

MODELLING AND OPTIMIZATION OF METHANE FROM ANAEROBIC DIGESTION OF ANIMAL WASTE (PIG DUNG) WITH ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

ABSTRACT

Agricultural wastes have increased in recent times due to an increased need for agricultural products by humans. These wastes causes environmental pollution and hazard to the society. Hence, the need to embark on anaerobic digestion to convert these waste to biogas. Biogas has been proven to be a good alternative to gases produced from fossil fuel due to its environmental friendliness. Production of biogas gases ensures cleaner environment and enhances clean growth. In this study, hydraulic retention time, temperature, moisture content, pH and carbon to nitrogen ratio are the factors used for generating the biogas from anaerobic digestion of pig dung. Independent variables range values obtained for each factor was subjected to design expert software application which gave the factor levels and number of runs under Central Composite Design (CCD) in Design of Experiment (DOE). The data generated from design expert was utilized in the laboratory for biogas yield via bio-digester. Pig dung was made to meet various process conditions after which 2kg of pig dung was feed into a 10liters digester and kept for various days. The yield obtained was subjected to four RSM models (linear model, interaction model, pure-quadratic model and quadratic model), ANFIS model and three kinetic models (gompert, modified gompertz and logistic model). Quadratic model was selected as the best RSM model having the best prediction accuracy performance with R-square value of 73.03%. When compared with ANFIS model, ANFIS model had R-square of 95.9983% there by making it a better model which can be utilized for further analysis. ANFIS was optimized and a three dimensional plot of surface and contour plot were used to determine the effect of the factors on the interaction and the optimal response obtained was 92.36% at hydraulic retention time of 11days, temperature of 50°C, moisture content of 93%, pH value of 7.01 and carbon to nitrogen ratio of 1 which was used as the first guess for kinetic studies. Furthermore, logistic model had the best prediction accuracy with R-square of 68.09% when compared with the other two kinetic models, hence, it was concluded that ANFIS model should be utilized in determination of the yield using the factors and logistic model, this could be used in the study of the anaerobic bio-digesters for the production of biogas from pig dung.

Keywords: Bio-digester, methane, ANFIS, biogas, anaerobic, Algorithm

1. INTRODUCTION

There have been worries on the under-utilization of agricultural waste in Nigeria as this waste leads to environmental deterioration and emission of carbon dioxide (CO₂) into the atmosphere. This has given rise to the recent research on anaerobic digestion process of agricultural waste using an anaerobic digester (Dhar *et al.*, 2017). Anaerobic digestion (AD) process has been

proven to be highly efficient in the production of biogas from agricultural waste (Yangin-Gomec *et al.*, 2013, Zou *et al.*, 2015, Ray *et al.*, 2013).

Anaerobic Digestion process is biological process involving the use of microorganism in the absence of oxygen to break down biodegradable materials into biogas. Biogas contains 50% to 70% of methane, 5-10% of hydrogen and up to 30-40% of carbon-dioxide (Ray *et al.*, 2013).

Anaerobic Digestion (AD) process is divided into four stages namely, hydrolysis, acidogenesis, acetogenesis and methanogenesis. Major benefits of going into anaerobic digestion process are little or no emission of harmful gases leading to climate change, it is also viable option for waste management system sustenance and the biogas produced from this process can be used as a source power/electricity generation and cooking/heating in homes (Jang *et al.*, 2015).. This process involves a reactor system without little or no presence of oxygen. Various factors affect the production of biogas such as temperature, moisture content, pH, organic loading rate and hydraulic retention time (Jang *et al.*, 2015).

To perform the laboratory experiment of anaerobic digestion process for production of biogas, design of experiment is required (Akpabio *et al.*, 1992). Design of experiment is necessary to determine the input parameters and the total number of runs needed to carry out the experiment. On completion of the laboratory experiment, modelling of the process condition is necessary using various modelling technique and tools such as RSM, ANFIS, ANN, FL as it allows monitoring, predicting and control of the system behaviour (Chelme *et al.*, 2011).

Artificial neural fuzzy inference system (ANFIS) is an artificial intelligent model that is used in modeling and optimizing a process, it determines a learning algorithm based on the connection between the output and input variables. ANFIS show great advantages in simulation, control, and prediction of the anaerobic process (Ramachandran *et al.*, 2019). This connection is achieved by mapping of input parameter into input membership function and transforming the membership function into sets of rules. These set of rules are then transformed into output membership function and subsequently to clear output. (D'Amato, *et al.*, 2014)

The response surface methodology (RSM) is a technique that is widely used in the modeling and analyzing a process whose response (dependent variable) is affected by singular or multiple variables (independent variable), with the sole objective of modeling and optimizing the response with respect to the effects of the independent variables (Cheng, 2013).

