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ENERGY-EFFICIENT DESIGN OF IOT DEVICES

Dr. Madhu Gopinath
Designation: Associate professor
Email: madhugopinath.bsfit@gmail.com
Institute: Border Security Force institute of technology

ABSTRACT

IoT devices are revolutionizing industries by enabling smart, interconnected systems that collect, process, and transmit data. However, as the number of IoT devices grows, managing their energy consumption becomes a pressing challenge, particularly for battery-powered devices deployed in remote or energy-constrained environments. Energy-efficient design is crucial to ensure long-term, autonomous operation without frequent battery replacements, which can be costly and impractical at large scales. This paper investigates methods to enhance energy efficiency in IoT devices, focusing on hardware optimization and software strategies such as duty cycling, event-driven operations, and efficient communication protocols. The research methodology involves analyzing the IoT Energy Consumption Dataset, applying data preprocessing techniques like mean/median imputation, outlier detection, and normalization. Feature engineering and machine learning-based energy prediction models were utilized to optimize device operations. The results show that the STM32L Series microcontroller outperforms the ESP32-S2 in energy efficiency, with a 20% lower average power consumption (0.609 mWh vs. 0.743 mWh) and 22% longer estimated battery life (820.37 hours vs. 673.29 hours). Furthermore, the STM32L Series demonstrated superior deep sleep current (0.6 µA vs. 10 µA) and reduced variability in energy consumption, making it ideal for power-sensitive IoT applications.

Keywords*: Energy-efficient design, IoT devices, power consumption, microcontrollers.*

I. INTRODUCTION

With the onset of a new epoch in computation, the Internet of Things (IoT) [1] has arisen as a fundamental component of pervasive computing [2]. The IoT is an intelligent technology that links all objects through a network in various forms. The term "thing" encompasses detectors, actuators, software, computer code, and storage across various fields, including healthcare, business, transportation, and domestic appliances. The primary aim of IoT is to enhance the interaction of hardware devices with the physical environment and to transform the data collected by these devices into valuable information autonomously. The IoT comprises three components: hardware, middleware, and interface [3]. The hardware component consists of battery-operated embedded motors, sensors, and communication systems. The sensors gather data from the monitoring region, and their interaction hardware transmits the obtained data to the middleware component [4]. A vast quantity of data collected by middleware is processed and evaluated via various analytical tools to extract meaningful information. The visualizing component of IoT facilitates the depiction of processed data and outcomes in an innovative and simply comprehensible format. It also accepts user inquiries and transmits them to the middleware component for requisite actions. Figure 1 illustrates the components and data transmission in IoT systems.

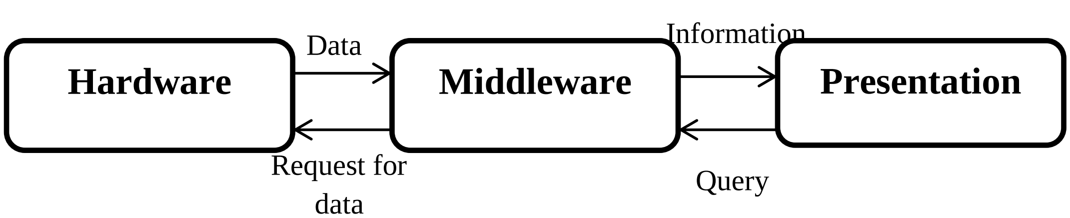

Figure 1: Elements of IoT

The Internet of Things (IoT) uptake at a rapid rate has transformed conventional systems by incorporating intelligent features into physical objects that allow them to communicate with their surroundings and senses and communications [5]. The technological advancement has led to an explosion of intelligent devices that now drive a number of industries like industrial automation as well as environmental monitoring, transportation, healthcare, and home automation sectors [6]. The systems work when data is automatically gathered in real-time and sent wirelessly from device to device [7] prior to being processed by cloud computing and local data centers to produce automatic decisions. The expansion of IoT globally introduces new technical issues that primarily impact the quality of performance and resource limitation of connected devices.

