



Optimization and Monitoring of Biogas Power Plants for Energy Management Using Genetic Algorithms and the Internet of Things (Case Study: Kendari City Slaughterhouse)

Al Ubai^{1*}, Asminar², Abdul Djohar³ Muhammad Nadzirin Anshari Nur⁴, Bunyamin⁵, Agustinus Lolok⁶

^{1,2,3,4,5,6}Department of Electrical Engineering, Universitas Halu Oleo, Indonesia

Correspondence E-mail: alubaiwork@gmail.com

ABSTRACT

This project seeks to build and optimize a Biogas Power Plant system connected with Internet of Things (IoT) technology and Genetic Algorithms (GA) for energy management purposes. The system is executed as a simulation at the Kendari City Slaughterhouse (RPH), employing organic waste as biogas feedstock. IoT-based monitoring is utilized to track essential data, such as methane concentration, temperature, pressure, voltage, and current, in real time. Genetic Algorithms are utilized to optimize load distribution, guaranteeing efficient energy consumption. The findings demonstrate that the monitoring system operates dependably, exhibiting great sensor precision, with voltage readings attaining an average accuracy of 98.91% and pressure sensors achieving 99.1% accuracy. Additionally, GA optimization effectively identifies an appropriate load supply combination that aligns closely with the generator capacity, avoiding overload problems. The integration of IoT and GA augments the performance, efficiency, and reliability of the PLTBG system, exhibiting its capacity for sustainable energy management in biogas-powered generation.

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1. INTRODUCTION

The demand for sustainable energy sources is increasing in the contemporary era, propelled by swift globalization and a rising worldwide population. Conversely, fossil fuel reserves are diminishing and contributing to numerous adverse environmental effects, including heightened greenhouse gas emissions. As fossil fuel supplies deplete and global energy consumption escalates, the prospect of an energy crisis has emerged as a significant concern in numerous nations. The International Energy Agency (IEA) reports that more than 80% of global energy requirements continue to depend on non-renewable resources, including natural gas, coal, and crude oil. This scenario demonstrates that excessive reliance on fossil fuels poses a threat of an impending energy crisis and intensifies environmental challenges like climate change, necessitating a shift to more sustainable renewable energy sources [1].

The disparity between demand and the supply of conventional energy has catalyzed the advancement of many alternative energy sources that are more ecologically sustainable. A notable renewable energy source with considerable potential is biogas, which can be utilized via biogas power plants. PLTBG employs organic waste as its principal feedstock; hence, this technology not only produces power but also enhances sustainable waste management. Indonesia, possessing a substantial agricultural and animal sector, has an ample source of biogas feedstock; nevertheless, its utilization is poor. Consequently, the advancement of biogas power plant technology represents a viable approach to fulfill energy requirements while mitigating the environmental repercussions of organic waste [2].

Nonetheless, the deployment of biogas power plants continues to encounter numerous obstacles, especially with energy conversion efficiency and system reliability. Innovative and integrated methodologies are essential to enhance the optimal functioning of biogas systems, particularly within the slaughterhouse sector, which produces substantial quantities of organic waste. Inadequately handled slaughterhouse waste can adversely affect the environment, rendering its usage as biogas feedstock a viable solution [3]. Research by Asminar et al. (2024) on the modeling and simulation of off-grid PV–biogas systems at the Kendari City slaughterhouse reveals that the system utilizes basic rule-based control, such as connecting or disconnecting batteries at predetermined levels, without accommodating fluctuations in biogas production or alterations in load. In that investigation, biogas generated approximately 1.175 kW of the total power during operation, demonstrating that the current system has limits in optimizing energy output and load control [4][5].

An optimization strategy is required to adaptively modify operational parameters to enhance the performance of the PLTBG system. A commonly employed technique in power system optimization is the genetic algorithm (GA). This method was selected because of its capability to address both confined and unconstrained optimization problems. Genetic algorithms operate by iteratively altering a population of solutions via selection, crossover, and mutation processes until the optimal solution is achieved. By emulating the principle of natural selection, genetic algorithms can identify the optimal solution within an extensive search space [6].

The development of integrated monitoring systems is also a key factor in improving the performance of biogas power plants. Research conducted by Junus et al. (2025) shows that the integration of sensors and Internet of Things (IoT) technology into biogas production monitoring and control systems can enhance the efficiency and reliability of biogas power plants in Indonesia [7]. IoT sensors such as methane (CH₄) sensors, pressure sensors, and temperature sensors connected to microcontrollers and communication modules are capable

of collecting operational data in real-time and displaying this information on the monitoring system. The integration of this technology not only improves data visibility and responsiveness to changes in system conditions but also supports decision-making processes in energy management[8].

2. METHODS

This study was conducted at the Electrical Power Systems Laboratory, Faculty of Engineering, Halu Oleo University, and at the Kendari City Slaughterhouse over a period of six months, from September to March 2026. The research phases included a literature review, data collection, instrument design and development, and instrument testing. Each phase was carried out systematically to ensure the validity and accuracy of the data obtained.

