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Design and Optimization of a Smart IoT-Integrated Bioreactor for Enhanced Biogas Production Using Multi-Algorithm Modelling Approaches

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Abstract

The growing global demand for clean and sustainable energy sources has intensified interest in biogas as a renewable alternative to fossil fuels. However, conventional biogas production systems often suffer from inefficiencies due to poor process monitoring and limited control mechanisms. This study focuses on the design, construction and optimization of a smart Internet of Things (IoT) system couple with anaerobic digestion (AD) bioreactor for improved biogas production and real time monitoring. Embedded sensors; temperature (DS18B20), carbon dioxide (MQ135), and methane (MQ4) were incorporated into the bioreactor connected to Thing-Speak IoT network for continuous visualization, remote system diagnostic and data acquisition. Three optimization schemes; Nelder-Mead Simplex Direct Search (NMSDS), Genetic Algorithm (GA) and Sequential Quadratic Programming (SQP) were employed for optimum biogas generation, dynamic parameter identification and predictive modelling of the bioreactor performance. Between this evaluated algorithm, the NMSDS scheme shows the best prediction accuracy with objective function (J) and mean absolute error (MAE) value of 93.577 and 0.098 respectively, illustrating its performance in capturing the non-linear behavior of the AD system, while its average standard error of prediction (SEP) and standard error of calibration (SEC) attained by the system are 0.0155 and 0.010 respectively. The operational efficiency, predictive capability and stability of AD process enhanced significantly with the integration of smart IoT monitoring system and advanced modelling.

Keywords: *model parameters identification, biogas improvement, hybrid optimization, renewable energy, methane monitoring, smart IoT AD bioreactor.*

1. Introduction

The increasing demand of world energy, combine with the environmental issues of fossil fuel dependency, leads to the request of renewable, more sustainable and cleaner energy substitutions. As the emissions of greenhouse gas heave and conventional energy supply decline, the conversion of clean energy technologies is not extensive an option but vital for energy safety and environmental protection (Holechek et al., 2022; Brede et al., 2013). Amongst these technologies, the AD process of organic waste to produced biogas, a product of bioenergy offers a dual benefit: waste management and renewable energy production (Shukla et al., 2024; Upadhyay et al., 2023). In many developing countries, energy shortage remains a persistent problem where urban and rural areas are still deeply dependent on non-renewable biomass and firewood. This practice promotes indoor air pollution and deforestation, intensifying both public health risk and ecological degradation (Odubo et al., 2019). AD technology offers a path to transform organic waste into clean energy, thus addressing energy shortage while contributing to circular economy principle (Falcone, 2023). AD is a microbial process that breakdowns organic materials in the absence of oxygen to produce biogas, mainly constitute of CH_4 and CO_2. (Mohammed et al., 2020). AD process is increasingly utilized for the treatment of animal waste, municipal waste, food waste and agricultural waste (Dima et al., 2020).

In spite of its economic and environmental potential, the extensive installation of AD technology is stuck by unstable microbial communities, operational inadequacies and lack of monitoring systems, specifically in minor and middle scale application (Daniyan et al., 2019). The traditional AD process is frequently designed without smart or real time monitoring system. This results to the followings challenge; process uncertainty and unfluctuating system failure due to unrestrained distinctions in volatile fatty acid accumulation, organic loading rate, pH and temperature, and also low biogas production (Madsen et al., 2011; Shaba et al., 2020). Additionally, conventional AD system depends on practical policymaking and physical data gathering which are insufficient for capturing complex non-linear behaviors of the AD process. Moreover, most current AD dynamic model, particularly the AD Model No. 1 (ADM1), however, it is robust, entail large parameters identification and fail to gather real time data for predictive analytic. It also frequently assumes even microbial communities, disregard active environmental fluctuation and microbial heterogeneity (Holubar et al., 2002; Rocha et al., 2024).

While several researchers have explored either bioreactor design or biogas modelling, the integration of real-time smart monitoring with multi-algorithm predictive modelling in a low-cost, scalable AD system remains underexplored. The lack of accessible, automated systems that combine IoT technologies with data-driven optimization models represents a significant gap in achieving reliable, decentralized bioenergy production. The objectives of this study focus on; (i) design and construction of an AD bioreactor for biogas production. (ii) To incorporate smart IoT on the bioreactor by integrating temperature (DS18B20) and gas (MQ135 and MQ4) sensor. (iii) To connect the smart IoT bioreactor to a Thing-Speak platform for real time visualization and data acquisition. (iv) To estimate the model parameters of the Smart bioreactor by comparing three optimization algorithm NMSDS, GA and SQP to predict the performance of biogas production. This proposes study underscores the existing challenges of the traditional AD bioreactor by incorporating IoT-based smart scheme integrated with hybrid-optimization techniques as a scalable solution for data driven and decentralized systems of biogas production.

