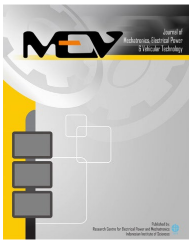


Journal of Mechatronics, Electrical Power, and Vehicular Technology 17 (2026) 28-37

Journal of Mechatronics, Electrical Power,
and Vehicular Technology

e-ISSN: 2088-6985
p-ISSN: 2087-3379

mev.brin.go.id

IoT-based monitoring system for biodigester production and purification

Suprihadi Prasetyono [a, *], Catur Suko Sarwono [a], Digdo Listyadi Setyawan [b], Azmi Saleh [a],
Bambang Sri Kaloko [a], Muhammad Naufal An Nafi [a]

[a] *Departement of Electrical Engineering, Faculty of Engineering, Universitas Jember*
Kalimantan St. No. 37, Sumbersari, Jember, East Java, 68121, Indonesia
[b] *Departement of Mechanical Engineering, Faculty of Engineering, Universitas Jember*
Kalimantan St. No. 37, Sumbersari, Jember, East Java, 68121, Indonesia

---

Abstract

Biogas is a promising renewable energy source, but its production and purification processes often lack real-time monitoring, leading to suboptimal yields and inconsistent gas quality. To address this gap, this study aimed to design a prototype for an integrated monitoring system based on the internet of things (IoT). The developed system facilitates the continuous observation of key parameters in both the anaerobic digestion and the subsequent purification stages. The prototype was constructed using an ESP32 microcontroller as the central processing unit, which collected data from a suite of sensors. These sensors measured critical process variables, including the digester's slurry temperature and pH, the volume of the produced gas in the gasholder, and the concentration of methane (CH_4) and hydrogen sulfide (H_2S) before and after the purification unit. Data were transmitted wirelessly via a Wi-Fi network to a cloud-based IoT platform, allowing for remote, real-time data visualization on a web dashboard. The results demonstrated that the prototype successfully captured and transmitted all parameter data with high reliability. The system provided a clear, real-time overview of the digester's operational stability and effectively quantified the increase in methane concentration and the reduction of impurities post-purification. Testing shows stable data transmission to Google Sheets and InfluxDB with minimal data loss. Delay times increase with distance in Google Sheets, from 3736.1 ms (2 m) to 3880.2 ms (8 m), while InfluxDB delay varies. RSSI values decrease with distance, with an accuracy range of 0.28 % to 5.11 %, peaking at 99.17 % accuracy at 6.05 meters.

Keywords: biogas monitoring; internet of things; gas purification; methane detection; CO_2 and H_2S detection; real-time monitoring.

I. Introduction

The increasing global demand for energy, coupled with the depletion of fossil fuel reserves and growing environmental concerns such as air pollution, has intensified the search for sustainable and renewable energy alternatives [1][2]. Among the various options, biogas presents a compelling solution as a low-cost, easily accessible fuel source [3]. Biogas is produced through the anaerobic fermentation of organic materials, such as agricultural waste and animal manure, a process that converts biomass into a combustible gas mixture [4]. This fuel primarily consists of methane (CH_4) and offers a cleaner

---

* Corresponding Author. suprihadi.teknik@unej.ac.id (S. Prasetyono)

https://doi.org/10.55981/j.mev.2026.1352

Received 17 December 2026; revised 13 March 2026; accepted 1 April 2026; available online 25 June 2026

How to Cite: S. Prasetyono *et al.*, “IoT-based monitoring system for biodigester production and purification,” *Journal of Mechatronics, Electrical Power, and Vehicular Technology*, vol. 17, no. 1, pp. 28-37, July, 2026.

combustion profile than fossil fuels, yielding significant energy with lower carbon emissions [5].

Despite its potential, the widespread adoption of biogas is hampered by challenges related to production efficiency and gas quality. The anaerobic digestion process is highly sensitive to environmental parameters, particularly temperature, where deviations from the optimal range (around 35 °C) can severely inhibit microbial activity and reduce biogas yield [6]. Furthermore, the quality of the produced biogas is often compromised by the presence of impurity gases. High concentrations of carbon dioxide (CO_2) decrease the fuel's calorific value, resulting in a less efficient flame, while the presence of hydrogen sulfide (H_2S) is highly problematic due to its corrosive nature, which can damage metal and electronic components [7][8]. Consequently, purification processes, such as adsorption using a calcium hydroxide ($Ca(OH)_2$) solution to remove CO_2 and H_2S, are essential for improving biogas quality [9].

To address these challenges, various monitoring systems have been developed. Research has explored computerized systems integrated with internet of things (IoT) platforms for biodigester monitoring [10] and Arduino-based systems for observing purification processes [11]. However, a significant barrier to the widespread use of biogas, particularly at the household or small community level, remains the high cost and complexity of commercially available monitoring and purification equipment [12]. This limitation creates a critical need for affordable, accessible, and user-friendly technologies that enable real-time process control. The IoT emerges as a powerful technology to fill this gap, offering the capability for real-time, remote monitoring of key parameters such as temperature, pressure, and the concentrations of CH_4, CO_2, and H_2S [13][14].

This study aims to address the aforementioned challenges by designing, building, and evaluating a low-cost prototype system for the real-time monitoring of biogas production and purification based on IoT technology. The system integrates an ESP32 microcontroller with a suite of affordable sensors to continuously track critical parameters, with data being visualized and stored locally on an LCD and MicroSD card, as well as remotely via the InfluxDB and Google Sheets cloud platforms.