Several RSM models have been used in the prediction and performance enhancement of responses. Out of the proposed models, four RSM model have been reported as most efficient and most widely used by related researches and they include: Linear model, interaction model, quadratic mode and pure –quadratic model (Baki, 2004).

Adama *et al.*, (2022) carried out a study on the modeling of anaerobic digestion of agricultural waste with RSM using least square method for the prediction of the response and obtained an R-Squared value of 65.02%. Also, Onwuliri *et al.*, (2013) used triplicate digesters in determining the scale of biogas yield from animal dung and obtained an optimum biogas yield of 39.29% and 41.30% in week 3 and week 2. This prediction accuracy can be improved by the use of an artificial intelligent model.

This study investigated the appropriate empirical model and intelligent model for the prediction of the methane yield generated based on laboratory data and also to optimize the response of the intelligent model.

It is expected that on completing the modeling and comparison of the models, the prediction accuracy should be greater than 50% (Niles 2002). This is necessary to ensure that high prediction accuracy was achieved for recommendation to biogas production engineers.

2. MATERIALS AND METHODS

2.1 Materials

The materials and applications for the modelling and simulation carried out in this study include pig dung from a pig farm in Lagos, Nigeria prior to each experiment, Design Expert 11, Matlab 2015 & 2019 were used for the generation of RSM models, ANFIS, Anova tables, Surface and Contour plots. Response surface methodology (RSM) models were utilized to obtain the independent and dependent variables of the process. Model performance was done to determine the degree of accuracy of the RSM model utilized using the analysis of variance prediction performance technique.

2.2 Methods

2.2.1 Experimental Design

Prior to the laboratory experiment, the generated experimental design codes to aid in the anaerobic digestion (AD) laboratory experiments shown in Table 1. The experimental design yielded a total of 32 runs using central composite design in Design Expert 11

Table 1: Input Parameters and Ranges for experiment

Input variables	Coded factors and ranges				
	- α	-1	0	+1	+ α
C1: HRT(days)	10	11	12	13	14
C2: Temperature($^{\circ}$ C)	45	50	55	60	65
C3: Moisture content (%)	90	91	92	93	94
C4: pH	6.8	6.9	7.0	7.1	7.2
C5: C/N	0.5	1.0	1.5	2.0	2.5

Where HRT is the hydraulic retention time, C/N is the ratio of carbon to Nitrogen.

2.2.2 Experimental Design

One of the modeling procedures used was (least square method of generating regression coefficients from the empirical models proposed) and used to compare with other models proposed in this study. After the laboratory experiment, the data obtained was used in generating response surface methodology (RSM) models and predicting the response of the process using adaptive neuro fuzzy inference system model. The response surface models used for the analysis are shown below.

i. Linear Model

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \quad \text{Equation 1}$$

ii. Interaction Model

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + a_6X_1X_2 + a_7X_1X_3 + a_8X_1X_4 + a_9X_1X_5 + a_{10}X_2X_3 + a_{11}X_2X_4 + a_{12}X_2X_5 + a_{13}X_3X_4 + a_{14}X_3X_5 + a_{15}X_4X_5 \quad \text{Equation 2}$$

iii. Pure-quadratic Model

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + a_6X_1^2 + a_7X_2^2 + a_8X_3^2 + a_9X_4^2 + a_{10}X_5^2 \quad \text{Equation 3}$$

iv. Quadratic Model

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + a_6X_1X_2 + a_7X_1X_3 + a_8X_1X_4 + a_9X_1X_5 + a_{10}X_2X_3 + a_{11}X_2X_4 + a_{12}X_2X_5 + a_{13}X_3X_4 + a_{14}X_3X_5 + a_{15}X_4X_5 + a_{16}X_1^2 + a_{17}X_2^2 + a_{18}X_3^2 + a_{19}X_4^2 + a_{20}X_5^2$$

Equation 4

Where Y is the response of the process and X_1 to X_5 represents C_1 to C_5 and are the input parameters or independent variables and $a_0 - a_{20}$ are the regression coefficients.

The parameters utilized for the prediction performance check are t-statistics, p-values, mean square errors, root mean square errors, R-square, adjusted R-square and sum of square errors which makes up the analysis of variance table (ANOVA table). The RSM models utilized in this study are; linear model, interaction model, quadratic model and pure quadratic model. Also, the response of the ANFIS model was compared with that of RSM model.

