IoT Based Air Quality Monitoring System Utilizing OpenRemote as an Application Server at University

Delfin Daffa Pebrian [1], Azzis Hervian Delphiano [2], Salsa Diniarti[3], Mas Aly Afandi[4]*, Melinda Br Ginting[5]
Department of Electrical Engineering Telkom University
Jl. DI Panjaitan No.128, Purwokerto Selatan
Purwokerto, Indonesia
Email: alyafandi@telkomuniversity.ac.id*

ARTICLE INFORMATION

Received 20 March 2025
Revised 21 April 2025
Accepted 05 May 2025

Keywords:
Air quality monitoring
LoRa
LoRaWAN
OpenRemote platform.

A B S T RACT

This research develops an IoT-based air quality monitoring system at a university, utilizing LoRaWAN technology and the OpenRemote platform to address urban air pollution, which poses significant health risks. The system employs MQ-7 and MQ-135 sensors to detect carbon monoxide (CO) and carbon dioxide (CO_2) levels. Results showed marked differences in pollution levels between two locations: the DSP Building recorded peak CO levels of 16 ppm and CO_2 levels of 550 ppm, categorized as "unhealthy," while the Rectorate Building maintained stable concentrations in the "Good" category. Communication parameters for uplink and downlink were analyzed, revealing variable signal strengths across buildings. The DSP Building exhibited an uplink RSSI of -71.13 dBm and an SNR of 8.72 dB, and a downlink RSSI of -78.13 dBm with an SNR of 3.33 dB, both of which were significantly better than those of other buildings. The integration of OpenRemote enhances data management and visualization capabilities, allowing for real-time monitoring and historical analysis. The system provides a dashboard interface for easy access to air quality data and supports strategic recommendations to mitigate pollution impacts. This system not only enhances campus air quality management by providing accurate, real-time data to inform decision-making but also holds the potential for replication in other urban environments, thereby contributing to broader efforts in mitigating air pollution challenges globally.

1. Introduction

Air pollution is a condition in which air quality deteriorates due to the contamination of harmful substances that can threaten human health, ecosystems, and the environment in general (Behinaein et al., 2023). This phenomenon frequently occurs in urban and industrial areas characterized by intensive human activities. These pollutants not only degrade air quality but also pose severe health risks to the population, making it crucial to monitor and manage air quality effectively (Dharmendra Kumar & Navin Singh Rajput, 2022). Emissions of pollutant gases that exceed safe thresholds are one of the main triggers, especially in areas with high population density and mobility (Ramadan et al., 2024). Human activities in urban environments, including campus areas, also contribute to air quality degradation. Major sources of pollution include motor vehicle emissions, construction activities, chemical use, and other environmental factors that cumulatively harm human health (Akomolafe et al., 2024).

Air quality can be monitored using various methods and technologies designed to measure pollutant concentrations in the atmosphere. These methods typically involve sensors capable of detecting harmful gases, such as carbon monoxide (CO) and volatile organic compounds (VOCs). However, many existing sensors lack effective integration into systems that facilitate real-time data processing, particularly in university environments. Improved monitoring solutions are essential for comprehensive air quality assessments (Anitha & Kumar, 2023).

There are several technologies that enable air quality measurement. For instance, Bluetooth allows air quality sensors to connect with other devices over short distances, facilitating data collection (Ling et al., 2020). Additionally, Wireless Fidelity (Wi-Fi) is often utilized to transmit data from sensors to servers or applications in real-time (Patil & Patil, 2016). The NB-IoT (Narrowband IoT) technology offers more stable connectivity for devices that require efficient data communication in areas with weak signals (Hendricks & Kabaso, 2024). Conversely, Long Range (LoRa) enables data transmission from sensors installed in remote locations, providing a wider range and lower power consumption (Jayasree et al., 2023).

Internet of Things (IoT) technology using LoRa has been implemented in various sectors beyond air quality, demonstrating its flexibility and efficiency in monitoring and control. In the agricultural sector, LoRa technology is utilized to monitor soil conditions, moisture levels, and temperature. This enables farmers to make data-driven decisions, optimizing agricultural practices and improving crop yields (Ting & Chan, 2024). In smart city management, this technology supports to monitor systems for streetlights, waste management, and traffic surveillance, allowing authorities to enhance operational efficiency (Babu et al., 2023). Additionally in the healthcare sector, LoRa is used for remote patient monitoring through wearable devices that transmit critical data to healthcare centers. (Abdulmalek et al., 2024).

LoRa became a popular choice for various IoT applications across different industrial sectors due to its wide range and low power consumption. In addition, LoRa enables data collection from sensors spread across multiple locations to support real-time air quality monitoring. Reliable for a communication range of up to several kilometers, LoRa is an ideal solution for extensive sensor networks (Mnguni et al., 2021). In contrast to bluetooth technology which is only capable of transmitting data within a short distance, Wi-Fi technology only can reach the coverage of range up to 100 meters, so it requires a lot of hotspots. Then NB-IoT technology requires complex infrastructure and expensive costs (Cheruvu et al., 2019). Current technologies, such as Bluetooth and Wi-Fi, often fall short due to their limited range and connectivity issues, while NB-IoT requires complex infrastructure (Ling et al., 2020; Hendricks & Kabaso, 2024). In contrast, LoRa technology offers a reliable solution for long-distance data transmission with low power consumption, making it ideal for extensive sensor networks (Mnguni et al., 2021). However, there remains a need for a comprehensive application server that can manage the diverse data from multiple devices seamlessly.

This research addresses these gaps by proposing an IoT-based air quality monitoring system that integrates LoRaWAN technology with the OpenRemote platform. This integration not only enhances data management and real-time analysis but also provides a centralized interface for monitoring air quality across the university campus. By enabling multiple nodes to connect to a single gateway without interference, the system ensures efficient data collection and visualization. The OpenRemote platform supports various communication protocols and offers historical data access, further improving user engagement. Ultimately, this study contributes to enhanced environmental monitoring practices, offering strategic recommendations to mitigate air pollution impacts within the university and highlighting the potential of IoT technologies in addressing urban air quality challenges.

This research proposes designing and implementing an IoT-based air quality monitoring system at university, with integrating Long Range Wide Area Network (LoRaWAN) technology with the OpenRemote platform to ensure efficient data management and analysis. By using LoRaWAN technology that enables efficient air quality monitoring and allows multiple nodes to connect to one central gateway without interference between nodes, LoRaWAN supports long-distance data transmission with low power consumption. This system ensures reliable and easily accessible real-time data collection (Farej & Adel, 2024). The integration of OpenRemote and LoRa allows air quality data to be collected and analyzed in real-time and displayed via the web. Because, OpenRemote centralizes all data, sensors, and controls, providing several features such as support for Message

Queuing Telemetry Transport (MQTT), Hypertext Transfer Protocol Secure (HTTPS), Application Programming Interface (API), and WebSocket communication protocols. Data visualization on the dashboard is available in various formats, and the device location feature makes it easy to find the sensors. Additionally, it can be integrated with other platforms, uses a database for data storage, and allows users to view data history (OpenRemote, 2024). In addition, this research also aims to analyze the air quality data obtained to provide strategic recommendations in reducing the impact of air pollution in the university environment.

2. Literature review

2.1 *Literature Review*

Previous research on "Enhancing Campus Environment: Real-Time Air Quality Monitoring Through IoT and Web Technologies" developed an IoT-based air quality monitoring system to create a healthier campus environment. The system utilizes an ESP32 microcontroller, pollutant sensors (CO, NO2, and HC), and communication technologies such as Wi-Fi. The collected data is sent to the SEMAR IoT application server for analysis and provides real-time notifications via a web application and Telegram when pollutant levels exceed safe limits. The system uses the Classification and Regression Tree (CART) algorithm for data analysis and the Air Quality Standard Pollutant Index as a reference. Data reliability is enhanced through validation, including cross-checking with other sensors and BMKG public data. The results are visualized through an interactive web interface. There are several limitations to this research, such as the use of Wi-Fi technology which has a short range, so it is not enough to cover the entire campus area. Requires adequate internet access, data visualization that only displays charts, limited data storage processing in receiving large amounts of data (Rahmadani et al., 2025).