The principal conclusion of this work is that the developed low-cost IoT system successfully and reliably monitors the entire biogas process in real-time. It effectively tracks the increase in methane concentration and the reduction of impurities during purification, demonstrating that such technology is a feasible and effective solution to optimize biogas production and encourage its broader adoption in society.

II. Materials and Methods

A. Biogas production and purification prototipe

The experimental setup consisted of a continuous-type biodigester system prototyped using three 19-liter water gallons, a design chosen for its accessibility and suitability for small-scale applications. The three gallons were designated for (1) biogas production, (2) biogas purification, and (3) purified biogas storage, respectively. The gallons were interconnected using a series of pipes, gas hoses, ball valves, and T-branch nepels to control the flow of gas between stages. The integrity of the prototype was validated through a 24-hour water-fill test to check for liquid leaks and a smoke test using a vape pen to ensure the system was hermetically sealed against gas leakage.

For the biogas production phase, the digester was filled with a 10-liter mixture of cow manure and water at a 1:3 ratio. Biogas purification was achieved through chemical adsorption by passing the produced gas through the second gallon, which contained a solution made from 200 grams of calcium hydroxide ($Ca(OH)_2$) powder. The entire process was monitored for 13 consecutive days, with data analysis focused on the 4th through the 13th day.

B. IoT monitoring system hardware

The core of the monitoring system was an ESP32 microcontroller, selected for its integrated Wi-Fi and Bluetooth capabilities, and low power consumption. A suite of low-cost sensors was employed to capture key process parameters. Gas concentrations were measured using an MQ-4 sensor for methane (CH_4), an MQ-136 for hydrogen sulfide (H_2S)-, and an MG-811 for carbon dioxide (CO_2). Environmental conditions were monitored using a DHT22 sensor for ambient temperature and humidity, while biogas pressure within the system was measured with a BMP280 sensor.

Supporting modules included a 20x4 liquid crystal display (LCD) for on-site, real-time data visualization, a DS3231 real-time clock (RTC) module for accurate data timestamping, and a MicroSD card module for offline data logging, ensuring data integrity in case of network failure. The entire electronic assembly was housed in a project box to protect the components. A detailed list of hardware components and their pin connections to the ESP32 is provided in the system schematic (Figure 1).

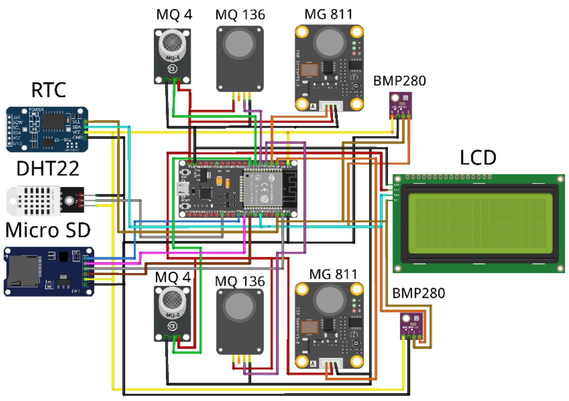


Figure 1. Schematic of the monitoring system.

C. System architecture and data management

The system was designed with a hierarchical data flow architecture, as depicted in the block diagram (Figure 2). The ESP32 served as the central processing unit, acquiring data from all connected sensors. The firmware for the ESP32 was developed in the Arduino IDE. The system's operational logic followed a flowchart (Figure 3), which included initializing components, reading sensor values, processing data, and managing data output to both local and remote platforms.

Data were managed through parallel online and offline channels. For online monitoring, the ESP32 used its built-in Wi-Fi to transmit time-stamped sensor data via HTTP POST requests to two cloud platforms:

- InfluxDB: A time-series database used for creating a real-time monitoring dashboard with graphical and numerical visualizations. Data were formatted using InfluxDB's Line Protocol for efficient handling.
- Google Sheets: Served as a simple cloud-based database for long-term data storage. Data were sent to a custom Google Apps Script, which acted as a web app to parse the incoming data and populate the spreadsheet.

For offline redundancy, all collected data was simultaneously saved locally to a file on the MicroSD card.

D. System validation and performance testing

To ensure the reliability and accuracy of the system, a multi-stage testing protocol was implemented.

1) Sensor calibration and validation

Each gas sensor was calibrated before deployment. The MQ-series sensors (MQ-4 and MQ-136) were calibrated by first determining their internal resistance in clean air (R_O) and then using the ratio of resistance in gas to resistance in clean air (R_S/R_O) to calculate gas concentration in parts-per-million (ppm). This calculation was based on a logarithmic regression model derived from the sensitivity curves in each sensor's datasheet. The electrochemical MG-811 sensor was calibrated by applying a calculated multiplier to its output voltage to align with the datasheet's reference values before converting the voltage to ppm using a natural logarithmic model.