2.2.3 Experimental Procedure

Pig dung was mixed with distilled water to form slurry. The method of (Liao *et al.*, 2006) was used to analyse the slurry to meet the required physiochemical properties where test such as pH, moisture content, temperature, carbon to nitrogen ratio was determined. Eight (8) digesters with temperature controlled electric heater were available for the anaerobic digestion (AD) experiment. The slurry state anaerobic digestion was performed using a 10 litre container at various thermophilic temperatures (45°C – 65°C) and other input parameters set. Each digester was feed with two kilogram (2kg) of the pig dung and connected with a tube and valve for gas output. The biogas produced flows through the gas outlet tube into a container, where water displacement method was employed, the gas tube is then connected to a methane analyzer (Perkin Elmer EA2800) to measure the amount of methane produced at various hydraulic retention time of 10 to 14 days.

3. RESULTS AND DISCUSSION

3.1 Characterisation of pig dung

Pig dung was characterized and the physiochemical properties determined. The feed conditions were met before feeding the dung into an anaerobic digester. Result of the Pig dung characteristics are shown in Table 2.

Table 2: Characterization of pig dung

Parameters	Values
pH	6.92

Particle size (micro meter)	112
Carbon content (%)	15.54
Nitrogen content (%)	0.82
C:N	18.95
Ash content (%)	21.37
Volatile solid (%)	68.33
Hemicellulose (%)	21.74
Cellulose (%)	16.12
Lignin (%)	6.14
Total fiber (%)	43.43
Moisture content (%)	14.73

3.2 Observed methane yield

The experiment was conducted using pig dung after 32 runs. The results of the experiment conducted are shown in Figure 1.

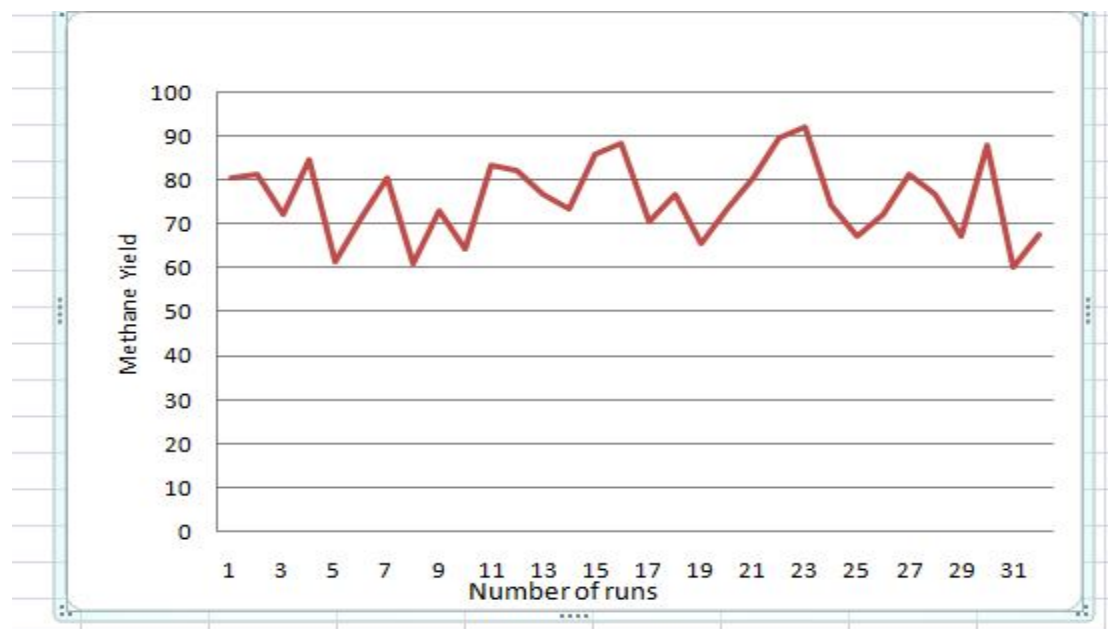


Figure 1 shows that the 23 runs had the highest methane yield of 92.07% with an hydraulic retention time of 11days, pH of 7.0, C/N of 1.00 and moisture content of 93%.

3.3 RSM results

The comparative plots of the actual (observed or experimental) methane yield (response) and the RSM models (linear, interaction, pure-quadratic and quadratic) predicted response are shown in Figure 2.

