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REVIEV ARTICLE

Low-Cost Sensor Based on Internet of Things for $PM_{2,5}$ Air Quality Monitoring

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Abstract. The issue of air pollution, particularly that of particulate matter (PM2.5), has recently garnered significant global attention. However, the implementation of effective air quality management is frequently impeded by a dearth of adequate monitoring and measurement equipment. In Yogyakarta City and its surrounding areas, monitoring ambient air concentration, particularly PM2.5, remains difficult due to the limitations of monitoring tools such as Air Quality Monitoring System (AQMS). These tools are costly to operate, which further worsens the challenges. Therefore, this research aimed to design Internet of Things (IoT)-based Low-Cost Sensor (LCS) as an economical and reliable alternative to PM2.5 monitoring tools. Research and Development method was used with Plomp development model, which included investigation, design, calibration, as well as implementation. The results showed that IoT-based LCS followed the SNI 9178: 2023 standard with precision (SD 0.659 $\mu g/m^3$; CV 23.59%), bias (slope 0.94; intercept 0.65 $\mu g/m^3$), linearity (R^2 = 0.9), and RMSE 1.43 $\mu g/m^3$. Moreover, the regression relationship between IoT-based LCS and AQMS was shown by the equation Y = 0.8633X + 2.7604, signifying a strong correlation between the two tools. During the analysis, IoT-based LCS appeared to be a promising solution for air quality monitoring, offering both effectiveness and affordability, with real-time data relevant to environmental management.. The IoT-based LCS has been designed simply, meets the calibration standards of SNI 9178:2023, and can be applied in suburban areas.

1. Introduction

Air pollution is constituting a persistent environmental problem and concern globally (Adedeji et al., 2016; Suresh & Palaniraj, 2018, Nicolaou & Checkley, 2021; Ahmed, 2024). Research of 1,600 cities across 91 countries showed that approximately 90% of urban residents were exposed to air quality, failing to meet established health-based standards (Mayor, 2016; Rentschler & Leonova, 2023). Therefore, further research is necessary to understand the full scope of this problem. Half of the global population has been exposed to levels of air pollution that exceed the established air quality standards by a factor of 2.5 (Nazarenko et al., 2021; Shaddick et al., 2020). Relating to this discussion, particulate is defined as a pollutant in the form of complex mixtures of particles in the air, including smoke, dust, dirt, and liquids with tiny sizes (Asif et al., 2022). Particulate matter 2.5 (PM2.5) can traverse the deepest parts of lungs and enter bloodstream (Falcon-Rodriguez et al., 2016; Thangavel et al., 2022). Research on PM2.5, PM with a dimension of less than 2.5 µm, has seen a marked increase in recent years (Santoso et al., 2024; Yan et al., 2024).

The presence of PM2.5 has been connected to adverse health outcomes, including acute respiratory infections (ARI), lung cancer, chronic obstructive pulmonary disease, cardiovascular disorders, and premature death (Cheepsattayakorn & Cheepsattayakorn, 2019; Chen & Hoek, 2020; Larson et al., 2022; Nan et al., 2023; Thangavel et al., 2022). These pollutants have been shown to avoid respiratory defense mechanisms and bind to blood components through air exchange process in the lung alveolus (Anggraeni & Lestari, 2023; Yang et al., 2020). Moreover, the deposition of PM2.5 in respiratory tract transpires through physical mechanisms such as sedimentation, interception, impaction, diffusion, and electronic precipitation (Darquenne, 2020).

The accelerated development in Yogyakarta City and its surrounding areas has advanced the imminent threat of environmental concerns, one of which is air pollution (Irsyada & Oktapatika, 2023). This predicament is further worsened by substantial annual surge in motorized vehicles. According to data from Yogyakarta Special Region (DIY) Transportation Office and Indonesian National Police (Polri), the number of vehicles in 2020-2024 was 1.4; 1.5; 1.6; and 1.7 million units, respectively. Motorized vehicles are predominant source of air pollution emissions in Yogyakarta City and its environs (Akbar, 2023).

AQMS was deployed in Yogyakarta in 2020; however, measurements were not feasible during 2020-2021 owing to the Covid-19 pandemic. Measurements commenced in 2022, revealing that the $PM_{2,5}$ pollutant parameter exhibited a moderate trend from April to September 2022. In the dry season, particularly from April to September, elevated $PM_{2.5}$ concentrations are affected by arid air conditions, resulting in the suspension of solid $PM_{2.5}$ pollutants in the atmosphere. In 2023, the concentration of $PM_{2.5}$ is often lower during the rainy months than in the dry months. The arid months transpire in July, August, and September. The maximum $PM_{2.5}$ concentration recorded was 29.64 μg/m³ in August, and the minimum was 14.79 μg/m³ in January. The results serve as data for the annual report in the region, where the AQMS readings are said to represent the entirety of Yogyakarta City.

This occurs primarily due to the limitations of AQMS, which is equipped with a single tool despite the extensive coverage area. Despite the system is capable of identifying concentration in a 5-kilometer radius, the variability in ambient air quality is influenced by numerous factors, including meteorological conditions, infrastructure, altitude, and environmental factors (Hou & Xu, 2022; Swamy et al., 2020; Tatavarti, 2021). This difference between ideal and actual AQMS results can be attributed to the influence of these confounding variables, as evidenced by investigations according to Aboosaedi et al. (2023). A significant lacuna in this result is the absence of an ideal amount of PM2.5 monitoring equipment. Moreover, the lack of the equipment can shortens the scope of data recorded and has the potential to hinder the efficacy of air quality management initiatives in the research area.

The expansion of AQMS is not a judicious solution due to its cost, specifically in instrument procurement and maintenance (Asim et al., 2018). Following the discussion, the use of manual reference tools, such as HVAS, is recommended. HVAS is considered suboptimal (Sugita et al., 2019), and its implementation may lead to increased air quality control expenditures. This research proposes a solution in the form of a cost-effective air quality monitoring tool LCS (Low-Cost Sensor) based on Internet of Things (IoT) (Ali et al., 2021). The tool can be reproduced and placed in various monitoring locations according to the purpose, providing maximum data for a specific area. Additionally, the model can be accessed in real time, at several moments, and from any location (Zakaria et al., 2018). The objectives of this study include the following 1). The design of an alternative air quality monitoring device for PM2.5 parameters in the form of an Internet of Things (IoT)-based Low-Cost Sensor (LCS), 2). The calibration of the IoT-based LCS PM2.5 measurement device, 3). The analysis of air quality conditions, particularly PM2.5 parameters, using the IoT-based LCS in the study area.

2. Methods

This research was conducted in Yogyakarta City and its surrounding areas as shown in Figure 1. This city and the southern part of Sleman Regency were located in Special Region of Yogyakarta, Indonesia. The geographical location of Yogyakarta City was defined by latitudes of approximately 7° 47′-7° 52′ S and longitudes of 110° 20′-110° 25′ E. Moreover, southern part of Sleman Regency had latitudes of approximately 7° 42′-7° 47′ S and longitudes of 110° 20′-110° 30′ E. The area was part of Yogyakarta urban agglomeration, situated near southern slopes of Mount Merapi, part of the most active volcanoes in the world, and close to Indian Ocean to the south.

The tropical monsoon climate of the area was marked by distinct wet and dry seasons, while the topography was predominantly flat to slightly undulating. The total area of Yogyakarta City was approximately 32.5 square kilometers, but Sleman Regency included a significantly larger area of approximately 574.82 square kilometers. The southern portion of Regency included densely populated urban areas and some agricultural land. In addition, the historical, cultural, and educational significance of the area rendered it a central hub for tourism as well as academic activities.

