

Design of an *IoT*-Based Waste Management System for Biogas Production as a Renewable Energy Source

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Abstract

The increasing volume of organic waste presents serious environmental challenges while the demand for renewable energy continues to rise. This study proposes the design and implementation of an Internet of Things (IoT)-based smart biodigester system for converting organic waste into biogas as a renewable energy source. The system integrates an ESP32 microcontroller with DHT22 temperature, MPX5700 pressure, and MQ-4 methane gas sensors for real-time monitoring of fermentation parameters. A K-Nearest Neighbor (KNN) regression algorithm is embedded to predict methane pressure and enable automated system control. Experimental results indicate that the optimal model configuration at $k = 4$ achieved a Mean Absolute Error (MAE) of 0.18 and a Root Mean Square Error (RMSE) of 0.21, demonstrating high predictive accuracy. The developed prototype improves methane production stability and enhances overall energy conversion efficiency. This research contributes to sustainable organic waste management and decentralized renewable energy systems.

Keywords: biogas, organic waste, ESP32, IoT, k-nearest neighbor, renewable energy

1. Pendahuluan

Human life is fundamentally dependent on energy, particularly electricity for operating domestic appliances. However, heavy reliance on fossil-based energy sources significantly contributes to environmental degradation and greenhouse gas emissions (Tryhuba et al., 2024). In response to this issue, various renewable energy alternatives have been developed, including biogas produced through the anaerobic decomposition of organic waste (Damayanti et al., 2021)(Mukti et al., 2021). The ability of biogas to convert waste into clean and usable energy makes it a promising solution for sustainable energy development.

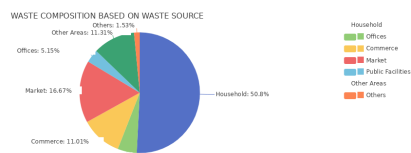


Figure 1. Waste Composition Based on Waste Source

Figure 1 illustrates the composition of waste based on its source. According to the Ministry of Environment and Forestry's 2024 report, Indonesia generated approximately 33.7 million tons of waste in 2024, with 50.8% originating from households. Alarming, 40.06% of this waste remains unmanaged, leading to environmental degradation and public health concerns (KLHK, n.d.). A significant por-

tion of this waste consists of biodegradable materials such as food scraps and kitchen residues, which have high potential for biogas production (Junus et al., 2025). Despite this potential, biogas contributes only about 0.5% to national energy consumption, largely due to limited implementation of efficient monitoring and control systems.

Previous studies have implemented IoT-based systems to monitor fermentation parameters in biogas production. (Michael et al., 2023) developed an IoT monitoring system to observe temperature and pressure variations during fermentation, while (Prasetya et al., 2022) designed a smart biogas plant integrating IoT sensors to optimize operational conditions. However, most existing systems focus primarily on monitoring rather than predictive control.

Due to its active involvement in community-based waste management, TPST 3R Mulyoagung in Malang Regency an integrated community-based waste processing facility (Tempat Pengolahan Sampah Terpadu) that applies the Reduce-Reuse-Recycle (3R) concept was selected as the pilot site for this research. Although biogas utilization has not been previously implemented at this facility, it provides an appropriate environment for exploring small-scale waste-to-energy conversion. This study introduces the design, implementation, and testing of an on-site intelligent biogas system integrated within the operational framework of TPST 3R Mulyoagung (Si-

tumeang et al., 2022).

Conventional biogas monitoring systems are generally reactive, relying on fixed threshold values and taking action only after a parameter has crossed a predetermined setpoint; this static approach cannot anticipate fluctuations or capture the nonlinear relationships among temperature, CO₂ concentration, and CH₄ concentration that govern methane pressure. Unlike conventional monitoring systems, this research integrates a K-Nearest Neighbor (KNN) regression model within the biodigester control loop to predict methane pressure levels based on temperature, CO₂ concentration, and CH₄ concentration inputs. The predictive output enables proactive system adjustment, enhancing methane production stability and improving energy conversion performance.

The system utilizes IoT-based sensing through ESP32 microcontrollers to collect real-time environmental and gas parameter data. Sensor measurements are transmitted to the Blynk IoT platform, enabling remote monitoring and system supervision.

