Energy Science & Engineering

ORIGINAL ARTICLE OPEN ACCESS

Optimization of Biogas Output From Biomaterials via Python and ANN, and Its Digester Design and Fabrication

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Received: 6 January 2025 | **Revised:** 17 July 2025 | **Accepted:** 21 August 2025

Funding: The authors received no specific funding for this work.

Keywords: AutoCAD digester design | biogas production | digester fabrication | local pear seeds | machine learning | spoilt stew-rice-eggs digestate

ABSTRACT

Due to the instability of the energy sector leading to the high cost of purchasing non-biomass fuel, there is a need to investigate an ideal biomass fuel that can be utilized in place of non-biomass fuel and whose biomaterials are within reach. Still, the issues/complexity of manual data processing minimize the optimal biogas generated. Thus, ANN and Python coding techniques were applied to digest the *Dacryodes edulis* seeds with spoiled cooked egg and stew-rice digestate in an anaerobic unit to maximize the output of biomass gas (biogas) generated. Different mixing ratios of substrate-to-inoculum of 1.09:1, 1.50:1, 2.50:1, 3.50:1, and 3.91:1 were deployed against 20.86, 25, 35, 45, and 49.14 days Hydraulic Reaction Time. The outcome demonstrates that ANN generated a maximum biogas output of 6.43 L with a mixing ratio of 3.5:1 over 45 days, comparable to 6.38 L via Python coding. Additionally, the ANN and the Python yielded model R^2 (coefficient of determination) values of 0.9909 and 1, respectively. Compared to ANN, the plots and data produced via Python coding are superior. The Gas Chromatography–Mass Spectroscopy (GC–MS) analysis of the produced biomass gas revealed 65.67% biomass methane and 24.21% carbon dioxide (CO_2) by volume, both within a reliable range for a sustainable biomass energy solution. Furthermore, the biogas flashpoint is reported as −178°C, indicating a significant degree of flammability, and the designed and fabricated digester met the requirement. Thus, the synthesized biomass gas optimal parameters can be deployed into the fabricated digester for domestic usage at a cheaper rate.

1 | Introduction

Globally, the menace posed by agro-waste has been rising due to population growth coupled with the exposure to hazards from non-biomass fuel emission and its expensive purchasing power [1, 2]. This gave birth to global warming, making society unhealthy and expensive [3–5], triggered by the inability to handle this environmental threat, leading to an unkempt environment within rural and urban communities in Nigeria [6, 7]. Currently, most homes are handicapped, rendering their storage facilities useless [3, 6, 8] due to poor power supply triggered by the inability of the national grid to meet the demand, coupled with the high purchasing power of non-biomass fuel products and political crisis. Thus, homes and some restaurants suffer heavy losses as a result of the enormous number of spoiled foods like rice and stew, beans, yam, potatoes, boiled and fried eggs, varieties of soup, and so forth, which when discharged in an open land cause environmental pollution and illness [9–11].

Dacryodes edulis is highly grown in Nigeria, Gabon, Cameroun, Equatorial Guinea, and so forth [8]. Although it is a seasonal fruit, it's highly sought after in Nigeria [8], and its seeds, as

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a b

FIGURE 1 | (a) Local pear seeds with their coat. (b) Local pear seeds without their coat.

highlighted in Figure 1a, are usually discarded after eating the fruit. The fruit is made succulent in heated water and then consumed with cooked maize before the seed is discarded [8]. Some researchers have documented its deployment for biomass oil, and biomass diesel but no documentation exists for biomass gas (biogas). Hence, the need to transform this abundant agro-waste in Figure 1b into biogas to promote its usage as an alternative energy for cooking, electricity, heating, gas-powered vehicles [12], and other utilities, thereby rejuvenating the ailing economy [13], to meet millennium development targets of biomass energy for all [14].

However, an anaerobic digester fed with feedstock produces biogas and digestate [14, 15]. This digestate can serve as bio-manure in farms as well as a catalyst in kick-starting another anaerobic reactor [12, 16, 17]. Most of the time, these digestates are underutilized, hence the need to use them to kick-start an active reactor with any substrate because of the microbes in it. Anaerobic digestion gives birth to microbial activities that take place inside a closed system, and it's favored by parameters like reaction time, mixing ratio, internal temperature, agitation rate, pH, and so forth [18, 19]. Furthermore, the kind of microbe and its cyclical movement within the digester determine the rate at which biomass gas (biogas) is synthesized from biowaste. Typically, the approach to biogas production comprises four terms: hydrolyses, acidogenesis, acetogenesis, and methanogenesis [3, 13]. Hydrolyses kick-start the approach while the methanogens convert acetate into carbon dioxide and clean gas [7, 20, 21]. Iweka et al. [13] reported that homogenous biomass fed in the digester yields less biogas compared to heterogeneous biomass. Different materials have been investigated using anaerobic digesters like corn chaff mixed with the rumen of cow, corn chaff mixed with cattle excreta digestate, cow dung treated with water, canola residues treated with cow manure, fowl manure [13, 22, 23], but this study intends to address the lack of an efficient biogas production approach using unconventional substrates like local pear seeds. Biomass gas is characterized by gas chromatography–mass spectroscopy (GC–MS) to know the constituents of biomass methane, carbon dioxide, and so forth present [3], but the sum of biomass methane in it, determines the heating power of the biomass gas (biogas), and the CO_2 determines its sustainability [3, 13]. Thus, the higher the portion of biomass methane (biomethane) in the biogas, the better the energy is, as this can drive energy utilities over an appreciable timeframe, especially when utilized in gas-powered vehicles, generators for electricity, or domestic cylinders for cooking, thereby, effectively mitigating growing environmental challenges [11, 24].