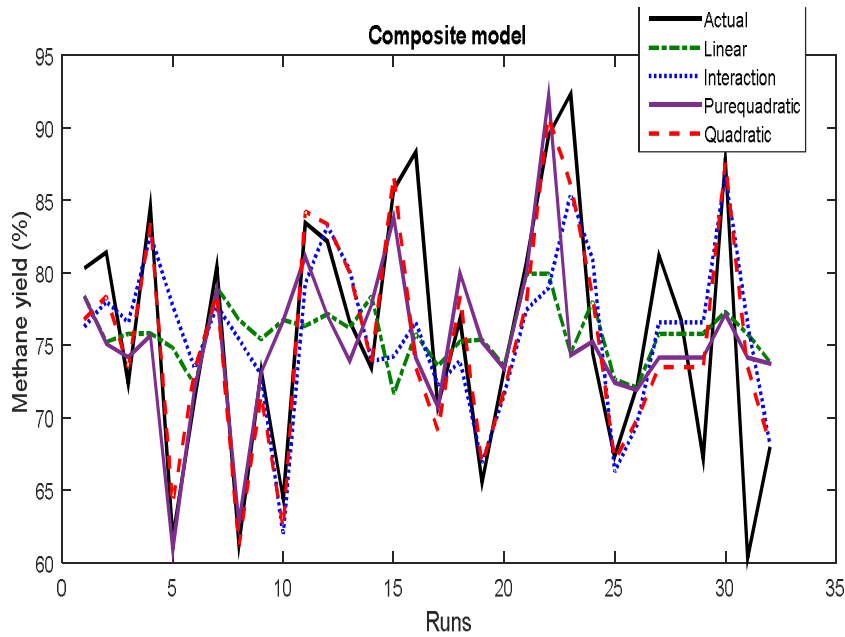


Figure 2: Comparative plot of all RSM models with the actual yield

It was observed that Quadratic model was able to track the experimental yield (response) better than other RSM models (Niles 2002), having the best prediction accuracy of R^2 value of 73% as compared to the linear, interaction and pure quadratic model that had a prediction accuracy of 5.9%, 38.7% and 38.5% respectively. The RSM models after simulation obtained as;

Table 3: RSM model equations for the predicted response Y

Model	Equation
Linear	$Y = 136.3097 - 0.2697c_1 - 0.2218c_2 - 0.1946c_3 - 4.7692c_4 + 4.1446c_5$
Interaction	$Y = 944.1115 - 49.1273c_1 - 49.7467c_2 - 54.4653c_3 + 897.7660c_4 - 466.2616 + 0.4648c_1c_2 + 0.3100c_1c_3 - 16.4525c_1c_4 + 7.0835c_5 + 0.9345c_2c_3 - 6.2955c_2c_4 + 1.2197c_2c_5 - 2.4378c_3c_4 + 9.7299c_3c_5 - 82.6599c_4c_5$
Pure-quadratic	$Y = 16148 - 38.602x_1 + 1.060x_2 + 29.794x_3 + 4317.9x_4 - 37.366x_5 + 1.5963x_1^2 - 0.011699x_2^2 - 0.16306x_3^2 - 308.75x_4^2 + 13.85x_5^2$
Quadratic	$Y = 9305.2 - 26.224x_1 + 55.767x_2 - 142.45x_3 + 5178.7x_4 - 548.39x_5 + 0.50684x_1x_2 + 0.74413x_1x_3 - 18.554x_1x_4 + 7.6259x_1x_5 + 1.0213x_2x_3 - 6.7159x_2x_4 + 1.3282x_2x_5 - 6.7788x_3x_5 + 10.398x_4x_5 - 88.084x_1^2 + 1.9525x_2^2 + 0.58203x_3^2 - 273.12x_4^2 + 15.275x_5^2$

3.4 ANFIS results

The ANFIS predicted response with the actual data was shown in Figure 3.

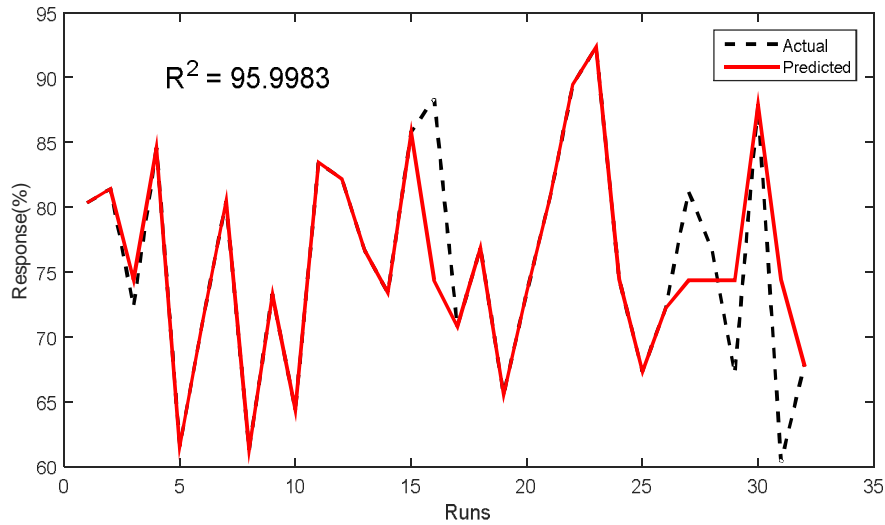


Figure 3: ANFIS predicted response

From Figure 3, it can be seen that the predicted to a large extent tracked the actual response with the prediction accuracy of 95.9983% (0.9599).

