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Enhancing Anaerobic Codigestion Technology with Machine Learning Approach for Climate Change Mitigation in Palm Oil Agro-Industries of Cameroon

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ABSTRACT

Applying machine learning to anaerobic co-digestion offers potential benefits for the palm oil industry and climate change mitigation. Conventional prediction models are often complex and lack generalization, while studies on palm oil mill effluent (POME) and cow dung have not fully addressed optimal substrate ratios and operating conditions. In this study, response surface methodology (RSM) and a decision tree (DT) were applied to model and optimize POME–cow dung co-digestion. RSM examined the relationship between mixing ratios, temperature, pressure, and pH, while the DT classified biogas volume as low, high, or very high. Results indicated that biogas yield significantly depended on mixing ratios, with optimal performance at 1:1 and 0.5:1 ratios, corresponding to temperatures of 19°C and 39°C. The correlation coefficient for prediction reached 31%, and sensitivity analysis revealed temperature as the most influential factor, followed by pH and pressure. Overall, integrating machine learning into co-digestion modeling can reduce operating costs and enhance the sustainability of palm oil agro-industries.

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INTRODUCTION

Climate change poses a challenge to achieving sustainable development objectives by 2030 (Hsieh & Yeh, 2024; Swart et al., 2003). The effects of climate change are evident worldwide, resulting in rising temperatures, drier conditions, agricultural losses, melting glaciers, and new disease outbreaks (Abbass et al., 2022). These consequences contribute to an increase in living standards and a rise in poverty levels. The causes of climate change are diverse. Industrial activities that use fossil energy sources contribute about 30% of greenhouse gas emissions. The agricultural sector contributes an additional 14% (Abbass et al., 2022).

Africa is significantly impacted by climate change, and agriculture is a key driver of the continent's development. Moyo et al. found that agriculture contributes 18% to greenhouse gas emissions, primarily due to the poor management of agricultural byproducts, including palm nut effluents (Moyo et al., 2023). These effluents are rich in methane and are often released into the environment or water sources. This leads to global warming and harm to aquatic life (Awoh et al., 2023). An estimated 3.4 tons of effluent per year are discharged into the environment (Lim et al., 2021).

Studies have shown that palm kernel effluents can serve as valuable sources of energy for anaerobic digestion, rapid pyrolysis, and combustion units (Lim et al., 2021; Promraksa & Rakmak, 2020; Razuan et al., 2010). Anaerobic fermentation units are particularly suitable for wet substrates, such as palm kernel effluents. Previous studies have shown that one liter of palm kernel effluent can produce 14 to 25 m^3 of biogas under thermophilic anaerobic digestion conditions (Krishnan et al., 2017).The co-digestion of palm kernel and cow dung effluents at different ratios has also been studied (Fajar et al., 2018; Lim et al., 2021; Nasir et al., 2012; Vahedi et al., 2022).

Anaerobic co-digestion has proven advantageous for mitigating climate change and environmental pollution. In fact, it plays a significant role in reducing the environmental impact of toxic substances and process inhibitors by lowering the concentrations of ammonia, sodium ions ($Na+$), calcium ions ($Ca2+$), magnesium ions ($Mg2+$), sulfides, inorganic salts, and heavy metals (López-Aguilar et al., 2023). Co-digesting POME with cow dung could overcome the limitations of using POME alone and provide an effective solution for reducing environmental pollution in the local palm oil industry.

Various mathematical models have been developed to predict the volume of biogas produced from the anaerobic fermentation of palm kernel effluents, taking into account hydraulic retention time and temperature (Li et al., 2018; Roy et al., 2018). However, a lack of universal models exists due to the variability of the conditions under which they are established. Emerging new modeling techniques, such as artificial intelligence–based methods like response surface methodology, decision trees, and artificial neural networks, are improving prediction accuracy (Kutyauripo et al., 2023; Parrenin et al., 2023).

Despite the potential benefits of anaerobic co-digestion, the complexity of nonlinear parameters and conversion processes often necessitates time-consuming, theoretical mathematical models. Machine learning approaches have increasingly been used for prediction and optimization studies in anaerobic co-digestion processes (Awhangbo et al., 2020a, 2020b; Kana et al., 2012). These approaches have shown promise in the efficient monitoring and control of such processes. Tools such as principal component analysis and particle swarm optimization have been applied to optimization studies (Kainthola et al., 2020; Krishnan et al., 2017). However, the composition of POME and cow dung varies from one environment to another, resulting in a lack of uniformity in POME and cow dung co-digestion procedures. Researchers still face challenges conducting POME and cow dung codigestion to obtain optimal co-digestion procedure ratios due to substrate chemical composition and transportation cost-effectiveness (Nasir et al., 2012; Ohale et al., 2023; Pererva et al., 2020).

Studies have used tools such as response surface methodology and decision trees to optimize biogas yield from anaerobic codigestion processes in the context of substrate mixing ratios (De Clercq et al., 2019). However, more research is needed using machine learning techniques to predict and optimize these processes, particularly in industries such as palm oil production. These studies could provide valuable insights into improving the efficiency of anaerobic codigestion and identifying key parameters for optimal performance and monitoring control of biogas plants. The present study uses response surface methodology and decision tree tools to predict biogas volume based on the ratio of palm oil effluent to cow dung, temperature, and pressure.

MATERIALS AND METHODS

Collection of Palm Oil and Cow Dung Effluents

Palm oil effluents were collected from an oil production facility in southwestern Cameroon. About 200 liters of the effluent were collected and stored at 28°C to prevent solidification. Cow dung was collected from a pulping farm at the University of Buea. Table 1 outlines the characteristics of the palm oil effluents and cow dung.

Table 1. Co-substrates characteristics

Parameters	POME	Cowdung
COD (mg/l)	51000	125
BOD (mg/l)	29500	-
VS (%)	30	82.8
TS (% or mg/l)	40500	15.6
Ph	5.5	7.8
Water content (%)	91	68

Determination of Palm Oil Effluent to Cow Dung Ratios

To investigate the impact of ratios on biogas volume, four ratios based on the volume of each substrate were established. The ratios were palm oil effluent to cow dung at 1:1, 0:1, 0.5:1, and 1:0.5. These ratios were selected based on research by Lim et al. (Lim et al., 2021). The volumes of each ratio are presented in Table 2 below. Mixing and measurements were conducted in a 20-liter container before transferring to the anaerobic fermentation reactor.

Table 2. Feedstocks quantity determination

Set	POME-cowdung ratio		Feeds			Total working volume (liter)
	POME	cowdung	POME (liter)	cowdung (liter)	water (liter)	
1 (control)	0	1	0.0	14.5	3	15
2	0.5	1	4.5	9.5	3.5	15
3	1	1	6.5	6.5	2	15
4	1	0.5	9.5	4.5	2	15

Anaerobic fermentation process and parameter determination

Co-digestion was conducted in a 15-liter anaerobic fermentation reactor. The fermentation process followed the methodology established by Lim et al. (Lim et al., 2021). Parameters such as fermentation temperature, biogas pressure, pH, and biogas volume were monitored. Daily pH measurements were taken using a calibrated pH meter (HI202-01 Edge from Hanna Instruments). Temperature readings were collected daily from three K-type thermocouple sensors placed at different points in the tank. Gas pressure was recorded daily using a pressure sensor attached to the gas pipe. Biogas volume was determined using the water displacement method at seven-hour intervals to enhance data variability (Anitha et al., 2015).

