NIPES Journal of Science and Technology Research 4(1) 2022 pp.78 - 89 pISSN-2682-5821, eISSN-2682-5821

NIPES

Journal of Science and Technology Research

Journal homepage: www.nipesjournals.org.ng

Modeling and Optimization of Anaerobic Biogas Digestion Process of Pig Dung Using Response Surface Methodology

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Article Info

Article history:
Received 17 January. 2022
Revised 07 February 2022
Accepted 12 February 2022
Available online 05 March 2022

Keywords:
Anaerobic digestion, Modeling, Optimization, Pig dung, Response surface methodology

https://doi.org/10.37933/nipes/4.1.2022.7

https://nipesjournals.org.ng

Abstract

In this study, the optimum methane yield and the requisite data which accounted for the effects of the independent variables on the yield of the response were investigated. The yield of methane via anaerobic digestion (AD) of pig dung was modeled and optimized with response surface methodology (RSM) using least square approach for the prediction of the response. Central composite design (CCD) with mixture design produced 32 batch anaerobic digestion experiments which were randomly executed in order to investigate hydraulic retention time (HRT) (10 – 14 days), temperature (45 – 65 °C), moisture content, (90 – 94 %), pH (6.8 – 7.2) and carbon to nitrogen ration (C/N) (0.5 – 2.5) on the methane yield. Linear and interaction models were developed and further subjected to optimization technique using genetic algorithm (GA) optimization criteria with analysis of variance (ANOVA) employed in determining the degree of accuracy of the RSM models utilized. Results obtained showed optimum methane yield of 95.63 % which was obtained at HRT, temperature, moisture content, pH and carbon – nitrogen ratio of 13 days, 50 °C, 88 %, 6.96 and 1 respectively. Coefficient of determination, R^2 (65.02%), sum of square error, *SSE* (213.13), sum of square residual, *SSR* (396.13), and total sum of square, *SST* (609.23) values indicated model predictive accuracy and ability to navigate the design space.

1. Introduction

The growth in the world population and energy demand globally continues to expand astronomically partly due to increased industrialization [1]. World energy supply is still predominantly from fossil fuels with the reserves gradually been exhausted more from exploitation and exploration than the rate of formation or discoveries of newer reserves. Energy demand has continued to increase globally and hence, researches in alternative, sustainable and renewable sources has increased tremendously [2]. The need for alternative sources of energy from the existing fossil sources has become eminent. Renewable and sustainable energy sources such as biogas, solar, wind and biodiesel has emerged as sustainable alternatives [3].

Biogas production using anaerobic digestion process is one of the many ways of generation of energy from industrial, agricultural and domestic wastes activities engaged by mankind. There have been major concerns on the non-utilization of agricultural waste in Nigeria. Agricultural and other household wastes from different production processes increasable constitute environmental challenges [4, 5]. The wastes generated leads to environmental degradation and emission of CO_x into the atmosphere. This has encouraged recent studies on anaerobic digestion process of agricultural wastes using anaerobic digesters. Anaerobic digestion involves the transformation of these waste materials to biogas through anaerobic processes and is a favourable technology for renewable and sustainable energy generation [6, 7]. However, many factors have been identified as influencing the performance of an anaerobic digestion system such as hydraulic retention time (HRT), pH, temperature and organic loading rate (OLR) [8, 9], total solids (TS) and volatile solids (VS) [10], inoculum to substrate ratio (ISR) and OLR [11, 12], carbon to nitrogen (C/N) ratio and digester feed composition [13]. The use of biogas as a fuel for power generation in internal combustion engines of transportation fuels, electric energy and cooking has been studied [14]. Also, studies have shown that biogas derived from organic wastes is a good alternative to petroleum fuels and can be used in compression ignition (CI) engines, because of its mixing ability with air and clean burning nature [15, 16]. Biogas consists mainly of methane (CH_4), carbon dioxide (CO_2), and traces of other gases depending on the source [17]. Biogas production has been observed to help in the diversification of energy sources, decrease in the utilization of fossil fuels and create alternatives for combined heat and power generation systems [18].