A comparative plot between ANFIS predicted response and quadratic RSM model predicted response shown in Figure 4.

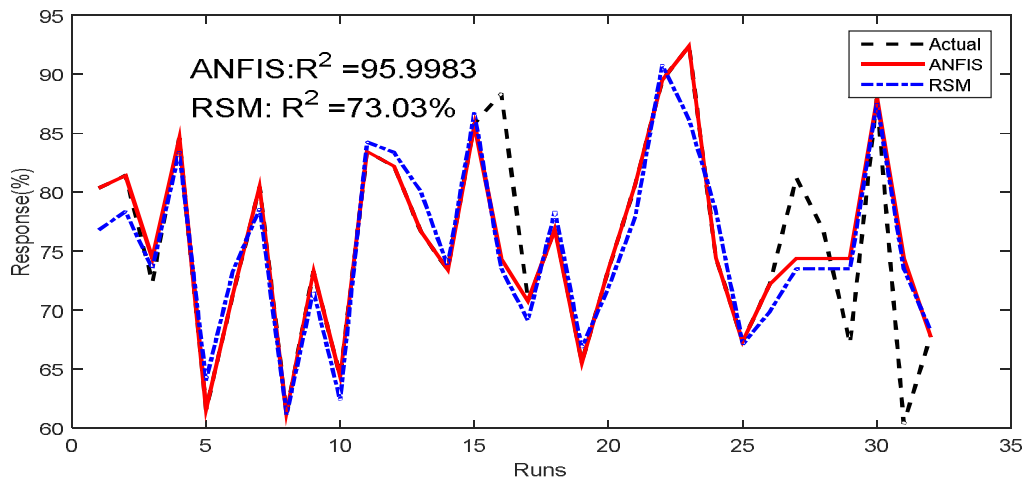
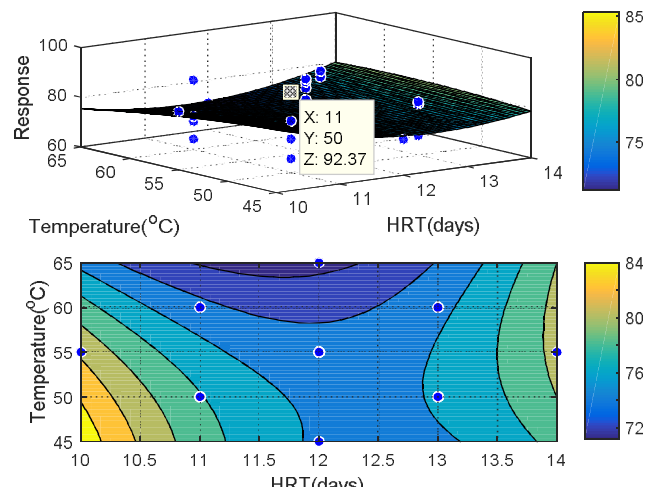
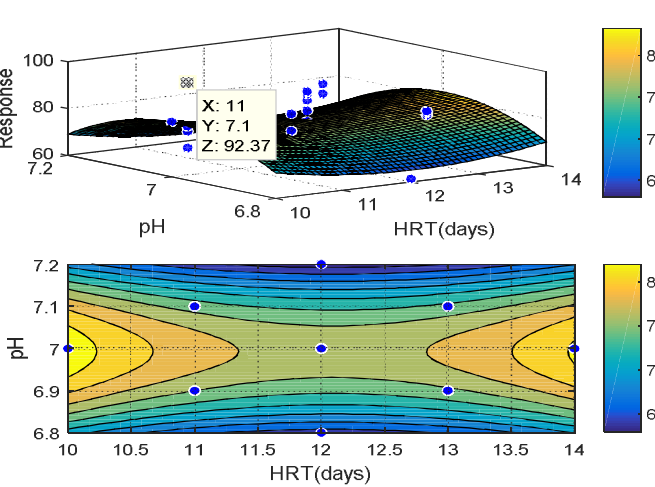
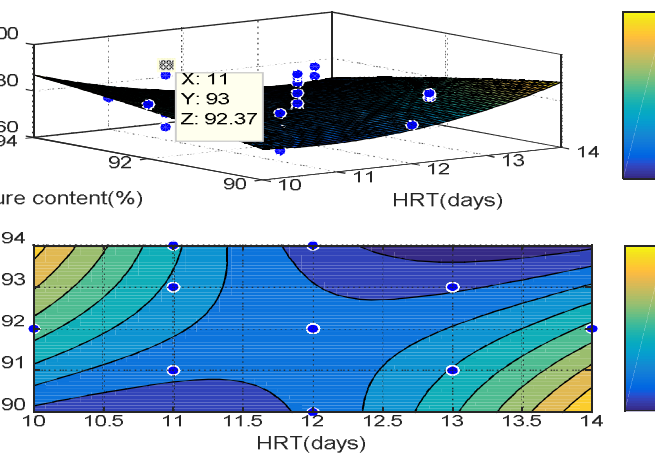


Figure 4: Comparative plot of ANFIS predicted response, Quadratic and actual yield

From the values of the prediction accuracy obtained and displayed in Figure 4, ANFIS model had a better prediction than the RSM model (Zvikomborero, 2020).