Another study by (Purkayastha et al., 2021) The research explores advancements in Wireless Sensor Networks (WSNs) and their applications, with a particular focus on an IoT-based Air Quality Monitoring System (AQMS). The system enables real-time tracking of air pollutants, including CO_2, CO, and NO_2, alongside environmental parameters such as temperature and humidity. To enhance accessibility, AQMS integrates both a web application and a mobile app, allowing users to conveniently monitor air quality data. But the data displayed is only in tabular form, so it lacks visualization. This absence of graphical representation makes it challenging for users to quickly interpret trends and patterns in air quality data. In addition, the application created cannot be integrated with other platforms and only uses API communication protocols.

A study conducted by (Sung et al., 2019) This study introduces the development of Amore, an advanced indoor air quality monitoring system designed to measure key pollutants, including PM_{10}, $PM_{2.5}$, CO, CO_2, and VOCs, alongside temperature and humidity. The system integrates multiple high-precision sensors and supports both short-range and long-range communication for seamless real-time data acquisition. A dedicated smartphone application enables continuous monitoring and intuitive data visualization, providing users with actionable insights for indoor air quality management. Validation tests demonstrate a high degree of accuracy, with measurements closely aligning with established reference devices.

Table 1. Comparison between the current existing air quality monitoring system

Ref	Hardware/software technology	Contributions	Advantages	Limitations
(Rahmadani et al., 2025)	- Measure the levels of CO, NO2, and HC - Use ESP32 to collect, process and send data	- The system highlighted its ability to monitor air quality fluctuations, trigger warnings of	- The system can transmit data in real-time	- Not applicable for long- range communication

Ref	Hardware/software technology	Contributions	Advantages	Limitations
	through Wi-Fi to the server - Use web applications for monitoring	hazardous conditions, and inform the campus community	- The system can be integrated with message communication applications such as telegram	- Limitations on data storage
(Purkayastha et al., 2021)	- Measure the levels of CO, CO_2, NO_2, Temperature and Humidity - Use ESP8266 to collect, process and send data through Wi-Fi to the server - Use android platform for monitoring	- The design an IoT Air Quality Monitoring System (AQMS) using a android platform	- The system can transmit data in real-time and visualize data on an android phone	- Not applicable for long- range communication - Data visualization can only be displayed on android phones.
(Sung et al., 2019)	- Measure the levels of Dust Sensor, CO, CO_2, VOC_s, Temperature and Humidity - Use ESP32 send data through Wi-Fi or Bluetooth for short distance communication - Use LoRa module to send data for long distance communication - Using Android Platform	- Design of an IoT Air Quality Monitoring System that can transmit data over short and long distances using an android platform	- The system can transmit data over short and long range - Real-time system	- Less attractive data visualization - Difficult to integrate with other communication platforms or protocols
The Proposed LoRaWAN-Based Air Quality Monitoring System	- Measure the levels of CO, CO_2, Temperature and Humidity - Use LoRaWAN to send data for long- or short-range communication - Using web application for monitoring - Use a network server to manage data flow	- Building an air monitoring system based on LoRaWAN communication using a web application that can send alert message notifications	- The system can transmit data over short and long range - Real-time system - Cross platform - Integrated with MQTT and HTTP protocols - Two-way communication system (Uplink and Downlink) - More attractive data visualization	

Table 1 summarizes and compares the main features of several previous studies on IoT-based air quality monitoring systems with those of the proposed LoRaWAN-based Air Quality Monitoring System. In previous research, some systems still use Wi-Fi connectivity to transmit data from sensor devices to be displayed on the application dashboard, thus requiring a wide range of Wi-Fi connectivity. Besides that, the application dashboard used mostly uses android applications, which can only be opened on mobile devices that use the android operating system. Looking at this gap, our proposed system intends to offer a more efficient, comprehensive, and user-friendly solution for remote air quality monitoring communications and web-based applications that can be used on all types of devices.

2.2 *Long Range (LoRa)*

LoRa is a long-range communication system that uses low-power radio frequency (RF) for small data transmissions. Currently, LoRa technology is widely used to send and receive data from gateways to end nodes over very long distances. LoRa is part of the Low Power Wide Area Network (LPWAN) technology, which offers long-range transmission capabilities, energy efficiency, and relatively small data transmission (Tovar-soto et al., 2021). LoRa operates in the Industrial, Scientific, and Medical (ISM) frequency bands, which is not require a license. The frequency bands used are different in each region based on the regulation, such as 2.4GHz, 868MHz, 915MHz, and 433MHz. In Indonesia, LoRa operates at a frequency of 915 - 923 MHz (Rijadi & Machdi, 2024). The LoRa technology has a wide transmission range while consuming low battery power. Therefore, LoRa is highly suitable for monitoring agricultural environments in Indonesia, referred to as an agrarian country with extensive agricultural land (Hendry & Manongga, 2024).

2.3 *Long Range Wide Area Network (LoRaWAN)*

LoRaWAN is expected to support a substantial number of the billions of IoT devices. It is specifically designed to optimize LPWAN networks for battery life, capacity, range, and cost (Adi et al., 2024). The physical layer of LoRa uses chirp spread spectrum technology, which allows for low power consumption while significantly extending communication range. This results in longer distances and more reliable communications. While LoRa WAN defines the communication protocol and system architecture for the network, the LoRa physical layer facilitates the long-range communication link (Hidayati & Nashiruddin, 2020).

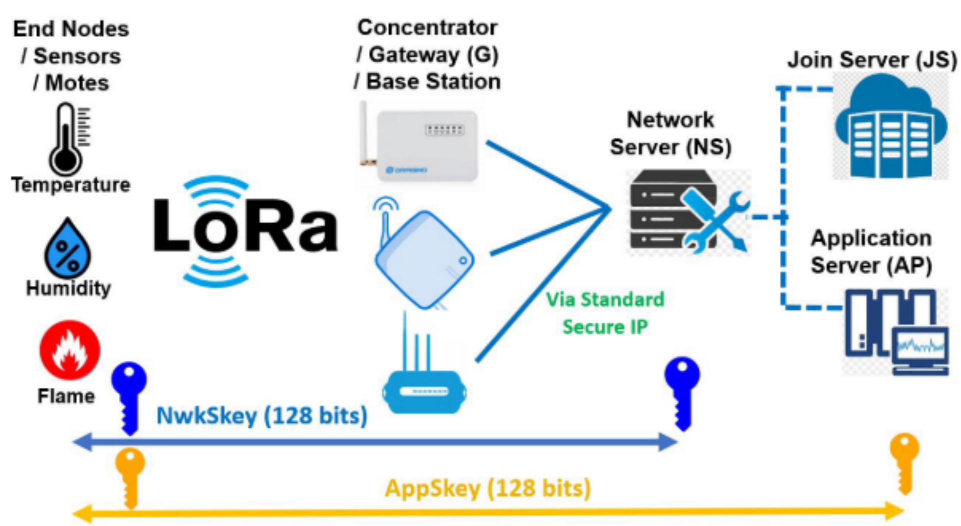

Figure 1. LoRaWAN Architecture (Hugo & Chalacan, 2020)

Figure 1 shows each component of the LoRaWAN architecture. End Nodes, also known as Mobile Terminations (MoTe) or nodes, are devices built with microcontrollers, sensors, and LoRa transceivers that enable long-range spread spectrum communication. Gateways, also referred to as base stations or concentrators, forward data between end-nodes (sensors) and the network server. The network server directs data from the sensors to the appropriate application server, which then responds back to the sensors. It also provides authentication for the sensors, manages network security (using a 128-bit NwkSkey), controls data rates, and eliminates duplicate data. Therefore, the primary responsibilities of the network server include optimizing battery usage (by controlling transmission power), ensuring security, and managing data routing. Meanwhile, the Application Server contributes to the security of the data payload (using a 128-bit AppSkey) and presents the data to users through an easy-to-use interface featuring widgets, graphs, and dashboards (Hugo & Chalacan, 2020).

2.4 *Message Queueing Telemetry Transport (MQTT)*

MQTT is a communication protocol commonly used in IoT systems. This protocol utilizes a publish-subscribe model, consisting of three main components: publisher, subscriber, and message broker. The publisher is responsible for sending sensor data, the subscriber is subscribed on the topic to receive data, and the message broker delivers data from the publisher to the subscriber. In this process, the publisher sends messages to the broker with a specific topic, and the broker forwards those messages to subscribers who have subscribed to the corresponding topic (Kashyap et al., 2018). This communication model allows for efficiency in large IoT environments. The subscribers are required to subscribe the topics without knowing the identity of the publisher's address directly. The MQTT protocol operates over TCP/IP that requires transportation to execute MQTT commands, by facilitated byte streams directly from client to server or directly server to client (Rodriguez et al., 2020).