Following calibration, the accuracy of each sensor was validated by comparing its readings against those from professional-grade, calibrated gas detectors: a

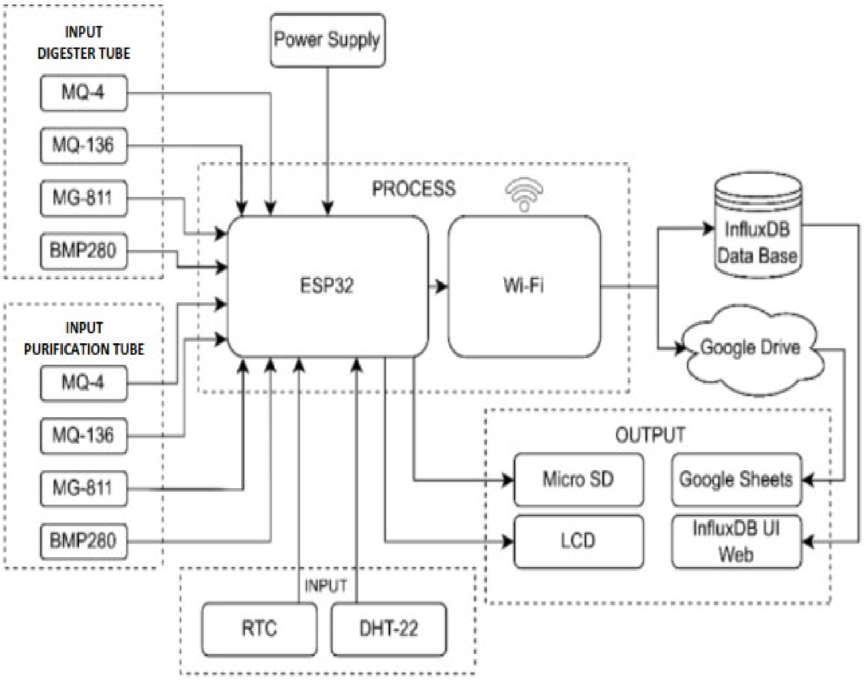


Figure 2. Block diagram.

MESTEK CGD02B for CH_4, a BOSEAN BH-90A for H_2S, and a SNDWAY SW-723 for CO_2. Accuracy was quantified using standard formulas for percentage error and accuracy.

2) IoT system performance evaluation

The performance of the IoT communication was evaluated through two key tests:

- Data transmission delay: The latency between data capture by the sensor and its appearance on the InfluxDB and Google Sheets platforms was measured over a 10-minute period at varying distances (2, 4, 6, and 8 meters) from the Wi-Fi access point.
- Wireless connection quality: The Received Signal Strength Indicator (RSSI) was measured at the same distances to assess the stability and strength of the Wi-Fi connection. A path loss propagation model was used to compare the actual RSSI values with theoretical estimates and to evaluate the accuracy of estimating distance based on signal strength.

E. Theoretical basis

1) Gas sensing principles

The monitoring system employed two distinct types of gas sensing technologies. The MQ-4 (CH_4) and MQ-136 (H_2S) sensors are chemoresistive sensors based on a tin dioxide (SnO_2) semiconductor layer. The operating principle of these sensors relies on the change in electrical resistance of the SnO_2 layer when it adsorbs target gas molecules. In clean air, oxygen molecules are adsorbed on the sensor surface, creating a potential barrier and resulting in high resistance. When reducing gases like CH_4 or H_2S are introduced, they react with the adsorbed oxygen, releasing trapped electrons back into the conduction band of the SnO_2. This process lowers the potential barrier and decreases the sensor's resistance. The magnitude of this resistance change is proportional to the concentration of the target gas, and this relationship is typically represented by the ratio of the sensor's resistance in gas (R_S) to its resistance in clean air (R_O).

In contrast, the MG-811 (CO_2) sensor operates on a solid electrolyte principle. It functions as an electrochemical cell where the target gas (CO_2) participates in an electrochemical reaction at the sensing electrode. This reaction generates an electromotive force (EMF), or an output voltage, between the sensing and reference electrodes. According to the Nernst equation, the magnitude of this output voltage is logarithmically proportional to the partial pressure, and thus the concentration, of the CO_2 gas.

2) Wireless signal propagation model

The performance of the system's wireless data transmission was evaluated using the log-distance path