Previously, Artificial Neural Networks (ANN) were deployed to replicate and accelerate biomass gas generation from fowl excretas, inoculated biomass, biodegradable waste, and slurry [13, 21]. Furthermore, Dahunsi et al. [25] utilized both ANN and rotatable central composite design (CCD) of Response Surface Methodology while working on biomass gas synthesis and reported that ANN provided greater yields. Additionally, Iweka et al. [3] utilized crushed Udara seeds with decomposed food waste and it yielded appreciable biomass gas output, but none has reported inoculation of *Dacryodes edulis* seeds (Nigerian local pear seeds) with this spoilt food digestate composition let alone using ANN-based NeuralPower and Python-based Jupyter tool approach in biomass gas production. As ANN and Python tools utilize machine learning approaches to forecast and improve the biogas output from anaerobic digestion, unlike earlier researchers who utilized experimental and predictive (machine learning) models like CCD versus ANN in biogas generation. Thus, we need to: (i) Compare the biomass gas output of crushed local pear seeds with already documented Udara seeds using the same digestate in a mesophilic environment. (ii) Compare the report from the Python and ANN approaches and validate the GC–MS report. (iii) Accelerating the process by designing a Floating Drum Digester with the optimal parameters and AutoCAD 2007, and validating with a fabricated prototype for household utilization to boost the economic potential of any country, and ultimately be beneficial to biomass gas optimization industries for commercial application, in addition to decarbonizing industries.

2 | Materials and Methods

2.1 | Gathering of Biomaterials

The inoculum known as digestate was taken from an operating biomass gas digester at Ajayi Crowther University's Chemistry Lab. Additionally, the digestate contains spoiled cooked eggs and stew rice utilized by Iweka et al. [3]. The native pear seeds from the residences of local food vendors in Kwale were another addition. The products were assembled and then promptly transported to the Chemistry Lab at Ajayi Crowther University, where the Total Solid (TS) and Volatile Solid (VS) were analyzed.

2.2 | Schematic Drawing

The schematic drawing of this study as indicated in Figure 2 has different steps such as gathering, pretreatment of the agro-waste, bio-digester, digestate, bio-digester, valve, biogas, and biogas burner for household utility.

2.3 | Preparation of the Biodegradable Materials

To confirm the connection between the rate of biomass gas yield and the chemical constituent of African Star Apple combined with digestate from biowaste, as described by Iweka et al. [3], the research will be in contrast with this investigation which comprises local pear co-digested with the unique biowaste digestate (a hybrid biowaste from spoilt egg and stew rice). The local pear was collected by a local merchant in Nigeria. The assembled local pear was washed, dehydrated, and crushed to powder form. Subsequently, the local pear was chilled for a day at refrigeration temperature to discharge the surrounding biomass methane. The standard method was deployed to compute the total solid (TS) and volatile solid (VS) [13, 26].

2.4 | Approach for Computing TS and VS

The quantity of total solids and volatile solids in the chosen biomass was investigated via a standard procedure [13, 26]. The weight variation of a sample that was kept in a muffler furnace at 105°C for a full day was measured to examine the substrate TS. The initial weight was scaled as well as the final weight after dehydrating via a muffler furnace. The samples were housed in the desiccator after removal to avert the soaking up of humid air as the crucibles cooled. The samples VS were ascertained in a furnace at 550°C for 2 h. The procedure was performed three times, as highlighted in Table 1a, 1b, 1c, 1d. The utilized biomass was put together based on the mixture ratio. Note that 1A, 1B, and 1C describe the different crucible numbers while SD stands for standard deviation.

2.4.1 | Tabular Computation of the VS and TS Deployed in This Experiment

$Q2 - Q1$ = wet biomaterial weight

$Q3 - Q1$ = biomaterial weight after drying @105°C

$Q4 - Q1$ = biomaterial weight after drying @550°C

$$\text{TS (g/kg)} = \frac{Q3 - Q1}{Q2 - Q1} \times 1000 \quad (1)$$

$$\text{VS (g/kg)} = \frac{(Q3 - Q1) - (Q4 - Q1)}{Q2 - Q1} \times 1000 \quad (2)$$

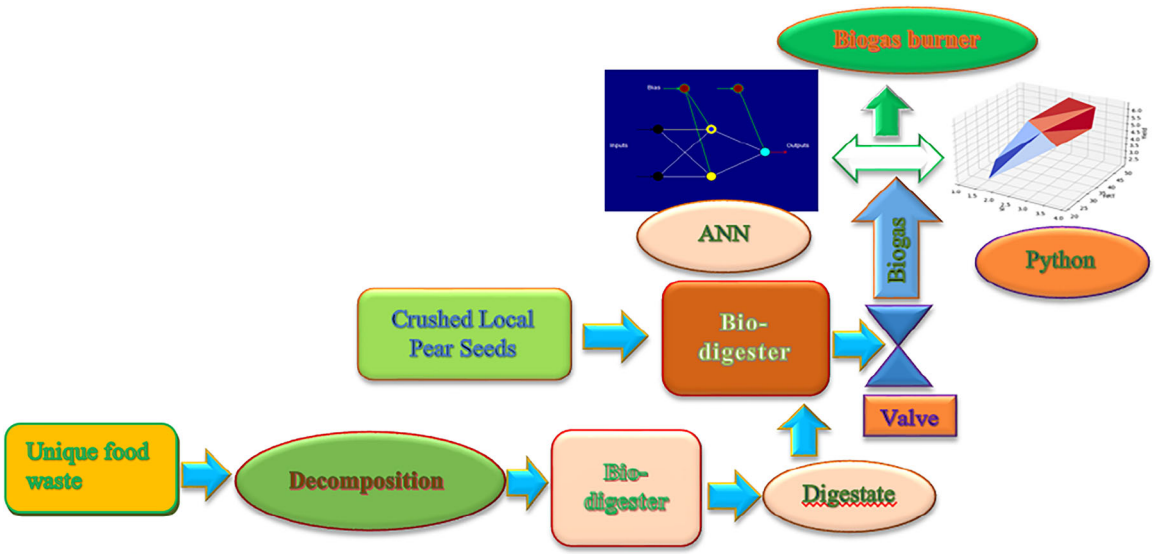


FIGURE 2 | Schematic drawing illustrating this biogas (biomass gas) production approach for home usage.

TABLE 1a | Local pear seeds TS and VS report.