Prediction and Optimization of Biogas Volume Using the RSM, the Decision Tree, the Regression Model

Response surface methodology

The response surface methodology used box-behnken designs (Beltramo et al., 2016), involving about 15 trials. The independent variables were the temperature of anaerobic fermentation, pH, and biogas pressure, while biogas volume served as the response variable. The design identified the key factors that influenced the response, and a code was simulated in MATLAB 2015a to establish quadratic linear models for each ratio set. Table 3 presents the 3-factor Box-Behnken design for biogas volume values, with coefficients of -1, 0, and +1 corresponding to temperature, pH, and biogas pressure.

Table 3. 3 factors design applied to the biogas volume corresponding to the fourth ratios

Factors			
Number of experiments	**Temperature**	**Ph**	**Pressure**
9	-1	-1	0
2	-1		
1	1	-1	0
6	1	1	0
11	-1	0	-1
15	-1	0	1
13	1	0	-1
10	1	0	1
8	0	-1	-1
14	0	-1	1
3	0	1	1
7	0	0	0
4	0	0	0
5	0	0	0

A series of experiments was conducted using the experimental design to determine the optimal temperature, pH, and biogas pressure for each ratio set. The ratio sets were considered the dependent variable.

Optimization process

The optimization process involved testing the temperature, pH level, and biogas pressure to determine their nonlinear relationship with biogas volume. A quadratic polynomial function was used for the multiple regression model, and the coefficients were determined using a minimization/maximization function in MATLAB. The fundamental equation for minimization/maximization is shown in Equation 2.

$$\text{Quadratic model} = \beta_1 * T + \beta_2 * pH + \beta_3 * P + \beta_4 * T * pH + \beta_5 * T * P + \beta_6 * pH * P + \beta_7 * T^2 + \beta_8 * pH^2 + \beta_9 * P^2 \quad (1)$$

With T: Temperature (°C),P:Pressure (bar),pH. Specifically, the coefficients β_1, β_2, β_3, ..., β_9 of the quadratic equation were determined using a minimization/maximization function in MATLAB. A code was written for this purpose. The fundamental equation of minimization/maximization is expressed as follows:

$$E = \sum_{i=1}^{k} (ax_i + b + y_i)^2 \quad (2)$$

E, Quadratic model, will be maximized with respect to b at constant a, and with respect to a at constant b. x and y are considered constants during the differentiation process with respect to either a or b

$$\frac{dE}{da} = 2\,\Sigma(ax_i + b + y_i)x_i = 0 \quad (3)$$

$$\frac{dE}{db} = 2\,\Sigma(ax_i + b + y_i)y_i = 0 \quad (4)$$

a,b represent the coefficients as β1,β2,β3,β9 and x_i,y_i represent parameters like the temperature,pH and pressure.

Linear regression

Linear regression analysis was used to determine the relationships between the anaerobic fermentation parameters. The data were input into Matlab 2015a software for analysis, and the coefficient of determination (R^2) was used to characterize the relationships.

$$Y_i = \beta_0 + \beta_1 X_i \quad (5)$$

With Y_i as dependant variable, X_i as independent variable and β_0,β_1,β_2 are coefficients

Decision tree

The decision tree was designed to identify correlations between ratio sets and biogas parameters. The data was divided into input and output, and the decision tree was used to predict the biogas volume based on the temperature, pH level, and biogas pressure of the studied ratios. The model was validated using test data, and a Python script assessed the model's accuracy on the training data. The split percentage was determined based on the models' ability to accurately predict the output variable without overfitting or underfitting the data, as shown in Table 4.

Table 4. Decision tree parameters

Attributes	Input	Output
Biogas volume	✓	
temperature		✓
pH		✓
Biogas pressure		✓

RESULTS AND DISCUSSION

Average biogas volume

The average biogas volume as a function of the POME-cow dung ratios is presented in Table 5 below. It shows that regardless of the ratio, the 1:0 ratio obtained the highest volume of biogas ($p<0.05$), followed by the ratio 0.5:1.

Table 5. Mean values of the biogas volume according to the type of ratio POME-cow dung

Ratio POME-cow dung	Mean biogas volume (cm^3)	95 % range value	Deviation	Deviation Interval
Ratio 1:1	2318.77***	[2029.91, 2607.63]	699.795	[546.42, 973.521]
Ratio 1:0.5	2467.89***	[2196.17, 2739.6]	658.252	[513.981, 915.728]
Ratio 0.5:1	4687.57**	[4070.94, 5304.2]	1493.85	[1166.44, 2078.17]
Ratio 1:0	7650.18*	[7018.2, 8282.17]	1531.04	[1195.48, 2129.91]

***mean values are non-significantly different

Conversely, no significant difference was observed between the 1:1 and 1:0.5 ratios, which had the lowest average biogas volumes. Regardless of the substrate mixing ratio, the range was low compared to that obtained by Lim et al. (Lim et al., 2021). This difference could be due to the quantity of substrate mixture used.

Evolution of Biogas Volumes (Cm^3) As A Function of Hydraulic Retention Period (Days)

Figure 1 below illustrates the evolution of biogas volumes as a function of the hydraulic retention period. Regardless of the hydraulic retention time, the curves have the same configuration. Daily methane production increased from the first to the 12th day of anaerobic digestion.

