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ORIGINAL RESEARCH ARTICLE

Techno-Economic and Kinetic Modelling of Household-Scale Biogas Production from Domestic Organic Waste in Nigeria

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ABSTRACT
This study presents a comprehensive techno-economic and kinetic modelling analysis of household-scale biogas production from domestic organic waste in Nigeria. Anaerobic digestion experiments were conducted using potato, onion, and banana peels co-digested with cow dung in a 25 L fixed-dome digester under mesophilic conditions. A total of fifteen substrate (digester) combinations were evaluated, varying proportions of potato, onion, banana peels, and cow dung. All experiments were conducted in triplicate ($n = 3$) for each substrate combination to ensure reproducibility and statistical validity. Biogas production was monitored over 180 days, and system performance was evaluated using First-Order, Chen–Hashimoto, and Modified Gompertz kinetic models, alongside artificial neural network (ANN) modelling. Results showed that digester A2 achieved the highest cumulative biogas yield, exceeding 300,000 mL, indicating superior substrate synergy. Among the kinetic models, the Modified Gompertz model provided the best fit ($R^2 > 0.99$), accurately describing methane production dynamics, while ANN modelling demonstrated high predictive accuracy for biogas yield. Thermodynamic analysis revealed stable gas properties with heat capacity ratios ($\gamma \approx 1.33$), confirming consistent energy quality across digesters. Statistical analysis (ANOVA, $p < 0.05$) confirmed significant differences among substrate combinations, identifying high-performing digesters (G2, K2, L2). Techno-economic evaluation indicated strong feasibility, with a payback period of 1.8–3.5 years. Sensitivity analysis revealed that system profitability is highly dependent on biogas yield and energy utilization efficiency. Despite limitations related to scale and feedstock variability, the study demonstrates the viability of decentralized biogas systems for sustainable energy generation and waste management in Nigeria. The findings provide a validated, integrated framework combining experimental, modelling, and economic approaches, supporting the deployment of household-scale biogas technologies in developing regions.

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INTRODUCTION
Access to reliable and affordable energy remains a significant challenge in Nigeria, particularly in rural and peri-urban areas where dependence on fossil fuels and traditional biomass persists (Audu *et al.*, 2020; Elavarasan, 2019). At the same time, inefficient waste management practices result in the accumulation of biodegradable domestic waste, contributing to environmental pollution and public health concerns (Adeleke *et al.*, 2023).

Biogas production through anaerobic digestion provides a sustainable pathway for addressing both energy and waste challenges by converting organic materials into methane-rich fuel and nutrient-rich digestate (Deublein & Steinhauser, 2011; Khalid *et al.*, 2011). Domestic wastes such as potato, onion, and banana peels are particularly suitable due to their high biodegradability and carbohydrate content (Zhang *et al.*, 2014).

However, most existing studies in Nigeria have focused primarily on laboratory-scale biogas production or general feasibility assessments, with limited attention to integrated techno-economic evaluation under realistic household-scale conditions (Akinbomi *et al.*, 2014; Oyedepo, 2012). In addition, many modelling studies rely on established frameworks such as the Anaerobic Digestion Model No. 1 (ADM1) or empirical kinetic models, but these are often applied to large-scale or controlled systems and may not adequately capture the variability and operational constraints of small, locally fabricated digesters (Batstone *et al.*, 2002; Oduor *et al.*, 2022).

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While Artificial Neural Networks (ANN) and Modified Gompertz models have been widely used for predicting biogas production (Mougari *et al.*, 2021), their combined application is not novel in itself. However, there remains a specific gap in their application to household-scale digesters using locally sourced materials and mixed domestic waste streams under Nigerian environmental conditions, particularly when integrated with techno-economic evaluation.

Therefore, the key research gap addressed in this study is the lack of a context-specific, experimentally validated framework that combines digestion performance, predictive modelling, and economic feasibility for decentralized household biogas systems in Nigeria. This study aims to evaluate biogas production from selected domestic organic wastes under mesophilic conditions, apply kinetic models and Artificial Neural Network (ANN) techniques to predict biogas production dynamics, and assess the techno-economic feasibility of implementing household-scale biogas systems in Nigeria.

MATERIALS AND METHODS

2.1 Feedstock Collection and Preparation

Domestic organic wastes (potato, onion, and banana peels) were collected, sorted, washed, and chopped into 1–2 cm sizes to enhance microbial degradation. Cow dung obtained from a local abattoir was used as inoculum to supply methanogenic microorganisms and improve the carbon-to-nitrogen (C/N) ratio (Khalid *et al.*, 2011; Sun *et al.*, 2018). The substrates were mixed with water in a ratio of 1:2 (w/v) to form a homogeneous slurry.

2.2 Digester Design and Construction

A 25 L laboratory-scale fixed-dome anaerobic digester was fabricated using high-density polyethylene (HDPE) and PVC fittings. The system was operated under mesophilic conditions (29–38 °C), representative of ambient Nigerian environments (Akinbomi *et al.*, 2014). The design and configuration of the digester setup are illustrated in Figure 1, which shows the main components including the digestion chamber, gas outlet, slurry inlet, and effluent outlet, adapted from Kumar et al. (2020).

