



# Biogas from food waste through anaerobic digestion: optimization with response surface methodology

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## Abstract

In the current study, anaerobic digestion method efficiency on biogas production and chemical oxygen demand (COD) degradation was assessed through a sequence of laboratory-scale batch experimentations to compute the role of chosen process parameters, viz., solid concentration (5–15%), pH (5–9), temperature (30–60 °C), and co-digestion (0–40% of poultry manure). Biogas production and COD degradation were significantly dependent on the selected process parameters with independent conditions to accomplish active performance of the process. Central composite design (CCD)-based response surface methodology (RSM) was adopted for evaluation and optimizing of the combined performance of system considering two responses. Among various combinations, it was observed that solid concentration of 7.38%, pH value as 7, temperature at 48.43 °C, and co-digestion as 29% produce biogas of 6344 ml and COD degradation as 38%. Confirmation experiment performed shows a deviation of 4.93% maximum between the predicted and experimental results.

**Keywords** Anaerobic digestion · Biogas production · Multi-objective optimization · Alternative energy · Food waste · Soft computing

## 1 Introduction

Energy and resource shortage is one of the most significant problems faced by the world nowadays. The rising price of petroleum products and increasing attention regarding environmental impacts together with the fossil fuel depletion have prompted considerable research to identify renewable and alternative fuel sources [1, 2]. Therefore, researchers concentrate on finding alternative energy sources and employing

them to reduce adverse effects. Most of the studies shown in the literature on renewable energy sources have focused on different waste energy sources. These wastes include used tires, trees, plastics, municipal solid wastes, etc. These wastes have several adverse impacts on environment and living organisms including human beings. These impacts can be reduced when they are transformed into fuel. Out of all the available wastes, food waste contains a considerably large quantity of organic matter, which can be fermented anaerobically to produce biogas [3, 4].

The food waste comprises un-consumed food items and leftovers during the preparation of foods from houses, hotels, institutional sources like college/school cafeterias, and industrial sources like factory lunchrooms [5]. In 2011, a report published on global food waste by UN Agriculture Organization stated that nearly one-third of the total food prepared for human consumption goes as waste that accounts for 1.3 billion tons annually [6]. Usually, food waste contains 69–93% of moisture, 85–96% of volatile solids (VS), and C/N ratio of 14.6–18.3 [5]. Because of the higher moisture content in food waste, biochemical processes like anaerobic digestion are more suitable when compared to thermochemical processes like gasification and combustion [7, 8]. Anaerobic digestion process involves the disintegration and stabilization of

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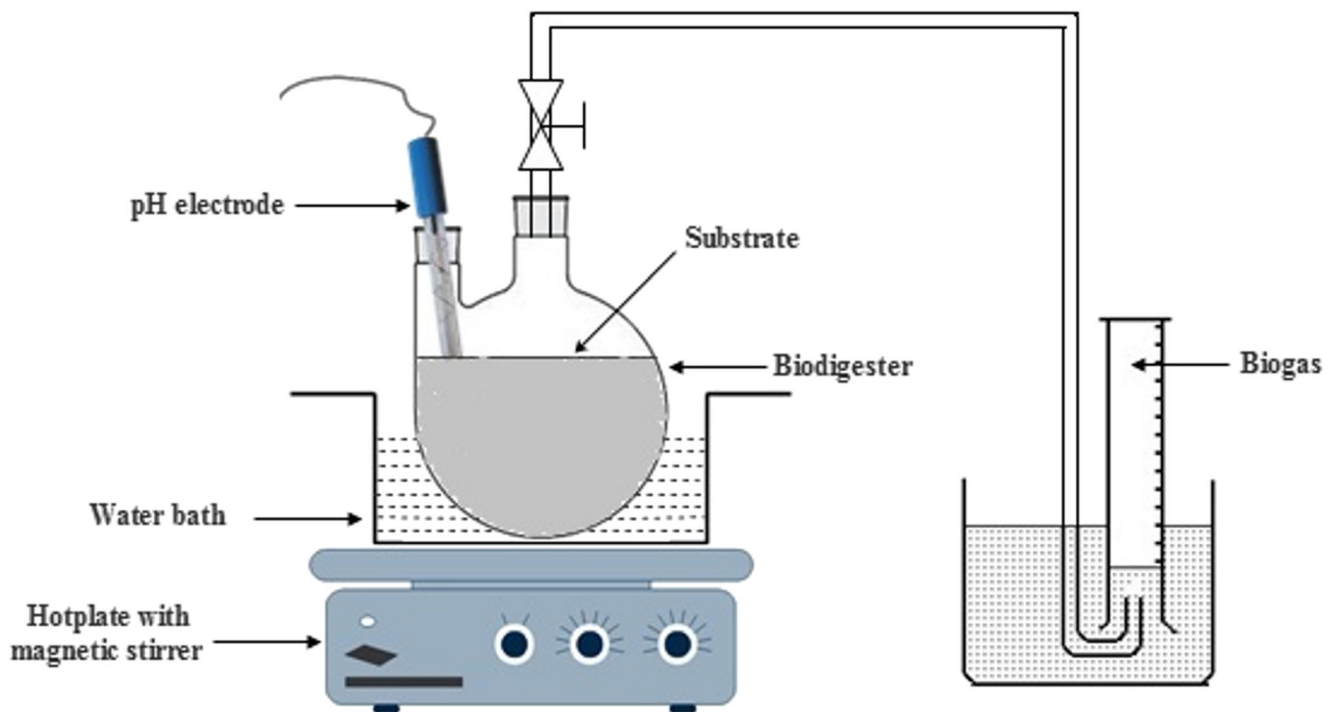


Fig. 1 Experimental setup [16]

complicated organic matter by a group of microorganisms leading to energy-rich biogas which can be used as alternative energy for the substitution of fossil fuel sources [9, 10]. Higher biogas production can be achieved through a correctly functioning anaerobic digestion system for fulfilling societal energy demands along with the production of high-quality fertilizer as a by-product [11, 12]. Various factors affect the performance and design of an anaerobic system that can be identified as reactor design, feedstock characteristics, and operating conditions [5, 7], and hence these parameters have to be optimized for effective biogas production.