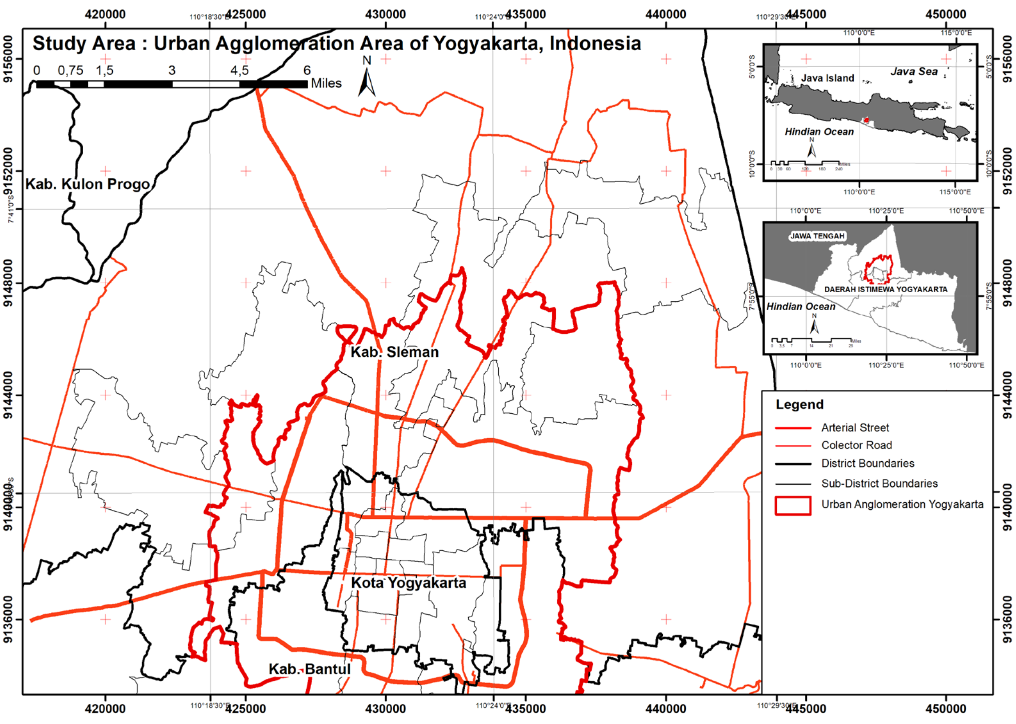

Figure1. Map of the research area and sample placement location with IoT-based LCS

Calibration test was conducted at DLH Office of Yogyakarta City, where PM2.5 monitoring was conducted for 2 weeks, starting on November 26 and concluding on December 10, 2024. The data used in this research consisted of PM2.5 concentration data from LCS and AQMS. Moreover, IoT-based LCS instrument comprised NodeMCU ESP32, PMS5003 Sensor, and Web Thingspeak. The research method used during this investigation was the research and development method (Mesra et al., 2023). The characteristics of PMS5003 are presented in Table 1.

This process was a necessity for air quality information and applying sensors assembled in the form of software, allowing the effectiveness of the product and application of information to user for testing. This present research was designed using development model of Plomp (Estuhono et al., 2019), which comprised several phases, including (1) initial investigation, (2) design, (3) calibration, and (4) implementation phase.

As shown in Figure 2, the process of reading and recording PM2.5 data is carried out as input through the PM2.5 sensor and then processed by the microcontroller. The data is forwarded via the Internet and stored on the cloud server. The data stored on the cloud server can then be accessed through the web Thingspeak as output.

The data calibration method on IoT-based LCS was conducted using a collocation method based on SNI 9178, 2023—Ambient air—Performance test of air quality monitoring devices using LCS. The calibration process included the following steps. Initially, three IoT-based LCS instruments were installed at a distance of approximately 10 meters and a height of roughly 2 meters from AQMS tool. This is in accordance with SNI9178:2023, which states that low-cost sensors must be tested at a minimum height of 1.5 m above ground level and at a minimum horizontal distance of 1 m and a maximum horizontal distance of 10 m from the reference

Table 1. The characteristics of PMS5003

Parameter	Index	Unit
Particle Range of measurement	0.3~1.0; 1.0~2.5; 2.5~10	Micrometer (μm)
Particle Counting Efficiency	50%@0.3um 98%@≥0.5μm	
Particle Effective Range (PM2.5 standard)	0~500	μg/m³
Particle Maximum Range (PM2.5 standard) *	≥1000	μg/m³
Particle Resolution	1	μg/m³
Particle Maximum Consistency Error (PM2.5 standard data)*	±10%@100~500μg/m3 ±10μg/m3@0~100μg/m3	μg/m³
Particle Standard Volume	0.1	Litre (L)
Single Response Time	<1	Second (s)
Total Response Time	<10	Second (s)
DC Power Supply	Typ: 5.0 Min:4.5 Max:5.5	Volt (V)
Active Current	≤100	Milliampere (mA)
Standby Current	≤10	Milliampere (mA)
Interface Level	L<0.8 @3.3 H>2.7@3.3	Volt (V)
Working Temperature Range	-10~+60	°C
Working Humidity Range	0~99	%
Storage Temperature Range	-40~+80	°C
MTTF	≥3	Year
Physical Size	50mm×38mm×21mm	mm

Sources: Plantower.com

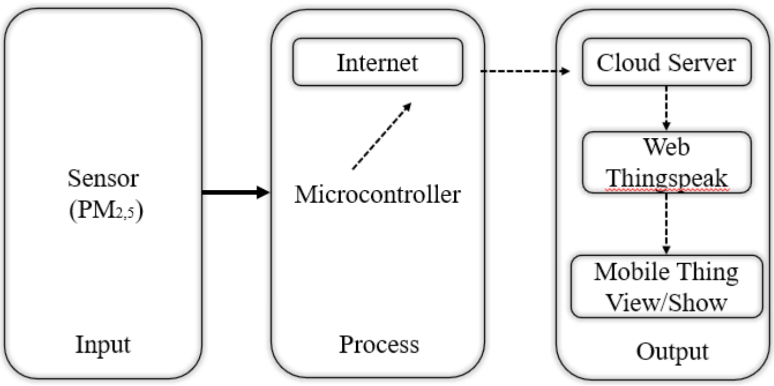

Figure 2. Flowchart of IoT-based LCS Instrument System for Monitoring PM2.5 Air Quality

measuring device sampling channel. Fi devices and servers were then installed, with this phase taking approximately 1-2 weeks. Following the process, recording phase lasted for approximately 1-2 weeks, and finally, data analysis phase used a collocation system.

The results of PM2.5 measurements via LCS IoT and AQMS were statistically analyzed to determine the precision, bias, linearity and error values with the acceptance requirements shown in Table 2.

The implementation of PM2.5 monitoring from IoT-based LCS devices was conducted in various locations categorized by distinct land use types, including residential, green open space, education, industry, and trade. The data collection period spanned 24 hours, comprising both working days and holidays. Additionally, the recorded data passed through spatial analysis using Inverse Distance Weighting (IDW) kriging method, a process of visualizing data in two dimensions (Sejati, 2019; Shukla et al., 2019).

3. Results and Discussions

3.1. IoT-based LCS Tool Design

The operational framework of IoT-based LCS Instrument for air quality monitoring was initiated by data collection stage, where the primary sensors namely, temperature, humidity, and PM2.5 sensors operated in real-time to capture environmental parameters. Subsequently, the data from these three sensors was transmitted to processing unit, where it experienced formatting and consolidation into a unified, structured data packet. Following this process, the subsequent stage was data visualization and storage. The processed data was then presented to the user through a visual interface, taking the form of a real-time graph, enabling direct monitoring of environmental conditions. Figures 2, 3, 4, 5, 6, and 7 showed the visualization of materials and ingredients in IoT-based LCS design.