Crucible	Crucible wt *Q1*	Wt of crucible + sample (wet) *Q2*	Wt of crucible + sample@105°C *Q3*	Wt of crucible + sample@550°C *Q4*	TS (g/kg) of sample	VS (g/kg) of sample
1A	56.31	76.11	74.66	56.71	926.77	906.57
1B	57.83	76.49	75.16	58.23	928.72	907.29
1C	49.07	69.52	68.08	49.45	929.58	911.00
Means	54.40	74.04	72.63	54.80	928.36	908.29
SD	4.68	3.92	3.95	4.69	1.44	2.38

TABLE 1b | Hybrid biowaste (digestate) TS and VS report [3].

Crucible	Crucible wt	Wt of crucible + sample (wet)	Wt of crucible + sample@105°C	Wt of crucible + sample@550°C	TS (g/kg) of sample	VS (g/kg) of sample
Means					6.70	2.80
Sd					0.85	0.20

TABLE 1c | African star apple seeds TS and VS report [3].

Crucible	Crucible wt	Wt of crucible + sample (wet)	Wt of crucible + sample@105°C	Wt of crucible + sample@550°C	TS (g/kg) of sample	VS (g/kg) of sample
Means					925.06	899.70
SD					0.97	8.25

TABLE 1d | TS and VS analysis for local corn chaff [13].

Crucible	Crucible wt	Wt of crucible + sample (wet)	Wt of crucible + sample@105°C	Wt of crucible + sample@550°C	TS (g/kg) of sample	VS (g/kg) of sample
Means					324.5	314.4
SD					6.06	5.17



FIGURE 3 | 250 mL sealed glass chamber.

Equations (1) and (2) were deployed to produce the TS and VS in Tables 1a, 1b, 1c, and 1d respectively.

Thus, the bio-materials (samples) considered are VS of Table 1a, derived from the substrate, and VS of Table 1b, derived from biowaste (food waste). Additionally, the outcome shows that Table 1a generated better VS than Tables 1c and 1d, since its mean VS value is higher. Thus, will produce more biogas than biowaste from Tables 1c and 1d. Note that the computation of the inoculum-to-substrate ratio (I/S) was based on the VS value.

2.5 | The Reactor and Its Investigation Approach

The inoculation experiment for this study was done in a sealed glass chamber of volume 250 mL with clip stoppers as depicted in Figure 3. The digesters were thoroughly sealed with a loading inlet, and it was placed on an auto-agitation unit. The biomaterial (sample) was collected via the top of the clip-stopper unit. The reaction process was run and sustained between the mesophilic temperature of 25°C–34°C, and the biomass gas output was calculated in pressure (mbar) and thereafter, transformed to volume measured in liters (L). In this study, physiochemical characteristics of the produced slurry are depicted in Table 2 after deriving the outputs from formulated S/I of 1.09:1, 1.50:1, 2.50:1, 3.50:1, and 3.91:1, and hydraulic retention time (HRT) of 20.86, 25, 35, 45, and 49.14 days by CCD for 13 digesters as displayed in Table 3 and Figure 3. The overall biomass gas yield derived from a 250 mL glass digester was computed in a methodical timeframe employing a biogas pressure expansion sensor.

The digestate, which came from an active reactor that had been filled with spoiled cooked eggs and stew rice, was put into the bioreactor in varying amounts to fill 60% of the bioreactor's total volume, leaving 40% available for the biogas to collect. The substrate in this case was milled local pear seeds. The batch reactor worked under mesophilic conditions, and the biomass gas volume generated from the inoculation was computed every 24 h utilizing a biogas (biomass gas) pressure expansion sensor.

2.6 | ANN and Python Optimization Approach

The raw optimized outcome and input from CCD were inserted into the ANN model (NeuralPower), creating two input columns and an output column. Thereafter, it was simulated till a desired iteration was observed. The data and plots were exported for interpretation. Additionally, for Python, the input and outcome values from CCD were inserted into an excel, and saved. Thereafter, the saved Excel was imported into the Jupyter platform and was analyzed via code.

The quadratic equation's actual parameters were built to formulate a multivariate polynomial connection between the accumulated biomass gas outcome (yield) and two founding process parameters, as showcased in

$$\mathrm{AGGO\,(L)} = -7.00364 + 4.78888A + 0.167265B - 0.035162AB - 0.447036A^2 + 0.000055B^2 \quad (3)$$

TABLE 2 | Physical and chemical components of the produced slurry.

	S/I	TS (g/kg)	VS (g/kg)	C/N	pH	Temperature (°C)
Slurry value	1.09:1	798.43	774.33	24.0	7.76	33
Slurry value	1.5:1	776.25	742.15	23.3	7.82	31
Slurry value	2.5:1	753.9	737.5	22.5	7. 85	30
Slurry value	3.5:1	733.51	722.67	21.7	7.88	28
Slurry value	3.91:1	725.2	711.6	20. 9	8.15	27

TABLE 3 | Local pear seeds mixed with derived biowaste digestate.

				Biomass gas output (L)			
Std	Run	A:S/I	B:HRT (days)	ANN True value	ANN Forecasted value	Python True value	Python Forecasted value
13	1	2.5	35	5.3815	5.0176	5.0196	5.0196
6	2	3.91421	35	5.8595	5.8868	5.9965	5.9965
2	3	3.5	25	5.5161	5.4944	5.4206	5.4206
7	4	2.5	20.8579	3.8001	3.8046	3.8538	3.8538
12	5	2.5	35	4.9080	5.0176	5.0196	5.0196
11	6	2.5	35	5.0327	5.0176	5.0196	5.0196
4	7	3.5	45	6.5341	6.4262	6.3815	6.3815
5	8	1.08579	35	2.2028	2.2148	2.2545	2.2545
9	9	2.5	35	5.1984	5.0176	5.0196	5.0196
3	10	1.5	45	4.5309	4.5135	4.4387	4.4387
8	11	2.5	49.1421	6.0722	6.1769	6.2073	6.2073
10	12	2.5	35	4.5759	5.0176	5.0197	5.0197
1	13	1.5	25	2.1064	2.1157	2.0713	2.0713

where AGGO is the accumulated biomass gas output, A is the mixture ratio of the substrate-to-digestate, and B is the hydraulic retention time.