**Table 1** Variables and their ranges considered for trials

Factors	Levels	Variables
Solid concentration ( $X_1$ )	-1	5
	0	10
	+1	15
pH ( $X_2$ )	-1	5
	0	7
	+1	9
Temperature ( $X_3$ )	-1	30
	0	45
	+1	60
Co-digestion ( $X_4$ )	-1	0
	0	20
	+1	40

A few studies have been carried on biogas production with optimization methodologies such as Taguchi's approach, genetic algorithm (GA), grey relational approach (GRA), artificial neural network (ANN), and principal component analysis (PCA), etc. [13–17]. Kuen-Sheng Wang et al. [18] studied the suitability of hybridization of Taguchi's methodology and RSM for predicting and optimizing the bio-hydrogen production from cow manure. Experimental trials were performed based on L18 orthogonal matrix, and CCD-based RSM design was applied for analyzing the outputs and optimization procedure. Qdais et al. [19] evaluated the biogas production and optimized the process factors pH, total solids, temperature, and total volatile solids using ANN technique. The model consists of two hidden layers for predicting the methane production having 0.87 correlation coefficient. Karichappan et al. [20] performed experimental trials for studying the biogas production using four parameters varied with three levels considering Box-Behnken methodology in RSM, with parameters and ranges such as pH (4–10), temperature of reactor (25–45 °C), alkalinity during the process (6–24%), and the time period of feedstock retention (6–30 days). The results obtained were evaluated through analysis of variance (ANOVA) and empirical model of second order for studying the process parameters interactive effects on the yield of biogas.

In this work, an effort was made to improve the biogas production and COD removal efficiency with good reproducibility levels. The process parameters taken in this study are solid concentration, pH, temperature, and co-digestion. A

**Table 2** Central composite experimental design matrix

Run	Coded values				Real values			
	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>
1	-1	-1	-1	-1	5.00	5.00	30.00	0.00
2	-1	-1	-1	+1	5.00	5.00	30.00	30.00
3	-1	-1	+1	-1	5.00	5.00	60.00	0.00
4	-1	-1	+1	+1	5.00	5.00	60.00	30.00
5	-1	0	0	0	5.00	7.00	45.00	15.00
6	-1	+1	-1	-1	5.00	9.00	30.00	0.00
7	-1	+1	-1	+1	5.00	9.00	30.00	30.00
8	-1	+1	+1	0	5.00	9.00	60.00	0.00
9	-1	+1	+1	+1	5.00	9.00	60.00	30.00
10	0	-1	0	0	10.00	5.00	45.00	15.00
11	0	0	-1	0	10.00	7.00	30.00	15.00
12	0	0	0	-1	10.00	7.00	45.00	0.00
13	0	0	0	0	10.00	7.00	45.00	15.00
14	0	0	0	0	10.00	7.00	45.00	15.00
15	0	0	0	0	10.00	7.00	45.00	15.00
16	0	0	0	0	10.00	7.00	45.00	15.00
17	0	0	0	0	10.00	7.00	45.00	15.00
18	0	0	0	0	10.00	7.00	45.00	15.00
19	0	0	0	+1	10.00	7.00	45.00	30.00
20	0	0	+1	0	10.00	7.00	60.00	15.00
21	0	+1	0	0	10.00	9.00	45.00	15.00
22	+1	-1	-1	-1	15.00	5.00	30.00	0.00
23	+1	-1	-1	+1	15.00	5.00	30.00	30.00
24	+1	-1	+1	-1	15.00	5.00	60.00	0.00
25	+1	-1	+1	+1	15.00	5.00	60.00	30.00
26	+1	0	0	0	15.00	7.00	45.00	15.00
27	+1	+1	-1	-1	15.00	9.00	30.00	0.00
28	+1	+1	-1	+1	15.00	9.00	30.00	30.00
29	+1	+1	+1	-1	15.00	9.00	60.00	0.00
30	+1	+1	+1	+1	15.00	9.00	60.00	30.00

large number of input factors parameters involved in the digestion process make it extremely complicated to perform a traditional method of optimization by studying the effect of one variable at a time. For this purpose, the response surface methodology was adopted in this investigation to optimize the parameters involved in the anaerobic digestion process.

**Table 3** Ultimate analysis of feedstock used

Material	Present study				Literature				Ref.
	C	H	N	O	C	H	N	O	
Food waste	49.96	10.35	1.13	38.28	48	6.40	2.60	37.60	[27]
Poultry manure	37.64	11.86	5.06	45.44	33.84	13.52	3.60	49.04	[28]
Cow dung	36.22	8.07	1.52	53.20	31.6	5.18	6.12	37.8	[29]

## 2 Materials, experimentation, and methods

### 2.1 Feedstock and experimental setup

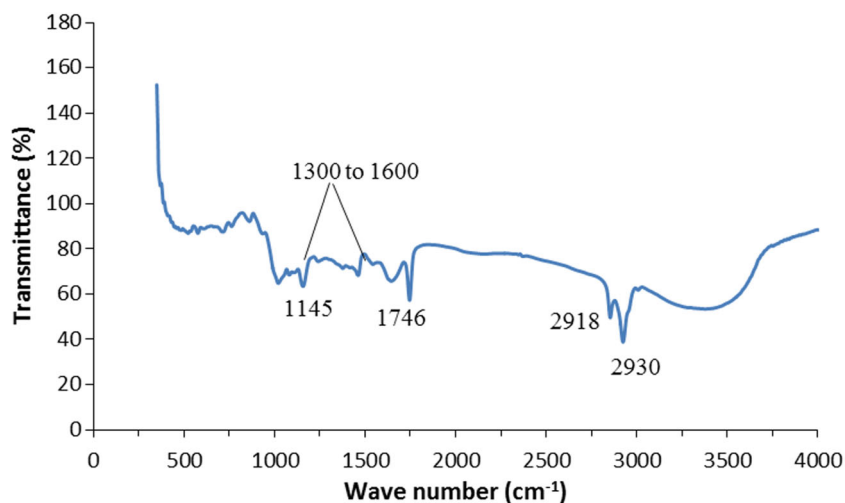
Food waste (FW) is a highly desirable substrate for anaerobic digestion with regard to its higher biodegradability and biogas/methane yield. This contains a substantially large amount of organic matter, which can be processed anaerobically to produce biogas. Also, the nutrient content analysis showed that the food waste contained well-balanced nutrients for anaerobic microorganisms [5]. FW collected from the student hostel mess of NIT Calicut, India, was used for the experiments. The waste collected was shredded into particles to increase the surface area available for microbial activities. Water was added to the waste to prepare the substrate with desired solid concentration, and 1 N NaHCO<sub>3</sub> solution was added to achieve the desired pH. C/N ratio of the feedstock was varied by co-digesting 10–30% of poultry manure with food waste before feeding into the digester. The poultry manure (PM) used in this study was taken from Regional Poultry Farm, Chathamangalam. Experiments were conducted in a laboratory-scale anaerobic batch reactors made up of glass as shown in Fig. 1. The reactor had a total and effective working volume of 2 l and 1.8 l, respectively. The daily biogas production was measured with an inverted measuring glass cylinder filled with water which was partly immersed in water bath.