The objective of this IoT-based LCS system was to monitor air quality using temperature, humidity, and PM2.5

Table 2. Acceptance Requirements for LCS Performance Test Particulate Parameters

No	Collocation performance test criteria in the field		Acceptability requirements
1.	Precision	a. Standard Deviation (SD)	≤ 5 μg/m³
		b. Coefficient of Variation (CV)	≤ 30%
2.	Bias	a. Slope	1,0 ± 0,35
		b. Intercept	-5≤ b ≤ 5μg/m³
3.	Linearity	Coefficient of determination (R^2)	≥ 0,70
4.	Error	Root Mean Square Error (RMSE)	RMSE ≤ 7 μg/m³

Sources: SNI 9178:2023


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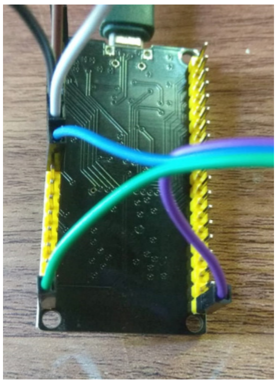
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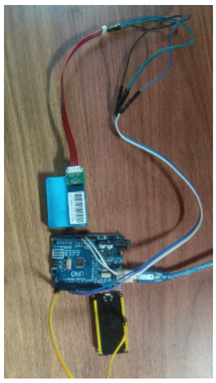
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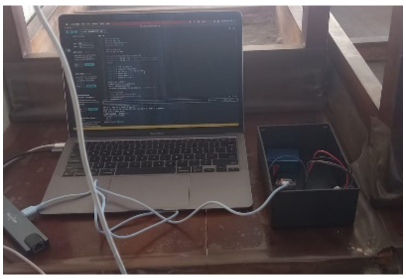
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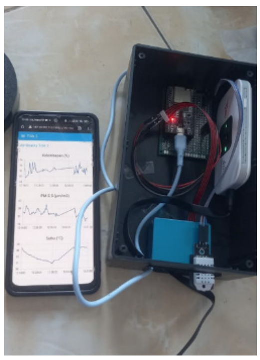
7).

Figure 2. NodeMCU ESP32 Front Part, 3. NodeMCU ESP32 Back Part 4. Sensor and mitrocontroller circuit 5. PMS7003 PM2.5 Sensor Tower Plan, 6. IoT-based LCS setting process, 7. IoT-based LCS access appearance using device.

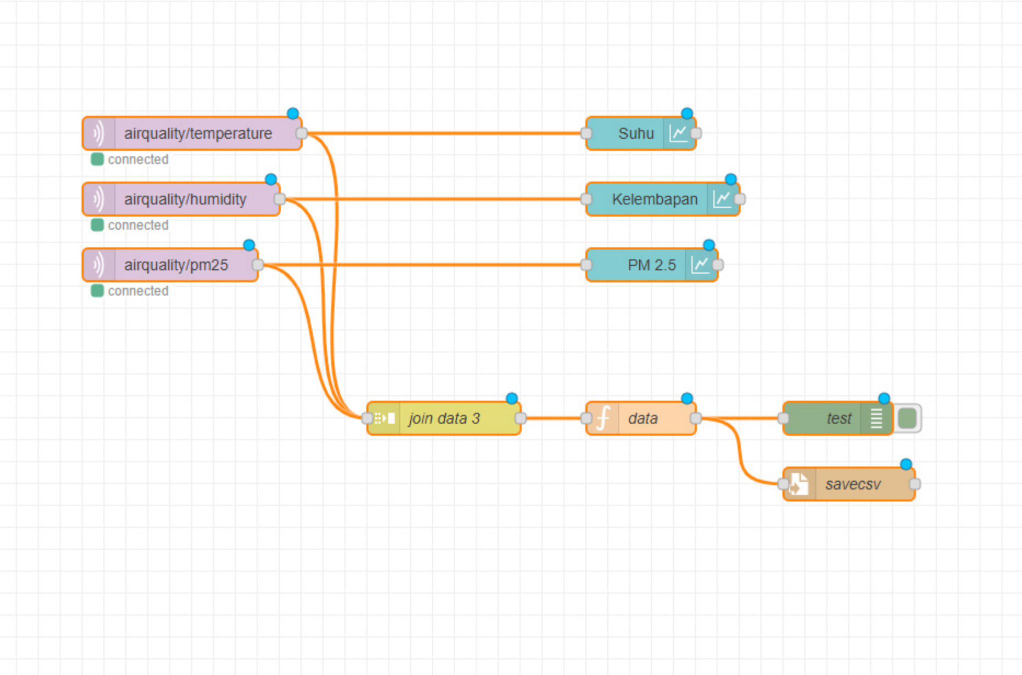

Figure 8. Flow data from sensors on an IoT-based LCS

Figure 9. Air Quality Monitoring System installed at DLH Yogyakarta City as a reference

sensors. During the research, MQTT communication protocol was used to facilitate collection of data from each sensor, enabling the transmission of real-time data to primary system. The data flow diagram showed that each data type, including temperature, humidity, and PM2.5, was retrieved from a distinct MQTT topic. Specifically, the data was retrieved as follows, including "airquality/temperature" for temperature, "airquality/humidity" for humidity, and "airquality/PM2.5" for PM2.5 particle concentration, respectively. The present study places greater emphasis on PM2.5 data. The process is simply shown in Figure 8.

3.2. Calibration of IoT-Based LCS Instrument

PM2.5 measurement data recorded from IoT-based LCS was not considered valid due to the absence of calibration of the system. Calibration served to standardize the measurement value produced by LCS instrument following the national reference standard tool.

A tool was selected to test the calibration for comparison according to the reference standard, namely AQMS, which was managed by Ministry of Environment and Forestry (KLHK) and DLH Yogyakarta City. The implementation of IoT-based LCS calibration was achieved through the use of an alternative standard instrument, namely AQMS, as shown in Figure 9. Moreover, the calibration process included the collection of measurement as well as AQMS data, followed by mapping of data into curves and determination of equations. Figure 10 showed that three IoT-based LCSs were installed close to the system. The equations used for this process included linear and exponential regression, as reviewed in the work of Chen, H. Y., & Chen, C. (2022). Relating to this discussion, the resulting equations were then subjected to confirmation. Validation was defined as a test of the equations determined by varying the true value that was different from the previous true value (Ufe et al., 2023).

The results of IoT-based LCS calibration, using AQMS as the reference measuring instrument were shown in Figure 11.

Figure 10. Installation of Iot-based LCS next to AQMS for calibration

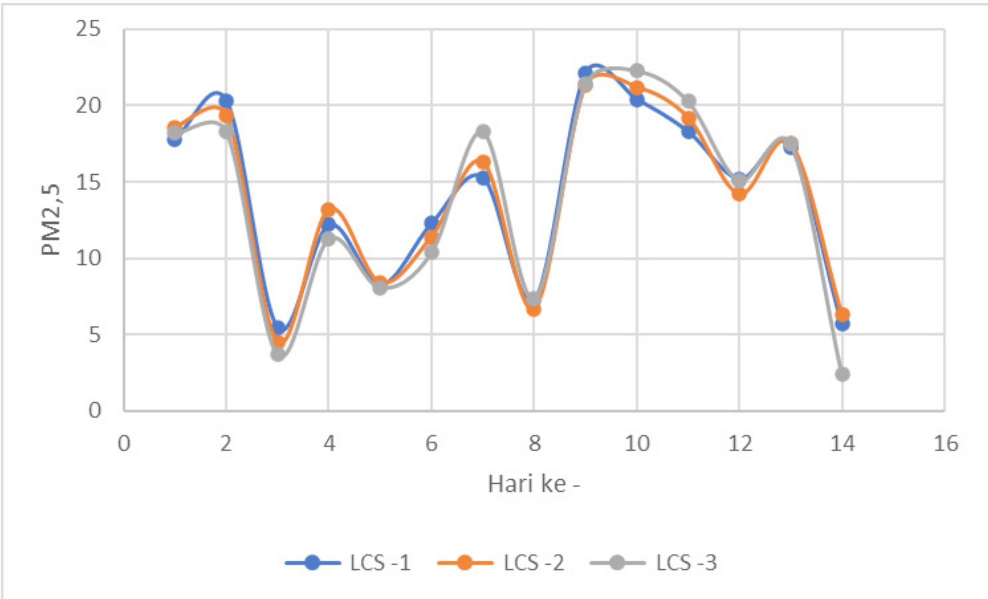

Figure 11. Comparison graph of PM2.5 value of LCS1, LCS 2, LCS 3 sensors

Figure 11 showed that the variation of PM2.5 concentration (in μg/m³) measured by three low-cost air monitors (LCS) over 14 days was identified. During the analysis, the daily average value showed significant fluctuations, with PM2.5 concentration ranging from 4.57 μg/m³ on day 3 to 21.60 μg/m³ on day 10. A substantial body of research has demonstrated that the Birmingham (UK) study exhibited a relatively robust average correlation between the sensor and the reference instrument, with an r2 value of approximately 0.7 for PM2.5(Cowell et al., 2022). In Salt Lake Valley, the correlation of this sensor was found to be moderate to low ($R2 < 0.49$) for PM10, with a tendency for the sensor to underestimate larger particle concentrations(Masic et al., 2020). The PMS5003 sensor has an approximate limit of detection (LoD) of 1.6–4.75 μg/m3. Following the implementation of calibration correction, the Pearson r value demonstrated a notable increase, ranging from 0.73–0.85 (raw) to 0.81–0.91. The R-squared value for PM10 in some studies reached 0.86–0.94 after calibration (Rabuan et al., 2023). The analysis implied that each LCS device presented a relatively consistent measurement pattern, with minor variations observed among the devices. However, individual results did signify slight variations, and the daily averages showed a trend of increasing this concentration on specific days (e.g., day 7 to day 10) followed by a subsequent decrease on the succeeding days.

