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RESEARCH PAPER

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Low-Cost Data Deduplication Method for Efficient Inter-Node Consistency Validation in Indoor Industrial Air Quality Monitoring Systems

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ABSTRACT

Indoor air quality (IAQ) monitoring in industrial spaces is vital for protecting workers from exposure to particulate matter (PM_1, $PM_{2.5}$, PM_{10}). However, many low-cost IoT systems prioritize outdoor, wide-area deployments and rarely confront two issues that matter indoors: inter-node measurement consistency when multiple identical sensors are co-located and firmware-level transmission efficiency for Wi-Fi nodes operating under energy and bandwidth constraints. This study addresses both issues by presenting a reproducible, low-cost IAQ node built on an ESP32 (S3) and PMS7003, coupled with a lightweight on-device data-deduplication routine that suppresses redundant packets before they reach the network stack. The node integrates temperature humidity sensing, RTC-GNSS for stable timestamps, local SD logging, a compact display for in-situ readouts, and standard Wi-Fi for infrastructure-friendly connectivity, enabling autonomous operation with optional MQTT backend integration.

We evaluated the design via a 24-hour co-location test of four identical nodes in a controlled indoor room (5-minute sampling). Minute-aligned time series were analyzed using one-way ANOVA to quantify inter-node agreement. The results indicated no statistically significant differences among nodes for PM_1, $PM_{2.5}$, and PM_{10} ($p_{value} > 0.05$), confirming internal consistency suitable for simultaneous multi-point monitoring. The deduplication routine reduces transmissions by ≈3.2% without information loss, modest per device, but compounding across dense deployments to lower network load and energy use. Together, these outcomes validate (i) a practical hardware–firmware stack for low-cost IAQ sensing in indoor factories, (ii) a deployable firmware strategy for network-efficient reporting, and (iii) an empirical inter-node consistency assessment using co-location and ANOVA. The approach facilitates scalable, accurate, and efficient IAQ surveillance for occupational safety programs and compliance workflows. Future work will extend to longer horizons, drift characterization, and integration with adaptive, event-driven analytics and calibration pipelines for robust industrial rollouts.

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I. INTRODUCTION

Particulate matter (PM), including PM_1, $PM_{2.5}$, and PM_{10}, has become a critical concern in indoor industrial environments because of its adverse effects on occupational health [1]–[3]. These fine and ultrafine particles can penetrate deep into the respiratory system, potentially causing cardiovascular[4]–[6], pulmonary[7], [8], and even neurological disorders with prolonged exposure[9]–[13]. Workers in factories, workshops, and production facilities are especially vulnerable, as particulate pollutants may originate from combustion processes, material handling, or manufacturing residues[14][16]. Therefore, continuous monitoring of indoor air quality is essential to ensure a safe and healthy work environment in accordance with occupational health standards and environmental safety regulations.

Despite this urgency, the deployment of commercial-grade air quality monitoring systems remains limited. The high acquisition and maintenance costs, combined with significant power requirements, render these systems impractical for many industrial applications[17]. Consequently, there is an unmet need for a solution that is not only low-cost and energy-efficient, but also easy to deploy and maintain in the long term. Affordable and

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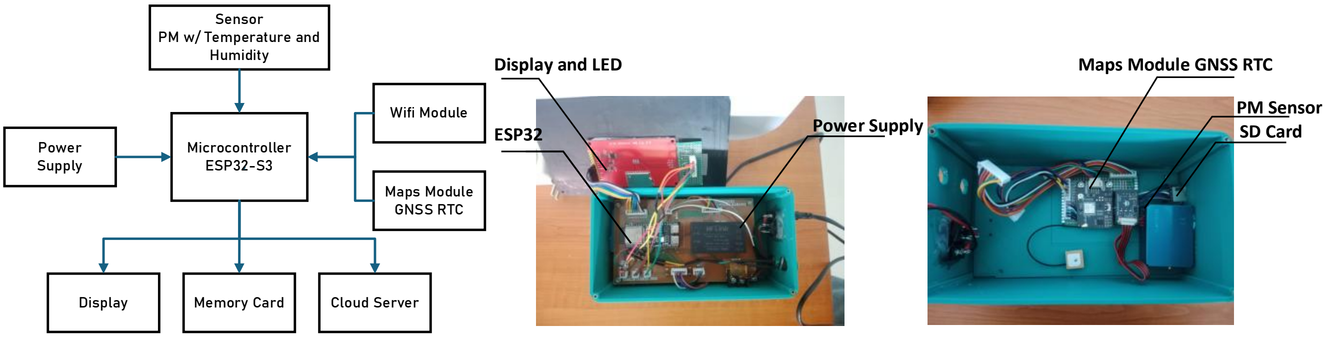

