

M-Care: Online Air Quality Monitoring System Utilizing LoRa Communication Technology

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Abstract—Air pollution, particularly fine Particulate Matter (PM_{2.5}), poses serious health risks and environmental challenges. Traditional monitoring stations, though accurate, are limited by high costs and sparse coverage. This study presents the M-Care system, an Internet of Things (IoT)-based air quality monitoring solution that integrates low-cost sensors with Long Range (LoRa) and Wi-Fi communication technologies for real-time data collection. The system measures PM_{1.0}, PM_{2.5}, and PM₁₀ concentrations along with temperature, humidity, and atmospheric pressure. It is supported by web and mobile applications developed on the Yakkaw platform, offering users intuitive access to geospatial visualizations and historical trends. Field deployment in Chiang Rai, Thailand, demonstrated that M-Care achieved a communication range of up to 200 m with 97% packet delivery under optimal conditions. Comparative analysis against reference-grade data from the Thai Pollution Control Department, OpenWeatherMap, and Dustboy sensors showed that M-Care had the lowest Mean Absolute Error (MAE) at 4.10 µg/m³. Statistical validation confirmed the system's reliability, with no significant difference compared to official data. These results establish M-Care as a reliable, scalable, and cost-effective solution for real-time air quality monitoring in both urban and rural contexts.

Keywords—air pollution, air quality monitoring, Long Range (LoRa)-based communication, internet of things, mobile applications, web applications

I. INTRODUCTION

Air pollution remains a critical global issue, particularly concerning fine Particulate Matter (PM_{2.5}), which has been linked to severe health complications, including cardiovascular diseases, respiratory infections, and increased mortality rates [1, 2]. PM_{2.5} particles penetrate deep into the lungs and enter the bloodstream, leading to significant long-term health risks [3, 4]. Additionally, air pollution has been identified as a contributing factor in increasing the lethality of viral respiratory infections, such as SARS-CoV-2, particularly in regions with high pollution levels [5–7]. Traditional air quality monitoring stations, equipped with instruments such as Beta Attenuation Monitors (BAM) and Tapered

Element Oscillating Microbalances (TEOM), provide accurate data but are limited by high operational costs and restricted spatial coverage [8–10]. To address these challenges, low-cost sensors have been developed as viable alternatives, enabling broader deployment. However, these sensors require frequent calibration due to environmental variations affecting accuracy [11, 12]. Evaluating the effectiveness of commercial low-cost air sensor platforms in real-world conditions is essential for ensuring reliable air quality assessments.

Advancements on the Internet of Things (IoT) and Low-Power Wide-Area Networks (LPWAN), such as Long Range (LoRa), have enabled scalable and real-time air quality monitoring systems. LoRa technology is recognized for its long-range communication capabilities, low power consumption, and minimal infrastructure requirements, making it ideal for air quality applications [13–15]. The integration of IoT and LoRa has facilitated innovative solutions capable of real-time data acquisition and transmission. Nevertheless, challenges remain, including data validation and potential network congestion in dense urban areas [16, 17]. Prior research has focused on enhancing the reliability of low-cost air quality sensors [18]. For instance, Malik developed a low-cost ESP8266-based PM_{2.5} monitoring system, which provided real-time air quality data, though its accuracy depended heavily on environmental calibration [19]. Rujivorakul and Vorapatratorn [20] proposed an online low-cost air quality monitoring system utilizing LoRa technology, highlighting its effectiveness in real-time data communication and suitability for large-area deployment.

Atmospheric conditions also significantly impact PM_{2.5} readings. Several studies have explored the effects of solar radiation on pollutant dispersion and the potential of satellite-based aerosol monitoring [21–23]. In addition, machine learning techniques have been increasingly used in air quality systems to provide predictive analytics and trend detection [24, 25]. However, such models require large, high-quality datasets and computational resources, which may not always be available, particularly in developing regions [26]. User engagement with air quality data has improved through the development of mobile and web-based platforms [27]. Global services like OpenWeatherMap provide air quality indices based

on a limited number of stations and interpolated models, which often lack local accuracy [28]. Other platforms such as AirVisual [29] and BreezoMeter [30] offer geospatial visualizations and real-time data to users. The DustBoy sensor, while widely adopted, has shown that accuracy is influenced by sensor type and age. Calibration is required for reliable long-term performance [31]. Despite improvements, challenges such as data standardization and the validation of crowdsourced data remain.

