

A Measurement-Based Study of Data Transmission Energy in Long-Term IoT Environmental

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Abstract

Long-term Internet of Things (IoT) deployments require predictable and realistic energy consumption estimates to ensure sustainable operation and effective maintenance planning. While many existing studies focus on energy-efficient protocols duty cycling or adaptive sensing strategies communication energy consumption is often estimated using analytical models or datasheet-based assumptions rather than direct hardware measurements. This limits the reliability of long-term energy estimation in real-world deployments. This paper presents a measurement-based study of data transmission energy consumption in a long-term IoT environmental monitoring system using an ESP32-based platform. The system was deployed continuously for approximately one year to collect environmental data while transmission current was measured experimentally using an external ammeter. By isolating the incremental current associated with each data transmission from baseline standby and sensing consumption, the per-transmission energy cost was experimentally characterized. Statistical analysis of the measured transmission current demonstrates low variability and stable behavior across multiple transmission samples enabling reliable estimation of communication energy over extended operational periods. Based on the measured per-transmission energy a practical framework is established to estimate monthly and annual communication energy consumption under a fixed transmission interval. Rather than proposing new optimization algorithms, this work provides empirical energy measurements derived from real hardware and long-term operation, offering a realistic reference for system designers and researchers. The results support informed battery capacity planning lifetime estimation, and energy-aware system design in environmental and agricultural IoT monitoring applications.

Keywords: Energy Consumption Measurement, Long-Term Environmental Monitoring, Low-Power Wireless Sensor Networks, Measurement-Based Energy Analysis, Internet of Things (IoT)

1. Introduction

The rapid growth of Internet of Things (IoT) technologies has enabled continuous and long-term environmental monitoring in applications such as smart agriculture, water quality assessment, and air pollution monitoring. In these systems, wireless sensor nodes periodically sense environmental parameters and transmit the collected data to cloud or edge platforms for further processing and visualization. Despite their practical benefits the sustainability of long-term IoT deployments remains a major challenge particularly for battery-powered sensor nodes operating under fixed sampling schedules [1],[2].

Extensive research has been conducted on improving energy efficiency in wireless sensor networks and IoT systems. Existing approaches primarily focus on network-level techniques, including energy-aware routing, clustering protocols duty cycling, and collaborative data collection mechanisms [3–5]. While these methods aim to prolong network lifetime most evaluations rely on analytical energy models or simulation-based studies, which may not accurately reflect the actual electrical energy consumption of real IoT hardware during wireless communication.

Several experimental studies have demonstrated low-power IoT deployments in agricultural and environmental monitoring scenarios confirming the feasibility of long-term sensing using wireless sensor networks [1],[6]. These systems typically employ periodic data transmission

strategies where sensing and communication are performed at predefined intervals. However energy consumption is often reported at a coarse system or device level without isolating the energy cost associated specifically with a single wireless data transmission event.

Recent studies have explored adaptive sensing and transmission mechanisms to reduce communication overhead including learning-based sensor selection and context-aware data transmission frameworks [7],[8]. Although such approaches show promise in reducing redundant transmissions, they frequently assume abstract or implicit communication costs. In practice the effectiveness of adaptive transmission strategies fundamentally depends on the baseline energy consumed by each transmission event which is rarely quantified through direct electrical measurements.

A critical limitation across existing literature is the lack of experimental analysis that explicitly decouples sensing, sampling, and transmission energy at the sensor node level. In many IoT systems, sensing and data transmission are treated as a single operation, even though wireless communication typically dominates energy consumption. Without precise measurement of the energy required for each transmission it is difficult to design or evaluate energy-aware transmission policies grounded in physical hardware behavior.

Motivated by this gap, this study presents a measurement-based analysis of electrical energy consumption per wireless data transmission in an ESP32-based IoT sensor node deployed for PM2.5

environmental monitoring. The system operates with a fixed sampling interval of 30 seconds consistent with prior long-term environmental monitoring deployments [6]. Importantly, sampling and transmission are treated as independent processes and the electrical current drawn during each wireless transmission is directly measured. By quantifying the energy cost per transmission event this work provides a concrete baseline for understanding the impact of transmission frequency on energy consumption in practical IoT sensor nodes.

The main contributions of this paper are as follows. First an experimental framework is developed to isolate and measure the electrical energy consumed by individual wireless data transmissions on an ESP32-based IoT platform. Second, the relationship between transmission frequency and cumulative energy consumption is analyzed under a fixed sampling regime. Finally the results provide practical insights that support the design of adaptive transmission control strategies grounded in empirical energy measurements rather than analytical or simulation-based models. This work complements existing energy-aware IoT research by providing experimentally validated evidence focused specifically on transmission energy consumption.