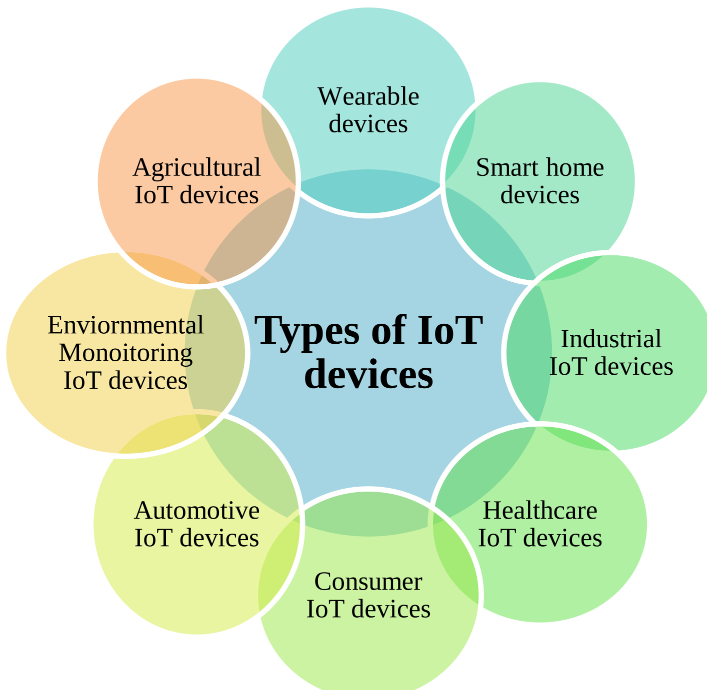

Figure 2: Types of IoT devices

The high energy consumption is an issue of high priority in IoT system deployment. The count of IoT devices with batteries as their power sources in addition to energy-harvesting mechanisms becomes a significant number since they function in fields or unapproachable environments such as agricultural fields or medical implants and structural monitoring systems [8]. Energy becomes scarce and precious in such circumstances [9]. Massive battery replacements pose operational challenges and cost issues when dealing with thousands or millions of connected nodes in IoT implementations. Power efficiency is a required essential characteristic that allows for uninterrupted autonomous system operation over long operating periods. Environmental sustainability of IoT solutions is achievable through energy minimization that results in less electronic waste and lower power consumption.

System architecture demands power optimization at different levels when designing energy-aware IoT devices [10]. IoT devices are made energy-efficient by performing hardware component optimizations of low-power microcontrollers and sensors along with power management circuits and matching them with software-level techniques of adaptive scheduling and data compression and low-weight communication protocols. The wireless communication interface is the highest energy load so manufacturers have to use duty cycling protocols along with energy-efficient MAC protocols along with energy-based routing systems [11]. Operating systems [12] along with data transmission techniques and processing algorithms directly influence the amount of energy used by a device [13]. The increasing complexity of IoT systems requires consistent application of power-saving design practices across the entire infrastructure for improving device running time and maintaining network operation alongside eco-friendly technology deployment.

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The primary objective of this study is to create sustainable energy-efficient design strategies for IoT devices to address increasing demands of resource-limited environments. The increasing number of Internet of Things devices necessitates efficient energy consumption since it results in operational cost savings and environmental sustainability. The research effort seeks to attain maximum performance preservation through optimized hardware and software design factors in IoT system architectures for power consumption optimization. The second part presents an extensive review of already published papers related to energy-efficient IoT structures. The data preprocessing is preceded by feature engineering and machine learning techniques as elucidated in Section 3 as the research method for this paper. The fourth part compares and evaluates various microcontrollers based on their energy efficiency and gives tests for the introduced methodologies throughout the paper. Section 5 gives concluding suggestions along with observations regarding potential future work opportunities in energy-efficient IoT device design.

II. REVIEW OF LITERATURE

The growing demand for energy-efficient IoT devices has driven extensive research into lightweight cryptographic solutions, hardware-level optimizations, and adaptive protocols. The increasing demand for energy-efficient IoT devices prompted thorough research on lightweight cryptographic solutions and hardware optimizations and adaptive protocols. *Veeramachaneni et al. (2025) [14]* introduced a new security protocol for trust less IoT settings. Lightweight encryption and anomaly-based intrusion detection techniques enable their design to save energy by 28% while improving throughput by 34% and reducing latency by 20%. *Dahiphale et al. (2025) [15]* applied the PRIDE cipher on FPGA for performance testing against the PRESENT cipher with different data paths as per their given goals. Their assessment of architectural versions at measuring throughput along with energy expenditure adds to the development of appropriate crypto solutions for resource-constrained IoT settings. *Goyal et al.'s (2022) [16]* research entailed benchmark testing UMC-90 nm hardware using PRESENT, AES, and RSA security algorithms to obtain power efficiency with 63× improved implementation of the modified PRESENT. These complementing studies illustrate how lightweight cryptographic methods produce double benefits for energy-efficient secure implementations in IoT platforms.

