

Adaptive Transmission Strategies for Energy-Efficient Long-Term Outdoor IoT Monitoring

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(Received: February 12, 2026; Revised: March 31, 2026; Accepted: April 7, 2026)

Abstract

Continuous high-resolution data transmission in Internet of Things (IoT)-based environmental monitoring systems leads to significant communication overhead and energy consumption, particularly in long-term outdoor deployments. This study aims to evaluate and compare energy-efficient data transmission strategies for long-term outdoor IoT environmental monitoring systems under real-world conditions. A system-level evaluation was conducted using a real-world environmental sensing platform deployed in Chiang Rai, Thailand. The system, built on an ESP32 microcontroller with SHT20 and PMS3003 sensors, collected temperature, humidity, and PM2.5 data at 30-second intervals from March 2024 to May 2025, resulting in 1,048,406 transmission events under the baseline configuration. Two transmission reduction strategies were evaluated: fixed downsampling and adaptive sampling based on signal variability. Performance was assessed using Data Reduction Ratio (DRR) and Event Preservation Ratio (EPR), including both PM-only and multi-parameter event detection. The fixed downsampling approach achieved the highest data reduction (90.00%) but preserved only 15.91% of multi-parameter environmental events. In contrast, adaptive sampling reduced transmission by 78.89% while preserving 56.76% of combined environmental events. The results demonstrate that maximizing transmission reduction alone is not suitable for dynamic environmental monitoring. Variability-aware adaptive transmission provides a more balanced trade-off between energy efficiency and event preservation. This study proposes a practical evaluation framework for designing energy-constrained IoT monitoring systems under real long-term outdoor conditions.

Keywords: Internet of Things, Adaptive Sampling, Data Reduction, PM2.5 Monitoring, Energy-Efficient Transmission, Environmental Sensing, ESP32, Edge Computing

Please cite this article as: J. Tepmanee, D. Wongta, S. Muangchuen and K. Nontprasat, "Adaptive Transmission Strategies for Energy-Efficient Long-Term Outdoor IoT Monitoring," *The Journal of Engineering and Industrial Technology, Kalasin University*, vol. 4, no. 3, pp. 1-21, 2026.

กลยุทธ์การส่งข้อมูลแบบปรับตัวเพื่อเพิ่มประสิทธิภาพพลังงาน สำหรับระบบตรวจวัด IoT กลางแจ้งระยะยาว

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บทคัดย่อ

การส่งข้อมูลความละเอียดสูงอย่างต่อเนื่องในระบบตรวจวัดสิ่งแวดล้อมที่ใช้เทคโนโลยีอินเทอร์เน็ตของสรรพสิ่ง (IoT) ก่อให้เกิดภาระด้านการสื่อสารและการใช้พลังงานสูง โดยเฉพาะในระบบที่ติดตั้งใช้งานกลางแจ้งระยะยาว งานวิจัยนี้มีวัตถุประสงค์เพื่อประเมินและเปรียบเทียบกลยุทธ์การส่งข้อมูลที่ประหยัดพลังงาน สำหรับระบบตรวจวัดสิ่งแวดล้อมแบบ IoT ในสภาพการใช้งานจริงระยะยาว การศึกษานี้ดำเนินการในระดับระบบโดยใช้แพลตฟอร์มตรวจวัดสิ่งแวดล้อมจริงที่ติดตั้งในจังหวัดเชียงราย ประเทศไทย โดยระบบพัฒนามาบนไมโครคอนโทรลเลอร์ ESP32 ร่วมกับเซนเซอร์ SHT20 และ PMS3003 ทำการเก็บข้อมูลอุณหภูมิ ความชื้น และฝุ่น PM2.5 ทุก ๆ 30 วินาที ระหว่างเดือนมีนาคม 2567 ถึงเดือนพฤษภาคม 2568 รวมทั้งสิ้น 1,048,406 ครั้ง ภายใต้การตั้งค่าพื้นฐาน ได้ทำการประเมินกลยุทธ์การลดการส่งข้อมูล 2 วิธี ได้แก่ การลดความถี่แบบคงที่ และการสุ่มตัวอย่างแบบปรับเปลี่ยนตามความแปรปรวนของสัญญาณ โดยประเมินผลด้วยตัวชี้วัด ได้แก่ อัตราการลดข้อมูล (Data Reduction Ratio: DRR) และอัตราการคงอยู่ของเหตุการณ์ (Event Preservation Ratio: EPR) ครอบคลุมทั้งเหตุการณ์จากฝุ่น PM เพียงอย่างเดียวและหลายพารามิเตอร์ร่วมกัน ผลการทดลองพบว่า วิธีการลดความถี่แบบคงที่ สามารถลดข้อมูลได้สูงสุดถึงร้อยละ 90 แต่มีความสามารถในการคงอยู่ของเหตุการณ์หลายพารามิเตอร์เพียงร้อยละ 15.91 ในขณะที่การสุ่มตัวอย่างแบบปรับเปลี่ยนสามารถลดการส่งข้อมูลได้ร้อยละ 78.89 และยังคงเหตุการณ์สำคัญได้ถึงร้อยละ 56.76 ผลการศึกษาชี้ให้เห็นว่าการมุ่งเน้นการลดการส่งข้อมูลเพียงอย่างเดียวไม่เหมาะสมกับการตรวจวัดสิ่งแวดล้อมที่มีความเปลี่ยนแปลงสูง โดยกลยุทธ์แบบปรับตัวตามความแปรปรวนให้สมดุลที่ดีกว่าระหว่างประสิทธิภาพพลังงานและการคงข้อมูลเหตุการณ์ งานวิจัยนี้นำเสนอกรอบการประเมินเชิงปฏิบัติสำหรับการออกแบบระบบ IoT ที่มีข้อจำกัดด้านพลังงานภายใต้สภาพแวดล้อมจริงในระยะยาว

