Evaluation of the Predictive Capability of Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in Estimating Biogas Yield from Poultry Droppings, Pig Manure and Brewery Spent Grain using Enzyme Amylase

M.I. Onyiah, Ph.D.[1*]; G.O. Mbah, Ph.D.[2]; and M.U. Ude, Ph.D.[1]

[1]Engineering Research Development and Production, Projects Development Institute (PRODA), Emene Industrial Estate, Enugu, Nigeria.
[2]Department of Chemical Engineering, Enugu State University of Science and Technology, ESUT, Nigeria.

E-mail: ugwuayi@yahoo.com*

ABSTRACT

One of the biggest obstacles investigators face is predicting biogas yields, which is an enormous challenge because study in the field of simulation and optimization of biogas yield is still restricted, particularly with the adaptive neuro-fuzzy inference system (ANFIS). This study aims to develop and compare models that best predict the oxygen-independent decomposition of poultry droppings, pig manure, and brewery spent grain for biogas production with the influence of enzyme amylase.

The Response Surface Modelling (RSM) and a hybrid algorithm, Adaptive Neuro Fuzzy Inference System (ANFIS), was evaluated by considering temperature, residence duration, enzyme concentration, and pH as independent variables, while biogas generation served as the response or output factor. Relevant statistical metrics like AAD, MAE, RMSE and R^2 were applied to relate the adequacy of the two models. The performance of both RSM and ANFIS were compared based on the performance metrics. The calculated value of the coefficient of determination (R^2) for the biogas yield by implementing RSM using the enzyme amylase gave ($R_{PD}^2=0.9974$, $R_{PM}^2=0.9910$ and $R_{BSG}^2=0.9975$). This was compared with ANFIS results with an R^2 value of ($R_{PD}^2=0.9986$, $R_{PM}^2=0.9985$ and $R_{BSG}^2=0.9985$). Analysis of the RSM and ANFIS results shows that the ANFIS prediction result is statistically marginal and presents the hybrid algorithm as a better prediction and optimization tool.

(Keywords: biogas, enzyme amylase, response surface methodology, adaptive neuro-fuzzy inference system, oxygen-independent fermentation)

INTRODUCTION

The importance of energy and its application to the growth of a nation cannot be overstated as they are invaluable to both sustainability and the establishment of a potent national identity [1]. Pollution, poor waste management, and energy supplies are key problems facing Nigeria and several other developing countries around the world. In this context, there is a need for various alternative energy sources that can allow sustainable development [2].

Biofuel technology can alleviate energy insecurity, which has proven to be a major impediment to Africa's growth [3]. Biogas energy could be used for this purpose, but it can also be managed with locally available resources and simple technology, which is particularly important in rural areas [4].

Biogas is colorless and combustible with a significant proportion of methane, making it an excellent replacement for conventional energy [5]. Oxygen-independent decomposition is a biochemical process that is extensively used for the treatment and energy recovery of various biomasses, notably animal waste, agricultural products and agro-industrial waste [6]. This is an effective approach that uses diverse microbial groups to convert biomass and waste products into biogas (helping to address energy challenges in many parts of the world).

One of the new main issues confronting researchers is predicting biogas production, which is an incredibly challenging task given the paucity of study in the field of modelling and optimization of biogas yield [7]. Artificial neural networks (ANN), genetic algorithms (GA), adaptive neuro-fuzzy inference systems (ANFIS), and logistic approaches are only a few examples of the typical machine learning technologies that have been used in the past to forecast biogas yield because of their speed, learning ability, predictability, and robustness. These approaches are useful tools for modeling nonlinear and multivariable complicated systems such as oxygen-deprived decomposition of organic waste. [1].

In this work, ANFIS and RSM were used to simulate the formation of biogas from brewer's spent grain, pig manure, and poultry droppings under the effect of the enzyme amylase. There have been numerous studies on the modelling and optimization of biogas using RSM, ANN, and ANFIS, or any combination of the three models, but none of them focused on the production of biogas under the impact of the amylase enzyme.

ANN was employed by Dibaba, *et al*. [8] to model some anaerobic factors and biogas output. According to reports, the output constantly followed the goals. The R^2 values for COD removal (0.9063), total suspended particles (0.9152), volatile fatty acid (VFA) (0.9557), and biogas yield (0.9152) all supported this conclusion.

Yusof, *et al.* [9] reported the use of an artificial neural network and a reaction surface method to increase swamp gas generation from a mixture of food waste (FW) and poultry manure (PM).

Najafi, *et al.* [10] studied the use of ANFIS, ANN and the Logistic Engineering in calculating swamp gas generation from discarded mushroom compost (SMC).

Samuel, *et al.* [11] investigated the utilization of independent parameters such as hydraulic retention time, temperature, moisture content, pH, and carbon to nitrogen ratio to produce biogas from oxygen-deprived fermentation of feces from pigs. Pig dung was made to satisfy various process conditions before being fed into a 10 liter digester and stored for several days. The resultant yield was evaluated using RSM models (linear model, interaction model, pure quadratic model, and quadratic model), ANFIS model, and three kinetic models (gompertz, modified gompertz, and logistic model). The quadratic model was chosen as the best RSM model for prediction accuracy, with an R-square value of 73.03%. When compared to the ANFIS model, the ANFIS model has an R-square of 95.9983%, indicating that it is a better model that may be used for further investigation.

Okwu, *et al.* [2] studied the use of a creative algorithm (RSM) and a hybrid algorithm (ANFIS) in a biodigester system to increase biofuel production from two decomposable animal wastes, poultry manure (PD) and cow manure (CD).

Using the response surface approach and an artificial neural network, Heydari, *et al.* [13] used AI algorithms such as ANN and ANFIS models to forecast the biogas produced by the wastewater treatment of spearmint essential oil in an upflow oxygen-deprived sludge blanket digester. The ANN model had an R^2-square of 0.956, an RMSE of 2651 mL/d, and a relative RMSE of 0.234%. At the same period, the ANFIS model had an R^2-square of 0.975, an RMSE of 3516 mL/d, and a relative RMSE of 0.316%.

These results demonstrated that the two AI-based models were good tools for evaluating biogas yield. The novelty of this study stems from the idea that while several biogas yields have previously been predicted using Machine Learning, biogas yield from fermentation of poultry droppings, pig manure, and brewery spent grain under the influence of the enzyme amylase has yet to be carried out. Statistical error guides such as root mean square error (RMSE), and determination coefficient (R^2) were also used to assess the framework for study performance.

MATERIALS AND METHODS

Substrate Preparation and Pretreatment

The main raw materials of this investigation are poultry droppings, pig manure and brewery spent grain. They were gathered from Hairichest Farms in Obinagu, Udi Municipality, Enugu State, Nigeria. Collected samples were sun dried and mechanically crushed using a mortar and pestle to maximize their surface area and ensure uniformity. A 1-liter beaker was filled with 250g of crushed sample. Five hundred milliliters of a

0.075% by weight aqueous mixture was placed in the beaker comprising the weighed samples.

Before introducing the $H2O_2$ solution, the mixture was adjusted to pH 11 with 0.1 M NaOH. The suspension was placed in the flask with the weighed sample and covered with cover foil. They were heated in a 90°C water bath for 2 hours and mixed by hand every 15 minutes. After the pretreatment, the sample was filtered through filter paper and rinsed with hot water to remove the alkali residues until the pH reached neutrality (7). The residue was cleaned and dried in a hot air oven at 60°C.

The Characteristics of the Substrates Used

The raw material samples were characterized to determine their properties using methods previously reported in [14]. The properties include volatile matter (VM), moisture content (MC), crude fiber (CF), total ash, energy content, fixed carbon and nitrogen. The optimal evaluation relates, among other things, to the components of pure carbon (C), hydrogen (H), nitrogen (N), oxygen (O) and sulfur (S) in the raw material under consideration.

Experimental Design Analysis for RSM Modeling

The process parameters (temperature, residence time, enzyme concentration, and pH) were selected as independent variables affecting biogas production via the oxygen-independent fermentation process, and the dependent response (biogas yield) or response was examined using Central Composite Design (CCD) Response Surface Methodology (RSM). The deviations in the process parameters are listed in Table 1.

They are: $27.5 - 57.5$ bioreactor temperature$(℃)$, $10 - 50$ (days) fermentation time, $2 - 8$ micromole enzyme amylase concentration and pH range of $5 - 9$. The four independent variables were graded as low (-1), medium (0), and high (+1) measures. Multiple regressions were used to fit the dependent variable's squared polynomial regression score. However, significance tests and analysis of variance (ANOVA) were used to analyze or investigate the strength of the fitted quadratic polynomial dependent variable (response) of the RSM model. Eq. (1) was used to assess the obtained data.

$$Y = \beta_o + \sum_{i=1}^{4} \beta_i X_i + \sum_{i=1}^{4} \beta_{ii} X_i^2 + \sum_{i=1}^{4} \sum_{j=1+1}^{4} \beta_{ij} X_I X_j \qquad 1$$

Table 1: Central Composite Design Range of Empirical Data used in this Investigation.