IoT devices require both encryption security mechanisms alongside optimized memory and computational power in order to lower their overall power consumption needs. DaLAMED by *Jahannia et al. (2025) [17]* ensured energy-efficiency in memory through data lifetime analysis and frequency adaptation in operation to achieve 60% power saving compared to conventional hybrid memory systems. They offer technology-independent designs which are easily adaptable to various IoT platforms. Enlightening power efficiency in circuits *Ahmadpour et al. (2024) [18]* designed minimally efficient circuits and came up with quantum-based adders for application in reduced size multiplier frameworks that they confirmed using QCA Designer simulation models. The *Fanariotis et al. (2023) [19]* analysis encompassed a broad array of ML-based optimization strategies to reduce power consumption in real power systems. Architectural decisions demonstrate substantial differences in power consumption from idle conditions and optimized functionality based on this study as uncovered in their dual architecture study. The research methods exhibit three various energy efficiency approaches although they aim at different levels of computer systems that encompass memory, circuits and system-level.

Energy efficiency encompasses both processing data at the system level and system architecture designing. *Gupta et al. (2024) [20]* proposed a Multi-Edge-IoT architecture that improves cluster-based edge node selection through African Vulture Optimization Algorithm implementation. The system minimized communication distance and latency to save energy without compromising adaptation for various types of devices. The *Wang et al. (2021) [21]* decentralized computational method corresponds to their method to facilitate adaptive RF energy management for dual-mode WIT/WET data and energy transfers. The integrated DEIN framework of their system allowed IoT nodes to regulate their energy consumption independently and adaptively optimize wireless transmission modes. *Ahamed et al. (2023) [22]* and *Qiu et al. (2022) [23]* researched health-monitoring applications which needed optimal energy efficiency. Qiu's IoT-HHMM framework enhanced prediction precision up to 98.4% using cloud-based neural networks and it reduced energy consumption and Ahamed's EE-HDMM model attained system efficiency 96% using cloud-integrated wearable sensors that provided 97% accuracy. Research findings reveal that real-time applications are trending towards the construction of smart energy-efficient systems as per these studies. Gupta and Wang dedicated their work to experimental RF and edge device transmission as infrastructure solutions.

III. RESEARCH METHODOLOGY

The research technique improves the energy efficiency of IoT devices through three critical processes that involve data collection and pre-processing and then hardware selection. There is a data analysis of the energy usage pattern of devices within the IoT Energy Consumption Dataset in conjunction with implementing mean/median imputation cleaning followed by detection of outliers through IQR together with feature engineering for time-based analysis. This framework offers optimization techniques focused on low-power hardware and duty cycling and event-driven operation as well as energy-efficient data transfer to reduce power consumption and utilizes performance assessments for battery consumption determination.