The M-Care system addresses these limitations by integrating a low-cost, sensor-based air quality monitoring platform with LoRa communication and user-friendly mobile and web applications. Unlike centralized systems that depend on interpolated datasets, M-Care utilizes distributed physical sensors to deliver real-time, location-specific data with enhanced accuracy and reliability. The system measures PM_{2.5}, temperature, humidity, and atmospheric pressure, and all data is made accessible through a cloud platform. Field deployment in northern Thailand, a region affected by seasonal pollution due to biomass burning, demonstrates the system's effectiveness in tracking pollution trends and supporting public awareness. The accompanying web and mobile applications enable real-time visualization, historical data review, and pollution alerts, empowering users to make informed decisions. This paper is structured as follows: Section II details the proposed methodology, including hardware, software, and communication protocols. Section III presents experimental results and system evaluations, while Section IV concludes with key findings and future directions.

II. PROPOSED METHOD

This section details the proposed M-Care system, focusing on its architecture, hardware design, and software applications. This method encompasses the integration of IoT technologies, LoRa communication, and user-centric software platforms to achieve cost-effective and scalable air quality monitoring. Each aspect of the system is carefully designed to address the limitations of traditional monitoring systems while ensuring reliability, precision, and ease of deployment.

A. System Architecture

The architecture of the M-Care system is designed to enable scalable, real-time environmental data monitoring and dissemination. At its core, the system consists of multiple M-Care clients, sensor nodes equipped to measure PM_{1.0}, PM_{2.5}, and PM₁₀ concentrations, as well as ambient temperature, humidity, and atmospheric pressure. Each node operates autonomously using an onboard microcontroller and periodically collects data from its sensors. For data transmission, the system supports a dual-mode communication strategy. In rural or low-connectivity environments, M-Care clients transmit data to the M-Care gateway via LoRa, a low-power, long-range wireless protocol suited for wide-area deployment with minimal infrastructure. In areas with available Wi-Fi coverage, M-Care clients or the gateway can upload data

directly to the internet via Wi-Fi, enhancing data transmission speed and reducing latency.

The M-Care gateway, built on the same hardware platform as the clients (Heltec Wi-Fi LoRa 32 V3), acts as a relay, collecting LoRa packets from nearby clients and forwarding the data via Wi-Fi to the cloud. This architecture provides a flexible deployment model that accommodates both urban and remote monitoring scenarios. The cloud-based central server is responsible for aggregating, processing, and storing incoming data streams. It supports user access through the Yakkaw web and mobile applications (<https://yakkaw.mfu.ac.th/>), offering features such as real-time monitoring, historical analytics, geospatial heatmaps, and air pollution alerts. Fig. 1 illustrates the complete architecture of the proposed system.

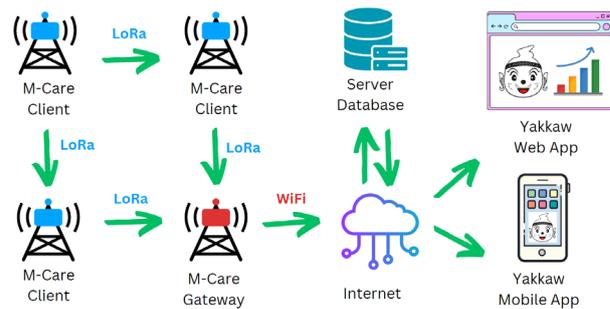


Fig. 1. Overall structure of our proposed system.

B. Hardware Design

The hardware design of the M-Care device prioritizes accuracy, affordability, and resilience. It integrates advanced sensors, a versatile microcontroller, and a weather-resistant enclosure to ensure reliable performance in various environmental conditions. The PMS5003 sensor, known for its high precision, measures particulate matter concentrations in three categories: PM_{1.0}, PM_{2.5}, and PM₁₀ [32]. This sensor is essential for monitoring fine particulate matter, which poses significant health risks. Additionally, the BMP280 sensor records temperature, humidity, and atmospheric pressure, providing contextual environmental data that enhances the system's analytical capabilities [33]. The microcontroller unit, Heltec Wi-Fi LoRa 32 (V3), is the core processing component of the device [34]. Detailed specifications of the M-Care hardware are presented in Table I. It handles data collection, local processing, and communication. Its dual communication capability allows seamless switching between LoRa and Wi-Fi, ensuring reliable data transmission in both rural and urban environments. The schematic depiction of M-Care hardware is illustrated in Fig. 2.

To ensure reliable data transmission under varied conditions, the M-Care system employs dual communication protocols. LoRa communication is utilized for long-range data transmission in remote areas, offering a tested range of up to 150 m with minimal packet loss. This capability makes it particularly suitable for monitoring in rural or resource-constrained regions. In

urban areas, where stable internet connections are more prevalent, Wi-Fi connectivity enables direct data transfer to the centralized server. This dual-protocol approach enhances the system’s adaptability and ensures uninterrupted data flow across different deployment scenarios.

