Optimization of process parameters for anaerobic co-digestion of cow dung and jatropha cake using Response Surface Methodology

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Abstract

Waste-to-energy technology using agricultural residues, especially in developing countries, can assist in achieving the sustainable development goals of (SDGs) of the United Nations. Large quantities of cow dung and jatropha cakes are released annually, leading to severe environmental challenges and urgent attention. Anaerobic co-digestion of two or more feedstocks is becoming more popular because it improves biogas yield and organic waste management. This study investigates the influence of three independent variables of temperature, retention time, and mixing ratio on the biogas yield of cow dung and jatropha cake. Central Composite Design of Response Surface Methodology (RSM) was used to optimize and predict biogas yield through an anaerobic co-digestion process. The observed result indicates that the linear model terms of temperature, retention time, and mixing ratio have significant interactive effects ($P \leq 0.05$). The optimum conditions were observed to be a temperature of 34 °C, a retention time of 29 days, and a 50:50 % mixing ratio (cow dung to jatropha cake). The model predicted 1.8 L/Kg VS_{added} at the optimum conditions with a correlation value (R^2) of 0.8390. The predicted result shows that RSM models can predict biogas yield. In general, this study has demonstrated that co-digestion of cow dung and jatropha cake is a promising way to enhance biogas yield by providing nutrient balance, and this can be replicated at the industrial scale.

Keywords: Biogas yield, Co-digestion, Cow dung, Jatropha cake, Response Surface Methodology (RSM).

1. Introduction

Biogas production from organic wastes as bioenergy retrieval and pollution control is a bright means of reducing greenhouse gas emissions and a sustainable means of waste management technology (Dhar, Kumar and Kumar, 2017). Biogas released from these organic wastes through the anaerobic digestion process can be utilized for heating, lighting, and electricity generation and can be refined and injected into the grid (Ellabban, Abu-Rub and Blaabjerg, 2014). The anaerobic digestion process is a multi-stage biological and chemical process that employs anaerobic microorganisms to transform biodegradable wastes into biogas rich in methane gas (Jekayinfa *et al.*, 2020). Residues from agricultural activities such as wheat straw, maize streak, cow dung, poultry manure, groundnut shells, rice straw, jatropha cake, loofah cake, etc. are some of the abundant and cheap lignocellulose feedstocks with high organic contents for biogas generation (Adebayo, Jekayinfa and Linke, no date; Patil *et al.*, 2016; Kehinde O. Olatunji *et al.*, 2022). Large quantities of animal wastes, agricultural residues, and bio-oil cakes have been traditionally produced and managed, leading to environmental challenges like pollution, eutrophication, and soil and groundwater contamination (Baek *et al.*, 2020). Conversion of animal wastes and oil cakes into biogas, fertilizer and other bye products will minimize the environmental challenges, enhance soil fertility, and generate clean and sustainable energy (Raheman and Mondal, 2012; Bhuvaneshwari, Hettiarachchi and Meegoda, 2019; Olatunji, Adebayo and Bolaji, 2020).

Jatropha cake is a bio-oil cake with a high content of lignocelluloses, making it ineffective during anaerobic digestion and producing moderate biogas yield with a higher retention period compared to other easily digestible feedstocks (Raheman and Mondal, 2012). On the contrary, cow dung has a higher percentage of degradable organic contents and carbon-nitrogen ratio than other organic substrates for biogas generation (Franqueto, da Silva and Konig, 2020). Therefore, co-digestion of cow dung and jatropha cake is suggested to overcome the challenges associated with the anaerobic digestion of each feedstock (Barik and Murugan, 2015). Anaerobic co-digestion of different residues/wastes during anaerobic digestion is commonly used to balance the nutrient contents shortage of other feedstocks, compensating for the nutrient limitation of each feedstock. Anaerobic co-digestion also avails the dilution of potentially toxic compounds and improves biogas yield and process kinetics (Pinpatthanapong *et al.*, 2022). Several studies have experimented with anaerobic co-digestion of various wastes and proposed a means of enhancing biogas yields (Beltramo *et al.*, 2016; Zupančič, Panjičko and Zelić, 2017; Safari *et al.*, 2018).

Biogas yield improvement requires optimizing the process parameters that greatly influence the process. In this case, biogas generation from organic wastes needs optimization and stabilization of process variables that affect the process significantly (Kehinde Oladoke Olatunji *et al.*, 2022a). An accurate selection of anaerobic digestion process parameters is required to achieve the optimization focus. The development of appropriate and dependable models that can accurately forecast biogas yield instead of following the optimization test space that is very demanding due to the non-linearities related to the process is necessary. Optimization of process parameters has been studied widely using ineffective traditional methods. These methods require many experiments that consume a lot of time and cost. To overcome these challenges, statistical programs like Response Surface Methodology (RSM) have been recommended as optimization tools in the literature (Alfarjani, 2012; Das *et al.*, 2015). It is a mathematical and dynamic simulation model that allows the variation of the process parameters of anaerobic digestion for different loading scenarios and configurations without disturbing the biogas digester. This model has been experimented with in industrial, agricultural, and chemical reactions that required empirical design (Arslan-Alaton Idil, Yalabik and Olmez-Hanci, 2010). The application of the RSM model experimented in the optimization of biodiesel production (Xu *et al.*, 2014), drug research (Li *et al.*, 2008), bioethanol generation (Wang *et al.*, 2011), and biogas production (Alfarjani, 2012).