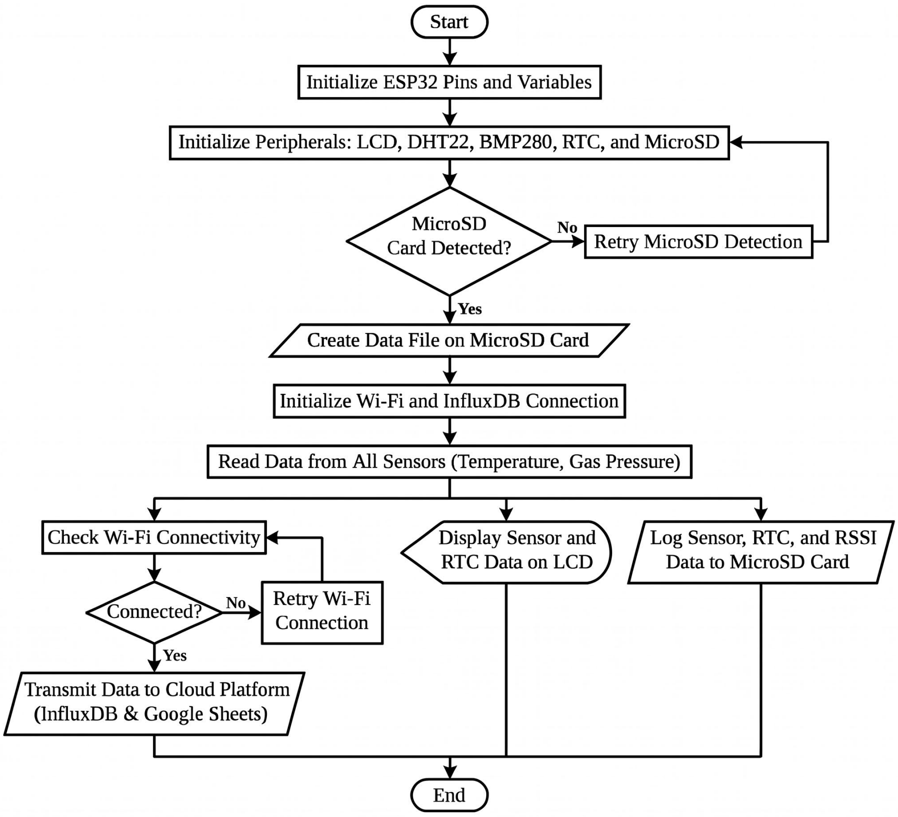


Figure 3. Flowchart.

loss model, a widely used model to describe the attenuation of radio signals over distance [13]. This model characterizes signal strength as a function of the distance between the transmitter and receiver. The received signal strength indicator (RSSI) is the measurement of the power present in a received radio signal. The model is expressed as equation (1):

$$RSSI_{(d)} = RSSI_{(d_0)} - 10 \times n \times log_{10}\left(\frac{d}{d_0}\right) \quad (1)$$

where $RSSI_{(d)}$ is the signal strength at distance d, $RSSI_{(d0)}$ is the reference signal strength at a reference distance d_0 (typically 1 meter), and n is the path loss exponent. The path loss exponent indicates the rate at which the signal strength decreases with distance and is dependent on the propagation environment (e.g., free space, indoor environments with obstacles).

F. Mathematical modeling and calculation

1) Concentration Modeling for MQ-4 and MQ-136 Sensors

To convert the analog output of the MQ sensors into a gas concentration in parts-per-million (ppm), a multi-step calculation was implemented in the firmware.

- The voltage across the sensor's load resistor (V_{RL}) was first determined from the ESP32's analog-to-digital converter (ADC) expressed as equation (2):

$$V_{RL} = \frac{ADC\_Value}{ADC\_Max} \times V_{ref} \quad (2)$$

where ADC_Value is the raw reading from the ADC, ADC_Max is the maximum resolution of the ADC (e.g., 4095 for 12-bit), and Vref is the reference voltage (3.3 V for the ESP32).

- The sensor's resistance in the presence of gas ($_{RS}$) was then calculated using the voltage divider expressed as equation (3):

$$R_S = \left(\frac{V_{CC}-V_{RL}}{V_{RL}}\right) \times R_L \quad (3)$$

where VCC is the supply voltage (5V) and RL is the value of the load resistor on the sensor module.

- The core of the calibration is establishing the sensor's resistance in clean air, R_O. This was determined by measuring R_S in a clean air environment and applying a standard ratio value from the sensor's datasheet. This calibrated R_O value was then stored in the device's memory.
- During operation, the ratio of R_S/R_O was calculated. The relationship between this ratio and the gas concentration (ppm) is logarithmic. A linear regression was performed on the log-log scale of the sensitivity curve from the sensor's datasheet to find the slope (a) and y-intercept (b) of the line. The final concentration was calculated using equation (4):

$$PPM = 10^{\left(\frac{log_{10}\left(\frac{R_S}{R_O}\right)-b}{a}\right)} \quad (4)$$

2) Concentration modeling for MG-811 sensor

For the MG-811 sensor, the output voltage (Vout) was first calculated. Due to potential deviations from the ideal datasheet values, a correction factor (PX) was calculated by comparing the measured voltage in clean air to the reference voltage from the datasheet. The final concentration (ppm) was calculated using a model based on the natural logarithm, derived from the sensor's sensitivity curve as shown in equation (5), equation (6), and equation (7):

$$V_{out(mV)} = \frac{ADC\_Value}{ADC\_Max} \times V_{ref} \times 1000 \quad (5)$$

$$V_{out(mV)PX} = V_{out(mV)} \times P_X \quad (6)$$

$$PPM = \exp\left(\frac{V_{out(mV)PX}-b}{a}\right) \quad (7)$$

where a and b are the slope and intercept derived from the sensor's characteristic curve.

3) Wireless performance and distance estimation

To evaluate the wireless connection, the log-distance path loss model was rearranged to estimate the distance (d) from the access point based on a measured RSSI value. Assuming a reference distance $d_0 = 1$ meter expressed as equation (8) [14]:

$$d = 10^{\left(\frac{RSSI_0-RSSI_{(d)}}{10n}\right)} \quad (8)$$

where $RSSI_0$ is the measured $RSSI$ at 1 meter and n is the calculated path loss exponent for the specific environment.

4) System accuracy and error metrics

The accuracy of all sensor measurements and distance estimations was quantified by calculating the percentage error and accuracy relative to a reference or standard measurement device, expressed as equation (9) and equation (10) [15]:

$$Error\ (\%) = \left|\frac{Reference\ Value - Measured\ Value}{Reference\ Value}\right| \times 100\ \% \quad (9)$$

$$Accuracy\ (\%) = 100\ \% - error(\%) \quad (10)$$

III. Results and Discussions

A. Sensor system validation

The performance of each sensor was validated against a calibrated, professional-grade instrument to establish its accuracy and reliability for the monitoring task. The key performance metrics for each sensor are summarized in Table 1.