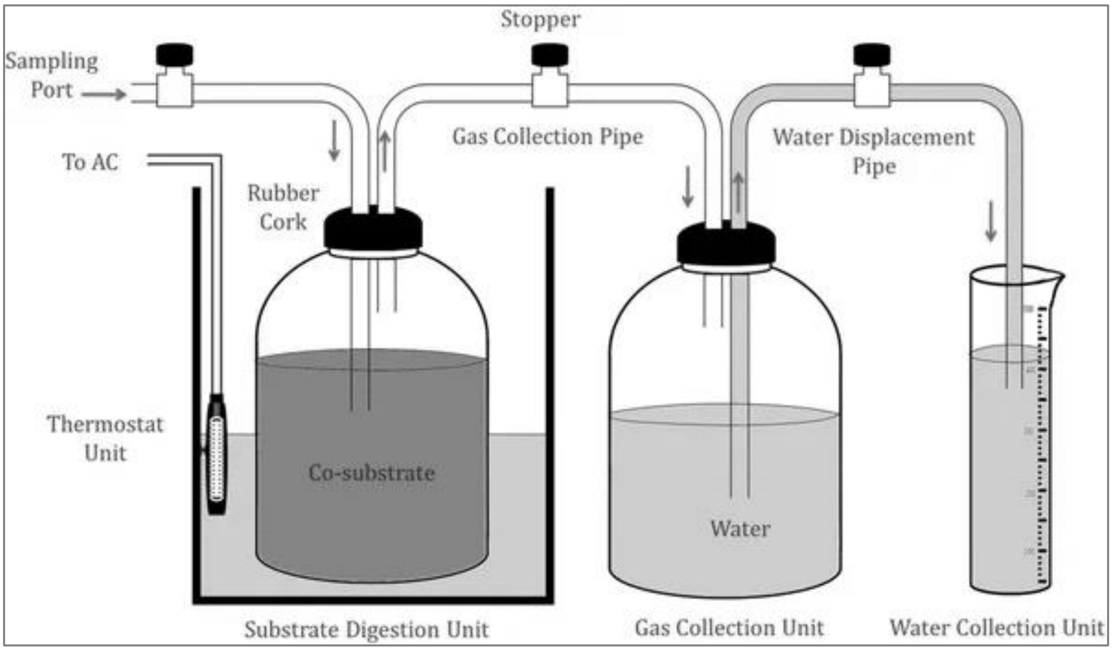

Figure 1 Schematic diagram of the digester setup (Kumar *et al.*, 2020)

2.3 Experimental Design and Operation

All experiments were conducted in triplicate (n = 3) for each substrate combination to ensure reproducibility and statistical validity. A total of fifteen substrates (digesters) combinations were evaluated, varying proportions of potato, onion, banana peels, and cow dung.

Semi-batch operation was defined as periodic feeding of fresh substrate at fixed intervals without complete removal of digestate, maintaining a constant working volume throughout the experiment. The digestion process lasted for up to 180 days.

The reactors were manually stirred once daily to prevent stratification and scum formation. Biogas production was measured using a calibrated water displacement method (Eaton *et al.*, 1995).

2.4 Modelling and Kinetic Analysis

2.4.1 Kinetic Models

To describe the rate of biogas generation and evaluate substrate degradation behaviour, three kinetic models were applied: the First-Order, Chen–Hashimoto, and Modified Gompertz models. These are widely used in anaerobic digestion studies because they capture both biochemical reaction rates and microbial growth dynamics (Batstone *et al.*, 2002; Oduor *et al.*, 2022).

i. First-Order Model

The First-Order model assumes that the degradation rate of volatile solids is proportional to the remaining biodegradable fraction (Lopes et al., 2018).

$$B_t = B_0 \times (1 - e^{-kt}) \qquad (1)$$

where

$B_t = cumulative\ biogas\ yield\ at\ time\ t\ (mL\ or\ m^3);$
$B_0 = ultimate\ biogas\ potential;$
$k = first - order\ rate\ constant\ (day^{-1}).$

This model is simple and suitable for homogeneous substrates with minimal mass-transfer limitation (El-Mashad & Zhang, 2010).

ii. Chen–Hashimoto Model

The Chen–Hashimoto model introduces microbial kinetics into the digestion rate by relating methane yield to the retention time and specific growth rate of methanogens (Chen & Hashimoto, 1980).

$$Y = \frac{Y_m}{1 + K\left(\frac{\mu_m \times \theta}{S_0} - 1\right)} \quad (2)$$

where

$Y = specific\ methane\ yield\ (m^3\ CH_4\ kg^{-1}\ VS);$
$Y_m = maximum\ methane\ yield;$
$\mu_m = maximum\ specific\ growth\ rate\ (day^{-1});$
$\theta = hydraulic\ retention\ time\ (day);$
$S_0 = substrate\ concentration (kgVSm^{-3});$
$K = model\ constant.$

This model effectively predicts digester performance over varying organic loading rates (Zhang *et al.*, 2014).

iii. Modified Gompertz Model

The Modified Gompertz model is an empirical representation of cumulative biogas production and is commonly used to estimate the lag phase (λ) and maximum production rate (R_m) (Lay *et al.*, 1997; Zwietering, 1990).

$$B(t) = P_m \times \exp\left(-\exp\left[\frac{R_m e}{P_m}(\lambda - t) + 1\right]\right) \quad (3)$$

where

$B(t) = cumulative\ biogas\ yield\ at\ time\ t\ (mL\ or\ m^3);$
$P_m = maximum\ biogas\ production\ potential;$
$R_m = maximum\ biogas\ production\ rate\ (mL\ day^{-1});$
$\lambda = lag\ phase\ period\ (day);$
$e = Euler's\ number\ (\approx 2.7183).$

Model parameters were estimated via nonlinear regression in MATLAB R2021a by minimizing the residual sum of squares (RSS), while the coefficient of determination (R^2) and root-mean-square error (RMSE) were used to evaluate model fit (Oduor *et al.*, 2022).

2.4.2 Artificial Neural Network (ANN) Modelling

A feedforward multilayer ANN model was developed using MATLAB R2021a to predict biogas production. Input variables included pH, temperature, TS, VS, and COD, while biogas yield was the output. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure model generalization and prevent overfitting. The model employed a tangent sigmoid activation function in the hidden layer and was trained using the Levenberg–Marquardt algorithm (Abiodun *et al.*, 2018). Model performance was evaluated using correlation coefficient (R), mean square error (MSE), and regression analysis between predicted and experimental values.

2.5 Techno-Economic Analysis

The techno-economic evaluation considered both capital and operational costs. Capital cost (₦85,000) included digester fabrication, while operational costs (~₦30,000/year) included maintenance and water usage.

Energy value was estimated using the equivalence:

1 m^3 biogas ≈ 6 kWh (Pavlas *et al.*, 2010).

Uncertainty in economic estimates was evaluated using ±15% variation in gas yield and energy utilization efficiency to reflect real household conditions**.** Payback period and annual savings were calculated accordingly.

2.6 Statistical and Error Analysis

All data were expressed as mean ± standard deviation (mean ± SD) from triplicate measurements. One-way ANOVA was performed at a 95% confidence level ($p < 0.05$) to assess significant differences among the fifteen substrate combinations (Digesters). To further identify specific group differences, Tukey's HSD post-hoc test was applied for pairwise comparisons, enabling classification of the substrate combinations into statistically distinct groups and clarifying which means differed significantly.

RESULTS AND DISCUSSION

3.1 Daily and Cumulative Biogas Production

The daily biogas production curves of digesters A2–O2 (Figure 2) demonstrate the temporal dynamics of anaerobic digestion over the 180-day period (plotted data available in Supplementary material as Table S1). Most digesters exhibited an initial lag phase during the first two to three weeks, reflecting microbial acclimatization to the feedstock. Peak production was observed between days 40 and 120, with digester A2 achieving the highest daily output of approximately 6000 mL. This superior performance suggests enhanced substrate biodegradability and favorable microbial interactions. Other digesters, such as B2 and C2, also showed strong peaks, while L2 and O2 produced lower but more sustained volumes. The decline in daily production after peak activity indicates substrate depletion and reduced microbial activity, a trend consistent with recent findings that highlight the importance of substrate quality and microbial resilience in sustaining biogas generation (Aworanti *et al.*, 2023).