### 2.2 Multiple parameter optimization

A statistical tool, RSM, was used for modeling the experimental procedure by performing both analyses, by modeling, by optimizing, and by identifying the relationship that was supposed to be between the outputs and inputs [21–23]. In most of the problems in RSM, the relationship that exists between the dependent and independent factors was unknown [24, 25]. Consequently, the initial procedure in RSM is to determine an appropriate efficient relationship between the “x” set of independent input variables and “y” set of dependent output variables. If the output variable can be modeled well by means of a linear function of input factor, the function is purely a model with first order [21].

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k \tag{1}$$

**Fig. 2** FTIR spectrum of food waste



A higher degree polynomial such as a model of second order may be used, if a curvature exists in the system.

A CCD approach of RSM technique was adopted in this study for optimizing the input conditions toward higher biogas production from the waste food feedstock. For this experimental condition, thirty experiments that include six center points were considered. For maximum production biogas, the collective effect of four inputs, viz., solid concentration, pH, temperature, and co-digestion, was experimentally studied, and multi-criterial optimization was done. The response variables measured were biogas production and efficiency in the removal of COD. Table 1 outlines the higher and lower values of input factors, and Table 2 presents the experimental plan as per the real coded and actual coded values.

### 3 Results and discussion

The characterization study was carried out for both food waste and poultry manure. Cow dung was used as an inoculum [26], which is also subjected to the characterization study. Table 3 gives the elemental composition of feedstock used in this study.

FTIR (Fourier transform infrared) analysis is an analytical method used to find the functional group of a molecule or compound. Exposed to IR radiations, a molecule will absorb IR energy only at frequencies matching the molecule's natural

frequency of vibration. As a consequence, the absorption pattern (frequencies and intensities) is unique for a given molecule. The frequencies of vibration of a molecule are directly related to the nature of the atoms and the structure of the molecule. The FTIR spectrum for food waste used is shown in Fig. 2, and the functional groups present are given in Table 4. The major compounds present in the food waste are carboxylic acids such as formic acid, acetic acid, propionic acid, etc. and amine such as methane, ethane, etc. In addition to these compounds, methyl formate, diethyl ether, nitromethane are also present in small quantity. Similarly, the FTIR spectra for poultry manure used in this study are shown in Fig. 3, and the functional groups are given in Table 5.

Experiments were conducted as per the standard order, and the output responses such as biogas production and COD removal efficiency were determined, which are tabulated in Table 6.

Initially the analysis of biogas production ( $Y_1$ ) and COD removal efficiency ( $Y_2$ ) is performed individually. Later the combined optimization of both the responses is carried out using desirability function.

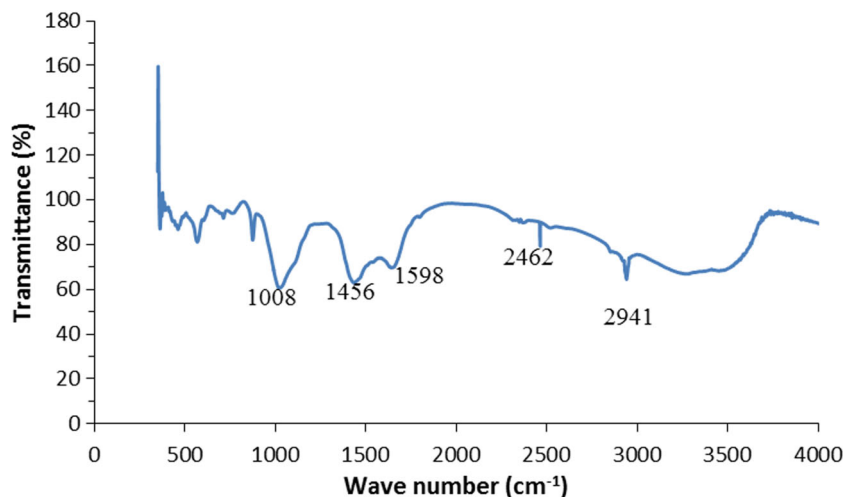
#### 3.1 Biogas production

Biogas production is carried out by setting the goal for maximizing the response, since the biogas production should be higher for a given substrate. Table 7 shows the ANOVA table

**Table 4** Functional group from FTIR for food waste

Transmittance range	Functional group	Major compounds	Type of vibration
1000–1300	Ethers	Methyl formate and diethyl ether	C–O stretch
1300–1600	Nitro groups	Nitromethane	N=O stretch and N=O bend
1746 and 2918	Carboxylic acids	Formic acid, acetic acid, propionic acid, etc.	Hydrogen-bonded O–H stretch
2930	Alkanes	Methane, ethane, etc.	H–C–H symmetric stretch

**Fig. 3** FTIR spectrum of poultry manure



for biogas production; the suggested model is quadratic where the second-order equation of chosen parameters was also considered. The model *F* value of 14.257 implies that the model is significant.

*P* values less than 0.0500 indicate model terms that are significant [30]. In this case, *D*, *AC*, *CD*, and *C*<sup>2</sup> are significant model terms, and other model terms are not significant. The lack of fit *F* value of 3.88 implies that there is a 7.38% chance that a lack of fit *F* value this large could occur due to noise. The predicted *R*<sup>2</sup> of 0.6870 is in reasonable agreement with the adjusted *R*<sup>2</sup> of 0.8649; i.e., the difference is less than 0.2. The normal probability plot indicates whether the residuals follow a normal distribution, in which case the points will follow a straight line, where all the points were scattered and lie on both sides of the straight line. Residuals versus run plot is a plot of the residuals versus the experimental run order, which is used for checking the lurking variables that may have influenced the response during the experiment. The plot should show a random scatter as in Fig. 4.

Figure 5 shows the response surface plots for the biogas production with various combinations of chosen parameters. The figure shows that the surface plot for biogas production obtained with all the parameters is ridge surface. Observation shows that, with increase in solid concentration, biogas production increases linearly. Biogas production increases up to a pH level of 7, after which the production rate decreases. For

higher pH values, lower biogas was produced. With hike in temperature until around 40 °C, biogas production was higher, and with further rise in temperature, biogas evolution was reduced. A min-max surface was visualized between pH and temperature, between pH and co-digestion, and between temperature and co-digestion. With higher co-digestion percentage, biogas production increases due to breakdown of ingredients present in food waste in a larger scale.