The device operates on a standard 5 V power supply, making it compatible with common USB power sources and battery-operated applications. With a power consumption of 1.15 W, the system is designed to be energy-efficient, allowing for long-term deployment in remote areas without frequent maintenance. Designed for portability and ease of installation, the M-Care system has a compact form factor with dimensions of 4.5 × 2.5 × 11 cm and a total weight of 110 g.

TABLE I. TYPE SIZES FOR FINAL PAPERS

No.	Parameter	Description
1.	LoRa Frequency	920 MHz
2.	TX Power	21 dBm
3.	RX Sensitivity	-136 dBm
4.	Particle	PM1.0, PM2.5, PM10
5.	PM2.5 Range	0 to 500 µg/m ³
6.	Temp Range	-40 to 85 °C
7.	Pressure range	300 to 1,100 hPa
8.	Humidity Range	0 to 100%
9.	Input voltage	5 V
10.	Power Consumption	1.15 W
11.	Weight	110 g
12.	Dimension	4.5 × 2.5 × 11 cm

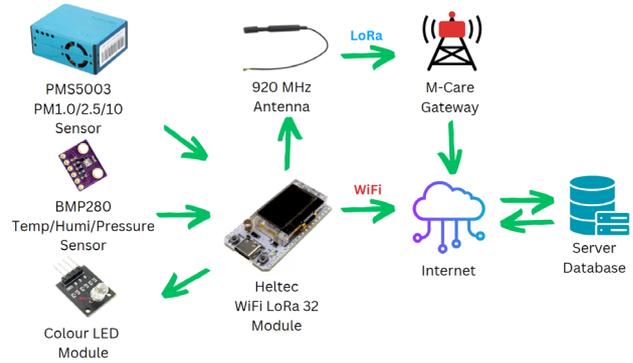


Fig. 2. M-Care hardware diagram overview.

To protect the internal components, the device is encased in a 3D-printed enclosure made from PLA-F filament. Fabricated with a Crea3 Ender-3 (V2) printer, the enclosure offers durability, lightweight construction, and resistance to environmental factors [35]. The design and printing of the M-Care 3D enclosure are depicted in Fig. 3. The hardware components are optimized for low power consumption, allowing the device to operate efficiently in field conditions. This is particularly beneficial for extended monitoring periods in remote locations where power sources may be limited. The deployment of the M-Care system follows a structured process to maximize its effectiveness. Devices are strategically installed at a height of 120 cm above ground level to ensure accurate air quality measurements.

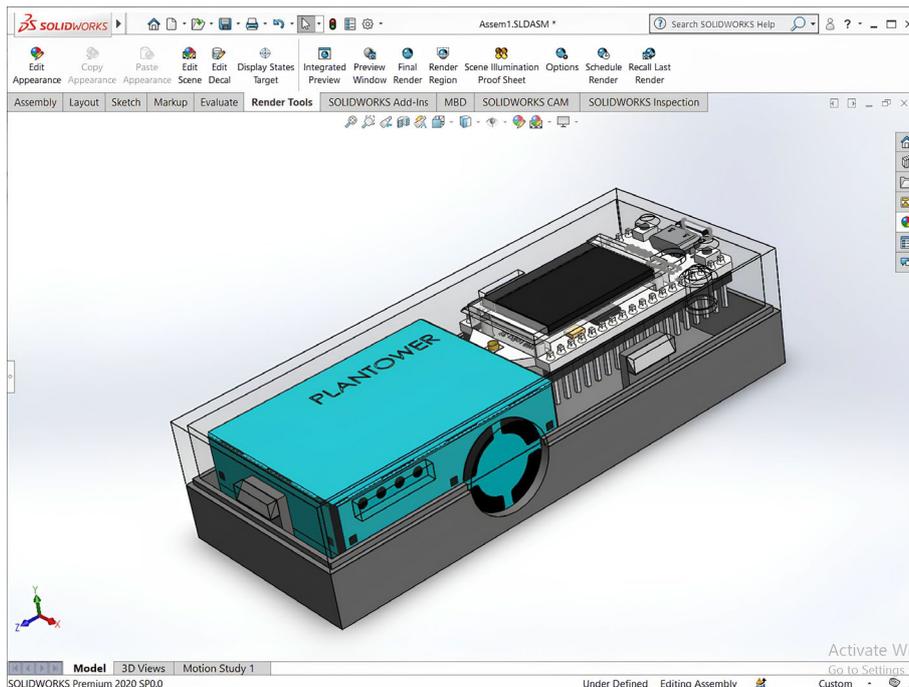


Fig. 3. M-Care 3D-case design and printing.