The cumulative biogas production profiles (Figure 3) provide a broader perspective on digester efficiency (plotted data available in Supplementary material as Table S2). All digesters showed progressive increases in cumulative yield, though at varying rates. A2 again outperformed the others, surpassing 300,000 mL, followed closely by B2 and C2, confirming their superior long-term productivity. Moderate producers such as H2, I2, and L2 accumulated between 100,000 and 150,000 mL, reflecting slower degradation kinetics or less favorable feedstock properties. Toward the end of the digestion period, most cumulative curves plateaued, indicating near-complete substrate conversion and limited residual biogas potential. This stabilization phase aligns with recent reviews that emphasize the exhaustion of readily degradable organic matter as the limiting factor in long-term biogas yield (Alengebawy *et al.*, 2024).

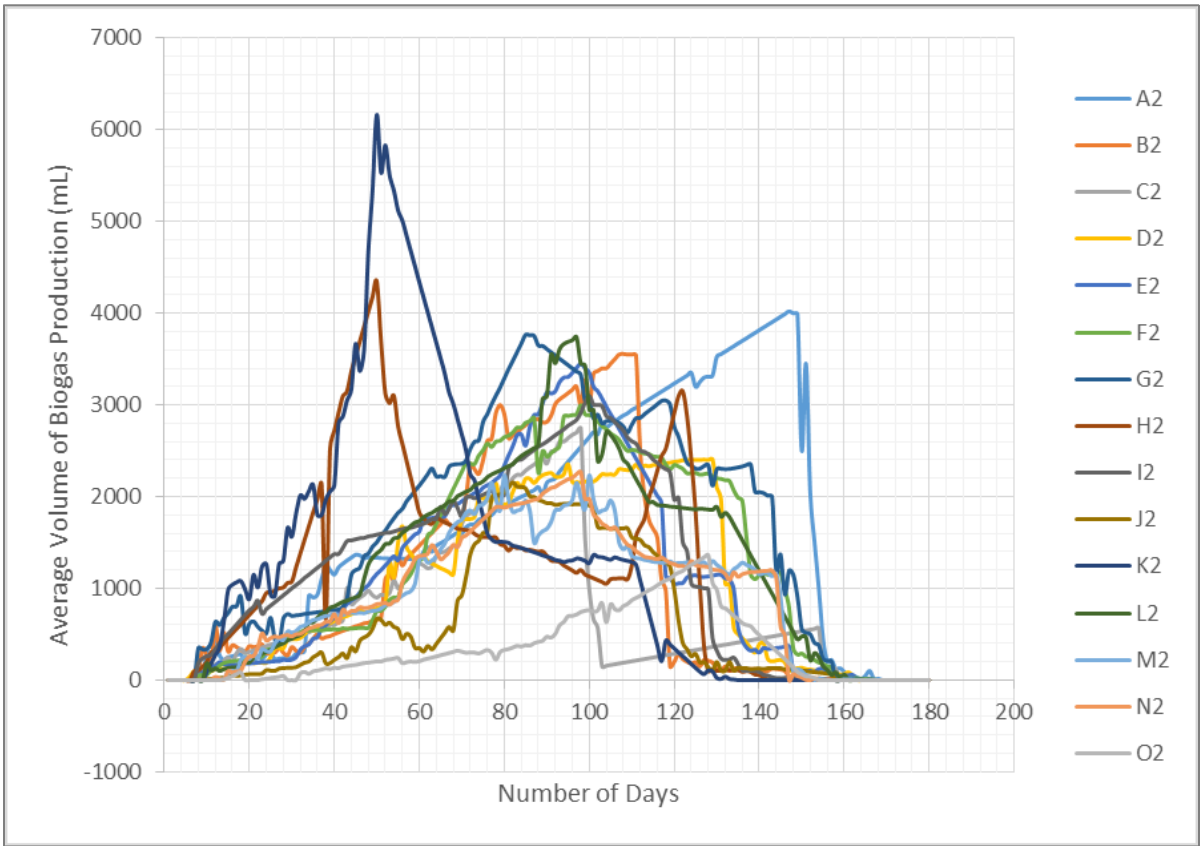

Figure 2 Daily biogas production curves of digesters A2–O2

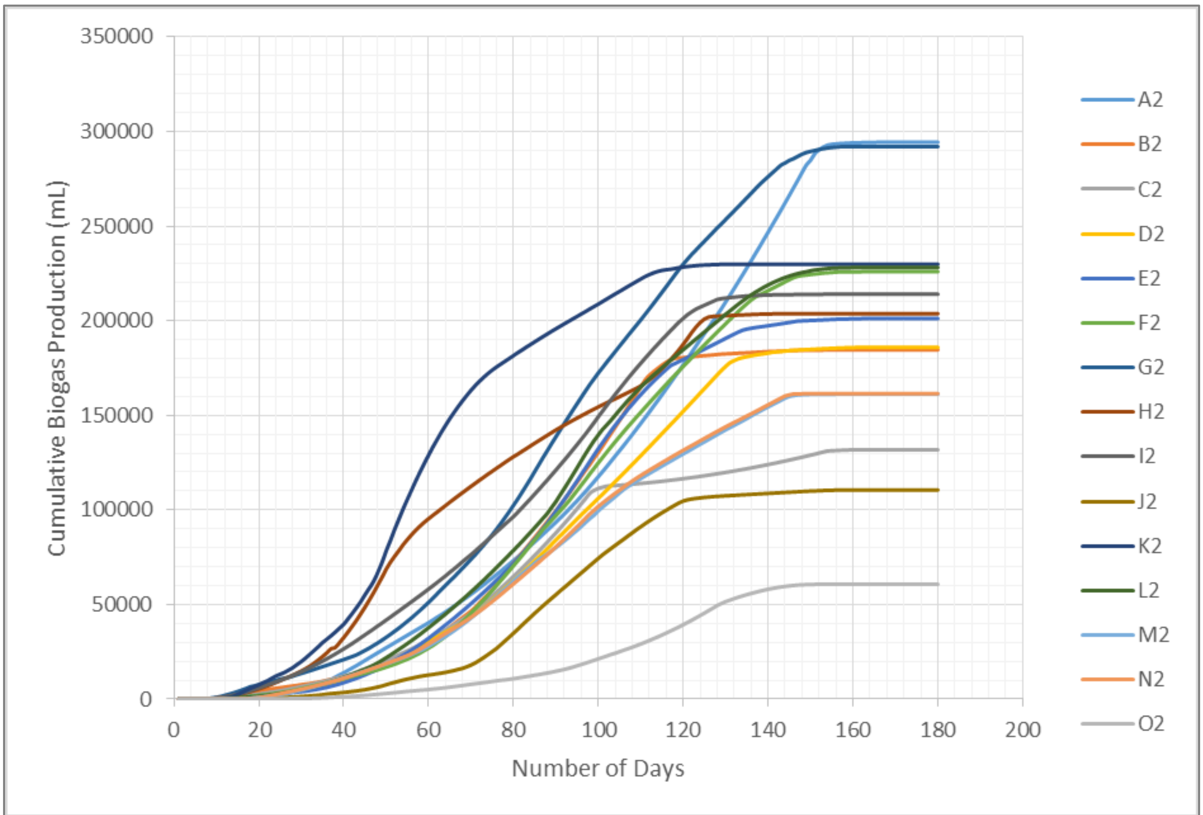

Figure 3 Cumulative biogas production profiles of digesters A2–O2 over the 180-day anaerobic digestion period

Table 1 Kinetic model parameters for cumulative biogas production

Digester	First-Order Model Parameters		Chen–Hashimoto Model			Modified Gompertz Model Parameters		
	B_0	K	Y_m	Kch	μ_m	Pm	Rm	λ
A2	59.05580	0.00000	0.00001339	0.968990	0.00000413	0.43090	0.00290	57.26790
B2	14.95030	0.00010	0.20000000	0.700000	0.10000000	0.19440	0.00320	55.85740
C2	30.27720	0.00000	0.00001468	0.999640	0.00000153	0.13500	0.00190	43.98200
D2	18.55870	0.00010	0.00001746	0.999676	0.00000144	0.20790	0.00240	52.76400