3.5 Surface and contour plots

Three dimensional plots showing the effects of the interaction of input parameters (factors) on the response (methane yield) predicted with ANFIS are shown below in Figures 5a through 5e.

Factors	Response Y (Methane yield)
<p>(a)</p> <p>Temperature and HRT on response C2 = 50 °C C1 = 11days Y = 92.37%</p>	 <p>3D surface plot showing Response vs Temperature (°C) and HRT (days). The peak response is at X: 11, Y: 50, Z: 92.37.</p> <p>2D contour plot showing Response vs Temperature (°C) and HRT (days).</p>
<p>(b)</p> <p>pH and HRT on response C4 = 7.1 C1 = 11days Y = 92.37%</p>	 <p>3D surface plot showing Response vs pH and HRT (days). The peak response is at X: 11, Y: 7.1, Z: 92.37.</p> <p>2D contour plot showing Response vs pH and HRT (days).</p>
<p>(c)</p> <p>Moisture content and HRT on response C3 = 93 C1 = 11days Y = 92.37%</p>	 <p>3D surface plot showing Response vs Moisture content (%) and HRT (days). The peak response is at X: 11, Y: 93, Z: 92.37.</p> <p>2D contour plot showing Response vs Moisture content (%) and HRT (days).</p>

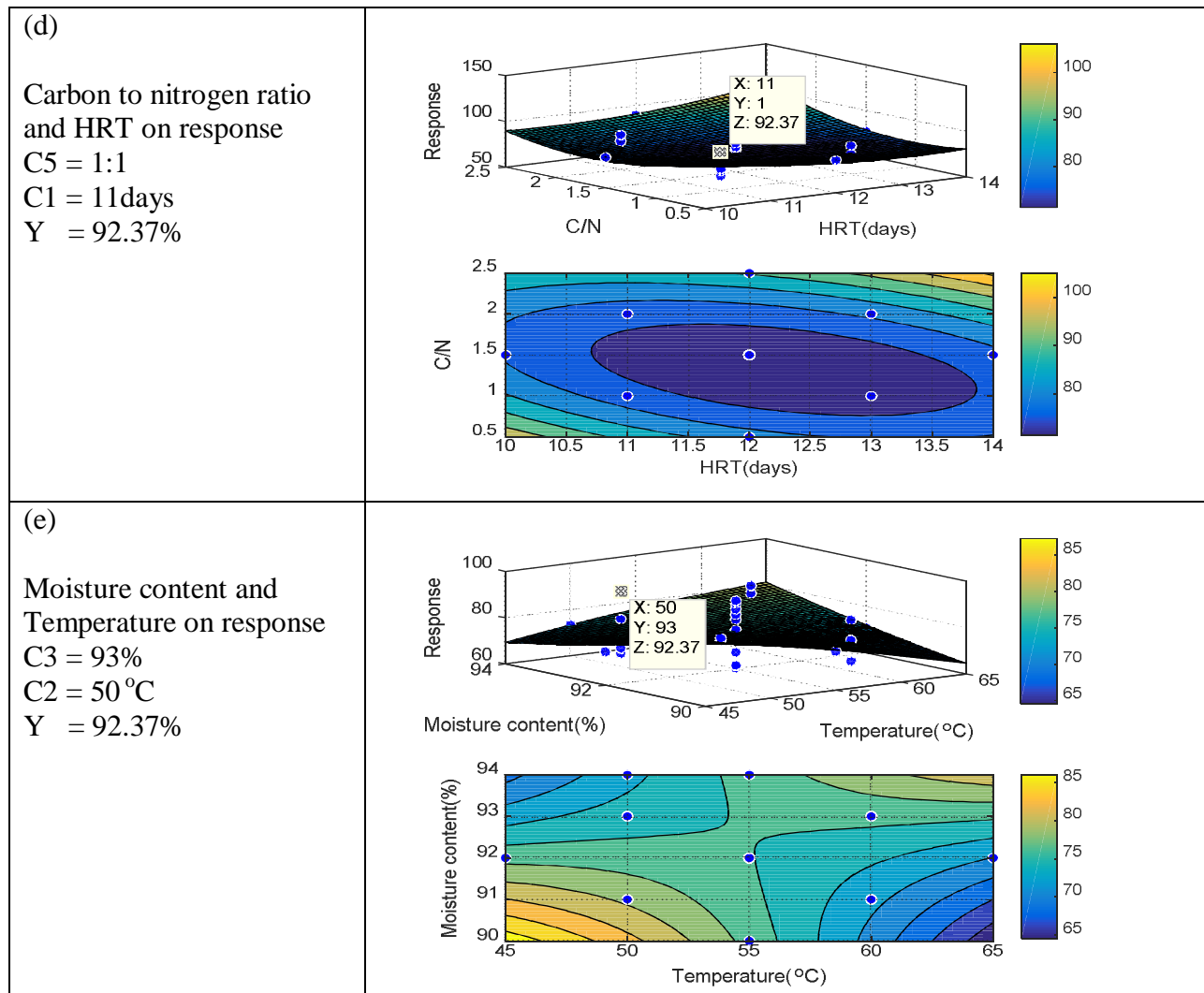


Figure 5: Interaction between input parameters and the response Y (methane yield)

3.6 Model validation and optimization

The developed model performance was evaluated and validated using Microsoft Excel spreadsheet. A comparison plot of the actual methane yield against quadratic model and a plot of the actual methane yield and ANFIS model were done and displayed in Figure 6a through 6b. Optimization of response Y (methane yield) was done using design expert 11, as the factors and the optimal response shown in Table 4.

Model	Validation
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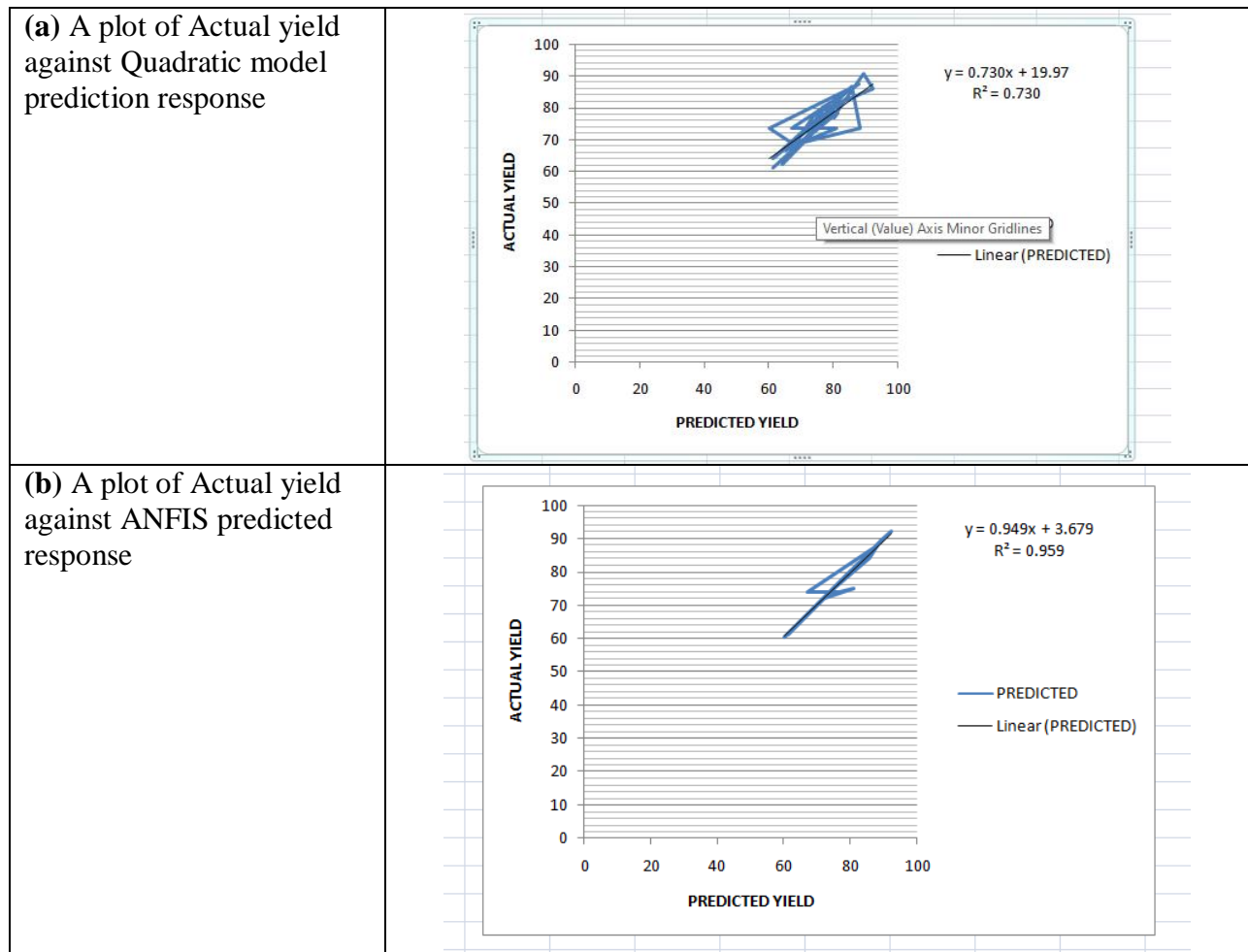