2.1. Biogas power plant system configuration

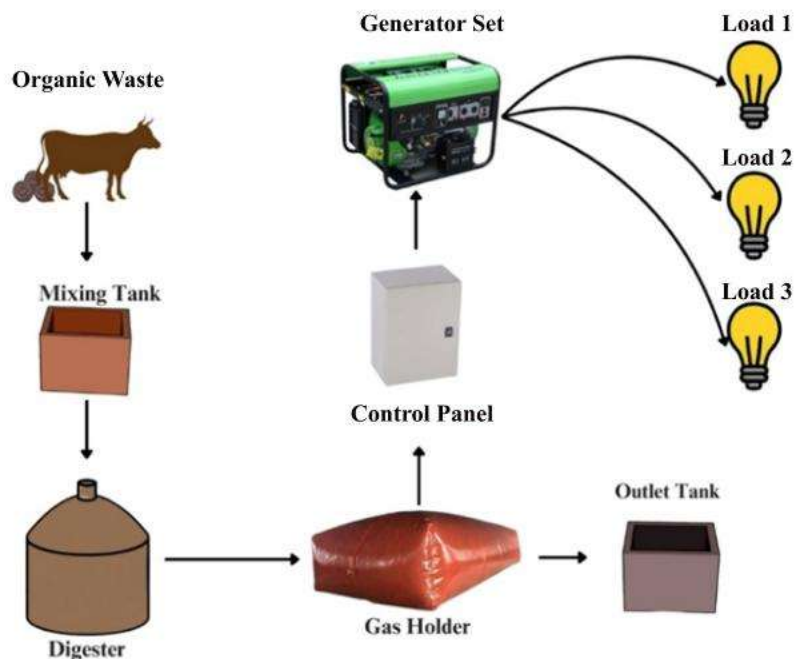


Figure 1. Biogas Power Plant System Configuration

Figure 1 above shows the design of a biogas power plant configuration, illustrating the structured process of converting organic waste into electrical energy through anaerobic digestion for 3 to 14 days [9][10][11]. The process begins by feeding organic waste, such as cow or livestock manure, into a mixing tank to be blended with water[12]. Next, the mixture is fed into the digester, an anaerobic reactor where methanogenic bacteria carry out fermentation without oxygen. These bacteria produce biomethane gas as the primary product of the fermentation process. To maintain stable pressure, the resulting gas is then directed into a gas storage tank. Afterward, the gas is routed through a pressure transmitter and controlled by a control panel to regulate the gas supply to the generator set. The generator produces electrical energy from the chemical energy of the biogas [13]. This electrical energy is then transmitted to loads such as lights or other electrical equipment. Meanwhile, the residual slurry from the digester is discharged into an outlet tank and can be used as liquid organic fertilizer [14].