E2	18.18800	0.00010	0.00002082	0.999624	0.00000166	0.21450	0.00300	54.15970
F2	36.80490	0.00000	0.00002631	0.999530	0.00000213	0.25160	0.00290	55.82190
G2	62.85810	0.00000	0.00002970	0.999609	0.00000174	0.33250	0.00330	47.61500
H2	0.50980	0.00340	0.05000000	0.900000	0.01000000	0.21390	0.00240	25.59310
I2	14.28310	0.00010	0.00002451	0.999630	0.00000157	0.23690	0.00260	38.81490
J2	2.80960	0.00020	0.00001215	0.999592	0.00000181	0.11470	0.00210	62.95900
K2	0.36210	0.00710	0.44673300	8.734510	0.07293730	0.24430	0.00250	10.53870
L2	31.75170	0.00000	0.00001708	0.999601	0.00000174	0.25160	0.00280	51.19950
M2	8.32810	0.00010	0.44673300	8.734510	0.07293730	0.17900	0.00190	47.54320
N2	10.43450	0.00010	8.12700000	307.571000	0.04600000	0.17860	0.00190	47.79710
O2	0.90630	0.00040	0.00000640	0.999500	0.00000233	0.07110	0.00090	72.25370

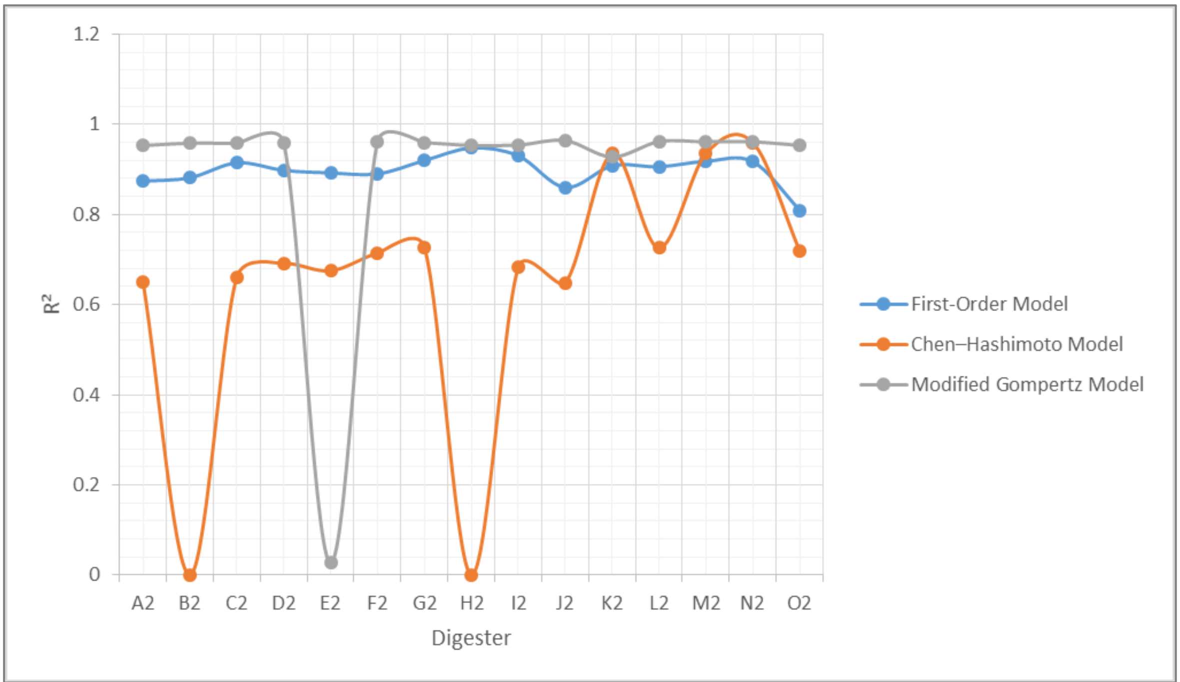

Figure 4 Comparison of experimental and fitted cumulative biogas production curves

Taken together, Figures 2 and 3 highlight the importance of evaluating both daily and cumulative production to fully understand digester performance. Digesters with sharp peaks but rapid declines may benefit from co-digestion or staged feeding strategies to sustain production, while those with steady but lower yields could be optimized through microbial consortia enhancement or nutrient supplementation. The consistent superiority of A2 suggests that substrate composition and microbial interactions were particularly favorable under its conditions. These findings underscore the need for tailored operational strategies to maximize both peak and sustained biogas production, ensuring efficiency across diverse feedstock (DelaVega-Quintero *et al.*, 2025).