As shown in Table 1, the core gas sensors for methane (MQ-4) and carbon dioxide (MG-811) demonstrated high average accuracies exceeding 90 %, confirming their suitability for this application. The DHT22 sensor proved exceptionally reliable for monitoring ambient temperature and humidity. While the MQ-136 sensor for hydrogen sulfide exhibited a higher average error, its readings consistently followed the trends of the reference device, making it sufficient for detecting the presence or absence of H_2S. The validation tests conclude that the selected low-cost sensors, after proper calibration, provide reliable and accurate data for the monitoring system.

Table 1.
Summary of sensor performance validation.,

Sensor	Parameter measured	Average accuracy (%)	Average error (%)
MQ-4	Methane (CH_4)	94.70	5.40
MQ-136	Hydrogen sulfide (H_2S)	85.30	14.80
MG-811	Carbon dioxide (CO_2)	92.00	7.80
DHT22	Temperature	98.60	1.40
DHT22	Humidity	91.80	8.20

B. IoT system and wireless performance

The performance of the IoT data transmission framework was evaluated based on its stability, latency, and wireless connection quality. The system demonstrated robust data transmission to both InfluxDB and Google Sheets, with no data loss observed during testing. The latency characteristics for each platform at varying distances are detailed in Table 2.

Table 2 highlights that the delay for Google Sheets increased proportionally with distance, whereas the delay for InfluxDB appeared to be more influenced by variable server-side processing loads in addition to signal quality. The quality of the wireless connection was assessed by measuring the Received Signal Strength Indicator (RSSI), with the results shown in Figure 4.

As depicted in Figure 4, the RSSI values behaved as theoretically expected, decreasing consistently as the distance from the access point increased. The developed path loss model for the environment proved highly accurate, allowing for reliable connection quality assessment.

C. Overall system performance in biogas monitoring

The fully integrated system was deployed for a 13-day continuous monitoring test. The effectiveness of the system in tracking the biogas production and the subsequent purification process is illustrated in Figure 5.

Figure 5 real-time monitoring of biogas production and purification. (a) Gas concentrations during the production stage, showing a concurrent rise in CH_4 and CO_2. (b) Gas concentrations after purification, demonstrating a significant increase in CH_4 and a decrease in CO_2.

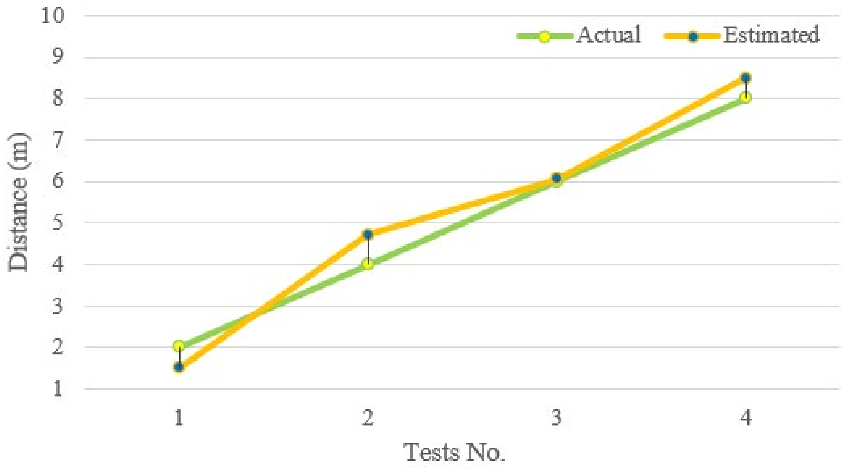
The system successfully monitored the anaerobic fermentation process, as shown in Figure 5(a), where the increase in methane was accompanied by a corresponding increase in carbon dioxide, confirming active digestion. Figure 5(b) clearly demonstrates the efficacy of the chemical purification stage. The monitoring data reveals a distinct shift in gas composition: methane concentration increased substantially, while carbon dioxide concentration was significantly reduced. For instance, on day 12, the system recorded that CH_4 levels rose from 606.48 ppm in the production vessel to 956.65 ppm after purification, while CO_2 levels dropped from 412.74 ppm to 341.89 ppm. This final, integrated test confirms that the developed low-cost IoT system can effectively monitor both the production and purification of biogas in real-time, providing valuable, actionable data to assess gas quality and optimize the overall process.

