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FUZZY MODELLING AND OPTIMIZATION OF ANAEROBIC CO-DIGESTION PROCESS PARAMETERS FOR EFFECTIVE BIOGAS YIELD FROM BIO-WASTES

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ABSTRACT
In this study, Adaptive Neuro Fuzzy Inference System (ANFIS) was employed in the modelling and optimization of anaerobic process parameters from co-digestion of bio-waste (food waste and Pig slurry) with different masses at constant water content. In six different experimental scenarios, mixture ratios of the bio-waste and water were 0.5:1, 1:1, 2:1, 2.5:1, 3:1 and 3.5:1. The range of parameters measured from the experimental process were used as input variables in the ANFIS model. Four experimentally measured parameters that led to maximum biogas yield as well as ANFIS input parameters and their corresponding output results in terms of maximum biogas yield were selected for validation. Optimum bio-digester temperature of 38^{o}C, pH of 7.1, Hydraulic Retention Time (HRT) of 11 and mixture ratio of 2:1 in the experiment process produced overall maximum biogas yield of 247g while optimum input parameters such as bio-digester temperature of 40^{o}C, pH of 7.1, HRT of 11 and mixture ratio of 2:1 in the ANFIS model produced overall maximum biogas yield of 248g. There was proximity between the experimental and predicted results, indicating that ANFIS model can be used as alternative tool for predicting and optimizing anaerobic process parameters from multiple feedstocks for desired biogas yield.

Keywords: Biogas yield, Bio-waste, Mixture ratio, Water content, Modelling and optimization.

1. INTRODUCTION
Municipal Solid Waste (MSW) generation is one of the most significant environmental problems bedevilling cities and the wellbeing of its inhabitants particularly in developing countries [1, 2]. Anaerobic digestion is widely employed in the treatment of organic fraction of MSW substrates for some purposes like reduction of odour, biogas production, organic manure and so on. In the area of biogas production, proper selection of optimum parameters and control of the anaerobic digestion process is necessary for maximum yield [3, 4].
This is oftentimes less expensive, more effective and accurate when conventional modelling tools are employed, which replicates the actual experimental scenarios and optimizes input data for desirable output. However, modelling of the anaerobic digestion process is rather cumbersome due to the nature of the process which varies

significantly with the physical and biological characteristics of substrates, biochemical reactions, microorganisms, configuration of treatment systems, operational and parametric conditions.

Anaerobic digestion process is prone to wide fluctuations in both flow and load conditions, resulting in performance reduction and decline in biogas yield. Therefore, it is very difficult to optimize the bio-methane yield under fluctuating conditions. Modelling of the process condition is important, as it allows monitoring, control, and prediction of the system behaviour even in transient conditions [5].

Artificial intelligence has a fast disposal capacity, logical processor and a nonlinear characteristics which makes it suitable for handling the free precision in any continual nonlinear function like the anaerobic digestion process. Some of the most commonly used artificial intelligence methods are the fuzzy logic (FL), wavelet transform (WT), neural network (NN), metaheuristic algorithms and genetic algorithms (GA) [6, 7]. Artificial intelligence based models can accurately model and optimize the anaerobic digestion process parameters for effective biogas yield. The fuzzy systems using neural network related tools are referred to as neural-fuzzy systems, and can offer significant improvement in the modelling and control of bioprocesses [8].

Hence, robust adaptive models such as the neural-fuzzy based concepts are necessary for the simulation and control of anaerobic digestion process in order to maximize biogas yielding rate. Unlike deterministic models, stochastic or non-deterministic models have inbuilt randomness factors and do not require differentiable objective functions, which allows the discovery of various solutions. Several domains of the problem can be searched in parallel and these models such as the neural-fuzzy based are suitable for solving real-world problems of this nature [5].

Based on the pioneering idea of Zadeh [9], fuzzy based models are effective tools that proffer viable solutions for solving complex, linear and nonlinear optimization problems such as organic or biological. Turkdogan-Aydinol and Yetilmezsoy [10] reported that the application of fuzzy logic models in predicting biogas production rates from pilot-scale anaerobic digesters is less challenging with a great deal of accuracy and precision in the input-output data, and requires little or no details on the complex reactions, mathematical equations or biochemical pathways.

ANFIS was proposed by Salehi [11] as a prediction model to predict biogas production rate from kitchen wastes. Correlation between the predicted data using ANFIS model and the actual experimental data for the training sets showed a correlation coefficient (R^2) and adjusted correlation coefficient (adjusted R^2) of 0.9946 and 0.9927, indicating accuracy of the ANFIS model as the R^2 value conformed with the experimental data.
Addario and Ruggeri [12] employed fuzzy macro-approach in the prediction of biogas production rate in full-scale landfill bioreactors using eleven deterministic inputs (pH, Redox potential, chemical oxygen demand, volatile fatty acids, ammonium content, age of the waste, temperature, moisture content, organic fraction concentration,

particle size and recirculation flow rate). The fuzzy model which was built and tested on seven lab-scale scenario predicted 90.3% of the total biogas production rate, suggesting that 9.7% of the waste volume had a different behaviour of the selected control volume of landfill due to its heterogeneities.

Regoa et al. [13] developed Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) models to predict biogas yield based on experimental anaerobic digestion of swine sewage and rice husk using temperature, pH, FOS/TAC ratio and type of bio-digesters as the process variables. ANN model had determination coefficient (R^2) value of 0.77704 at its best topology while ANFIS model had R^2 value of 0.81209 at its best configuration, showing better performance than ANN.

Based on experimental anaerobic digestion process of cow manure and maize straw using total solid content (TS), Carbon to Nitrogen (C/N) ratio and stirring intensity as the process variables, Zareei and Khodaei [14] employed adaptive neuro-fuzzy inference system (ANFIS) model in the prediction of biogas yield. The model R^2 value was 0.99 while highest biogas yield was obtained at C/N ratio of 26.76, TS of 9% and moderate stirring. An increase of 8% was observed in biogas yield with optimum conditions suggested by the ANFIS model.

