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# Energy-Efficient Green IoT System for Real-Time Air Quality Monitoring of $PM_1$–$PM_{10}$

**Agus Purnomo[1], Asep Andang[2,*], Siti Badriah[3]**

[1]Department of Medical Laboratory Technology, Poltekkes Kemenkes Tanjung Karang, Indonesia
[2]Department of Electrical Engineering, Faculty of Engineering, Universitas Siliwangi, Indonesia
[3]Department of Nursing, Poltekkes Kemenkes Jakarta III, Indonesia

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**Abstract** Particulate matter ($PM_1$, $PM_{2.5}$, and $PM_{10}$) represents a critical environmental and occupational health concern, particularly in industrial environments where airborne dust frequently exceeds safe thresholds. Prolonged exposure contributes to respiratory, cardiovascular, and neurological disorders, underscoring the need for effective, continuous monitoring systems. This study aims to develop an energy-efficient Green Internet of Things (Green IoT) framework for real-time monitoring of air quality using low-cost sensor nodes designed to operate sustainably in industrial settings. The system integrates ESP32-S3 microcontrollers, Wi-Fi connectivity, and a data deduplication algorithm that reduces redundant transmissions to optimize power consumption. Three sensor nodes were deployed at a feed mill facility in Lampung, Indonesia, to evaluate performance under real operational conditions. During 24-hour continuous monitoring, each node generated 1,270–1,418 valid data points while achieving an approximately 20% reduction in unnecessary transmissions. Pearson correlation analysis showed strong intra-node consistency (r = 0.94–1.00) and moderate correlation (r ≈ 0.5) between nodes, validating reliability for localized particulate assessment. The results demonstrated that the proposed system effectively captured spatiotemporal variations in particulate concentrations while maintaining low energy use, making it suitable for scalable deployment in industrial environments. The findings contribute to the advancement of Green IoT by demonstrating a practical approach to sustainable communication and data management in distributed sensor networks. Research implications include the potential integration of this framework into large-scale environmental surveillance systems and the development of adaptive algorithms for predictive monitoring using machine learning. Practically, the system offers an affordable and replicable solution to support regulatory compliance, occupational health management, and environmental protection. Socially, the implementation of continuous, transparent air quality monitoring promotes community awareness and supports policy initiatives aimed at reducing industrial pollution. Future work will explore long-term deployments and advanced analytics for predictive air quality forecasting.

**Keywords** Green IoT, Air Quality Monitoring, Low-Cost Sensors, Particulate Matter, Data Deduplication, Industrial Environment

## 1. Introduction

Airborne particulate matter (PM), particularly $PM_1$, $PM_{2.5}$, and $PM_{10}$, has been recognized as a major environmental and health challenge worldwide [1]. Industrial activities such as feed production, manufacturing, and food processing generate high concentrations of airborne particles, which frequently exceed the air quality thresholds recommended by the World Health Organization (WHO) [2]. Prolonged exposure to fine particulate matter is strongly associated with respiratory and cardiovascular diseases, stroke, and certain types of cancer, especially in vulnerable populations [3]. In industrial environments, where workers face daily exposure, the risks are even greater, necessitating effective monitoring strategies to protect occupational health and ensure compliance with environmental standards [4], [5].

Conventional particulate matter monitoring methods, which rely on sample collection and laboratory analysis, are accurate but often costly, time-consuming, and unsuitable for continuous or real-time monitoring [6]. These limitations have driven increasing interest in low-cost particulate matter sensors (LCPMS), which offer continuous and scalable monitoring capabilities. However, LCPMS devices face accuracy challenges due to environmental influences such as humidity, temperature, and ambient light [7]. To overcome these limitations, calibration techniques and advanced data processing strategies, such as machine learning and algorithm-based error correction, have been explored. Despite these efforts, ensuring reliable and energy-efficient deployment of LCPMS in industrial settings remains a critical research gap [8]-[10].

The concept of Green IoT emphasizes reducing energy consumption while enhancing eco-sustainability, with the primary objective of improving energy efficiency across IoT systems [11]. Its goal is to ensure that IoT applications become energy-efficient at every stage, from system design and planning to deployment and operation. One of the key strategies in Green IoT lies in the optimization of software processes, particularly in data communication and transmission [12]. In this context, data deduplication has emerged as an effective method for detecting and eliminating redundant data, originally developed to minimize storage overhead in memory systems [13]. When applied to the transmission process of low-cost particulate matter sensor nodes, data deduplication significantly reduces unnecessary communication, thereby lowering energy consumption and extending the operational lifespan of sensor networks [14], [15].

A number of studies have highlighted the critical role of particulate matter monitoring and the challenges associated with existing methods. Conventional monitoring techniques, while accurate, are costly and limited in their ability to provide real-time and spatially distributed data [16]. To overcome these limitations, low-cost particulate matter sensors (LCPMS) have gained traction as alternatives for continuous and scalable monitoring [17], [18]. However, their performance is often affected by environmental conditions such as humidity and temperature, which necessitate calibration and correction techniques [19], [20]. Advanced approaches including artificial neural networks and field calibration strategies have been employed to enhance accuracy [21], [22]. In parallel, the integration of IoT technologies has enabled real-time monitoring across urban and industrial environments [23], [24]. Nevertheless, IoT-based systems raise sustainability concerns due to energy consumption, driving the emergence of the Green IoT paradigm [25]. Studies have proposed strategies such as data deduplication and optimized transmission protocols to reduce redundant communication and improve energy efficiency [26]. These works collectively emphasize that while progress has been made in low-cost and IoT-enabled PM monitoring, further innovation is required to ensure reliable accuracy, energy efficiency, and practical deployment in industrial environments where air quality control is most critical [27].

This research extends our previous work [28], where an outdoor air quality monitoring system was developed using long-range (LoRa) communication under the Green IoT framework—an energy-efficient, environmentally friendly approach to Internet of Things technology. Unlike the earlier study, the present work focuses on deploying the monitoring system within industrial buildings, addressing the often-overlooked issue of indoor particulate exposure in occupational environments.

This study advances previous Green IoT research [28] by extending the concept from outdoor to indoor industrial environments, where particulate exposure is more localized and dynamic. The novelty of this work lies in the integration of an adaptive data deduplication algorithm within a WiFi–based architecture, enabling energy-efficient real-time monitoring without sacrificing data fidelity. Unlike existing systems that rely on fixed sampling or periodic transmission, the proposed framework introduces conditional, event-driven data communication validated through deployment in a working feed mill facility. This combination of energy optimization, industrial validation, and applicability to confined occupational spaces represents a practical and transferable innovation in sustainable air quality monitoring.

The structure of this article is organized as follows: Section 1 presents the introduction, highlighting the background, motivation, research gap, and related studies on particulate matter monitoring and Green IoT. Section 2 describes the research methodology, including the system architecture, hardware components, data deduplication strategy, and web application design. Section 3 discusses the results and analysis, focusing on system performance, energy efficiency, and data reliability obtained from field implementation in an industrial environment. Section 4 concludes the study by summarizing the key findings, emphasizing the contributions of the proposed Green IoT-based monitoring system, and outlining directions for future research.

## 2. Materials and Methods

### 2.1. System Architecture

Figure 1 illustrates the overall architecture of the proposed Green IoT-based air quality monitoring system, which integrates sensor nodes, communication networks, and a centralized server.

The system is designed to continuously measure particulate matter ($PM_1$, $PM_{2.5}$, and $PM_{10}$) and environmental parameters such as temperature and humidity. Data collected from the sensor nodes undergo pre-processing before being transmitted to the server. By employing Wi-Fi as the communication backbone, the system takes advantage of existing local networks in industrial facilities, ensuring reliable data transfer without requiring additional infrastructure.

At the core of the architecture are the sensor nodes, each equipped with a low-cost particulate matter sensor, humidity and temperature sensor, and an ESP32-S3 microcontroller. The microcontroller manages data acquisition, pre-processing, and the deduplication algorithm, which ensures that only significant changes in sensor readings are transmitted. Each node can function independently, allowing flexible deployment at multiple points inside an industrial building. This distributed configuration enhances spatial coverage and provides detailed information on localized air quality conditions.