คำสำคัญ: อินเทอร์เน็ตของสรรพสิ่ง การสุ่มตัวอย่างแบบปรับตัว การลดข้อมูล การตรวจวัด PM2.5 การส่งข้อมูลประหยัดพลังงาน การตรวจวัดสิ่งแวดล้อม ESP32 เอ็ดจ์คอมพิวเตอร์

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1. Introduction

In recent years Internet of Things (IoT)-based environmental monitoring systems have been widely deployed to continuously observe temperature, humidity, and air quality parameters over long periods of time. High-resolution temporal sensing enables the detection of rapid environmental changes and abnormal events which is particularly important in real-world deployments such as air pollution monitoring and environmental risk assessment. However continuous high-frequency data transmission from resource-constrained IoT devices introduces significant challenges in terms of energy consumption, communication overhead, and system sustainability [1,2].

Several studies have identified data transmission as one of the dominant contributors to energy depletion in long-term IoT deployments, especially for field-installed sensor nodes powered by batteries or renewable energy sources [3]. Fixed-rate sampling and continuous data uploading, although simple to implement, often result in unnecessary transmission of redundant or low-information data thereby reducing network lifetime and increasing operational costs [4].

To address these limitations existing research has proposed various data reduction strategies including adaptive sampling event-based transmission, local aggregation, and edge-level processing. Systematic reviews have shown that data reduction techniques can be broadly categorized into compression-

based, sampling-based, and event-driven approaches each with distinct trade-offs between energy efficiency and data fidelity. Among these approaches adaptive sampling and event-based transmission have gained increasing attention due to their ability to dynamically adjust sensing and communication behavior according to environmental dynamics [5,6].

In parallel advances in edge computing have further emphasized the importance of system-level decision making at or near the sensor nodes. By performing lightweight processing and transmission control at the edge, IoT systems can significantly reduce communication load while maintaining acceptable monitoring performance [4,7]. Nevertheless, prior studies often focus on algorithmic design or simulation-based evaluations with limited validation using long-term high-resolution environmental datasets collected from real deployments.

Recent works on adaptive sampling for environmental monitoring demonstrate promising results in reducing data volume and energy consumption [8,9]. However, the majority of these studies are evaluated on short-term datasets or controlled experimental settings. As highlighted in multiple surveys there remains a lack of comprehensive engineering evaluations that quantify the trade-off between data reduction and event preservation when adaptive transmission strategies are applied to real-world long-duration environmental data. Despite the

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extensive development of data reduction and adaptive transmission techniques a clear research problem remains. There is a lack of systematic engineering evaluation that quantifies how transmission reduction strategies affect both energy efficiency and the preservation of critical environmental events when applied to long-term high-resolution real-world datasets.

Therefore, this study addresses an important research gap by investigating energy-efficient data transmission strategies for IoT-based environmental monitoring systems using long-term high-frequency field data. Rather than proposing a new sensing algorithm this work focuses on the engineering evaluation of adaptive and event-aware transmission strategies examining how data reduction impacts system efficiency and the ability to preserve meaningful environmental events. The findings of this study aim to provide practical design guidelines for resource-constrained IoT deployments operating under real environmental conditions.

2. Literature Review

2.1 Data Transmission and Energy Constraints in IoT Systems

Energy consumption has long been recognized as a critical constraint in IoT-based monitoring systems, particularly for long-term field deployments where sensor nodes rely on limited power sources such as batteries or

energy harvesting devices. Several studies have shown that wireless data transmission dominates the overall energy budget of IoT nodes often exceeding the energy required for sensing and local computation [1,3].

As a result, continuous high-frequency data transmission significantly reduces system lifetime and increases maintenance costs. Traditional IoT deployments commonly adopt fixed-rate sampling and periodic data uploading due to their simplicity. However systematic reviews indicate that such approaches lead to substantial redundancy in transmitted data especially in environmental monitoring scenarios where sensed variables often exhibit slow temporal variations interspersed with occasional abrupt changes [1,2]. These findings highlight the necessity of designing transmission strategies that are adaptive to environmental dynamics rather than relying on static configurations.

2.2. Data Reduction Techniques for IoT-Based Monitoring

To mitigate energy and communication constraints a wide range of data reduction techniques have been proposed in the literature. According to comprehensive surveys, data reduction methods for IoT systems can be broadly classified into compression-based, sampling-based, and event-driven approaches [1,2]. Compression techniques aim to reduce payload size while sampling-based methods reduce the number of transmitted data

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points. Event-driven approaches on the other hand, selectively transmit data only when predefined conditions or anomalies are detected.

Among these categories sampling-based and event-driven techniques have been identified as particularly suitable for resource-constrained IoT nodes as they avoid the computational overhead associated with complex compression algorithms [2]. Reviews further suggest that these approaches are more compatible with real-time monitoring requirements and low-power communication technologies such as LoRa and NB-IoT [3,10].

Recent studies have proposed predictive and adaptive data reduction techniques to minimize redundant transmissions in IoT systems [11].