The empirical model developed for biogas production considering the chosen input variables is shown in Eq. (2). From the ANOVA table, it is identified that only significant terms only contribute and the nonsignificant terms must be removed from the model. Hence, Eq. (3) was developed removing the nonsignificant terms from Eq. (2).

$$\begin{aligned} \text{Biogas Production} = & 1920.185 + 38.28158 * \text{SC} + 442.8048 * \text{pH} + 119.0038 * \text{Temp} \\ & - 4.3655 * \text{CD} + 5.15 * \text{SC} * \text{pH} - 1.15667 * \text{SC} * \text{Temp} \\ & + 0.0475 * \text{SC} * \text{CD} + 1.125 * \text{pH} * \text{Temp} + 1 * \text{pH} * \text{CD} \\ & + 0.371667 * \text{Temp} * \text{CD} - 1.28491 * \text{SC}^2 - 40.7807 * \text{pH}^2 \\ & - 1.36055 * \text{Temp}^2 - 0.36281 * \text{CD}^2 \end{aligned} \tag{2}$$

$$\begin{aligned} \text{Biogas Production} = & 1920.185 - 4.3655 * \text{CD} - 1.15667 * \text{SC} * \text{Temp} \\ & + 0.371667 * \text{Temp} * \text{CD} - 1.36055 * \text{Temp}^2 \end{aligned} \tag{3}$$

**Table 5** Functional group from FTIR for poultry manure

Transmittance	Functional group	Major compounds	Type of vibration
1008	Ethers	Diethyl ether	C–O stretch
1456	Alkanes	Methane, ethane, etc.	H–C–H bend
1598	Nitro groups	Nitromethane	N=O stretch and N=O bend
2462	Carboxylic acids	Formic acid, acetic acid, propionic acid, etc.	Hydrogen-bonded O–H stretch
2941	Alkanes	Methane, ethane, etc.	H–C–H symmetric stretch

**Table 6** Input and output responses

Std. order	Run order	Input parameters				Output parameters	
		Solid concentration (%TS)	pH	Temperature (°C)	CD (%PM)	Biogas production (ml)	COD (g/l)
30	1	5	9	30	40	5462	26.59
2	2	5	5	30	40	5620	29.89
3	3	5	7	45	20	6314	35.56
28	4	5	9	60	40	6040	37.67
1	5	5	5	60	40	5972	33.45
26	6	5	9	30	0	5427	26.86
21	7	5	5	60	0	5602	25.75
25	8	5	5	30	0	5872	21.55
8	9	5	9	60	0	5495	29.29
14	10	10	7	45	0	5886	32.19
5	11	10	7	45	20	6435	36.97
23	12	10	7	45	20	6380	37.08
27	13	10	7	45	20	6435	35.83
4	14	10	7	45	20	6294	35.08
17	15	10	7	45	20	6480	36.55
13	16	10	7	45	20	6320	36.91
11	17	10	9	45	20	6212	33.98
10	18	10	7	60	20	5953	36.11
18	19	10	7	30	20	5941	34.99
15	20	10	5	45	20	5968	33.05
9	21	10	7	45	40	6330	34.82
29	22	15	9	60	0	5453	27.49
24	23	15	5	60	0	5389	22.16
16	24	15	7	45	20	6128	36.92
20	25	15	9	30	0	5718	25.49
12	26	15	5	30	40	5697	32.86
7	27	15	5	60	40	5770	30.12
19	28	15	9	60	40	5785	31.56
6	29	15	9	30	40	5862	28.61
22	30	15	5	30	0	5780	25.01

### 3.2 COD degradation

Analysis of COD degradation is performed in order to maximize it. Degradation of COD in the anaerobic digestion process is utilized for sludge generation, and the rest were converted into methane/biogas. COD provides a measure of the oxygen present in a sample of sludge that can be consumed in a reaction with oxidizing agents and reflects the number of organics present in a sludge, and the efficiency of anaerobic digestion can be evaluated using COD. The ANOVA table determined for COD degradation is shown in Table 8.

The  $F$  value of 25.19 achieved for the developed model shows that it is significant. Considering 95% confidence interval, probability values lower than 0.05 are significant model terms and higher than 0.05 are nonsignificant terms. These nonsignificant terms should be eliminated for achieving better

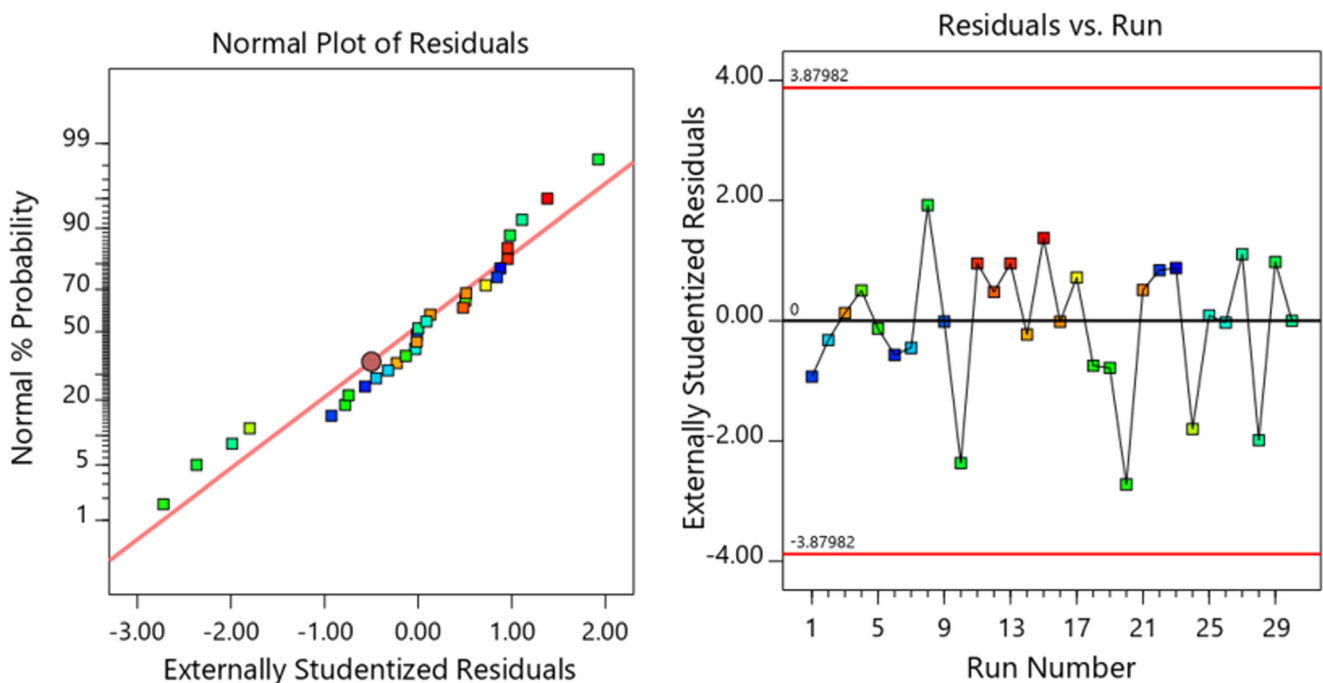
results. In this study, B, C, D, AC, BC, BD, B<sup>2</sup>, and D<sup>2</sup> are significant model terms. The predicted  $R^2$  of 0.7412 is in reasonable agreement with the adjusted  $R^2$  of 0.9211 since the difference is less than 0.2. The signal-to-noise ratio is measured by means of adequate precision value, which is 15.061 in this case, which is most desirable.