Once processed at the node level, data are transmitted via Wi-Fi to the central server. The communication uses lightweight protocols such as HTTP or MQTT to minimize transmission overhead and energy consumption. The server hosts a structured database system (MySQL) that stores the incoming data and makes it available for analysis and visualization. Through this centralized architecture, the system supports multi-node scalability and ensures consistent data integration across different monitoring locations.

The final layer of the architecture is the user interface, where real-time data are displayed through a web-based dashboard accessible via the platform *monitoring-udara.id*. This dashboard provides numerical values, graphical trends, and automatic calculation of the Air Quality Index (AQI), enabling stakeholders to monitor indoor industrial air quality effectively. Importantly, the system incorporates the Green IoT paradigm by reducing redundant transmissions and optimizing energy use, ensuring that the monitoring solution remains sustainable, scalable, and practical for long-term deployment in industrial environments.

### 2.2. Sensor Node Design

Figure 2 shows the internal structure of the developed sensor node, which serves as the core component of the monitoring system. Each node is equipped with a low-cost particulate matter sensor capable of measuring $PM_1$, $PM_{2.5}$, and $PM_{10}$ concentrations in real time, along with integrated humidity and temperature sensors for contextual calibration. The ESP32-S3 microcontroller functions as the processing unit, handling data acquisition, pre-processing, and execution of the deduplication algorithm. Additional modules, such as the Real-Time Clock (RTC) and GNSS positioning, provide accurate timestamps and optional location data, while a local LCD screen and SD card module enable on-site visualization and backup storage. This design ensures that each sensor node operates autonomously and can be deployed flexibly within indoor industrial environments.

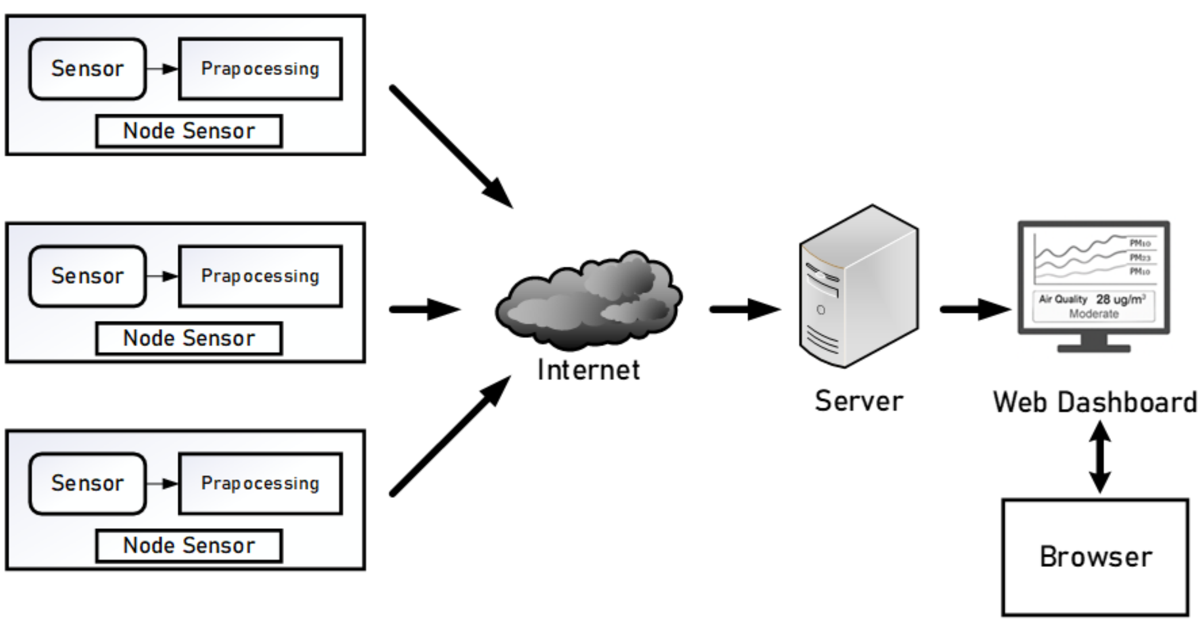



**Figure 1.** Air quality monitoring system architecture

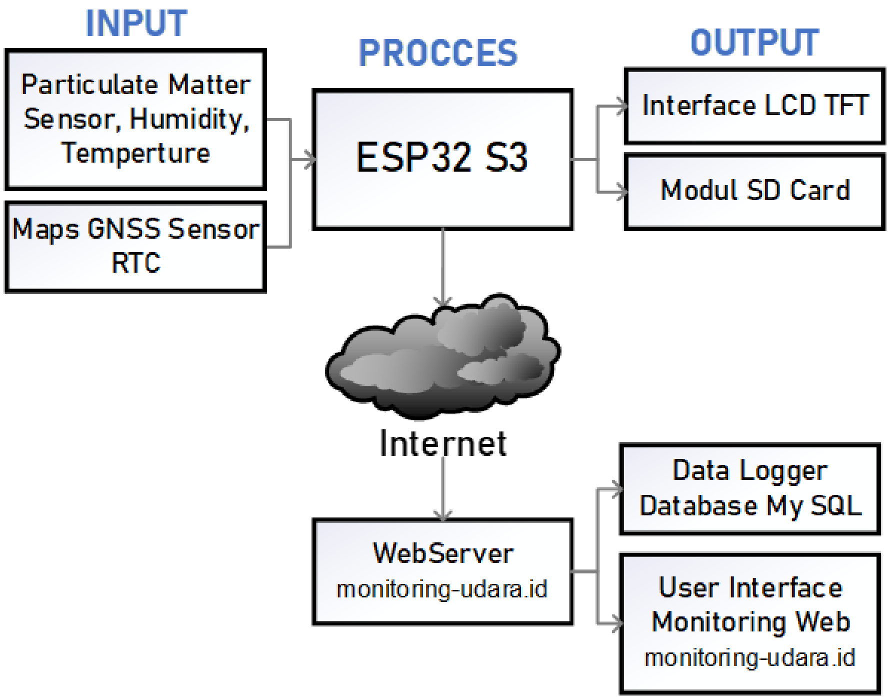



**Figure 2.** Sensor nodes and communication to the server

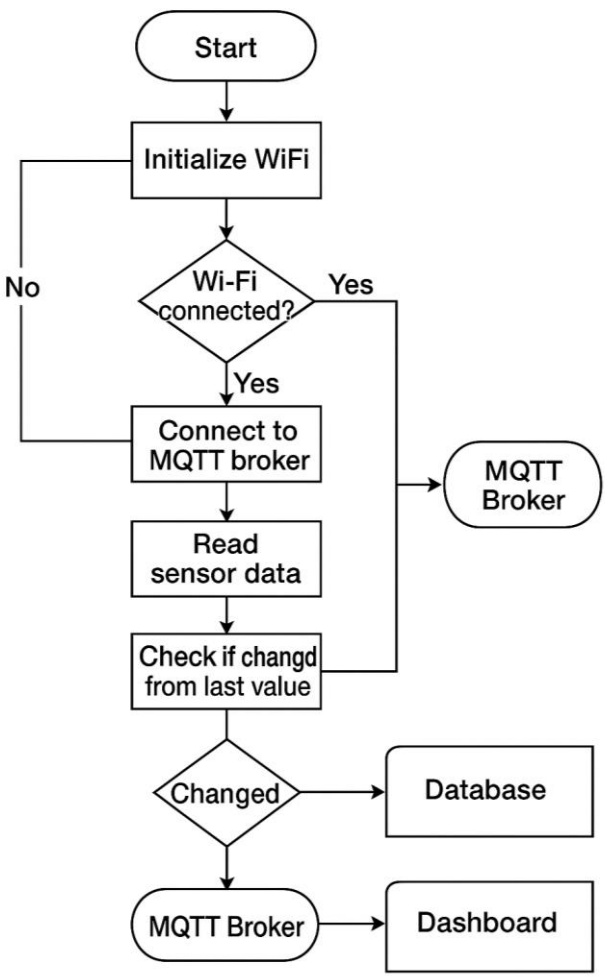



**Figure 3.** Sensor nodes and communication to the server

Figure 3 presents the flowchart describing the connection process between the sensor node and the central server within the proposed Green IoT-based air quality monitoring system. The flow begins with the initialization of the ESP32-S3 microcontroller, followed by the activation of connected modules such as particulate matter (PM) sensors, humidity and temperature sensors, and auxiliary components like the RTC and GNSS modules. Once initialized, the system continuously collects environmental data, which are processed locally by the microcontroller before any communication occurs. This flow ensures that only validated and structured data proceed to the next stage.