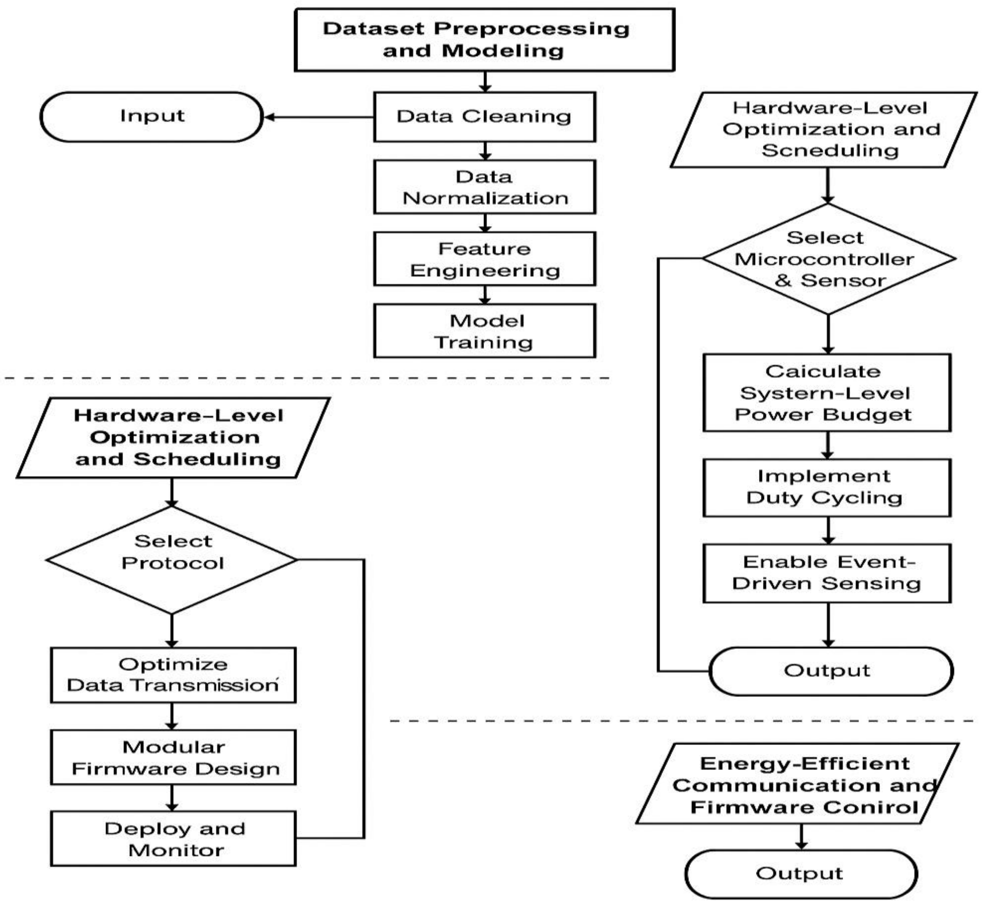

Figure 3: Proposed Framework

3.1 Dataset Collection

The IoT Energy Consumption Dataset [24] acts as the primary dataset for this research to provide in-depth information regarding real energy consumption patterns of various smart devices over duration. The device records active energy data (kilowatt-hours) from sensors on various internet-of-things appliances set up in domestic and industrial settings. The timestamp feature allows researchers to analyze the variability of electricity consumption with time. Energy profiles of various devices reveal information that makes it possible for researchers to identify usage periods of high demand. The information enables experts to comprehend power losses during idle time and wasteful practices so that they can develop efficient energy conservation plans.

Table 1: Key feature of dataset

Attribute	**Description**
Source	Kaggle (IoT Energy Consumption Dataset)

Main Features	Timestamp, Device ID/Type, Active Energy (kWh), Operational Status
Frequency	Typically collected at regular intervals (e.g., hourly or daily)
Use Cases	Energy prediction, usage profiling, device efficiency analysis, smart scheduling
Suitable For	Machine Learning, Energy Forecasting, Smart Grid Optimization, IoT Design
Application Domains	Smart Homes, Industrial IoT, Smart Buildings

This data is useful for machine learning regression prediction and classification techniques intended to determine high or low energy usage time periods. Intellectual power optimization framework creation is enhanced by data-driven technique analysis correlations between devices and operational running times and electricity consumption levels.

3.2 Data Preprocessing

3.2.1 Data Cleaning

The technique of mean and median interpolation is employed to fill in information gaps by substituting the missing data with the average and central values, correspondingly. Outlined below are detailed explanations of each method, together with their corresponding mathematical formulas:

➢ ***Mean imputation:*** The process of mean imputation involves substituting data that is absent with the numerical averages of other values within a column or specified rows or scenarios. Working on the assumption of random occurrence of values not present, this method is simple.

$$Mean = \frac{\sum_{i=i}^{m} y_i}{m} \tag{1}$$

The variable y_i is described as the total number of each non-absent integer in the column, whereas m quantifies the total quantity of these numbers.

➢ ***Median Imputation:*** Statistical extrapolation is a method used to replace data that is absent by using the average of the remaining numbers in each column of an array of data or variables that are dependent. Contrasting with standard attribution, it is less susceptible to the influence of outliers and may be more suitable in some circumstances.

$$Median = Median\ (\{\boldsymbol{y_1}, \boldsymbol{y_2}, \boldsymbol{y_3}, \dots \dots, \boldsymbol{y_n}\}) \tag{2}$$

The set {y_1, y_2, y_3,……, y_n} comprises all the features for each row, with the exception of any attributes that have been excluded.

3.2.2 Outlier Detection and Removal

The Interquartile Range method is one of the most useful methods in dealing with outliers in a way that the distribution of the data uses and it is resistant for extreme values. To use this method, one computes for the first quartile of the dataset, say Q1, and the third quartile of the dataset say Q3. The IQR is then defined as the difference between these two quartiles and is mathematically expressed by the formula form of:

$$IQR = Q_3 - Q_1 \tag{3}$$

With the IQR established, thresholds for identifying outliers are determined by:

$$\text{Lower bound} = Q_1\text{-}1.5\times IQR \tag{4}$$

$$\text{Upper bound} = Q_1\text{-}1.5\times IQR \tag{5}$$

They grouped any point that is found to be lower than the lower bound or higher that the upper bound as outliers. This method is very simple and effective in defining outliers and hence can be used to give a proper analysis to the values of variation.