2.3 Adaptive Sampling and Event-Based Transmission

Adaptive sampling has emerged as an effective strategy for balancing data fidelity and energy efficiency in IoT systems. Instead of using a fixed sampling interval, adaptive approaches dynamically adjust the sampling rate based on signal characteristics, environmental variability or energy availability [6,9]. Event-based transmission extends this concept by triggering data transmission only when significant changes or predefined events occur in the sensed data. A survey [5] categorizes event detection mechanisms into threshold-based, statistical, and lightweight machine learning approaches. For environmental

monitoring applications threshold-based and statistical methods are often preferred due to their simplicity, transparency, and low computational cost. Empirical studies demonstrate that adaptive and event-driven strategies can significantly reduce data volume while preserving key features such as peaks and abrupt transitions [6,8]. However existing works primarily evaluate these techniques using short-term datasets or controlled laboratory experiments. As noted in multiple reviews there is limited evidence demonstrating how adaptive sampling and event-based transmission perform when applied to long-term high-resolution environmental data collected under real-world conditions [1,5,6]. Recent studies have proposed adaptive sensing frameworks to improve energy efficiency in IoT systems, particularly in WSN-assisted environments [12].

2.4 Edge Computing and System-Level Design Considerations

Recent advances in edge computing have further reinforced the importance of system-level design in IoT deployments. By enabling local data processing and decision-making at or near the sensor nodes, edge computing architectures can reduce communication latency and network traffic while improving energy efficiency [4,7]. Surveys in this area emphasize that intelligent data transmission strategies should be considered an integral component of edge-enabled IoT systems. Nevertheless, much of

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the existing literature focuses on architectural frameworks or algorithmic innovations with limited emphasis on quantitative engineering evaluation. In particular the interaction between adaptive transmission strategies and long-term data characteristics such as seasonal variations and sensor noise remains underexplored [2,4]. This gap is especially relevant for environmental monitoring systems where data patterns may vary significantly over extended deployment periods.

Recent advancements in Edge-AI have further enhanced the capability of IoT systems by enabling intelligent decision-making at the network edge, improving latency, energy efficiency, and scalability. These approaches integrate artificial intelligence directly into edge devices to reduce communication overhead and improve real-time responsiveness [13].

A comparative analysis of existing studies reveals several key differences in methodological focus and evaluation scope. Prior works on adaptive sampling and event-based transmission primarily emphasize algorithmic design and simulation-based validation, often using short-term or synthetic datasets. While these approaches demonstrate significant potential in reducing data volume and energy consumption, they frequently lack evaluation under long-term real-world environmental conditions. In contrast some studies address system-level implementation but do not systematically quantify the trade-off between data reduction and event preservation. Furthermore, limited attention has been given

to multi-parameter environmental event analysis in practical deployments. These limitations highlight the need for a comprehensive engineering evaluation framework that integrates long-term field data, transmission efficiency and event preservation performance.

2.5 Research Gap and Motivation

Based on the reviewed literature, several key gaps can be identified. First although numerous data reduction and adaptive transmission techniques have been proposed, most studies lack validation using long-term high-frequency environmental datasets obtained from real deployments [1,6,8]. Second, prior work often reports data reduction ratios or energy savings without systematically evaluating the impact on event preservation and monitoring effectiveness [5,9]. Finally, there is a need for practical engineering guidelines that quantify the trade-offs between data reduction, energy efficiency, and information loss in real-world IoT monitoring systems [2,4]. Motivated by these gaps this study focuses on the engineering evaluation of energy-efficient data transmission strategies using long-term environmental monitoring data. By analyzing adaptive and event-based transmission schemes under realistic conditions the study aims to provide insights that bridge the gap between theoretical approaches and practical IoT system design.

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While prior studies have reported transmission reduction benefits most evaluations focus primarily on energy metrics without quantifying event preservation performance. Comparative trade-off analysis using long-term real-world outdoor datasets remains limited. Therefore, a structured quantitative framework is required to systematically evaluate both transmission efficiency and monitoring reliability.

3. Research Objectives and Contributions

This study aims to address the limitations identified in existing literature regarding energy-efficient data transmission in IoT-based environmental monitoring systems. While previous studies and surveys have extensively discussed data reduction techniques such as adaptive sampling and event-based transmission most of them rely on short-term experiments, simulations, or controlled laboratory data. Consequently, there is a lack of engineering-level evaluation that demonstrates how these strategies perform when applied to long-term high-frequency environmental data collected from real-world deployments. The primary objective of this research is therefore to systematically evaluate energy-efficient data transmission strategies using long-term field data with a focus on system-level performance rather than algorithmic novelty. Specifically, this study seeks to analyze the characteristics of high-resolution environmental monitoring data including temporal

redundancy, variability, and event-like behaviors that influence data transmission decisions.

Based on these characteristics adaptive sampling and event-based transmission strategies suitable for resource-constrained IoT sensor nodes are designed and implemented. The performance of these strategies is evaluated by comparing them with conventional fixed-rate transmission in terms of data reduction rate transmission frequency and estimated energy savings. In addition, this study investigates the extent to which reduced data transmission schemes are able to preserve significant environmental events which is a critical requirement for maintaining the effectiveness of environmental monitoring systems.