Parameter	Symbol	Low	Centre	High
Temperature (℃)	A	35	42.5	50
Residence Time (days)	B	20	30	50
Enzyme Conc. (μmol/l)	C	2	4	6
p^H	D	6	7	8

Adaptive Neuro-Fuzzy Inference System

Hybrid algorithm (ANFIS) is a type of Adaptive Neuro Fuzzy Inference System which comes up with technique for effectively solving indiscriminate real-world problems. Multi-Input Single Output (MISO) Neural Fuzzy model tool box in Matlab version R2013a was employed to forecast the production of biogas from poultry droppings, pig manure and brewer's spent grain with the influence of enzyme Amylase [15].

ANFIS synthesis training algorithm which integrates the inclination technique, and the least square estimate (LSE) were adopted for the optimization process [16]. Fuzzification, multiplication, normalization, defuzzification and summation are the five functions of the five layers of the ANFIS tool [7]. The network design of the hybrid process design is exemplified in Figure 1; with five layers of neural network.

The multiple-input variables are temperature (℃), residence time (days), enzyme concentration ($\mu mol/l$), and pH. The parameters were chosen to investigate the mutual influence of the encoded variables on the product signals and to lessen the time required to execute one factor at a time. In the first layer (input layer), the received input data is portrayed into membership functions to discover the membership degree of that input. In the second layer, Fuzzy rules are applied to relate between input and output. The third layer standardize the output and passes to the fourth layer. The fourth layer maps the output data and provides the output membership function. The outcomes are combined in the fifth layer to produce a single output or output variable (biogas yield). The computation flow chart of the proposed model is displayed in Figure 2.

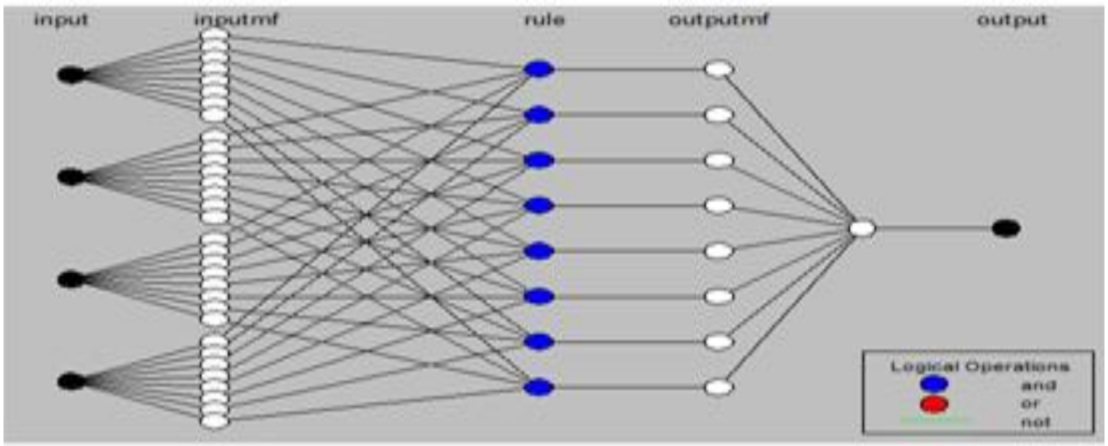

Figure1: ANFIS Architecture of Enzymatic Production of Biogas.

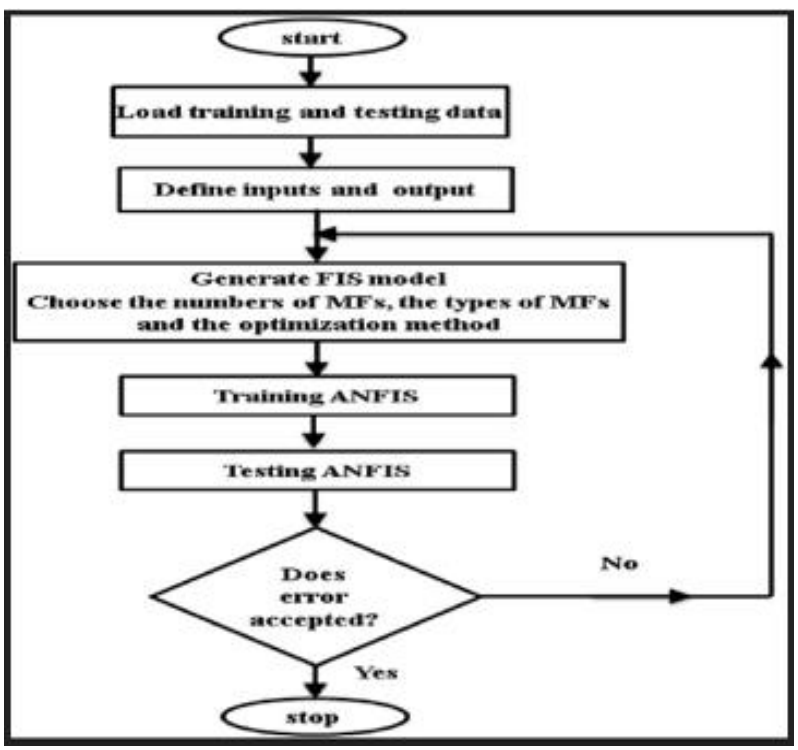

Figure 2: Schematic Flow Chart Administered for ANFIS Model Development.

Measurement and Analysis of Biogas Production

The approach described by [17] was used to measure and analyze daily biogas production. A digital manometer with a three-way valve at the top of the port was used to measure the amount of gas produced. The pressure in each reactor is measured by this manometer. This pressure is manually measured by attaching a previously calibrated manometer to the reactor's two-way valve (Figure 3a). The amount of biogas produced under standard conditions was determined using the following equation from the recorded pressure value.

$$\Delta S_2 = \frac{\Delta P_1\, X\, V_1 X\, T_2}{T_1\ X\ P_2} \qquad [2]$$

where ΔS_2 = Volume of biogas produced between two measurements and corrected to the standard conditions (ml), $\Delta P_1 =$ Pressure difference between two measurements in the reactor (Pa).

S_1 = Volume of gas headspace of the reactor (ml),
T_1 = Temperature in the reactor (308.15 K).
T_2= Standard condition of temperature (273.15 K),
P_2 = Atm. pressure at std. conditions (101,325 Pa).

The produced biogas was analyzed for its molecular composition using the gas chromatography (GC) technique with GPA 2286 as the standard test method. A gaseous mobile phase was used in gas chromatography (GC) to transfer components of the sample through packed cylinders or empty capillary cylinders containing a polymeric liquid inactive phase. Percent stoichiometry and gas characteristics of individual waste raw materials were determined using the GC machine shown in Figure 3b.

Data Verification

The effectiveness of the RSM & ANFIS optimization tool was determined by comparing predicted and experimental results. The coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE) and average absolute deviation (AAD) were calculated, and their values were used to compare the evaluated results for the models in order to identify the best techniques. Equations. (3), (4), (5) and (6) were used to evaluate R^2, RMSE, MAE, and AAD, respectively:

Figure 3: Measurement and Analysis of Biogas Production. a) Measurement of pressure. b) Analysis of composition of biogas produced.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(B_{a.i} - B_{t.i})^2}{\sum_{i=1}^{n}(B_{t.i} - B_{a.ave})^2} \qquad [3]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(B_{a.i} - B_{t.i})^2} \qquad [4]$$

$$MAE\ = \frac{1}{n}\sum_{i=1}^{n}\left|B_{a,i}\ - B_{p,i}\right| \qquad [5]$$

$$AAD\ = \left(\frac{1}{n}\left(\sum_{i=1}^{n}\left(\frac{B_{pred} - B_{exp}}{B_{exp}}\right)\right) \times 100 \qquad [6]$$

From Equations (3) to (6) $B_{a.i}$, $B_{exp}$is the empirical value, and $B_{t.i}$ and B_{pred} is the model's projected value. $B_{a.ave}$ indicates the average empirical value, and n is the numerical strength of the empirical data.

In general, a model's accuracy and attractiveness depend on the high R^2 value and the small values of AAD, MAE, RMSE and the like.

RESULTS AND DISCUSSION

Characterization of the Substrates

Proximate and ultimate analysis were performed to study the properties of each biomass feedstock as displayed in Table 2.

Table 2: Characteristics of the Substrates (%) used in the Investigation.