Huang et al. [15] employed Fuzzy Wavelet Neural Network (FWNN) based on genetic algorithm (combines the advantages of fuzzy logic, neural network, and wavelet transform) and other traditional intelligent couplings such as Fuzzy Neural Network (FNN), Wavelet Neural Network (WNN) and Neural Network (NN) models in the prediction of biogas production rates in a full-scale anaerobic wastewater treatment process. The FWNN model showed better prediction accuracy with determination coefficients (R^2) of 0.9681 compared to FNN with R^2 of 0.8846, WNN with R^2 of 0.8789, and NN with R^2 of 0.6446, and achieved better performance in predicting biogas production rates.

The fuzzy wavelet neural network (FWNN) can effectively increase the detection rate and the level of model optimization by improving the discernment, generalization, and approximation capacities [16, 17], for effective prediction of biogas production rate. The fuzzy logic framework adopts the robustness of fuzzy control systems and the learning ability of neural networks, to improve its adaptability potential for various applications [8], which the optimization sequence of anaerobic digestion process parameters for effective biogas yield is one of such.

Formulated and solved with particle swarm optimization algorithm using multi-layer perceptron neural network, Wei and Kusiak [18] employed a single-objective optimization model to optimize biogas production. The computational results indicated that biogas production can have over 5.3% increase at an optimal temperature of 39.0 ^{o}C. The optimal total solids concentration was found to be 12% with maximum biogas production increase of 12.1%. It was determined that volatile solids and pH slightly influenced the biogas production over their ranges. Over 20.8%

increase was achieved when all controllable values were set to the optimal values at the same time.

Modelling and optimization of biogas production from mixed substrates of saw dust, cow dung, banana stem, rice bran and paper waste using Artificial Neural Network (ANN) coupling Genetic Algorithm (GA) was proposed by Kana et al. [19]. An optimized substrate profile emerged with a predicted biogas performance of 10.144L. Evaluation of the optimal profile produced biogas yield of 10.280L, thus an increase of 8.64%.

Modelling of anaerobic digestion process is very complex and causes significant changes to the process due to the operating conditions and various influential parameters such as temperature, pH, Hydraulic Retention Time (HRT) and moisture content which were the operating data in this study. Various potential advantages based on ANFIS for real-time evaluation of biogas production rates were fully explored in this study as well as optimization of the operation process parameters of biogas production rate from anaerobic co-digestion of food waste with Pig slurry.

2. EXPERIMENTAL APPROACH

2.1. Materials

The materials employed in the experimental process of this study are highlighted as follows:

A. Samples: Food waste, Pig slurry and distilled water. The food waste contained Rice, Beans, Garri, Yam, Plantain, Banana and Fufu.
B. Apparatus: Plastic vessel, bio-digester fitted with plastic pipes, rubber hose, ball valves, pressure gauge, pH meter, temperature gauge, weighing balance.

2.1.1. Sample collection

Pig slurry used for the experimental process was obtained from Piggeries in Ikpoba-Okha local government, Benin, Edo state. The food wastes were obtained from cafeterias in the University of Benin and its environs.

2.1.2. Experimental Set-up of the Bio-digester

Figure 1 is an illustration of the experimental set-up. It comprises of a plastic bio-digester (50 liters capacity) equipped with the following features:

i. Control valves at the inlet and the outlet for regulating substrate feeding and removal.
ii. Gas extraction hose (4-inch in diameter).
iii. Pressure gauge: It was used to measure the pressure of the gas produced
iv. Thermometer: Used to determine the temperature of organic waste decomposing inside the bio-digester.
v. pH meter: Used to determine the pH of substrate before and after digestion.

Figure 1. Experimental set-up for anaerobic digestion

2.1.3. Description of the Experimental setup

The experimental setup comprised of a bio-digester equipped with ball valves at the inlet and outlet, biogas gas extraction hose, pressure gauge (5 bar), thermometer and deflated bicycle tube. The feedstock was fed into the digester through the inlet while the substrate was removed from the digester through the outlet after digestion. The ball valves mounted at the inlet and outlet was used to control the substrate feeding and removal rate into and from the digester. The gas extraction hose conveyed the gas from the digester into the deflated tube. Deflated bicycle tube of known mass (496g) mounted at the other end of the gas extraction pipe was used to store the biogas produced which in the process of entering the rubber tube caused it to inflate.

2.2. Methods

The experimental procedure was carried out in six different set of experiments, starting with co-digestion of 2kg each of food waste and Pig slurry (making it 4kg of organic feedstock) at a constant water contents (distilled water) of 8kg. For the mixing proportion, combination of both food waste and Pig slurry in each of the six experimental sets were represented as 0.5, 1, 2, 2.5, 3 and 3.5 kg(s) at constant water content of 1, making a mixture ratio (MR) of 0.5:1, 1:1, 2:1, 2.5:1, 3:1 and 3.5:1. Hence, the mix ratios of organic feedstock to water content in the six experimental setups were defined as follows:

i. 0.5:1 = 4kg of organic feedstock + 8kg of water
ii. 1:1 = 8kg of organic feedstock + 8kg of water
iii. 2:1 = 16kg of organic feedstock + 8kg of water
iv. 2.5:1 = 20kg organic feedstock + 8kg of water
v. 3:1 = 24kg organic feedstock + 8kg water
vi. 3.5:1 = 28kg organic feedstock + 8kg of water

The experimental procedures are outlined as follows:

i. Using a weighing balance, the total mass of each set of the six experiments weighed 12, 16, 24, 28, 32 and 36 kg respectively.
ii. The distilled water or moisture content (MC) and each set of substrates were thoroughly mixed together until the mixture became slurry.
iii. The distilled water and substrates mixture were poured into the bio-digester (through the inlet and after which, the digester inlet valve was closed).
iv. The initial gauge pressure was calibrated to 0.0 bar and recorded.
v. pH of substrate was tested before and after the digestion process (using digital handheld pH meter).
vi. The anaerobic digestion process temperature was recorded from a thermometer installed in the bio-digester.
vii. The biogas produced was collected in the bicycle tube and measured with the help of a weighing balance to know the actual quantity produced at each gas evacuation time.
viii. The same procedure was applied for all the six experiments.

3. FUZZY LOGIC MODELLING

Fuzzy logic system (FLS) can be described as a non-linear mapping of an input data set to a scalar output data. The process involved in fuzzy logic modelling are highlighted as follows:

i. Define the inputs and output (linguistic variables) and terms (initialization)
ii. Convert the crisp variable to fuzzy sets (fuzzification)
iii. Create membership function (initialization)
iv. Construct the rule base (initialization)
v. Convert the output data to non-fuzzy values (defuzzification)

In this study, fuzzy logic system was developed to predict biogas yield based on four input variables (temperature, pH, moisture content and hydraulic retention time), and one output response (biogas yield).