After acquisition, the microcontroller performs pre-processing to filter noise and validate sensor readings. A critical step in the flowchart is the deduplication logic, where the current readings are compared with previously stored values. If no significant changes are detected within a defined tolerance range, the system suppresses transmission to avoid redundant data flow. This mechanism reflects the Green IoT principle of minimizing energy consumption by reducing unnecessary communication, thereby conserving battery life and improving the sustainability of sensor node operations.

When the deduplication algorithm identifies a significant change in PM concentration or environmental parameters, the processed data are prepared for transmission. Using Wi-Fi as the communication protocol, the node sends the data packet to the central server via HTTP or MQTT. The flowchart illustrates error-handling mechanisms as well, ensuring that if the connection fails, the data are stored locally on the SD card as a backup. This redundancy guarantees data integrity even in cases of temporary network instability, which is crucial for maintaining reliable industrial monitoring.

Once received by the server, the data are stored in a MySQL database and made accessible through the web platform *monitoring-udara.id*. The flowchart highlights this final step, which transforms sensor outputs into actionable information for stakeholders. The platform not only provides real-time visualization of PM levels and Air Quality Index (AQI) values but also supports historical data analysis and multiuser access. By combining data deduplication at the node level with robust server integration, the flowchart demonstrates how the system achieves both energy efficiency and scalable monitoring, key elements of the Green IoT paradigm in industrial applications.

### 2.3. Data Transmission and Deduplication Strategy

Efficient data transmission is a critical component in the design of sustainable IoT-based monitoring systems, as communication is often the most energy-consuming operation in sensor networks. In the proposed system, Wi-Fi was selected as the primary communication protocol due to its availability and reliability in industrial environments. Sensor nodes transmit particulate matter ($PM_1$, $PM_{2.5}$, $PM_{10}$), temperature, and humidity data to the central server, where they are stored and visualized via the *monitoring-udara.id* platform. To minimize bandwidth usage and conserve energy, transmission is not continuous but event-driven, relying on conditional logic that prioritizes significant changes in sensor readings. This approach ensures that the system remains responsive to real environmental variations while avoiding unnecessary communication overhead.

A key innovation in this strategy is the implementation of data deduplication at the node level. Before transmission, each new measurement is compared against previously recorded values; if the difference falls within a predefined tolerance range, the data are not sent to the server. This process effectively eliminates redundant transmissions, reducing both network traffic and power consumption. Experimental results demonstrated that the deduplication mechanism decreased the number of transmitted records by approximately 18–22% during a 24-hour monitoring period, without compromising the accuracy or reliability of the dataset. By integrating deduplication with Wi-Fi-based communication, the system successfully aligns with the principles of Green IoT, offering an energy-efficient and scalable solution for real-time air quality monitoring in industrial environments.

The deduplication algorithm employs an adaptive threshold of ±5 μg/m³ or ±5% of the previous value, dynamically adjusted based on short-term variability. This ensures efficient energy use while maintaining adequate temporal resolution for detecting industrial particulate fluctuations.

### 2.4. Web Application and Server

The proposed monitoring system is supported by a centralized server that receives, stores, and processes the data transmitted from sensor nodes. The server is equipped with a MySQL database to manage structured records of particulate matter, temperature, and humidity readings. Data access is facilitated through an Application Programming Interface (API), which enables efficient integration with the web application. By adopting a lightweight architecture, the system ensures fast data retrieval and scalability, making it suitable for industrial environments where multiple nodes operate simultaneously. Additionally, the server incorporates backup and security mechanisms to guarantee data integrity and protect against loss during network interruptions.

The web application, available through monitoring-udara.id, provides stakeholders with a real-time dashboard that visualizes air quality parameters across different monitoring locations. Features include numerical displays of PM concentrations, graphical trends, and automatic computation of the Air Quality Index (AQI), categorized into standard health-based classifications (e.g., good, moderate, unhealthy). Historical data can be accessed for trend analysis, while multiuser access allows simultaneous use by factory managers, environmental officers, and the general public. This integration of server and web application transforms raw sensor data into actionable information, supporting timely decision-making and compliance with air quality standards.

Figure 4 presents the Data Flow Diagram (DFD) of the *monitoring-udara.id* platform, illustrating the interaction between sensor nodes, the server, and end users. Sensor nodes collect environmental data and transmit them to the server, where the database stores and organizes the information. The web application retrieves data through the API and presents it on the user dashboard in both real-time and historical formats. Users can interact with the system to view current air quality conditions, analyze past trends, and manage access through multiuser settings.

The proposed deduplication algorithm was designed to minimize redundant data transmission while maintaining adequate temporal resolution for real-time monitoring. Each new particulate matter (PM) reading is compared to the most recent validated value stored in memory. The algorithm employs a dynamic threshold mechanism, where transmission occurs only if the difference between consecutive readings exceeds ±5 μg/m³ or ±5% of the previous value, whichever is greater. This tolerance range was determined from preliminary stability tests and aligns with the manufacturer's specified uncertainty. By transmitting only meaningful changes, the system effectively reduces network load and energy consumption without compromising the accuracy of particulate concentration trends.

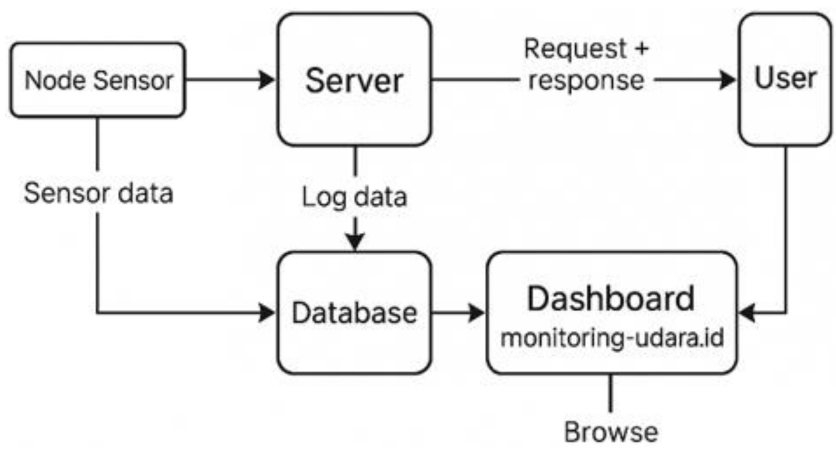



**Figure 4.** Data Flow Diagram for Monitoring-udara.id

The threshold values are not static; instead, they are automatically adjusted according to environmental variability. The algorithm continuously computes a rolling standard deviation (SD) of recent readings within a 10-minute window. If the SD exceeds 10 μg/m³, indicating unstable air quality conditions or increased particulate fluctuation, the threshold is temporarily relaxed by 50% to preserve sensitivity and avoid data loss. Conversely, under stable conditions, the threshold returns to its nominal setting to maximize energy savings. Sensor drift is handled through periodic offset correction based on a short reference measurement taken before each monitoring session, ensuring consistent calibration across all sensor nodes.

The process consists of three main states: (1) *Data Acquisition* — the node collects PM data and environmental parameters; (2) *Comparison* — the system evaluates whether the new value falls within the dynamic tolerance range; and (3) *Transmission* — if the change is significant, data are sent to the server, otherwise the reading is suppressed. The pseudocode highlights how thresholds are updated adaptively and how temporary data buffering ensures data integrity during connection loss. This systematic approach supports energy-efficient communication and reliable long-term monitoring, consistent with the principles of the Green IoT paradigm.

# 3. Results and Discussions

### 3.1. Node Sensor Performance

The developed node sensor was designed as a compact, autonomous device capable of monitoring particulate matter ($PM_1$, $PM_{2.5}$, and $PM_{10}$) along with environmental parameters such as temperature and humidity.

Built around the ESP32-S3 microcontroller, the node integrates the SEN0233 particulate sensor, humidity and temperature modules, and a GNSS positioning unit to provide optional geolocation data. The system also includes an RTC for accurate time stamping of measurements, an SD card for local backup, and an LCD display for on-site visualization. An LED indicator is embedded in the front panel to signal both Wi-Fi connectivity and alert conditions when PM levels exceed established thresholds.