Physicochemical properties	Before pretreatment			After pretreatment		
	PD	PM	BSG	PD	PM	BSG
Volatile matter	11.61	8.42	16.33	9.73	6.16	14.81
Moisture content	7.88	27.73	5.26	0.28	0.42	0.25
Crude fiber	9.20	13.85	10.44	7.94	12.69	9.07
Total ash	17.52	23.85	26.89	16.10	20.53	20.27
Lipid	52.35	68.11	11.02	0.05	0.00	0.08
Nitrogen	1.96	1.34	2.46	1.18	0.85	1.66
Protein	12.21	8.35	15.32	7.35	5.29	8.34
Carbohydrate	52.84	25.97	34.93	68.28	61.07	61.09
Carbon	33.74	33.26	38.10	45.74	44.65	47.23
Hydrogen	4.55	4.32	4.78	6.11	6.08	5.91
Oxygen	40.08	39.62	41.17	46.87	48.31	45.31
Sulphur	0.15	0.19	0.22	0.06	0.09	0.08

The moisture content is given as a percentage of the raw material weight and represents the amount of moisture available in the raw material. According to [18], a good moisture content is between 8 and 12 percent and lower, which is considered crucial for good and sustainable combustion, whereas a high moisture content leads to an exceptionally reduced carbon rate.

Pig manure has the highest moisture content (27.73 percent) for the raw biomass sample, followed by pig manure (7.88%), while brewery spent grain has the least (5.26 percent). The vapor element content of the three examined biomass samples before pre-treatment varied between 8.42 and 16.33% and took in the order of spent grains (16.33%), poultry manure (11.61%) and pig manure (8.42%). away.

In comparison, the result of the pre-treated biomass samples also shows that the percentage of volatile matter decreases slightly. The percent configuration of the ash in a biomass sample affects the assembly rate, and the configuration differs by class of lignocellulosic material. The ash content of the raw samples was highest in the brewery's spent grains (26.89 percent) and lowest in poultry droppings (17.52 percent). After the pre-treatment, there was a slight reduction in the available ash content in the biomasses.

The crude fiber content of the three samples shows values close to each other, with pig manure having the highest value (13.85%) and poultry manure having the lowest (9.20%). After pre-treatment, pig manure showed a significantly higher value than poultry manure and spent grains.

The nitrogen content was highest in spent grains with a value of (2.46) and lowest in pig slurry with a value of (1.34). The value recorded for protein was highest for brewery spent grains (15.32) and lowest for pig slurry (8.35). The carbohydrate value was highest in poultry manure (52.84) while it was lowest in pig manure (25.97). The carbon content of the three substrates was relatively close, with brewery spent grains having the highest value (38.10), followed by poultry manure (33.74), and the lowest being pig manure (33.26).

Prior to sample pretreatment, the highest values for hydrogen, oxygen, and sulphur were found in brewery spent grain (4.78, 41.77, and 0.22). It was discovered that following pretreatment, the value of the hydrogen content in poultry droppings increased more than that of pig manure and brewery spent grain. After pretreatment, the oxygen concentration of pig manure was (48.31), followed by poultry droppings (46.87), and brewery spent grain (45.31).

Biochemical Analysis of the Feedstocks

The composition of the biomass materials, which comprises cellulose, polyose, and pectin as well as extractable and deposits, is one of the most relevant components for assessment [19].

Disaccharides and polyose are carbohydrates that can be fermented into alcohol after being broken down into monosaccharide sugars. The accumulation of pectin in lignocellulosic material is an impediment to the overall process since it hinders the pathogen breakdown, but it may be valuable for other purposes. Biomass with high pectin and/or ash content is unsuitable for biomethane production [20].

According to Table 3, the feedstocks had high lignin contents, high hemicellulose contents except pig dung and low cellulose before pretreatment. Brewery spent grains had the highest lignin concentration (24.52%), followed by poultry droppings (8.92%) and finally pig manure (6.21%). Also, brewery spent grain had the highest hemicellulose concentration (30.41 percent), followed by poultry manure (20.86 percent), and pig dung had a very low hemicellulose level (1.58 percent).

Following pretreatment, the lignin content of three biomass raw materials, namely poultry droppings, pig manure, and brewery spent grains, was reduced to 0.49 percent, 0.86 percent, and 0.51 percent, respectively.

The hemicellulose contents of the feedstocks significantly decreased after pretreatment while the cellulose content greatly improved as shown in Figure 4. Pig manure had the highest cellulose content (68.11 percent) in raw samples, followed by poultry manure (52.35 percent) and brewery spent grain (11.02 percent). Similarly, the cellulose content of poultry manure increased to 82.55 percent, the highest, pig manure increased slightly and brewery spent grain showed a significant increase (78.23 percent and 78.55 percent, respectively).

Table 3: Substrate % Composition Before and After Pretreatment.

Chemical analysis	Before pretreatment			After pretreatment		
	PD	PM	BSG	PD	PM	BSG
Lipid	0.35	0.25	7.16	0.05	0.00	0.08
Lignin	8.92	6.21	24.52	0.49	0.86	0.51
Hemicellulose	20.86	1.58	30.41	0.81	0.38	0.59
Total ash	17.52	23.85	26.89	16.10	20.53	20.27
Cellulose	52.35	68.11	11.02	82.55	78.23	78.55
PD - Poultry droppings	PM - Pig manure			BSG - Brewery spent grain		

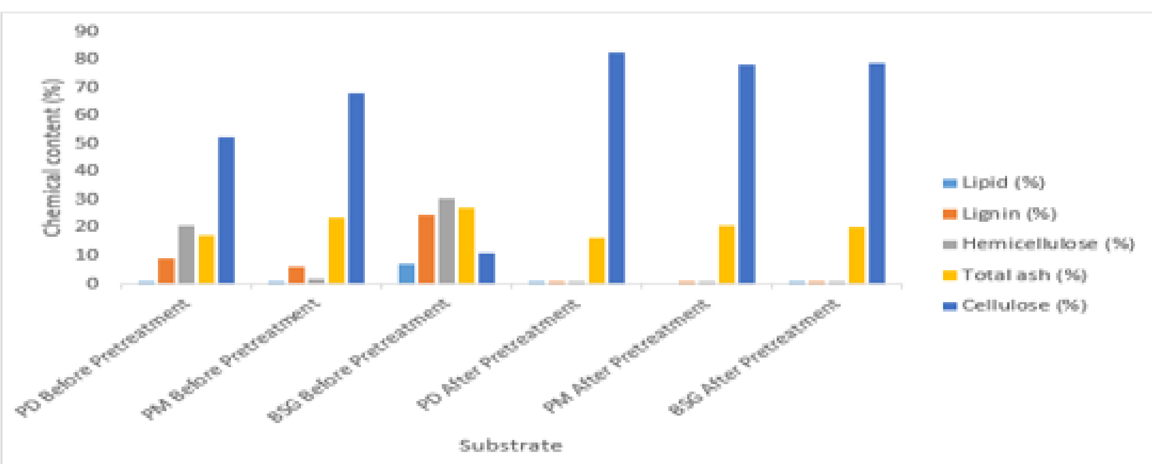

Figure 4: Lignocellulosic Compositions of Substrates Before and After Pretreatment.

Enzymatic Production of Biogas Result Based on Experimental Design

Based on the experimental database, Tables 4 and 5 displays the experimental design matrix as well as the results obtained after carrying out the fermentation process in accordance with the experimental design. It was utilized to analyze the fermentation process's statistical analysis under the influence of the enzyme amylase.

At day 30, the minimum daily biogas output for poultry droppings was 0.95$(cm^3/g)\ VS$, with a pH of 7, a temperature of 42.5°C, and an enzyme concentration of 4µmol/L. At day 30, the lowest daily biogas yield produced from pig dung was 0.70 $(cm^3/g)\ VS$ at 42.5°C, pH 7, and enzyme content of 4µmol/L. At day 30, the daily minimum biogas output for brewery spent grain was 0.94 (cm3/g) VS at 42.5°C, pH 5, and an enzyme content of 4µmol/L. However, the daily maximum biogas output from the three biomass feedstocks is highlighted below.

For poultry droppings, the maximum daily output was obtained at day 20, a temperature of 50℃, an enzyme concentration of 6µmol/L and a pH of 8. For pig manure, the maximum biogas obtained from the experimental matrix was at day 20, temperature of 35℃, pH of 6, and enzyme concentration of 6µmol/L. The maximum obtained for the brewery spent grain was at day 20, temperature of 50℃, enzyme concentration of 2 µmol/L, and pH of 6, however, daily maximum biogas output from the three biomass feedstock are highlighted below. For poultry droppings, the maximum daily output was obtained at day 20, temperature of 50℃, enzyme concentration of 6µmol/L and pH of 8. For pig manure, maximum biogas obtained from the experimental matrix was at day 20, temperature of 35℃, pH of 6 and enzyme concentration of 6µmol/L. Maximum obtained for the brewery spent grain was at day 20, temperature of 50℃, enzyme concentration of 2µmol/L and pH of 6.