2. Materials and Method

2.1 Materials Used for Smart Bioreactor Construction.

The smart bioreactor was designed and constructed with both mechanical and electronic components. Key materials included: Mechanical parts: galvanized steel sheet (5 mm), stainless steel shaft and bolts, bearings, valves and pipe fittings, angle iron, rubber hoses, clips, and a tricycle tire tube (gas collector). Electronic and smart system parts: ESP32 microcontroller, MQ4 methane sensor, MQ135 CO_2 sensor, DS18B20 temperature sensor, LED display, power unit (AC/DC adapter and Li-ion battery), circuit board, MIFI module, and Thing-Speak IoT cloud interface. These components were selected for their robustness, corrosion resistance, ease of integration, and real-time data handling capabilities.

2.2 Bioreactor Design and Construction

2.2.1 Bioreactor Chamber Fabrication

The bioreactor was fabricated with an assume volumetric capacity of 100 L, using galvanized steel for corrosion resistance and thermal retention. The steps in construction included:

1. Guillotine cutting and rolling of steel sheets.
2. Welding of sheets into a cylindrical tank with a rectangular base and a domed head.
3. Installation of a Z-shaped 1.5 m gas pipe, base supports, and gas collection holder.
4. Integration of inlets for substrate feeding and outlets for digestate removal.

2.2.2 Design Parameters

i. Operating volume (V_o)

The operating volume of the bioreactor is simply the volume of slurry in the bioreactor. The operating volume of the bioreactor is 75 % of the total volume of the bioreactor capacity which was assume to be 100 liters. It is computer using Equation 1.

$$V_o = Q \times HRT \qquad (1)$$

Where;

Q: is the feed flow rate (m^3/day), and HRT: is the hydraulic retention time (Day)

ii. Height of bioreactor

Considering ergonomics factor for an average man height in Nigeria which is 1.7 m (Egbe et al., 2014). Therefore, the height of the bioreactor (H_b) developed was 1m for convenient usage and operation which was computed using Equation 2.

$$\left(H_b \times \frac{1}{3}\right) - H_b \qquad (2)$$

iii. Thickness of the bioreactor

The thickness of the bioreactor is designed based on the volume and pressure of gas generated within the system. In accordance with Dalton’s Law, the total gas pressure in the digester (P) is equal to the sum of the partial pressures (p_i) of the individual gases present. These total pressure and partial pressure are calculated using Equation (3) and (4), and the corresponding bioreactor wall thickness is then determined using Equation (5).

$$P = \sum_{i=1}^{n} p_i \qquad (3)$$

$$p_i = \frac{m_i RT}{V} \qquad (4)$$

Where;

P is the partial pressure of biogas, N/mm^2, V is the volume of biogas, m^3, m_i is the mass of gas, kg, R is the specific gas constant and T is the temperature of the gas, K.

$$t = \frac{PR}{\sigma\eta - 0.6P} \qquad (5)$$

Where: R is the radius of digester (m); σ is the shear stress of mild steel plate (N/mm^2); Ƞ is the joint efficiency; t is the thickness of the cylindrical bioreactor wall (mm) and P is the maximum internal pressure of gas in the digester (N/mm^2).

Anaerobic digestion flourishes the most at pressures below 1.2×10 5 Pa and a further increment of the pressure will cause the digestion process to cease. Thus, the design of the digester tank was made to tolerate digestion activities at a pressure of 1.2 bar. Using a Factor of Safety (FOS) of 5, a maximum design pressure P calculated as 3.6 bar (360 kPa) was utilized. The internal radius of the tank is 0.1005 m and joint efficiency of weld, Ƞ is 0.8. The maximum tensile strength of galvanized steel is between 550-750 MPa (Costa et al., 2019), and the shear stress was computer using equation 6, at a maximum tensile strength of 560 MPa.

$$\sigma = \frac{Maximum\ Tensile\ Strength}{FOS} \qquad (6)$$

2.4 Smart System Integration

The IoT monitoring system was built around the ESP32 microcontroller, which supports Wi-Fi and Bluetooth for real-time sensor data transmission to the cloud (Thing Speak platform). Key sensors included: MQ4 sensor: Detects CH_4 concentration (range: 2 – 100 ppm), MQ135 sensor: Monitors CO_2, and DS18B20 sensor: Measures substrate temperature (range: 28 °C to 50 °C). The system also included an LED indicator, a power switch, cloud backup via MIFI, and an SD card for offline storage (pandian et. al., 2021). A schematic of the smart control system is shown in Figure 1.