By integrating IoT-based sensing, K-Nearest Neighbor (KNN) regression modeling, and automated actuator control, this study proposes an intelligent real-time monitoring and predictive control framework to enhance methane production stability and improve overall biogas energy utilization efficiency. The proposed approach is scalable, cost-effective, and suitable for implementation in rural and semi-urban communities with limited energy infrastructure.

2. Metode

This study employed an experimental Research and Development (R&D) design aimed at developing and testing a smart monitoring and controlling system for biogas utilization. The system integrates multiple sensors, an ESP32 microcontroller, and a K-Nearest Neighbor (KNN) regression model to predict methane pressure and optimize biogas production automatically.

2.1 Type of Research

Using a quantitative methodology, this research is an applied experimental investigation. This research addresses the accumulation of household organic waste and the increasing demand for affordable renewable energy for small-scale domestic electrical loads, such as a fan system. The designed system converts organic waste into biogas and applies a K-Nearest Neighbor algorithm to predict methane pressure levels. The predictive results are used to optimize generator activation and improve overall system efficiency.

Using an experimental approach, the research measures and analyzes sensor data in real-time, including temperature, pressure, and CO₂ and methane levels. The analysis's findings dictate system actions,

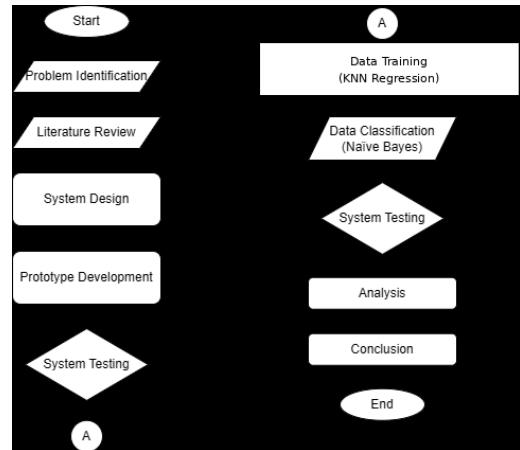


Figure 2. Research Framework and Workflow

like whether to permit the flow of biogas. At TPST 3R Mulyoagung, biogas produced on-site from a blend of cow dung and food waste was used for testing.

As the project involves the design and construction of a functional prototype, complete with sensors, a microcontroller, a valve, a generator, a fan, and mobile monitoring through the Internet of Things, it is also classified as developmental research. The system combines aspects of environmental sustainability, machine learning, and electronics to provide a workable, community-based solution.

2.2 Data Preprocessing

Before model training, the raw dataset underwent preprocessing to ensure data quality and compatibility with the regression model. Invalid sensor readings were removed, outliers were filtered using the interquartile range (IQR) method, and feature values were normalized using Min-Max scaling to a range of [0,1], defined as $x' = (x - x_{min}) / (x_{max} - x_{min})$, so that temperature, CO₂ concentration, and CH₄ concentration inputs were placed on a comparable scale. This normalization step is necessary because KNN is a distance-based algorithm and is therefore sensitive to differences in the scale of its input features. The three input features (temperature, CO₂ concentration, and CH₄ concentration) were selected based on prior literature on anaerobic fermentation, which identifies these parameters as the primary factors directly influencing gas pressure buildup inside a biodigester; a formal statistical feature-selection procedure was not performed and is noted as a limitation of this study. The dataset was divided into 70% training data and 30% testing data to objectively evaluate predictive performance.

2.3 Data Collection and Analysis

A total of 120 data samples were collected over a 30-day fermentation period, with sensor readings logged automatically at fixed 6-hour intervals (four samples per day) to capture the complete lifecycle

of biogas production while limiting the volume of redundant readings. Each sample consists of three independent input features: Temperature ($^{\circ}\text{C}$), CO_2 concentration (ppm), and CH_4 concentration (ppm). The target variable was defined as methane pressure (kPa), obtained from the MPX5700 pressure sensor measurements. This sample size, constrained by the 30-day testing period available for this study, is relatively limited for machine learning purposes and is acknowledged as a limitation in the Discussion section.