3.2 Kinetic Modelling

The comparative evaluation of the **First-Order, Chen–Hashimoto, and Modified Gompertz models (**Table 1**)** across digesters A2–O2 revealed distinct differences in methane potential, microbial kinetics, and predictive accuracy.

The **First-Order Model** provided reasonable preliminary estimates of methane yield, with A2 (59.06 mL g^{-1} VS) and G2 (62.86 mL g^{-1} VS) recording the highest ultimate methane yields, indicating superior substrate biodegradability. However, its simplified assumption of a constant degradation rate limited its ability to adequately capture the dynamic phases of anaerobic digestion, particularly for heterogeneous substrates (Kythreotou *et al.*, 2014; Zahan *et al.*, 2018).

The **Chen–Hashimoto Model** offered mechanistic insights into microbial growth and substrate utilization. Most digesters showed Kch values close to 1, suggesting efficient substrate affinity, whereas K2/M2 (8.73) and N2 (307.57) indicated poor microbial substrate utilization and possible mass-transfer limitations. Similarly, the highest μ_m values were observed in B2 (0.10 d^{-1}) and K2/M2 (~0.073 d^{-1}), reflecting rapid microbial growth. Nevertheless, the model exhibited inconsistent R^2 values, particularly in B2 and H2, confirming its sensitivity to feedstock variability (Deepanraj *et al.*, 2015).

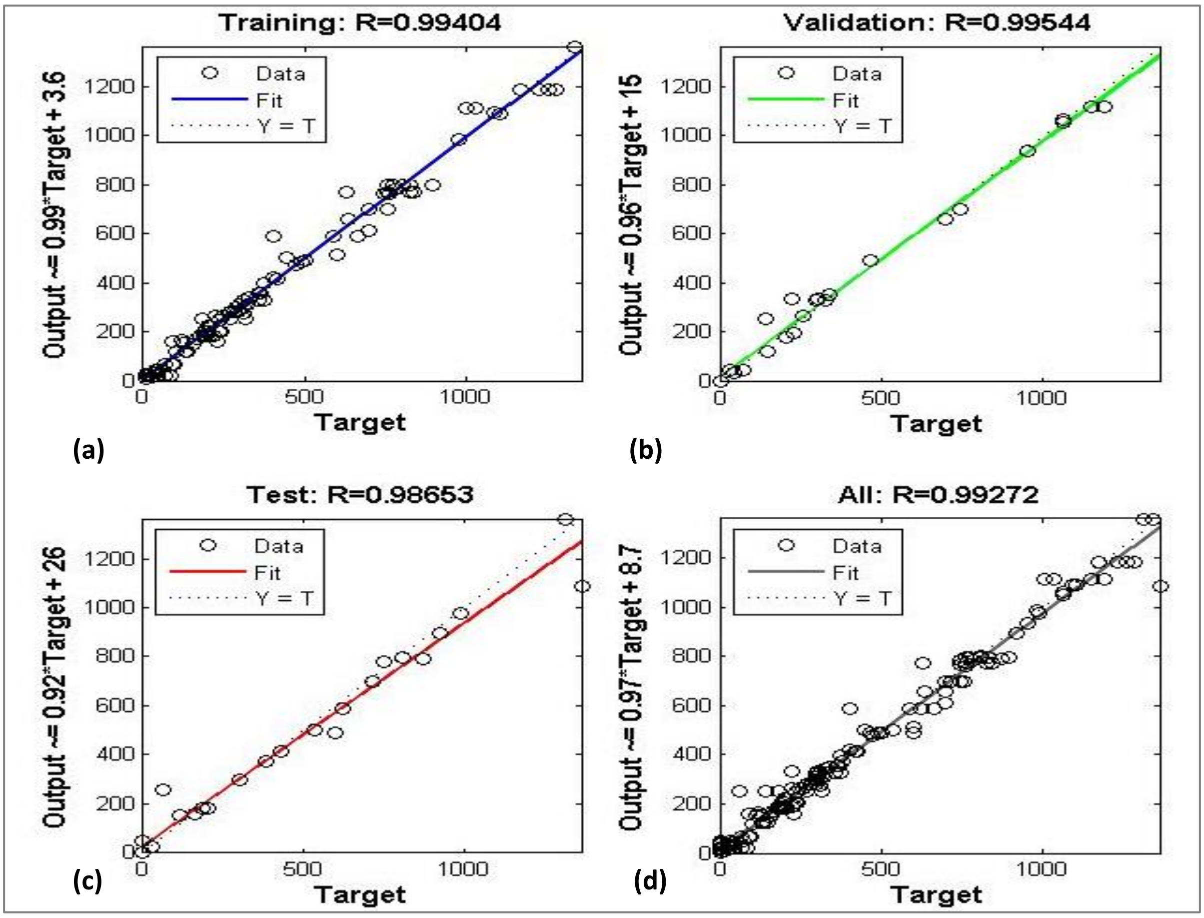

Figure 5 Regression Coefficient (R) (Training, Validation, Testing and all R) for the Neural Network Modeling (ANN) for Biogas Production of Digester O2

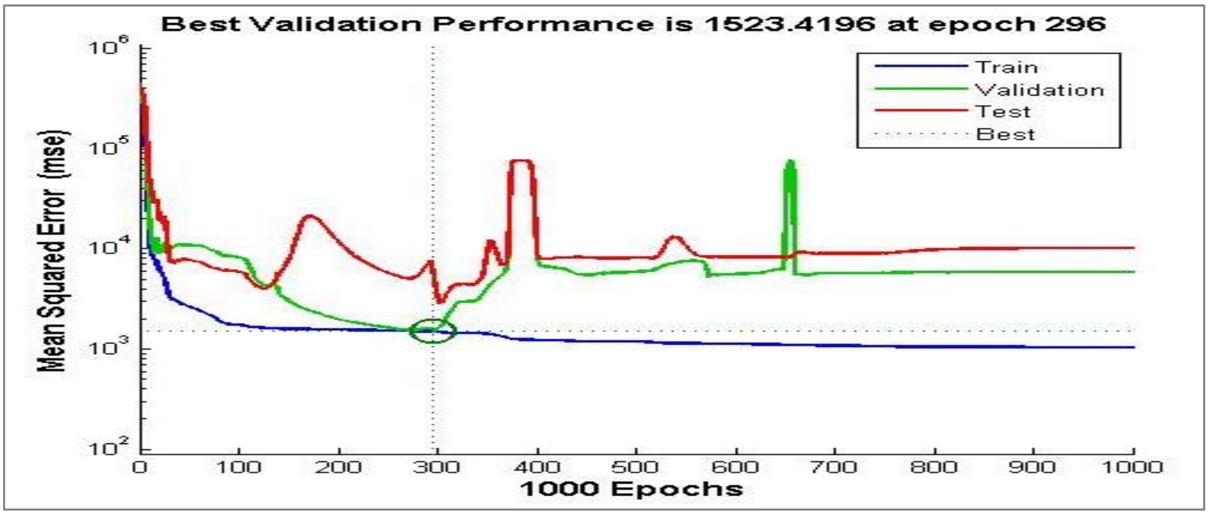

Figure 6 Performance Plot of the ANN Modeling of Biogas Production for Digester O2

