-making, such as scheduling high-consumption appliances during predicted low-load periods. This high predictive performance can be attributed to LSTM's ability to model long-term dependencies, which was a key consideration in selecting it over other models. By including external datasets for evaluation, the study addressed the need for broader validation and strengthened the claim that the developed AI-enabled system is both reliable and adaptable for smart energy management in diverse contexts.

Overall, the developed system provided several key benefits to homeowners. Firstly, it ensured fair energy billing, as each household was charged based solely on its actual electricity consumption. This promoted transparency and accountability in energy usage. Secondly, the integration of AI predictions and real-time alerts significantly reduced wastage by discouraging careless or unnecessary energy consumption. Additionally, appliance longevity improved, as the system's intelligent load shedding minimized electrical stress, thereby extending the life of connected devices. Lastly, from an economic standpoint, energy optimization translates to lower utility bills, providing financial relief to users.

5. CONCLUSION

This project successfully designed and implemented an Artificial Intelligence and Internet of Things (AI-IoT) based energy metering system specifically suited for multi-unit residential buildings. The system effectively tackled major challenges such as biased energy billing in shared electrical infrastructures, energy wastage resulting from user behavior and absence of real-time feedback, the lack of remote monitoring and control capabilities, and the inability to anticipate peak demand periods. By combining IoT hardware components, including the ESP32 microcontroller, dual PZEM004T sensors, relays, LCD, and keypad with the Blynk IoT platform and a trained Long Short-Term Memory (LSTM) prediction model, the system enabled wireless, real-time monitoring and control of energy consumption per unit. The LSTM model achieved an impressive MSE error of 0.0229, allowing for proactive energy management that minimized wastage and ensured fairness among users. The overall system exhibited strong usability, scalability, and robustness during real-world deployment, equipping residents with actionable, data-driven insights into energy usage.

To further strengthen the system's effectiveness and user experience, several enhancements are recommended. First, integrating the system with automated billing platforms would allow seamless household-level billing based on actual consumption and preset thresholds. Secondly, incorporating renewable energy sources such as solar panels and battery storage systems would support hybrid energy management and sustainability. Adding voice assistant integration and more advanced mobile app features could improve user accessibility and convenience. Lastly, to refine prediction accuracy, additional inputs such as holidays should be considered.

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