Design of experiment is a powerful statistical data collection and analysis tool that can be used in different varieties of experimental situations [19]. The design analysis permits multiple independent factors to be tuned. It has been observed that the number of experimental runs can be reduced greatly when designs of experiments are used as opposed to one-factor-at-time method [20]. Response surface methodology (RSM) modeling technique is necessary to carry out the modeling of the results obtained at the end of any laboratory experimental process as a form of optimizing the process for efficiency and effectiveness. It is a technique that is widely used in the modeling and analysis of a process whose response (dependent variable) is affected by singular or multiple variables (independent variable). Afterward, an intelligent optimization technique is required to determine the optimal response and the independent variable values that yield the response. This involves carrying out the analysis of variance (ANOVA) which determines the measure of the prediction of the response surface methodology models. Genetic algorithm (GA) is applied in solving unconstrained and constrained optimization problems based on natural selection and high accuracy in determining the optimal (which could be minimum or maximum) response. The genetic algorithm technique solves problems that contain mixed integer programming, where some components are restricted to be integer-valued [21].

Barrangan-Escandon et al., [22] developed mathematical model through which biogas generation was estimated. The study reported that biogas as a renewable energy source enables electricity generation from wastes. Buraimoh et al. [7] focused on the bioconversion of organic wastes for sustainable biogas generation as an alternative to fossil fuel. The study revealed that the co-digestion of sawdust, fruit and food wastes using cow manure as an inoculum produced the highest volume of biogas which could be an auspicious technology for renewable energy generation. Alhassan *et al.*, [23] was involved in the modelling and optimization of biogas production via anaerobic digestion from agricultural waste using factorial design analysis. The result gave optimum concentration as 20% and retention time as 28days. Abu Qdais *et al*, [24] modeled and optimized biogas production using artificial neural network and generic algorithm. Organic wastes from slaughterhouse, restaurants, fruits, vegetable markets and from diary industry as well as landfills was utilized in digester with daily capacity of 60 tons. The results obtained showed optimum temperature to be 36.23 ^oC, pH - 6.4, volatile solid of 52.85 mg./L, and total solids of 6.59 mg/L. The maximum value of methane production was obtained as 77%. Nevertheless, none of these related studies was able to determine the optimal parameter and values of other independent variables that would lead to higher yield of methane thereby minimizing the yield of CO_2 produced.

Consequently, this study was undertaken to generate the most appropriate empirical model for the prediction of the methane yield obtained from experimental data reservoir. Model performance was done to determine the degree of accuracy of the RSM model utilized using the analysis of variance prediction performance technique (ANOVA). The RSM models utilized were; linear model and interaction model. GA optimization technique was also further utilized as a necessity to determine the values of the independent variables that would give higher proportion of methane yield and a minimum CO_2 yield.

2. Materials and Method

2.1 Sample collection

The main substrate used for the generation of the biogas was fresh pig dung obtained from a piggery farm located in a suburb in Kawo, Kaduna, Nigeria. The samples were collected each time the anaerobic digestion was to be loaded. The substrate was thoroughly blended to form the slurry with fresh water. Substrate samples were implemented in accordance with World Health Organization [25] standards and all reagents used were of analytical grades locally sourced from appropriate vendors. The pH of the different substrate samples were recorded on collection and stored until when needed.

2.2 Digester configuration

The design of the anaerobic digester was for the digestion process involving the pig dung wastes. The digester was designed in such a way as to operate in batch mode. It has a total reactor volume of 5 L with an effective slurry capacity of 3.75 L and 1.25 L for biogas collection capacity as previously reported [26, 27, 28]. It is made from polyvinyl chloride material with a cylindrical reactor tank, a gasometer unit comprising of a gas holder and a displaced solution tank. The digestion process was operated at a mesophilic temperature of 38 °C for 32 days. The substrate was thoroughly blended with fresh water to form the requisite slurry. Stirring was done to ensure uniformity and homogeneity using a polyvinyl chloride material to prevent substrate contamination. The anaerobic digestion process as well as data collection was carried out in the third quarter of 2020 following scheduled batch operation mode.