2.5 *Application Server*

Figure 2. Platform OpenRemote (OpenRemote, 2024)

Figure 2 shows OpenRemote, which serves as the application server in this research. This server provides a network management interface that allows for adjusting parameters and settings while interacting with databases to store device information and facilitate communication with network servers. Additionally, Application Server enables the decryption of application payloads for data storage, collection, and visualization. Typically, the application server features a web interface for configuring devices, users, and services, alongside a RESTful API for data retrieval. Furthermore, application servers can monitor the state of the gateway to ensure it is operational, display its location, and provide real-time logs of live frames or events entering the server (Paganelli et al., 2020).

2.6 *LoRaWAN Network Server*

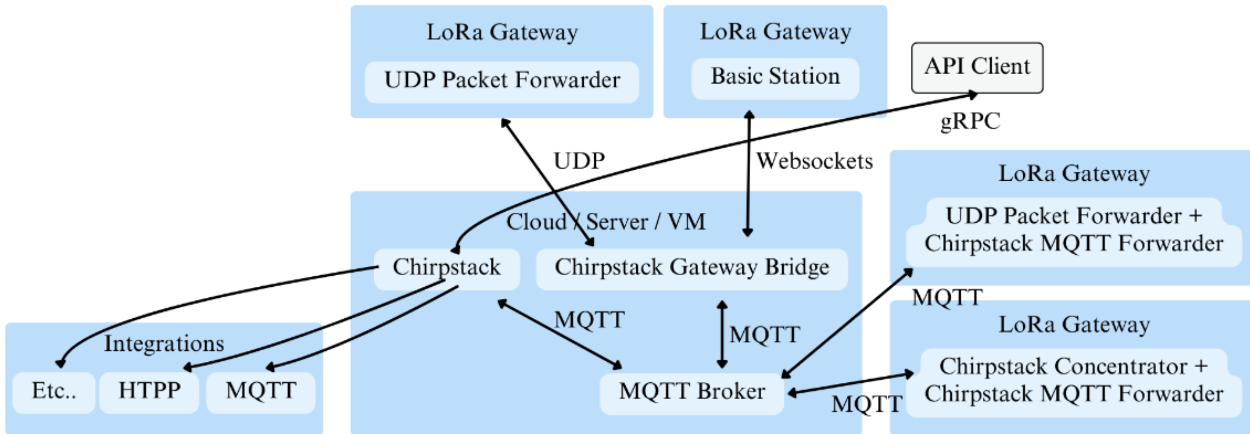

Figure 3. LNS Chirpstack Architecture (ChirpStack, 2024)

Figure 3 shows the Chirpstack used in this research as a LoRaWAN Network Server. The LoRaWAN Network Server (LNS) serves as central component in network to facilitating connectivity, management, and monitoring of device, gateways, and end user applications. Its primary function is to ensure the security, scalability, and reabilitiy of data routing within the LoRaWAN network. (The Things Industries, 2024) (Semtech, 2023).

This research utilizes the ChirpStack LoRaWAN Network Server, an opensource LoRaWAN network server designed for managing both private and public LoRaWAN network. ChirpStack provides a web interface for configuring gateways, end device as well as for integrating data with cloud provider, database, and other common services used for device management. Additionally, Chirpstack over gRPC-based API, wich can be used to integrate or extend its functionally (ChirpStack, 2024).

2.7 *Air Pollution Threshold*

The air quality thresholds are typically measured based on the Air Quality Index (AQI). The AQI serves as a reference for how clean or polluted the air is concerning surrounding pollutants, such as CO, CO_2, PM2.5, and PM10. The following Table 1 presents the air quality thresholds based on AQI (Dharmendra Kumar & Navin Singh Rajput, 2022).

Table 2. Air Quality Threshold (Dharmendra Kumar & Navin Singh Rajput, 2022)

AQI	Health Alert	CO (ppm)	CO_2 (ppm)	PM2.5 (ug/m^3)	PM10 (ug/m^3)
0-50	Good	0,0 – 4,4	0-400	0,0 – 12,0	0– 54
51-100	Moderate	4,5 – 9,4	401-500	12,1 – 35,4	55– 154
101-150	Unhealthy for sensitive groups	9,5 – 12,4	501-800	35,5 – 55,4	155– 254
151-200	Unhealthy	12,5 – 15,4	801-3000	55,5 – 150,4	255– 354
201-300	Very unhealthy	15,5 – 30,4	3001-6000	150,5 – 250,4	355– 424
301-400	Hazardous	30,5 – 40,4	6001-10000	250,5 – 350,4	425– 504

AQI	Health Alert	CO (ppm)	CO_2 (ppm)	PM2.5 (ug/m^3)	PM10 (ug/m^3)
401-500	Very Hazardous	40,5 –50,4	>10000	350,5 – 500,4	505– 604.

2.8 *LoRa Signal Level Parameters*

LoRa technology is designed to provide robust communication over long distances with minimal power consumption. Understanding the signal level parameters is crucial for optimizing network performance and ensuring reliable data transmission. These parameters help to evaluate the quality of the signal between the transmitter and receiver, which can significantly impact the overall efficiency of the LoRa network (Silva et al., 2023). Table 2 shows the standard for the LoRa received signal strength index (RSSI).

Table 3. RSSI Signal Level (Enriko et al., 2024)

RSSI (dBm)	Level
-30 to -60	Very strong
-60 to -90	Very good
-90 to -105	Good
-105 to -115	Bad
-115 to -120	Very bad.

Table 3 shows the categories of Signal-to-Noise Ratio (SNR) based on the range of values, which are used to evaluate signal quality in LoRaWAN communication. The SNR is a measure that describes the quality of a signal in communication systems. SNR quantifies the ratio between the strength of the desired signal and the strength of the unwanted noise (interference) (Yun, 2021).

Table 4. SNR Signal Level (Achmad Kirang, Alfin Hikmaturokhman, 2023)

SNR (dB)	Level
$-\infty$ to -10	Very bad
-10 to 0	Bad
0 to 15	Normal
15 to -30	Good
30 to ∞	Very good.

3. Method

OpenRemote and ChirpStack were selected for this project due to their robust capabilities and compatibility with IoT applications. OpenRemote serves as an application server that centralizes data management, allowing seamless integration of various sensors and devices. Its user-friendly interface supports real-time data visualization and monitoring, making it easier for users to access and analyze air quality data. Additionally, OpenRemote's support for multiple communication protocols, such as MQTT and HTTPS, enhances its flexibility in managing diverse IoT environments. On the other hand, ChirpStack, as a LoRaWAN Network Server, is specifically designed to handle the unique requirements of long-range, low-power communication typical in IoT networks. It optimizes data routing, security, and scalability, ensuring reliable connectivity among numerous devices spread over large areas. Together, these platforms provide a comprehensive solution that enhances the effectiveness of air quality monitoring while ensuring efficient data handling and device management, making them ideal choices for this research project.

3.1 *Research Method*

Figure 4 shows several steps for air pollution monitoring systems. In general, we start with an initialization system, where the OpenRemote server is configured to receive data from IoT devices. Following this, the IoT devices are connected to the server, which involves connection configuration and parameter settings. Once the connection is established, the server begins receiving and processing real-time data, which is then filtered for further analysis. The server performs additional data analyses to generate key insight including device status, performance report, and notification in case of anomalies.