2. System Architecture and Measurement Setup

2.1 Overall System Architecture

The proposed system is an IoT-based environmental monitoring platform designed for long-term PM2.5 data collection. The system architecture follows a conventional sensor–cloud model consisting of a sensor node a wireless communication interface, and a cloud server for data storage and visualization. This architecture is commonly adopted in environmental and agricultural IoT deployments due to its simplicity and scalability [1],[2].

At the sensor node level an ESP32 microcontroller is employed as the main processing and communication unit. The ESP32 integrates a dual-core processor with built-in Wi-Fi capability making it suitable for low-cost IoT applications that require periodic data transmission to cloud platforms. A PM2.5 sensor is interfaced with the ESP32 to acquire particulate matter concentration data which are sampled locally at a fixed interval. The sampled data are packetized and transmitted wirelessly to a remote server for long-term storage and analysis.

Unlike many existing IoT systems that treat sensing and transmission as a single operation this study explicitly separates the sensing process from the data transmission process. PM2.5 sampling is performed locally at the sensor node while wireless transmission is triggered independently according to a predefined transmission schedule. This separation enables a clear analysis of the electrical energy consumed solely by the wireless communication process.

2.2 Hardware Configuration of the Sensor Node

The sensor node consists of three main components: the ESP32 microcontroller the PM2.5 sensor module and the power supply subsystem. The ESP32 operates as both the data acquisition controller

and the wireless communication interface. The PM2.5 sensor provides real-time particulate concentration measurements, which are read by the ESP32 through a serial communication interface.

The sensor node is powered by a regulated DC power source allowing stable voltage supply during long-term operation and precise current measurement. Although battery-powered operation is common in practical deployments [6], a regulated supply is adopted in this experimental setup to ensure repeatability and accuracy of electrical measurements. This approach is consistent with prior experimental studies focusing on precise power and energy characterization of IoT devices [6].

It is important to note that the electrical current measurement in this study is performed at the system level meaning that the measured current includes contributions from both the ESP32 microcontroller and the PMS3003 sensor module.

2.3 Sampling and Transmission Strategy

The system operates with a fixed sampling interval of 30 seconds. This sampling period is selected to be consistent with prior environmental monitoring deployments and previous work conducted by the authors where a 30-second interval was shown to be sufficient for capturing temporal variations in environmental parameters. Importantly sampling is performed continuously regardless of whether data transmission occurs.

Wireless data transmission is performed periodically based on the predefined transmission schedule. Each transmission event involves the packaging of the most recent PM2.5 measurement into a data packet and its transmission to the cloud server via Wi-Fi. In this study the focus is placed exclusively on the electrical energy consumed during this transmission event. Other energy-consuming activities, such as sensing local processing, and idle operation, are not included in the transmission energy analysis.

2.4 Electrical Current Measurement Setup

To quantify the electrical energy consumed during wireless data transmission, the supply current drawn by the ESP32 is measured directly. A current sensing module is inserted in series with the current supply line of the ESP32 enabling real-time measurement of the instantaneous current during system operation.

The electrical current was measured using a clamp ammeter UNI-T UT203 digital clamp multimeter with a specified accuracy of $\pm 2\% + 3$ digits. Due to the characteristics of the clamp measurement technique, the exact sampling frequency of the device is not specified and the instrument is not optimized for capturing very small or high-frequency transient current variations. Therefore, very fast transient peaks associated with Wi-Fi radio activation may not be fully captured. However, the measurement approach is considered sufficient for analyzing the average transmission current behavior across repeated transmission events.

The electrical diagram of the measurement setup is shown in **Figure 1**. The system consists of a DC power supply, an ESP32 microcontroller and a PMS3003 PM2.5 sensor. The current measurement is performed using a clamp ammeter placed on the supply line between the power source and the sensing node, allowing non-intrusive measurement of the total system current during operation.

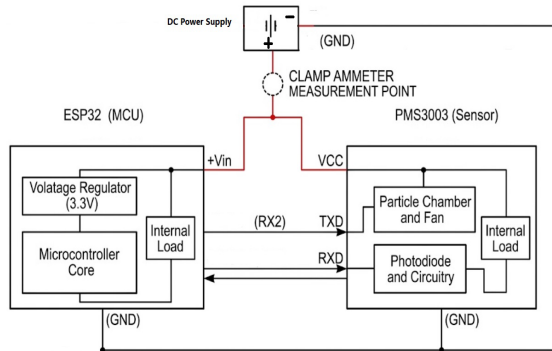


Figure 1 Electrical diagram of the ESP32-based PM2.5 monitoring system showing the current measurement point using a clamp ammeter.