3.1. Linguistic Variables and Terms

Linguistic variables are the input or output variables of the system whose values are words or sentences from a natural language, instead of numerical values, and is generally decomposed into a set of linguistic terms. For a given anaerobic digestion process aimed at predicting biogas yield, bio-digester temperature, substrate pH, mixture ratio and HRT were selected as the linguistic variables to determine biogas yield. To qualify the bio-digester temperature, substrate pH, mixture ratio and HRT, linguistic terms (minimum, optimum and maximum) were used as obtained from the experimental procedure. The output response was also qualified in real term as: Biogas yield (minimum, optimum and maximum). The terms in bracket represent the set of decompositions for the linguistic variables namely: bio-digester temperature, substrate pH, mixture ratio and HRT and biogas yield. Each member of this decomposition is known as linguistic term. For this problem, the linguistic variables and their range of values are listed as follows:

i. Bio-digester temperature: 20 to 45 °C
ii. Substrate pH: 6.5 to 7.5
iii. HRT: 10 to 40 days
iv. Feedstock to water mix ratio: 0.5:1 to 3.5:1
v. Biogas yield: 30 to 250 g

The range of the input and output variables were selected from the anaerobic digestion process experiment. The fuzzy logic model interphase and the fuzzy logic tool box that defines the input and output variables are presented in Figure 2 a-b.

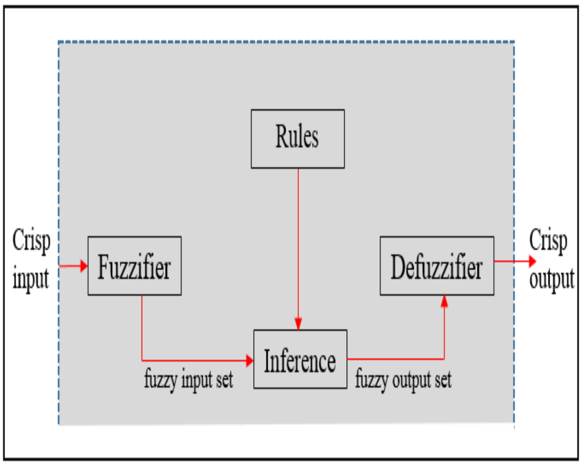


Figure 2a. Process diagram for fuzzy logic

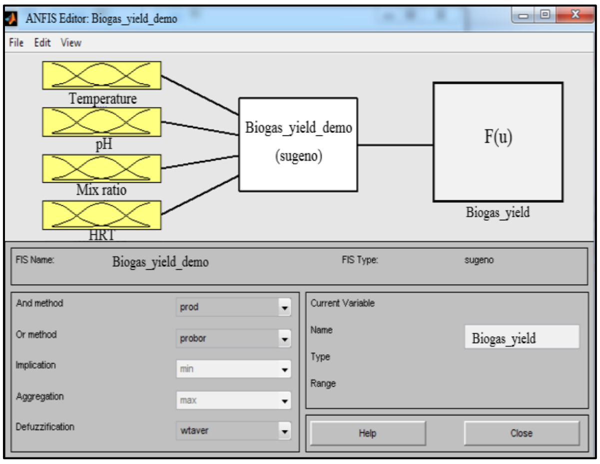


Figure 2b. Defining input and output variables

Fuzzy logic controllers are based on fuzzy sets whose elements have degrees of membership. In this study, the triangular membership function were adopted for the input process variables such as bio-digester temperature, substrate pH, mixture ratio and HRT to predict biogas yield. The type of fuzzy logic controller employed was Mamdani-type, as it is rule based comprising of rules and one of the most commonly applied fuzzy approach [10].

To convert the crisp variables (actual experimental data) into fuzzy sets, ANFIS was employed to generate a fuzzy inference system (FIS). To generate the FIS morphology, the raw experimental data were selected as input variables in ANFIS edit tool box. Having done that, the crisp data were sent to adaptive neuro fuzzy for possible conversion into fuzzy sets, since fuzzy does not accept the crisp data. The process of converting the crisp data into fuzzy sets is known as fuzzification. In this case, the fuzzification step was carried out using ANFIS as shown in Figure 3a.