The normal plot of residuals and residuals vs. run plot for COD degradation is shown in Fig. 6. Observation shows that the residuals follow a straight line path and that in residuals vs. each experimental run, the residuals were observed to line on both sides of the center line with run no. 9 producing the higher residual.

Figure 7 shows the surface plots for COD degradation. Observations show that, with increase in solid concentration, a linear increase in degradation of COD was observed. With pH values, a max-min condition was obtained, and biogas

**Table 7** ANOVA table for biogas production

Source	Sum of squares	DoF	Mean sum of squares	F value	Prob. > F	
Model	3,073,750	14	219,553.6	14.25724	< 0.0001	Significant
A-solid concentration	2738	1	2738	0.177799	0.6793	
B-pH	2592	1	2592	0.168318	0.6874	
C-temperature	355.5556	1	355.5556	0.023089	0.8813	
D-CD	203,947.6	1	203,947.6	13.24382	0.0024	
AB	42,436	1	42,436	2.755683	0.1177	
AC	120,409	1	120,409	7.819047	0.0136	
AD	361	1	361	0.023442	0.8804	
BC	18,225	1	18,225	1.183484	0.2938	
BD	25,600	1	25,600	1.662397	0.2168	
CD	198,916	1	198,916	12.91709	0.0027	
A <sup>2</sup>	2673.494	1	2673.494	0.17361	0.6828	
B <sup>2</sup>	68,941.63	1	68,941.63	4.47689	0.0515	
C <sup>2</sup>	242,797.1	1	242,797.1	15.76661	0.0012	
D <sup>2</sup>	54,566.18	1	54,566.18	3.543385	0.0793	
Residual	230,991.7	15	15,399.45			
Lack of fit	204,628.4	10	20,462.84	3.880928	0.0738	Not significant
Pure error	26,363.33	5	5272.667			
Cor total	3,304,742	29				
Std. dev.	124.0945		<i>R</i> <sup>2</sup>	0.930103		
Mean	5934		Adjusted <i>R</i> <sup>2</sup>	0.864866		
C.V. %	2.091246		Predicted <i>R</i> <sup>2</sup>	0.68705		
PRESS	1,034,220		Adequate precision	11.36292		