Nevertheless, it is impossible to conclude that process optimization using RSM is suitable for all bioprocess optimization. The RSM model was examined by studying the kinetic constant of alkaline protease from *Bacillus mojavensis* and lipase-catalyzed in the combination of docosahexaenoic acid (DHA) into borage oil, and the model was not suitable (QK et al. 2002). Likewise, it was observed that at the beginning of an enzymatic reaction's reaction rate, the polynomial equation could not be used to interpret the influence of pH and feedstock concentration (Ba and Boyaci, 2007). Hence, this work was focused on examining the influences of independent process parameters of temperature, retention time, and mixing ratio on the biogas yield of cow dung co-digested with jatropha cake and optimizing the process variables using RSM. This investigation is expected to provide vital information for decision-makers in the biogas industry on the anaerobic co-digestion for biogas generation and organic waste management.

2. Materials and method

2.1 Anaerobic digestion

Cow dung and jatropha cake were sourced locally, and five 5-liters containers were used as the digester. A laboratory-scale batch experiment was set up according to the European standard (organischer Stoffe Substratcharakterisierung, 2016). The substrates were analyzed in the laboratory for physicochemical characteristics, and the result was used in calculating the quantity of substrate loaded. The setup was similar to what was used by Olojede et al for the co-digestion of cow dung and sunflower leaves (Olojede, Ogunkunle and Ahmed, 2018). Five digesters were set up simultaneously with compositions shown in Table 1, and were observed at ambient temperature for 40 days of retention time. The feedstocks were examined for stones and other impurities before mixing with water. The mixing was carried out in a ratio of 1:2 (solid: liquid), as previously reported as the mixture for optimum biogas yield (Keanoi, Hussaro and Teekasap, 2014). The feedstocks were appropriately stirred, and the digesters were fed as follows using their volatile solid concentration: Digester 1, 7 kg of cow dung; Digester 2, 5.25 kg of cow dung and 1.75 kg of jatropha cake; Digester 3, 3.5 kg of cow dung and 3.5 kg of jatropha cake; Digester 4, 1.75 kg of cow dung and 5.25 kg of jatropha cake; and Digester 5, 7 kg of jatropha cake. The proportion of the loading was adopted from the previous study (Kavuma, no date; Raheman and Mondal, 2012). Ambient temperature and pressure and slurry temperature and pressure were recorded by mid-day daily. The biogas produced was collected with tyre tubes tightly attached to the gas outlet of the digester. The experiment was stopped after 40 days when the daily biogas yield was below one percent of the total released. The volume of gas yield was calculated using equation 1 (Yaru, Adewole and Adegun, 2014). Gas composition was determined using the gas analyzer (Multi 4 Stage Biogas Analyzer).

$$Biogas\ yield = \frac{R_{o\ mixture}\ \ X\, T_{digester}}{P_e} \quad (1)$$

$$R_{o\ mixture} = R_{CO_2} + R_{CH_4} \quad (2)$$

$$R_o = \frac{R}{M}\, X\ \%\ composition \quad (3)$$

Where: R_o = specific gas constant of a gas (J/kgK), R = standard gas constant (J/kgK), M = molecular mass of the specific gas, $R_{o\ mixture}$ = total specific gas constant of the biogas mixture (i.e CH_4 and CO_2), P_e = daily pressure of the digester, $T_{digester}$ = daily temperature of the digester (°C), and V = volume of gas released (m^3).

Table 1: Co-digestion treatment for the digesters

Treatment /Digester	Cow dung (%)	Jatropha cake (%)
1	100	0
2	75	25
3	50	50
4	25	75
5	0	100

2.2 Experimental design and analysis with RSM

The central composite design of RSM was employed to make the experimental runs for the process parameters that influence biogas yield. Design Expert 13.0 version software was employed to launch the RSM, where temperature, retention time, and mixing ratio were denoted with A, B, and C, respectively. Based on previous studies, the independent variables varied across levels between -1 and +1 (Douglas, 2009). Equation 4 presents the total number of experimental runs for the selected factors, which is 30, and the appraised response is given in equation 5. The second-order polynomial regression equation was applied to predict biogas yield and was generated using Analysis of Variance (ANOVA) (Douglas, 2001).

$$F = 2^d + 2d + 6 \tag{4}$$

Where: d = number of factors (d = 4), and 6 = constant factor.

$$X = \gamma_o + \epsilon\gamma_{ii}Z_1 + \gamma_o + \epsilon\gamma_{ij}Z_iZ_j \tag{5}$$

Where: X = the measured response, γ_o = the intercept term, γ_{ii} = quadratic coefficient, γ_{ij} = interaction coefficient, Z_i and Z_j are the coded independent variables.