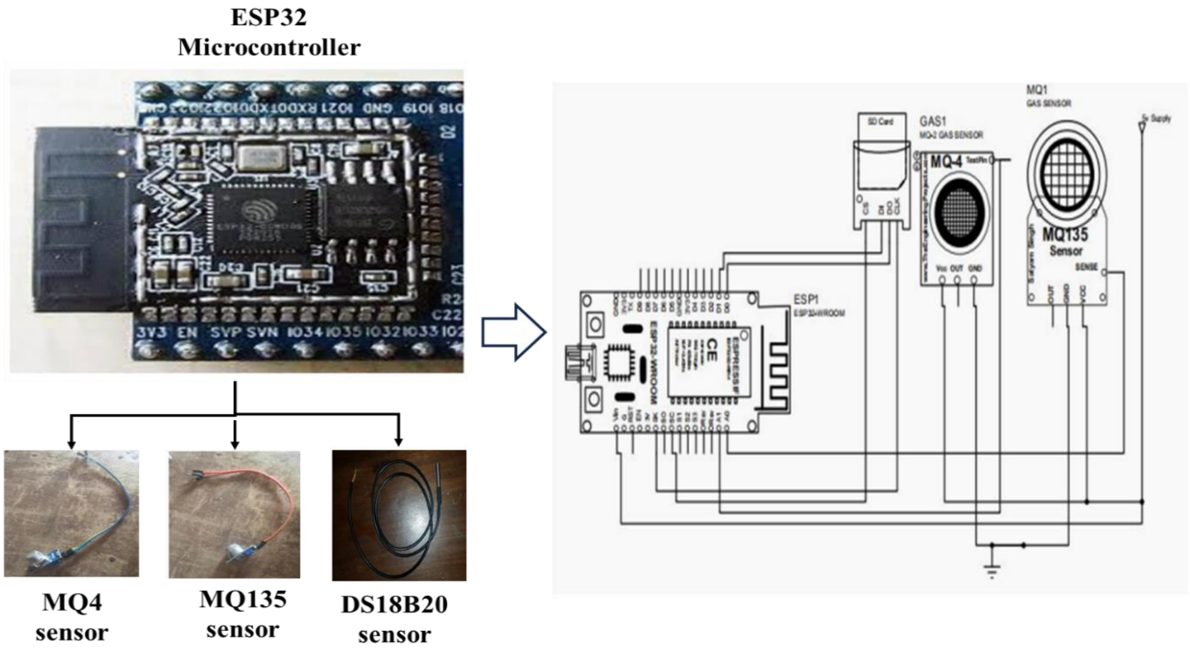

Figure 1: Schematic Proteus design of the Microcontroller

In this experiment the Smart IoT monitoring system for AD bioreactor to predict biogas generation is carried out experimentally in 100 L bioreactor. The methane, carbon-dioxide and temperature values are calibrated by the sensors and stored in the Thing-Speak server. Table 1 illustrations the minimum and maximum range of methane, carbon-dioxide and temperature in order to obtained a reliable result from the sensors as recommended by Pandian et al. (2021). A single bioreactor was adopted in this study to illustrate the initial performance and functionality of the Smart IoT scheme. This minimizes resources whereas confirming the design of the system works efficiently.

Table 1: Calibration Range of Methane, Carbon-dioxide and Temperature

S/N	Parameters	Values	
		Min ± Std	Max ± Std
1	Methane	2 ppm ± 0.5	200 ppm ± 0.5
2	Carbon-dioxide	2 ppm ± 0.25	100 ppm ± 0.25
3	Temperature	28 ^{O}C ± 5 ^{O}C	45 ^{O}C ± 5 ^{O}C

Std: Standard deviation

2.6 Feedstock Preparation and Bioreactor Loading

The rice husk used in this study was collected from the department of Federal university of Technology, Minna, Niger State. The rice husk was ground using a ball mill, then small portions were placed in bags. To prepare the feedstock, a portion of rice husk was mixed with paper to achieve a C/N ratio of ~40 to decrease inhibition by ammonia. Cow dung was then mixed with the ground rice husk at a mass ratio of 2:1. The prepared feedstock was then placed in a horizontal cylindrical bioreactor (effective volume 100 L) which was kept at ~ 40 °C and stirred frequently to allow degassing and to ensure that the feedstock was adequately mixed. The biogas that was generated was stored in a gas bag. Some digestate was collected when the feedstock was added and the remaining digestate (excluding the returned digestate) was treated as surplus. The volatile compound and total solid contents of the feedstock were ~20% and ~30%, respectively. The sludge in the reactor remained at the mesophilic temperature of 32 °C. (Shimizu et al., 2021)

2.7 Dynamic Modeling of the Bioreactor

A simplified dynamic model equation for anaerobic digestion process developed by Shaba *et al.* (2022) shown in Equation 8 were adopted to predict the process outputs (biogas generation), as well as to estimate the model parameters presented in Figure 7.

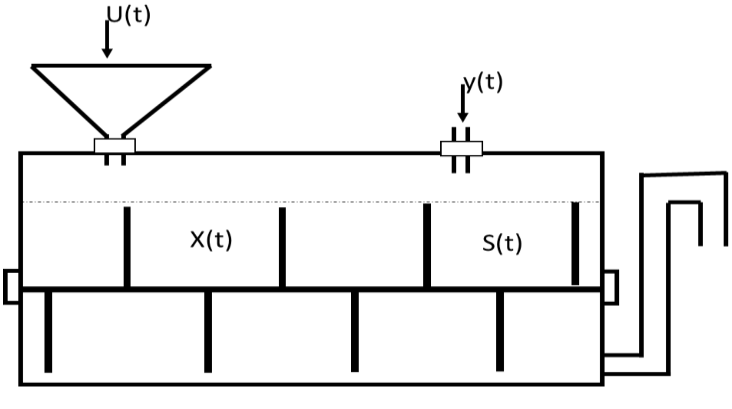

Figure 2: Bioreactor Modelling Diagram

$$\frac{dX(t)}{dt} = (\mu(s) - a)X(t)\left(1 - \frac{X(t)}{X_{max}}\right) + U_x(t) \tag{7}$$