Thus, Equation (3) obtained from CCD was utilized with Python instructions in Jupyter working space to compute the biomass gas yield using SI as substrate-to-inoculum ratio and HRT as operating variables as stated in the appendix.

2.7 | Biomass Gas Characterization

A gas chromatography (GC)-flame ionization detector was utilized to characterize the derived biogas. 6890 Agilent Technology from USA, manufactured the GC utilized in this study, which had an Elite-5 capillary column with $30\,m \times 0.25\,mm \times 0.25\,\mu m$ specification and a FID detector. The programmed temperature of the column oven, detector, and injector were 120°C, 160°C, and 120°C, respectively, at 10°C/min increase, while the injection port programmed temperature was at 250°C. The experiment was performed with all the needed apparatus and materials, and a total of 43 min were spent running a sample.

The produced biomass gas sample underwent the flashpoint check as documented by Iweka et al.'s study [11]. The biomass gas collected was ignited to check the temperature; it would generate a flame. The time taken concerning the calorific value of the biomass gas (biogas) was reported by Iweka et al. [3, 13] and Dahunsi et al. [27].

2.8 | Biomass Gas Flashpoint Approach

The flashpoint of the biomass methane was checked with an automatic cleavage-enclosed cup method to detect the temperature via a node coupled with a compartment meant for injecting the collected clean gas in conjunction with the temperature scale and time. Thus, the local pear seeds flashpoint was compared to that of Iweka et al. [3].

3 | Results and Discussion

3.1 | Physiochemical Compositions of the Substrate, Digestate and Slurry

As displayed in Table 1, the physicochemical constituent of the local pear seeds is more robust and has maximum output than that generated from local corn chaff and African Star Apple seeds, as documented by Iweka et al. [3, 13]. Additionally, this

is corroborated by the 7.88 pH of this digestate unlike 7.82 and 7.78 pH produced from local corn chaff and African Star Apple Seeds, respectively. Thus, this study was processed for further evaluation.

The physiochemical characteristics of the produced slurry are depicted in Table 2. Before mixing the local pear seeds with the derived biowaste digestate for the main experiment, a pre-treatment was done to determine the total solids, volatile solids, carbon-to-nitrogen (C/N) ratio, pH, and slurry temperature. A slurry comprises the addition of the crushed local pear seeds, egg-stew rice digestate, and a specific quantity of water. Columns 1, 3–7 are the derived values at different mixing ratios of substrate-to-inoculum (S/I) of 1.09:1, 1.50:1, 2.50:1, 3.50:1, and 3.91:1 with 20.86, 25, 35, 45, and 49.14 days of HRT, and so forth. Column 1 is the derived Slurry values at different optimal inputs considered and water.

3.2 | Modeling Outcomes of Anaerobic Processing of Local Pear Seeds With Derived Biowaste Inoculum

In this study, ANN was utilized to formulate and optimize the anaerobic processing of local pear seeds with derived biowaste inoculum from the input factors and the ANN True value, generated from rotatable CCD experimental output values as highlighted in Table 3. Two factors subjected are the mixture of substrate-to-inoculum (S/I) ratio and HRT. Thirteen distinct S/I and HRT running conditions generated the 13 examined runs, all of which were maintained at a mesophilic temperature between 25°C and 33°C. The summation of biogas outputs generated for each running condition is highlighted in Table 3.

From the reports/results, the mixture ratio of milled native pear seeds to digestate (3.5:1) and HRT of 45 days produced a maximum accumulated biomass gas yield, while the milled native pear seeds to the substrate-to-inoculum ratio of (1.5:1) and 25 days of HRT produced the minimal accumulated biomass gas output. Thus, generating a reasonable quantity of substrate-to-inoculum at a periodic interval of HRT is tantamount to a maximum biomass gas (biogas) harvest.

The model employed in this process is significant with $p < 0.0001$ [3, 4, 28]. Additionally, the R^2 is close to 1, an indication that the ANN outcome produced is trustworthy and expected. The R^2 of 0.9909 depicts that the model generated can describe 99.09% variability stated in the design output, which further corroborates the trustworthiness of the results as highlighted in Table 4, which also displays all the data derived by the Python–Jupyter tool. Thus, the R^2 is used to determine how well a regression model fits, but a high R^2 doesn't justify the model's accuracy, hence, other metrics like the p value are considered to corroborate findings [29].

The chart of forecasted against the true values of biomass gas output is displayed in Figure 4a and this further supports the probity of the values derived. As shown, all the particulars are either in alignment or very close to the good-condition line. This further affirms why R^2 derived for this model is high. The 3D chart of the cumulative biogas volume generated from the ANN operational process against the mixture ratio and HRT is shown in Figure 5a. The mixture ratio actually impacts the cumulative biogas yield as depicted in Figure 5a. Additionally, $p < 0.0001$ depicts how important they are. When its p value is less than 0.05 [3, 13, 30], it shows that the design term is bright.

Note, the red in 3D chart (Figure 5a,b) indicates maximum output, yellow indicates a decline from maximum output and blue indicates lower output at a specified operational conditions and the colors spread according to the conditions.

TABLE 4 | Model fitness parameters.

Parameters	ANN values	Python values
SD	5.778	1.34
Mean	4.344	4.75
R^2	0.9909	1
Adjusted R^2		1
Predicted R^2		1
Iteration	4,391,600	—
Min.	1.868	2.07
Max.	15.01	6.38
p value	< 0.0001	1.5533e−88
Omnibus	—	3.817
Skew	—	0.990
Kurtosis	—	2.976
Durbin–Watson	—	1.602

3.3 | Forecasted Results via Python–Jupyter Tool

The Python–Jupyter tool is the second machine learning technique employed after ANN in this study to monitor and run biomass gas (biogas) units to accelerate their production efficiency, in comparison to ANN modeling [3, 31]. ANN (NeuralPower) is like Excel that does not need coding like Python but generates results via iteration. Table 3 displays the biomass gas output results of the models utilized relative to the data needed for each Python coding language factor and ANN.