The **Modified Gompertz Model** consistently produced the best fit and most realistic description of cumulative methane production, as illustrated in Figure 4**.** Higher methane potentials were observed in A2 (0.43 L g^{-1} VS) and G2 (0.33 L g^{-1} VS), while G2 also recorded the highest methane production rate (0.0033 L g^{-1} VS d^{-1}). The model effectively captured the lag phase, with O2 (72.25 days) and J2 (62.96 days) showing prolonged adaptation periods, compared with K2 (10.54 days), which adapted rapidly. These findings confirm the robustness of the Gompertz model in representing lag behaviour and methane production kinetics (Pramanik *et al.*, 2019; Zahan *et al.*, 2018).

Overall, the **Modified Gompertz Model outperformed** the First-Order and Chen–Hashimoto models, with consistently higher R^2 values (>0.99), indicating excellent agreement between observed and predicted methane yields. This supports previous studies identifying Gompertz-based models as the most reliable tools for forecasting methane production from heterogeneous organic substrates (Kythreotou *et al.*, 2014; Pramanik *et al.*, 2019).

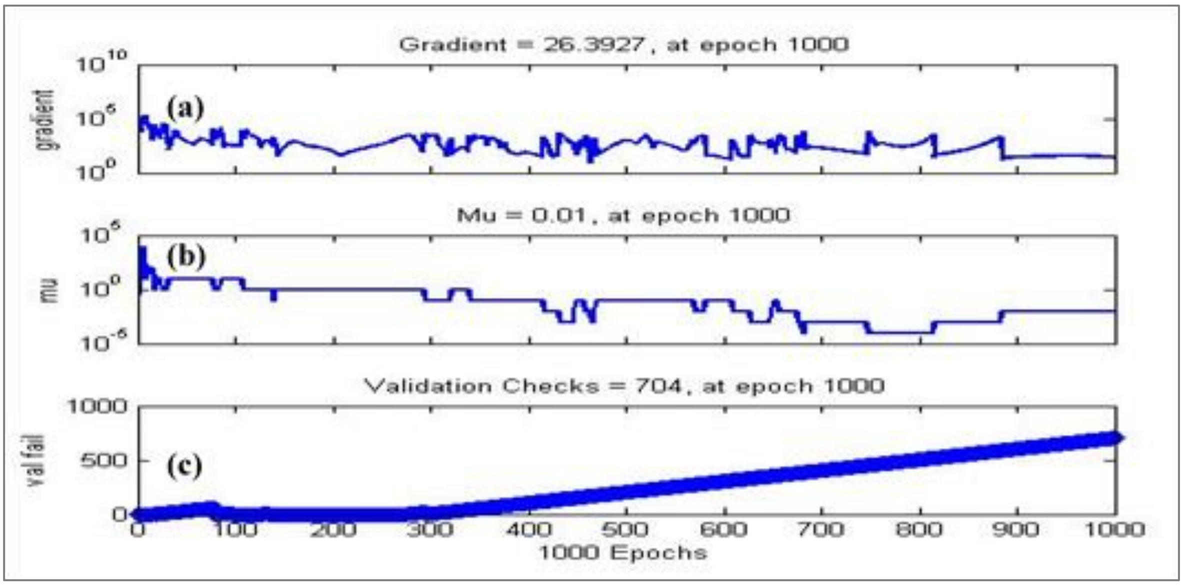

Figure 7 Gradient Plot of the ANN Modeling of Biogas Production for Digester O2

Table 2 Specific heat capacities at constant volume (Cv) and constant pressure (Cp), and heat capacity ratio (γ = Cp/Cv) for biogas from digesters A2–O2.

Digester	Cv(J kg⁻¹ K⁻¹)	Cp J kg⁻¹ K⁻¹	Cp/Cv (γ)
A2	1264.86	1686.48	1.33333
B2	1302.49	1736.65	1.33333
C2	1284.73	1712.97	1.33333
D2	1239.37	1652.49	1.33333
E2	1260.44	1680.59	1.33333
F2	1275.12	1700.16	1.33333
G2	1285.17	1713.56	1.33333
H2	1267.46	1689.95	1.33333
I2	1251.83	1669.11	1.33333
J2	1296.21	1728.27	1.33333
K2	1271.29	1695.05	1.33333
L2	1294.14	1725.52	1.33333
M2	1305.25	1740.33	1.33333
N2	1264.21	1685.61	1.33333
O2	1274.94	1699.92	1.33333

Table 1 **and** Figure 4 **together demonstrate** that the Modified Gompertz Model best described the anaerobic digestion process across digesters A2–O2 due to its superior fit quality and ability to capture both lag phase and methane production rates. The First-Order Model was useful for preliminary yield estimation, whereas the Chen–Hashimoto Model provided mechanistic insights into microbial kinetics but showed lower consistency. These findings further confirm that Gompertz-based modelling remains the most suitable framework for predicting methane production in heterogeneous feedstocks.

3.3 ANN Modelling

The artificial neural network (ANN) model achieved high predictive accuracy with a correlation coefficient of $R = 0.99$, confirming its ability to capture the nonlinear dynamics of anaerobic digestion. This level of precision demonstrates that ANN can effectively learn from experimental datasets, such as the daily biogas production values of digesters A2–O2, and predict biogas yields with minimal deviation from observed results. The model's performance highlights its robustness in handling complex interactions between substrate composition, microbial activity, and operational conditions. Figures 5, 6, and 7 present the regression coefficient (R) for the training, validation, testing, and overall dataset, the performance plot (MSE convergence), and the gradient plot of the artificial neural network (ANN) model for biogas production in Digester O2, respectively, illustrating the model's predictive accuracy, training performance, and optimization stability. For the remaining digesters, the corresponding ANN outputs can be accessed in the supplementary material.