**Fig. 4** Residual plot for biogas production

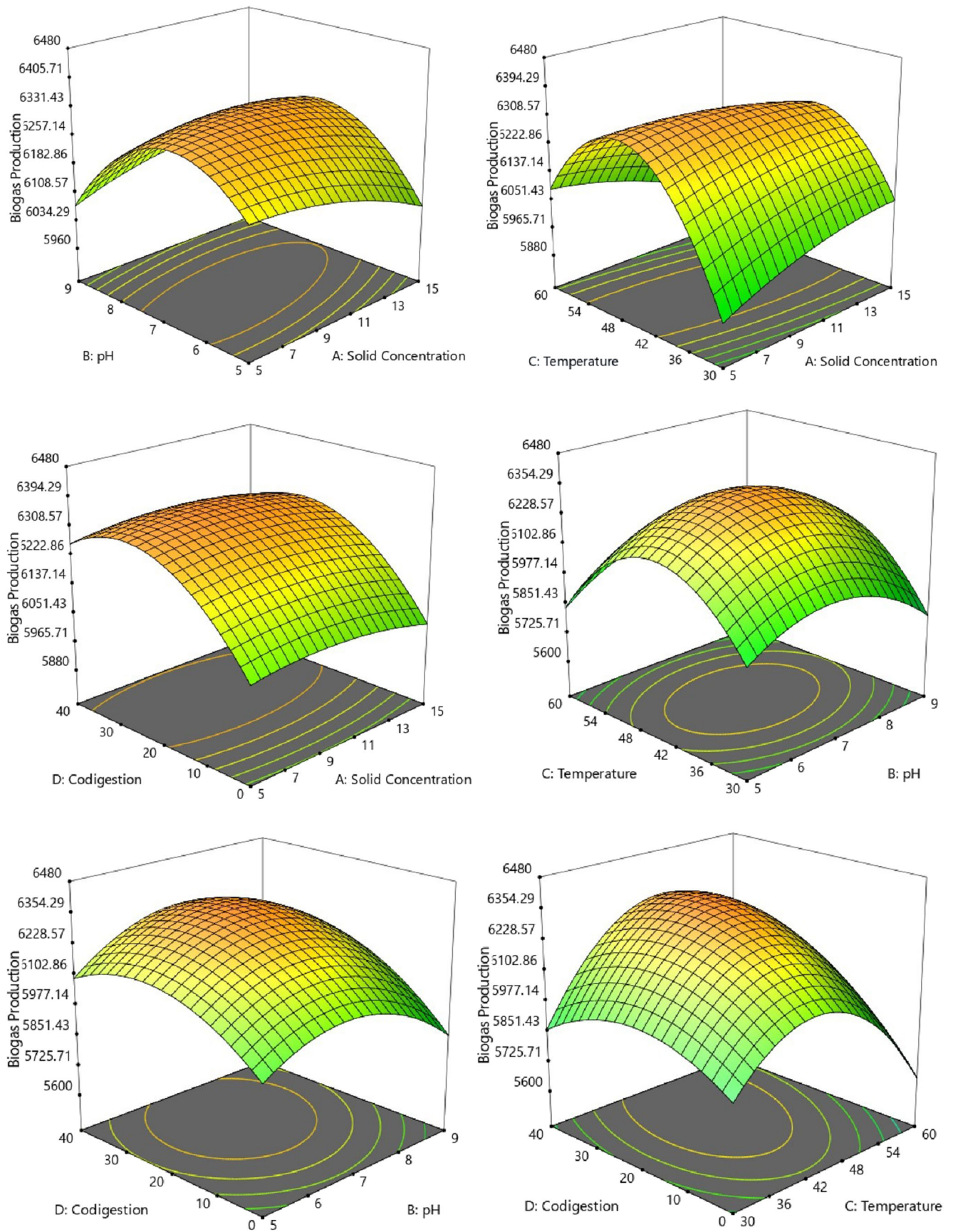
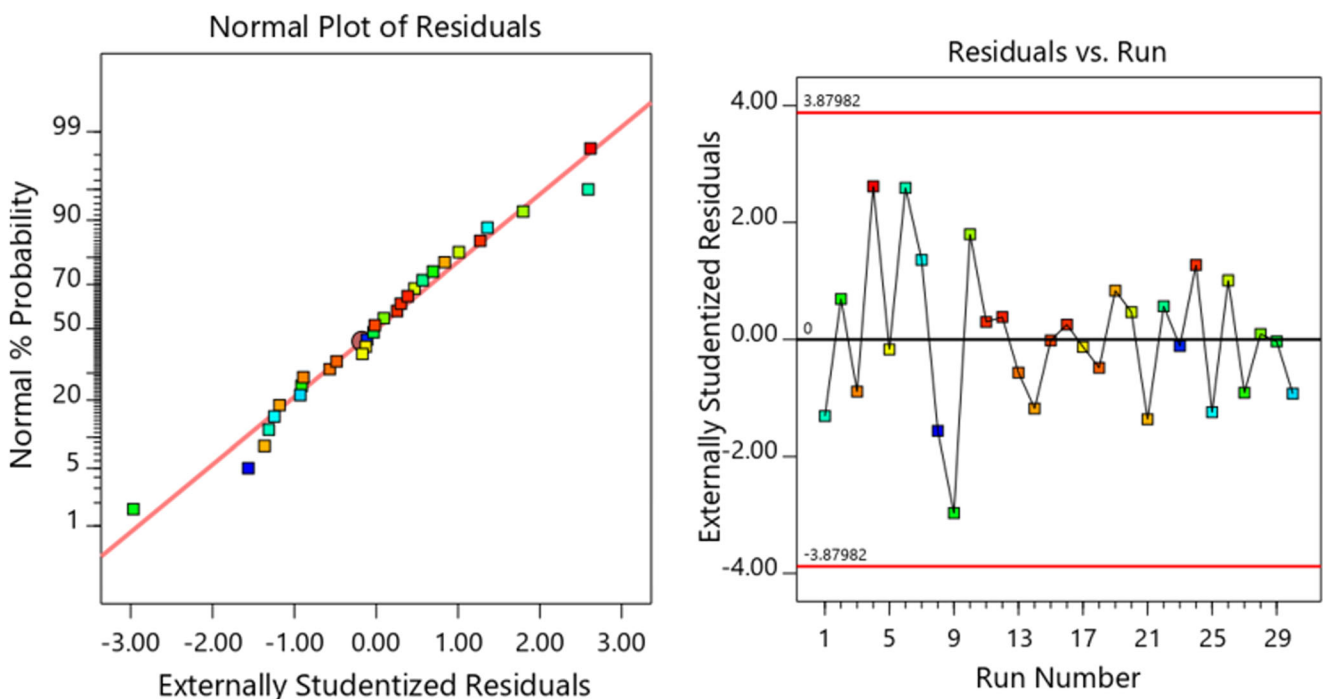


Fig. 5 Surface plots for biogas production



**Table 8** ANOVA table for COD degradation

Source	Sum of squares	DoF	Mean sum of squares	F value	Prob. > F	
Model	639.2944	14	45.66389	25.19166	< 0.0001	Significant
A-solid concentration	2.26845	1	2.26845	1.251449	0.2809	
B-pH	10.42722	1	10.42722	5.752447	0.0299	
C-temperature	26.28125	1	26.28125	14.49873	0.0017	
D-CD	137.6694	1	137.6694	75.94886	< 0.0001	
AB	2.864556	1	2.864556	1.580306	0.2279	
AC	30.00301	1	30.00301	16.55193	0.0010	
AD	0.082656	1	0.082656	0.045599	0.8338	
BC	16.58526	1	16.58526	9.149685	0.0085	
BD	17.11891	1	17.11891	9.444087	0.0077	
CD	5.141556	1	5.141556	2.836472	0.1128	
A <sup>2</sup>	0.650457	1	0.650457	0.358842	0.5581	
B <sup>2</sup>	26.96467	1	26.96467	14.87576	0.0016	
C <sup>2</sup>	3.67548	1	3.67548	2.027674	0.1749	
D <sup>2</sup>	27.13209	1	27.13209	14.96812	0.0015	
Residual	27.18988	15	1.812659			
lack of fit	24.05275	10	2.405275	3.833555	0.0755	Not significant
Pure error	3.137133	5	0.627427			
Cor total	666.4843	29				
Std. dev.	1.34635		<i>R</i> <sup>2</sup>	0.959204		
Mean	31.67967		Adjusted <i>R</i> <sup>2</sup>	0.921128		
C.V. %	4.249887		Predicted <i>R</i> <sup>2</sup>	0.741197		
PRESS	172.4879		Adequate precision	15.06132		