RSM Modeling Application

The Central Composite Design (CCD) statistical technique was used in the reaction surface methodology for the maximization study of biogas production under airtight conditions under the influence of the enzyme amylase at various concentrations.

Table 4: Experimental Design Matrix for Anaerobic Fermentation of Poultry Droppings, Pig Manure and Brewer's Spent Grain.

Run order	Temperature (°C) (A)		Residence Time (Days) (B)		Enzyme Conc. $(\mu mol/l)$ (C)		p^H (D)	
	Coded	Real	Coded	Real	Coded	Real	Coded	Real
1	-1	35	-1	20	-1	2	-1	6
2	+1	50	-1	20	-1	2	-1	6
3	-1	35	+1	40	-1	2	-1	6
4	+1	50	+1	40	-1	2	-1	6
5	-1	35	-1	20	+1	6	-1	6
6	+1	50	-1	20	+1	6	-1	6
7	-1	35	+1	40	+1	6	-1	6
8	+1	50	+1	40	+1	6	-1	6
9	-1	35	-1	20	-1	2	+1	8
10	+1	50	+1	20	-1	2	+1	8
11	-1	35	-1	40	-1	2	+1	8
12	+1	50	+1	40	-1	2	+1	8
13	-1	35	-1	20	+1	6	+1	8
14	+1	50	+1	20	+1	6	+1	8
15	-1	35	-1	40	+1	6	+1	8
16	+1	50	+1	40	+1	6	+1	8
17	-2	27.5	0	30	0	4	0	7
18	+2	57.5	0	30	0	4	0	7
19	0	42.5	-2	10	0	4	0	7
20	0	42.5	+2	50	0	4	0	7
21	0	42.5	0	30	-2	0	0	7
22	0	42.5	0	30	+2	8	0	7
23	0	42.5	0	30	0	4	0	7
24	0	42.5	0	30	0	4	0	7
25	0	42.5	0	30	0	4	-2	5
26	0	42.5	0	30	0	4	+2	9
27	0	42.5	0	30	0	4	0	7
28	0	42.5	0	30	0	4	0	7
29	0	42.5	0	30	0	4	0	7
30	0	42.5	0	30	0	4	0	7

A total of thirty test runs with different setup conditions were generated from the matrix, with four process variables (Temperature, residence time, enzyme concentration and pH). A high coefficient of determination (R^2) close to unity, and low standard deviation (SD) values were used to determine the most suitable model for the biogas production under the influence of enzyme amylase from the CCD of the RSM model summary statistics as shown in Table 7. Hence the quadratic model gave the highest R^2 values and the lowest standard deviation values of (0.9986, 0.9910, 0.9975) and (0.0692, 0.1184, 0.0619) respectively for the three biomass feedstocks. The values of the adjusted R^2 obtained showed a close correlation to the R^2 value for the quadratic model. The outcome also put forward that the chosen quadratic model was sufficient in predicting the response variable for the experimental data [9].

Table 5: RSM and ANFIS models for Biogas Yield$(cm^3/g)VS$.

RSM			ANFIS		
PD	PM	BSG	PD	PM	BSG
AV PV	AV PV	AV PV	AV PV	AV PV	AV PV
3.81 3.82	3.01 2.94	3.13 3.14	3.81 3.80	3.01 3.00	3.13 3.13
5.26 5.20	3.31 3.25	4.10 4.10	5.26 5.25	3.31 3.30	4.10 4.08
4.37 4.34	2.34 2.30	3.01 3.02	4.37 4.37	2.34 2.34	3.01 2.99
2.40 2.40	2.14 2.23	2.49 2.47	2.40 2.40	2.14 2.16	2.49 2.49
5.12 5.20	3.26 3.25	3.90 3.93	5.12 5.12	3.26 3.26	3.90 3.91
4.60 4.64	3.38 3.30	4.02 4.01	4.60 4.59	3.40 3.39	4.02 4.02
3.20 3.20	2.41 2.42	2.74 2.76	3.20 3.20	2.41 2.41	2.74 2.75
3.00 2.95	2.13 2.21	2.51 2.51	3.00 2.99	2.13 2.17	2.51 2.53
4.52 4.54	2.11 2.01	3.63 3.63	4.52 4.52	2.11 2.11	3.63 3.63
2.23 2.21	1.50 1.52	2.32 2.34	2.23 2.23	1.50 1.50	2.32 2.34
3.71 3.71	3.03 2.97	3.82 3.81	3.71 3.73	3.03 3.01	3.82 3.82
2.88 2.93	1.73 1.75	2.76 2.76	2.88 2.88	1.73 1.74	2.76 2.74
5.20 5.20	3.40 3.40	3.84 3.93	5.20 5.20	3.40 3.39	3.84 3.85
5.30 5.20	3.20 3.25	3.85 3.93	5.30 5.28	3.20 3.18	3.85 3.87
3.12 3.17	1.88 1.98	2.71 2.73	3.12 3.13	1.88 1.91	2.71 2.71
3.53 3.57	1.14 1.19	2.45 2.45	3.53 3.51	1.14 1.17	2.45 2.45
5.15 5.20	3.17 3.25	4.00 3.93	5.15 5.15	3.17 3.17	4.00 4.00
2.47 2.48	1.66 1.66	2.07 2.07	2.47 2.47	1.66 1.65	2.07 2.07
4.13 4.03	2.84 2.75	3.42 3.41	4.13 4.11	2.84 2.84	3.42 3.42
0.95 0.94	0.82 0.70	1.36 1.36	0.95 0.95	0.82 0.81	1.36 1.36
2.03 2.04	1.81 1.89	1.91 1.90	2.03 2.03	1.81 1.79	1.91 1.91
2.29 2.30	1.02 1.03	1.94 1.92	2.29 2.31	1.02 1.01	1.94 1.94
5.08 5.09	2.75 2.98	4.08 4.08	5.08 5.07	2.75 2.83	4.08 4.08
1.87 1.87	1.15 1.18	2.38 2.38	1.87 1.87	1.15 1.15	2.38 2.36
0.99 0.93	0.9 0.82	0.94 0.94	0.99 0.98	0.9 0.91	0.94 0.92
5.14 5.20	3.17 3.25	3.86 3.93	5.14 5.14	3.17 3.17	3.86 3.86
2.37 2.32	1.13 1.19	2.47 2.49	2.37 2.36	1.13 1.16	2.47 2.48
3.56 3.51	0.70 0.70	2.48 2.46	3.56 3.56	0.70 0.73	2.48 2.48
3.87 3.88	2.20 2.06	3.10 3.11	3.87 3.88	2.20 2.20	3.10 3.10
1.61 1.73	1.08 1.11	1.64 1.64	1.61 1.61	1.08 1.08	1.64 1.63

AV = Actual Value, PV = Predicted Value, PD = Poultry dropping, PM = Pig manure & BSG = Brewery Spent Grain.

Table 6a: ANOVA Table for Biogas Yield from Poultry Droppings using Enzyme Amylase.

Source	SS	DF	MS	F-value	Prob$> F$	Remark
Model	52.01	14	3.71	775.74	<0.0001	Significant
A-Temperature	10.43	1	10.43	2177.54	<0.0001	
B-Residence Time	8.07	1	8.07	1685.90	<0.0001	
C- Enzyme Conc.	3.35	1	3.35	698.51	<0.0001	
D- pH	5.21	1	5.21	1087.52	<0.0001	
AB	0.0400	1	0.0400	8.35	0.0112	
AC	0.0930	1	0.0930	19.43	0.0005	
AD	0.1764	1	0.1764	36.84	<0.0001	
BC	0.0380	1	0.0380	7.94	0.0130	
BD	0.0144	1	0.0144	3.01	0.1034	
CD	0.0702	1	0.0702	14.66	0.0016	
A^2	14.86	1	14.86	3102.94	<0.0001	
B^2	5.07	1	5.07	1058.00	<0.0001	
C^2	8.56	1	8.56	1786.81	<0.0001	
D^2	5.46	1	5.46	1139.51	<0.0001	
Residual	0.0718	15	0.0048			
Lack of Fit	0.00459	10	0.0046	0.8841	0.5957	Not significant
Pure Error	0.0259	5				
C or Total		29				

Std. Dev. = 0.0692, mean = 3.46, C.V% = 2.00, Adj. R^2 = 0.9973, Pred. R^2 = 0.9942, Adeq. Precision =87.1088, $R^2 = 0.9986$

Table 6b: ANOVA Table for Biogas Yield from Pig Manure using Enzyme Amylase.