The K-Nearest Neighbor (KNN) algorithm is a non-parametric regression method widely used for predictive modeling due to its simplicity and effectiveness in handling nonlinear relationships (Cover & Hart, 1967)(Murphy, 2012). Compared with heavier machine learning models such as support vector machines or neural networks, KNN requires minimal computational resources and no iterative training process, making it well suited for deployment on a resource-constrained embedded platform such as the ESP32; it is therefore not an excessive solution compared to conventional threshold-based methods, but rather a lightweight approach capable of capturing nonlinear sensor relationships that fixed-threshold methods cannot. To determine the similarity between a new input sample and the training dataset, the Euclidean distance metric is applied as follows:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1)$$

where x_i represents the input feature values and y_i represents the corresponding feature values from the training dataset.

To determine the optimal number of neighbors, several values of k ranging from 1 to 10 were evaluated experimentally by training and testing the model sequentially for each value of k and comparing the resulting error metrics, as summarized later in Table 3. The upper bound of $k = 10$ was chosen in consideration of the limited dataset size (120 samples, with 84 samples used for training); larger k values relative to a small training set tend to over-smooth the predictions and reduce sensitivity to local variation, which is consistent with the rising error observed for $k > 4$ in Table 3. Model performance was assessed using two regression evaluation metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

where y_i denotes the actual methane pressure value and $\hat{y}_i$ denotes the predicted value. MAE and RMSE are widely used regression evaluation metrics that quantify the average prediction error and error dis-

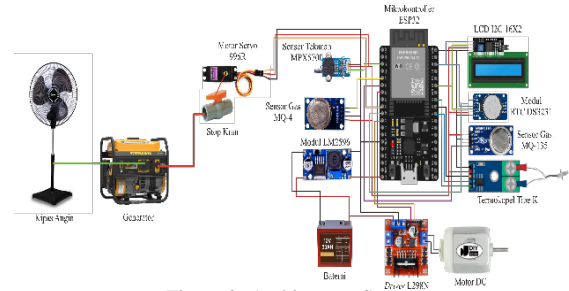


Figure 3. Architecture System

person, providing an objective assessment of model performance (Géron, 2019).

2.4 System Architecture and Material

Figure 3 illustrates the overall hardware architecture of the proposed system, showing the interconnection between the sensors, the ESP32 microcontroller, the actuators, and the generator unit.

a. ESP32 Microcontroller

For Internet of Things applications, the ESP32 is a low-power, high-performance microcontroller with Bluetooth and Wi-Fi capabilities. It has the ability to interpret data in real time and manage several devices at once. ESP32 is extensively used in environmental monitoring and smart home systems because of its dual-core architecture and integrated wireless connectivity (Rosa et al., 2020).

b. K-Type Thermocouple Sensor

K-type thermocouple's broad range and robustness make it a popular temperature sensor for environmental and industrial monitoring. Through the use of an amplifier circuit, it produces a tiny voltage that is proportionate to the temperature differential and can be read. To guarantee the ideal fermentation temperature, thermocouples are frequently utilized in biogas digesters (Roja et al., 2024).

c. MQ-4 Gas Sensor

A metal oxide semiconductor (MOS) sensor called MQ-4 is intended to measure the concentration of methane gas in parts per million. Depending on the amount of CH_4 in the ambient air, it produces an analog signal. Since methane is the main energy carrier in biogas, this sensor is crucial for evaluating the quality of biogas (Rahman et al., 2024).

d. MQ-135 Gas Sensor

MQ-135 is frequently used to detect CO_2 as well as other dangerous gases as benzene, NO_x , and NH_3 . When determining the purity of biogas and possible gas pollutants, its readings are essential. A more comprehensive examination of the composition of biogas

can be obtained by combining MQ-135 and MQ-4 (Rusdiyanto et al., 2021).

e. MPX5700 Pressure Sensor

In a non-corrosive gas environment, the MPX5700 piezoresistive transducer is intended to detect changes in pressure. It assists in keeping an eye on the pressure accumulation inside the digester or gas storage in biogas applications. Safety and control of biogas production are supported by accurate pressure data (Iqbar & Riyanti, 2020).