**Fig. 6** Residual plot for COD degradation

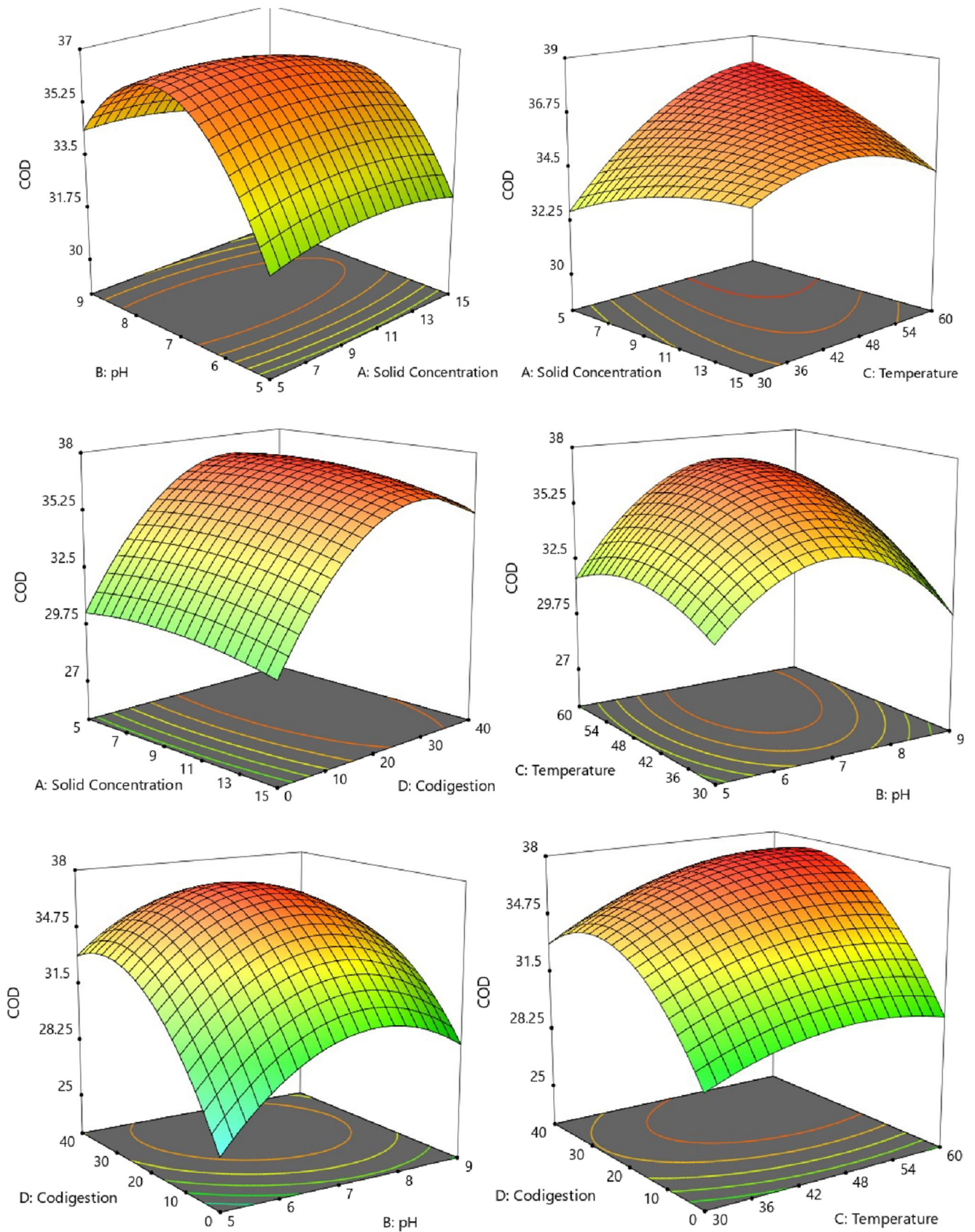


Fig. 7 Surface plots for COD degradation

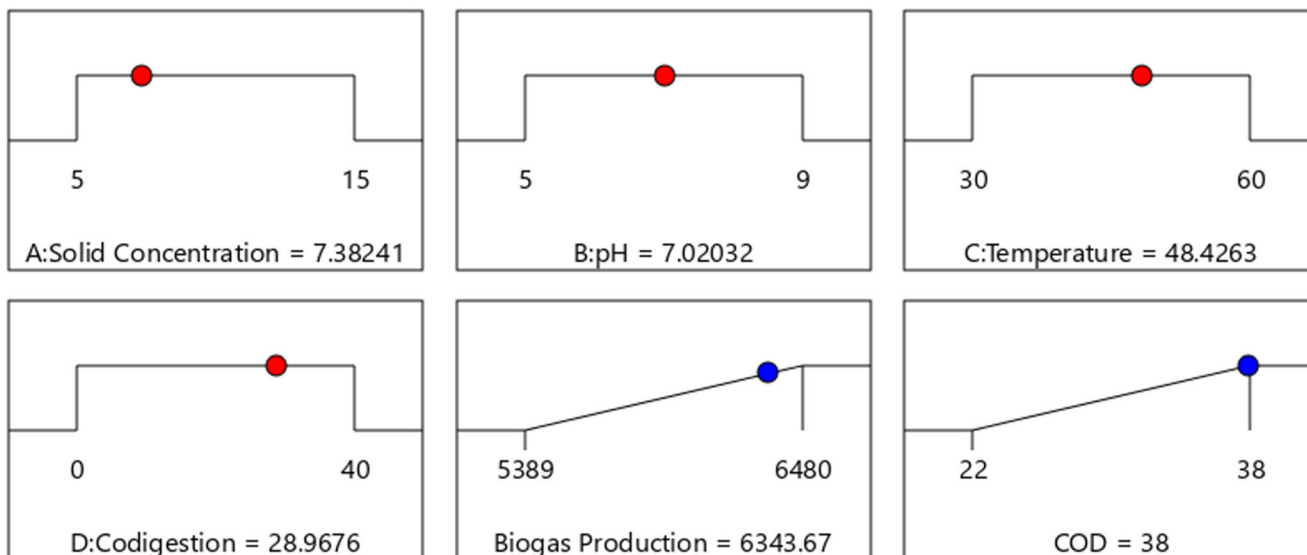


Fig. 8 Ramp plot for desirability analysis

production increases up to 7, after which it reduces. By maintaining higher temperature inside the reactor, COD degradation can be achieved through which higher biogas can be produced with lower sludge. With higher % of co-digestion, i.e., adding poultry manure around 40%, higher COD degradation was observed. A min-max type of ridge surface was obtained between pH and temperature.