Source	SS	DF	MS	F-value	Prob$> F$	Remark
Model	23.08	14	1.65	117.53	<0.0001	Significant
A-Temperature	0.2053	1	0.2053	14.64	0.0017	
B-Residence Time	6.66	1	6.66	474.64	<0.0001	
C- Enzyme Conc.	3.14	1	3.14	223.82	<0.0001	
D- Ph	0.6080	1	0.6080	43.35	<0.0001	
AB	0.0420	1	0.0420	3.00	0.1040	
AC	0.0552	1	0.0552	3.94	0.0658	
AD	0.5402	1	0.5402	38.52	<0.0001	
BC	0.1560	1	0.1560	11.12	0.0045	
BD	0.0072	1	0.0072	0.5151	0.4840	
CD	0.4032	1	0.4032	28.75	<0.0001	
A^2	8.67	1	8.67	618.51	<0.0001	
B^2	1.73	1	1.73	123.25	<0.0001	
C^2	1.73	1	1.73	123.25	<0.0001	
D^2	2.76	1	2.76	196.88	<0.001	
Residual	0.2104	15	0.0140			
Lack of Fit	0.1689	10	0.0169	2.04	0.2239	Not significant
Pure Error	0.0415	5	0.0083			
C or Total	23.29	29				

Std. Dev. = 0.1184, mean = 2.15, C.V% = 5.52, Adj. R^2 = 0.9629, Pred. R^2 = 0.9557, Adeq. Precision =31.1173, $R^2 = 0.9910$

Table 6c: ANOVA table for Biogas Yield from Brewery Spent Grain using Enzyme Amylase.

Source	SS	DF	MS	F-value	Prob > F	Remark
Model	22.67	14	1.62	422.39	<0.0001	Significant
A-Temperature	3.41	1	3.41	888.64	<0.0001	
B-Residence Time	3.44	1	3.44	896.12	<0.0001	
C- Enzyme Conc.	3.27	1	3.27	853.23	<0.0001	
D- pH	1.36	1	1.36	355.62	<0.0001	
AB	0.0900	1	0.0900	23.48	0.0002	
AC	0.0324	1	0.0324	8.45	0.0108	
AD	0.0650	1	0.0650	16.96	0.0009	
BC	0.0361	1	0.0361	9.42	0.0078	
BD	0.1056	1	0.1056	27.55	<0.0001	
CD	0.0380	1	0.0380	9.92	0.0066	
A^2	8.50	1	8.50	2218.01	<0.0001	
B^2	0.7874	1	0.7874	204.71	<0.0001	
C^2	1.24	1	1.24	324.30	<0.0001	
D^2	3.27	1	3.27	853.58	<0.0001	
Residual	0.0575	15	0.0038			
Lack of Fit	0.0036	10	0.0004	0.0329	1.00000	Not significant
Pure Error	0.0539	5	0.0108			
C or Total	22.73	29				

Table 7: Model Summary Statistics.

Source	Std. Dev.	R^2	Adj. R^2	Pred. R^2	C.V (%)	Mean	Adeq. Prec.
PD	0.6692	0.9986	0.9973	0.9942	2.00	3.46	87.1088
PM	0.1184	0.9910	0.9629	0.9957	5.52	2.15	31.1173
BSG	0.0619	0.9975	0.9951	0.9957	2.14	2.90	71.6690

Analysis of variance (ANOVA)

Table 6a, b & c displayed the summary of the ANOVA for the optimization of biogas production from poultry droppings, pig manure & brewery spent grain with the influence of enzyme amylase. As observed, F-values for the empirical model established for the biogas production displayed in Tables 6a-c is 775.74, 117.53 and 422.39. There is only 0.01% chance that a "Model F-value could occur due to noise. Owing to the high F-value, the postulated biogas model is reliable and reproducible.

The p-Value represents the significance of the variables in which the smaller the p-Value, the higher the significance of each variable. The p-Value was less than 0.05 which indicated the model terms are significant.

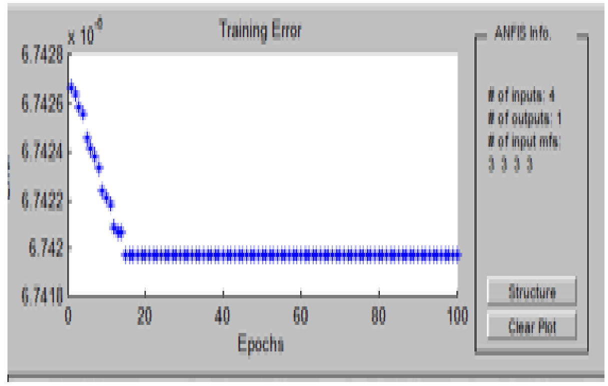

Figure 5a: Training Error of ANFIS Matrix for PD.

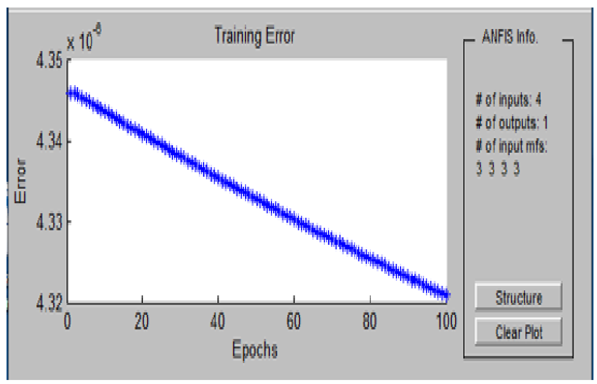

Figure 5b: Training Error of ANFIS Matrix for PM.

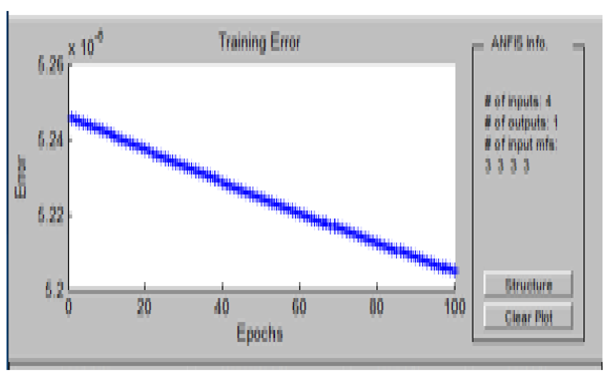

Figure 5c: Training Error of ANFIS Matrix for BSG.

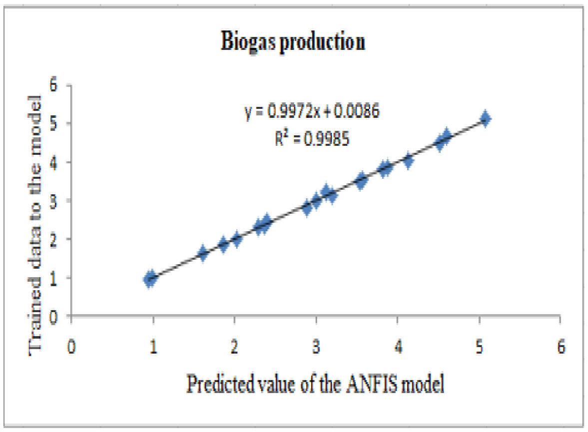

Figure 6a: Training Data for Biogas Production from PD.

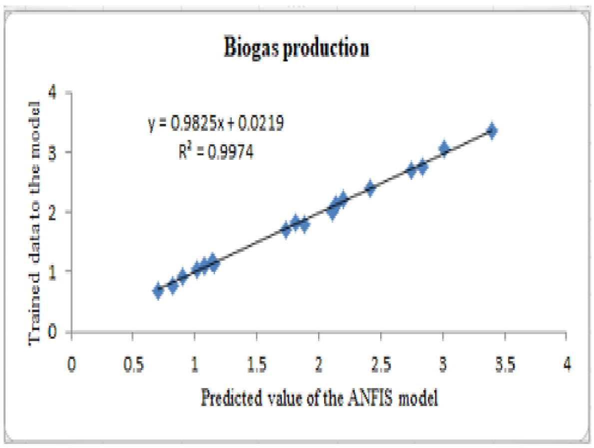

Figure 6b: Training Data for Biogas Production from PM.

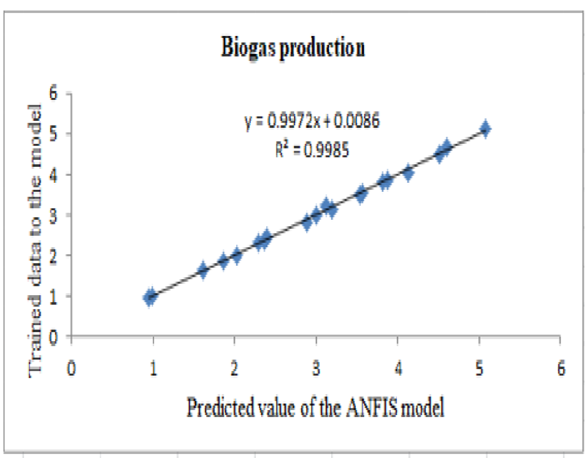

Figure 6c: Training Data for Biogas Production from BSG.