D. Discussions

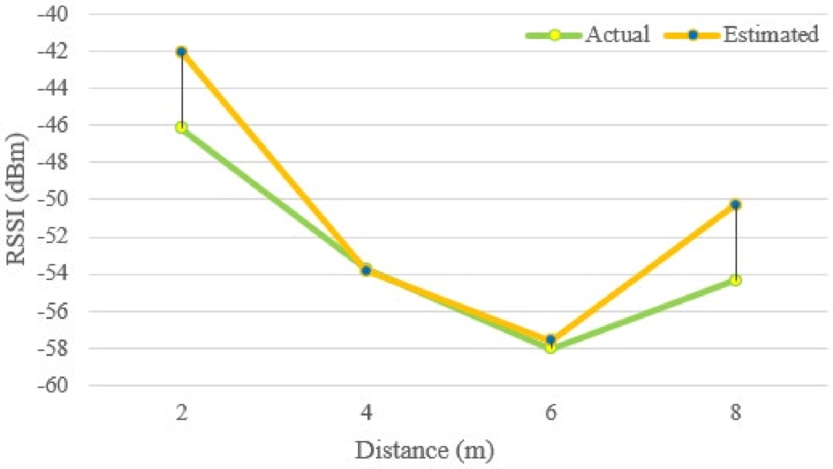
This study successfully demonstrated the design, implementation, and validation of a low-cost, IoT-based system for the real-time monitoring of biogas production and purification. The results confirm the primary hypothesis that an affordable technology stack, centered around the ESP32 microcontroller and readily available sensors, can provide reliable and actionable

Table 2.
IoT data transmission latency performance.

Distance (m)	Average latency to google sheets (ms)	Average latency to influxDB (ms)
2	3736.1	220.4
4	3805	337.7
6	3815.3	310.5
8	3880.2	273.1



(a)



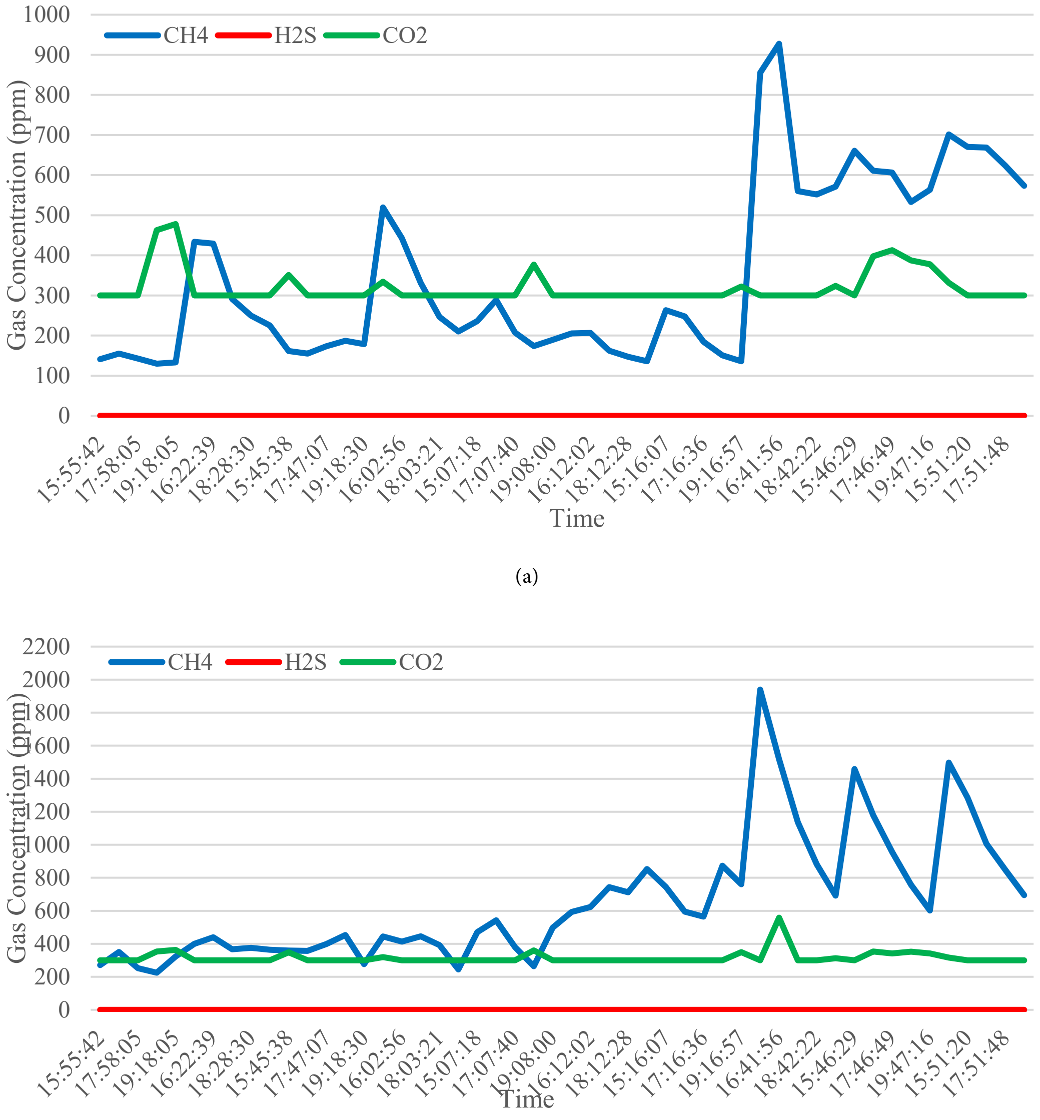
(b)

Figure 4. (a) the accuracy between the actual distance and the estimated distance; (b) wireless connection quality showing the relationship between distance from the access point and the corresponding RSSI value, the signal strength predictably decreases as distance increases.

data for optimizing small-scale biogas processes. The discussion will now interpret these findings in the context of previous studies, explore their broader implications, and outline future research directions.