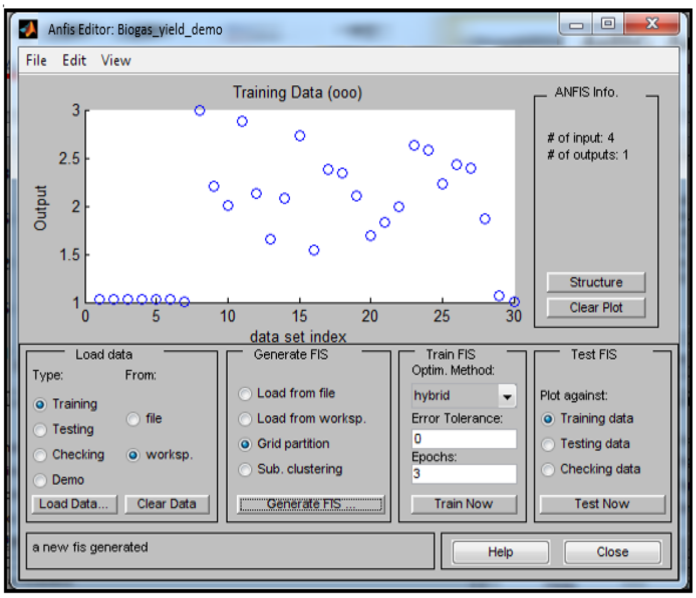


Figure 3a. ANFIS edit tool box showing the crisp data

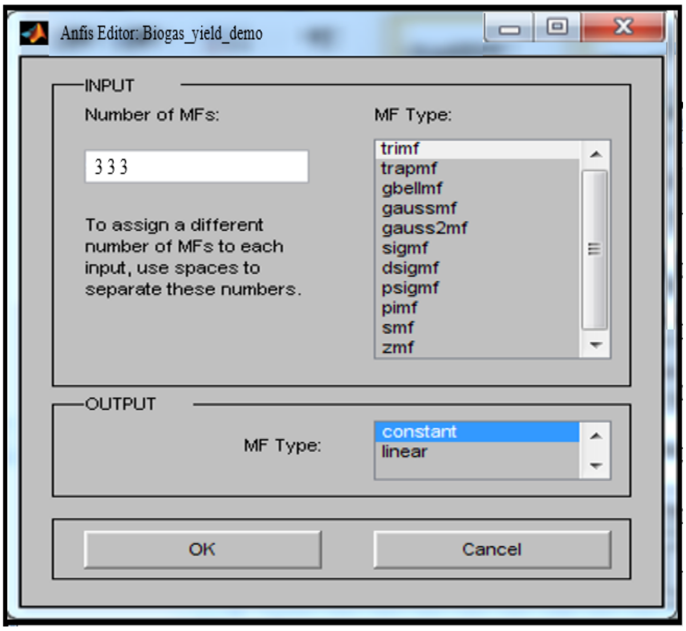


Figure 3b. Description of membership function

Grid partition method was employed to generate the fuzzy inference system, while the FIS button was clicked to initiate the process. Three membership functions were selected for each input variable. For this problem, the triangular membership function was used. The simplicity and flexibility of the triangular membership function coupled with its ability to define wider range of decomposed sets of linguistic variables account for its selection. For the input variables, three membership functions (minimum, optimum and maximum) were selected as well as the output response.

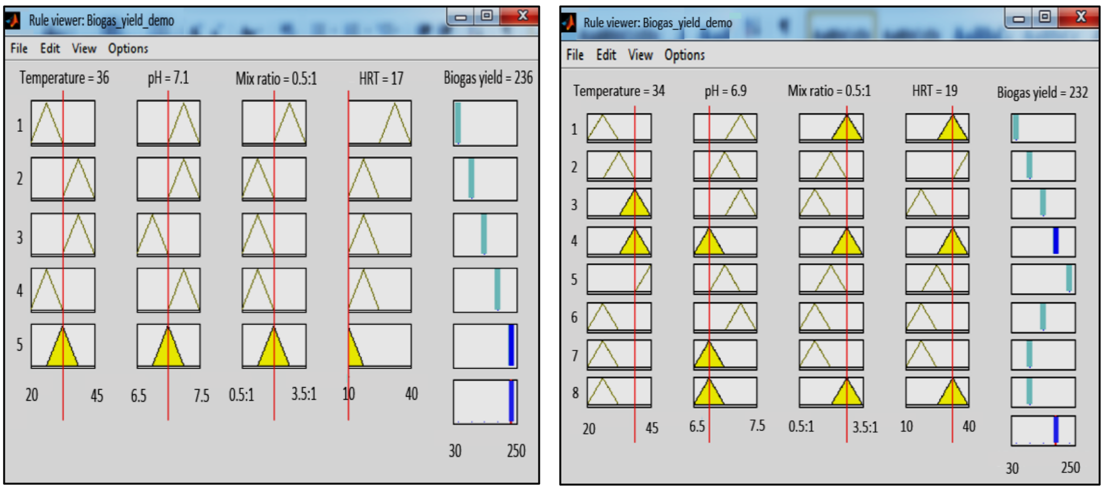
Figure 3b shows the number of membership function that was assigned to each linguistic variable and the type of membership function that was selected for each input and output variable. Membership functions are used in the fuzzification and defuzzification steps of a Fuzzy Logic Systems (FLS), to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. A membership function is used in most cases to quantify a linguistic term. An important characteristic of fuzzy logic is that a numerical value does not have to be fuzzified using only one membership function. In other words, a value can belong to multiple sets at the same time.

4. RESULTS AND DISCUSSIONS

The anaerobic digestion of organic matter is a chemical process reaction process which occurs in four different stages namely: hydrolysis, acidogenesis, acetogenesis and methanogenesis. The second and third stages are known as the acid formation stage while the last stage is known as methane formation stage. There are several conditions that must be controlled in the anaerobic digestion process for effective biogas yield. The growth rate of microorganisms is paramount in anaerobic digestion process, therefore, the operating parameters must be controlled in order to enhance the microbial activities, thus increasing the rate of anaerobic degradation in the system. Organic materials have the tendency to decompose anaerobically but the rate of decomposition is dependent on factors such as the lignin content, the quantity of water (water content) intermixed with feed substrates, pH, bio-digester temperature and so on. Lignin is the indigestible components present in organic materials, and the lower its content in bio-waste or organic matter, the higher the rate of decomposition [20].