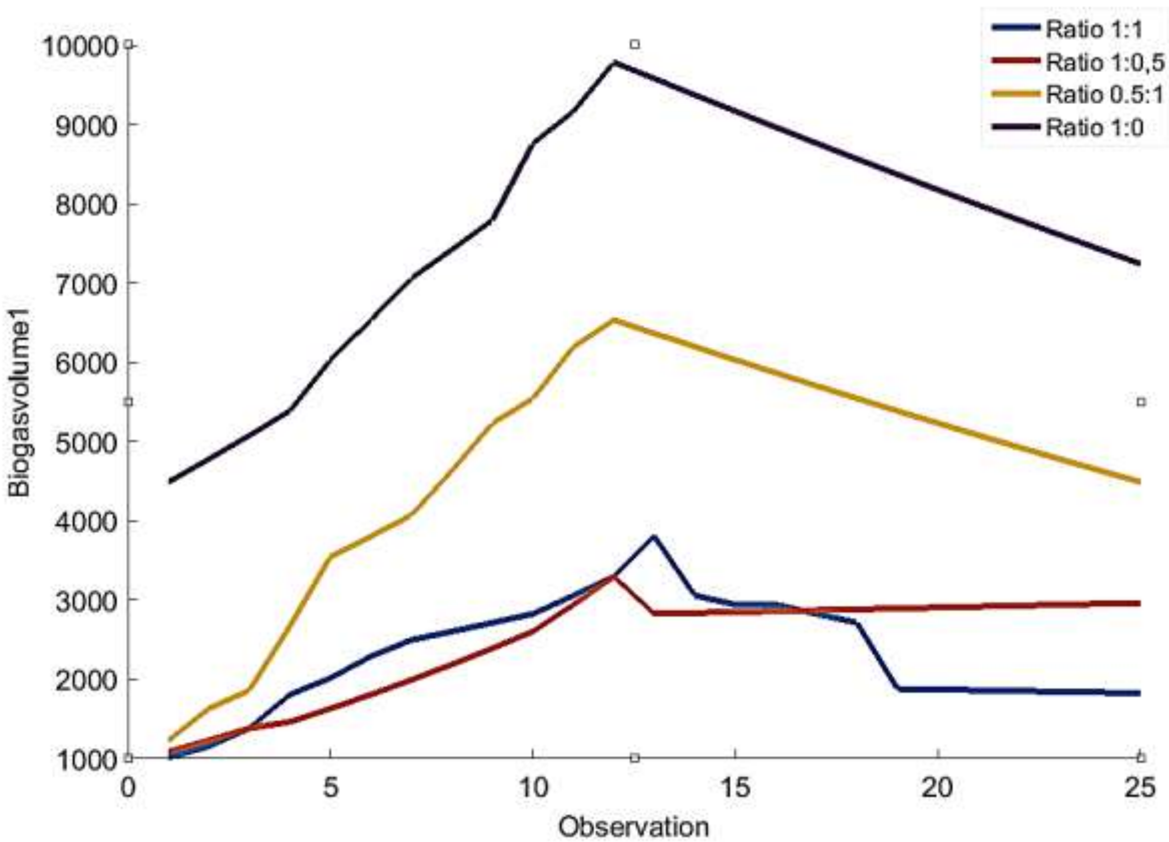

Figure 1. Evolution of biogas volumes as a function of hydraulic retention time

From day 12th to 25th of anaerobic digestion, the volume of biogas decreases. For all substrate mixing ratios, the methane-forming bacteria are still growing, which reduces the timing of biogas production (an increase in the lag phase) due to the presence of high percentages of acid-forming bacteria from POME. Similar observations were made by López-Aguilar et al. though the timing differed (López-Aguilar et al., 2023). Case 1:0 without POME demonstrates this as well. Later, we noticed a clear separation between the 0.5:1 ratio, which increased rapidly until the end, and the 1:0.5 and 1:1 ratios. This could be explained by temperature and pH fluctuations related to the high lag phase. The methane-forming bacteria for all three ratios are in the growth phase, which reduces biogas production timing due to the presence of high percentages of acid-forming bacteria from POME.

Frequency Distribution of Anaerobic Codigestion Temperature

The frequency distribution of anaerobic codigestion temperatures is illustrated in figure 2 below. Regardless of the POME-cow dung ratios, the anaerobic fermentation temperatures are between 20°C and 39°C. These values reflect mesophilic anaerobic digestion.

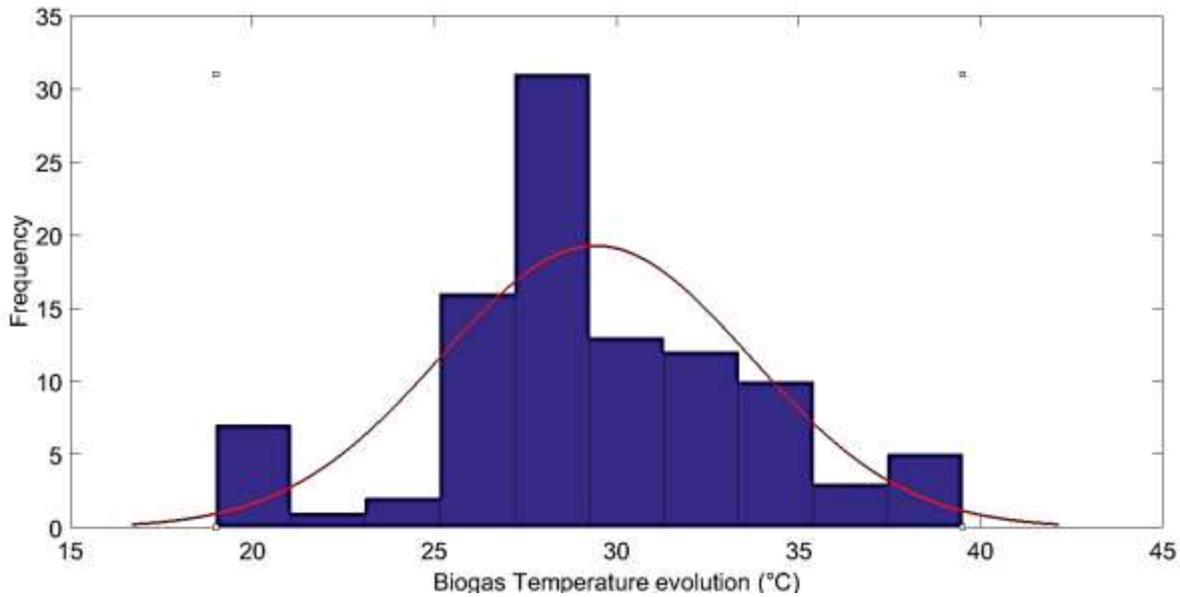

Figure 2. Frequency of distribution of anaerobic fermentation temperatures

This temperature range represents experimental values for the implementation of an industrial anaerobic fermentation unit without additional energy input for heating. In terms of frequencies, the most representative temperature during our anaerobic digestion tests would be between 25°C and 35°C. This range of values is similar to that obtained by the following authors.

Evolution of the Biogas Volume as a Function of Anaerobic Digestion Temperature and the POME-Cow Dung Ratios

Figure 4 shows the volume of biogas in relation to temperature and the POME-cow dung ratio. It shows that the highest volume of biogas was produced by anaerobic fermentation at a temperature of 34°C and a ratio of 0.5:1. Conversely, the lowest volume of biogas was observed at a precise temperature of 20.1°C with the ratio of 1:1. However, biogas is produced more quickly at the 1:1 and 0.5:1 ratios than at the 0:1 and 1:0.5 ratios, where biogas is produced at temperatures of 25°C and 26.5°C, respectively.