The low value of coefficient of variation (2.00, 5.52 & 2.14) indicated a high degree of precision and a good deal of reliability of the experimental values [25].

All the single terms in the quadratic model were examined for their significance or otherwise using the p-value. A significant level of 95% probability test for p-value was used; indicating that the terms with p-values less than or greater than 0.05 are considered significant and non-significant respectively. The proportion between the residual error and the mean square of a model equals the Fisher's F-test figure. Hence, the significance of the suggested RSM quadratic model with its independent input terms was furthermore, examined with Fisher's F-test figure. For a model term to be significant, the F-value should be higher. With the p and F-values of obtained, the adequacy of the suggested model was also established. The interactive terms as well as the main factors are the contents of the quadratic model. At the significance level of 0.05, the main parameters were significant. Importance and acceptability of the confirmed design were elucidated by big coefficients of determination (R^2) value of (0.9910, 0.9986 and 0.9975) and adj. R^2 values of (0.9825, 0.9973 and 0.9951 respectively suggesting model fitness.

Equations (4), (5), and (6) show the practical correlation between the biogas yield (Y) and the four parameters in coded values to identify the thresholds of factors that gave the maximum biogas yield for the three biomass feedstocks poultry droppings, pig manure and brewery spent grain.

$$Y_{PM}=3.25+0.0925A+0.5267B+0.3617C-0.1592D+0.0513AB+0.0588AC+0.1838AD-0.0987BC+0.0213BD-0.1587CD-0.5623A^2-0.2510B^2-0.2510C^2-0.317D^2 \quad (4)$$

$$Y_{PD}=4.19+0.7986A+0.6979B+0.3579C-0.5329D+0.2444AB+0.0894AC-0.2744AD+0.0906BC-0.1281BD-0.1056CD-0.5218A^2-0.1820B^2-0.3795C^2-0.2395D^2 \quad (5)$$

$$Y_{BSG}=3.93+0.376A+0.3783B+0.3692C-0.2383D+0.0750AB-0.0450AC-0.0637AD-0.0475BC-0.0812BD+0.0488CD-0.5568A^2-0.1691B^2-0.2129C^2-0.3454D^2 \quad (6)$$

($Y_{PD}.Y_{PM}$ and Y_{BSG}) are the predicted responses (biogas yields) from poultry droppings, pig manure and brewery spent grain. A-D are the encrypted data of the self-sufficient parameters.

A positive sign in front of the terms indicates a high impact, while a minus value indicates that the factors have a resistant impact. To assess the suitability of the above-mentioned model, the Design Expert sequential model, sum of squares, and model test statistics were used.

Effect of temperature and Time using Enzyme Amylase

Figures 7a, 7b and 7c show the influence of temperature and time on the amount of biogas produced from the three biomass feedstocks. Between 0 and 15 days, the rate of substrate degradation of the three substrates (poultry droppings, pig manure and brewery spent grain) to form biogas was noticeable at a reaction condition of pH 7 and an enzyme concentration of $4\mu mol/l$ to form biogas within the temperature range of $27.5°C - 57.5°C$.

The study found that poultry droppings produced the highest biogas volume yield of 32ml at a temperature of 50°C on day 15. Maximum biogas volume yield obtained from the plot of pig manure under the same prevailing reaction condition as above gave $22.5ml$ at day 14 and at a temperature of $42.5°C$. For the brewery spent grain it was observed that the biogas yield gave $30ml$ at day 17 at a temperature of $42.5°C$.

Analogous tests performed by [20] resulted in an optimal gas generation with an improved biomethane content of 68% at 60°C. As the temperature rises, the lignocellulose material becomes less viscous due to the dissolution of the structural complexes, potentially speeding up the biomethanization process.

The figures demonstrate that the biodigester configuration with the lowest biogas yield occurred at a temperature of 57.5°C, confirming that enzymes are sensitive to their surroundings.

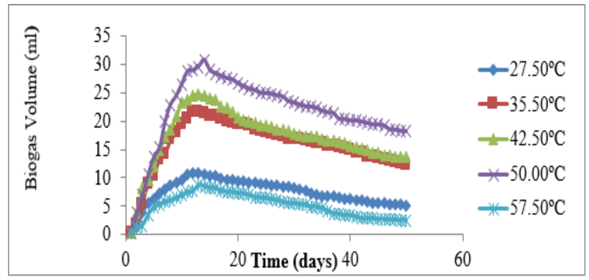

Figure 7a: Poultry Droppings.

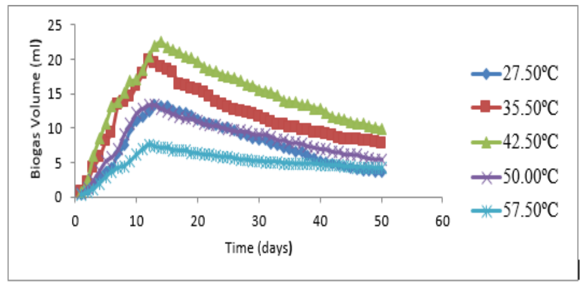

Figure 7b: Pig Manure.

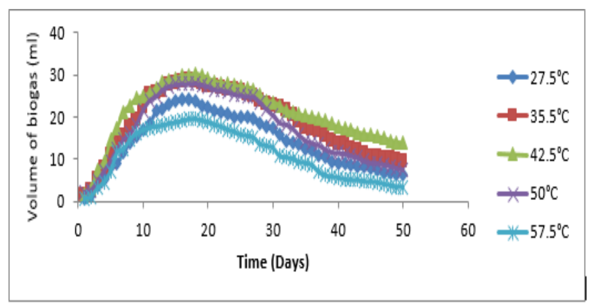

Figure 7c: Brewery Spent Grain.

Figures 7a, b & c: Influence of Temp. and Time on Biogas Production from Poultry Droppings, Pig Manure and Brewery Spent Grain. Reaction conditions: enzyme conc. = 4μmol/l, pH = 7

Effect of Enzyme Concentration and Time

Figures 8a–8c show the effects of enzyme concentration and time on biogas volume for the three feedstocks studied. For poultry droppings (Fig. 8a), the enzyme amylase concentration of (6 μmol/l) produced the highest biogas yield of 34ml on day 15, followed by (4 μmol/l) producing 32ml on day 14, (8μmol/l) produced 22ml on day 12, (2 μmol/l), produced 18ml on day 11, and lastly the digester with no enzyme concentration produced 10ml on the 11th day for reaction conditions of pH 7 and a reaction temperature of 50°C.

For Fig. 8b at the same operating conditions, it was discovered that an enzyme conce8ntration of (8µmol/l) produced the highest biogas yield of (29ml) on the 10th day, followed by (6µmol/l) producing 25mL of biogas on the 11th day, (4µmol/l) produced 22.5ml on day 14, (2µmol/l) produced 14.5ml on day 14, and finally the digester with no enzyme concentration produced 4.6mL. Figure 8c shows that enzyme addition at various concentrations positively influenced biogas yield.

Enzyme concentration (6µmol/l) gave the highest biogas volume yield of 33ml on day 17, (4µmol/l) gave a biogas volume of 31ml on day 17, (8µmol/l) gave a volume yield of 22ml on day 16, enzyme concentration (2µmol/l) produced a maximum biogas yield of 18ml at day 15, and lastly the biodigester with zero enzyme concentration gave the least biogas volume yield at day 18 of 7.5ml.

The graph of enzyme concentration versus time presented in the figures below shows that as the substrates degrade increasingly after the first 18 days, the yield of biogas produced from the fermented substrates began to decrease until all the substrates in the biodigester were depleted or consumed.

Naseem an Anbarasu [20] described the use of Alpha amylase in lucerne pellets and birch leaf pellets to evaluate methane production volume. The inclusion of a starch disintegrating enzyme increased the amount of marsh gas and reduce the lag phase which is evident in absence of enzyme, suggesting that using amylase enzyme in the anaerobic digestion of biomasses can hasten their breakdown and facilitate biogas production, increasing biofuel output.

Effect of pH and Time

The effects of pH and time on the three substrates (poultry droppings, pig manure, and brewery spent grain) with the aid of enzyme amylase are depicted in Figures 9a- 9b. The pH of the substrates in the reactor was adjusted to the acceptable range (5–9) under a reaction condition of $6\mu mol$ and a temperature of $42.5°C$.