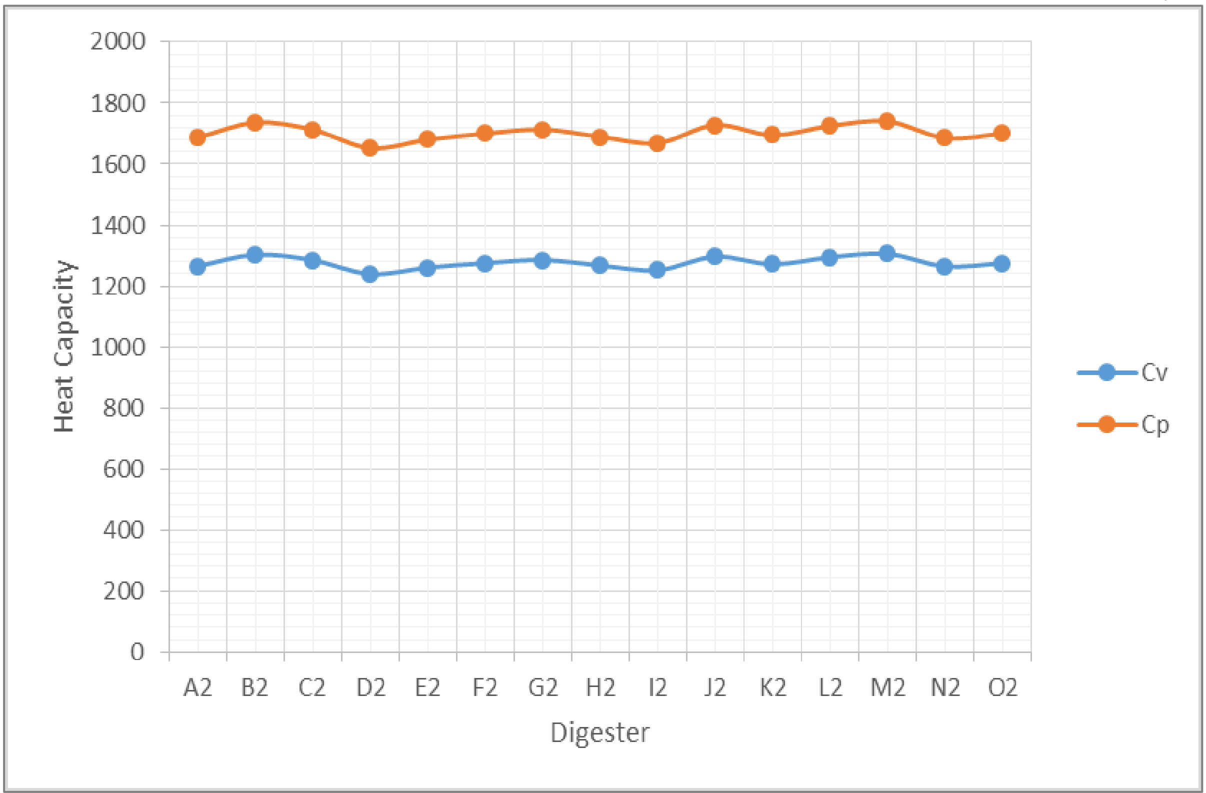

Figure 8 Variation of specific heat capacities at constant volume (Cv) and constant pressure (Cp) across digesters A2–O2.

Table 3 ANOVA Table

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.25E+08	14	23238724	38.11055	1.26E-85	1.70012
Within Groups	7.23E+08	1185	609771.4			
Total	1.05E+09	1199				

Based on ANOVA ($F = 38.11$, $p = 1.26\times10^{-85}$) and Tukey's HSD, the groups can be statistically organized into three performance tiers.

Table 4 Statistical Grouping Based on Tukey's HSD

Tier	**Groups**	**Mean Range (Approx.)**	**Statistical Characterization**
High-performance cluster	G2, K2, L2	~2100 – 2610	Significantly higher than most groups ($p < 0.05$), internally similar
Mid-performance cluster	A2, B2, D2, E2, F2, I2, M2, N2	~1200 – 1800	No significant differences within cluster; overlaps observed
Low-performance cluster	C2, O2	~450 – 1300	Significantly lower than all high-performing groups

Table 5: Sensitivity analysis of payback period and annual savings for household-scale biogas digesters (A2, G2, O2) under varying economic conditions

Variation (%)		**Payback (years)**			**Savings (₦)**	
	A2	**G2**	**O2**	**A2**	**G2**	**O2**
-15	0.345	0.288	0.092	246,377	295,833	923,913
-10	0.330	0.275	0.088	257,576	309,091	965,909
-5	0.315	0.263	0.084	269,841	323,190	1,011,905
0	0.300	0.250	0.080	283,333	340,000	1,062,500
+5	0.285	0.238	0.076	298,246	357,143	1,118,421
+10	0.270	0.225	0.072	314,815	377,778	1,180,556
+15	0.255	0.213	0.068	333,333	399,061	1,250,000

Recent studies have further validated the applicability of artificial neural network (ANN) approaches in biogas research. ANN-based predictive models have been shown to significantly outperform conventional regression methods in estimating methane yields from agricultural residues (Chen *et al.*, 2022). Similarly, hybrid ANN frameworks have been reported to improve digester stability and optimize feedstock composition, thereby enhancing overall process efficiency (Ling *et al.*, 2024).These documented outcomes are consistent with the present findings, which indicate that ANN modelling delivers reliable forecasts of biogas production dynamics, thereby providing a validated decision-support instrument for operational optimization. The high accuracy achieved here underscores the potential of ANN modelling as a predictive and optimization framework for anaerobic digestion systems. By integrating experimental data with machine learning, operators can anticipate production patterns, identify potential process instabilities, and design strategies to maximize cumulative yields.

3.4 Thermodynamic Analysis

As presented in Table 2 and Figure 8, the thermodynamic evaluation of biogas produced across digesters A2–O2 revealed relatively stable specific heat capacities at constant volume (Cv) and constant pressure (Cp), with values ranging from 1239.37–1305.25 J kg^{-1} K^{-1} and 1652.49–1740.33 J kg^{-1} K^{-1}, respectively. The figure clearly shows that Cp consistently remained higher than Cv across all digesters, which is expected due to the additional energy required for expansion work under constant-pressure conditions. This behaviour is characteristic of methane–carbon dioxide gas mixtures commonly generated during anaerobic digestion (Bandgar *et al.*, 2022; Ruwa *et al.*, 2022).