2.2. Design and theoretical planning

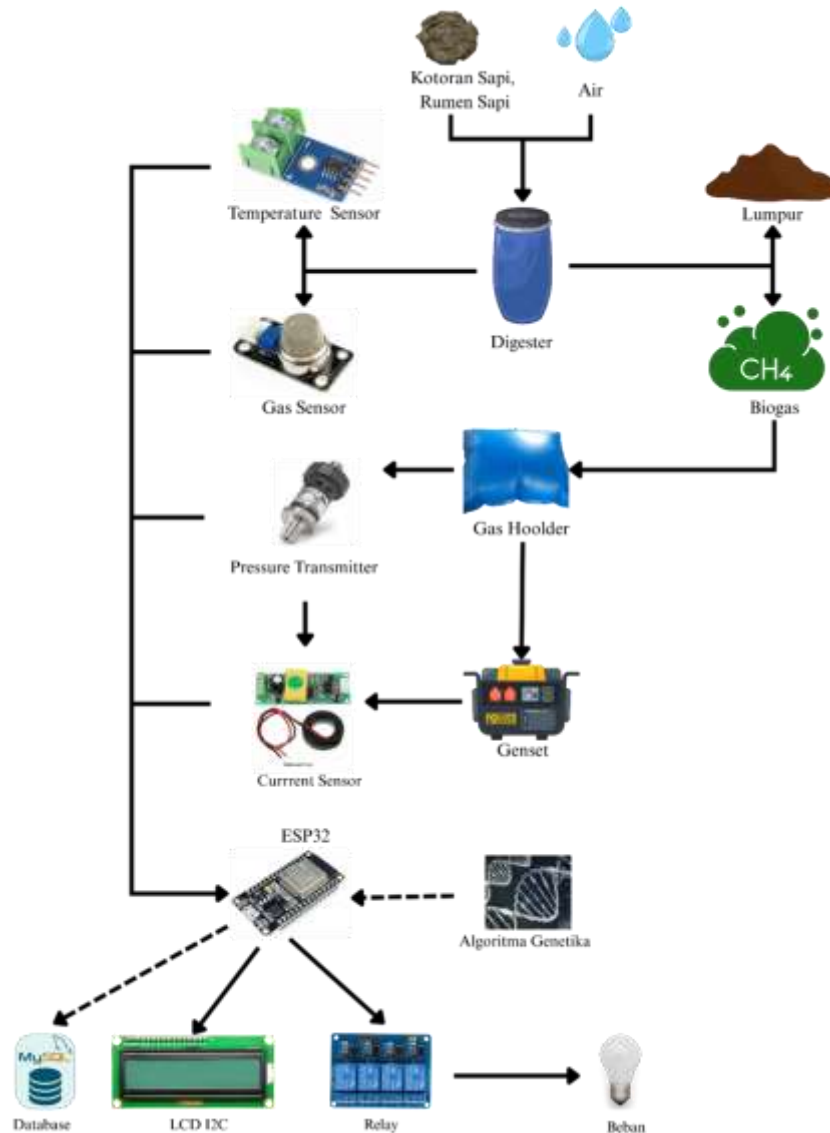


Figure 2. Architecture of The Proposed Biogas Monitoring System

The **Figure 2** system begins by introducing cow manure and rumen contents as input, mixed with water in a 1:1 ratio to remove coarse solids [15]. The next step evaluates the biogas potential of the input materials. The material is then fed into a digester for anaerobic fermentation. Inside the digester, an MQ4 sensor is used to detect the methane gas produced, and a temperature sensor is used to measure the temperature to optimize fermentation results [16]. The digester produces biogas as well as residual slurry that can be used as organic fertilizer. The biogas output is channeled through a pipe to a gas storage tank for collection, and the pressure inside is measured using a pressure transmitter [17]. The biogas is then routed to a generator, and a current sensor measures the electrical current output from the generator. The system is optimized using a genetic algorithm to determine the optimal load configuration. The data obtained is displayed on an LCD screen, stored in a MySQL database, and displayed in real-time via a monitoring website.

2.3. Genetic algorithm flowchart

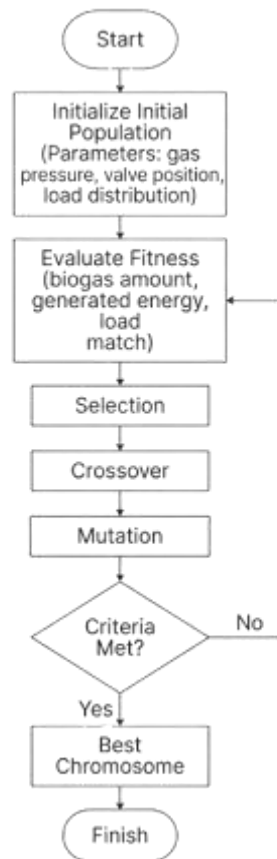


Figure 3. Flowchart of The Genetic Algorithm Process

In **Figure 3**, a Genetic Algorithm is used to optimize the configuration of a biogas power generation system. The process begins with population initialization, where a set of initial solutions (chromosomes) is randomly generated with predetermined parameters such as gas pressure, valve positions, and power distribution across the three load combinations [18]. Each individual in the population is then evaluated using a fitness function, which indicates the solution's success based on parameters such as the amount of energy generated, methane utilization, and the ability to meet load requirements. Selection is then performed to identify the best solutions, which are subsequently replicated through the crossover mechanism—the combination of two chromosomes to produce a new one. This is followed by a mutation process, where random changes are made to a small portion of the genetic values to prevent getting stuck in local optima. The results of the new crossover and mutation are then re-evaluated. If neither of the two termination criteria is met—whether the maximum number of generations or the conversion of an unstable solution—the process proceeds to the next cycle. Once the optimal configuration is found, the real-world system is configured, and the GA process concludes [19].

2.4. Sensor Performance Test Planning

System testing was conducted to evaluate the accuracy and reliability of the sensors in measuring environmental parameters in grain storage. This testing involved comparing sensor readings with those from reference instruments to determine the error rates and accuracy of each sensor. Measurement accuracy was calculated using the following formula [20]:

$$Accuracy = \left(\frac{ReferenceValue - SensorValue}{ReferenceValue} \right) \times 100\% \quad (1)$$

This formula indicates the degree of closeness between the sensor's measurement results and the reference value, expressed as a percentage. The higher the accuracy value obtained, the better the sensor's performance in providing precise data. This testing includes a thermocouple temperature sensor compared to a digital thermometer, a Wisner WPT83G pressure sensor compared to a pressure gauge, and a PZEM sensor compared to a multimeter.

2.5. Data Collection Methods

Data collection in this study was conducted using several approaches aimed at obtaining accurate and relevant information regarding the optimization of biogas power plants and Internet of Things-based monitoring systems. One of the methods used was a literature review, which involved examining and analyzing various scientific references related to the research topic. These sources include scientific journals, books, conference proceedings, and research articles from reputable institutions. Through this literature review, the researcher can understand the basic concepts of biogas power plants, optimization methods that have been used previously, and various challenges that may arise in the implementation of technology-based energy monitoring and optimization systems.