f. DC Motor

DC motors are frequently utilized in systems that need to rotate or be activated since they transform electrical energy into mechanical movement. This study may use a DC motor to operate a mechanical valve or to stir automatically during fermentation. These motors' dependability and controllability make them popular in embedded systems that utilize less energy (Mukhtar et al., 2024).

g. Servo 996R

The MG996R servo motor is a high-torque digital servo commonly used in embedded systems for precise mechanical movements such as automated valve operation or robotic arm control. With a maximum torque of approximately 9.4 kg-cm at 4.8 V and 11 kg-cm at 6 V, and a metal gear design that ensures durability and positioning accuracy up to 180°, the MG996R is widely applied in automation and agricultural robotics systems. For instance, (Rusdiyanto et al., 2021) successfully implemented the MG996R servo as an actuator for a robotic nozzle sprayer arm, demonstrating effective control within a 110°–180° movement range (Raju et al., 2023). Its dependability, programmability via PWM signals, and compact form factor make it highly suitable for driving mechanical valves or stirring components automatically during biogas fermentation processes.

h. RTC (Real Time Clock)

The RTC (Real-Time Clock) module is essential in embedded systems for providing accurate time-keeping, particularly for logging time-series sensor data such as pressure and gas volume. Modules like the DS3231 or PCF8563 offer low-power, high-precision time tracking, which is critical for systems that store or transmit sensor readings at regular intervals (Mun et al., 2019). The battery powers the chip, so the clock stays up-to-date even when the computer is turned off. Because it uses a crystal oscillator, the RTC is considered fairly accurate as a timer.

i. LifePO4 Battery

LiFePO₄ batteries are well-known for their extended cycle life, non-toxicity, and thermal stability. Off-grid solar and biogas systems commonly employ them, and they are perfect for standalone energy systems. Their resilience guarantees that sensors and actuators will continue to receive electricity.

j. Generator

Generator is a mechanical device that uses combustion to transform the chemical energy of biogas into electrical energy. The electric water heater system in this study is powered by a biogas-driven generator. Decentralized energy solutions have shown success with the incorporation of biogas-powered generators into small-scale energy systems.

k. Fan

A stand fan is an electric device designed to circulate air within a room to provide cooling and improve ventilation. It typically consists of a motor, rotating blades, and an adjustable height stand, allowing users to direct airflow as needed. Stand fans are commonly used in homes, offices, and industrial settings due to their portability, energy efficiency, and ease of operation. They function by converting electrical energy into mechanical rotation, which propels air to create a breeze and enhance thermal comfort.

2.5 Flowchart System

Figure 4 shows the steps involved in the biogas-based fan control system's functioning, from input/output initialization to the valve's final actuation and data monitoring. Sensors and control pins are among the input/output components that are initialized at the start of the operation. After initialization, the system reads data from the MQ-4 and MQ-135 gas sensors to determine the CO₂ and methane levels in real time and Thermocouple to determine temperature. Additionally, it uses the MPX5700 pressure sensor I to read pressure readings. A predetermined setpoint is then assessed by the system to determine whether the gas concentration and pressure have been reached. Otherwise, servo rotate the valve, which is ordinarily open or NO, stays closed to avoid purifying the gas too soon. When the setpoint is reached, the valve opens, letting biogas proceed to the purification phase. After verifying the manual ON/OFF button input, the system once more reads values from MQ-4, MQ-135, Thermocouple and MPX5700 sensor II. This button acts as an extra layer of control for manual override and safety. The mechanism maintains button ON/OFF Servo in valve to ON/OFF position, which stops the flow of gas, if the button is not touched. When the button is pressed, the purified biogas can