Figure 6: Model validation

Table 4: Optimum parameters generated by the surface plots

Parameters	Optimum values
HRT	11
Temperature	50
Moisture content	93
pH	7.1
C/N	1
Methane yield	92.36

3.7 Kinetic model results

The optimum factors was taken as input parameters to the laboratory for anaerobic digestion process of pig dung to monitor the methane yield with respect to time with the results shown in Table 5. The result was fitted into three different kinetic models namely; Gompertz, Modified Gompertz and Logistic model to determine which model had the best fit and other kinetic parameters.

Table 5: Methane yield and time

HRT (days)	Response (%)
1	31.3723
2	36.1149

3	39.4418
4	42.3398
5	58.4492
6	63.4553
7	69.9984
8	72.4487
9	75.6615
10	77.9981
11	93.3329
12	85.2271
13	90.3319
14	83.1184
15	89.4438
16	73.3332
17	64.8827
18	61.7321
19	64.2218
20	52.1718

Data was fitted into Gompertz, Modified Gompertz and logistic model using non-linear curve fitting toolbox in Matlab 2019. The parameters generated are shown in Table 6.

Table 6: kinetic model

Model	Parameters	Outcome
Gompertz	General model: Coefficients (with 95% confidence bounds): Goodness of fit:	$f(t) = B \cdot (1 - \exp(-k \cdot t))$ B = 76.42 (68.31, 84.54) k = 0.3147 (0.1659, 0.4636) SSE: 2367 R-square: 0.6375 Adjusted R-square: 0.6174 RMSE: 11.47
Modified Gompertz	General model: Coefficients (with 95% confidence bounds): Goodness of fit:	$f(t) = B \cdot \exp(-\exp(R \cdot e / B \cdot (\text{Lamda} - t) + t))$ B = 76.51 (67.54, 85.48) e = 15.06 (-6.205e+15, 6.205e+15) Lamda = 0.3852 (-0.2938, 1.064) R = 7.021 (-2.893e+15, 2.893e+15) SSE: 2193 R-square: 0.6641 Adjusted R-square: 0.6011 RMSE: 11.71
Logistic	General model: Coefficients (with 95% confidence bounds): Goodness of fit:	$F(x) = B / (1 + \exp(4 \cdot R \cdot ((L - t) / B + 2)))$ B = 76.4 (68.82, 83.99) L = -150.3 (-165.1, -135.5) R = 9.149 (2.607, 15.69) SSE: 2083 R-square: 0.6809

		Adjusted R-square: 0.6434 RMSE: 11.07
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As seen from the table above, Logistic model has the best goodness of fit with R^2 value of 68% (0.6809) compared to Gompertz model with R^2 value of 63.75% (0.6375) and Modified Gompertz with R^2 value of 66% (0.6641). Other kinetic parameters were also obtained from the analysis.

5. CONCLUSION

From this study, it was obtained that five factors were utilized in producing the biogas yield from pig dung. The factors were HRT, Temperature, moisture content, pH and carbon to nitrogen ratio. Quadratic model proved to be the best model for response surface methodology base on the prediction of the yield as obtained from the analysis of variance table with R-square of 73.03%. However, ANFIS intelligent model displayed a better prediction performance with R-square of 95.9983%. It was keenly observed that the use of ANFIS model is best for the prediction of the yield. Hence, ANFIS was considered the best model. Surface and contour plots were used in studying the effect of the interaction of the factors on the yield and also in obtaining the optimal values. The optimal values obtained was subjected to kinetic modelling by obtaining the best kinetic model for study of the bio-digester which logistic model being the best had R-square values of 68.09%. Having undergone the laboratory experiment, the modelling, optimization and kinetic application of the production of biogas from pig dung, it is recommended that intelligent model should be used in determining the amount of biogas yield by interpolative or extrapolative means as long as the factors utilized in this study are applied. It is also recommended that the independent variables obtained to achieve the optimal response (yield) be recommended to biogas engineer as these factors can/may be used as control variables for biogas production in a larger production scale or continuous process production of biogas. Furthermore, it is recommended that a metaheuristic optimization technique (ANFIS & Particle Swarm) be carried out by other researchers.

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COMPETING INTEREST

Authors have declared that no competing interests exist.

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