In addition to a literature review, data collection was also conducted through consultations and field observations. Consultations were held with the supervising lecturer as well as staff and field supervisors at the Kendari City Slaughterhouse to obtain the information needed for the study, such as data on cattle weight and the number of cattle slaughtered each day. Meanwhile, observations were conducted directly at the research site to understand the actual conditions of the environment to be monitored. These observation activities included monitoring the average weight of incoming cattle, machine operating times at the slaughterhouse, total electricity consumption in the surrounding area, and various challenges that might be encountered in implementing a Biogas Power Plant system. By combining these methods, the data collected is expected to support a more comprehensive analysis and system design process.

3. RESULTS AND DISCUSSION

3.1. Design of an Internet of Things-Based Monitoring System for a Biogas Power Plant

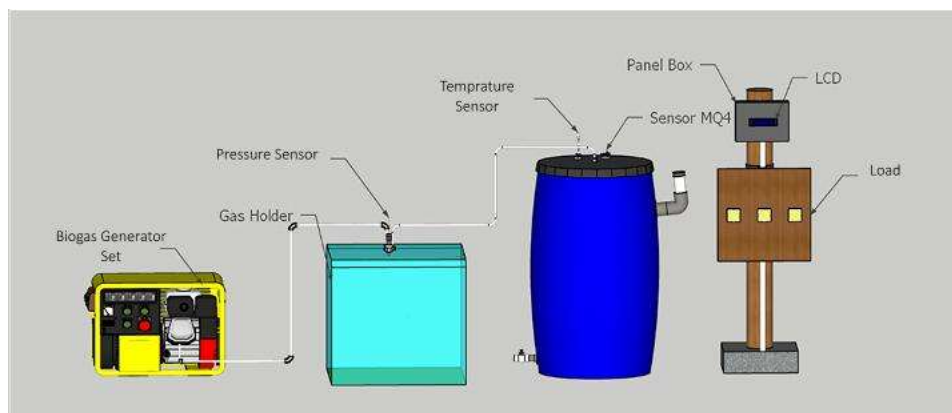


Figure 4. Visual Representation of The Proposed Biogas Power Generation System

Figure 4 shows a visual representation of the prototype design for the proposed biogas power generation system. This system integrates the process of converting organic waste into

electrical energy through several interconnected main components. These include a digester, a gas holder, a biogas generator set, a control panel, a load, and several sensors installed within the system.