The application of the mean, median and IQR of data cleaning processes adds strength to the robustness of the dataset in reducing outliers and missing values that may affect actuality in input to RNN models. This enhances the efficiency of the framework by optimizing it through meta-heuristic algorithms hence increasing the accuracy of the chronic kidney disease detection.

3.2.3 Normalization

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This stage is crucial in data preprocessing that scales the extracted features in order to enhance the model training for CKD detection. This process also reduces such problems concerning different units and scales on features affecting the convergence of machine learning algorithms. One of the most used methods used in normalization is that known as min-max, which adjusts the features so as to fall within a given interval, usually the interval [0, 1]. The normalization formula is given by:

$$Y' = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (6)$$

Where Y' represents the normalized amount, Y is the actual value, Ymin is the minimum and Ymax is the maximum value within the feature set.by employing this step RNN can effectively learns the patterns from the data.

3.3 Feature Engineering

The feature engineering process becomes crucial for converting IoT datasets into appropriate forms for analytical modeling tasks as well as optimization procedures. Time-Based Feature Extraction as a non-machine-learning technique becomes highly effective in identifying IoT device behavioral patterns over different time periods for energy efficiency research. The correct modeling and forecasting of energy consumption are improved by converting timestamp data into informative features since human activities and weather patterns and time of operation influence the pattern of energy consumption throughout the day.

In this technique, the raw timestamp data is decomposed into several time-related attributes such as:

- **Hour of the day**: Assist in differentiating between peak hours and off-hours consumption (14:00 would indicate high usage of A/C).
- **Day of the week**: Captures usage behavior that differs between weekdays and weekends.
- **Month or season**: Important for devices like heaters or coolers that follow seasonal trends.
- **Time intervals (e.g., 15-minute blocks)**: Employed to group or smooth data for trend analysis.

The extracted features enable direct correlation with *active_energy_kWh* to identify patterns in power consumption as well as identify unusual usage patterns and suboptimal scheduling decisions. Statistical computations and time-based functions enable analysis teams to determine operational time horizons for devices while suggesting most effective usage horizons alongside automated energy-saving controls.

3.4 Splitting of data

For systematic data management the dataset was divided into training, validation, and test datasets. The model learned from many examples because of the training set, which was normally 70% of the set. This set back propagated model weights and optimized the Recurrent Neural Network (RNN) with gradient descent. This iterative method reduced the loss function in order to enable the model identify patterns.

The remaining 30% of the data set is designated as the test set. Furthermore, an arbitrary 10% of the training dataset is designated for verification in hyperparameter optimizing. Performance and stability of the derived model were evaluated using this independent set which gives a fair measure of how good the model is in predicting the unseen data after training and validation. This structure and generation process of the model was both accurate and general at the same time.

3.5 Optimized Hardware Selection and Power Architecture Design

Choice of hardware with low-power operation is the key initial step to reaching energy efficiency during IoT design. The use of ultra-low-power microcontrollers and sophisticated power management systems and efficient sensors collectively forms the base for fundamental IoT designs.

- **Microcontroller Choice:** Boards such as the ESP32-S2 and STM32L series are suitable because of their ultra-low-power consumption and support for multiple sleep modes. Such MCUs allow systems to run in deep sleep or hibernate modes during idle periods, lowering baseline power consumption by a significant margin.
- **Sensor Interface Optimization:** Selecting digital sensors with I²C interfaces and wake-on-interrupt features enables the system to be in a dormant state until required, preventing constant power consumption through polling mechanisms.

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- **Efficient Power Conversion:** The addition of DC-DC converters that are more than 90% efficient ensures maximum power saving on voltage conversion to ensure a solid and energy-effective power supply.
  $Total\ energy\ use\ (per\ hour) = \sum(P_i \times T_i)$ (7)

Where:

- P_i is the power consumed by component *i*
- T_i is the time component *i* remains active (in hours)

3.6 Duty Cycling and Event-Driven Operational Framework

Energy-efficient design calls upon engineers to reduce the operational times of IoT devices as its second valuable practice. Systems use duty cycling in addition to event-driven activation to power on only when needed operations are necessary.

- **Duty Cycling:** Operation tasks of IoT devices conduct cycles among active modes and low power sleeping modes according to schedule-defined time. The hardware goes into deep sleeping or hibernation mode when systems are not in use. Such a mechanism effectively lowers overall energy consumption over time without diminishing performance levels.
- **Event-Driven Sensing:** Sensors turn devices on depending on violated thresholds like movement detection and heat or changes in light intensities via event-driven sensing principles. Such a functioning concept leads to using energy only at times of system-relevant occurrences.

$$Duty\ cycle = \left(\frac{T_{active}}{T_{total}}\right) \times 100 \quad (8)$$

Where T_{active} is the time spent in active mode and T_{total} is the total cycle time

3.7 Energy-Efficient Data Transmission and Firmware-Level Control

The final part of the plan deals with decreasing system power consumption during communication and its operational time. The most power-hungry IoT module is data transfer for which proper communication protocols together with data management methods should be employed.