The performance of the individual sensors is a cornerstone of this study's contribution. While previous research has utilized similar low-cost sensors for biogas monitoring, this work places a strong emphasis on the calibration and validation process against professional-grade instruments. The high accuracies achieved for the methane (MQ-4) and carbon dioxide (MG-811) sensors (94.7 % and 92.0 %, respectively) validate the feasibility of this low-cost approach, which is critical for overcoming the economic barriers that hinder the adoption of biogas technology at a community level. The slightly lower accuracy of the MQ-136 sensor highlights an inherent trade-off with low-cost components; however, its ability to reliably track trends remains valuable for process control. This finding suggests that for many practical applications, the absolute precision of expensive lab-grade equipment may not be necessary if affordable sensors can be properly calibrated to provide consistent and directionally correct data.

From an IoT architecture perspective, the system's performance underscores the flexibility of modern cloud platforms. The differing latency characteristics between Google Sheets and InfluxDB provide a practical insight for future developers: Google Sheets offers an accessible, spreadsheet-based interface ideal for long-term data logging and analysis, while InfluxDB is superior for high-frequency, real-time dashboard visualizations where minimal delay is critical. The robust performance of the Wi-Fi communication, validated through RSSI analysis, confirms that standard wireless protocols are sufficient for this application within a typical operating range. This approach, using common off-the-shelf cloud services, contrasts with studies that develop custom platforms and offers a more replicable and accessible model for other researchers and practitioners.



(a)

(b)

Figure 5. Real-time monitoring of biogas production and purification. (a) gas concentrations during the production stage, showing a concurrent rise in CH_4 and CO_2; (b) gas concentrations after purification, demonstrating a significant increase in CH_4 and a decrease in CO_2.

The most significant outcome is the system's demonstrated ability to monitor the entire biogas process chain, from production to purification. The real-time data successfully visualized the efficacy of the calcium hydroxide ($Ca(OH)_2$) purification method, confirming previous findings on its ability to scrub CO_2 and enhance methane purity. The innovation here is not the purification method itself, but the integration of continuous, real-time monitoring. This transforms the process from a "black box" into a transparent system, where operators can immediately assess gas quality and the effectiveness of the purification agent, leading to more efficient resource use and consistently higher-quality fuel. The observed absence of H_2S further suggests that with certain feedstocks, the resulting biogas may be less corrosive, an important factor for the longevity of application hardware like generators or stoves.

In the broadest context, this work serves as a blueprint for the democratization of renewable energy technology. By significantly lowering the cost and complexity of process monitoring, this system can empower small-scale farmers, rural communities, and educational institutions to more effectively manage and optimize their biogas digesters. This contributes to a more circular economy by promoting efficient waste valorization and reducing reliance on fossil fuels. The findings have direct implications for sustainable agriculture, off-grid energy solutions, and the application of applied IoT for environmental management.

Despite the successful results, this study has limitations that open avenues for future research. As a prototype, the system was tested on a small scale with a single feedstock composition and purification concentration. Future work should focus on scaling the system and testing its robustness with different organic wastes and process parameters. Based on the findings, several specific future research directions are recommended:

- Developing a closed-loop control system: The current system is for monitoring only. The next logical step is to integrate actuators for automated control of temperature and substrate mixing, further optimizing biogas yield.
- Expanding sensor capabilities: Incorporating additional sensors to measure parameters like pH, gas flow rate, and nitrogen levels would provide a more holistic understanding of the anaerobic digestion process.
- Exploring alternative communication protocols: Investigating protocols like LoRa or MQTT could offer advantages in scenarios requiring long-range, low-power communication, particularly in remote agricultural settings.
- Conducting techno-economic analysis: A comparative study on the operational cost and energy output of the purified biogas versus conventional fuels like LPG for applications such as electricity generation would be highly valuable.

Ultimately, the successful deployment of this low-cost monitoring system provides a strong foundation for the development of more intelligent, autonomous, and accessible biogas production systems.

IV. Conclusion

This study has successfully demonstrated the design, development, and validation of a low-cost, integrated Internet of Things (IoT) prototype for the real-time monitoring of both biogas production and purification processes. The system proved capable of reliably capturing and transmitting critical operational parameters—namely, digester slurry temperature and pH, biogas volume, and the concentrations of methane (CH_4) and hydrogen sulfide (H_2S). The principal finding of this work is the viability of using an integrated, low-cost sensor network to provide a holistic overview of the entire biogas process chain. By monitoring parameters within the anaerobic digester, the system offers a valuable tool for maintaining process stability and optimizing conditions for methanogenesis. Concurrently, by measuring gas composition before and after the purification unit, the prototype provides a quantitative, real-time assessment of the upgrading efficiency, clearly tracking H_2S removal and CH_4 enrichment. The significance of this research lies in its potential to make advanced process monitoring accessible to small-to-medium-scale biogas facilities, which typically cannot afford expensive commercial monitoring systems. The immediate, remote access to data empowers operators to make informed, timely decisions to prevent process failures and enhance overall energy output. Future work should focus on the long-term field deployment of this prototype in a continuous, operational biogas plant to assess its durability and long-term sensor stability. Furthermore, the data architecture developed here provides a solid foundation for the future integration of machine learning algorithms for predictive analysis and automated process control, transitioning from a simple monitoring system to an intelligent management tool.