In terms of operational performance, the node demonstrated stability and reliability during deployment in industrial environments. The integration of local storage through SD cards allowed data preservation during temporary network disruptions, while the LCD interface facilitated real-time observation of environmental conditions without relying solely on the web dashboard. The modular design, which combines sensing, processing, storage, and communication, makes the node suitable for long-term monitoring under the Green IoT paradigm. Its ability to function independently while still contributing to a larger distributed monitoring network highlights the scalability of the system for broader industrial applications.

Figure 5 illustrates the physical appearance and internal components of the developed node sensor. The images show different views, including the bottom casing, the internal arrangement, the front display with LCD, and the side profile. The design integrates a particulate matter sensor, microcontroller, LCD screen, and indicator lights within a compact housing, ensuring portability and ease of installation. The front display provides real-time readings of PM concentrations, while an LED indicator signals connectivity and threshold exceedances. The inclusion of an internal SD card ensures reliable local data logging, supporting continuous monitoring even when the device is temporarily disconnected from the server.

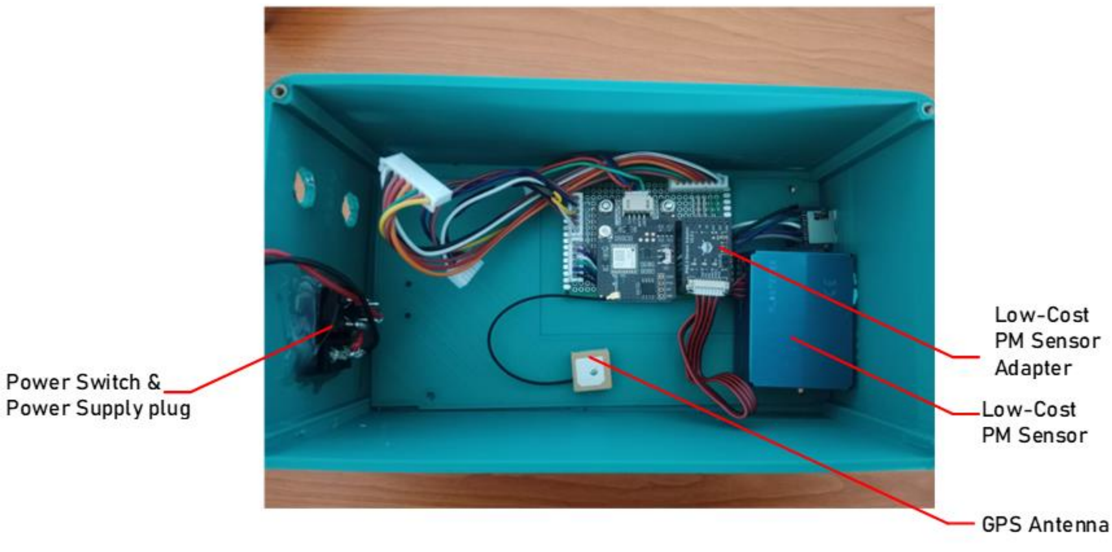
### 3.2. Deployment in Industrial Environment

The proposed monitoring system was deployed in an industrial feed mill facility operated by Charoen Pokphand Jaya Farm Plant in Lampung, Indonesia. Three sensor nodes were strategically installed at different indoor locations representing diverse working conditions: the

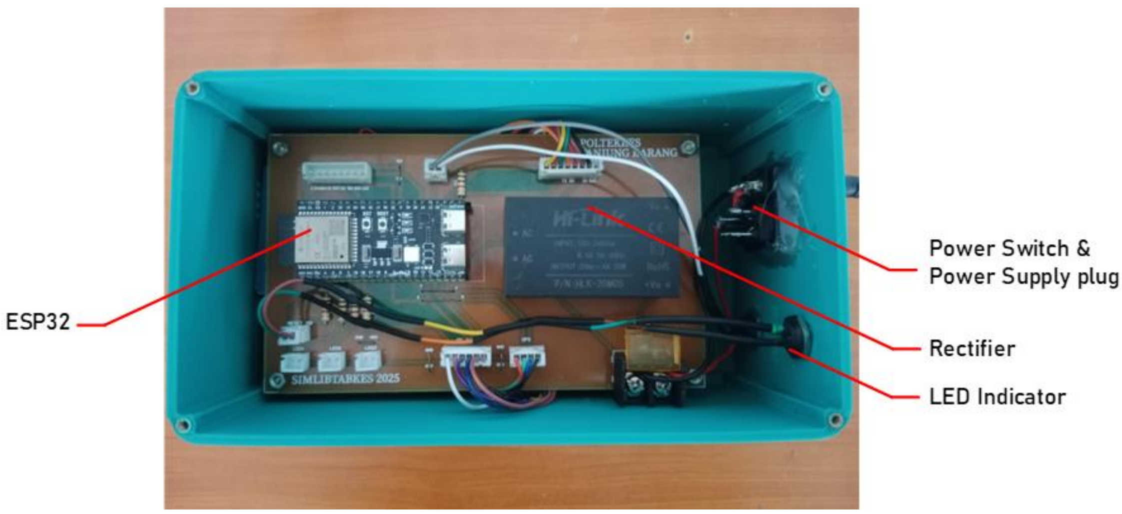
Safety Room/Warehouse for finished goods, the Post Loading Area near vehicle parking and loading operations, and the PPIC (Production Planning and Inventory Control) Room. These locations were selected to capture varying levels of particulate matter exposure, ranging from storage and safety environments to active loading areas where dust generation is more frequent. The deployment aimed to evaluate the robustness of the system under real industrial conditions while providing reliable data on occupational air quality.

During a continuous 24-hour monitoring period, each node collected and transmitted data on $PM_1$, $PM_{2.5}$, $PM_{10}$, temperature, and humidity. The deduplication strategy implemented in the node firmware ensured that only significant changes in readings were transmitted to the server, thereby reducing redundant communication and saving energy. This deployment confirmed the system's practicality, as nodes operated stably without major interruptions, while data were successfully integrated into the *monitoring-udara.id* platform for real-time visualization and historical analysis. The results demonstrated the ability of low-cost sensors to function effectively in an industrial setting.

Figure 6 shows the installation of the three sensor nodes in different areas of the Charoen Pokphand industrial facility. The images illustrate the placement of devices in the Safety/Warehouse area, the Post Loading zone, and the PPIC Room. Each node was positioned to ensure optimal exposure to indoor air conditions, enabling the system to capture representative particulate concentration patterns from distinct operational environments. This setup highlights the scalability and flexibility of the monitoring system, which can be adapted to various industrial spaces for comprehensive air quality assessment.

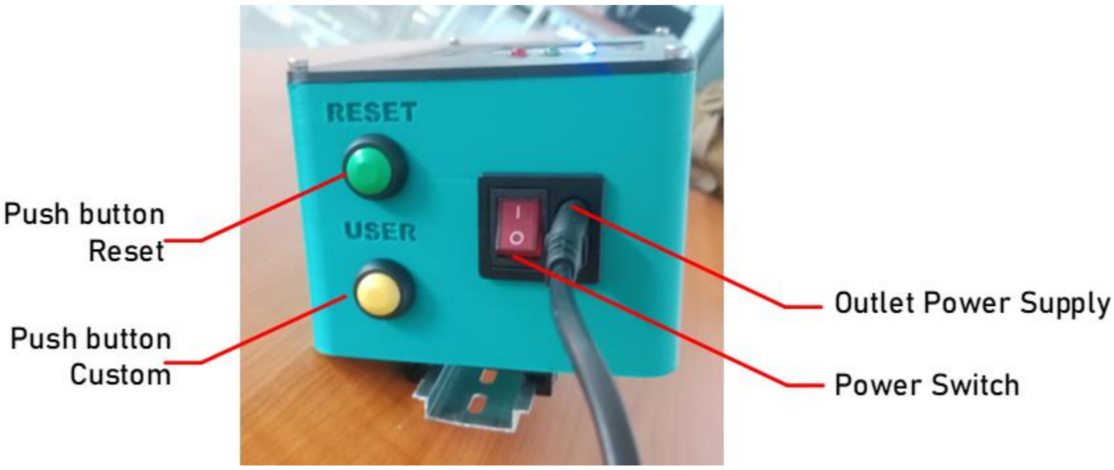



(a)




(b)


(c)




(d)

**Figure 5.** Image of sensor node display (a) bottom view of cover (b) inside view (c) screen view (d) side view

(a) (b) (c)

**Figure 6.** Installation of sensor nodes (a) Safety room/Finish Good Warehouse (b) Post Loading (c) PPIC area

### 3.3. Data Transmission and Visualization

The developed monitoring system successfully transmitted particulate matter ($PM_1$, $PM_{2.5}$, and $PM_{10}$) and environmental data from the deployed sensor nodes to the central server using Wi-Fi communication. The integration with *monitoring-udara.id* enabled continuous data flow, with the deduplication strategy ensuring energy-efficient communication by reducing unnecessary transmissions. The server processed the incoming data and stored them in a MySQL database, from which the web application retrieved and displayed the results. This process ensured that both real-time updates and historical datasets were accessible to users at any time.