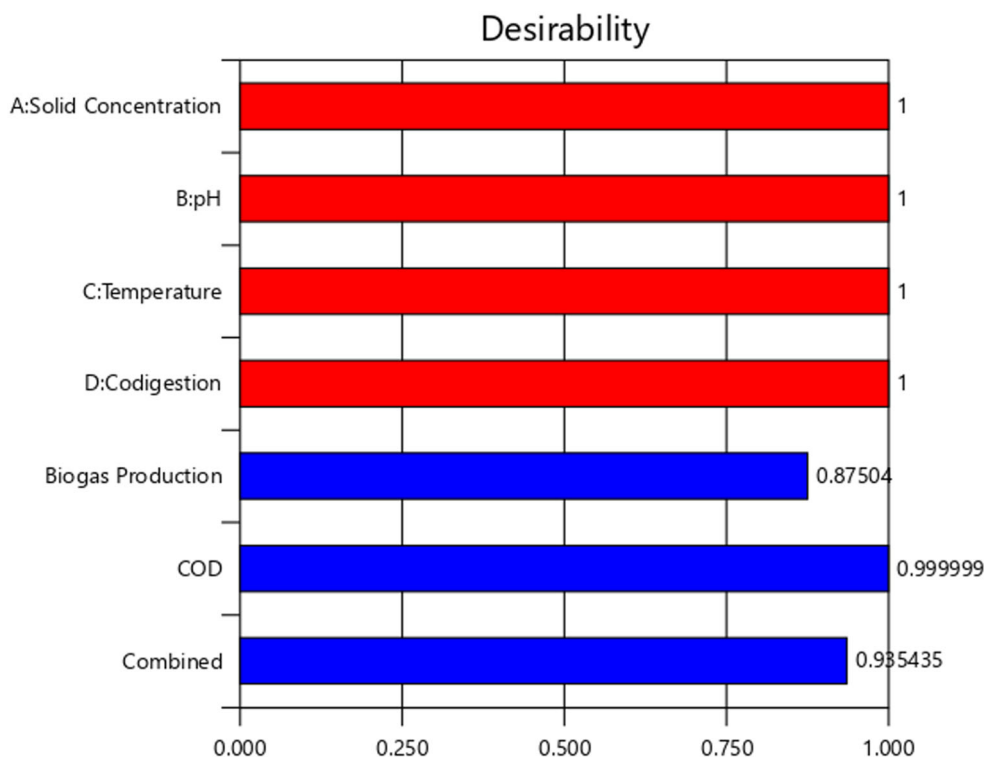
For COD degradation, the developed empirical model should be reduced by eliminating the nonsignificant terms identified from the ANOVA table of COD degradation. The

actual coded equation obtained during analysis is given in Eq. (4), and the empirical model obtained after removing the non-significant term is given in Eq. (5).

$$\begin{aligned}
 \text{COD} = & -29.8024 + 1.46203 * \text{SC} + 11.08486 * \text{pH} + 0.464206 * \text{Temp} \\
 & + 0.565055 * \text{CD} - 0.04231 * \text{SC} * \text{pH} - 0.01826 * \text{SC} * \text{Temp} \\
 & - 0.00072 * \text{SC} * \text{CD} + 0.033938 * \text{pH} * \text{Temp} - 0.02586 * \text{pH} * \text{CD} \\
 & + 0.00189 * \text{Temp} * \text{CD} - 0.02004 * \text{SC}^2 - 0.80651 * \text{pH}^2 \\
 & - 0.00529 * \text{Temp}^2 - 0.00809 * \text{CD}^2
 \end{aligned}$$

(4)

Fig. 9 Bar graph for desirability analysis



**Table 9** Predicted and observed optimum values of responses

Input parameter	Low level	High level	Optimum		
Solid concentration	5	15	7.495892		
pH	5	9	7.036339		
Temperature	30	60	48.41894		
CD	0	40	29.05531		
Responses	Goal	Predicted	Observed	Error (%)	
Biogas production	Maximize	6344	6657	4.93%	
COD degradation	Maximize	38	39.6	4.21%	

$$\begin{aligned} \text{COD} = & -29.8024 + 11.08486 * \text{pH} + 0.464206 * \text{Temp} + 0.565055 * \text{CD} \\ & - 0.01826 * \text{SC} * \text{Temp} + 0.033938 * \text{pH} * \text{Temp} - 0.02586 * \text{pH} * \text{CD} \\ & - 0.80651 * \text{pH}^2 - 0.00809 * \text{CD}^2 \end{aligned} \quad (5)$$

### 3.3 Multi-objective optimization using desirability analysis

In RSM, for performing multi-objective optimization, all the responses are considered simultaneously using desirability analysis, a useful approach for optimization more than one response. The parameter setting achieving higher desirability value close enough to 1 was considered to be the optimum conditions, and the simultaneous objective function is a geometric mean of all responses. In this experimental investigation, the optimum input parameter setting was evaluated with the objective formulated as maximizing biogas production and maximizing COD degradation. The ramp plot given in Fig. 8 shows the optimum input values and the predicted output responses, which were solid concentration as 7.38, pH value as 7, temperature at 48.43 °C, and co-digestion as 29 which produces a biogas of 6344 and COD degradation of 38.

The desirability plot of the multi-objective optimization is shown in Fig. 9. Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. For several responses and factors, all goals get combined into one desirability function. The desirability value is completely dependent on how closely the lower and upper limits are set relative to the actual optimum. The overall desirability value is 0.94 for the combined objective, which is a good measure since it is nearer to 1.

Once the optimum values of the input parameters were through multi-objective optimization, the consecutive step is to validate the optimum values and to verify performance characteristics of the optimized input parameters. Another set of experiment was performed by setting the above optimum input values with the same experimental setup, and the

output responses were measured. Table 9 shows the RSM predicted and experimentally observed optimum response values and the corresponding percentage error during experimental validation of the developed models. It was observed that the maximum error is 4.93%. Hence, a close relationship is identified between the predicted and the observed values.

## 4 Conclusion

Experimental investigation on biogas production through degradation of poultry manure was done employing RSM-based optimization approach; the conclusions obtained from the analysis were as follows:

1. Food waste collected from the student hostel mess of NIT Calicut, India, was used for the experiments. The waste collected was shredded into particles to increase the surface area available for microbial activities.
2. The FTIR spectrum for food waste shows carboxylic acids such as formic acid, acetic acid, propionic acid, etc. and amine such as methane, ethane, etc. In addition to these compounds, methyl formate, diethyl ether, and nitromethane are also present in small quantity.
3. For biogas production terms, D, AC, CD, and  $C^2$  are significant model terms with an  $R^2$  value of 93%. Surface plot of biogas production shows a linear increase in biogas for increase in solid concentration, with increase in pH biogas production gets reduced, a concave surface was produced for temperature variation where up to 40 °C, biogas production increases and after that it tends to decrease. Similarly, nonlinear increase in biogas production is observed for an increase in co-digestion.
4. For COD degradation, B, C, D, AC, BC, BD,  $B^2$ , and  $D^2$  are significant model terms with an  $R^2$  value of 95.92%.
5. Desirability approach produces a combined optimum condition as follows: solid concentration as 7.38, pH value as 7, temperature at 48.43 °C, and co-digestion as 29 which produces a biogas of 6344 and COD degradation as 38 with an overall desirability value of 0.94.
6. The maximum error % between RSM predicted and experimentally observed optimum response values was 4.93%, which proves the efficiency of the multi-objective optimization procedure.

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