Fig. 1. Block diagram of the proposed hardware and prototype of the sensor installed at the location with a description of the installed components

scalable systems are necessary to enable real-time, granular monitoring of indoor particulate matter, thereby supporting early intervention and long-term air quality management[18], [19].

Previous research on IoT-based air quality monitoring has produced a range of architectures and communication protocols tailored for different environments and deployment scenarios. LoRa-based systems, for instance, are popular in outdoor and remote area deployments owing to their long-range, low-power characteristics[20], [21], while GSM-based designs provide wide accessibility via cellular networks[22], [23]. These systems are commonly integrated with centralized dashboards to visualize real-time PM_1, $PM_{2.5}$, and PM_{10} data, thereby contributing significantly to environmental awareness and public health.

From an engineering standpoint, Wi-Fi was selected as the communication medium because of its practical advantages in indoor industrial environments. Unlike LoRa, which may experience attenuation and gateway dependence in enclosed metallic halls, Wi-Fi provides higher data throughput, lower latency, and seamless integration with existing factory network infrastructure. Although Wi-Fi operates in the crowded 2.4 GHz band, interference can be effectively managed through short-range deployment, channel allocation, and stable power availability. These characteristics make Wi-Fi a suitable choice for dense indoor sensor networks that require continuous connectivity and infrastructure compatibility.

However, these implementations typically rely on fixed-interval data transmission, where measurements are sent at predetermined time steps, regardless of the significance of the data changes[24]–[26]. Although this approach is straightforward, it may result in redundant transmissions and inefficient energy usage, which is critical in power-constrained and portable systems.

In addition, most existing studies tend to focus on single-node deployment scenarios or on optimizing data transmission across a network[27], [28]. Although these approaches advance the scalability and communication efficiency of PM monitoring systems, they often overlook an essential aspect of system robustness: the internal consistency and reliability of sensor readings when multiple identical nodes are deployed in parallel within the same environment. This study fills this gap by combining firmware-level deduplication with inter-node statistical validation, providing both energy-efficient data handling and reliable measurement consistency.

Recent studies on low-cost particulate matter (PM) sensors have reported promising performance but have also highlighted challenges, including environmental influences and calibration requirements. Bai and Yu [1] emphasized the role of control technology in addressing indoor air pollution, while Masri et al. [2] demonstrated that worker-led evaluations of $PM_{2.5}$ exposure can be effectively conducted using low-cost devices in industrial settings. Long-term stability and intersensor consistency remain critical issues. Bulot et al.[29] reported moderate correlations (r = 0.61–0.88) between nodes, whereas Vogt

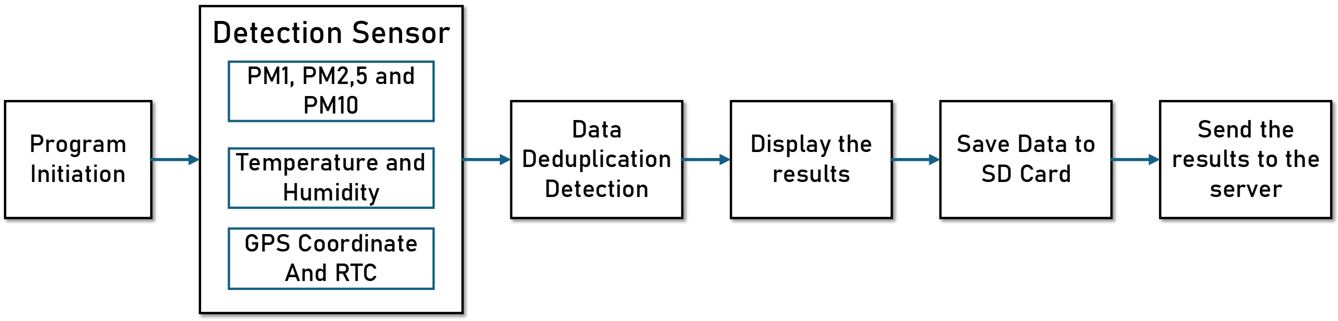

Fig. 2. Detailed block diagram of the firmware data processing sequence, illustrating the flow from sensor initialization and data acquisition to the deduplication process and final data storage