$$\frac{dS(t)}{dt} = -\frac{1}{R}\mu(s)X(t) + U_s(t)$$

$$y(t) = \left(L_{k_1}\frac{1}{R}\mu(s) + L_{k_2}a\right)ZX(t) \tag{8}$$

where;

$$\mu(s) = \mu_{max} \cdot \frac{S(t)}{K_s + S(t) + bS^2(t)}$$

Where: X(t) is the bacterial concentration (kg/m^3), μ(s) is specific growth rate of the mixed population (days^{-1}), S(t) is initial concentration of substrate, mg/l, a is autolysis rate (s^{-1}), X_{max} is the bacteria-carrying capacity (kg/m^3), U_x is the bacteria input (kg/(m^3 h), U_s is the substrate input, R is the bacteria cell yield, K_s is the dissociation constant (kg/m^3), b is the inhibition coefficient, L_{k_1} and L_{k_2} are gas generation coefficients, μ_{max} is the maximum specific growth rate (h^{-1}), y(t) is the yield (g/L), Z is the sludge volume (m^3).

2.8 Optimization Techniques

Consequently, the model comprises seven parameters, which were estimated using the fourth-order Runge-Kutta method to solve the system of differential equations, based on defined initial conditions and a specified time step. In finding the set of design parameters, $x = \{x_1, x_2, ..., x_n\}$, optimization techniques were used, To solve this, a minimization or maximization of a predefined system characteristic, dependent on *x*, was considered. Constrained minimization is the problem of finding a vector *x* that is, a local minimum to a scalar function *J*(*x*) subject to constraints on the allowable *x* as presented in Equations 9 and 10.

$$\min_{x} J\ (x) \tag{9}$$

$$\sum_{i=1}^{k} \sum_{j=1}^{m} (Y_{ij} \ - \hat{Y}_{ij}\ )^2 \tag{10}$$

Where *x* is the vector of design parameters, *J*(*x*) is the objective function, *k* is the number of process variables, *m* is the number of data points, *Yij* represents the observed experimental data values, and $\hat{Y}_{ij}$ represents model predicted values. The parameter estimation process was further enhanced by incorporating three optimization techniques: SQP, NMSDS, and GA (Chorukova et al., 2022).

2.9 Model Performance

The model was validated using the experimental data obtained, and its predictive performance was evaluated by comparing the SEC and SEP. These evaluation metrics are defined in Equations (11) and (12), respectively.

$$\mathrm{SEC} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_{exp} - y_{model})^2} \tag{11}$$

$$\mathrm{SEP} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_{exp} - y_{model}) - (\bar{y}_{exp} - \bar{y}_{model})^2} \tag{12}$$

Where: y_{exp} is the average value of measured biogas yield (L/h), y_{model} is the average value of estimated biogas yield (L/h), while *N* is the number of data point.

3. Results and Discussion

3.1 Smart Bioreactor system Architecture

The smart bioreactor system was configured in three interconnected phases: from the bioreactor, to the microcontroller, and finally to the cloud storage, as illustrated in Figure 3.