Each device is configured using the EspTouch mobile application, which allows users to input Wi-Fi credentials for internet connectivity. For LoRa-enabled installations, devices are positioned within a 200-meter range of gateway nodes to maintain efficient data relay. The system is designed to operate autonomously, requiring

minimal manual intervention. Regular calibration of sensors ensures data accuracy, while the modular design facilitates easy maintenance and upgrades. The deployment strategy emphasizes scalability, allowing the system to be expanded as needed to cover larger geographical areas or additional monitoring parameters.

Fig. 4 illustrates the assembly of M-Care with its respective enclosure.



Fig. 4. M-Care assembled with the 3D-printed case.

C. Software Design

The third component of the M-Care system is its digital interface, powered by the Yakkaw platform, which comprises both a web application and a mobile application. These applications are designed to offer intuitive access to air quality data while supporting advanced functionalities such as geospatial visualization, trend analysis, and personalized insights.

The web application serves as the primary interface for real-time data visualization and analytics. Developed using HTML5, jQuery [36], and Bootstrap [37], it ensures responsive design and compatibility across devices. Integration with Google Maps API enables users to explore location-based pollution data, identify hotspots, and monitor temporal-spatial trends [38]. Features such as historical data tracking and customizable dashboards enhance usability and support data-driven decision-making for stakeholders. The interface of the Yakkaw web application is presented in Fig. 5.

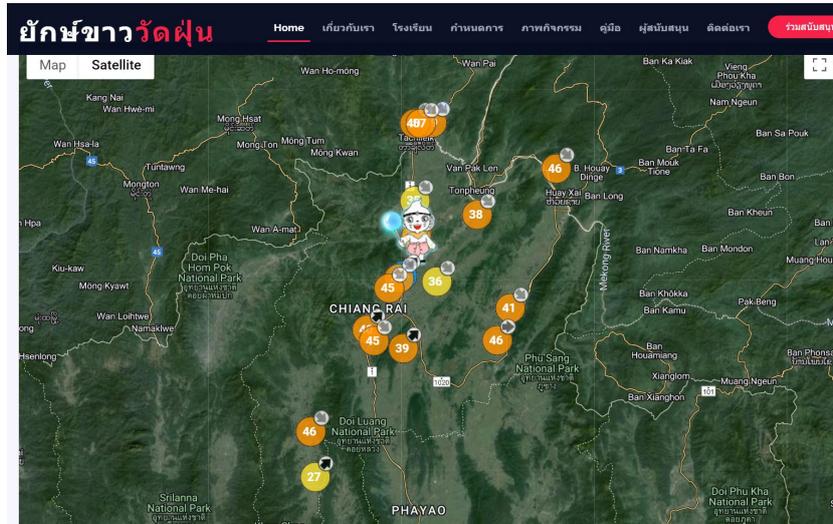


Fig. 5. Yakkaw's web application user interface.

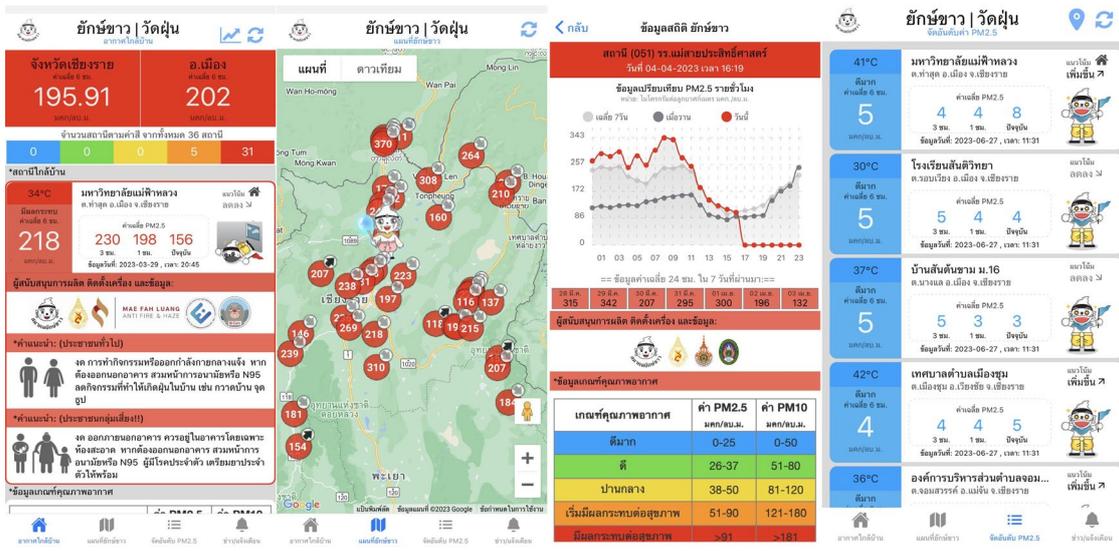


Fig. 6. Yakkaw's mobile application user interface.