The estimated biomass gas output from ANN is not the same as Python values, and this is affirmed by Run 7 in Table 3. The difference justifies that the ANN model gave the maximum output of 6.43 L as against Python 6.38 L at Run 7 in Table 3, which have comparable/similar values, but the corresponding mean values of ANN 4.34 L and Python 4.75 L justify that the Python mean value is better due to its higher mean value. Another predictor is the adjusted R^2. This does not allow the addition of irrelevant input elements that do not aid the model's performance. Thus, Adjusted R^2 provides a more reliable interpretation of model fitness, especially in multiple regression models. NeuralPower iteration provides R^2 and R^2 predicted values only, making it less valuable to Python models. Figures 4b and 5b of the Python–Jupyter tool yielded a better outcome and a robust 3D plot outlook in contrast to Figures 4a and 5a of the ANN. Furthermore, the model fitness of skewness (0.990) and

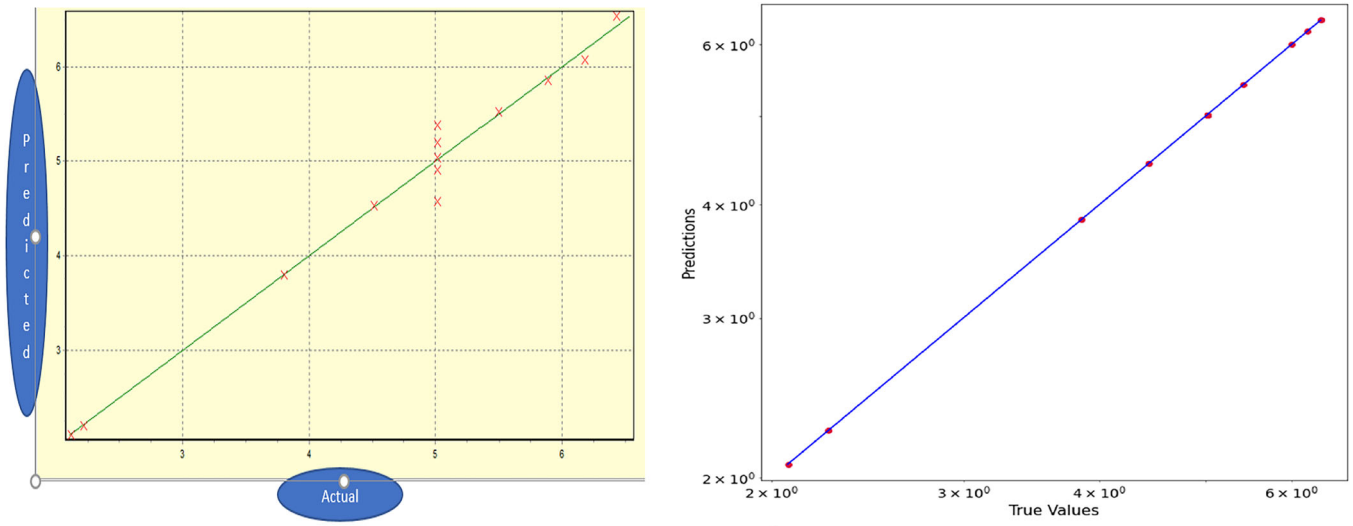


FIGURE 4 | (a) Graph of ANN biomass gas predicted output against actual output. (b) Graph of Python-predicted biomass gas output against actual output.

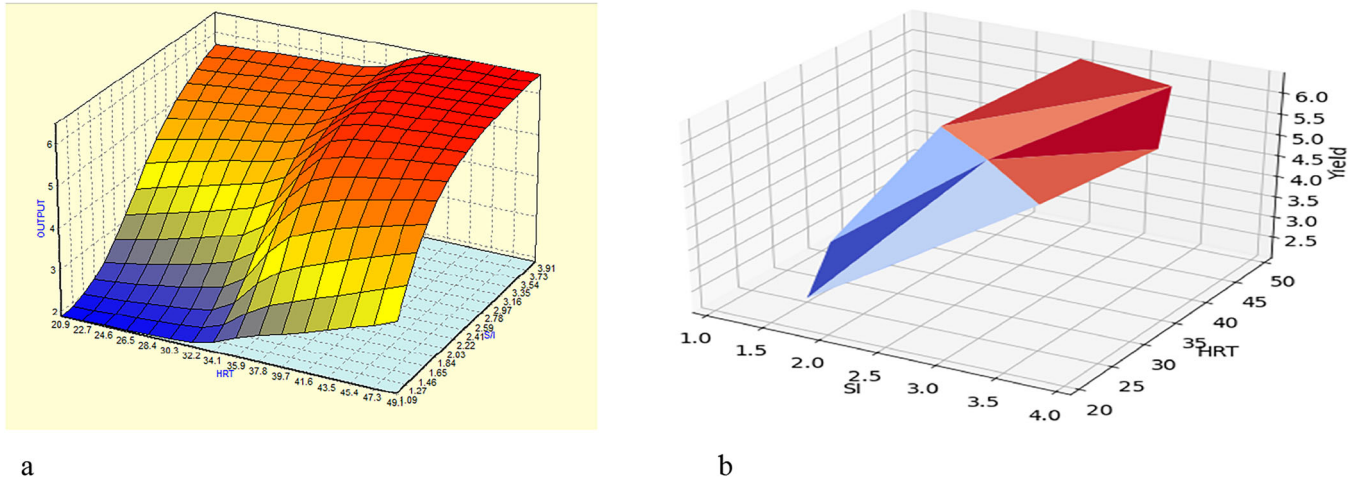


FIGURE 5 | (a) ANN 3D chart of the accumulated biomass gas output versus mixture ratio and HRT. (b) Python 3D chart of the accumulated output versus mixture ratio and HRT.

kurtosis (2.976) in Table 4, as derived from OLS multivariate statistical analysis of the Jupyter model via Python coding, are both within acceptable brackets [14, 15, 32]. The outcomes revealed that Python outperformed ANN, yet both techniques can reliably forecast the production of biomass gas since the R^2 and p values are significant, and this biogas generated can be used as an option to light up homes, heat, and power biogas vehicles. Additionally, the design performance for the biomass gas output produced will be validated using R^2, and the impact of the optimized operating parameters on the outcomes from the GC–MS.