The current signal is sampled at a sufficiently high rate to capture transient variations occurring during wireless transmission.

A single transmission event is defined as the time interval from the initiation of the wireless communication process to the completion of data upload to the cloud server. During this interval the current waveform typically exhibits a distinct peak corresponding to radio activation and data transmission. By integrating the measured current over the duration of a transmission event and multiplying by the supply voltage the electrical energy consumed per transmission is obtained.

This measurement-based approach differs from many existing studies that estimate communication energy using analytical models or protocol-level assumptions [3],[5]. By directly measuring the current drawn by the ESP32 during actual wireless transmission, the resulting energy values reflect real hardware behavior under practical operating conditions.

2.5 Definition of Transmission Energy Metric

The electrical energy consumed by a single wireless transmission event E_{tx} is computed using Eq. (1).

$$E_{tx} = \int_{t_0}^{t_1} V \cdot I(t) dt \quad (1)$$

V is the supply voltage I_t is the measured current as a function of time and t_0 and t_1 denote the start and end times of the transmission event respectively. This definition enables a direct and unambiguous quantification of transmission energy independent of network-level assumptions or protocol-specific models.

The measured transmission energy serves as a baseline metric for evaluating the impact of transmission frequency on cumulative energy consumption and provides a foundation for the development of energy-aware transmission control strategies in future IoT deployments.

3. Experimental Methodology and Data Collection

3.1 PM2.5 Data Acquisition and Cloud-Based Storage

The PM2.5 monitoring system is implemented using an ESP32 microcontroller integrated with a PMS3003 particulate matter sensor. The sensor node is deployed to continuously measure ambient PM2.5 concentration and transmit the collected data to a cloud platform for storage and visualization. This system architecture follows established IoT-based environmental monitoring approaches previously applied in outdoor environmental sensing applications [9].

PM2.5 data are sampled and transmitted automatically at a fixed interval of 30 seconds. This sampling interval is selected based on prior work, where a 30-second interval was demonstrated to be sufficient for capturing temporal variations in environmental conditions while maintaining stable system operation [9]. The system operates continuously over an extended period resulting in a total of 1,048,576 PM2.5 data records stored in the cloud database.

The cloud platform provides long-term data storage and visualization, enabling retrospective analysis of PM2.5 trends and supporting the evaluation of transmission-related energy consumption over prolonged operation.

3.2 PM2.5 Data Acquisition and Cloud-Based Storage

In this study a data transmission event is defined as a complete cycle consisting of packet preparation, wireless data transmission from the ESP32 to the cloud server and confirmation of successful data upload. Each PM2.5 measurement is transmitted individually as a single data packet. Sampling and transmission are treated as separate processes, where PM2.5 sensing is performed locally by the sensor, and energy analysis focuses exclusively on the wireless transmission phase.

This definition allows the electrical energy associated specifically with wireless communication to be isolated from other system operations such as sensing local processing and idle states.

Figure 2 shows the PM2.5 dataset collected continuously by the ESP32-based monitoring system and stored on the cloud platform. The time-series plot on the left presents long-term variations in PM2.5 concentration while the table on the right shows an excerpt of the corresponding PM2.5 records with timestamps stored in the cloud database.

The ESP32 maintains a persistent connection to the Wi-Fi access point during operation and does not

perform a full reconnection for each transmission interval. Therefore, each transmission event only involves data packet preparation and wireless transmission, resulting in a short transmission duration under stable network conditions.

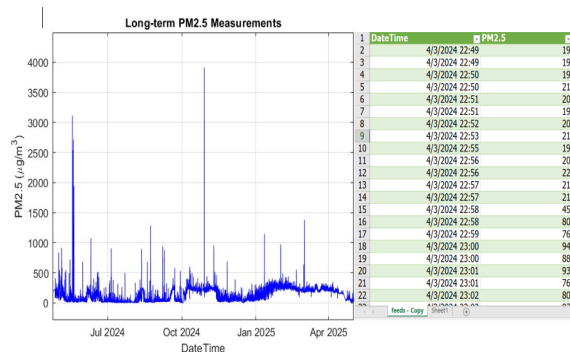


Figure 2 Long-term PM2.5 dataset collected and stored on the cloud platform.

3.3 Electrical Current Measurement Procedure

The electrical energy consumption associated with wireless data transmission is evaluated by directly measuring the supply current drawn by the ESP32 during transmission events. An ammeter is connected in series with the power supply line of the ESP32 to measure the instantaneous current consumption. The measured current values are recorded in units of milliamperes (mA).