Figure 12 showed a comparison was made between PM2.5 concentration measured by IoT-based LCS and standard AQMS. The graph signified the trend of data over a period of 14 days, with this concentration measured in μg/m^3. It is probable that the elevated PM2.5 concentration on the initial day was a result of the limited dispersion of pollutants and the increased human activities and meteorological conditions. The minimal amounts observed on the 3rd and 14th days were likely attributable to advantageous weather conditions, like vigourous winds or precipitation, which facilitated air purification, coupled with diminished pollution sources. The same pattern noted between the LCS IoT sensor and the AQMS reference instrument suggests that these trends represent genuine environmental conditions rather than sensor inaccuracies. A general observation of the patterns of PM2.5 concentration fluctuations from both devices showed similarities, although there were differences in value at specific measurement points, especially on certain days, such as days 2, 3, and 14. These discrepancies implied that IoT-based LCS device had minor deviations relative to AQMS standard device. Potential causes of these deviations included differences in device sensitivity or calibration factors. However, the parallelism in the trends showed by both devices signified the potential of IoT-based LCS device as a cost-effective alternative for air quality monitoring, particularly in scenarios where the deployment of AQMS device was impractical. LCS has been shown to incur significantly lower investment costs (Capex), typically ranging from tens to hundreds of US dollars, in comparison to AQMS, which can reach tens to hundreds of thousands of US dollars per unit. In regard to operational expenditures, LCS demonstrates enhanced cost-effectiveness due to its low power requirements, minimal maintenance needs, and straightforward calibration procedures. In contrast, AQMS requires periodic maintenance and costly professional calibrations, resulting in higher operational expenses. However, AQMS has been shown to offer higher accuracy and reliability, leading to its frequent use as a reference tool. LCS is a viable option for large-scale monitoring due to its cost-effectiveness, though it is noted that its precision is inferior to that of AQMS.

During the analysis, CV value ranged from 0.29% to 62.07%, signifying significant fluctuations between days. On day 5, the value reached maximum of 62.07%, while on day 14, it reached minimum of 0.29%. These fluctuations indicated variations in the measurement consistency of LCS tool, which was influenced by environmental factors, tool performance, or other variables. Generally, higher CV value showed unreliability in measurements on specific days, while lower value on other days implied more stable measurements. This observation signified the necessity for further evaluation to ensure the reliability of LCS tool.

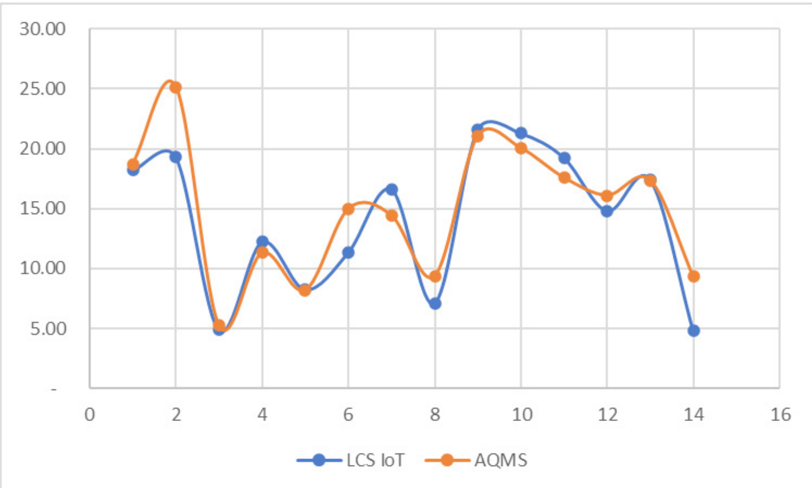

Figure 12. Comparison graph of PM2.5 value between LCS and AQMS

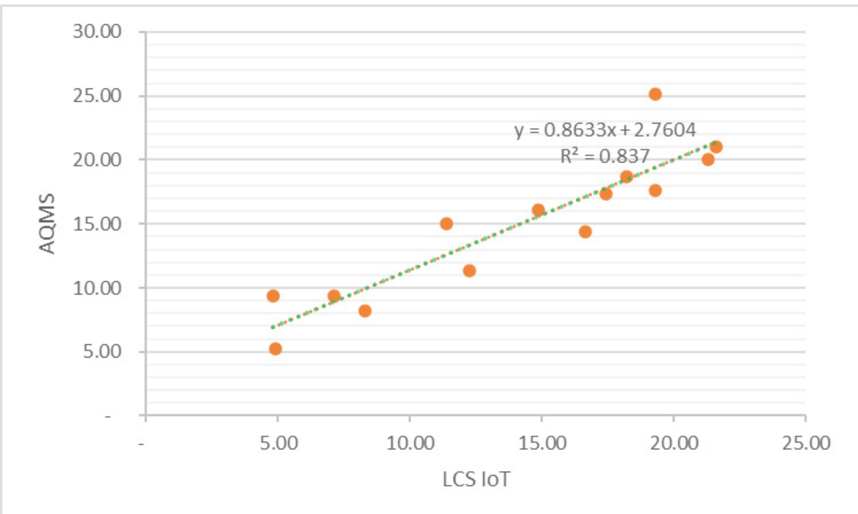

Figure 13. Linear regression graph of PM2.5 concentration data from AQMS and IoT-based LCS

Figure 13 showed the relationship between PM2.5 concentration measured by IoT-based LCS (x-axis) and AQMS (y-axis) over 14 days. The graph showed a robust positive linear relationship between the two devices. This relationship was quantitatively characterized by linear regression equation Y = 0.8633x + 2.7604, where *y* represented the concentration as measured by AQMS and x was PM2.5 concentration as measured by IoT-based LCS. In addition, coefficient of determination (R^2) was a measure of how well the regression model explained the variability of PM2.5 concentration on AQMS. The regression model showed 83.7% of the variability of this concentration on AQMS based on the data generated by IoT-based LCS. This result signified a strong correlation between the measurements obtained from the two devices.

The gradient of the regression equation was 0.8633, which was less than 1. This result signified that IoT-based LCS measurements tended to show slightly lower PM2.5 concentration compared to those measured by AQMS for equivalent concentration. Moreover, the intercept of 2.7604 showed the presence of a fixed bias in the measurement outcomes, where AQMS consistently produced a higher value of approximately 2.76 PM2.5 units, even when IoT-based LCS measurement approached zero. This discrepancy was attributable to variations in sensor sensitivity or calibration methods used by the two instruments. Recalibration with a more large and varied set of reference data helps the PMS5003 (LCS) sensor to have higher precision. Sophisticated calibration models—including non-linear regression and machine learning approaches—can help to capture measurement variability related to environmental influences. To guarantee the consistency and dependability of the experimental outcomes, it is absolutely necessary to include environmental variables such temperature and humidity. Furthermore, basic maintenance and calibration processes on a regular basis are essential to guarantee the ongoing operation of instruments. At last, field validation using colocation testing with an AQMS will assist to improve the calibration technique and find measurement biases.