3. Results and discussion

3.1 Experimental and RSM predicted

The biogas yield experimental result and the predicted responses following the co-digestion of cow dung and jatropha cake are presented in Table 2. The 30 runs presented in the Table showed that the considered process variables are significant to biogas production. For example, biogas released varied when the process temperature was 34 °C and retention time was 36 days but with varying mixing ratios (Runs 15 and 30). The influence of the mixing ratio on biogas yield of co-digestion of cow dung and jatropha cake was also noticed in runs 8 and 29. The temperature value (34 °C) and retention time of 30 days with different mixing ratios release different biogas yields. This support was reported earlier that anaerobic co-digestion of two feedstocks influences the biogas yield (Lebiocka *et al.*, 2019). Co-digestion of the lignocellulose materials with co-substrates such as manures and sludge in the digester can address these challenges of lignocellulose materials digestion (Kainthola, Kalamdhad and Goud, 2019). The mixing proportion in anaerobic co-digestion was reported reported to influence the biogas release in a previous study (Geerolf -ii- *et al.*, 2018), and this study re-affirmed the report. The influence of temperature on the biogas yield of cow dung and jatropha cake co-digestion can be observed in runs 7 and 15. At these runs, the retention time was 34 days, while the mixing ratio was the same but at different temperatures, which led to variation in biogas yields. This agreed with what was earlier reported on the significant effect of temperature on biogas yield (Rajendran, Aslanzadeh and Taherzadeh, 2012; Kehinde Oladoke Olatunji *et al.*, 2022b). It has been observed that there is a particular range of temperatures whereby methanogenic bacteria thrive well, but below or above that range, it can be harmful to bacterial activities (Barik and Murugan, 2015). The retention time was observed to influence biogas yield significantly, as seen in runs 9 and 10. The temperature was 32 °C with the same mixing ratio but different retention times. This has led to differences in biogas yield, and it corroborates what was previously observed that retention time influences biogas production (Okwu *et al.*, 2021). Biogas yield increases with an increase in retention time until when a time is reached when there is not enough feedstock for methanogens to carry out their activities. At this point, the biogas yield starts to decline (Kehinde O. Olatunji *et al.*, 2022).

It can be inferred from this study that the mixing ratio of 75% cow dung and 25% jatropha cake produce the optimum biogas yield (run 24). This implies that mixing 75% of cow dung with 25% of jatropha cake has a blend of nutrients that the methanogenic bacteria needs to function optimally. Single digestion in biogas production is usually unstable and mostly suffers from acidification that hinders digestion with time. Another related research observed that biogas yield was enhanced when plantain peels were co-digested with cow dung (Oloko-Oba *et al.*, 2018). Some selected animal wastes were co-digested in a fed-batch reactor at mesophilic temperature, and improvements in biogas and methane yield were recorded (Adebayo *et al.*, 2019). In a similar study, optimum biogas yield of cattle slurry and maize stalk was reported when the mixing ratio was 75: 25% cattle slurry: maize stalk (Adebayo, Jekayinfa and Linke, no date), and it agrees with the finding of this study. Anaerobic co-digestion of maize stalk with cattle slurry was reported to improve the methane yield (Adebayo, Jekayinfa and Linke, no date).

Tables 2: Experimental and RSM predicted biogas yield

Run No	Temperature (°C)	Retention Time (Days)	Mixing Ratio (%)	Biogas Yield (L/Kg VS_{added})

				Observed yield	RSM predicted yield
1.	33	28	2	1.40	1.24
2.	32	32	4	1.11	1.14
3.	34	30	5	1.06	1.06
4.	32	28	1	0.95	1.06
5.	36	25	3	1.60	1.44
6.	32	35	4	1.05	1.07
7.	34	26	2	1.38	1.26
8.	34	30	3	1.25	1.37
9.	32	34	1	0.98	1.08
10.	32	23	1	0.81	0.81
11.	34	23	4	0.90	0.98
12.	30	22	2	0.86	0.88
13.	32	32	5	1.01	0.97
14.	30	32	1	1.01	1.01
15.	34	36	2	1.52	1.35
16.	34	29	3	1.22	1.35
17.	31	33	1	1.01	1.03
18.	35	25	4	1.35	1.19
19.	33	33	2	1.48	1.29
20.	32	33	3	1.21	1.21
21.	35	25	1	1.18	1.25
22.	34	24	4	0.97	1.05
23.	32	29	5	0.99	0.97
24.	38	25	2	1.80	1.87
25.	33	31	5	1.04	1.00
26.	32	22	3	0.86	0.91
27.	30	34	5	0.97	0.94
28.	30	22	1	0.78	0.71
29.	34	30	4	1.15	1.26
30.	34	36	3	1.17	1.32