The mobile application complements the web platform by providing real-time air quality information accessible from any location. Built with React Native [39] for cross-platform support, it offers features including push notifications for air quality alerts, user-contributed data through crowdsourcing, and personalized exposure tracking. These functionalities encourage user participation and enhance public awareness. The application’s backend infrastructure is powered by Node.js [40] and MariaDB [41], ensuring reliable data management, fast response times, and secure cloud integration. The RESTful API architecture facilitates interoperability, allowing seamless future integration with external platforms. Fig. 6 displays the Yakkaw mobile application user interface.

III. EVALUATION AND RESULTS

The evaluation of the M-Care system was conducted through extensive field testing and analysis to assess its performance, reliability, and user experience. This section presents the results of these tests, focusing on system accuracy, communication performance, seasonal trends, and user feedback. Field trials were carried out in northern Thailand, a region characterized by seasonal air pollution caused by agricultural burning and forest fires, providing an ideal context for assessing the system’s capabilities.

A. Communication Range Performance

To assess the communication capability of the M-Care system, field experiments were conducted to determine the effective range between the Heltec Wi-Fi LoRa 32 (V3) client device and the gateway, operating at a transmission power of 21 dBm with a receiver sensitivity threshold of -136 dBm. Tests were carried out under clear, line-of-sight conditions in an open field to minimize environmental interference. Table II presents the results, showing the Received Signal Strength Indicator (RSSI) and the percentage of packets successfully received at various distances from 50 to 300 m. At distances of 50 and 100 m, the system achieved 100% packet delivery, with strong RSSI values of -70 dBm and -82 dBm, respectively. At 150 m, packet delivery remained high at 97%, with an RSSI of -87

dBm. These results confirm stable and reliable communication over short and mid-range distances.

TABLE II. LoRa COMMUNICATION PERFORMANCE BETWEEN GATEWAY AND CLIENT DEVICE

Distance (m)	RSSI (dBm)	Packets Received (%)
50	-70	100
100	-82	100
150	-87	97
200	-114	84
250	-	0
300	-	0

Performance degradation was observed at 200 m, where packet reception dropped to 84% and the RSSI weakened to -114 dBm. Beyond this point, at 250 and 300 m, no packets were received, indicating that the signal had likely dropped below the receiver’s sensitivity threshold or was significantly attenuated due to distance-related propagation loss. These findings align with theoretical expectations of LoRa signal behavior and highlight the system’s practical communication range. Under optimal conditions, the M-Care system can reliably transmit data up to approximately 200 m. This range is suitable for various deployment scenarios, especially in semi-urban or rural areas where traditional network infrastructure is limited. Additionally, the dual-mode communication design (LoRa and Wi-Fi) enhances the system’s adaptability for diverse environmental conditions.

B. Seasonal and Daily Trends

The M-Care system was deployed to monitor PM2.5 levels over various temporal scales, offering detailed insights into both seasonal and diurnal variations. Fig. 7 presents hourly PM2.5 concentration data from three perspectives: current day, previous day, and the average over the past seven days. The results consistently show that PM2.5 levels tend to rise sharply during the early morning hours (8:00–10:00 AM), coinciding with peak traffic and potential temperature inversions. A secondary increase is observed in the late afternoon, followed by a decline in the evening and nighttime hours. These diurnal trends reflect the combined impact of human activities and atmospheric behavior on air pollution dynamics.