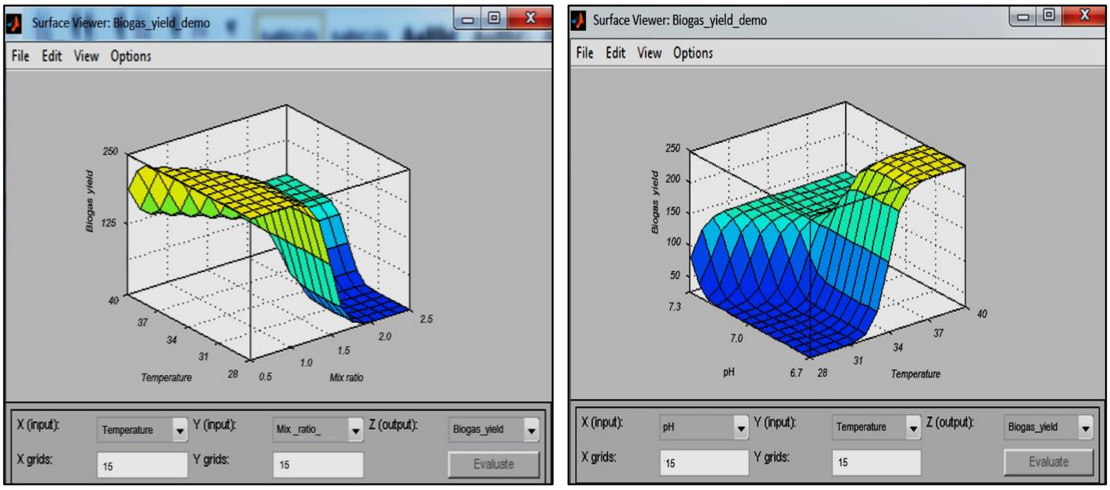
The ratio of water to dry matter content in feed substrates is also an important factor to consider in anaerobic digestion process. To achieve proper solubilization of organic materials and maximum biogas yield, Adelekan and Bamgboye [21] recommended livestock waste to water mixing ratio of 3:1 for waste slurry from piggery, 3:1 for poultry droppings and 2:1 for cow dung. Bio-digester temperature is one of the most important parameter in anaerobic digestion process. Different species of methanogens function optimally in three different temperature ranges namely: 45-60°C for thermophilic temperature, 20-45°C for mesophilic temperature and below 20°C for psychrophilic temperature. In anaerobic digestion of organic substrates, mesophilic and thermophilic temperature ranges are considered to be very essential because microbial activities as well as the biochemical reactions are almost inactive below 10°C [22]. The bacteria available for digestion process are sensitive to rapid changes in temperature, so, it is necessary to maintain a constant range of temperature for effective breakdown of feedstock by microorganisms. Thermophilic bacteria favours the hydraulic retention time, loading rate and yield of biogas produced, but they need higher heat input and are also sensitive to temperature fluctuations and environmental variables than mesophilic [23]. The optimum pH for a generally stable anaerobic digestion process and high biogas yield lies in the range of 6.5-7.5. During digestion, the processes of hydrolysis and acidogenesis occur at acidic pH levels (pH 5.5-6.5) compared to the methanogenic phase which occurs at neutral and alkaline pH levels (pH 6.5-8.2). The methanogenic process cannot occur in acidic medium, hence, methane cannot be produced in acidic medium [24]. HRT is the period the substrate remains in the digester. In other words, it is the total time spent by the substrates or feedstock inside the digester. The required retention time for completion of the anaerobic digestion reactions varies with different technologies, characteristics feed substrate, process temperature and mix ratio. Therefore, HRT for anaerobic digestion process must not be too short (as the period may not be long enough to reach optimum results) and must not be too long (as this may indicate slow anaerobic digestion process and attracts high maintenance cost) [25].

From each set of the six experimental procedures, experimental results consisting of process parameters measured and output response were obtained. The measured process parameters were bio-digester temperature, substrate pH, water content and Hydraulic Retention Time (HRT) while the output response was biogas yield. The maximum and minimum values obtained as the measured process parameters were considered as ranges defined for input variables in the ANFIS model while the maximum and minimum values obtained as the output response were also considered as ranges defined for the output response in the ANFIS model. Each set of experiment had a constant mix ratio while the other input values varied. Five experimental and ANFIS predicted output results with maximum biogas yield were selected along with their input variables for validation. Figures 4a-b, 5a-b and 6a-b represents two out of five ANFIS predicted models with optimum input variables and maximum output responses in terms of biogas yield at feed substrate to mix ratios of 0.5:1, 1:1 and 2:1 respectively. Figure 4c-d, 5c-d and 6c-d represent surface plots for the ANFIS predicted models, which indicates that changes in the input values can affect the output response.



a. b.

Figure 4a-b. Prediction of input variables and output responses at mix ratio of 0.5:1

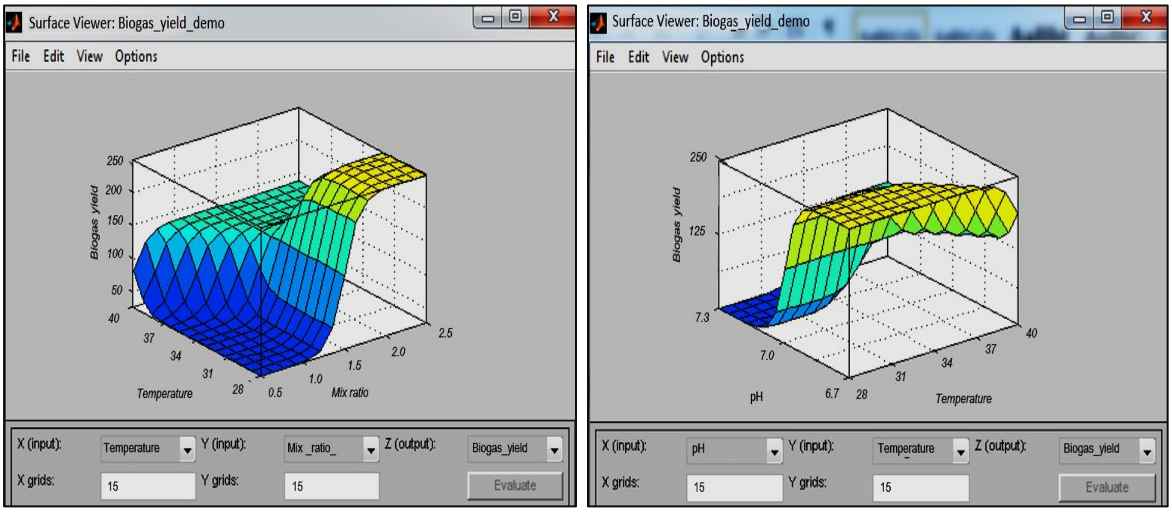


c. d.

Figure 4c-d. Surface plots showing effects of input on biogas yield at mix ratio of 0.5:1

a. b.

Figure 5a-b. Prediction of input variables and output responses at mix ratio of 1:1

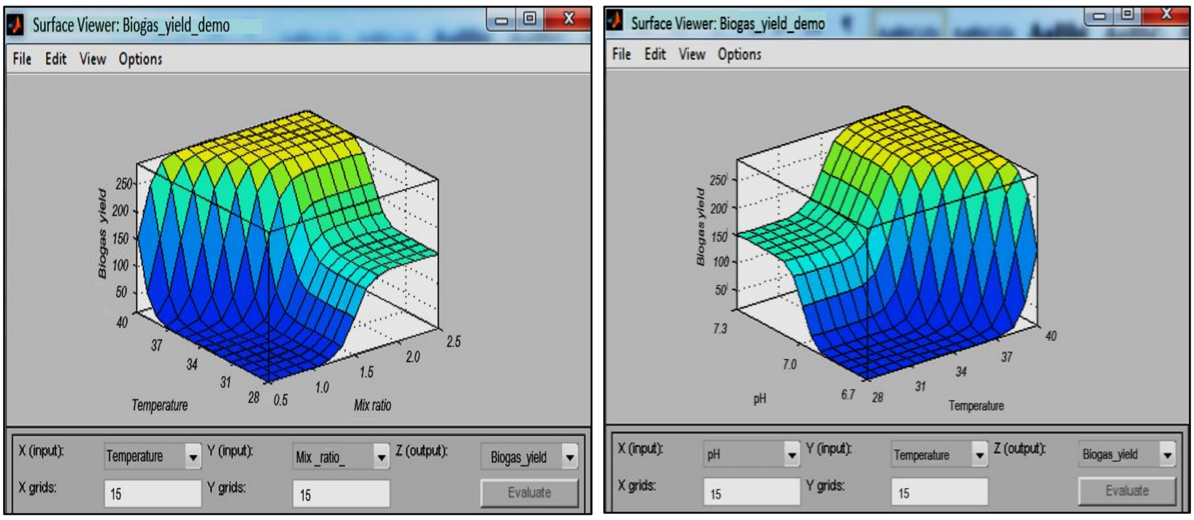


c. d.