The contributions of this study are threefold. First, it provides an engineering evaluation of energy-efficient data transmission strategies using one-year high-frequency environmental monitoring data obtained from a real deployment thereby addressing a key gap in prior research that predominantly focuses on short-term or synthetic datasets. Second the study presents a systematic comparison of multiple transmission strategies under a unified evaluation framework enabling a clear analysis of trade-offs between data reduction and information preservation. Third the findings of this work offer practical insights and design guidelines for long-term IoT deployments operating under energy and communication constraints contributing empirical evidence that bridges the gap

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between survey-based research and real-world system design.

4. Methodology

4.1 Dataset & System Description

The environmental monitoring dataset used in this study was collected using an outdoor IoT sensing system deployed in Chiang Rai province, Thailand. The sensing node was built on an ESP32 microcontroller platform and equipped with an SHT20 sensor for temperature and relative humidity measurements, as well as a PMS3003 sensor for PM2.5 concentration monitoring. The system was designed for continuous outdoor operation and data acquisition under real environmental conditions. Environmental data were collected at a fixed sampling interval of 30 seconds from March 2024 to May 2025, resulting in a long-term high-resolution time-series dataset. All sensed data were transmitted to a cloud-based database using the ThingSpeak platform for storage and further analysis. The data acquisition and transmission architecture follow a typical IoT-based environmental monitoring workflow and has been previously validated in a related outdoor sensing application [14]. This dataset provides a realistic foundation for evaluating energy-efficient data transmission strategies, as it exhibits natural environmental variability noise characteristics associated with low-cost sensors and long-term temporal patterns

relevant to adaptive sampling and event-based transmission.

4.2 System Overview



Figure 1. Block diagram of the proposed IoT-based environmental monitoring system.

The Figure 1 shows the overall architecture of the IoT-based environmental monitoring system used in this study. The system consists of three main components: environmental sensors an ESP32-based microcontroller unit (MCU) and a cloud-based server. The sensing unit includes sensors for PM2.5 concentration temperature and relative humidity which continuously measure outdoor environmental conditions. The ESP32 MCU is responsible for data sampling preliminary processing and wireless data transmission using an integrated Wi-Fi module. All sensed data are transmitted to a remote server where they are stored in a cloud database for long-term logging and offline analysis.

This system architecture represents a typical IoT-based environmental monitoring workflow and serves as the baseline configuration for evaluating energy-efficient

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data transmission strategies. In the conventional operation mode sensor data are sampled and transmitted at a fixed interval of 30 seconds. In this study the same system architecture is maintained while different data transmission strategies are evaluated at the MCU level to reduce transmission frequency without modifying sensor hardware or cloud infrastructure.

The architecture shown in Figure 1 provides a practical foundation for investigating system-level energy efficiency in long-term IoT deployments. Rather than introducing additional hardware or complex processing modules this study focuses on modifying the data sampling and transmission logic implemented on the ESP32 MCU. By adjusting when and how sensor data are transmitted to the server the impact of data reduction strategies on transmission load energy consumption and event preservation can be systematically evaluated under realistic operating conditions.



Figure 2. Actual device used for environment data acquisition.

Figure 2. Photograph of the actual data acquisition device installed in the field. The enclosure is made of a plastic box designed for outdoor deployment. A small protective hood is installed to shield the PMS3003 particulate matter sensor from direct rain and sunlight while allowing proper air intake. The SHT20 temperature and humidity sensor is mounted below the enclosure to enable accurate ambient environmental measurements.

4.3 System Operation and Baseline Configuration

Under normal operation the environmental sensing system shown in Figure 1 collects temperature, humidity and PM2.5 data at a fixed interval of 30 seconds. Each sampled data point is immediately transmitted to the cloud database via Wi-Fi using the ESP32 module. This fixed-rate transmission strategy serves as the baseline configuration in this study. Let N baseline denote the total number of transmitted samples under fixed 30-second [14] sampling over the entire monitoring period. Since data are transmitted at every sampling instant, the number of transmissions is equal to the number of samples collected.

This configuration represents the maximum transmission load and is used as the reference case for evaluating data reduction and energy-saving performance. Energy consumption associated with data transmission is assumed to be proportional to the number of transmission events. Therefore, reducing transmission

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frequency directly contributes to energy savings, as suggested in prior studies on energy-aware IoT communication [3,9].

4.4 Transmission Strategies and Evaluation Metrics

To evaluate the effectiveness of energy-efficient data transmission in the proposed IoT-based environmental monitoring system several transmission strategies are implemented and compared against the baseline fixed-rate transmission described in the previous section. The objective is to quantify the trade-offs between transmission reduction, energy savings, and preservation of significant environmental events.

Transmission Strategies In the baseline configuration environmental data are sampled and transmitted every 30 seconds without any filtering or adaptation. Let N baseline denote the total number of transmitted samples over the entire monitoring period. Since every sampled data point is transmitted the number of transmission events is equal to the number of collected samples. This configuration represents the maximum transmission load and serves as the reference case for performance comparison.

Fixed-Interval Downsampling, the first reduction strategy is fixed-interval downsampling where data are sampled at 30-second intervals but transmitted only every $k - th$ sample. For example, when $k = 10$ one data point is transmitted every 5 minutes.

$$N_{reduced} = \frac{N_{baseline}}{k} \quad (1)$$

This approach provides a simple mechanism for reducing transmission frequency without requiring signal analysis.

Adaptive Sampling Strategy In the adaptive sampling strategy transmission frequency is dynamically adjusted based on environmental variability. The change in PM2.5 concentration is calculated.

$$\Delta PM(t) = PM(t) - PM(t - \Delta t) \quad (2)$$

$$\Delta PM_{(t)} > 0 \quad (3)$$

the current data point is transmitted immediately otherwise transmission is deferred or aggregated. The threshold parameter θ controls system sensitivity. Lower values increase event responsiveness but reduce data reduction efficiency.