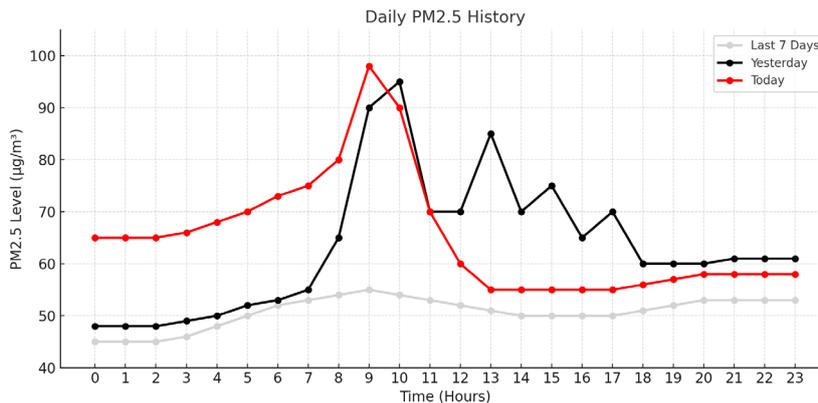


Fig. 7. Hourly PM2.5 data collected for today, yesterday, and the average over the past week.

Fig. 8 illustrates the monthly average PM2.5 levels recorded over a four-year period (2021–2024). A consistent seasonal trend is evident, with significantly elevated pollution levels during the dry season, particularly in March and April. These peaks coincide with widespread biomass burning in northern Thailand, a known seasonal contributor to poor air quality. In contrast, the rainy season months (June through September) show markedly lower PM2.5 values, confirming the cleansing effect of precipitation on airborne particulates. Notably, the 2024 data reflect a higher overall pollution level compared to previous years, suggesting either intensified burning or unfavorable meteorological conditions. The observed seasonal and

daily patterns correspond well with established regional environmental behaviors. Morning and afternoon peaks indicate urban activity-related emissions, while seasonal spikes in March and April underscore the role of agricultural fires. These findings highlight the necessity of deploying targeted mitigation measures during critical periods, especially the burning season. By capturing both short-term fluctuations and long-term trends, the M-Care system supports effective policy decisions and environmental health interventions. Its high temporal resolution and real-time capabilities make it an indispensable tool for addressing air pollution challenges in northern Thailand.

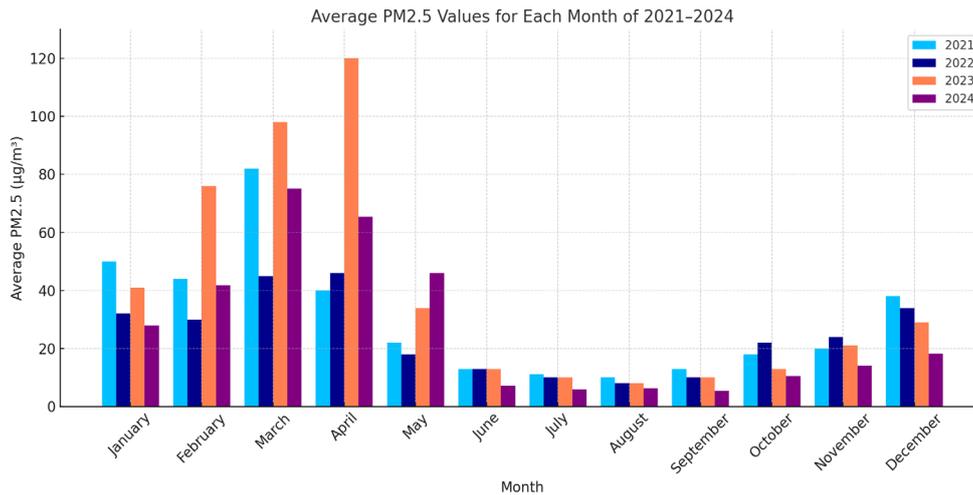


Fig. 8. Monthly average PM2.5 levels for the years 2021 through 2024.

C. System Accuracy and Reliability

To comprehensively evaluate the accuracy and reliability of the M-Care system in measuring PM2.5 concentrations, a comparative experiment was conducted throughout the 12-month period of 2024. The M-Care data were benchmarked against three reference datasets: the official air quality measurements from the Thailand Pollution Control Department (PCD) [42], OpenWeatherMap’s interpolated data service [28], and the Dustboy sensor network operated by CCDC [43].

These sources represent varying degrees of measurement precision: PCD using regulatory-grade instruments, OpenWeatherMap employing model-based estimations, and Dustboy exemplifying widely used low-cost sensor technology. To ensure fair evaluation, a M-Care device was co-located with a PCD reference station in Chiang Rai, Thailand. As shown in Table III, M-Care consistently demonstrated higher accuracy compared to the alternative systems.