Furthermore, Table 2 shows that the heat capacity ratio (γ = Cp/Cv) remained constant at 1.3333 for all digesters, while Figure 8 confirms this uniform trend visually. This near-constant γ value suggests that the biogas composition remained within a narrow methane–carbon dioxide range despite differences in digester performance. Similar γ values (1.28–1.33) have been reported for methane-rich biogas systems, indicating the polyatomic behaviour of the gas mixture and supporting its suitability for combustion and thermodynamic modelling (Godara *et al.*, 2026).

A comparison of the digesters in Table 2 and Figure 8 further indicates that M2 exhibited the highest Cv (1305.25 J kg^{-1} K^{-1}) and Cp (1740.33 J kg^{-1} K^{-1}), followed closely by B2, J2, and L2, demonstrating superior thermodynamic efficiency and higher methane-rich energy content. The figure highlights this by showing M2 as the peak among all digesters. In contrast, D2 recorded the lowest Cv (1239.37 J kg^{-1} K^{-1}) and Cp (J kg^{-1} K^{-1}), confirming its comparatively lower energy recovery potential. This trend suggests that digesters with higher methane fractions exhibit improved energy storage capacity, combustion stability, and heating performance, which agrees with previous thermodynamic and exergy analyses of biogas systems(Gholizadeh *et al.*, 2019).

Critically, the relatively narrow spread of Cv and Cp values observed in both Table 2 and Figure 8 suggests that although co-digestion significantly influenced methane yield, its impact on the intrinsic thermodynamic properties of the gas mixture was moderate. This indicates that the primary thermodynamic advantage of co-digestion lies in enhanced methane volume and energy recovery efficiency, rather than major changes in gas-phase heat capacity properties. Similar observations have been reported in previous thermodynamic studies of anaerobic digestion systems (Muvhiiwa, 2015).

Overall, results confirm that digesters M2, B2, J2, and L2 exhibited the best thermodynamic performance, while D2 and I2 were comparatively less efficient. The constant γ value further simplifies isentropic process and engine-cycle modelling, making these digesters particularly suitable for renewable energy recovery applications.

3.5 Statistical Analysis

The single-factor ANOVA conducted on the dataset revealed highly significant differences among the fifteen groups (columns A2–O2). The F-statistic of 38.11, far exceeding the critical value of 1.70, alongside a p-value of 1.26E-85, strongly rejects the null hypothesis that all group means are equal (Table 3). This indicates that the observed variability across groups is not due to random chance but reflects genuine differences in performance.

The Tukey's HSD post-hoc analysis (Table 4) revealed a clear stratification of group means into three statistically distinct clusters, consistent with the significant omnibus ANOVA result ($F = 38.11$, $p < 0.001$). The high-performing cluster (G2, K2, L2) demonstrated consistently superior mean responses and was significantly different from all low-performing groups (C2 and O2), with non-overlapping confidence intervals across all pairwise comparisons.

In contrast, the mid-performance cluster exhibited internal homogeneity, with most pairwise comparisons showing non-significant differences ($p > 0.05$), indicating statistical similarity among these groups. This suggests that variability within this cluster is primarily random rather than systematic. The low-performing cluster (C2, O2) was consistently and significantly lower than all other groups, confirming a distinct baseline performance category. These findings indicate that the system exhibits non-linear performance stratification rather than a continuous gradient, suggesting the presence of underlying structural or treatment-dependent effects.

3.6 Techno-Economic Evaluation – Sensitivity Analysis

The sensitivity analysis (Table 5) of payback period and annual savings was conducted using the following constants: capital cost = ₦85,000, energy content = 6 kWh/m^3, and electricity price = ₦100/kWh. Baseline payback periods were established as 0.30 years for A2 (high-performing digester), 0.25 years for G2 (medium-performing digester), and 0.08 years for O2 (low-performing digester).

Table 5 summarizes the variation of payback periods and corresponding annual savings under ±5%, ±10%, and ±15% changes in economic conditions.

- **Payback Periods:** A2 ranged from 0.345 years (−15%) to 0.255 years (+15%), G2 from 0.288

years (−15%) to 0.213 years (+15%), and O2 from 0.092 years (−15%) to 0.068 years (+15%). This indicates that all digesters are sensitive to yield and efficiency changes, with O2 consistently maintaining the shortest payback.

- **Annual Savings:** Savings increased as payback shortened. For A2, savings rose from ₦246,377 (−15%) to ₦333,333 (+15%). G2 improved from ₦295,833 (−15%) to ₦399,061 (+15%). O2 exhibited the highest savings, ranging from ₦923,913 (−15%) to ₦1,250,000 (+15%), reflecting its rapid recovery despite lower cumulative yield.
- **Comparative Insights:** Yield and efficiency variations exerted the strongest influence, shifting payback by ~0.1 years and savings by ~₦80,000–₦100,000. Operational cost changes had comparatively smaller effects. Among the digesters, O2 demonstrated the most attractive economic profile, though its small scale may limit long-term stability. G2 provided balanced performance, while A2 showed resilience with substantial savings despite slightly longer payback.

3.7 Limitations and Scalability

While the study demonstrates strong technical and economic feasibility, several limitations must be acknowledged. First, the experiments were conducted under controlled laboratory conditions, which may not fully replicate real household environments where feedstock variability, inconsistent loading, and maintenance challenges occur. Second, the digester scale (25 L) represents a pilot system, and performance may differ at larger household or community scales. Third, economic estimates were based on average market values, which are subject to fluctuations in material costs and energy tariffs. Scalability also requires consideration of cultural acceptance, training for local operators, and policy support for renewable energy adoption. Despite these limitations, the framework provides a replicable model for decentralized biogas systems, with potential for integration into rural electrification programs and sustainable waste management initiatives in Nigeria.

CONCLUSION

This study establishes a comprehensive framework for evaluating household-scale biogas production from domestic organic wastes in Nigeria. Experimental results confirmed that potato, onion, and banana peels co-digested with cow dung can yield substantial biogas under mesophilic conditions. Kinetic modelling identified the Modified Gompertz model as the most reliable predictor of methane production, while ANN demonstrated exceptional accuracy in forecasting biogas dynamics. Thermodynamic analysis validated the combustion suitability of the produced biogas, and techno-economic evaluation confirmed the system's financial viability with payback periods of 2.5–4 years. Although scalability challenges remain, the findings highlight the potential of decentralized biogas systems to simultaneously address energy poverty and waste management in Nigeria. Future work should focus on field-scale validation, integration with community energy programs, and policy frameworks to accelerate adoption.

SUPPLEMENTARY MATERIAL

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