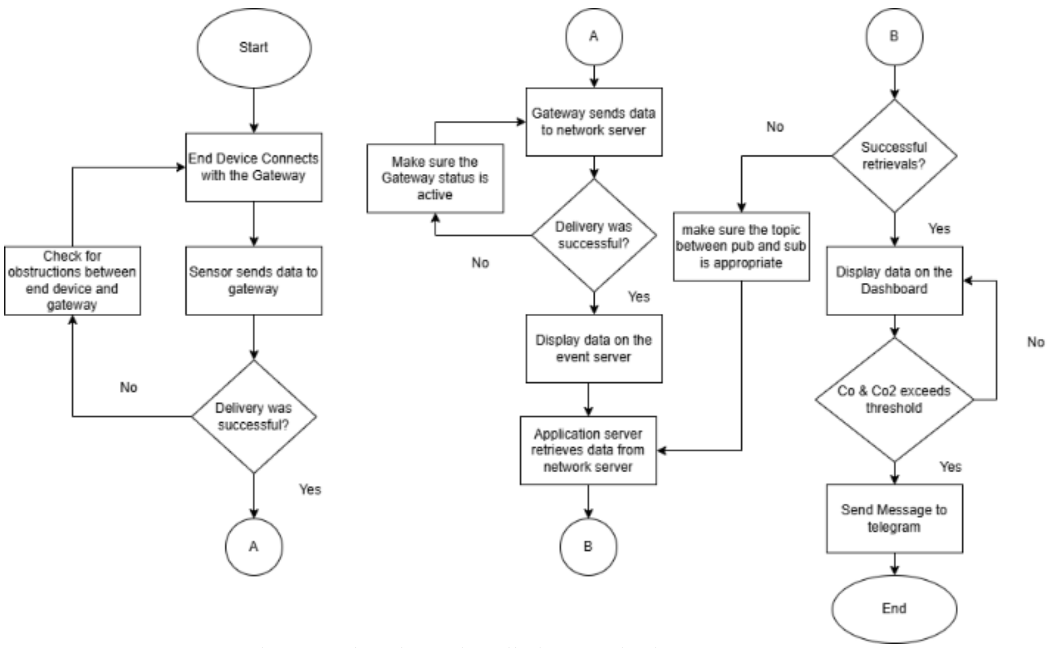

Figure 4. Flowchart Air Pollution Monitoring System

The results of these analyzes are displayed on the user interface, allowing for real-time monitoring and appropriate action. Additionally, the system supports data integration with external applications to extend its functionalities. In the final stage, testing and evaluation are conducted to ensure that the system functions properly and meets user requirements.

3.2 *System Architecture*

Figure 5 shows that the architecture of the air pollution monitoring system has fulfilled the LoRaWAN architecture criteria. The communication mode for each component in the air pollution monitoring system architecture is two-way communication, namely downlink and uplink communication. The application server functions to monitor the air pollution device through the dashboard. The application server (Openremote) is connected to the network server via the internet network using the MQTT protocol as communication. Network server (Chirpstack) is connected to the Gateway via an internet connection wirelessly using the MQTT protocol. The network server has a function to process and forward data sent from the Gateway (uplink communication) and data from the application server (downlink communication). In addition, the Gateway device functions to forward data from the network server to the end device and vice versa. Data transmission from the end device is done via LoRa communication.

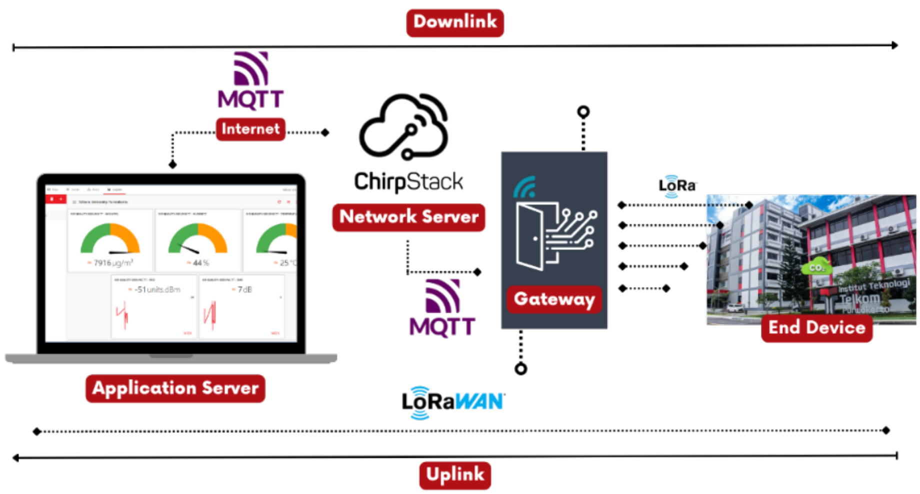

Figure 5. Data Communications Block Diagram

3.3 *Block Diagram*

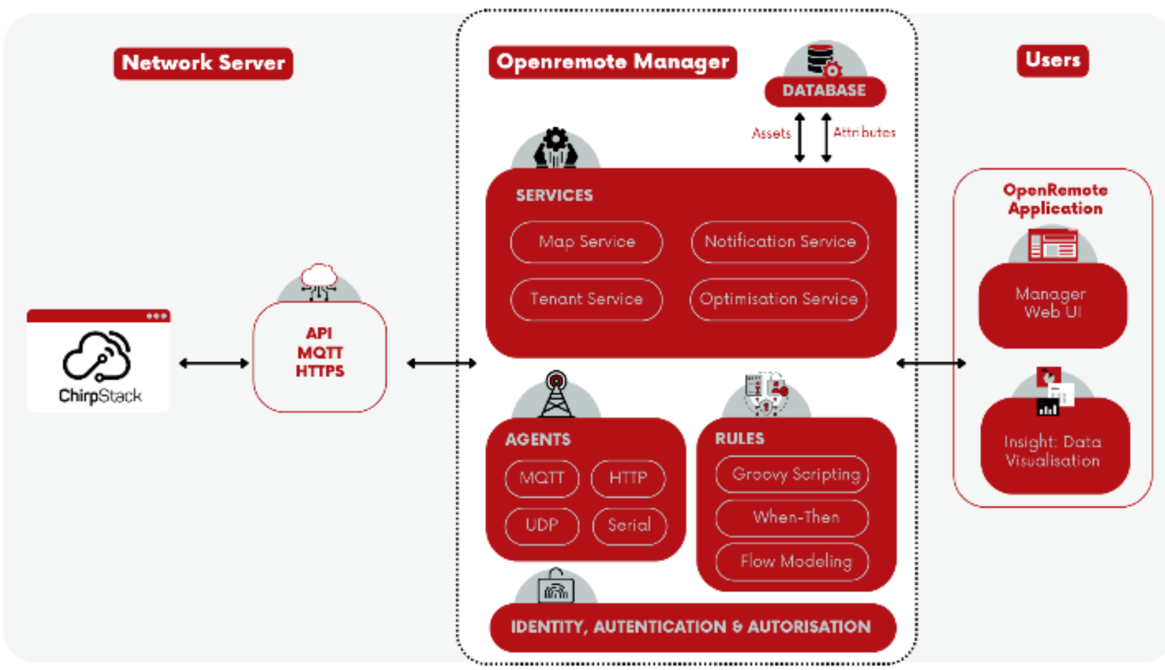

Figure 6. Block Diagram System

Figure 6 shows the block diagram system consisting of three main parts. For the first part is the network server represented by ChirpStack, which is managed LoRaWAN devices and transmits data to the system using API, MQTT, and HTTPS protocols. The second part is the OpenRemote Manager, which serves as the main system for managing data and IoT devices. It provides services such are Map Service for geographical mapping, Tenant Service for secure multi-user management, Notification Service for sending alerts, and Optimization Service for improving resource efficiency. It also includes Agents for communication with devices via MQTT, HTTP, UDP, or Serial, and a Rules Engine for automation using Groovy scripts, "When-Then" as logic rules, or workflow modelling. Data is stored in a Database for real-time and historical analysis. The final part is the User

Application, offering tools for users to manage and monitor the system. Through the OpenRemote Manager Web UI, users can configure devices, create automation rules, and monitor system performance. The Insight Data Visualization feature allows data to be displayed in graphs, dashboards, and other visual formats.

4. Results and Discussion

4.1 *Process of Sensor Calibration*

Figure 7. Calibration Sensor

Figure 7 shows the calibration process for the MQ-135 and MQ-7 sensors. The MQ-135 sensor is calibrated by burning paper to measure Carbon dioxide (CO_2) concentration, which is compared to a CO_2 Detector and assessed against ISPU thresholds from normal to hazardous. Similarly, the MQ-7 sensor is calibrated by burning paper to measure CO concentration, compared to a CO Detector and also measured against the same thresholds. This calibration process ensures high accuracy in detecting gas concentrations and aligns the sensor's results with reference standards, making the data reliable for air quality monitoring. Additionally, calibration reduces potential measurement errors from environmental factors like temperature and humidity, ensuring optimal sensor performance over time.