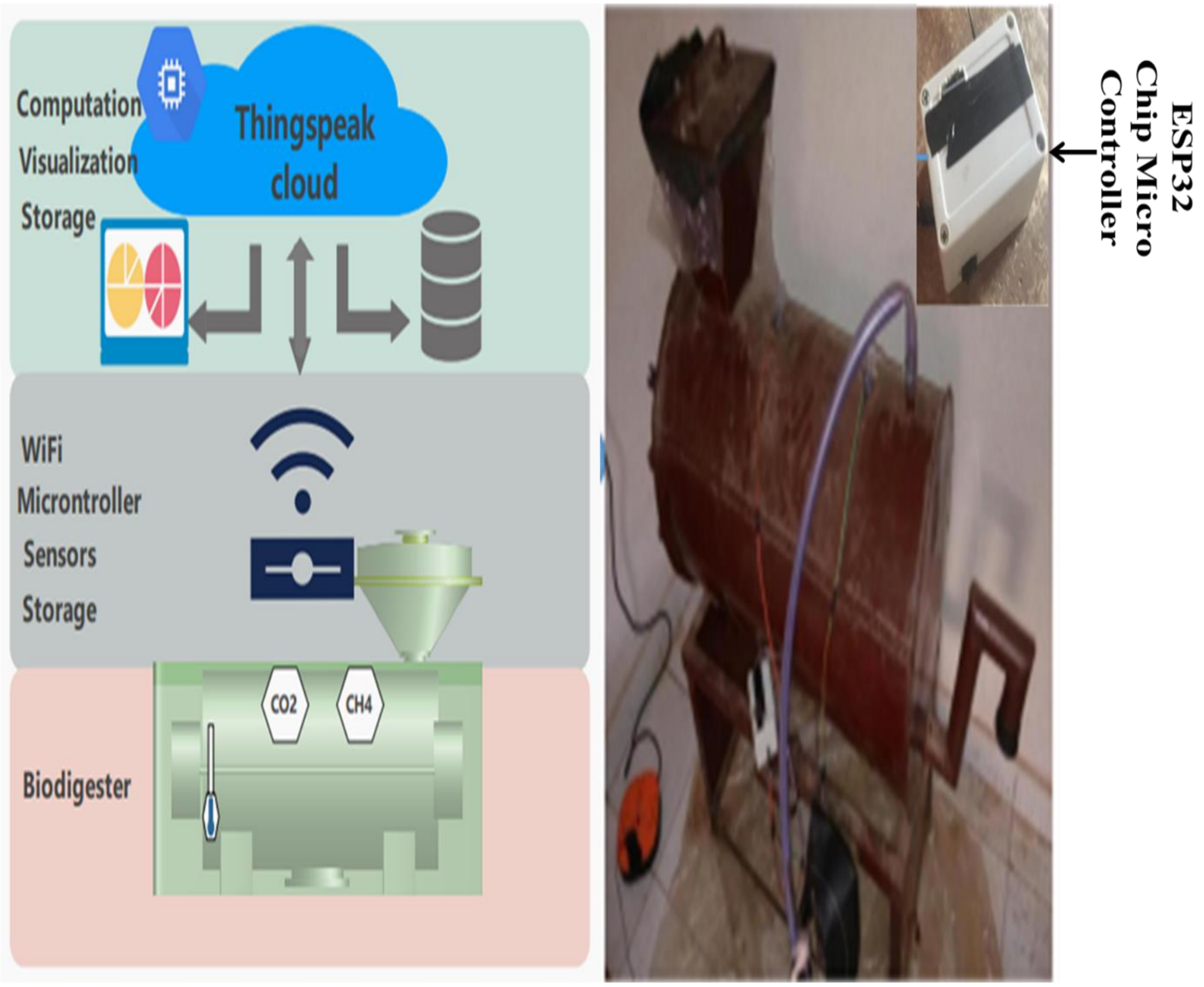

Figure 3: Illustrative mechanism of the smart bioreactor system

To enable real-time monitoring of parameters, the temperature sensor was embedded beneath the bioreactor chamber to track the internal operating temperature. Meanwhile, methane (CH_4) and carbon dioxide (CO_2) sensors were strategically mounted on the biodigester to detect and measure the concentration of biogas produced during anaerobic digestion. The measured gas concentration data are transmitted from the sensors to the ESP32 microcontroller, which serves as the central processing and communication unit. The microcontroller processes the incoming data and relays it in real time to the Thing Speak IoT cloud platform for visualization and monitoring (Figure 4). Simultaneously, the system performs a local data backup by writing the sensor readings to an SD card module, ensuring data redundancy and offline accessibility, as shown in Figure 1. The Thing-Speak channel displayed signal every 25 seconds which was assessed for temperature sensor, methane gas sensor and carbon-dioxide gas sensor values from the bioreactor, and was observed for three (3) months.

The temperature sensor of the bioreactor measured was between the ranges of 33 to 35 °C compared to the ambient temperature of 30 to 32 °C which indicate that the bioreactor is operating on mesophilic temperature range (Cruz, et al., 2021). The increase in temperature as a result of environmental conditions leads to the reduction of methane generation above the said range. These ranges are visualized in Thing-Speak platform, and helpful measure like heating, adding substrate or stirring process are perform to improve the methane generation.