Figure 5c-d. Surface plots showing effects of input on biogas yield at mix ratio of 1:1

a. b.

Figure 6a-b Prediction of input variables and output responses at mix ratio of 2:1



c. d.

Figure 6c-d. Surface plots showing effects of input on biogas yield at mix ratio of 2:1

Table 1 represents a summary of results with maximum biogas yield obtained from the experimental procedure and the ANFIS model. The results are from the first three experiments which all have different mix ratios of 0.5:1, 1:1 and 2:1. Out of the numerous results obtained from the experimental and ANFIS model, five experimental runs with maximum biogas yield along with the measured parameter for each were selected and tabulated.

Similiarly, five ANFIS predicted runs with maximum biogas yield and their corresponding inputs were also selected and tabulated beside the experimental results as shown in Table 1. Optimum measured parameters from the experiment as well as optimum input parameters from ANFIS model that produced maximum biogas yield are presented in Table 1.

Table 1. Experimental and ANFIS predicted results from the first three experiments

Runs	Experimentally Measured parameters				output	Fuzzy Logic optimized input parameters				output
	Temperature	pH	Mix ratio	HRT	Biogas Yield	Temperature	pH	Mix ratio	HRT	Biogas Yield
1	28	6.7	0.5:1	28	223	28	6.7	0.5:1	28	222
2	30	7.2	0.5:1	26	225	30	6.8	0.5:1	25	224
3	32	7.3	0.5:1	23	228	32	7.3	0.5:1	23	227
4	34	7.1	0.5:1	18	232	34	6.9	0.5:1	19	232
5	35	6.9	0.5:1	17	235	36	7.1	0.5:1	17	236
1	28	7.3	1:1	24	230	28	7.2	1:1	25	229
2	31	6.8	1:1	22	231	32	6.7	1:1	23	231
3	33	6.7	1:1	20	235	34	7.3	1:1	20	235
4	36	7.1	1:1	14	238	36	7.1	1:1	15	237
5	37	6.9	1:1	13	240	38	6.9	1:1	13	242
1	31	7.2	2:1	19	235	32	7.3	2:1	19	235
2	34	7.3	2:1	16	237	34	6.7	2:1	16	238
3	36	6.7	2:1	15	242	36	6.8	2:1	14	242
4	37	6.9	2:1	12	245	37	6.9	2:1	13	245
5	38	7.1	2:1	11	247	40	7.1	2:1	11	248

Figure 7a is a graphical representation of biogas yield and bio-digester temperature from experimental procedure and ANFIS model at different mix ratios. Also, Figure 7b is a graphical representation of biogas yield and HRT from experimental procedure and ANFIS model at different mix ratios. The experimental results revealed that optimum bio-digester temperature values in the range of 31-38 ^{o}C, optimum pH values in the range of 6.7-7.3, feedstock to water mix ratio of 2:1 and optimum HRT in the range of 11-19 days will yield maximum biogas quantity in the range of 235-247g. On the other hand, The ANFIS predicted results revealed that optimum bio-digester temperature values in the range of 32-40 ^{o}C, optimum pH values in the range of 6.7-7.3, feedstock to water mix ratio of 2:1 and optimum HRT in the range of 11-19 days will yield maximum biogas yield in the range of 235-248g. It can be observed that the values recorded for biogas yield from each of the first three experimental sets and ANFIS predicted model increased as the bio-digester temperature increased. Moreover, similar trend was observed as biogas yield also increased with increasing moisture content in the feedstock to water mix ratios. As shown in Figure 7b, increasing biogas yield were observed at decreasing HRT. This is because the bio-digester temperature which is observed in the mesophilic range is optimum for methane producing bacteria while volatile solids in the feedstock appeared to be adequate with high biodegradable content and low fraction of refractory volatile solid

(RVS). The abbreviations Ex represents experiment while Fz represents Fuzzy logic in Figure 7a-b.

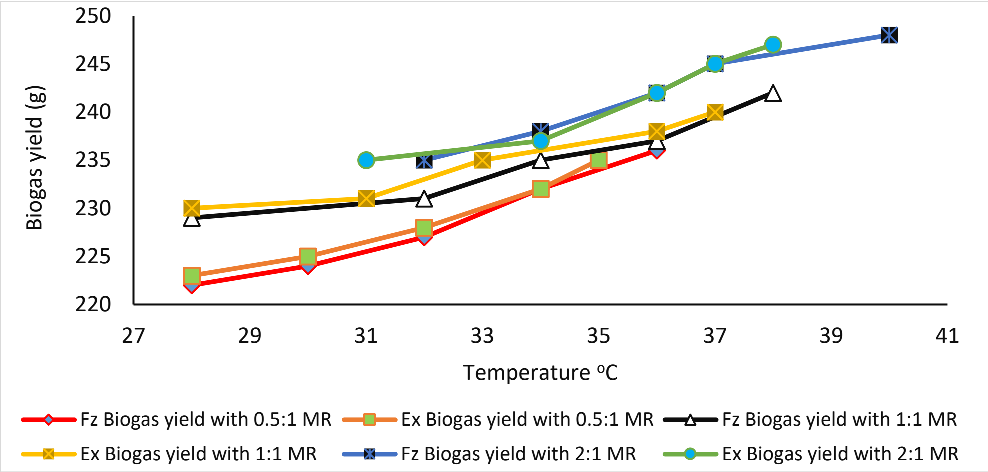


Figure 7a. Ex and Fz plot of biogas yield vs temperature at 0.5:1, 1:1 and 2:1 MRs