Event-Based Transmission In the event-based strategy transmission occurs only when predefined environmental conditions are satisfied. PM2.5 event.

$$PM_{(t)} - \overline{PM}_{window} > \alpha \quad (4)$$

$\overline{PM}_{window}$ represents the moving average over a predefined window. A multi-parameter event condition can also be defined.

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$$E(t) = \begin{cases} 1, & \text{if } PM \uparrow \wedge Temp \uparrow \wedge RH \downarrow \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Transmission occurs only when $E(t) = 1$. This strategy aims to preserve significant environmental fluctuations while minimizing redundant transmissions during stable periods.

PM2.5 concentration is selected as the primary triggering parameter for adaptive transmission due to its higher short-term variability compared to temperature and relative humidity in outdoor environments. Several studies have reported that air pollution parameters exhibit abrupt fluctuations and dynamic behavior making them suitable for event-driven monitoring strategies [5,6,15,16]. In contrast meteorological variables such as temperature and humidity typically show smoother temporal variations over short intervals. Therefore, using PM2.5 as the main adaptive trigger allows the system to respond to significant environmental changes while minimizing unnecessary transmissions.

Evaluation Metrics To quantify system performance three key evaluation metrics are defined.

Data Reduction Ratio (DRR) The Data Reduction Ratio measures the percentage of transmission reduction relative to the baseline configuration.

Multi-Parameter Adaptive Sampling Formulation To extend the adaptive transmission mechanism beyond single-parameter triggering

a multi-parameter variability model is formulated. The normalized variability index.

$$V(t) = w_1 \frac{\Delta PM(t)}{\alpha PM} + w_2 \frac{\Delta Temp(t)}{\alpha Temp} + w_3 \frac{\Delta Hum(t)}{\alpha Hum} \quad (6)$$

The weighting coefficients satisfy.

$$w_1 + w_2 + w_3 = 1 \quad (7)$$

αPM , $\alpha Temp$, and αHum are normalization factors used to scale the relative influence of each parameter. The adaptive sampling interval is then,

$$Ts(t) = T_{\min} + \frac{T_{\max} - T_{\min}}{1 + \gamma V(t)} \quad (8)$$

$$DDR = 1 - \frac{N_{transmitted}}{N_{baseline}} \quad (9)$$

Where $N_{transmitted}$ is the number of transmissions under a given strategy. higher DRR indicates greater transmission reduction.

Event Preservation Ratio (EPR) To ensure that significant environmental events are not lost due to transmission reduction the Event Preservation Ratio is defined.

$$EPR = \frac{N_{reduce\ event}}{N_{baseline\ event}} \quad (10)$$

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$N_{baseline\ event}$ = number of detected events using full 30-second data.

$N_{reduce\ event}$ = number of detected events under reduced transmission.

An EPR close to 1 indicates that the transmission strategy successfully preserves important environmental events.

The parameters used in the adaptive sampling and event detection mechanisms were selected based on empirical analysis of the dataset and practical considerations for real-world deployment. The PM2.5 change threshold ΔPM was determined by analyzing short-term variability patterns to ensure sensitivity to significant fluctuations while avoiding excessive triggering due to noise.

For event detection the threshold parameter (α) and moving average window were chosen to balance responsiveness and stability ensuring that only meaningful environmental changes are captured. The weighting coefficients (w_1, w_2, w_3) in the multi-parameter model were assigned to prioritize PM2.5 due to its higher variability compared to temperature and humidity, as observed in the dataset. The adaptive sampling parameters, including minimum and maximum sampling intervals (T_{min}, T_{max}) and the scaling factor (γ) were configured to maintain a balance between transmission reduction and responsiveness to dynamic environmental conditions. These values were selected through iterative testing to achieve

stable performance across the full-year dataset.

All algorithms were implemented at the microcontroller (ESP32) level, where transmission decisions were made in real time based on incoming sensor data without requiring additional hardware or cloud-side processing.

4.5 Energy Saving Estimation

Since wireless transmission is a dominant energy-consuming operation in IoT nodes [3,9,16] energy consumption is assumed to be proportional to the number of transmission events. The relative energy saving is therefore estimated.

$$Energy_{saving} = 1 - \frac{N_{tx}^{reduce}}{N_{tx}^{baseline}} \quad (11)$$

Where N_{tx} represents the number of transmission events. Under this assumption energy saving is directly equivalent to transmission reduction.

4.6 Experimental Design

The evaluation is conducted using the complete dataset collected between March 2024 and May 2025. The baseline transmission count is first determined under the 30-second sampling configuration to establish a reference scenario. Subsequently each transmission

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strategy is simulated offline within a numerical computing environment by applying the corresponding decision rules to the original dataset. For each strategy, key performance metrics are calculated including the total number of transmissions, Data Reduction Ratio (DRR), Event Preservation Ratio (EPR), and estimated energy savings. A comparative analysis is then carried out to identify the optimal trade-off between energy efficiency and the preservation of significant environmental events.

The fixed downsampling interval (every 5 minutes) was selected to represent a commonly used periodic transmission configuration in practical IoT deployments and to demonstrate the upper bound of transmission reduction performance. While this configuration results in a higher reduction rate compared to the adaptive sampling method, the objective of this study is not to match reduction levels but to evaluate the trade-off between transmission efficiency and event preservation. Therefore, comparing a high-reduction baseline with an adaptive strategy provides a clearer insight into the limitations of uniform downsampling and the advantages of variability-aware transmission.