3.2 Interactive relationship of process variables on biogas production

The interactive effect of the independent process variables selected on the biogas yield of cow dung co-digested with jatropha cake was analyzed using analysis of variance (ANOVA), and the result is shown in Table 3. The Table depicts that the F-value recorded for biogas is 11.58, indicating that the model is significant. The tendency of having a higher F-value of this size because of noise is 0.01%. P-values from the ANOVA result show that the model is significant because the P value is below 0.05. This result observed that the significant model terms are A, B, C, A^2, B^2, and C^2. Values higher than 0.1000 indicate that the model terms are insignificant. In this case, some terms of the model are nominal (except those required to assist hierarchy), so it is possible to improve the model by model reduction. The predicted R^2 value of 0.5964 can be considered to be in reasonable accord with the adjusted R^2 of 0.7665 since the difference is not up to 0.2. Adequate precision determines the signal-to-noise ratio; a ratio above 4 is needed (Jiménez *et al.*, 2014). A ratio of 16.788 was recorded, indicating a satisfactory signal that can be used to boycott the design space (Yan *et al.*, 2015). Second-order polynomial equation 4 can be used to present the final regression terms to explain the biogas yield. Equation 4, in terms of coded factors, can be employed to forecast the given level of each factor. The +1 coded factor is for the high levels, while the -1 coded factor is for low levels, and these were by default. This equation helps determine the relative influence of the factors compared to coefficients. The degree of accuracy of a model is depicted by the coefficient of prediction (R^2). The value of R^2 recorded in this model is 0.8390 (84%). This value is higher when compared with R^2 values reported in other similar literature in a similar study (Erdirencelebi and Yalpir, 2011; Pierucci *et al.*, 2019; Kehinde Oladoke Olatunji *et al.*, 2022b) but lower compared to what was reported for other anaerobic digestion experiments (Safari *et al.*, 2018; Gopal *et al.*, 2021). R^2 values ranging between 0.75 and 1 (75 – 100%) have been adjudged to be an excellent predictive strength of the RSM model (Niladevi *et al.*, 2009; Reungsang, Pattra and Sittijunda, 2012). The R^2 value recorded in this study is within the recommended range, which shows that the accuracy level of this model is high and can be experimented with at the industrial scale.

Table 3: Regression analysis of variance (ANOVA) of the model for biogas yield

Sources	Sum of Squares	Df	Mean Square	F-value	p-value	p>F
A-Temp.	0.3733	1	0.3733	26.15	<0.0001	
B- Ret. Time	0.1187	1	0.1187	8.32	0.0092	
C- Mix Ratio	0.0808	1	0.0808	5.66	0.0275	
AB	0.0094	1	0.0094	0.6595	0.4263	
AC	0.0208	1	0.0208	1.46	0.2415	
BC	0.0026	1	0.0026	0.1855	0.6713	
A^2	0.1090	1	0.1090	7.63	0.0120	
B^2	0.0820	1	0.0820	5.74	0.0264	
C^2	0.1146	1	0.1146	8.03	0.0103	
ANOVA						
Model	1.49	9	0.1653	11.58	<0.0001	Significant
Residual	0.2855	20	0.0143	-	-	-
Cor Total	1.77	29	-	-	-	-
Std. Dev.	0.1195	-	-	-	-	-
Mean	1.14	-	-	-	-	-
C.V. %	10.52	-	-	-	-	-
R^2	0.8390	-	-	-	-	-
Adj. R^2	0.7665	-	-	-	-	-
Pred. R^2	0.5964	-	-	-	-	-
Adeq. Precision	16.7877	-	-	-	-	-

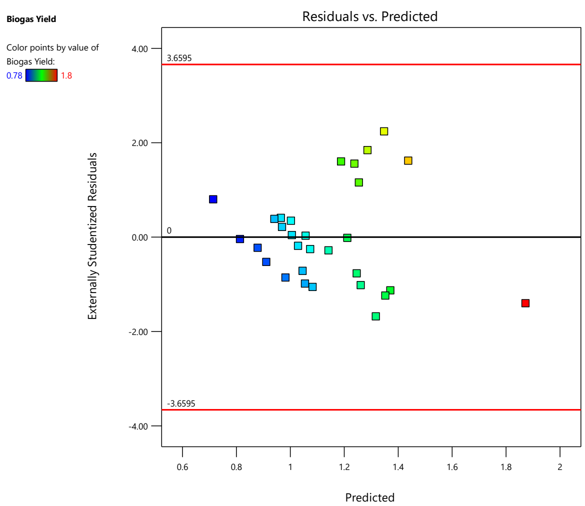
A – Temperature, B – Retention time, C – Mixing ratio

$$Biogas\ yield\ \left(\frac{L}{Kg}VS_{added}\right) = 1.35 + 0.4068A + 0.1584B - 0.1204C + 0.1000AB - 0.1313AC - 0.0352BC + 0.2554A^2 - 0.1936B^2 - 0.1888C^2 \qquad (4)$$