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Table 1. Data tabulation to assess the performance of the data deduplication process over a 24-hour period

Period of Observation	Data Points Collected	Data Points Transmitted	Reduction (%)
24 hours (5-min interval, 4 nodes)	283	274	3.2%

et al.[30] showed r > 0.99 in calibrated systems, underscoring the importance of systematic validation.

Other recent works[1], [27], [29]–[32] emphasize challenges in multi-sensor consistency, calibration, and data optimization, underscoring the novelty of our approach Several Green IoT approaches have been proposed from the perspective of transmission efficiency. Maulana et al.[31] introduced inline data deduplication for IoT-based air monitoring, saving over 3% in energy consumption. Similarly, Wang et al. [32] applied machine learning models to optimize the accuracy of low-cost sensors, and Ali et al [33] explored neural network calibration methods for embedded air quality devices. In terms of communication protocols, Jabbar et al.[21] confirmed that Wi-Fi offers higher data throughput and availability in indoor industrial environments compared to LoRa or GSM, making it preferable where coverage is stable. However, few studies have explicitly evaluated the consistency among multiple identical nodes deployed simultaneously in indoor industrial contexts. This study addresses this gap by combining firmware-level deduplication with inter-node statistical validation to ensure both energy-efficient data handling and reliable measurement consistency.

Despite the growing body of literature on IoT-based air quality monitoring, most existing studies emphasize communication-layer optimization or single-node sensing performance. Limited attention has been paid to inter-node measurement consistency when multiple identical low-cost sensors are deployed simultaneously in the same indoor environment. Furthermore, many systems rely on fixed-interval transmission schemes, which may result in redundant data packets and inefficient energy use, particularly in Wi-Fi-based deployments. Consequently, an unresolved research gap remains concerning integrated approaches that jointly address firmware-level transmission efficiency and statistical validation of sensor-node agreement under real indoor conditions. This study aims to bridge this gap by (i) designing a low-cost Wi-Fi particulate matter sensor node with embedded data deduplication logic and (ii) validating inter-node measurement consistency using one-way ANOVA during a controlled indoor co-location experiment.

The objective of this study is to (i) design a low-cost Wi-Fi-enabled PM sensor node using a PMS7003 dust sensor[34] with firmware-level deduplication and (ii) validate inter-node measurement consistency through ANOVA testing under identical indoor conditions.

Previous iterations explored LoRa[34] and GSM[35] for network communication, but these were deemed less effective in indoor factory environments because of coverage and signal interference issues. Wi-Fi was chosen for this study due to its typical availability in industrial indoor settings.

Contributions This study makes four contributions: (1) a reproducible, low-cost indoor IAQ node for factory settings based on ESP32 and PMS7003 with Wi-Fi connectivity, where reproducibility refers to the use of commercially available hardware components and deterministic firmware logic that other researchers can independently reimplement. While the complete hardware schematics and firmware source code are not released as open source in this study, the architectural design, data flow, and algorithmic procedures are described in sufficient detail to support independent replication and validation; (2) a lightweight firmware-level data deduplication routine that suppresses redundant transmissions (~3.2%) without information loss; (3) an inter-node consistency evaluation using a 24-hour co-location test and one-way ANOVA, showing no significant differences across four identical nodes ($p_{value} > 0.05$); and (4) a scalability discussion that justifies Wi-Fi for indoor factories and outlines seamless integration with MQTT back-ends for efficient, large-scale deployments.

The first section presents the problem of inconsistent indoor PM monitoring, reviews existing IoT-based solutions, highlights the research gap, and states the objective and contributions of this study. The second section describes the hardware and firmware designs for the low-cost PM sensor nodes and the experimental setup for consistency testing across four units deployed side by side. The third section presents the consistency evaluation results based on statistical analysis of measurements from the four sensor nodes. The fourth section interprets the results, discusses their limitations, and compares the findings with those of related studies. The conclusion summarizes the main findings and outlines potential directions for future research.