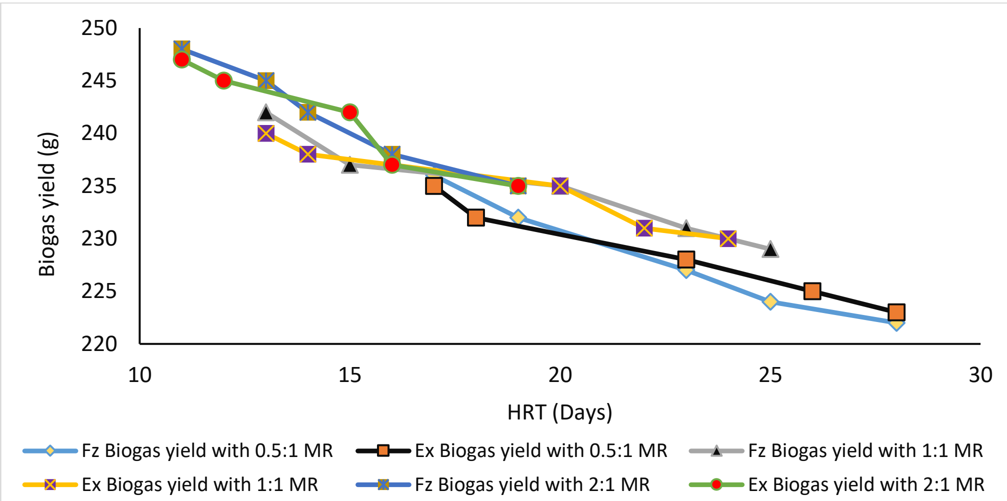


Figure 7b. Ex and Fz plot of biogas yield vs HRT at 0.5:1, 1:1 and 2:1 MRs

Table 2 shows optimum measured parameters from the experiment as well as optimum input parameters from the ANFIS model that produce maximum biogas yield. The results are from the last three experiments which all have different feedstock to water mix ratios of 2.5:1, 3:1 and 3.5:1. The experimental results revealed that optimum bio-digester temperature values in the range of 26-33 ºC, optimum pH values in the range of 6.7-7.2, feedstock to water mix ratio of 2.5:1 and optimum HRT in the range of 26-32 days yielded maximum biogas in the range of 60.2-70.6g. On the other hand, the Anfis predicted results revealed that optimum bio-digester temperature values in the range of 27-33 ºC, optimum pH values in the range of 6.7-7.3, feedstock to water mix ratio of 2.5:1 and optimum HRT in the range of 27-31 days yielded maximum biogas in the range of 61.3-71.5g.

Table 2. Experimental and ANFIS predicted results from the last three experiments

Runs	Experimentally Measured parameters				output	Fuzzy Logic optimized input parameters				output
	Temperature	pH	Mix ratio	HRT	Biogas Yield	Temperature	pH	Mix ratio	HRT	Biogas Yield
1	26	6.7	2.5:1	32	60.2	27	6.8	2.5:1	31	61.3
2	28	6.8	2.5:1	30	62.5	28	6.7	2.5:1	30	63.4
3	29	7.2	2.5:1	29	65.3	30	7.3	2.5:1	29	66.2
4	31	6.9	2.5:1	27	67.4	31	7.1	2.5:1	28	68.7
5	33	7.1	2.5:1	26	70.6	33	6.9	2.5:1	27	71.5
1	27	7.2	3:1	34	52.4	27	6.8	3:1	34	51.8
2	28	6.7	3:1	32	53.2	28	7.3	3:1	33	53.5
3	29	6.8	3:1	31	55.3	29	6.7	3:1	31	55.7
4	30	7.1	3:1	30	57.1	31	6.9	3:1	29	58.2
5	31	6.9	3:1	28	60.2	32	7.1	3:1	28	60.6
1	26	6.7	3.5:1	38	40.3	26	7.3	3.5:1	38	41.4
2	27	6.8	3.5:1	37	44.2	27	6.7	3.5:1	36	43.1
3	28	7.2	3.5:1	35	45.8	28	7.2	3.5:1	35	46.7
4	29	7.1	3.5:1	34	48.4	29	6.9	3.5:1	33	47.2
5	30	6.9	3.5:1	32	50.7	30	7.1	3.5:1	32	50.5

Figures 8a-b are graphical representation of biogas yield and bio-digester temperature as well as biogas yield and HRT from experimental procedure and ANFIS model at different mix ratios of 2.5:1, 3:1 and 3.5:1. Both Figures 8a-b are observed to exhibit the same trend as Figures 7a-b where biogas yield increased with increasing bio-digester temperature and decreased with decreasing HRT. Figure 9a-c represent surface plots for the input variables and output response from the ANFIS model at different mix ratios. The surface plot indicates that any change in the input variables will cause changes in the output response, and this can be observed on the colour profile where blue colour represents minimum output response (biogas yield while red colour represents maximum output response (biogas yield)

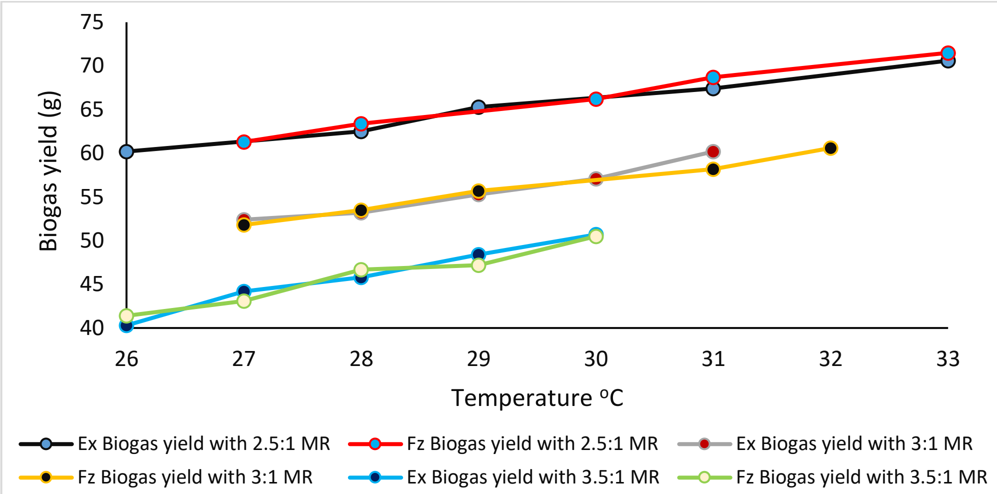


Figure 8a. Ex and Fz plot of biogas yield vs temperature at 2.5:1, 3:1 and 3.5:1 MRs