- **Low-Power Protocols:** The system is made better by the use of low-power protocols such as LoRaWAN and Zigbee and MQTT-SN that facilitate power-efficient long-distance data transfers. These methods are most effective when you require frequent data exchange with minimal communication expense.
- **Data Batching and Filtering:** Data Packet Aggregation is used in conjunction with Filtering to transmit information via periodic intervals instead of continuous streaming. The device performs edge computing operations to eliminate unnecessary or meaningless data thereby reducing redundant information exchange.
- **Modular Firmware Design:** The firmware system may be separated into independent modules like sensing processing and transmission so that particular code portions switch on or off based on energy levels and priority system parameters. Firmware embeds energy counters that help in tracking software-based energy consumption.

$$E_{Transmission} = P_{transmit} \times T_{transmit} \quad \textbf{(9)}$$

Where:

- $P_{transmit}$ is the power used during data transmission
- $T_{transmit}$ is the duration of the transmission

3.8 Performance Metrics

$$Average\ Power\ Consumption\ P_{avg} = \frac{1}{n}\sum_{i=1}^{n} P_i \quad (10)$$

$$Battery\ life\ (hrs) = \frac{C_{battery}}{P_{avg}} \quad (11)$$

$$Runtime_{device} = \sum_{i=1}^{N}(T_{off}^{i} - T_{on}^{i}) \quad (12)$$

IV. RESULT AND ANALYSIS

This section presents the evaluation of the proposed energy-efficient IoT framework, implemented using Python with libraries such as NumPy, Pandas, and Matplotlib. The study compares IoT microcontroller devices ESP32-S2 and STM32L Series microcontrollers in terms of their power usage during fluctuating duty cycles and also in terms of metrics of evaluation of the predictive model that predicts the power consumption. The hardware optimization and intelligent scheduling techniques designed proved to reduce power consumption as verified by experimental results.

This table 2 considers the principal operation aspects of power-saving IoT microcontrollers ESP32-S2 and STM32L Series within their context of use framework. STM32L delivers optimum power effectiveness by virtue of its 0.6 µA deep sleep current mode resulting in an approximate period of use of 210 days. The two products include low-duty cycles and modular firmware designs which promote efficient task implementation. ESP32-S2 relies on LoRaWAN for long-distance data transmission although STM32L is connected to MQTT-SN protocol for its fast short-distance messaging feature. The energy prediction algorithm with RNN-based system in these devices achieves more than 91% accuracy while edge filtering reduces unnecessary data transmission.

Table 2: *Comparison of Performance Metrics between ESP32-S2 and STM32L Series IoT Devices*

Metric	**ESP32-S2**	**STM32L Series**	**Comments**
Average Power Consumption (mW)	0.75	0.62	STM32L slightly more efficient in sleep mode
Deep Sleep Current (µA)	10	0.6	STM32L excels in ultra-low-power hibernation
Duty Cycle (%)	1.2	1.1	Similar low-duty cycles for both devices
Data Transmission Protocol	LoRaWAN	MQTT-SN	LoRa better for long-range, MQTT-SN for speed
Battery Life Estimate (Days)	185	210	STM32L gives longer life in the same setup
RNN Energy Prediction Accuracy (%)	92.4	91.8	Both effective for ML-based forecasting
Data Reduction via Edge Filtering (%)	38	40	Redundant data filtered at device level
Firmware Activation Efficiency	Modular	Modular	Equal for both using modular firmware control