II. METHOD

A. Sensor Node Architecture

The system architecture consists of an ESP32-S3 microcontroller as the central processing and communication unit. The system was connected to particle sensors PMS7003 (PM_1, $PM_{2.5}$, and PM_{10}), temperature and humidity sensors, and an RTC-GNSS module to provide time and location data. Power was supplied via a 5V DC adapter, although the system can be easily modified for battery operation, making it portable

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and versatile. The sensor node was also equipped with a local display module for real-time visualization, an SD card module for local data logging, and Wi-Fi communication support for remote data uploading. Fig. 1 illustrates the architecture, highlighting the ESP32 as the processing unit and PMS7003 as the optical sensor, which was chosen for its low cost and broad adoption in indoor monitoring [29]. The display hardware and its connection are shown in Figure 1. This node was designed to operate independently, without relying on a cloud connection, while maintaining compatibility with

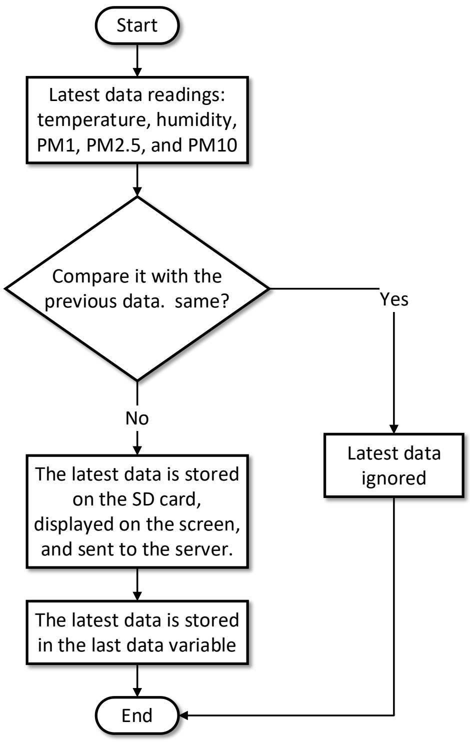

Fig. 3. Flowchart for sorting data from sensor nodes stored in memory and sent using the proposed data deduplication method

MQTT-based cloud platforms for future integration. This modular architecture supports real-time air quality monitoring and local data redundancy. The test was conducted in an enclosed indoor room (8 m × 15 m × 3 m) without active ventilation. The potential PM sources included light human activity and residual dust. Calibration was performed by conducting a baseline zero-check using filtered, clean air prior to deployment.

B. Theoretical Background

Inter-node consistency was evaluated using a one-way analysis of variance (ANOVA). The F-statistic was calculated as the ratio of the mean square between groups (MS_between) to the mean square within groups (MS_within). A p_{value} greater than 0.05 was used as the criterion to indicate the absence of statistically significant differences between the sensor nodes.

C. Firmware-Level Deduplication Algorithm

The firmware data processing on the sensor node is illustrated in Fig. 2. After program initiation, the sensor sequentially detected PM_1, $PM_{2.5}$, and PM_{10} values, temperature and humidity, location, and time. Then, a data deduplication detection process was performed, after which the data were displayed, stored on an SD card, and sent to the server.

A data deduplication detection process was performed to improve energy efficiency and reduce unnecessary data transmissions. This was studied in a previous article using the low-overhead inline data deduplication method, which

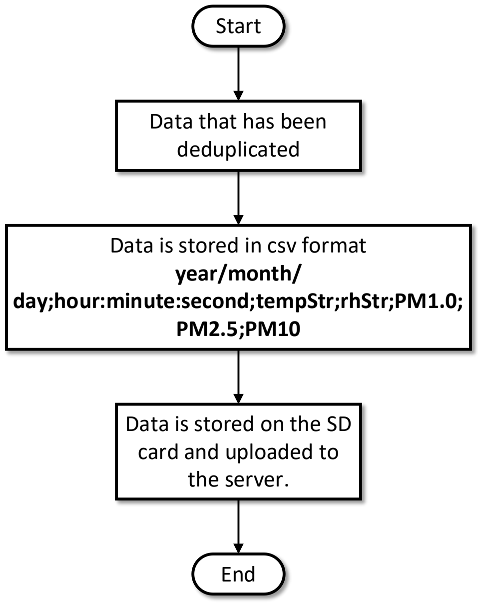

Fig. 4. Flowchart of the data storage process resulting from deduplication, complete with time stamps

successfully saved 3.2% of the energy[31]. Based on this research, this study employed a deduplication process, as outlined in the algorithm shown in Fig. 3.