The distribution of data points on the graph signified that the majority of data points were focused close to regression line, implying a consistent relationship between IoT-based LCS and AQMS measurements. However, certain data points deviated from the regression line, showing the presence of outliers or discrepancies in the measurement process. These disparities were attributed to various factors, including environmental disturbances, variations in atmospheric conditions, or differences in sensor sensitivity. The primary factors contributing to measurement variations in IoT-based Low-Cost Sensors (LCS) for PM2.5 include sensor calibration, sensitivity variations among sensor units, ambient conditions such as temperature and humidity, and the employed calibration models. Raysoni et al. (2023) assert that the most significant aspect is accurate calibration, which is coupled with sophisticated calibration models such as non-linear regression or machine learning to manage atmospheric variability. Moreover, as emphasised by Raheja et al. (2023), ambient circumstances exert a significant influence on sensor bias. As emphasised by Miskell et al. (2019), sensor degradation and drift are pivotal factors that induce performance deterioration over time. This underscores the necessity for periodic recalibration and maintenance procedures to ensure optimal functionality. In addition, Giordano et al. (2021)enhanced calibration techniques have been shown to reduce biases. These techniques include the measurement of particle size and composition, as well as spatial and data-driven algorithms.

During the analysis, the graph showed the relationship over 14 days. The representativeness of these results depended on the concentration variation during this time. When PM2.5 concentration over 14 days remained relatively stable, the relationship was considered fairly representative. However, substantial fluctuations in PM2.5 concentration caused by meteorological shifts, anthropogenic activities, or variations in emission sources, required further scrutiny to evaluate the reliability of correlation between the two instruments under more dynamic conditions.

Table 3 showed that the results of the tool calibration process were contingent upon the criteria for collocation performance tests in the field, comprising precision, bias, linearity, and error. In terms of precision, the tool met SD ≤ 5 μg/m³ with a value of 0.659 and CV ≤ 30% having a value of 23.59%. Concerning bias, the device showed a slope of 0.94 (falling in the range of 1.0 ± 0.35) and an intercept of 0.65 (ranging between -5 to 5 μg/m³). During the analysis, R^2 for linearity was found to be 0.9, which exceeded the minimum requirement of ≥ 0.70, signifying a strong relationship between device and reference. However, RMSE value of 1.43 μg/m³ remained in the required RMSE ≤ 7 μg/m³ range. The calibration results signified that the tool met all performance test criteria, implying it possessed acceptable accuracy and consistency in the field.

IoT-based LCS during the research showed a strong correlation with AQMS in measuring PM2.5 concentration. Despite the presence of biases and discrepancies in the results, IoT-based LCS tool was used as a PM2.5 m. A strong association is demonstrated between the Internet of Things (IoT)-based Air Quality Monitoring System with Low-Cost Sensors (LCS) and AQMS; however, there are numerous significant shortcomings. One such element is measurement bias, which is affected by environmental elements including temperature and humidity, as well as variances in sensor sensitivity amongst

Table 3. Calibration Results Based on Colloquy Performance Test Criteria in the Field

No	Collocation performance test criteria in the field		Acceptability requirements	Calibration result	Description
1	Precision	a. Standard Deviation (SD)	≤ 5 μg/m³	0.659	accepted
		b. Coefficient of Variation (CV)	≤ 30%	23,59%	accepted
2	Bias	a. Slope	1,0 ± 0,35	0,94	accepted
		b. Intercept	-5≤ b ≤ 5μg/m³	0,65	accepted
3	Linearity	Coefficient of determination (R^2)	≥ 0,70	0,9	accepted
4	Error	Root Mean Square Error (RMSE)	RMSE ≤ 7 μg/m³	1.43 μg/m³	accepted

units. In addition, LCS sensors are susceptible to drift and accuracy degradation over time in the absence of regular maintenance and calibration. Furthermore, fundamental calibration techniques frequently prove ineffective in addressing the intricacies inherent to atmospheric condition fluctuations, resulting in data anomalies. It is therefore evident that LCS requires more sophisticated calibration techniques and consistent maintenance in order to guarantee higher dependability, despite the fact that its efficiency and cost-effectiveness are impressive monitoring alternative, particularly given its simplicity as well as cost-effectiveness.

3.3. The Ambient Air Concentration Value of PM 2.5 is derived from IoT-based LCS

The calibrated IoT-based LCS was used to monitor PM2.5 ambient air quality in the designated research area. The recorded value from IoT-based LCS were then processed and analyzed through calibration using the previously obtained equation $Y = 0.8633x + 2.7604$, ensuring the proximity of the value to that of the standard tool. In this particular scenario, the installation of five IoT-based LCS devices was implemented. The selection of sites for the installation of these IoT-based LCS devices was informed by the variation in land use types, including education areas, residential zones, green open spaces, commercial areas, and rice fields (see Figure 14).

IoT-based LCS was designed to record real-time data every minute, which was monitored through a server on a cellphone or laptop. Data recording was conducted on weekdays and holidays for a duration of 24 hours each, thereby enabling the determination of variations in PM2.5 concentration value between these days. The collection of working-day data started on Monday, while holiday data collection resumed on Sunday. The temporal division of a day into morning, afternoon, and night periods was used to obtain more detailed information. The collected data was then grouped as well as averaged, and subsequently calibrated using the equation, which was presented in the following graph.

PM2.5 measurement results on weekdays was shown in Figure 154. During daylight hours, PM2.5 concentration showed a downward trend across all land use categories, with settlements registering the lowest concentration of 9.980 µg/m^3. This decline was attributed to various factors, including the direction and velocity of the wind in the research area, as evidenced by the results of (Chen et al., 2020). Higher wind speeds during the day were shown to affect PM2.5 concentration (Xu et al., 2023). Consequently, the education sector showed the highest PM2.5 concentration during the day, reaching 24,310 µg/m^3, which was attributable to the substantial activity present in school or college environments. Nighttime signified an increase in this concentration across certain land use types. The education sector showed the highest PM2.5 concentration during nighttime hours, with a recorded value of 36,271 µg/m^3. Equally, permanent settlements signified the lowest concentration, with an average of 17.346 µg/m^3.

The data showed that PM2.5 concentration fluctuated according to time of day and land use type. The highest concentration was recorded during the morning in industrial neighborhoods, while the lowest concentration was recorded in the afternoon in residential areas. The PM2.5 concentration in the industrial sampling area is about three times higher in the morning than in the afternoon primarily due to meteorological and anthropogenic factors. During the morning hours, a temperature inversion often occurs, where cooler air is trapped near the ground under a layer of warmer air, limiting vertical mixing and causing pollutants to accumulate near the surface. Additionally, wind speeds are generally lower in the morning, reducing the dispersion of particulate matter. Morning hours also coincide with increased industrial activities and heavy traffic as shifts start, contributing to higher emissions. Furthermore, limited sunlight in the early morning