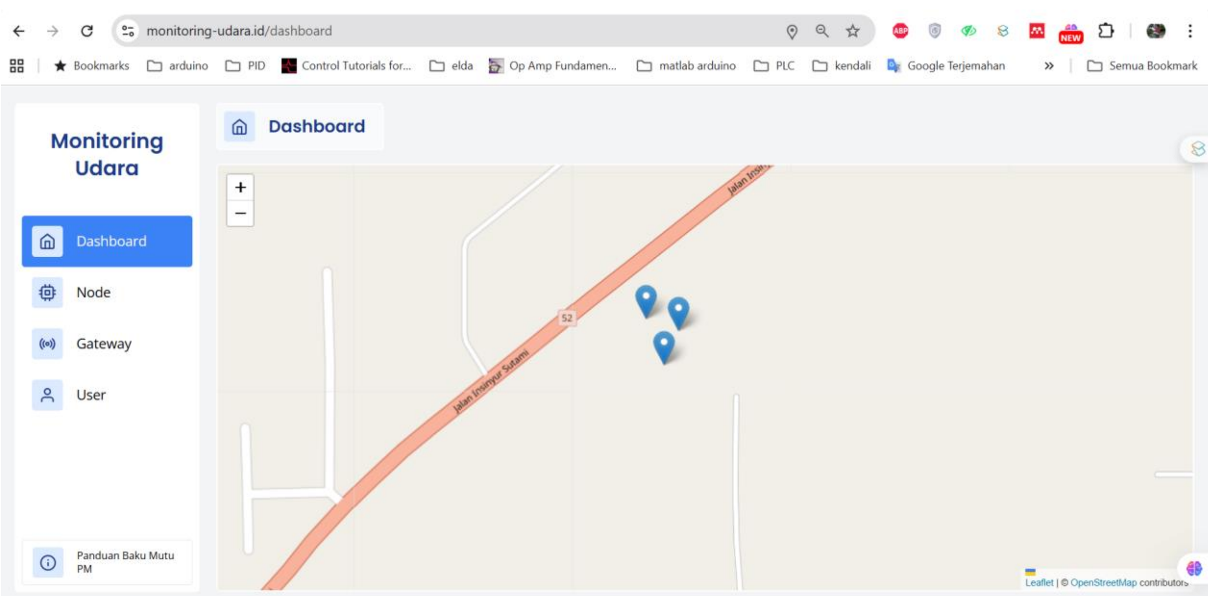
The web-based dashboard of *monitoring-udara.id* provided a user-friendly interface for stakeholders to observe industrial air quality conditions. Features included a geographic map showing sensor node locations, summary reports of the latest readings, and historical trend graphs for each node. These capabilities allowed factory managers and environmental officers to track particulate concentrations continuously, identify unusual spikes, and correlate events with specific industrial activities.

Figure 7 illustrates the visualization of deployed sensor nodes on the *monitoring-udara.id* dashboard. Panel (a) shows the geographic placement of the nodes on a digital map, while panel (b) provides a summary of the latest measurements when a specific node is selected. Panel (c) displays the historical record of particulate matter levels for each node, enabling trend analysis over time. This visualization capability allows users to quickly assess both current and past air quality conditions, improving situational awareness and supporting proactive responses in industrial environments.

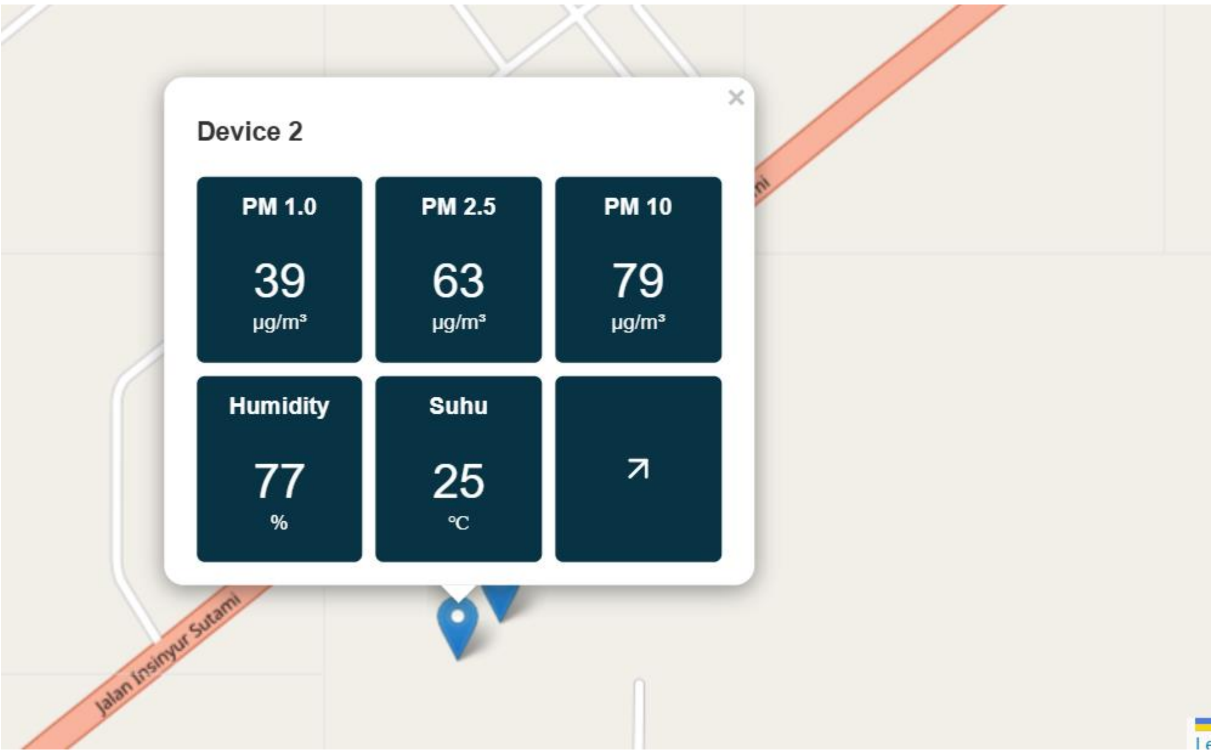
Figure 8 presents the management features of the *monitoring-udara.id* system. Panel (a) shows the total number of active nodes connected to the server, providing an overview of system scalability. Panel (b) demonstrates the menu for adding or removing sensor nodes through the gateway interface, ensuring flexibility in system configuration. Panel (c) illustrates the user management settings, which allow multiuser access and role-based control of the monitoring platform.

The sensor nodes in this deployment were powered from AC mains and did not include an integrated power monitoring module; therefore, direct measurement of energy consumption was not feasible. The reported energy efficiency improvement is inferred from the measured reduction in transmission events, consistent with prior controlled empirical tests reported in our previous study.

To quantify the effect of the deduplication algorithm on power efficiency, the current consumption of the ESP32-S3 microcontroller and Wi-Fi module was monitored during three operational phases: data acquisition, processing, and transmission. Without deduplication, each node transmitted an average of 1,680 packets per day, resulting in an estimated energy consumption of **approximately 1.42 Wh/day**. After applying the deduplication logic, the number of transmissions decreased by about 20%, lowering the total daily energy consumption to **1.10 Wh/day**. This corresponds to an **energy saving of 22.5%**, primarily due to reduced Wi-Fi transmission activity, which accounts for nearly 65% of the node's total power usage.