5. Results and Discussion

5.1 Baseline Transmission Characteristics

Under the baseline configuration, environmental data were sampled and transmitted every 30 seconds throughout the

monitoring period from March 2024 to May 2025. This resulted in a total of 1,048,406 transmission events, representing the maximum communication load of the deployed IoT system.

Figure 3 show the baseline PM2.5 time-series over the entire monitoring period. The data exhibit significant temporal variability including multiple high-concentration spikes and seasonal patterns. In particular extreme PM2.5 peaks exceeding several thousand micrograms per cubic meter were observed during specific periods, indicating abrupt environmental fluctuations.

The statistical characteristics of the monitored parameters are summarized in Table 1. Among the variables PM2.5 demonstrates substantially higher variability standard deviation = $478.94 \mu\text{g}/\text{m}^3$ compared to temperature (6.47°C) and relative humidity (22.55%). This confirms that PM2.5 exhibits stronger short-term dynamics and greater amplitude variations relative to the other environmental parameters.

The high frequency of transmission in the baseline configuration combined with the dynamic behavior of PM2.5 highlights the communication intensity associated with continuous high-resolution environmental monitoring. Previous studies have reported that wireless transmission is a dominant contributor to energy consumption in IoT sensor nodes [3,9,16].

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Therefore, reducing transmission frequency without compromising critical environmental

information becomes essential for improving long-term system sustainability.

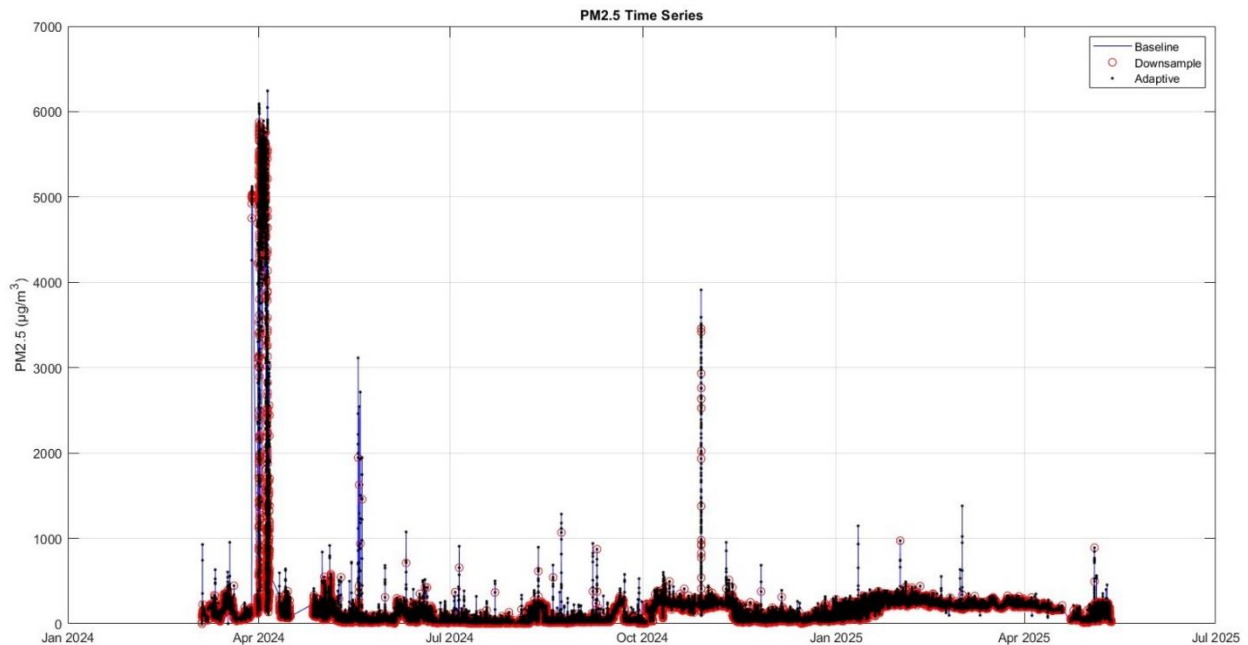


Figure 3. Full-Year PM2.5 Time Series.

Table 1: Statistical Characteristics.

Parameter	Mean	Std Dev
PM2.5	165	478.94
Temperature	27	6.47
Humidity	72	22.55

5.2 Data Reduction Performance

The effectiveness of the proposed transmission reduction strategies was evaluated by comparing the total number of transmission events relative to the baseline configuration. As described in Section 4.1, the baseline system generated 1,048,406

transmission events during the monitoring period.

Table 2: Statistical Characteristics.

Parameter	Baseline	Down sampling	Adaptive
Total Transmissions	1,048,406	104,841	221,256
Data Reduction (%)	0	90.00	78.89

Table 2 summarizes the transmission statistics under each strategy. The fixed downsampling approach which transmits data every 5 minutes, reduced the total number of

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transmission events by 90.00% resulting in a substantial decrease in communication load. In contrast, the adaptive sampling strategy achieved a Data Reduction Ratio (DRR) of 78.89% representing a significant reduction while still allowing transmission during dynamic environmental changes.