Due to practical limitations of manual measurement and instrumentation, it is not feasible to record the current consumption for all 1,048,576 PM2.5 transmission events. Instead current measurements are conducted independently from the PM2.5 data logging process. A total of approximately 50–100 transmission events are manually measured under normal operating conditions.

For each measured transmission event the peak and average current values are recorded. The arithmetic mean of these measured current values is then computed and used as a representative transmission current for subsequent energy analysis. This approach is consistent with experimental studies that characterize transmission energy using sampled measurements rather than exhaustive logging, particularly when transmission behavior is repetitive and stable across events [6].

Figure 3 shows an example of electrical current measurement for the PM2.5 monitoring system based on an ESP32 microcontroller integrated with a PMS3003 sensor. A clamp ammeter is connected in series with the power supply line to measure the current drawn by the device.

Figure 3(a) presents the current consumption of the system in the standby state where the ESP32 and the PM2.5 sensor remain active without data transmission.

Figure 3(b) presents the current consumption during wireless transmission of PM2.5 data to the

cloud platform, where a noticeable increase in current is observed compared to the standby state.

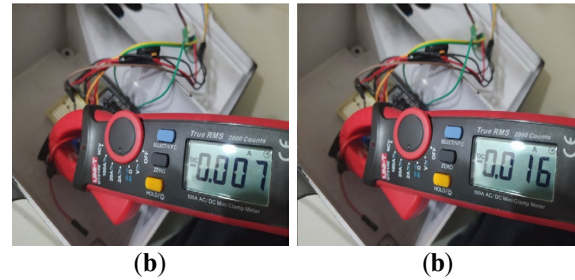


Figure 3 Electrical current measurement of the ESP32-based PM2.5 monitoring system during standby and wireless data transmission states.

3.4 Integration of PM2.5 Data and Energy Analysis

The averaged transmission current obtained from the electrical measurements is analyzed in conjunction with the PM2.5 transmission schedule. Since PM2.5 data transmission occurs at a fixed interval of 30 seconds the total number of transmission events over the monitoring period is directly derived from the PM2.5 dataset size.

By combining the average electrical current per transmission event with the known transmission frequency the cumulative energy consumption associated with wireless data transmission is estimated. This analysis enables an evaluation of how periodic data transmission contributes to overall energy usage independent of sensing and data processing operations.

Although current measurements are obtained from a limited number of samples, the measurement-based approach provides practical insight into the transmission energy characteristics of the ESP32-based IoT node. The results serve as a baseline for understanding transmission-related energy consumption and support future development of adaptive transmission strategies based on empirical energy measurements.

3.5 Experimental Limitations

It is acknowledged that electrical current measurements are performed on a limited subset of transmission events rather than across the entire PM2.5 dataset. However because the transmission process and packet structure remain consistent throughout system operation, the measured current values are considered representative of typical transmission behavior. The low standard deviation of the measured current (0.47 mA) indicates highly consistent and repeatable behavior, supporting the representativeness of the sampled measurements for long-term system operation. This trade-off allows realistic energy characterization while maintaining feasibility in long-term field deployment scenarios.

In addition, the use of a clamp ammeter introduces limitations in capturing high-frequency transient current spikes during wireless transmission. While the measurement device may not fully capture instantaneous peak behavior the results show consistent and repeatable

current values across multiple transmission events. This consistency supports the validity of using the average transmission current for energy estimation in long-term IoT deployments.

The transmission duration was approximated as a constant value of 1 second based on observations under stable network conditions. In practical IoT deployments variations in network conditions such as Wi-Fi signal strength, interference, and retransmissions may introduce fluctuations in transmission duration. These variations could affect the cumulative energy consumption over long-term operation. However, under the controlled experimental setup used in this study, the transmission behavior was observed to be stable and repeatable supporting the use of an average transmission duration for energy estimation.

the experimental setup uses a regulated DC power supply to ensure stable voltage conditions and improve measurement accuracy. In practical battery-powered IoT deployments the supply voltage may fluctuate over time due to battery discharge characteristics and internal resistance. Such voltage variations may influence both the current consumption and the resulting transmission energy calculated using the model $E_{tx} = V \times \Delta I \times t$. Therefore the reported energy values represent measurements under controlled voltage conditions and may vary in real-world battery-powered scenarios.

In addition the experimental setup was conducted under a fixed deployment condition with a stable Wi-Fi connection, where the distance between the sensor node and the access point remained constant. In practical IoT deployments, variations in distance and network conditions may influence transmission energy consumption. Therefore, the results presented in this study represent baseline measurements under controlled conditions. Future work may investigate the impact of distance and network variability on transmission energy in more dynamic deployment scenarios.