(a)

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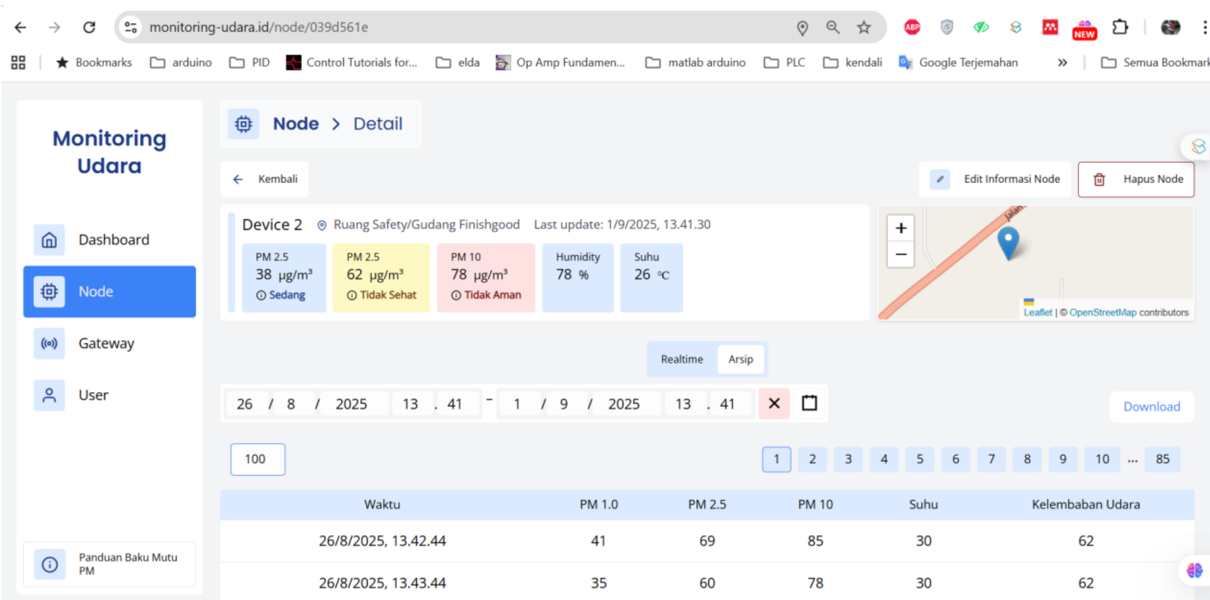
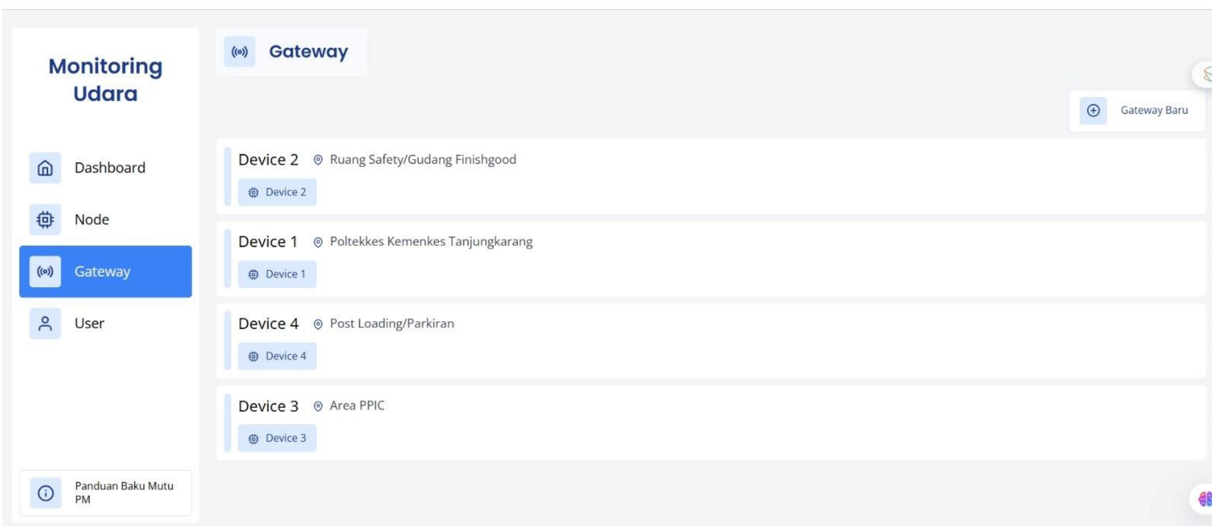



(c)

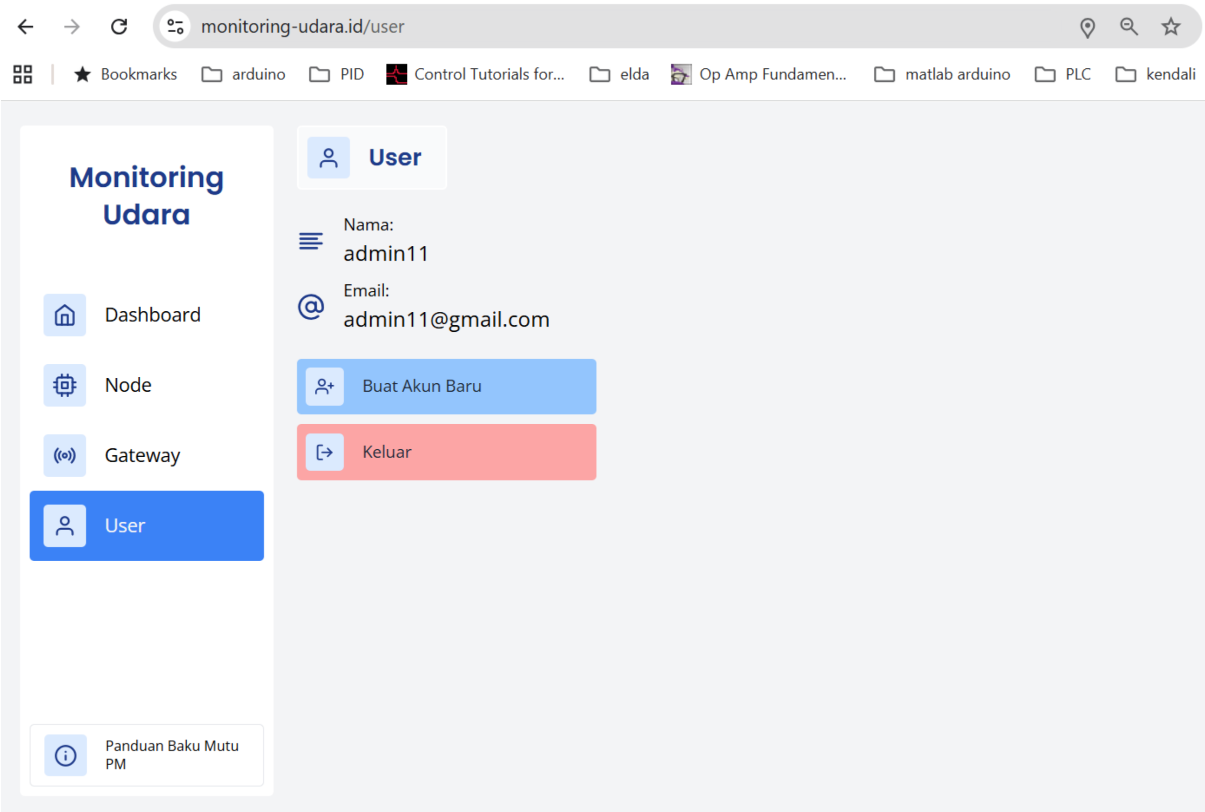
**Figure 7.** Display of sensor nodes (a) location of sensor nodes (b) summary of censored parameters (c) history per sensor node