2.3 Design of experiment

Anaerobic digestion experiments were designed using MATLAB 2019 prior to the digestion process to investigate the individual as well as the interactive effects of composition of substrates (pig dung) fed into the digesters and some operating conditions of the digesters including the hydraulic retention time (HRT), Temperature, Moisture content, pH, and carbon to nitrogen (C/N) ratio, on methane yield as the response variable. In order to ensure simultaneous optimization of both the substrate mixture and process variables, a 5-components mixture design was combined with a five-level-five-factors central composite design (CCD) [29, 30] to generate a set of 32 randomly executed experimental runs. The percentage methane yield was estimated by substituting experimental data into Equations 1.

$$\%\,methane\ yield = \frac{cummulative\ methane\ production}{total\ initial\ volatile\ solids\ in\ the\ digester} \times 100\% \qquad (1)$$

2.4 Biogas measurement

Using the two volumetric tanks attached to the digester, the biogas produced was collected and subsequently stored. Water displacement procedure was employed in determining the volume of biogas produced.

2.5 Data analysis

On completion of the anaerobic digestion process, the data obtained from the process was then employed for the optimization process which served as the called-up data in the development of the different response surface methodology (RSM) models.

Table 1: Coded factors and levels

Independent variables	Coded factors and levels				
	$-\alpha$	-1	0	+1	$+\alpha$
X_1: HRT (days)	10	11	12	13	14
X_2: Temperature (^oC)	45	50	55	60	65
X_3:Moisture content (%)	80	81	82	83	84
X_4: pH	6.8	6.9	7.0	7.1	7.2
X_5: C/N	0.5	1.0	1.5	2.0	2.5

The central composite design (CCD) was utilized in developing the statistical models that were used to study the desired response and also determine the optimum combinations of the independent variables for optimizing the percentage methane yield.

Table 2: Central Composite Design Table

S/N	X_1	X_2	X_3	X_4	X_5	%Yield
1	+1	-1	-1	+1	+1	81.42
2	+1	-1	-1	-1	-1	83.40
3	0	0	0	0	0	85.42
4	+1	+1	+1	+1	+1	84.76
5	0	0	0	+α	0	87.22
6	-1	+1	+1	+1	-1	79.41
7	+1	-1	+1	-1	+1	80.77
8	0	0	0	-α	0	82.55
9	0	0	+α	0	0	88.22
10	-1	+1	-1	+1	+1	77.14
11	-α	0	0	0	0	80.22
12	+1	+1	-1	-1	+1	79.55
13	0	0	-α	0	0	87.29
14	-1	-1	+1	+1	+1	76.29
15	0	0	0	0	-α	82.22
16	0	0	0	0	0	89.42
17	0	+α	0	0	0	86.12
18	+α	0	0	0	0	85.41
19	-1	-1	+1	-1	-1	78.22
20	-1	+1	-1	-1	-1	76.91
21	-1	-1	-1	-1	+1	77.42
22	0	0	0	0	+α	86.71
23	-1	-1	+1	+1	-1	78.11
24	0	-α	0	0	0	78.62
25	+1	+1	+1	-1	-1	77.22
26	+1	+1	-1	+1	-1	76.66
27	0	0	0	0	0	89.40
28	0	0	0	0	0	89.60
29	0	0	0	0	0	98.77

30	-1	+1	+1	-1	+1	80.11
31	0	0	0	0	0	89.67
32	+1	-1	+1	+1	-1	86.15

The research procedure entailed the acquisition of data in terms of methane yield from the experimental anaerobic digestion process. These data accounted for the effects of the independent variables on the yield of the response functions. Analysis of variance (ANOVA) was employed on the various models developed after which the best model was adopted and subjected to optimization technique using genetic algorithm optimization criteria.