The current measurement approach in this study focuses on repeated per-transmission observations rather than continuous logging. While this method is suitable for characterizing average transmission current it may not fully capture transient current spikes caused by dynamic network conditions. A data logger-based measurement system could provide more detailed insight into time-varying current behavior and is considered as a potential direction for future work.

4. Experimental Results and Analysis

4.1 PM2.5 Data Characteristics

The PM2.5 dataset consists of long-term measurements transmitted to the cloud platform at a fixed interval of 30 seconds [9]. The data were collected continuously from March 2024 to June 2025 in Chiang Rai Province, Thailand. This high-resolution temporal sampling enables detailed observation of both short-term fluctuations and long-term trends in ambient PM2.5 concentration.

Statistical analysis of the dataset indicates that the minimum recorded PM2.5 concentration is $1.00 \mu\text{g}/\text{m}^3$, while the maximum value reaches $6,243.00 \mu\text{g}/\text{m}^3$. It should be noted that the reported maximum value exceeds the typical effective measurement range of the PMS3003 sensor. Such extreme readings may occur due to transient high-concentration events dense smoke or limitations of the sensor under saturation conditions. Therefore, these values should be interpreted with caution, reflecting the occurrence of extreme pollution events during the monitoring period. The overall mean PM2.5 concentration is $168.21 \mu\text{g}/\text{m}^3$ suggesting persistently elevated particulate matter levels over long-term operation.

The wide range between minimum and maximum values highlights significant temporal variability in air quality which is characteristic of seasonal and episodic pollution conditions in the study area. These characteristics confirm that the dataset is suitable for evaluating long-term environmental behavior and for analyzing the impact of periodic data transmission on energy consumption in continuous IoT-based monitoring systems.

During the data collection period, no significant data loss was observed. The system operated continuously under stable power and network conditions and all data were successfully transmitted and stored on the cloud platform.

Figure 2 provides contextual information on the PM2.5 data acquisition process. However, the primary focus of this study is on the electrical current measurements associated with data transmission which are discussed in the following sections.

4.2 Transmission Current Measurement Results

To accurately quantify the energy consumption associated with data transmission the current drawn by the ESP32-based sensing node was measured using an external ammeter during transmission events. Rather than reporting the total system current this study focuses on the incremental current attributable solely to the data transmission process. This approach allows the transmission-related energy cost to be isolated from the baseline power consumption of the ESP32 microcontroller and the PM2.5 sensor operating in sensing and standby modes.

Although data transmission is performed at a fixed interval of 30 seconds the actual duration required to complete each transmission event is approximately 1 second. This short duration is referred to as the transmission window during which the wireless communication process is active.

Let I_{base} denote the baseline current measured during normal sensing and idle operation, and I_{tx} denote the current measured during active data transmission. The incremental transmission current ΔI was calculated using Eq. (2).

$$\Delta I = I_{tx} - I_{base} \quad (2)$$

It should be emphasized that the PMS3003 sensor including its internal fan remains active during both the

baseline and transmission states. Therefore, the energy consumption associated with the sensing process is present in both measurements. By subtracting the baseline current from the transmission current, the resulting incremental current effectively eliminates the contribution of the sensor and isolates only the additional current associated with wireless communication. This ensures that the reported transmission energy reflects the actual communication overhead rather than the total system consumption. This baseline subtraction approach is commonly used in experimental energy profiling to isolate specific operational components in embedded systems.

A total of 100 transmission events were measured to capture the statistical characteristics of the transmission current. The results show that the incremental current per transmission has a mean value of approximately 9.02 mA with a standard deviation of 0.47 mA. The minimum and maximum observed values ranged from 8.5 mA to 9.7 mA respectively. The relatively small standard deviation indicates that the transmission process exhibits stable and repeatable current behavior across multiple transmission events.

By focusing on the incremental transmission current rather than the aggregate system current the proposed measurement methodology provides a more precise characterization of communication-related power consumption. This per-transmission profiling approach is particularly relevant for long-term IoT deployments, where data transmission is known to be one of the dominant contributors to overall energy consumption [3], [6].

4.3 Energy Consumption per Data Transmission

Based on the measured incremental transmission current the energy consumed per data transmission event was estimated using a direct electrical energy model. The transmission energy E_{tx} is expressed using Eq. (3).

$$E_{tx} = V \times \Delta I \times t \quad (3)$$

Where V is the supply voltage of the ESP32 ΔI is the incremental transmission current obtained from Eq. (2) and t is the duration of a single data transmission event. In this study the ESP32 operates at a supply voltage of 3.3 V and the average transmission duration was approximately 1 s. Given the relatively low variance of the measured current values the average transmission energy was estimated using the mean incremental current uI resulting in using Eq. (4).

$$E_{tx,avg} = V \times uI \times t \quad (4)$$

Substituting the measured values into Eq. (4) the mean energy consumption per transmission was calculated as approximately 29.8 mJ which corresponds to 8.28 μ Wh. Based on the observed minimum and maximum current values the transmission energy ranges from approximately 28 mJ to 32 mJ per transmission.