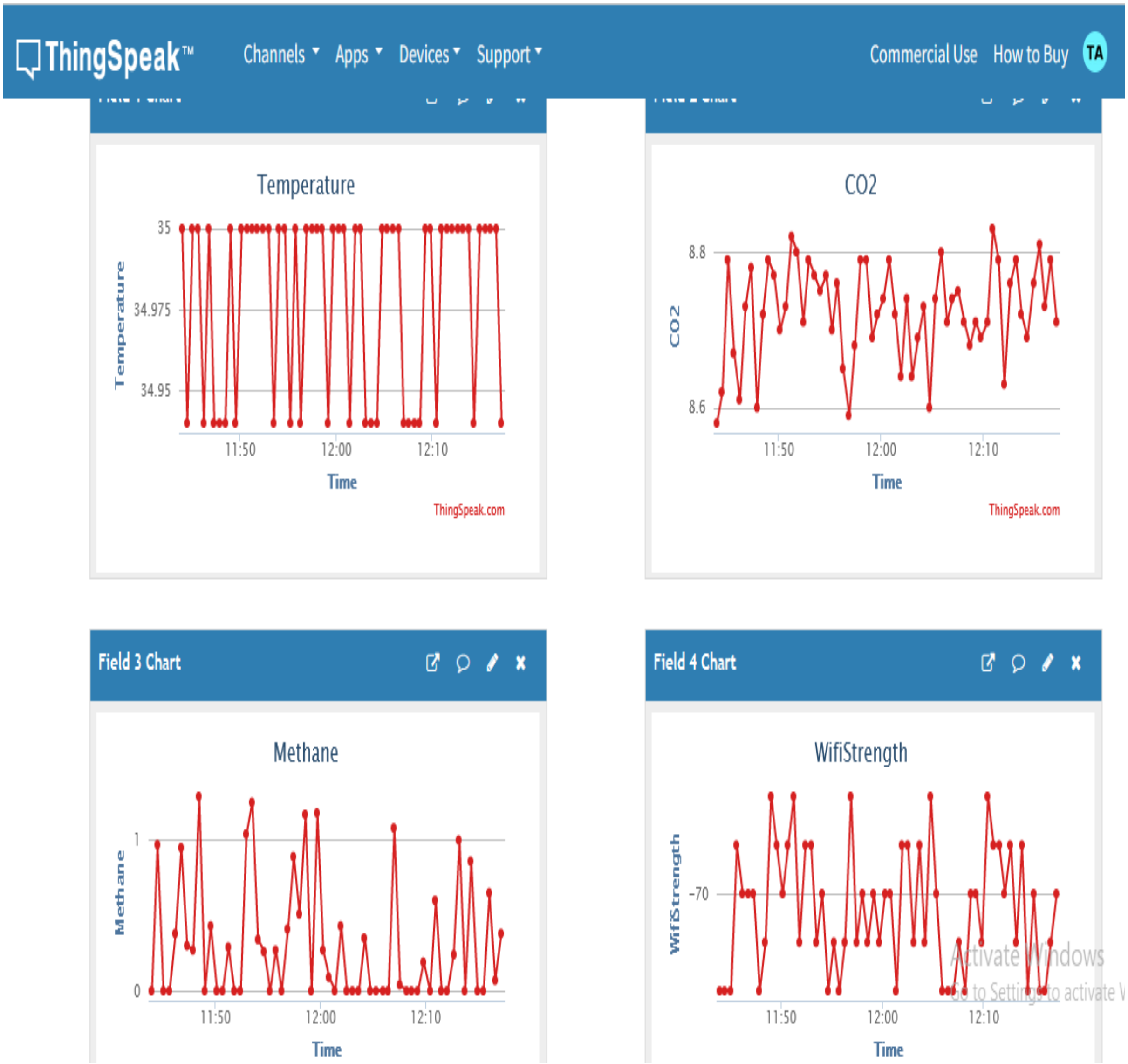

Figure 4: Thing-Speak Temperature, Methane, and Carbon-dioxide Signals

Figure 5 presents the experimental gas concentration profiles generated during anaerobic digestion in the smart bioreactor. Figure 5. (a) shows the methane concentration, which ranged from a minimum of 1.2 ppm to a maximum of 14 ppm, with a mean value of 3.6 ppm over the digestion period. The concentration increased steadily after the lag phase, indicating active methanogenesis. Figure 5 (b) illustrates the carbon dioxide concentration, starting at 3.5 ppm, peaking at 6.2 ppm, and averaging 4.2 ppm. The CO_2 profile reflects the acidogenic and acetogenic activities prior to methane dominance in the bioreactor. In Figure 5 (c), the total biogas concentration is plotted, which showed a cumulative gas output ranging from 3.8 ppm to 14.23 ppm, with a mean biogas yield of approximately 6.8 ppm.

The biogas curve closely aligns with the CH_4 and Co_2 trend, confirming Co_2 as the major component of the gas mixture produced. These concentration values validate the effectiveness of the bioreactor system and sensor integration for capturing gas dynamics during the digestion process (Shaba et al., 2022).