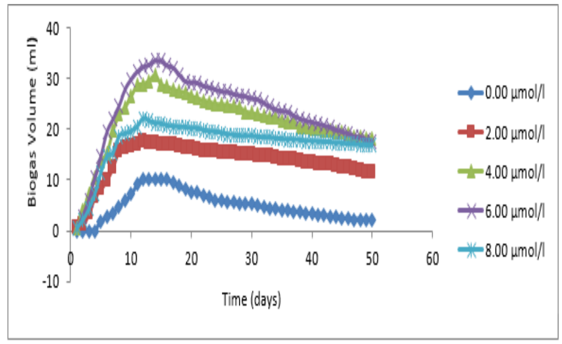

Figure 8a: Poultry Droppings.

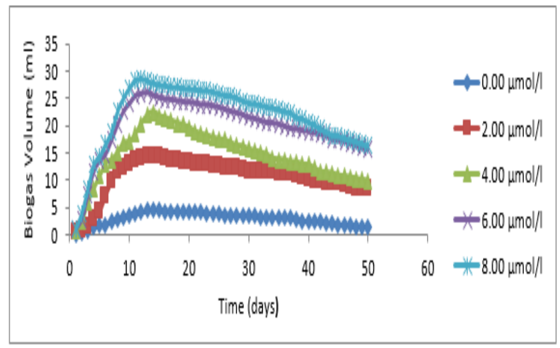

Figure 8b: Pig Manure.

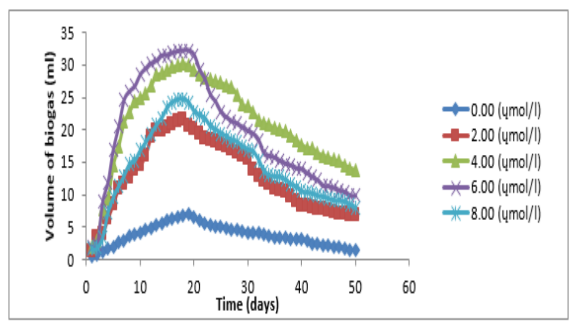

Figure 8c: Brewery Spent Grain.

Figures 8a, b & c: Influence of Enzyme Conc. and Time on Biogas Production from Poultry Droppings, Pig Manure and Brewery Spent Grain. Reaction conditions: pH = 7, temperature at 50℃.

The plots below show that the substrates with pH 7 at the above-mentioned reacting conditions provided the best biogas output of 33ml for poultry droppings, 33ml for pig manure, and 32ml for brewery spent grain.

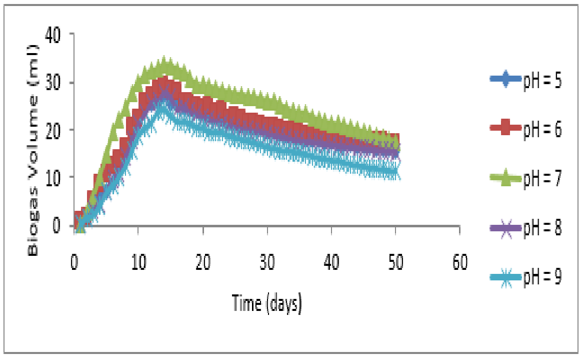

Figure 9a: Poultry Droppings.

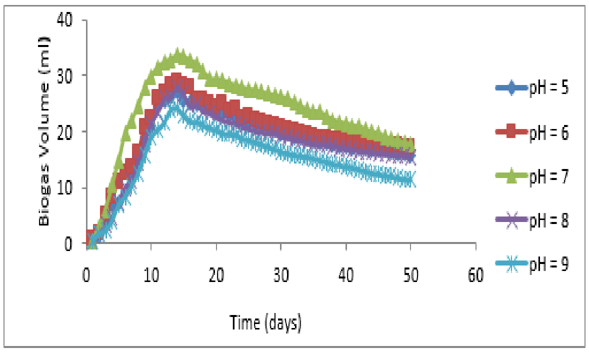

Figure 9b: Pig Manure.

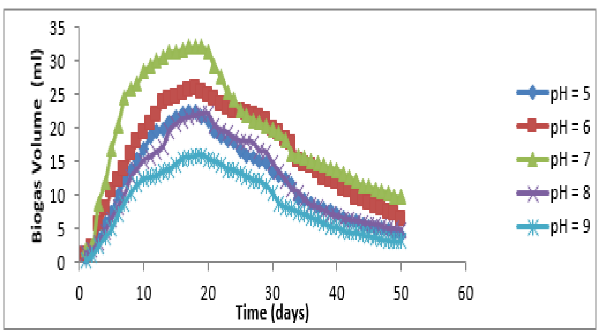

Figure 9c: Brewery Spent Grain.

Figure 9 a, b & c: Impact of pH and Time on Biogas Production from Poultry Droppings, Pig Manure and Brewery Spent Grain. Reaction conditions: enzyme concentration = 6μmol/l, temperature 50℃.

The results show that the pH of the substrates has a significant impact on the biofuel production as it regulates the activity of the pathogens involved in the degradation process, especially methanogenic microorganisms.

According to Naseem and Anbarasu [22], most oxygen-independent bacteria produce high output when the pH is between 7 and 8.5. Beyond this specified range, the biogas process becomes more and more sensitive to ammonia concentrations as the pH increases. Figure 9a generated the lowest biogas volume of 13 mL at pH 9, Figure 9b generated a volume of 13mL at day 50, and Figure 9c generated a volume of 3mL at the same reaction setting. It was also found that pH 6 and 7 produced the same amount of biogas (17 mL), but pH 5 and 8 produced 15 mL at the end of the experiments. A similar trend is observed in Figure 9b. Figure 9c showed a clear trend compared to the other two charts. At the end of the experiment, pH 5 and pH 8 produced the same biogas volume of 4mL.

Biogas Composition and Analysis using Enzyme Amylase

According to Table 9, methane content produced from brewery spent grain utilizing the enzyme amylase was higher than that of poultry droppings and pig manure. Brewery spent grain has a methane and carbon concentration of 60.11%, 28.83%, followed by chicken droppings at 57.81%, 32.66%, and pig manure at 51.91%, 32.83%. The outcomes demonstrate how excellent a raw material the substrates are for producing biogas. The biogas production dramatically enhanced with the addition of the enzyme amylase.

Table 9: Composition of Biogas Produced from the three Substrates using Enzyme Amylase.

Gas Composition (%)	Feedstocks		
	PD	BSG	PM
Methane	57.81	60.11	51.91
Carbon (iv) Oxide	32.66	28.83	32.83
Carbon (ii) Oxide	8.19	9.07	13.77
Hydrogen-Sulphide	1.34	1.99	1.49

CONCLUSION

In this work, the effectiveness of Response Surface Methodology (RSM) and Adaptive Network Based Inference System (ANFIS) in predicting biogas under the influence of the enzyme amylase was evaluated and their individual prediction abilities were compared. These two different models have been established as efficient modeling tools for biogas production. The accuracy of the tools was evaluated using R^2, AAD, RMSE and MAE. These statistical error indices confirm that the adaptive neuro-fuzzy inference model (ANFIS) was slightly higher in terms of accuracy and precision between the evaluated models. The goal of optimization (RSM & ANFIS) is to find the values of the variables in the process that give the best value of the performance criterion.

The following conclusions were drawn from the available findings: The RSM model for the enzyme amylase gave R^2 values of 0.9910 for poultry manure, 0.9986 for pig manure and 0.9975 for brewer's grains. The ANFIS model returned 0.9985 for poultry manure, 0.9974 for pig manure, and 0.9981 for brewery spent grain. In the case of poultry droppings, the maximum daily output was reached on day 20, a temperature of 50 °C, an enzyme concentration of 6 µmol/L and a pH value of 8. In the case of pig manure, the maximum biogas obtained from the test matrix was reached on the 20th day, at a temperature of 35℃, a pH of 6 and an enzyme concentration of 6 µmol/L. The maximum achieved for brewery spent grains was reached on day 20 at a temperature of 50 °C, an enzyme concentration of 2 µmol/L and a pH of 6. The study also revealed that poultry droppings, pig manure and brewery spent grain are good biomass materials for biogas production.

DECLARATIONS

Ethical Approval

Not applicable.

Competing Interest

The authors state that they are not aware of any competing financial interests or personal ties that may have influenced the work reported in this article.

Authors Contributions

The experiment was conceived and executed in the lab by M.I. Onyiah., M.U. Ude., and G.O. Mbah. Proof-read the manuscript..

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of Data and Materials

The data that supports the findings of this study are available on request from the corresponding author.