By isolating the energy contribution of the data transmission process from the baseline sensing and standby operations this analysis provides a realistic and

deployment-oriented estimation of per-transmission energy consumption. Such characterization is essential for understanding the cumulative energy impact of long-term data transmission in IoT-based air quality monitoring systems where communication overhead can dominate total power usage over extended operational periods [3], [6].

Figure 4 illustrates the measured current consumption of the ESP32 microcontroller during a single data transmission (per-transmission) in the proposed PM2.5 monitoring system using the PMS3003 sensor. The current was measured using an external ammeter during the uplink transmission phase to the cloud platform. A total of 100 transmission events were recorded under identical operating conditions.

To accurately reflect the communication-related energy cost the reported current values do not represent the total system current. Instead, they correspond to the incremental current drawn during data transmission, which was obtained by subtracting the baseline current (standby operation of the ESP32 combined with the PMS3003 sensing process) from the current measured during the active transmission period.

The experimental results indicate that the average per-transmission current consumption is approximately 9.02 mA with a standard deviation of 0.47 mA. The minimum and maximum observed values range from 8.5 mA to 9.7 mA respectively. This narrow variation suggests a stable and repeatable communication energy cost across multiple transmission cycles.

The current consumption behavior shown in **Figure 3** confirms that the proposed system exhibits a nearly constant per-packet energy cost which is a desirable characteristic for long-term IoT deployments. Such stability is particularly important for energy-constrained environmental monitoring applications, where wireless communication is known to be a dominant contributor to overall energy consumption

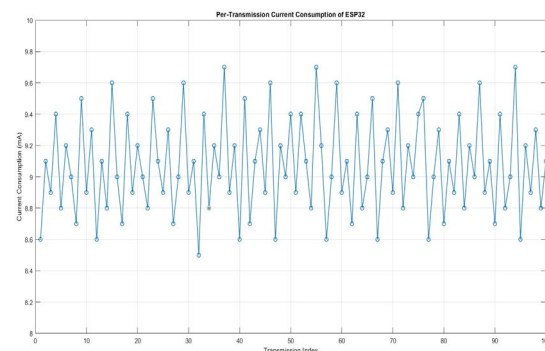


Figure 4 Per-Transmission Current Consumption of the ESP32-based system

Figure 5 presents the statistical distribution of the measured incremental current consumption associated with individual data transmission events. The histogram was constructed using the same set of 100 transmission samples shown in **Figure 4** providing a probabilistic view of the transmission-related current behavior.

The distribution exhibits a clear unimodal shape centered around the mean current value of approximately 9.02 mA with most measurements concentrated within a narrow range. The limited spread of the distribution, as indicated by a standard deviation of 0.47 mA confirms that the transmission current remains highly consistent across repeated transmission events. No significant outliers were observed suggesting stable communication behavior under the tested operating conditions.

This distributional analysis complements the time-series results presented in **Figure 1** by demonstrating that the observed stability is not limited to individual measurements but persists statistically across multiple transmissions. Such low variability in per-transmission current consumption is particularly advantageous for long-term IoT deployments as it enables reliable estimation of cumulative energy consumption over extended periods.

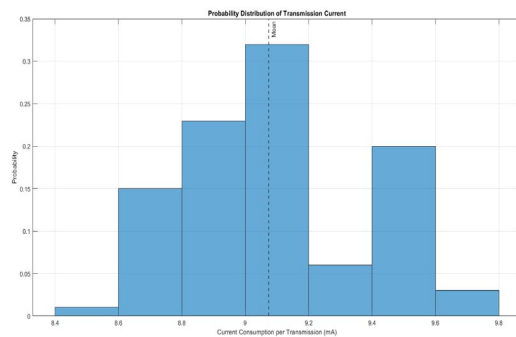


Figure 5 Distribution of Per-Transmission Current Consumption

In **Figure 6**, Histogram of energy consumption per data transmission of the ESP32-based PM2.5 monitoring system. The energy values were calculated from measured incremental transmission current using the energy model Eq. (3) assuming a supply voltage of 3.3 V and a transmission duration of 1 s.

Figure 6 presents the statistical distribution of energy consumption per data transmission, expressed in millijoules (mJ) derived from the measured transmission current samples. The energy values were computed using the incremental current associated with data transmission excluding the baseline standby current of the ESP32 and PMS3003 sensor.