The cumulative result based on experimentally generated percentage methane yields for the anaerobic process with reference to the independent variables for average of thirty-two (32) days is shown in Table 3.

Table 3: Actual independent variable data with percentage methane yield

S/N	X_1	X_2	X_3	X_4	X_5	%Yield
1	13	50	81	7.1	2.0	90.90
2	13	50	81	6.9	1.0	90.48
3	12	55	82	7.0	1.5	91.88
4	13	60	83	7.1	2.0	82.98
5	12	55	82	7.2	1.5	77.88
6	11	60	83	7.1	1.0	83.08
7	13	50	83	6.9	2.0	77.48
8	12	55	82	6.8	1.5	83.18
9	12	55	84	7.0	1.5	79.38
10	11	60	81	7.1	2.0	79.38
11	10	55	82	7.0	1.5	83.78
12	13	60	81	6.9	2.0	91.28
13	12	55	80	7.0	1.5	83.98
14	11	50	84	7.1	2.0	78.88
15	12	55	82	7.0	0.5	85.08
16	12	55	82	7.0	1.5	85.48
17	12	65	82	7.0	1.5	85.38
18	14	55	82	7.0	1.5	85.18
19	11	50	83	6.9	1.0	79.48
20	11	60	81	6.9	1.0	86.80
21	11	50	81	6.9	2.0	77.98
22	12	55	82	7.0	2.5	78.48
23	11	50	83	7.1	1.0	77.58
24	12	45	82	7.0	1.5	78.48
25	13	60	83	6.9	1.0	83.98
26	13	60	81	7.1	1.0	83.58
27	12	55	82	7.0	1.5	79.48
28	12	55	82	7.0	1.5	83.08
29	12	55	82	7.0	1.5	76.48
30	11	60	83	6.9	2.0	77.78
31	12	55	82	7.0	1.5	84.98
32	13	50	83	7.1	1.0	78.88

Table 3 shows the independent variable data used to perform the AD process which gave the response (percentage methane yield).

2.6 RSM modeling

The data in Table 3 was used in the development of RSM models. Two RSM models were employed in the prediction of the responses. The models were: linear and interaction models. The format for the linear model is given as:

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \quad (2)$$

Where 'Y' = percentage methane yield
X_1 = hydraulic retention time in days
X_2= temperature in degree Celsius,
X_3 = percentage moisture content of the feed stock,
X_4 = pH of the process,
X_5 = carbon to nitrogen ratio and
$a_o\ to\ a_5$ = regression coefficient (regressors) of the linear model which will be determined with least square method.

The format for the interaction model is given as:

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + a_6X_1X_2 + a_7X_1X_3 + a_8X_1X_4 + a_9X_1X_5 + a_{10}X_2X_3 + a_{11}X_2X_4 + a_{12}X_2X_5 + a_{13}X_3X_4 + a_{14}X_3X_5 + a_{15}X_4X_5 \quad (3)$$

The interaction of the independent variables occupies between the regressions coefficients of $a_6\ to\ a_{15}$.

2.7 Determination of regression coefficients via least square methods

The various steps utilized in the least square method implementation are outlined as follows:

Step 1: An error term is attached to the linear equation model as shown:

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + \in \quad (4)$$

Step 2: The error term is then made the subject of the model.

$$\in = Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5) \quad (5)$$

Step 3: Both sides of equation (5) are then squared as shown:

$$\in^2 = \left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)^2 = S \quad (6)$$

Step 4: Differentiating 'S' in equation (6) with each regression coefficient term gives:

$$\frac{dS}{da_0} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right) \quad (7)$$

$$\frac{dS}{da_1} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)X_1 \quad (8)$$

$$\frac{dS}{da_2} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)X_2 \quad (9)$$

$$\frac{dS}{da_3} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)X_3 \quad (10)$$

$$\frac{dS}{da_4} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)X_4 \quad (11)$$

$$\frac{dS}{da_5} = -2\left(Y - (a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5)\right)X_5 \quad (12)$$