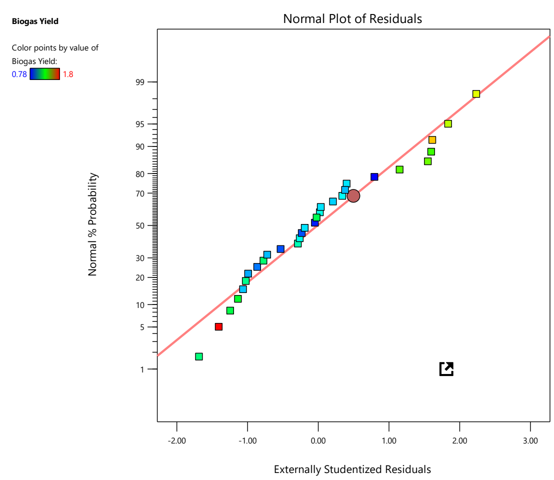
3.2 Analysis of anaerobic co-digestion residual plots

The interaction between predicted biogas yield and the external studentized residues is illustrated in Figure 1A. The Figure indicates that the studentized residues were scattered mainly around the '0' plot line, implying that the model is suitable for the analysis (Kehinde O.

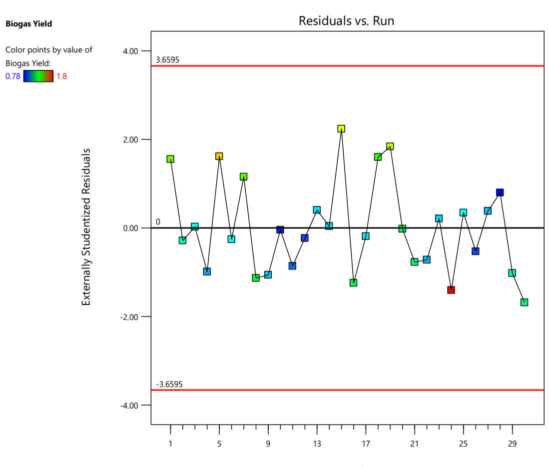
Olatunji *et al.*, 2022). The relationship between the distribution of standard probability and the process parameters of the biogas yield is presented in Figure 1B. The residual points shown in the plot show a probable curve closer to the fitting line of the modeled data. It can be observed that there is no significant challenge between the residual value and normality (Wu *et al.*, 2012). The correlation between the observed and residual biogas yield of anaerobic co-digestion of cow dung and jatropha cake is illustrated in Figure 1C. The data point in Figure 1C indicated that no transformational reaction was experienced from this analysis [29]. A scattered plot that presents the interaction between the observed value and forecasted values of biogas yield is presented in Figure 1D. It can be inferred from this Figure that RSM predicted values are closer to the prediction line, showing the model's accuracy level. All the scattered points were along the 45° line indicating a higher degree of accuracy between the observed and forecasted biogas yield. The closer the data points to 45°, the higher the model's accuracy (Adeleke *et al.*, 2021). Essential functions analyzed showed a similar association, showing that the empirical model is viable for the process.



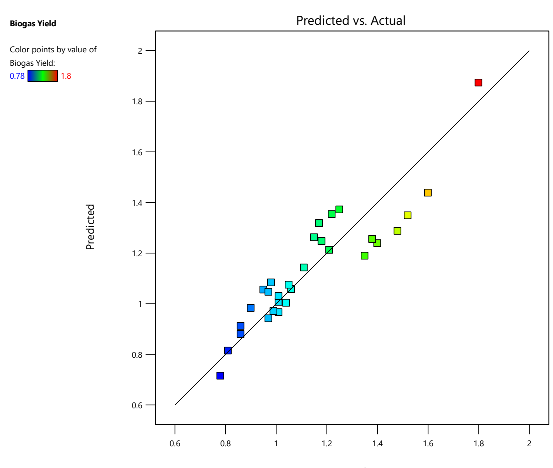
(A)



(B)



(C)



(D)

Figure 1: Plots of (A) externally studentized residual against predicted, (B) normal probability against residual, (C) residual against the run number, and (D) predicted against actual response values response for biogas yield.