In the testing with a comparison device (calibration), the measurement error equation is used to evaluate the accuracy of the sensor by comparing the sensor measurement results with the standard values measured using a calibrated comparison device. The measurement error is calculated using the error Equation 1 defined as follows.

$$Error\ (\%) = \left(\frac{Sensor\ Result - Comparative\ Result}{Comparative\ Result}\right) x\ 100\% \quad \text{...1)}$$

The testing of the MQ-7 sensor was carried out to measure the accuracy of the sensor in detecting CO concentrations using a tool, namely the CO Detector. Table 4 above shows the results of testing the MQ-7 sensor in ppm units, the error percentage is calculated using a predetermined formula. The calculation results show an average error of 1.82%. This error value shows that the sensor has a fairly good level of accuracy in detecting levels of air pollution in the form of CO.

Table 5. MQ-7 Sensor Calibration

MQ–7 (ppm)	Carbon Monoxide Detector (ppm)	Error (%)
10,38	10	3,80
30,33	30	1,10
41,41	41	1,00
50,69	50	1,38
Average		1,82

Testing of the MQ-135 sensor was carried out to measure the accuracy of the sensor in detecting CO_2 concentrations with a tool, namely the CO_2 Detector. This test is carried out in accordance with the specified ISPU thresholds. Table 4 shows the test results of MQ-135 in ppm units. The measurement results show that the values produced by the MQ-135 sensor have a small deviation compared to the comparison tool. Based on error calculations, MQ-135 shows a good level of accuracy in detecting carbon dioxide concentrations with an average result of 0.24%.

Table 6 MQ-135 Sensor Calibration

MQ – 135 (ppm)	*Carbon Dioxide Detector* (ppm)	Error (%)
370,46	370	0,12
622,67	622	0,11
1251,72	1252	0,02
1676,14	1688	0,71
Average		0,24

4.2 *Air Quality Measurement from End Devices in University Areas*

Figure 8 shows a comparison of the average concentrations of carbon monoxide pollutants (measured in ppm) in two buildings: the DSP Building and the Rectorate Building over a period of seven days. The data indicates that the DSP Building experiences significant fluctuations in pollutant levels, with a noticeable peak on day 4, reaching around 16 ppm, which falls into the "Very Unhealthy" category. This increase in pollution on that day suggests heightened vehicle activity, likely due to the parking area located beneath the building. In contrast, the Rectorate Building exhibits relatively stable concentrations, ranging from 6 to 8 ppm, categorized as "Moderate," with slight decreases observed on days 5 and 6. The differences in air quality can be critically Furthermore, monitoring on additional days is necessary to fully understand the factors influencing carbon monoxide fluctuations in both buildings. Data from subsequent monitoring may reveal air dispersion factors, such as wind direction and intensity, which could also equalize pollution levels at both locations. Analyzing these dynamics is essential for identifying the primary sources of pollution within the university environment and implementing effective mitigation strategies.

In summary, the stark contrast in air quality values between the two buildings underscores the importance of sensor placement and the need for targeted interventions to address pollution sources effectively.

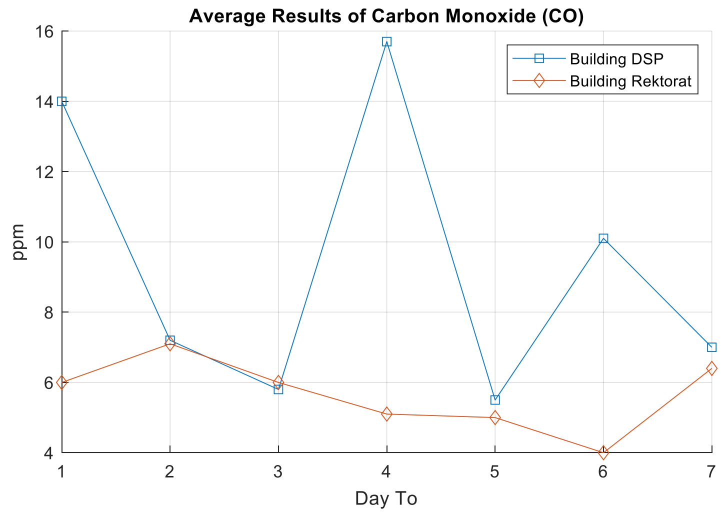

Figure 8. Results of Carbon Monoxide

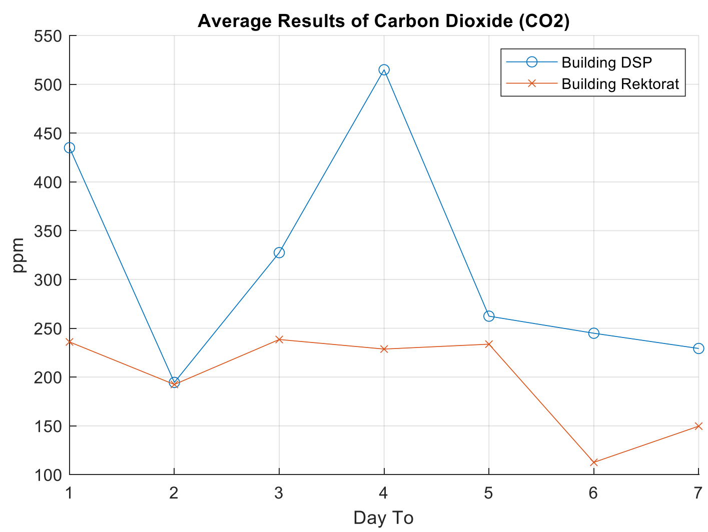

Figure 9. Result of Carbon Dioxide

Figure compares CO_2 concentrations (measured in ppm) in the DSP Building and the Rectorate Building over seven days. The DSP Building shows significant fluctuations, peaking at approximately 550 ppm on day 5, categorized as "Unhealthy for Sensitive Groups." This spike likely results from high human activity and vehicle emissions nearby. In contrast, the Rectorate Building maintains stable CO_2 levels ranging from 150 to 250 ppm, categorized as "Good." The sensors in the DSP Building are located closer to the parking area, which is the primary source of higher pollutant concentrations. These differences in air quality underscore the importance of sensor location. Further investigation into the activities and environmental conditions around the DSP Building is essential for developing effective pollution control strategies.

4.3 *Application Server Result*

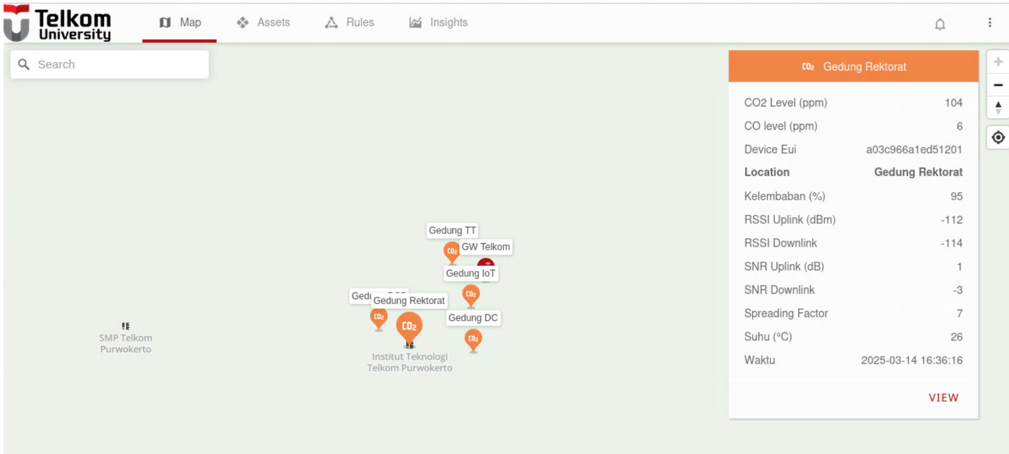

Figure 10. Map Location Assets

Figure 10 shows the interactive map view or display from the application server. This makes it easy for users to see and monitor the position of the installed air quality sensors. On the map, there are several sensor points marked with markers, which indicate the location of air quality sensors. Table 6 shows the distance between the end device location to the gateway.

Table 7. Distance of Measurement Location

Location	Distance to Gateway
TT Building	25 m
IoT Building	35 m
DC Building	58 m
Rektorat Building	78 m
DSP Bulding	85 m

In addition, beside the map is an information panel that presents the latest data on air quality devices at each location. This panel includes several important parameters, such as the CO_2 (ppm) air quality value which indicates the concentration of carbon dioxide in the air, CO (ppm) which indicates the level of carbon monoxide. In addition, there are measurements of Humidity (%) and Temperature (°C) values. In addition to signal quality measurements covering both Uplink and Downlink communications. This information panel provides a comprehensive, real-time overview of air quality conditions at the monitored location.