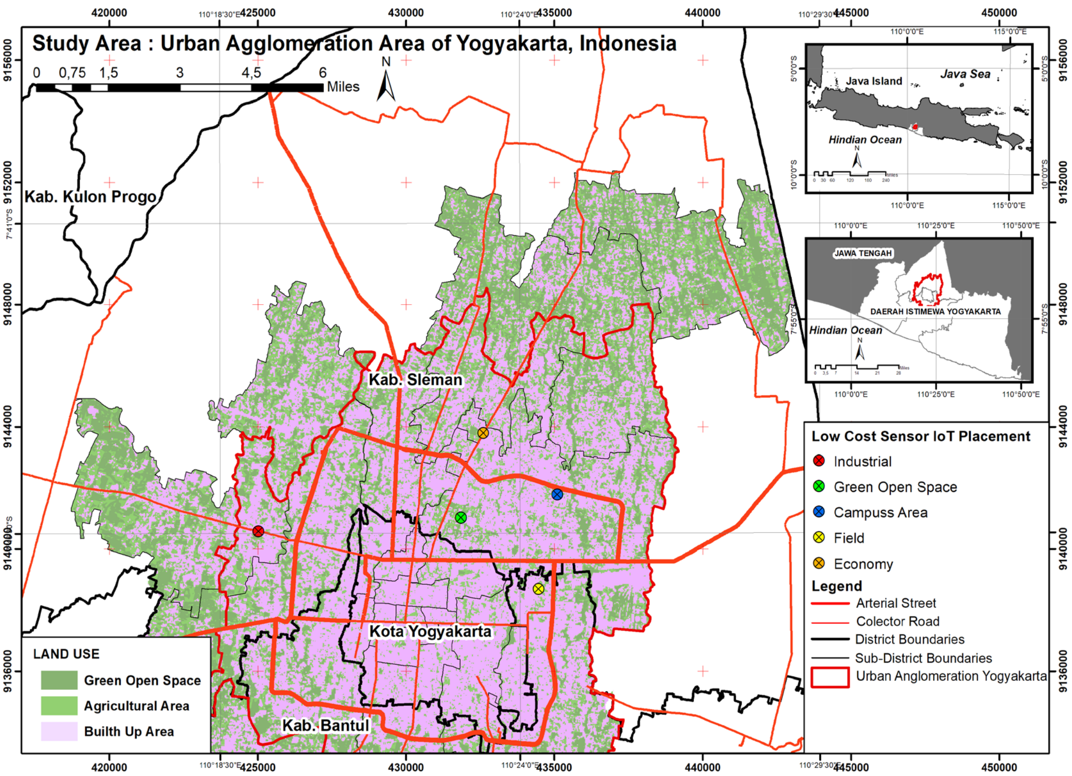

Figure 14. Map of PM2.5 measurement sampling locations using IoT-based LCS

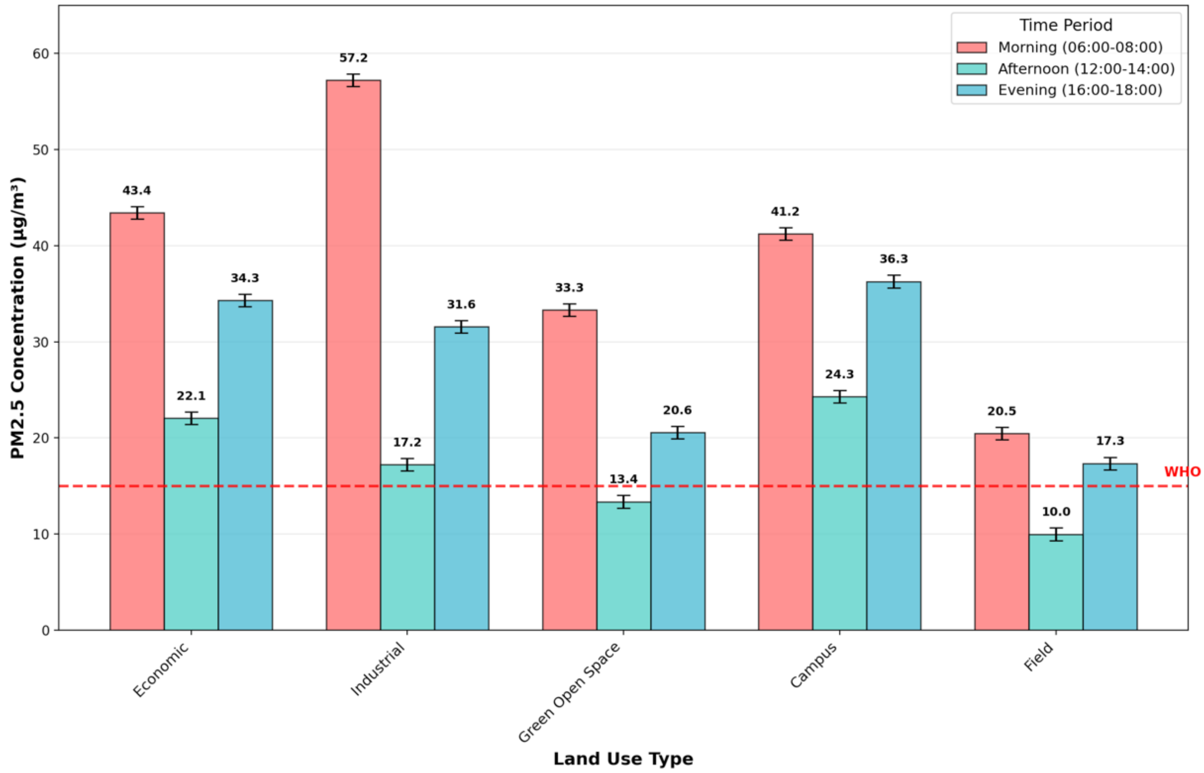

Figure 15. Graph of PM2.5 Concentration on Weekdays

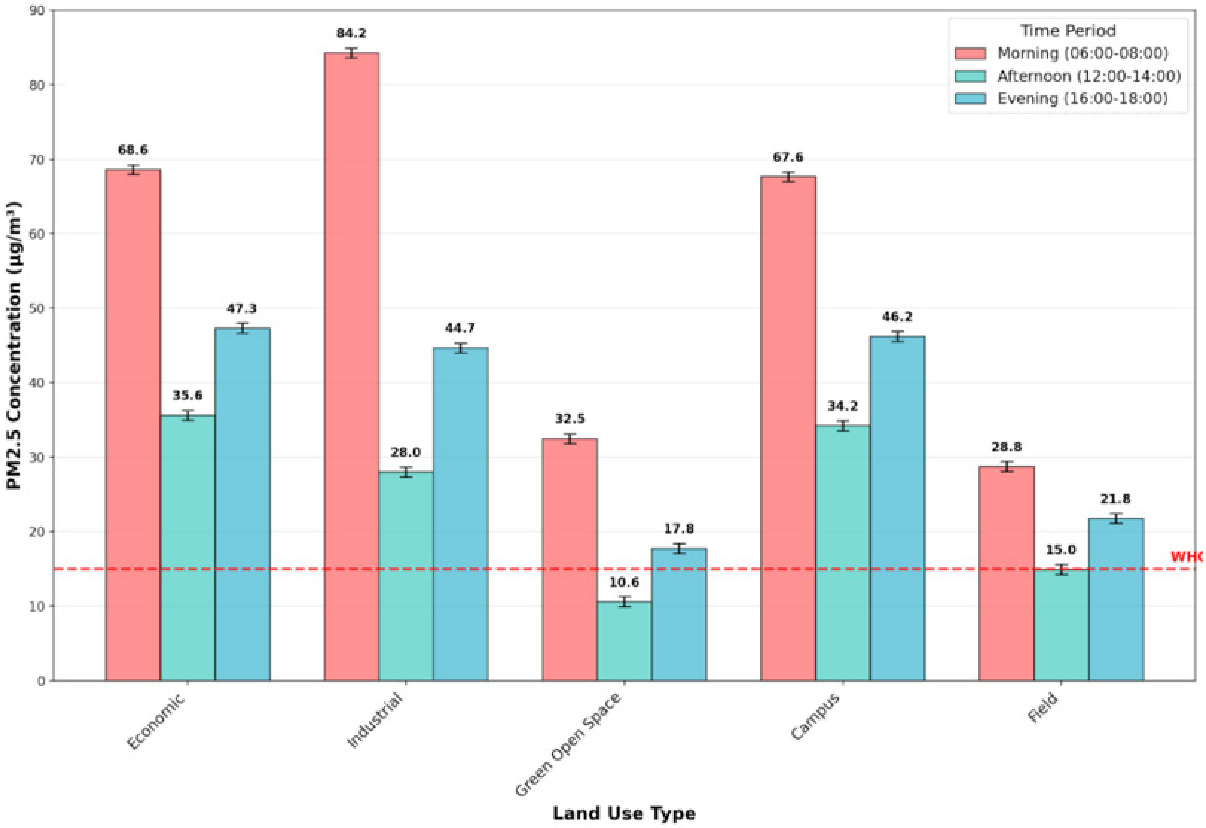

Figure 16. PM2.5 Concentration Graph on Weekend

restricts photochemical reactions that would normally help break down and disperse pollutants. Together, these factors create conditions for significantly elevated PM2.5 levels in the morning compared to the afternoon in industrial areas. The data signified that weekend variations in PM2.5 concentration were influenced by both land use and the time of day. The highest recorded concentration (84.245 μg/m³) was observed in the industrial area during the morning hours. This outcome was attributable to the commencement of industrial activities during this period, leading to elevated levels of air pollution. Consequently, green open spaces (RTH) showed the lowest concentration, measuring at 32.520 μg/m³, signifying that these areas experienced more favorable air quality during morning hours.