3.4 | Biomass Gas Yields Characterization

The constituents of the biomass gas yields from local pear seeds co-digested with biowaste digestate are displayed in Table 5. The biogas collected from this study run was examined with GC–MS. As shown from all samples, biomass methane is the major component of the biomass gas characterized (49.42%–65.76% by volume) followed by CO_2 (23.46%–39.98% by volume) which is in alignment with previous studies of 45%–75% biomethane [33] and 50%–70% biomethane [34]. Biomass gas with a high biomethane component is preferred because it works well with diesel-powered engines [3, 35]. The outcomes show that the biomass gas (biogas) with higher HRT had a greater percentage of biomethane than the biogas with lower HRT. The effect of the mixture ratio on biogas composition is less profound since all samples, irrespective of the mixture ratio, contain a high amount of methane (CH_4) by volume at high HRT. Additionally, the bio-reactor with a 3.5 mixture ratio for 45 days gave 6.4 L volume with 64.02% biomass methane while the bio-reactor with a 2.5 mixture ratio for 49.1 days gave 6.21 L volume with 65.76% biomethane, and both percentages are within 45%–75% biomethane [33]. Thus, the biodigester with the highest cumulated quantity does not replicate a better biomass methane outcome as depicted in Table 5. This study justifies Iweka et al. [13] in their assertion that quality is indirectly proportional to quantity. The flashpoint

TABLE 5 | The composition of selected biomass gas (biogas) runs analyzed with GC–MS.

Run	*S/I* (mixture ratio)	HRT (days)	True value	Biomethane CH_4 (%)	Carbon dioxide CO_2 (%)	Sulfur dioxide SO_2 (%)	Ethyl acetate $C_4H_8O_2$ (%)	Acetic acid $C_2H_4O_2$ (%)
7	3.5	45	6.5341	64.02	25.65	3.54	0.82	5.07
2	3.9	35	5.8595	63.34	26.10	3.69	0.66	5.09
5	2.5	35	4.9080	61.58	28.73	1.37	0.98	6.29
11	2.5	49.1	6.0722	65.76	24.21	3.12	0.75	5.06
13	1.5	25	2.1064	49.42	32.97	6.97	1.83	7.71

TABLE 6 | Biomethane (biomass methane) potential (BMP) results of present and previous study.

No.	Sample	BMP (L CH_4/g VS)	Hydraulic reaction time (day)	Temperature (°C)
This study	Local pear	0.21	65	25–33
Iweka et al. [13]	Corn chaff	0.17	61	25–33
Iweka et al. [3]	African star apple seeds	0.20	62.5	25–33

of 65.76% by volume of biomass methane was checked with the digital cleavage-enclosed cup method and it detected −178°C. Thus, the local pear seeds yielded better biomass methane in contrast to African Star Apple Seeds' biomass methane of 63.29% and CO_2 of 26.71% as published by Iweka et al. [3].

Runs' 7, 5, and 13 in Table 5 represent the highest, average, and lowest biomass gas outcome and their respective GC–MS analyzed results. This composition selection was based on the highest, average, and lowest biomass gas outcomes derived from varied input elements in Table 3. These GC–MS results initially generated in ppm were converted to a percentage (%) using Equation (4). Additionally, HRT is more desirable than *S/I* as indicated in Table 5 for maximum biomass methane CH_4(%) output. Note that the higher GC–MS from run 7 in Table 5 shows that the quantity of biomass gas produced in Table 3 might contain more non-methane content, as published by Iweka et al. [7, 13]

$$\%\,\text{of biomass gas produced} = \frac{\text{Concentration of each gas produced (ppm)} \times 100}{\text{Total concentration of the gas produced (ppm)}} \quad (4)$$

3.5 | Biomethane Potential (BMP) Results

The biomass methane potential of the substrate from documented research is presented in Table 6 with temperature under mesophilic conditions.

From Table 6, we can conclude that the mixing of local pear with biowaste has a longer reaction time than corn chaff mixed with cow dung digestate and African Star Apple Seeds as published by Iweka et al. [3, 13]. Additionally, with the nose-diving of our economy in Nigeria, accelerating the use of local pear as substrate in communities where it is abundant, will help to alleviate poverty, reduce the emission of greenhouse gases from non-renewable energy, mitigate the aftermath of political, economic, and energy security crises facing the world.

3.6 | Digester Design for Household Utilization

3.6.1 | Assumptions

3.6.1.1 | Unstirred Anaerobic Digester. Active digester volume = 150 L = 0.150 m^3

Hydraulic reaction time (HRT) = 30 days

5 L of water = 5 kg of water

Wet anaerobic digestion with TS of 20%

Mesophilic Temperature Range (20°C–40°C)

1 m^3 biogas = 0.62 L of kerosene = 0.46 kg LPG [36]

3.6.2 | Feedstock Parameters

TS = 928.36 g/kg = 92.8% of wet waste

VS = 908.30 g/kg = 90.83% of wet waste

VS = 978.38 g/kg = 97.84% TS

Biogas composition = 65.67% CH_4

BMP = 0.21 m^3 CH_4/kg VS

BGP = 0.32 m^3 biogas/kg VS.