Table 8. Uplink Parameters Result by Location

Location	Average RSSI (dBm)	Average SNR (dB)
TT Building	-71,13	8,72
IoT Building	-86,80	9,43
DC Building	-104,93	5,07
Rektorat Building	-110,07	1,03
DSP Bulding	-83,60	9,42

Table 7 presents the uplink parameters results by location, detailing the average RSSI and SNR for various buildings. The TT Building exhibits an average RSSI of -71.13 dBm, categorized as "Very Good," with an SNR of 8.72 dB, classified as "Normal," indicating solid signal quality. In contrast, the IoT Building shows a lower average RSSI of -86.80 dBm, which is still considered "Very Good," but with a higher SNR of 9.43 dB, suggesting that while signal strength is adequate, the quality remains stable. The DC Building, however, reports an average RSSI of -104.93 dBm, placing it within the "Good" range but approaching "Bad," along with an average SNR of 5.07 dB, also classified as "Normal." This indicates that while the signal is usable, it is close to suboptimal. Similarly, the Rectorate Building shows an average RSSI of -110.07 dBm, categorizing it as "Bad," with a correspondingly low SNR, reflecting poor signal quality.

The significantly lower signal performance in the DC and Rectorate Buildings can largely be attributed to their sensor locations, which are obstructed by nearby physical structures, such as walls and other buildings. These obstructions hinder signal propagation, resulting in reduced RSSI values and lower overall signal quality. In contrast, the DSP Building, with an average RSSI of -83.60 dBm (also classified as "Very Good") and an SNR of 9.42 dB, reflects a balanced signal strength and quality. Its positioning likely benefits from fewer obstructions compared to the DC and Rectorate Buildings.

Overall, the TT and IoT Buildings demonstrate the best signal performance, attributed to optimal sensor placements that minimize interference and obstructions. In contrast, the challenges faced by the DC and Rectorate Buildings highlight the critical importance of sensor location in ensuring reliable signal strength and quality in wireless communication systems.

Table 9. Downlink Parameters Result by Location

Location	Average RSSI (dBm)	Average SNR (dB)
TT Building	-78,13	3,33
IoT Building	-98,20	4,87
DC Building	-112,33	-4,67
Rektorat Building	-113,13	-3,67
DSP Bulding	-75,53	2,60

Table 8 shows the downlink parameters results by location, highlighting the average RSSI and SNR for various buildings. The TT Building has an average RSSI of -78.13 dBm and an average SNR of 3.33 dB, indicating relatively good signal strength, although there is room for improvement in signal quality. The IoT Building shows an average RSSI of -98.20 dBm, reflecting good signal strength, but the average SNR of 4.87 dB indicates that the signal quality is still acceptable.

In contrast, the DC Building has a concerning average RSSI of -112.33 dBm and an average SNR of -4.67 dB, both categorized as "Bad," indicating poor signal quality. Similarly, the Rectorate Building exhibits an average RSSI of -113.13 dBm and an average SNR of -3.67 dB, further confirming its inadequate signal performance. These low values are largely due to the sensor locations, which are obstructed by thick walls and nearby structures, significantly hindering signal propagation.

The DSP Building, however, shows a better average RSSI of -75.53 dBm, categorized as "Very Good," and an average SNR of 2.60 dB, classified as "Normal," reflecting a balanced signal strength and quality. Its advantageous location with fewer obstructions contributes to better signal reception. Overall, the effectiveness of wireless communication in these buildings is significantly influenced by sensor placement and surrounding physical barriers, leading to variations in signal quality.

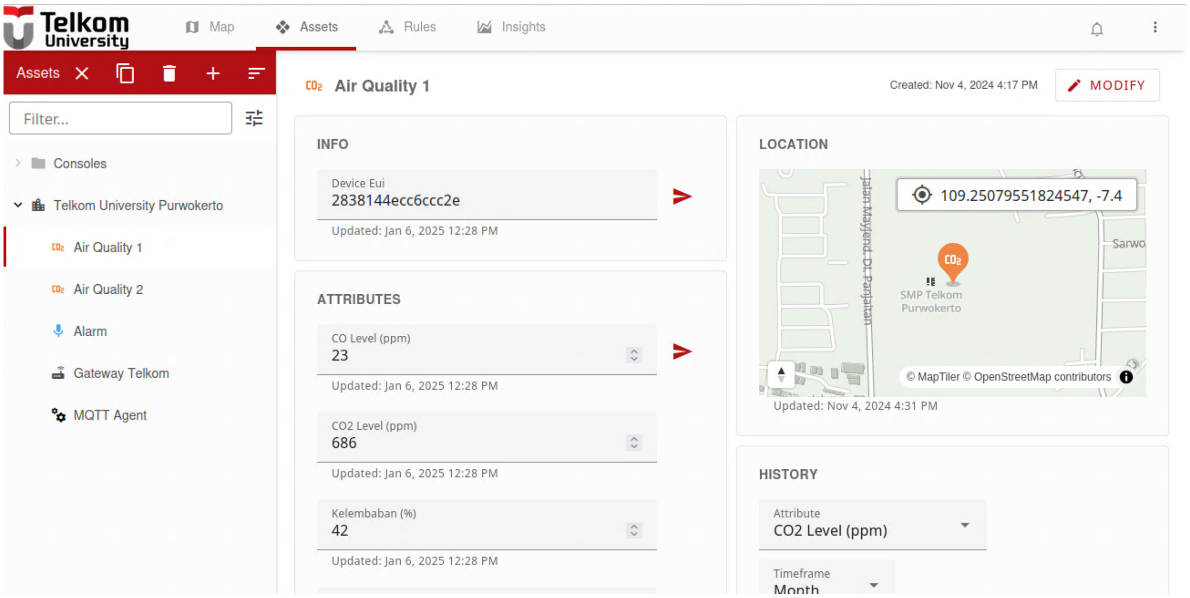

Figure 11. Attribute Assets

Figure 11 shows the 'Air Quality' asset, which contains attributes designed to reflect the important parameters associated with air quality monitoring. One of the key attributes is CO_2 which is usually measured in ppm (parts per million). This attribute is labelled for easy identification and comes with an Agent Link that connects it to the relevant measurement agent. In addition, the CO attribute, measured in ppm, also has a similar configuration to ensure data collection accuracy. The remaining attributes, such as Humidity and Temp (Temperature), play an important role in understanding environmental conditions. Humidity is measured in per cent (%), while Temp is usually measured in degrees Celsius (°C). Both of these attributes come with labels and Agent Link to support connectivity with related sensors.

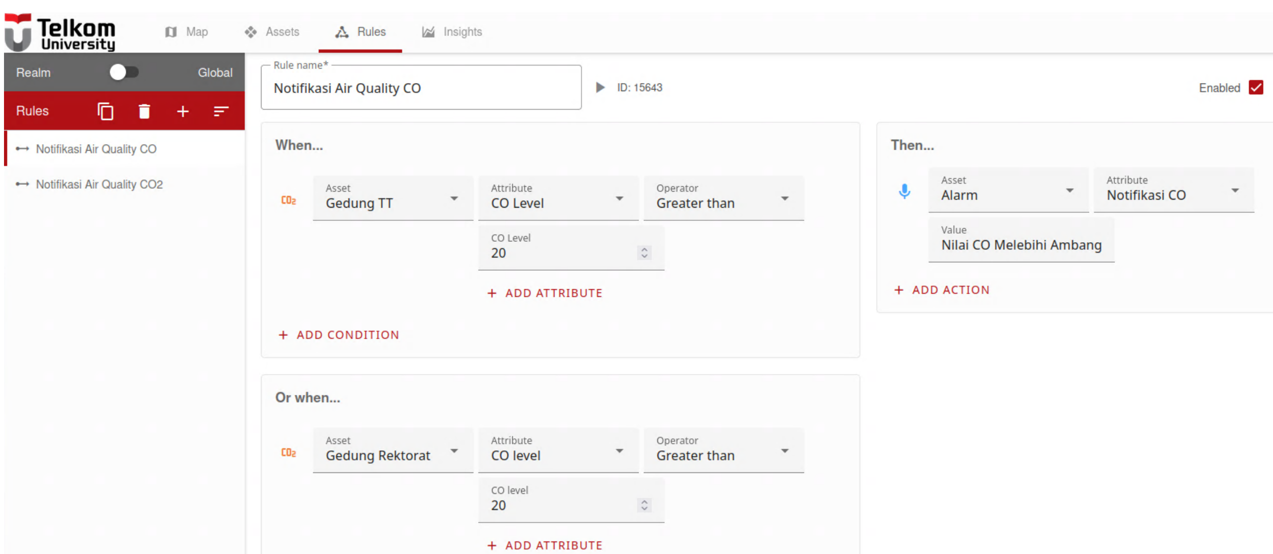

Figure 12. Setting Alarm

Figure 12 shows system interface setting "rules" for air quality monitoring, which is used to detect and levels of pollutants in the air. In this "rules", conditions are set that if the CO level on the Air Quality sensor exceeds the threshold of 20 ppm, the system will take several automatic actions. These actions include activating an alarm as a warning, sending a notification with the message ‘Caution Exceeds Threshold’. The system also provides flexibility with the option to add additional conditions and actions according to the user's needs. With these settings, the system can automatically detect hazardous conditions and provide early warnings to users, enabling a quick response to mitigate risks. This is relevant to support your air pollution monitoring project in managing sensor data effectively.