Step 5: Introducing the summation term and equating the models to zero and introducing the summation as well yields:

$$\sum Y = a_0\sum n + a_1\sum X_1 + a_2\sum X_2 + a_3\sum X_3 + a_4\sum X_4 + a_5\sum X_5 \quad (13)$$

$$\sum YX_1 = a_0\sum X_1 + a_1\sum X_1^2 + a_2\sum X_1X_2 + a_3\sum X_1X_3 + a_4\sum X_1X_4 + a_5\sum X_1X_5 \quad (14)$$

$$\sum YX_2 = a_0\sum X_2 + a_1\sum X_1X_2 + a_2\sum X_2^2 + a_3\sum X_2X_3 + a_4\sum X_2X_4 + a_5\sum X_2X_5 \quad (15)$$

$$\sum YX_3 = a_0\sum X_3 + a_1\sum X_1X_3 + a_2\sum X_2X_3 + a_3\sum X_3^2 + a_4\sum X_2X_4 + a_5\sum X_2X_5 \quad (16)$$

$$\sum YX_4 = a_0\sum X_4 + a_1\sum X_1X_4 + a_2\sum X_2X_4 + a_3\sum X_3X_4 + a_4\sum X_4^2 + a_5\sum X_4X_5 \quad (17)$$

$$\sum YX_5 = a_0\sum X_5 + a_1\sum X_1X_5 + a_2\sum X_2X_5 + a_3\sum X_3X_5 + a_4\sum X_4X_5 + a_5\sum X_5^2 \quad (18)$$

This forms the required matrix as Equation (19).

$$\begin{pmatrix} \sum Y \\ \sum YX_1 \\ \sum YX_2 \\ \sum YX_3 \\ \sum YX_4 \\ \sum YX_5 \end{pmatrix} = \begin{pmatrix} \sum n & \sum X_1 & \sum X_2 & \sum X_3 & \sum X_4 & \sum X_5 \\ \sum X_1 & \sum X_1^2 & \sum X_1X_2 & \sum X_1X_3 & \sum X_1X_4 & \sum X_1X_5 \\ \sum X_2 & \sum X_1X_2 & \sum X_2^2 & \sum X_2X_3 & \sum X_2X_4 & \sum X_2X_5 \\ \sum X_3 & \sum X_1X_3 & \sum X_2X_3 & \sum X_3^2 & \sum X_2X_4 & \sum X_2X_5 \\ \sum X_4 & \sum X_1X_4 & \sum X_2X_4 & \sum X_3X_4 & \sum X_4^2 & \sum X_4X_5 \\ \sum X_5 & \sum X_1X_5 & \sum X_2X_5 & \sum X_3X_5 & \sum X_4X_5 & \sum X_5^2 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{pmatrix} \quad (19)$$

Equation (19) can be reduced to

$Y = MA$

To determine *A* (regression coefficient), inverse of matrix *M* was obtained and multiplied with vector *Y*. The least square method was applied to the interaction model with Matrix Laboratory (MATLAB 2019) software.

2.8 Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) was utilized in this study in determining the prediction performance of the response surface methodology models used in the prediction of the response (prediction of the percentage methane yield). The parameters of one-way ANOVA utilized were; *R*-square statistic value, sum of square error (*SSE*), sum of square residual (*SSR*) and total sum of square (*SST*). The model relations of each ANOVA component are outlined in Equation (20).

$$SSE = \sum(y_{ei} - y_{pi})^2$$
$$SSR = \sum(y_{pi} - y_m)^2$$
$$\text{SST} = SSE + SSR$$
$$R^2 = \frac{SSR}{SST} \quad (20)$$

y_{ei} = the actual or experimentally obtained response (percentage methane yield) data obtained from the field

y_{pi} = the predicted yield for each response surface methodology model

y_m = the mean of the actual response.