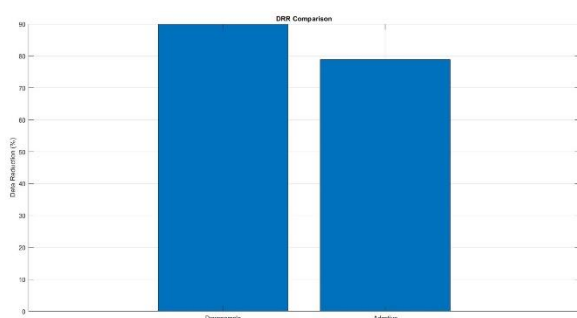


Figure 4. Data Reduction Ratio (DRR) comparison between fixed downsampling and adaptive transmission strategies.

Figure 4 further show the DRR comparison between the two strategies. While periodic downsampling achieves the highest reduction rate adaptive sampling maintains a lower but still substantial transmission reduction.

The observed reduction levels are consistent with previous studies that report significant energy savings when transmission frequency is reduced in IoT systems [9,16].

Since wireless transmission is widely recognized as one of the dominant contributors to energy consumption in sensor nodes,

reducing transmission events directly translates to improved energy efficiency.

However, data reduction alone does not guarantee monitoring effectiveness. Therefore, event preservation performance must also be analyzed, which is discussed in the following section.

5.3 PM-Only Event Preservation Performance

While transmission reduction improves energy efficiency it may degrade the system's ability to detect significant environmental events. To evaluate this effect event preservation performance was assessed based on PM_{2.5} deviations from a moving average threshold The Event Preservation Ratio (EPR) was computed by comparing the number of detected events under each transmission strategy relative to the baseline configuration.

The results indicate a substantial difference between the two reduction strategies. Fixed downsampling achieved a PM-EPR of only 12.74% meaning that nearly 87% of PM-related events detected in the baseline data were not preserved in the reduced dataset. This result demonstrates that periodic reduction severely compromises the detection of short-term pollution spikes.

In contrast, the adaptive transmission strategy achieved a PM-EPR of 49.65% preserving nearly half of the baseline-detected events while still achieving a 78.89% reduction in transmission frequency.

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Figure 5 show the comparison of PM-EPR values between the two strategies. The significant improvement observed in adaptive sampling confirms that variability-based triggering mechanisms are more effective in maintaining environmental signal dynamics compared to uniform interval reduction.

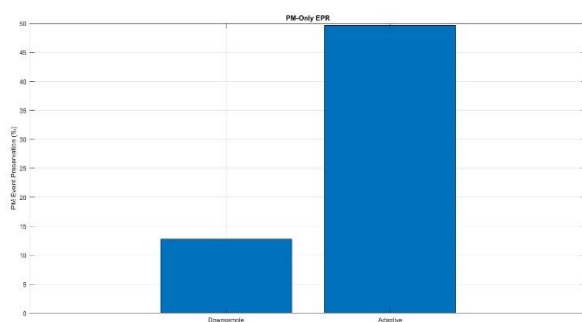


Figure 5. PM-only Event Preservation Ratio (EPR) comparison between transmission strategies.

These findings are consistent with previous studies that emphasize the importance of event-aware transmission mechanisms in IoT-based monitoring systems [6,9,16]. In particular, adaptive approaches that respond to signal variability are better suited for dynamic environmental conditions where abrupt fluctuations carry meaningful information.

5.4 Multi-Parameter Event Preservation Performance

To further evaluate system robustness under more complex environmental dynamics, a combined event detection mechanism incorporating PM_{2.5}, temperature, and relative

humidity was implemented. Unlike the PM-only evaluation in Section 5.3 this approach considers multi-parameter environmental fluctuations through a weighted index, allowing a more comprehensive representation of environmental anomalies.

The combined event preservation results reveal a clear distinction between the two transmission strategies. Fixed downsampling achieved a Combined-EPR of only 15.91% indicating that most multi-parameter environmental events were not preserved under periodic reduction. In contrast, the adaptive sampling strategy achieved a Combined-EPR of 56.76% preserving more than half of the baseline-detected multi-parameter events while still reducing transmission frequency by nearly 79%.

Figure 6 presents the comparison of Combined-EPR values. The substantial improvement observed under adaptive transmission suggests that variability-aware triggering mechanisms are more suitable for complex environmental monitoring scenarios where multiple parameters jointly contribute to event formation. The results further confirm that aggressive periodic reduction strategies may oversimplify environmental dynamics, leading to significant loss of contextual information. Adaptive strategies by responding to dynamic changes, provide a more balanced compromise between energy efficiency and environmental awareness.

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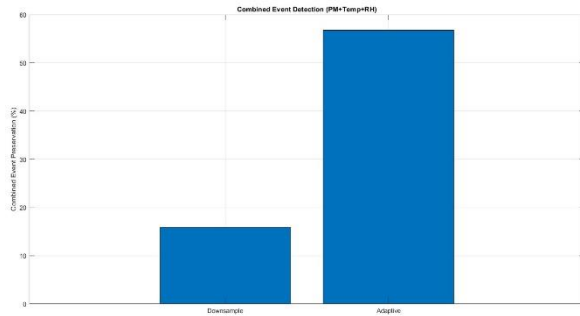


Figure 6. Multi-parameter PM, Temperature, Humidity Event Preservation Ratio comparison.

Table 3: Performance comparison of transmission strategies.