TABLE III. COMPARISON OF OPENWEATHERMAP, DUSTBOY, M-CARE, AND REFERENCE STATION DATA PCD

Month-Year	¹ PCD [42]	Average Monthly PM2.5 (µg/m ³)			MAE		
		OpenWeather Map [28]	Dustboy [43]	M-Care (Our Propose)	OpenWeather Map [28]	Dustboy [43]	M-Care (Our Propose)
Jan-2024	26	26.08	38.45	27.98	0.08	12.45	1.98
Feb-2024	35	30.68	43.39	41.77	4.32	8.39	6.77
Mar-2024	58	37.73	82.71	75.11	20.27	24.71	17.11
Apr-2024	66	40.29	91.71	65.33	25.71	25.71	0.67
May-2024	39	12.95	47.51	45.98	26.05	8.51	6.98
Jun-2024	10	7.10	11.19	7.07	2.90	1.19	2.93
Jul-2024	9	6.34	9.05	5.93	2.66	0.05	3.07
Aug-2024	6	10.81	6.20	6.15	4.81	0.20	0.15
Sep-2024	8	9.52	11.18	5.38	1.52	3.18	2.62
Oct-2024	11	16.32	23.43	10.49	5.32	12.43	0.51
Nov-2024	11	23.76	28.52	14.19	12.76	17.52	3.19
Dec-2024	15	36.01	37.68	18.18	21.01	22.68	3.18
Total	24.5	21.47	35.92	26.96	10.62	11.42	4.10

Note: ¹ Reference station at Thailand pollution control department.

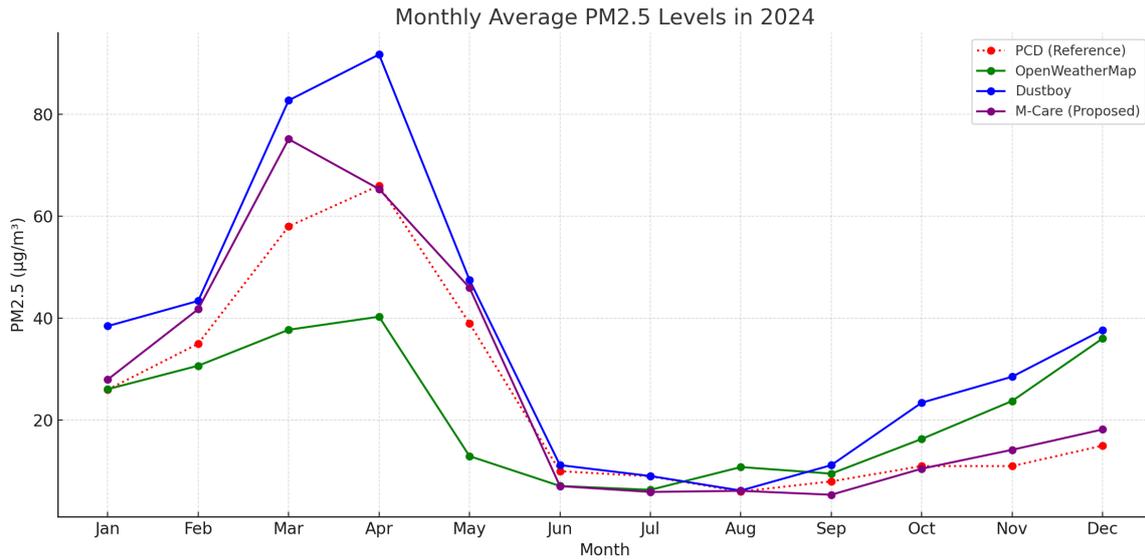


Fig. 9. Comparative monthly average PM2.5 for each system.

Fig. 9 illustrates a comparative analysis of Mean Absolute Error (MAE) values across the year 2024 among the four systems—PCD (reference), OpenWeatherMap, Dustboy, and M-Care. The line chart highlights M-Care’s superior consistency and proximity to the PCD benchmark, especially during peak pollution months such as March and April. This visual comparison further validates the M-Care system’s effectiveness in accurately capturing localized air quality trends.

The MAE for M-Care was 4.10 µg/m³, significantly lower than that of OpenWeatherMap (10.62 µg/m³) and Dustboy (11.42 µg/m³). In high-pollution months like March and April 2024, M-Care recorded MAEs of 17.11 µg/m³ and 0.67 µg/m³ respectively, still outperforming the other platforms. These results underscore M-Care’s ability to maintain accurate readings across various pollution conditions, from extreme haze periods to clean air seasons. OpenWeatherMap exhibited wider error margins due to its reliance on sparse data points and generalized atmospheric models. Dustboy, though designed for localized deployment, showed notable overestimations during peak pollution months. In contrast, M-Care’s real-time sensing and adaptive calibration mechanisms helped maintain reliable performance in both high and low PM2.5 scenarios.