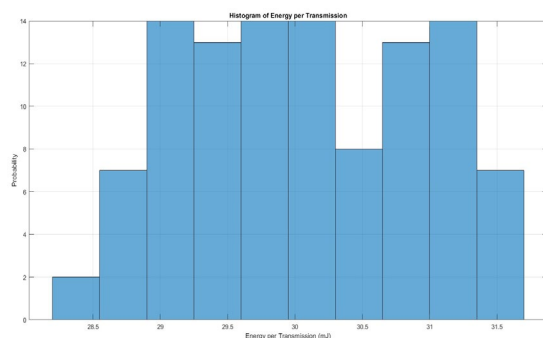


Figure 6 Energy Consumption per Data Transmission (mJ)

The histogram shows that the energy consumption per transmission is tightly distributed within a narrow range of approximately 28–32 mJ with a clear concentration around the mean value of 29.8 mJ. This narrow distribution indicates stable transmission behavior and consistent energy usage across repeated data uploads. The absence of extreme outliers suggests that the proposed system maintains reliable communication performance without significant energy spikes, even under real deployment conditions. Such stability is particularly important for long-term IoT deployments where predictable per-transmission energy cost directly impacts battery lifetime estimation and energy-aware system design.

Compared with prior energy-aware IoT studies that rely on analytical or simulation-based energy models [3], [6] the results in **Figure 4** provide measurement-based validation of transmission energy consumption using real hardware and field deployment data. This strengthens the practical relevance of the proposed system for long-term environmental and agricultural monitoring applications.

Table 1 presents a statistical summary of the incremental electrical current associated with individual wireless data transmission events in the ESP32-based IoT monitoring system. The table reports the number of measured samples along with the mean standard deviation and range of the transmission-related current which was obtained by subtracting the baseline standby current from the current measured during active transmission. The results indicate that the per-transmission current exhibits low variability with a narrow range between minimum and maximum values. This statistical stability confirms that the wireless transmission process has a consistent and repeatable electrical behavior supporting the use of an average current value for long-term energy estimation and system-level analysis.

Table 1 Statistical summary of per-transmission current consumption

Parameter	Value
Number of samples	100
Mean incremental current (mA)	9.02
Standard deviation (mA)	0.47
Minimum (mA)	8.5
Maximum (mA)	9.7
Transmission duration (s)	1
Supply voltage (V)	3.3

4.4 Long-Term Transmission Energy Estimation

This section evaluates the long-term energy consumption of the proposed ESP32-based PM2.5 monitoring system by extrapolating the measured per-transmission energy cost to a one-year operational period. Based on the experimental results in Section 4.3 the average energy consumption per data transmission was approximately 29.8 mJ derived from real current measurements during actual data uploads. The system was configured to transmit PM2.5 data at a fixed interval

of 30 seconds following the sensing strategy adopted from prior fire detection research to ensure timely event monitoring. Using this transmission interval, the total number of data transmissions per day can be expressed using Eq. (5), and the daily energy consumption for data transmission is estimated using Eq. (6).

$$N_{day} = \frac{24 \times 60 \times 60}{30} = 2880 \text{ transmission/day} \quad (5)$$

$$E_{day} = N_{day} \times E_{tx} \quad (6)$$

Where E_{tx} denotes the average energy per transmission. The cumulative monthly and annual transmission energy consumption were then calculated by aggregating the daily energy usage over time.

Figure 7 show the cumulative transmission energy consumption over a 12-month period. The results show an approximately linear increase in total energy usage, indicating a stable and predictable transmission energy profile. After one year of continuous operation, the cumulative energy consumption attributed solely to data transmission reaches approximately 8.68 Wh.

This result is particularly significant for long-term IoT deployments, as it demonstrates that frequent data transmission at a 30-second interval can be sustained with relatively low energy overhead. Unlike many existing studies that rely on analytical models or simulations, the estimation presented here is grounded in measurement-based per-transmission energy data obtained from real hardware deployments.

Isolating the transmission-related energy cost—by subtracting baseline standby consumption—provides a clearer understanding of communication overhead which is essential for energy-aware system design battery capacity planning and future optimization strategies such as adaptive transmission scheduling or event-driven sensing.