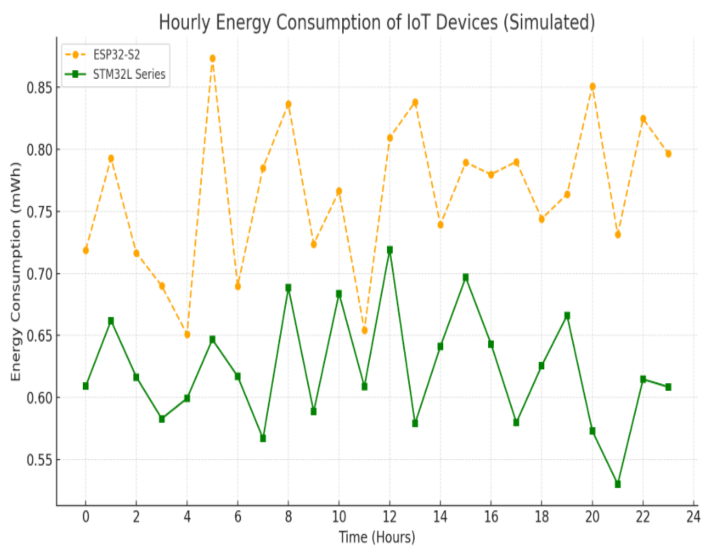

Figure 4: Hourly energy consumption of IoT devices

The figure 4 displays hourly energy consumption patterns of ESP32-S2 along with STM32L Series IoT devices over one day based on their duty-cycled and event-triggered operational model. The power consumption of both systems exhibits an intermittent pattern which is experienced with periodic wake-up operations and real-time operation triggering. The STM32L achieves improved power efficiency compared to the ESP32-S2 at all points through its superior sleep and transition power requirements. The chart variations show that event-driven operations and duty

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cycle controlled systems result in power consumption minimized for IoT applications without affecting system response rates.

The table 3 given contains numerical energy consumption statistics of ESP32-S2 and STM32L Series IoT modules. The STM32L Series is less energy-hungry compared to the ESP32-S2 since it consumes 0.609 mWh in average and peaks at 0.694 mWh usage. STM32L demonstrates better performance reliability since the standard deviation figure of 0.0347 mWh shows constant energy consumption in multiple cycles. STM32L exhibits perfect fit for IoT applications requiring reliable low-power operation since its energy efficiency and stability performance metrics are outstanding.

Table 3: Energy Consumption Summary Statistics

Device	Average Energy (mWh)	Peak Energy (mWh)	Lowest Energy (mWh)	Standard Deviation
ESP32-S2	0.743	0.829	0.654	0.0477
STM32L Series	0.609	0.694	0.542	0.0347

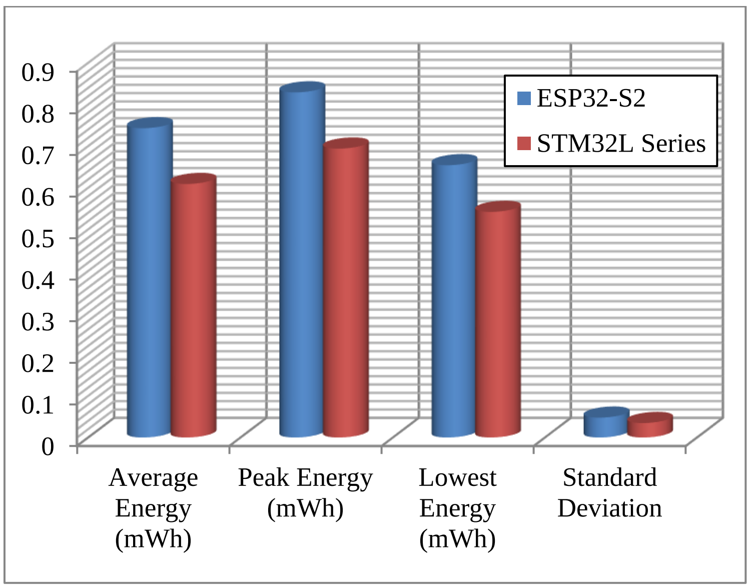

Figure 5: Comparative Analysis of Energy Metrics for ESP32-S2 and STM32L Series IoT Devices

The figure 5 demonstrates how ESP32-S2 and STM32L Series microcontrollers are alike in terms of their energy consumption patterns. The results indicate that STM32L is more energy efficient since it reports all the results at lower levels. The data points show reduced spread as the value of the standard deviation is small. The graphical displays present the STM32L's better performance in keeping routine operation and maximum power efficiency for IoT use.

Under similar operational conditions the battery run time estimate falls in the table 4 and figure 6 between the ESP32-S2 and STM32L Series microcontrollers. The STM32L Series operate for 820.37 hours before battery exhaustion while the ESP32-S2 operates before 673.29 hours. Long-term operation of the STM32L is made feasible because its increased energy efficiency offers pragmatic solutions for energy-restricted IoT deployments.