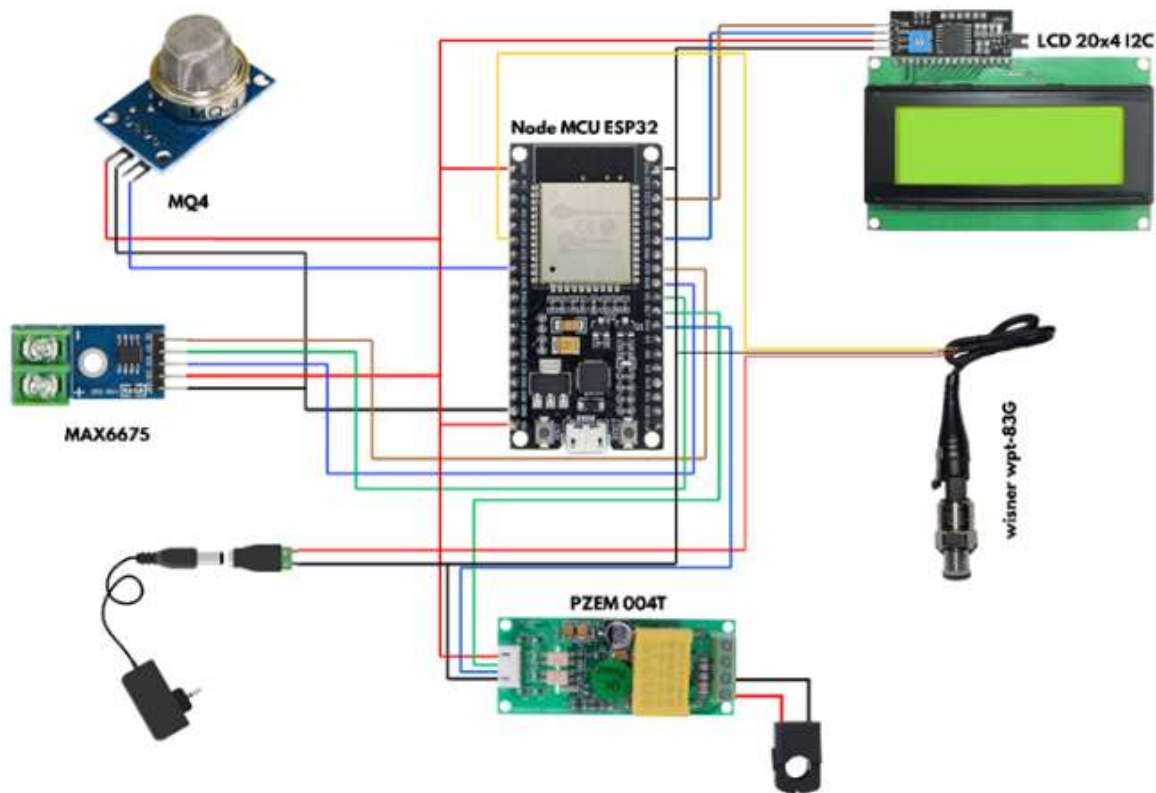


Figure 5. Wiring Diagram of The Monitoring System

In **Figure 5**, based on the wiring diagram shown, this monitoring system draws power from the mains electrical grid, which is converted to DC voltage via an adapter to serve as the primary power source for the ESP32 microcontroller, sensors, and other supporting devices. All components share the same ground to ensure circuit stability. This system utilizes several sensors to monitor key parameters in the biogas plant, such as the MQ-4 sensor to detect methane (CH₄) concentration from the digester fermentation process, a Type-K thermocouple connected to the MAX6675 module to measure digester temperature via SPI communication, and the WPT-83G pressure sensor to measure gas pressure in the biogas bag. Additionally, the PZEM-004T module is used to monitor electrical parameters such as voltage, current, and power at the generator's output to the load via TX and RX serial communication with the ESP32 and a CT current sensor. The readings from all sensors are displayed locally via a 20×4 I2C-based LCD connected to the SDA and SCL pins, while the acquired data is also transmitted by the ESP32 via a WiFi network to a MySQL database so it can be monitored in real-time via a website.

3.2. Evaluation

Table 1. Testing voltage with a multimeter

No	Voltage Measurement Results (V)		Error Value (%)	Accuracy (%)
	PZEM Sensor	Multimeter		
1	11.80	11.92	1.01	98.99
2	11.83	11.96	1.09	98.91
3	11.91	12.04	1.08	98.92
4	12.17	12.32	1.22	98.78
5	12.24	12.37	1.05	98.95
Average Error (%)			1.09	
Average Accuracy (%)			98.91	

Table 1 shows the results of the voltage comparison between the multimeter and the PZEM-004T sensor was conducted five times, yielding an average error of 1.09% and an average voltage reading accuracy of 98.91%, indicating that the sensor performs very well in measuring voltage and comes very close to the actual value.

Table 2. Testing current values with a multimeter

No	Current Measurement Results (A)		Error Value (%)	Accuracy (%)
	PZEM Sensor	Multimeter		
1	1.18	1.12	5.09	94.91
2	0.8	0.76	5.26	94.74
3	0.89	0.78	14.10	85.90
4	0.93	0.88	5.68	94.32
5	0.91	0.8	13.75	86.25
Average Error (%)			8.78	
Average Accuracy (%)			91.22	

Table 2 shows the result of the current comparison between the multimeter and the INA219 sensor was performed five times, yielding an average error of 8.78% and an average current reading accuracy of 91.2%, indicating that the sensor performs very well in measuring current and comes very close to the actual value.

Table 3. MQ4 sensor response test results

Gas Exposure Duration	Gas Concentration Reading MQ-4 Sensor (ppm)
1 Minute	4273.20
	4262.20
	4284.30
	4328.60
	4339.80
Average	4404,73

Table 3 shows the results of a 1-minute test of the MQ-4 methane sensor in the digester, methane gas concentration readings ranged from 4262.20 to 4557.20 ppm, with an average of 4404.73 ppm. This average value was used as the baseline methane concentration under normal digester conditions.

Table 4. Testing the WPT-83G sensor with a pressure gauge

No	Pressure Measurement Results (BAR)		Error Value (%)	Accuracy (%)
	SWPT-83G Sensor	Pressure Gauge		
1	1,01	1	1,0	99,0
2	2,03	2	1,5	99,5
3	3,02	3	0,7	99,3
4	5,03	5	0,6	99,4
5	7,05	7	0,7	99,3
Average Error (%)			0,90	
Average Accuracy (%)			99,1	

Table 4 shows a comparison of pressure readings between the WPT-83G sensor and a pressure gauge was conducted on five samples, yielding an average error of 0.90% and an average pressure reading accuracy of 99.1%. These results indicate that the sensor effectively measures pressure within a chamber and closely approximates the actual value.