As the day progressed, a general trend of decreasing PM2.5 concentration was observed, consistent across all land use categories. This decline was attributed to factors such as improved wind speed. The lowest recorded concentration, 10.623 μg/m³, was observed in the green open space category, signifying that this area maintained the highest air quality in the day. Equally, residential areas showed the second lowest concentration, registering at 14.955 μg/m³.

PM2.5 measurement results on weekend was shown in Figure 16. During nocturnal hours, the concentration signified an increase, although it was not pronounced as the rise observed in the morning. The maximum concentration recorded during the night was observed in the education sector, reaching 46,233 μg/m³. This phenomenon was attributed to a decline in natural ventilation and nighttime activities, which contributed to elevated levels of air pollution. Green open spaces showed the lowest concentration, with an average of 17,757 μg/m³. Following the discussion, the comprehensive analysis signified that industrial areas showed the highest PM2.5 concentration during morning hours, while green open spaces implied the lowest concentration during daytime periods.

1.4. Spatial Condition of PM2.5 in the Suburbs of Yogyakarta City

The study area utilized IDW (inverse distance weighting) interpolation, employing three calibrated sensors initially. However, due to adjustments made to the area and land use characteristics, two additional sensors were incorporated, resulting in a total of five sensors being used. The grid size was selected based on the area, the number of sensors installed, and the balance between spatial resolution and interpolation reliability. Consequently, a grid size of approximately 300 m was selected.The installation of IoT-based LCS instruments was conducted in five locations, with the selection of these sites based on the specific land use characteristics of each area. The distribution was then subjected to analysis using IDW interpolation method in ArcGIS software, considering three distinct periods (morning, afternoon, and evening) and comparing weekdays as well as holidays. The visualization in Figure 18 showed the variation in air pollutant concentration influenced by human activities and environmental conditions.

The outcome was observed that on holidays, PM2.5 concentration tended to be higher in the morning, as evidenced by the predominance of red to orange colors on the map. This phenomenon, as postulated by Yan et al. (2020), was attributed to an increase in air pollution, potentially attributable to an augmentation in domestic activities and a concomitant rise in private transportation during weekends. Consequently, a significant decrease in PM2.5 concentration was observed during the daytime, as shown by the transition to a lighter yellow color on the map. This decline was attributed to the dispersion process of pollutants, which was facilitated by increased temperature and air circulation during daytime hours. At night, the concentration showed a slight increase, but remained lower than morning levels.

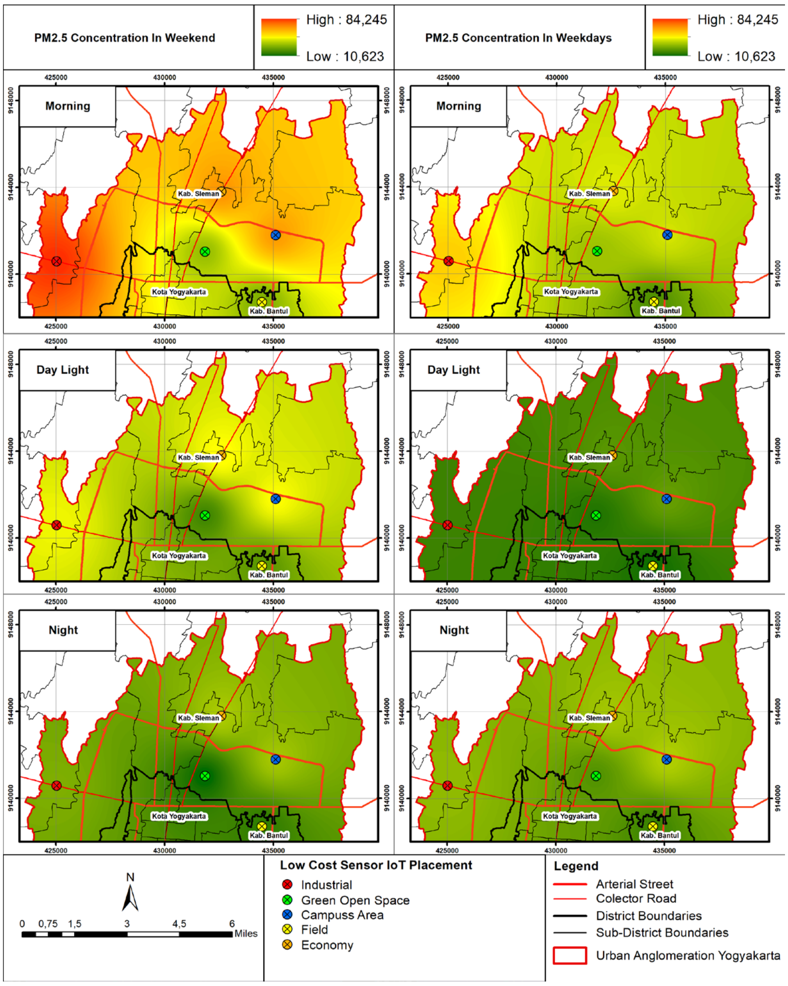

Figure17: Visualization of PM2.5 Coverage Map in Yogyakarta Suburbs by Time
Source: (Data analysis, 2024)

During weekdays, PM2.5 concentration showed a more pronounced decrease compared to holiday periods. In morning hours, the concentration presented a more uniform distribution, characterized by a predominant yellow hue, signifying a greater degree of manageability concerning air pollution levels. These observations supported the results reported in the research by Kusuma (2024).

The phenomenon was attributed to the presence of more regular patterns of human activity and the control of emissions from industrial sources or public transportation. A more pronounced decrease in PM2.5 concentration was observed during the day, with a shift toward a green color, signifying improved air quality. Equally at night, the concentration remained low with an even distribution across the research area.

The spatial distribution of PM2.5 as shown in Figure 16 showed that mornings signified the highest concentration in both day as well as night conditions (holidays and workdays, respectively), with holidays experiencing more significant spikes. This observation implied that weekend mornings experienced increased influence from more intensive human activities when compared to weekdays. IDW which was a geospatial interpolation method used in this research, facilitated the identification of areas with the highest PM2.5 concentration, providing a foundation for the formulation of policies aimed at mitigating air pollution in the suburban areas of Yogyakarta. Consequently, efforts to improve air quality should prioritize the control of morning emission sources, particularly during weekends.

1.5. Discussion and recommendations

This research produced research that could be recommended as an alternative air quality monitoring tool, although the investigation did not replace the main role of standard tools such as AQMS and HVAS, specifically on PM2.5 parameters. The design of IoT-based LCS tools was conducted by previous research with various objectives. For instance, Glass et al. (2020) developed LCS to monitor air quality in highly polluted urban areas, while Ruiter et al. (2023) focused on LCS designed for industrial areas to assess exposure to flour dust. Moreover, Reddy et al. (2020) developed LCS aimed at improving spatial and temporal understanding of matter particles using IoT-based LCS. Alfano et al. (2020) conducted a review of various LCS that these technologies could assist in air pollution measurement in areas with limited monitoring coverage.