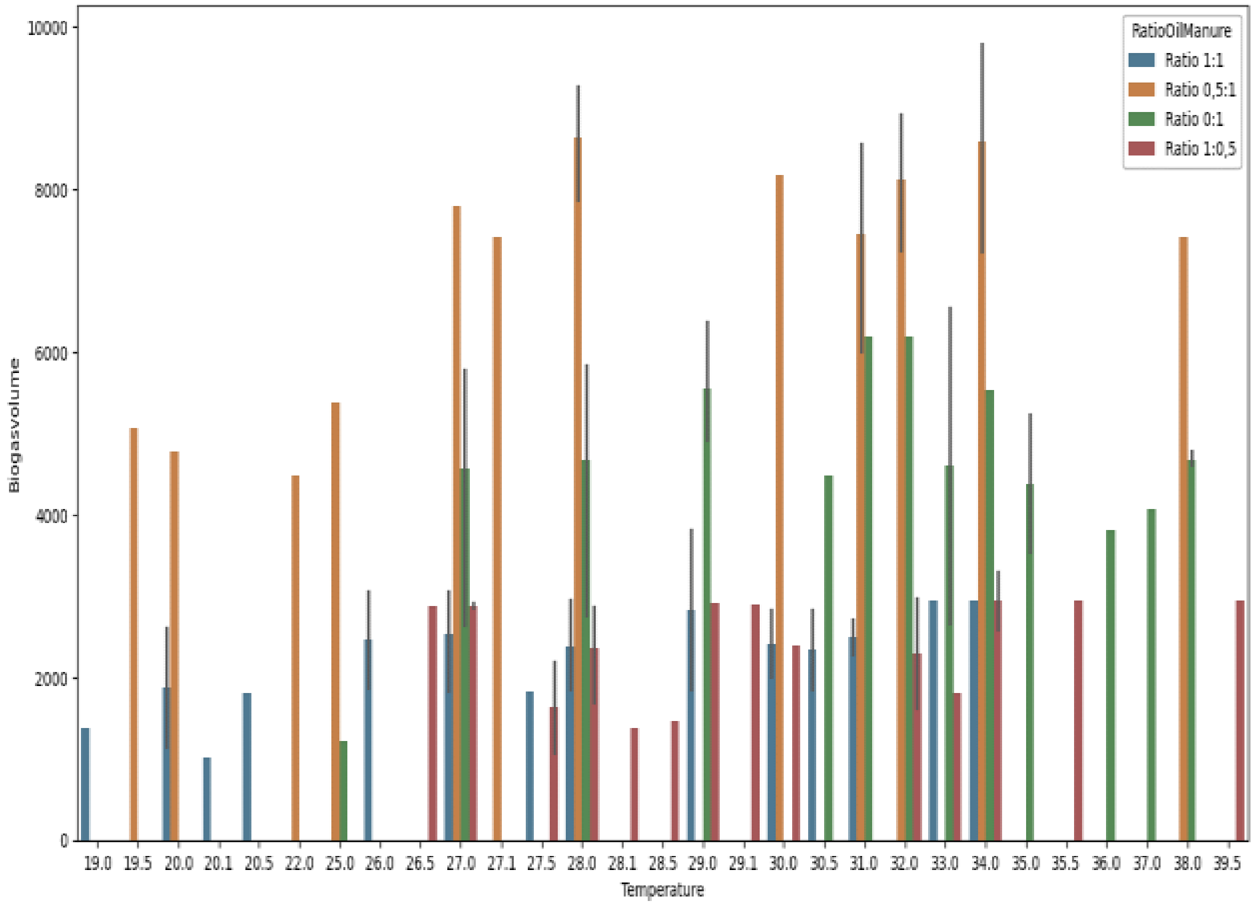

Figure 3. Evolution of the biogas volume as a function of anaerobic fermentation temperature and POME-cow dung ratios

These results show that there is no need to heat the bioreactor tank because the temperature of co-substrates behaves naturally under mesophilic conditions, reducing the energy consumption and providing a low-cost implementation for such a ratio (Choong et al., 2018; Mao et al., 2015). In addition, Ohale et al. signify that the minimum temperature for bacteria to grow during anaerobic fermentation is 15°C (Ohale et al., 2023).

Evolution of the Biogas Volume as a Function of Anaerobic Digestion Ph and POME-Cow Dung Ratios

The volume of biogas as a function of the pH of the anaerobic digestion and the POME-cow dung ratios is shown in figure 4. It appears that the highest volume of biogas was observed at a pH close to 7 in the ratio 0.5:1.

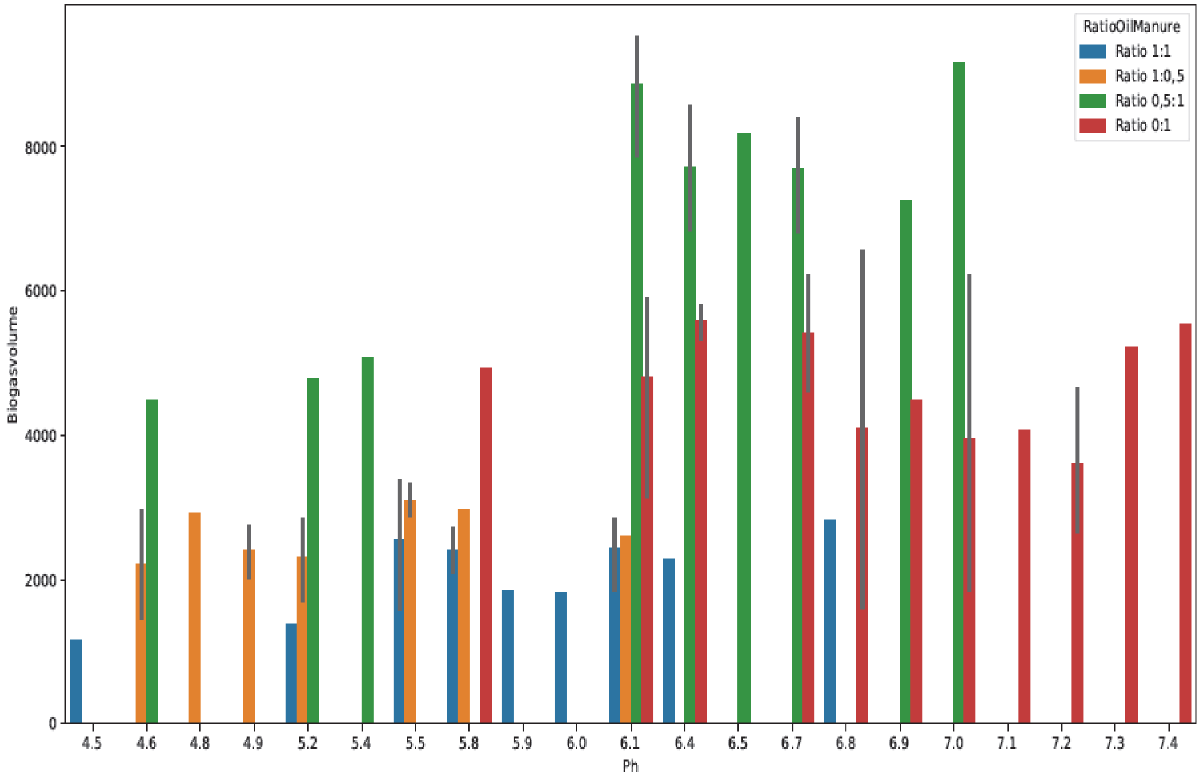

Figure 4. Evolution of the biogas volume as a function of anaerobic digestion pH and POME-cow dung ratios

Despite the small volume of biogas produced, there is faster and more instantaneous production of biogas at a pH close to 3 in a 1:1 ratio. In contrast, biogas production was observed at ratios of 1:0.5, 0.5:1, and 0:1 at pH values of 4.6, 4.6, and 5.83, respectively. All of these values remain below the reference value of 6.2. Conversely, biogas production is only effective at pH ≥ 7 for the 0.5:1 and 0:1 ratios. The mixture of POME and cow dung at a ratio of 0.5:1, with a large quantity of organic matter, undergoes rapid hydrolysis at the beginning of fermentation. This produces an accumulation of volatile fatty acids, which are responsible for the drop in pH. This phenomenon clearly explains the mechanism of pH variation in anaerobic digestion (Choong et al., 2018; Sukkar et al., 2021).

Evolution of the volume of biogas as a function of its pressure and the POME-cow dung ratio

Figure 5 shows the evolution of biogas volume as a function of pressure and the POME-cow dung ratio. While the 0.5:1 ratio produces the greatest volume of biogas, the gas pressure for this ratio ranges from 0 to 1.1 bar.