3.3. Analysis of Energy Management Optimization Using Algorithms

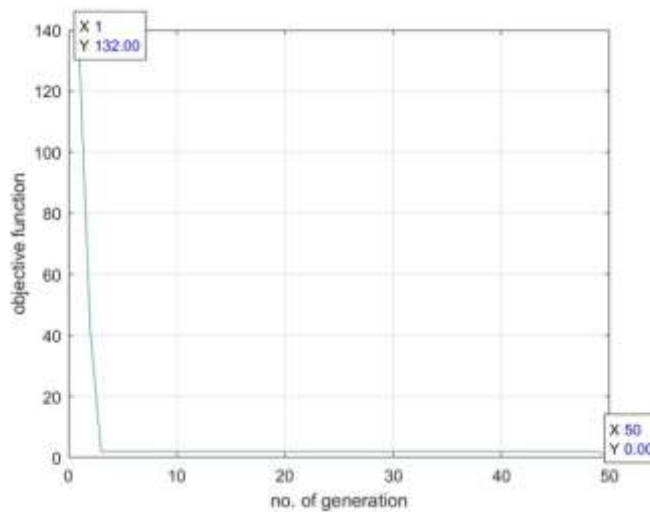


Figure 6. Optimization Results for Run 2

Based on the results of the GA optimization simulation from **Figure 6**, the best chromosome percentages were 61, 100, and 89 in the 50th generation, and validation was performed over 0 iterations. In the second simulation run, the best chromosome percentages were 61, 100, and 89.

$$400 A + 500 B + 400 C = 1100$$

$$400 (61\%) + 500 (100\%) + 400 (89\%) = 1100$$

$$244 + 500 + 356 = 1100 W$$

The resulting combination is: Load A = 244 W; Load B = 500 W; Load C = 356 W.

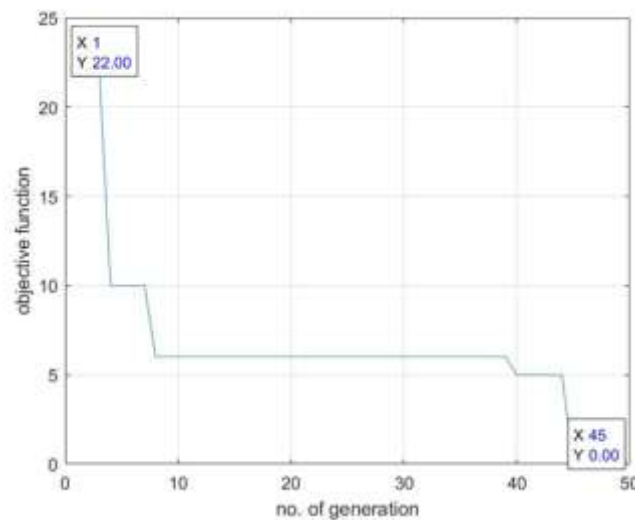


Figure 7. Optimization Results for Run 5

Based on the results of the GA optimization simulation from **Figure 7**, the best chromosome percentages were 78, 80, and 97 in the 39th generation, and validation was performed over 5 iterations. In the fifth simulation run, the best chromosome percentages were 78, 80, and 97

$$400 A + 500 B + 400 C = 1100$$

$$400 (78\%) + 500 (80\%) + 400 (97\%) = 1100$$

$$312 + 400 + 388 = 1100 \text{ W}$$

The resulting combination is load A = 312 W, load B = 400 W, load C = 388 W.

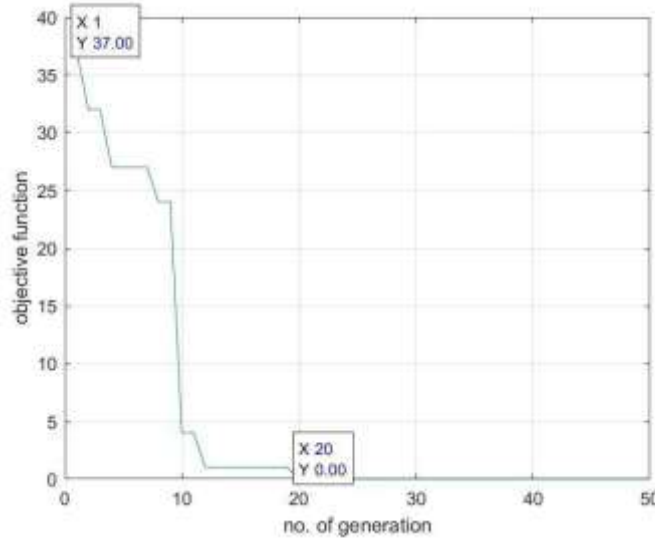


Figure 8. Top Optimization Results 3

Based on the results of the GA optimization simulation from **Figure 8**, the best chromosome percentages were 84, 76, and 96 in the 20th generation, and validation was performed over 30 iterations. In the first simulation run, the best chromosome percentages were 84, 76, and 96

$$400 A + 500 B + 400 C = 1100$$

$$400 (84\%) + 500 (76\%) + 400 (96\%) = 1100$$

$$336 + 380 + 384 = 1100 \text{ W}$$

The resulting combination is load A = 336 W, load B = 380 W, load C = 384 W.