3.6.3 | Design Equations for the Digester

The flow rate and TS concentration of 20% were computed using Equations (5) and (6), respectively:

$$\text{Flow rate}\left(\frac{\text{m}^3}{\text{day}}\right) = \text{Volume of digester /HRT} \quad (5)$$

$= 0.150(\text{m}^3)/30\text{days} = 0.005\ \text{m}^3/\text{day}.$

At TS concentration of 20%

$$\text{TS} = 20/92.8 = 0.216 \quad (6)$$

Equation (6) value was used to derive the value of the VS as depicted in

$$\therefore \text{VS} = 97.8 \times 0.216 = 0.211\,\text{kg VS} \quad (7)$$

The OLR was computed using

$$\begin{aligned}&\text{Organic loading rate (OLR)}\\&= \text{VS concentration per day(kgVS/day)}\\&\quad /\text{digester volume (m}^3\text{)}\end{aligned} \quad (8)$$

$$\text{OLR} = 0.211(\text{kgVS/day})/0.150\,(\text{m}^3)$$

$$\text{OLR} = 1.41\,\text{kgVS/m}^3\text{day}$$

from the experimental value of VS in substrate,

$$0.211\,\text{kg VS} \equiv 0.232\,\text{kg wet substrate}$$

The composition of the slurry was derived from the following equation:

$$\text{Composition of slurry} = 0.232\text{kg waste} + 4.77\text{L of water} \quad (9)$$

From OLR of 1.41 kg VS/m^3 day and BMP of 0.21 m^3 CH_4/kg VS

1 kg VS = 0.21 m^3 CH_4

1.41 kg VS = 0.2961 m^3 CH_4 = 0.45 m^3 biogas.

The daily biogas yield was computed as follows:

$$\begin{aligned}\text{Daily biogas yield} &= \text{OLR(kgVS/m}^3\text{ day)}\\&\quad \times \text{Biogas potential(m}^3\text{biogas/kgVS)}\\&\quad \times \text{active digester volume}\\&= 1.41 \times 0.32 \times 0.150\\&= 0.0678\,^3\text{biogas /day}\end{aligned} \quad (10)$$

This is equivalent to $0.0678 \times 0.62\,\text{L} = 0.042036\,\text{L}$ of kerosene.

Also, $0.0678 \times 0.46\,\text{kg} = 0.031\,\text{kg}$ of LPG.

3.6.4 | Dimension and Layout of the Floating Drum Digester

The floating drum, as depicted in Figure 6, is designed to have an estimated volume of 0.15 m^3.

The volume of the floating drum digester was computed using

$$\begin{aligned}V &= \pi r^2 h\\&= 3.142 * (0.4)^2 * 0.3\\&= 0.15\,\text{m}^3\end{aligned} \quad (11)$$

where $r = 0.4$ m and $h = 0.3$ m.

Thus, the volume of the floating Drum Digester is 150 L = 150,000 cm^3 = 0.15m^3.



FIGURE 6 | AutoCAD conceptual 3D.



FIGURE 7 | Fabricated bio-digester prototype.

3.6.4.1 | Digester Volume: Gas Holder Volume = 4:1. From Figure 7 measurement using Equation (11) to corroborate the designed digester volume with the fabricated digester volume.

Radius (r) = 9 in.

Height of the cylinder = 3 ft

1 ft = 0.08333 in.

$V = 3.142 \times (9 \times 0.08333)^2 \times 3$

$V = 5.3\ \text{ft}^3 = 1615.44\ \text{mm}^3$

$1\ \text{ft}^3 = 28.3169\ \text{L}$

$5.3\ \text{ft}^3 = X$

$X = 150.08\ \text{L} = 150\ \text{L}$

Volume of the inter pipe

Height of the inter pipe = 2 ft

$V = 3.142 \times (9 \times 0.08333)^2 \times 2$

$V = 3.53\ \text{ft}^3 = 100\ \text{L} = 1075.9\ \text{mm}^3$

Note: $1\ \text{ft}^3 = 50\ \text{L} = 304.8\ \text{mm}^3$.

3.6.4.2 | Substrate Level. The substrate level and its height are computed as depictedin the following equations:

$$V_1 = ¾ \times 5.3 \tag{12}$$

$V_1 = 3.97\ \text{ft}^3 = 1211.58\ \text{mm}^3$

$$V_1 = \pi r^2 h \tag{13}$$

$3.975 = 3.142 \times (0.75)^2 \times h$

Substrate height (h) = 2.26 = 2.3 ft = 701.04 mm

Note: $3.975\ \text{ft}^3 = 113\ \text{L} = 1211.58\ \text{mm}^3$.

3.6.4.3 | Gas Holder. Aiming at 188 L of biomass gas, since the gasholder is the top portion of the entire digester, the radius remains the same, and then the height of the holder is computed using Equations 14 and 15.

$$\begin{aligned}\text{Gas holder} &= ¼ \times 5.3 \\ &= 1.325\ \text{ft}^3\end{aligned} \tag{14}$$

OR

$5.3 - 3.975 = 1.325\ \text{ft}^3 = 403.86\ \text{mm}^3$

$$V_2 = \pi r^2 h_a \tag{15}$$

$1.325 = 3.142 \times (0.75)^2 \times h_a$

Height of gasholder (h_a) = 0.75 ft = 228.6 mm

The total height (H) and volume of the digester was computed as

$$\begin{aligned}\text{Total } H &= 0.75\ \text{ft} + 3\text{ft} = 3.75\ \text{ft} \\ &= 1143\ \text{mm}\end{aligned} \tag{16}$$

$$\begin{aligned}\text{Total volume of the digester} &= 5.3 + 1.325 = 6.625\ \text{ft}^3 \\ &= 187.599\ \text{L} = 2019.3\ \text{mm}^3\end{aligned} \tag{17}$$

Other equipment needed for fabrication, along with Table 7 contents, are a welding machine, PVC pipe, Pan, welding guard, engineering chalk, measuring tape, electrode, gas hose, A-B gum, and so forth. And the cost of fabricating the bio-digester is 139,400 in Nigeria. Thus, a cheap investment compared to the cost of 1100 per liter of non-biomass fuel. Assuming, 5500 for certain hours in a day, for at least 3 months = 5500*30 = 165,000 to power non-biomass fuel generators. Additionally, labor cost is the welder's charge for fabricating the bio-digester with the supplied materials and guided by the drafted AutoCAD in Figure 6.

3.7 | Corroboration of the Optimized and Its Drafted AutoCAD via Fabrication Approach

The optimized biomass gas yield and the operational parameters employed in this bio-digester approach were utilized by

TABLE 7 | Materials selection for fabrication.