Acknowledgements

I would like to express my thanks to everyone who helped me faithfully to finish the job. I would also like to thank the reviewers who gave very useful suggestions which help me improve the quality of research.

Declarations

Author contribution

S. Prasetyono., Catur S. S., Digdo L. S., Azmi S., B. S. Kaloko, M. Naufal An Nafi contributed equally as the main contributor of this paper. All authors read and approved the final paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The use of AI or AI-assisted technologies

During the preparation of this work the authors used ESP32 microcontroller in order to controling and data acquisition. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Additional information

Reprints and permission: information is available at https://mev.brin.go.id/.

Publisher's Note: National Research and Innovation Agency (BRIN) remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

[1] F. Manta, K. D. Artika, D. Suanggana, P. D. Tondok, “Analisis campuran substrat kotoran sapi dan limbah organik pasar terhadap produktivitas biogas,” *Jurnal Elemen*, 9(1), 31–39, 2022.

[2] A. N. Matheri, V. L. Sethunya, M. Belaid, and E. Muzenda, "Analysis of the biogas productivity from dry anaerobic digestion of organic fraction of municipal solid waste," *Renewable and Sustainable Energy Reviews*, vol. 81, part 2, pp. 2328-2334, Jan. 2018.

[3] K. Kusnadi, M. A. Wahid, M. F. M. Yasin, A. Rajani, and A. Fudhol, “Sustainable energy production: Performance evaluation of a generator-set using cow dung-based biogas”, *Journal of Mechatronics, Electrical Power, and Vehicular Technology*, vol. 15, no. 2, pp. 150-157, 2024.

[4] H. E. G. Prasetya, R. Amalia, A. F. B. Azisa, A. L. Fitri, and M. R. Jibran, "Rancang bangun smart biogas plant menggunakan teknologi internet of things (IoT)," *Suara Teknik: Jurnal Ilmiah*, vol. 13, no. 2, pp. 5–12, 2022.

[5] A. Gupta, "Making biogas SMART using Internet of Things (lOT)," in *2020 4th International Conference on Electronics, Materials Engineering and Nano-Technology (IEMENTech)*, 2020, pp. 1-5.

[6] A. M. Ritonga and M. Masrukhi, "Optimasi kandungan metana (CH_4) biogas kotoran sapi menggunakan berbagai jenis adsorben," *Rona Teknik Pertanian*, vol. 10, no. 2, pp. 11–22, 2017.

[7] H. Harmiansyah, R. D. Pratama, L. P. Afisna, M. Syaukani, and R. Efendi, "Karakteristik sisa slurry pada produksi biogas berbahan kotoran sapi," *JMPM (Jurnal Material dan Proses Manufaktur)*, vol. 6, no. 2, pp. 46–53, 2022.

[8] H. Fakhrurroja, E. T. Nuryatno, A. Munandar, M. Fahmi, and N. A. Mahardiono, “Water quality assessment monitoring system using fuzzy logic and the internet of things,” *Journal of Mechatronics, Electrical Power, and Vehicular Technology*, vol. 14, no. 2, pp. 198-207, 2023.

[9] F. P. H. de Andrade, J. H. da Silva Félix, F. H. de Lemos Andrade, D. A. C. Paz, J. C. A. Alcócer, and O. R. de Oliveira Pinto, "Monitoring of biodigesters through a computerized system integrated to IoT platform," *Revista Ibero-Americana de Ciências Ambientais*, vol. 9, no. 2, pp. 523–537, 2022.

[10] N. R. Vidiasari and A. B. Nugroho, "Pemurnian biogas dari limbah kotoran sapi di PT. Biro Teknik Sinar Baru dengan metode absorbsi menggunakan larutan kapur," *J. Tek. Elektro dan Komputasi (ELKOM)*, vol. 6, no. 1, pp. 98–104, 2024.

[11] M. H. Yulianto, E. Ferdiansyah, and A. W. Wastumirad, "Rancang bangun sistem monitoring gas CH_4 dan CO_2 berbasis internet of things studi kasus TPST Bantar Gebang," *Jurnal JTIK (Jurnal Teknologi Informasi dan Komunikasi)*, vol. 8, no. 2, pp. 247–254, 2024.

[12] S. O. Novantri and U. Y. Oktiawati, "Rancang bangun monitoring kadar gas metana pada pengolahan sampah organik berbasis IoT menggunakan mikrokontroler ESP32," *Jurnal Listrik, Instrumentasi, dan Elektronika Terapan*, vol. 3, no. 2, pp. 49–53, 2022.

[13] N. Mishra and S. Pandya, "Internet of Things applications, security challenges, attacks, intrusion detection, and future visions: A systematic review," *IEEE Access*, vol. 9, pp. 59353-59377, 2021.

[14] S. C. Agustinur, M. Yantidewi, and U. A. Deta, "Kalibrasi sensor MS1100-P111 sebagai detektor gas formaldehid (HCHO) dan sensor DHT22 untuk mendeteksi kelembaban relatif dan temperatur," *J. Komputasi dan Sains*, vol. 7, no. 7, pp. 2245–2257, 2024.

[15] S. N. Hida, S. Prabowo, M. Kirom, and A. Suhendi, "Monitoring system of biogas production volume and digester pressure control," in *Proceedings of the 5th International Conference on Applied Science and Technology on Engineering Science (iCAST-ES)*, 2022, vol. 1, pp. 493-498.