Previous research constructed LCS that used diverse sensor types, which led to disparate data recording outcomes. In the context of results from an investigation by Jiao et al. (2016), evaluating the performance of low-cost PM2.5 sensors under various environmental conditions. The study demonstrates that by showing precision with a standard deviation (SD) of 0.659 µg/m1 and a coefficient of variation (CV) of 23.59%, the LCS IoT PM2.5 sensor satisfies the stated standards of SD < 5 µg/m1 and CV ≤ 30%. Sensor bias is evidenced by a slope value of 0.94 and an intercept of 0.65 µg/m^1 in line with the slope range of 1.0 ± 0.35 and an intercept between -5 and 5 µg/m^1. A coefficient of determination (R^2) of 0.9 and a root mean square error (RMSE) of 1.43 µg/m^3 show the linearity of the sensor, therefore indicating the accuracy

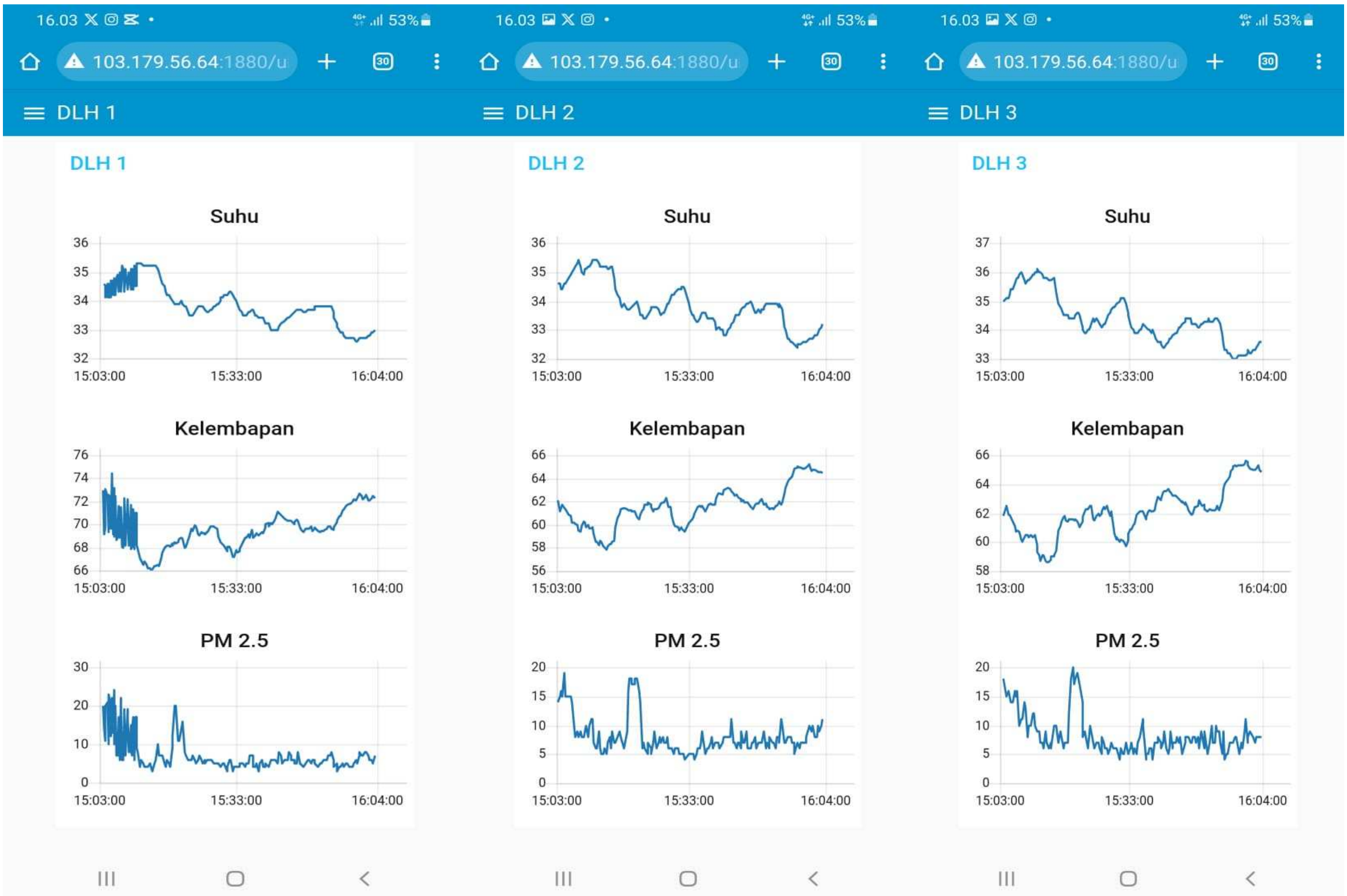

Figure 17. ThingSpeak Dashboard Air Quality Monitoring using IoT

and consistency of the measurements. This falls also below the maximum RMSE threshold of 7 μg/m³. Reporting calibration data for the PMS5003 sensor, Jiao et al. (2016) noted a minor intercept within the ±5 μg/m¹ range and a calibration slope between 0.85 and 1.1. Complementing the standard deviation (SD) below 5 μg/m¹ and a coefficient of variation (CV) of 20–25% the study also indicated equivalent sensor performance in urban environmental circumstances. At the same time, research by Sousan et al. (2016) revealed low-cost sensor root mean square error (RMSE) values between 2.0 and 3.5 μg/m1. Although this spectrum surpasses the results of the current research, it stays within the reasonable boundaries for non-regulating uses. Although the claimed accuracy and bias of the sensors were judged sufficient, it was underlined that regular calibration is absolutely necessary to guarantee the validity and dependability of the findings.

Developed IoT-based LCS successfully passed the calibration test using the collocation method as recommended by KLHK according to the Standard of Indonesia (SNI) 9178: 2023. A salient benefit of IoT-based LCS included its capacity to provide real-time data with high temporal resolution. Moreover, the data recorded by microcontroller was stored in the cloud and could be accessed using a laptop or mobile device through an internet server, as shown in Figure 17. The tool was capable of recording data at one-minute intervals, both in the form of numbers and graphs, which could then be used for monitoring at various locations such as four-way intersections, shopping centers, and educational environments. This result supported the research by Reddy et al. (2020), which showed the significance of high-density air pollution monitoring using IoT-based LCS nodes. Research by Snyder et al. (2013) signified that the development of IoT-based sensors facilitated more incorporated monitoring with big data-based systems.

The implementation of PM2.5 concentration measurement using IoT-based LCS was conducted at five points with varying land use types. The results showed that green open space areas signified lower PM2.5 concentration levels compared to industrial, education, residential, and trade areas. This observation supported the results reported in the research by Badura et al. (2018), explaining that vegetation acted as a natural filter for airborne particles. However, other investigations such as Jin et al. (2014) produced contradictory results, signifying that PM2.5 concentration in areas with abundant vegetation were higher due to the influence of specific local activities. Sousan et al. (2016) also showed that air particle sensor performance varied depending on environmental conditions and calibration settings.

Research findings indicate that sensors monitoring parameters critical to the Air Quality Index (AQI), such as PM10, NO2, SO2, CO, O3, and HC, should be incorporated into subsequent IoT-based LCS systems. The objective of this study was to assess the reliability of PM2.5 sensor data over an extended period, with the aim of determining the optimal sensor replacement interval during operation. However, the implementation of IoT-based LCS had various limitations which included the necessity for regular recalibration as well as sensor maintenance and replacement under certain conditions (Badura et al., 2018). This research provided recommendations to interested parties to consider further development of IoT-based LCS as an efficient and affordable air quality monitoring solution, specifically for PM2.25 parameters. This innovative approach also contributes to achieving SDG 11 (Sustainable Cities and Communities).

3. Conclusion

In conclusion, IoT-based LCS Design was implemented and could be used for air quality monitoring, particularly PM2.5 sensor. The outcome was shown by the calibration results with a standard or reference tool AQMS, which met the standards of SNI 9178: 2023—Ambient air—Performance test of air quality monitoring devices using LCS (SNI 9178, 2023). Following this process, the precision value also met the standard as mentioned earlier. The collocation performance in the field met all accepted requirements, as shown by the calibration results. Precision with SD of 0.659 μg/m³ and CV of 23.59% satisfied the criteria of SD ≤ 5 μg/m³ as well as CV ≤ 30%. The bias, signified by a slope of 0.94 and an intercept of 0.65 μg/m³, also satisfied the criteria of a slope of 1.0 ± 0.35 as well as an intercept ranging from -5 to 5 μg/m³. Linearity, with R^2 of 0.9, met the criterion of ≥0.70, while the error with RMSE of 1.43 μg/m³ met the requirement of RMSE ≤7 μg/m³. This result implied that LCS showed reliable performance and was suitable for use in a field setting. IoT-based LCS could also be implemented for monitoring PM2.5 concentration in suburban areas, with results that varied according to time conditions and differences in variables affecting the models. The IoT-based LCS has been designed simply, meets the calibration standards of SNI 9178:2023, and can be applied in suburban areas.

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