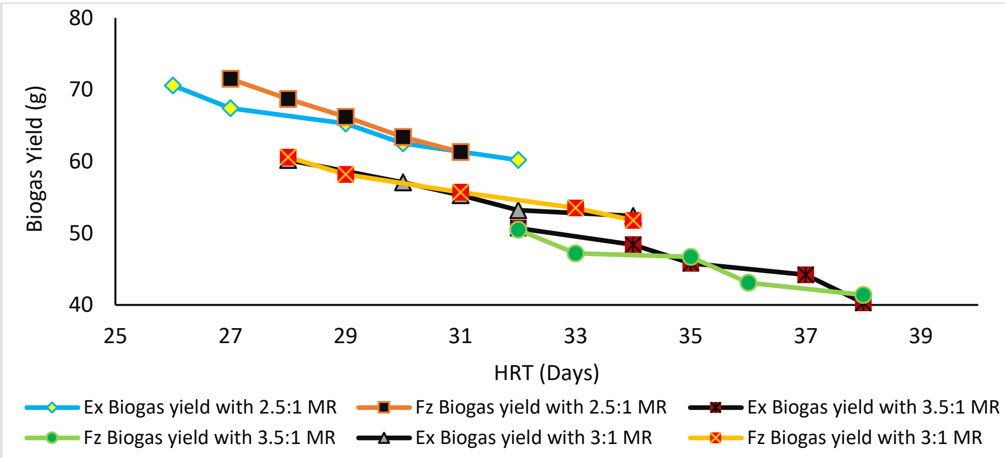
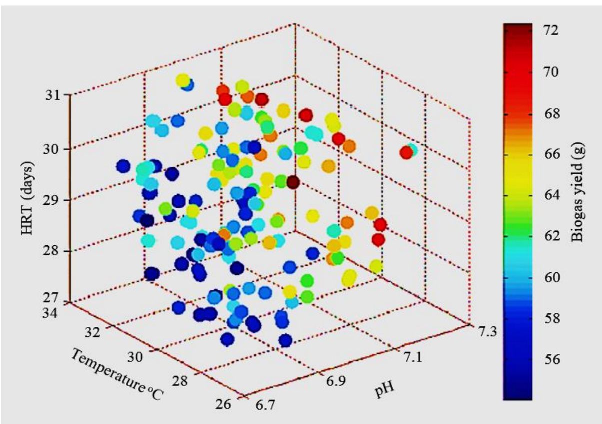
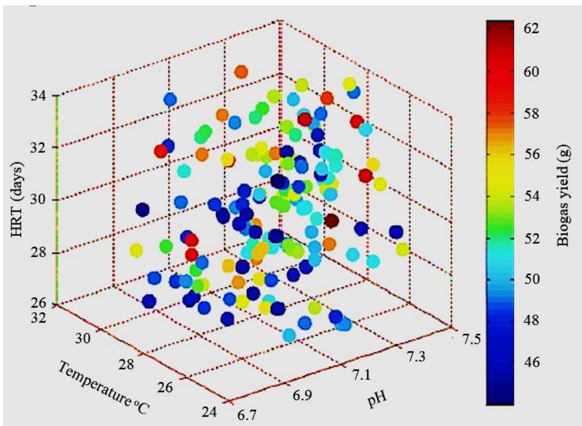


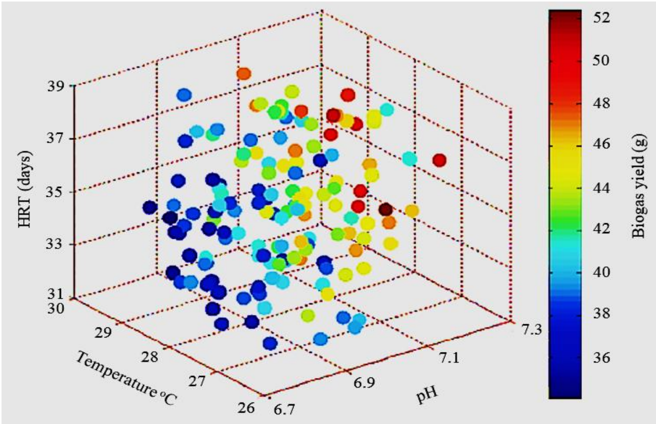
Figure 8b. Ex and Fz plot of biogas yield vs HRT at 2.5:1, 3:1 and 3.5:1 MRs



a. Mix ratio of 2.5:1



b. Mix ratio of 3:1



c. Mix ratio of 3.5:1

Figure 9. Surface plots showing effects of input on biogas yield at different mix ratios

5. CONCLUSION

Anaerobic co-digestion process parameters was successfully modelled and optimized in this study using adaptive neuro fuzzy inference system. There was correlation between the experimental and ANFIS predicted results in terms of maximum biogas yields which were 247g and 248g obtained at feedstock to water mix ratio of 2:1. In both the experimental process and the ANFIS modelling, the result indicated that selecting anaerobic digestion process parameters such as temperature in the range of 28-40^{o}C, pH in the range of 6.7-7.3, feed substrates and water mix ratio between 1:1 and 2:1 can attract a shorter HRT for desired biogas yield. The present study have shown bio-digester temperature to be a highly influential anaerobic digestion process parameter, as it accelerates substrate digestion and shortens HRT when optimum or prolongs substrate digestion and lengthens HRT when selected below optimum range. It was observed in all the six sets of experimental procedure as well as the ANFIS modelling that biogas yield increased and decreased in pari passu with biogas temperature. On the other hand, the same proportion of water and feedstock or optimum ratio is recommended for the feed substrate to water mix ratio. The present study revealed biogas yield to be optimum and maximum at feed substrate to water mix ratios of 1:1 and 2:1, while it also indicated gradual decline in biogas production rate (with increasing water content) at feedstock to water mix ratio of over 2.5:1 and above.

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