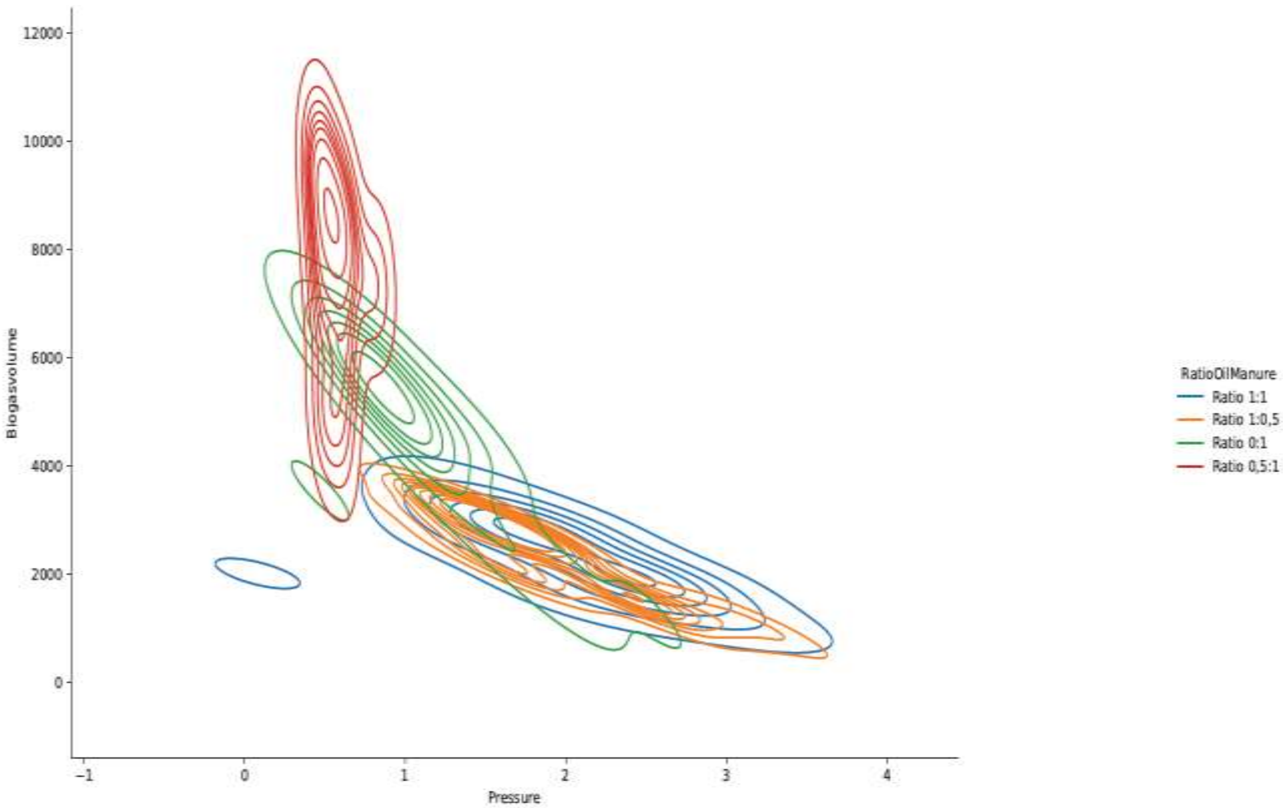

Figure 5. Evolution of the biogas volume as a function of its pressure and the POME-cow dung ratio

Conversely, for ratios of 1:1, 1:0.5, and 0:1, the volume of biogas decreases as gas pressure increases. This decrease in biogas volume is more noticeable in the 1:1 and 1:0.5 ratios. However, the gas pressure range is between 1.1 and 3.7 bars, which is higher than the 0.5:1 ratio, which had the highest biogas volume. We observe pressure value stability for the three ratios, with the lowest pressure value obtained at the 0.5:1 ratio. According to Tshemese et al. low, stable pressures promote good biogas production and high methane content (Tshemese et al., 2023).

Cumulative Volume of Biogas as a Function of POME-Cow Dung Ratios

The cumulative volume of biogas as a function of the POME-cow dung ratios is shown in figure 6. It appears that apart from the reference ratio (1:0), the cumulative volume of biogas was highest in the 0.5:1 ratio, followed by the 1:0.5 ratio and finally the 1:1 ratio.

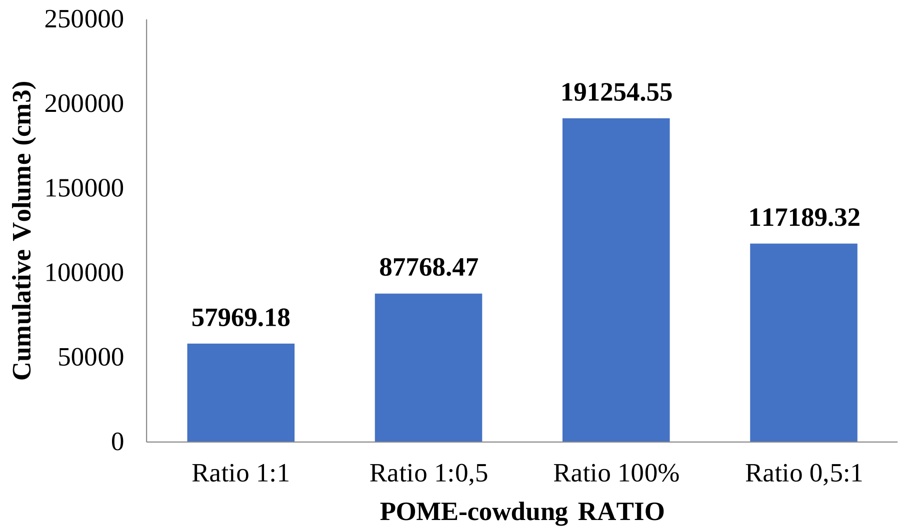

Figure 6. Cumulative volume of biogas as a function of POME-cow dung ratios

This cumulative volume of biogas is correlated with the daily biogas volume. Taking into account the parameters studied above such as temperature, pH, and pressure during anaerobic fermentation, we can see that the volume of biogas was highest with the ratio 0.5:1. By decreasing the quantity of POME in the mixture, we suspect a decrease in the volatile fatty acids with an increase in methanogenic bacteria growth, which could have enhanced the cumulative biogas volume. Moreover, the cumulative biogas volumes are related to temperatures and pH corresponding to each POME-cow dung ratio.

Biogas Optimization Process Using Response Surface Methodology

The optimization process of biogas volume was established based on the biogas temperature, pH, and pressure values corresponding to each set of POME-cow dung ratios (1:1, 1:0.5, 0.5:1, and 1:0). The coefficients of the polynomial equation (6) related to the Box-Behnken design (BBD) are presented in Table 6.

$$\begin{aligned}\text{Quadratic model} = {} & \beta_1 * T + \beta_2 * pH + \beta_3 * P \\ & + \beta_4 * T * pH + \beta_5 * T * P \\ & + \beta_6 * pH * P + \beta_7 * T^2 \\ & + \beta_8 * pH^2 + \beta_9 * P^2\end{aligned} \quad (6)$$

With T, Temperature (°C), PPressure (bar) and pH.

It shows that kernels are the best predictor of the iodine index, followed by crushed and whole seeds, with correlation coefficients of 0.74, 0.62, and 0.48 respectively..

Table 6. Coefficient of the quadratic model for different ratios

Ratio POME-cow dung	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	R^2	RMSE
Ratio 1:1	390.92	-135.16	-96.01	28.27	-241.69	51.98	255.98	-470.88	977.67	0.63	476
Ratio1:0.5	243.46	92.39	14.354	15.835	-254.44	-2.502	-721.3	-704.26	635.98	0.88	255
Ratio0.5:1	741.7	64.59	-6.47	125.17	-0.372	-311.4	4.52	-763.14	2569.6	0.83	719
Ratio 1:0	663.66	10.091	23.543	110.83	-445.36	4.525	-37.73	-780.64	2480.1	0.71	979

$$\text{Biogas volume for Ratio } 1:1 = 390.92 * T - 135.16 * pH - 96.01 * P + 28.27 * T * pH - 241.69 * T * P + 51.98 * pH * P + 255.98 * T^2 - 470.88 * pH^2 + 977.67 * P^2 \quad (7)$$

$$\text{Biogas volume for Ratio } 1:0.5 = 243.46 * T + 92.39 * pH + 14.354 * P + 15.835 * T * pH - 254.44 * T * P - 2.502 * pH * P - 721.3 * T^2 - 704.26 * pH^2 + 635.98 * P^2 \quad (8)$$

$$\text{Biogas volume for Ratio } 0.5:1 = 741.7 * T + 64.59 * pH - 6.47 * P + 125.17 * T * pH - 0.372 * T * P - 311.4 * pH * P + 4.52 * T^2 - 763.14 * pH^2 + 2569.6 * P^2 \quad (9)$$

$$\text{Biogas volume for Ratio } 1:0 = 663.66 * T + 10.091 * pH + 23.543 * P + 110.83 * T * pH - 445.36 * T * P + 4.525 * pH * P - 37.73 * T^2 - 780.64 * pH^2 + 2480.1 * P^2 \quad (10)$$

Determination of optimum solutions for quadratic models

Table 7 shows the optimum values of temperature, pH, and pressure corresponding to each ratio POME-cow dung. As far as the biogas temperature is concerned, the ratio 1:0.5 is found to have the highest temperature. As for the pH, the ratio 0.5:1 showed the highest pH (7.4). Finally, the ratio 1:0.5 produces the highest optimum value of gas pressure (3.16 bars).