Figure 2 shows the perturbation plot, which presents the interaction between all the process parameters at the center of the response to biogas yield. The influence of individual process parameters from the selected reference point is also discovered from the perturbation plot, while all other variables were kept constant (Qiu *et al.*, 2014). For this particular study, the reference point was chosen at the center of the design space, and this was the zero-coded level of the individual feature. It can be observed that in temperature (A), the biogas yield was noticed to increase. This is due to the ability of methanogenic bacteria to thrive well when the temperature is in the mesophilic range. In contrast, increasing temperature beyond the recorded value will decrease biogas yield. At the point indicated in this Figure, the methanogenic bacteria are already saturated, and a subsequent increase in temperature makes the bacteria uncomfortable. This is agreed with a previous report on a similar study (Martínez-Gutiérrez, 2018; Franqueto, da Silva and Konig, 2020). As the retention time (B) increases, the biogas yield increase until a point is reached when a further increase in retention period does not translate into biogas yield. At this point, the feedstocks available in the digester for methanogenic bacteria activities have reduced drastically, and as the feedstock keeps declining, the biogas yield will also decrease (Haryanto, Triyono and Wicaksono, 2018). Likewise, this Figure indicates that as the percentage of jatropha cake is increasing in the mixing ratio, improvement in biogas yield was noticed. When the mixing ratio was 50: 50% (cow dung : jatropha cake), the biogas yield reached its optimum condition. At these, the nutrient for optimum performance of the methanogenic bacteria is achieved. Further increase in jatropha cake and reduction in cow dung resulted in imbalance in the nutrient in the digester. This reports support what was previously reported in a similar study of co-digestion process of animal waste and crop residue (Adebayo, Jekayinfa and Linke, 2000). The biogas yield was majorly influenced by the temperature ($F = 26.15$, $p < 0.0001$), as shown in Table 3.

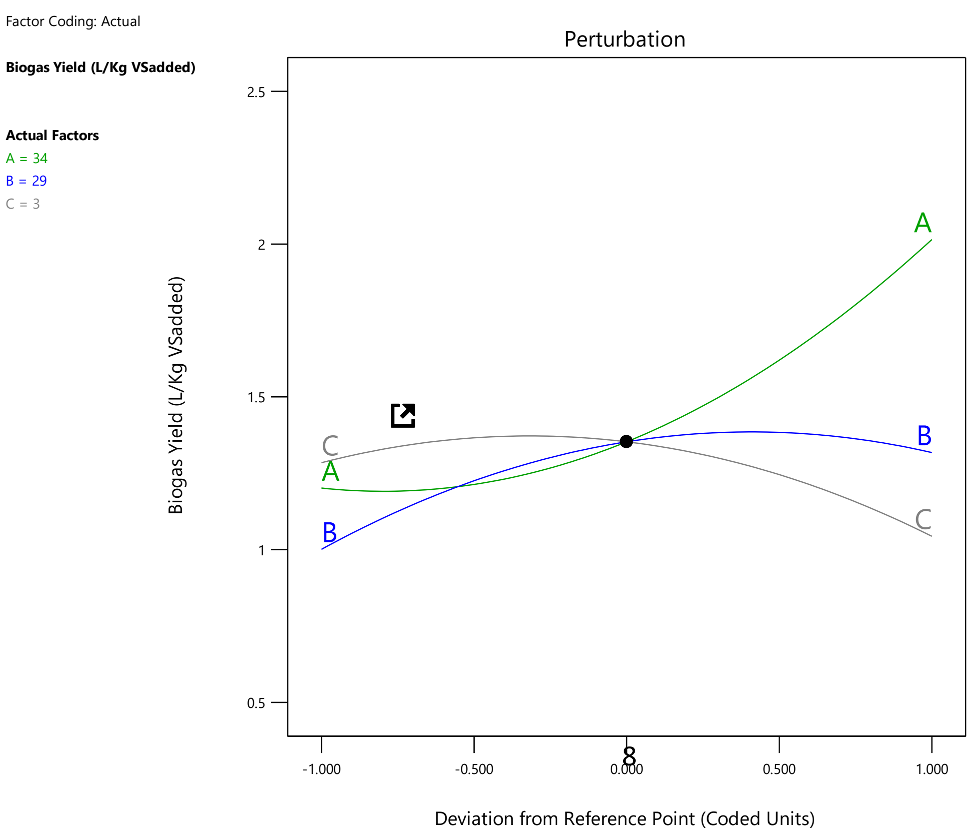
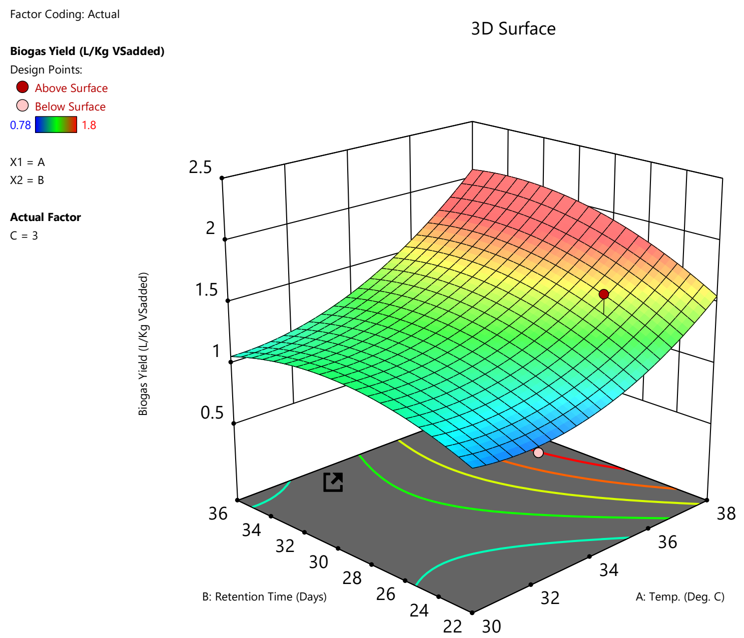