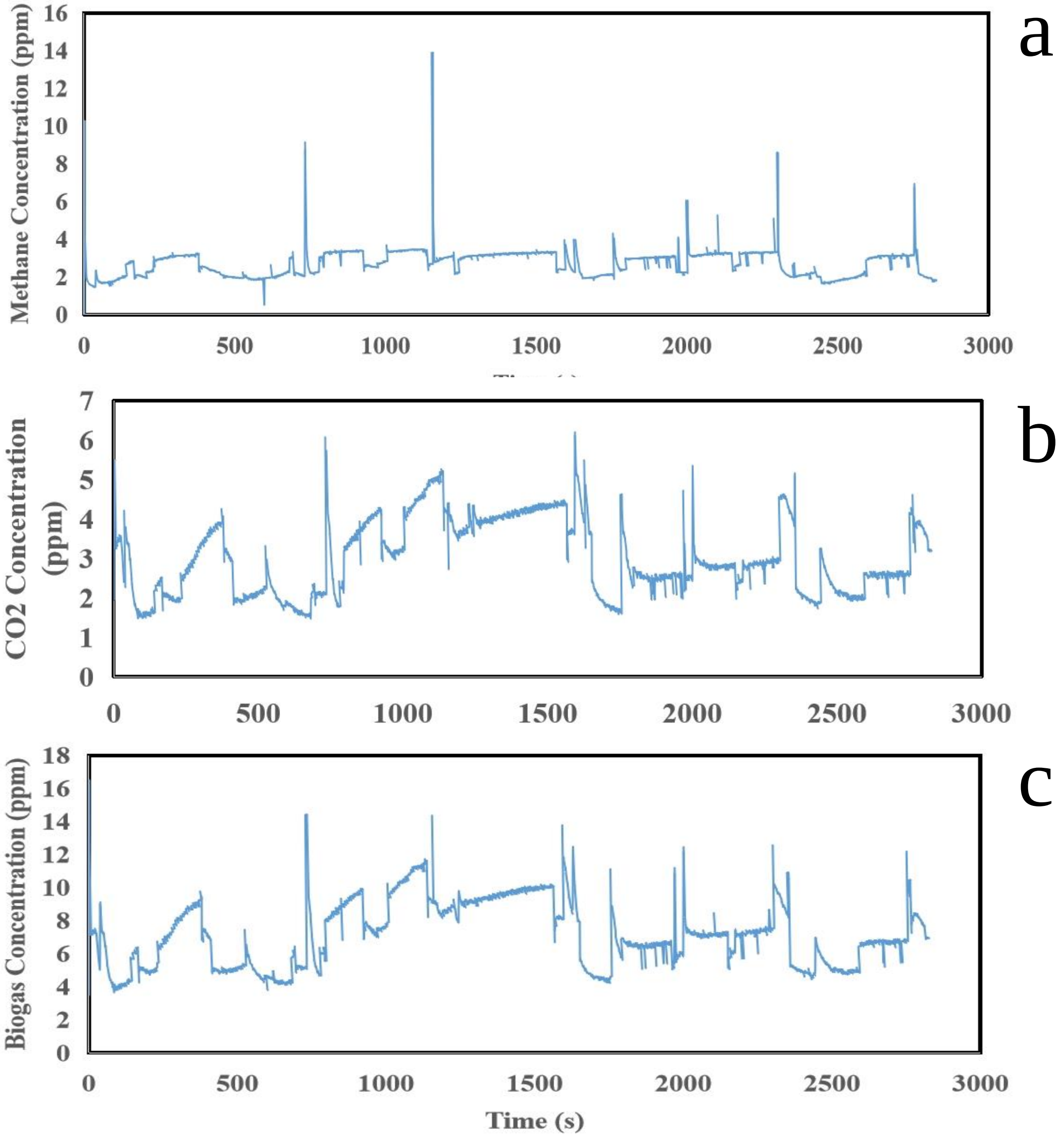

Figure 5: Experimental data generated (a) methane concentration, (b) carbon-dioxide concentration (c) biogas concentration (c)

3.2 Model Prediction Performance Comparison

Figure 6 presents a comparative analysis between the experimental biogas concentration data and the predicted outputs generated by three optimization-based models: NMSDS, SQP, and GA. The experimental data (Exp), plotted in black, exhibit a dynamic and fluctuating pattern throughout the reaction time, ranging from approximately 8.5 to 14.5 g/L. This variability reflects real-time microbial activity, feedstock conversion rates, and gas production dynamics within the bioreactor (Chorukova et al., 2022). Among the three models: The NMSDS model (blue curve) showed the closest alignment with the experimental data, maintaining a near-constant prediction in the 9.5–10.5 g/L range. Its stability and minimal deviation underscore the model's high fidelity in tracking actual biogas generation behavior.

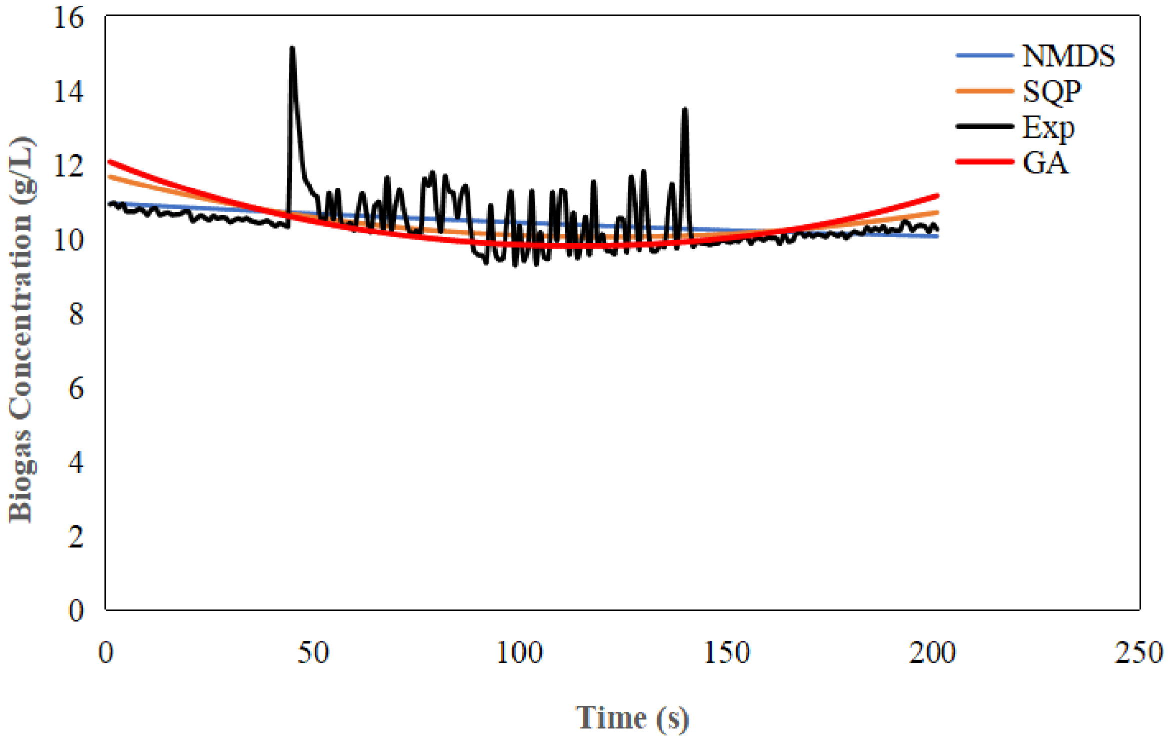

Figure 6: Comparison of experimental Biogas data and model prediction for SQP, NMSDS and GA