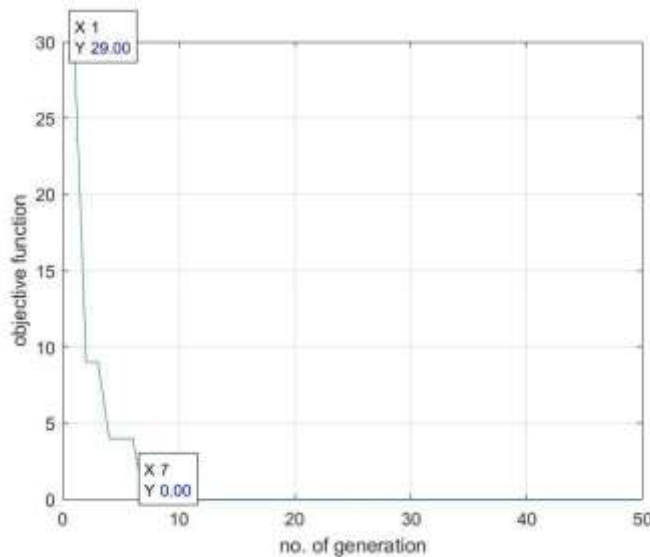


Figure 9. Top optimization results 4

Based on the results of the GA optimization simulation from **Figure 9**, the best chromosome percentages were 96, 64, and 99 in the 7th generation, and validation was performed over 93 iterations. In the third program run, the best chromosome percentages were 96, 64, and 99

$$400 A + 500 B + 400 C = 1100$$

$$400 (96\%) + 500 (64\%) + 400 (99\%) = 1100$$

$$384 + 320 + 396 = 1100 \text{ W}$$

The resulting combination is load A = 384 W, load B = 320 W, load C = 396 W.

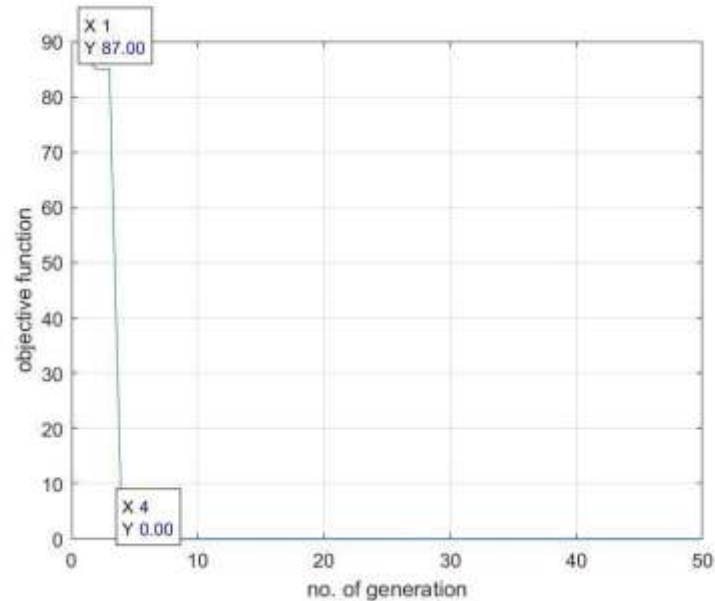


Figure 10. Top optimization results 5

Based on the results of the GA optimization simulation from **Figure 10**, the best chromosome percentages were 98, 66, and 97 in the 4th generation, and validation was performed over 96 iterations. In the first program run, the best chromosome percentages were 98, 66, and 97

$$400 A + 500 B + 400 C = 1100$$

$$400 (98\%) + 500 (66\%) + 400 (97\%) = 1100$$

$$392 + 330 + 388 = 1100 \text{ W}$$

The resulting combination is load A = 392 W; load B = 330 W; load C = 388 W.

3.4. Prototype Load Supply Combination

Table 5. Results of the genetic algorithm prototype simulation

Load	Supply Percentage (%)	Maximum Power (W)
Load A	89 %	20 W
Load B	60 %	5 W
Load C	100 %	10 W
Total		35 W

Table 5 shows that the optimization results show that the Genetic Algorithm successfully identified the optimal load-supply combination. In this combination, Load A is supplied at 89%, Load B at 60%, and Load C at 100%. This combination yields a total power of 26W. This condition still meets the system’s operational limits since the value remains below the power plant’s maximum capacity of 35W. The percentage results of the optimization are then transmitted from MATLAB to the ESP32 microcontroller via serial communication, processed

into load control logic displayed on the LCD, and sent to the monitoring website. Thus, the system can monitor the results of the Genetic Algorithm optimization in real-time, demonstrating that this method is capable of providing an efficient power supply control solution for a PLTBG system with multiple load groups.