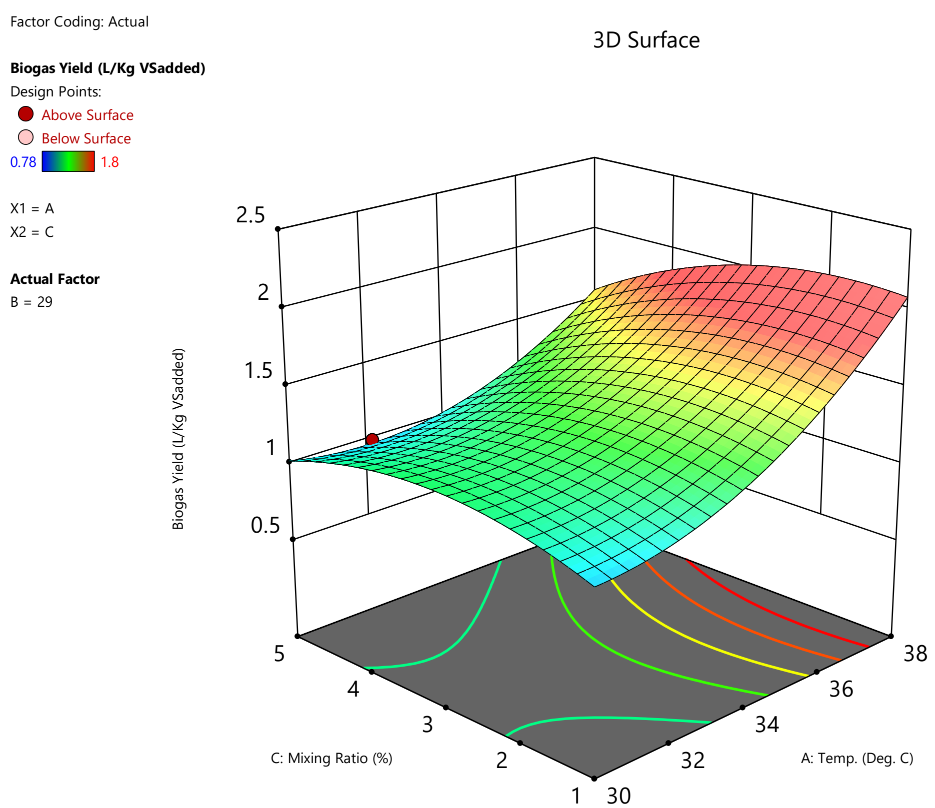
Figure 2: Perturbation analysis plot of anaerobic co-digestion of cow dung and jatropha cake.