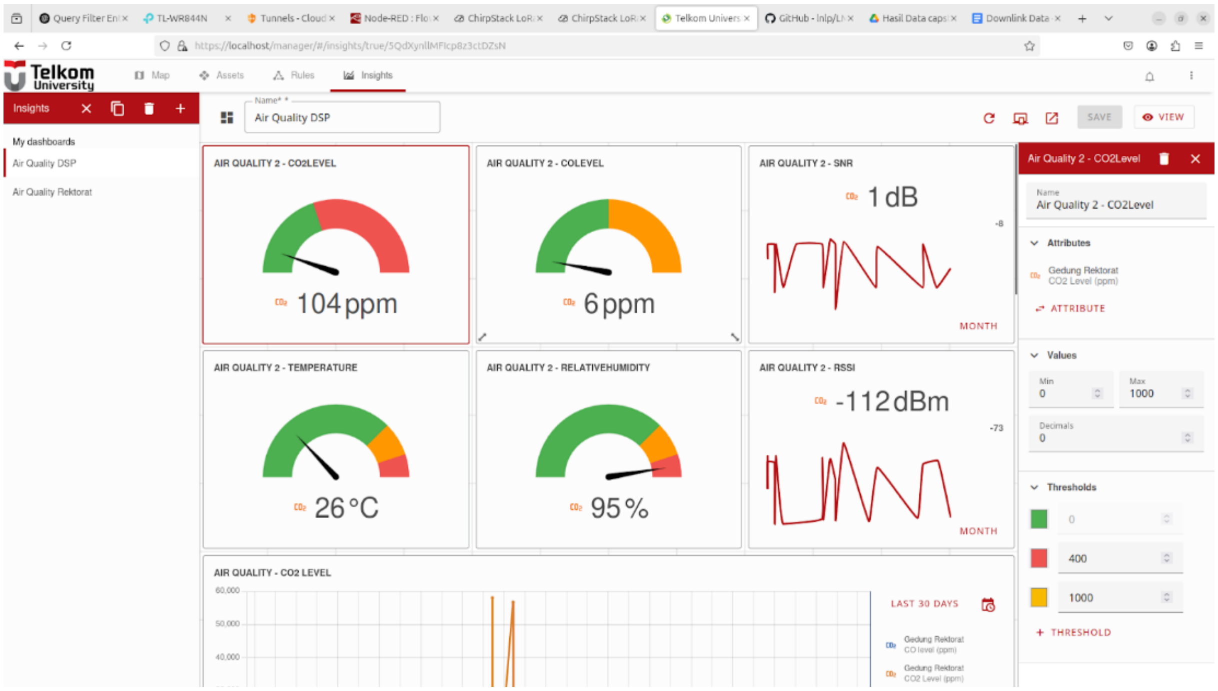

Figure 13. Dashboard Insight

Figure 13 shows the interface dashboard of the air quality monitoring system. This dashboard displays gauges or levels for each type of air pollutant. Additionally, it shows the RSSI and SNR signal values during the data transmission process from the end device to the gateway. The graph feature can be used to observe fluctuations in pollutant levels, which can be viewed hourly, daily, weekly, monthly, and annually. This feature allows users to identify trends over time, assess the effectiveness of air quality interventions, and make informed decisions based on historical data.

5. Conclusion

The test results indicated that the developed system had a good level of accuracy in detecting air pollutant gas concentrations. The MQ-7 sensor for CO showed an average error of 1.82%, while the MQ-135 sensor for CO_2 demonstrated an average error of 0.24%, confirming the reliability of both sensors. Significant differences in pollution levels were observed between the DSP Building and the Rectorate Building. The DSP Building experienced a notable spike in carbon monoxide levels, peaking at around 16 ppm on Day 4, categorized as "Very Unhealthy," while the Rectorate Building maintained stable concentrations of 6 to 8 ppm, categorized as "Moderate." For carbon dioxide, the DSP Building recorded approximately 550 ppm, classified as "Unhealthy for Sensitive Groups," whereas the Rectorate Building's levels ranged from 150 to 250 ppm, categorized as "Good." These findings indicate distinct sources or processes affecting air quality in each building.

Meanwhile, the uplink and downlink parameters further revealed clear differences in signal quality. The TT Building excelled with an uplink RSSI of -71.13 dBm and SNR of 8.72 dB, and a downlink RSSI of -78.13 dBm and SNR of 3.33 dB, both categorized as "Very Good." The IoT Building also performed well, though its

SNRs were classified as "Normal." In contrast, the Rectorate and DC Buildings exhibited poor signal performance, emphasizing the need for strategic placement of devices in less obstructed locations.

The deployment of various sensors and a robust communication network effectively collected and analyzed air quality data, providing valuable insights into pollution levels. The dashboard interface enabled easy data visualization, facilitating informed decision-making regarding air quality management. Overall, this research highlights the potential of IoT technologies in enhancing environmental monitoring within the university, demonstrating effective coverage across multiple building locations.

For future implementations, it is recommended to extend the system beyond the campus to monitor air quality in surrounding communities, allowing for a broader understanding of regional pollution trends. Additionally, integrating artificial intelligence and machine learning could enhance the system's capabilities by developing pollution prediction models, enabling proactive measures to mitigate air quality issues. Such advancements could significantly improve air quality management strategies, benefiting both the university and its surrounding environment.

6. Acknowledgements

The authors would like to express their sincere gratitude to their supervisors, Mas Aly Afandi and Melinda Br Ginting, for their invaluable guidance and support throughout this research. Their expertise and encouragement, both academically and materially, were instrumental in the successful development of this study. This research aims to contribute to air quality measurement efforts within the university environment, particularly at Telkom University Purwokerto.

References

Abdulmalek, S., Nasir, A., & Jabbar, W. A. (2024). LoRaWAN-based hybrid internet of wearable things system implementation for smart healthcare. *Internet of Things (Netherlands)*, *25*(February), 101124. https://doi.org/10.1016/j.iot.2024.101124

Achmad Kirang, Alfin Hikmaturokhman, K. N. (2023). JITE (Journal of Informatics and Telecommunication Engineering). *Journal of Informatics and TelecommunicationEngineering*, *7*(1), 102–111. https://www.researchgate.net/publication/335117624_Malang_City_Polytechnic_Web_Based_Student_Attendance_Information_System_Telecommunications_Engineering_Study_Program_Using_Fingerprint/fulltext/5d515fe34585153e594ef214/Malang-City-Polytechnic-Web-Based-S

Adi, P. D. P., Ardi, I., Plamonia, N., Wahyu, Y., L, A. M., Novita, H., Mahabror, D., ZUlkarnain, R., Wirawan, A., Prastiyono, Y., Waryanto, Susilo, S. A. B., Rahmatullah, R., & Kitagawa, A. (2024). Analysis of IoT-LoRa to Improve LoRa Performance for Vaname Shrimp Farming Monitoring System. *Jurnal Ilmiah Teknik Elektro Komputer Dan Informatika (JITEKI)*, *10*(1), 99–122. https://doi.org/10.26555/jiteki.v10i1.27598