To further assess statistical alignment, a paired t-test was applied, comparing each system’s monthly PM2.5 averages with PCD data. Results in Table IV show that Dustboy displayed statistically significant differences from the PCD data ($p = 0.0016$), indicating a systematic deviation. OpenWeatherMap did not show statistical significance ($p = 0.4855$), but its performance varied greatly by month. Importantly, M-Care’s results did not significantly differ from PCD ($p = 0.1662$), confirming the system’s statistical reliability. In summary, these findings validate the M-Care system as a dependable and accurate air quality monitoring platform. It offers near-reference-grade performance at a fraction of the cost, making it highly suitable for large-scale deployment in

both urban and rural contexts where official infrastructure may be lacking.

TABLE IV. T-TEST RESULTS COMPARISON OF OPENWEATHERMAP, DUSTBOY, M-CARE WITH PCD

Method	t-stat	p-value	Significant at 0.05
OpenWeather Map [28]	0.7219	0.4855	False
Dustboy [43]	-4.1646	0.0016	True
M-Care (Our Propose)	-1.4828	0.1662	False

TABLE V. COMPARATIVE SUMMARY OF AIR QUALITY MONITORING SYSTEMS

Metric	System		
	M-Care (Our Propose)	Dustboy [43]	OpenWeatherMap [28]
Cost	~\$ 90	~\$ 150	N/A
MAE	4.10	11.42	10.62
Range	200 m.	150 m	N/A
Comm.	LoRa/Wi-Fi	Wi-Fi	N/A
Platform	Web/Mobile	Web	Web/Mobile

Table V provides a comparative overview of three air quality monitoring systems: M-Care (our proposed system), Dustboy, and OpenWeatherMap. The comparison is based on five key metrics: cost, measurement accuracy, range, communication method, and platform accessibility. The M-Care system is a cost-effective solution, priced at approximately \$ 90. It offers high measurement accuracy with a Mean Absolute Error (MAE) of 4.10 µg/m³ and supports both LoRa and Wi-Fi communication. Its effective transmission range reaches up to 200 m. Additionally, M-Care is accessible through both web and mobile platforms, enabling flexible real-time monitoring and user interaction. Dustboy, on the other hand, is priced higher at around \$150 and has a larger MAE of 11.42 µg/m³. It supports only Wi-Fi communication with a range of about 150 m and is limited to web platform accessibility. OpenWeatherMap does not involve direct hardware costs but provides model-based estimations with a MAE of 10.62 µg/m³. While it offers access through both web and mobile

applications, it does not involve physical communication modules or allow for localized data collection.

IV. CONCLUSION

This study introduced the M-Care system, an IoT-based air quality monitoring platform designed for real-time PM_{2.5} detection using LoRa and Wi-Fi communication technologies. Developed with a low-cost architecture, the system demonstrated high accuracy and reliability when benchmarked against official pollution control data. Through extensive field testing in Chiang Rai, northern Thailand, M-Care consistently outperformed comparable solutions in terms of measurement precision and practical deployment range. Its seamless integration with web and mobile platforms enables users to access real-time data, geospatial insights, and historical trends to support informed environmental decision-making. The system's design emphasizes affordability, scalability, and versatility. It is suitable for semi-urban and rural applications where traditional infrastructure is limited. The hardware configuration, built around the Heltec Wi-Fi LoRa 32 (V3) and the PMS5003 sensor, achieves reliable long-range transmission under open conditions and supports flexible deployment scenarios.

Despite its strengths, the system has certain limitations. The PMS5003 sensor is susceptible to humidity-related variations and requires regular calibration in high-moisture environments. Moreover, the current system measures only particulate matter and lacks capabilities for detecting gaseous pollutants. The communication range may also be affected in obstructed environments or during inclement weather. Additionally, using hourly averages may limit the detection of short-term pollution peaks that are critical for exposure assessment. Future developments will focus on expanding pollutant detection capabilities by incorporating sensors for gaseous pollutants such as carbon monoxide (CO), nitrogen dioxide (NO₂), and ozone (O₃). Further enhancements will include the integration of real-time data analytics, adaptive calibration algorithms, and edge computing to improve resilience and bandwidth efficiency. The long-term vision includes building a decentralized, community-powered sensor network to strengthen environmental awareness and support proactive public health interventions across Southeast Asia.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Surapol Vorapatratorn: Conceptualization, methodology, validation, hardware implementation, experiment and discussion, writing reviewing and editing. Vittayasak Rujivorakul: Data curation, visualization, investigation, software implementation, writing reviewing and editing. All authors had approved the final version.

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