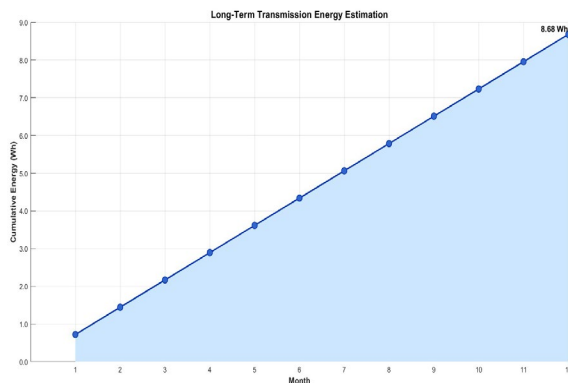


Figure 7 Estimated Long-Term Cumulative Energy Consumption for Data Transmission in the ESP32-Based IoT Monitoring System

Table 2 summarizes the estimated energy consumption associated with wireless data transmission at different time scales derived from the experimentally measured per-transmission energy cost. By extrapolating the average transmission energy to daily, monthly, and annual operation under a fixed 30-second transmission

interval, the table provides a clear and practical view of cumulative communication energy usage. This multi-scale energy summary enables rapid assessment of long-term energy requirements and highlights the relatively low energy overhead of frequent data transmission. Such information is particularly valuable for battery capacity planning lifetime estimation, and energy-aware design of long-term IoT environmental monitoring systems.

Table 2 Estimated transmission energy consumption

Period	Energy
Per transmission	29.8 mJ (8.28 μ Wh)
Per day (30 s interval)	0.0868 Wh
Per month	2.6 Wh
Per year	8.68 Wh

5. Contribution

This paper presents a measurement-based study of data transmission energy consumption in a long-term IoT environmental monitoring system. Unlike many existing studies that rely primarily on analytical models, simulations, or datasheet-based assumptions for estimating communication energy consumption [3],[4],[10],[11] this work is grounded in real current measurements obtained from an ESP32-based system deployed continuously for approximately one year [6], [12].

The main contribution lies in the experimental characterization of per-transmission energy cost, where the incremental current associated specifically with data transmission is isolated from baseline standby consumption. This measurement-oriented approach complements prior research on energy-aware IoT and wireless sensor networks that emphasize duty cycling, routing optimization, or adaptive sensing strategies without explicitly quantifying per-packet energy using real hardware measurements [3],[7],[8],[13].

Statistical analysis of the measured transmission current is provided to demonstrate the stability and variability of energy usage per transmission, which is essential for reliable lifetime estimation in long-term deployments [10],[14]. The study establishes a practical long-term energy estimation framework, linking per-transmission energy measurements to cumulative monthly and annual energy consumption under a fixed transmission interval. The results offer practical insights for energy-aware system design, battery capacity planning and long-term deployment assessment in real-world IoT environmental and agricultural monitoring applications [1],[2],[6],[9].

6. Conclusion

This paper presented a measurement-based analysis of data transmission energy consumption in a long-term IoT environmental monitoring system using an ESP32-based platform. Unlike many existing studies that estimate communication energy through analytical models or system-level assumptions this work relied on direct current measurements obtained

from real hardware operating under continuous deployment conditions. By isolating the incremental current associated with each data transmission from baseline standby and sensing consumption the study provided a realistic characterization of per-transmission energy cost.

Experimental results demonstrated that the transmission energy consumption exhibits low variability and stable statistical behavior enabling reliable estimation of cumulative energy usage over extended operational periods. Based on the measured per-transmission energy a practical framework was established to estimate monthly and annual communication energy consumption under a fixed transmission interval. This long-term perspective is particularly valuable for IoT deployments where predictable energy usage battery capacity planning, and maintenance scheduling are critical considerations.

Rather than proposing new energy optimization algorithms or protocol modifications, the contribution of this work lies in providing empirical evidence and realistic energy metrics derived from a real-world deployment. The results complement existing energy-aware IoT research by offering concrete measurement data that can be used to validate models, inform system design decisions and support long-term sustainability analysis in environmental and agricultural IoT monitoring applications [1–3],[6],[9].

7. Limitations

This study has several limitations that should be acknowledged. First the energy analysis focused specifically on the communication-related energy consumption per data transmission and did not attempt to model or optimize the total system energy budget, which may also include sensing processing, and idle operation. Second, the current measurements were obtained from a specific hardware configuration based on the ESP32 platform and a fixed transmission interval therefore, the absolute energy values may vary for different hardware architectures communication protocols or duty-cycle configurations. In addition, the transmission duration was assumed to be constant for energy estimation whereas variations in network conditions or payload size could introduce additional energy fluctuations. Finally while the system was deployed over a long-term period the study did not investigate adaptive transmission strategies or energy-aware scheduling mechanisms which could further reduce overall energy consumption.

Despite these limitations the presented results provide a reliable baseline for understanding real per-transmission energy costs in practical IoT deployments. The findings can serve as a reference point for future studies that aim to integrate measurement-based energy characterization with adaptive communication strategies protocol optimization or intelligent power management techniques.

8. References

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