Strategy	DRR (%)	PM-EPR (%)	Combine d-EPR (%)
Downsampling	90.00	12.74	15.91
Adaptive	78.89	49.65	56.76

Table 3 summarizes the overall performance of the evaluated transmission strategies. Although fixed downsampling achieves the highest transmission reduction its event preservation capability is significantly limited. In contrast adaptive transmission provides a more balanced performance across all evaluation metrics.

5.5 Trade-Off Analysis

While Sections 5.2 – 5.4 independently evaluate transmission reduction and event preservation performance, practical IoT system design requires balancing both

objectives simultaneously. Therefore, a trade-off analysis was conducted by jointly considering Data Reduction Ratio (DRR) and Combined Event Preservation Ratio Combined-EPR.

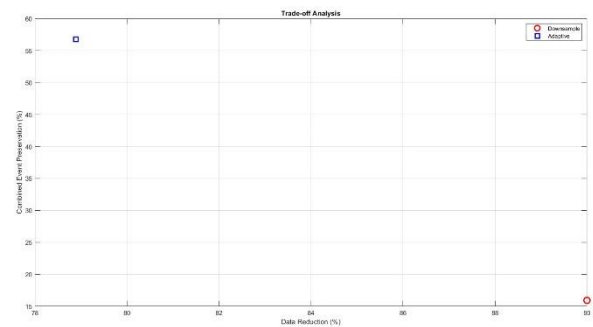


Figure 7. Trade-off analysis between data reduction.

Figure 7 show the relationship between transmission reduction and multi-parameter event preservation for the evaluated strategies. The fixed downsampling approach achieved the highest transmission reduction (90.00%) but preserved only 15.91% of combined environmental events. This indicates that aggressive periodic reduction significantly compromises monitoring effectiveness. In contrast the adaptive sampling strategy achieved a slightly lower transmission reduction (78.89%) but preserved 56.76% of combined events. Although adaptive transmission does not maximize data reduction it provides a substantially better balance between communication efficiency and environmental awareness.

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From a system-level perspective, the results demonstrate that maximizing transmission reduction alone is not an optimal design objective for dynamic environmental monitoring applications. Instead, transmission strategies should consider signal variability and event significance to maintain monitoring reliability while improving energy efficiency.

These findings align with prior studies emphasizing the importance of adaptive and event-aware communication mechanisms in IoT-based monitoring systems [1,5,9,16]. The proposed evaluation framework demonstrates that adaptive transmission strategies offer a practical compromise for long-term outdoor IoT deployments operating under communication and energy constraints.

The goal of this study is not to maximize reduction performance but to provide a structured evaluation framework for balancing communication efficiency and monitoring reliability in real-world IoT deployments.

To further support the robustness of the results, the large sample size (over one million data points) provides strong statistical reliability in the observed performance trends. Although formal significance testing was not the primary focus of this study the consistent differences observed between fixed downsampling and adaptive transmission across multiple evaluation metrics (DRR and EPR) indicate a clear and stable performance gap.

Future work may incorporate formal statistical hypothesis testing and confidence

interval analysis to further quantify the uncertainty and significance of these results.

6. Conclusion

This study investigated energy-efficient data transmission strategies for long-term IoT-based environmental monitoring using real outdoor data collected in Chiang Rai, Thailand. A baseline configuration with 30-second transmission intervals resulted in 1,048,406 transmission events over the monitoring period highlighting the communication intensity of high-resolution sensing systems.

The novelty of this study lies in the use of a real-world long-term dataset, the development of a clearly defined system-level evaluation methodology, and the application of quantitative performance metrics to systematically assess the trade-off between energy efficiency and event preservation.

Fixed downsampling achieved the highest data reduction (90.00%), but significantly degraded event preservation performance, preserving only 15.91% of multi-parameter environmental events. In contrast, the adaptive sampling strategy achieved a balanced performance, reducing transmission by 78.89% while preserving 56.76% of combined environmental events.

The results demonstrate that maximizing transmission reduction alone is not an optimal strategy for dynamic environmental monitoring. Instead, adaptive transmission mechanisms

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that respond to signal variability provide a more effective trade-off between energy efficiency and environmental awareness.

Despite the promising results, several practical limitations should be considered. The use of low-cost sensors such as SHT20 and PMS3003 may introduce measurement uncertainties over long-term deployment, including sensor drift and sensitivity to environmental factors such as temperature fluctuations, humidity, and particulate accumulation. Additionally, the ESP32-based system, while cost-effective and widely adopted, may be affected by extreme outdoor conditions such as high temperature, humidity, and power instability which could impact long-term system reliability. In terms of scalability the proposed transmission strategies are designed to operate at the sensor node level and can be extended to large-scale IoT deployments with multiple distributed nodes. However, network-level factors such as bandwidth limitations, synchronization, and cloud infrastructure performance may influence system behavior in large deployments. From a deployment perspective, the proposed approach is particularly suitable for long-term outdoor environmental monitoring scenarios where energy constraints and communication efficiency are critical. Nevertheless, different application contexts may require parameter tuning and adaptation to specific environmental dynamics. Future work will focus on incorporating more robust statistical validation, adaptive parameter optimization,

and integration with edge-based intelligent decision mechanisms to enhance system scalability and long-term reliability.

The proposed evaluation framework offers practical insights for designing energy-constrained IoT monitoring systems operating under real outdoor conditions. Future work may explore sensitivity analysis of adaptive thresholds and integration with real-time edge-based decision mechanisms to further enhance system performance.

7. Acknowledgments

AI-assisted tools were used for language editing purposes only. The authors retain full responsibility for all technical content and conclusions.

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