The SQP model (orange curve) demonstrated a parabolic trend, with an initial concentration of about 12 g/L, declining to approximately 9 g/L before increasing again. Although it captured the general magnitude of gas output, it diverged more significantly from the experimental profile, especially during the mid-phase. The GA model (red curve) displayed the greatest deviation from the experimental data, with predicted concentrations consistently ranging between 10.5 and 13 g/L. Its smoothed curve did not reflect the inherent fluctuations of the actual process, indicating reduced sensitivity to transient dynamics. This figure further supports the numerical results presented in Table 1, where the NMSDS model outperformed both SQP and GA in terms of lower J, MAE, SEC and SEP. A close fitting of the experimental gas dataset with the NMSDS scheme confirm its suitability and robustness to real time methane prediction in smart IoT AD bioreactor (Chorukova et al., 2022)

3.3 Model Parameter Identification and Performance Comparison

The performance evaluation of the individual scheme was based on the SEP, MAE, J and SEC, alongside with biological and kinetic parameters. Between the three schemes, NMSDS displayed the highest performance, with the minimum value of J which is 93.577, signifying a good predict to experimental dataset while that of the J values predict by SQP and GA, are 100.921 and 113.009 respectively. The MAE further confirmed the accuracy of NMSDS (0.098), compared to significantly higher values in GA (1.167) and SQP (10.463). In terms of predictive reliability, NMSDS also recorded the lowest SEC and SEP values at 0.0155 and 0.010, respectively, demonstrating its effectiveness in capturing system dynamics with minimal calibration and prediction errors. GA, on the other hand, showed the highest errors (SEC = 0.7899, SEP = 0.235), suggesting a lower capacity to replicate observed behavior accurately. SQP showed moderate performance with SEC = 0.146 and SEP = 0.097.

Table 1: Results from Model Parameter Identification based on SQP, GA, NMSDS

Parameters	Nelder-Mead Simplex Direct Search	Metaheuristic Algorithms	Determinant Algorithm
	NMSDS	**GA**	**SQP**
	Value	**Value**	**Value**
J	93.577	113.009	100.921
MAE	0.098	1.167	10.463
SEC	0.0155	0.7899	0.146
SEP	0.010	0.235	0.097
μ_{max}	0.20	0.25	0.189
b	0.004	0.023	0.01
W	12.391	9.281	14.999
Ks	16.820	14.409	14.999
a	0.133	0.090	0.098
L_{k_1}	0.338	0.492	0.5
L_{k_2}	0.0319	0.0453	0.05

The maximum specific growth rate (μ_{max}) ranged from 0.189 (SQP) to 0.25 (GA), with NMSDS at 0.20. The decay rate (b) was lowest for NMSDS (0.004), indicating reduced microbial washout compared to GA (0.023) and SQP (0.01). The highest results obtained by NMSDS scheme was 16.820 kg/m^3 for K_s, while that of SQP and GA are 14.999 kg/m^3 and 14.409 kg/m^3 respectively. This mean that 50 % of their maximum rate operate at methane producing archaea. The bacteria cell yield (R), gas generation constants (L_{k1} and L_{k2}) and inhibition coefficient (a) obtained are vary slightly between the optimization scheme, with NMSDS scheme having the most conservative estimates and biologically stability (Shimizu et al., 2022).

4. Conclusion

In this study a smart IoT AD bioreactor was effectively design and constructed for biogas generation, featuring a total volume of 100 L with an operating capacity of 75 L. This bioreactor was furnished with DS18B20, MQ135 and MQ4 sensors, which allowed data acquisition and real time monitoring through IoT network, making the bioreactor feasible for effective and decentralized biogas generation. Three optimization schemes were employed, based on the performance evaluation indices, NMSDS scheme verified to be the most fitted and consistent scheme for parameters Identification in this study. It reliably achieved over GA and SQP across all indices of evaluation (MAE, SEP, J and SEC), while estimating reasonable biologically parameters of the kinetic. SQP exhibit a modest performance while GA in spite of being a global optimization scheme, displayed the minimum promising result in this framework. Consequently, NMSDS scheme provide the best predictive accuracy, steadiness, and biological significance for smart IoT bioreactor modelling and can be suggested for real time predictive application in AD system. In future an active automatic system with IoT environmental platform coupled with advanced sensor to predict and analyze the biological parameters of the AD process to improve the scalability and prediction accuracy.

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