Table 7. Optimal values of biogas temperature, pH, and pressure for ratio POME-cow dung

Optimum values of parameter corresponding to Peroxide value				**Corresponding equations number**
Ratio POME-cow dung	**Temperature (°C)**	**pH**	**Pressure (Bars)**	
Ratio 1:1	19	6.8	2.21	8
Ratio1:0.5	39.5	6.1	3.16	9
Ratio0.5:1	38	7.4	2.23	10
Ratio 1:0	38	7	0.85	11

Linear regression model

A linear regression model was established for each POME-cow dung ratio in anaerobic digestion, and the parameters are presented in Table 8. The 1:0.5 and 0.5:1 POME-cow dung ratios fit better with the linear regression model, as indicated by R and the P-value.

Table 8. Linear regression parameters corresponding to each set of ratio

Set of ratio	**R^2**	**RSME**	**P-value**
Ratio 1:1	0.63	476	0.00106
Ratio1:0.5	0.88	268	$3.7*10^{-8}$
Ratio0.5:1	0.83	719	$1.45*10^{-5}$
Ratio 1:0	0.71	979	0.00128

Decision tree results

Figure 7 in addition with table 9 show the prediction model for anaerobic fermentation of POME and cow dung. The biogas volume is characterized by three performance categories: very high, high, and low. The model achieved 85% prediction accuracy on the test data.

Table 9. Accuracy data for the decision tree model

	Precision	Recall	F1-score	Support
High	0.82	0.90	0.86	10
Low	1.00	0.60	0.75	5
Very High	0.83	1.00	0.91	5
Accuracy			0.85	20
Macro avg	0.88	0.83	0.84	20
Weighted avg	0.87	0.85	0.84	20

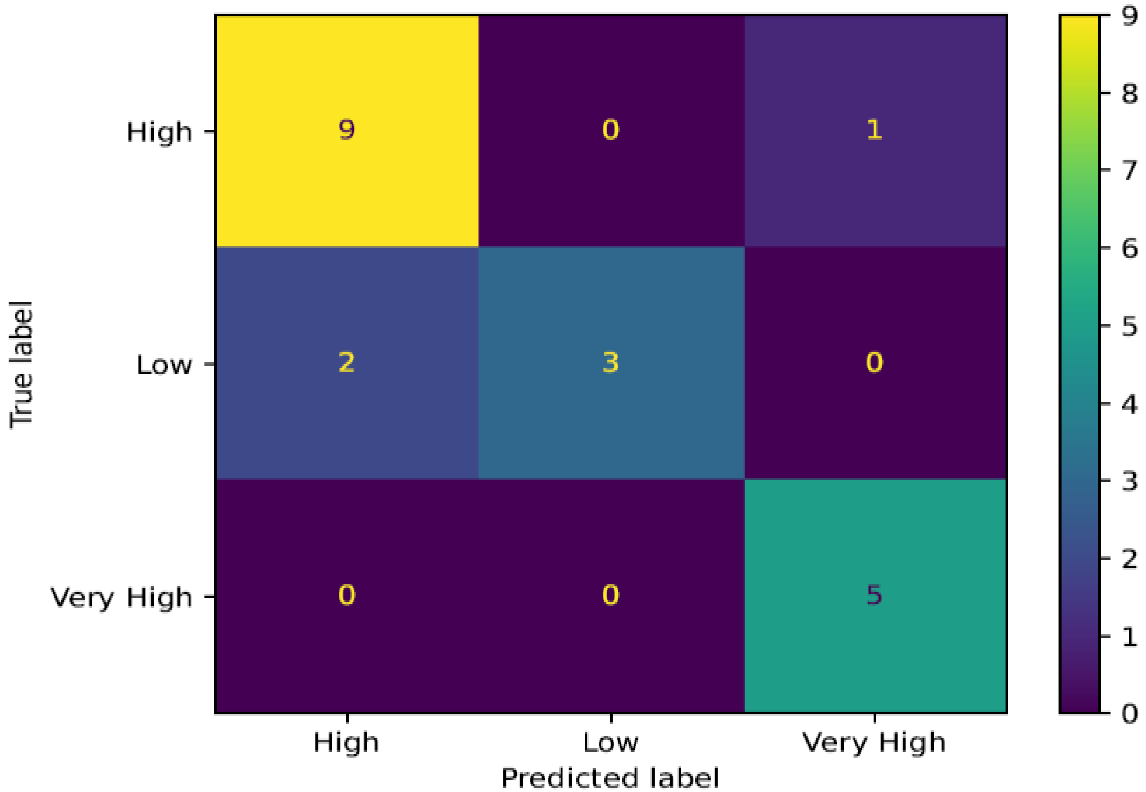

Figure 7. Prediction performance of POME-cow dung codigestion using scikit-learn

This high level of precision reflects the robustness of the model. As the above figure shows, the model effectively classifies anaerobic fermentation based mainly on high and low biogas volume values. Within the training dataset, the model accurately identified 9, 3, and 5 biogas volumes as having very high, high, and low performance, respectively. On the same graph, only two biogas volumes were misclassified by the model. Furthermore, figure 8 shows a decision tree with three quantitative parameters that can be used to predict the performance of POME-cow dung anaerobic codigestion.

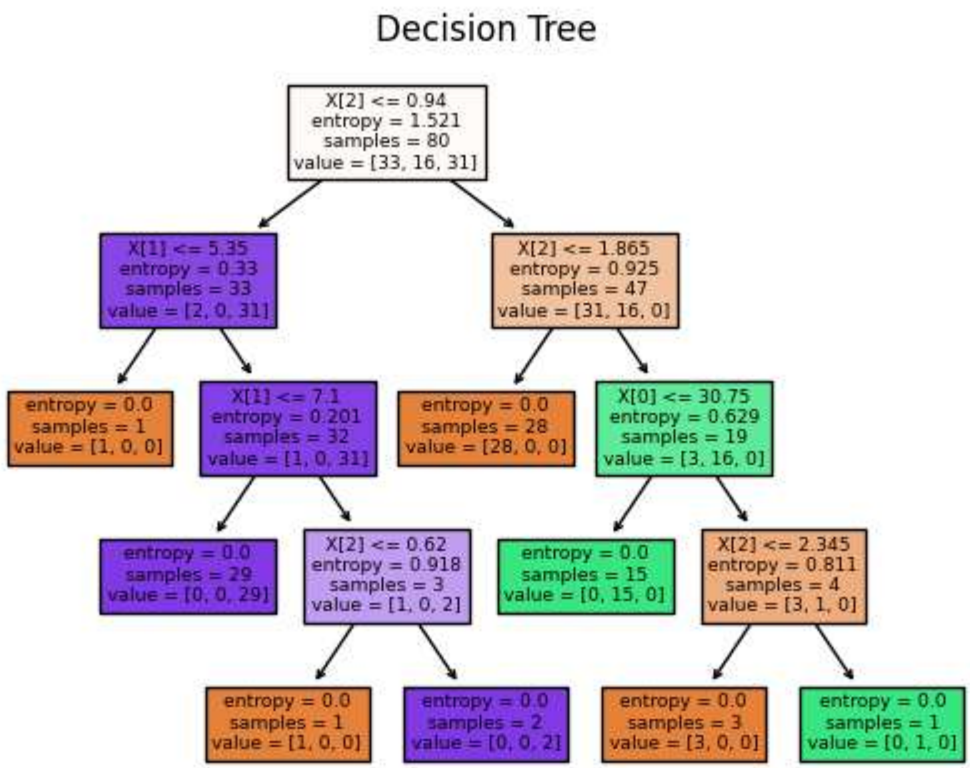

Figure 8. Decision tree for the POME-cow dung anaerobic codigestion

From figure 8, four levels with fifteen leaves are presented. The first parameter is the biogas temperature (X[0]), followed by the pH (X[1]) and finally the biogas pressure (X[2]). The range of values for each predictive parameter is also displayed in Table 10 below, corresponding to high or low POME-cow dung anaerobic fermentation performance.