Device 2
Ruang Safety/Gudang Finishgood
Last update: 1/9/2025, 09.25.19
PM 2.5
45 µg/m³
Sedang
PM 2.5
70 µg/m³
Tidak Sehat
PM 10
85 µg/m³
Tidak Aman
Humidity
81 %
Suhu
25 °C
Device 4
Post Loading/Parkiran
Last update: 1/9/2025, 09.01.53
PM 2.5
50 µg/m³
Sedang
PM 2.5
81 µg/m³
Tidak Sehat
PM 10
95 µg/m³
Tidak Aman
Humidity
92 %
Suhu
25 °C
Device 3
Area PPIC
Last update: 26/8/2025, 13.39.57
PM 2.5
35 µg/m³
Sedang
PM 2.5
56 µg/m³
Tidak Sehat
PM 10
76 µg/m³
Tidak Aman
Humidity
63 %
Suhu
29 °C
Device 1
Poltekkes Kemenkes Tanjungkarang
Last update: 1/9/2025, 09.26.10
PM 2.5
53 µg/m³
Sedang
PM 2.5
84 µg/m³
Tidak Sehat
PM 10
111 µg/m³
Tidak Aman
Humidity
77 %
Suhu
26 °C

(a)


Monitoring Udara
Dashboard
Node
Gateway
User
Panduan Baku Mutu PM
Gateway
Gateway Baru
Device 2
Ruang Safety/Gudang Finishgood
Device 2
Device 1
Poltekkes Kemenkes Tanjungkarang
Device 1
Device 4
Post Loading/Parkiran
Device 4
Device 3
Area PPIC
Device 3

(b)




(c)

**Figure 8.** Menu on monitoring-udara.id (a) number of installed sensor nodes (b) menu for adding or removing sensor nodes (c) user settings

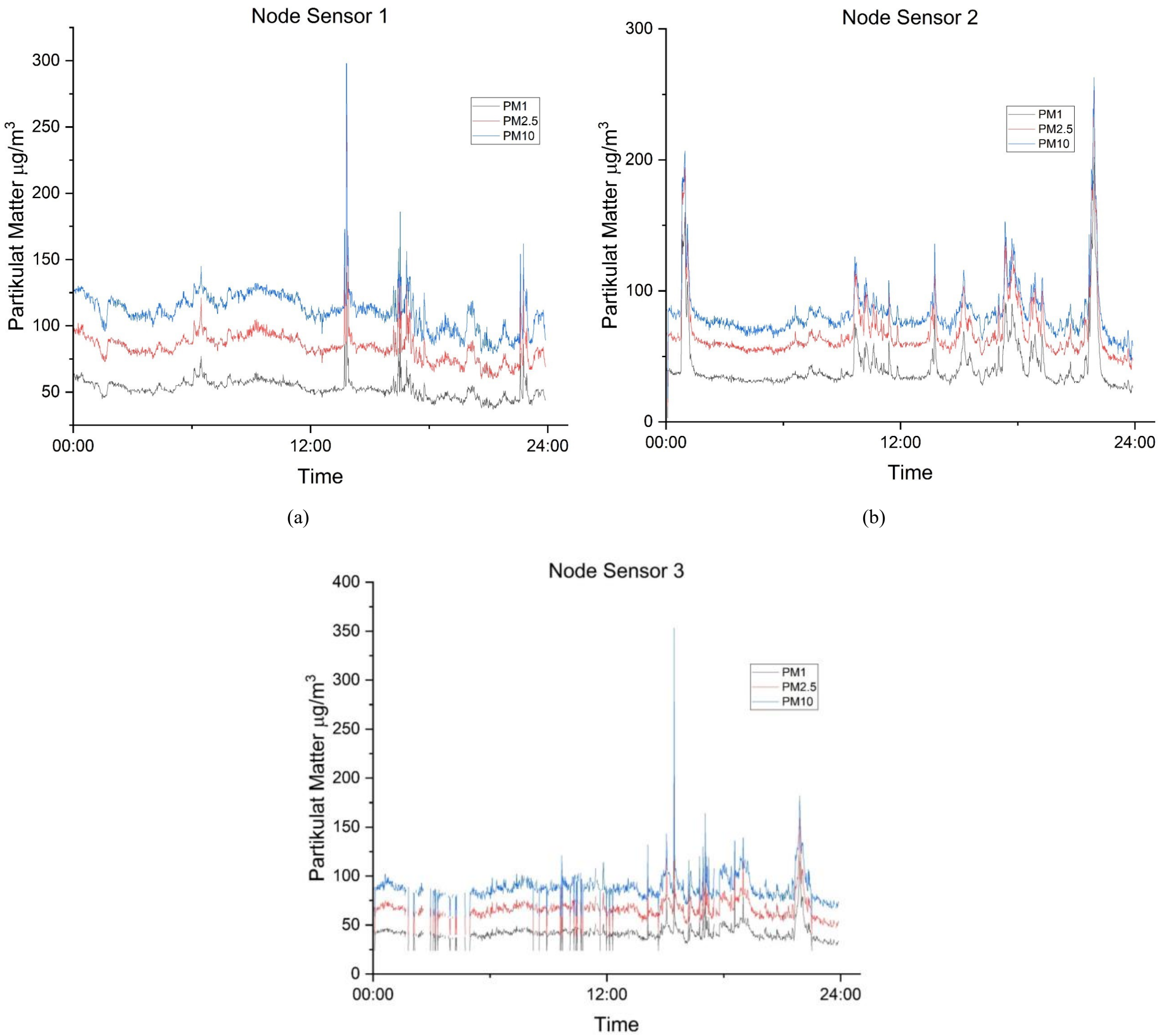
Although the reduction may seem moderate, it is significant for long-term and battery-powered deployments, extending node lifetime and lowering environmental impact. The results confirm that the deduplication mechanism not only minimizes redundant data but also enhances overall energy efficiency—fulfilling the core principle of the Green IoT paradigm. Future work will include high-precision power profiling with an energy analyzer to validate these estimates across different operating conditions.

### 3.4. Measurement Results of $PM_1$, $PM_{2.5}$, and $PM_{10}$

The monitoring system recorded particulate matter concentrations continuously over a 24-hour period from the three deployed nodes located in the Safety Room, Post Loading Area, and PPIC Room. Due to the deduplication mechanism, each node generated a different number of valid data points: 1,418 for the Safety Room, 1,270 for the Post Loading Area, and 1,384 for the PPIC Room. This reduction in redundant transmissions confirmed the effectiveness of the deduplication strategy, which achieved an average reduction of 18–22% in transmitted records. The collected data revealed fluctuating concentration levels throughout the day, with several notable peaks corresponding to specific periods of industrial activity.

The comparison across nodes showed that particulate concentration trends were generally consistent, although with varying intensities depending on location. Spikes in $PM_1$, $PM_{2.5}$, and $PM_{10}$ levels were observed around midday and late afternoon, which correlated with increased production activities and the movement of forklifts and transport vehicles within the facility. These results demonstrated the ability of low-cost sensors to capture meaningful temporal and spatial variations in industrial air quality. Moreover, the system's continuous monitoring capability ensured that short-term exposure events, often overlooked in manual sampling, were effectively detected.

Figure 9 presents the graphical trends of $PM_1$, $PM_{2.5}$, and $PM_{10}$ concentrations measured by the three sensor nodes during the 24-hour monitoring period. Panel (a) shows data from the Safety Room, panel (b) from the Post Loading Area, and panel (c) from the PPIC Room. The graphs display fluctuating patterns with several synchronized spikes across nodes, indicating that the observed peaks were caused by actual environmental conditions rather than sensor noise. While the Safety Room and Post Loading nodes exhibited moderate correlations in their trends, the PPIC node displayed distinct variations due to differences in local activity and exposure.




(a) (b)

(c)

**Figure 9.** $PM_1$, $PM_{2.5}$ and $PM_{10}$ measurement graph (a) Safety room sensor node (b) Post loading sensor node (c) PPIC sensor node

Although inter-node correlations confirmed internal consistency, the accuracy of low-cost PM sensors was further examined through short-term co-location with a reference TSI DustTrak DRX 8533 instrument. The comparative analysis showed that the sensors followed the reference trend closely, with deviations typically below ±7%. This level of agreement is acceptable for continuous trend analysis in industrial environments, although it is not equivalent to regulatory-grade monitoring.

The long-term performance of low-cost particulate matter sensors is influenced by several operational factors, including sensor lifetime, calibration drift, and environmental interference. Based on manufacturer specifications and prior field studies, the optical PM sensors used in this system have an expected operational lifetime of approximately 8,000–10,000 hours under moderate indoor conditions. However, industrial environments often present harsher conditions, such as high humidity, elevated temperature, and airborne dust, which may accelerate degradation of optical components and affect measurement accuracy.