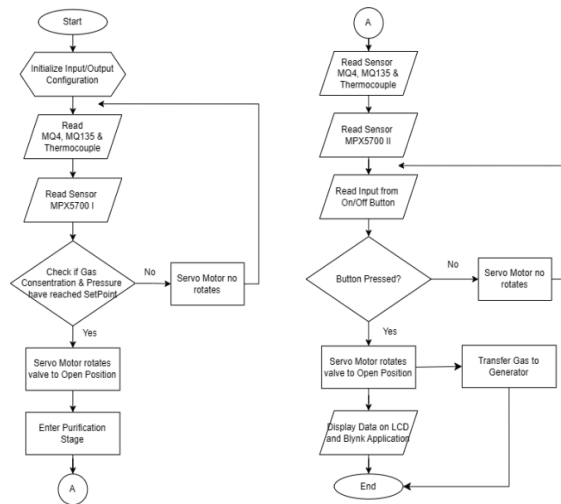


Figure 4. Flowchart System

enter the generator since the valve opens. In order to allow users to remotely monitor the system, sensor readings and system status (gas parameters, valve condition) are simultaneously transmitted to an LCD display and the Blynk mobile application. This flow gives users the flexibility to manually override the flow and guarantees that biogas is only used when it satisfies safety and performance requirements. Additionally, it permits transparent system operations and real-time tracking.

3. Results and Discussion

3.1 Results

The system's performance was evaluated through a series of tests focusing on hardware reliability, energy conversion efficiency, and the accuracy of the machine learning model.

a. Sensor Performance Evaluation

To validate the reliability of the data collection hardware, each sensor was tested against a calibrated reference instrument. The results, summarized in Table 1, show exceptionally high accuracy across all sensors, confirming that the data used for regression modeling is reliable. The mean relative error for all sensors was less than 0.02%, indicating a strong correlation with the reference measurements and validating their suitability for this monitoring application. Although these errors are small, they can be further reduced by applying a simple linear regression calibration that maps each sensor's raw reading to its corresponding reference value, an approach considered for future refinement of the data acquisition pipeline.

Based on Figure 5, which compares the K-Type Thermocouple sensor against a calibrated digital reference thermometer (accuracy of $\pm 0.5^{\circ}\text{C}$), there is a very strong correlation between the two measurements. The line representing the thermocouple's

Table 1. Summary of Sensor Accuracy Test

Sensor	Mean Relative Error (%)
Thermocouple Type-K (Temperature)	0.0018%
MPX5700AP (Pressure)	0.0018%
MQ-135 (CO_2)	0.006%
MQ-4 (CH_4)	0.007%

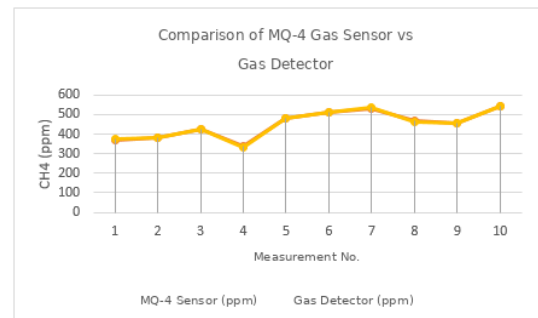


Figure 5. Graph Methane

readings consistently and closely follows the line for the reference thermometer across all 10 measurement points, even as the temperature changes. This visual consistency indicates that the sensor's measurement error is minimal. The analysis confirms this, showing an extremely low mean error rate of only 0.018%, which proves that the K-Type Thermocouple provides highly accurate and reliable temperature data for the system.

Figure 6 shows graph illustrates the comparison between the MQ-135 sensor and a reference Air Quality Detector for measuring CO_2 concentration. The readings from the MQ-135 sensor consistently track the values reported by the reference device, with only minimal differences observed across the test points. This demonstrates the sensor's high sensitivity and responsiveness to changes in CO_2 levels. The calculated mean error rate for the CO_2 measurement is a mere 0.006%, which confirms that the MQ-135 sensor is very accurate and suitable for air quality monitoring applications within this system.