Table 10. Predicted parameters of POME-cow dung anaerobic fermentation performance

Parameters	**Range of values**	**Performance**
Temperature (X[0])	<= 30.75	Low
	> 30.75	High
pH (X[1])	>5.35	High
	<=5.35	Low
Pressure (X[2])	<= 0.94	Low
	> 1.87	High

Indeed, anaerobic digestion operating at temperatures above 30.75°C is expected to produce high-performance biogas. Conversely, a biogas reactor with a pH below 5 is expected to produce less biogas and perform poorly. Finally, the biogas volume can be predicted based on the biogas pressure. In this study, a biogas pressure of less than 0.94 bars is expected to result in low performance, whereas a pressure greater than 1.87 bars could result in high performance at the end of the process. Figure 9 illustrates the correlation between the actual and predicted biogas volumes.

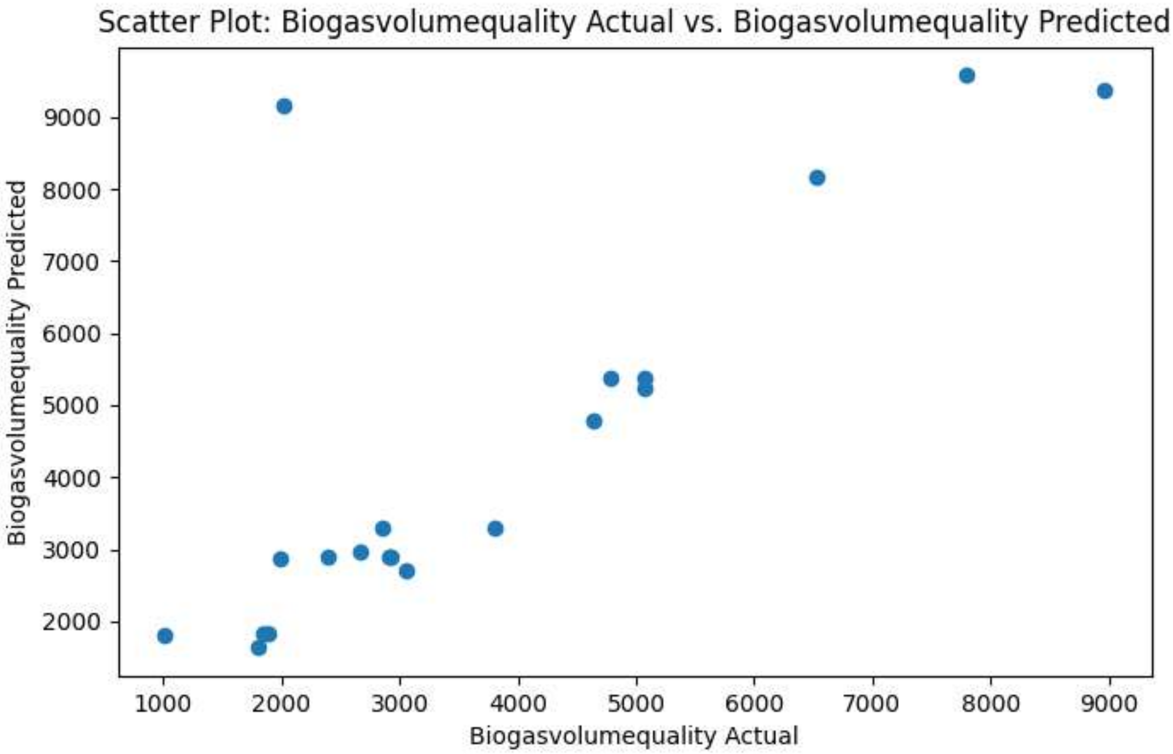

Figure 9. POME-cow dung biogas volume prediction

It appears from the above figure that the calculated biogas volume fits well with the experimental biogas volume. This is shown by the value of the coefficient of correlation R^2 = 31%.

CONCLUSIONS

The main objective of this study was to predict the substrate mixing ratio during anaerobic codigestion of POME and cow dung using response surface methodology and decision tree. The POME-cow dung ratio affects the biogas volume. The ratio of 0.5:1 produced the highest biogas volume, temperature, and pH, followed by the ratio of 1:0.5. These results present an advantage in terms of reduced transportation costs if a biogas power plant is implemented using POME and cow dung as substrates. Response surface methodology and decision trees provided accurate predictions of the POME-cow dung mixing ratio. Optimal values of temperature, pH, and pressure were determined for each POME-cow dung ratio studied. Additionally, quadratic equations were established to predict biogas volume based on temperature, pH, and pressure. The decision tree revealed that temperature had the most significant effect on biogas volume, followed by pH and then biogas pressure, regardless of the POME-to-cow dung ratio. A correlation coefficient of 32% was determined for the correlation between the predicted and experimental biogas volumes. Based on these findings, large-scale co-digestion of POME and cow dung could be implemented in Cameroon using the model established in this study. Future research will focus on reducing the lag phase of anaerobic codigestion of POME and cow dung over an extended fermentation period.

CREDIT AUTHORSHIP CONTRIBUTIONS

Nsah-ko Tchoumboue worked on investigation, methodology, conceptualization, software, and data curation, original draft, writing of the manuscript. Njila Ntankouo Roger provided the data analysis, prediction tools.

Djoukeng Henry Grisseur worked in project administration and formal analysis. Tedongmo Ngouana Jospin worked on investigation and methodology. Tangka Julius Kewir worked in the supervision, data curation, validation, review, and editing of the manuscript.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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REFERENCES

Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental science and pollution research*, *29*(28), 42539-42559. https://doi.org/10.1007/s11356-022-19718-6

Anitha, M., Kamarudin, S., Shamsul, N., & Kofli, N. (2015). Determination of bio-methanol as intermediate product of anaerobic co-digestion in animal and agriculture wastes. *International Journal of Hydrogen Energy*, *40*(35), 11791-11799. https://doi.org/10.1016/j.ijhydene.2015.06.072

Awhangbo, L., Bendoula, R., Roger, J.-M., & Béline, F. (2020a). Detection of early imbalances in semi-continuous anaerobic co-digestion process based on instantaneous biogas production rate. *Water Research, 171*, 115444. https://doi.org/10.1016/j.watres.2019.115444

Awhangbo, L., Bendoula, R., Roger, J.-M., & Béline, F. (2020b). Multi-block data analysis for online monitoring of anaerobic co-digestion process. *Chemometrics and Intelligent Laboratory Systems, 205*, 104120. https://doi.org/10.1016/j.chemolab.2020.104120