3.3 Interactive effects of process parameters on biogas yield

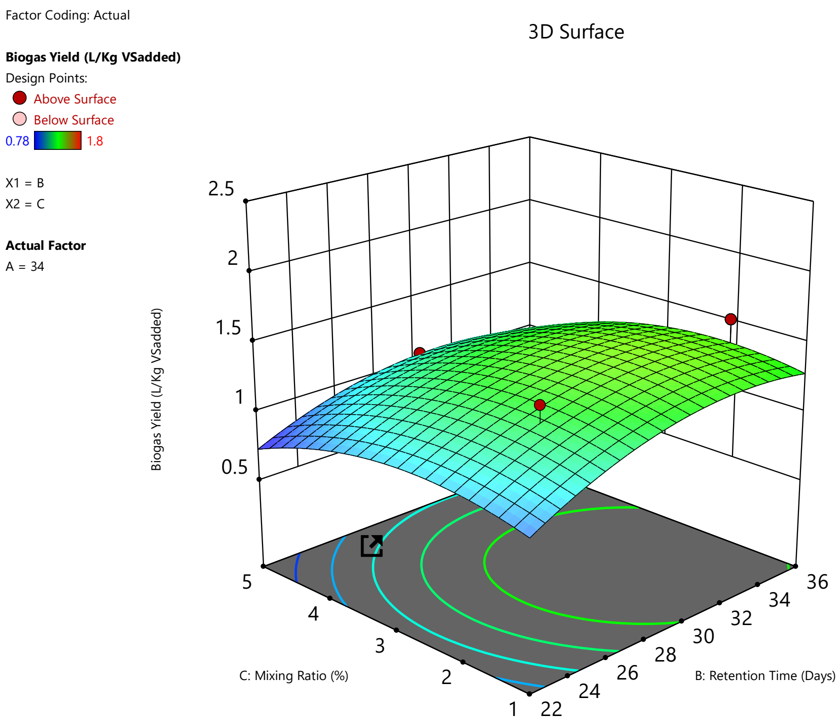
To study the interactive influence between the process parameters and biogas yield, three-dimensional (3D) plots were produced from the model. One input variable was kept constant, and the values for other variables were varied. The interactive 3D surface plots of the forecasted biogas yield (response) from the relationship between the process parameters selected are presented in Figure 3. Figure 3A illustrates that the biogas generation improves with a rise in temperature until 34 °C; beyond that, biogas yield starts to decrease with an increase in process temperature. Methanogenic bacteria have specified temperature ranges for optimum performance and are susceptible to temperature changes. Higher temperatures during anaerobic digestion can lead to an increase in volatile fatty acids (VFAs) that will change the pH of the process, and bacteria are sensitive to pH changes (Shrestha *et al.*, 2020). Previous investigations also recorded that temperature beyond a particular range negatively affects methanogenic bacterial activities (Sathish and Vivekanandan, 2016; Safari *et al.*, 2018). The interactive effect between the mixing ratio and temperature on biogas yield is presented in Figure 3B. The biogas released was noticed to improve with an increase in temperature compared to the mixing ratio. Improving the combined influence between temperatures with a percentage mixing ratio improved the biogas release. The optimum biogas yield was noticed when the variables reached the optimum conditions. The subsequent increase in temperature and percentage mixing ratio resulted in biogas yield declining drastically. As can be observed from the response surface curve, the influence of temperature was more pronounced compared to the percentage mixing ratio when retention time was kept constant. The same trend was noticed in Figure 3C, indicating that biogas yield depends on mixing ratio and retention time. The biogas yield was enhanced with an increased mixing ratio and retention time until both process parameters reached their maximum point. A subsequent increase in these variables led to a decline in biogas yield. The most suitable conditions for optimum biogas production from anaerobic co-digestion of cow dung are examined by response surface methodology analysis and predicted by optimal tools employing “Design Expert 13.0”. The optimum condition noticed from the experimental results are temperature (38 C), retention time (25 days), and mixing ratio (50% cow dung and 50% jatropha cake).


Factor Coding: Actual
Biogas Yield (L/Kg VSadded)
Design Points:
Above Surface
Below Surface
0.78
1.8
X1 = A
X2 = B
Actual Factor
C = 3
3D Surface
Biogas Yield (L/Kg VSadded)
2.5
2
1.5
1
0.5
B: Retention Time (Days)
36
34
32
30
28
26
24
22
A: Temp. (Deg. C)
30
32
34
36
38

(A)


Factor Coding: Actual
Biogas Yield (L/Kg VSadded)
Design Points:
Above Surface
Below Surface
0.78
1.8
X1 = A
X2 = C
Actual Factor
B = 29
3D Surface
Biogas Yield (L/Kg VSadded)
2.5
2
1.5
1
0.5
C: Mixing Ratio (%)
5
4
3
2
1
A: Temp. (Deg. C)
30
32
34
36
38

(B)



(C)

Figure 3: 3D response surface plot of biogas yield: (A) interactive effect of retention time and temperature, (B) interactive effect of mixing ratio and temperature, and (C) interactive effect of mixing ratio and retention time.

4. Conclusion

The optimum biogas yield was successfully generated from anaerobic co-digestion of cow dung and jatropha cake. This study has substantiated that cow dung and jatropha cake co-digestion can enhance biogas release. It was also discovered that temperature is the most significant process parameter, followed by retention time and mixing ratio. This study showed that a maximum biogas yield of 1.8 L/Kg VS_{added} was recorded at the optimum process conditions at a temperature of 38 °C, retention time of 25 days, and 50% cow dung and jatropha cake with the desirability of 0.8390 (84%). The findings of this study provide vital information to enhance the efficiency and stability of co-digestion of cow dung and jatropha cake. The model can be employed to forecast the biogas yield to save time and cost.

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