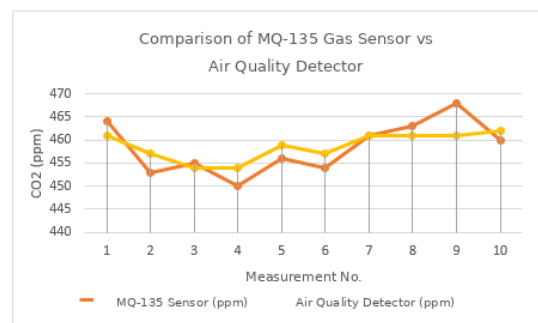


Figure 6. Graph Carbon Dioxide

Figure 7 shows that the CH_4 (methane) concentration readings from the MQ-4 sensor are nearly identical to those from the reference Gas Detector at every test point. The consistency of the measurements proves that the sensor responds to changes in methane concentration with excellent accuracy, even at lower

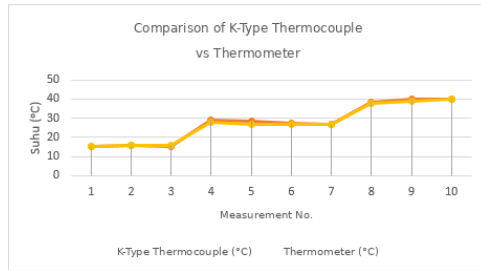


Figure 7. Graph Temperature

levels. The performance is quantitatively validated by a mean error rate of just 0.007%. This result confirms that the MQ-4 sensor is highly sensitive and reliable for detecting the primary component of biogas in this research.

Figure 8 above shows a comparison between the MPX5700AP sensor and a digital pressure gauge. It's important to note that the absolute pressure data from the MPX5700AP was first converted to relative pressure (by subtracting atmospheric pressure) to allow for a direct comparison. After this conversion, the results are highly aligned, as shown by the two lines on the graph which follow a nearly perfect linear relationship. This strong correlation is confirmed by a very low mean error rate of 0.018%, demonstrating that the MPX5700AP sensor is exceptionally precise and reliable for the crucial task of monitoring gas pressure within the biogas system.

b. Energy Conversion Efficiency

Table 2 shows the system's end-to-end functionality was tested by measuring its ability to convert the chemical energy from biogas into electrical energy to power a fan. During a 10-minute (≈ 0.167 hour) operational test, the system consumed 0.1 m^3 of biogas. Based on the biogas's caloric value, this volume corresponds to a potential energy input of 0.6 kWh. Throughout this period, the generator produced a total electrical energy output of 0.2 kWh. By calculating the ratio of the energy output to the energy input, the system was determined to have an energy conversion efficiency of 33.3%.

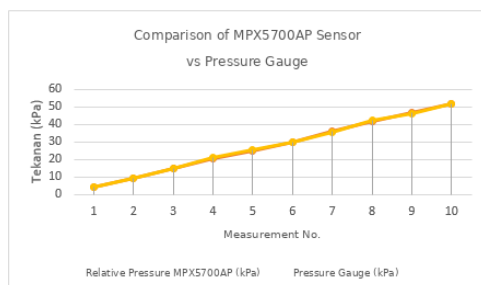


Figure 8. Graph Pressure

As illustrated in the pie chart, that shows at Figure 9 this result indicates that approximately one-third (33%) of the biogas's potential energy was successfully converted into usable electricity. The remaining 67% represents the energy that was lost dur-

Table 2. Efficiency Energy

Parameter	Mark	Information
Testing Duration	10 minutes (≈ 0.167 hours)	
Volume of Biogas Used	0.1 m^3	$0.6 \text{ m}^3 / (\text{hours} \times 0.167 \text{ hours})$
Input Energy Potential (Biogas)	0.6 kWh	$0.1 \text{ m}^3 \times 6 \text{ kWh} / \text{m}^3$
Electrical Energy Output (Generator)	0.2 kWh	Power $1.2 \text{ kW} \times 0.167 \text{ hours}$
Energy Conversion Efficiency	33.3%	$(0.2 \text{ kWh} / 0.6 \text{ kWh}) \times 100\%$

ing the conversion process, primarily as heat and mechanical losses from the generator. This efficiency level is reasonable for a small-scale generator and confirms that the system can effectively transform household waste into functional electricity.