S/N	Items	Quantity	Unit cost (Naira)	Total cost (Naira)
1	16 mm gauge pan	3	20,400	60,200
2	Galvanized 1 in. pipe	1	5400	5400
3	12 mm rod	1	9000	9000
4	$\frac{1}{2}$ Cap	2	1000	2000
5	$\frac{1}{2}$ ball gauge	3	2000	6000
6	Clip	2	400	800
7	$1\frac{1}{2}$ in. rubber pipe	1	5600	5600
8	$\frac{1}{2}$ Rubber pipe	1	2000	2000
9	Big gum and 1 in. back nut	1	3500	3500
10	$\frac{1}{2} \times 45$ elbow	1	600	600
11	Brush and Sharon Paint	1	8300	8300
12	Labor		25,000	25,000
13	Miscellaneous		10,000	10,000
Grand total			93,200	139,400

resolving the regression equation. The ideal environment of the autonomous parameters selected for this biogas synthesis from the inoculation of spoiled food waste digestate [3] and local pear seeds was derived via an ANN and a Python approach. A preference of 100% was used for optimizing to expedite the synthesis of biogas. Different mixing ratios of substrate-to-inoculum (S/I) of 1.09:1, 1.50:1, 2.50:1, 3.50:1, and 3.91:1 were deployed against 20.86, 25, 35, 45, and 49.14 days HRT. The highest factor for biogas synthesis was statistically forecasted; 45-day HRT and S/I 3.5, having a 6.53 L equivalent output. The optimization was repeated three times via the mentioned conditions, and the mean cumulative biomass gas volume of 4.75 L was generated experimentally. This value corroborates with the average accumulated value (4.75 L) forecasted by Python coding via the Jupyter tool for the same environment as showcased in Table 4. Additionally, Figure 7 justified the workability of this floating bio-digester design specification in Figure 6 with a prototype (Figure 7), which can digest and produce biomass gas for household usage. However, the prototype was fabricated with one handle each instead of two, as indicated in Figure 6, to dampen cost and material wastage. Note that the experimental run using this fabricated prototype will be documented in subsequent research.

3.8 | Validation with GC–MS

It has been documented by Jameel et al. [37] that biomass gas constitutes mainly 70%–50% biomass methane (CH_4), and 50%–30% carbon (iv) oxide (CO_2) while others are in minute amount by volume. Thus, the produced biogas containing 65.67% biomass methane and 24.21% CO_2 by volume via GC–MS analysis is an indication that it is ideal for a sustainable biomass energy solution since the percentage by volume of CO_2 is below the recommended range [37]. This suggests that biomass gas can drive a gas-powered generator effectively due to its high CH_4 value, and its low CO_2 value suggests it is a good biomass fuel with no modification to the gas engine needed [13]. Thus, it's a great benefit to humans in terms of its utilization for cooking and electricity to power homes via a gas-powered generator and its eco-friendly nature based on low amount of dangerous emissions inconstrast to gases from non-biowaste.

3.9 | Future Study

Prospectus researchers can employ another modern-day optimization package like machine learning techniques (algorithms) such as particle swarm, random forest, support vector regression, Gradient boosting machine like XGBoost and so forth, overlooking python via Jupyter tool and ANN to accelerate biomass gas optimization outcome for the good of "the society at large", as this study demonstrates that Python is ideal for machine learning application in biomass gas production compare to ANN.

Furthermore, prospectus researchers should look towards potential improvements in substrate preparation, scaling up the process, and exploring cost-effectiveness for a more comprehensive outlook.

4 | Conclusion

Using abundant biomass from animal and agricultural products for cleaner/biomass fuel could usher in an eco-friendly environment for the populace's well-being. Additionally, the two machine learning methods, ANN and Python-based Jupyter tool, were utilized to design and optimize biomass gas production from biowaste (egg and stew-rice) digestate and local pear in a bio-reactor. Utilization of Python encryption (coding) produced a model with better performance than ANN because it is built with more libraries/packages for data generation than

the ANN-based NeuralPower. The model R^2 of 0.9909 was obtained using ANN, while the R^2 of 1 was derived from the polynomial (multivariate) regression model using Python encryption. The data and plots generated by the Jupyter tool are more robust and visually appealing than those generated by ANN. However, the highest output of 6.43 L recorded at a mixing ratio of 3.5 and 45 days HRT from ANN is similar to 6.38 L produced by the Jupyter tool. Generally, it has been justified that the two artificial intelligence subsets can help maximize biomass gas production, but the Jupyter tool using Python encryption (coding) is better because of its higher R^2 value, appealing plots, and robust values. Furthermore, the bio-digester prototype with a 3.5 mixture ratio (S/I) for 45days generated 6.53 L of biomass gas (biogas) containing 64.02% biomethane while the bio-digester with a 2.5 mixture ratio (S/I) for 49.1 days generated 6.07 L volume but 65.76% biomass methane. This corroborates the fact that the reactor depends more on the S/I ratio and HRT rather than volume for better biogas quality. Thus, HRT plays a key role than the mixing ratio in influencing the highest yield. Also, the produced biogas containing 65.67% biomethane and 24.21% CO_2 by volume via GC–MS analysis is an indication that it is ideal for a sustainable biomass energy solution, and it recorded a flashpoint of −178°C, which is within a flammable bracket. This suggests that biomass gas can drive a gas-powered generator effectively due to its high CH_4 value, and its low CO_2 value suggests it is a good biomass fuel with no modification to the gas engine needed. Additionally, the AutoCAD-designed model was fabricated at a cost of 139,400 Nigerian Naira, an equivalent of 91.17 USD, which can sustain a moderate household compared to the use of non-biomass fuel-based generators. Hence, the utilization of the derived biowaste (spoiled cooked egg and stew-rice) digestate to inoculate local pear has proven to be an authentic approach to generating biomass gas via a bio-reactor. This technique can be transferred to the modeled AutoCAD validated by the fabricated biomass gas plant for household utilization, thereby, mitigating vulnerability and emission rate from non-biomass fuel utilization.

Author Contributions

All authors have agreed to be held responsible for the contents of this manuscript and have approved the submission.

Acknowledgments

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data sets are available on request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
R3 Appendix ESE Biogas Pear.