The firmware implements a rule-based inline data deduplication mechanism. At each sampling instant t, the current measurement vector is compared with the most recently transmitted dataset. If all monitored parameters remain unchanged, the transmission is suppressed; otherwise, the dataset is transmitted and stored as a new reference dataset. This algorithm continuously reads the sensor values for temperature, humidity, and PM levels and compares them with the last dataset sent. If all the parameters were identical, the data were considered redundant, and the transmission was skipped. The firmware continued to transmit and record data only when there was a significant change in at least one parameter. After transmission, the current dataset was stored as a reference for future comparisons. This method eliminates the need for external scheduling or real-time operating systems and ensures data efficiency by minimizing

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transmission events, thereby saving energy in continuous monitoring applications.

D. Data Logging and Formatting

After being verified by the deduplication method, each new dataset was formatted as a log file in .txt format,

Fig. 6. Simultaneous testing of four sensor nodes for 24 hours under homogeneous room conditions

containing timestamps (year, month, day, hour, minute, and second) and environmental readings (temperature, humidity, PM_1, $PM_{2.5}$, and PM_{10} levels). This formatted string is stored on an SD card, providing offline data storage for backup, reviews, and further analyses. The flowchart is illustrated in Fig. 4. Although the firmware prepares data in a format compatible with MQTT for future transmission, the communication and cloud storage components are beyond the scope of this paper. Instead, the emphasis is on ensuring the node's reliability and autonomy to collect meaningful indoor air quality data with minimal redundancy.

III. RESULTS

A. Evaluation of Data Transmission under Deduplication Logic

To evaluate the deduplication mechanism implemented in the sensor node, a test was conducted using a dataset

Fig. 7. Text file containing data sent from sensor nodes during simultaneous testing every 5 minutes for 24 hours

with 12 data points. Among these, two entries, specifically the seventh entry at 11:51:51 and the eighth at 11:52:51, were intentionally set to have identical values. The data were processed using a deduplication algorithm. Consequently, only the first of the two identical entries

Table 2. Statistical data from testing four sensor node devices under simultaneous conditions for 24 hours with PM1, PM2.5, and PM10

Device	Pollutant	Count	Sum	Average (μg/m³)	Variance
Device 1	PM_1	283	10.823	38.24	1.99
Device 2	PM_1	283	10.811	38.20	1.93
Device 3	PM_1	283	10.810	38.20	1.94
Device 4	PM_1	283	10.815	38.22	1.94
Device 1	$PM_{2.5}$	283	16.977	59.99	4.06
Device 2	$PM_{2.5}$	283	16.980	60.00	3.89
Device 3	$PM_{2.5}$	283	16.983	60.01	3.93
Device 4	$PM_{2.5}$	283	16.984	60.01	3.99
Device 1	PM_{10}	283	20.876	73.78	6.11
Device 2	PM_{10}	283	20.872	73.77	6.08
Device 3	PM_{10}	283	20.873	73.78	6.12
Device 4	PM_{10}	283	20.871	73.76	6.09

(11:51:51) was transmitted, whereas the second was suppressed.