2.9 Genetic Algorithm Optimization

Genetic algorithm is known to be an intelligent optimization tool applied to empirical and intelligent models. The purpose of utilizing this optimization technique is to determine the optimum yield (either as minimum or maximum yield). In this study, the optimum (maximum) percentage yield was obtained with the equivalent input values obtained. The requisite procedures were carried out to obtain the optimum methane yield with genetic algorithm in MATLAB 2019.

3. Results and Discussion

The predictions of the % methane yield with the RSM models are presented in Table 4.

Table 4: Predicted percentage methane yield.

S/N	Actual yield	Linear	Interaction
1	90.9	83.501	89.286
2	90.48	86.607	90.154
3	91.88	82.759	82.513
4	82.98	81.895	82.468

5	77.88	81.508	80.607
6	83.08	80.766	84.183
7	77.48	81.028	77.002
8	83.18	84.01	84.42
9	79.38	79.035	78.735
10	79.38	82.634	79.574
11	83.78	79.774	78.873
12	91.28	86.87	89.654
13	83.98	86.483	86.291
14	78.88	74.931	78.778
15	85.08	84.614	84.031
16	85.48	82.759	82.513
17	85.38	84.877	85.286
18	85.18	85.743	86.153
19	79.48	79.899	80.616
20	86.8	85.741	88.282
21	77.98	81.768	78.207
22	78.48	80.904	80.996
23	77.58	78.648	79.074
24	78.48	80.641	79.74
25	83.98	85.001	84.706
26	83.58	87.474	83.221
27	79.48	82.759	82.513
28	83.08	82.759	82.513
29	76.48	82.759	82.513
30	77.78	80.162	79.11
31	84.98	82.759	82.513
32	78.88	81.632	78.174

The analysis of variance (ANOVA) Table for the linear model is shown in Table 5

Table 5: ANOVA table for the linear model

Coefficient	Square errors	p-values	Statistics parameters
271.08	85.45	0.0038573	*SST* = 609.23
1.4922	0.78001	0.066807	*SSE* = 374.16
0.21178	0.156	0.18627	*SSR* = 235.07
-1.862	0.75046	0.019887	R^2 = 0.3858
-6.2558	7.8001	0.42981	
-1.8552	1.55	0.24214	

The comparative plot of the linear model prediction of methane yield with the experimental yield is shown in Figure 3 (A). Figure 3 (A) shows the two dimensional graphical view of the predicted response with linear model and the actual response. It can be seen that the predicted variable (represented with the broken line) fairly tracked the actual data. However, the prediction performance of the linear model can readily be known from the ANOVA table shown in Table 5 which had R^2 value of 38.58%. This implies that the prediction performance of the linear model is low [7, 22-24]. From Table 5, the first column contains the determined regression coefficient of the linear model after undergoing least square method analysis. The linear model equation then becomes:

$$y = 271.08 + 1.4922X_1 + 0.21178X_2 - 1.862X_3 - 6.2558X_4 - 1.8552X_5 \qquad (21)$$

The linear equation (21) was used in predicting the values of 'y' when the independent parameters were inputted. The predicted 'y' values for linear model is displayed in the second column of Table 5 and a comparative plot of the predicted yield and the experimentally obtained yield (actual yield) is shown in Figure 3 (A).

The ANOVA table for the interaction model is shown in Table 6.

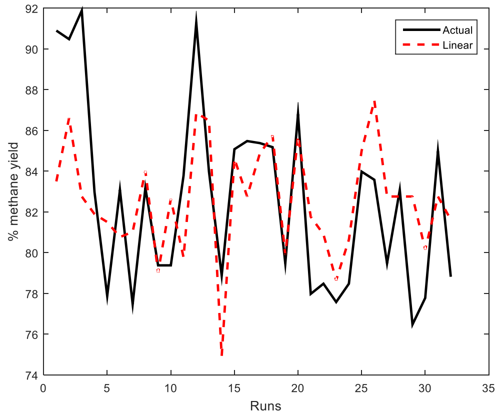
Table 6: ANOVA table for interaction model