REFERENCES

1. Moses, O.F., A.L. Olumuyiwa, A.A. Adekunle, P.I. Peter, O.B. Ayokunle, and P. Prabhu. 2023. “Prediction of Biogas Yield from Codigestion of Lignocellulosic Biomass Using Adaptive Neuro-Fuzzy Inference System (ANFIS) Model”. *Journal of Engineering Hindawi*. 2023: 1-16. https://doi.org/10.1155/2023/9335814.

2. Okwu, M.O., O.D. Samuel, D.R.E. Ewim, and Z. Huan. 2021. “Estimation of Biogas Yields Produced from Combination of Waste by Implementing Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS)”. *International Journal of Energy and Environmental Engineering*. 12(2): 353–363. https://doi.org/10.1007/s40095-021-00381-5.

3. Alfa, I.M., S.O. Dahunsi, O.T. Iorhemen, C.C. Okafor, and S.A. Ajayi. 2014. “Comparative Evaluation of Biogas Production from Poultry Droppings, Cow Dung and Lemon Grass”. *Bioresource Technology*. 157: 270–277. (https://doi.org/10.1016/j.biortech.2014.01.108).

4. Khajehpour, H. and N. Norouzi. 2021. “Simulation of Methane Gas Production Process from Animal Waste in a Discontinuous Bioreactor,” *Biointerface Research in Applied Chemistry*. 11(6) Article ID 13859.

5. Gueguim Kana., E.B., J.K. Oloke, A. Lateef, and M.O. Adesiyan 2012. “Modeling and Optimization of Biogas Production on Saw Dust and Other Co-Substrates using Artificial Neural Network and Genetic Algorithm”. *Renewable Energy*. 46: 276-281. https://doi.org/10.1016/j.renene.2012.03.027.

6. Ahmad Kamal, N., S.N. Osman, D.Y. Lee, and M. Ab-Wahid. 2021. “Analysis of Biogas Production from Biomass Residue of Palm Oil Mills using an Anaerobic Batch Test”. *Sains Malaysiana*. 50(12): 3583–3592.

7. Yang, Y., S. Zheng, Z. Ai, and M.M.M. Jafari. 2021. “On the Prediction of Biogas Production from Vegetables, Fruits, & Food Waste by ANFIS and LSSVM-Based Models”. *BioMed Research International*. Article ID 9202127: 1-8. https://doi.org/10.1155/2021/9202127.

8. Dibaba, O.R., S.K. Lahiri, S. T'jonck, and A. Dutta. 2016. “Experimental and Artificial Neural Network Modeling of a Upflow Anaerobic Contactor (UAC) for Biogas Production from Vinasse”. *International Journal of Chemical Reactor Engineering*. 14(6): 1241–1254. https://doi.org/10.1016/j.ces.2007.11.030.

9. Christopher, N.I., N.U. Callistus, and I.O. Maxwell. 2022. “Evaluation of RSM and ANFIS Modeling Performance in Fermentable Sugar Production from Enzymatic Hydrolysis of *Colocynthis vulgaris* Shrad Seeds Shell”. *Egyptian Journal of Petroleum*. 31: 31-36. https://doi.org/10.1016/j.ejpe.2022.06.002.

10. Najafi, B. and S. Faizollahzadeh Ardabili. 2018. “Application of ANFIS, ANN and Logistic Methods in Estimating Biogas Production from Spent Mushroom Compost (SMC)”. *Resources, Conservation and Recycling*. 133: 169-178. https://doi.org/10.1016/j.resconrec.2018.02.025.

11. Samuel, A.E., E.I. Uwem, and O.O. Innocent. 2023. “Modelling and Optimization of Methane from Anaerobic Digestion of Animal Waste (Pig Dung) with Adaptive Neuro Fuzzy Inference System (ANFIS)”. *Journal of Engineering Research and Reports.* 25(1): 50-60, Article no.JERR.98803. https://doi.org/10.9734/JERR/2023/v25i1869.

12. Najafi, B. and S. Faizollahzadeh Ardabili. 2018. “Application of ANFIS, ANN and Logistic Methods in Estimating Biogas Production from Spent Mushroom Compost (SMC)”. *Resources, Conservation and Recycling*. 133: 169-178. https://doi.org/10.1016/j.resconrec.2018.02.025.

13. Heydari, B., S.E. Abdollahzadeh, S. Rafiee, and S.S. Mohtasebi. 2021. “Use of Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System for Prediction of Biogas Production from Spearmint Essential Oil Wastewater Treatment in Up-flow Anaerobic Sludge Blanket Reactor”. *Fuel*. 306, Article I https://doi.org/10.1016/j.fuel.2021.121734.

14. Sathish, S. and S. Vivekanandan. 2016. “Parametric Optimization for Floating Drum Anaerobic Bio-Digester using Response Surface Methodology and Artificial Neural Network”. *Alexandria Engineering Journal*. 25(3): 3297-3307. https://doi.org/10.1016/j.aej.2016.08.010.

15. El Asri, O., M.E. Afilal, H. Laiche, and A. Elfarh. 2020. “Evaluation of Physicochemical, Microbiological, and Energetic Characteristics of Four Agricultural Wastes for use in the Production of Green Energy in Moroccan Farms”. *Chemical & Biological Technologies in Agriculture*. 7:21. https://doi.org/10.1186/s40538-020-00187-3.

16. Okwu, M.O., O.D. Samuel, D.R.E. Ewim, and Z. Huan. 2021. “Estimation of Biogas Yields Produced from Combination of Waste by Implementing Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS)”. *International Journal of Energy and Environmental Engineering*. 12(2): 353–363. https://doi.org/10.1007/s40095-021-00381-5

17. Erdirencelebi, D. and S. Yalpi. 2011. “Adaptive Network Fuzzy Inference System Modelling for the Input Selection and Prediction of Anaerobic Digestion Effluent Quality”. *Applied Mathematical Modelling*. 35(8): 3821-3832. https://doi.org/10.111016/j.apm.2011.02.015.

18. El Asri, O. and M.E. Afilal. 2016. “Potential for Biogas Production from the Anaerobic Digestion of Chicken Droppings in Morocco”. *International Journal of Recycling of Organic Waste in Agriculture*. 5: 195-204. https://doi.org/10.1007/s40093-016-0128-4.

19. Yang, H., R. Yan, H. Chen, C. Zheng, D.H. Lee, and T.D. Liang. 2006. “In-Depth Investigation of Biomass Pyrolysis Based on Three Major Components: Hemicellulose, Cellulose & Lignin”. *Energy & Fuels*, 20(1): 388-393.

20. Pauly, M. and K. Keegstra. 2008. “Cell-Wall Carbohydrates and their Modification as a Resource for Biofuels”. *The Pant Journal*. 54: 559-568. https://doi.org/10.1111/j.1365-313x.2008.03463.x.

21. Onochie, U.P., A.I. Obanor, S.A. Aliu, and O.O. Ighodaro. 2017. “Proximate and Ultimate Analysis of Fuel Pellets from Oil Palm Residues”. *Nigerian Journal of Technology (NIJOTECH)*. 36(3): 987-990. https://doi.org/10.4314/njt.v36i3.44.

22. Aworanti, O.A., S.E. Agarry, and O.O. Ogunleye. 2017. "Biomethanization of Cattle Manure, Pig Manure and Poultry Manure Mixture in Co-digestion with Waste of Pineapple Fruit and Content of Chicken-Gizzard- Part I: Kinetic and Thermodynamic Modelling Studies”. *The Open Biotechnology Journal*. 11: 36-53. https://doi.org/10.2174/1874070701711010036.

23. Dubrovski, V., I. Plume, and I. Straume. 2019. "Use of Enzyme Alpha Amylase to Increase Biogas Yield from Lucerne Pellets and Birch Leaves Pellets". *Proceedings of the 18th International Scientific Conference on Engineering for Rural Development*. Jelgava, Latvia.1394-1400.

24. Naseem Khayum, S. and S.M. Anbarasu. 2018. "Biogas Potential from Spent Tea Waste: A Laboratory Scale Investigation of Co-Digestion with Cow Manure". EGY 13857. https://doi.org/10.1016/j.energy.2018.09.163.

25. Tengku, R.T.Y., C.M. Hasfalina, A.R. Nor' Aini, and S.H. Halimatun. 2014. "Optimization of Methane Gas Production from Co-Digestion of Food Waste and Poultry Manure Using Artificial Neural Network and Response Surface Methodology". *Journal of Agricultural Science*. 6(7): 27-37. http://dx.doi.org/10.5539/jas.v6n7p27.

SUGGESTED CITATION

Onyiah, M.I., G.O. Mbah, and M.U. Ude. 2025. "Evaluation of the Predictive Capability of Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in Estimating Biogas Yield from Poultry Droppings, Pig Manure and Brewery Spent Grain using Enzyme Amylase". *Pacific Journal of Science and Technology*. 26(1): 56-72.