Beyond this illustrative example, the deduplication performance was further validated during a full 24-hour deployment using four nodes. Of the 283 data entries collected, only 274 were transmitted, resulting in a reduction of approximately 3.2% (Table 1). This confirms that the deduplication algorithm not only works on small-scale tests but also effectively reduces redundant transmissions in long-term operation without compromising data integrity

B. Main Finding: Inter-Node Consistency in Shared Indoor Environment

To evaluate the consistency and reliability of the developed low-cost sensor nodes, a simultaneous deployment was conducted using four identical units

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Table 3. Results of the one-way ANOVA test for PM_1, $PM_{2.5}$, and PM_{10} measurements across four identical sensor nodes to evaluate inter-node consistenc

ANOVA PM1						
Source of Variation	*SS*	*df*	*MS*	*F*	p_{value}	*F crit*
Between Groups	0.370141	3	0.12338	0.063247	0.979217	2.612792
Within Groups	2200.466	1128	1.950768			
Total	2200.837	1131				

ANOVA PM2.5						
Source of Variation	SS	df	MS	F	p_{value}	F crit
Between Groups	0.915194	3	0.305065	0.075645	0.973115	2.612792
Within Groups	4549.081	1128	4.032873			
Total	4549,996	1131				

ANOVA PM10						
Source of Variation	SS	df	MS	F	p_{value}	F crit
Between Groups	1.257951	3	0.419317	0.055421	0.982833	2.612792
Within Groups	8534.466	1128	7.566016			
Total	8535.724	1131				

placed in the same indoor industrial room. All nodes were exposed to the same environmental conditions during a 1-day observation window, with 24-hour monitoring and data collection every five minutes. The primary objective was to assess whether each node could independently produce consistent measurements for $PM_{1.0}$, $PM_{2.5}$, and PM_{10}, even when the results of the 24-hour data tabulation from four devices, including measurements of PM_1, $PM_{2.5}$, and PM_{10}, along with the total number of data points, cumulative values, average concentrations, and variances, are presented in Table 2, which summarizes the deduplication test, showing that from 283 raw data entries, only 274 were transmitted after redundancy filtering, corresponding to a 3.2% reduction. All particulate matter concentrations were expressed in μg/m³, and the variance values were reported in (μg/m³)². The sensor nodes are illustrated in Fig. 6. The data obtained from the txt file are shown in Fig. 7. To examine whether there were statistically significant differences in the four PM readings (PM_1, $PM_{2.5}$, and PM_{10}) across the four devices, ANOVA was conducted. The results are presented in Table 3.Although time-series plots are commonly used to visualize sensor agreement, this study prioritized statistical validation using full-resolution tabulated datasets. Time-series visualizations will be incorporated into future extended deployments.

IV. DISCUSSION

A. Effectiveness of Deduplication Firmware

Deduplication simulation shows that the system transmits data only when the particle value (PM) changes, rejecting identical data packets. For example:

```
The 8th data point had the same PM values as
the 7th → Not transmitted
```

This selective transmission significantly reduces the total number of data packets sent, thereby saving energy and reducing network load without compromising air monitoring quality. This has already been tested, showing that without deduplication, 960 mW is required, whereas with deduplication, only 820 mW is needed. Similarly, during transmission from the node to the server, power consumption decreases when the deduplication method is applied, from 2270 mW to 2180 mW[31].

B. Inter-Node Sensor Consistency (ANOVA Test)

To assess the consistency of all sensor nodes used, a One-Way ANOVA test [36], [37] was performed on PM_1 and $PM_{2.5}$, and PM_{10} readings collected over a 24-hour period from four devices at the same location. The results of the One-Way ANOVA test, presented in Table 3, show p_{values} of 0.979217 for the PM_1 sensor, 0.973115 for $PM_{2.5}$ and 0.982833 for PM_{10}, all of which are substantially (p_{value}) > 0.05. This statistically confirms that the measurement results of the four nodes from the three sensors tested simultaneously at the same location do not show significant differences. Such high consistency is

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very important in industrial environments, where data redundancy is often required to ensure the validity of air quality measurements at different locations.