Coefficient	Square errors	p-values	Statistics parameters
6315.4	6575.9	0.35115	*SST* = 609.23
183.8	101.07	0.08775	*SSE* = 213.1277
-0.71937	20.26	0.97211	*SSR* = 396.1025
-70	67.124	0.31252	R^2 = 0.6502
-1107.1	994.34	0.282	
-157.76	219.15	0.48199	
-0.14149	0.20432	0.49855	
-1.8566	0.9862	0.078074	
-0.92546	10.216	0.92894	
2.0561	1.9256	0.30147	
0.12118	0.19724	0.54759	
-1.1701	2.0432	0.57482	
-0.17579	0.38511	0.6542	
12.191	9.862	0.23425	
-1.0737	2.1926	0.63098	
34.289	19.256	0.093949	

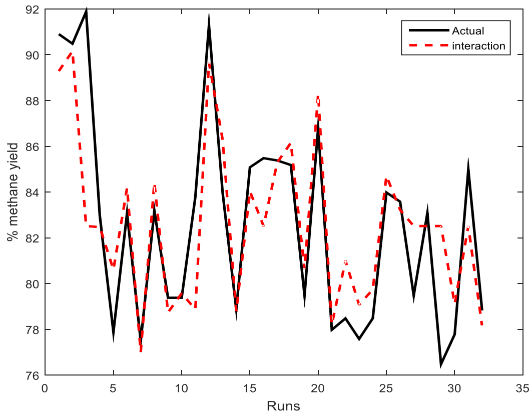
With the regression coefficient of the interaction model shown in the first column of Table 6, the interaction model becomes;

$$y = 6315.4 + 183.8X_1 - 0.71937X_2 - 70X_3 - 1107.1X_4 - 157.76X_5 - 0.14149X_1X_2 - 1.8566X_1X_3 - 0.92546X_1X_4 + 2.0561X_1X_5 + 0.12118X_2X_3 - 1.1701X_2X_4 - 0.17579X_2X_5 + 12.191X_3X_4 - 1.0737X_3X_5 + 34.289X_4X_5 \quad (22)$$

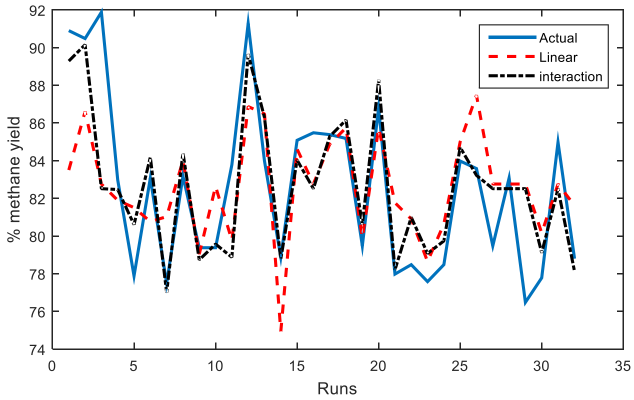
On inputting the independent variable values, the percentage methane yield prediction with the interaction model was achieved and shown in the third column of Table 6 with the comparative plot shown in Figure 3 (B).



(A)



(B)



(C)

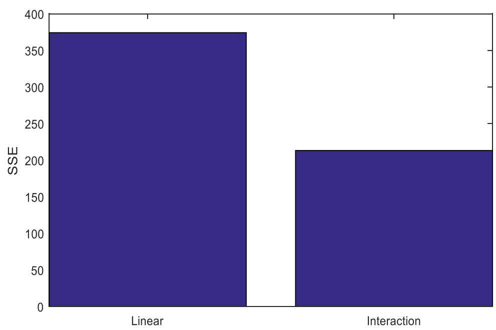
Figure 3: (A) % methane yield prediction with linear model. **(B)** % methane yield prediction with interaction model **(C)** % methane yield prediction of all the RSM models

The comparative analysis of the models used in the prediction of methane yield with the actual yield obtained experimentally is shown in Figure 3 (C). From the plot shown in Figure 3 (C), it can be seen that the interaction model is closer to the actual yield than the linear model. The *R*-square values and sum of square errors (*SSE*) obtained from the ANOVA table of each model was used in determining the best model based on low error and high degree of accuracy of prediction [7, 19, 22 24]. The summary of the *SSE* values and *R*-square values for each model is shown in Table 7.