3.5. Data Collection

Data collection was conducted using a 1:2:2 ratio (feces:water:rumen) in a 120-liter digester. Samples were collected every hour for a total of 8 hours over a 15-day period, specifically from December 1 to 15, 2025. From this series of tests, a total of 120 data points were obtained, each reflecting the temperature, gas presence, gas pressure, voltage, and current during the testing period.

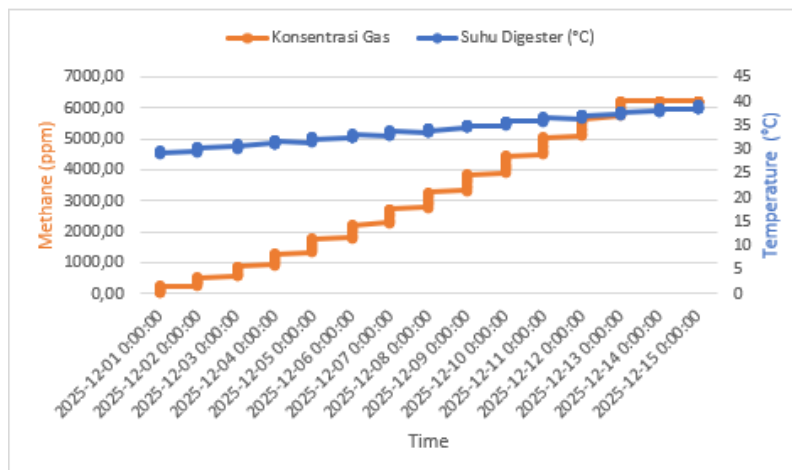


Figure 11. Correlation Between Methane Concentration and Digester Temperature

Figure 11 graph shows a positive correlation between methane production and temperature. As methane gas production increases, the temperature within the system also tends to rise. The anaerobic processes occurring within the digester across all treatments took place within a temperature range of ± 29 °C to 39 °C, known as the mesophilic range. This temperature range is considered optimal for the activity of biogas-producing microorganisms, although various literature sources offer differing views regarding the ideal temperature for maximum biogas production.

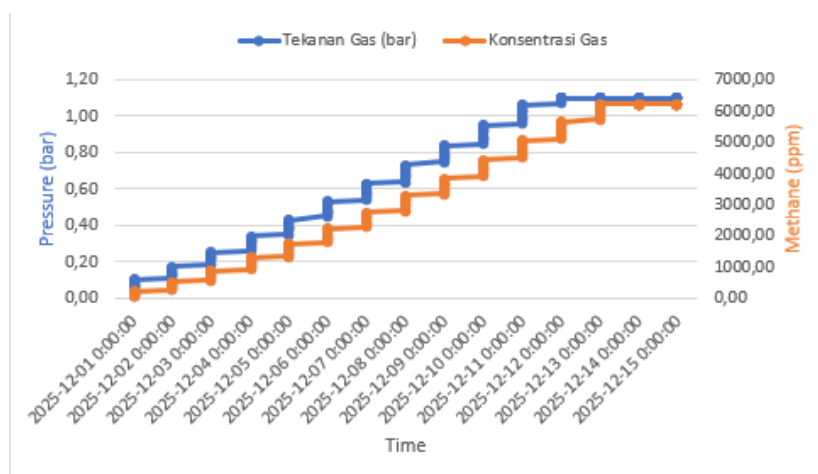


Figure 12. Correlation Between Gas Pressure and Methane Concentration

The **Figure 12** graph shows that pressure has a positive correlation with methane production. As methane production in the biodigester increases, pressure also rises slightly, although this does not significantly affect the course of the anaerobic process. This increase in pressure reflects the accumulation of methane produced by the ongoing anaerobic fermentation process. Therefore, pressure is considered one of the key parameters in assessing the success of the biogas production process.

4. CONCLUSION

Based on the results of testing and research conducted on the optimization and monitoring of biogas power plants using Genetic Algorithms and the Internet of Things, it can be concluded that an Internet of Things (IoT)-based biogas power plant monitoring system can be effectively designed and utilized to monitor parameters such as gas pressure, temperature, methane content, and electrical parameters in real time. Additionally, this system can display measurement data remotely, which facilitates the monitoring and supervision of system performance. On the other hand, the energy management system in the biogas power plant is capable of effectively regulating the power supply combination to loads A, B, and C in accordance with the plant's capacity. The use of Genetic Algorithms to calculate the supply percentage for each load yields good results, where the total power generated can approach the plant's capacity of 1.1 kW without causing an overload condition. Consequently, the resulting load supply combination is in an optimal state, and the designed energy management system is capable of maximizing power utilization from the plant. In addition, the results of testing the Internet of Things-based monitoring system indicate that all major components function properly, although there are some limitations with certain sensors that may affect measurement accuracy; however, overall, the designed system has met the research objectives and can be used to monitor and manage an IoT-based biogas power plant. Furthermore, the optimization process conducted using the Genetic Algorithm showed that the best fitness values improved in quality with each generation until optimal conditions were reached when the total power supplied approached the maximum generator capacity.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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