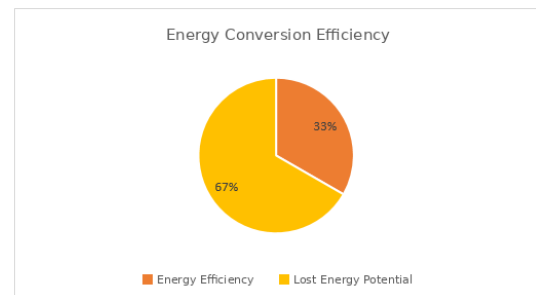


Figure 9. Chart of Energy Conversion Efficiency

The results presented in Table 3 indicate that the optimal performance was achieved at $k = 4$, producing the lowest MAE and RMSE values. This value of k was determined empirically by training and evaluating the model for each integer value from $k = 1$ to $k = 10$ and comparing the resulting MAE and RMSE, as described in the Methodology section. Increasing the value of k beyond 4 leads to higher prediction errors due to over-smoothing effects, while lower k values tend to produce unstable predictions.

Table 3. Optimal Performance

k Value	MAE	RMSE
1	0.31	0.42
2	0.25	0.34
3	0.21	0.29
4	0.18	0.21
5	0.20	0.27
6	0.23	0.30
7	0.26	0.33
8	0.28	0.36
9	0.30	0.39
10	0.33	0.41

3.2 Discussion

The experimental results confirm that the developed system is highly effective for real-time monitoring and predictive estimation of methane pressure in biogas production. The high accuracy of the sensors

Table 4. Comparison of Actual and Predicted Methane Pressure Values

Sample	Actual Pressure (kPa)	Predicted Pressure (kPa)	Absolute Error
1	98.2	98.0	0.2
2	101.4	101.1	0.3
3	105.6	105.5	0.1
4	110.2	110.0	0.2
5	115.8	115.6	0.2

provides a solid foundation for the machine learning model, ensuring that its decisions are based on reliable data. The system's ability to convert biogas to electricity with 33.3% efficiency further validates its practical utility as a sustainable energy solution.

The KNN-based predictive approach demonstrates clear advantages over conventional threshold-based monitoring systems, which typically rely on fixed setpoint values without forecasting capability. Unlike static control strategies, the proposed model predicts methane pressure trends based on multi-parameter sensor input, enabling proactive system adjustment before critical fluctuations occur.

The experimental results, with MAE of 0.18 and RMSE of 0.21 at $k = 4$, confirm that the predicted methane pressure values closely approximate actual measurements with minimal deviation. This low prediction error indicates reliable forecasting performance under dynamic fermentation conditions.

By anticipating methane pressure variations rather than reacting after threshold violations, the system enhances production stability, reduces pressure overshoot, and minimizes potential operational risks such as gas leakage or inefficient combustion. Furthermore, the integration of the KNN model within the embedded ESP32 platform demonstrates that predictive intelligence can be implemented efficiently in real-time IoT-based energy systems.

While an 80/20 training-testing split is a standard validation procedure, it is important to acknowledge that the evaluation was conducted on a limited test set of 24 samples. Although the results are strong, future work should aim to validate the model's robustness on a larger and more diverse dataset to further confirm its generalizability across different operational conditions. Nonetheless, the high predictive performance achieved in this study proves the feasibility of implementing an on-device KNN regression model for real-time automated biogas monitoring and control.

4. Conclusion

This study successfully designed, implemented, and evaluated an intelligent IoT-based monitoring and predictive control system for methane pressure estimation in biogas production from organic waste. The developed system demonstrated high reliability, with

integrated sensors achieving excellent accuracy; the mean relative errors were 0.018% for temperature and pressure measurements, and 0.006% and 0.007% for CO_2 and CH_4 measurements, respectively.

Experimental evaluation of the K-Nearest Neighbor (KNN) regression model showed that the optimal configuration at $k = 4$ achieved a Mean Absolute Error (MAE) of 0.18 and a Root Mean Square Error (RMSE) of 0.21, indicating minimal deviation between predicted and actual methane pressure values.

The integration of the KNN model within the embedded ESP32 platform enabled stable real-time monitoring and predictive control under dynamic fermentation conditions. By forecasting methane pressure trends, the system enhances operational stability, improves energy conversion performance, and supports sustainable organic waste-to-biogas energy management.

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