Table 7: Summary of the statistical error measurement values

RSM model	*SSE*	*R*-square
Linear	374.1611	0.3858
Interaction	213.1277	0.6502

The bar-charts for *SSE* and *R*-square values are shown in Figure 4(A) and (B) respectively.



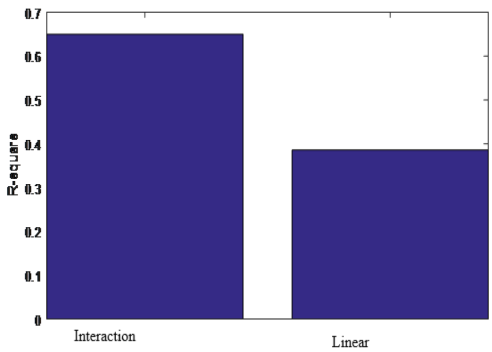


Figure 4: (A) *SSE* values of the RSM models (B) *R*-square values for each model

When the values of *SSE* is lower for a particular model, it means the model have a higher accuracy of prediction. Hence, the model with the lowest *SSE* value was interaction model with *SSE* value of 213.1277, followed with linear model having *SSE* value of 374.1611 making it the least accurate [7, 12, and 19, 24]. This is further supported by the bar-chart of the *R*-square values shown in Figure 4. The higher the *R*-square value of the prediction, the more accurate the predicted data [14, 22, 23]. The model with the highest *R*-square value is interaction model with 0.6502, while linear model has its value as 0.3858. From the analysis presented in the bar charts displayed in Figure 4, it can be deduced that interaction model had the best prediction accuracy as such was utilized in the genetic algorithm optimization technique

Genetic Algorithm

The optimized independent variable data for the genetic algorithm optimization is presented in Table 8.

Table 8: Optimum values of the independent variables

Independent variables	values
HRT (days)	13
Temperature (^oC)	50
Moisture content (%)	91
pH	6.9
Carbon to Nitrogen (C/N) ratio	1

The values of the independent variables shown in Table 8 were the initial estimate to the genetic algorithm optimization. After simulating, the final optimum percentage methane yield as performed with the genetic algorithm optimization technique on the interaction model was 95.631% at HRT of 13 days, temperature of 50 ^oC, moisture content of 88 %, pH of 6.96 and C/N ratio of 1 which were similar in trends and observations of other studies conducted [6 - 10, 18 – 20, 22-24].

4.0. Conclusion

The importance of anaerobic digestion as patterns to agricultural enhancement and environmental friendliness cannot be over-emphasized as such, this study was carried out to determine the optimal percentage methane yield and obtain the various points of independent variables required to achieve the yield. The experimental data obtained showed that five independent variables were used experimentally at five levels tuned for each parameter to obtain the percentage methane yield. This experimentally obtained yield with the values of the independent variable were applied in the two response surface models to determine the regression coefficient values with the aid of least square method. The coefficients of the RSM models were used in determining the response predictions with the prediction performance carried out with analysis of variance (one-way ANOVA table). From the results presented in this study, it can be seen that interaction model had the best prediction accuracy with *R*-square value of 65.02%. Linear model had R-square value of 38.58%. The interaction model being the best model was optimized with genetic algorithm optimization. The independent variable plots obtained were the initial guess to the genetic algorithm optimization technique. From the results obtained when genetic algorithm was applied, it was possible based on the interaction model to achieve an optimal methane yield of 95.63 % at hydraulic retention time of 13 days, temperature of 50 $^\circ C$, moisture content of 88 %, pH of 6.96 and carbon nitrogen ratio of 1.

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