Awoh, E. T., Kiplagat, J., Kimutai, S. K., & Mecha, A. C. (2023). Current trends in palm oil waste management: A comparative review of Cameroon and Malaysia. *Heliyon*, *9*(11), e21410. https://doi.org/10.1016/j.heliyon.2023.e21410

Beltramo, T., Ranzan, C., Hinrichs, J., & Hitzmann, B. (2016). Artificial neural network prediction of the biogas flow rate optimised with an ant colony algorithm. *Biosystems Engineering, 143*, 68-78. https://doi.org/10.1016/j.biosystemseng.2016.01.006

Choong, Y. Y., Chou, K. W., & Norli, I. (2018). Strategies for improving biogas production of palm oil mill effluent (POME) anaerobic digestion: A critical review. *Renewable and Sustainable Energy Reviews, 82*, 2993-3006. https://doi.org/10.1016/j.rser.2017.10.036

De Clercq, D., Jalota, D., Shang, R., Ni, K., Zhang, Z., Khan, A., Wen, Z., Caicedo, L., & Yuan, K. (2019). Machine learning powered software for accurate prediction of biogas production: A case study on industrial-scale Chinese production data. *Journal of cleaner production*, *218*, 390-399. https://doi.org/10.1016/j.jclepro.2019.01.031

Fajar, M. F., Faizal, M., & Novia, N. (2018). Effects of mesophilic and thermophilic temperature condition to biogas production (methane) from palm oil mill effluent (POME) with cow manures. *Science and Technology Indonesia*, *3*(1), 19-25. https://doi.org/10.26554/sti.2018.3.1.19-25

Hsieh, Y.-L., & Yeh, S.-C. (2024). The trends of major issues connecting climate change and the sustainable development goals. *Discover Sustainability*, *5*(1), 31. https://doi.org/10.1007/s43621-024-00183-9

Kainthola, J., Kalamdhad, A. S., & Goud, V. V. (2020). Optimization of process parameters for accelerated methane yield from anaerobic co-digestion of rice straw and food waste. *Renewable* *energy*, *149*, 1352-1359. https://doi.org/10.1016/j.renene.2019.10.124

Kana, E. G., Oloke, J., Lateef, A., & Adesiyan, M. (2012). Modeling and optimization of biogas production on saw dust and other co-substrates using artificial neural network and genetic algorithm. *Renewable energy*, *46*, 276-281. https://doi.org/10.1016/j.renene.2012.03.027

Krishnan, S., Singh, L., Sakinah, M., Thakur, S., Wahid, Z. A., & Ghrayeb, O. A. (2017). Role of organic loading rate in bioenergy generation from palm oil mill effluent in a two-stage up-flow anaerobic sludge blanket continuous-stirred tank reactor. *Journal of cleaner production*, *142*, 3044-3049.

Kutyauripo, I., Rushambwa, M., & Chiwazi, L. (2023). Artificial intelligence applications in the agrifood sectors. *Journal of Agriculture and Food Research*, *11*, 100502. https://doi.org/10.1016/j.jafr.2023.100502

Li, Y., Jin, Y., Li, H., Borrion, A., Yu, Z., & Li, J. (2018). Kinetic studies on organic degradation and its impacts on improving methane production during anaerobic digestion of food waste. *Applied Energy*, *213*, 136-147. https://doi.org/10.1016/j.apenergy.2018.01.033

Lim, Y. F., Chan, Y. J., Hue, F. S., Ng, S. C., & Hashma, H. (2021). Anaerobic co-digestion of palm oil mill effluent (POME) with decanter cake (DC): effect of mixing ratio and kinetic study. *Bioresource Technology Reports*, *15*, 100736. https://doi.org/10.1016/j.biteb.2021.100736

López-Aguilar, H. A., Morales-Durán, B., Quiroz-Cardoza, D., & Pérez-Hernández, A. (2023). Lag phase in the anaerobic Co-digestion of Sargassum spp. and organic domestic waste. *Energies*, *16*(14), 5462.

Mao, C., Feng, Y., Wang, X., & Ren, G. (2015). Review on research achievements of biogas from anaerobic digestion. *Renewable and sustainable energy reviews*, *45*, 540-555. https://doi.org/10.1016/j.rser.2015.02.032

Moyo, E., Nhari, L. G., Moyo, P., Murewanhema, G., & Dzinamarira, T. (2023). Health effects of climate change in Africa: A call for an improved implementation of prevention measures. *Eco-Environment & Health*, *2*(2), 74-78. https://doi.org/10.1016/j.eehl.2023.04.004

Nasir, I., Ghazi, T. M., Omar, R., & Idris, A. (2012). Palm oil mill effluent as an additive with cattle manure in biogas production. *Procedia Eng*, *50*, 904-912. https://doi.org/10.1016/j.proeng.2012.10.098

Ohale, P. E., Ejimofor, M. I., Onu, C. E., Abonyi, M., & Ohale, N. J. (2023). Development of a surrogate model for the simulation of anaerobic co-digestion of pineapple peel waste and slaughterhouse wastewater: Appraisal of experimental and kinetic modeling. *Environmental Advances*, *11*, 100340. https://doi.org/10.1016/j.envadv.2022.100340

Parrenin, L., Danjou, C., Agard, B., & Beauchemin, R. (2023). A decision support tool for the first stage of the tempering process of organic wheat grains in a mill. *International Journal of Food Science and Technology*, *58*(10), 5478-5488. https://doi.org/10.1111/ijfs.16406

Pererva, Y., Miller, C. D., & Sims, R. C. (2020). Existing empirical kinetic models in biochemical methane potential (BMP) testing, their selection and numerical solution. *Water*, *12*(6), 1831. https://doi.org/10.3390/w12061831

Promraksa, A., & Rakmak, N. (2020). Biochar production from palm oil mill residues and application of the biochar to adsorb carbon dioxide. *Heliyon*, *6*(5), e04019. https://doi.org/10.1016/j.heliyon.2020.e04019

Razuan, R., Chen, Q., Zhang, X., Sharifi, V., & Swithenbank, J. (2010). Pyrolysis and combustion of oil palm stone and palm kernel cake in fixed-bed reactors. *Bioresource Technology*, *101*(12), 4622-4629. https://doi.org/10.1016/j.biortech.2010.01.079

Roy, A. D., Prakash, O., Kumar, A., Kaviti, A., & Pandey, A. (2018). Design and Selection Criteria of Biogas Digester. In *Low Carbon Energy Supply: Trends, Technology, Management* (pp. 91-112). Springer. https://doi.org/10.1007/978-981-10-7326-7_6

Sukkar, K. A., Al-Zuhairi, F. K., & Dawood, E. A. (2021). Evaluating the influence of temperature and flow rate on biogas production from wood waste via a packed-bed bioreactor. *Arabian Journal for Science and Engineering*, *46*(7), 6167-6175. https://doi.org/10.1007/s13369-020-04900-0

Swart, R., Robinson, J., & Cohen, S. (2003). Climate change and sustainable development: expanding the options. *Climate policy*, *3*(sup1), S19-S40. https://doi.org/10.1016/j.clipol.2003.10.010

Tshemese, Z., Deenadayalu, N., Linganiso, L. Z., & Chetty, M. (2023). An overview of biogas production from anaerobic digestion and the possibility of using sugarcane wastewater and municipal solid waste in a South African context. *Applied System Innovation*, *6*(1), 13. https://doi.org/10.3390/asi6010013

Vahedi, E., Rabbani, H., & Faramarzi, P. (2022). Redesigning a Stalk Chopper Mechanism for Reducing Cutting Energy and Optimizing Its Bite Length. *Biomechanism and Bioenergy Research, 1*(2), 69-73. https://doi.org/10.22103/bbr.2022.20466.1030