The stability of these readings can be attributed to two primary factors. First, the use of PMS7003 sensors, which operate on the laser-scattering principle, offers greater accuracy than inexpensive infrared sensors for PM_1, $PM_{2.5}$, and PM_{10} particles. Second, the implementation of a stable power supply on the ESP32-S3 minimized electrical noise, which frequently interferes with signal conversion in low-cost air quality sensors. Furthermore, the deduplication algorithm embedded in the firmware does not compromise the integrity of the original data; it merely filters out redundancies without altering the average measurement values, thereby maintaining consistency between nodes even as the data transmission load is significantly reduced.The 24-hour co-location experiment should be regarded as an initial assessment. While it is adequate for evaluating short-term inter-node consistency, it does not account for seasonal variability, long-term sensor drift, and performance in highly dynamic industrial environments, which typically require weeks to months of co-location to be fully characterized [36], [37] It is also essential to differentiate between measurement precision and absolute accuracy. No validation was conducted against a reference-grade PM monitor (such as FRM/FEM or BAM) [38], [39] yet inter-node consistency primarily reflects precision and network homogeneity [39], [40]. Given that low-cost optical PM sensors are known to exhibit biases dependent on humidity, composition, and size, as well as long-term drift, systematic bias cannot be excluded even when inter-sensor correlations remain high, despite the nodes demonstrating statistically consistent behavior [41], [42].

Numerous studies have investigated IoT-based air quality monitoring systems using various protocols and architectures. This is shown in Table 4. Li et al. [43] evaluated nine low-cost particulate matter (PM) monitors against laboratory-grade references, demonstrating that user calibration significantly improves absolute accuracy. However, their study primarily focused on sensor-to-reference agreement rather than examining statistical equivalence among identical nodes operating concurrently. In contrast, the present study emphasizes inter-node homogeneity under shared exposure conditions and validates the equality of means using analysis of variance (ANOVA) without prior calibration. Bulot et al. t[29]identified a moderate correlation (r = 0.61–0.88), highlighting the influence of environmental variability and sensor drift. Vogt et al.[30] reported a very high correlation (r > 0.99), although their system necessitated calibration against a reference instrument. Frederickson et al. [44] demonstrated the feasibility of dense networks, while stressing the importance of correction models. This study diverges in two principal aspects. Firstly, statistical validation was conducted using a one-way ANOVA rather than relying solely on the correlation coefficient. While correlation assesses linear relationships, ANOVA directly tests the equality of group means, thereby providing more robust evidence of distributional equivalence across nodes. Secondly, experiments were conducted without external calibration, yet still exhibited statistical homogeneity in short-term deployments. Furthermore, previous research predominantly concentrated on sensor accuracy or network scalability. Few studies have combined inter-node statistical validation with a focus on firmware-level data. Consequently, this research offers a system-level perspective that integrates statistical consistency and embedded communication efficiency.

Table 4. Comparison of other studies based on methods, environment, matrix consistency, and test results with the study conducted

Author	Method	Environment	Result	Consistency Metric
Li et al.[43] [43]	Evaluation of 9 low-cost PM sensors vs reference monitor	Laboratory & controlled	Calibration significantly improved agreement	Accuracy improved after user calibration
Bulot et al.[29]	Field co-location	Outdoor urban	r = 0.61–0.88	Moderate inter-sensor correlation
Vogt et al.[30]	Calibrated system	Outdoor Norway	$r > 0.99$	Very high consistency after calibration
Frederickson et al.[44]	Long-term deployment	Urban	Seasonal drift observed	Correction models required
This study	24h indoor co-location + ANOVA	Indoor industrial	$p > 0.97$	No significant difference

V. Conclusion

In conclusion, this study aimed to design and implement a reproducible, low-cost Wi-Fi particulate matter sensor

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node (ESP32–PMS7003) with a lightweight firmware-level deduplication mechanism, and to evaluate inter-node measurement consistency via a 24-hour indoor co-location test using one-way ANOVA. The proposed low-cost Wi-Fi PM sensor nodes demonstrated consistent readings across four identical devices, with ANOVA results indicating no statistically significant differences ($p_{value} > 0.05$). The firmware-level deduplication further reduced redundant transmissions by approximately 3.2%, thereby enhancing efficiency without compromising data integrity. Collectively, these outcomes highlight the robustness of hardware–firmware integration and confirm the system's suitability for scalable indoor industrial deployment. Future work will evaluate long-term reliability under more dynamic environmental conditions and integrate the nodes into IoT infrastructures with advanced energy-aware transmission and calibration strategies [32], [33]. The authors would like to express their sincere gratitude to the Department of Electrical Engineering at Siliwangi University and the Tanjung Karang Ministry of Health Polytechnic for their invaluable support and resources provided throughout this research. The facilities, academic environment, and encouragement from the lecturers have played a major role in the completion of this work.

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