Akomolafe, O. O., Olorunsogo, T., Anyanwu, E. C., Osasona, F., Ogugua, J. O., & Daraojimba, O. H. (2024). Air Quality and Public Health: a Review of Urban Pollution Sources and Mitigation Measures. *Engineering Science & Technology Journal*, *5*(2), 259–271. https://doi.org/10.51594/estj.v5i2.751

Anitha, M., & Kumar, L. S. (2023). Development of an IoT-Enabled Air Pollution Monitoring and Air Purifier System. *Mapan - Journal of Metrology Society of India*, *38*(3), 669–688. https://doi.org/10.1007/s12647-023-00660-y

Babu, C. V. S., Monika, R., Dhanusha, T., Vishnuvaradhanan, K., & Harish, A. (2023). Smart street lighting system for smart cities using IoT (LoRa). *Effective AI, Blockchain, and E-Governance Applications for Knowledge Discovery and Management*, *June 2023*, 78–96. https://doi.org/10.4018/978-1-6684-9151-5.ch006

Behinaein, P., Hutchings, H., Knapp, T., & Okereke, I. C. (2023). The growing impact of air quality on lung-related illness: a narrative review. *Journal of Thoracic Disease*, *15*(9), 5055–5063. https://doi.org/10.21037/jtd-23-544

Cheruvu, S., Smith, N., Kumar, A., & Wheeler, D. M. (2019). Demystifying Internet of Things Security: Successful IoT Device/Edge and Platform Security Deployment. In *Demystifying Internet of Things Security: Successful IoT Device/Edge and Platform Security Deployment*. https://doi.org/10.1007/978-1-4842-2896-8

ChirpStack. (2024). *The ChirpStack project*. https://www.chirpstack.io/docs/

Dharmendra Kumar, & Navin Singh Rajput. (2022). Air Pollution in mining Industries has very adverse effects on Human Health, Flora, and Fauna, and proper assessment is needed around the mining areas. *International Journal of Engineering Technology and Management Sciences*, *6*(5), 734–741. https://doi.org/10.46647/ijetms.2022.v06i05.114

Enriko, I. K. A., Gustiyana, F. N., & Giri, G. C. (2024). LoRA Gateway Coverage and Capacity Analysis for Supporting Monitoring Passive Infrastructure Fiber Optic in Urban Area. *Elinvo (Electronics, Informatics, and Vocational Education)*, *8*(2), 164–170. https://doi.org/10.21831/elinvo.v8i2.59280

Farej, Z. K., & Adel, A. Y. (2024). Review on LoRa Communication Technology , Its Issues , Challenges and Applications in Healthcare System. *European Journal of Computer Science and Information Technology*, *12*(8), 1–17.

Hendricks, W., & Kabaso, B. (2024). Evaluating Signal Quality and System Performance in NB-IoT Communications. *Journal of Telecommunications and the Digital Economy*, *12*(2), 115–138. https://doi.org/10.18080/jtde.v12n2.955

Hendry, & Manongga, D. (2024). Implementation of Multi-Node Sensor Data Delivery Using the Master-Slave Method in Lora Communication. *Journal of Technology Informatics and Engineering*, *3*(2), 117–338. https://doi.org/10.51903/jtie.v3i2.179

Hidayati, A., & Nashiruddin, M. I. (2020). LPWA-based IoT Technology Selection for Smart Metering Deployment in Urban and Sub Urban Areas: A State Electricity Company Perspective. *Buletin Pos Dan Telekomunikasi*, *18*(2), 75–94. https://doi.org/10.17933/bpostel.2020.180201

Hugo, V., & Chalacan, L. (2020). *Performance Evaluation of Long Range (LoRa) Wireless RF Technology for the Internet of Things (IoT) Using Dragino LoRa at 915 MHz Performance Evaluation of Long Range (LoRa) Wireless RF Technology for the Internet of Things (IoT) Using Dragino LoR*. University of North Florida.

Jayasree, G., Anjali, G., Saraswathi, D. L., Tech, M., & Engineering, C. (2023). *LoRa Based Smart City Air Quality Monitoring System*. *11*(4), 760–766.

Kashyap, M., Sharma, V., & Gupta, N. (2018). Taking MQTT and NodeMcu to IOT: Communication in Internet of Things. *Procedia Computer Science*, *132*(Iccids), 1611–1618. https://doi.org/10.1016/j.procs.2018.05.126

Ling, Q., Wang, G., & Wang, M. (2020). Design of air quality detection system based on bluetooth communication. *Journal of Physics: Conference Series*, *1656*(1), 0–6. https://doi.org/10.1088/1742-6596/1656/1/012030

Mnguni, S., Mudali, P., Mahfouz, A. M. A., & Adigun, M. (2021). Performance Evaluation of Spreading Factors in LoRa Networks. *12th EAI International Conference*, 203–215. https://doi.org/10.1007/978-3-030-70572-5_21

OpenRemote. (2024). *OpenRemote documentation*. OpenRemote, Inc. https://www.openremote.io/about/

Paganelli, F., Turchi, S., & Giuli, D. (2020). A Web of Things Framework for RESTful Applications and Its Experimentation in a Smart City. *IEEE Systems Journal*, *10*(4), 1412–1423. https://doi.org/10.1109/JSYST.2014.2354835

Patil, S. P., & Patil, S. C. (2016). A real time sensor data monitoring system for wireless sensor network. *Proceedings - IEEE International Conference on Information Processing, ICIP 2015*, *December 2015*, 525–528. https://doi.org/10.1109/INFOP.2015.7489440

Purkayastha, K. D., Mishra, R. K., Shil, A., & Pradhan, S. N. (2021). IoT Based Design of Air Quality Monitoring System Web Server for Android Platform. *Wireless Personal Communications*, *118*(4), 2921–2940. https://doi.org/10.1007/s11277-021-08162-3

Rahmadani, A. A., Syaifudin, Y. W., Setiawan, B., Panduman, Y. Y. F., & Funabiki, N. (2025). Enhancing Campus Environment : Real-Time Air Quality Monitoring Through IoT and Web Technologies. *Journal of Sensor and Actuator Networks*, *14*(2), 1–26.

Ramadan, M. N. A., Ali, M. A. H., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. *Ecotoxicology and Environmental Safety*, *283*(April), 116856. https://doi.org/10.1016/j.ecoenv.2024.116856

Rijadi, B. B., & Machdi, A. R. (2024). Distance Testing On Point To Point Comunication With Lora Basd On Rssi And Log Normal Shadowing Model. *Journal Of Energy And Electrical Engineering*, *5*(2), 89–93.

Rodriguez, A., Kristensen, L. M., & Rutle, A. (2020). On modelling and validation of the MQTT IoT protocol for M2M communication. *CEUR Workshop Proceedings*, *2138*, 99–118.

Semtech. (2023). *LoRaWAN Network Servers*. https://learn.semtech.com/mod/page/view.php?id=34

Silva, E. F., Figueiredo, L. M., de Oliveira, L. A., Chaves, L. J., de Oliveira, A. L., Rosário, D., & Cerqueira, E. (2023). Adaptive Parameters for LoRa-Based Networks Physical-Layer. *Sensors*, *23*(10), 1–20. https://doi.org/10.3390/s23104597

Sung, Y., Lee, S., Kim, Y., & Park, H. (2019). Development of a smart air quality monitoring system and its operation. *Asian Journal of Atmospheric Environment*, *13*(1), 30–38. https://doi.org/10.5572/ajae.2019.13.1.030

The Things Industries. (2024). *What is a LoRaWAN Network Server*. https://www.thethingsindustries.com/docs/reference/components/application-server/

Ting, Y. T., & Chan, K. Y. (2024). Optimising performances of LoRa based IoT enabled wireless sensor network for smart agriculture. *Journal of Agriculture and Food Research*, *16*(February), 101093. https://doi.org/10.1016/j.jafr.2024.101093

Tovar-soto, J. P., Pareja-figueredo, C. F., & Gutiérrez-martínez, L. C. (2021). *Performance evaluation of LoRa technology for implementation in rural areas*.

Yun, S. (2021). *Lora Performance and Its Phy Layer Parameters in 915Mhz Ism Band in Indoor Environments* (Issue December) [Purdue University]. https://hammer.purdue.edu/articles/thesis/LORA_PERFORMANCE_AND_ITS_PHY_LAYER_PARAMETERS_IN_915MHZ_ISM_BAND_IN_INDOOR_ENVIRONMENTS/16811659