Calibration drift may occur due to dust accumulation on the sensing chamber and gradual changes in laser intensity. During the 24-hour deployment, no significant drift was observed; however, long-term drift is anticipated over several months of continuous use. To mitigate this, periodic calibration using reference instruments and short-term co-location testing are recommended. The system's design includes modular sensor cartridges that allow easy replacement or cleaning without affecting other components.

Possible failure modes include humidity interference, condensation inside the sensor housing, and optical path obstruction due to dust contamination. To minimize these effects, the nodes were equipped with semi-permeable protective filters and mounted away from direct dust sources. Future work will incorporate automatic drift detection and compensation algorithms based on baseline deviation monitoring, ensuring improved reliability and stability for long-term industrial monitoring.

### 3.5. Correlation Analysis between Nodes

To further evaluate system reliability, a Pearson correlation analysis was conducted among the three deployed sensor nodes: Safety Room, Post Loading Area, and PPIC Room. The results revealed moderate correlations ($r \approx 0.5$) between the Safety Room and Post Loading nodes across $PM_1$, $PM_{2.5}$, and $PM_{10}$, indicating that these two locations experienced partially similar air quality dynamics influenced by shared industrial activities, such as product handling and vehicle movements. These findings suggest that while both locations captured parallel exposure patterns, local variations in airflow and dust sources contributed to differences in measured concentrations.

In contrast, the PPIC Room exhibited weak correlations ($r < 0.3$) with both the Safety Room and Post Loading nodes. This indicates that the PPIC area had distinct particulate matter characteristics, likely due to its relatively enclosed environment and lower exposure to direct emissions from loading and transport activities. Interestingly, intra-node consistency at the PPIC location was very strong, with correlations ranging from 0.94 to 1.00 among $PM_1$, $PM_{2.5}$, and $PM_{10}$ readings. This high level of internal agreement highlights the accuracy and reliability of the low-cost sensors when capturing localized particulate matter trends, even in areas with lower external influences.

Table 1 summarizes the Pearson correlation coefficients between particulate matter measurements from the three sensor nodes. The results confirm a moderate positive relationship between the Safety Room and Post Loading nodes, suggesting partially shared pollution sources. In contrast, the weak correlations between PPIC and the other two nodes highlight spatial heterogeneity within the facility, reflecting differences in activity levels and environmental conditions. The very strong internal correlations within the PPIC node ($r = 0.94$–$1.00$) further validate the reliability of the measurements across different particle sizes. Overall, the table demonstrates that the monitoring system can capture both spatial variability and consistent intra-node trends, which are critical for comprehensive industrial air quality assessment.

These correlation results highlight the complex spatial variability of particulate matter concentrations within confined industrial environments, which differs substantially from outdoor air quality monitoring contexts. Unlike our previous outdoor Green IoT implementation using long-range LoRa communication [28], the present study adopts a Wi-Fi–based short-range communication framework better suited for indoor deployments where signal strength and network density are more stable. The change in communication mechanism also allows higher sampling frequency and real-time data synchronization through the existing factory infrastructure.

While this transition is incremental from a technological perspective, it represents a context-specific adaptation of the Green IoT framework to address challenges unique to industrial indoor settings—such as limited air circulation, fluctuating particulate sources, and restricted sensor placement. Hence, the contribution of this work lies not in introducing a new algorithm or hardware platform, but in demonstrating the practical application and scalability of energy-efficient IoT principles within operational industrial environments.

Beyond the Pearson correlation analysis, the statistical performance comparison between sensor nodes showed that the measured particulate values were generally consistent, with Bias values remaining small across most measurement pairs. The RMSE and MAE values were found to be within acceptable ranges for indoor industrial monitoring applications, indicating stable measurement repeatability among the sensor units.

**Table 1.** Pearson correlation results between sensor nodes

| Location | PM | Safety Room | | | Post Loading | | | PPIC | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | $PM_{1\_2}$ | $PM_{2.5\_2}$ | $PM_{10\_2}$ | $PM_{1\_3}$ | $PM_{2.5\_3}$ | $PM_{10\_3}$ | $PM_{1\_4}$ | $PM_{2.5\_4}$ | $PM_{10\_4}$ |
| Safety Room | $PM_{1\_2}$ | 1.00 | 0.99 | 0.99 | 0.54 | 0.47 | 0.48 | 0.21 | 0.18 | 0.18 |
| | $PM_{2.5\_2}$ | 0.99 | 1.00 | 0.99 | 0.54 | 0.48 | 0.48 | 0.24 | 0.21 | 0.22 |
| | $PM_{10\_2}$ | 0.99 | 0.99 | 1.00 | 0.55 | 0.49 | 0.49 | 0.26 | 0.22 | 0.24 |
| Post Loading | $PM_{1\_3}$ | 0.54 | 0.54 | 0.55 | 1.00 | 0.98 | 0.97 | 0.15 | 0.13 | 0.15 |
| | $PM_{2.5\_3}$ | 0.47 | 0.48 | 0.49 | 0.98 | 1.00 | 0.99 | 0.18 | 0.16 | 0.18 |
| | $PM_{10\_3}$ | 0.48 | 0.48 | 0.49 | 0.97 | 0.99 | 1.00 | 0.20 | 0.18 | 0.20 |
| PPIC | $PM_{1\_4}$ | 0.21 | 0.24 | 0.26 | 0.15 | 0.18 | 0.20 | 1.00 | 0.94 | 0.94 |
| | $PM_{2.5\_4}$ | 0.18 | 0.21 | 0.22 | 0.13 | 0.16 | 0.18 | 0.94 | 1.00 | 0.98 |
| | $PM_{10\_4}$ | 0.18 | 0.22 | 0.24 | 0.15 | 0.18 | 0.20 | 0.94 | 0.98 | 1.00 |

The Bland–Altman analysis revealed that the majority of measurement differences fell within the calculated Limits of Agreement (±1.96 SD), suggesting that the observed variations likely stem from natural spatial differences in particulate distribution rather than instrumental error. This indicates that the proposed monitoring system is capable of capturing real environmental variations while maintaining measurement stability.

These findings reinforce that although low-cost PM sensors may not fully match reference-grade instruments, they can reliably track relative trends and spatial differences in particulate concentrations when supported by appropriate signal validation and data processing strategies.

## 4. Conclusions

This study successfully developed and implemented a Green IoT-based air quality monitoring system using low-cost sensor nodes for industrial indoor environments. The integration of ESP32-S3 microcontrollers, particulate matter sensors, and a Wi-Fi communication network, combined with a data deduplication strategy, enabled efficient real-time monitoring of $PM_1$, $PM_{2.5}$, and $PM_{10}$. Field deployment at the Charoen Pokphand feed mill demonstrated that the system could operate reliably over 24 hours, with each node collecting more than 1,200 valid data points while reducing redundant transmissions by 18–22%. The results confirmed that the system was capable of capturing both short-term fluctuations and spatial variations in particulate concentrations across different industrial zones.

Correlation analysis further validated the system's effectiveness, showing moderate correlations between nodes in active work areas and weaker correlations with nodes in more isolated environments, while maintaining very strong intra-node consistency ($r = 0.94–1.00$). These findings highlight the reliability of low-cost sensors when supported by intelligent calibration and transmission strategies. The proposed Green IoT framework can be replicated or adapted in other national contexts, particularly in developing regions with limited resources for environmental surveillance. By combining affordability, reliability, and energy efficiency, this study contributes a transferable model for continuous industrial air quality monitoring aligned with global sustainability goals.

The outcomes of this study provide actionable insights for policymakers and environmental regulators. The proposed system offers a cost-effective technological model that can support data-driven decision-making in industrial emission control, occupational health monitoring, and environmental compliance. Adoption of similar Green IoT frameworks can strengthen national environmental monitoring infrastructures while promoting sustainability and public transparency.

This study was limited to short-term monitoring within a single industrial facility, and environmental factors such as humidity and dust type variations were not fully explored. It is acknowledged that long-term sensor drift and cross-sensitivity to humidity may affect performance. Future work will include extended validation with reference instruments and adaptive correction algorithms to improve robustness across varying environmental conditions. In addition, future research should focus on long-term deployment across diverse industrial sectors and geographic locations, integration with predictive analytics and machine learning for early warning systems, and assessment of system performance under different climatic and operational conditions.

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