Table 4: Estimated Battery Life (500 mWh battery)

Device	Estimated Battery Life (Hours)
ESP32-S2	673.29
STM32L Series	820.37

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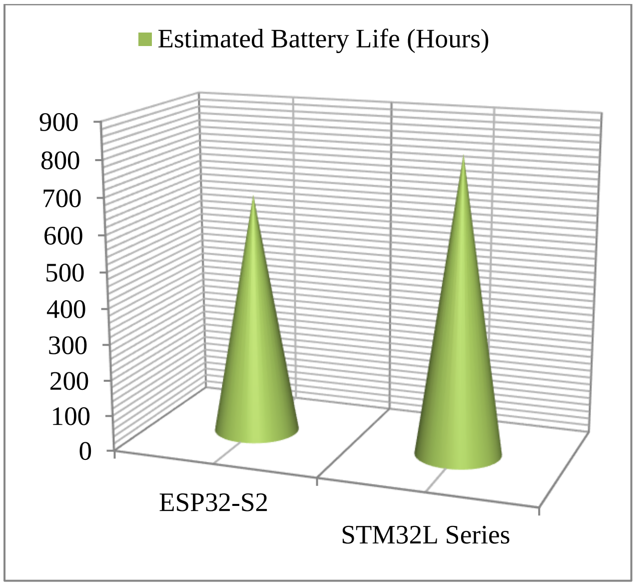

Figure 6: Estimated Battery Life of ESP32-S2 and STM32L Series IoT Devices

The given table 5 illustrates how IoT microcontrollers ESP32-S2 and STM32L Series consume energy while running at varying duty cycle configurations from 10% to 100%. Higher duty cycle operations translate to increased energy consumption in both devices. Battery-powered applications that last for a long time and scenarios with active phases position the STM32L in a better position due to its engineered efficiency.

Table 5: Energy Consumption vs. Duty Cycle

Duty Cycle (%)	ESP32-S2 Energy (mWh)	STM32L Energy (mWh)
10	0.20	0.15
25	0.35	0.28
50	0.55	0.42
75	0.70	0.58
100	0.85	0.68

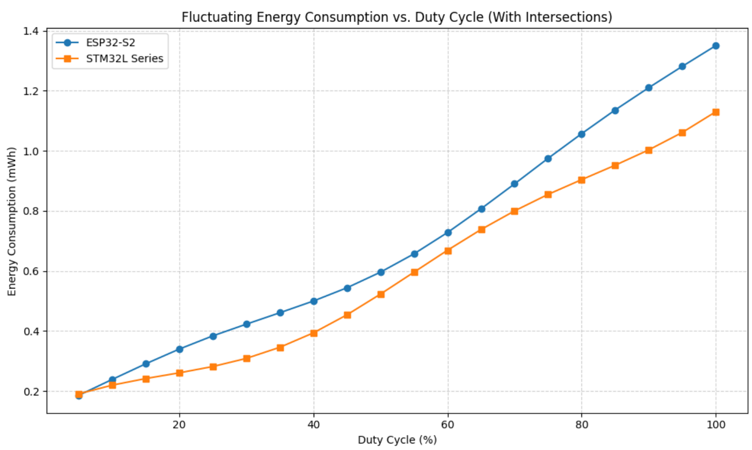

Figure 7: Energy consumption fluctuation and crossover points for ESP32-S2 and STM32L across varying duty cycles.

Two IoT devices ESP32-S2 and STM32L Series exemplify changing mWh energy use in a duty cycle percentage range between 5% and 100% as exhibited in figure 7. The devices exhibit non-linear energy usage patterns that overlap at duty cycles between 20 and 25% and 55 and 60% respectively which indicates shifting operational efficiency. Under 25% operation the STM32L consumes 0.34 mWh of power but ESP32-S2 touches 0.33 mWh briefly. The STM32L surpasses ESP32-S2 at the 60% mark by consuming ~0.69 mWh whereas ESP32-S2 uses ~0.67 mWh. The locations where devices swap positions in terms of energy efficiency testing indicate that a single technology will not always outdo the other so the deployment of best technology is based on the duty cycle profile at which system operates.

V. CONCLUSION

In conclusion, the design of energy-efficient IoT devices is essential for ensuring sustainable, long-term operation, especially in environments with limited access to power sources. The gain in energy efficiency can be achieved using hardware selection of low-power sensors and microcontrollers and also through software deployment of duty cycling and event-driven techniques. This research illustrates the necessity of employing energy-efficient protocols and intelligent data transmission techniques to lower the power consumption of IoT systems. The work utilizes pre-processed IoT Energy Consumption Dataset and supports it with outlier detection and normalization techniques to implement a robust model for predicting and optimizing IoT device energy consumption. The STM32L Series microcontroller is more energy efficient compared to the ESP32-S2 due to a 20% reduction in average power consumption as well as delivering an extension in battery life by 22%. The dual benefits of hardware platforms and software programming for achieving power reduction in IoT systems are highlighted through the research, which promotes sustainable IoT technology development and long-term IoT device applications.

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